Energy Policy and Corporate Eco-Efficiency: Evidence from US Manufacturers

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Abstract

In the aftermath of the Energy Policy Act of 2005 (EPAct), the Energy Independence and Security Act of 2007 (EISA) introduced market-based instruments to boost efficient energy use and renewable fuel production. Following this event, my findings distinctly claim support of the "weak" form of the Porter hypothesis and an additional series of analyses using a market-based measure of firm competitiveness finds little evidence that invalidates the "strong" form of the hypothesis. In other words, EISA propelled the adoption of green innovative technologies and as a result despite the decreased near-term profitability observed in more eco-innovative firms, they correspondingly invested in R&D activities and were in parallel accompanied by positive abnormal returns over an extended period of time—thereby embedding eco-efficient aspects into their sustainable strategies and improving their shareholder values. Moreover, the 2007–2009 financial crisis hardly prevented larger firms from adopting these technologies, while small firms lagged behind in this space.

Keywords: Porter hypothesis, environmental regulation, innovation, financial crisis, EPAct 2005, EISA 2007

JEL Classification: G14, G30, K32, Q48, Q55

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1 Introduction

The energy transition to a carbon-neutral economy simultaneously calls for an efficient use of fossil fuel energy as well as a continuous shift to renewable energy and thus sound policymaking is becoming more and more indispensable. Accordingly, to better inform environmental and climate policies, it is imperative that policymakers understand the underlying incentive mechanism and expected repercussions of the policy instruments that can foster these transitions. In this regard, the "strong" form of the Porter hypothesis posits that a stringent and flexible environmental regulation can accelerate corporate innovation in the domain of competitiveness-enhancing technologies, the benefit of which can surpass short-run regulatory costs and in the end turn the all-embracing effect of the regulation into a net positive. To date, however, the empirical evidence on this hypothesis is mixed and remains to be explored.

Moreover, although the "weak" form of the Porter hypothesis states—and a wealth of related literature empirically validates—that environmental regulation is a driving force of eco-innovation,[1] the extant research on the direction and magnitude at which an economic downturn conjoins with a preceding environmental regulation is virtually nil. In other words, how does a recession moderate the relationship between the environmental regulation and innovation postulated by the Porter hypothesis? A recession wreaks havoc on the economy and adversely affects financial performance of firms. However, a newly established environmental policy may also provide an additional window of opportunity for firms to restructure and search for innovation strategies that are cost-efficient as well as eco-friendly, which might have been overlooked in a normal period of time. This can naturally translate into an accelerated long-term performance in the financial dimension along with the environmental dimension, thereby achieving *eco-efficiency*.

In this respect, the term eco-efficiency was originally coined by the World Business Council for Sustainable Development (WBCSD) and is defined to be achievable "by the delivery of competitively priced goods and services that satisfy human needs and bring quality of life, while progressively reducing ecological impacts and resource intensity throughout the life-cycle to a level at least in line with the Earth's estimated carrying capacity" (WBCSD, 2006). In essence, it is about creating more economic value with less ecological impact and is in fact becoming identical with a corporate philosophy striving for a winning combination of

[1]Oftentimes, the terms eco-innovation, environmental innovation, and green innovation are used synonymously (Schiederig, Tietze, and Herstatt, 2011). In this paper, I use *innovation*, *eco-innovation*, and *environmental innovation* interchangeably because innovation activities are assumed in the context of the Porter hypothesis and are thus specifically measured in the environmental dimension (see Table 3)

ecological and economic efficiency; moreover, this concept also resonates with the "strong" form of the Porter hypothesis.

Against this background, the objective of this paper is to explore the validity of the "weak" and "strong" forms of the Porter hypothesis and empirically identify the relationship between environmental regulation, innovation, and firm competitiveness. For this purpose, the US energy policy enacted in 2007, the Energy Independence and Security Act of 2007 (EISA), provides an ideal experiment. This is because EISA primarily tackles energy efficiency issues by introducing market-based instruments, which aims to make efficient use of fossil fuel energy sources and to produce more renewable energy. Alongside, it is also possible under this setup to evaluate the joint effect of EISA and the 2007–2009 financial crisis.

To undertake an empirical investigation, I construct my sample by drawing on CRSP/Compustat Merged database for market and accounting variables: I limit the firms to US-headquartered manufacturers over the period 2002–2017. Moreover, Thomson Reuters Refinitiv offers a platform for assessing corporate sustainability performance and I leverage this database to obtain CSR ratings. This platform specifically adopts a percentile-ranked scoring methodology within industry groups of Thomson Reuters Business Classification (TRBC), indicating that the scores can be viewed as a relative ranking within peer groups. In particular, I make frequent use of Innovation, Resource Use, and Emissions subscores throughout this paper that specifically capture the intensity of corporate responsibility in the environmental dimension.

First, in view of what the "weak" form of the Porter hypothesis posits, I empirically investigate whether firms boosted their eco-innovative capabilities following the enactment of EISA. Concerning the empirical identification, I leverage two approaches. With reference to the first approach using regressions with panel data, I circumvent the challenge in measuring the direct impact of EISA on eco-innovation; rather, I examine whether the relationship between eco-innovation and resource use or emissions management activities was strengthened thereafter. The main reason lies in the nature of the CSR ratings that Thomson Reuters provides, which is essentially a relative ranking within peer groups and thus is incapable of measuring the impact in absolute terms. In the second approach, I use a model-free method and visualize the time trends in the eco-innovative technologies adopted by firms where firms are classified into small, midsize, and large categories. As a whole, these empirical investigations result in an unambiguous confirmation of the "weak" form of the Porter hypothesis and also reveal that larger firms were quite resilient to the influence of the financial crisis, whereas small firms struggled to transition into a more environmentally-friendly paradigm.

Next, in relation to the "strong" form of the Porter hypothesis, I measure firm competitiveness based on stock market data; this contrasts with extant research whereby competitiveness has been measured by real measures such as productivity or financial measures such as price-cost margins or Tobin's Q. To be specific, owing to the fact that the impact of EISA was unlikely to realize instantaneously, I measure its impact by capturing the dynamics of stock returns as suggested by Schwert (1981), where the abnormal return is interpreted as the deviation from the normal return that the security would have otherwise realized without the regulation. I obtain regression estimates using (i) calendar time portfolio method, which is less sensitive to a poorly specified asset pricing model, as well as (ii) a pooled regression model using Fama-MacBeth estimation, which can mitigate the concern that the abnormal-returns resulted from a firm characteristic not captured by the risk factors. The findings strongly suggest that eco-innovation is positively linked to subsequent returns.

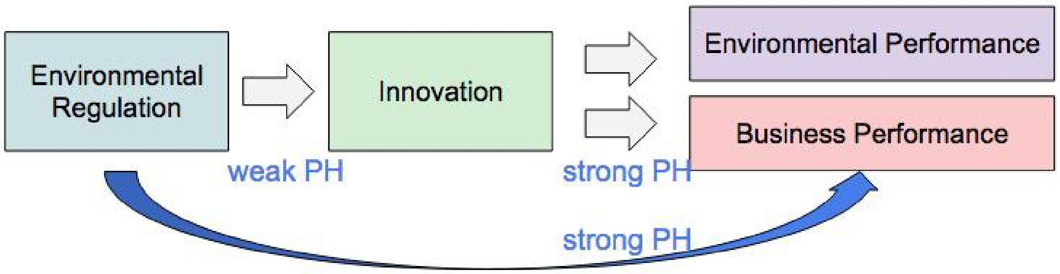
In this regard, it is imperative to elucidate the two fundamentally different interpretations concerning the positive link between eco-innovation and subsequent returns, especially because they have opposite implications for the validity of the strong PH. The first interpretation based on mispricing is that eco-innovation is value-relevant but the associated benefits (costs) are underestimated (overestimated) and this information is not impounded to the stock price; this implies that eco-innovation enhances shareholder value and thus conforms to the strong PH. The second interpretation based on risk is that eco-innovation is deemed risky with respect to the associated future cash flows, which translates into an increase in the discount rate and a drop in price; this indicates that eco-innovation reduces shareholder value and thus goes against the strong PH.

Extending this exploration, I inspect the sources of the superior returns vis-á-vis eco-innovation. First, I empirically probe whether highly eco-innovative firms were positively associated with operating performance after the enactment of EISA, thereby leading to positive abnormal returns. As a result, I find the opposite relationship, that is, eco-innovative firms were in fact negatively associated with operating performance in the post-EISA period. An additional analysis on the earnings announcement events proves that this negative relation was not surprising to the stock market participants. This result suggestively points to the possibility that superior returns were confirmed in highly eco-innovative firms because eco-innovation carries a premium for risk. Notwithstanding, this is not necessarily the case because operating performance is not the only channel that firms can improve their shareholder values. Thus, in light of the prior literature documenting mixed evidence on whether or, if so, how quickly, R&D information is capitalized by the stock market, I further examine the relationship between eco-innovation and R&D intensity in a similar manner employed in the operating performance analysis. As a result, a positive relationship between eco-innovation and R&D emerges in the post-EISA period. To directly test whether the excess returns observed in highly eco-innovative firms emerged from the mispricing channel, one would ideally examine the announcements on (i) a new R&D-intensive project or (ii) a change in R&D of a running project but the former is burdensome as it requires manual collection of announcement news and the latter is rarely announced. Therefore, I instead investigate whether eco-innovation affects expected returns, or cost of capital, through the risk channel, where risk is proxied by return volatility. My empirical findings suggest that eco-innovation is in fact associated with certainty after controlling for R&D intensity, which rather implies a decrease in cost of capital, although this link apparently weakened in the post-EISA period. Put differently, I find little evidence that disproves the strong PH.

In the end, I recapitulate three possible scenarios behind the observed positive link between eco-innovation and future returns: systematic mispricing, latent risk factor, and additionally a moderator. The last scenario is that the positive relation between eco-innovation and returns surfaces because an unobserved variable causes both and I show that this scenario is unlikely in Appendix E. However, I do not take a definite stand on which of these scenarios, especially the first two, is truly valid given the considerable effort additionally required. In particular, I note that an unambiguous confirmation of the strong PH can be achieved only if the excess returns are observed owing to mispricing and not owing to risk.

This paper especially adds to two strands of literature. The first strand is the studies on the nexus between environmental performance and financial performance. The notion that better environmental performance and better financial performance can co-exist has been proven resilient after a battery of tests including portfolio analyses, event studies, and long-term studies (Ambec and Lanoie, 2008). Additionally from a recent study, Shapiro and Walker (2018) show that air pollution emissions from US manufacturing firms dropped by 60% over the period 1990–2008 following a change in environmental regulation despite the substantial increase in production output. Guenster et al. (2011) advocate that firms promoting environmental policies have the potential to steadily benefit from intangibles (e.g., good management culture, technological innovation, brand), while environmental misconduct can immediately damage corporate reputation and profitability.

Figure 1: Porter hypothesis: "weak" and "strong" forms



(Source: Ambec et al. (2013); Lanoie et al. (2011))

Furthermore, the second strand of literature embraces the topic of corporate resilience in innovation capabilities amid economic downturns. For instance, Filippetti and Archibugi (2011) stress that about a two-thirds of the firms from Innobarometer survey surprisingly did not alter the trajectory of their investments in innovation even in the midst of the financial crisis. In a similar fashion, Thum-Thysen et al. (2017) report that unlike the investments in tangible assets, investments in intangible assets in the US and EU, over half of which constitute R&D, were substantively less depressed by the 2007–2009 financial crisis.

This paper is organized as follows. Section 2 outlines the theoretical framework of environmental innovation diffusion as well as the regulatory framework of the US energy policies enacted in the 2000s. Section 3 describes the scope of data used and the variable construction. Section 4 displays strong evidence that supports the "weak" form of the Porter hypothesis and also finds little evidence that invalidates the "strong" form of the Porter hypothesis. Section 5 concludes.

2 Theoretical and regulatory frameworks

2.1 Environmental innovation and Porter hypothesis

What is environmental innovation to begin with? Although there is no general consensus, one definition below provided by MEI Report (2008) is frequently cited by researchers. This definition of eco-innovation is results-oriented rather than motivation-oriented in the sense that the motive to reduce the ecological impact in a way that is novel to the firm is not a necessary condition.

> The production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a

reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives.

Moreover, while environmental innovation is known to be stimulated and determined by environmental regulation, there are other diverse channels that can foster and diffuse eco-friendly technologies and therefore the holistic landscape of eco-innovation determinants constitutes multi-dimensions. For instance, Horbach, Rammer, and Rennings (2012) separate the determinants of eco-innovation into four groups: firm specific factors, technology, market, and regulation, all of which can inform firm's decision to introduce a variety of eco-innovations in different ways. The authors further contend that environmental technology fields are disproportionately influenced by regulation and equally stress that even those among market-oriented technologies do not necessarily translate into an ideal environment free of government support since market failures are widespread. In this context, empirical literature suggests that market-based measures as a policy instrument are, if not definitive, decidedly more effective than command-and-control measures in promulgating the cost-effective adoption and diffusion of innovative technologies (Jaffe, Newell, and Stavins, 2003). In a similar fashion, Oltra (2008) warns that regulation, albeit crucial, is not the only systemic factor attributed to environmental innovations and thus it is essential to underline the equally important role of supply and demand-side determinants. Nonetheless, the border between the regulation and market forces blurs if the regulation is founded on market-based interventions rather than command-and-control based measures.

In relation to environmental regulation, what has since become known as the Porter hypothesis (Porter and van der Linde, 1995) posits that environmental regulation can—if well-designed in its stringency as well as flexibility—foster firms to lead innovation in the area of competitiveness-enhancing technologies, the benefit of which can outweigh short-run regulatory costs and eventually turn the total effect of the regulation into a net positive. To be specific, the Porter hypothesis advocates flexible market-based environmental regulation—such as environmental taxes and tradable permits—and does not in principal embrace inelastic command-and-control type regulation (Lanoie et al., 2011; Ambec et al., 2013). This hypothesis runs counter to a traditional trade-off view in which regulatory mandates would compel firms to allocate labor or capital inputs to pollution abatement, leading to incremental societal welfare at the expense of private costs imposed upon firms. Notwithstanding, studies such as Tobey (1990) and Jaffe et al. (1995) find little evidence that tighter environmental regulations significantly reduce competitiveness, possibly attributed to the small costs for complying with pollution standards.

On a more technical level, the "weak" version of the Porter hypothesis (henceforth weak PH) relates to the dynamics that environmental regulation triggers innovation, which corresponds to the left middle area of Figure 1.[2] Furthermore, the "strong" version of the Porter hypothesis (henceforth strong PH) centers on the interconnection between environmental regulation and competitiveness, proposing that regulation-induced innovation (i.e., indirect channel) will offset the compliance cost of environmental regulation (i.e., direct channel): this concept maps onto the entire flowchart in Figure 1. To date, however, the empirical evidence especially linked to the strong PH is still vastly mixed and left inconclusive.

2.2 Energy Independence and Security Act of 2007

A series of energy policies has been approved by the U.S. Congress in the first decade of the 21st century.[3] Especially, following the Energy Policy Act of 2005 (EPAct 2005), EISA 2007 was designed to minimize the dependence on traditional energy resources and achieve energy security—this was effectively in response to (a) the unstable price fluctuation of oil and natural gas as well as the geopolitical risk in relation to the Middle East and (b) the climate change risk (ACEEE, 2015). Table 1 outlines the regulatory framework of EISA 2007 and EPAct 2005.

Although EISA 2007 and EPAct 2005 are both energy policies, the objectives substantively differ. On the one hand, EISA 2007 specifically aims to (i) make efficient use of fossil fuel energy sources (e.g., Title I, III, IV) and (ii) to produce more renewable energy such as biofuels, solar, and geothermal (e.g., Title II, VI). As a result, the regulatory standards of EISA facilitated product innovation and induced performance improvement. For instance, the fuel economy of corporate, residential, and federal vehicles was greatly enhanced (Title I). Especially, Corporate Average Fuel Economy (CAFE) credit trading provisions is a fuel economy credit transferring program and a quintessential example of the market-based instruments. Another example is the increase in light bulb energy efficiency (Title III). Initial standards for general service incandescent lamps (GSILs), which came into force around 2012–2014, replaced traditional incandescent light bulbs with more efficient halogen models.

On the other hand, the main objective of EPAct 2005 was to combat growing energy

[2]Originally, Jaffe and Palmer (1997) proposed "weak," "narrow," and "strong" version of the Porter hypothesis.

[3]To be specific, the Energy Policy Act of 2005 (EPAct 2005); the Energy Independence and Security Act of 2007 (EISA); the Energy Improvement and Extension Act (EIEA), enacted as Division B of the Emergency Economic Stabilization Act of 2008 (EESA); and the American Recovery and Reinvestment Act (ARRA) (Congressional Research Service, 2020).

Table 1: Regulatory framework of EISA 2007 and EPAct 2005

Panel A and Panel B partly report the regulatory framework of EISA 2007 (Title I to Title XIII) and EPAct 2005 (Title I to Title XVI), respectively.

Panel A: Energy Independence and Security Act of 2007

Title I	Energy Security through Improved Vehicle Fuel Economy
Title II	Energy Security through Increased Production of Biofuels
Title III	Energy Savings through Improved Standards for Appliance and Lighting
Title IV	Energy Savings in Buildings and Industry
Title V	Energy Savings in Government and Public Institutions
Title VI	Accelerated Research and Development
Title VII	Carbon Capture and Sequestration
Title VIII	Improved Management of Energy Policy
Title IX	International Energy Programs
Title X	Green Jobs
Title XI	Energy Transportation and Infrastructure
Title XII	Small Business Energy Programs
Title XIII	Smart Grid

(Source: U.S. Government Printing Office (2007))

Panel B: Energy Policy Act of 2005

Title I	Energy Efficiency
Title II	Renewable Energy
Title III	Oil and Gas
Title IV	Coal
Title V	Indian Energy
Title VI	Nuclear Matters
Title VII	Vehicles and Fuels
Title VIII	Hydrogen
Title IX	Research and Development
Title X	Department of Energy Management
Title XI	Personnel and Training
Title XII	Electricity
Title XIII	Energy Policy Tax Incentives
Title XIV	Miscellaneous
Title XV	Ethanol and Motor Fuels
Title XVI	Climate Change

(Source: U.S. Government Printing Office (2005)) supply problems by providing tax incentives and loan guarantees for energy production of various types. Notwithstanding, EPAct 2005 does include provisions in support of energy efficiency primarily in the residential, commercial, and transportation sectors (ACEEE, 2015) following the Energy Policy Act of 1992 (EPAct 1992). Furthermore, to stimulate the economy distressed by the financial crisis, American Recovery and Reinvestment Act of 2009 (ARRA) injected $43 billion into renewable energy and energy conservation programs authorized in EISA (U.S. Government Printing Office, 2009; ACEEE, 2015; Wright and Boorse, 2017). Although the goal of doubling the energy from renewable sources by 2012 was not fully realized, the use of renewable energy was nevertheless greatly propelled.

3 Data and descriptive statistics

My sample draws on CRSP/Compustat Merged (CCM) database for market and accounting data. I limit my sample to US-headquartered manufacturers (SIC 4-digit code: 2000–3999) over the period 2002–2017. Thomson Reuters offers a platform, Thomson Reuters Refinitiv, for evaluating corporate sustainability performance and I use this database to obtain CSR data, which was retrieved in September 2019. I merge Refinitiv database with CCM database using CUSIP and fiscal year information: the summary statistics are shown in Table 2. Thomson Reuters adopts a percentile-ranked scoring methodology within industry groups of Thomson Reuters Business Classification (TRBC).[4] Ultimately, the composite metric ESG score is calculated based on 178 underlying metrics grouped into three pillar scores and 10 subscores. Table 3 presents the CSR ratings framework together with the weighting scheme and calculation methodology.

Moreover, to construct financial constraint measures, KZ and WW indexes, I follow Farre-Mensa and Ljungqvist (2016). Consistent with extant literature, firms are sorted into tertiles based on the index values in the previous year. Least constrained firms are classified to tertile 1 (T1) group, while the most constrained firms are classified to tertile 3 (T3) group. Moreover, I construct additional variables related to accounting information that may have power for explaining firms' resource use or emissions activities: revenue, sales growth, ROA, and total assets. ROA is the income before extraordinary items (ib) over total assets (at). Sales growth is the annual increase in sales, $sale_{i,t}/sale_{i,t-1} - 1$, using item *sale*. Revenue is the total revenue ($revt$) in logarithm and total assets (at) is in the form of logarithm as well.

[4]TRBC classifies companies at five levels: 13 economic sectors, 33 business sectors, 62 industry groups, 154 industries, 898 activities. Thus the number of TRBC industry groups are comparable with that of industries classified by SIC 2-digits.

For convenience, I base firm size on market capitalization and classify them into tertiles by taking the average firm size throughout the sample period 2002–2017 and then rank them, thus assigning a time-invariant size label to each firm. Admittedly, there are a few shortcomings in this strategy. First, the possibility cannot be ruled out that firms change their size groups in reality. Second, the number of firms in a given year is not equally divided into three groups in general. It is thus appealing to dynamically classify firms by considering the cross-section for each year, in which case three firm size groups with equal number of observations are by design ensured in any given year. Nonetheless, I avoid this method because it is less transparent in capturing the dynamics of subscore transitions (Appendix A) whereby subscores are relative percentile within TRBC industry groups for a given year. Table 4 presents the breakdown of Innovation subscore distribution into firm size groups: larger firms exhibit a tendency to be assigned with a higher score.

On a different note, the data obtained from CCM database suggest that no manufacturers received funding in the form of government grants: the item Government Grants (GOVGR) represents accumulated, unamortized grants, and subsidies received from central authorities. This is in line with the fact that some programs in EISA provisions were never funded in the first place (e.g., Energy Sustainability and Efficiency Grants and Loans for Institutions, Waste Energy Recovery Incentive Grants) (ACEEE, 2015).

Table 2: Summary statistics of variables in the initial sample

This table reports the summary statistics of the data set used in the initial sample. In constructing financial constraint measures, firms are sorted into tertiles based on the index values in the previous year. Least constrained firms are classified to tertile 1 (T1) group, while the most constrained firms are classified to tertile 3 (T3) group. The table show the values before winsorizing accounting variables. ROA is the income before extraordinary items (*ib*) over total assets (*at*). Sales growth is the annual increase in sales, $sale_{i,t}/sale_{i,t-1} - 1$, using item *sale*. Revenue is the total revenue (*revt*) in logarithm and total assets (*at*) is in the form of logarithm as well.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Innovation	50.40	25.10	0.40	2.80	33.00	50.00	67.90	98.30	99.80	5756
Resource Use	47.60	28.20	0.30	5.40	25.00	43.00	72.10	99.00	99.80	5756
Emissions	46.20	28.00	0.20	1.50	23.70	41.10	69.60	98.90	99.80	5756
KZ Index (T1)	0.26	0.44	0.00	0.00	0.00	0.00	1.00	1.00	1.00	5756
KZ Index (T2)	0.40	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00	5756
KZ Index (T3)	0.21	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00	5756
WW Index (T1)	0.61	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00	5756
WW Index (T2)	0.22	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00	5756
WW Index (T3)	0.12	0.33	0.00	0.00	0.00	0.00	0.00	1.00	1.00	5756
Log Revenue	7.94	1.83	-6.91	1.51	7.22	8.07	8.93	11.77	12.98	5695
Sales Growth	0.56	13.86	-1.00	-0.55	-0.02	0.06	0.15	2.12	710.68	5588
Log Total Assets	8.23	1.50	2.73	4.53	7.39	8.20	9.12	11.98	12.84	5756
ROA	0.03	0.20	-6.47	-0.71	0.02	0.06	0.10	0.29	1.25	5756

Table 3: CSR ratings framework and subscore computation

The table below reports the CSR ratings framework from Thomson Reuters.

Total Score				
	Pillar Score			Pillar Weights
		Subscore	Subscore Weights	
ESG	Environmental	Resource Use	11%	34%
		Emissions	12%	
		Innovation	11%	
	Social	Workforce	16%	35.50%
		Human Rights	4.5%	
		Community	8%	
		Product Responsibility	7%	
	Governance	Management	19%	30.50%
		Shareholders	7%	
		CSR Strategy	4.50%	

To compute the 10 subscores, dozens of element metrics (mostly boolean values but some also taking numeric values) serve as building blocks. For instance, elements such as Environmental Products (boolean value) or Fleet CO_2 Emission (numeric value) are under the umbrella of Innovation subscore (see Appendix B for details). Subscores are relative percentile ranks within an TRBC industry group in a given year and the following percentile score formula is applied specifically—a subscore is constructed by transforming an equally-weighted average of element-level percentiles into one representative percentile using equation (1), where each element-level percentile is also produced by the formula starting from either a boolean (1 or 0) or numeric value:

$$percentile = \frac{\sharp\, with\, worse\, values\, than\ X\, in\, Y}{\sharp} + 0.5 \times \frac{\sharp\, with\, same\, value\, with\ X\, in\, Y}{\sharp} \tag{1}$$

where $\sharp$ stands for the number of peer firms within an industry group. Intuitively, this formula can be linked to empirical distribution function $F(\cdot)$. One can compute the area left to firm X by computing the first term and then adjust this value by adding the second term: note that (i) the coefficient 0.5 is convenient since if all firms in industry Y have the same value they all achieve 50th percentile, and (ii) firm X itself is included in the numerator of the second term so that *percentile* is always above zero.

I demonstrate how to compute Innovation subscore of firm X in three steps. First, *percentile* is computed for each element in the Innovation (e.g., Environmental Products) using equation (1): this results in element-level percentiles available for all Innovation elements of all firms in industry Y. Second, for each firm in Y, the average (sum) of *percentile* over all elements in Innovation category is taken to compute *average (sum) of percentiles*—whether taking average or sum does not alter the final result. Lastly, one achieves Innovation subscore for firm X, by feeding the cross-sectional information of *average (sum) of percentiles* into the formula in equation (1). On a side note, Appendix D addresses the systematic percentile miscalculation observed in May 2020.

(Source: Thomson Reuters (2017, 2018, 2019, 2020))

Table 4: Manufacturers' trends in firm-year observations and Innovation subscore by firm size

This table reports the trends in the number of US-headquartered manufacturers and its Innovation subscore by year and firm size tertiles from the data set used in Tables 5–8. The sample—in the table below as well as visualized in Figures 9– 12 in Appendix C—is constructed by merging Innovation subscore with the entire universe of US-headquartered manufacturers provided by CRSP/Compustat Merge database via CUSIP number.

Midsize and large firms exhibited in Panels B and C clearly increased environmental innovation score in the post-crisis period, whereas the effect on small firms in Panel A is more obscure. It should not escape our attention, however, that subsamples in each tertile size-category are not uniformly distributed over time, not only because market capitalization is time-variant but there is a new firm-entry every year due to the firm universe expansion of Thomson Reuters Refinitiv database.

	Panel A: Small manufacturers						**Panel B: Midsize manufacturers**						**Panel C: Large manufacturers**						**Total**
	Obs.	Min	25th	50th	75th	Max	Obs.	Min	25th	50th	75th	Max	Obs.	Min	25th	50th	75th	Max	**Obs.**
2002	24	7.1	39.3	45.7	48.7	69.4	60	15.0	45.7	50.0	53.6	96.2	84	3.8	45.1	50.0	53.8	97.8	168
2003	22	25.0	40.0	45.7	50.0	66.1	61	20.0	45.0	50.0	50.0	81.6	86	15.4	42.3	50.0	53.2	96.4	169
2004	28	12.5	41.7	45.8	50.0	72.3	82	11.0	45.8	50.0	52.1	97.9	101	2.1	43.5	50.0	51.1	99.3	211
2005	32	16.7	35.0	47.9	50.0	73.1	88	5.8	46.4	50.0	55.8	98.2	117	5.8	38.9	50.0	55.8	97.9	237
2006	31	13.1	33.5	49.0	50.0	86.2	88	2.9	36.7	49.0	63.5	98.3	120	5.4	36.3	50.0	63.5	98.2	239
2007	29	10.7	30.4	33.0	50.0	97.9	95	2.4	30.4	47.0	63.3	97.9	121	0.7	31.7	51.4	79.2	99.4	245
2008	43	1.5	20.8	37.0	57.5	95.8	123	2.5	23.2	43.2	75.5	98.1	126	4.2	34.6	58.1	84.0	99.4	292
2009	66	1.4	22.1	46.8	61.3	97.4	141	2.2	26.2	44.3	66.7	98.2	126	4.6	37.2	66.7	84.8	99.5	333
2010	79	1.3	24.7	45.0	71.2	98.5	144	8.5	28.6	49.4	74.4	98.4	128	4.5	41.0	66.6	86.4	99.6	351
2011	78	1.2	25.0	48.2	70.8	99.2	143	7.4	30.7	46.4	72.1	98.3	126	5.4	42.7	69.6	85.2	99.6	347
2012	74	1.2	22.9	46.8	67.1	99.2	141	5.8	29.5	48.3	69.3	98.3	126	4.7	44.0	66.7	85.7	99.6	341
2013	72	1.2	22.2	48.6	67.9	99.2	138	6.3	31.2	47.7	71.9	98.4	128	4.3	42.9	66.3	87.3	99.6	338
2014	72	1.2	22.8	52.2	67.8	99.2	134	6.9	34.7	52.8	72.0	99.0	128	1.6	40.3	64.2	86.9	99.6	334
2015	233	0.6	24.2	50.0	50.0	99.5	173	1.6	26.2	49.6	68.2	99.7	133	0.5	39.6	63.4	81.9	99.7	539
2016	500	0.4	22.9	49.4	53.3	99.6	175	3.1	30.1	54.5	69.8	99.7	132	0.4	41.1	65.3	86.7	99.7	807
2017	536	0.4	23.8	50.0	54.1	99.7	147	0.5	34.1	57.7	70.0	99.8	122	1.1	41.7	66.6	89.7	99.4	805

4 Corporate environmental-financial performance

I demonstrate in this section that EISA 2007 played a crucial role for promulgating eco-friendly technologies among firms, thereby augmenting their green orientation and status. In doing so, this shift in eco-innovation regime exerted substantial influence on the cross-section of returns and corporate performance. This section proceeds as follows. In Section 4.1, I confirm the weak PH by estimating a panel regression model—that the regime shift in corporate eco-innovative strategies occurred following the enactment of EISA. I simultaneously take a model-free approach and verify that the dynamics of technology diffusion are indeed in correspondence to the regulatory scheme of EISA outlined in Section 2.2. In Section 4.2, I discuss the scheme of the strong PH together with firm competitiveness measure. In Section 4.3, I investigate the magnitude and period over which eco-innovative firms experienced excess returns. In Section 4.4 and 4.5, I inspect the channel of excess returns from the perspective of operating performance and R&D activities, respectively. Section 4.6 debates the rationale behind the observed excess returns.

4.1 The green shift in corporate innovation strategies

To test the weak PH, extant research predominantly used R&D activities or the number of registered patents as a proxy for innovation (Ambec et al., 2013). In this paper, in contrast, the weak PH is evaluated by different approaches. Specifically, I draw on the aforementioned definition of eco-innovation (MEI Report, 2008)[5] in Section 2.1 and take a regression approach as well as a model-free approach to the assessment of the weak PH.

With respect to the regression approach, I side-step the difficulty of directly measuring the impact of EISA on environmental innovation and instead examine whether the relationship between environmental innovation and resource use or emissions management activities was strengthened thereafter. The reasoning is the following. In response to an external regulatory shock, firms are anticipated to alter their environmental innovation strategies thereby shifting the eco-innovation regime. In this respect, although a range of environmental innovation activities could possibly be triggered by EISA, an identification strategy only centering on Innovation subscore is challenging given the nature of its relative ranking (i.e., percentile) measure. In other words, (i) Thomson Reuters database constructs its own

[5]Environmental innovation is stipulated as a process or product that can be associated with more resource efficiency or less pollution (MEI Report, 2008). This is in line with the definition of Innovation subscore (e.g., Thomson Reuters, 2019) i.e., “a company’s capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products.”

CSR ratings and assigns relative scores (i.e., percentile ranking) to firms within the same TRBC industry groups but (ii) all firms in a given industry-year can ramp up their innovation activities in the environmental domain in response to an regulation or a technology shock, and thus their Innovation subscore can remain unchanged. Figure 5 in Appendix A precisely illustrates that the percentile ranking distribution is flat over time for any given environment-related subscore.

As regards the model specification, I estimate the panel regression model with fixed effects in equation (2) for each subperiod, pre-EISA (2002–2006) and post-EISA (2007–2017).[6] I do not expect EPAct 2005 had material influence on firms' eco-efficiency because (i) it was EISA 2007 that vehemently tackled energy efficiency and sought renewable energy as alternative sources unlike EPAct 1992 or EPAct 2005 (ACEEE, 2015, p. 1) and (ii) Appendix C empirically verifies this point confirming that variation in the elements of Innovation subscore is moderate at best before 2007. Additionally, there are two accounts for the reason post-EISA period starts from 2007 as opposed to 2008, when the legislation truly became effective: first, firms might have anticipated and proactively initiated green investments before its enactment in December 2007, because EISA passed the House and the Senate in January 2007 and June 2007, respectively; second, although over 74% of the firm-year observations in my sample exhibit fiscal year end in December, around 10% of the observations have the fiscal year end month lying between January and May, indicating that these data in fiscal year 2007 include the early months of calendar year 2008. Not surprisingly, firms do display a swift response to EISA from fiscal year 2007 as exhibited in Appendix C.

$$y_{i,j,t} = \beta_0 + \beta_1 \,\mathrm{Innovation}_{i,t} + b'\mathrm{X}_{i,t} + \alpha_i + \alpha_{j,t} + \varepsilon_{i,j,t} \tag{2}$$

Now, the dependent variable $y_{i,j,t}$ in equation (2) is either Resource Use or Emissions subscore. The variable of interest is $\mathrm{Innovation}_{i,t}$ and I expect that $\beta_1 > 0$ holds in the post-EISA period. The premise that Innovation and Resource Use (Emissions) are not endogeneously determined may appear strong but I posit that it is not entirely unrealistic inasmuch as this assumption is predominantly tied to the post-EISA period as opposed to an unconditional time horizon. Besides, note that I do not rule out the possibility that the *lagged* Resource

[6] Alternatively, introducing an interaction term between Innovation subscore and post-EISA dummy over the full sample period 2002–2017 is thinkable but I do not adopt this strategy. This is because industry-specific year fixed effects need to be included so as to (i) account for the (annually-varying) heterogeneity across industries, (ii) control for cross-sectional dependence within industries (e.g., Abadie et al., 2017), and (iii) meaningfully interpret Innovation, Resource Use, and Emissions subscores, which are essentially relative rankings within peer groups. However, the inclusion of the industry-specific year fixed effects will also remove the necessary variation between pre-EISA and post-EISA period that is to be exploited.

Use or Emissions, which can proxy for firms' knowledge of environmental technologies, is a determinant of Innovation—Cañón-de-Francia, Garcés-Ayerbe, and Ramírez-Ales (2007) plausibly stress that firm-specific technical knowledge moderates the effect of a new environmental regulation.

With regards to control variables $X_{i,t}$, I specifically control for lagged financial constraint measures by using KZ and WW indexes because the wealth of internal sources could play an essential role in implementing innovative strategies especially surrounding the financial crisis period (Filippetti and Archibugi, 2011; Archibugi, Filippetti, and Frenz, 2013). In addition, I control for firm characteristics such as sales growth, revenue, ROA, and total assets: these variables are winsorized at the 1st and 99th percentile. Industry-specific year fixed effects $\alpha_{j,t}$ are specified by the interaction of industry (SIC 2-digit) and fiscal year and I also include firm-fixed effects α_i. For additional interest, I further investigate three variations that deviate from the baseline case. First, to specifically highlight the eco-innovation pursuits during the financial crisis, I replace post-EISA period 2007–2017 with the period 2007–2009 and term it as crisis period. Second, to mitigate the endogeneity concern arising from the potential reverse causality running from Resource Use (Emissions) to Innovation, I lag Innovation for one period (i.e., $\text{Innovation}_{i,t-1}$) in equation (2). Third, I divide the firm size into three groups (i.e., small, midsize, large) and separately estimate the regression model for each size group.

I present the estimated results in Tables 5–8. The baseline case presented in Table 5 confirms that corporate innovation strategies became significantly aligned with better management of resource use and emissions activities in the post-EISA period. Regarding the magnitude of the coefficients, for instance, a one-standard-deviation increase in the Innovation (25.1) is associated with 2.53 (2.33) point increase in Resource Use (Emissions). The magnitude per se is not remarkable but the results are reasonably interpretable owing to the fact that Innovation is composed of miscellaneous elements, a large portion of which is orthogonal to activities captured by Resource Use (Emissions): I relegate the details of subscore elements to Appendix B. Moreover, the extent to which corporate innovation activities are hampered by financial constraints likely depends on the firm size. Overall, Table 5 does not confirm the negative effect of financial constraints on adopting better resource use and emissions related technologies. Table 6 further shows regression estimates after lagging Innovation for one period (i.e., $\text{Innovation}_{i,t-1}$) in equation (2) and re-estimating the regressions. Besides, while Table 7 displays that firms apparently increased Resource Use except for small firms in the post-EISA period, Table 8 shows that all size groups of firms increased Emissions. On a related note, Figures 6–8 in Appendix A present the dynamics of Innovation, Resource Use, and Emissions over the period 2002–2017. Firm size groups are based on 2006, the year prior to the enactment of EISA 2007. Using 2006 as a baseline year, new firm entries are prohibited in any given year and therefore the figures only feature the cross-section of firms that existed in 2006. Overall, these figures show that large firms particularly augmented their greenness following EISA and reinforce the regression estimates in Tables 5–8.

Now, I account for the model-free approach. If EISA is genuinely the driver of the eco-innovation regime shift observed after 2007, one would naturally anticipate that the diffusion of these technologies occurred in correspondence to the regulatory framework of EISA. Thus, I further seek evidence using data points granular than the Innovation subscore. Figures 9–12 in Appendix C present the cumulative trends of elements that belong to the umbrella of Innovation subscore and represent innovative technologies apiece. I further categorize the diffusion level of the adopted technologies into three groups (i.e., intensive, moderate, limited) and also show the trends by the firms size group (i.e., large, midsize, small) that adopted the technology: the diffusion level is simply based on the firm counts that adopted the corresponding technology. This classification procedure, albeit not rigorous, can help capture the overarching landscape of the shift in eco-innovation regime and, as a result, I find supporting evidence that the outcome of technologies following 2007 was a swift and dynamic response to EISA 2007. In contrast, EPAct 2005 does not seem to have strongly channeled eco-innovation towards better energy use or emission.[7]

Finally, I feature the role that the financial crisis played in the crisis period. I argue in this regard that an economic crisis can, on top of its detrimental effect on economy, also possibly bring an opportunity to facilitate productivity and strategies at the firm, industry and national level—albeit seemingly contradictory. This is especially because a strand of studies documents that cost-efficiency is the de facto motivation for firms to go green, in particular adopting cleaner production technologies in lieu of end-of-pipe technologies (e.g., Frondel, Horbach, and Rennings, 2007; Horbach, 2008; Florida, 1996). Therefore, the financial crisis may have fostered, rather than stifled, the diffusion of new technologies especially among midsize and large manufacturers following EISA—this is even more so if environmental regulation can reduce the uncertainty and promote investments (Porter and van der Linde, 1995). Accordingly it is an empirical question whether corporate managers

[7]This pattern is in agreement with its regulatory design promoting energy supply diversification (e.g., decreasing the dependence on foreign energy supplies) rather than energy efficiency (ACEEE, 2015).

attempt to (i) tap into cost-saving technologies with growth potential that are advocated by the government programs and are expected to generate cash flows in the future or (ii) delay the adoption in the face of financial constraints together with the uncertainty exacerbated by the financial crisis. These possibilities may explain the observed disproportional patterns across firm size groups regarding the technology adoption triggered by EISA.

Indeed, my empirical results find some evidence in support of this debate. For instance, in Table 5, although the coefficients on the financial constraints overall shift to negative and the magnitude intensifies during the crisis period in comparison to the pre- or post-EISA period, the statistical significance is either insignificant (KZ index) or only significant at the 10% level (WW index). Moreover, Figures 9–12 in Appendix C show that midsize and large manufacturers seem to have reacted quickly to EISA amid the financial crisis and adopted innovation technologies. Thus, these figures illustrate that even during the crisis, the diffusion of environmentally-friendly technologies can continue especially with respect to larger firms, while small firms seem to be lagging in the adoption of technologies.

In further justification of my argument, extant research in line with my results can be found. Filippetti and Archibugi (2011) stress that about 65 percent of the firms from Innobarometer survey surprisingly did not alter the trajectory of their investments in innovation even in the midst of the financial crisis. In a similar vein, Thum-Thysen et al. (2017) report that investments in intangible assets in the US and EU, over half of which consist of R&D, were significantly less depressed by the 2007–2009 financial crisis unlike the investments in tangible assets.[8] Moreover, while small firms may take the leading role in creating a new market opportunity according to Schumpeter, larger firms (or their suppliers) can also be the lead innovator in traditional industries (Oltra, 2008). Archibugi, Filippetti, and Frenz (2013) showcase a different flavor and claim that during a normal period incumbent firms are likely to expand innovation investment, whereas in the face of the crisis and thereafter small firms invest more in innovation to exploit the opportunity endowed by the economic shock. Admittedly, these findings cannot be reconciled with my findings, yet their argument is devoid of environmental regulation.

[8]Note that, as per innovation captured by R&D activities, Archibugi, Filippetti, and Frenz (2013) claim that R&D expenditures are incapable of systematically capturing short-term responses to the financial crisis because (i) R&D projects are typically commitments made for several years and (ii) R&D is concentrated in a fraction of firms and sectors.

Table 5: The shift in manufacturers' eco-innovative strategies towards resource use and emissions

The estimated results of the following regression models are presented below. The dependent variable in Panel A and Panel B is Resource Use and Emissions, respectively. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 (2007–2009) is termed as post-EISA (crisis) period.

	Panel A: Resource Use						**Panel B: Emissions**					
	Pre-EISA		Post-EISA		Crisis		Pre-EISA		Post-EISA		Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation	0.063	0.063	0.101***	0.101***	0.134***	0.133***	0.071	0.077	0.093***	0.093***	0.106**	0.110**
	(0.880)	(0.877)	(3.624)	(3.615)	(2.740)	(2.679)	(1.096)	(1.232)	(3.794)	(3.797)	(2.396)	(2.400)
KZ Index (T1)	2.131		0.879		-2.674		1.433		0.638		-2.614	
	(0.634)		(0.505)		(-0.849)		(0.343)		(0.455)		(-0.671)	
KZ Index (T2)	0.362		-0.166		-3.073		1.007		-0.018		-1.900	
	(0.105)		(-0.098)		(-1.048)		(0.305)		(-0.013)		(-0.538)	
KZ Index (T3)	3.403		0.261		-3.833		4.586		0.470		1.617	
	(0.918)		(0.152)		(-1.274)		(1.200)		(0.312)		(0.431)	
WW Index (T1)		10.470		1.410		-7.523		7.802		-0.197		-13.930*
		(1.460)		(0.820)		(-1.647)		(1.402)		(-0.113)		(-1.715)
WW Index (T2)		8.597		1.305		-4.368		2.838		-0.850		-16.018*
		(1.157)		(0.823)		(-0.920)		(0.452)		(-0.485)		(-1.792)
WW Index (T3)		12.261		1.497		-5.007		2.671		-0.849		-12.007
		(1.511)		(0.984)		(-1.054)		(0.388)		(-0.459)		(-1.385)
Log Revenue	2.672	3.072	1.267	1.220	-0.921	0.368	1.632	0.752	9.081***	9.050***	5.148	6.324
	(0.666)	(0.761)	(0.804)	(0.764)	(-0.250)	(0.098)	(0.351)	(0.161)	(4.253)	(4.216)	(1.071)	(1.426)
Sales Growth	3.553	3.569	-2.755**	-2.710**	-4.311	-5.183	0.883	1.757	0.413	0.429	1.613	1.351
	(1.126)	(1.124)	(-2.392)	(-2.328)	(-1.186)	(-1.335)	(0.285)	(0.576)	(0.267)	(0.274)	(0.436)	(0.381)
Log Total Assets	-0.514	-1.099	3.848**	3.909**	1.136	1.215	0.615	0.336	-2.129	-2.140	-2.365	-2.505
	(-0.115)	(-0.258)	(2.505)	(2.532)	(0.344)	(0.367)	(0.149)	(0.085)	(-1.275)	(-1.288)	(-0.581)	(-0.617)
ROA	-2.021	-1.293	-8.337**	-8.302**	2.262	1.100	11.881	10.920	4.509	4.649	8.268	9.921*
	(-0.291)	(-0.191)	(-2.038)	(-2.002)	(0.400)	(0.193)	(1.629)	(1.488)	(0.958)	(0.983)	(1.451)	(1.651)
Intercept	21.960	14.702	2.400	1.121	43.059	35.650	20.569	24.675	-13.009	-11.980	20.395	24.118
	(0.652)	(0.428)	(0.183)	(0.085)	(1.359)	(1.122)	(0.544)	(0.641)	(-0.982)	(-0.891)	(0.456)	(0.585)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC-2 $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1006	1006	4387	4387	806	806	1006	1006	4387	4387	806	806
Adj. R^2	0.627	0.628	0.833	0.833	0.872	0.872	0.652	0.653	0.828	0.828	0.866	0.866

t-statistics are adjusted for heteroskedasticity and in the parentheses: standard errors are clustered at the firm level.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 6: The shift in manufacturers' eco-innovative strategies towards resource use and emissions (Innovation lagged)

The estimated results of the following regression models are presented below. The dependent variable in Panel A and Panel B is Resource Use and Emissions, respectively. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 (2007–2009) is termed as post-EISA (crisis) period.

	Panel A: Resource Use						**Panel B: Emissions**					
	Pre-EISA		Post-EISA		Crisis		Pre-EISA		Post-EISA		Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation lagged	-0.041	-0.039	0.055**	0.055**	0.065*	0.067*	-0.009	0.005	0.049**	0.049**	0.052	0.056*
	(-0.544)	(-0.526)	(2.485)	(2.490)	(1.815)	(1.913)	(-0.118)	(0.061)	(2.334)	(2.336)	(1.562)	(1.695)
KZ Index (T1)	-2.724		1.410		-2.677		-4.809		1.175		-2.518	
	(-0.580)		(0.644)		(-0.693)		(-0.796)		(0.703)		(-0.548)	
KZ Index (T2)	-3.003		0.054		-3.666		-3.532		0.455		-2.647	
	(-0.643)		(0.026)		(-0.996)		(-0.806)		(0.277)		(-0.633)	
KZ Index (T3)	2.342		0.598		-3.896		3.518		1.034		-0.122	
	(0.459)		(0.279)		(-0.970)		(0.688)		(0.558)		(-0.027)	
WW Index (T1)		8.993		3.042		-6.801		1.841		1.735		-12.148
		(0.889)		(1.493)		(-1.273)		(0.378)		(0.783)		(-1.453)
WW Index (T2)		9.781		3.099		-2.493		-2.690		0.956		-11.551
		(0.940)		(1.528)		(-0.464)		(-0.535)		(0.419)		(-1.307)
WW Index (T3)		14.490		3.418*		-2.436		-3.244		1.307		-6.937
		(1.278)		(1.657)		(-0.440)		(-0.500)		(0.501)		(-0.798)
Log Revenue	4.019	6.989	1.244	1.125	-0.408	1.211	1.924	1.498	6.107**	6.020**	4.523	6.460
	(0.665)	(1.084)	(0.663)	(0.593)	(-0.098)	(0.280)	(0.282)	(0.210)	(2.391)	(2.348)	(1.012)	(1.534)
Sales Growth	-0.052	-1.169	-3.708**	-3.655**	-6.861	-7.700*	-2.574	-2.022	-3.017	-2.938	4.030	3.662
	(-0.017)	(-0.392)	(-2.384)	(-2.331)	(-1.566)	(-1.698)	(-0.602)	(-0.477)	(-1.561)	(-1.508)	(1.221)	(1.159)
Log Total Assets	-1.512	-2.263	4.220**	4.369**	0.528	0.614	-2.361	-2.272	0.588	0.593	-2.284	-2.336
	(-0.336)	(-0.481)	(2.393)	(2.468)	(0.166)	(0.193)	(-0.517)	(-0.473)	(0.302)	(0.305)	(-0.545)	(-0.546)
ROA	9.616	11.013	-9.895**	-9.780**	2.517	1.102	19.861	16.233	5.070	5.206	7.454	7.675
	(0.779)	(0.902)	(-2.021)	(-1.967)	(0.425)	(0.189)	(1.451)	(1.187)	(0.938)	(0.958)	(1.188)	(1.188)
Intercept	27.031	-2.649	3.806	0.993	51.259	39.504	51.682	50.647	-8.895	-8.991	32.005	25.285
	(0.499)	(-0.048)	(0.252)	(0.066)	(1.441)	(1.126)	(0.968)	(0.929)	(-0.624)	(-0.619)	(0.764)	(0.641)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC-2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	738	738	3620	3620	677	677	738	738	3620	3620	677	677
Adj. R^2	0.653	0.652	0.817	0.817	0.853	0.853	0.681	0.678	0.817	0.817	0.855	0.856

t-statistics are adjusted for heteroskedasticity and in the parentheses: standard errors are clustered at the firm level.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 7: The shift in manufacturers' eco-innovative strategies towards resource use by tertile-based firm size

The estimated results of the following regression models are presented below. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 is termed as post-EISA period. Firm size is divided into tertiles after taking the average of market capitalization over the period 2002–2017.

	Panel A: Small manufacturers				**Panel B: Midsize manufacturers**				**Panel C: Large manufacturers**			
	Pre-EISA		Post-EISA		Pre-EISA		Post-EISA		Pre-EISA		Post-EISA	
Resource Use	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation	0.094	0.092	0.020	0.020	-0.004	0.013	0.171***	0.169***	0.102	0.098	0.072*	0.074*
	(1.283)	(1.273)	(0.437)	(0.433)	(-0.033)	(0.111)	(3.143)	(3.053)	(1.040)	(0.976)	(1.827)	(1.875)
KZ Index (T1)	0.118		1.841		5.828		6.396*		1.380		-4.017	
	(0.134)		(1.116)		(1.447)		(1.665)		(0.209)		(-1.165)	
KZ Index (T2)	1.599		-0.216		4.842		8.059**		-2.987		-5.700*	
	(1.231)		(-0.135)		(1.101)		(2.453)		(-0.440)		(-1.729)	
KZ Index (T3)	5.249*		2.556		5.555		7.716**		1.106		-3.794	
	(1.940)		(1.298)		(1.084)		(2.401)		(0.153)		(-1.020)	
WW Index (T1)		8.635**		2.665		25.071*		5.232		6.540		-4.469
		(2.514)		(1.068)		(1.867)		(1.593)		(0.630)		(-1.359)
WW Index (T2)		8.262**		1.300		21.046		6.754**		10.321		-5.838*
		(2.288)		(0.678)		(1.505)		(2.056)		(0.843)		(-1.674)
WW Index (T3)		11.002***		0.420		26.107*		4.156		11.280		-2.255
		(3.528)		(0.260)		(1.769)		(0.946)		(0.752)		(-0.696)
Log Revenue	-0.479	1.004	-2.408	-2.731	-10.847	-11.926	0.184	-0.392	9.968	12.532	6.147	5.920
	(-0.328)	(0.529)	(-1.321)	(-1.479)	(-1.177)	(-1.341)	(0.046)	(-0.099)	(1.352)	(1.568)	(1.481)	(1.414)
Sales Growth	0.565	-0.620	1.146	1.307	9.194	9.927*	-4.604	-4.742*	8.272	7.010	-9.305***	-8.892***
	(0.406)	(-0.391)	(1.150)	(1.302)	(1.607)	(1.832)	(-1.590)	(-1.661)	(1.317)	(1.080)	(-2.860)	(-2.730)
Log Total Assets	-4.855	-6.123*	2.747	2.826	5.294	4.953	2.911	3.249	-0.859	-2.560	3.154	3.120
	(-1.368)	(-1.730)	(1.478)	(1.558)	(0.779)	(0.745)	(0.770)	(0.864)	(-0.113)	(-0.363)	(0.964)	(0.930)
ROA	8.392**	7.436***	-3.663	-3.276	4.448	3.392	-15.804*	-16.286*	2.895	2.539	11.389	13.317
	(2.422)	(3.515)	(-0.909)	(-0.786)	(0.380)	(0.308)	(-1.815)	(-1.852)	(0.158)	(0.138)	(0.790)	(0.931)
Intercept	61.760**	53.921**	28.495*	29.698*	75.079	65.861	6.451	9.831	-35.221	-49.993	-21.319	-19.000
	(2.365)	(2.297)	(1.817)	(1.920)	(1.242)	(1.150)	(0.265)	(0.414)	(-0.610)	(-0.816)	(-0.646)	(-0.589)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC-2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	116	116	1465	1465	358	358	1490	1490	477	477	1318	1318
Adj. R^2	0.763	0.754	0.829	0.828	0.401	0.415	0.772	0.770	0.598	0.597	0.773	0.771

t-statistics are adjusted for heteroskedasticity and in the parentheses: standard errors are clustered at the firm level.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 8: The shift in manufacturers' eco-innovative strategies towards emissions by tertile-based firm size

The estimated results of the following regression models are presented below. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 is termed as post-EISA period. Firm size is divided into tertiles after taking the average of market capitalization over the period 2002–2017.

	Panel A: Small manufacturers				**Panel B: Midsize manufacturers**				**Panel C: Large manufacturers**			
	Pre-EISA		Post-EISA		Pre-EISA		Post-EISA		Pre-EISA		Post-EISA	
Emissions	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Innovation	0.226	0.150	0.092**	0.095**	-0.122	-0.122	0.113***	0.113***	0.149*	0.157*	0.064	0.068*
	(1.517)	(0.839)	(2.004)	(2.051)	(-1.102)	(-1.134)	(2.688)	(2.709)	(1.703)	(1.781)	(1.587)	(1.683)
KZ Index (T1)	-5.352		1.302		-0.052		0.733		5.343		2.350	
	(-1.415)		(0.623)		(-0.023)		(0.246)		(0.647)		(1.068)	
KZ Index (T2)	-5.068		2.259		-0.184		0.361		3.717		-0.960	
	(-1.701)		(1.108)		(-0.055)		(0.134)		(0.579)		(-0.420)	
KZ Index (T3)	-3.709		2.750		-0.478		-0.249		10.037		0.756	
	(-0.901)		(1.178)		(-0.156)		(-0.091)		(1.290)		(0.231)	
WW Index (T1)		-6.569		0.313		6.934		1.093		7.106		-0.151
		(-1.421)		(0.116)		(1.069)		(0.360)		(0.720)		(-0.051)
WW Index (T2)		-6.855		-2.168		4.591		2.124		0.246		-0.477
		(-1.466)		(-0.885)		(0.651)		(0.698)		(0.017)		(-0.140)
WW Index (T3)		-3.382		-4.072*		0.223		-0.200		-0.161		1.785
		(-0.716)		(-1.841)		(0.026)		(-0.046)		(-0.011)		(0.538)
Log Revenue	6.662**	8.701**	11.029***	11.000***	-8.329	-8.952	6.300	6.154	3.647	0.518	-1.561	-1.386
	(2.119)	(2.549)	(3.747)	(3.711)	(-0.973)	(-1.077)	(1.328)	(1.307)	(0.478)	(0.060)	(-0.404)	(-0.358)
Sales Growth	-2.925	-2.895	5.979***	5.996***	-1.054	-0.327	-9.712***	-9.915***	4.539	5.819	-6.518**	-6.120**
	(-0.938)	(-0.960)	(3.838)	(3.780)	(-0.204)	(-0.060)	(-3.294)	(-3.386)	(0.704)	(0.926)	(-2.189)	(-2.003)
Log Total Assets	-24.465***	-25.016***	-4.994**	-5.587**	9.147	8.913	-0.373	-0.059	0.194	1.468	6.338*	6.386**
	(-3.692)	(-3.382)	(-2.015)	(-2.347)	(1.389)	(1.326)	(-0.096)	(-0.015)	(0.030)	(0.217)	(1.968)	(1.978)
ROA	5.742	4.994	7.967	8.685	16.072	14.767	4.021	4.000	6.900	6.284	2.458	2.315
	(0.843)	(0.747)	(1.397)	(1.503)	(1.500)	(1.425)	(0.462)	(0.458)	(0.367)	(0.335)	(0.167)	(0.158)
Intercept	159.783***	155.635***	-9.129	-1.013	35.533	35.767	-10.580	-13.030	6.809	21.391	14.601	12.642
	(3.614)	(3.588)	(-0.380)	(-0.042)	(0.521)	(0.589)	(-0.378)	(-0.473)	(0.109)	(0.323)	(0.728)	(0.625)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC-2 × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	116	116	1465	1465	358	358	1490	1490	477	477	1318	1318
Adj. R^2	0.367	0.346	0.814	0.815	0.566	0.569	0.786	0.786	0.612	0.610	0.792	0.791

t-statistics are adjusted for heteroskedasticity and in the parentheses: standard errors are clustered at the firm level.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

4.2 Environmental regulation and firm competitiveness measure

Environmental regulation can exert a multitude of influences on productivity through multiple channels and over different time scale. On the one hand, a surge in the compliance cost directly associated with the regulation may decrease the productivity in the short run. On the other hand, regulation can help facilitate firms' knowledge base, which facilitates productivity in the long run. In this respect, existing literature on the validity of the strong PH points to mixed conclusions. Although a strand of studies fails to validate the strong PH, some studies nonetheless confirm or conditionally confirm it depending on situational factors. For instance, a seminal work from Lanoie et al. (2011) provides evidence that environmental policy spurs firms to ramp up investment in environmental R&D, which in turn enhances business performance, but they fail to find evidence lending support to the strong PH—put differently, the second-order positive effect via R&D does not outweigh the first-order negative effect of stringent environmental policy on business performance. Similarly, using total factor productivity as competitiveness measure, Rubashkina, Galeotti, and Verdolini (2015) do not find supportive evidence for the strong PH. Moreover, Rexhäuser and Rammer (2014) reach the conclusion that the strong PH does not universally hold but relies on the type of eco-innovation. Using a structural modeling approach, van Leeuwen and Mohnen (2013) strongly confirm the weak PH and also find some evidence suggestive of the strong PH.

As posited by the strong PH, can the economic and ecological aspects of firm performance truly be harmonized? The remainder of this paper endeavors to answer this question by using the measure of firm competitiveness based on stock market data. Specifically, I test the strong PH using stock returns as a primary variable, an approach that differs from extant literature. In the previous research testing the strong PH, competitiveness has been usually proxied by either real measures (e.g., productivity, market entry and exits) or financial measures (e.g., price-cost margins, profits, Tobin's Q) (Rubashkina, Galeotti, and Verdolini, 2015). Yet, the advantage of using financial market data is that (i) stock prices are forward-looking and thus provide an estimate of the firm value based on ex-ante information and (ii) the effect of intangible assets such as knowledge base and reputation cannot be captured otherwise.

Admittedly, some researchers may dispute the use of market-based measures. For instance, Lieberman and Kang (2008) criticize that the comparison of business performance is traditionally implemented using stock market measures (or accounting profits) but these measures are only value-relevant to investors. Therefore, the authors argue that productivity-related indicators such as total factor productivity are more suitable to estimate the overarching corporate value. Nonetheless, I would argue that the use of a competitiveness measure based on the stock market data stands to reason insomuch as the classical financial theory holds true—that managers' objective is to maximize the total long-run market value of the firm, where the total firm value is the value summation of all financial claims on the firm (e.g., Jensen (2002)).

4.3 Eco-innovation and subsequent returns

As an initial step of assessing the strong PH, I examine in this subsection the impact of EISA 2007 on the cross-section of returns. The test of whether eco-innovation has a predictive power of subsequent returns builds on the joint hypothesis that (i) eco-innovation is value-enhancing for firms and (ii) the information of eco-innovation is not fully capitalized by stock market investors because the firms' adoption of eco-friendly technologies are not sufficiently recognized by the market—this includes the case whereby the associated benefits (costs) are underestimated (overestimated) by investors even though the adoptions of new technologies are ex ante recognized. Statement (ii) is actually substantiated by the confirmatory evidence that even insiders, let alone outsiders, are incapable of foreseeing how an eco-friendly corporate strategy can enhance firm value. A case in point is from McKinsey & Company (2012) reporting that one third of executive responded to a survey expressing that it remains hazy how beneficial their corporate sustainability initiatives are for shareholders. Notwithstanding, these executive respondents overall showed better comprehension of sustainability initiatives and its hoped-for benefits in comparison to the past—ranging from reputation enhancement to cost-effectiveness and increased growth in new market share.

For the following tests, I draw on the conceptual framework from Schwert (1981). In equation (3), the price of asset i, denoted by $P_{i,t}$, is the discounted value of future cash flows; the cash flow to asset i, denoted by $d_{i,t+k}$, occurs in period $t+k$; $P^*_{i,t}$ and $d^*_{i,t+k}$ are the equilibrium price and the expected net cash flow after the regulatory change, respectively. In reality, the regulation impact does not instantaneously come into effect (i.e., an immediate price change from $P_{i,t}$ to $P^*_{i,t}$); it is rather realized over a certain period of time, thereby making the attempt to measure the changes between before- and after-regulation prices difficult. Thus, as suggested by Schwert (1981), I instead measure the regulation impact by capturing the dynamics of stock returns, where the abnormal return is interpreted as the deviation from the normal return that the security would have otherwise realized in the absence of the regulation. Additionally, I quote two extreme cases outlined by Schwert (1981): the discount rate r_i is assumed constant over time for brevity. At one end of the spectrum, if a regulation induces a shift in projected future cash flows but does not alter the riskiness (i.e., discount rate) of the cash flow, the change in asset price can be formulated by equation (4); at the other end of the spectrum, if a regulation hardly involves a shift in projected future cash flows but alters the riskiness of the cash flow, the change in asset price can be formulated by equation (5).

$$P_{i,t} = \sum_{k=1}^{\infty} \frac{d_{i,t+k}}{(1+r_i)^k} \tag{3}$$

$$P^*_{i,t} - P_{i,t} = \sum_{k=1}^{\infty} \frac{(d^*_{i,t+k} - d_{i,t+k})}{(1+r_i)^k} \tag{4}$$

$$P^*_{i,t} - P_{i,t} = \sum_{k=1}^{\infty} d_{i,t+k} \left[\frac{1}{(1+r^*_i)^k} - \frac{1}{(1+r_i)^k}\right] \tag{5}$$

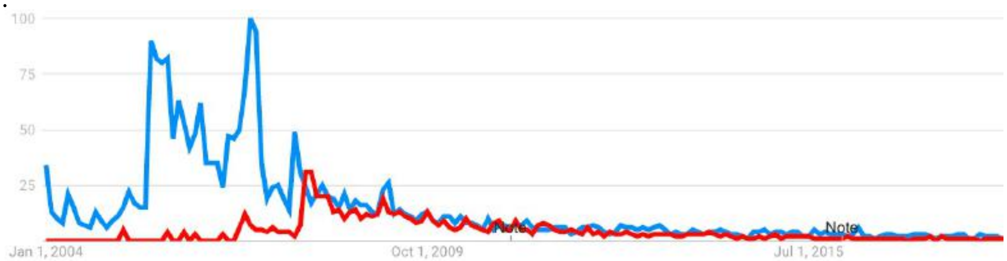
Particularly, I demonstrate two fundamentally different interpretations of a case where eco-innovation has a positive predictive power of subsequent returns: this contrastingly informs the validity of the strong PH. The first interpretation based on equation (4) is that eco-innovation is value-relevant (i.e., relates to $d^*_{i,t+k}$) but the associated benefits (costs) are underestimated (overestimated) and this information is not impounded to the stock price; this implies that eco-innovation enhances shareholder value and thus conforms to the strong PH. The second interpretation based on equation (5) is that eco-innovation is deemed risky with respect to the associated future cash flows, which translates into an increase in the discount rate r^*_i and a drop in price $P^*_{i,t}$; this indicates that eco-innovation reduces shareholder value and thus goes against the strong PH.

