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

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Abstract

Following 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.

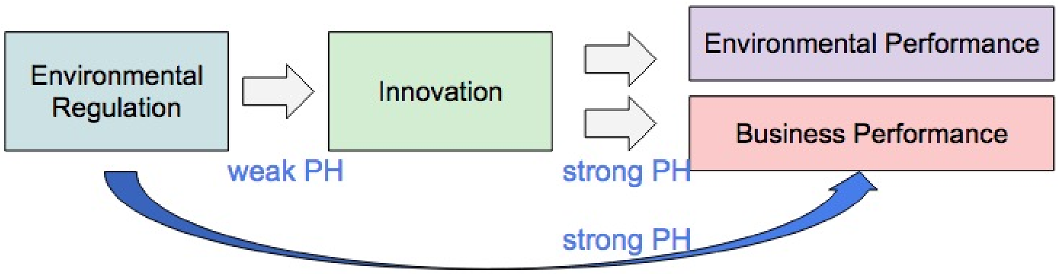
In this regard, it is imperative to elucidate the two fundamentally different interpretations concerning the positive link between eco-innovation and subsequent returns, especially because they have opposite implications for the validity of the strong PH. The first interpretation based on mispricing 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:

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

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.

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

Now, the dependent variable $y_{i,j,t}$ in equation (2) is either Resource Use or Emissions subscore. The variable of interest is $\text{Innovation}_{i,t}$ 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 × 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 $\times$ 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).

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

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

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

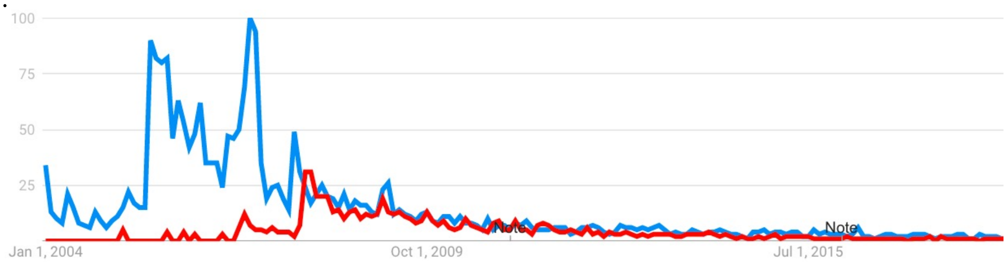
Particularly, I demonstrate two fundamentally different interpretations of a case where eco-innovation has a positive predictive power of subsequent returns: this contrastingly informs the validity of the strong PH. The first interpretation based on equation (4) is that eco-innovation is value-relevant (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:

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

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

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, which 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).