In relation to this argument, it is equally noteworthy that the sequence of regulations in the mid- to late-2000s had a continuous effect over several years (Section 2.2). Identifying the beginning of the anticipation of the regulatory change is thus burdensome and warrants an additional examination of abnormal security return periods before the regulation is implemented to ensure that the full effect of regulation is captured (Schwert, 1981). In light of the historical background that EISA passed the House and the Senate in January 2007 and June 2007, respectively, as presented in Section 4.1, the post-EISA period refers to the period starting from the beginning of 2007 throughout this paper.

First, in empirically assessing the cross-section of stock returns, I employ calendar time portfolio method, which can control for cross-sectional dependence among sample firms and is less sensitive to a poorly specified asset pricing model. The drawback is that it may have low power to detect abnormal performance. I sort each monthly return observation into a

Figure 2: Search volume comparison in the US: EPAct 2005 and EISA 2007

The blue line plots the search volume on "Energy Policy Act of 2005" (Topic) while the red line plots the search volume on "Energy Independence and Security Act of 2007" (Topic) peaking during Dec 2007.



(Source: Google Trends)

bin according to the quintile rank of Innovation subscore at the beginning of the month: note that the distribution of firms is not uniform across bins in any given month. I form a long-short portfolio using the top and bottom quintiles and compute Jensen's alpha. I iterate the procedure for all five quintiles of Innovation subscore:

$$R_t^{\text{zero}} = \alpha_p + \beta_{MKT}\,\text{MKT}_t + \beta_{SMB}\,\text{SMB}_t + \beta_{HML}\,\text{HML}_t + \beta_{MOM}\,\text{MOM}_t + \varepsilon_t \tag{6}$$

$$R_{p,t} - R_{f,t} = \alpha_p + \beta_{MKT}\,\text{MKT}_t + \beta_{SMB}\,\text{SMB}_t + \beta_{HML}\,\text{HML}_t + \beta_{MOM}\,\text{MOM}_t + \varepsilon_t \tag{7}$$

MKT_t is the value-weighted market return minus the risk-free rate $R_{f,t}$ in month t, and the terms SMB_t (small minus big), HML_t (high minus low), and MOM_t (momentum) are the returns on zero-investment factor-mimicking portfolios in month t designed to capture size, book-to-market, and momentum effects, respectively. R_t^{zero} is the monthly return difference between the highest quintile and lowest quintile portfolios sorted on the Innovation subscore: therefore, the alpha in equation (6) is the abnormal return on a zero-investment strategy that longs the highest quintile portfolio and shorts the lowest quintile portfolio. Moreover, $R_{p,t}$ is the monthly return of the corresponding quintile portfolio sorted on the Innovation subscore and $R_{f,t}$ is the risk-free rate. Figure 3 illustrates the cumulative returns of the quintile portfolios sorted on Innovation and Table 9 shows the summary statistics of Innovation subscore by each year.

The empirical results are presented in Tables 10 and 11, where each portfolio contains at least around 50 securities. Panels A and B in Table 10 represent the period of pre-EISA and post-EISA, respectively; in a similar vein, Panels C and D in Table 11 represent the period of crisis and full sample period, respectively. The figures in pre- and post-EISA periods point to dissimilar results. Regarding the pre-EISA period in Panel A of Table 10, the values of alpha are insignificant except for the bottom quintile equally-weighted portfolio, which exhibits an alpha of 89 basis point monthly and significant at the 10% level. In contrast, regarding the post-EISA period in Panel B of Table 10, it exhibits an alpha of 90 basis point monthly and significant at the 5% level. Another intriguing empirical pattern is that the values of alpha across different quintile groups show, albeit not overall statistically significant, a considerably nonlinear trend especially in the post-EISA period. For instance, the second, third, and fourth quintile groups have substantially higher alpha values for both value-weighted and equally-weighted portfolios. This may imply that among the firms initiated the transition of environmental innovation strategies in the post-EISA period, the mid-range groups had particularly more capabilities to improve upon its eco-innovative capabilities. Furthermore, if the post-EISA period is narrowed down to the crisis-period (2007–2009) in Panel C of Table 11, a conclusion consistent with Panel B can be drawn with higher statistical significance. The full period featured in Panel D of Table 11 does not provide additional insight and reconfirms the patterns in Panels A–C. As an aside, untabulated results show that Fama-French five-factor model is qualitatively similar with this result in terms of the magnitude and significance level of alpha.

In the second test, I run a pooled regression with monthly returns using Fama-MacBeth (1973) estimation (e.g., Brennan, Chordia, and Subrahmanyam, 1998; Gompers, Ishii, and Metrick, 2003; Edmans, 2011)—this mitigates the concern vis-á-vis the first test that the abnormal-returns resulted from a firm characteristic not captured by the risk factors (i.e., an omitted variable) but correlated with Innovation subscore:

$$r_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t} + bZ_{i,t} + \varepsilon_{i,t} \tag{8}$$

where $r_{i,t}$ is monthly return in logarithm, and $Z_{i,t}$ is a vector of firm characteristics taken from Brennan, Chordia, and Subrahmanyam (1998). To alleviate the extreme skewness associated with these variables, all of these variables are transformed into logarithmic form except the dividend yield (over a third of observations equal to zero). Book-to-market is constructed following Fama and French (1992): the book value for July of year t is computed from the fiscal yearends in calendar year $t-1$; the market equity for July of year t is similarly computed from the fiscal yearends[9] in calendar year $t-1$; and the book-to-market ratio is held constant for 12 months starting from July. YLD is the dividend yield defined as the total dividends paid over 12 months, scaled by the stock price measured at the calendar

[9]As opposed to using fiscal-yearend market equity, another approach is to set the market equity to the value in December. Although in this case the market value in the denominator is not aligned with the book value in the numerator, if firms do not have fiscal yearends in December, the former fiscal-yearend approach also has its share of trouble stemming from the susceptibility to stock market fluctuation. All in all, Fama and French (1992) report that theses two approaches have negligible impact on their empirical tests.

year end in $t-1$ and thus it analogously follows the method of constructing book-to-market ratio. Since Innovation subscore is only updated at annual frequency, it is held constant throughout the year: given that CSR ratings are generally persistent over time, this treatment is unlikely to generate serious measurement errors.

Table 12 presents the results, which are by and large in line with the numbers in Edmans (2011). In brief, it reinforces the results of the first test by mitigating the possibility that the first test is driven by unobserved firm characteristics. It also shows that eco-innovative firms are associated with an additional return of 44 basis points.

Figure 3: Gross cumulative returns by quintile portfolio

The figures below on the left (right) hand side illustrate the gross cumulative returns of value-weighted portfolios (equal-weighted portfolios) whereby the first (second) row represents the period 2002–2009 (2007–2017).

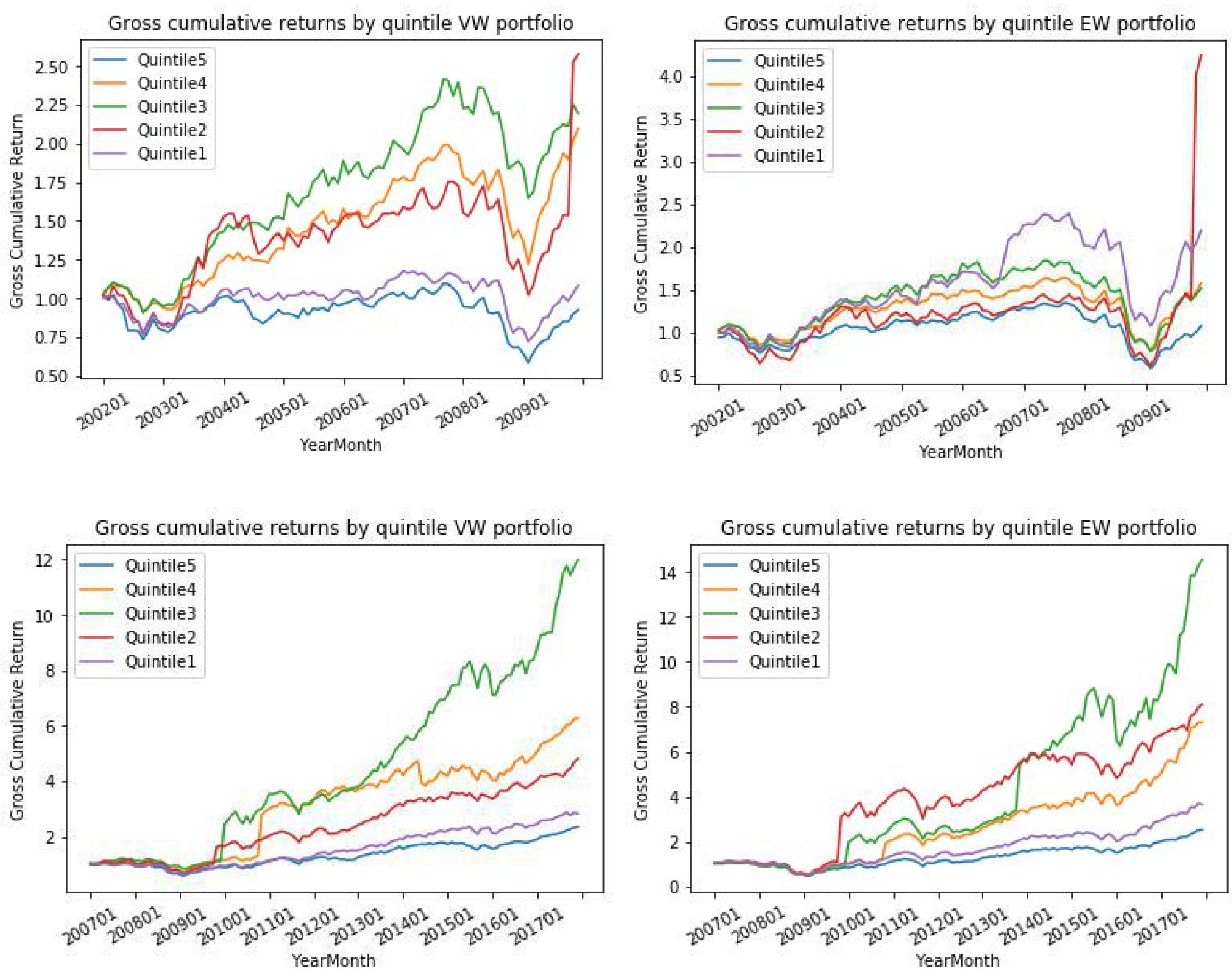


Table 9: Summary statistics of variables in portfolio analysis

This table reports the summary statistics of Innovation subscore used for portfolio anlaysis. The number of securities for each year exhibited in Table 9 is essentially same with the column in the right end of Table 4.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Innovation (2002)	48.8	13.0	3.8	21.3	43.3	50.0	53.6	69.4	97.8	168
Innovation (2003)	48.9	13.1	15.4	22.8	42.1	50.0	53.2	66.1	96.4	169
Innovation (2004)	49.6	13.4	2.1	23.1	43.5	50.0	51.1	72.3	99.3	211
Innovation (2005)	49.0	17.9	5.8	22.6	39.0	50.0	55.8	85.0	98.2	238
Innovation (2006)	49.4	21.0	1.7	14.1	36.7	50.0	63.5	90.1	98.3	236
Innovation (2007)	50.1	25.6	0.7	12.8	30.4	47.0	74.1	96.9	99.4	245
Innovation (2008)	50.9	28.0	1.5	10.6	25.4	44.1	77.3	95.7	99.4	292
Innovation (2009)	50.7	27.4	1.4	8.8	28.1	51.6	72.1	94.6	99.5	333
Innovation (2010)	53.9	28.1	1.3	9.4	31.0	50.3	78.1	95.2	99.6	351
Innovation (2011)	54.4	27.4	1.2	9.1	31.8	54.5	80.0	94.0	99.6	347
Innovation (2012)	54.0	27.1	1.2	8.6	31.8	56.4	76.9	94.8	99.6	341
Innovation (2013)	53.9	27.6	1.2	7.9	33.8	54.2	77.0	93.8	99.6	338
Innovation (2014)	53.9	27.1	1.2	9.2	34.5	55.7	74.2	93.1	99.6	334
Innovation (2015)	48.6	25.9	0.5	6.8	26.2	50.0	65.4	92.9	99.7	539
Innovation (2016)	47.4	25.4	0.4	8.7	27.1	49.4	61.8	92.8	99.7	806
Innovation (2017)	48.0	25.2	0.4	9.5	29.8	50.0	63.4	93.6	99.8	804

Table 10: Monthly abnormal returns on quintile portfolios: pre- and post-EISA period

In Panel A (Panel B), I use Newey-West corrected standard errors with two (three) lags for the pre-EISA (post-EISA) period to adjust the error term for serial-correlation and heteroskedasticity.

Panel A: Pre-EISA	Subpanel A1: Value-weighted					Subpanel A2: Equal-weighted				
	α	MKT	SMB	HML	MOM	α	MKT	SMB	HML	MOM
Top-bottom long-short	0.07	-0.05	0.16	-0.43*	-0.11	-0.7	-0.49***	-0.27*	0.11	0.01
	(0.15)	(-0.24)	(0.68)	(-1.79)	(-1.05)	(-1.55)	(-3.7)	(-1.95)	(0.57)	(0.14)
Top quintile group	0.19	0.82***	-0.18	-0.51***	-0.09	0.19	0.85***	0.06	-0.25**	-0.01
	(0.65)	(5.33)	(-0.99)	(-2.88)	(-0.92)	(1.08)	(12.41)	(0.78)	(-2.14)	(-0.22)
Fourth quintile group	0.41	0.73***	-0.01	0.39**	0.02	0.13	0.82***	0.23**	0.12	0.03
	(1.38)	(5.51)	(-0.05)	(2.44)	(0.16)	(0.66)	(11.54)	(2.37)	(1.1)	(0.33)
Third quintile group	0.49	0.78***	0.25	0.36*	0.01	0.13	1.03***	0.56***	0.14	0.02
	(1.51)	(4.86)	(1.62)	(1.74)	(0.05)	(0.54)	(11.34)	(4.21)	(0.81)	(0.22)
Second quintile group	0.14	1.23***	0.4**	-0.15	0.09	-0.38	1.51***	0.62***	0.01	-0.08
	(0.4)	(6.7)	(2.34)	(-0.69)	(0.66)	(-1.09)	(9.91)	(4.53)	(0.02)	(-0.54)
Bottom quintile group	0.12	0.87***	-0.34***	-0.08	0.02	0.89*	1.35***	0.33***	-0.37*	-0.02
	(0.44)	(12.17)	(-3.62)	(-0.52)	(0.33)	(1.8)	(10.82)	(2.88)	(-1.81)	(-0.27)

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Panel B: Post-EISA	Subpanel B1: Value-weighted					Subpanel B2: Equal-weighted				
	α	MKT	SMB	HML	MOM	α	MKT	SMB	HML	MOM
Top-bottom long-short	-0.19	0.13*	-0.17	0.17**	0.04	-0.3	0.01	-0.2**	0.01	0.03
	(-0.84)	(2.16)	(-1.4)	(2.33)	(0.74)	(-1.55)	(0.21)	(-2.16)	(0.11)	(0.48)
Top quintile group	0.02	1.01***	-0.14***	-0.04	0.02	0.01	1.12***	0.41***	-0.09	-0.16***
	(0.16)	(30.24)	(-3.06)	(-0.87)	(0.73)	(0.05)	(28.55)	(6.07)	(-1.34)	(-3.85)
Fourth quintile group	1.1	0.8***	0.57	-0.29	0.03	0.9**	1.06***	0.95**	-0.33***	-0.14*
	(1.33)	(7.21)	(0.79)	(-1.32)	(0.25)	(1.99)	(14.61)	(2.43)	(-2.86)	(-1.72)
Third quintile group	1.82	0.59	0.26	-0.32*	-0.24	1.93	0.86**	1.04***	-0.44**	-0.48
	(1.44)	(1.6)	(1.18)	(-1.92)	(-0.67)	(1.44)	(2.26)	(4.37)	(-2.25)	(-1.33)
Second quintile group	0.58	1.17***	-0.36	-0.04	0.02	1.19	1.81***	-0.52	0.1	-0.07
	(1.48)	(5.69)	(-0.98)	(-0.58)	(0.38)	(1.08)	(2.9)	(-0.47)	(0.45)	(-0.42)
Bottom quintile group	0.21	0.88***	0.03	-0.21***	-0.01	0.31	1.11***	0.6***	-0.11	-0.19***
	(1.31)	(19.57)	(0.26)	(-3)	(-0.38)	(1.49)	(17.6)	(7.02)	(-0.66)	(-4.02)

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 11: Monthly abnormal returns on quintile portfolios: crisis and full sample period

In Panel C (Panel D), I use Newey-West corrected standard errors with two (three) lags for the crisis (full sample) period to adjust the error term for serial-correlation and heteroskedasticity.

Panel C: Crisis	Subpanel C1: Value-weighted					Subpanel C2: Equal-weighted				
	α	MKT	SMB	HML	MOM	α	MKT	SMB	HML	MOM
Top-bottom long-short	0.09	0.18	-0.4	0.03	0.03	-0.7	-0.1	-0.09	-0.13	-0.04
	(0.19)	(1.67)	(-1.52)	(0.25)	(0.36)	(-1.29)	(-0.95)	(-0.35)	(-0.36)	(-0.49)
Top quintile group	0.34	0.98***	-0.2**	-0.09*	0.02	-0.02	1.07***	0.4**	-0.26***	-0.24***
	(1.59)	(19.66)	(-2.17)	(-1.73)	(0.44)	(-0.09)	(19.75)	(2.32)	(-3.53)	(-5.16)
Fourth quintile group	0.97***	0.84***	0.12	0.04	-0.03	0.52**	1.06***	0.62***	-0.26***	-0.26***
	(3.87)	(10.48)	(1.35)	(0.43)	(-0.85)	(2.66)	(16.18)	(5.88)	(-3.18)	(-5.66)
Third quintile group	0.74*	0.8***	-0.39**	-0.16*	0.02	0.05	1.1***	0.57***	-0.29	-0.27***
	(1.91)	(11.56)	(-2.18)	(-1.97)	(0.23)	(0.1)	(10.53)	(3.61)	(-1.38)	(-4.96)
Second quintile group	3.13	1.66***	-1.23	0.07	0.18	8.34	3.14*	-2.97	0.42	0.3
	(1.41)	(2.96)	(-1.16)	(0.25)	(1.06)	(1.23)	(1.81)	(-0.91)	(0.44)	(0.53)
Bottom quintile group	0.25	0.8***	0.19	-0.12	-0.01	0.67	1.17***	0.49*	-0.14	-0.19**
	(0.63)	(9.4)	(0.92)	(-0.86)	(-0.17)	(1.05)	(8.93)	(1.78)	(-0.36)	(-2.33)

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Panel D: Full sample	Subpanel D1: Value-weighted					Subpanel D2: Equal-weighted				
	α	MKT	SMB	HML	MOM	α	MKT	SMB	HML	MOM
Top-bottom long-short	-0.21	0.11*	-0.07	0.03	-0.01	-0.42**	-0.1*	-0.26***	0.11	0.06
	(-1.13)	(1.89)	(-0.65)	(0.39)	(-0.34)	(-2.35)	(-1.67)	(-3.04)	(0.96)	(0.79)
Top quintile group	-0.03	0.99***	-0.18***	-0.13***	-0.02	0	1.06***	0.28***	-0.02	-0.12**
	(-0.25)	(24.2)	(-2.99)	(-2.82)	(-0.73)	(0.03)	(20.23)	(4.37)	(-0.29)	(-2.06)
Fourth quintile group	0.96	0.78***	0.34	-0.12	0.04	0.68**	0.99***	0.67***	-0.14	-0.08
	(1.76)	(12.06)	(0.79)	(-0.6)	(0.68)	(2.12)	(19.25)	(2.76)	(-1.09)	(-0.93)
Third quintile group	1.56	0.6*	0.28	-0.18	-0.15	1.47	0.85***	0.9***	-0.24*	-0.34
	(1.74)	(1.93)	(1.64)	(-1.58)	(-0.53)	(1.56)	(2.67)	(4.97)	(-1.72)	(-1.22)
Second quintile group	0.5	1.17***	-0.06	-0.1	0.05	0.78	1.74***	-0.12	0.03	-0.02
	(1.57)	(6.96)	(-0.22)	(-1.47)	(0.82)	(0.96)	(3.49)	(-0.15)	(0.2)	(-0.12)
Bottom quintile group	0.17	0.88***	-0.11	-0.16**	-0.01	0.43**	1.15***	0.53***	-0.13	-0.19***
	(1.36)	(23.4)	(-1.49)	(-2.52)	(-0.34)	(2.27)	(21.77)	(7.67)	(-1.02)	(-4.85)

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 12: Monthly return regressions using Fama-MacBeth estimation

The estimated results of the regression models are presented in the table below in which the dependent variable monthly return $R_{i,t}$ is in logarithm. Subperiod 2002–2006 is termed as pre-EISA, and subperiod 2007–2017 (2007–2009) is termed as post-EISA (crisis). All standard errors are Newey-West adjusted following Greene (2020): pre-EISA and crisis period are adjusted with two lags and post-EISA and full period are adjusted with three lags. Since Innovation subscore is only measured at 12-month intervals, it is held constant throughout the year. YIELD is the dividend yield defined as the total dividends paid over 12 months scaled by the stock price measured at the calendar yearend in $t-1$.

	Subperiod						Full period	
	Pre-EISA		Post-EISA		Crisis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inn50–100	0.23		0.44***		0.38**		0.37***	
	(0.76)		(3.44)		(2.04)		(2.88)	
Inn75–100		-0.31		0.44***		0.35		0.21
		(-0.67)		(2.72)		(1.24)		(1.22)
Inn50–75		0.30		0.43***		0.32		0.39***
		(0.92)		(2.79)		(1.19)		(2.65)
LNSIZE	0.40	0.42	0.30	0.29	0.54	0.54	0.33**	0.33*
	(1.53)	(1.58)	(1.41)	(1.36)	(0.86)	(0.85)	(1.98)	(1.96)
Log B/M	0.28	0.29	-0.05	-0.06	-0.15	-0.15	0.05	0.05
	(1.63)	(1.64)	(-0.68)	(-0.70)	(-0.67)	(-0.68)	(0.64)	(0.65)
YIELD	0.01	0.01	-0.00	-0.00	-0.01	-0.01	0.00	0.00
	(1.19)	(1.03)	(-0.43)	(-0.47)	(-1.08)	(-1.15)	(0.69)	(0.56)
RET2–3	-2.84	-2.73	0.51	0.53	2.52	2.50	-0.54	-0.49
	(-1.56)	(-1.50)	(0.46)	(0.48)	(0.97)	(0.94)	(-0.56)	(-0.51)
RET4–6	-0.95	-1.11	-0.64	-0.65	-1.56	-1.51	-0.74	-0.80
	(-0.82)	(-0.97)	(-0.69)	(-0.69)	(-1.20)	(-1.17)	(-1.01)	(-1.08)
RET7–12	-0.51	-0.46	-0.30	-0.29	0.21	0.26	-0.37	-0.34
	(-0.64)	(-0.58)	(-0.43)	(-0.42)	(0.13)	(0.16)	(-0.68)	(-0.64)
DVOL	-0.46*	-0.45*	-0.41**	-0.41**	-0.45	-0.47	-0.42***	-0.42***
	(-1.99)	(-1.92)	(-2.10)	(-2.10)	(-0.91)	(-0.93)	(-2.78)	(-2.75)
PRC	-0.30	-0.33	-0.52**	-0.51**	-0.80	-0.78	-0.45**	-0.45**
	(-0.71)	(-0.76)	(-2.59)	(-2.54)	(-1.48)	(-1.43)	(-2.37)	(-2.38)
Intercept	8.79***	8.44***	7.43***	7.50***	5.03	5.26	7.86***	7.79***
	(3.19)	(2.94)	(3.48)	(3.48)	(0.93)	(0.96)	(4.61)	(4.51)
Obs.	10210	10210	38705	38705	7923	7923	48915	48915
Time Periods	60	60	132	132	36	36	192	192

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

4.4 Operating performance and earnings announcements

In this subsection and the next, I assess the plausible channels that may corroborate the observed positive link running from eco-innovation to excess returns. Specifically, I inspect in this subsection the relationship between eco-innovation and operating performance. Two contrasting accounts exist with respect to the sign of this relationship. On the one hand, a traditional trade-off view predicts that while the regulation will help the society to gain additional welfare, it will dampen the profitability of firms and shift them away from the optimal state by imposing private costs. On the other hand, the strong PH dictates that the negative effect of regulatory costs will be in the long run outweighed by the positive effect generated by the regulation-induced innovation. In this regard, it stands to reason that the strong PH led to rejections in previous studies if the time horizon that the strong PH requires may have been underestimated. Some studies expressly argue on this matter that it is crucial to expect a few years from the initiation of innovation process to the growth in productivity and the correction in inefficiencies (Griffith, Redding, and van Reenen, 2004; Lanoie, Patry, and Lajeunesse, 2008; Ambec et al., 2013). In a similar fashion, other studies advocate that better environmental performance likely results in revenue increase as wells as cost reduction (e.g., Ambec and Lanoie, 2008).[10]

To this end, I empirically explore the effect of eco-innovation on operating performance and I specifically frame my analysis around the tests employed by Core, Guay, and Rusticus (2006) (henceforth CGR) and Gompers, Ishii, and Metrick (2003) (henceforth GIM). The model specification is described in equation (9). I measure operating performance using industry-adjusted ROA (operating income divided by year-end total assets) as well as industry-adjusted ROE (operating income divided by shareholders' equity). Equally important, Fama-Macbeth estimation in conjunction with Newey-West procedure (Newey and West, 1987) can help cope with cross-sectional dependence and serial correlation, respectively. In the spirit of CGR, I consider other potential sources of operating performance differentials by controlling for firm size (logarithm of market capitalization) and logarithm of book-to-market equity because these variables are likely correlated with profitability measure (e.g., Fama and French, 1995) on the left hand side and also with Innovation subscore on the right hand side of equation (9):

$$\text{Adj. Performance}_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t-1} + \beta_2 \text{logBME}_{i,t-1} + \beta_3 \text{logMVE}_{i,t-1} + \varepsilon_{i,t} \quad (9)$$

[10] Ambec and Lanoie (2008) maintain that the revenue channel can be subdivided into the following: smooth access to markets; product differentiation; and sales of pollution-abatement technology. Similarly the cost channel as follows: risk management and relations vis-á-vis external stakeholders; cost of material, energy, and services; cost of capital; and cost of labor.

Following GIM and CGR, operating performance variables are industry-adjusted by subtracting the median value in the corresponding Fama-French 48 Industrial Classifications (Fama and French, 1997). In computing the median for each industry, I include firms for which Thomson Reuters CSR ratings are unavailable—that is, consistent with CGR, median is computed based on the full sample of CCM database. Nonetheless, I also test the case whereby only the subset of firms for which CSR ratings are available is used to compute the median value. The results are qualitatively very similar.[11] On a related note, Innovation subscore is already industry-adjusted based on TRBC industry group. I acknowledge that this classification method is not strictly identical with the above-mentioned Fama-French 48 Industrial Classifications (Fama and French, 1997) but nevertheless comparable with each other given that the number of categories are sufficiently close. Again, in the spirit of CGR, I run both median regression and OLS regression but instead use OLS regression as a baseline specification. In this case, I winsorize the accounting variables at the 2.5% and 97.5% level to mitigate the effect of outliers.

Table 13 presents the summary statistics of the data set used for this analysis and Table 14 presents the regression estimates. In sum, I find clear evidence that eco-innovation is adversely associated with operating performance in the post-EISA period. As against the levels approach using Fama-MacBeth procedure, the fixed effects approach exploiting the within-firm time variation is also feasible but less preferred in this analysis because Innovation subscore is especially time-invariant in the pre-EISA period. The estimated results of median regressions are qualitatively very similar (unreported).[12]

Moreover, the effect of Innovation on operating performance in the post-EISA period is economically large and significant. As an example, I use the specification (3) of Subpanels B1 and B2 in Table 14: note that coefficients on logBME and logMVE are untabulated. With respect to Subpanel B1, given that the coefficients (standard deviations) of Innovation, logBME, and logMVE are -0.00042 (25.1), -0.04702 (0.90), and 0.02448 (1.40), one standard deviation increase in these variables will change the industry-adjusted ROA by -0.011 ($-0.00042 \times 25.1 = -0.011$), -0.042 ($-0.04702 \times 0.90 = -0.042$), and 0.034 ($0.02448 \times 1.40 = 0.034$), respectively. Similarly in Subpanel B2, given that the coefficients

[11] Operating income variables in CCM database are adjusted for R&D expense (i.e., computed in accordance with US GAAP ASC 730 whereby R&D costs are expensed as incurred), indicating that operating income can decrease due to the increase in R&D costs.

[12] As opposed to the case of running OLS regressions where asreg package can accommodate Newey-West procedure, Stata environment does not immediately allow me to run median regressions jointly with Newey-West procedure. Thus I leverage qreg2 package and cluster at the firm level to mitigate the autocorrelation of error terms. The estimated results are unreported.

Table 13: Summary statistics: operating performance and eco-innovation

This table reports the summary statistics of the variables in the analysis examining the relationship between operating performance and eco-innovation. ROA is computed as operating income after depreciation and appreciation over total assets and then industry-adjusted by subtracting the median value of each industry using the full sample of CCM database. ROE is computed as operating income before depreciation and appreciation over book value of equity. The figures are before winsorization.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Innovation	50.40	25.10	0.40	2.70	33.00	50.00	67.90	98.30	99.80	5752
logBME	-1.20	0.90	-7.30	-4.10	-1.60	-1.10	-0.70	0.70	4.30	5592
logMVE	8.50	1.40	3.20	5.40	7.50	8.40	9.30	12.10	13.60	5750
Ind.adj.ROA	0.07	0.17	-3.25	-0.35	-0.00	0.04	0.10	0.57	1.62	5752
Ind.adj.ROE	0.30	5.88	-168.28	-4.18	0.00	0.11	0.30	4.76	262.67	5750

(standard deviations) of Innovation, logBME, and logMVE are -0.00053 (25.1), -0.25161 (0.90), and 0.0101 (1.40), one standard deviation increase in these variables will change the industry-adjusted ROE by -0.013 ($-0.00053 \times 25.1 = -0.013$), -0.226 ($-0.25161 \times 0.90 = -0.226$), and 0.014 ($0.0101 \times 1.40 = 0.014$), respectively.

Table 14: The effect of eco-innovation on operating performance: cross-sectional OLS regressions by year

Panels A and B present the effect of eco-innovation on ROA and ROE over the pre- and post-EISA period, respectively, by estimating OLS regressions by year. Subpanels A1 and B1 (A2 and B2) construct ROA with operating income after depreciation (ROE). The operating performance in year t is regressed on Innovation, MVE, and BME in year $t-1$ ($t = 2003, 2004, ...2017$). OLS regressions are estimated by year in the potential presence of cross-sectional dependence and serial correlation, following GIM and CGR. Standard errors are adjusted for serial correlation by implementing the Newey and West (1987) procedure with one lag. Accounting variables are winsorized at the 2.5% and 97.5% level.

$$\text{Industry Adj. Operating Performance}_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t-1} + \beta_2 \text{logBME}_{i,t-1} + \beta_3 \text{logMVE}_{i,t-1} + \varepsilon_{i,t}$$

Panel A: Pre-EISA	Coefficients on Innovation (β_1)							
	Subpanel A1: Adjusted ROA				Subpanel A2: Adjusted ROE			
	(1)	(2)	(3)	Obs.	(1)	(2)	(3)	Obs.
2003	0.00053	0.00069	0.00055	161	0.00246	-0.00058	-0.00062	161
2004	0.00155	0.00078	0.00054	164	0.00181	0.00099	0.00101	164
2005	0.00216	0.00146	0.00129	211	0.00478	0.00174	0.00169	211
2006	-0.00002	-0.00035	-0.00061	231	0.00102	0.00001	-0.00014	231
2007	0.00004	0	-0.00008	227	0.0001	0.00046	0.0004	227
Control variables	None	BME	BME, MVE		None	BME	BME, MVE	
Time-series mean	0.00085	0.00051	0.00034	5	0.00203*	0.00052	0.00047	5
t-statistic	(1.91)	(1.66)	(1.13)		(2.74)	(1.44)	(1.27)	

Panel B: Post-EISA	Coefficients on Innovation (β_1)							
	Subpanel B1: Adjusted ROA				Subpanel B2: Adjusted ROE			
	(1)	(2)	(3)	Obs.	(1)	(2)	(3)	Obs.
2008	0.00027	0.00006	-0.00015	232	0.00061	-0.00025	-0.00006	232
2009	0.00014	0.00015	0.00002	281	0.00062	-0.00013	0.00008	281
2010	-0.00004	-0.0001	-0.00031	314	0.00006	-0.00028	-0.00046	314
2011	-0.00044	-0.00036	-0.00057	326	-0.00179	-0.00175	-0.00204	326
2012	-0.00039	-0.00037	-0.00063	330	0.0004	-0.00016	-0.00021	330
2013	-0.00034	-0.00037	-0.00064	325	0.00026	-0.0004	-0.00038	325
2014	-0.00032	-0.00032	-0.00061	319	-0.00098	-0.00116	-0.00122	318
2015	-0.0005	-0.00045	-0.00075	309	0.00024	0.00008	-0.00001	308
2016	-0.00028	-0.00028	-0.00054	497	0.00025	0.00012	-0.0001	497
2017	0.0002	0.00025	-0.00005	664	0.00016	0.00042	-0.00093	664
Control variables	None	BME	BME, MVE		None	BME	BME, MVE	
Time-series mean	-0.00017	-0.00018*	-0.00042***	10	-0.00002	-0.00035	-0.00053**	10
t-statistic	(-1.57)	(-1.94)	(-3.96)		(-0.07)	(-1.74)	(-2.72)	

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

In the next step, I conduct an event study on earnings announcement returns to examine whether investors were surprised by the announcement, which may account for the source of the excess returns observed in eco-innovative firms.[13] On the one hand, a positive surprise (Case A) can serve as a source of superior returns observed in highly eco-innovative firms, and can be reconciled with the confirmed negative link between eco-innovation and operating performance inasmuch as investors—who are aware that complying with EISA is costly but excessively overestimate the cost—are positively surprised by the better-than-expected earnings announcements of eco-innovation intensive firms. Conversely, a negative surprise (Case B) can serve as evidence that the market is surprised by the negative operating performance of highly eco-innovative firms, yet it is at odds with the superior returns observed in highly eco-innovative firms—this possibility, albeit puzzling, still cannot be ruled out insofar as other channels dominate this effect and thus further investigation in Section 4.5 is crucial. Finally, no surprise (Case C) indicates that the market expected the negative link between eco-innovation and operating performance. Cases B and C may warrant a different channel that accounts for the observed superior returns of eco-innovative firms.

The study of earnings announcements proceeds as follows. I construct quintile portfolios following the procedure akin to Section 4.3 and identify event dates of earnings announcements in the portfolios: the same firm may appear in different quintile groups at different points in time because quintile portfolios are annually reset and thus the firm distribution in the portfolio develops over time. Next, for each quintile portfolio, I adopt a time-series portfolio approach (e.g., La Porta, Lakonishok, Shleifer, and Vishny, 1997; CGR) and compute the value-weighted quarterly returns and equally average them over the study period. Accordingly, based on Fama and MacBeth (1973) procedure, I evaluate the significance of the mean return using the time-series standard error of the quarterly returns, where the standard error is derived by computing the estimate of standard deviation over the square root of sample size. The reason for this is that (i) earnings announcements dates are in general clustered by industry and (ii) news about one firm in an industry transcends to others, in which case cross-sectional dependence becomes a serious issue.

The empirical results are documented in Table 15. In brief, little systematic patterns are confirmed in earnings announcements across quintile portfolios: unreported results using the window $(-3, 1)$ also confirm similar patterns. In the end, two caveats are in order. First, the intercept in the expected return model (i.e., alpha) captures the excess return—that is, the

[13] Ideally, I should conduct earnings forecast error analysis in parallel but the access limitation to I/B/E/S database restricts available options.

return that exceeds what is predicted by the model—but, as noted by CGR, the abnormal return in this discussion throws light on the unexpected return that is even beyond what this alpha points to. Second, one of the shortcomings of using security price data is that it may understate the surprises if firms preannounce a fraction of information and investors reactions partially take place outside the short-lived event study window (CGR).

Table 15: Returns surrounding earnings announcements over the post-EISA period

Panels A and B present the returns for each Innovation subscore quintile portfolio, over announcement dates surrounding the $(-1, +1)$ window, during the pre- and post-EISA period, respectively. In the spirit of CGR, all announcement returns are value-weighted within quarter and then averaged over the quarters. The t-statistics are based on the time series of quarterly returns. Note that changing the start of post-EISA period from January 2007 to January 2008 does not qualitatively alter the results.

Panel A: Pre-EISA	Returns for quintile portfolios over $(-1, 1)$ window					
	Raw return	t-statistic	Obs.	Excess return	t-statistic	Obs.
Top quintile	0.43%	0.64	687	0.17%	0.24	687
Fourth quintile	0.26%	0.97	1257	0.12%	0.36	1257
Third quintile	0.28%	1.02	1109	0.09%	0.28	1109
Second quintile	0.16%	0.41	732	0.05%	0.14	732
Bottom quintile	-0.82%	-1.21	585	-0.64%	-1.32	585

Panel B: Post-EISA	Returns for quintile portfolios over $(-1, 1)$ window					
	Raw return	t-statistic	Obs.	Excess return	t-statistic	Obs.
Top quintile	0.32%	1.33	3018	0.03%	0.2	3018
Fourth quintile	0.3%	0.89	2949	0.08%	0.24	2949
Third quintile	-0.76%*	-1.95	2670	-0.82%*	-1.93	2670
Second quintile	0.47%**	2.46	2854	0.17%	0.96	2854
Bottom quintile	0.17%	0.67	2749	-0.08%	-0.4	2749

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

4.5 R&D investments and stock return volatility

On the grounds that notable systematic patterns were not confirmed in earnings surprises (Section 4.4), it is tempting to infer that excess returns of eco-innovation intensive firms are higher because they carry a premium for risk. Yet, one should not jump to this conclusion, for operating performance is not the only channel that firms improve shareholder values (e.g., LeRoy and Porter, 1981; Edmans, 2011) and thus other value-relevant channels requires inspection. In particular, if the introduction of EISA fuels corporate investments in R&D,[14] this would naturally alter firms' future profitability but it remains to be seen whether the market fully incorporates this information. More precisely, EISA may adversely affect operating performance in the short run but the shareholder value can increase through the channel of heightened R&D activities to the extent that the gain (e.g., increased intangible assets such as knowledge base, long-term sustainability) outweighs the loss (i.e., reduced operating performance); however, this prospect certainly hinges on the presumption that the stock market incorporates long-term aspects.

Moreover, it is certainly true that R&D intensity affects cash flow streams and thus should be value-relevant but the efficient market theory dictates that the stock price immediately impounds the value of a firm's R&D capital thus leading to no association between R&D intensity and expected stock returns (e.g., Chan, Lakonishok, and Sougiannis, 2001). In this respect, there is mixed empirical evidence on whether or, if so, how quickly, R&D information is capitalized by the stock market. Some literature reveals that the value of intangible assets such as R&D (Lev and Sougiannis, 1996) and patent citations (Deng, Lev, and Narin, 1999) are not fully evaluated by stock market investors.[15] Grandi, Hall, and Oriani (2009) contend that R&D policies can substantially shape the corporate landscape in terms of performance, future profits, and expected cash flow but the effects are spread over a long period of time. In sum, the joint test is an empirical question regarding whether eco-innovation is causally linked to firms' future profitability through R&D investment and whether this link is observable because the information on R&D does not instantly flow into the knowledge base of stock market participants; equally important, this experiment can indicatively inform the validity of the strong PH. However, as discussed later, it is infeasible to directly test this joint hypothesis and therefore I adopt a version of this approach.

Against this backdrop, I first study the effect of eco-innovation on R&D intensity. To highlight the nexus between eco-innvation and R&D, I reiterate the analysis presented in Table 14 (Section 4.4), which is represented by equation (10). I anticipate that a positive correlation between eco-innovation and R&D intensity emerges represented by $\beta_1 > 0$ after

[14] The following sections are the examples in EISA that involve research and development activities (also see Table 1): Title I (Sec 112), Title II (Subtitle B), Titel III (Sec 321.g) Title IV (Sec 492), Title VI, Title VII (Subtitle A), Title XII (Sec 1204), Title XIII (Sec 1304).

[15] In addition, Eberhart, Maxwell, and Siddique (2004) document that investors' recognition of the benefit of R&D investments develops sluggishly: over the five year period after their R&D increases, firms experience significantly positive abnormal operating performance coupled with significantly positive abnormal stock returns. By contrast, Deng, Lev, and Narin (1999) claim that R&D investments are sufficiently recognized but intermediate outputs such as citation impacts and patent counts are under-recognized by investors, for these hand-constructed characteristics are not conventionally exploited in security analysis.

the enactment of EISA. This conjecture is consistent with the illustration in Figure 6 of Appendix A that particularly among larger firms, which are ex-ante more eco-innovative, further augmented their green status presumably because the investment in R&D led to more adoption of eco-innovative technologies. In addition to the R&D intensity measure computed by R&D expenditure over sales, I introduce another measure by taking the ratio of R&D expenditures to the market value of equity (e.g., Chan, Lakonishok, and Sougiannis, 2001). I include the book-to-market variable in the baseline model specification because intangible assets generated by R&D intensities are positively (negatively) correlated with market-to-book (book-to-market) ratios. I also control for the size variable because the difficulty of securing financing for research activities from outside sources may lead to under-investment in research activities. This situation may particularly apply to small firms, which have less internally generated cash and/or less access to financial markets (Jaffe, Newell, and Stavins, 2003).

$$\text{Adj. R\&D intensity}_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t-1} + \beta_2 \text{logBME}_{i,t-1} + \beta_3 \text{logMVE}_{i,t-1} + \varepsilon_{i,t} \tag{10}$$

Equation (10) is also an analogue of the identification strategy employed in prior research that tests the weak PH whereby R&D is the dependent variable and the regulation compliance expenditure PACE (i.e., proxy for environmental regulation) serves as one of the independent variables (e.g., Jaffe and Palmer, 1997; Lanoie et al., 2011; Rubashkina, Galeotti, and Verdolini, 2015). A caveat concerning equation (10) is that the total R&D is only a proxy for environmental R&D, the R&D amount unique to the environmental dimension.[16] While Jaffe and Palmer (1997) use total R&D expenditure in assessing the weak PH, Lanoie et al. (2011) cast doubt on their specification and criticize that the Porter Hypothesis needs to be more eloquent on the environmental dimension of R&D: the authors address this ambiguity by specifically estimating environmental R&D using a probit model.

The empirical results presented in Table 17 reinforce the confirmation of the weak PH in Section 4.1, demonstrating that while there is no significant relationship between eco-innovation and R&D intensity before the enactment of EISA (Subpanels A1 and A2), the relationship becomes positive significant in the baseline model specification (3) after the

[16] Conversely, the regression of Innovation subscore on lagged R&D intensity also appears plausible that aims to estimate how R&D contributes to Innovation subscore. Yet, this identification poses a difficulty on two accounts. First, R&D expenditures are generally aimed for projects with duration of several years and although it is possible to include more lags in the model specification, this would also drive down the number of time-dimension observations. Second, Innovation subscore is a relative percentile rank within TRBC industry group and it may not lead to an absolute increase in the subscore if the majority of the firms in the group simultaneously invests in a similar technological development.

Table 16: Summary statistics: R&D intensity and eco-innovation

This table reports the summary statistics of the variables in the analysis examining the relationship between R&D intensity and eco-innovation. R&D intensity is either scaled by sales or market capitalization and then industry-adjusted by subtracting the median value of each industry using the full sample of CCM database. The figures are before winsorization.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Innovation	50.40	25.10	0.40	2.70	33.00	50.00	67.90	98.30	99.80	5752
logBME	-1.20	0.90	-7.30	-4.10	-1.60	-1.10	-0.70	0.70	4.30	5592
logMVE	8.50	1.40	3.20	5.40	7.50	8.40	9.30	12.10	13.60	5750
Ind.adj.R&D int. (sales)	5.76	185.96	-1.48	-1.32	-0.02	0.00	0.02	13.10	12989.52	5691
Ind.adj.R&D int. (MC)	0.01	0.06	-0.13	-0.06	-0.01	0.00	0.01	0.23	1.50	5750

enactment of EISA (Subpanels B1 and B2). Overall, evidenced by Subpanels B1 and B2, R&D intensity in the post-EISA period is positively associated with Innovation subscore, indicating that ex-ante more eco-innovative firms ramped up R&D investment and further boosted their environmentally-friendly status.

Moreover, the effect of Innovation on R&D intensity in the post-EISA period is economically large and significant. As an example, I use the specification (3) of Subpanels B1 and B2 in Table 17: note that coefficients on logBME and logMVE are untabulated. Regarding Subpanel B1, given that the coefficients (standard deviations) of Innovation, logBME, and logMVE are 0.00078 (25.1), -0.01261 (0.90), and -0.04205 (1.40), one standard deviation increase in these variables will change the R&D intensity by 0.020 ($0.00078 \times 25.1 = 0.020$), -0.011 ($-0.01261 \times 0.90 = -0.011$), and -0.059 ($-0.04205 \times 1.40 = -0.059$), respectively. Similarly in Subpanel B2, given that the coefficients (standard deviations) of Innovation, logBME, and logMVE are 0.00006 (25.1), 0.00525 (0.90), and -0.00457 (1.40), one standard deviation increase in these variables will change the R&D intensity by 0.002 ($0.00006 \times 25.1 = 0.002$), 0.005 ($0.00525 \times 0.90 = 0.005$), and -0.006 ($-0.00457 \times 1.40 = -0.006$), respectively.

Table 17: The effect of eco-innovation on R&D intensity: cross-sectional OLS regressions by year

Panels A and B present the effect of eco-innovation on R&D intensity over the pre- and post-EISA period, respectively, by estimating OLS regressions by year. Subpanels A1 and B1 (A2 and B2) draw on R&D intensity measure scaled by sales (market cap). The R&D intensity in year t is regressed on Innovation, MVE, and BME in year $t-1$ ($t = 2003, 2004, ...2017$). OLS regressions are estimated by year in the potential presence of cross-sectional dependence and serial correlation, following GIM and CGR. Standard errors are adjusted for serial correlation by implementing the Newey and West (1987) procedure with one lag. Accounting variables are winsorized at the 2.5% and 97.5% level.

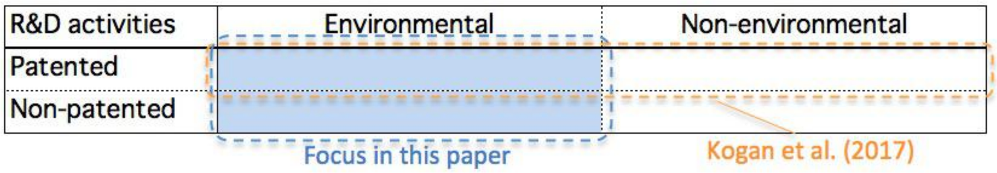
$$\text{Adj. R\&D intensity}_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t-1} + \beta_2 \text{logBME}_{i,t-1} + \beta_3 \text{logMVE}_{i,t-1} + \varepsilon_{i,t}$$

Panel A: Pre-EISA	Coefficients on Innovation (β_1)							
	Subpanel A1: R&D expenditure/sales				Subpanel A2: R&D expenditure/market cap			
	(1)	(2)	(3)	Obs.	(1)	(2)	(3)	Obs.
2003	-0.00179	-0.00187	-0.00166	161	-0.00002	-0.00002	0	161
2004	-0.00202	-0.00151	-0.00117	164	-0.00038	-0.00018	-0.00016	164
2005	-0.00172	-0.00131	-0.00112	211	-0.00023	-0.00018	-0.00017	211
2006	0.00035	0.00051	0.00076	231	-0.00004	-0.00001	0	231
2007	-0.00018	-0.00012	-0.00001	227	0.00002	0.00002	0.00003	227
Control variables	None	BME	BME, MVE		None	BME	BME, MVE	
Time-series mean	-0.00107	-0.00086	-0.00064	5	-0.00013	-0.00008	-0.00006	5
t-statistic	(-1.91)	(-1.66)	(-1.29)		(-1.70)	(-1.67)	(-1.36)	

Panel B: Post-EISA	Coefficients on Innovation (β_1)							
	Subpanel B1: R&D expenditure/sales				Subpanel B2: R&D expenditure/market cap			
	(1)	(2)	(3)	Obs.	(1)	(2)	(3)	Obs.
2008	-0.00008	-0.00006	0.00019	232	-0.00003	0.00002	0.00007	232
2009	-0.00029	-0.00031	-0.00017	281	-0.00001	-0.00002	0	281
2010	-0.00012	-0.00014	0.00005	314	-0.00005	-0.00005	-0.00002	314
2011	0.00021	0.00023	0.00047	326	0.00005	0.00004	0.00008	326
2012	0.0005	0.00049	0.00076	330	0.00007	0.00005	0.00009	330
2013	0.00051	0.00052	0.00083	325	0.00004	0.00003	0.00007	325
2014	0.00073	0.00075	0.00115	319	0.00004	0.00004	0.00009	319
2015	0.00129	0.00131	0.00183	308	0.00004	0.00003	0.00008	309
2016	0.00062	0.00053	0.00156	493	0.00001	0	0.00003	497
2017	-0.00025	-0.00048	0.00111	653	-0.00004	-0.00005	0.00007	664
Control variables	None	BME	BME, MVE		None	BME	BME, MVE	
Time-series mean	0.00031	0.00028	0.00078**	10	0.00001	0.00001	0.00006***	10
t-statistic	(1.58)	(1.37)	(2.83)		(0.73)	(0.70)	(4.19)	

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Figure 4: Partitioning R&D activities



Next, I attempt to reconcile the previously observed abnormal returns of eco-innovative firms with the emerged positive link between eco-innovation and R&D following EISA. To empirically inspect whether the observed abnormal returns stem from mispricing, it is ideal to study the surprises in R&D announcements by extending the earnings announcement framework in Section 4.4. This is because R&D activities are by and large viewed as a value-enhancing scheme by investors and thus investors are expected to react positively to firm announcements of a new R&D project.[17] However, this requires manual collection of announcement news. Another concern is that an *increase* in R&D is rarely announced (Eberhart, Maxwell, and Siddique, 2004). In a different study, while Kogan, Papanikolaou, Seru, and Stoffman (2017) propose an important measure of the economic value of innovations by relying on stock market reactions on patent grants collected from Google Patents, I do not apply this measure to this study because (i) innovation activities are not necessarily patented given the fact that patents are awarded to inventions and (ii) their measure is not limited to the environmental dimension but captures broad-based innovative activities (Figure 4).[18]

Under these circumstances, I circumvent the issue of whether the positive link running from eco-innovation to excess return is due to mispricing and instead investigate whether eco-innovation affects expected returns through the risk channel, where risk is proxied by return volatility. Although Chan, Lakonishok, and Sougiannis (2001) find no evidence that there is on average stock return differentials between firms that do and do not engage in R&D activities, their empirical results suggest that heightened R&D activities lead to increased volatility of returns, which in turn has an implication for the cost of capital of R&D intensive firms. Gu (2016) also finds that firms exhibit differential expected returns according to R&D intensity especially in competitive industries because R&D activities are positively associated with riskiness.

[17] Chan, Martin, and Kensinger (1990) confirm significantly positive abnormal returns in an event study surrounding the announcements of increased R&D expenditure, even when the announcement occurs in the face of an earnings decline. The authors further claim that the market takes a long-run view of R&D investments and rewards firms that pursue an aggressive R&D strategy, even in the face of earnings declines.

[18] On the one hand, Jaffe and Palmer (1997) uncovers that environmental regulation significantly affects R&D investment but has no impact on patents. On the other hand, Brunnermeier and Cohen (2003) show a positive, albeit small, impact of environmental regulation on granted environmental patents. Thus, I take a conservative approach and refrain from using patent data.

To this end, I estimate the model specification employed by Chan, Lakonishok, and Sougiannis (2001) but additionally include Innovation subscore to their specification, which is formulated in equation (11). Moreover, consistent with the previous analyses, I split the sample period into pre- and post-EISA period as a baseline case and estimate a cross-sectional regression at the end of each June using Fama-MacBeth procedure. The dependent variable $\sigma_{i,t}$ is the stock return volatility computed as the standard deviation of monthly log returns, which is measured in the subsequent 12 month period and proxies the risk. R&D intensity$_{i,t}$ is the R&D expenditure either scaled by sales or market capitalization: for the latter case, I use the market capitalization measured at the end of December of year $t-1$. LNSIZE$_{i,t}$ is the firm size in logarithm and I use market equity at the end of December of year $t-1$. LNAGE$_{i,t}$ is the firm age in logarithm and I use the first trading date in the exchange as a proxy for the firm's age. IND$_{i,j,t}$ is the industry classification based on 2-digit SIC code.

Particularly, controlling for R&D intensity is essential to shed light on the potential that eco-innovation is associated with return volatility in the post-EISA period beyond the relationship between R&D activities and return volatility. Thus, the variable of interest is Innovation and $\beta_2 \leq 0$ is the null hypothesis suggestive of the strong PH, while $\beta_2 > 0$ serves as an economic rationale pushing for the notion that the eco-innovation's predictability of excess returns surfaces due to risk.

$$\begin{aligned}\sigma_{i,t} = \beta_{0,t} &+ \beta_{1,t}\,\text{R\&D Intensity}_{i,t} + \beta_{2,t}\,\text{Innovation}_{i,t} \\ &+ \beta_{3,t}\,\text{LNSIZE}_{i,t} + \beta_{4,t}\,\text{LNAGE}_{i,t} + \sum_{j=1}^{L}\phi_{j,t}\,\text{IND}_{i,j,t} + \varepsilon_{i,t}\end{aligned} \tag{11}$$

The summary statistics are presented in Table 18 and the estimated results are presented in Tables 19 and 20. The baseline case represented in specifications (1), (4), (7), (10) includes Innovation subscore and I also consider two versions of this specification. The first version also includes Resource Use and Emission subscores represented in specifications (2), (5), (8), (11). The reason for this is that (i) these variables show moderate levels of correlation with Innovation (both cases around 30%) and (ii) Innovation might be just proxying for good environmental management, thereby leading to less return volatility. The second version replaces Innovation with dummies Inn75–100 and Inn50–75: Inn75–100 equals to one if Innovation is greater than 75; and Inn50–75 equals to one if Innovation is between 50 and 75.

Table 18: Summary statistics of return volatility analysis

This table reports the summary statistics of the return volatility analysis. R&D expenditure is either scaled by sales or market capitalization: for the latter case, I use market capitalization measured at the end of December of year $t-1$. LNSIZE$_{i,t}$ is the firm size in logarithm and I use market equity at the end of December of year $t-1$. LNAGE$_{i,t}$ is the firm age in logarithm and I use the first trading date in the exchange as a proxy for the firm's age. The figures are before winsorization.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Return volatility	0.10	0.08	0.00	0.03	0.06	0.08	0.12	0.37	1.71	5710
Innovation	50.40	25.10	0.40	2.70	33.20	50.00	68.00	98.30	99.80	5717
Resource Use	47.70	28.10	0.30	5.40	25.00	43.00	72.20	99.00	99.80	5717
Emissions	46.20	28.00	0.20	1.50	23.70	41.30	69.60	98.90	99.80	5717
LNSIZE	8.50	1.44	3.17	5.45	7.54	8.37	9.34	12.16	13.67	5715
LNAGE	3.07	0.95	0.00	0.00	2.64	3.26	3.81	4.20	4.22	5717
R&D/Sales	5.97	186.57	0.00	0.00	0.01	0.03	0.10	14.80	12991.00	5656
R&D/MC	0.04	0.07	0.00	0.00	0.01	0.02	0.04	0.29	1.41	5715

In all cases, eco-innovation consistently exhibits a non-positive relationship with return volatility although the degree of statistical significance varies. This indicates that eco-innovation is in fact associated with certainty rather than uncertainty, suggesting that once the innovation process is beyond the stage of R&D, the process becomes more associated with certain future cash flows. The non-positive relationship between eco-innovation and return volatility also suggests that after controlling for R&D intensity, there is no empirical evidence supporting the view that the firm's eco-innovative status led to additional cost of capital following the enactment of EISA—although the significant and strictly negative association between Innovation and return volatility observed in the pre-EISA period is no longer confirmed in the post-EISA period.

Table 19: Regressing return volatility on R&D relative to sales and Innovation

Using Fama-MacBeth estimation, the results of the regression models are presented in the table below. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 (2007–2009) is termed as post-EISA (crisis) period. The dependent variable is return volatility computed from log returns. t-statistics are adjusted for serial correlation by using the Newey-West procedure with two lags for pre-EISA or crisis period and three lags for post-EISA or full period. R&D/Sales is winsorized at the 2.5% and 97.5% level.

	Subperiod									Full period		
	Pre-EISA			Post-EISA			Crisis					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R&D/Sales	0.0450***	0.0444***	0.0447***	0.0203	0.0209	0.0202	-0.0431	-0.0399	-0.0441	0.0280**	0.0282**	0.0279**
	(12.27)	(10.70)	(10.10)	(1.08)	(1.16)	(1.07)	(-0.96)	(-0.94)	(-0.99)	(2.16)	(2.28)	(2.13)
Innovation	-0.0002**	-0.0002**		-0.0000	-0.0000		-0.0001	-0.0002		-0.0001*	-0.0001*	
	(-3.72)	(-3.71)		(-0.79)	(-0.77)		(-1.07)	(-1.69)		(-1.94)	(-1.90)	
Resource Use		-0.0002**			-0.0000			0.0001			-0.0001	
		(-2.82)			(-0.15)			(0.54)			(-1.02)	
Emissions		0.0001*			0.0000			0.0000			0.0000	
		(2.42)			(0.03)			(0.02)			(0.74)	
Inn75–100			-0.0090			-0.0023			-0.0073			-0.0044*
			(-1.86)			(-1.07)			(-2.04)			(-1.93)
Inn50–75			-0.0076			-0.0045			-0.0120			-0.0054*
			(-2.06)			(-1.29)			(-1.77)			(-2.07)
LNSIZE	-0.0092***	-0.0086***	-0.0095***	-0.0138***	-0.0135***	-0.0139***	-0.0181**	-0.0193**	-0.0186**	-0.0124***	-0.0120***	-0.0125***
	(-6.80)	(-4.91)	(-7.15)	(-7.32)	(-6.18)	(-7.10)	(-5.33)	(-6.73)	(-5.08)	(-8.43)	(-7.03)	(-8.30)
LNAGE	-0.0113**	-0.0111**	-0.0113**	-0.0079*	-0.0080*	-0.0080*	-0.0184	-0.0191	-0.0188	-0.0090**	-0.0090**	-0.0090**
	(-3.17)	(-2.97)	(-3.23)	(-1.98)	(-2.00)	(-1.94)	(-1.49)	(-1.61)	(-1.49)	(-2.75)	(-2.73)	(-2.70)
Intercept	0.1922***	0.1897***	0.1877***	0.2317***	0.2302***	0.2323***	0.3146*	0.3220*	0.3168*	0.2193***	0.2175***	0.2184***
	(7.36)	(6.81)	(7.11)	(7.12)	(6.85)	(7.15)	(3.31)	(3.57)	(3.43)	(8.86)	(8.47)	(8.69)
SIC-2 dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1019	1019	1019	4628	4628	4628	867	867	867	5647	5647	5647
Time Periods	5	5	5	10	10	10	3	3	3	15	15	15

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 20: Regressing return volatility on R&D relative to market cap and Innovation

Using Fama-MacBeth estimation, the results of the regression models are presented in the table below. Subperiod 2002–2006 is termed as pre-EISA period, while subperiod 2007–2017 (2007–2009) is termed as post-EISA (crisis) period. The dependent variable is return volatility computed from log returns. t-statistics are adjusted for serial correlation using the Newey-West procedure with two lags for pre-EISA or crisis period and three lags for post-EISA or full period. R&D/market cap is winsorized at the 2.5% and 97.5% level.

	Subperiod									Full period		
	Pre-EISA			Post-EISA			Crisis					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
R&D/MC	0.1853***	0.2060***	0.1799***	0.2162***	0.2326***	0.2138***	0.1983**	0.2035***	0.1894**	0.2066***	0.2243***	0.2032***
	(9.61)	(9.56)	(8.89)	(6.72)	(7.83)	(6.83)	(6.42)	(12.06)	(6.05)	(9.10)	(10.52)	(9.11)
Innovation	-0.0002**	-0.0002**		-0.0000	-0.0000		-0.0001	-0.0002		-0.0001*	-0.0001*	
	(-3.72)	(-3.52)		(-0.98)	(-0.61)		(-1.14)	(-1.56)		(-2.13)	(-1.76)	
Resource Use		-0.0003*			-0.0001			0.0000			-0.0001	
		(-2.71)			(-0.60)			(0.08)			(-1.56)	
Emissions		0.0001			-0.0001			0.0000			-0.0000	
		(2.08)			(-0.75)			(0.11)			(-0.09)	
Inn75–100			-0.0115*			-0.0026			-0.0074			-0.0054*
			(-2.16)			(-1.21)			(-1.93)			(-2.09)
Inn50–75			-0.0081*			-0.0042			-0.0123			-0.0054*
			(-2.26)			(-1.24)			(-2.04)			(-2.09)
LNSIZE	-0.0084***	-0.0070**	-0.0086***	-0.0128***	-0.0116***	-0.0129***	-0.0166**	-0.0169**	-0.0171**	-0.0114***	-0.0102***	-0.0116***
	(-5.51)	(-3.48)	(-5.76)	(-7.23)	(-5.63)	(-7.04)	(-5.31)	(-6.65)	(-5.02)	(-8.13)	(-6.21)	(-8.04)
LNAGE	-0.0138**	-0.0134**	-0.0138**	-0.0098**	-0.0096**	-0.0097**	-0.0188	-0.0192	-0.0191	-0.0110***	-0.0108***	-0.0110***
	(-4.06)	(-3.68)	(-4.08)	(-2.70)	(-2.63)	(-2.61)	(-1.60)	(-1.69)	(-1.59)	(-3.63)	(-3.52)	(-3.54)
Intercept	0.1928***	0.1853***	0.1879***	0.2283***	0.2217***	0.2283***	0.3010*	0.3035*	0.3030*	0.2172***	0.2103***	0.2157***
	(7.26)	(6.54)	(7.06)	(7.47)	(7.02)	(7.50)	(3.30)	(3.52)	(3.41)	(9.29)	(8.67)	(9.10)
SIC-2 dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1019	1019	1019	4689	4689	4689	867	867	867	5708	5708	5708
Time Periods	5	5	5	10	10	10	3	3	3	15	15	15

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

4.6 Why does eco-innovation predict future returns?

This subsection expounds three possible scenarios behind the observed positive link between eco-innovation and future returns: systematic mispricing, latent risk factor, and additionally a moderator. The first scenario is that eco-innovation contributes to shareholder value and points to the strong PH; the second scenario is that eco-innovation leads to increased cost of capital and implies reduced shareholder value and thus contradicts the strong PH; and the last scenario is that eco-innovation is not directly relevant to firm value. However, I do not take a definite stand on which of these scenarios—especially the first two—is truly valid given the considerable effort additionally required. Schwert (1981) adds on this matter that it is challenging to disentangle the regulation-induced effect on the *expected value* of future cash flows from the same effect on the *risk* of future cash flows, especially because discount rate is unlikely to be constant over all periods in the future.