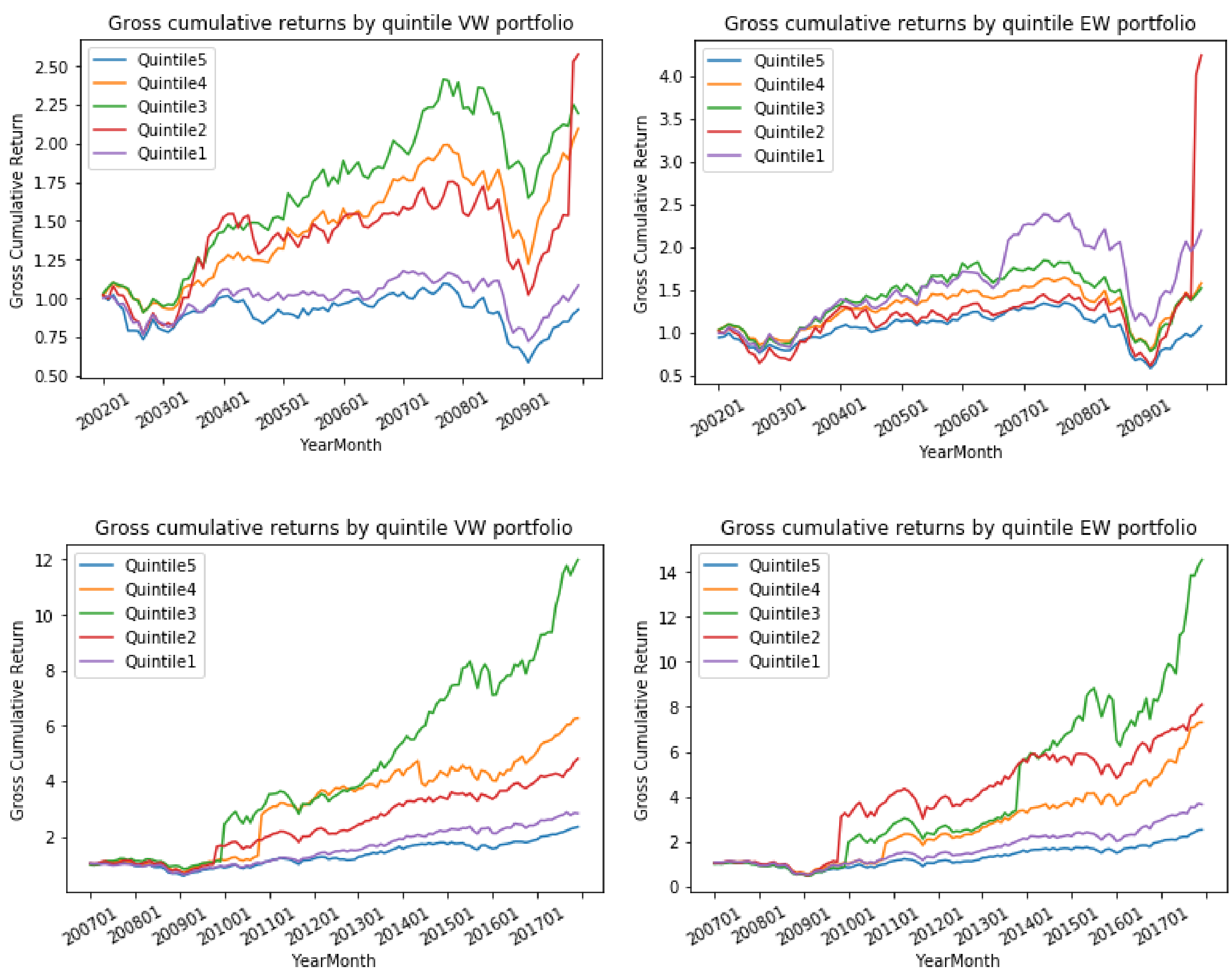


Table 9: Summary statistics of variables in portfolio analysis

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):

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

Klasen 1996 Fig2

[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).

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

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. (sale)	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.

ind adj

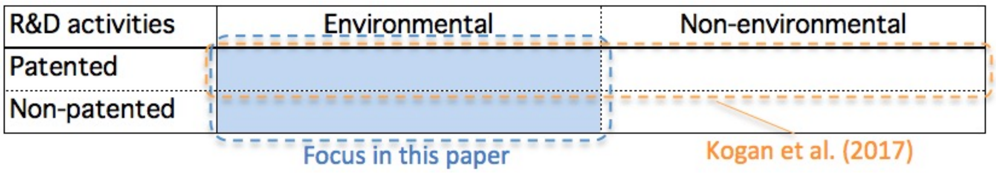
$$\text{R\&D intensity}_{i,t} = \beta_0 + \beta_1 \text{Innovation}_{i,t-1} + \beta_2 \text{logBME}_{i,t-1} + \beta_3 \text{logMVE}_{i,t-1} + \varepsilon_{i,t}$$

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.

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

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	
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).