First, as referred to in previous sections, the mispricing scenario dictates that environmental innovation is value-relevant and causes corporate performance improvement but investors underreact to the eco-innovation and R&D related information (e.g., underestimating benefits, overestimating costs of compliance to EISA) and thus the information is not immediately impounded to stock prices. In the spirit of Edmans (2011), the possibility of two additional mispricing-based scenarios stemming from investors' irrational expectation needs consideration: (i) eco-innovation has no beneficial effect on firm's fundamental value but investors substantially overvalue eco-innovative firms merely because of its greenness, thereby putting upward pressure on stock prices; or (ii) eco-innovation is not value-relevant, again, but investors unjustifiably undervalues eco-innovative firms because of its associated cost (e.g., regulation compliance), leading to discounted initial value. These two subscenarios, however, are not truly persuasive because earnings announcements are not met with surprises and thus no correction is confirmed at least through the channel of short-term profits.

Second, the latent risk-factor scenario is that the expected returns of highly eco-innovative firms are systematically different primarily because they carry a premium for some missing risk factors other than common risk factors. In this regard, the risk premium arises from the additional compensation investors require for the higher uncertainty associated with risky assets either emerging from (i) non-sustainable risk factors or (ii) sustainable risk factors. For the case of the first subscenario, it is not difficult to anticipate that non-sustainability premium is considerably embedded within firms given the growing attention to corporate sustainability and responsibility issues (Manescu, 2011): besides, investors naturally expect that firms incur nontrivial costs for environmental cleanup and that these costs are lower for firms with better environmental records (Dowell, Hart, and Yeung, 2000). However, highly eco-innovative firms should then have *lower* returns under this subscenario, which is inconsistent with my empirical findings. For the case of the second subscenario, highly eco-innovative firms confront additional uncertainty associated with their innovation dynamics, while other firms do not receive such pressure from investors. Given that (i) environmental R&D is a risky investment in nature (e.g., Kothari, Laguerre, and Leone, 2002) and (ii) the financial crisis may have brought more uncertain future prospects to firms, it is not unnatural that investors demanded more risk premia for highly eco-innovative firms, especially when risk premia may have been magnified during the crisis. Notwithstanding, this subscenario is not empirically supported by Tables 19 and 20 in Section 4.5. The analysis reveals no evidence that eco-innovation is positively associated with uncertainty proxied by stock return volatility.

The last scenario is that the positive relation between eco-innovation and returns surfaces because an unobserved variable causes both. Eco-innovation is in this case merely a proxy for this third variable (e.g., good governance) and I especially consider two subscenarios. First, even if environmental regulation positively affects environmental performance and is thus positively associated with subsequent returns, this may only be due to a signal of better management and not because of environmental performance per se (Ambec and Barla, 2006)—the correlation between returns and eco-innovation is in this case virtually spurious. Second, the results could be driven by a particular feature of social capital, which is proxied by eco-innovation—that is, highly eco-innovative firms may accumulate social capital and their stakeholders may take reciprocal behaviors to support these firms during the time of hardship (e.g., Lins, Servaes, and Tamayo, 2017). To investigate these possibilities, Appendix E conducts placebo tests: I specifically test (i) the case of CSR-related variables other than eco-innovation as a driver of excess returns and (ii) industries other than manufacturing. The tests prove that these subscenarios are unlikely.

5 Conclusion

It is empirically known that regulation is key to promoting environmental innovation. This paper extends the body of literature examining the Porter hypothesis by empirically exploring the impact of EISA 2007 on (i) corporate innovation strategies and (ii) firm competitiveness using a market-based measure. The verification of the weak PH using a panel regression model with fixed effects could be admittedly driven by unobserved time-varying firm heterogeneity but this concern is alleviated with the aid of visualization in Appendix A and Appendix C. This paper additionally examines the joint effect of market-based policy instruments and an economic crisis on the diffusion of eco-innovative technologies. My findings suggest that the 2007–2009 financial crisis did not prevent larger firms from swiftly adopting eco-innovative technologies, while small firms lagged behind in this space.

Furthermore, in relation to the observed positive link running from eco-innovation to subsequent returns, it should not escape our attention that a decisive confirmation of the strong PH can be ensured only if the excess returns are observed due to mispricing and not due to risk. In this respect, I do not find first-order evidence that refutes the strong PH since eco-innovation is in fact associated with certainty after controlling for R&D intensity, which rather implies a decrease in cost of capital, although this link did weaken in the post-EISA period. Thus, this paper is consistent with the claim that eco-efficiency can create value and leads to superior performance (e.g., Derwall, Guenster, Bauer, and Koedijk, 2005; Guenster, Bauer, Derwall, and Koedijk, 2011). Ambec et al. (2013) also stress that in an era when there are more market-based instruments, it is not surprising to see more studies confirming the (strong) PH.

Finally, this paper has a policy implication especially for nations that are struggling to transition into a clean energy paradigm. Given that countries have their own characteristics of innovations system, my findings cannot be easily extended to other nations. Yet, there is a growing consensus on the mission to decarbonize the global economy and this paper empirically supplements this view at least from the aspect of the US stock market.

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Appendix A. Transition of manufacturers' environment-related subscores

Figure 5: Environment-related subscores in manufacturing industry (*including* new firm entries)

The figures below exhibit the distribution of Innovation, Resource Use, and Emissions subscores over time, where all types of firm size group are included and new firm entries are allowed for each year. These figures indeed show that the distributions of the subscores are percentile ranks, which is essentially designed to be flat (Thomson Reuters, 2017, 2018, 2019, 2020).

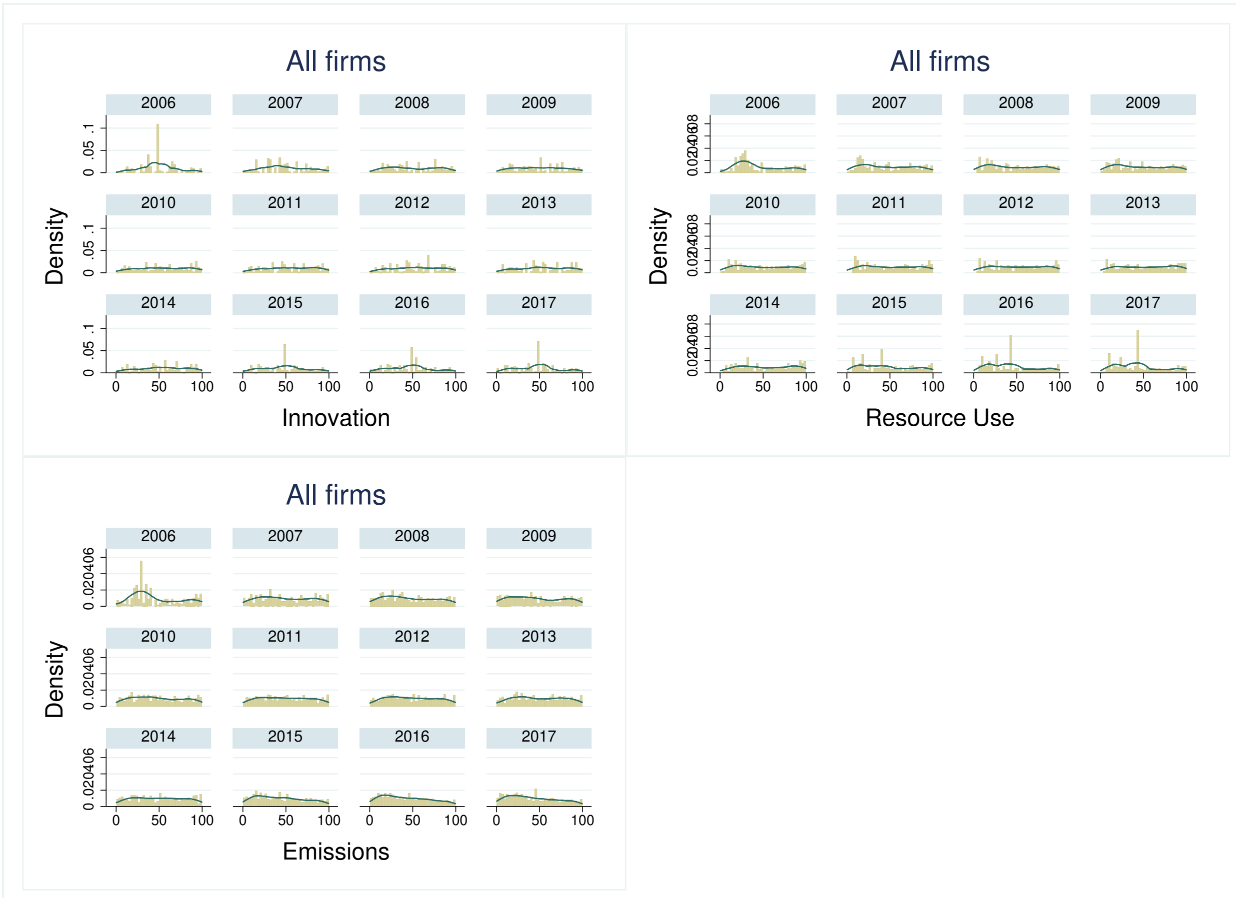


Figure 6: Innovation subscore by manufacturer size and fiscal year (*excluding* new firm entries)

The figures below exhibit the distribution of Innovation subscore across different firm size groups based on 2006 as well as over time in manufacturing industry—the top-left figure is a mixture across firm size groups. New firm entries are prohibited in any given year using 2006 as a baseline year and therefore the figures only feature the cross-section of firms that existed in 2006.

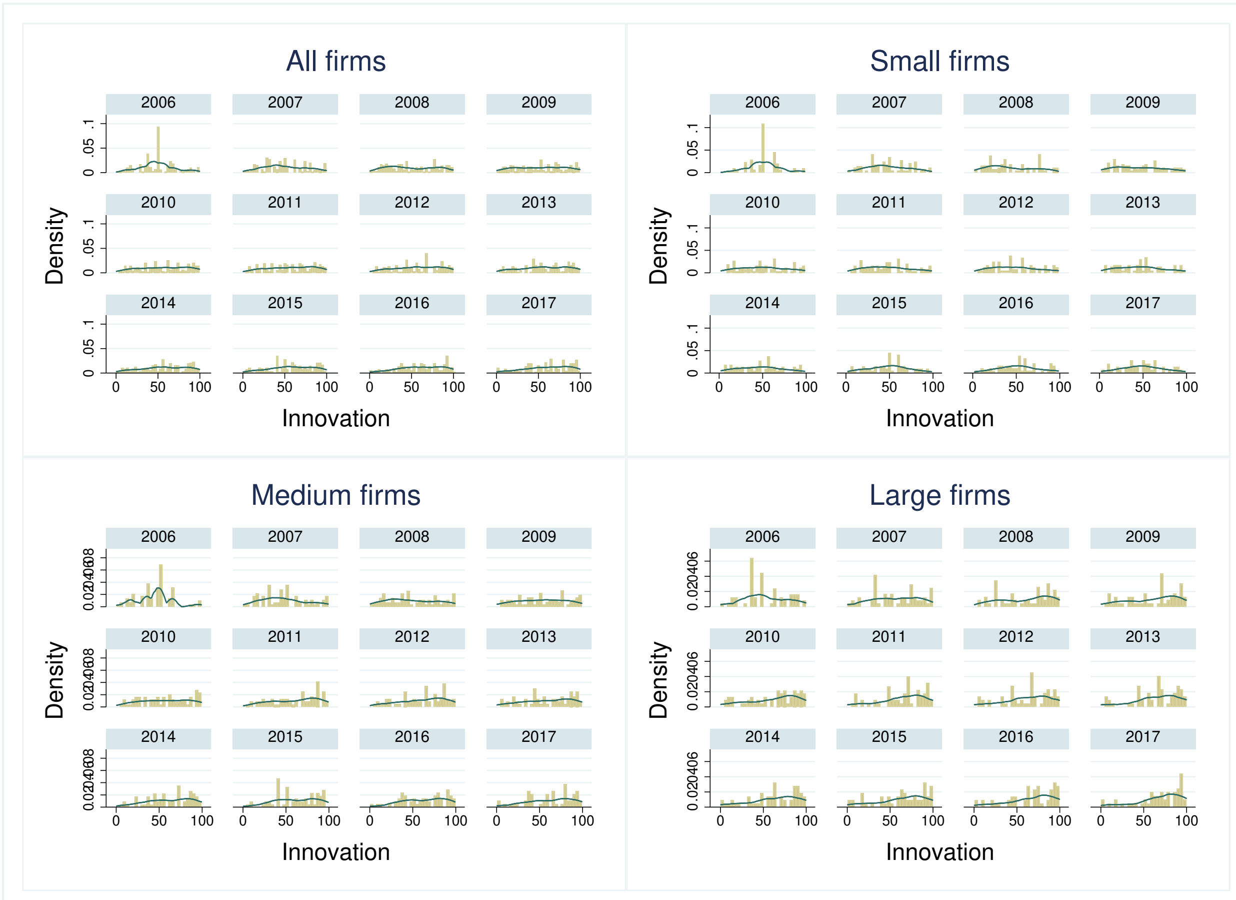


Figure 7: Resource Use subscore by manufacturer size and fiscal year (*excluding* new firm entries)

The figures below exhibit the distribution of Resource Use subscore across different firm size groups based on 2006 as well as over time in manufacturing industry—the top-left figure is a mixture across firm size groups. New firm entries are prohibited in any given year using 2006 as a baseline year and therefore the figures only feature the cross-section of firms that existed in 2006. Thus, the uneven distributions in the top-left figure observed in later years—especially driven by midsize and large manufacturers—are not unnatural since new firm entries are prohibited as opposed to Figure 5.

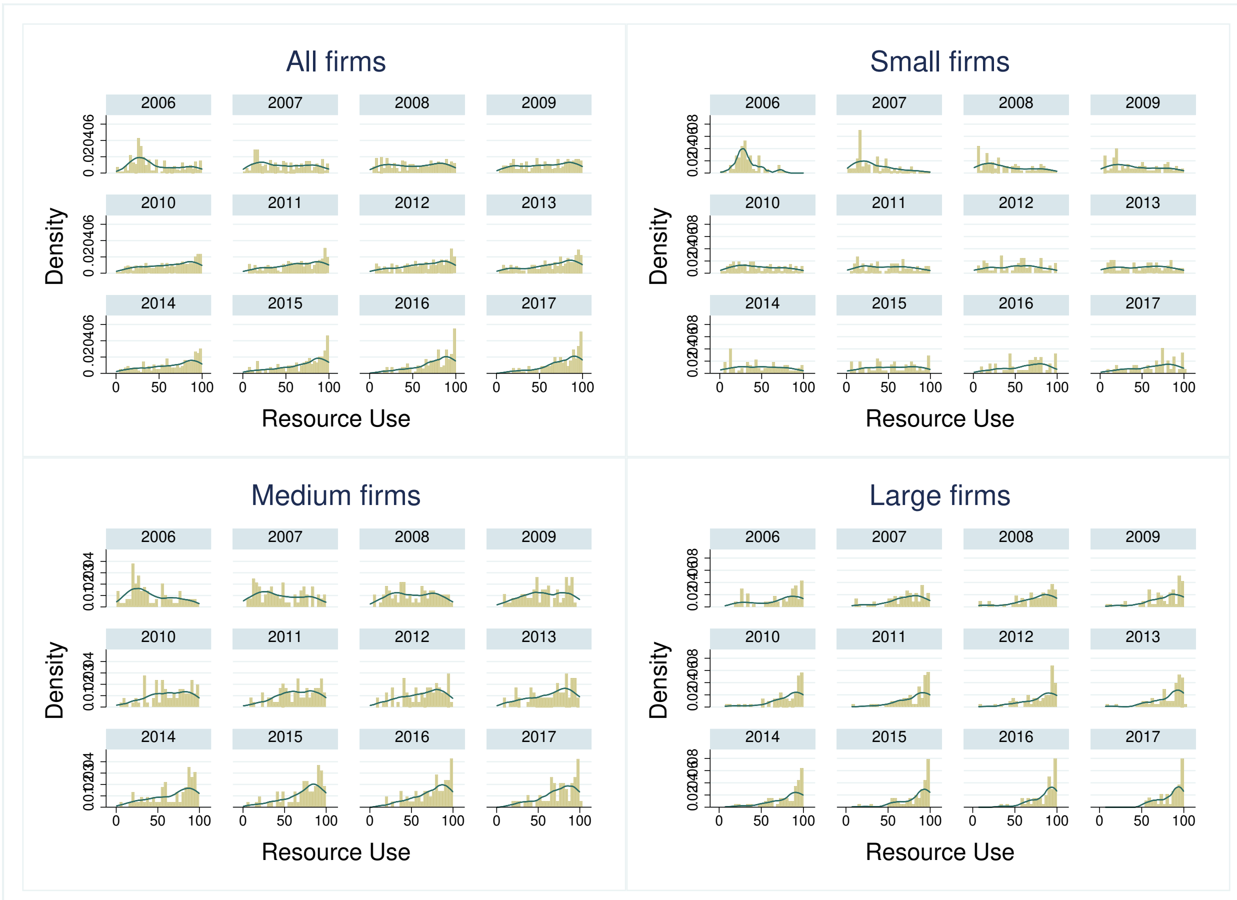
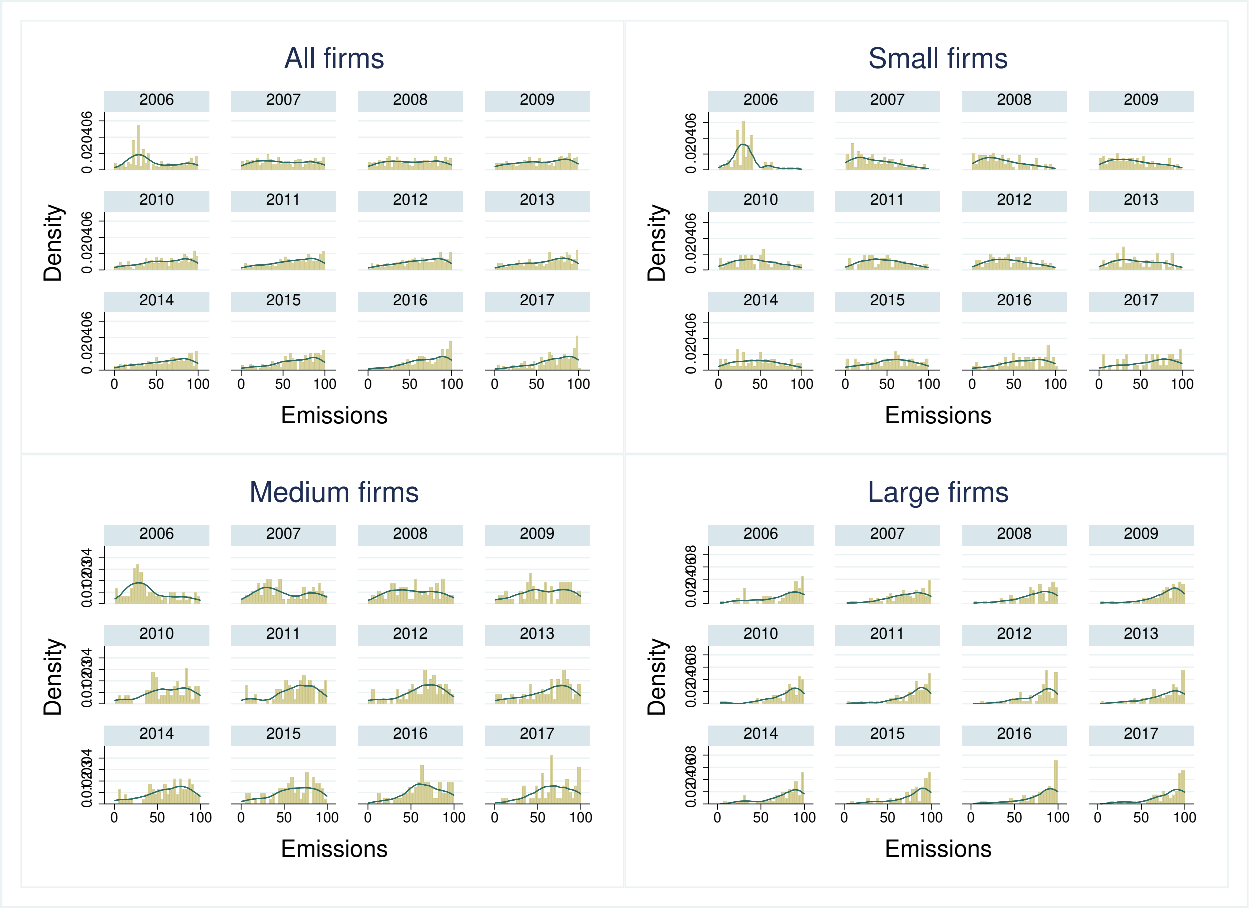


Figure 8: Emissions subscore by manufacturer size and fiscal year (*excluding* new firm entries)

The figures below exhibit the distribution of Emissions subscore across different firm size groups based on 2006 as well as over time in manufacturing industry—the top-left figure is a mixture across firm size groups. New firm entries are prohibited in any given year using 2006 as a baseline year and therefore the figures only feature the cross-section of firms that existed in 2006. Thus, the uneven distributions in the top-left figure observed in later years—especially driven by midsize and large manufacturers—are not unnatural since new firm entries are prohibited as opposed to Figure 5.



Appendix B. Elements of environment-related subscores

Table 21: Elements of Innovation subscore

Environmental Products	Does the company report on at least one product line or service that is designed to have positive effect on the environment or which is environmentally labeled and marketed?
Environmental R&D Expenditures	Total amount of environmental R&D costs (without clean up and remediation costs).
Noise Reduction	Does the company develop new products that are marketed as reducing noise emissions?
Fleet Fuel Consumption	Total fleet's average fuel consumption in l/100km.
Hybrid Vehicles (Technology)	Is the company developing hybrid vehicles (technology)?
Fleet CO2 Emissions	Total fleet's average CO2 and CO2 equivalent emissions in g/km.
ESG Screened Asset Under Management	Does the company report on ESG screeened Assets Under Management?
Equator Principles	Is the company a signatory of the Equator Principles (commitment to manage environmental issues in project financing)?
Environmental Project Financing	Does the company claim to use ESG criteria as part of its investment or lending or underwriting decisions?
Equator Principles or Environmental Project Financing	Is the company a signatory of the Equator Principles (commitment to manage environmental issues in project financing) or does it claim to evaluate projects on the basis of environmental or biodiversity risks as well?
Nuclear	Does the company construct nuclear reactors, produce nuclear energy or extract uranium?
Nuclear Production	Percentage of total energy production from nuclear energy.
Labeled Wood Percentage	The percentage of labeled wood or forest products from total wood or forest products.
Labeled Wood	Does the company claim to produce or distribute wood or forest products that are labeled?
Organic Products Initiatives	Does the company report or show initiatives to produce or promote organic food or other products?
Take-back and Recycling Initiatives	Does the company reports about take-back procedures and recycling programs to reduce the potential risks of products entering the environment?
Product Environmental Responsible Use	Does the company report about product features and applications or services that will promote responsible and environmentally preferable use?
GMO Products	Does the company produce or distribute genetically modified organisms (GMO)?
Agrochemical Products	Does the company produce or distribute agrochemicals like pesticides, fungicides or herbicides?
Agrochemical 5 % Revenues	Are the revenues generated by the company from agrochemicals 5% or more of company sales?
Animal Testing	Is the company involved in animal testing?
Animal Testing Cosmetics	Is the company involved in animal testing for cosmetics?
Animal Testing Reduction Initiative	Has the company established a program or an initiative to minimize or phase out animal testing?
Clean Technology	Is the company developing clean technology (wind, solar, hydro and geo-thermal and biomass power)?
Water Technology	Does the company develop products or technologies that are used for water treatment, purification or that improve water use efficiency?
Sustainable Building Products	Does the company develop products and services that improve the energy efficiency of buildings?
Eco-Design Products	Does the company report on specific products which are designed for reuse, recycling or the reduction of environmental impacts?
Real Estate Sustainability Certification	Does the company claim to lease, rent or market buildings that are certified by BREEAM, LEED or any other nationally recognized real estate certification?
Revenue from Environmental Products	Percentage of revenue from environmental products and services offered by the company.
Fossil Fuel Divestment Policy	Does the financial company have a public commitment to divest from fossil fuel?
Value - Product Innovation/Environmental R&D Expenditures	Total amount of environmental R&D costs (without clean up and remediation costs) divided by net sales or revenue.
Value - Product Innovation/Environmental Project Financing	Is the company a signatory of the Equator Principles (commitment to manage environmental issues in project financing)? OR Does the company claim to evaluate projects on the basis of environmental or biodiversity risks as well?
Value - Product Innovation/Renewable Energy Supply	Total energy distributed or produced from renewable energy sources divided by the total energy distributed or produced.
Value - Product Innovation/Product Impact Minimization	Does the company reports about take-back procedures and recycling programs to reduce the potential risks of products entering the environment? OR Does the company report about product features that will promote responsible, efficient, cost-effective and environmentally preferable use?

(Source: Thomson Reuters)

Table 22: Elements of Resource Use subscore

Value - Resource Reduction/Policy	Does the company have a policy for reducing the use of natural resources or to lessen the environmental impact of its supply chain?
Value - Resource Reduction/Improvements	Does the company set specific objectives to be achieved on resource efficiency?
Environment Management Team	Does the company have an environmental management team?
Environment Management Training	Does the company train its employees on environmental issues?
Resource Efficiency Processes/Policy Water Efficiency	Does the company have a policy to improve its water efficiency?
Resource Efficiency Processes/Policy Energy Efficiency	Does the company have a policy to improve its energy efficiency?
Resource Efficiency Processes/Policy Sustainable Packaging	Does the company have a policy to improve its use of sustainable packaging?
Resource Efficiency Processes/Policy Environmental Supply Chain	Does the company have a policy to include its supply chain in the company's efforts to lessen its overall environmental impact?
Resource Efficiency Objectives/Targets Water Efficiency	Has the company set targets or objectives to be achieved on water efficiency?
Resource Efficiency Objectives/Targets Energy Efficiency	Has the company set targets or objectives to be achieved on energy efficiency?
Materials Sourcing Environmental Criteria	Does the company claim to use environmental criteria to source materials?
Toxic Substances Reduction Initiatives	Does the company report on initiatives to reduce, reuse, substitute or phase out toxic chemicals or substances?
Energy Use Total	Total direct and indirect energy consumption
Direct Energy/Energy Purchased Direct	Direct energy purchased
Direct Energy/Energy Produced Direct	Direct energy produced
Indirect Energy Use	Indirect energy consumption
Electricity/Electricity Purchased	Electricity purchased
Electricity/Electricity Produced	Electricity produced
Cement Energy Use	Total energy use in gigajoules per tonne of clinker produced.
Renewable Energy Total/Renewable Energy Purchased	Total primary renewable energy purchased
Renewable Energy Total/Renewable Energy Produced	Total primary renewable energy produced
Renewable Energy Use	Does the company make use of renewable energy?
Green Buildings	Does the company report about environmentally friendly or green sites or offices?
Water Withdrawal Total	Total water withdrawal
Fresh Water Withdrawal Total	Total fresh water withdrawal
Water Recycled	Amount of water recycled or reused
Environmental Supply Chain Selection Management	Does the company use environmental or sustainable criteria in the selection process of its suppliers or sourcing partners?
Environmental Supply Chain Partnership Termination	Does the company report or show to be ready to end a partnership with a sourcing partner, in the case of severe environmental negligence and failure to comply with environmental management standards?
Land Environmental Impact Reduction	Does the company report on initiatives to reduce the environmental impact on land owned, leased or managed for production activities or extractive use?
Coal Produced (raw material in tonnes)	Amount of Coal produced in tonnes (raw material)
Natural Gas Produced (raw material in million m3)	Amount of Natural Gas produced in million m3 (raw material)
Oil Produced (raw material in barrels)	Amount of Oil Produced in barrels (raw material)
Environmental Supply Chain Monitoring	Does the company conduct surveys of the environmental performance of its suppliers?
Environmental Resource Impact Controversies	Number of controversies related to the environmental impact of the company's operations on natural resources or local communities.
Recent Environmental Resource Impact Controversies	Number of controversies related to the environmental impact of the company's operations on natural resources or local communities since the last fiscal year company update.
Value - Resource Reduction/Energy Use	Total direct and indirect energy consumption in gigajoules divided by net sales or revenue in US dollars.
Value - Resource Reduction/Renewable Energy Use	Total energy generated from primary renewable energy sources divided by total energy.
Value - Resource Reduction/Water Use	Total water withdrawal in cubic meters divided by net sales or revenue in US dollars.
Value - Resource Reduction/Environmental Resource Impact Controversies	Is the company under the spotlight of the media because of a controversy linked to the environmental impact of its operations on natural resources or local communities?

(Source: Thomson Reuters)

Table 23: Elements of Emissions subscore

Emission Reduction Processes/Policy Emissions Reduction	Does the company have a policy to improve emissions reduction?
Emission Reduction Objectives/Targets Emissions Reduction	Has the company set targets or objectives to be achieved on emissions reduction?
Biodiversity Impact Reduction	Does the company report on its impact or on activities to reduce its impact on biodiversity?
CO2 Equivalents Emission Total	Total CO2 and CO2 equivalents emissions
CO2 Equivalents Emission Direct	Direct CO2 and CO2 equivalents emissions
CO2 Equivalents Emission Indirect	Indirect of CO2 and CO2 equivalents emissions
Flaring of Natural Gas	Total direct flaring or venting of natural gas emissions
Cement CO2 Equivalents Emission	Total CO2 and CO2 equivalents emission in tonnes per tonne of cement produced.
Ozone-Depleting Substances	Total amount of ozone depleting (CFC-11 equivalents) substances emitted
NOx and SOx Emissions Reduction Initiatives	Does the company report on initiatives to reduce, reuse, recycle, substitute, or phase out SOx (sulfur oxides) or NOx (nitrogen oxides) emissions?
NOx Emissions	Total amount of NOx emissions emitted
SOx Emissions	Total amount of SOx emissions emitted
VOC Emissions Reduction Initiatives	Does the company report on initiatives to reduce, substitute, or phase out volatile organic compounds (VOC)?
Particulate Matter Reduction Initiatives	Does the company report on initiatives to reduce, substitute, or phase out particulate matter less than ten microns in diameter (PM10)?
VOC Emissions	Total amount of volatile organic compounds (VOC) emissions
Waste Total	Total amount of waste produced
Non-Hazardous Waste	Total amount of non-hazardous waste produced
Waste Recycled Total	Total recycled and reused waste
Hazardous Waste	Total amount of hazardous waste produced
Water Discharged	Total volume of water discharged
Water Pollutant Emissions	Total weight of water pollutant emissions
Waste Reduction Initiatives	Does the company report on initiatives to recycle, reduce, reuse, substitute, treat or phase out any type of waste?
e-Waste Reduction Initiatives	Does the company report on initiatives to recycle, reduce, reuse, substitute, treat or phase out e-waste?
Emissions Trading	Does the company participate in any emissions trading initiative, as reported by the company?
Environmental Partnerships	Does the company report on partnerships or initiatives with specialized NGOs, industry organizations, governmental or supra-governmental organizations, which are focused on improving environmental issues?
ISO 14000 or EMS	Does the company claim to have a certified Environmental Management System?
ISO 14000 or EMS Certified Percent	The percentage of company sites or subsidiaries that are certified with any environmental management system.
Environmental Restoration Initiatives	Does the company report or provide information on sizable company-generated initiatives to restore the environment?
Staff Transport Impact Reduction Initiatives	Does the company report on initiatives to reduce the environmental impact of transportation used for its staff?
Volume of Accidental Spills	Direct and accidental oil and other hydrocarbon spills
Climate Change Risks/Opportunities	Is the company aware that climate change can represent commercial risks and/or opportunities?
Environmental Expenditures	Total amount of environmental expenditures.
Environmental Provisions	Environmental provisions as reported within the balance sheet.
Environmental Investments Initiatives	Does the company report on making environmental investments to reduce future risks or increase opportunities?
CO2e Indirect Emissions, Scope 3	Total CO2 and CO2 equivalent Scope Three emissions
Carbon Offsets/Credits	The equivalent of the CO2 offsets, credits and allowances purchased and/or produced by the company during the fiscal year.
Waste Recycling Ratio	The waste recycling ratio as reported by the company.
Self-Reported Environmental Fines	Environmental fines as reported by the company
Estimated CO2 Equivalents Emission Total	The estimated total CO2 and CO2 equivalents emission in tonnes.
CO2 estimation method	CO2 estimate method
TRBC used for Median Calculation	TRBC code used to calculate estimate if the Median model is used
Value - Emission Reduction/Greenhouse Gas Emissions	Total CO2 and CO2 equivalents emission in tonnes divided by net sales or revenue in US dollars.
Value - Emission Reduction/VOC Emissions Reduction	Does the company report on initiatives to reduce, substitute, or phase out volatile organic compounds (VOC) or particulate matter less than ten microns in diameter (PM10)?
Value - Emission Reduction/Waste	Total amount of waste produced in tonnes divided by net sales or revenue in US dollars.
Value - Emission Reduction/Waste Recycling Ratio	Total recycled and reused waste produced in tonnes divided by total waste produced in tonnes.
Value - Emission Reduction/Hazardous Waste	Total amount of hazardous waste produced in tonnes divided by net sales or revenue in US dollars.
Value - Emission Reduction/Discharge into Water System	Total weight of water pollutant emissions in tonnes divided by net sales or revenue in US dollars.
Value - Emission Reduction/Environmental Expenditures	Does the company report on its environmental expenditures or does the company report to make proactive environmental investments to reduce future risks or increase future opportunities?

(Source: Thomson Reuters)

Appendix C. Response to EPAct 2005 and EISA 2007

The firm-size classification described in Section 3 and Section 4.1 is based on in-sample relative performance within manufacturing industry and certainly there are alternate classification methods, for instance, relying on absolute criteria. Yet, note that the trends below are robust to no matter how firms are classified—that is, it is self-evident that the firm counts are sharply on the rise after 2007—and are thus strongly suggestive of the impact of EISA (see Panel A of Table 1 for regulatory framework). Equally important, the trends are not driven by the growth in sample size, which only develops gradually over years (see Table 4). As per Thomson Reuters Refinitiv database, data measurement starts from 2002 for all CSR-related metrics. There are 32 elements in total for Innovation subscore and a majority of element metrics are boolean type (i.e., True or False) but several metrics are numeric type. All five elements of Innovation subscore in Figure 9 below are boolean type.

Below, Eco Design Products and Env Products appear to be prompted by EISA 2007, while Takeback Recycling Initiatives, Analytic Product Impact Min, and Product Env Responsible Use appear to be spurred by both EPAct 2005 and EISA 2007. It stands to reason that the spike—observed surrounding 2015–2016 in Env Products, Analytic Product Impact Min, and Product Env Responsible Use—is attributable to greenhouse gas regulation in 2014 or Advanced Technology Vehicles Manufacturing Loan Program in 2015; still it could have also merely stemmed from the sudden increase in the sample size (see Table 4).

Figure 9: Trends in intensively-adopted elements of Innovation subscore

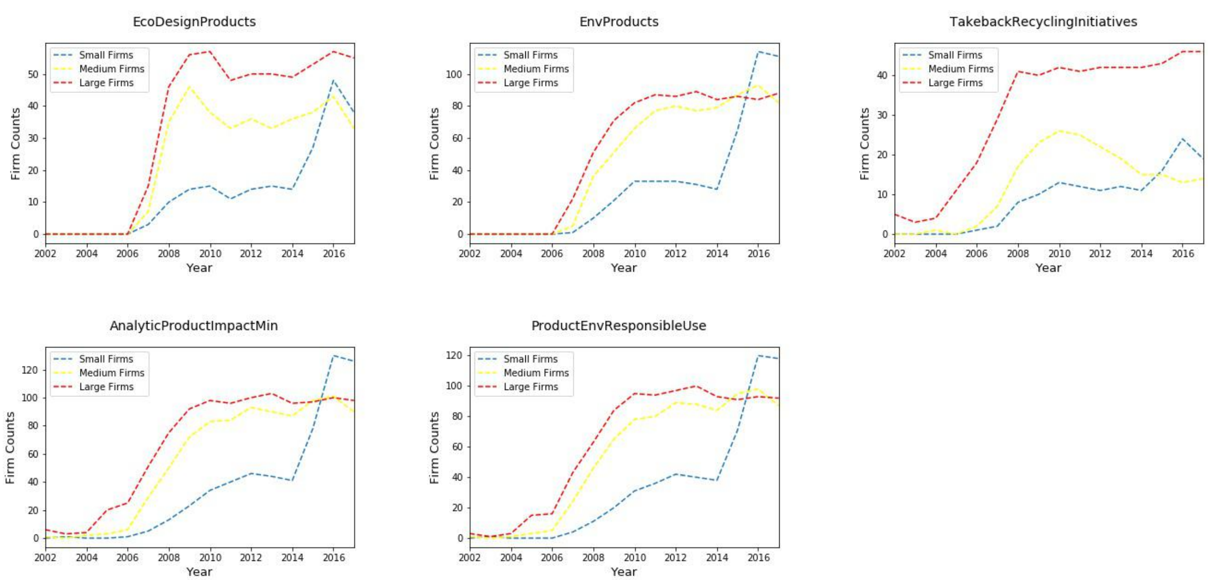


Figure 10: Trends in moderately-adopted elements of Innovation subscore

All eight elements of Innovation subscore below are boolean type. Water Technologies (Title IV), Clean Energy Products (Title II, VI), and Sustainable Building Products (Title IV) appear to be prompted by EISA. In addition, Hybrid Vehicles (Title I) and Organic Products Initiative (Title II) appear to be facilitated by both EPAct 2005 and EISA 2007. The Roman numerals in the parentheses correspond to the Title in EISA 2007 (U.S. Government Printing Office, 2007): see Table 1 for the regulatory framework. Animal Testing Reduction is irrelevant to EISA 2007 or EPAct 2005.

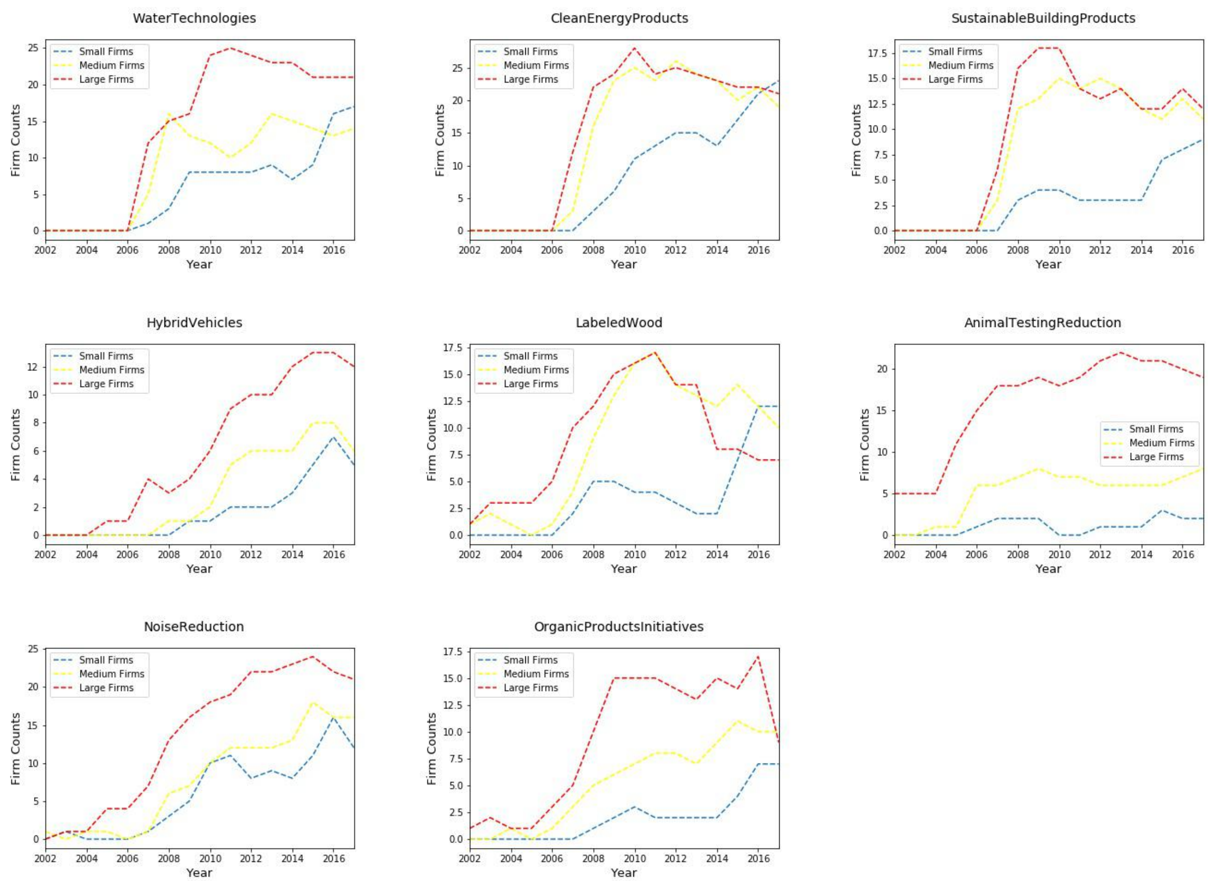


Figure 11: Trends in limitedly-adopted elements of Innovation subscore

All 12 elements of Innovation subscore below are boolean type. Although Nuclear could have been prompted by EPAct 2005 (Title VI), or Price-Anderson Amendments Act of 2005, the link is not obvious. Moreover, Animal Testing is irrelevant to EPAct 2005 or EISA 2007. It was presumably prompted by the Humane Cosmetics Act introduced to the U.S. Congress in 2014 but did not eventually advance.

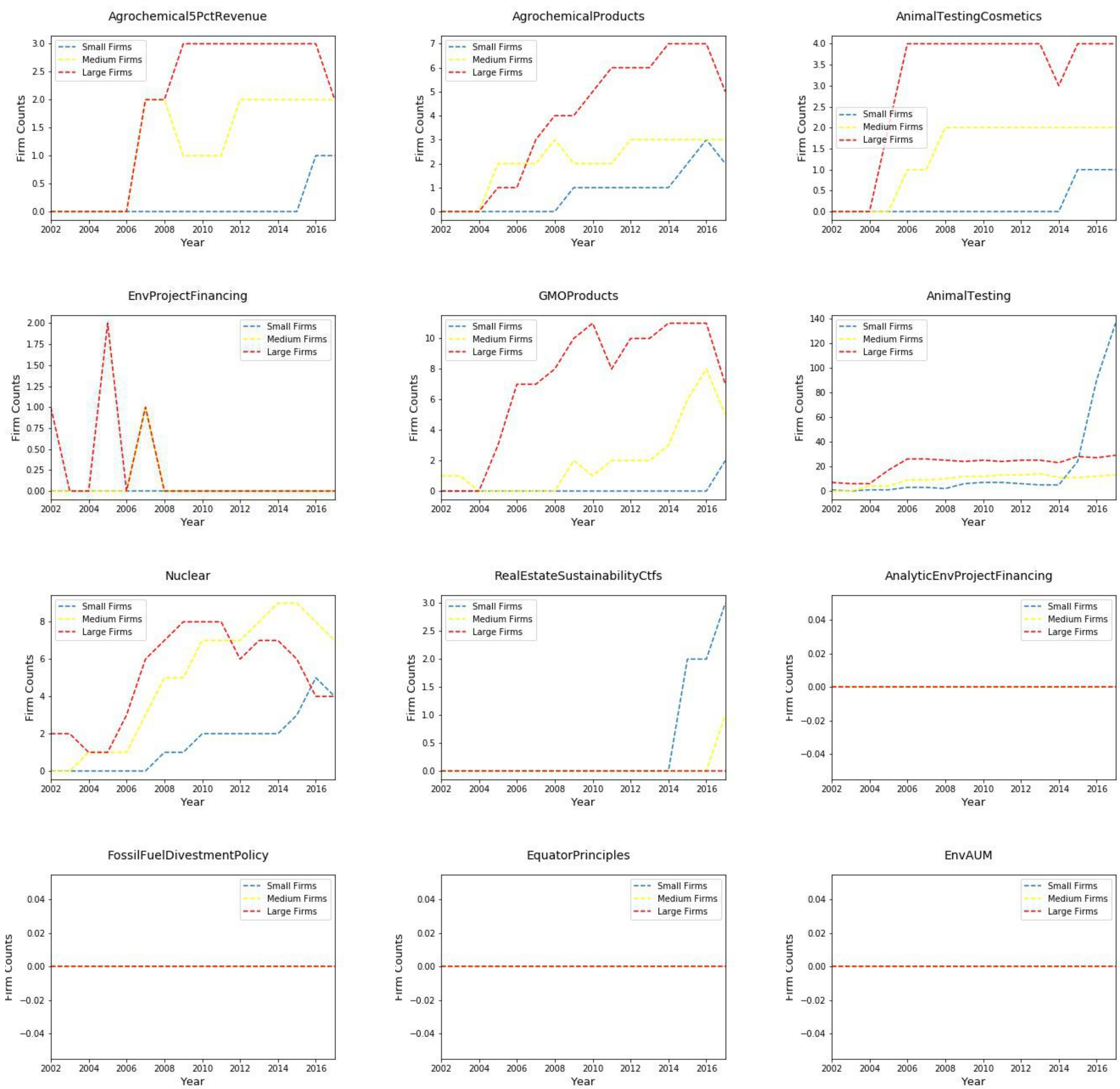
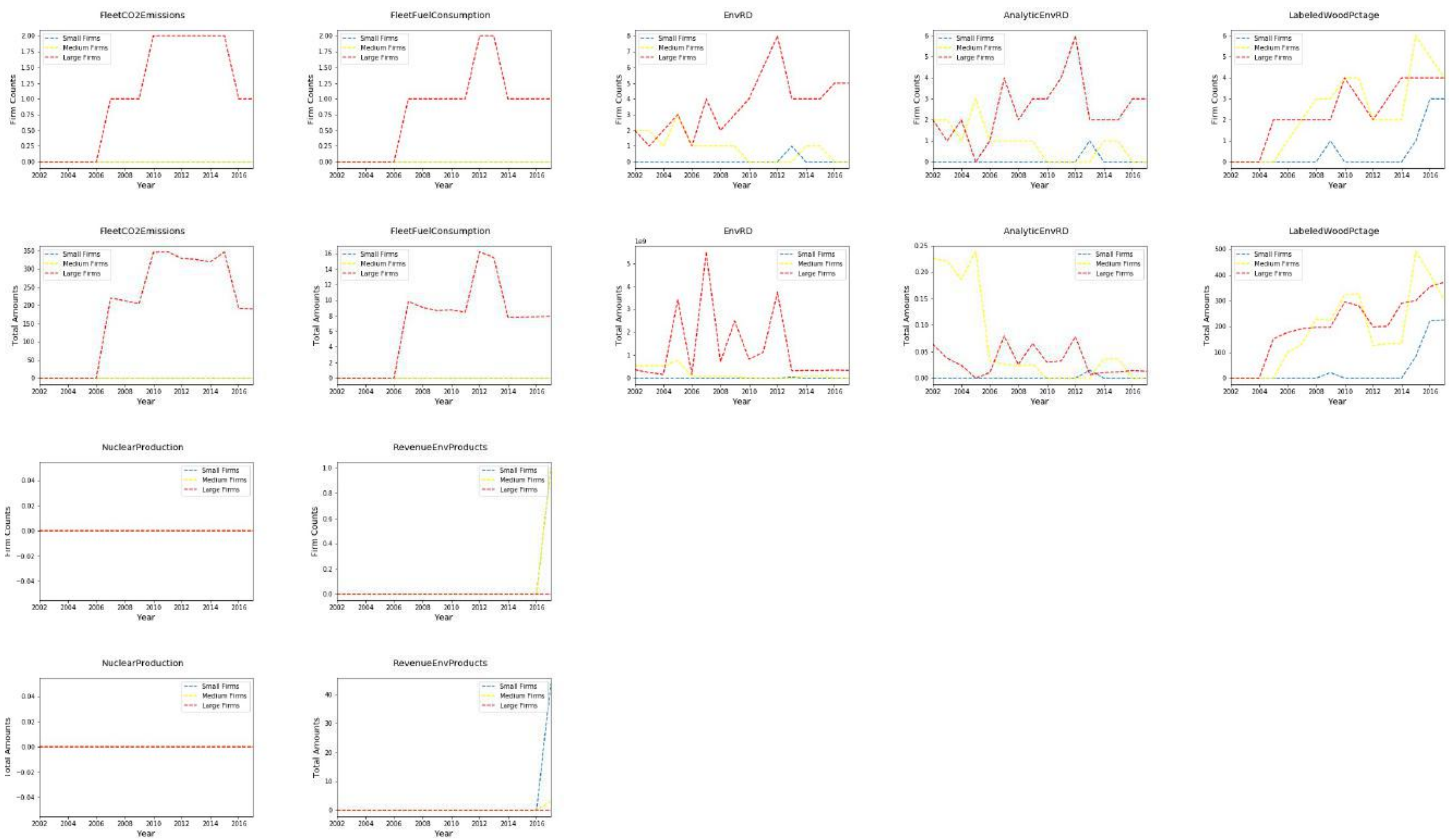


Figure 12: Trends in limitedly-adopted elements of Innovation subscore (numeric elements)

All seven elements below are numeric type. The first and second (the third and fourth) rows are pairs, measuring the firm counts as well as total amounts in the y-axes. Only a handful of firms ever adopted elements such as *Fleet CO2 Emissions*, *Fleet Fuel Consumption*, *Env RD*, *Analytic Env RD*, and *LabeledWoodPctage*. Moreover, *Fossil Fuel Divestment Policy*, *Env AUM*, *Nuclear Production*, and *Equator Principles* do not show any growth.



Appendix D. Data entry errors in CSR-related (sub)scores

In this appendix, I show that systematic miscalculation and data entry errors are prevalent in CSR-related (sub)scores following the recent score update, which was confirmed in May 2020. Thus, in this paper I thoroughly use the scores retrieved in September 2019. Although Thomson Reuters (2017, 2018, 2019, 2020) reports that "Percentile rank score is based on the rank, and therefore it is not very sensitive to outliers. The distribution of the scores generated with percentile rank score is almost flat; for this reason, average and standard deviation of the scores generated with percentile rank score are not overly useful"—and I do confirm these characteristics in any given year if the data are retrieved *before* the 2020 score update—I hardly confirm this statement *after* the score update. Thus, I take a two-step procedure to construct after-update sample to investigate the change from before-update data: First I construct the firm universe using the entire CRSP/Compustat Merged database: the time frame ranges from 2002 to 2017 and the scope focuses on listed firms that are headquartered in the US. Next, I assign CSR-related scores as well as element metrics to all firm-year observations using CUSIP number and fiscal year information.[19]

Across firm-year observations spanning 2002–2017, I find the following features. First, as to Innovation subscore, two thirds of the firm-year observations has a value of zero. This is obviously against the stated "flat distribution" nature.[20] To begin with, zero percentile is not achievable under the given percentile formula in equation (1).[21] Moreover, the possibility is denied regarding the fundamental change in i) the scope of target firms or ii) the value of the element metrics, which are the building blocks of the 10 subscores; I confirm that the firm universe only marginally increases and that among more than 20 element metrics (see Table 24 together with Appendix B), the only major change was Analytic Product Impact Min. Second, as to Shareholders subscore, all values are "NULL" without an exception; nevertheless, the values of higher-layer scores such as Governance and ESG are confirmed, which leaves another question since Shareholders is required as an input for calculation. Third, the other eight subscores besides Innovation subscore and Shareholders subscore do not show flat distribution as well, although the situation is less extreme. Finally, higher-level scores

[19] CUSIP number is not unconditionally time-invariant but few choices are available as an identifier.

[20] Innovation appears to be miscalculated by using an absolute criterion since those firms with zero Innovation subscore are likely to have their element metrics equal to zeros. Zero subscore is an obvious violation of equation (1), which does not produce a zero percentile. Even though it is tempting to assign a subscore of zero to a firm if all of the element metrics under Innovation subscore equal to the lowest possible values—the lowest value is mostly zero but this depends on the positive/negative polarity of the element metric—the equation (1) would still assign a percentile above zero.

[21] In reality there is a small fraction of zero-percentile subscores observed even in the before-update data.

such as Environmental score (weighted average of Resource Use, Emissions, and Innovation) or ESG score do not show a flat distribution.

In sum, unusual contradictory patterns are observed against the relative score assignment using percentile ranking. The worst affected subscores are Innovation and Shareholders and, alongside, Resource Use and Emissions have a non-negligible portion of firms with zero values. I conclude that this issue is highly indicative of data entry error and thus I opt to not use the latest scores. It is very unlikely that this inconsistency stems from the change in score computation methodology, given that I compared the documents of Thomson Reuters (2020, pp. 16–17) and before 2020 i.e., the theoretical aspect of computation methodology appears to be thoroughly consistent.

Figure 13 further substantiates my claim. The data contain all industries but I also examined the case conditional on manufacturing industry (SIC: 2000–3999) as well. Theoretically, the first-row figures featuring ESG should center around 50th percentile.[22] However, the after-update data (second-column figure) are rather left-tilted in comparison to the before-update data (first-column figure). As for the second-row figures, first-column figure (the before-update data) is flatly distributed as expected. Nevertheless, the second-column figure (after-update data) is substantially skewed to the left, suggestive of miscalculations. The figures in the third- and fourth-row plot how the before-update data (x-axis) are mapped onto after-update data (y-axis) at the firm-year observation level. Specifically, the first-column figure shows ESG score mapping; it appears that a firm is most likely to be reassigned a lower score or maintains its score at best—it may help to think of $y = x$ line, which separates the lower triangular area from the upper triangular area.[23] On the other hand, Innovation is handled in the second-column figure in the third row coupled with the fourth-row figures. They illustrate that a large portion of firm-year observations in the before-update data (x-axis) are reassigned with zero values in the after-update data (y-axis); to further disaggregate this effect by year, the fourth row contains three figures representing 2006, 2010, and 2015. Although the correlation between before and after score-update data appears to be more positive in later years, in any given year a non-negligible portion of before-update data is mapped into zero score realm (i.e., x-axis) in after-update data.

[22]This is somewhat analogous to central limit theorem. ESG score is the weighted average of 10 subscores, all of which represent percentile ranking and therefore flatly distributed by design (e.g., the first-column figure in the second row).

[23]This finding is consistent with what is observed in the first-row figures.

Figure 13: Comparison of CSR-related (sub)scores between before and after score update

The first-row figures display the comparison of ESG score between before and after score update (all industry, 2002–2017). The second-row figures display the comparison of Innovation subscore between before and after score update (all industry, 2002–2017). The third-row figures plot the firm-year observation mapping from the old data to new data with regards to ESG score (first column) and Innovation subscore (second column). The fourth-row figures plot the transition of firm-year observation mapping from the before to after score update regards to Innovation subscore (for given years 2006, 2010, and 2015 in manufacturing industry).

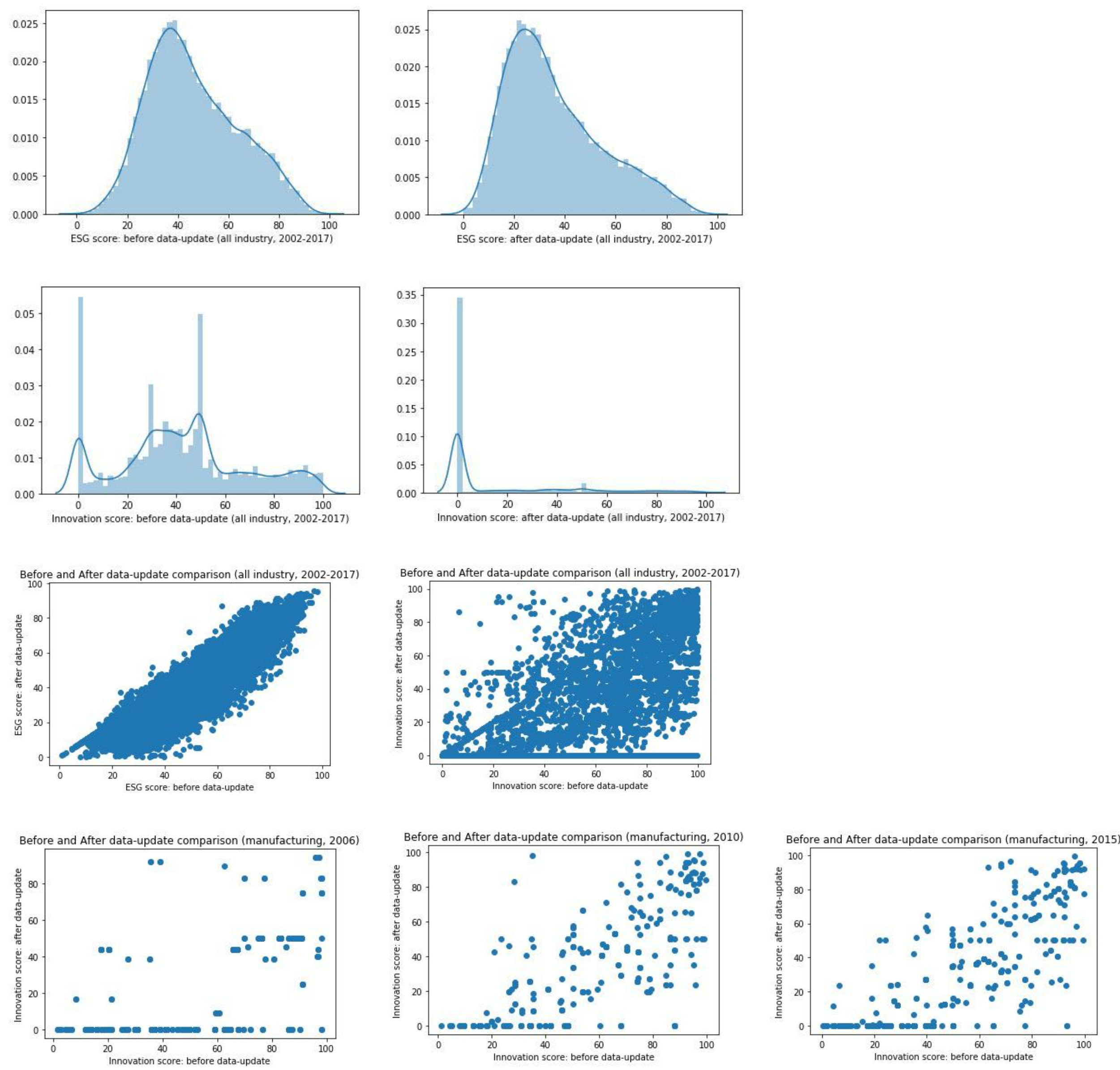


Table 24: Comparison of Innovation subscore elements: before and after score-update (all industries, 2002–2017)

This table provides corroborative evidence that the difference between before and after score update is marginal regarding the elements in Innovation subscore, indicating that the aforementioned systematic miscalculation is driven by percentile computation (i.e., equation (1)) and not by fundamental reform of criteria or selection. The sample ranges from 2002 to 2017 and among 32 elements in Innovation subscore, 25 elements are boolean type (1 or 0 representing true or false) and seven elements are numeric type. I do not use spacing for element labels, following the Thomson Reuters's product design. The table reports the number of firms with "true" for boolean type and the number of firms with non-zero (i.e., positive) values for numeric type. Analytic Product Impact Min is the only element that displays a substantial change following the update. Labeled Wood Pctage and Analytic Env Project Financing are relatively new and were absent when the data were retrieved before the score update (early 2019). All industries are in the sample.

	Cumulative Counts (2002–2017)	
Innovation element	Before score update	After score update
EnvProducts	3483	3562
EcoDesignProducts	1445	1415
AnalyticEnvRD	99	75
EnvRD	117	117
NoiseReduction	467	468
FossilFuelDivestmentPolicy	2	4
FleetFuelConsumption	13	13
FleetCO2Emissions	17	17
HybridVehicles	216	213
EnvAUM	173	176
EquatorPrinciples	47	47
AnalyticEnvProjectFinancing	–	196
EnvProjectFinancing	227	228
Nuclear	604	606
NuclearProduction	185	185
LabeledWood	564	559
LabeledWoodPctage	–	113
OrganicProductsInitiatives	496	494
AnalyticProductImpactMin	4593	2142
TakebackRecyclingInitiatives	1179	1181
ProductEnvResponsibleUse	4331	4353
GMOProducts	194	194
AgrochemicalProducts	157	159
Agrochemical5PctRevenue	72	72
AnimalTesting	870	873
AnimalTestingCosmetics	90	90
AnimalTestingReduction	397	394
CleanEnergyProducts	1189	1189
WaterTechnologies	676	698
SustainableBuildingProducts	545	549
RealEstateSustainabilityCtfs	346	349
RevenueEnvProducts	4	8

Appendix E. Placebo tests for abnormal returns

In this appendix, I replicate the empirical results of Lins, Servaes, and Tamayo (2017). In constructing the sample, I iterate the procedure in Lins, Servaes, and Tamayo (2017, pp. 1792–1794) except that the CSR ratings are from Thomson Reuters Refinitiv database instead of MSCI ESG Stats Database. The sample consists of 600 firms including those headquartered *outside* the US, which differs from the initial sample described in Table 4. CSR-related (sub)scores are all measured in fiscal year 2006, prior to the beginning of the crisis for fear that firms might have adjusted their CSR activities in anticipation of the crisis. The financial crisis period is defined from August 2008 to March 2009: note that Lehman Brothers bankruptcy follows August 2008, whereas in March 2009 S&P 500 experiences its lowest point of the crisis.[24] Sapienza and Zingales (2012) report that this time period experienced a severe decline in trust. Firms in financial services industry (SIC: 6000–6999) are excluded.

Table 25: Breakdown of firms based on Standard Industrial Classification

The following table presents the breakdown of firms in the sample based on 4-digit code Standard Industrial Classification.

SIC	**Division**	**No. of firms**	**Share**
0100–0999	Agriculture, Forestry and Fishing	0	0 %
1000–1499	Mining	52	8.7 %
1500–1799	Construction	10	1.7 %
2000–3999	Manufacturing	306	51.0 %
4000–4999	Transportation, Communications, Electric, Gas and Sanitary service	89	14.8 %
5000–5199	Wholesale Trade	13	2.2 %
5200–5999	Retail Trade	50	8.3 %
6000–6799	Finance, Insurance and Real Estate	0	0 %
7000–8999	Services	75	12.5 %
9100–9729	Public Administration	0	0 %
9900–9999	Nonclassifiable	5	0.8 %
Total		600	100 %

[24] As an aside, note that the "crisis period" defined for brevity throughout this paper is January 2007–December 2009 and thus differs from their specification.

Table 26: Descriptive Statistics of the sample replicating

This table reports the summary statistics of the main variables used in the analysis. Panel A reports firm characteristics and Panel B reports CSR-related (sub)scores.

	Obs.	Mean	SD	Min	Max
Panel A					
Crisis-Period Raw Return	600	-0.375	0.240	-0.927	0.253
Crisis-Period Abn. Return	600	-0.014	0.262	-0.722	0.666
Market Capitalization	600	26,851	43,888	1,225	251,975
Long-Term Debt	600	0.193	0.150	0.000	0.703
Short-Term Debt	600	0.040	0.055	0.000	0.263
Cash Holdings	600	0.128	0.131	0.001	0.622
Profitability	600	0.154	0.083	-0.151	0.398
Book-to-Market	600	0.390	0.268	-0.178	1.596
Negative B/M	600	0.008	0.091	0.000	1.000
Momentum	600	-0.112	0.307	-0.736	1.026
Idiosyncratic Risk	600	0.007	0.013	0.000	0.068
Panel B					
ESG	600	52.3	16.4	22.6	88.3
Environment	600	49.6	19.8	15.9	94.4
Social	600	53.4	20.4	15.6	96.8
Governance	600	54.2	20.7	10.7	93.1
Resource Use	600	48.8	27.4	2.0	99.0
Emissions	600	50.0	27.6	2.8	99.0
Innovation	600	49.8	18.5	4.9	97.1
Workforce	600	48.6	29.4	1.7	98.9
Human Rights	600	50.9	20.2	28.2	99.1
Community	600	66.6	23.6	9.4	99.1
Product Responsibility	600	51.1	24.8	16.0	98.9
Management	600	54.4	28.3	1.9	99.2
Shareholder	600	53.7	28.1	1.7	99.5
CSR Strategy	600	54.1	24.9	8.5	99.0

The sample consists of 600 firms for which CSR data are available from Thomson Reuters Refinitiv database as of year-end 2006.. Crisis-Period Raw Return is the raw return computed over the period August 2008 to March 2009. Crisis-Period Abn. Return is the market model-adjusted return over the period August 2008 to March 2009, with market model parameters computed over the five-year period ending in July 2008 using the CRSP value-weighted index as the market proxy. Accounting data are based on the fiscal year ending of 2007. Market Capitalization is in millions of dollars. *Long-Term Debt* is computed as long-term debt divided by assets. *Short-Term Debt* is computed as debt in current liabilities divided by assets. *Cash Holdings* is computed as cash and marketable securities divided by assets. *Profitability* is computed as operating income divided by assets. Book-to-Market is computed as book value of equity divided by market value of equity. *Negative B/M* is a dummy variable set to one when the book-to-market ratio is negative and zero otherwise. *Momentum* is the raw return over the period August 2007 to July 2008. *Idiosyncratic Risk* is computed as the residual variance from the market model estimated over the five-year period ending in July 2008, using monthly data. Financial firms are removed from the sample. Control variables and returns are winsorized at the 1st and 99th percentiles.

Table 27: The cross-section of crisis-period returns across CSR-related scores

The estimated results of the following cross-sectional regression models are presented below. The result of the first model is presented in Panel A whereas the result of the second model is presented in Panel B.

$$\text{Return}_i = b_0 + b_1\text{ESG}_{i,2006} + b_2'\mathbf{X_i} + \text{Four Factor Loadings}_i + \text{Industry Dummies} + e_i$$

$$\text{Return}_i = b_0 + b_1\text{Environment}_{i,2006} + b_2\text{Social}_{i,2006} + b_3\text{Governance}_{i,2006} + b_4'\mathbf{X_i} + \text{Four Factor Loadings}_i + \text{Industry Dummies} + e_i$$

	Panel A				**Panel B**			
	Raw return (1)	Abnormal return (2)	Raw return (3)	Abnormal return (4)	Raw return (1)	Abnormal return (2)	Raw return (3)	Abnormal return (4)
ESG	0.00105*	0.00006	0.00087	-0.00019				
	(0.00056)	(0.00052)	(0.00072)	(0.00065)				
Environmental					0.00098	0.00081	0.00104	0.00083
					(0.00062)	(0.00061)	(0.00065)	(0.00063)
Social					0.00001	-0.00039	-0.00015	-0.00059
					(0.00063)	(0.00064)	(0.00066)	(0.00067)
Governance					0.00005	-0.00040	-0.00002	-0.00042
					(0.00055)	(0.00049)	(0.00055)	(0.00050)
Log Market Cap			-0.00146	0.00354			-0.00233	0.00238
			(0.01197)	(0.01184)			(0.01190)	(0.01194)
Long-Term Debt			-0.00774	-0.00263			-0.01098	-0.00652
			(0.08580)	(0.08293)			(0.08578)	(0.08259)
Short-Term Debt			-0.19458	-0.24878			-0.17655	-0.22637
			(0.15819)	(0.15132)			(0.16048)	(0.15240)
Cash Holdings			0.26885***	0.24674**			0.26711***	0.24530**
			(0.10014)	(0.09806)			(0.10049)	(0.09872)
Profitability			0.26502*	0.11461			0.26776*	0.11760
			(0.13987)	(0.14253)			(0.14114)	(0.14392)
Book-to-Market			-0.07498	0.01402			-0.07867	0.00960
			(0.05317)	(0.04997)			(0.05372)	(0.05050)
Negative B/M			-0.05506	0.04350			-0.04858	0.05110
			(0.11442)	(0.11738)			(0.11411)	(0.11839)
Momentum			0.04553	-0.02326			0.04319	-0.02574
			(0.03796)	(0.04275)			(0.03815)	(0.04289)
Idiosyncratic Risk			-1.97512**	-3.03687***			-2.01173**	-3.08349***
			(0.85379)	(0.83463)			(0.85258)	(0.82589)
Intercept	-0.20269**	-0.15463*	-0.19202	-0.16806	-0.19533**	-0.14536*	-0.17378	-0.14589
	(0.08583)	(0.08465)	(0.13392)	(0.13731)	(0.08606)	(0.08480)	(0.13475)	(0.13763)
Four-factor loadings	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	600	600	600	600	600	600	600	600
Adj. R^2	0.197	0.365	0.238	0.387	0.196	0.365	0.238	0.387

Heteroskedasticity-consistent standard errors are presented in the parentheses.

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 28: The cross-section of crisis-period returns across 10 subscores

The estimated results of the following cross-sectional regression model are presented below, in which one of the 10 subscores are selected as an explanatory variable and, accordingly, the coefficients on $\text{Subscore}_{i,2006}$ (b_1) are reported. The dependent variable is either cumulative raw return or cumulative abnormal return during the crisis period, measured from August 2008 to March 2009.

$$\text{Return}_i = b_0 + b_1 \text{Subscore}_{i,2006} + b_2' \mathbf{X_i} + \text{Four Factor Loadings}_i + \text{Industry Dummies} + e_i$$

	Coefficients on $\text{Subscore}_{i,2006}$ (b_1)			
	Raw return	Abnormal return	Raw return	Abnormal return
	(1)	(2)	(3)	(4)
Resource Use	0.00046	0.00008	0.00034	0.00003
	(0.00033)	(0.00032)	(0.00040)	(0.00039)
Emissions	0.00044	0.00016	0.00040	0.00017
	(0.00033)	(0.00031)	(0.00039)	(0.00037)
Innovation	0.00136***	0.00078*	0.00114***	0.00063
	(0.00043)	(0.00043)	(0.00044)	(0.00044)
Workforce	0.00066**	0.00009	0.00053	-0.00003
	(0.00032)	(0.00032)	(0.00037)	(0.00037)
Human Rights	0.00023	0.00018	-0.00004	0.00004
	(0.00045)	(0.00042)	(0.00049)	(0.00047)
Community	-0.00046	-0.00034	-0.00069*	-0.00048
	(0.00038)	(0.00038)	(0.00041)	(0.00042)
Product Responsibility	0.00049	-0.00006	0.00039	-0.00015
	(0.00037)	(0.00036)	(0.00040)	(0.00038)
Management	0.00018	-0.00012	0.00007	-0.00017
	(0.00035)	(0.00032)	(0.00036)	(0.00034)
Shareholders	0.00027	-0.00030	0.00013	-0.00032
	(0.00036)	(0.00032)	(0.00035)	(0.00033)
CSR Strategy	0.00037	0.00011	0.00028	0.00004
	(0.00038)	(0.00038)	(0.00044)	(0.00043)
Firm characteristics	–	–	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Obs.	600	600	600	600

Heteroskedasticity-consistent standard errors are presented in the parentheses.

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 29: The effect of Innovation subscore on returns surrounding the crisis by industry

The table below presents the estimated results of the following panel regression models (subsample period: 2007–2013). Firms are conditioned on specific industries, that is, manufacturing, transportation, services, and retail (Panels A–D). The dependent variable is either cumulative raw return or cumulative abnormal return during the crisis period, measured from August 2008 to March 2009.

$$\text{Return}_{i,t} = b_0 + b_1 \text{Innovation}_{i,year} \times \text{Crisis}_t + b_2 \text{Innovation}_{i,year} \times \text{Post-Crisis}_t + b_3' \mathbf{X_{i,t-1}} + \text{Four Factor Loadings}_{i,t} + \text{Time Fixed Effects} + \text{Firm Fixed Effects} + e_{i,t}$$

	Coefficients on interaction terms (b_1 and b_2)			
	Raw return	Abnormal return	Raw return	Abnormal return
	(1)	(2)	(3)	(4)
Panel A: Manufacturing				
Innovation × Crisis	0.00028**	0.00034***	0.00040***	0.00045***
	(0.00012)	(0.00011)	(0.00013)	(0.00011)
Innovation × Post-Crisis	-0.00003	0.00011	0.00005	0.00015*
	(0.00007)	(0.00007)	(0.00010)	(0.00009)
Firm characteristics	–	–	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Obs.	21,393	21,393	21,393	21,393
Panel B: Transportation etc.				
Innovation × Crisis	0.00013	-0.00011	0.00029	0.00010
	(0.00026)	(0.00025)	(0.00036)	(0.00025)
Innovation × Post-Crisis	-0.00035**	-0.00020	-0.00029	-0.00013
	(0.00016)	(0.00014)	(0.00025)	(0.00024)
Firm characteristics	–	–	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Obs.	6,033	6,033	6,033	6,033
Panel C: Services				
Innovation × Crisis	0.00043	0.00083**	0.00036	0.00070*
	(0.00051)	(0.00036)	(0.00053)	(0.00039)
Innovation × Post-Crisis	-0.00002	-0.00016	0.00039	0.00005
	(0.00019)	(0.00020)	(0.00035)	(0.00036)
Firm characteristics	–	–	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Obs.	5,460	5,460	5,460	5,460
Panel D: Retail				
Innovation × Crisis	-0.00023	-0.00035	-0.00022	-0.00029
	(0.00020)	(0.00026)	(0.00025)	(0.00025)
Innovation × Post-Crisis	-0.00008	0.00005	0.00009	0.00018
	(0.00019)	(0.00018)	(0.00027)	(0.00023)
Firm characteristics	–	–	Yes	Yes
Four-factor loadings	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Obs.	3,759	3,759	3,759	3,759

Numbers in parentheses are heteroskedasticity-consistent standard errors clustered at the firm level.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Doctrine of Socially Responsible Investors: Clash of Government Policies

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Abstract

Through the lens of CSR, I explore three channels—firm-specific, market pessimism, and "green optimism"—that may account for the differentials in the higher moments of stock market returns. As to the latter two channels, I find empirical patterns that CSR strongly acts as a critical filter through which market sentiment influences the cross-section of returns by distinctively sifting the expectations of wide-ranging investors. Especially, regarding the green optimism channel, I gauge the dynamics of the cross-section of returns by conducting a case study on the parallel announcements in June 2017: the US federal government withdrawal from the 2015 Paris Agreement and the formation of US Climate Alliance states. I find supporting evidence that this nation-wide event consolidated beliefs in environmentally-friendly firms, while amplifying heterogeneous beliefs in non-eco-friendly firms: these beliefs manifested themselves as increased (decreased) return skewness and decreased (increased) trading volume in the subsequent six-month horizon, respectively, irrespective of whether headquartered in the climate alliance states or not. I further uncover that the broad-based stock market reactions largely predicted the corporate efforts to reduce emissions except for carbon-intensive industries.

Keywords: SRI, investor sentiment, US Climate Alliance, Paris Agreement, differences of opinion, tail asymmetry, tail size

JEL Classification: G12, G14, Q54, Q58

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1 Introduction

Socially responsible investing—comparably ESG investing, sustainable investing, or impact investing—is gaining momentum as an alternative investment vehicle. Mirroring this trend, a growing number of literature has so far conducted a performance comparison between socially responsible and conventional investments among different asset classes (e.g., equity, mutual fund, index). Interestingly, previous studies have found ample evidence for or against the notion that social impact goes hand in hand with financial performance. The mixed evidence from prior literature implies that the performance difference between socially responsible investment and conventional investment is modest at best if evaluated within the mean-variance paradigm. One drawback, however, running through a vast majority of these studies is the limitation that the investment performance analysis is mostly bounded within the traditional mean-variance framework. The narrow selection of the first two moments is suitable only for the investors whose utility can be largely approximated by a quadratic form and thus material information germane to investment performance could possibly be discarded by this conduct (Belghitar, Clark, and Deshmukh, 2014).

There is, as a matter of fact, crucial evidence that higher moments matter for the cross section of returns. As one example, it is clear that the covariance, coskewness, and cokurtosis of individual assets with the market portofolio have implications for their expected returns because investors exhibit skewness-loving and kurtosis-averse attributes (Fang and Lai, 1997; Dittmar, 2002). As another example, Conrad, Dittmar, and Ghysels (2013) report that after controlling for differences in these co-moments, the risk-neutral volatility, skewness, and kurtosis of individual assets still have a substantial bearing on the cross-section of subsequent returns. Even more, the integration of resilient skewness and kurtosis measures into our understanding of stock return behaviours can better inform us since variance alone is insufficient to measure risk (Kim and White, 2004) and it also entails the auxiliary benefits of providing insight into the tail risk (Kelly and Jiang, 2014; Gormsen and Jensen, 2020).

Nonetheless, extant SRI research has surprisingly not paid sufficient attention to this front. Among the scant literature highlighting higher moments of SRI returns, Kim, Li, and Li (2014) find favourable evidence that CSR activities mitigate crash risk (defined as the conditional skewness in return) through a firm-specific channel. Drawing on extreme value theory, Diemont, Moore, and Soppe (2016) uncover the significant relationship between several aspects of CSR and downside tail risk, yet this relation is moderated by factors such as regions, stakeholders, and time. At the other end of the spectrum, Belghitar, Clark, and

Deshmukh (2014) strongly argue in favor of conventional investment over SRI using index level data. Given this limited body of literature, the objective of this paper is to fill this void and examine three potential channels through which CSR may lead to fundamental differences in higher moments of returns: the firm-specific, market pessimism, and "green optimism" channels.

To empirically estimate the effect of CSR on the higher moments of stock returns, I construct a panel data set using financial market and accounting data from CRSP/Compustat Merged (CCM) database together with CSR data from Thomson Reuters Refinitiv database. More precisely, I examine the link between CSR and future skewness or kurtosis under a setup of fixed effects panel regression. Regarding the dependent variables, the selection of the period intervals in measuring the higher moments of returns boils down to a subjective choice and I measure variables differently at 3-, 6-, and 12-month intervals. The reason for this is that (i) a longer period interval can mitigate the concern of measurement errors and (ii) I may otherwise overlook systematic patterns that could develop over different horizons. Moreover, I compute three variations of daily returns in logarithmic form: market-adjusted return, excess return, and residual return. Beside the CSR score provided by Thomson Reuters Refinitiv, I include an additional set of control variables that are expected to determine future skewness and kurtosis, ranging from (i) firm size, (ii) share turnover, (iii) past returns over the 36-month horizon, to (iv) accounting variables.

Now, as to the firm-specific channel, I examine whether CSR leads to higher idiosyncratic skewness and lower idiosyncratic kurtosis in returns owing to the fact that socially responsible firms are less likely to be linked to unfavourable events including corporate misconduct and wrongdoing (Hypothesis 1). The estimates of fixed effects panel regression suggest that CSR indeed serves as a source of higher skewness and lower kurtosis for all return specifications, that is, market-adjusted return, excess return, and residual return. Yet, my results simultaneously cast doubt on the conjecture that this empirical pattern purely stems from the firm-specific channel. This is primarily because the t-statistics for the coefficients on CSR variable are greater when using the excess return specification relative to the other two return specifications, indicating that the excess return specification is the strongest in terms of the association with subsequent skewness and kutrosis. Thus, I reveal evidence suggestive of a systematic channel in which CSR likewise leads to higher skewness and lower kutrosis.

In light of the evidence indicative of the systematic market channel, I further scrutinize whether CSR leads to higher systematic skewness and lower systematic kurtosis in returns

(Hypothesis 2). In this regard, I hypothesize that market pessimism is the primary driver of this systematic channel since prior research suggests that the effect of CSR is specifically prominent during the bad states in the economy. The underlying mechanism is the following. Amid the crisis periods during which stock prices are inclined towards downward pressure, CSR-intensive firms are less subject to this market force, thereby leading to alleviated negative skewness (tail asymmetry). In a similar fashion, the kurtosis (tail size) in the distribution, which represents the likelihood of extreme return values, is likely expected to lessen. To empirically investigate this broad-based effect of market pessimism, I deploy two different strategies: (i) forecasting the return of high-CSR minus low-CSR long-short portfolio using market sentiment proxies and (ii) visualizing coefficients on CSR variables in the model specifications employed under Hypothesis 1 over subperiods during 2002–2017. As to the first strategy, the empirical estimates show that the subsequent return of the zero investment portfolio is positively associated with market pessimism proxies, put differently, CSR-intensive firms are increasingly viewed as a lucrative choice over the month when the beginning-of-period proxies for market pessimism is high. Equally, as for the second strategy, the model specification appears to successfully forecast future skewness in times of high-uncertainty periods.

Furthermore, as regards the "green optimism" channel, I examine whether corporate differentials in environmental orientation create a striking difference in the cross-section of returns following the parallel announcements. Here, "green optimism" is defined as the investors' propensity to speculate on the firm's future cash flows by heavily resting on its environmental orientation: from a neutral investor's perspective, green (ungreen) firms are valued with an upward (downward) bias by a socially oriented investor. Moreover, a brief context of the parallel events surrounding June 2017—the disengagement of the US government from the Paris Agreement and the formation of the United States Climate Alliance—is as follows. The Trump administration announced on June 1, 2017 that the US would cease all participation in the 2015 Paris Agreement[1] claiming that it would undermine the US economy and thus would leave the US in a disadvantageous position. To countervail this political action, the governors of California, New York, and Washington simultaneously announced the US Climate Alliance as a coalition of governors committed to transitioning to

[1]Succeeding the goal of the Kyoto Protocol, the Paris Agreement was adopted by consensus on 12 December 2015, opened for signature on 22 April 2016, and came into effect on 4 November 2016. It primarily targets to decrease global warming by limiting global temperature rise to "well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C." Furthermore, it states that countries must reach peak emissions immediately "so as to achieve a balance between human-induced emissions by sources and removals by sinks of greenhouse gases in the second half of this century."

a clean economy and meeting the goals of the Paris Agreement on climate change. Alliance states are thus committed to advancing policies pursuant to the Paris Agreement as well as continually monitor and report the records. Furthermore, collective climate actions in support of the Paris Agreement surged among cities, states, businesses and organizations and more than 80 mayors pledged to adhere to this agreement.[2] In particular, a spate of firm managers in the US expressed their concern against the decision of the Trump administration through social media.

Now, exploiting this event as a natural-experiment case study, I empirically investigate the stock market reactions in relation to corporate greenness by using return, turnover, and skewness measures. In this regard, I use Environmental score provided by Thomson Reuters Refinitiv database to proxy for firm's environmental orientation. I classify all firms based on Environmental score measured in 2017, where a firm is considered green if the score is above 50, and ungreen if the score is below 50. I also classify firms into two groups, more precisely, the firms headquartered in alliance states (alliance-state firm) and the firms headquartered in non-alliance states (non-alliance-state firm). In what follows, I conduct three series of analysis.

First, I conjecture that (un)green firms experienced positive (negative) abnormal returns surrounding the parallel announcements (Hypothesis 3a). For each specific industry, I compute cumulative abnormal returns over a five day window using the market model and consequently find that substantially negative stock market responses were observed in the non-climate-alliance firms, especially in the carbon-intensive industries. Moreover, in a cross-sectional regression approach, I find that green firms regardless of whether located in climate alliance states or not experienced 0.4%–1.6% higher cumulative abnormal returns.

Second, I hypothesize that (un)green firms experienced a negative (positive) abnormal turnover surrounding the parallel announcements (Hypothesis 3b). As a result, I reveal supporting evidence that (i) green firms were associated with less abnormal turnover and (ii) firms headquartered in climate alliance states were associated with more abnormal turnover, where the effect described in (i) exceeds the effect described in (ii). Under the framework of differences in opinions, these patterns of lower (higher) abnormal turnover can be interpreted as an indication of (dis)agreement among investors. In another specification, I replace abnormal turnover with abnormal return volatility, which is proxied by the absolute value

[2] These actors showed solidarity by signing the "We're Still In" declaration: https://www.wearestillin.com/

of abnormal returns but as a consequence hardly find similar patterns with the results using abnormal turnover. The considerable differences in regression estimates indicate that these two variables capture quite dissimilar information.

Third, I postulate that (un)green firms subsequently experienced a positive (negative) skewness shock following the parallel announcements, which reflects the (dis)agreement among investors (Hypothesis 3c). I uncover that green firms experienced higher return skewness and lower turnover in trend, again regardless of whether headquartered in climate alliance states: firms in the carbon-intensive industries such as power plants and mining are excluded. This trend was measured until the end of 2017 and apparently continued to develop until February 2018. All in all, this finding is in line with the Hong-Stein model (Hong and Stein, 2003) based on the theory of differences in opinions, predicting that the sign and magnitude of skewness depends on the degree to which opinions differ surrounding the events. Nonetheless, the results of market adjusted turnover are sensitive to how market turnover is computed: more nuanced patterns are presented especially when using equal-weighted index as a market turnover relative to value-weighted index.

In the end, given that the climate alliance was formed with the objective to reduce the greenhouse gas emissions, I additionally examine whether the stock market reactions on the parallel announcements overall predicted the subsequent reduction in greenhouse gas emissions (Hypothesis 4). In doing so, I use the data provided by Greenhouse Gas Reporting Program (GHGRP) to capture corporate emissions: firms are usually equipped with multiple production facilities and in this context GHGRP conveniently provides data at the facility level. The results are threefold and show a colorful landscape. To begin with, the aggregate estimate excluding carbon-intensive industries (i.e., power plants, oil & gas) shows evidence that counties with intensive climate concern proportionally reduced greenhouse gas emissions following 2017; at the same time, there is little evidence that this trend is attributable to the formation of the climate alliance states. In contrast, the heavily-regulated power plants industry shows the exact opposite results and materially reduced greenhouse gas emissions, pointing to the influence of the the climate alliance initiatives. Lastly, oil & gas industry was hardly responsive to this event, showing little sign of emissions reduction. As a whole, these estimates are robust to the placebo tests using social capital instead of climate beliefs.

This paper proceeds as follows. Section 2 develops a series of hypotheses. Section 3 describes the data and sample description. Section 4–6 present the empirical findings and Section 7 conducts robustness checks. Section 8 concludes.

2 Hypotheses development

I develop a series of hypotheses in this section. Hypothesis 1 highlights the firm-specific channel, whereas Hypothesis 2 addresses the market pessimism channel, both of which may lead to differential skewness and kutorsis in returns conditional on CSR. Moreoever, Hypothesis 3 explores the green optimism channel, which is framed around a case study of the parallel announcements in 2017. In connection with Hypothesis 3, Hypothesis 4 additionally postulates the ensuing effect of the cross-section of returns on corporate green strategies.

Hypothesis 1 centers on the notion that CSR may be able to contribute to a reduced downside risk through a firm-specific channel. On the one hand, the view that socially responsible firms are substantially linked to stock return stability arises from the documented evidence that they entail less firm-specific unfavourable events (Diemont, Moore, and Soppe, 2016). After all, typical unethical news of corporate misconduct and wrongdoing—such as opaque financial reporting, corporate tax avoidance, and executive equity incentives—can be avoided if firms faithfully comply with financial reporting guidelines (Kim, Li, and Li, 2014). Moreover, Albuquerque, Koskinen, and Zhang (2019) verify that CSR decreases systematic risk thus reducing broad-based exposure to the influence from the market, thereby implicitly pointing to the prominence of idiosyncratic factors. On the other hand, there is also a view that CSR activities can be exploited as a disguise mechanism to mask corporate misconduct and wrongdoing, which can ultimately lead to a collapse of shareholder value. Inasmuch as the negative sides of CSR do not prevail, this line of reasoning based on stylized facts leads to Hypotheses 1:

Hypothesis 1: CSR contributes to higher idiosyncratic skewness and lower idiosyncratic kurtosis in returns via a channel through which firm-specific factors are at play

On top of the posited mechanism in Hypothesis 1 supporting the view of the idiosyncratic channel, some literature distinctively suggests that the effect of CSR is systematically tied to a favourable time-specific benefit and specifically pronounced during bad economic states. In this context, it is essential to differentiate between the two notions: while securities with positive idiosyncratic skewness are valuable particularly to those who show strong preference for lottery-like payoff irrespective of the state of the markets, securities with higher systematic return skewness can provide insurance-like benefits against the bad states of the market (Langlois, 2020). In case of the latter, for example, Nofsinger and Varma (2014) report that SRI funds display an asymmetric return: they perform better during market crisis periods but at the cost of performing worse during non-crisis periods. In a similar vein, Lins, Servaes, and Tamayo (2017) document positive risk-adjusted returns during the crisis. In congruence with these cases, Bénabou and Tirole (2010) point out the possibility that CSR has a differential effect on expected returns either because high-CSR firms are exposed to systematic risk in a different way (i) due to its ability to weather crisis periods or (ii) because CSR is a risk factor. Furthermore, in relation to this systematic channel, Bakshi and Kapadia (2003) maintain that securities that are very sensitive to market volatility risk can serve as a hedge against market downside risk: the investors' preference for coskewness makes assets with high sensitivities to market volatility innovations more in demand, thereby leading to lower returns. In parallel, stocks that underperform in times of increased market volatility generally show negatively skewed returns over medium-term horizons, while stocks that outperform in such periods show positively skewed returns (Ang et al., 2006). Thus it is implied that amid the crisis periods when stock prices are generally exposed to downward pressure, CSR-intensive firms suffer less from this market force, leading to mitigated negative skewness (tail asymmetry); similarly the kurtosis (tail size) in the distribution—representing the likelihood of extreme return values—is likely expected to lessen.

Alongside, studies have also shown that socially oriented investors are qualitatively distinctive from average investors with respect to their preference. Socially responsible investors are known to have non-financial utility (Riedl and Smeets, 2017), are less concerned about negative returns, and hold on to their investments longer (Renneboog, Horst, and Zhang, 2011); on the other side of the coin, CSR attracts long-term investors (Glossner, 2019). To sum up, whether CSR-intensive firms are more or less susceptible to market movements and sentiments is an empirical question. To the extent that the influence of average investors who are vulnerable to market-wide sentiment is more salient relative to that of socially oriented investors, this line of reasoning leads to Hypothesis 2:

Hypothesis 2: The valuation of CSR is reinforced by investor pessimism amid market crises, thereby leading to higher systematic skewness and lower systematic kurtosis in returns

Hypotheses 3a–3c center around the parallel announcements in 2017: an announcement of the withdrawal from the Paris Agreement on June 1 was paralleled by the formation of the United States Climate Alliance in the first week of June. In this regard, it calls into question whether the announcement of the climate alliance formation was only limited to the firms located in the alliance states—put differently, it is an open question whether the firms located in the non-alliance states were completely unaffected by the announcement of this alliance formation. First, firms located in the non-alliance states can be still exposed to the parallel announcements because their subsidiaries and/or supply chain network are geographically interwoven within the climate alliance states: as for the latter, Schiller (2018) finds that ESG policies transmit through supply chains. Second, investor sentiment may prevail. The broad definition of investor sentiment refers to a belief about future cash flows and investment risks that is not justified by the facts at hand, which manifests itself as an over- and under-reaction to information or mispricing (Baker and Wurgler, 2007). For brevity, I use henceforth the term "green firm" ("ungreen firm") for a firm with a high (low) degree of environmental orientation. In a similar fashion, "green optimism" is defined as the investors' propensity to speculate on the firm's future cash flows by heavily resting on its environmental orientation: from a neutral investor's perspective, green (ungreen) firms are valued with an upward (downward) bias by a socially oriented investor. In explaining the potential exposure to the parallel announcements of firms located in the non-alliance states, in reality it may be difficult to disentangle the subsidiary/supply chain channel from the green optimism channel.

With respect to the green optimism channel, three sequences of hypotheses are in order. The first hypothesis concerns the price changes of securities upon an arrival of new information and, consistent with prior literature, I interpret it as the investors' evaluation of the market condition. Specifically, the hypothesis postulates that socially oriented investors may view the parallel announcements as an increased upward potential of green firms in the climate alliance states so long as they are in favor of the green initiatives in these states. Taking a more aggressive view conforming to the green optimism, socially oriented investors may also positively evaluate the potential of firms located in non-climate-alliance states with the hope that these firms are armed with better future prospects. In sum, to the extent that the influence of socially oriented investors is salient enough to counter that of the investors with different preferences, this leads to Hypothesis 3a:

Hypothesis 3a: Surrounding the parallel announcements, (un)green firms experienced positive (negative) abnormal returns

Furthermore, extant literature suggests that the investor heterogeneity stemming from differences in preferences, endowments, or information is key to understanding their trading behaviours. Studies have shown that the abnormal volume surrounding a new information event is a barometer of the degree of investors' disagreement on its interpretation (e.g., Beaver, 1968; Karpoff, 1987; Kandel and Pearson, 1995). Periods of high disagreements are often associated with high volume as well as high volatility return (e.g., Campbell, Grossman, and Wang, 1993; Donders and Vorst, 1996; Banerjee and Kremer, 2010). While an arrival of new information can generate divergence in opinions leading to increased volume, investors' beliefs could conversely converge leading to decreased volume if investors unanimously interpret the public information. Thus, inasmuch as socially oriented investors occupy a decent share of diverse investor base, the parallel announcements experienced in the climate-alliance states can generate opinions leading to decreased (increased) trading volume in relation to (un)green firms. Again, extending the green optimism view, it is equally possible that this tendency applies to firms based in the non-climate-alliance states despite the only exposure to the single announcement on the Paris Agreement withdrawal. Motivated by differences-of-opinion theory, this line of reasoning leads to Hypothesis 3b:

Hypothesis 3b: Surrounding the parallel announcements, (un)green firms experienced a negative (positive) abnormal turnover

With respect to the relationship between investors' disagreement and return skewness, I draw on the theoretical framework of Hong-Stein model (Chen, Hong, and Stein, 2001; Chen, Hong, and Stein, 2002; Hong and Stein, 2003). This model builds on two key assumptions: (i) the differences of opinion in securities' fundamental values exist among investors, and (ii) a fraction of investors faces short-sales constraints. It predicts that a certain degree of ex-ante heterogeneity in investors' opinions, proxied by trading volume, leads to negatively skewed returns. Moreover, Diether, Malloy, and Scherbina (2002) find that stocks with higher analyst forecast dispersion generate significantly lower future returns *ceteris paribus*: the authors add that their results are consistent with the view that lower future returns are realized because the wider disagreement about security's fundamental value at the beginning of the period translates into overvaluation. Xu (2007) stresses that although his work is related to Chen, Hong, and Stein (2001) the differences are distinctive because he verifies that contemporaneous skewness, as opposed to subsequent skewness, is positively correlated with turnover—thus it should not escape our attention that while Hypotheses 3a and 3b are limited to the contemporaneous dimension, Hypothesis 3c is framed based on a two period setting. Insofar as (i) the discrepancy in terms of realized trading volume differentials is salient between investors' agreement on green firms and investors' disagreement on ungreen firms, (ii) contemporaneous and subsequent skewnesses are reasonably differentiated, and (iii) the green optimism channel is at play following Hypotheses 3a and 3b, this line of reasoning leads to Hypothesis 3c:

Hypothesis 3c: Following the parallel announcements, (un)green firms subsequently experienced a positive (negative) skewness shock, reflecting the (dis)agreement among investors

In connection with Hypotheses 3a–3c, a fundamental question arises with respect to how the stock market reaction to the parallel announcements ($t = 0$) was received by the firm managers based in alliance states ($t = 1$) and potentially influenced the ensuing corporate green investments ($t = 2$). A natural starting point is to explore why corporate managers based in the climate alliance states would put a value on—after observing the investor reactions in the stock market—the green policies promoted by their states over the federal government decision to disengage from the Paris Agreement. Equally, the possibility that even corporate managers based outside the climate alliance states would care about these reactions cannot be dismissed. Evidenced by the concerns against the Trump administration's decision voiced by a strand of US firm managers via social media, I maintain that geographical proximity with investors and with other firms plays a salient role, because the concept of locality is fundamental to CSR and intertwined with corporate decision making. In fact, one of the widely accepted definitions of CSR proposed by the World Business Council for Sustainable Development (WBCSD) is as follows:

> The continuing commitment by business to behave ethically and contribute to economic development while improving the quality of life of the workforce and their families as well as of the local community and society at large.

Empirical studies abound showing that locality can affect firm managers' corporate policies directly as well as indirectly via investors. This is in conformity with what Marquis and Battilana (2009) posit—that the influence of local communities on firms is in no decline even in this age of globalization. Gao, Ng, and Wang (2011) confirm that corporate headquarters location matters for firm capital structure. Strands of literature document that investors grossly tilt their portfolios toward local companies, implying that investors are better at gathering information on companies located nearby. Becker, Ivković, and Weisbenner (2011) provide evidence that companies respond to the preferences of their current shareholders and fine-tune their corporate actions. Moreover, Pirinsky and Wang (2006) argue that geographically close investors in a community can exchange and transmit investment sentiment as well as information through social interaction. Dougal, Parsons, and Titman (2015) find that corporate investment is highly sensitive to other geographically proximate corporate headquarters across various industries with respect to their investments, cash inflows/outflows, and stock price fluctuations.

To simplify the expected responses of the financial market to the parallel announcements, let $(return, turn, skew)$ denote the structure of the stock market reaction at $t = 0$, where $return$, $turn$, and $skew$ stand for the return, turnover, and skewness in excess of a market benchmark, respectively: $(+, -, +)$ indicates a positive reaction and $(-, +, -)$ indicates a negative reaction. In particular, applying the framework provided by Morck, Shleifer, and Vishny (1990), a positive reaction may predict a green investment based on active informant hypothesis, while a negative reaction may predict a green investment based on market pressure hypothesis[3]: accordingly, both positive and negative reactions at $t = 0$ may similarly predict an incremental green investment at $t = 2$ for different reasons determined at $t = 1$. One case of negative reaction is exemplified by Konar and Cohen (1997), showing that firms which experienced the largest stock price fall on the day the information on toxic release inventory (TRI) was released eventually contributed to emissions reduction more than their industry peers. To put this into perspective, opposing stock market responses to the parallel announcements experienced by a spectrum of firms may have similarly predicted the subsequent corporate green investments. Inasmuch as the agenda to tackle climate change is deemed as a unanimous goal by firms and investors thereby supporting the green optimism view, this argument leads to Hypothesis 4:

Hypothesis 4: In the aftermath of the parallel announcements, firms responded to the preceding stock market reaction by enhancing their environmental orientation

3 Data and sample description

My initial sample draws on publicly traded US firms that are covered by CRSP/Compustat Merged (CCM) database to obtain market-related variables over the period 1999–2017[4]:

[3] In relation to the influential channel running from investors to corporate managers, Morck, Shleifer, and Vishny (1990) hypothesize that if the stock market affects real economic activity, then the investor sentiment that affects stock prices could also indirectly affect real activity. The underlying logic is that, if stock returns are infected by sentiment, and if stock returns foresee investment, then sentiment can influence investment. Furthermore, they identify four theories that may explicate the correlation between stock returns and subsequent investment: (i) the stock market is a passive predictor of future activity which managers do not rely on to make investment decisions (passive informant hypothesis); (ii) in making investment decisions, managers rely on the stock market as a source of information, which may or may not be correct about future fundamentals (active informant hypothesis); (iii) the stock market affects investment through its influence on the cost of funds and external financing (financing hypothesis); (iv) the stock market exerts pressure on investment quite aside from its informational and financing role, because managers have to cater to investors' opinions in order to protect their livelihood (stock market pressure hypothesis). The fourth hypothesis is particularly interesting in that the green investment is the manifestation of SRI investors' philosophy, or green optimism.

[4] Skewness and kurtosis estimates are sensitive to return horizon (e.g., Amaya et al., 2015). I avoid using lower frequency returns (e.g., weekly) to reduce the concern of measurement errors originating from fewer samples but this issue will be revisited in Section 7.

firms in financial services industry (SIC: 6000–6999) are excluded. For monthly trading volume and outstanding shares of stocks, I additionally collect these variables from CRSP Monthly Stock File because CCM database only provides outstanding shares of stocks at quarterly frequency.[5] Moreover, the data from Thomson Reuters Refinitiv database are collected over the period 2002–2017. As to merging data, I use GVKEY as the primary identifier but use CUSIP to match market-related data with CSR data; I also use PERMCO to match market-related data (from CCM database) with monthly trading volume and outstanding shares. My sample consists of firms listed in NYSE and AMEX and, unlike Chen, Hong, and Stein (2001) (henceforth CHS), I also include NASDAQ firms in the sample. The benefit of an enlarged sample size comes at a cost because the institutional differences among stock exchanges (e.g., turnover measurement) pose another challenge that cannot be simply ignored. Thus, following Boyer, Mittion, and Vorkink (2010), I include a NASDAQ dummy to control for the peculiar institutional feature of NASDAQ.[6]

Now, with respect to the dependent variables, the selection of the period intervals in measuring the higher moments of returns is ultimately a subjective choice. As a case in point, CHS write about the case of a skewness measure construction as follows:

> The choice of a six-month period for measuring skewness is admittedly somewhat arbitrary. In principle, the effects that we are interested in could be playing themselves out over a shorter period interval, so that trading volume on Monday forecasts skewness for the rest of the week, but has little predictive power beyond that. Unfortunately, the model of Hong and Stein does not give us much guidance in this regard. Lacking this theoretical guidance, our choice to use six months' worth of daily returns to estimate skewness is driven more by measurement concerns. For example, if we estimated skewness using only one month's worth of data, we would presumably have more measurement error; this is particularly relevant given that a higher-order moment like skewness is strongly influenced by outliers in the data.

On top of the above-mentioned concern on measurement errors, all the variables in Section 4 are measured at 3-, 6-, and 12-month intervals to address the possibility that I may overlook systematic patterns that could develop over different horizons. In what follows, I specifically borrow the notations from CHS for return-related variables. Below are the standard deviation

[5] Trading volume is provided at the monthly level for both databases.

[6] Another conceivable way is to use an exchange-adjusted turnover XTURNOVER (Chen, Hong, and Stein, 2002) but I do not adopt this approach in this paper.

SIGMA and the skewness measures CSKEW and DUVOL, which are all adjusted for the sample size:[7]

$$\text{SIGMA}_{i,t} = \sqrt{\frac{\sum(R_{i,t} - \bar{R}_{i,t})^2}{n-1}} \tag{1}$$

$$\text{CSKEW}_{i,t} = \frac{n(n-1)^{1/2}\left[\sum(R_{i,t} - \bar{R}_{i,t})^3\right]}{(n-2)\left[\sum(R_{i,t} - \bar{R}_{i,t})^2\right]^{3/2}} \tag{2}$$

$$\text{DUVOL}_{i,t} = \log \frac{(n_d - 1)\sum_{UP}(R_{i,t} - \bar{R}_{i,t})^2_{i,t}}{(n_u - 1)\sum_{DOWN}(R_{i,t} - \bar{R}_{i,t})^2_{i,t}} \tag{3}$$

where $R_{i,t}$ is daily log changes in stock i in period t. De-meaned daily returns are $\widetilde{R}_{i,t} = R_{i,t} - \bar{R}_{i,t}$, where $\bar{R}_{i,t}$ is the average return of stock i during period t. Note that the use of returns in logarithmic form will transform the distribution into a more negatively skewed one on average and also weakens the distinct contemporaneous correlation between skewness and volatility (CHS). As an aside, CHS construct another skewness measure DUVOL (down-to-up volatility) and find very similar regression estimates with their baseline skewness measure, NCSKEW: this paper also incorporates DUVOL but does not tabulate the regression estimates. Moreover, I additionally introduce a kurtosis measure. Note that similar to the other return-related variables, the sample excess kurtosis fails to serve as an unbiased estimator of the population excess kurtosis without an adjustment for the sample size. I term the adjusted version as the coefficient of excess kurtosis (CEKURT):

$$\text{CEKURT}_{i,t} = \frac{(n+1)n(n-1)\left[\sum(R_{i,t} - \bar{R}_{i,t})^4\right]}{(n-2)(n-3)\left[\sum(R_{i,t} - \bar{R}_{i,t})^2\right]^2} - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{4}$$

As regards the specifications of returns, I compute three variations of daily returns in logarithmic form: market-adjusted return, excess return, and residual return. Market-adjusted returns are the log change in stock i less the log change in the value-weighted CRSP index for the corresponding day. Excess returns are the log change in stock i less the T-bill return. Residual returns are the residuals from Fama-French three factor model converted to logarithmic form.[8] In accordance with CHS, when computing CSKEW and CEKURT under

[7]Opting for a coefficient suitable for this paper, the slight difference from CHS is that I do not put a negative sign in front of $\text{CSKEW}_{i,t}$ or $\text{DUVOL}_{i,t}$.

[8]This treatment stems from the following reason: Kelly and Jiang (2014) warn that in estimating tail risk, dependence among returns can lead to a biased result but this can be mitigated if common return factors are removed and residual returns are used. On a different note, one small difference between CHS and this paper is that CHS use beta-adjusted returns as residual returns.

the market-adjusted (excess) return specification, SIGMA and RET are computed naturally using market-adjusted (excess) returns; contrarily, when computing CSKEW and CEKURT under the residual return specification—these measures are essentially what is known as idiosyncratic skewness and kurtosis—SIGMA and RET are computed using market-adjusted returns. Overall, the descriptive statistics are largely in line with the previous two studies. For instance, the mean value of market adjusted CSKEW equals to -0.20, which lies between the values reported by CHS and Kim, Li, and Li (2014) (henceforth KLL).

Next, I draw on CHS and Kim, Li, and Li (2014) (henceforth KLL) to determine the set of independent variables that are expected to control for the determinants of future skewness and kurtosis in addition to CSR score. This pool of variables range from (i) firm size, (ii) share turnover, (iii) past returns over the 36-month horizon, and (iv) accounting variables.

First, the firm size variable is computed as the logarithm of the market capitalization and Table 2 implies that the mean value is 5087 million,[9] which is larger relative to the mean value of $1634 million reported by KLL. This is because firms for which CSR ratings proved by Thomson Reuters are available are in general largers firms.

Second, TURNOVER is the average monthly share turnover of stock i and defined as shares traded over shares outstanding in period t. Unlike CHS or KLL, I do not use the de-trend turnover variable (DTURNOVER) and only use a raw measure of turnover (TURNOVER) together with a NASDAQ dummy to account for the institutional differences of stock exchanges.[10] The mean turnover 0.23 is by far greater than—the standard deviation as well—the values reported in CHS or KLL. This discrepancy likely stems from the difference in data sources. While CHS and KLL use daily files to compute daily turnover averaged over the month, I draw on CRSP Monthly Stock File where the numerator is the *sum* of the trading volumes during the month. On a different note, the differentials of mean turnover between the NYSE/AMEX firms (0.21) and NASDAQ firms (0.27) is 0.05 but these numbers are untabulated.

Third, past returns need to be included owing to the fact that (i) trading volume is correlated with past returns (e.g., Shefrin and Statman, 1985; Odean, 1998) and (ii) positive

[9] Unlike CHS or KLL, the natural logarithm of market capitalization is computed without adjusting the units (i.e., in millions). Therefore, the mean value of LOGSIZE is substantially higher but the standard deviation is nevertheless in line with their reported values.

[10] CHS confirm that the use of a raw measure of turnover doubles the coefficient magnitude, implying that the use of detrended turnover is a conservative approach.

returns over the prior 36 months may have predicting power over large stock price movements in the next period if there are stochastic bubbles (Blanchard and Watson, 1982; Harvey and Siddique, 2000). In addition, given the prevalence of models that point to the correlation between volatility and skewness, volatility is included in my model specification.

Fourth, I include a few accounting variables following KLL. LEV is the leverage defined as total long-term debts over total assets. ROA is the profitability measure defined as income before extraordinary items over total assets. BK/MKT is the book-to-market ratio defined as the book value of equity over the market value of equity. Under the specification of monthly overlapping observations, these variables are computed as the weighted-average over the 3-, 6-, or 12-month intervals using quarterly data. Similar to KLL, one may wish to include the abnormal accruals variable, which is a proxy for earnings management, on the grounds that earnings management is negatively related to future return skewness (e.g., Hutton, Marcus, and Tehranian, 2009). Yet, the modified Jones model requires a large number of firm observations for the estimation period prior to the event, indicating that the number of observations will be inevitably reduced. Given the objective to conduct cross-sectional tests, I opt to use the full set of data by excluding the discretionary accruals variable. In my defense, KLL display that discretionary accruals have little explanatory power for the future return skewness because its absolute value of t-statistic results in less than 0.01: one would ideally examine its correlation with other variables but a correlation table is unfortunately not provided. On a different note, accounting variables are winsorized at the 2.5% and 97.5% level to mitigate the influence of outliers.

As a summary, Table 1 presents return- and volume-related variables in relation to Hypotheses 1–3. Table 2 presents the summary statistics with variables measured at 6-month intervals with the specification of monthly overlapping observations. Table 3 presents the correlation matrix with variables measured at 6-month intervals.

Table 1: Exposition of return- and volume-related variables

This table reports the return- and volume-related variables of interest. $\bar{R}_{i,t}$ is the average return of stock i during period t.

$$\text{SIGMA}_{i,t} = \sqrt{\frac{\sum(R_{i,t} - \bar{R}_{i,t})^2}{n-1}}$$

$$\text{CSKEW}_{i,t} = \frac{n(n-1)^{1/2}\left[\sum(R_{i,t} - \bar{R}_{i,t})^3\right]}{(n-2)\left[\sum(R_{i,t} - \bar{R}_{i,t})^2\right]^{3/2}} \qquad \text{DUVOL}_{i,t} = \log\frac{(n_d - 1)\sum_{UP}(R_{i,t} - \bar{R}_{i,t})^2_{i,t}}{(n_u - 1)\sum_{DOWN}(R_{i,t} - \bar{R}_{i,t})^2_{i,t}}$$

$$\text{CEKURT}_{i,t} = \frac{(n+1)n(n-1)\left[\sum(R_{i,t} - \bar{R}_{i,t})^4\right]}{(n-2)(n-3)\left[\sum(R_{i,t} - \bar{R}_{i,t})^2\right]^2} - \frac{3(n-1)^2}{(n-2)(n-3)}$$

	Channel			**Return**	**SD**	**Skewness**			**Kurtosis**		**Trading Volume**
	Firm Specific	Market Pessimism	Green Optimism	RET	SIGMA	CSKEW	DUVOL	*Skew*	CEKURT	*Kurt*	TURNOVER
H1	○					✓			✓		
H2		○		✓		✓	✓		✓		
H3a			○	✓							
H3b			○		✓						✓
H3c			○			✓					✓
H4			○	✓	✓	✓					
Robust								✓		✓	

The symbol ○ indicates which channel is at play.
"green optimism" is defined as the investors' propensity to speculate on the firm's future cash flows by heavily resting on its environmental orientation.

The symbol ✓ indicates that the variable is the key focus in the corresponding hypothesis.

CSKEW and DUVOL measures are borrowed from CHS but I do not adopt the minus signs: the regression estimates using DUVOL measure are untabulated.

CEKURT measure is derived by naturally extending CSKEW measure.

Skew and *Kurt* measures are derived in the *Robustness checks* section by extending the methodology of Ghysels, Plazzi, and Valkanov (2016).

Table 2: Summary statistics: variables measured at 6-month period intervals

The sample period ranges from January 2002 to December 2017 and I show the case where variables are measured at six-month period t with the specification of monthly overlapping observations. CSKEW_t is the coefficient of daily skewness measured in period t. SIGMA_t is the standard deviation of daily returns measured in period t. LOGSIZE_t is the log of market capitalization measured at the end of period t. LEV_t, ROA_t and BK/MKT_t are the weighted average of the quarterly information at the end of period t. TURNOVER_t is the average monthly turnover measured in period t. RET_t is the cumulative return in logarithm in period t. For the case of the residual return specification, while CSKEW and CEKURT are computed using residual returns, RET and SIGMA are computed using market adjusted returns: this style echoes CHS. Accounting variables exhibit the values before winsorization.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
CSR score	49.39	17.35	8.01	18.61	35.89	46.87	62.39	88.31	97.89	136527
Environmental score	47.05	21.61	2.79	10.32	30.20	42.74	63.48	94.73	98.70	136527
LOGSIZE	22.35	1.40	16.59	19.32	21.45	22.24	23.20	25.98	27.51	136527
TURNOVER	0.23	0.22	0.00	0.02	0.11	0.17	0.28	1.05	19.03	136500
NASDAQ	0.34	0.47	0.00	0.00	0.00	0.00	1.00	1.00	1.00	136527
RET market adj.	-0.02	0.26	-2.79	-0.83	-0.12	-0.00	0.11	0.62	4.12	136253
RET excess	0.02	0.30	-3.04	-0.93	-0.10	0.05	0.17	0.71	4.20	136253
RET residual	-0.02	0.26	-2.79	-0.83	-0.12	-0.00	0.11	0.62	4.12	136253
SIGMA market adj.	0.02	0.01	0.00	0.01	0.01	0.02	0.02	0.07	0.41	136253
SIGMA excess	0.02	0.02	0.00	0.01	0.01	0.02	0.03	0.07	0.41	136253
SIGMA residual	0.02	0.01	0.00	0.01	0.01	0.02	0.02	0.07	0.41	136253
CSKEW market adj.	-0.20	2.14	-11.30	-9.95	-0.62	0.04	0.64	4.52	11.26	136253
CSKEW excess	-0.25	1.87	-11.28	-9.63	-0.52	-0.04	0.40	3.67	11.26	136253
CSKEW residual	-0.20	2.18	-11.30	-9.98	-0.66	0.03	0.67	4.68	11.25	136085
DUVOL market adj.	-0.03	1.07	-9.67	-4.25	-0.47	0.05	0.54	2.14	8.20	136253
DUVOL excess	-0.11	0.94	-10.70	-3.96	-0.46	-0.04	0.37	1.83	8.23	136253
DUVOL residual	-0.04	1.09	-9.68	-4.29	-0.50	0.04	0.56	2.20	7.98	136085
CEKURT market adj.	9.40	17.58	-0.96	-0.24	1.34	3.45	9.40	109.67	128.15	136253
CEKURT excess	7.10	16.14	-0.98	-0.34	0.84	2.16	5.88	105.19	127.83	136253
CEKURT residual	9.74	17.74	-0.91	-0.20	1.44	3.67	9.96	110.03	128.14	136085
LEV	0.24	0.20	0.00	0.00	0.10	0.22	0.33	0.84	3.83	135287
ROA	0.01	0.09	-15.67	-0.16	0.00	0.01	0.02	0.08	1.03	136379
BK/MKT	0.41	0.48	-38.48	-0.25	0.21	0.35	0.55	1.52	32.74	136280

Table 3: Correlation matrix: variables measured at 6-month period intervals

This table reports the cross-correlation matrices of the main variables (Panel A) and variables related to market-adjusted return (Panel B), respectively. Variables are measured at six-month period intervals with the specification of monthly overlapping observations.

Panel A: Main variables

	CSR	Env.	LOGSIZE	TURNOVER	NASDAQ	RET mark.	RET exce.	RET beta	LEV	ROA	BK/MKT
CSR score	1.000										
Environmental score	0.873	1.000									
LOGSIZE	0.556	0.506	1.000								
TURNOVER	-0.074	-0.068	-0.142	1.000							
NASDAQ	-0.181	-0.115	-0.176	0.112	1.000						
RET (market adj.)	-0.007	-0.010	0.068	-0.054	0.010	1.000					
RET (excess)	-0.004	-0.004	0.070	-0.086	0.019	0.921	1.000				
RET (residual)	-0.007	-0.010	0.068	-0.054	0.010	1.000	0.921	1.000			
LEV	0.008	0.005	-0.040	0.007	-0.140	-0.010	-0.004	-0.010	1.000		
ROA	0.054	0.042	0.148	-0.066	-0.059	0.012	0.016	0.012	-0.018	1.000	
BK/MKT	-0.036	-0.044	-0.121	0.048	-0.089	-0.106	-0.120	-0.106	-0.148	-0.002	1.000

Panel B: Variables related to market-adjusted return

	RET	RET-1	RET-2	RET-3	RET-4	RET-5	SIGMA	CSKEW	DUVOL	CEKURT
RET	1.000									
RET-1	-0.047	1.000								
RET-2	-0.039	-0.051	1.000							
RET-3	-0.029	-0.038	-0.054	1.000						
RET-4	-0.044	-0.028	-0.040	-0.044	1.000					
RET-5	-0.014	-0.042	-0.030	-0.039	-0.049	1.000				
SIGMA	-0.165	-0.104	-0.081	-0.079	-0.023	-0.006	1.000			
CSKEW	0.539	-0.055	-0.039	-0.034	-0.035	-0.026	-0.258	1.000		
DUVOL	0.562	-0.071	-0.043	-0.037	-0.038	-0.025	-0.232	0.961	1.000	
CEKURT	-0.246	0.030	0.013	0.020	0.025	0.032	0.543	-0.530	-0.473	1.000

4 CSR and future skewness and kurtosis

While non-parametric approach is useful for its wider application usage, it is essential to control for a number of variables in this paper. Thus, I opt to employ a parametric approach and use data available at period t to forecast performance at period $t+1$ to avoid look-ahead bias. In particular, I explore two regression specifications: pooled regression with time dummies from Chen, Hong, and Stein (2001) (henceforth CHS) and fixed effects OLS regression from Kim, Li, and Li (2014) (henceforth KLL) whereby the CHS specification serves as a benchmark that is compared against the KLL specification, the primary interest in this analysis. I include CSR score variable only in the KLL specification together with other control variables and industry-specific time fixed effects (SIC 2-digit $\times$ year-month): CSR score is by design a relative percentile ranking within a peer group and requires industry fixed effects to maintain its meaningful interpretation across different industries. Similar to the specification where CSKEW_t is included to forecast CSKEW_{t+1}, I include the CEKURT_t in forecasting CEKURT_{t+1} to proxy for omitted firm-specific variables and to account for the persistence in the kurtosis.

After estimating regressions using nonoverlapping intervals, I obtain poor statistical significance (unreported) especially in terms of the relationship between the dependent variable and TURNOVER. This is possibly attributed to the smaller sample size relative to CHS. Accordingly, I re-estimate regressions with monthly overlapping observations to enhance statistical power.[11] In estimating these regressions, heteroscedasticity and autocorrelation (by clustering at the firm unit level) are adjusted—I cluster by firm to correct for spurious autocorrelation stemming from the assumption of CSR score (i.e., constant throughout each year). The year-month fixed effects can also alleviate problems arising from time-series dependence. Furthermore, the challenge inherent to integrating CSR score into a monthly overlapping specification is that it is only measured at 12-month intervals. Therefore, I assume that CSR score is constant throughout each year to construct a metric at monthly level; I recalculate it each year at the beginning of the fiscal year. Although this imputation may pose a measurement error, it is unlikely to go beyond a peripheral issue particularly because CSR score is time persistent in its nature and only change gradually. Indeed, my sample suggests that the correlation between neighboring years ranges from 0.77 to 0.97 (median 0.93)[12]

[11] CHS refer to the (monthly) overlapping intervals but only implement this setting in the market time-series regressions; they report that as per cross-sectional analysis, substantial statistical power is already achieved with nonoverlapping intervals and thus there is no need for adopting overlapping intervals.

[12] Using MSCI ESG data, Lins, Servaes, and Tamayo (2017) similarly report that CSR levels are persistent over time.

Tables 4–6 present the estimates of skewness predictions. Overall, I confirm regression results qualitatively similar to KLL despite the difference in the CSR data sources (MSCI or Thomson Reuters) or the frequency of returns (weekly or daily).[13] For instance, consistent with KLL, LOGSIZE_t, RET_t and ROA_t are negatively (positively) associated with CSKEW_{t+1} (NCSKEW_{t+1}).[14] In particular, CSR_t is positively associated with CSKEW_{t+1} at a statistically and economically significant level.[15] For example, the magnitude of the coefficient on CSR_t is 0.004 in column (2) of Table 4 under the market-adjusted return specification with 6-month period intervals and the standard deviation of CSR is 17.35; therefore, a one standard deviation change in CSR leads to an increase of 0.069 in skewness. To put this into perspective, a one standard deviation change in LOGSIZE and TURNOVER leads to a decrease of 0.120 ($-0.086 \times 1.40 = -0.085$) and 0.057 ($-0.258 \times 0.22 = -0.055$) in skewness, respectively, highlighting the gravity CSR carries.

Moreover, Tables 7–9 present the estimates of kurtosis predictions. Similarly, for all return specifications, CSR score is negatively associated with CEKURT_{t+1} at a statistically and economically significant level. For example, the magnitude of the coefficient on CSR_t is -0.021 in column (2) of Table 7 under the market-adjusted return specification with 6-month period intervals and the standard deviation of CSR is 17.35; therefore, a one standard deviation change in CSR leads to a decrease of 0.364 in kurtosis. Putting this into perspective, a one standard deviation change in LOGSIZE and TURNOVER leads to a decrease of 0.669 ($-0.478 \times 1.40 = -0.669$) and 0.439 ($1.994 \times 0.22 = -0.439$) in kurtosis, respectively.

Furthermore, one particular feature that needs to be emphasized is that the t-statistics for the coefficients on CSR score are greater—or equivalently, standard errors are smaller given that the values of the coefficients on CSR score are the same across different return specifications—when using the excess return specification compared to the other two return specifications. This is even so irrespective of (i) period intervals or (ii) the dependent variable CSKEW_{t+1} or CEKURT_{t+1}. These patterns starkly contrast with other firm-specific variables such as LOGSIZE or ROA, which yield the greatest coefficient and t-statistic (in

[13] Note that KLL only use residual returns computed from an expanded market model (with lead and lag market index return) under 12-month nonoverlapping period intervals.

[14] In terms of the sign of the coefficient on SIGMA, my result is aligned with CHS but at odds with KLL. The sign displayed by KLL appears to be a typo.

[15] Under the KLL specification with 3-month period intervals forecasting CSKEW_{t+1}, the coefficients on CSR_t also yields, albeit moderate, statistically significant results (untabulated): market-adjusted return (coefficient: 0.018, t-stat: 2.79), excess return (coefficient: 0.017, t-stat: 3.04), residual return (coefficient: 0.017, t-stat: 2.50).

absolute terms) when using the market adjusted or residual return specification. These opposing estimates are puzzling if one only takes the standpoint that CSR influences the higher moments of returns exclusively through a firm-specific channel[16] and thus hints at the systematic market pessimism channel. Therefore, Hypothesis 2 further scrutinizes and provides explanation for this market-wide channel influenced by investor pessimism in Section 5.

[16]KLL argue that CSR mitigates firm-specific crash risk by examining idiosyncratic skewness but are silent on total skewness.

Table 4: Forecasting CSKEW_{t+1} using market-adjusted returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CSKEW_{t+1}, which is computed based on market-adjusted returns (in logarithm). Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		0.004***		0.008***
		(3.602)		(3.854)
CSKEW_t	0.010	-0.005	0.014	-0.014
	(1.333)	(-0.630)	(1.254)	(-1.151)
SIGMA_t	4.408***	3.459**	8.497***	7.482***
	(3.625)	(2.324)	(3.383)	(2.763)
LOGSIZE_t	-0.061***	-0.086***	-0.073***	-0.104***
	(-4.757)	(-4.928)	(-2.847)	(-3.010)
TURNOVER_t	-0.248***	-0.258***	-0.358***	-0.392***
	(-3.758)	(-3.479)	(-2.901)	(-2.784)
NASDAQ_t	-0.007	-0.011	-0.060	-0.059
	(-0.189)	(-0.275)	(-0.815)	(-0.730)
RET_t	-0.564***	-0.419***	-0.870***	-0.610***
	(-9.879)	(-5.639)	(-10.351)	(-5.817)
RET_{t-1}	-0.353***	-0.267***	-0.641***	-0.544***
	(-7.206)	(-4.481)	(-9.621)	(-6.929)
RET_{t-2}	-0.260***	-0.195***	-0.503***	-0.415***
	(-5.666)	(-3.612)	(-7.237)	(-4.998)
RET_{t-3}	-0.354***	-0.268***		
	(-6.888)	(-4.523)		
RET_{t-4}	-0.254***	-0.245***		
	(-5.214)	(-4.508)		
RET_{t-5}	-0.171***	-0.136**		
	(-3.462)	(-2.423)		
LEV_t		0.064		0.393*
		(0.570)		(1.782)
ROA_t		-2.992***		-5.962***
		(-3.678)		(-3.519)
BK/MKT_t		0.012		0.117
		(0.177)		(0.934)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115935	113394	105860	103060
Adj. R^2	0.017	0.025	0.030	0.044

t-statistics are adjusted for heteroskedasticity and serial correlation.