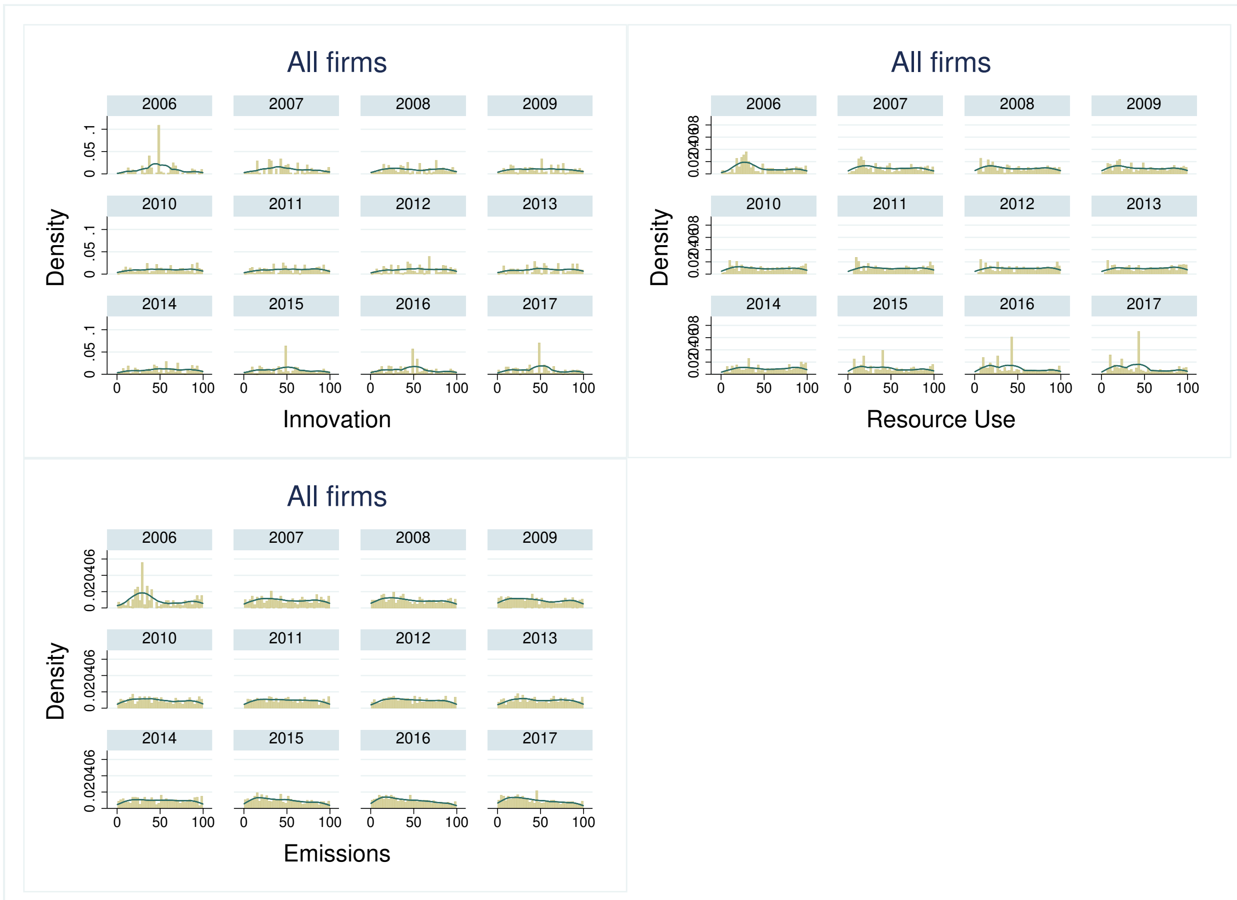


Figure 6: Innovation subscore by manufacturer size and fiscal year (*excluding* new firm entries)

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.