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 5: Forecasting CSKEW_{t+1} using excess returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CSKEW_{t+1}, which is computed based on excess returns (in logarithm). Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		0.004***		0.008***
		(4.309)		(4.293)
CSKEW_t	0.012	-0.006	0.016	-0.008
	(1.608)	(-0.673)	(1.562)	(-0.745)
SIGMA_t	4.794***	3.795***	10.014***	9.077***
	(4.456)	(2.955)	(4.516)	(3.662)
LOGSIZE_t	-0.050***	-0.077***	-0.055**	-0.088***
	(-4.488)	(-4.952)	(-2.443)	(-2.802)
TURNOVER_t	-0.226***	-0.237***	-0.356***	-0.387***
	(-3.795)	(-3.603)	(-3.249)	(-3.069)
NASDAQ_t	0.006	-0.007	-0.044	-0.060
	(0.190)	(-0.202)	(-0.673)	(-0.835)
RET_t	-0.496***	-0.355***	-0.767***	-0.554***
	(-9.630)	(-5.400)	(-10.292)	(-5.923)
RET_{t-1}	-0.320***	-0.246***	-0.579***	-0.512***
	(-7.318)	(-4.646)	(-9.629)	(-7.371)
RET_{t-2}	-0.241***	-0.194***	-0.439***	-0.368***
	(-5.917)	(-4.152)	(-6.982)	(-4.988)
RET_{t-3}	-0.326***	-0.253***		
	(-7.224)	(-5.040)		
RET_{t-4}	-0.234***	-0.234***		
	(-5.381)	(-4.994)		
RET_{t-5}	-0.150***	-0.121**		
	(-3.414)	(-2.492)		
LEV_t		0.012		0.315
		(0.121)		(1.594)
ROA_t		-2.546***		-4.913***
		(-3.492)		(-3.214)
BK/MKT_t		-0.028		0.059
		(-0.494)		(0.539)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115935	113394	105860	103060
Adj. R^2	0.020	0.032	0.032	0.049

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 6: Forecasting CSKEW_{t+1} using residual returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CSKEW_{t+1}, which is computed based on residual returns (in logarithm) derived from Fama-French Three-factor Model. Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		0.004***		0.008***
		(3.304)		(3.652)
CSKEW_t	0.012	-0.002	0.015	-0.011
	(1.637)	(-0.289)	(1.348)	(-0.920)
SIGMA_t	5.128***	4.040***	9.718***	8.468***
	(4.191)	(2.657)	(3.896)	(3.121)
LOGSIZE_t	-0.062***	-0.084***	-0.074***	-0.100***
	(-4.747)	(-4.724)	(-2.860)	(-2.878)
TURNOVER_t	-0.238***	-0.244***	-0.355***	-0.382***
	(-3.540)	(-3.251)	(-2.825)	(-2.668)
NASDAQ_t	0.013	-0.002	-0.034	-0.051
	(0.350)	(-0.059)	(-0.450)	(-0.622)
RET_t	-0.557***	-0.429***	-0.868***	-0.631***
	(-9.605)	(-5.729)	(-10.275)	(-5.911)
RET_{t-1}	-0.350***	-0.277***	-0.641***	-0.551***
	(-6.874)	(-4.474)	(-9.534)	(-6.862)
RET_{t-2}	-0.255***	-0.198***	-0.506***	-0.428***
	(-5.499)	(-3.592)	(-7.296)	(-5.154)
RET_{t-3}	-0.351***	-0.278***		
	(-6.673)	(-4.481)		
RET_{t-4}	-0.262***	-0.257***		
	(-5.300)	(-4.643)		
RET_{t-5}	-0.171***	-0.137**		
	(-3.448)	(-2.430)		
LEV_t		0.085		0.432*
		(0.748)		(1.951)
ROA_t		-3.117***		-6.205***
		(-3.781)		(-3.608)
BK/MKT_t		0.006		0.116
		(0.082)		(0.910)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115819	113302	105768	102998
Adj. R^2	0.017	0.024	0.030	0.044

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 7: Forecasting CEKURT_{t+1} using market-adjusted returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CEKURT_{t+1}, which is computed based on market-adjusted returns (in logarithm). Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		-0.021**		-0.076**
		(-2.002)		(-2.590)
CEKURT_t	0.083***	0.052***	0.036*	0.033
	(7.377)	(4.202)	(1.735)	(1.508)
CSKEW_t	0.252***	0.243***	0.407*	0.638**
	(3.555)	(3.200)	(1.732)	(2.546)
SIGMA_t	-73.451***	-50.347***	-63.830	-75.156
	(-4.959)	(-2.809)	(-1.455)	(-1.415)
LOGSIZE_t	-0.654***	-0.478***	-0.664**	-0.520
	(-5.928)	(-3.149)	(-2.055)	(-1.161)
TURNOVER_t	1.574**	1.994***	1.533	2.341
	(2.332)	(2.872)	(0.939)	(1.287)
NASDAQ_t	1.889***	0.712*	3.189***	1.654
	(5.535)	(1.960)	(3.355)	(1.587)
RET_t	2.733***	1.233**	7.691***	4.621***
	(5.375)	(1.987)	(6.355)	(3.223)
RET_{t-1}	1.736***	0.814	6.974***	5.401***
	(4.335)	(1.502)	(7.783)	(5.408)
RET_{t-2}	1.577***	0.967**	5.488***	4.214***
	(4.213)	(2.142)	(7.111)	(4.665)
RET_{t-3}	2.247***	1.317***		
	(5.672)	(2.831)		
RET_{t-4}	2.318***	1.945***		
	(5.838)	(4.555)		
RET_{t-5}	1.683***	1.198***		
	(4.688)	(2.966)		
LEV_t		-2.072**		-4.702*
		(-2.175)		(-1.722)
ROA_t		1.125		3.310
		(0.169)		(0.164)
BK/MKT_t		-2.161***		-5.146***
		(-3.678)		(-3.191)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115935	113394	105860	103060
Adj. R^2	0.027	0.045	0.028	0.043

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 8: Forecasting CEKURT_{t+1} using excess returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CEKURT_{t+1}, which is computed based on excess returns (in logarithm). Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		-0.028***		-0.082***
		(-3.012)		(-3.127)
CEKURT_t	0.058***	0.040***	0.027	0.026
	(4.876)	(3.009)	(1.339)	(1.184)
CSKEW_t	0.278***	0.312***	0.407*	0.650**
	(3.276)	(3.479)	(1.654)	(2.502)
SIGMA_t	-42.038***	-28.927*	-61.528	-66.582
	(-3.180)	(-1.715)	(-1.586)	(-1.345)
LOGSIZE_t	-0.520***	-0.371***	-0.471	-0.322
	(-5.501)	(-2.787)	(-1.601)	(-0.783)
TURNOVER_t	1.761***	2.191***	2.618*	3.112*
	(2.938)	(3.474)	(1.802)	(1.863)
NASDAQ_t	1.366***	0.649**	2.379***	1.575*
	(4.639)	(2.034)	(2.744)	(1.658)
RET_t	2.228***	0.892	6.531***	4.003***
	(4.690)	(1.544)	(5.991)	(3.079)
RET_{t-1}	1.654***	0.812	6.240***	4.948***
	(4.476)	(1.596)	(7.437)	(5.251)
RET_{t-2}	1.449***	0.923**	4.915***	3.914***
	(4.141)	(2.187)	(6.892)	(4.683)
RET_{t-3}	2.123***	1.199***		
	(5.636)	(2.691)		
RET_{t-4}	2.114***	1.839***		
	(5.715)	(4.599)		
RET_{t-5}	1.572***	1.189***		
	(4.728)	(3.223)		
LEV_t		-1.762**		-4.258*
		(-2.012)		(-1.668)
ROA_t		-3.063		-5.877
		(-0.491)		(-0.313)
BK/MKT_t		-2.242***		-5.004***
		(-4.405)		(-3.424)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115935	113394	105860	103060
Adj. R^2	0.027	0.042	0.029	0.044

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 9: Forecasting CEKURT_{t+1} using residual returns

The estimated regressions with the specification of monthly overlapping observations are presented below in Panel A (Panel B), where all variables are measured at 6-month (12-month) period intervals. The sample period is Jan 2002–Dec 2017. The dependent variable is CEKURT_{t+1}, which is computed based on residual returns (in logarithm) derived from Fama-French Three-factor Model. Odd columns represent CHS specification using pooled OLS with time dummies (year-month); even columns represent KLL specification using industry-specific time fixed effects (SIC 2-digit × year-month). The accounting variables are winsorized at the 2.5% and 97.5% level and are the weighted average of the quarterly information at the end of period t. Heteroscedasticity-consistent standard errors are clustered by firm in CHS specification and are double-clustered by firm and year-month in KLL specification. Intercept is estimated but unreported.

	Panel A: 6-month period		**Panel B: 12-month period**	
	(1)	(2)	(3)	(4)
CSR_t		-0.022**		-0.076***
		(-2.008)		(-2.604)
CEKURT_t	0.084***	0.050***	0.038*	0.032
	(7.708)	(4.204)	(1.863)	(1.484)
CSKEW_t	0.271***	0.245***	0.437*	0.638***
	(3.928)	(3.370)	(1.911)	(2.619)
SIGMA_t	-71.070***	-44.892**	-60.830	-63.755
	(-4.789)	(-2.497)	(-1.364)	(-1.182)
LOGSIZE_t	-0.768***	-0.593***	-0.827**	-0.678
	(-6.986)	(-3.917)	(-2.560)	(-1.513)
TURNOVER_t	1.306*	1.784**	1.183	2.014
	(1.958)	(2.541)	(0.726)	(1.090)
NASDAQ_t	1.767***	0.576	2.985***	1.496
	(5.130)	(1.561)	(3.118)	(1.413)
RET_t	2.698***	1.285**	7.592***	4.685***
	(5.261)	(2.069)	(6.385)	(3.278)
RET_{t-1}	1.781***	0.900*	6.886***	5.357***
	(4.402)	(1.655)	(7.726)	(5.376)
RET_{t-2}	1.513***	0.930**	5.289***	4.076***
	(4.013)	(2.021)	(6.803)	(4.466)
RET_{t-3}	2.241***	1.372***		
	(5.611)	(2.942)		
RET_{t-4}	2.196***	1.828***		
	(5.475)	(4.244)		
RET_{t-5}	1.552***	1.062***		
	(4.287)	(2.657)		
LEV_t		-2.330**		-5.231*
		(-2.432)		(-1.907)
ROA_t		0.352		1.558
		(0.052)		(0.076)
BK/MKT_t		-2.160***		-5.209***
		(-3.605)		(-3.180)
Year-Month Dummy	Yes	–	Yes	–
SIC-2 × Year-Month FE	–	Yes	–	Yes
Obs.	115819	113302	105768	102998
Adj. R^2	0.026	0.044	0.026	0.042

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

5 Market pessimism, CSR, and future returns

Hypothesis 2 postulates that CSR serves as a filter through which market pessimism exerts disproportional influences on return skewness and kurtosis. To empirically investigate this broad-based effect of market pessimism, a simple approach is to incorporate an interaction term between a market sentiment index and CSR into the previous model specifications in Section 4 to allow for different slopes. However, this approach turns out to be vastly ineffective, presumably because these models are misspecified—skewness and kurtosis measures are likely beyond what can be simply reduced to a linear regression model. Thus, I instead probe two different strategies in this section: (i) forecasting the return of high-CSR minus low-CSR long-short portfolio using market sentiment proxies and (ii) visualizing coefficients on CSR variables in the previous model specifications over subperiods during 2002–2017.

In the first strategy, to find out how sensitive the return is to market pessimism, I regress the monthly portfolio return of top CSR decile minus bottom CSR decile $R_{\mathrm{CSR}\,10,\,t} - R_{\mathrm{CSR}\,1,\,t}$ on sentiment index in month $t-1$ as well as risk factors in month t. This baseline model specification is analogous to Baker and Wurgler (2006) and is represented in equation (5). If necessary, I additionally run regressions where the dependent variable is replaced with the monthly return on a long portfolio within a given CSR decile $R_{\mathrm{CSR\,dec},\,t}$, which is represented in equation (6). Hypothesis 2 predicts that with respect to sentiment indexes representing market pessimism, the sign of the coefficient on the index is expected to be positive significant, indicating that the *subsequent* return of the zero investment portfolio is positively associated with market pessimism proxies—in other words, CSR-intensive firms are prominently viewed as an attractive choice over the month when the beginning-of-period proxies for market pessimism is high. In principle, I collect and experiment with sentiment proxies available at the monthly level. With respect to indexes available at the daily level (e.g., VIX), the end of the month value is sampled for monthly index construction. I focus on equal-weighted portfolios, which echoes prior studies on investor sentiment.

$$R_{\mathrm{CSR}\,10,\,t} - R_{\mathrm{CSR}\,1,\,t} = c + d\,\mathrm{Index}_{t-1} + \beta \mathrm{MKT}_t + h\mathrm{HML}_t + s\mathrm{SMB}_t + m\mathrm{MOM}_t + \varepsilon_t \tag{5}$$

$$R_{\mathrm{CSR\,dec},\,t} - R_{f,t} = c + d\,\mathrm{Index}_{t-1} + \beta \mathrm{MKT}_t + h\mathrm{HML}_t + s\mathrm{SMB}_t + m\mathrm{MOM}_t + \varepsilon_t \tag{6}$$

I employ a set of sentiment indexes specifically associated with market pessimism. VIX, for example, notably serves as a proxy for aggregate stock market uncertainty. Developed by Caldara and Iacoviello (2018), Geopolitical Risk (GPR Index) is a monthly index constructed by counting the occurrence of words pertaining to geopolitical tensions from 11 prominent global newspapers. Economic Policy Uncertainty (EPU) is a policy-related composite index building on three components: news coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expiring over the next 10 years, and the disagreement among analysts. Husted, Rogers, and Sun (2017) construct a monthly index of Monetary Policy Uncertainty (MPU) by searching for keywords that capture monetary policy uncertainty in three major US newspapers. Baker et al. (2019) developed a set of newspaper-based indexes, Equity Market Volatility, harmonized with VIX and in particular Infectious Disease Equity Market Volatility Tracker captures the risk unique to the dimension of infectious disease at the daily level. Developed by Lukas Püttmann, FSI is a newspaper-based Financial Stress Indicator constructed from the news article titles published in five US newspapers. St. Louis Fed Financial Stress Index (STLFSI2) measures the extent to which the market is financially distressed and is available at the daily level.

Next, I experiment with sentiment indexes that are more generic, for they are suitable for conducting a placebo test. On top of SENTIMENT (henceforth BW index) and SENTIMENT$^{\perp}$ (henceforth BW$^{\perp}$ index) constructed by Baker and Wurgler (2006)—BW$^{\perp}$ index eliminates macroeconomics conditions by removing business cycle variation—I draw on the University of Michigan Consumer Sentiment Index. I additionally leverage PDCD, one of the components of BW index for a reason described below.

Table 12 presents the results of the regression estimates. In brief, I broadly find positive significant results in Panel A. In terms of the magnitude, for instance, one standard deviation increase in VIX index translates into a 0.84% ($0.001 \times 8.37 = 0.84\%$) higher monthly return on the top-bottom decile portfolio. Moreover, in Panel B, all the results generated by BW index, BW$^{\perp}$ index, and MCI are not accompanied with statistical significance under the specifications in equation (5), as expected: this also holds under all the specifications in equation (6) with different CSR decile ranks (untabulated). After rerunning each five component of BW index, I find that only dividend premium PDND is significant.[17] An ex-post characterization of this empirical fact is that PDND is positively correlated with—and possibly capturing similar information with—these sentiment indexes related to market pessimism as shown in Table 11, thereby resulting in a comparable level of significance.

The negative significant coefficients on the intercepts displayed in Table 12 warrant further accounts. In the spirit of Nofsinger and Varma (2014), Table 13 presents the differential performances of top and bottom decile portfolios in the crisis and non-crisis period. Al-

[17] They subsequently drop NYSE share turnover, or TURN, from their sample, ending up with five components.

though high-CSR firms show a positive significant alpha during the crisis period (Panel A), this characteristic dissapears in the non-crisis period (Panel B). By contrast, low-CSR firms do not exhibit positive significant alpha during the crisis period (Panel A), but they are associated with a positive significant alpha in the non-crisis period (Panel B). Since the non-crisis period is substantially longer, negative alpha is expected to be manifested on average: Panel C indeed confirms a negative alpha ($\alpha = -0.005$, t-statistic $= -2.30$). Thus, it is also plausible that the intercepts in Table 12 are in most cases negative significant.

In gaining insight from the empirical return patterns generated during a turbulent period, First Quadrant (2014) maintains that VIX can be interpreted as—in addition to the common association of an extremely volatile period accompanied by fluctuating market characteristics—a sign of heightened tail risk exemplified by greater downtrend movements than uptrend movements in size and frequency (i.e., negative skewness).[18] Moreover, Bollerslev and Todorov (2011) document that the average equity and variance risk premia are primarily explained by the compensation for rare events. In line with these claims, Kelly and Jiang (2014) stress that securities that hedge tail risk are more attractive and have lower expected returns because tail risk is positively linked with bad states of the economy and high marginal utility. These statements lend support to the evidence found in Table 13, where the alpha of low-CSR firms is substantially higher than that of high-CSR firms in a normal period.

As an aside, note that extending the range of the both ends of the top-bottom portfolio in Table 12—for instance, expanding to the top two deciles and bottom two deciles—does not yield significant results (unreported). This indicates that market investors have a very narrow spectrum of choice in selecting high-CSR firms and/or avoiding low-CSR firms. Indeed, Table 14 endorses this view, demonstrating suggestive evidence that CSR score has a disproportional effect on skewness and kurtosis. In Panel A, CSR is positively associated with skewness and this effect concentrates on high-CSR firms. In Panel B, in constrast, CSR is negatively associated with kurtosis and this effect is widely confirmed among above-average CSR firms, indicating that most notably low-CSR firms are significantly associated with greater kurtosis.

The second strategy, in inspecting the disproportional effects of market pessimism on skewness and kurtosis where CSR serves as a mediator, is to visualize the coefficients on

[18] Although the VIX is popularly known as the investor fear gauge, Bollerslev, Todorov, and Xu (2015) warn that only a small fraction of the VIX on average is arguably attributable to market fear.

CSR variables. Figure 1 (Figure 2) presents the time-varying coefficients on a CSR variable in forecasting CSKEW_{t+1} (CEKURT_{t+1}). Specifically, in each figure, Panel A (Panel B) plots a series of coefficients on CSR score (CSR75–100 dummy) whereby the point estimates, confidence intervals, and significance level represented by stars are displayed. In brief, these estimates are substantively suggestive of the market pessimism channel through which CSR contributes to higher systematic skewness and lower systematic kurtosis in returns. With the highly volatile periods illustrated in Figure 3 in mind, it stands to reason that all specifications in Figure 1 show significant (insignificant) coefficients with greater (smaller) magnitude in a subperiod of turbulent (calm) time across different interval specifications. In other words, it appears to successfully forecast future skewness (CSKEW_{t+1}) when uncertainty is generally high. The estimates using DUVOL measure are unreported but similar patterns are confirmed. Moreover, for the case of kurtosis forecasting (CEKURT_{t+1}) in Figure 2, the time-series patterns of the coefficients are remarkably similar (i) irrespective of CSR score or CSR75–100 dummy and (ii) across different interval specifications (i.e., 3-, 6-, or 12-month intervals).

In Section 4, the empirical results of the regression estimates exhibited in Tables 4–9 displayed that the *t*-statistics for coefficients on CSR score are more positively associated with future skewness and kurtosis under the excess return specification relative to the market adjusted or residual return specification. Overall, these patterns are more plausible in light of the findings from the two approaches employed in this section. I acknowledge that this interpretation, albeit partly supported by my findings, remains in the realm of a speculation and a more formal investigation is warranted for future research. Besides, the differential estimates observed across different period interval specifications could have emerged from the measurement in *daily* returns—accordingly, Section 7 explores the higher moments of lower frequency returns, which likely mirror macroeconomic uncertainty more reasonably. In conclusion, I throw some light on the foundation of the market pessimism channel that CSR likely contributes to higher systematic skewness and lower systematic kurtosis—which does not necessarily negate the firm-specific channel posited by KLL—and this market-wide channel functions when investors prefer CSR-intensive firms during the time of market crisis. Hence, the findings in this subsection complements Hypothesis 1, is in line with prior literature (e.g., Nofsinger and Varma, 2014; Lins, Servaes, and Tamayo, 2017; Bakshi and Kapadia (2003); Ang et al., 2006), and is an empirical confirmation of what is posited by Bénabou and Tirole (2010).

Table 10: Descriptive statistics of sentiment indexes

Panels A and B show the summary statistics of sentiment indexes specific to market pessimism and generic sentiment indexes, respectively. Developed by Caldara and Iacoviello (2018), Geopolitical Risk (GPR Index) is a monthly index constructed by counting the occurrence of words pertaining to geopolitical tensions from 11 prominent global newspapers. Economic Policy Uncertainty (EPU) is a policy-related composite index building on three components: news coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expiring over the next 10 years, and the disagreement among analysts. Husted, Rogers, and Sun (2017) construct a monthly index of Monetary Policy Uncertainty (MPU) by searching for keywords that capture monetary policy uncertainty in three major US newspapers. Baker et al. (2019) developed a set of newspaper-based indexes, Equity Market Volatility, harmonized with VIX and in particular Infectious Disease Equity Market Volatility Tracker captures the risk unique to the dimension of infectious disease at the daily level. Developed by Lukas Püttmann, FSI is a newspaper-based Financial Stress Indicator constructed from the news article titles published in five US newspapers. St. Louis Fed Financial Stress Index (STLFSI2) measures the extent to which the market is financially distressed and available at the daily level. BW and $BW^{\perp}$ are from SENTIMENT and $SENTIMENT^{\perp}$ constructed in Baker and Wurgler (2006), respectively, whereby $BW^{\perp}$ index eliminates macroeconomics conditions by removing business cycle variation. MCI is the University of Michigan Consumer Sentiment Index and PDND is one of the five components of BW index.

	Mean	Median	SD	Min	Max	Obs.
Panel A: Sentiment specific to market pessimism						
VIX	19.3	16.80	8.37	9.51	59.89	192
GPR	99.04	80.31	65.52	40.51	545.09	192
EPU	114.89	104.91	36.68	57.20	245.13	192
MPU	107.53	99.12	54.65	19.75	357.67	192
FSI	101.02	100.83	0.98	99.54	105.89	180
STLFSI2	0	-0.32	1.16	-1.16	6.94	192
Infectious	0.61	0.51	0.48	0.05	4.93	192
Panel B: Generic sentiment						
BW	-0.20	-0.21	0.33	-0.94	1.35	192
$BW^{\perp}$	-0.05	-0.03	0.39	-0.89	1.60	192
MCI	82.78	84.80	11.37	55.30	103.80	192
PDND	-3.98	-5.37	6.59	-16.18	17.13	192

Table 11: Correlation matrix of sentiment indexes

This table reports the Pearson correlation coefficients between the sentiment indexes. Developed by Caldara and Iacoviello (2018), Geopolitical Risk (GPR Index) is a monthly index constructed by counting the occurrence of words pertaining to geopolitical tensions from 11 prominent global newspapers. Economic Policy Uncertainty (EPU) is a policy-related composite index building on three components: news coverage of policy-related economic uncertainty, the number of federal tax code provisions set to expiring over the next 10 years, and the disagreement among analysts. Husted, Rogers, and Sun (2017) construct a monthly index of Monetary Policy Uncertainty (MPU) by searching for keywords that capture monetary policy uncertainty in three major US newspapers. Baker et al. (2019) developed a set of newspaper-based indexes, Equity Market Volatility, harmonized with VIX and in particular Infectious Disease Equity Market Volatility Tracker captures the risk unique to the dimension of infectious disease at the daily level. Developed by Lukas Püttmann, FSI is a newspaper-based Financial Stress Indicator constructed from the news article titles published in five US newspapers. St. Louis Fed Financial Stress Index (STLFSI2) measures the extent to which the market is financially distressed and available at the daily level. BW and BW$^{\perp}$ are from SENTIMENT and SENTIMENT$^{\perp}$ constructed in Baker and Wurgler (2006), respectively, whereby BW$^{\perp}$ index eliminates macroeconomics conditions by removing business cycle variation. MCI is the University of Michigan Consumer Sentiment Index and PDND is one of the five components of BW index.

	Panel A: Sentiment specific to market pessimism							**Panel B**: Generic sentiment (placebo)			
	VIX	GPR	EPU	MPU	FSI	STLFSI2	Infectious	BW	BW$^{\perp}$	MCI	PDND
VIX	1.000										
GPR	0.045	1.000									
EPU	0.540	-0.094	1.000								
MPU	-0.027	0.428	0.159	1.000							
FSI	0.748	0.152	0.242	-0.078	1.000						
STLFSI2	0.865	-0.035	0.409	-0.022	0.715	1.000					
Infectious	0.191	0.157	-0.024	0.012	0.255	0.205	1.000				
BW	-0.262	-0.052	-0.390	0.072	-0.116	-0.152	-0.048	1.000			
BW$^{\perp}$	-0.396	-0.101	-0.380	0.040	-0.218	-0.302	-0.091	0.912	1.000		
MCI	-0.624	0.277	-0.614	0.191	-0.352	-0.547	0.031	0.234	0.262	1.000	
PDND	0.554	0.417	0.243	0.044	0.598	0.507	0.134	-0.217	-0.373	-0.181	1.000

Table 12: Monthly returns on top-bottom decile portfolio (equal-weighted)

The sample runs from January 2002 to December 2017. I regress the monthly return of equal-weighted portfolio constructed by top CSR decile minus bottom CSR decile $R_{\mathrm{CSR}\,10,\,t} - R_{\mathrm{CSR}\,1,\,t}$ on sentiment index in month $t-1$ as well as risk factors in month t. t-statistics are adjusted for serial correlation by implementing Newey-West correction with three lags.

$$R_{\mathrm{CSR}\,10,\,t} - R_{\mathrm{CSR}\,1,\,t} = \; c + d\,\mathrm{Index}_{t-1} + \beta \mathrm{MKT}_t + h\mathrm{HML}_t + s\mathrm{SMB}_t + m\mathrm{MOM}_t + \varepsilon_t$$

	Panel A: Sentiment specific to market pessimism							**Panel B**: Generic sentiment (placebo)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VIX	0.001**										
	(2.276)										
GPR		0.000**									
		(2.053)									
EPU			0.000**								
			(2.117)								
MPU				0.000							
				(0.806)							
FSI					0.005**						
					(2.156)						
STLFSI2						0.003**					
						(2.079)					
Infectious							0.005**				
							(2.135)				
BW								-0.002			
								(-0.387)			
$\mathrm{BW}^{\perp}$									-0.003		
									(-0.554)		
MCI										-0.000	
										(-0.316)	
PDND											0.001***
											(2.884)
MKT_t	-0.118**	-0.134***	-0.135***	-0.137***	-0.100*	-0.112**	-0.131**	-0.138***	-0.137***	-0.131**	-0.111**
	(-2.354)	(-2.627)	(-2.722)	(-2.603)	(-1.843)	(-2.131)	(-2.568)	(-2.744)	(-2.717)	(-2.505)	(-2.329)
SMB_t	-0.639***	-0.620***	-0.620***	-0.619***	-0.637***	-0.636***	-0.619***	-0.618***	-0.621***	-0.623***	-0.663***
	(-6.967)	(-7.276)	(-7.057)	(-7.125)	(-6.623)	(-7.204)	(-7.191)	(-7.116)	(-7.013)	(-6.889)	(-7.332)
HML_t	0.030	-0.007	0.006	-0.021	0.029	0.025	-0.009	-0.002	0.001	-0.018	0.010
	(0.246)	(-0.066)	(0.052)	(-0.200)	(0.249)	(0.218)	(-0.086)	(-0.021)	(0.006)	(-0.160)	(0.087)
MOM_t	0.126***	0.103***	0.111***	0.095***	0.119***	0.121***	0.103***	0.105***	0.107***	0.099***	0.115***
	(3.354)	(2.782)	(3.081)	(2.644)	(3.180)	(3.164)	(2.917)	(3.064)	(3.134)	(2.910)	(3.285)
Intercept	-0.015***	-0.008**	-0.015**	-0.007*	-0.498**	-0.004*	-0.007**	-0.004	-0.004*	0.001	-0.001
	(-2.715)	(-2.583)	(-2.398)	(-1.829)	(-2.167)	(-1.868)	(-2.389)	(-1.594)	(-1.788)	(0.062)	(-0.627)
Obs.	191	191	191	191	180	192	191	192	192	191	191

t-statistics are adjusted for serial correlation.

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 13: Difference in portfolio performances over crisis and non-crisis periods

The table below presents the differential performances of top decile portfolio, the bottom decile portfolio, and the zero-investment portfolio over the crisis and non-crisis periods. Following Nofsinger and Varma (2014), the crisis period is defined as Janunary 2002–October 2002 and October 2007–March 2009. I implement Newey-West correction with three lags.

	Top decile		Bottom decile		Top–Bottom	
	Crisis	Non-Crisis	Crisis	Non-Crisis	Crisis	Non-Crisis
Alpha (Fama-French 4 Factor)	0.008**	-0.000	0.002	0.005**	0.006	-0.005**
	(2.65)	(-0.00)	(0.30)	(2.42)	(0.97)	(-2.30)
Obs.	28	164	28	164	28	164

t-statistics are adjusted for serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 14: Predicting CSKEW_{t+1} and CEKURT_{t+1}: CSR score replaced with dummies

Following the KLL specification, Panels A and B present estimated regression where the procedure in Tables 4–6 and Tables 7–9 are iterated, respectively. The dummy variable CSR75–100 equals to one if the firm's CSR score is above 75; similarly, the dummy variable CSR50–75 (CSR25–50) equals to one if the firm's CSR score ranges between 50 and 75 (25 and 50). In this case, the firms with CSR score below 25 are the baseline. The other regressors in Tables 4–9 remain unchanged in the model specifications but untabulated here to save space.

	Panel A: predicting CSKEW_{t+1} using CSR dummies					
	6-month period			12-month period		
	market-adj. ret.	excess ret.	residual ret.	market-adj. ret.	excess ret.	residual ret.
CSR75–100	0.177*	0.192**	0.164*	0.395**	0.400***	0.368**
	(1.96)	(2.53)	(1.77)	(2.31)	(2.70)	(2.12)
CSR50–75	0.093	0.081	0.086	0.225	0.203	0.209
	(1.25)	(1.30)	(1.12)	(1.56)	(1.64)	(1.42)
CSR25–50	-0.003	-0.002	-0.006	0.032	0.033	0.020
	(-0.04)	(-0.04)	(-0.08)	(0.24)	(0.28)	(0.14)
Obs.	113394	113394	113302	103060	103060	102998

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

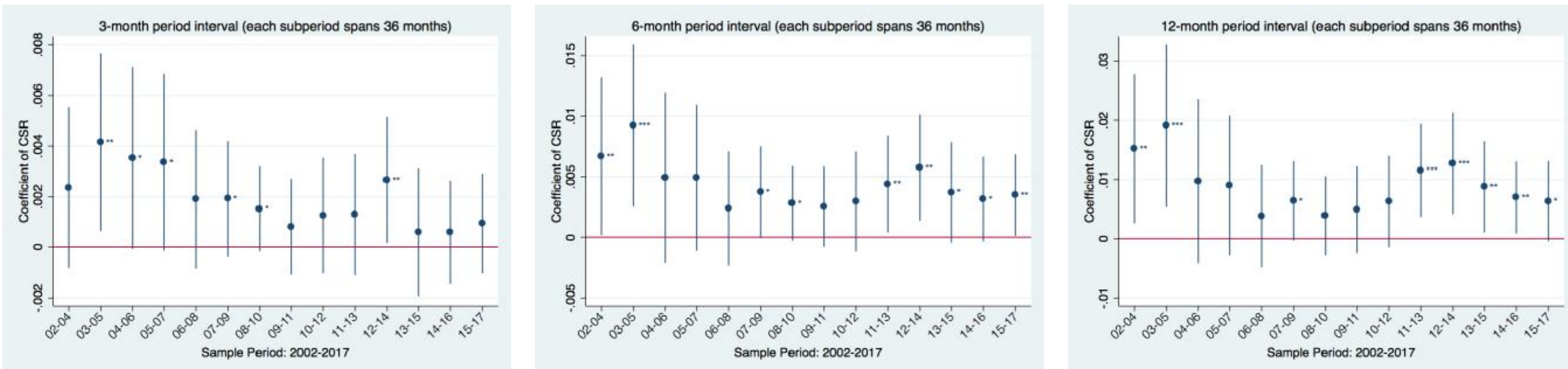
	Panel B: predicting CEKURT_{t+1} using CSR dummies					
	6-month period			12-month period		
	market-adj. ret.	excess ret.	residual ret.	market-adj. ret.	excess ret.	residual ret.
CSR75–100	-1.557*	-1.912**	-1.490*	-4.755**	-5.016**	-4.663**
	(-1.84)	(-2.52)	(-1.77)	(-2.10)	(-2.47)	(-2.06)
CSR50–75	-0.991	-1.404**	-1.041	-3.070	-3.485**	-3.143
	(-1.37)	(-2.12)	(-1.44)	(-1.61)	(-2.03)	(-1.64)
CSR25–50	-0.444	-0.765	-0.451	-1.089	-1.443	-1.099
	(-0.67)	(-1.25)	(-0.69)	(-0.62)	(-0.90)	(-0.62)
Obs.	113394	113394	113302	103060	103060	102998

t-statistics are adjusted for heteroskedasticity and serial correlation.
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Figure 1: Predicting CSKEW_{t+1}: time-varying regression coefficients on CSR score and CSR75–100 dummy (excess returns)

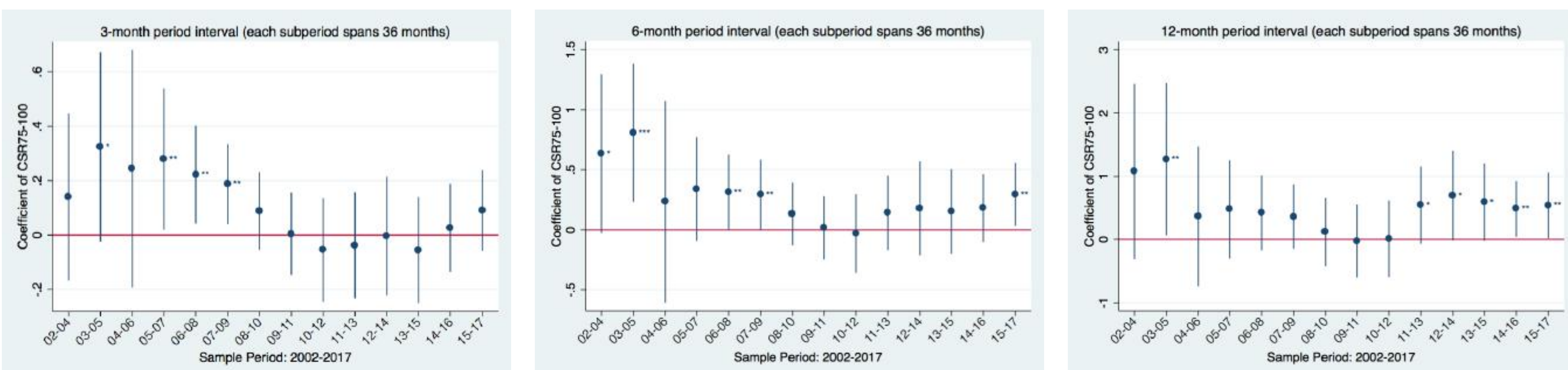
The figures in Panel A (Panel B) plot the time-varying regression coefficients on CSR score (CSR75–100 dummy) over different period intervals (3-, 6- and 12-month periods) whereby CSKEW_{t+1} is predicted in the model specification. Within the sample period of 2002–2017, each subperiod starts at the beginning of each year and equally spans over 36 months thereafter. That is, the first subperiod is Jan 2002–Dec 2005, then the next Jan 2003–Dec 2006 and goes on until subperiod Jan 2015–Dec 2017. The whiskers indicate 95% confidence intervals.

Panel A: Coefficients on CSR score (3-, 6- and 12-month period intervals)



*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Panel B: Coefficients on CSR75–100 dummy (3-, 6- and 12-month period intervals)

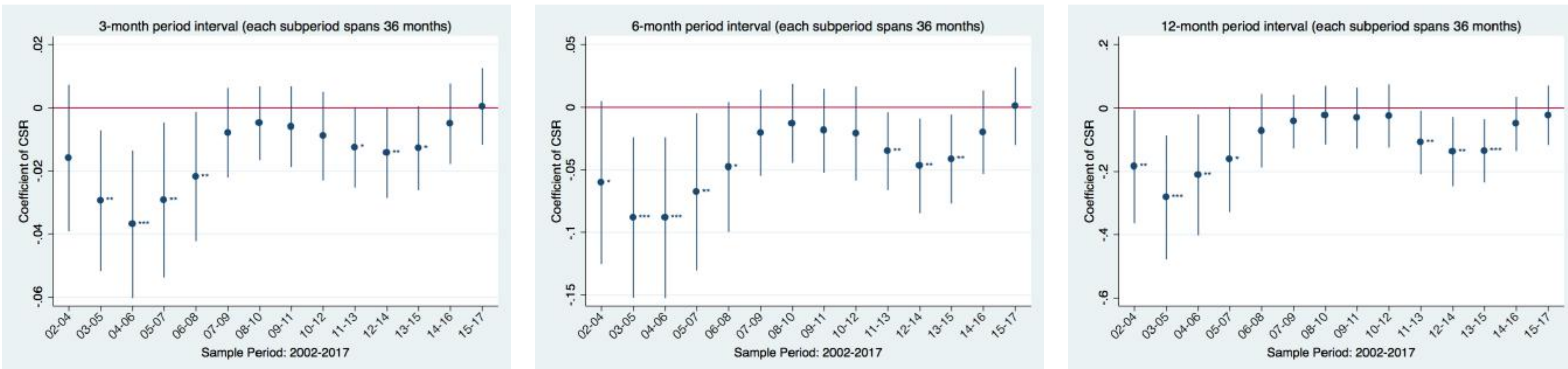


*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Figure 2: Predicting CEKURT$_{t+1}$: time-varying regression coefficients on CSR score and CSR75–100 dummy (excess returns)

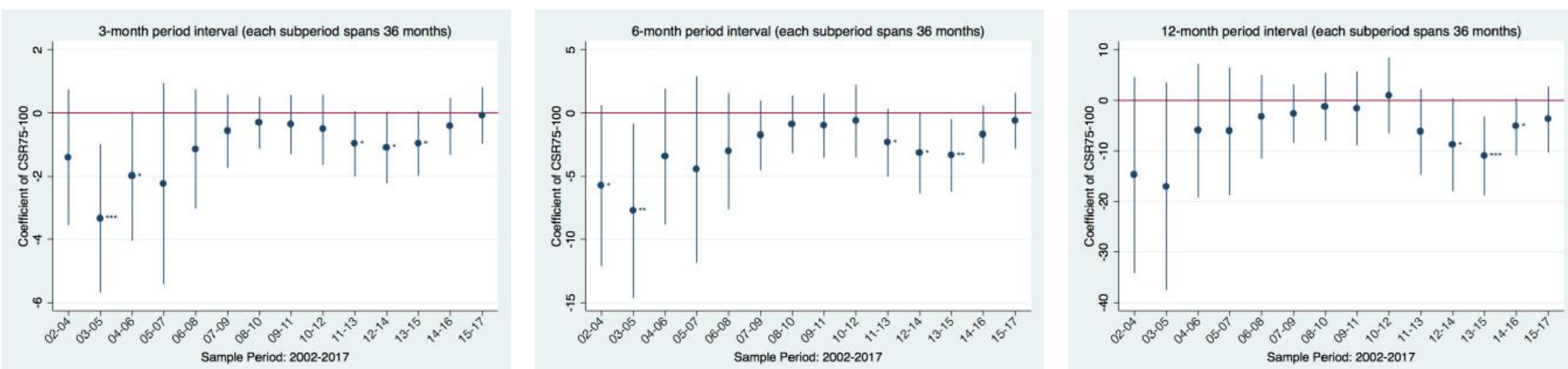
The figures in Panel A (Panel B) plot the time-varying regression coefficients on CSR score (CSR75–100 dummy) over different period intervals (3-, 6- and 12-month periods) whereby CEKURT$_{t+1}$ is predicted in the model specification. Over the full sample period 2002–2017, each subperiod starts at the beginning of each year and equally spans over 36 months thereafter. That is, the first subperiod is Jan 2002–Dec 2005, then the next Jan 2003–Dec 2006 and goes on until subperiod Jan 2015–Dec 2017. The whiskers indicate 95% confidence intervals.

Panel A: Coefficients on CSR score (3-, 6- and 12-month period intervals)



*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Panel B: Coefficients on CSR75–100 dummy (3-, 6- and 12-month period intervals)



*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Figure 3: Transition indexes specific to market pessimism over the period 2002–2017

This figure exhibits a set of standardized indexes specific to market pessimism over the period 2002–2017. FS Indicator and STLFSI2 are not demonstrated as they are grossly similar to VIX index.

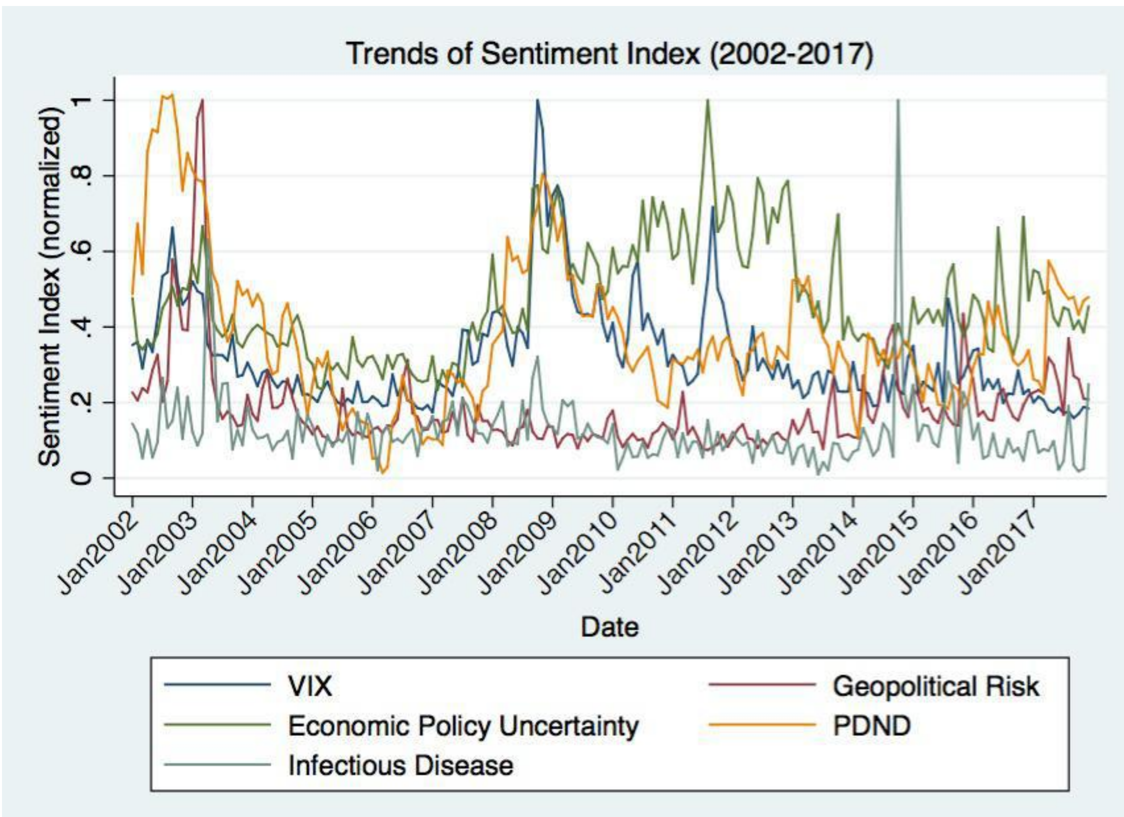
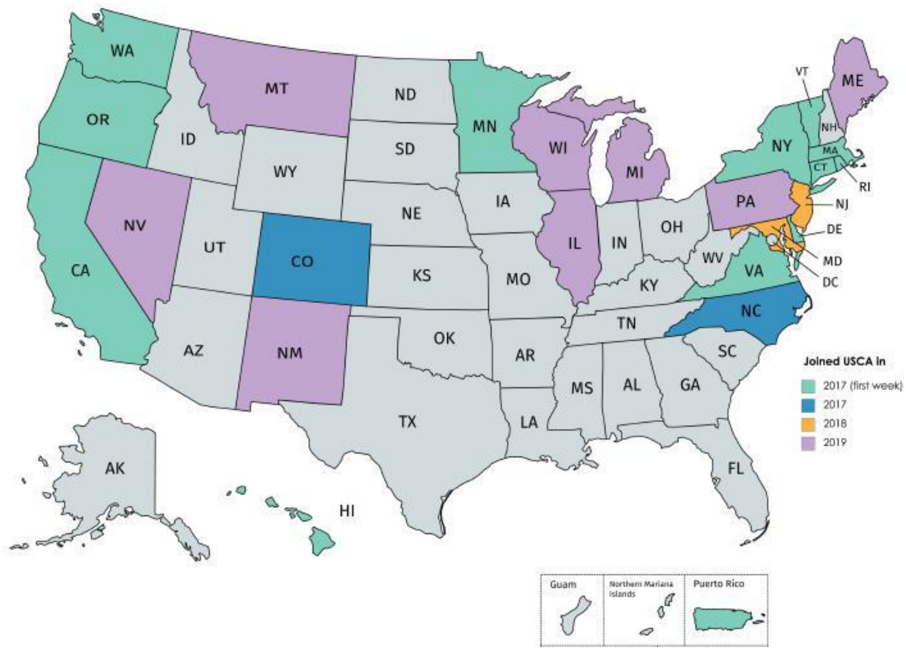


Figure 4: US Climate Alliance states



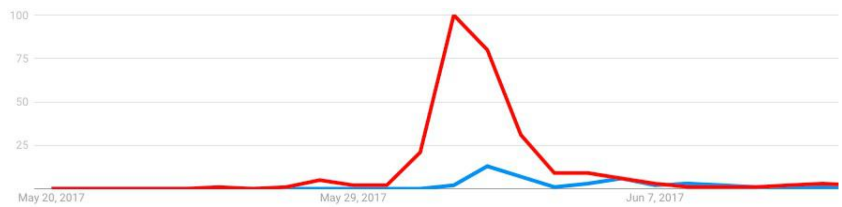
6 The propagation of green optimism among investors

6.1 Stock market reactions on the parallel announcements in 2017

In reference to Hypothesis 3a–3c, I study in this subsection the stock return dynamics following the parallel announcements in early June, 2017—when the US federal government announced the disengagement from the Paris Agreement and the US Climate Alliance was concurrently formed. For brevity, I hereafter use the term "alliance-state firm" for a firm headquartered in alliance states; likewise, the term "non-alliance-state firm" is used for a firm headquartered in non-alliance states.

In empirically testing Hypotheses 3a–3c, four caveats are in order. The first caveat is that the member status of the alliance is not randomly assigned to states: the decision of state governors to participate in the alliance is endogenous as states are less likely to join the climate alliance, the more they are accountable for the emissions in the nation. Determinants of the participation may range from local industries (e.g., carbon-intensive), demographics and culture (e.g., red/blue state), and geography (i.e., coastal area more prone to climate risks). The second caveat is that although Google search volume index, a proxy for investors' attention, captures the volume dynamics in a timely fashion as illustrated in Figure 5, it may be predominantly driven by individual investors (Da, Engelberg, and Gao, 2011). Therefore, despite the vast search volume gap between the two topics in Figure 5, this may not neces-

Figure 5: Search volume comparison in the US: "United States withdrawal from the Paris Agreement (Topic)" [red] vs. "United States Climate Alliance (Topic)" [blue]



(Source: Google Trends)

sarily be representative of the attention of the whole stock market participants, especially if (i) institutional investors occupy a large portion of the investor base and (ii) this sensational topic spurred a flurry of individuals' search activities. The third caveat is that the later announcements of some states can reversely affect the pre-announcements of other states (i.e., June 1, 2) by augmenting the precision of the news in those states. Finally, there is a minority of firms that had earnings and dividends announcements surrounding the event, but I do not expect that these firms exert a material effect on the empirical results.

Hypothesis 3a performs an event study examining the cumulative abnormal returns observed in alliance-state and non-alliance-state firms over a five day window. I classify all firms based on Environmental score measured in 2017, where a firm is considered green if the score is above 50, and ungreen if the score is below 50. In addition, I classify the states that joined the coalition on June 1, 2, and 5 as Cohort A (CA, NY, WA), Cohort B (CT, HI, MA, OR, RI, VT), and Cohort C (DE, MN, PR, VA), respectively; I classify the rest as non-alliance states including the states that joined the alliance at a later point in time as illustrated in Figure 4.[19]

Whether within-industry ranks represented by Environmental score is viewed as salient by investors is an open question. For instance, it remains to be seen whether a relatively environmentally-friendly firm in a carbon intensive industry is viewed as pro-environmental in absolute terms. In line with this argument, Klassen and McLaughlin (1996) posit that environmental management carries disproportionate weight across industries and it has a stronger impact on the financial performance of dirty industries than that of clean industries. Therefore, in light of the possibility that the stock market responses may differ by industry classification, I first partition industries based on 4-digit SIC industry classification as follows: mining (1000–1499) & construction (1500–1799), manufacturing (2000–3999),

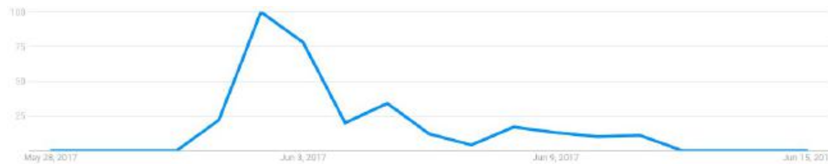
[19] California, New York, and Washington participated in the coalition on June 1; Connecticut, Rhode Island, Massachusetts, Vermont, Oregon, and Hawaii joined on June 2; and Virginia, Minnesota, Delaware, and Puerto Rico joined on June 5.

transportation (4000–4799), communication (4800–4899), utilities (4900–4999) and services (7000–8999).

Table 16 shows by industry whether (un)green firms experienced positive (negative) abnormal returns in climate-alliance states and non-climate-alliance states. The empirical results suggest that the signs and statistical significance greatly hinge on industry segments. While systematically different responses appear to exist across green and ungreen categories, especially among carbon-intensive industries, the differentials between alliance-state and non-alliance-state firms are not clear-cut. In Panel A, mining and construction industries show that the non-alliance-state firms were significantly and negatively affected by the parallel announcements at the 1% level; in contrast, it is hard to infer anything decisive from the firms headquartered in the climate alliance states due to the limited number of observations. In Panels B and C, there is no prominent feature that is associated with significance. In Panel D, communication industry in the climate alliance states were exposed to negative abnormal returns but this is only statistically significant at the 10% level. In Panel E, utilities industry displays that alliance-state firms experienced 0.8% (t-statistic 1.23) and non-alliance state firms experienced -1.4% (t-statistic -2.47) abnormal returns. In Panel F, ungreen firms in services industry that are headquartered in the climate alliance states were exposed to negative abnormal returns but this is only statistically significant at the 10% level. In sum, negative stock market responses of a greater magnitude were observed in the non-climate-alliance firms especially in the carbon-intensive industries.

Furthermore, to shed more light on the abnormal return difference between green and ungreen firms after controlling for industry differentials, I employ a cross-sectional regression and empirically examine whether green firms experienced *relatively* higher abnormal returns than ungreen firms. Specifically, I follow the OLS regression framework from Ahern and Dittmar (2012, pp. 157–158): I use the market model to generate the abnormal returns wherein CRSP Value Weighted Index proxies for the market portfolio. One may reasonably argue that the application of their specification to this setting is inappropriate where public announcements will simultaneously impact the cross-section of firms and likely induce a clustering of abnormal returns, let alone normal returns. There is no denying that in this case the standard errors will be generally biased but note that OLS can nonetheless provide unbiased coefficient estimates. Indeed, as far as short-return studies are concerned such as daily and weekly returns, OLS is unlikely to pose a serious problem (Christie, 1987), which mitigates the concern on my identification method. In contrast, studies using quarterly or annual stock returns cannot ignore the serious bias stemming from cross-sectional dependen-

Figure 6: Search volume in the US: "United States Climate Alliance (Topic)"



(Source: Google Trends)

cies (Bernard, 1987).

With respect to the event study window, I opt to use a five day window $(-2, 2)$ following again Ahern and Dittmar (2012) owing to the fact that this window range encompasses different announcement days and can also account for price changes for thinly traded stocks. Accordingly, I set $t = 0$ on June 1 indicating that the window $(-2, 2)$ equates to the period ranging from May 30 to June 5: the stock market is closed on this weekend (i.e., June 3 and 4). Figure 6 shows that the illustrated shape of search volume on "United States Climate Alliance" is multimodal: the first hump culminating on June 2 is triggered by the news about Cohort A and B joining the US Climate Alliance (e.g., Bloomberg, Reuters), while the second hump resurging on June 5 similarly stems from the news about Cohort C.

Thomson Reuters Refinitiv database incorporates a percentile-ranked scoring methodology using Thomson Reuters Business Classification (TRBC) and TRBC classifies companies at five levels: 13 economic sectors, 33 business sectors, 62 industry groups, 154 industries, 898 activities. Since the number of TRBC industry groups are closely comparable with that of industries classified by SIC 2-digits, I cluster at the SIC 2-digit level in all cases and set the model specification including SIC 2-digit dummies as a baseline case but also show results without these dummies to examine the sensitivity.

The empirical results are shown in Table 17. Clearly, Environmental score dummies, regardless of Env50–100 or Env75–100, are positively and significantly associated with the cumulative abnormal returns (CAR) over the five day window, resulting in 0.4%–1.6% higher CAR. Of particular interest are the patterns observed in the coefficients on (i) AS2017 dummy and (ii) the interaction term between Environmental score dummy and AS2017 dummy. In case of the AS2017 dummy, signs are all positive across all specifications, but statistical significance is not confirmed in any specification; moreover, in the case of the interaction term between Environmental score dummy and AS2017 dummy, the coefficients are all negative and the statistical significance is mixed. These pieces of evidence likely suggest that investors positively viewed the greenness of the firms irrespective of whether the firm was headquartered in Cohort A, B, C or not. This is in line with the empirical fact in Table 16 that non-alliance-state firms were affected by the parallel announcements as much as alliance-state firms.

Two contrasting explanations may account for these investor behaviours. One explanation is that the news of climate alliance formation was not prominent enough for investors and was thus dominated by the news of the Paris Agreement withdrawal. Other explanations are that (i) non-alliance firms were exposed to the stock market reaction because their subsidiaries and/or supply chain networks are intertwined with climate alliance states or (ii) the green optimism channel indicating the news effect of climate alliance formation spilled over into other states beyond Cohort A–C and altered the expectation of broad-based investors. The former explanation based on the dominance of the single announcement, however, has difficulty in reconciling itself with the negative market reactions to the carbon-intensive industries observed in Table 16 and the positive significant coefficients on Environmental score dummies shown in Table 17.

Hypothesis 3b further highlights the differences of opinions in the valuation of green and ungreen firms, which are expected to emerge surrounding the parallel announcements. I study the abnormal turnover as a baseline proxy for the differences of opinions but also examine abnormal return volatility. Similar to Hypothesis 3a, it is essential for both cases to isolate unrelated market-wide forces that might distort the inference and thus I compute the abnormal turnover as the residuals from the one-factor market model. First, I define log turnover $\tau_{i,t}$ in equation (7) where trading volume $n_{i,t}$ and outstanding shares $S_{i,t}$ of stock i ($i = 1, 2, .., N$) at day t are the inputs. As 0.2% of the observations in my sample show zero daily trading volume, I follow Cready and Ramanan (1991) to avoid log(0) by adding 0.000255: the histogram of daily log turnover appears to follow a normal distribution centered close to zero. Then, I define abnormal log turnover in equation (8) computed through the one-factor market model,[20] where value-weighted market portfolio turnover $\tau_{m,t}$ in the one-factor market model is computed with the help of price $p_{i,t}$ from equations (9) and (10): note that this is in line with prior literature (Tkac, 1999; Lo and Wang, 2000; Chae, 2005; Bailey, Karolyi, and Salva, 2006). As per abnormal return volatility, I use the absolute value of abnormal returns as a proxy (Kim and Verrecchia, 1991; Bailey, Karolyi,

[20]The cross-sectional correlation across securities arising from clustering events poses a challenge in the identification of abnormal trading volume but the use of market trading volume can alleviate this problem (Ajinkya and Jain, 1989). Besides, the use of abnormal turnover subdues the institutional trading characteristics peculiar to NASDAQ.

and Salva, 2006).

$$\tau_{i,t} = \ln\left[100 \cdot \frac{n_{i,t}}{S_{i,t}} + .000255\right] \tag{7}$$

$$\ddot{\tau}_{i,t} = \tau_{i,t} - \hat{\alpha}_i - \hat{\beta}_i \tau_{m,t} \tag{8}$$

$$\tau_{m,t} = \sum_{i=1}^{N} \omega_{i,t}\tau_{i,t} \tag{9}$$

$$\omega_{i,t} = \frac{p_{i,t}S_{i,t}}{\sum_{i=1}^{N} p_{i,t}S_{i,t}} \tag{10}$$

The results are provided in Tables 18 and 19. Table 18 shows uniform patterns in that the signs of Environmental score dummies are all negative albeit with varying degrees of statistical significance; put differently, the green firms relatively decreased trading volume in comparison to ungreen firms surrounding the parallel announcements. Moreover, firms with very high green status (i.e., Env75–100) and headquartered in Cohort A–C additionally experienced decreased trading volume according to specification (6) because the net effect of AS2017 and AS2017 $\times$ Env75–100 is negative, while the net effect in specification (8) is positive, thereby conforming to the results under Hypothesis 3a: notwithstanding, both cases are not accompanied by statistical significance. In contrast, Table 19 exhibits substantially different patterns from Table 18. All the coefficients on the variables of interest are insignificant and the coefficients on LOGSIZE are all negative and significant at the 1% level. This suggests that abnormal turnover and the abnormal return volatility, which is proxied by the absolute value of abnormal returns, captures quite dissimilar information.

Finally, Hypothesis 3c inspects the return skewness in relation to turnover after the parallel announcements. One thinkable strategy is a parametric approach employing a cross-sectional regression that can elucidate the relationship between turnover and subsequent return skewness. Yet, the limited number of the available cross-sectional observations will likely pose a challenge on achieving adequate statistical power. Hence, I simply draw on the visualization of these variables of interest averaged within portfolios, where portfolios are sorted on firm's environmental orientation. Although this approach cannot highlight the direct relationship between the variables of interest—that is, turnover and subsequent return skewness—it can flexibly track the dynamics of the return skewness and turnover across portfolios sorted on firm's environmental orientation.

Moreover, the choice of (i) the measurement period of skewness as well as (ii) the event period requires careful consideration. On the one hand, a longer period is preferred for both because (i) it naturally mitigates the measurement concern of skewness and (ii) empirical literature suggests that trading activities embodying the disagreement on the valuation of stock can continue for an extended period of time. In particular, for the case of (ii), Jiang and Zhu (2017) find that limited investor attention leads to short-term underreaction; moreover, Cao and Ou-Yang (2009) maintain that when information arrives which induces investors' disagreements, stock trading diffuses over periods while options trading responds in a short span of time. On the other hand, extending the period of the skewness measurement or the event period itself raises another concern that the trend might be infected with market-wide phenomena unrelated to the parallel announcements. To this end, I opt to study the six month period following the parallel announcements in June 2017 and use three types of rolling window specifications that span one, two, or three months. Moreover, return and turnover variables are market-adjusted to minimize the effect of market-wide events. The measurement of these rolling windows starts from July onwards so that the effect after the event is sufficiently captured: to be specific, for each one, two, or three month rolling window specification, the measurement of average skewness and average turnover within portfolios starts on June 15, July 3, July 17, respectively—when at least half the window length covers the period after June 1. The measurement period ends at the end of 2017 for all rolling window specifications.

The procedure of constructing portfolios sorted on Environmental score also warrants an in-depth explanation. To begin with, the number of firms for which Thomson Reuters CSR ratings are available in 2017 amounts to over 1300 cross-sectional observations and I classify them into five portfolio groups according to Environmental score: portfolio 1 (portfolio 5) is the least (most) environmentally-friendly group. Moreover, on the one hand, setting equidistant breakpoints based on Environmental score (i.e., 0–20, 20–40, 40–60, 60–80, 80–100) is clearly advantageous in clustering firms into groups with similar green orientation. On the other hand, this strategy does not necessarily lead to a balanced distribution across portfolios in terms of the number of observations. Insofar as the portfolios with fewer observations are largely driven by noise, the effort becomes largely ineffective to interpret the sample mean of skewness or turnover within these portfolios as an estimate of the true value. Nevertheless, I adopt the former approach due to its transparency in interpretability: additionally, this approach is robust to splitting the sample into two subsamples (i.e., alliance-state and non-alliance-state firms).

In forming portfolios, I explicitly exclude oil & gas (SIC: 1000–1499), construction (SIC: 1500–1799) and utilities (SIC: 4900–4999) industries because investors may not deem these firms pro-environmental no matter what the firm's relative environmental orientation within these industries is.[21] The baseline case of the portfolio selection does not differentiate between firm headquartered in alliance states or non-alliance states and thus includes all firms. In this case, the cross-section of firms in portfolio 1–5 contains 143, 540, 341, 199, and 105 observations, respectively, and thus the portfolio with the smallest number of firms still constitutes at least 100 firms. However, I also repeat the procedure by only targeting alliance-state firms or non-alliance-state firms.

Now, I expound the construction of market-adjusted turnover. Turnover is defined as daily trading volume over shares outstanding and I use the full sample in constructing value-weighted and equal-weighted indexes that aim to capture the market turnover—put differently, firms that are not covered by Thomson Reuters CSR ratings as well as firms in mining, construction, and utilities industries are all inclusive. CRSP value-weighted index is used to adjust the returns as explained in Section 3. The institutional peculiarity of NASDAQ is not explicitly addressed in this analysis but this is unlikely to pose a challenge in interpreting the time trends.

As a result, Figures 7–9 show time trends in the average market-adjusted skewness and turnover across the five portfolio: Figure 7 includes all firms, while Figures 8 and 9 only include alliance-state firms and non-alliance-state firms, respectively. The first row in Figure 7 portrays that portfolios 4 and 5 experienced an upward trend in skewness, while portfolios 1 and 2 are inclined towards downward movements across different rolling windows, albeit with some noise contained especially in the one-month rolling window: note that according to Panel C2 in Table 20 which shows the descriptive statistics of the market-adjusted skewness over the full sample period, the mean skewness is lower in the eco-friendly portfolios while it is higher in the non-eco-friendly firm portfolios. Moreover, the second and third rows in Figure 7 depict that portfolios 4 and 5 experienced a downward trend in market adjusted turnover, while portfolios 1 and 2 relatively experienced an upward movement. With regards to the distinction between alliance states and non-alliance states, I do not find a substantial difference as illustrated in Figures 8 and 9, which conforms to the findings under Hypotheses 3a and 3b suggesting that non-climate-alliance states were significantly affected by the parallel announcements as well.

Moreover, Figure 10 distinctly demonstrates that during the latter half of 2017 the average

[21] I also exclusively target these carbon-intensive firms and iterate the procedure (unreported). As expected, the trends do not apparently follow those demonstrated in Figures 7–9.

skewness correlation between eco-friendly and non-eco-friendly portfolios were substantively negative and gradual patterns are shown especially in the two figures representing two- and three-month rolling windows.[22] Besides, Figure 11 addressing the correlation across value-weighted index adjusted turnover portfolios echoes these patterns except for portfolio 5. These findings strongly conform to the theory of differences in opinions—Hong-Stein model (Hong and Stein, 2003) predicts that the sign and magnitude of skewness depends on the degree to which opinions differ surrounding the events. Contrarily, more nuanced patterns are presented in Figure 12 where equal-weighted index adjusted turnover is addressed. In sum, this may indicate that smaller firms are more subject to noise in trading activities but this explanation does not go beyond speculation and needs further investigation in future research.