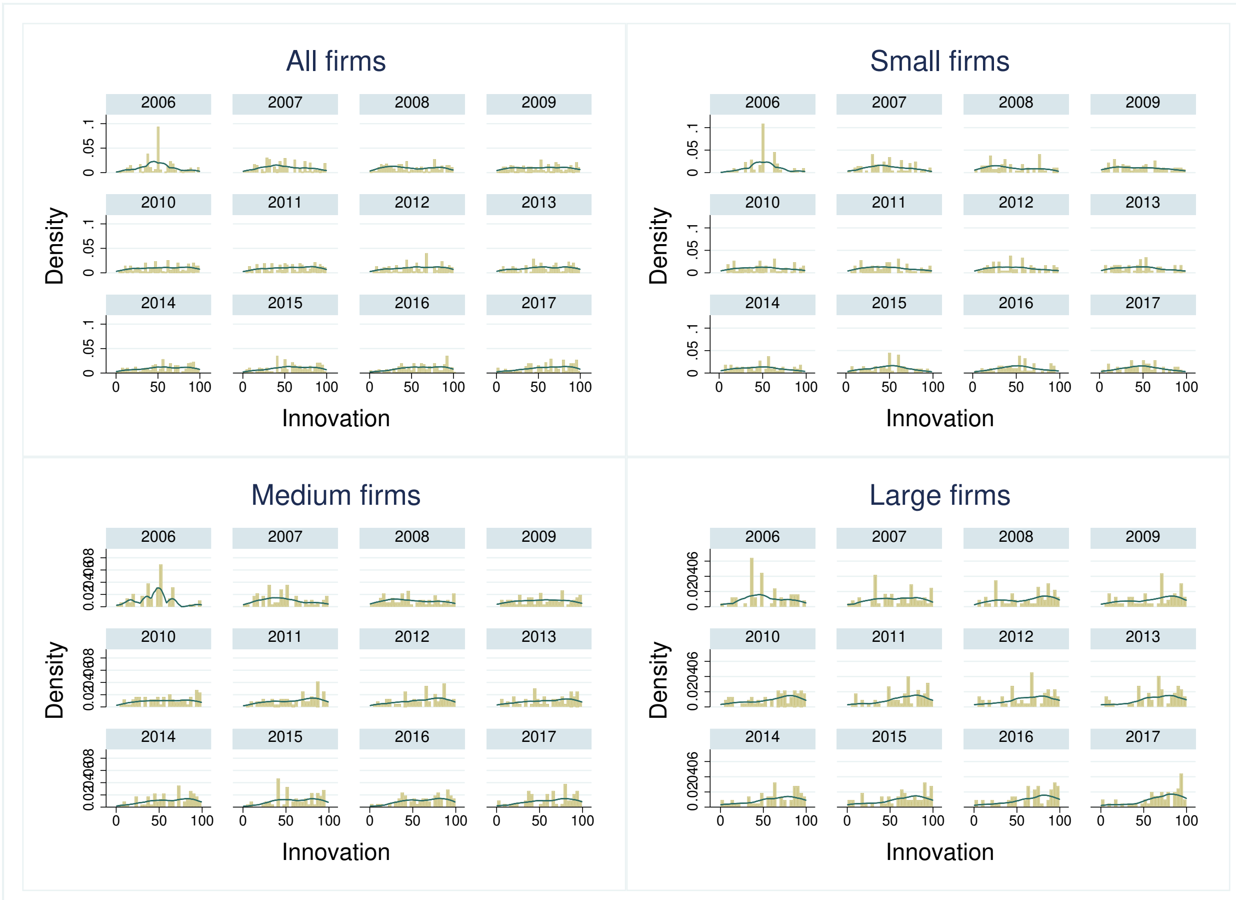


Figure 7: Resource Use subscore by manufacturer size and fiscal year (*excluding* new firm entries)

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.