Table 15: Descriptive statistics of the data set used in Hypotheses 3a and 3b

The table below shows the summary statistics of variables. Env50–100 (Env75–100) dummy equals to one if Environmental score is above 50 (75) and otherwise equals to zero including the case where there is no rating provided by Thomson Reuters Refinitiv database; similarly, Env50–75 dummy equals to one if Environmental score is between 50 and 75 and otherwise set to zero including the no rating case. CAR $(-2, 2)$ and CAT $(-2, 2)$ stand for the cumulative abnormal return and turnover over the five day window $(-2, 2)$, respectively.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Env. score	44.19	21.07	4.98	9.07	27.67	39.83	59.48	94.19	97.81	1512
Env50–100	0.19	0.39	0.00	0.00	0.00	0.00	0.00	1.00	1.00	2786
Env75–100	0.06	0.23	0.00	0.00	0.00	0.00	0.00	1.00	1.00	2786
Env50–75	0.13	0.34	0.00	0.00	0.00	0.00	0.00	1.00	1.00	2786
TR Uncovered	0.46	0.50	0.00	0.00	0.00	0.00	1.00	1.00	1.00	2786
AS2017	20.52	2.18	14.83	15.77	19.03	20.58	22.00	25.53	27.40	2786
LOGSIZE	20.52	2.18	14.83	15.77	19.03	20.58	22.00	25.53	27.40	2786
CAR $(-2, 2)$	-0.00	0.07	-1.18	-0.17	-0.02	0.00	0.02	0.16	1.47	2786
CAT $(-2, 2)$	0.02	2.41	-10.25	-6.16	-1.31	0.00	1.38	6.21	12.27	2357

[22] These trends apparently continue until early February in 2018 (unreported).

Table 16: Differential cumulative abnormal returns over the daily window $(-2, 2)$

The table below presents the cumulative abnormal returns over the daily window ranging from May 30 to June 5: the stock market does not operate on the weekend, June 3 and 4. The market model is used to compute abnormal returns. Green/ungreen firm criteria are based on Environmental score and I set 50 (i.e., 50th percentile) as the threshold score. I draw on eventstudy2 package (Stata) developed by Kaspereit (2019) to compute abnormal returns. Subtotal category includes firms, especially smaller firms, which are uncovered by Thomson Reuters Refinitiv database. Firms with unknown SIC are dropped.

	Alliance-state firms			Non-alliance-state firms		
	Thomson Reuters		Subtotal	Thomson Reuters		Subtotal
	Green	Ungreen		Green	Ungreen	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Mining & Construction						
Average	-0.032	-0.006	-0.001	-0.039***	-0.042***	-0.037***
t-statistic	(-0.932)	(-0.297)	(-0.060)	(-3.884)	(-4.526)	(-5.661)
Obs.	2	8	18	29	74	183
Panel B: Manufacturing						
Average	0.003	0.000	0.004	0.005	-0.003	0.001
t-statistic	(0.576)	(-0.03)	(0.892)	(1.133)	(-0.809)	(0.176)
Obs.	153	207	691	152	255	711
Panel C: Transportation						
Average	-0.002	-0.001	-0.002	0.002	-0.026	-0.021
t-statistic	(-0.123)	(-0.023)	(-0.104)	(0.196)	(-1.090)	(-1.598)
Obs.	3	13	20	12	26	65
Panel D: Communication						
Average	-0.107	-0.002	-0.024*	0.031	0.001	0.011
t-statistic	(-8.451)	(-0.102)	(-1.886)	(0.470)	(0.047)	(0.722)
Obs.	6	14	33	3	24	41
Panel E: Utilities						
Average	0.013*	-0.001	0.008	0.000	-0.004	-0.014**
t-statistic	(1.744)	(-0.061)	(1.230)	(-0.308)	(-0.404)	(-2.468)
Obs.	14	11	32	33	22	93
Panel F: Services						
Average	0.009	0.010*	0.004	0.004	0.002	0.003
t-statistic	(1.333)	(1.663)	(1.071)	(0.628)	(0.545)	(0.683)
Obs.	35	116	283	45	119	281

t-statistics are presented in the parentheses: standard errors are based on t-tests

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 17: Regressing abnormal returns on corporate greenness and climate alliance status

The table below presents the cross-sectional OLS regressions to examine the drivers of the cumulative abnormal returns over the daily window $(-2, 2)$, where $t = 0$ is set to June 1 in 2017 and abnormal returns are generated by the market model. AS2017 dummy equals to one if the firm is headquartered in the states that joined the alliance in the first week of 2017 (i.e., Cohort A, B, or C). TR Uncovered dummy equals to one if the firm's CSR rating is uncovered by Thomson Reuters Refinitiv database. Env50–100 (Env75–100) dummy equals to one if Environmental score is above 50 (75) and otherwise set to zero including the case where there is no rating provided by Thomson Reuters Refinitiv database. LOGSIZE is the logarithm of market capital measured at the end of May 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Env50–100 dummy	0.006	0.008*	0.007*	0.009**				
	(1.60)	(1.95)	(1.74)	(2.07)				
Env75–100 dummy					0.011**	0.015**	0.012**	0.016**
					(2.08)	(2.39)	(2.07)	(2.41)
Env50–75 dummy					0.004	0.006	0.005	0.007
					(1.04)	(1.54)	(1.26)	(1.66)
AS2017 dummy	0.000	0.001	0.005	0.006	0.000	0.001	0.005	0.006
	(0.07)	(0.33)	(1.42)	(1.60)	(0.03)	(0.33)	(1.39)	(1.59)
Env50–100 × AS2017		-0.005		-0.005				
		(-1.11)		(-1.29)				
Env75–100 × AS2017						-0.007*		-0.009*
						(-1.80)		(-1.95)
Env50–75 × AS2017						-0.004		-0.004
						(-0.76)		(-0.85)
LOGSIZE	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(-1.01)	(-0.99)	(-1.49)	(-1.46)	(-1.14)	(-1.12)	(-1.58)	(-1.55)
TR Uncovered dummy	0.002	0.002	0.001	0.001	0.001	0.001	0.001	0.001
	(0.54)	(0.54)	(0.30)	(0.30)	(0.46)	(0.46)	(0.24)	(0.23)
Intercept	-0.010	-0.011	0.015	0.015	-0.007	-0.007	0.018	0.018
	(-0.77)	(-0.82)	(1.16)	(1.10)	(-0.45)	(-0.50)	(1.31)	(1.25)
SIC 2-digit dummies	Yes	Yes	–	–	Yes	Yes	–	–
Clustered at SIC 2-digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2786	2786	2786	2786	2786	2786	2786	2786
Adj. R^2	0.019	0.019	0.001	0.001	0.019	0.019	0.001	0.001

t-statistics adjusted for heteroskedasticity are in the parentheses
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 18: Regressing abnormal turnover on corporate greenness and climate alliance status

The table below presents the cross-sectional OLS regressions examining the drivers of the cumulative abnormal turnover over the window $(-2, 2)$ whereby $t = 0$ is set to June 1, 2017 and abnormal turnover is generated by the one-factor market model. AS2017 dummy equals to one if the firm is headquartered in the states that joined the alliance in the first week of 2017 (i.e., Cohort A, B, or C). TR Uncovered dummy equals to one if the firm's CSR rating is uncovered by Thomson Reuters Refinitiv database. Env50–100 (Env75–100) dummy equals to one if Environmental score is above 50 (75) and otherwise set to zero including the case where there is no rating provided by Thomson Reuters Refinitiv database. LOGSIZE is the logarithm of market capital measured at the end of May 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Env50–100 dummy	-0.268*	-0.258	-0.310**	-0.329*				
	(-1.97)	(-1.51)	(-2.41)	(-1.97)				
Env75–100 dummy					-0.392*	-0.293	-0.412**	-0.362
					(-1.98)	(-1.08)	(-2.14)	(-1.34)
Env50–75 dummy					-0.221	-0.253	-0.273*	-0.324*
					(-1.55)	(-1.43)	(-2.00)	(-1.85)
AS2017 dummy	0.094	0.099	0.173*	0.163*	0.096	0.100	0.176*	0.164*
	(0.88)	(0.98)	(1.78)	(1.71)	(0.91)	(0.99)	(1.83)	(1.73)
Env50–100 × AS2017		-0.024		0.045				
		(-0.13)		(0.24)				
Env75–100 × AS2017						-0.213		-0.108
						(-0.83)		(-0.43)
Env50–75 × AS2017						0.077		0.127
						(0.34)		(0.54)
LOGSIZE	0.002	0.002	0.020	0.020	0.006	0.006	0.023	0.024
	(0.05)	(0.05)	(0.67)	(0.67)	(0.16)	(0.17)	(0.75)	(0.76)
TR Uncovered dummy	0.058	0.058	0.137	0.138	0.065	0.066	0.142	0.144
	(0.34)	(0.34)	(0.82)	(0.82)	(0.38)	(0.38)	(0.86)	(0.87)
Intercept	-1.176	-1.181	-0.450	-0.444	-1.275*	-1.274*	-0.516	-0.522
	(-1.61)	(-1.62)	(-0.73)	(-0.72)	(-1.70)	(-1.70)	(-0.81)	(-0.82)
SIC 2-digit dummies	Yes	Yes	–	–	Yes	Yes	–	–
Clustered at SIC 2-digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2357	2357	2357	2357	2357	2357	2357	2357
Adj. R^2	0.010	0.009	0.003	0.003	0.009	0.009	0.003	0.002

t-statistics adjusted for heteroskedasticity are in the parentheses
*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 19: Regressing volatility proxy on corporate greenness and climate alliance status

The table below presents the cross-sectional OLS regressions examinig the drivers of the absolute cumulative abnormal returns (i.e., volatility proxy) over the daily window $(-2, 2)$ whereby $t = 0$ is set to June 1, 2017 and abnormal returns are generated by the market model. AS2017 dummy equals to one if the firm is headquartered in the states that joined the alliance in the first week of 2017 (i.e., Cohort A, B, or C). TR Uncovered dummy equals to one if the firm's CSR rating is uncovered by Thomson Reuters Refinitiv database. Env50–100 (Env75–100) dummy equals to one if Environmental score is above 50 (75) and otherwise set to zero including the case where there is no rating provided by Thomson Reuters Refinitiv database. LOGSIZE is the logarithm of market capital measured at the end of May 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Env50–100 dummy	0.002	0.003	0.003	0.002				
	(0.86)	(1.12)	(0.75)	(0.60)				
Env75–100 dummy					0.002	0.002	0.003	0.002
					(0.79)	(0.39)	(0.60)	(0.36)
Env50–75 dummy					0.002	0.004	0.003	0.002
					(0.80)	(1.43)	(0.78)	(0.68)
AS2017 dummy	0.001	0.002	0.002	0.001	0.001	0.002	0.002	0.001
	(0.81)	(0.81)	(0.56)	(0.41)	(0.81)	(0.80)	(0.56)	(0.41)
Env50–100 × AS2017		-0.001		0.002				
		(-0.34)		(0.47)				
Env75–100 × AS2017						0.002		0.002
						(0.45)		(0.41)
Env50–75 × AS2017						-0.003		0.002
						(-0.56)		(0.37)
LOGSIZE	-0.005***	-0.005***	-0.006***	-0.006***	-0.005***	-0.005***	-0.006***	-0.006***
	(-5.59)	(-5.56)	(-4.31)	(-4.32)	(-5.50)	(-5.48)	(-4.25)	(-4.26)
TR Uncovered dummy	0.004*	0.004*	0.003	0.003	0.004**	0.004**	0.003	0.003
	(1.98)	(1.98)	(1.22)	(1.22)	(2.00)	(2.00)	(1.23)	(1.24)
Intercept	0.142***	0.142***	0.164***	0.165***	0.142***	0.142***	0.164***	0.164***
	(7.63)	(7.54)	(5.16)	(5.17)	(7.46)	(7.39)	(5.10)	(5.11)
SIC 2-digit dummies	Yes	Yes	–	–	Yes	Yes	–	–
Clustered at SIC 2-digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2786	2786	2786	2786	2786	2786	2786	2786
Adj. R^2	0.077	0.077	0.049	0.049	0.077	0.077	0.049	0.048

t-statistics adjusted for heteroskedasticity are in the parentheses

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 20: Descriptive statistics of securities within each portfolio under Hypothesis 3c: return-related variables (all states)

Panels below on the left (right) hand side show the daily level summary statistics of the returns, standard deviation of returns, and skewness of returns, respectively, across five portfolios during the latter half of 2017 (the full sample period). The standard deviation and skewness of daily returns are measured over one-month rolling window where the returns are adjusted by the market return using the CRSP value-weighted portfolio. Portfolio 1 (portfolio 5) is the least (most) eco-friendly group.

	Panel A1: market adj. return (latter half of 2017)							**Panel A2**: market adj. return (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	-0.0	-0.069	-0.010	-0.0	0.009	0.073	20380	-0.0	-0.062	-0.009	-0.0	0.009	0.065	223384
P2	0.0	-0.065	-0.009	-0.0	0.009	0.070	75563	-0.0	-0.064	-0.009	-0.0	0.009	0.066	872149
P3	0.0	-0.072	-0.009	-0.0	0.009	0.078	47905	-0.0	-0.060	-0.008	-0.0	0.008	0.061	687470
P4	-0.0	-0.052	-0.007	-0.0	0.007	0.050	27462	-0.0	-0.051	-0.007	-0.0	0.007	0.052	449472
P5	-0.0	-0.040	-0.006	-0.0	0.006	0.038	14490	-0.0	-0.043	-0.007	-0.0	0.006	0.042	243247

	Panel B1: market adj. std. dev. (latter half of 2017)							**Panel B2**: market adj. std. dev. (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	0.021	0.006	0.012	0.017	0.024	0.081	20224	0.020	0.005	0.011	0.016	0.023	0.071	222807
P2	0.021	0.006	0.012	0.017	0.025	0.078	75287	0.020	0.005	0.011	0.016	0.024	0.078	870388
P3	0.023	0.005	0.012	0.018	0.027	0.095	47649	0.019	0.005	0.010	0.015	0.022	0.073	686265
P4	0.016	0.004	0.009	0.013	0.018	0.059	27462	0.016	0.005	0.009	0.013	0.019	0.059	449197
P5	0.013	0.004	0.008	0.010	0.014	0.048	14490	0.014	0.004	0.008	0.011	0.016	0.047	243207

	Panel C1: market-adj. skewness (latter half of 2017)							**Panel C2**: market-adj. skewness (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	0.085	-3.510	-0.491	0.080	0.702	3.341	20224	0.067	-3.621	-0.494	0.075	0.654	3.409	222807
P2	-0.004	-3.717	-0.589	0.021	0.615	3.437	75287	0.063	-3.742	-0.484	0.082	0.648	3.364	870388
P3	-0.034	-3.675	-0.634	-0.008	0.615	3.561	47649	0.057	-3.633	-0.474	0.073	0.632	3.318	686265
P4	-0.079	-3.774	-0.647	-0.028	0.568	3.335	27462	0.036	-3.573	-0.486	0.057	0.606	3.242	449197
P5	-0.105	-3.638	-0.741	-0.099	0.518	3.499	14490	0.024	-3.555	-0.500	0.053	0.602	3.250	243207

Table 21: Descriptive statistics of the securities within each portfolio in Hypothesis 3c: turnover-related variables (all states)

Panels below on the left (right) hand side show the daily level summary statistics of the turnover, value-weighted index adjusted turnover, and equal-weighted index adjusted turnover, respectively, across five portfolios during the latter half of 2017 (the full sample period). Portfolio 1 (portfolio 5) is the least (most) eco-friendly group.

	Panel D1: raw turnover (latter half of 2017)							**Panel D2**: raw turnover (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	0.009	0.000	0.003	0.005	0.009	0.053	20388	0.011	0.001	0.004	0.007	0.012	0.070	223414
P2	0.011	0.000	0.004	0.006	0.011	0.070	75575	0.012	0.000	0.005	0.008	0.014	0.066	872229
P3	0.012	0.001	0.004	0.007	0.013	0.078	47918	0.011	0.000	0.005	0.008	0.013	0.064	687529
P4	0.009	0.001	0.004	0.006	0.010	0.048	27462	0.011	0.001	0.005	0.008	0.012	0.055	449479
P5	0.008	0.001	0.004	0.005	0.008	0.046	14490	0.009	0.002	0.004	0.007	0.011	0.040	243249

	Panel E1: VW-index adj. turnover (latter half of 2017)							**Panel E2**: VW-index adj. turnover (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	0.002	-0.007	-0.003	-0.001	0.002	0.045	20388	0.003	-0.009	-0.004	-0.001	0.004	0.061	223414
P2	0.004	-0.007	-0.003	-0.000	0.005	0.063	75575	0.004	-0.008	-0.003	0.000	0.005	0.058	872229
P3	0.005	-0.007	-0.002	0.001	0.006	0.071	47918	0.004	-0.008	-0.003	0.000	0.005	0.055	687529
P4	0.002	-0.006	-0.002	-0.000	0.004	0.041	27462	0.003	-0.007	-0.003	-0.000	0.004	0.046	449479
P5	0.001	-0.006	-0.003	-0.001	0.002	0.038	14490	0.001	-0.007	-0.003	-0.001	0.002	0.030	243249

	Panel F1: EW-index adj. turnover (latter half of 2017)							**Panel F2**: EW-index adj. turnover (2002–2017)						
	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.	Mean	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
P1	-0.002	-0.012	-0.007	-0.005	-0.002	0.041	20388	0.000	-0.011	-0.006	-0.003	0.001	0.059	223414
P2	0.000	-0.012	-0.007	-0.004	0.001	0.058	75575	0.001	-0.011	-0.005	-0.002	0.003	0.055	872229
P3	0.001	-0.011	-0.006	-0.003	0.002	0.067	47918	0.001	-0.011	-0.005	-0.002	0.003	0.053	687529
P4	-0.002	-0.011	-0.006	-0.004	-0.000	0.036	27462	0.000	-0.010	-0.005	-0.003	0.002	0.044	449479
P5	-0.003	-0.012	-0.007	-0.005	-0.002	0.034	14490	-0.002	-0.010	-0.006	-0.003	-0.000	0.028	243249

Figure 7: Trends in average market-adjusted skewness and turnover across portfolios sorted on Environmental score (all states)

The figures in the first row illustrate the market-adjusted skewness averaged within each five portfolio: these portfolios are sorted on Environmental score whereby portfolio 1 (portfolio 5) is the least (most) eco-friendly group. Similarly, the figures in the second (third) row illustrate the value-weighted index (equal-weighted index) adjusted turnover averaged within each five portfolio. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample but are included when computing VW/EW turnover indexes. Both types of firms headquartered in alliance and non-alliance states are included.

Figure 8: Trends in average market-adjusted skewness and turnover across portfolios sorted on Environmental score (USCA)

The figures in the first row illustrate the market-adjusted skewness averaged within each five portfolio: these portfolios are sorted on Environmental score whereby portfolio 1 (portfolio 5) is the least (most) eco-friendly group. Similarly, the figures in the second (third) row illustrate the value-weighted index (equal-weighted index) adjusted turnover averaged within each five portfolio. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample but are included when computing VW/EW turnover indexes. Only firms headquartered in alliance states are included.

Figure 9: Trends in average market-adjusted skewness and turnover across portfolios sorted on Environmental score (non-USCA)

The figures in the first row illustrate the market-adjusted skewness averaged within each five portfolio: these portfolios are sorted on Environmental score whereby portfolio 1 (portfolio 5) is the least (most) eco-friendly group. Similarly, the figures in the second (third) row illustrate the value-weighted index (equal-weighted index) adjusted turnover averaged within each five portfolio. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample but are included when computing VW/EW turnover indexes. Only firms headquartered in non-alliance states are included.

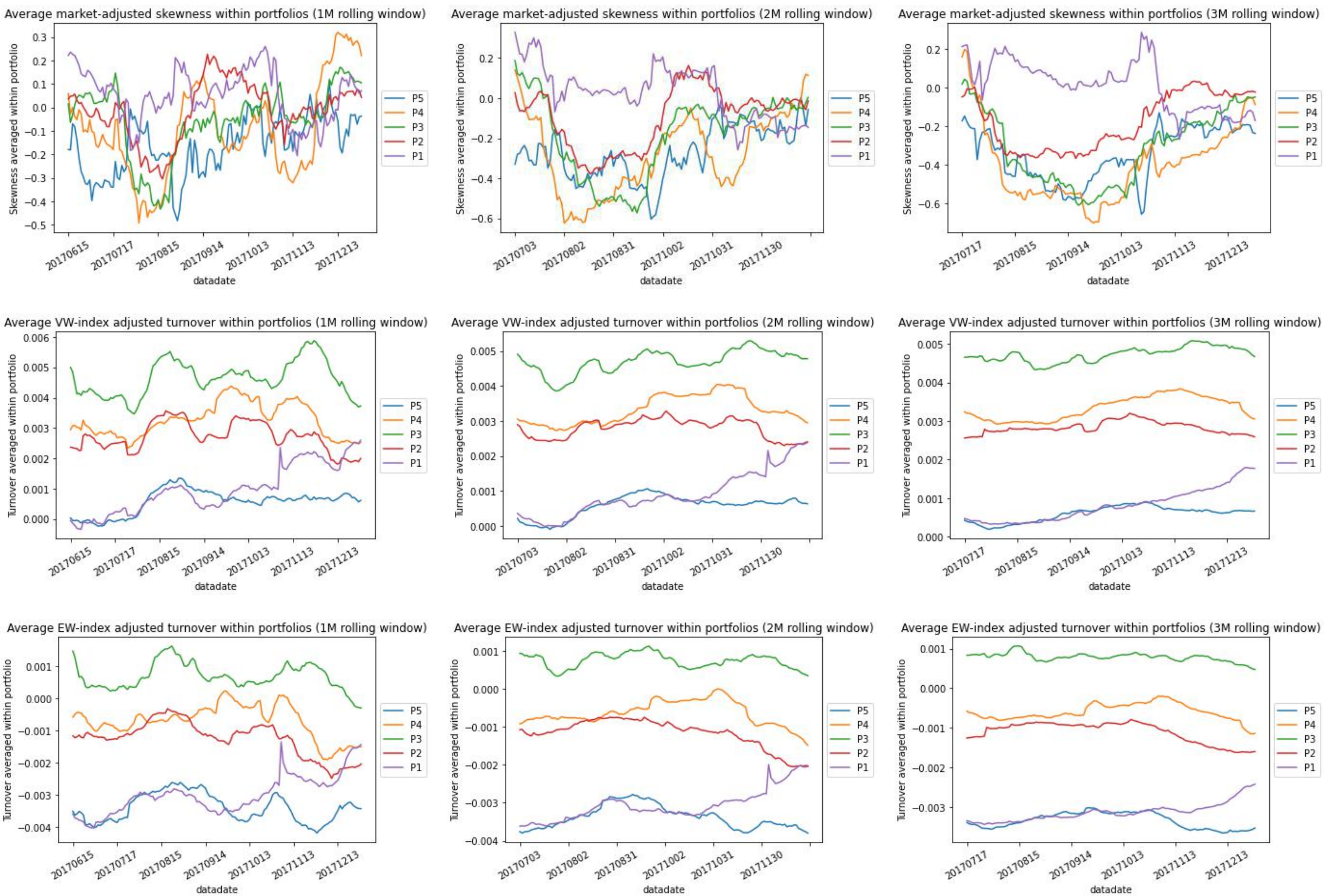


Figure 10: Correlation between average market-adjusted skewnesses across portfolios sorted on Environmental score (all states)

The figures in the first (second) row illustrate the correlation of market-adjusted skewness measures across five portfolios over the latter half of 2017 (the whole sample period), where the skewness of market-adjusted returns of individual securities is averaged within each five portfolio sorted on Environmental score. The left-end, middle, and right-end columns compute the market adjusted skewness using a rolling window over a one-, two-, and three-month period, respectively. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample. Both types of firms headquartered in alliance and non-alliance states are included.

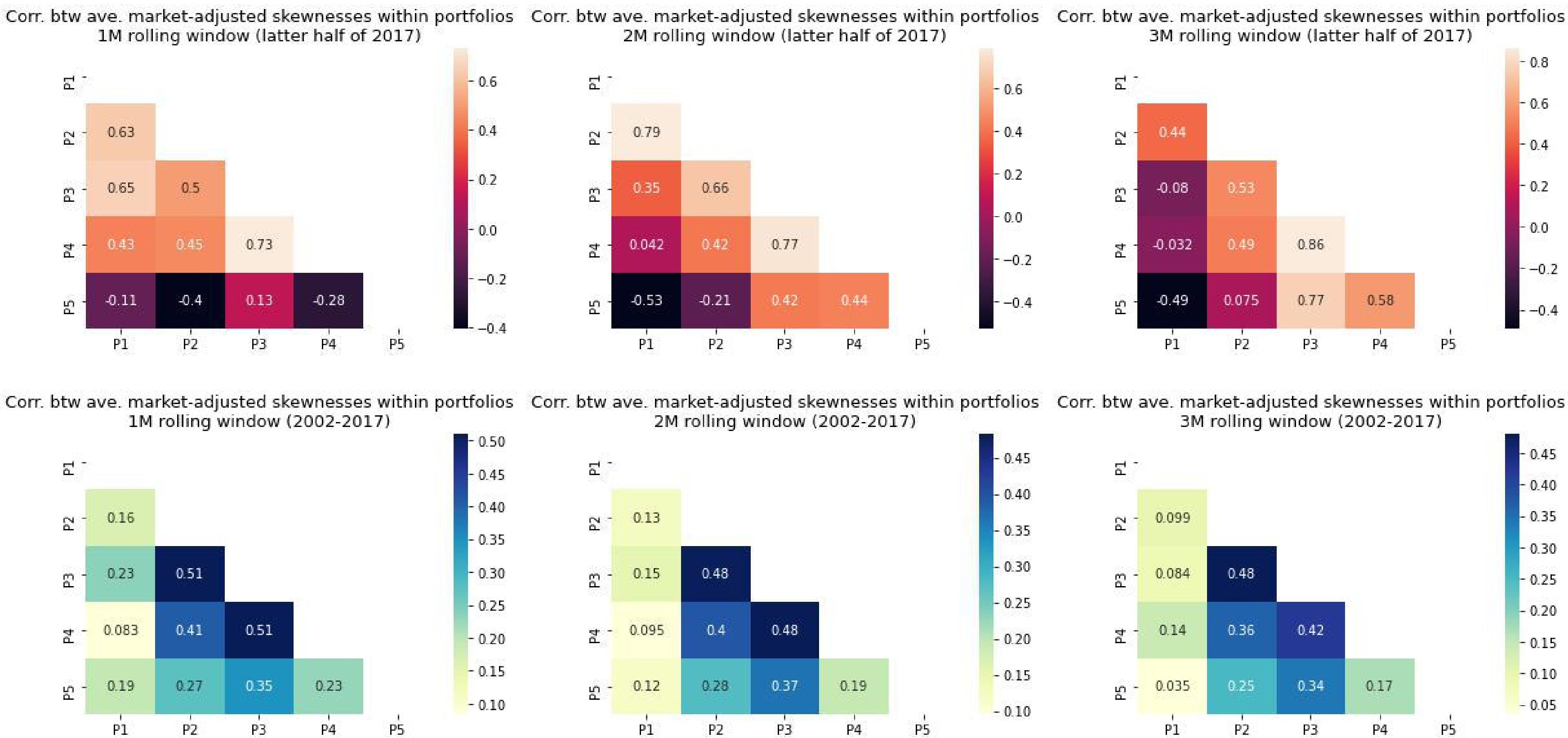


Figure 11: Correlation between average VW-index adjusted turnovers across portfolios sorted on Environmental score (all states)

The figures in the first (second) row illustrate the correlation of VW-index adjusted turnover across five portfolios over the latter half of 2017 (the whole sample period), where raw turnover minus VW-index of individual securities is averaged within each five portfolio sorted on Environmental score: see Lo and Wang (2000) for VW turnover index. The left-end, middle, and right-end columns compute the VW-index adjusted turnover using a rolling window over a one-, two-, and three-month period, respectively. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample but are included when computing VW/EW turnover indexes. Both types of firms headquartered in alliance and non-alliance states are included.

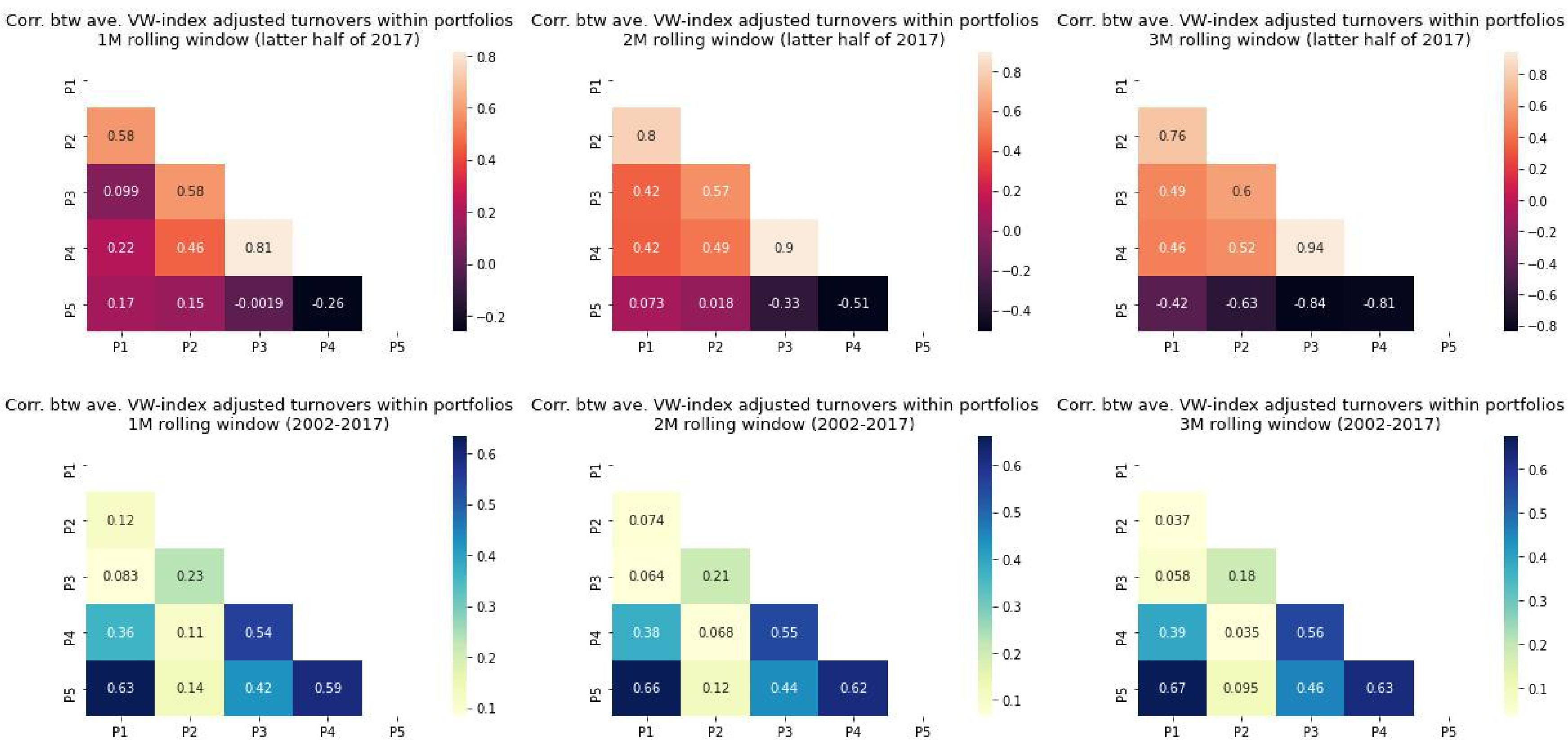
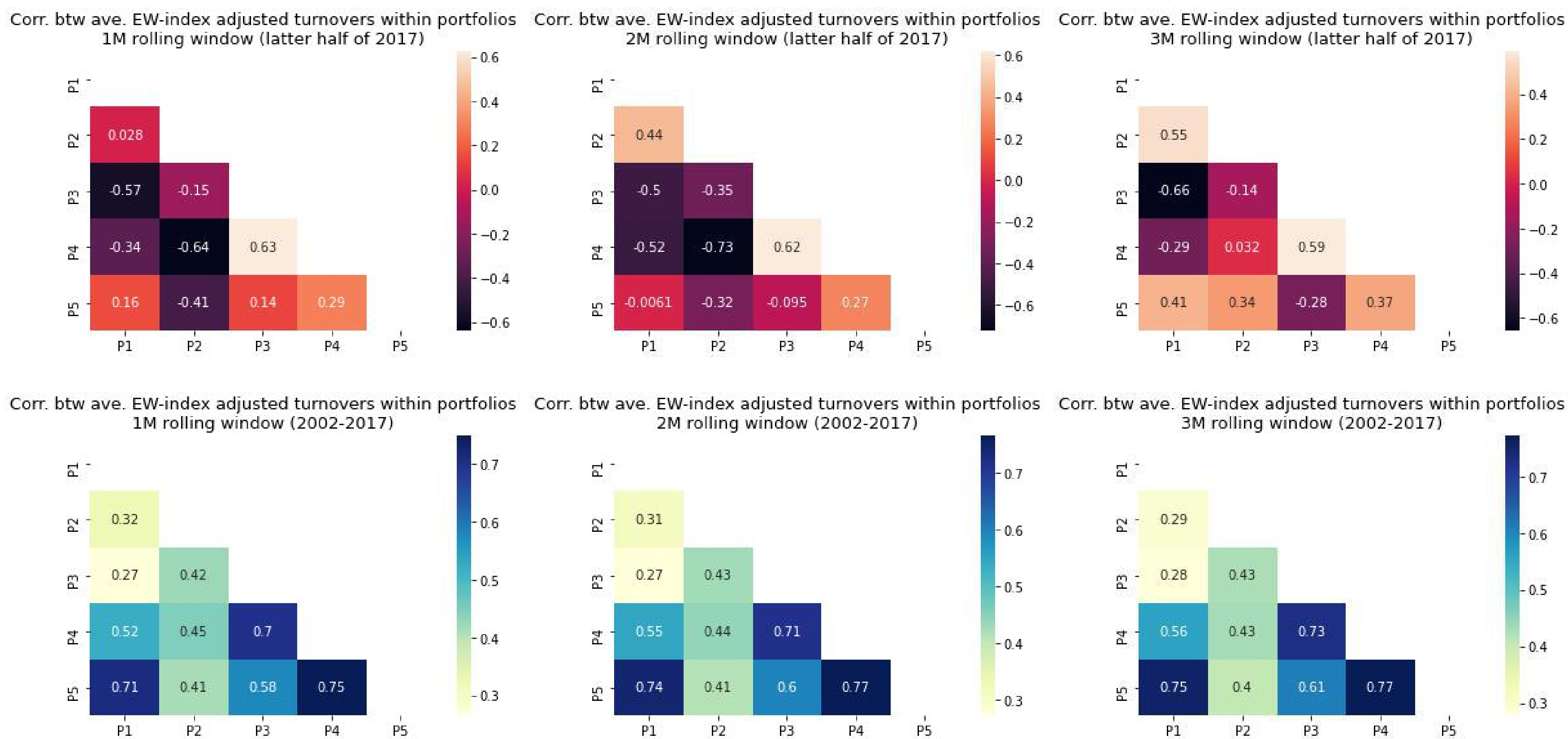


Figure 12: Correlation between average EW-index adjusted turnovers across portfolios sorted on Environmental score (all states)

The figures in the first (second) row illustrate the correlation of EW-index adjusted turnover across five portfolios over the latter half of 2017 (the whole sample period), where raw turnover minus EW-index of individual securities is averaged within each five portfolio sorted on Environmental score: see Lo and Wang (2000) for EW turnover index. The left-end, middle, and right-end columns compute the EW-index adjusted turnover using a rolling window over a one-, two-, and three-month period, respectively. Firms in carbon-intensive industries such as mining, construction, and utilities industries are excluded from the sample but are included when computing VW/EW turnover indexes. Both types of firms headquartered in alliance and non-alliance states are included.



6.2 Emissions reduction in the ensuing parallel announcements

The climate alliance was called for with the ultimate policy objective of reducing the greenhouse gas emissions. Nonetheless, the results in Section 6.1 suggest that even firms headquartered in non-alliance states were significantly affected by the announcement on the alliance formation against the Paris Agreement withdrawal. Again, while it is possible that these firms were exposed to the stock market reaction because their subsidiaries and/or supply chain networks are embedded within climate alliance states, another explanation is that these reactions went beyond market fundamentals—a manifestation of green optimism—yet, I do not take a definite stand on which channel is more prominent in this paper given the difficulty to disentangle one effect from the other. Against this backdrop, I empirically test in this subsection whether these stock market reactions on the parallel announcements overall predicted the subsequent reduction in greenhouse gas emissions (Hypothesis 4).

I draw on the data provided by Greenhouse Gas Reporting Program (GHGRP), one of the US EPA programs, to illuminate corporate emissions. Typically, firms are equipped with multiple production facilities and GHGRP conveniently provides data at the facility level. This is especially important because studies have shown that firms not only weigh environmental strategies differently (Bansal and Roth, 2000; Sharma, 2000) but even within-firm facilities exhibit substantive heterogeneity in environmental performance level (Doshi, Dowell, and Toffel, 2013). Moreover, although GHGRP gathers data from three entity types, direct emitters, suppliers, and CO_2 injection facilities,[23] my sample only targets direct emitters because a great deal of facility data related to suppliers and CO_2 injection is not disclosed: besides, direct emitters constitute by far the largest share of the database.

Table 22 reports the summary statistics and Figure 13 illustrates the emissions transition over the period 2010–2019. According to the table, oil & gas, utilities, manufacturing, transportation and waste management industries consist of about 19%, 23%, 30%, 8%, and 17% of the sample, respectively, based on the number of facilities.[24] However, as illustrated in Figure 13, power plants (utility) industry is by far the most predominant in terms of the emissions amount. Note that if a facility is owned by multiple parent companies, there are

[23]According to GHGRP, direct emitters are the facilities that engage in fuel combustion or in another way directly emit GHGs into the atmosphere; suppliers are the facilities that supply products into the economy which indirectly—if combusted, released or oxidized—emit GHGs into the atmosphere; and CO_2 injection facilities are the facilities that inject a stream of CO_2 into the subsurface.

[24]For the case of oil & gas industry, NAICS 2-digit code 21 primarily corresponds to mining industry (SIC 1000–1499) but also to manufacturing (i.e., SIC 2819, 3295). For the case of power plants industry, NAICS 2-digit code 22 corresponds to utilities industry (SIC 4900–4999).

corresponding multiple entries in the original data set. In this case, I select the entry with the largest ownership parent company among the same facility-year entries and drop the rest of the entries, since otherwise the emissions amount will be double-counted.

The primary interest lies in whether the reduction in greenhouse gases in the post-2017 period is more notable in alliance states relative to non-alliance states. In doing so, the systematic differentiation based on regulation is pivotal because power plants industry is heavily regulated by environmental policies (e.g., RGGI, renewable electricity standards) and thus may react differently from other industries that do not have such equivalents. Equation (11) describes the baseline model specification whereby the subscript f denotes facility, j denotes the industry classification of the facility measured at 2-digit NAICS code, and t denotes the reporting year. The dependent variable is the total emission of greenhouse gases, or CO_2 equivalents (CO_2eq), in logarithm. AS_f equals to one if the facility is located in the states that joined the climate alliance by the end of 2019. Post_t equals to one if reporting year t corresponds to 2017 or later.[25] Moreover, α_f is the unobserved facility heterogeneity modeled as fixed effects and $\delta_{j,t}$ is the industry-specific year fixed effects whereby the industry category of the facility is based on NAICS 2-digit code. Hypothesis 4 expects $\beta_1 = 0$ in equation (11).

$$\ln(\text{CO}_2\text{eq}_{f,j,t}) = \beta_0 + \beta_1 \text{AS}_f \times \text{Post}_t + \alpha_f + \delta_{j,t} + \varepsilon_{f,j,t} \tag{11}$$

Alternatively, I introduce several variants of the baseline model specification. The first variant addresses the possibility that AS_f variable actually proxies for a region with intense climate belief. The reason for this is that (i) states are more willing to join the climate alliance, if they embrace more areas with pro-climate beliefs and (ii) if facilities are located in the areas that are more climate sensitive, these facilities would naturally face a stronger pressure for the community to reduce greenhouse gas emissions (Dowell, n.d.). In doing so, I employ climate survey data on a local scale from Yale Climate Opinion data. In particular, I opt to choose the survey in 2016 on the grounds that (i) these data are provided almost annually but the numeric values are not comparable across different years, thus I cannot reliably draw on its panel structure and (ii) it is conservative to use the survey dated before the formation of the climate alliance in 2017.[26] Precisely, I use two proxies of climate belief,

[25] Morck, Shleifer, and Vishny (1990) claim that it is essential to rationalize the horizon over which their growth rate regressions are estimated. The authors continue that estimations over a relatively short period such as one year may not fully capture lagged investment in response to altered firm valuation, whereas an endogeneity problem becomes a central concern as the period length is extended (e.g., three to four years).

[26] After estimating the models using data surveyed in 2018, the results turn out to be qualitatively very similar—data from 2017 are unavailable. This includes new variables like corporations, which measures the

Regulate and SupportRPS variables. Regulate represents the "estimated percentage who somewhat/strongly support regulating CO_2 as a pollutant," while SupportRPS represents the "estimated percentage who somewhat/strongly support requiring utilities to produce 20% electricity from renewable sources."

The regression model incorporating the climate belief variable is specified in equation (12). The interaction between Belief_c (the climate belief at the county level) and Post_t addresses the possibility that corporate managers may value the local climate opinions differently following 2017—that is, the corporate managers pay additional attention to decarbonizing strategies—even if the local climate belief itself is hardly time-varying. Note that county fixed effects do not appear in the model specification because they are subsumed into the facility fixed effects. Besides, under the fixed effects approach, it is infeasible to include time-invariant control variables and this set of variables include time persistent variables such as local climate opinions and socioeconomic constructs in the local community (Dowell, n.d.). A minor revision to equation (12) is described in equation (13), where $\text{Belief}_c \times \text{Post}_t$ in equation (12) is replaced with $\text{AS}_f \times \text{Belief}_c \times \text{Post}_t$ and $\text{NAS}_f \times \text{Belief}_c \times \text{Post}_t$. Hypothesis 4 implies that $\beta_1 = 0$ and $\beta_2 < 0$ in equation (12) and $\beta_1 = 0$, $\beta_2 < 0$ and $\beta_3 < 0$ in equation (13).

$$\ln(\text{CO}_2\text{eq}_{f,j,c,t}) = \beta_0 + \beta_1 \text{AS}_f \times \text{Post}_t + \beta_2 \text{Belief}_c \times \text{Post}_t + \alpha_f + \delta_{j,t} + \varepsilon_{f,j,c,t} \tag{12}$$

$$\begin{aligned}\ln(\text{CO}_2\text{eq}_{f,j,c,t}) = &\beta_0 + \beta_1 \text{AS}_f \times \text{Post}_t + \beta_2 \text{AS}_f \times \text{Belief}_c \times \text{Post}_t \\ &+ \beta_3 \text{NAS}_f \times \text{Belief}_c \times \text{Post}_t + \alpha_f + \delta_{j,t} + \varepsilon_{f,j,c,t}\end{aligned} \tag{13}$$

As the second variant of the baseline model, I use the number of facilities owned by parent as a proxy for the parent firm size. Other things equal, a firm owning more facilities could possibly face more pressure to decarbonize due to the more attention, impact, and responsibility it carries. Furthermore, as the final variant, I replace the local belief of climate change with social capital measured in the local community, which can serve as a placebo test. This is because a different channel could be at play—that is, the post-2017 reduction in emissions as a part of CSR activities could occur due to the channel of social capital (e.g., Lins, Servaes, and Tamayo, 2017) rather than climate change concern. I draw on the social capital index from U.S. Congress, Joint Economic Committee containing over 3000 county-level data.[27] The social capital index consists of four components: family unity,

"estimated percentage who think corporations and industry should be doing more/much more to address global warming."

[27]Source: https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america

community health, institutional health, and collective efficacy.

Now, Tables 25–27 present the results of regression estimates. Table 25 shows the aggregate estimate excluding industries that investors may deem as carbon-intensive (i.e., power plants, oil & gas), which were also excluded from the analysis under Hypothesis 3c for the same reason. The coefficients on AS $\times$ Post are insignificant across all specifications but instead the coefficients on the interaction terms containing climate belief variables are all negative and significant. In terms of the economic magnitude, for instance, the coefficient on Regulate $\times$ Post in column (2) is -0.011 and since the standard deviation of Regulate variable is 4.64, a one-standard-deviation increase in Regulate will lead to a 5.1% ($-0.011 \times 4.64 = -0.051$) decrease in emissions conditional on 2017 or later. Moreover, the significant coefficients on both of the triple interaction terms containing Regulate suggest that the decarbonization movement after 2017 is not conditional on alliance states of the climate alliance but is prevalent nation-wide: similar patters are confirmed as well when using SupportRPS as the climate belief proxy. Columns (6) and (7) in Table 25 further exhibit that facilities whose parents own many other facilities were more engaged in decarbonization and this trend was particularly distinctive in non-alliance states. Columns (8) and (9) further show that the coefficients on the social capital indexes are positive, which additionally verifies the results using climate belief variables. Since the states that embrace the high-ranked counties in the social capital index are very likely from traditional red states,[28] it stands to reason that the index is negatively correlated with climate beliefs, thereby showing opposite signs in the estimated results.

Moreover, Table 26 shows the results of the heavily-regulated power plants industry. The estimated results are in stark contrast with Table 25 as the coefficients on AS $\times$ Post are significantly negative across the majority of the specifications and the coefficients on the interaction terms including climate belief variables are all insignificant. Of particular importance is the extremely large magnitude of the coefficients on AS $\times$ Post. This indicates that facilities in the power plants industry located in the alliance states considerably reduced greenhouse gas emissions and that this reduction in emissions can be indeed attributed to the effect of the climate alliance formation.

The regression estimates of the oil & gas industry presented in Table 27, which is also carbon intensive but face less carbon regulation relative to power plants industry, comple-

[28]For instance, the states that contain the top 30 counties are as follows: Alaska, Georgia, Iowa, Kansas, Kentucky, Minnesota, Missouri, Montana, Nebraska, North Dakota, and South Dakota.

ment this point. It shows that the signs of the coefficients are mixed across specifications and there is also little consistent pattern in the significance level, thereby posing a challenge in meaningful interpretation.

Last but not least, the pro-climate measures that the climate alliance states can draw on span multidimensional aspects.[29] Hence, using other data sources (e.g., Thomson Reuters Emissions score) would be an interesting next step. Yet, one caveat in merging GHGRP database—or TRI database, which is also administrated by US EPA—with other databases is that there is no common identifier and thus a matching procedure by firm names is necessary.[30] A successful resolution to this problem will open up a lucrative avenue for future research.

[29]Examples abound. For instance, electric vehicles are increasingly gathering popularity in New York and Governor Andrew Cuomo announced in 2020 that a statewide "EV Made Ready" program will facilitate the deployment of electric vehicle charging station; in 2018 Governor Northam signed the Grid Transformation and Security Act 8 to lay the foundation of extensive renewable energy deployment; in 2019 he further signed Executive Order 43 to ensure that 30% of electric system in Virginia will be powered by renewable energy resources within the next decade.

[30]After deploying a preliminary fuzzy matching method and setting a conservative accuracy threshold, the sample becomes orders of magnitude smaller.

Table 22: Number of facilities across climate alliance status and NAICS industries

The table below presents the number of facilities in the sample across climate alliance status and industries measured at NAICS code (2-digit). Alliance states include those which joined the climate alliance later than 2017. The 2-digit NAICS code represent the following major industries: code 21 corresponds to oil & gas (mining) industry; code 22 corresponds to power plant industry; code 31–33 correspond to manufacturing industry and especially code 32 includes refineries; code 48 corresponds to transportation industry; and code 56 corresponds to waste management industry. In case a facility is owned by multiple parent companies, there are corresponding multiple entries in the original data. In this case, I select the entry with the largest ownership parent company and drop the rest of the entries, since otherwise the emissions amount will be double-counted. As a result, 11279 facility-year observations were dropped.

NAICS (2-digit)	Alliance states	Non-alliance states	Total
11	31	25	56
21	2,192	12,285	14,477
22	5,978	11,496	17,474
23	10	25	35
31	1,150	2,505	3,655
32	2,836	11,715	14,551
33	888	3,785	4,673
42	12	39	51
48	865	5,549	6,414
49	10	58	68
52	0	4	4
53	39	0	39
54	85	95	180
55	0	1	1
56	4,063	8,576	12,639
61	487	651	1,138
62	120	129	249
71	0	10	10
72	17	26	43
81	19	0	19
92	262	315	577
Total no. facilities	19,064	57,289	76,353

Figure 13: Emissions trends across alliance membership status and industries

The figures below demonstrate the emissions trends of greenhouse gases (CO_2 equivalents) across climate alliance status and industries over the period 2010–2019. The solid (dotted) line represents the emissions in alliance states (non-alliance states). Moreover, the scale of y-axis on the left (right) hand side is based on the total (average) emissions. Note that an identical facility corresponds to multiple entries in the original data if it has multiple parent companies, which induces a double-counting of the emissions amount. Thus, the total and average values are computed by replacing the emissions of all entries with zero, except for the first entry of each facility. The unit is in million metric tons.

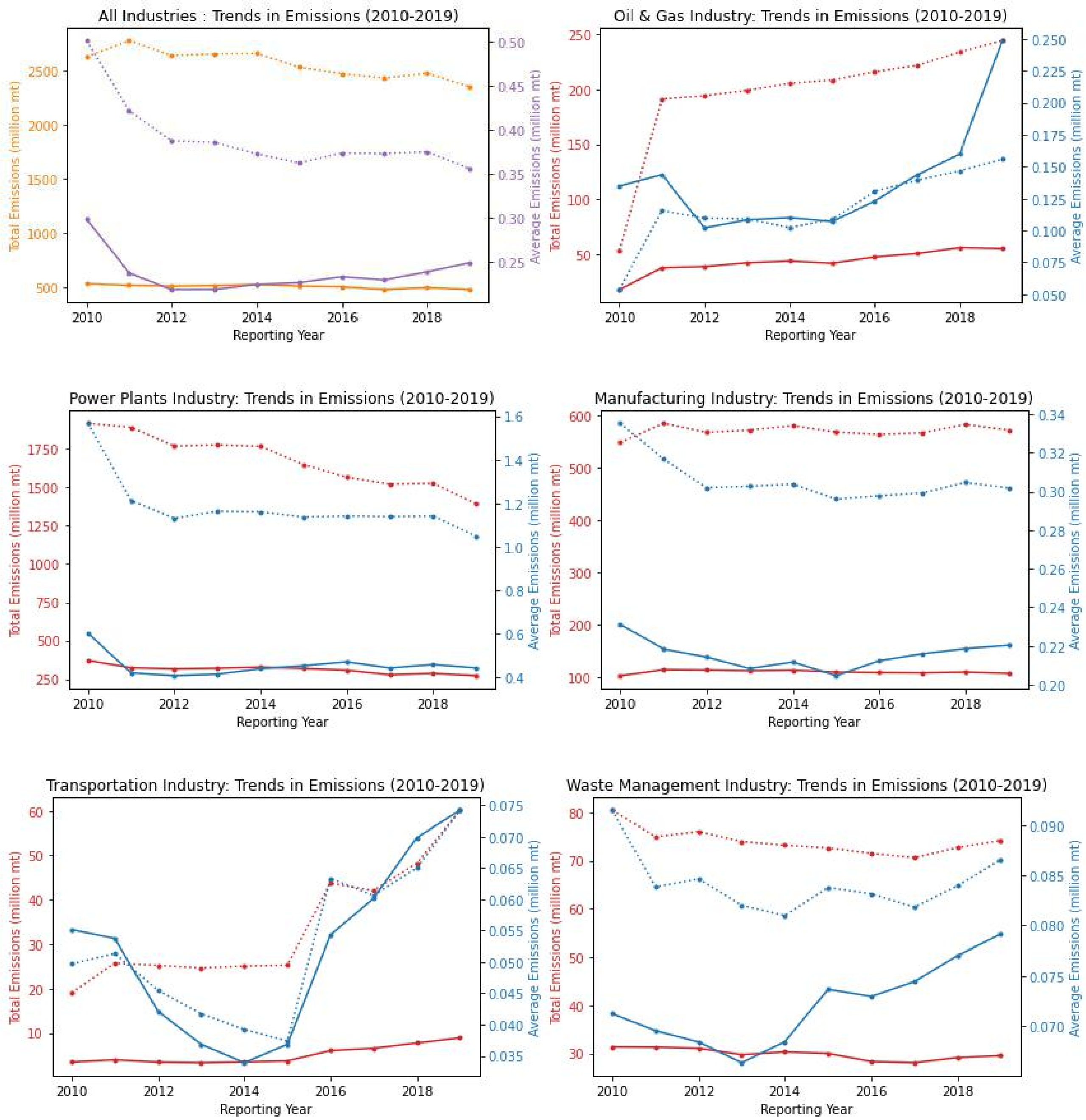


Table 23: Descriptive statistics of emissions, local climate belief, and social capital variables under Hypothesis 4

Emissions is in million metric ton. The number of facilities owned by parent (in logarithm) is used as a proxy for the parent firm size. Social capital index consists of four components: family unity, community health, institutional health, and collective efficacy. Social capital^{-} index excludes collective efficacy.

	Mean	SD	Min	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Max	Obs.
Emissions	0.40	1.31	0.00	0.00	0.03	0.06	0.18	7.28	22.99	76221
No. facilities	25.81	49.49	1.00	1.00	1.00	6.00	25.00	229.00	235.00	76349
Ln(No. facilities)	1.91	1.64	0.00	0.00	0.00	1.79	3.22	5.43	5.46	76349
Regulate	72.18	4.64	56.62	60.62	69.14	72.19	75.60	81.77	83.13	74028
SupportRPS	63.23	4.98	48.12	52.63	59.50	63.15	66.66	73.96	75.93	74028
CO2limits	65.16	8.52	34.99	40.33	59.82	65.69	71.52	81.48	83.94	74028
Happening	66.85	6.38	48.79	52.40	62.16	66.41	71.03	80.61	84.04	74028
HarmUS	55.54	5.45	44.73	46.62	51.43	54.62	59.24	69.13	72.07	74028
Social capital	-0.42	0.96	-4.14	-2.82	-1.13	-0.40	0.24	1.69	2.59	73276
Social capital^{-}	-0.29	0.85	-2.76	-2.07	-0.91	-0.37	0.24	1.89	2.79	73276

Table 24: Cross-correlation table of main variables under Hypothesis 4

The table below exhibits the Pearson correlation coefficients of the above-mentioned variables.

Variables	Ln(Emissions)	Ln(No. fac.)	Regulate	Sup.RPS	CO2limits	Happening	HarmUS	SC	SC^{-}
Ln(Emissions)	1.000								
Ln(No. facilities)	0.036	1.000							
Regulate	-0.073	-0.118	1.000						
SupportRPS	-0.050	-0.103	0.918	1.000					
CO2limits	-0.080	-0.104	0.891	0.929	1.000				
Happening	-0.051	-0.101	0.857	0.946	0.939	1.000			
HarmUS	-0.008	-0.071	0.700	0.847	0.827	0.920	1.000		
Social capital	-0.046	-0.021	-0.118	-0.214	-0.229	-0.245	-0.370	1.000	
Social capital^{-}	-0.050	-0.044	-0.001	-0.052	-0.070	-0.087	-0.224	0.907	1.000

Table 25: CO_2 equivalent emissions from facilities: all industries (excl. oil & gas and power plants)

The table below presents the regression estimates. The number of facilities owned by parent (in logarithm) is used as a proxy for the parent firm size. Social capital index measured at 2018 is used as a placebo. Social capital$^-$ is the social capital index excluding the component of collective efficacy. Intercept is estimated but unreported.

	All industries (excl. oil & gas and power plants)								
	Baseline	Regulate		Support RPS		Ln(No. facilities)		Placebo	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AS × Post	-0.034	0.004	0.466	-0.004	0.204	-0.006	-0.047	-0.040	-0.038
	(-1.50)	(0.18)	(1.33)	(-0.18)	(0.71)	(-0.25)	(-1.68)	(-1.74)	(-1.65)
Regulate × Post		-0.011***				-0.011***	-0.011***		
		(-4.26)				(-4.21)	(-4.22)		
SupportRPS × Post				-0.008***					
				(-4.18)					
Ln(No. facilities) × Post						-0.028**			
						(-2.91)			
AS × Regulate × Post			-0.016***						
			(-3.49)						
NAS × Regulate × Post			-0.010***						
			(-3.57)						
AS × SupportRPS × Post					-0.011**				
					(-2.89)				
NAS × SupportRPS × Post					-0.008**				
					(-3.24)				
AS × Ln(No. facilities) × Post							-0.011		
							(-0.94)		
NAS × Ln(No. facilities) × Post							-0.033***		
							(-3.34)		
Social capital × Post								0.019*	
								(2.26)	
Social capital$^-$ × Post									0.010
									(1.26)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	44008	43322	43322	43322	43322	43319	43319	43021	43021
Adj. R^2	0.849	0.848	0.848	0.848	0.848	0.848	0.848	0.848	0.848

Standard errors are clustered at the facility and reporting year level

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 26: CO_2 equivalent emissions from facilities: power plants

The table below presents the regression estimates in power plants industry. The number of facilities owned by parent (in logarithm) is used as a proxy for the parent firm size. Social capital index measured at 2018 is used as a placebo. Social capital$^-$ is the social capital index excluding the component of collective efficacy. Intercept is estimated but unreported.

	Power plants industry								
	Baseline	Regulate		Support RPS		Ln(No. facilities)		Placebo	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AS $\times$ Post	-0.242**	-0.210**	0.311	-0.215**	-0.484	-0.211**	-0.232	-0.245**	-0.244**
	(-3.05)	(-2.70)	(0.34)	(-2.68)	(-0.67)	(-2.72)	(-1.83)	(-3.04)	(-3.03)
Regulate $\times$ Post		-0.007				-0.007	-0.007		
		(-1.45)				(-1.47)	(-1.47)		
SupportRPS $\times$ Post				-0.006					
				(-1.32)					
Ln(No. facilities) $\times$ Post						-0.009			
						(-0.60)			
AS $\times$ Regulate $\times$ Post			-0.012						
			(-1.18)						
NAS $\times$ Regulate $\times$ Post			-0.005						
			(-0.97)						
AS $\times$ SupportRPS $\times$ Post					-0.003				
					(-0.30)				
NAS $\times$ SupportRPS $\times$ Post					-0.007				
					(-1.36)				
AS $\times$ Ln(No. facilities) $\times$ Post							-0.002		
							(-0.07)		
NAS $\times$ Ln(No. facilities) $\times$ Post							-0.013		
							(-0.70)		
Social capital $\times$ Post								0.001	
								(0.04)	
Social capital$^-$ $\times$ Post									-0.010
									(-0.31)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17108	16720	16720	16720	16720	16720	16720	16573	16573
Adj. R^2	0.879	0.879	0.879	0.879	0.879	0.879	0.879	0.878	0.878

Standard errors are clustered at the facility and reporting year level

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

Table 27: CO_2 equivalent emissions from facilities: oil & gas

The table below presents the regression estimates in oil & gas industry. The number of facilities owned by parent (in logarithm) is used as a proxy for the parent firm size. Social capital index measured at 2018 is used as a placebo. Social capital^{-} is the social capital index excluding the component of collective efficacy. Intercept is estimated but unreported.

	Oil & Gas industry								
	Baseline	Regulate		Support RPS		Ln(No. facilities)		Placebo	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
AS × Post	0.063	0.121	-2.018	0.082	-1.916*	0.122	0.379**	0.050	0.038
	(0.77)	(1.47)	(-1.25)	(1.03)	(-1.84)	(1.49)	(2.97)	(0.56)	(0.41)
Regulate × Post		-0.009				-0.011	-0.010		
		(-1.19)				(-1.54)	(-1.40)		
SupportRPS × Post				-0.001					
				(-0.22)					
Ln(No. facilities) × Post						-0.026*			
						(-2.01)			
AS × Regulate × Post			0.016						
			(0.71)						
NAS × Regulate × Post			-0.013						
			(-1.82)						
AS × SupportRPS × Post					0.022				
					(1.40)				
NAS × SupportRPS × Post					-0.008				
					(-1.31)				
AS × Ln(No. facilities) × Post							-0.139**		
							(-3.12)		
NAS × Ln(No. facilities) × Post							-0.004		
							(-0.35)		
Social capital × Post								0.039	
								(1.15)	
Social capital^{-} × Post									0.044
									(0.95)
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	14084	12857	12857	12857	12857	12857	12857	12580	12580
Adj. R^2	0.758	0.755	0.755	0.755	0.755	0.755	0.755	0.758	0.758

Standard errors are clustered at the facility and reporting year level

*: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level

7 Robustness checks

In Hypotheses 1 and 2, considerable attention was paid to skewness and kurtosis in *daily* returns measured at different time period intervals. It is noteworthy that while the everyday news helps investors forecast firms' expected cash flows and discount rates thereby impacting daily returns, equity markets also incorporate less-frequent fundamental variations in demographics, in technological innovation, or in consumption, dividends, and macroeconomic uncertainty (Calvet and Fisher, 2007). What makes this topic more intriguing is the empirical fact that the relationship between the higher moments of long and short horizon returns is not confined to a linear one and thus can be realized in various forms (Neuberger and Payne, 2018). Hence, it is of equal interest to scrutinize how the higher moments of longer horizon returns (e.g., monthly, quarterly) play out on the interface between CSR, market pessimism, and future returns. One problematic issue, however, is that the skewness in long horizon returns is increasingly difficult to measure (Neuberger, 2012) and indeed higher moment estimates such as skewness and kurtosis are sensitive to return horizon (e.g., Amaya et al., 2015); moreover, returns are exceedingly susceptible to outliers during a period of high stock market uncertainty, which is especially relevant to Hypothesis 2. Against this backdrop, MIDAS regression can effectively address these concerns by (i) using high frequency returns (i.e., daily) to compute lower frequency returns and (ii) mitigating the influence of outliers with the help of quantile-based measures.

In measuring skewness and (excess) kurtosis—the third and fourth standardized moments (cumulants)—these metrics are representative of the tails of the probability distribution, as indicated by the greater weight assigned through the exponent in their formulae: while skewness compares the relative size of the two tails (i.e., asymmetry), kurtosis is a measure of the summed sizes of the two tails. In light of their susceptibility to outliers, it is essential to implement robust metrics to alleviate measurement errors.[31] It should not escape our attention, however, that there is a fine line between an extreme event which is explained by a single probability model, and an outlier which is by definition not considered to be generated by the model. There is no canonical approach to defining an outlier and thus the threshold ultimately boils down to a subjective decision. Although winsorization or truncation is a legitimate treatment for outliers when they are caused by data errors (i.e., deviation from the data-generating process), applying these treatments prior to regression estimation can also lead to either less efficient or biased estimates when the extreme values are generated

[31] DUVOL does not require the third moment for its computation and thus less susceptible to outliers in comparison to CSKEW.

from the underlying data-generating process (Leone, Minutti-Meza, and Wasley, 2019).