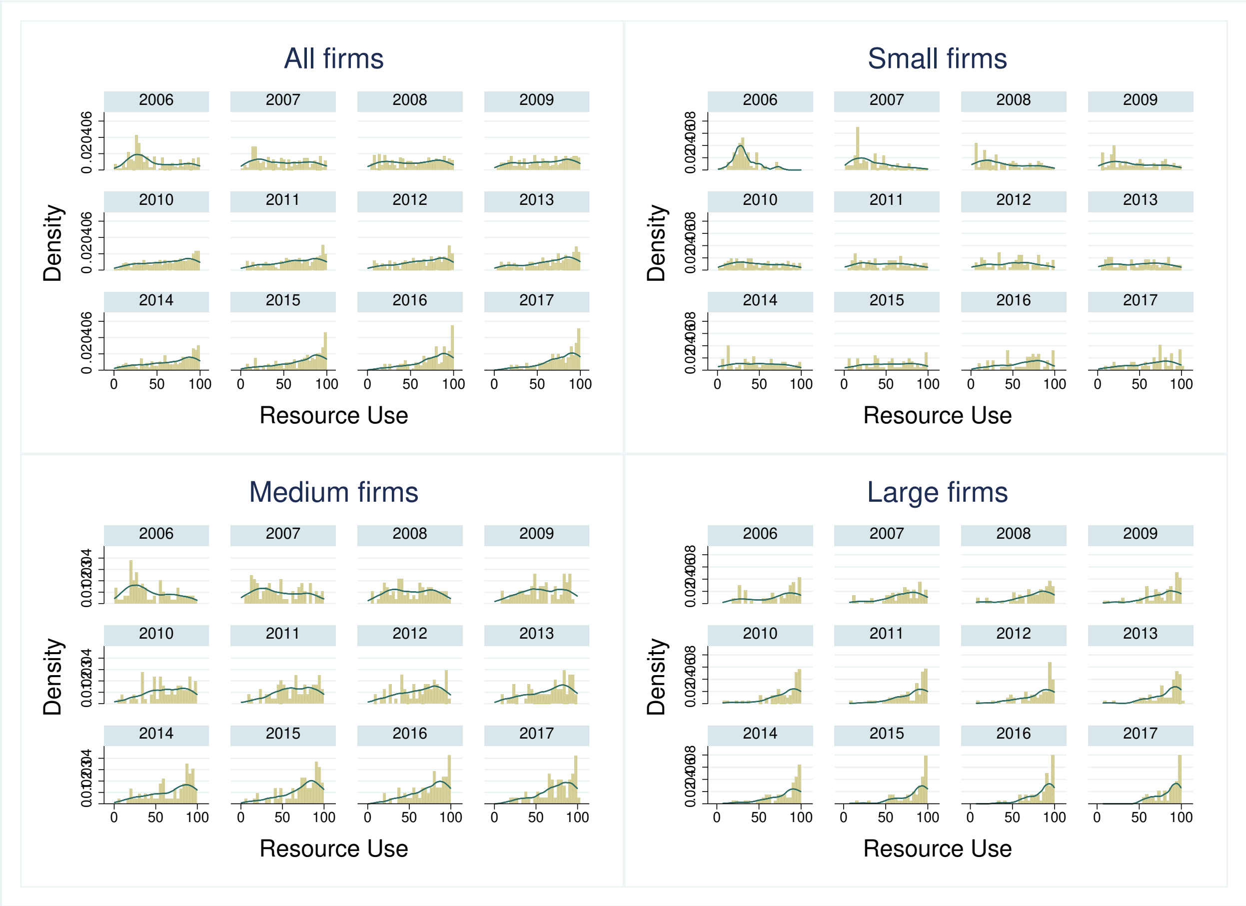
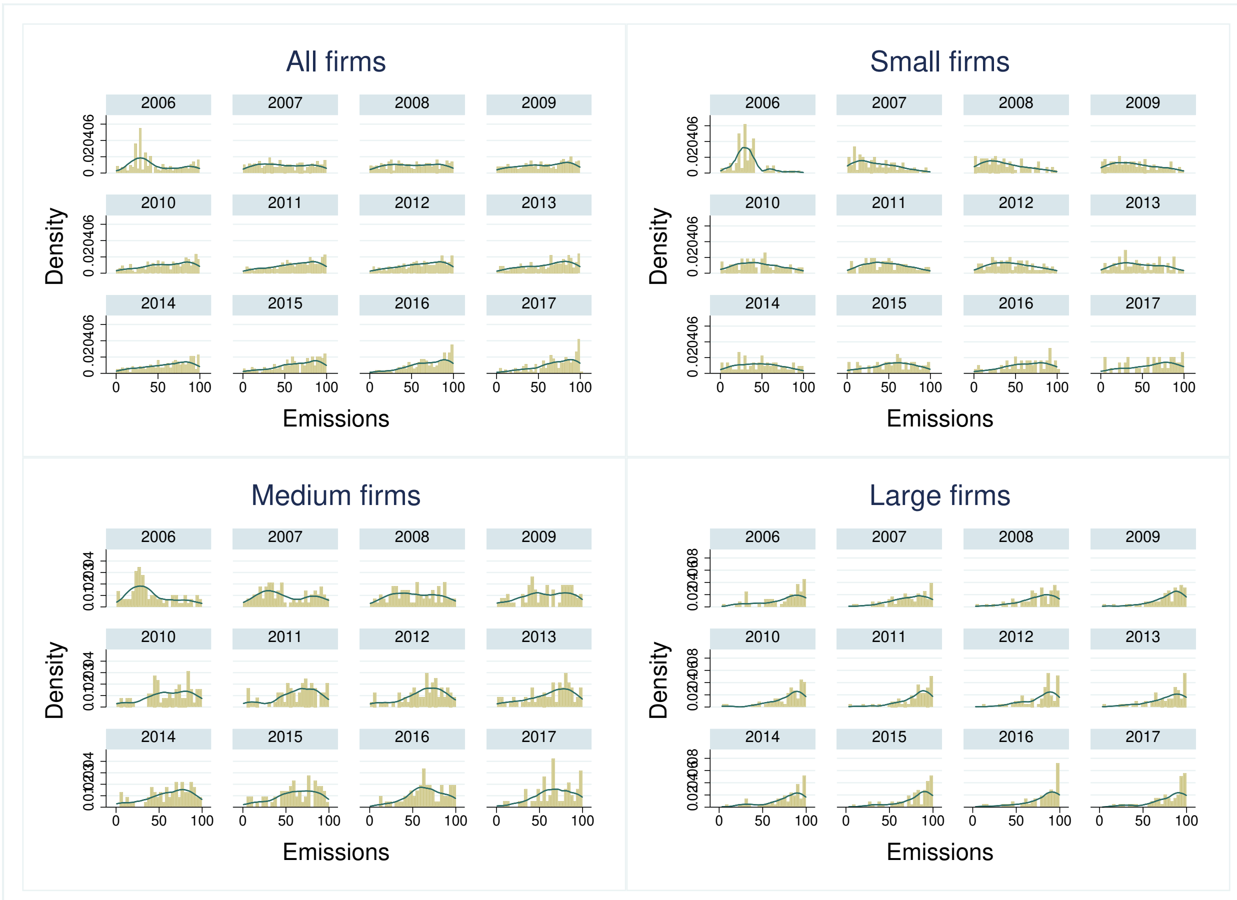


Figure 8: Emissions subscore by manufacturer size and fiscal year (*excluding* new firm entries)

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

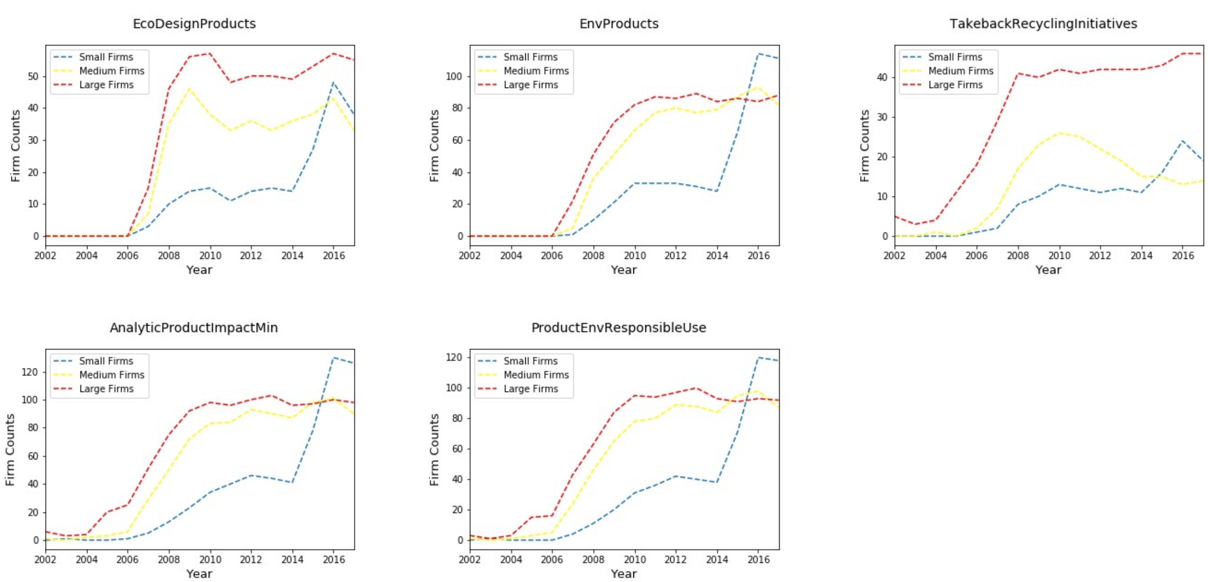


Figure 10: Trends in moderately-adopted elements of Innovation subscore

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.