7.1 Quantile-based approach to deriving skewness and kurtosis

Extant literature suggests that there are two approaches to measuring tail risk: physical moments relying on backward-looking information or risk-neutral moments relying on forward-looking information in options. Equally important, the disparity between the physical and the risk-neutral densities could be immense.[32] With this in mind, I construct skewness and kurtosis measures using quantile-based approach instead of using options data so that I can continue to implement analyses within the realm of physical moment measure, while suppressing the influence of outliers at the same time. Specifically I extend the framework of Ghysels, Plazzi, and Valkanov (2016) (henceforth GPV)[33] and derive both skewness and kurtosis measures from conditional quantiles, for quantile-based measures are insensitive to outliers by design. I adopt the measures of quantile-based skewness proposed by (i) Groeneveld and Meeden (1984) (based on Hinkley (1975)) as well as quantile-based (excess) kurtosis proposed by (ii) Moors (1988) and (iii) Hogg (1974). It is noteworthy that the degree of sensitivity to outliers varies across measures.[34]

I outline the logistics of the procedure. In the first step, I employ Cornish-Fisher expansion to approximate a quantile of a given probability distribution with the help of (i) the cumulants $\{\kappa_i\}_{i=1,2,...}$ of the distribution and (ii) a normal distribution. Thus I can express the above-mentioned quantile-based measures through the third standardized cumulant κ_3 (i.e., skewness *parameter*) and the fourth standardized cumulant κ_4 (i.e., excess kurtosis *parameter*) of the distribution (see Appendix A for details).[35] In the second step, the quantiles are estimated by MIDAS regression using time series of each stock return and quantile-based measures are thus obtained through computation. In the third step, the theoretical aspect (first step) and the empirical aspect (second step) are combined to solve for the cumulant parameters (κ_3, κ_4). Details with numerical examples follow.

[32] For example, Bakshi, Kapadia, and Madan (2003) argue that the substantive gap between risk-neutral and physical skewness mainly arise from risk aversion and the long-tail feature of physical distributions.

[33] GPV report that their quantile-based skewness estimators versus moment-based skewness estimators yield mean-squared-error performance overall ranging from equal to superior when confronted with fat tails, outliers, or both.

[34] For instance, Moors coefficient completely shuts out the effect from outliers: see Kim and White (2004) for details.

[35] For a given random variable, $\mu_1 = \kappa_1$, $\mu_2 = \kappa_2$, $\mu_3 = \kappa_3$, and $\mu_4 - 3\mu_2^2 = \kappa_4$ hold. This indicates $\mu_3/\mu_2^{1.5} = \kappa_3/\kappa_2^{1.5}$ and $\mu_4/\mu_2^2 - 3 = \kappa_4/\kappa_2^2$, that is, (i) the third standardized moment (i.e., skewness) equals to the third standardized cumulant and (ii) the fourth standardized moment less three (i.e., excess kurtosis) equals to the fourth standardized cumulant. However, the observed parameters (κ_3, κ_4) in the

In the first step, I apply Cornish-Fisher expansion to skewness and kurtosis measures (see Appendix B for details). Let the n-period return of an asset $r_{t,n}$ be $r_{t,n} = \prod_{j=0}^{h-1}(1+r_{t+j})-1$: daily (monthly) return corresponds to $n = 1$ ($n = 22$). Using the skewness measure proposed by Groeneveld and Meeden (1984) as an example, I then employ the trapezoidal rule below to compute the integral along a non-uniform grid of $\alpha = \{0.99, 0.975, 0.95, 0.90, 0.85, 0.80, 0.75, 0.50\}$ and $1-\alpha$. The estimation method of conditional quantiles $F^{-1}_{r_{t,n|t-1}}(\alpha)$ in equation (14) follows in the second step.

$$S^{GM}_{t-1}(r_{t,n}) = \frac{\int_{0.5}^{1}[F^{-1}_{r_{t,n|t-1}}(\alpha) - F^{-1}_{r_{t,n|t-1}}(0.50)]d\alpha - \int_{0.5}^{1}[F^{-1}_{r_{t,n|t-1}}(0.50) - F^{-1}_{r_{t,n|t-1}}(1-\alpha)]d\alpha}{\int_{0.5}^{1}[F^{-1}_{r_{t,n|t-1}}(\alpha) - F^{-1}_{r_{t,n|t-1}}(1-\alpha)]d\alpha} \tag{14}$$

In the second step, I estimate the quantiles using Mixed Data Sampling (MIDAS) regression. MIDAS regression is capable of running parsimoniously parameterized regressions with data of mixed frequencies. MIDAS regression together with asymmetric absolute loss function are used to estimate conditional n-period return quantiles $q_{\alpha,t-1}(r_{t,n})$. Note that $q_{\alpha,t-1}(r_{t,n};\boldsymbol{\theta}_{\alpha,n})$ in equation (15) is conditioned on the information set I_{t-1}, whereby the information set I_{t-1} is a D day rolling window. Emboldened symbols are vectors.

$$\begin{aligned} q_{\alpha,t-1}(r_{t,n};\boldsymbol{\theta}_{\alpha,n}) &= \beta^0_{\alpha,n} + \beta^1_{\alpha,n}\sum_{d=0}^{D}\omega_d\, x_{t-1-d} && (15)\\ &= \beta^0_{\alpha,n} + \beta^1_{\alpha,n}\sum_{d=0}^{D}\omega_d(\boldsymbol{k}_{\alpha,n})\, x_{t-1-d} && (16)\\ &= \beta^0_{\alpha,n} + \gamma_0(k_{2,\alpha,n})\,|r_{t-1}| + \gamma_1(k_{2,\alpha,n})\,|r_{t-2}| + ... + \gamma_D(k_{2,\alpha,n})\,|r_{t-1-D}| && (17) \end{aligned}$$

As per the transition from equation (15) to (16), I follow GPV and specify $\omega_d = \omega_d(\boldsymbol{k}_{\alpha,n})$ as a beta polynomial, where $\boldsymbol{k}_{\alpha,n} = (k_{1,\alpha,n}, k_{2,\alpha,n})$ and $\sum_{d=0}^{D}\omega_d(\boldsymbol{k}_{\alpha,n}) = 1$. Here the unrestricted estimation in equation (18) is challenging to implement and therefore a downward-sloping weighting scheme is imposed by the restriction $k_{1,\alpha,n} = 1$, namely $\boldsymbol{k}_{\alpha,n} = (1, k_{2,\alpha,n})$. This series of treatment allows me to significantly reduce the parameters to be estimated. Consistent with previous literature, I use absolute daily returns $|r_{t-1-d}|$ as regressors x_{t-1-d}, which is represented in equation (17).

$$\omega_d(\boldsymbol{k}_{\alpha,n}) = \frac{f(\frac{d}{D}, k_{1,\alpha,n}, k_{2,\alpha,n})}{\sum_{d=1}^{D} f(\frac{d}{D}, k_{1,\alpha,n}, k_{2,\alpha,n})} \tag{18}$$

formula obtained via Cornish-Fisher expansion should not be viewed as actual skewness and excess kurtosis in a strict sense. This is because the parameters and actual values approximately coincide only when the parameter values are "small" (i.e., "closer" to a normal distribution): see Maillard (2012) and Lamb, Monville, and Tee (2016) for more discussion.

where $f(z,a,b) = z^{a-1}(1-z)^{b-1}/[\Gamma(a)\Gamma(b)/\Gamma(a+b)]$. Now, $\boldsymbol{\theta}_{\alpha,n} = (\beta^0_{\alpha,n}, \beta^1_{\alpha,n}, k_{2,\alpha,n})$ are the unknown parameters to be estimated. The estimated $\hat{\boldsymbol{\theta}}_{\alpha,n}$ is derived such that asymmetric absolute loss function is minimized (e.g., Cameron and Trivedi, 2012).

$$\hat{\boldsymbol{\theta}}_{\alpha,n} \coloneqq \underset{\boldsymbol{\theta}_{\alpha,n}}{\arg\min} \left[\sum_{t:\, e\geq 0}^{T} \alpha \left| e_{\alpha,n,t} \right| + \sum_{t:\, e<0}^{T} (1-\alpha) \left| e_{\alpha,n,t} \right| \right] \tag{19}$$

where $e_{\alpha,n,t} = r_{t,n} - q_{\alpha,\,t-1}(r_{t,n}; \boldsymbol{\theta}_{\alpha,n})$.

In the third step, I solve the simultaneous equations originated from previous steps (see Appendix B for the derivation): here I use the combination of GM skewness and Hogg kurtosis as an example. The theoretical approximation based on Cornish-Fisher expansion is applied on the left hand side, while trapezoidal rule is adopted to compute the integral on the right hand side. $(skew, kurt)$ is the solution to the simultaneous equation, solving for $(\kappa_3^{t,n}, \kappa_4^{t,n})$, where the superscript originates from n-period return $r_{t,n}$ at time period t. Note that $F^{-1}_{r_{t,n|t-1}}(\alpha)$ in equation (14) is replaced by $\hat{q}_{\alpha,\,t-1}(r_{t,n})$, the quantile estimates from MIDAS regression.

$$\frac{\kappa_3^{t,n}/12}{0.3989 - 0.0166\kappa_4^{t,n} + 0.0111(\kappa_3^{t,n})^2} = \frac{\int_{0.5}^{1} \left[[\hat{q}_{\alpha,\,t-1}(r_{t,n}) - \hat{q}_{0.50,\,t-1}(r_{t,n})] - [\hat{q}_{0.50,\,t-1}(r_{t,n}) - \hat{q}_{1-\alpha,\,t-1}(r_{t,n})] \right] d\alpha}{\int_{0.5}^{1} [\hat{q}_{\alpha,\,t-1}(r_{t,n}) - \hat{q}_{1-\alpha,\,t-1}(r_{t,n})] d\alpha}$$

$$10 \cdot \frac{0.1031 + 0.0073\kappa_4^{t,n} - 0.0126(\kappa_3^{t,n})^2}{0.3989 - 0.0166\kappa_4^{t,n} + 0.0111(\kappa_3^{t,n})^2} - 2.59 = \frac{\int_{0.95}^{1} \hat{q}_{\alpha,\,t-1}(r_{t,n}) d\alpha - \int_{0}^{0.05} \hat{q}_{\alpha,\,t-1}(r_{t,n}) d\alpha}{\int_{0.5}^{1} \hat{q}_{\alpha,\,t-1}(r_{t,n}) d\alpha - \int_{0}^{0.5} \hat{q}_{\alpha,\,t-1}(r_{t,n}) d\alpha} - 2.59$$

7.2 Results with robust measures

This subsection replaces the skewness and kurtosis measures of previous analyses with the robust skewness and kurtosis measures constructed by MIDAS regression to examine whether I obtain coherent findings. The analytical framework is laid out up to this point and the empirical results are left for future research: MATLAB code readily provided by Ghysels, Plazzi, and Valkanov (2016) can be modulated to fit the needs of my analysis.

8 Conclusion

From the perspective of CSR, this paper studies three channels that account for the differentials in the higher moments of stock market returns. The suggestive evidence on the market pessimism channel—that is, CSR valuation is reinforced by market pessimism and leads to higher systematic skewness and lower systematic kurtosis in returns amid market crises—

complements the findings of the firm specific channel examined by KLL. As regards the green optimism channel, crucial evidence was confirmed that (i) the parallel announcements affected not only the firms headquartered in alliance states but the firms headquartered in non-alliance states and (ii) a nation-wide corporate effort to reduce emissions was observed in the aftermath of this event, except for the power plants and mining industries. Therefore, the solidarity of socially oriented investors and the corporate green philosophies were in a sense revealed and, in this context, the findings suggest that the initiatives in environmental policies are widely affirmed by diverse actors.

However, this paper is subject to some limitations. For example, the market pessimism channel requires more rigorous examination by studying the higher moments of low-frequency returns (e.g., monthly), which is described in Section 7. Additionally, I acknowledge that I put forward the green optimism channel without full confirmatory evidence. This is particularly because, in explaining the reason firms located in the non-alliance states were also considerably exposed to the announcement on the climate alliance formation, it is burdensome to disentangle the channel through which the effects of subsidiaries and/or supply chains are at play from the channel in which investors speculate based on firm's environmental orientation. Hence, additional inspection on this matter is left for future research.

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Appendix A. Cornish-Fisher expansion

Cornish-Fisher expansion (Cornish and Fisher, 1938) is a method that approximates the α^{th} quantile of a probability distribution F_X by using cumulants $\{\kappa_i\}_{i=1,2,3..}$ of the distribution and a standard normal distribution Φ. In addition, alternative approximation methods exist such as Edgeworth expansion and Gram-Charlier expansion, yet I extend the work of GPV and opt for Cornish-Fisher expansion.

Now, Cornish-Fisher (inverse) expansion can be formulated as $F_X^{-1}(\alpha) = \sum_{k=0}^{\infty} a_k(\Phi^{-1}(\alpha))^k$, where a_k is a polynomial in the cumulants of X and Φ is the standard normal distribution. In this regard, I consider up to the fourth order ($k = 3$) as opposed to the third order ($k = 2$) in GPV so as to include the fourth standardized cumulant.[36] The truncation after the fourth order is also supported by conventions (Lamb, Monville, and Tee, 2016).

In what follows, I standardize distributions but the discussion can be easily generalized to non-standardized distributions. Let X^* be a random variable that follows a standardized distribution F_{X^*} with zero mean and a unit standard deviation. Moreover, let Φ be a standard normal distribution. The following case uses two cumulants $\{\kappa_i\}_{i=3,4}$ for approximation[37]—the third standardized cumulant κ_3 is the *skewness parameter*, and the fourth standardized cumulant κ_4 is the *excess kurtosis parameter*. I base my analysis on the following formulae, where the last equation is rearranged in terms of κ_3, κ_4, and κ_3^2.

$$
\begin{aligned}
F_{X^*}^{-1}(\alpha) \approx & \sum_{k=0}^{3} a_k(\Phi^{-1}(\alpha))^k \\
= & -\frac{\kappa_3}{6} + (1 + 5 \cdot \frac{\kappa_3^2}{36} - 3 \cdot \frac{\kappa_4}{24})\, \Phi^{-1}(\alpha) + \frac{\kappa_3}{6}(\Phi^{-1}(\alpha))^2 + (\frac{\kappa_4}{24} - 2 \cdot \frac{\kappa_3^2}{36})(\Phi^{-1}(\alpha))^3 \\
= & \Phi^{-1}(\alpha) + (\Phi^{-1}(\alpha)^2 - 1) \cdot \frac{\kappa_3}{6} + [\Phi^{-1}(\alpha)^3 - 3\Phi^{-1}(\alpha)] \cdot \frac{\kappa_4}{24} - [2\Phi^{-1}(\alpha)^3 - 5\Phi^{-1}(\alpha)] \cdot \frac{\kappa_3^2}{36}
\end{aligned}
$$

For the general case of a random variable X with mean μ and standard devitation σ, the α^{th} quantile of X can be readily obtained by using the corresponding α^{th} quantile of X^* together with the transformation $X = X^*\sigma + \mu$. I denote the respective coefficients on the cumulants in the last equation above as $a(\alpha)$, $b(\alpha)$, $c(\alpha)$, and $d(\alpha)$ as follows:

[36] In further justification, Cornish-Fisher expansion belongs to a class of asymptotic expansions but the approximation is increasing only if the highest power of k is odd.

[37] $\{\kappa_i\}_{i=1,2}$ equal to zero and one, respectively, in a standardized distribution.

$$
\begin{aligned}
a(\alpha) =& \Phi^{-1}(\alpha) \\
b(\alpha) =& \frac{1}{6}(\Phi^{-1}(\alpha)^2 - 1) \\
c(\alpha) =& \frac{1}{24}[\Phi^{-1}(\alpha)^3 - 3\Phi^{-1}(\alpha)] \\
d(\alpha) =& -\frac{1}{36}[2\Phi^{-1}(\alpha)^3 - 5\Phi^{-1}(\alpha)]
\end{aligned}
$$

With simple computation, $a(1-\alpha) = -a(\alpha)$, $b(1-\alpha) = b(\alpha)$, $c(1-\alpha) = -c(\alpha)$, and $d(1-\alpha) = -d(\alpha)$ hold. Moreover, $a(0.5) = c(0.5) = d(0.5) = 0$, and $b(0.5) = -1/6$.

Appendix B. Robust measures of skewness and kurtosis

Approximations of quantile-based measures follow below, where the notation succeeds from Appendix A. For each case, the denominator serves as a scaling factor which guarantees the identical outcome even in the presence of a linear transformation of the random variable (Kim and White, 2004). Thus, F_X can be viewed as the distribution F_{X^*} with zero mean and unit standard deviation without loss of generality, in which case the argument in Appendix A is readily applicable:

1. Skewness measures: Hinkley (1975) and Groeneveld and Meeden (1984)

$$
\begin{aligned}
S_\alpha^{Hinkley}(X) =& \frac{[F_X^{-1}(\alpha) - F_X^{-1}(0.50)] - [F_X^{-1}(0.50) - F_X^{-1}(1-\alpha)]}{F_X^{-1}(\alpha) - F_X^{-1}(1-\alpha)} \\
=& \frac{F_X^{-1}(\alpha) + F_X^{-1}(1-\alpha) - 2F_X^{-1}(0.50)}{F_X^{-1}(\alpha) - F_X^{-1}(1-\alpha)} \\
=& \frac{[a(\alpha) + b(\alpha)\kappa_3 + c(\alpha)\kappa_4 + d(\alpha)\kappa_3^2] + [-a(\alpha) + b(\alpha)\kappa_3 - c(\alpha)\kappa_4 - d(\alpha)\kappa_3^2] + \frac{2}{6}\kappa_3}{[a(\alpha) + b(\alpha)\kappa_3 + c(\alpha)\kappa_4 + d(\alpha)\kappa_3^2] - [-a(\alpha) + b(\alpha)\kappa_3 - c(\alpha)\kappa_4 - d(\alpha)\kappa_3^2]} \\
=& \frac{\frac{2}{6}(\Phi^{-1}(\alpha)^2 - 1)\kappa_3 + \frac{2}{6}\kappa_3}{2a(\alpha) + 2c(\alpha)\kappa_4 + 2d(\alpha)\kappa_3^2} = \frac{\frac{1}{6}\Phi^{-1}(\alpha)^2\kappa_3}{a(\alpha) + c(\alpha)\kappa_4 + d(\alpha)\kappa_3^2}
\end{aligned}
$$

Thus $S_\alpha^{Hinkley} = \Phi^{-1}(\alpha)^2\kappa_3/6[a(\alpha) + c(\alpha)\kappa_4 + d(\alpha)\kappa_3^2]$ and its integrated variation over α

proposed by Groeneveld and Meeden (1984) is as follows:

$$
\begin{aligned}
S^{GM}(X) &= \frac{\int_{0.5}^{1}[F_X^{-1}(\alpha) - F_X^{-1}(0.50)]d\alpha - \int_{0.5}^{1}[F_X^{-1}(0.50) - F_X^{-1}(1-\alpha)]d\alpha}{\int_{0.5}^{1}[F_X^{-1}(\alpha) - F_X^{-1}(1-\alpha)]d\alpha} \\
&= \frac{1}{6} \cdot \frac{\kappa_3 \int_{0.5}^{1} \Phi^{-1}(\alpha)^2 d\alpha}{\int_{0.5}^{1} a(\alpha)d\alpha + \kappa_4 \int_{0.5}^{1} c(\alpha)d\alpha + \kappa_3^2 \int_{0.5}^{1} d(\alpha)d\alpha} \\
&\approx \frac{1}{12} \cdot \frac{\kappa_3}{0.3989 - 0.0166\kappa_4 + 0.0111\kappa_3^2}
\end{aligned}
$$

Note that $\int_{0.5}^{1} \Phi^{-1}(\alpha)d\alpha \approx 0.3989$, $\int_{0.5}^{1} \Phi^{-1}(\alpha)^2 d\alpha \approx 0.5$, and $\int_{0.5}^{1} \Phi^{-1}(\alpha)^3 d\alpha \approx 0.7979$.

2. Kurtosis measure: Moors (1988)

Moors proposed the following kurtosis measure:

$$
K^{Moors} = \frac{(T_7 - T_5) + (T_3 - T_1)}{T_6 - T_2}
$$

Centered coefficient version (analogous to coefficient of excess kurtosis)

$$
K^{Moors} = \frac{(T_7 - T_5) + (T_3 - T_1)}{T_6 - T_2} - 1.23
$$

Calculation:

$$
\begin{aligned}
K^{Moors}(X) =& \frac{[F_X^{-1}(0.875) - F_X^{-1}(0.625)] + [F_X^{-1}(0.375) - F_X^{-1}(0.125)]}{F_X^{-1}(0.750) - F_X^{-1}(0.250)} \\
=& \frac{[F_X^{-1}(0.875) - F_X^{-1}(0.125)] - [F_X^{-1}(0.625) - F_X^{-1}(0.375)]}{F_X^{-1}(0.750) - F_X^{-1}(0.250)} \\
=& \frac{2[a(0.875) + c(0.875)\kappa_4 + d(0.875)\kappa_3^2] - 2[a(0.625) + c(0.625)\kappa_4 + d(0.625)\kappa_3^2]}{2[a(0.750) + c(0.750)\kappa_4 + d(0.750)\kappa_3^2]} \\
=& \frac{a(0.875) - a(0.625) + [c(0.875) - c(0.625)]\kappa_4 + [d(0.875) - d(0.625)]\kappa_3^2}{a(0.750) + c(0.750)\kappa_4 + d(0.750)\kappa_3^2}
\end{aligned}
$$

3. Kurtosis measure: Hogg (1974)

Hogg proposed the following kurtosis measure. Hogg (1974) reports that $\alpha = 0.05$ and $\beta = 0.5$ give the most desirable result.

$$K^{Hogg}(X) = \frac{\frac{1}{\alpha}\int_{1-\alpha}^{1} F_X^{-1}(t)dt - \frac{1}{\alpha}\int_{0}^{\alpha} F_X^{-1}(t)dt}{\frac{1}{\beta}\int_{1-\beta}^{1} F_X^{-1}(t)dt - \frac{1}{\beta}\int_{0}^{\beta} F_X^{-1}(t)dt}$$

Centered coefficient:

$$K^{Hogg}(X) = \frac{\frac{1}{\alpha}\int_{1-\alpha}^{1} F_X^{-1}(t)dt - \frac{1}{\alpha}\int_{0}^{\alpha} F_X^{-1}(t)dt}{\frac{1}{\beta}\int_{1-\beta}^{1} F_X^{-1}(t)dt - \frac{1}{\beta}\int_{0}^{\beta} F_X^{-1}(t)dt} - 2.59$$

Calculation:

$$K^{Hogg}(X) = 10 \cdot \frac{\int_{0.95}^{1} F_X^{-1}(t)dt - \int_{0}^{0.05} F_X^{-1}(t)dt}{\int_{0.5}^{1} F_X^{-1}(t)dt - \int_{0}^{0.5} F_X^{-1}(t)dt}$$

$$= 10 \cdot \frac{\int_{0.95}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0}^{0.05}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt}{\int_{0.5}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0}^{0.5}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt}$$

If we replace t with $t = 1 - s$ in the second integrals in both the numerator and denominator,

$$10 \cdot \frac{\int_{0.95}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{1}^{0.95}[a(1-s) + b(1-s)\kappa_3 + c(1-s)\kappa_4 + d(1-s)\kappa_3^2](-ds)}{\int_{0.5}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{1}^{0.95}[a(1-s) + b(1-s)\kappa_3 + c(1-s)\kappa_4 + d(1-s)\kappa_3^2](-ds)}$$

$$= 10 \cdot \frac{\int_{0.95}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0.95}^{1}[a(1-s) + b(1-s)\kappa_3 + c(1-s)\kappa_4 + d(1-s)\kappa_3^2]ds}{\int_{0.5}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0.95}^{1}[a(1-s) + b(1-s)\kappa_3 + c(1-s)\kappa_4 + d(1-s)\kappa_3^2]ds}$$

Applying the results in Appendix A,

$$=10 \cdot \frac{\int_{0.95}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0.95}^{1}[-a(s) + b(s)\kappa_3 - c(s)\kappa_4 - d(s)\kappa_3^2]ds}{\int_{0.5}^{1}[a(t) + b(t)\kappa_3 + c(t)\kappa_4 + d(t)\kappa_3^2]dt - \int_{0.5}^{1}[-a(s) + b(s)\kappa_3 - c(s)\kappa_4 - d(s)\kappa_3^2]ds}$$

Replacing s with t (i.e., notational change),

$$=10 \cdot \frac{\int_{0.95}^{1}[a(t)+b(t)\kappa_3+c(t)\kappa_4+d(t)\kappa_3^2]dt-\int_{0.95}^{1}[-a(t)+b(t)\kappa_3-c(t)\kappa_4-d(t)\kappa_3^2]dt}{\int_{0.5}^{1}[a(t)+b(t)\kappa_3+c(t)\kappa_4+d(t)\kappa_3^2]dt-\int_{0.5}^{1}[-a(t)+b(t)\kappa_3-c(t)\kappa_4-d(t)\kappa_3^2]dt}$$

$$=10 \cdot \frac{\int_{0.95}^{1} 2[a(t)+c(t)\kappa_4+d(t)\kappa_3^2]dt}{\int_{0.5}^{1} 2[a(t)+c(t)\kappa_4+d(t)\kappa_3^2]dt}$$

$$=10 \cdot \frac{\int_{0.95}^{1} a(t)dt+\kappa_4\int_{0.95}^{1} c(t)dt+\kappa_3^2\int_{0.95}^{1} d(t)dt}{\int_{0.5}^{1} a(t)dt+\kappa_4\int_{0.5}^{1} c(t)dt+\kappa_3^2\int_{0.5}^{1} d(t)dt}$$

Using $\int_{0.95}^{1}\Phi^{-1}(\alpha)d\alpha \approx 0.1031$, $\int_{0.95}^{1}\Phi^{-1}(\alpha)^2 d\alpha \approx 0.2196$, and $\int_{0.95}^{1}\Phi^{-1}(\alpha)^3 d\alpha \approx 0.4853$,

$$= 10 \cdot \frac{0.1031+0.0073\kappa_4-0.0126\kappa_3^2}{0.3989-0.0166\kappa_4+0.0111\kappa_3^2}$$

Does Climate Change Concern Lead to Greenium?

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August 13, 2022

Abstract

To date the (non-)presence of green bond premium (i.e., greenium) has been debated. It is still unclear, however, how broadly and genuinely the notion of climate change is perceived by investors and urges them to mitigate its risk and uncertainty through green investments—a likely effective channel of greenium. To this end, I draw on the data from the US municipal bond market, which is largely populated by retail investors and segmented by states due to heterogeneous tax exemptions. I take a model-free matching approach and construct a matched bond data set to conduct a series of descriptive analyses. I find substantially higher demands for green munis in some states, which may point to the serious concern about human-induced climate change as well as to a call for environmental sustainability. Exploiting a quasi-experimental design based on natural disasters, the future agenda is to examine the degree to which an exogenous disaster-induced *change* in individual preferences for climate risk—as opposed to the *level*, which has been the focal point in extant research—leads to more demand for green bonds (relative to brown bonds).

Keywords: green bond, extreme weather, natural disaster, climate change, WTP–WTA disparity, red/blue state, air pollution, COVID-19

JEL Classification: D14, G12, Q51, Q54

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1 Introduction

The scale and frequency of natural catastrophic events are reportedly accelerating due to global warming and the attention to climate change is proportionally on the rise. Investors in the financial markets are no exception to this impact and the investment landscape is undoubtedly being reshaped. Indeed, climate change is a pressing phenomenon (i) which may drive a socially oriented investor to donate a portion of wealth for its mitigation, but (ii) which could be too elusive for an average investor given its intangibility represented by the global scale and polarized public opinion. In these circumstances, green bonds—green assets that are earmarked for environmentally-friendly projects[1]—can serve as an effective measure against the climate risk, enabling issuers and investors to inform strategies on its mitigation and adaptation (WEF, 2018).

Of particular interest is how this relatively new financial instrument is valued in the financial market. Using municipal or corporate bond data, some researchers suggest that there is no greenium (Larcker and Watts, 2019; Flammer, 2020).[2] Anecdotal evidence also supports this view, reporting that a vast majority of retail and institutional investors (in the municipal bonds market) are reluctant to sacrifice a financial return for an environmental benefit by virtue of the continually opaque relationship between environmental benefit and lower risk (S&P Global Ratings, 2019b; Chiang, 2018). Moreover, the slow growth of US companies to issue corporate green bonds is arguably the reflection that the greenium is marginal at best and insufficient to cover the additional cost born by extra paperwork (e.g., regular reporting) (S&P Global Ratings, 2019a). It is true that the eco-friendly status of municipal green bonds can attract attention from environmentally-conscious individuals, but their lower yields also keep these green bonds out of the hands of investors who cannot take advantage of tax exemption, in particular, many major green bond buyers such as foreign insurance companies and pension funds (Chiang, 2017). The US green bond market thus remains largely retail-driven through SRI funds and wealth management channels. Other scholars, nevertheless, do find some empirical evidence that green bonds trade at a premium (or at a discount) (Baker et al., 2018; Zerbib, 2019; Alessi, Ossola, and Panzica,

[1] Green project use-of-proceeds categories include "renewable energy, energy efficiency, pollution prevention and control, environmentally sustainable management of living natural resources and land use, terrestrial and aquatic biodiversity conservation, clean transportation, sustainable water and waste water management, climate change adaptation, eco-efficient and/or circular economy adapted products, production technologies and processes, green buildings which meet regional, national or internationally recognized standards or certifications" (MSRB, 2018a).

[2] Greenium is the premium that green assets trade to otherwise identical non-green securities (Larcker and Watts, 2019).

2019; Kapraun and Scheins, 2019). In addition, Chiang (2017) endorses the notion that high-net-worth individual investors are more likely to show disposition for non-peculiarity in comparison to institutional investors. In sum, the existence of greenium continues to be a legitimate controversy.

Despite this rich body of literature on greenium, however, surprisingly little attention has been given to the interplay between greenium and climate change concern. At the individual level, a wealth of studies does document the link between an amplified concern on climate change through natural disaster experiences and the corresponding behavioral responses which usually follow. As an example, Spence et al. (2011) contend that a likely reasoning of a person's unwillingness to resort to climate change mitigation measures is the simple lack of first-hand experience and the association with its potential consequences—put differently, individuals who have direct exposure to events that are likely linked with climate change are more concerned and inclined to undertake sustainable behaviours accordingly. For another example, Bergquist, Nilsson, and Schultz (2019) examine the impact of an extreme-weather-event experience, the hurricane Irma, on beliefs about climate change, and find that intentions to take actions that can help prepare for and mitigate the climate change were afterwards strengthened. To put this into perspective, individuals correct their bias against the climate risk through personal experiences.

Even more, cognitive bias on the climate risk is not only limited to individuals but is observed in institutional actors as well. Another related strand of studies spans the impact of natural disasters on individual's perception and behavior. For instance, a growing literature on the financial markets indicates that climate risks may not be correctly priced and an accurate estimate of climate change risk poses a challenge to investors (Krueger, Sautner, and Starks, 2020; Hong, Li, and Xu, 2019; Daniel, Litterman, and Wagner, 2016). Alok, Kumar, and Wermers (2020) document that due to salience bias professional money managers misestimate climatic disaster risk, which can enter their portfolio if a disaster affects portfolio firms, as they unreasonably underweight their portfolio holdings of firms located in the disaster area. These pieces of evidence are consistent with the fact that climate risks modelling and the financial sector cannot efficiently price it without obtaining high-quality data and tools (WEF, 2018).

Against this backdrop, this paper empirically investigates the unexplored channel of greenium by throwing additional light on the climate change concern on a local scale. That is, one of the key sources of greenium is likely expected to emerge from the environmental concerns about anthropogenic climate change, or the long-term shift in climate patterns as a result of human activities. In this regard, this paper develops conjectures inspired by as well as nested within a body of research addressing the link between the perception climate risk and the ensuing behavioural response. My first hypothesis (Hypothesis 1) postulates that the valuation of green bonds accommodates the intensity of climate change concern at the local level. Some literature underpinning this conjecture documents that the reactions to personal experience of natural disasters are moderated by the state of mind, especially the ex-ante climate belief (Kunreuther et al., 2014; Mildenberger et al., 2017). Furthermore, one of the particular features in this paper is the focus on the municipal bond investors in the US, who are essentially high-income households and thus are hardly financially constrained and hold on to the asset on a long term basis. I give particular attention to this aspect owing to the fact that (i) US municipal bonds are typically bought by taxable investors including via intermediaries (e.g., mutual funds) and (ii) investors can benefit from the state and municipal taxes exemption—corresponding to their residential area—in addition to federal tax exemption.

After examining the association between the intensity of local climate belief and the green bond pricing in levels, I elucidate the *change* in the preference for sustainability. More precisely, my second hypothesis (Hypothesis 2) conjectures that that investors who have been personally exposed to extreme weathers and natural disasters—which can be arguably attributed to the result of human activities and connects with the broader story of climate change—may respond by investing more in green assets. In particular, I exploit a variation in the preferences for climate risk, which can be exogenously induced by personal experiences of extreme weather and natural disaster events. These events may (temporarily) impact the pricing of green bonds—endorsed by a wealth of literature suggesting that the effect only lasts in a short-term of window—but could be washed out in the entire period, indicating that greenium may not be confirmed under *levels* approach. Put differently, the temporary shock to the sustainability preference induced by weather-related disaster events may be too elusive to be captured in a levels approach to identifying greenium, which has been the mainstream extant research. To my knowledge only a few in climate finance literature exploits this research design, which leverages the shock to the preference for sustainability (e.g., Brandon and Krueger, 2018; Duan and Li, 2019; Choi, Gao, and Jiang, 2020).

As regards data and methods, I adopt a matching method to examine the differential pricing between green and brown bonds in the US municipal bond market: I implement the matching procedure based on same issuer, same dated date, maturity within one year difference, same aggregate ratings, and same coupon rates. As a result, I find empirical evidence under Hypothesis 1 that strongly lends support to the idea that differential pricing between green bonds and brown bonds arises according to different local regions with different climate belief intensity: the local region is measured at the state level on this matter using the survey of local climate change belief from Yale Climate Opinion Map. This finding is indeed substantiated by the anecdotal account in Massachusetts claiming that the green investors were willing to pay the premium for the green label and the issuer had the luxury of resetting the issuance size upwards and thus lowering the offering yield. Furthermore, other states such as in New York, Washington D.C., and even Texas show greenium–esque characteristics akin to Massachusetts. However, California surprisingly shows that green bonds are priced and traded at a discount. Moreover, I extend this analysis by using a bivariate frequency distribution between bond yields and intensity of climate belief. In doing so, I consider two variables, Human and CO_2limits, which are measured both at the state and county levels. In either case, local areas with lower climate change belief appear to associate green bonds with higher yields: in particular, this feature is more notable for the callable bond universe.

Hence, I add to the body of literature concerning the controversial topic of whether greenium exists by pointing to the corroborated evidence on a local scale. With regards to the second hypothesis, I experiment with weather-related disasters (e.g., heat wave, wind storm) but only report the preliminary results. The drawback of the matching methods underpinning the analysis under Hypothesis 1, however, is that it is infeasible to control for a host of variables. Thus, a regression approach together with access to Mergent database is left as a lucrative avenue for future study. The key is to examine the degree to which an exogenous disaster-induced *change* in individual preferences for climate risk—as opposed to the *level*, which has been the focal point in extant research—leads to more demand for green bonds (relative to brown bonds).

As a robustness check of behavioral sensitivity, I additionally postulate that the COVID-19 pandemic might have induced local residents to perceive air quality as a pressing issue, thereby shifting their preference for environmental problems encompassing air quality and urging them to act by taking countermeasures. It is certainly true that this behavioral mechanism takes place entirely through a different channel devoid of climate change concern, but the idea here is to elucidate how behaviourally responsive locals can be in the presence of the perceived aggravation in the external environment. This test is left for future research as well.

The remainder of the paper is organized as follows. Section 2 develops hypotheses and

Section 3 outlines the data collection process. Section 4 exhibits the empirical results. Section 5 tests the robustness of the results by using a different shock, COVID-19, to sustainability preference. Section 6 concludes.

2 Hypotheses development

The exposure to natural catastrophes in the US—such as droughts, severe storms, heat waves, wildfires, and other climate change induced hazards—is increasingly surging (Melillo, Richmond, and Yohe, 2014). On the one hand, a sizeable amount of scientific studies assessing contextual factors documents that these natural disasters and extreme weather events are proportionally attributed to anthropogenic climate change (Figure 1). On the other hand, there are studies stressing that the overall environmental awareness in the US is still dormant. For example, Egan and Mullin (2017) report that Americans still attach a low level of salience to climate change. Another study from Leiserowitz (2006) claims that although Americans consider climate change as a moderate risk, they do not view it as a pressing issue that calls for immediate measures—socioeconomic issues such as the state of the economy, public financing, and healthcare and environmental issues that are pertinent to daily life such as the standard of sanitation rank as higher priority because of their high relevance to locality. In other words, global climate change is perceived as a distant issue and not as pressing as local issues by Americans.

Furthermore, the work of Mildenberger et al. (2017) can be classified as the middle ground of this debate. The authors argue that climate opinion polarization among the general US public cannot be reduced to a simple political dichotomy between Republicans and Democrats. They find substantial within-party geographic variation on the intensity of climate beliefs, which shows spatial divergence at state and local scales. In line with this observation, empirical research in social science does show how one perceives climate change risks and uncertainties through external reality as well as observers' internal states, needs, and the cognitive and emotional functions (Kunreuther et al., 2014). These pieces of evidence may be able to explain why greenium is not substantively confirmed at the spatial aggregate level in previous studies whereby region-specific characteristics cancel out each other. This line of reasoning leads to Hypothesis 1:

Hypothesis 1: The valuation of green bonds reflects the intensity of local belief in climate change

According to Bennett and Wang (2019), the demand for municipal bonds in the primary market falls following natural disaster events and they attribute this behavior to salience theory of choice—that is, investors unjustifiably demand less bonds despite the little concern of issuer's default owing to the financial aid from federal and state governments. Besides, Cole, Ness, and Ness (2018) find that natural disasters such as tornadoes and wildfires lower municipal bond spreads but find no evidence that hurricanes affect municipal bond spreads in a similar manner.

This paper does not directly support nor negate these claims but instead engages in the framework encompassing the opposing effects on green and brown municipal bonds that may arise after the personal experience of disaster events. In particular, I argue that the net effect of the disaster on green bonds is more ambiguous in comparison to brown bonds. Although it is a legitimate expectation that the demand for green bonds will similarly drop in the absence of non-pecuniary preference, this logic does not apply to a socially oriented investor, who is by definition equipped with non-pecuniary utility. More important, even a neutral investor may possess a vested interest in holding green assets inasmuch as this investor feels concerns about climate change induced disasters and comes to view the investment as an effective mitigation measure against human-induced climate risk. A probable scenario is that the neutral investor internalizes the state of his surrounding environment in the aftermath of a natural disaster and integrates its intrinsic value into the domain of his (pecuniary) utility.

This line of reasoning centers on what is termed as WTP–WTA disparity in prior literature. A wider disparity between WTA and WTP is observed to a greater degree in public goods such as environmental goods than in items that are ordinarily traded in the markets (Horowitz and McConnell, 2002; Haab and McConnell, 2002; Irwin, 1994). Boyce et al. (1992) argue that although the several explanations for this phenomenon in relation to environmental goods is available, the intrinsic "moral" values characteristic to these commodities are the driver; intrinsic values are captured by WTA measures but excluded from WTP measures. Brown and Gregory (1999) claim that both economic and psychological account for WTP–WTA disparity: economic reasons range from income effects, transaction costs to implied value, and the profit motive; psychological reasons encompass the endowment effect, legitimacy, ambiguity, and responsibility.

In strong connection with the notion of WTP–WTA disparity, literature addressing the reaction of individuals (including individual investors) to climate risk realized through extreme weathers and natural disasters abound as exhibited in Table 1. In this regard, my conjecture genuinely hinges on the assumption that these natural-disaster experiences have sizeable impact on preference, attitude, and belief to the point that it encourages investors to (temporarily) change their behavior and mitigate climate change. Certainly, it empirically calls into question whether investors show desire for mitigation measures of climate change; as Stern (1992) points out, even in the presence of climate change risk people may not attempt to take efforts to mitigate it but rather adjust their personal values and adapt to what they are confronted with. To come to the point, the intensity of one's behaviours, and actions stimulated by the climate change concern boils down to the extent to which one genuinely comes to believe in climate change, internalize the value, and link the root cause to human activities. Given the underlying psychological aspects of how environmental concern may arise in the wake of natural disaster events, I postulate Hypothesis 2 as follows.

Hypothesis 2: Personal experience of natural disaster events reinforces the perception of human-induced climate change, thereby leading to higher valuation of green bonds in the post-disaster period

In the end, I provide supplementary information on the above-mentioned hypotheses. Specifically, I put forward Hypothesis 1 and 2 together with the premise that for tax-exemption motive, households correspondingly invest in the state they reside in through municipal bonds (e.g., Ang, Bhansali, and Xing, 2010; Cole, Liu, and Smith, 1994). This is because the municipal bond market is supported primarily by individual investors seeking to shield income from taxes, most of whom buy municipal bonds to hold them rather than to trade them—leading to the low market liquidity (Chiang, 2018).[3] From issuers' standpoint, this tax exemption allows them to benefit from lower financing cost (i.e., lower yields) but within the green muni bond market, this entails benefits as well as shortcomings (Chiang, 2018).

[3] In the US, investors can purchase bonds in the primary market or the secondary market and most ordinary investors, along with large institutions, buy bonds in the secondary market. Moreover, in the US municipal bond market, the lion's share is held by individual investors directly (40.8%) and indirectly via large cap mutual funds (24.6%) (Chiang, 2018)—the indirect ownership via mutual funds presumably occurs because of the low minimum investment thresholds (e.g., $2,500).

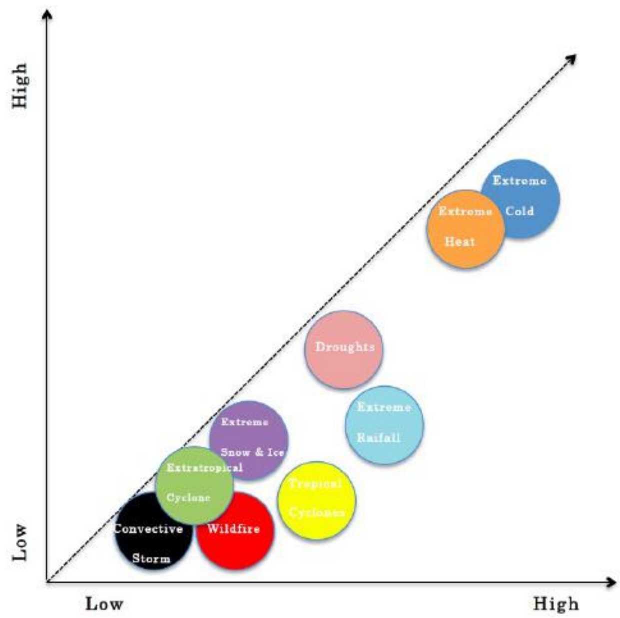
Table 1: Systematic literature review on the link between personal disaster experience and the ensuing behavioral patterns

In relation to Hypothesis 2, this table presents a systematic literature review on the link between personal disaster experience and the ensuing behavioral responses.

Authors	Country	Hazard	Design	Summary of findings
Baldauf, Garlappi, and Yannelis (2019)	US	Sea level rise	Theory, Regression	Climate change beliefs affected by sea level rise, in turn, influence real estate market prices
Duan and Li (2019)	US	Temperature increase	Regression	Abnormally high local temperature has a substantial negative effect on approval rate of mortgage lending at the county level in the US
Goldsmith-Pinkham et al. (2020)	US	Sea level rise	Regression	Local beliefs, incorporating regional exposure to sea level rise, have a bearing on municipal bond pricing as purchasers are mostly local retail investors because of the tax advantages of in-state ownership
Hazlett and Mildenberger (2019)	US	Wildfire	Regression	Experiences with wildfires enhance willingness-to-act only in groups that are more concerned and believe in human-caused climate change. Climate threats can enhance willingness-to-act, but predominately where the public already holds pro-climate beliefs
Konisky, Hughes, and Kaylor (2015)	US	Extreme weather	Regression	Positive association between personal extreme weather were revealed experience and expressions of concern on climate change
Lang and Ryder (2016)	US	Wind storm	Regression	Climate change related online searches surge after months following a wind storm event, suggesting that the people are displaying concern on climate change due to first hand experience
Li, Johnson, and Zaval (2011)	US, AU	Temperature increase	Survey, Regression	People were more likely to make pro-environmental donations after interpreting local temperature increases as evidence for global warming
Rudman, McLean, and Bunzl (2013)	US	Wind strom	Survey, Descriptive statistics	New Jersey residents were found to be more likely to support a green politician after experiencing Hurricane Sandy and Hurricane Irene than before each hurricane occurred, suggesting that exposure to extreme weather enhances pro-environmentalism
Spence et al. (2011)	UK	Flooding	Survey	A link between climate change perceptions and the willingness to reduce personal energy use was found stronger in the group who had personally experienced recent flooding

Figure 1: The attribution of specific events to anthropogenic climate change

The horizontal axis evaluates the perceived strength of the link between climate change and the event type. The vertical axis assesses the same link based on scientific methods (National Academies of Sciences, Engineering and Medicine, 2016)



3 Data and sample description

My initial sample under Hypothesis 1 builds on a matching procedure based on the structure of issued date, maturity, coupon rate, and credit ratings. The advantage of matching similar two securities is that to a large extent it can control for the confounding factors that affect the bond yields. I take this model-free matching approach and describe the matching procedure in what follows.

First, I prepare two CUSIP lists of green bonds from Bloomberg sorted on callable property after filtering out attributes such as federally taxable and being subject to AMT: I use the Green Instrument Indicator to identify green bonds. Municipal bond issuance before June 2013 are dropped because they are unlikely to have been originally marketed as Green bonds—essentially excluding CREB and QECB green bonds (Baker et al., 2018; LW). Second, using these CUSIP lists I pull dated date,[4] maturity, and coupon rates from MSRB database. Third, I use the first 6 digits of CUSIP (i.e., issuer identifier), dated date, maturity (one year difference is allowed), and coupon rates of these green bonds to pull potential brown bond matches from MSRB database for each green bond—obviously I have to ex-

[4]Unlike LW, I do not use issuance date because MSRB only offers dated date: I do not have access to Mergent. Still, issuance date and dated date most of the time exactly match.

clude the green-labelled bonds from these potential matches. Fourth, I web scrape Fidelity website to pull credit ratings, issuance amount, issuance state, and information of callability for green bonds as well as these potentially matched brown bonds. Given that data entry errors are prevalent in Bloomberg, I opt to identify an embedded call option based on both Bloomberg and fidelity data—if there is a disagreement between these two data sources, I drop the observations.[5] In the last step, I sift the matched brown bonds based on the following attributes: same issuer, same dated date, maturity within one year difference, same aggregate ratings, and same coupon rates, whereby the ratings are converted to a scale of 1 to 22 following LW: 1 is the highest rate, 22 is the lowest or unrated, and the aggregate rating is the average of S&P and Moody's ratings. In the end, the period of the final sample ranges from September 2014 to June 2020. The observations associated with the sample construction procedure are tabulated in Table 2. In the end, I obtain 360 non-callable green bonds and 395 callable green bonds.

An additional note is needed on the process of same coupon rate matching. In this study, coupon rates are exactly matched, while LW allow in their baseline case different coupon rates conditional on non-callable bond universe. In other words, they match coupon rates only when there is a callable feature attached to the bonds. Although it is imperative to match coupon rates for the callable bond universe—given that a bond embedded with a call option may exert a non-negligible influence on the pricing of bonds—I essentially take a conservative approach and also strictly match coupon rates for non-callable bond universe since anecdotal accounts and prior studies indicate that coupon rates and issuance size can affect pricing (LW).

Moreover, in constructing a subsample limited to the primary market (or the secondary market), I use List Offering Price/Takedown indicator consistent with LW, showing that "the transaction price was reported as a primary market sale transaction executed on the first day of trading of a new issue." Moreover, around 0.9% of bond transactions show zero or negative yields. Although a non-positive yield is theoretically achievable, I eventually drop all of the transactions with non-positive yields. This is because they are inconsistent with the dollar price, which is expected to be substantially high—this was not confirmed, however, indicating that these observations are likely to be data entry errors.

Panels A and B of Table 3 show that the mean yield differential between green and brown

[5] LW employ Mergent data to identify embedded call option of municipal bonds. The authors use both Bloomberg and Mergent to decide on the green labels of municipal bonds.

Table 2: Sample construction

The table below summarizes the construction of the matched bond sample based on the issuer, dated date, same aggregate credit ratings, and coupon rate. A margin of error of one year is allowed for maturity. The sample is limited to municipal bonds issued after June 2013. The first (second) column shows the number of green (brown) bonds in the sample.

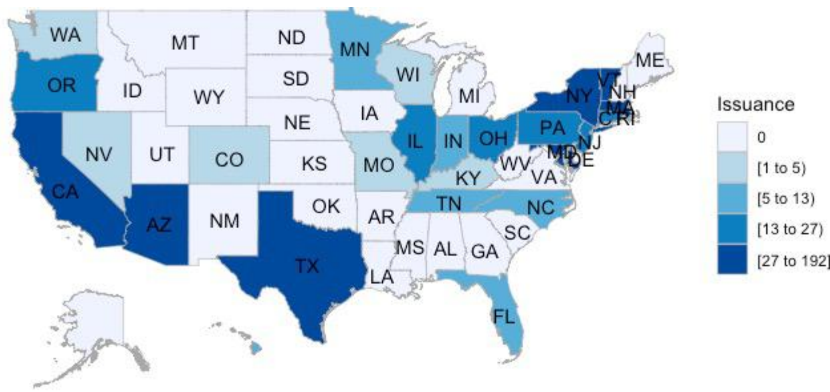
	Green bonds	Matched brown bonds
Full green bond sample (Bloomberg)	8420	–
Non-callable universe	3435	–
Callable universe	4985	–
MSRB matched	1045	1253
Non-callable universe	577	731
Callable universe	468	522
Same issuer/rating/coupon rate/dated date	755	807
Non-callable universe	360	397
Callable universe	395	410

bonds in my sample is −1.1 bps. However, if the whole sample is divided into non-callable and callable bond universes as shown in Table 4, the mean yield differential between green and brown bonds in non-callable (callable) universe becomes −5.6 (4.4) bps. In this respect, in addition to the difference in sample period, a difference between the descriptive statistics of yields can emerge principally from the difference in the data source. Specifically, while LW uses initial offering yield from Mergent, I use transaction data in the primary and secondary markets from MSRB. For comparison, I replicate the sample of LW by restricting my sample up to July 2018 and eliminating the distinction between non-callable and callable bond universes. According to the statistics provided by LW as well as Panels C and D of Table 3, the descriptive statistics of the green bond sample of LW (my sample) are 2.24% (2.84%) for mean yield, 2.23% (2.93%) for median yield, 5.36 (5.91) for mean issuance amount ($MM), 3.90% (4.24%) for mean coupon rates, and 2.62 (6.82) for mean aggregate ratings. My sample consists more of lower ratings bonds and this is driven by unrated bonds: the median of the aggregate ratings is 3.50 and thus much higher (Panel C of Table 3). Overall, this tendency leads to systematically higher yields in my sample.

In order to proxy for environmental concern on a local scale, I use the survey of local climate change belief from Yale Climate Opinion Map constructed by Howe, Mildenberger, Marlon et al. (2015)—in attempt to quantify how personal experiences with environmental

Figure 2: Cumulative municipal issuance of green bonds by state

This figure illustrates the cumulative number of municipal issuance counted at the state level over the period 2014–2020. The data only includes the green bonds that are matched with brown bonds.



phenomena are associated with climate change perceptions, beliefs, attitudes, behaviors, and policy support, the authors collectively refer to these constructs as public opinion about climate change, or climate opinions.[6] These data are measured both at the state and county levels and include a rich set of climate opinion related variables. As clarified in the database website, the inability to disentangle the effect of model improvement in mapping local climate belief from the genuine shift in actual belief over 2014, 2016, 2018, 2019, and 2020 data makes it challenging to fully draw on the panel structure of these data. Therefore, I use the survey data in 2018 in this study. In particular, I use as baseline cases the Human variable (the percentage estimate of "who think that global warming is caused mostly by human activities") and the CO_2limits variable (the percentage estimate of "who somewhat/strongly support setting strict limits on existing coal-fire power plants"). I also examine three more variables, Happening ("who think that global warming is happening"), Worried ("who are somewhat/very worried about global warming"), and HarmUS ("who think global warming will harm people in the US a moderate amount/a great deal") but only report these results briefly. Pearson correlation coefficients among these variables are substantially high—over 90% at the state level and over 77% at the county level .

[6]They validate high-resolution opinion estimates using a multilevel regression and poststratification (MRP) model whereby the model accurately predicts climate change beliefs, risk perceptions and policy preferences at the state, congressional district, metropolitan and county levels, using a concise set of demographic and geographic predictors.

Table 3: Summary statistics: full sample and LW replication

Panels A and B summarize the matched green and brown bonds, respectively, where callable and non-callable universes are combined. Panels C and D quasi-replicate the sample of LW by restricting the sample period up to July 2018 and the primary market data. The symbol † indicates that the data exclusively come from primary market source.

Panel A: GB (combined)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	2.48	0.77	0.80	1.94	2.47	3.03	4.06	51203
Dollar price (% Par)	113.37	8.40	98.15	106.04	115.41	119.52	128.85	51203
Yield to maturity (%)†	2.80	0.88	0.89	2.1	2.9	3.6	4.30	5722
Dollar price (% Par)†	108.38	10.64	98.10	100.0	100.0	119.4	129.21	5722
Issue amount ($MM)	4.93	9.14	0.09	0.62	2.08	4.79	44.5	755
Coupon rate (%)	4.24	1.02	1.78	3.45	5.00	5.00	5.0	755
Aggregate rating	6.69	5.31	1.00	2.00	3.50	12.50	22.0	755

Panel B: BB (combined)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	2.41	0.74	0.82	1.89	2.40	2.93	4.07	55441
Dollar price (% Par)	113.87	7.79	98.01	108.74	115.45	119.22	128.74	55441
Yield to maturity (%)†	2.70	0.89	0.93	2.0	2.72	3.44	4.17	4227
Dollar price (% Par)†	109.42	10.85	97.95	100.0	100.00	119.97	130.61	4227
Issue amount ($MM)	5.67	11.10	0.05	0.82	2.37	5.6	52.35	807
Coupon rate (%)	4.29	1.01	1.75	3.70	5.00	5.0	5.00	807
Aggregate rating	6.47	5.28	1.00	2.00	3.50	12.5	22.00	807

Panel C: GB (LW replic.)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)†	2.84	0.82	1.24	2.15	2.93	3.55	4.30	4344
Dollar price (% Par)†	108.46	10.70	97.99	99.75	100.00	119.59	128.78	4344
Issue amount ($MM)	5.91	10.61	0.11	0.52	2.43	5.46	49.69	511
Coupon rate (%)	4.19	1.05	1.75	3.15	5.00	5.00	5.00	511
Aggregate rating	6.82	5.15	1.00	2.50	3.50	12.50	12.50	511

Panel D: BB (LW replic.)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)†	2.83	0.83	1.21	2.15	2.86	3.59	4.17	3284
Dollar price (% Par)†	108.62	10.61	97.95	99.84	100.00	119.26	129.24	3284
Issue amount ($MM)	6.59	12.73	0.06	0.94	2.8	5.87	63.77	555
Coupon rate (%)	4.26	1.05	1.75	3.50	5.0	5.00	5.00	555
Aggregate rating	6.45	5.05	1.00	2.50	3.5	12.50	12.50	555

Table 4: Summary statistics of matched bonds across non-callable and callable universes

This table summarizes the descriptive statistics of the matched bonds whereby Panels A and B represent non-callable universe and Panels C and D represent callable universe. Yield and dollar price are the transactions data from both the primary and secondary market. Aggregate rating is the average of S&P and Moody's ratings whereby 1 is the highest rate and 22 is the lowest or unrated.

Panel A: GB (non-call)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	1.86	0.55	0.54	1.48	1.90	2.26	3.04	14808
Dollar price (% Par)	115.70	7.56	99.50	111.35	116.96	121.07	130.07	14808
Issue amount ($MM)	2.79	4.48	0.02	0.37	1.08	2.9	21.27	360
Coupon rate (%)	4.17	1.18	1.63	2.90	5.00	5.0	5.00	360
Aggregate rating	6.98	5.76	1.00	2.00	3.50	12.5	22.00	360

Panel B: BB (non-call)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	1.92	0.56	0.6	1.52	1.95	2.30	3.22	19910
Dollar price (% Par)	115.46	6.90	99.5	111.84	116.28	119.99	129.44	19910
Issue amount ($MM)	4.47	8.76	0.00	0.44	1.6	3.83	44.77	397
Coupon rate (%)	4.21	1.16	1.65	3.00	5.0	5.00	5.00	397
Aggregate rating	6.70	5.77	1.00	2.00	3.5	12.50	22.00	397

Panel C: GB (callable)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	2.73	0.71	1.02	2.28	2.76	3.2	4.10	36395
Dollar price (% Par)	112.41	8.54	97.99	104.10	114.56	118.8	128.57	36395
Issue amount ($MM)	6.88	11.56	0.09	1.06	3.02	6.9	50.97	395
Coupon rate (%)	4.30	0.85	2.12	3.70	5.00	5.0	5.00	395
Aggregate rating	6.43	4.86	1.00	2.50	3.50	12.5	12.53	395

Panel D: BB (callable)	Mean	SD	$p^{1\%}$	$p^{25\%}$	$p^{50\%}$	$p^{75\%}$	$p^{99\%}$	Obs.
Yield to maturity (%)	2.68	0.69	1.04	2.24	2.71	3.14	4.10	35531
Dollar price (% Par)	112.97	8.11	97.88	105.83	114.93	118.76	128.15	35531
Issue amount ($MM)	6.84	12.88	0.08	1.68	3.25	6.36	72.84	410
Coupon rate (%)	4.37	0.84	2.13	3.88	5.00	5.00	5.00	410
Aggregate rating	6.24	4.76	1.00	2.50	3.50	12.50	12.50	410

4 Descriptive analysis based on matched bonds

4.1 Univariate analysis in levels

In this subsection and the next, I examine the potential yield differentials between green and brown bonds. Armed with the bond sample constructed through matching procedure, I employ levels approach here as opposed to the approach exploiting the natural experiment setting emerging from disaster events. Following LW, I investigate the differentials between green and brown bonds with the framework of Gaussian kernel density and Silverman rule for bandwidth selection. Unlike LW, however, I separate the callable and non-callable bond universes for three reasons. First, the callable bond universe shows much higher yields and is more frequently traded as well than the non-callable bond universe, resulting in the discrepancy in the number of observations at the MSRB transaction level. Second, the differential pricing of green and brown bonds tends to show inconsistent results across non-callable and callable universes—for instance, sometimes there is a green bond premium (discount) in the (sub)sample of non-callable bond universe, while there is a green bond discount (premium) in the (sub)sample of callable bond universe. Blending these two (sub)samples will likely subdue each other's characteristics and blur important aspects. Third, as the yield distribution of each universe exhibits a unimodal distribution, a mixture of both universes likely follows a bimodal distribution. While the mean (median) is the most effective in capturing the central tendency of a symmetrical (asymmetrical) unimodal distribution, this is not the case for a bimodal distribution and therefore mode is a more suitable measure. Hence, I refrain from combining these two universes.

Table 5 shows the results of bond yield differentials and issuance amount across particular states. The choice of states relies on the intensity of green bond issuance as illustrated in Figure 2. In testing the median difference of green and brown bond distributions, I use Mann-Whitney-Wilcoxon (MWW) test. Although Wilcoxon (matched-pairs) signed-rank test is also used to assess whether medians across matched samples differ, the observations have to be exactly matched—note that my sample is based on observations at the transaction level and this condition does not realistically hold. Another potential choice is the Mood median test but this test has its shares of trouble as well regarding power and efficiency issues. A critical feature on Mann–Whitney–Wilcoxon (MWW) test is that it is an equality evaluation of two distributions and thus does not specifically address the medians of the distributions. The null hypothesis is stated such that two samples are drawn from an identical distribution with an identical scale parameter—on the other side of the coin, the alternative hypothesis is postulated such that one distribution is stochastically larger than the other.

Technically, there are additional conditions (e.g., location shift) to interpret MWW test as a median test but these topics are beyond the scope of the paper.

Overall, the empirical results exhibited in Table 5 point to a mixed view. This claim is even more substantiated after visualizing the yield differentials as a whole as well as for each state (Figures 3–9). In particular, taking a closer look at individual states, Massachusetts surfaces as a noteworthy subject because of its unambiguous evidence in support of the greenium. The mean (median) yield differential between green and brown bonds in Massachusetts is -0.4 (-2.0) bps for the non-callable universe and is -22.9 (-17.5) bps for the callable universe—significantly suggestive of green bond premium especially for the callable universe. What makes this fact ever more encouraging for environmentalists is that this is indeed the case even though the issuance amount of green bonds substantively outnumbers that of brown bonds. In reference to Hypothesis 1, this firm evidence of greenium conforms to the fact that Yale Climate Opinion Map clearly ranks Massachusetts as one of the top states with strong climate belief. Moreover, Green City Bonds Coalition (2015) documents anecdotal evidence that green bonds were indeed priced at premium in Massachusetts.[7] It writes as follows:

> [T]he green bond sale was 3x oversubscribed and the AA+ rated green bonds sold at lower yields than the muni market's AAA yield curve.... [W]hen we first

[7] The following is an in-depth quote from Green City Bonds Coalition (2015):

> Much can be learned from the Massachusetts offering because the Commonwealth was offering green and non-green bonds at the same time, with the same rating. In some ways, Massachusetts had an even easier time marketing the green bonds than the non-green bonds because they were able to tell potential investors a more persuasive story about the impact of the bonds and the projects the proceeds were going to fund. The green bond sale was 3x oversubscribed and the AA+ rated green bonds sold at lower yields than the muni market's AAA yield curve! Massachusetts was also able to expand its investor base, as residents and local retail investors who hadn't considered buying municipal bonds before were attracted by the green story: the Commonwealth received $260 million in orders from retail investors, an unprecedented amount for them. These new investors reported that they appreciated knowing the specific projects their investments were funding, as well as the fact that, as residents, they would experience the benefits of the projects first-hand into the future.

Another insightful quote from Green City Bonds Coalition (2015) is the following:

> In fact, when we first came to market with an initial $300 million offer, we got a little over $1.1 billion of orders! So in response, we upped the size to $350 million and lowered the spread by 15 basis points.... Some of this pricing benefit can be attributed to the green credentials of the bond, in the sense that $100 million of orders were from SRI investors that would not have bought one of our non-green bonds, but of course, it is difficult to quantify how much of the pricing benefit can be attributed solely to the green label. But, it was clear that we benefited financially from having a green label.

came to market with an initial \$300 million offer, we got a little over \$1.1 billion of orders! So in response, we upped the size to \$350 million and lowered the spread by 15 basis points.

My empirical results indeed endorse this anecdotal account and are clearly illustrated in Figure 6. Furthermore, although the anecdote is unique to the period of 2014–2015, I continue to find strong patterns of greenium in this region, especially in the callable bond universe, even after restricting the sample to (i) the period after 2014–2015, (ii) secondary market, or (iii) the intersection of both conditions. In reference to the other states, it stands to reason that similar patterns can be found in Washington D.C. area.