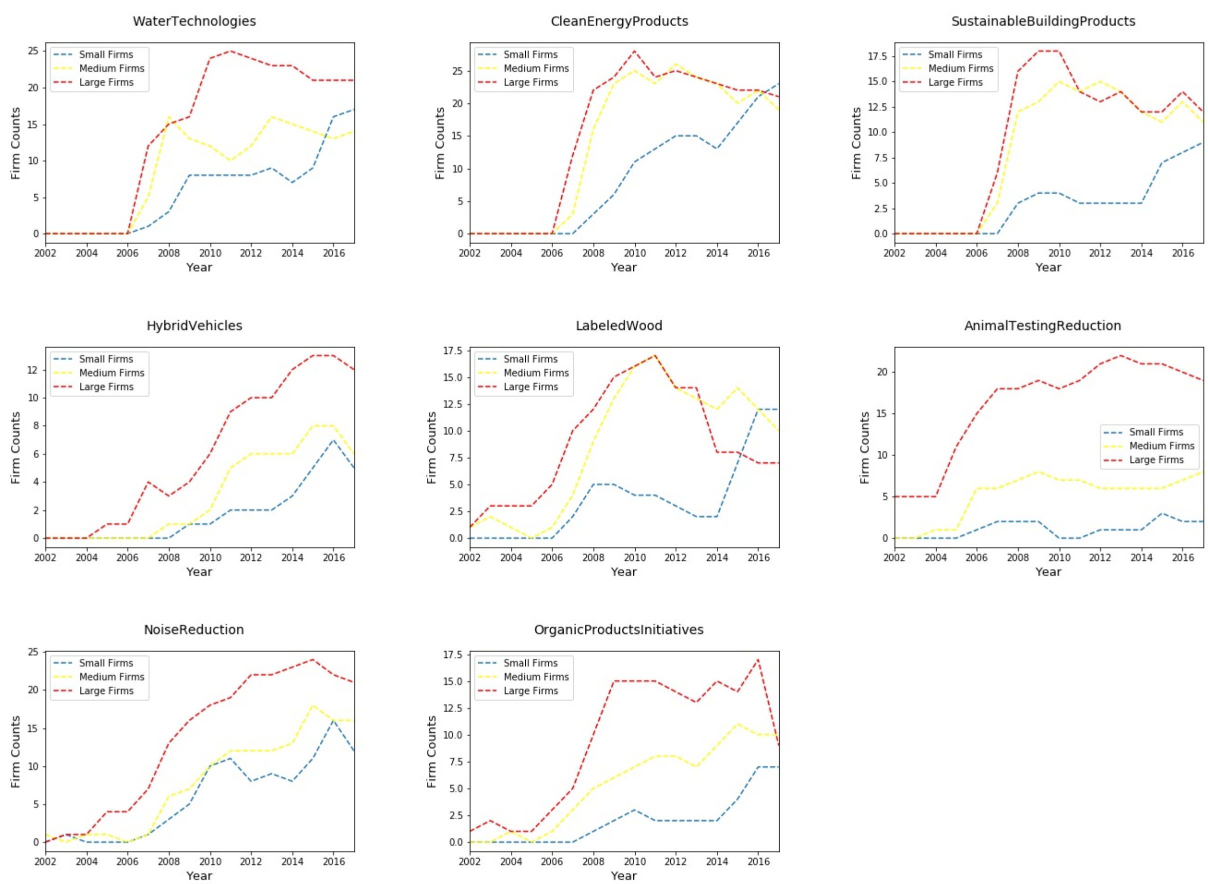


Figure 11: Trends in limitedly-adopted elements of Innovation subscore

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.

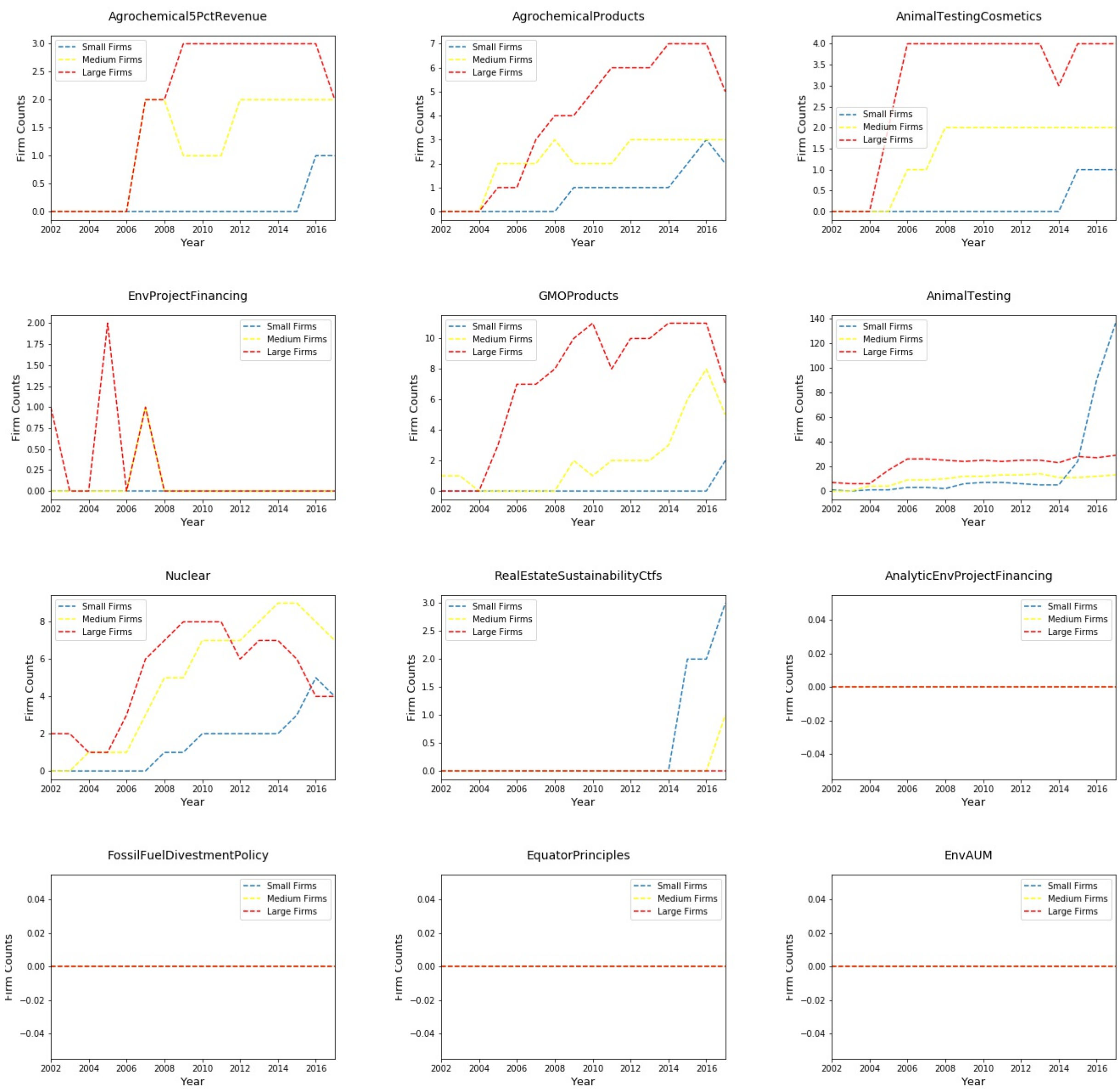


Figure 12: Trends in limitedly-adopted elements of Innovation subscore (numeric elements)

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).

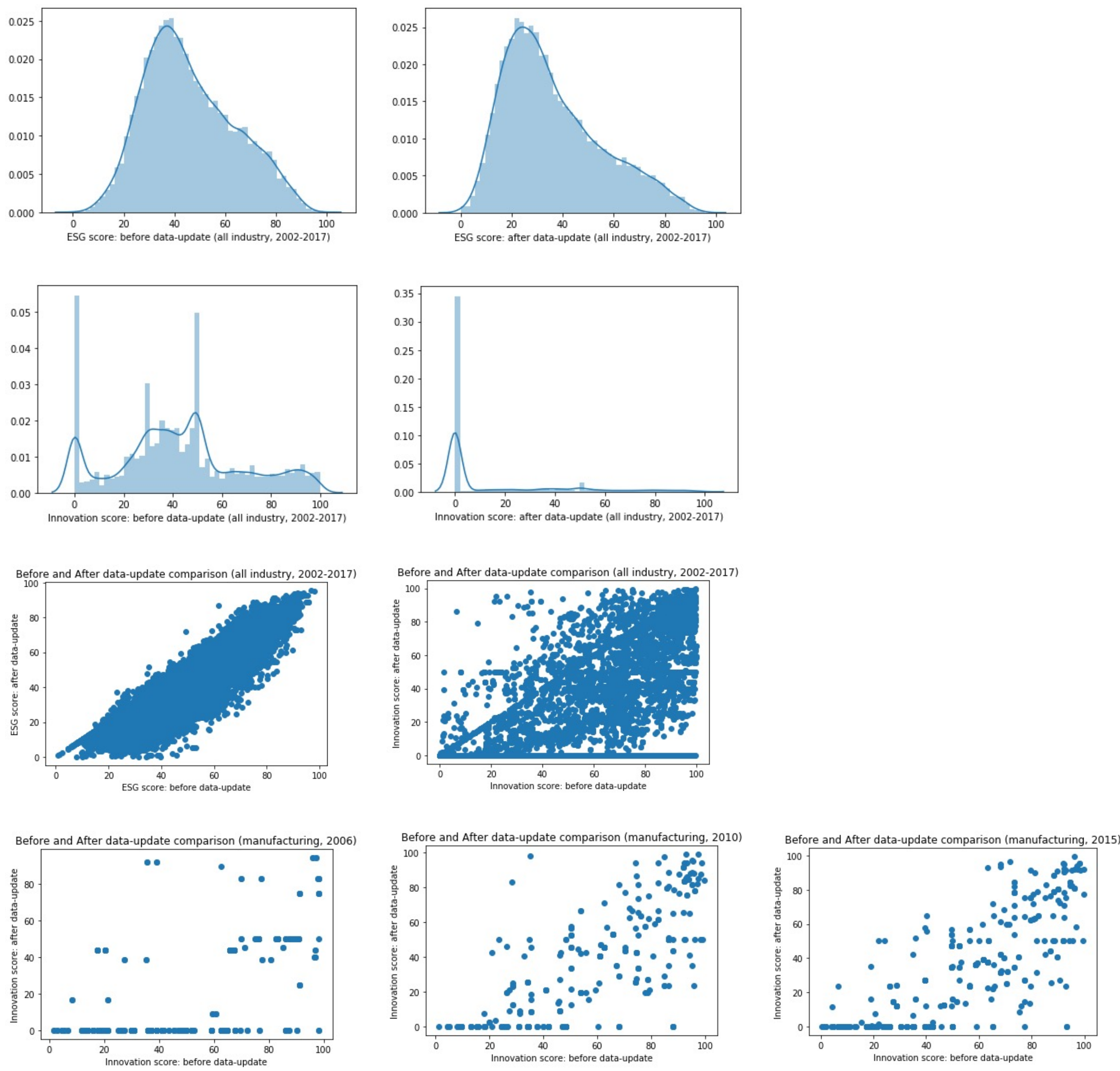


Table 24: Comparison of Innovation subscore elements: before and after score-update (all industries, 2002–2017)

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 (1)	Abnormal return (2)	Raw return (3)	Abnormal return (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.

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

	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