In California, however, green bonds are surprisingly priced and traded at a discount as shown in Figure 5. The mean (median) yield differential between green and brown bonds is 4.2 (11.9) bps for the non-callable bond universe and 3.5 (1.1) bps for the callable bond universe. These characteristics starkly contrast with those of Massachusetts and Washington D.C. Besides, the differences in issuance amount make it more puzzling to interpret this discrepancy because the issuance amount of green bonds is smaller than that of brown bonds. Nevertheless, one potential reason of this discount could be that a good deal of municipal bonds targeting financing environmentally-friendly projects do not use a green label and thus investors do not have a strong preference for the green bond labels in California. As a matter of fact, the outstanding amount of these unlabeled climate-friendly bonds significantly exceed labeled green bonds (Chiang, 2017; MSRB, 2018a).

Furthermore, even the patterns shown by states that are traditionally considered to be conservative are mixed. For instance, in Texas the mean (median) yield differential is -13.7 (-15.0) bps and green bonds are significantly priced and traded at a premium in the non-callable universe: there is no significant yield differential in the callable universe. In Arizona, by contrast, the mean (median) yield differential is 18.1 (17.8) bps and green bonds are significantly priced and traded at a discount in the callable universe: there is no significant yield differential in the non-callable universe.

Nonetheless, an immediate concern arises that it is not the local climate opinion that drives up the green bond valuation but other confounding factors are at play. In one case, to examine the possibility of issuance amount serving as a confounder, the statistics are in parallel shown in Table 5 as well as in Figures 3–9. Another possibility is the difference in institutional ownership between green and brown bonds that affects the bond valuation. Chiang (2017) reports that "U.S. institutional investors unanimously say they are not currently willing to sacrifice yield for green bonds" and that "brokerage firms and underwriters stressed that institutional clients are unwilling to pay up for green bonds." Chiang (2017) continues that unlike high-net-worth individuals, a vast majority of institutional investors will not readily pay a premium. Hence, this concern requires further investigation and will be left for future.

Table 5: Bond yield differentials and issuance amount: comparison across green bond intensive states

Panels A, B, and C below summarize the bond yield differentials and issuance amounts with respect to states with a prominent history of green bond issuance. Note that (i) Washington D.C. is additionally included for interest despite the moderate number of issuance and (ii) the last rows in Panels A and B and the row in Panel C represent all the states in the US. The last column shows the cumulative issuance amount (in millions). Yields are from MSRB transaction database and include both the primary and the secondary market data. The mean and median yield differences are examined based on Welch-Test and Mann–Whitney–Wilcoxon (MWW) test, respectively.

Panel A: Non-callable universe

	# unique bonds		Yield (mean)				Yield (median)				Issuance ($MM)	
	GB	BB	GB	BB	Difference	*p*-value (Welch)	GB	BB	Difference	*p*-value (MWW)	GB	BB
Arizona	26	24	1.936	1.936	0.0	0.989	1.97	2.0	-0.03	0.328	102.68	86.055
California	56	60	1.739	1.696	0.042	0.008	1.78	1.661	0.119	0.0	249.72	374.205
Massachusetts	26	26	1.855	1.859	-0.004	0.715	1.89	1.91	-0.02	0.239	187.09	451.025
New York	107	108	2.025	2.136	-0.111	0.0	2.109	2.198	-0.089	0.0	198.835	78.465
Texas	9	8	1.891	2.028	-0.137	0.036	1.93	2.08	-0.15	0.006	7.87	5.08
Washington D.C.	–	–	–	–	–	–	–	–	–	–	–	–
All states	360	397	1.861	1.917	-0.056	0.0	1.9	1.95	-0.05	0.0	1003.445	1773.105

Panel B: Callable universe

	# unique bonds		Yield (mean)				Yield (median)				Issuance ($MM)	
	GB	BB	GB	BB	Difference	*p*-value (Welch)	GB	BB	Difference	*p*-value (MWW)	GB	BB
Arizona	37	33	2.647	2.466	0.181	0.0	2.7	2.522	0.178	0.0	275.83	177.03
California	113	139	2.502	2.467	0.035	0.0	2.54	2.529	0.011	0.0	973.765	1293.24
Massachusetts	27	30	2.469	2.698	-0.229	0.0	2.585	2.76	-0.175	0.0	683.185	198.87
New York	85	86	3.441	3.429	0.012	0.314	3.558	3.638	-0.08	0.0	387.31	298.5
Texas	25	22	3.108	3.151	-0.043	0.207	3.2	3.177	0.023	0.107	33.675	23.27
Washington D.C.	5	5	2.541	2.621	-0.081	0.011	2.581	2.692	-0.111	0.005	86.055	126.275
All states	395	410	2.725	2.681	0.044	0.0	2.757	2.71	0.047	0.0	2718.5	2803.465

Panel C: Combined universe

	# unique bonds		Yield (mean)				Yield (median)				Issuance ($MM)	
	GB	BB	GB	BB	Difference	*p*-value (Welch)	GB	BB	Difference	*p*-value (MWW)	GB	BB
All states	755	807	2.475	2.406	0.069	0.0	2.47	2.4	0.07	0.0	3721.945	4576.57

Figure 3: Differential pricing across non-callable and callable bond universes (full sample)

The sample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is -5.6 (-5.0) bps for the non-callable bond universe and is 4.4 (4.7) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

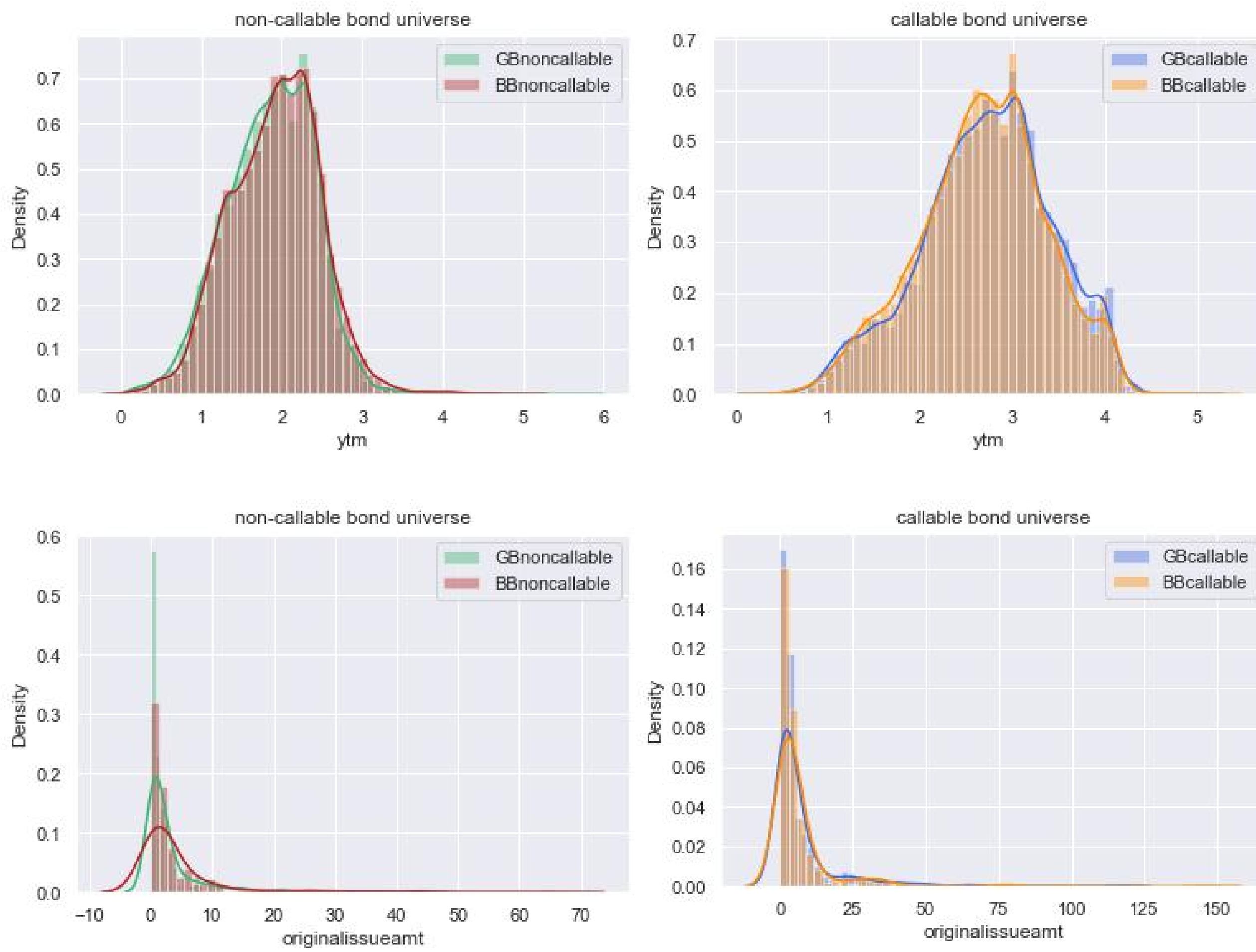


Figure 4: Differential pricing across non-callable and callable bond universes (Arizona)

Conditioning on Arizona state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is 0.0 (-0.3) bps for the non-callable bond universe and is 18.1 (17.8) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

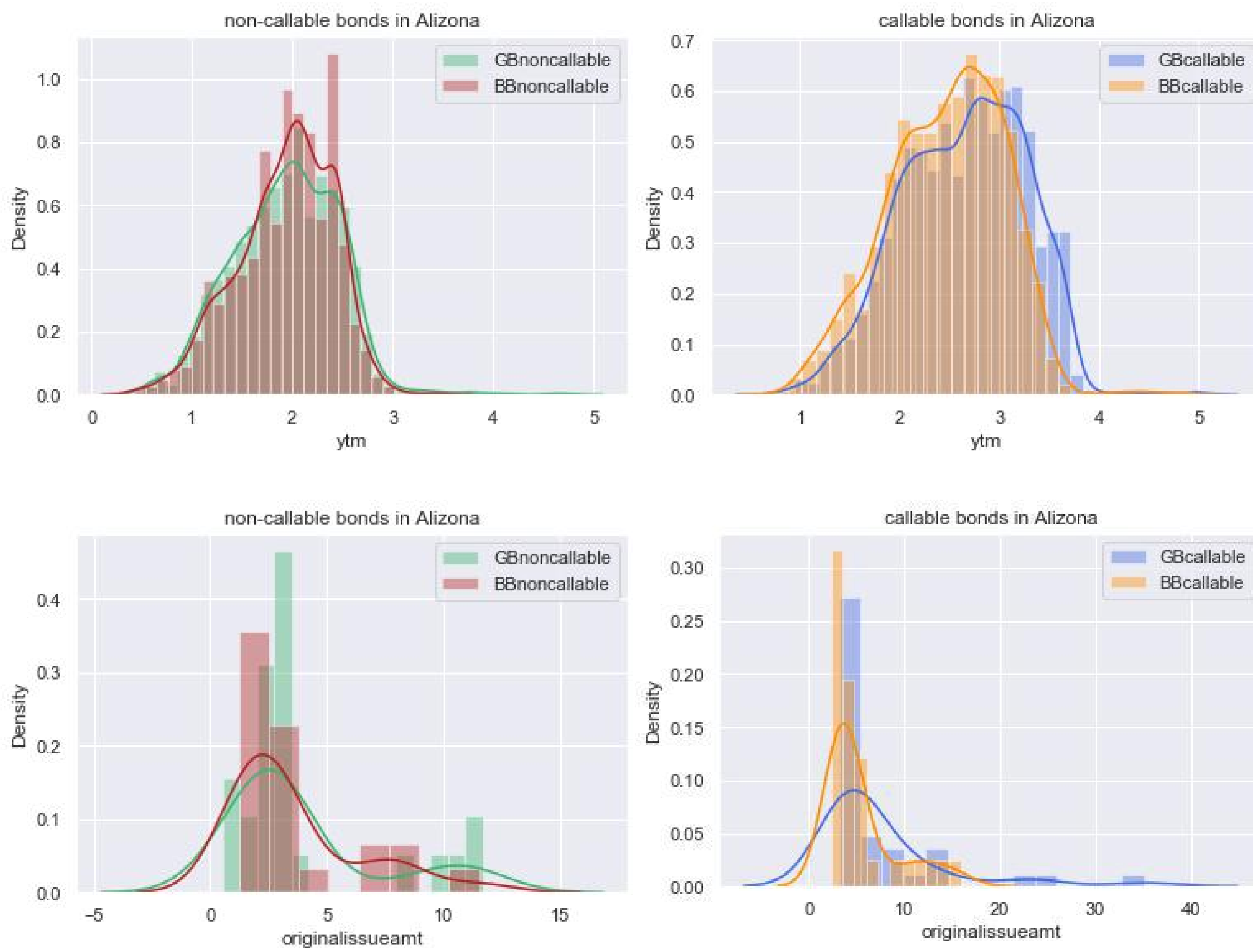


Figure 5: Differential pricing across non-callable and callable bond universes (California)

Conditioning on California state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is 4.2 (11.9) bps for the non-callable bond universe and is 3.5 (1.1) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

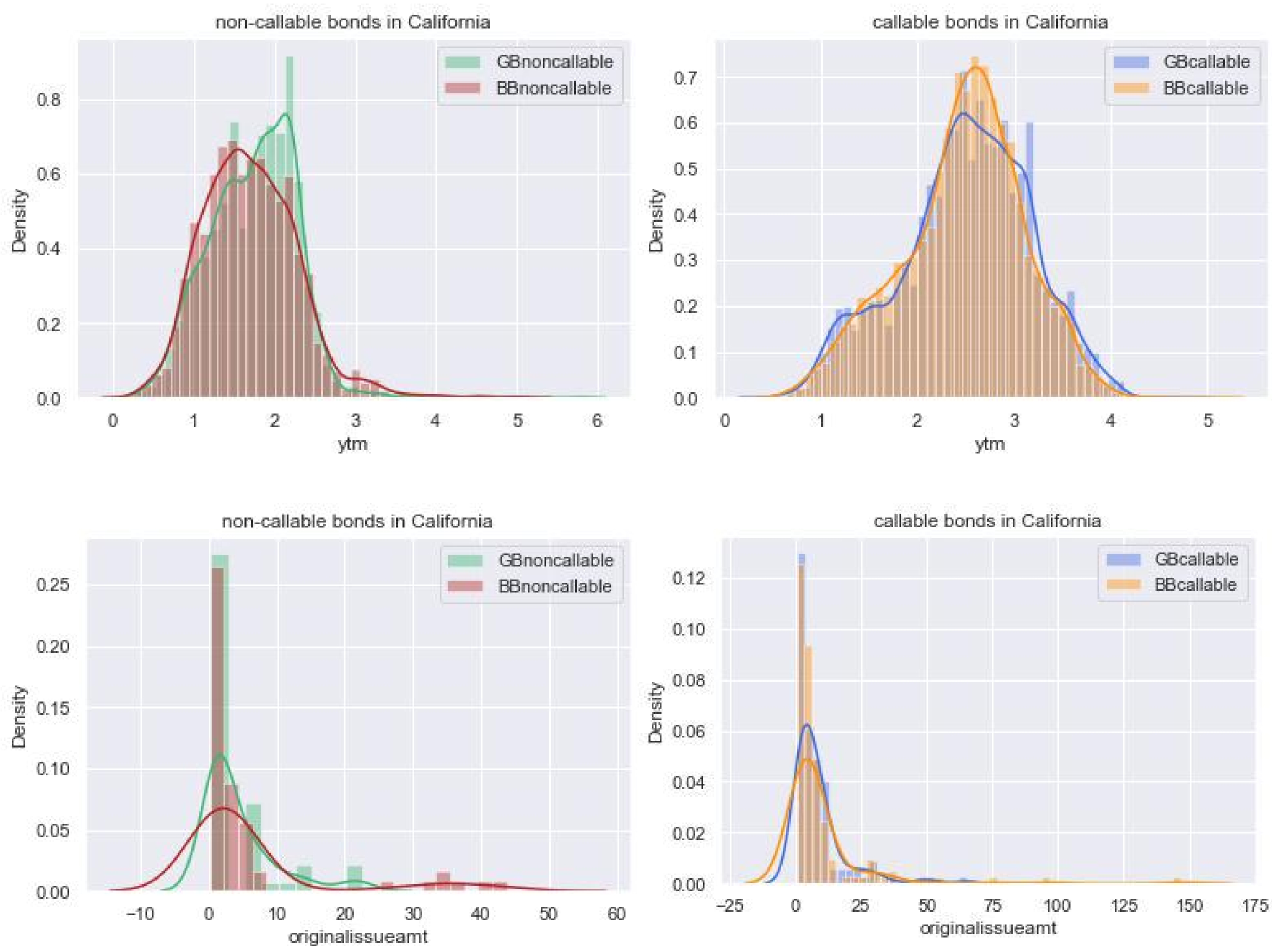


Figure 6: Differential pricing across non-callable and callable bond universes (Massachusetts)

Conditioning on Massachusetts state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is -0.4 (-2.0) bps for the non-callable bond universe and is -22.9 (-17.5) bps for the callable bond universe—significantly suggestive of green bond premium especially for callable bonds.

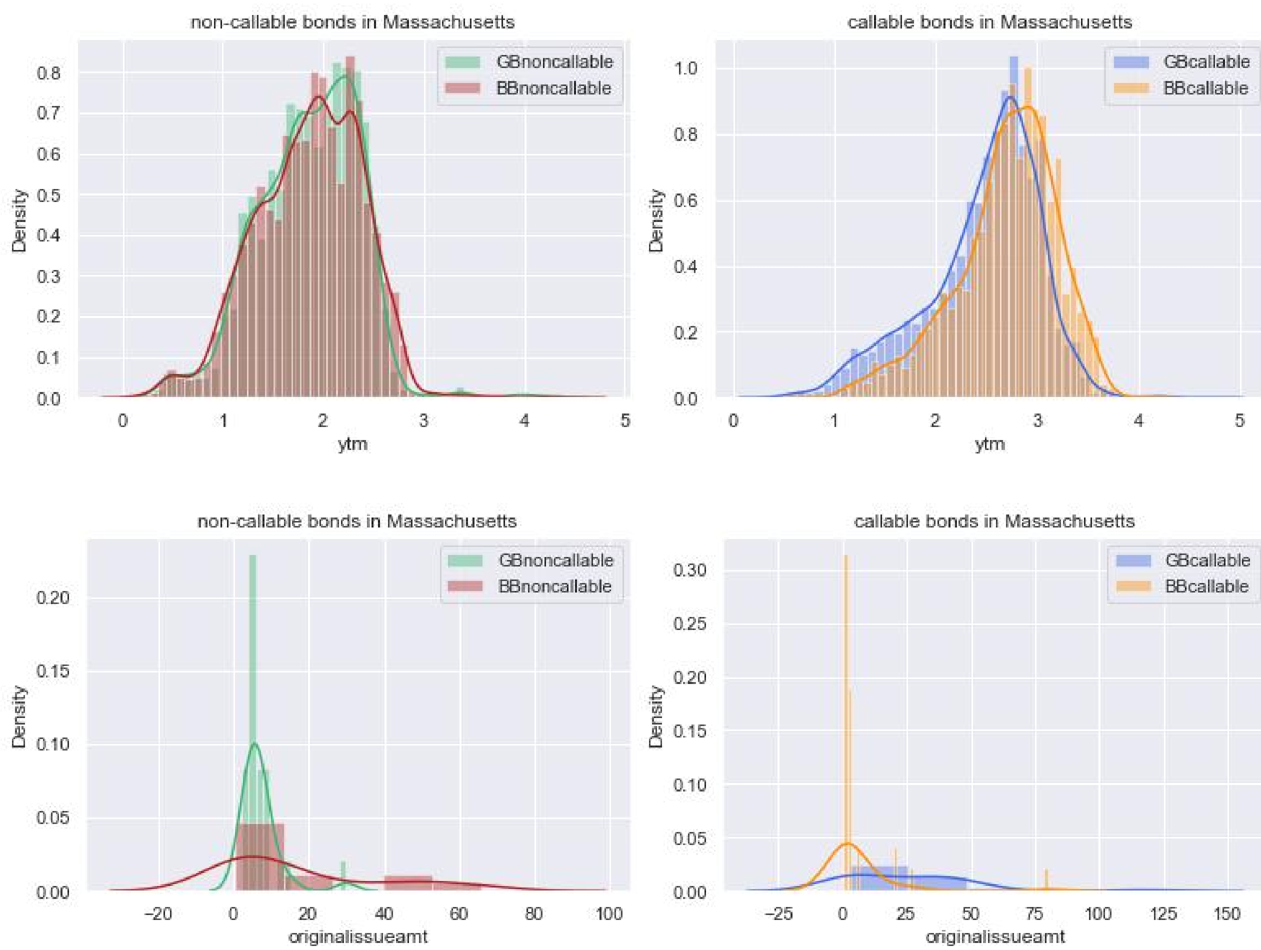


Figure 7: Differential pricing across non-callable and callable bond universes (New York)

Conditioning on New York state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is -11.1 (-8.9) bps for the non-callable bond universe and 1.2 (-8.0) bps for the callable bond universe.

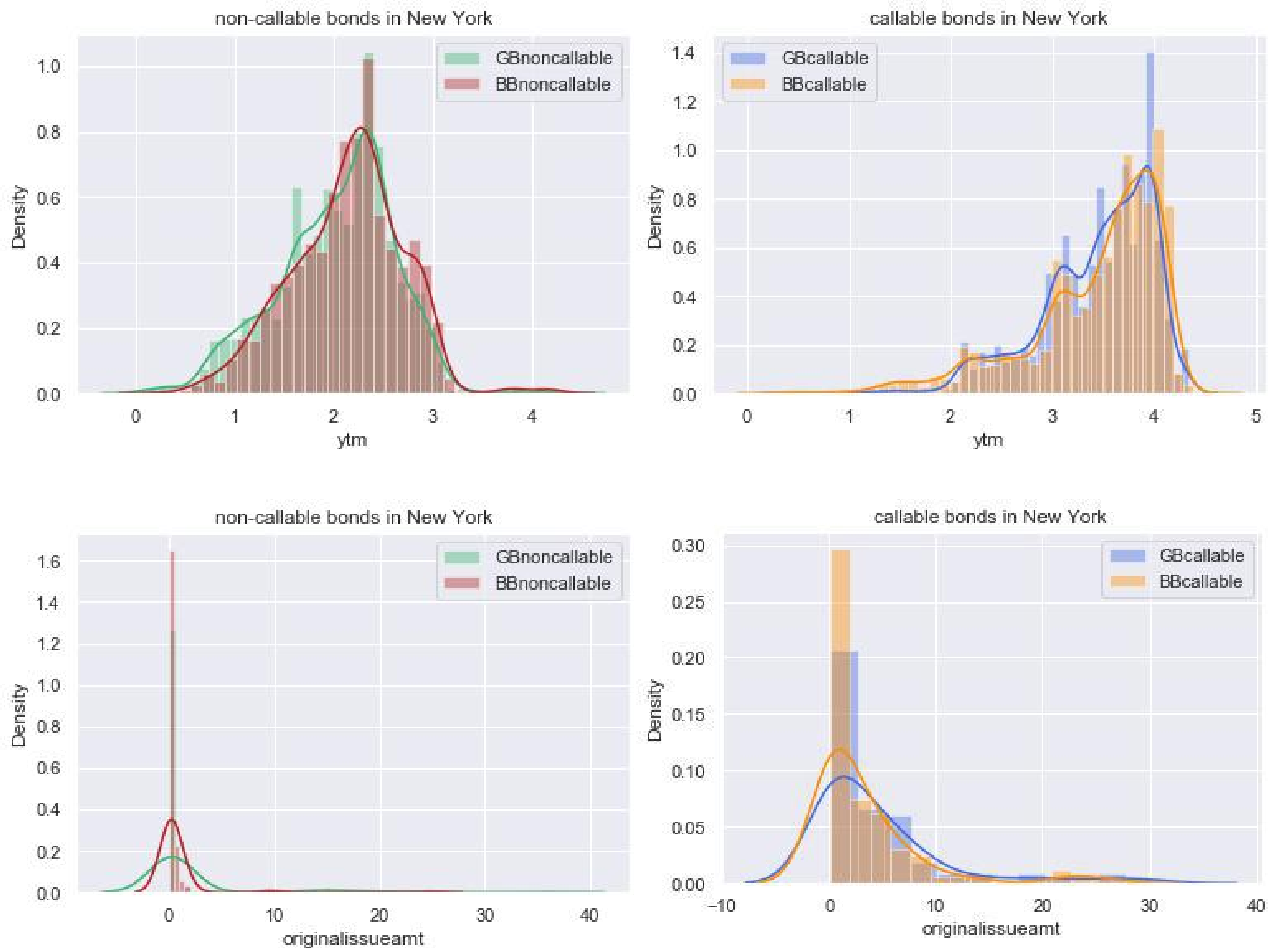


Figure 8: Differential pricing across non-callable and callable bond universes (Texas)

Conditioning on Texas state, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is -13.7 (-15.0) bps for the non-callable bond universe and is -4.3 (2.3) bps for the callable bond universe.

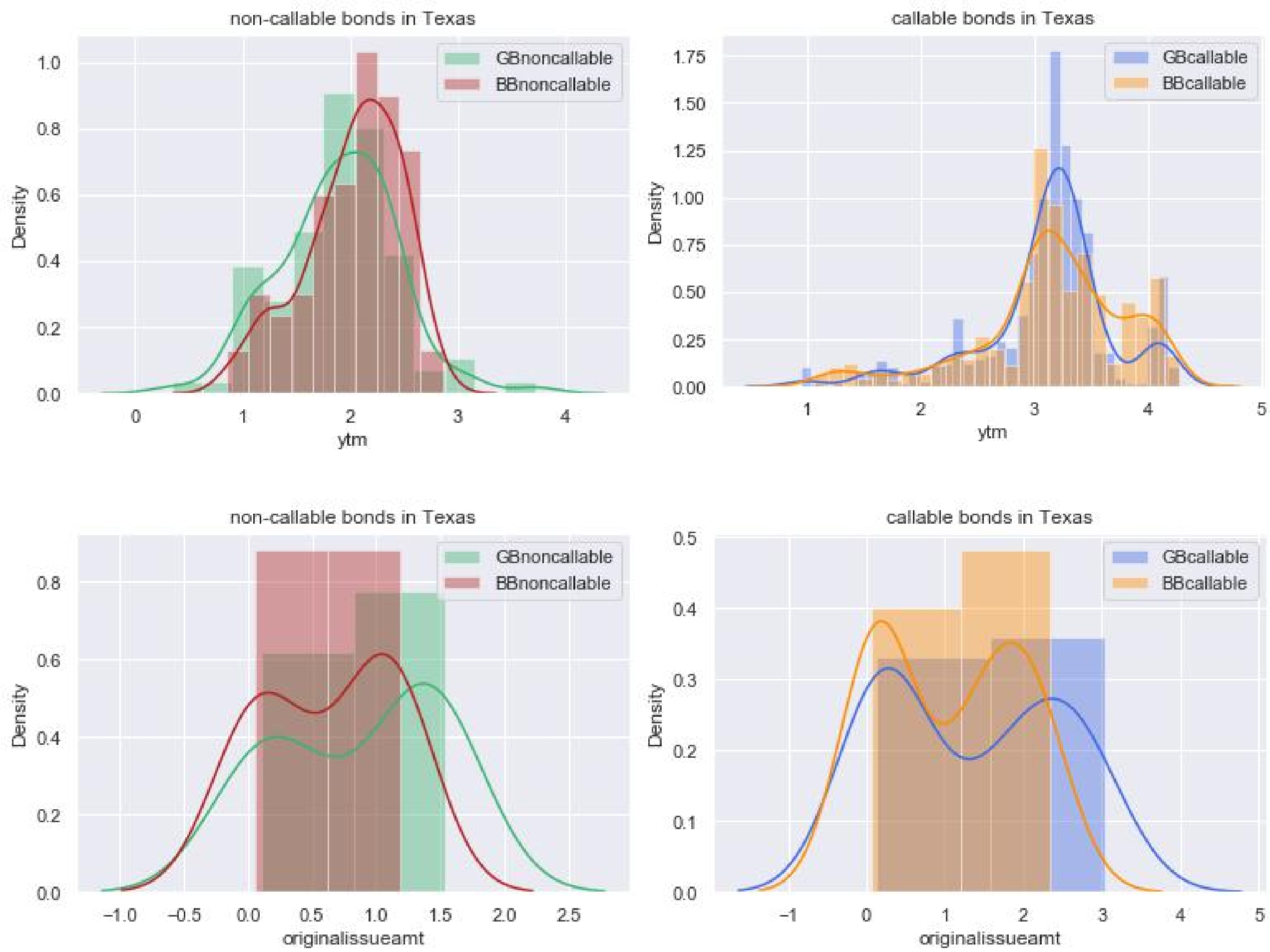
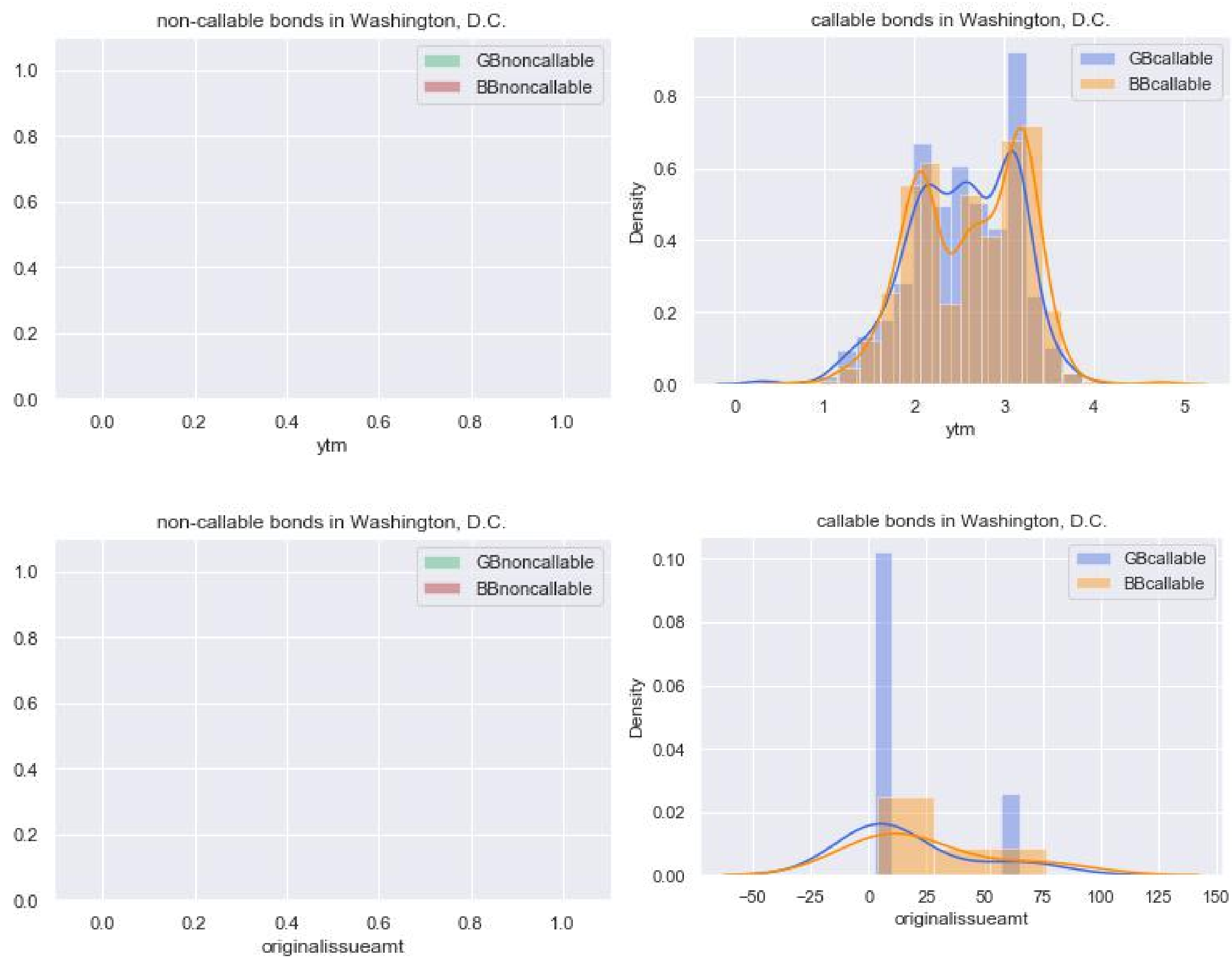


Figure 9: Differential pricing across non-callable and callable bond universes (Washington D.C.)

Conditioning on the District of Columbia, the subsample spans the entire period Sep 2014–June 2020. The first (second) row demonstrates the differential structure of yield (original issuance amounts) distributions between the non-callable and callable universes. Yields are recorded at the transactional level (MSRB) and both the primary and secondary market data are included. The mean (median) yield differential between green and brown bonds is −8.1 (−11.1) bps for the callable bond universe. No data for non-callable bonds. Five green callable bonds are matched with five brown callable bonds.



4.2 Bivariate analysis in levels

Hazlett and Mildenberger (2019) document that actions in response to a direct wildfire experience are moderated by climate opinion. Here I extend the analysis in the previous subsection by additionally conditioning on the geographic areas based on the intensity of local climate belief. In doing so, I present the results with Human and CO_2limits variables, which are measured both at the state and county levels. In this respect, across-state as well as within-state variation of climate beliefs paints a colorful picture.[8] To put this into perspective, the state-level values are not necessarily a good representation of its entirety given that there is a significant amount of within-state variation.

With this contextual information in mind, I plot the relationship between bond yield and local belief in climate change. Using local climate belief measured both at the state and county level, Figure 10 and 11 illustrate bivariate frequency distributions with contour lines, where x-axis represents yield and y-axis represents climate belief intensity: each figure targets Human and CO_2limits variables, respectively, to measure local climate belief. Moreover, as to the callable bond universe on the right-hand side of Figures 10 and 11, areas with lower climate change belief (lower y values) are apparently more likely to associate green bonds with higher yields (higher x values). Regarding the non-callable bond universe on the left-hand side, the patterns do not contradict those of callable bond universe but the magnitudes in differences between green and brown bonds appear to be minimal.

Figure 12 and Figure 13 further illustrate differential pricing across high and low climate belief areas: again, Figure 12 (Figure 13) targets Human (CO_2limits) variable. Overall, I find perplexing results, particularly arising from the low climate belief areas in the non-callable universe. On the one hand, high climate belief areas do not show substantial differences in pricing between green and brown bonds. On the other hand, low climate belief areas show lower valuation of green bonds in both figures with respect to the callable bond universe—consistent with Hypothesis 1—while *higher* valuation of green bonds are shown with respect to the non-callable universe. Insofar as the results are driven by noise rather than signal—note that the width of the bars is wider, indicating observations are fewer relative to other figures—a meaningful interpretation is challenging and thus judgement should be postponed.

[8] For instance, Happening measured at the state level ranges from the lowest at 58.6 in West Virginia to the highest at 82.2 in District of Columbia (Washington D.C.). This variable takes the value of 74.8 in Massachusetts at the state level and within-state variation is relatively small, ranging from 70.5 to 81.3. In contrast, it equals to 76.2 in California at the state level and within-state variation is larger, ranging from 62.9 to 84.2. Even more prominent, it is recorded at 69.5 in Texas at the state level and within-state variation is extremely large, ranging from 50.7 to 80.7.

Figure 10: Bivariate frequency distributions with contour lines: Human

The sample spans the entire period Sep 2014–June 2020. The left (right) column illustrates noncallable (callable) bonds. In the first (second) row, local climate belief represented by Human variable is measured at the state (county) level. The observations include both the primary market and secondary market data.

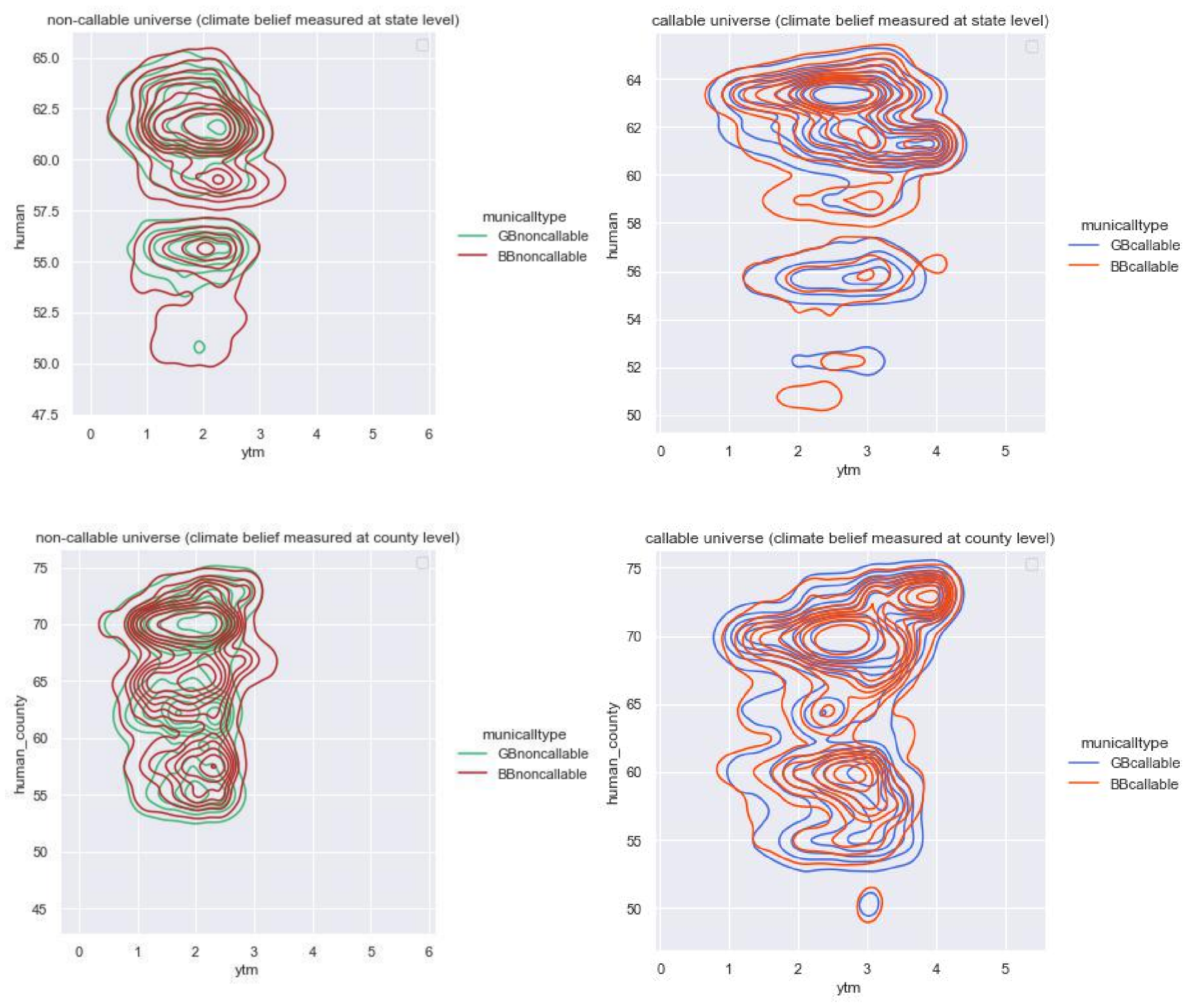


Figure 11: Bivariate frequency distributions with contour lines: CO_2limits

The sample spans the entire period Sep 2014–June 2020. The left (right) column illustrates noncallable (callable) bonds. In the first (second) row, local climate belief represented by CO_2limits variable is measured at the state (county) level. The observations include both the primary market and secondary market data.

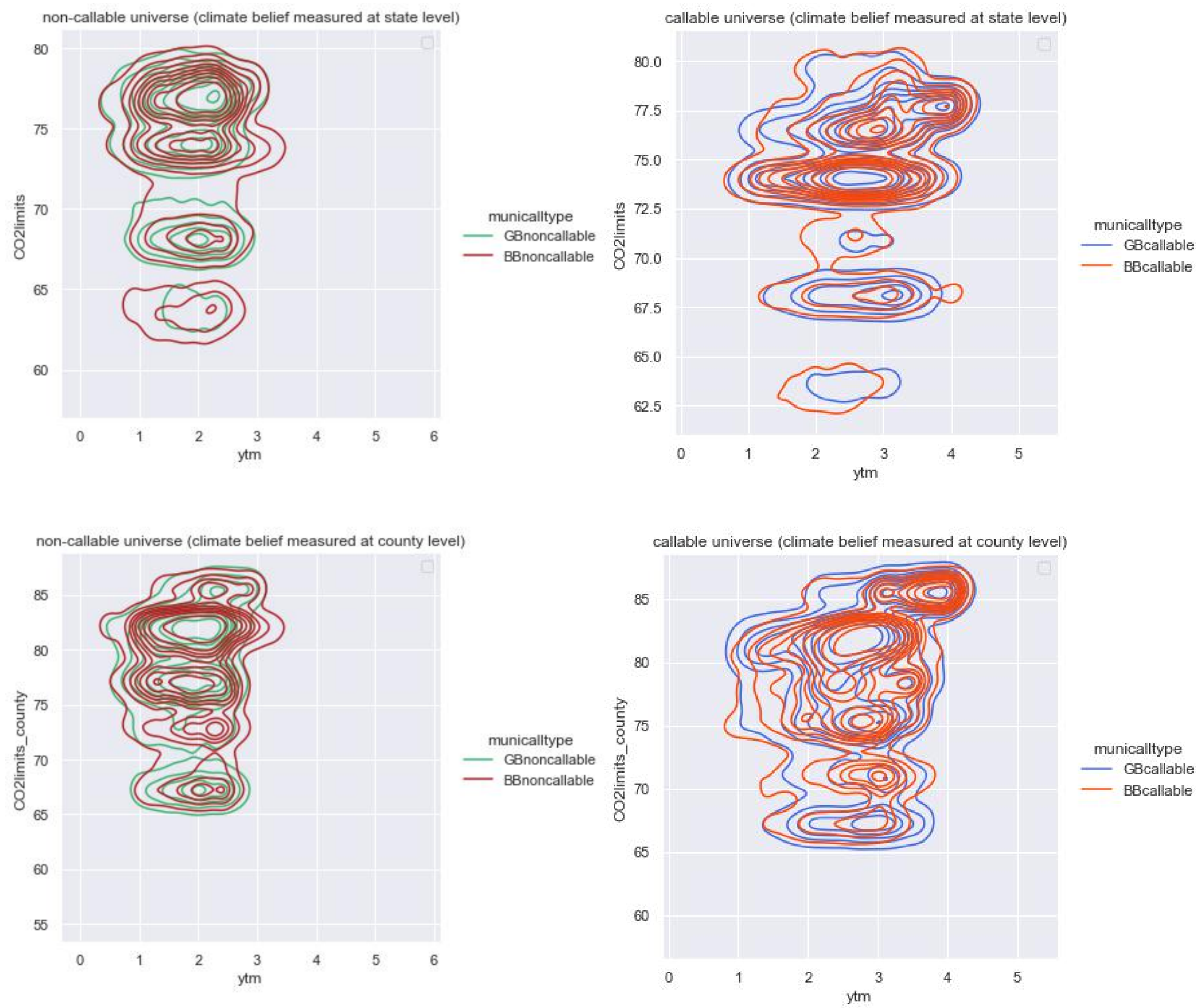


Figure 12: Differential pricing across high and low climate belief areas: Human

The sample spans the entire period Sep 2014–June 2020 and the local climate belief represented by Human is measured at the state level. The median value of Human variable is use to categorize high/low climate-belief areas. The left (right) column illustrates non-callable (callable) bond universe. The first (second) row illustrates the observations in high (low) climate belief areas.

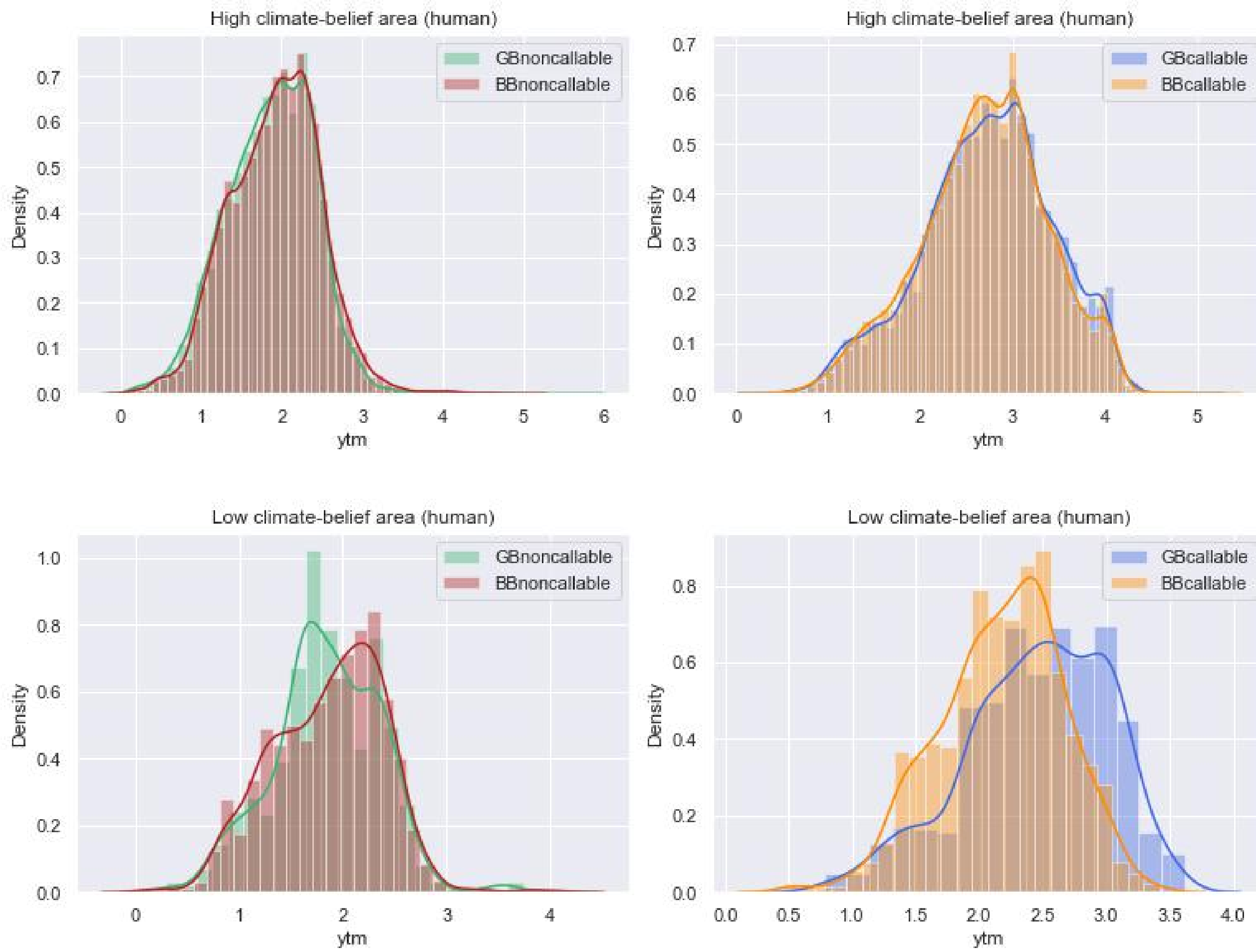


Figure 13: Differential pricing across high and low climate belief areas: CO_2limits

The sample spans the entire period Sep 2014–June 2020 and the local climate belief represented by CO_2limits is measured at the state level. The median value of CO_2limits variable is use to categorize high/low climate-belief areas. The left (right) column illustrates non-callable (callable) bond universe. The first (second) row illustrates the observations in high (low) climate belief areas.

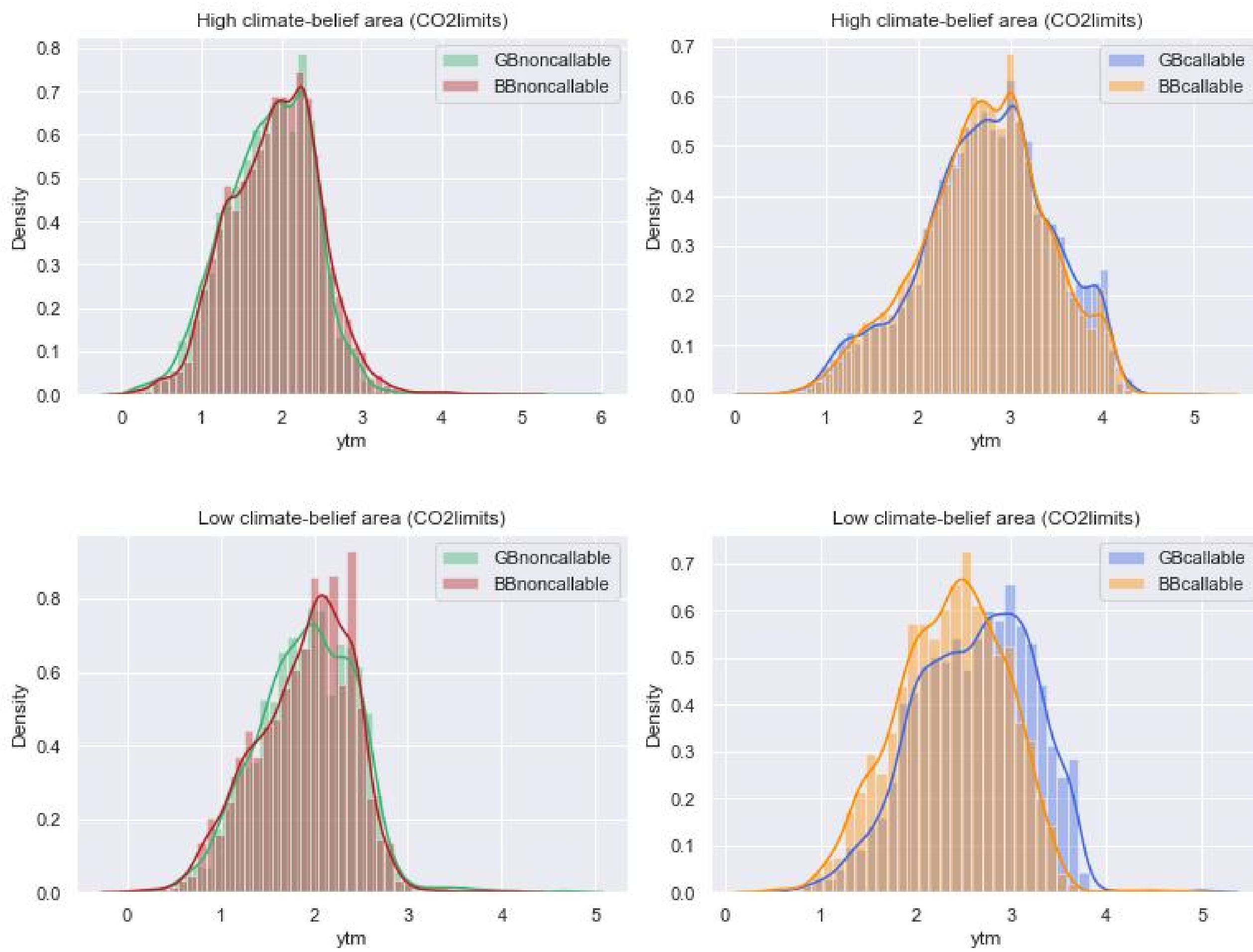
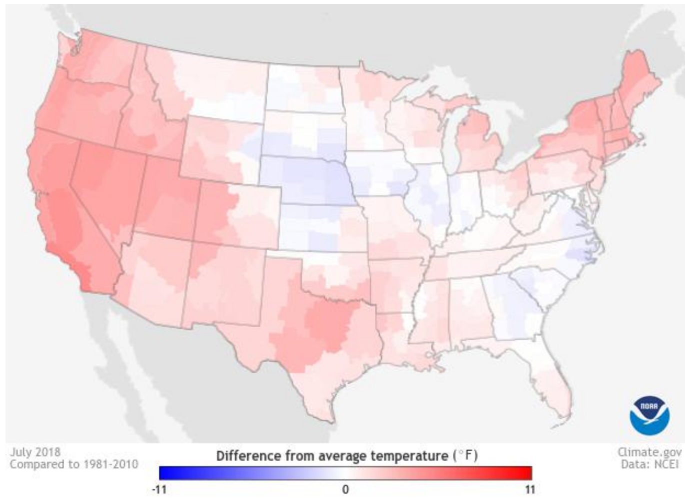


Figure 14: Heat wave in July 2018

The figure below sourced from NOAA demonstrates the deviation of the average monthly temperature in July 2018 from the benchmark computed over the period 1981–2010.



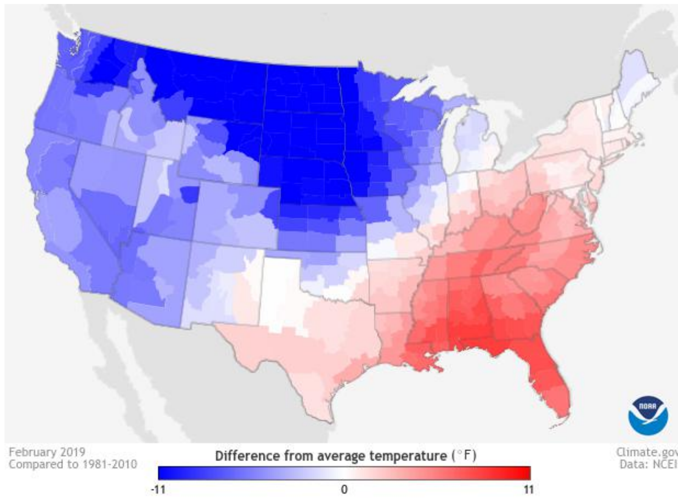
4.3 Yield differential analysis following extreme weather events

A variety of natural catastrophes can wreak havoc on US residents ranging from tropical cyclones, droughts, wildfire to floods. These events are intrinsically different from one another with respect to their risk and uncertainty, expected financial damage, and perceptional consequences (Howe et al., 2019). In relation to Hypothesis 2, I attempt to conduct in this subsection a few case studies on the extreme weather events—heat wave in 2018 as well as cold wave in 2014, 2015, and 2019—because they are geographically wide-ranging and generate substantial variation in data. Prior research suggests that relative abnormalities in temperature direct the attention of local people to climate change (e.g., Sisco, Bosetti, and Weber, 2017). Besides, another reason that justifies the focus on this hazard type is that other disasters such as flooding may not generate sufficient data variation due to its relatively narrow geographical range relative to extreme weathers—this is especially problematic when using the matched approach intrinsically accompanied by a smaller sample size and poses a serious challenge for statistical inference. It is thus vital that I focus on the reported short-term effect (e.g., Howe et al., 2019; Lang and Ryder, 2016; Choi, Gao, and Jiang, 2020; Egan and Mullin, 2012; Konisky, Hughes, and Kaylor, 2015),[9] and consider a few-month window

[9] Consistent with previous research, Konisky, Hughes, and Kaylor (2015) suggest that ideology, partisanship, and other attributes are more essential in accounting for personal climate opinions than personal disaster experiences. They report that the marginal effect of a single event is small and short lived—if an extreme event was experienced more than three months ago, the effect on the individual's view largely disappears; notwithstanding, they add that a substantial increase in the frequency or severity of extreme weather-related episodes has a nontrivial effect on individuals' climate change concerns.

Figure 15: Cold wave in February 2019

The figure below sourced from NOAA demonstrates the deviation of the average monthly temperature in February 2019 from the benchmark computed over the period 1981–2010.



following the extreme weather events. However, it was revealed in the previous analyses that even after controlling for a set of variables, the remaining difference between green and brown bonds emerging from confounders (e.g., issuance amount, institutional ownership) poses a great challenge in drawing an unambiguous conclusion on the existence of greenium. Therefore, a thorough examination of the few month window following extreme weather events is difficult to implement without using parametric approach—which allows for the control of multiple variables at the expense of a priori fixing the structure of parameters. Employing a regression approach, after gaining access to Mergent database together with county-level hazard data from SHELDUS, would be a fruitful avenue for future research.[10]

[10]Nevertheless, here I briefly cover preliminary results using descriptive analysis as motivating facts for future research. The effects of cold wave in 2019 and the heat wave in 2018 are nuanced, suggesting that it is hard to draw an informed conclusion from these data points. This is consistent with the findings from Howe et al. (2019) who report that although research are to some extent convinced of the positive link running from the short-term variation in temperature to climate opinions, the magnitude of this effect is not significant. Furthermore, even if climate change perception deepens, it remains ambiguous and debatable whether one makes further efforts to take mitigating measure actions or simply concede and adapt to it. Indeed some studies report the latter case (Wachinger et al., 2013; Brügger, A., Dessai, S., Devine-Wright et al., 2015).

5 Robustness checks: air quality and COVID-19

It is unquestionable that greenhouse gases are the leading cause of global warming. However, it is not justifiable to let this fact overshadow the gravity of air pollution problems. As a matter of fact, a spectrum of sources documents that climate change and air pollution are intertwined with one another and thus the reduction efforts should be united under one framework (e.g., Ramanathan and Feng, 2009). With respect to how local residents dynamically react to the change in air quality, a closer look at prior studies can effectively inform the direction of sustainability policies. Bord, O'Connor, and Fisher (2000) and Whitmarsh (2008) suggest that personal experience of illness induced by air pollution alters the perceptions of and behavioural responses to climate-related risks, thereby embedding enhanced pro-environmental values. Similarly, after conducting a survey Tvinnereim, Liu, and Jamelske (2017) report that Chinese respondents, capable of conceptually distinguishing between climate change and air pollution, were aware of the similar causes and detrimental impacts of the both phenomena. On a related note, Chang, Huang, and Wang (2018) interestingly find that more health insurance contracts are sold to Chinese locals when the air is polluted, but they are more likely to be canceled if air quality improves shortly afterward.

By distilling the similar behavioral patterns emerging from these documents, I further hypothesize that the COVID-19 pandemic may induce local people to perceive air quality as a non-negligible issue, thereby shifting their sustainability preference and urging them to take countermeasures such as investing in eco-friendly projects. There is no denying that this postulated behavioral mechanism takes place entirely through a different channel devoid of climate change concern, yet my focal debate here is to highlight how behaviourally responsive and resilient locals can be in the presence of the change in the external environment. Indeed, there are a good amount of sources that likely underpins this conjecture. For instance, mass media kept reporting the link between lockdown measures and the reduced GHG emissions and air pollution levels at the initial stage of the pandemic. Proportionally, corroborative evidence has been accumulating that supports the link between lower air quality and higher mortality rate due to COVID-19 (Wu et al., 2020; Pozzer et al., 2020).

In measuring the increased perception of COVID-19, one way is to follow Alfaro et al. (2020) and use the daily number using Google Trends on a local scale. Figure 16 shows that the search volume on the combination of "coronavirus" and "air pollution" begins to surge in late February and continues to grow until late April, after which the volume shows a downward trend. Figure 17 additionally demonstrates the search volume by regions. A

Figure 16: Searching volume trends on “coronavirus” and “air pollution”

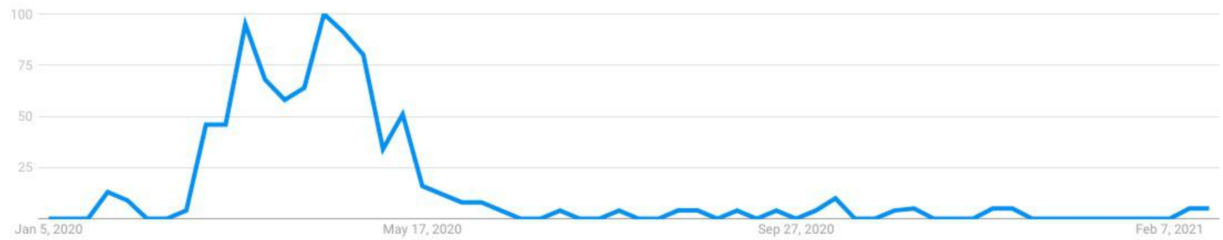
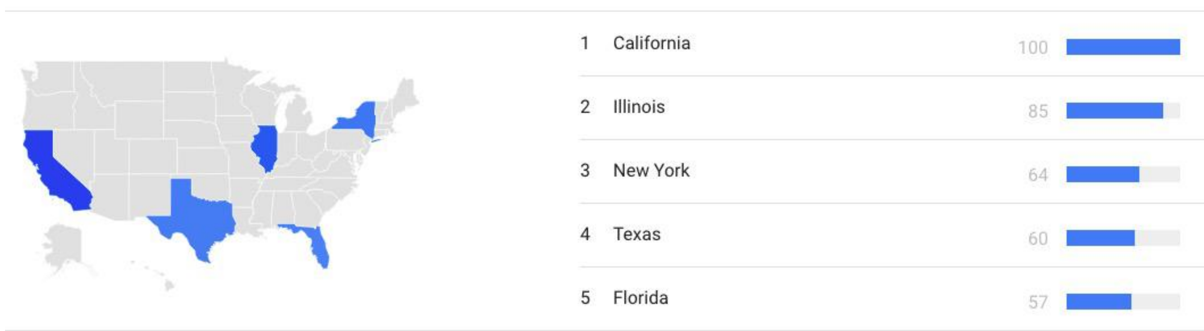


Figure 17: Searching volume trends on “coronavirus” and “air pollution” by subregion



thinkable approach to capturing the effect of COVID-19 on differential bond pricing is to divide the matched bond sample into two subsamples based on pre-COVID and post-COVID periods. Yet, this application is naïve in the sense that it neglects the confounding factors such as issuance amount and the structure of institutional investor, a central issue that was already uncovered in the levels analysis. Additionally, macroeconomic variables such as interest rates, inflation, yield curve, and economic growth are another set of factors that may influence bond yields. Hence, the ideal setup to study the exogenous shock of COVID-19 requires regression analysis, which is capable of controlling for a wide range of variables. However, this setup additionally requires access to Mergent database and thus should be left for future research.

6 Conclusion

Local information plays an imperative role in informing policy makers to decide on how to tackle climate change risks through mitigation and adaptation (Howe, Mildenberger, Marlon et al., 2015). In this study, using a model-free matching approach under the first hypothesis, I find strong evidence at the state level that green bonds are priced and traded at a premium (e.g., Massachusetts, Texas, Washington D.C.), at a discount (e.g., California), or mixed depending on the bond callability (e.g., New York). These patterns starkly contrast with the conclusion of LW in which they disprove the existence of greenium. This discrepancy arises presumably because their analysis is implemented in the absence of systematic regional characteristics, thereby balancing out each other's region-specific attributes at the aggregate level. In the presence of confounders, however, it remains to be explored whether the local environmental concern is truly the driver of the observed phenomena suggestive of greenium.

The second hypothesis in this paper postulates that greenium may temporarily arise from the environmental concerns about anthropogenic climate changes amplified by personal disaster experiences. Once again, the descriptive analysis set forth in this paper served as a stepping stone for the next step of regression analysis that can control for a number of confounding factors such as issuance amount and institutional ownership. Thus, a complementary investigation of natural disaster events alongside county level data from SHELDUS database—as opposed to state level data primarily used in this study—is left as an lucrative avenue for future research. This is ever more so as Konisky, Hughes, and Kaylor (2015) stress that geospatial analysis at a granular level is helpful in uncovering the relationship between a personal experience in climatic extreme events and informed climate opinions.

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