Is “Being Green” Rewarded in the Market? An Empirical Investigation of Decarbonization and Stock Returns

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Climate change could have potentially devastating effects on societies and economies globally. In order to prevent the worst climate-related outcomes, the International Energy Agency (2014) estimates that $53 trillion is needed by 2035. This quantum of capital demands the participation of fiduciary bound, commercial investors, such as pension funds, but this form of investment has been hampered by the unclear relationship between corporate environmental performance (EP) and financial performance (FP). This study seeks to remedy this by empirically investigating the risk-return relationship of low-carbon investment and characteristics of carbon-efficient firms. Based on 74,486 observations of U.S. firms from January 2005 to December 2015, we construct a carbon efficient-minus-inefficient (EMI) portfolio by carbon intensity, revenue-adjusted GHG emissions at firm-level. We find that our EMI portfolio generates positive abnormal returns since 2010, which cannot be explained by well-known risk factors. The findings demonstrate that an investment strategy of “long carbon-efficient firms and short carbon-inefficient firms” would earn abnormal returns of 3.5–5.4% per year. These carbon-efficient firms tend to be “good firms” in terms of financial performance and corporate governance. Our findings are not driven by a small set of industries, variations in oil price, or changing preferences of bond investors caused by low interest rates regime starting with the 2008 financial crisis.

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1 Introduction

Rising temperatures due to climate change will radically damage the functioning of human societies and specifically global economic activity (Burke et al. 2015; Dell et al. 2014; Hsiang et al. 2013). According to the International Energy Agency (2014), combating climate change is projected to require $53 trillion in cumulative investment by 2035.[1] The critical question is, then, how to source this massive capital. The funding gap far exceeds any single government's budgetary capacity, so it is crucial to address it with broader funding sources and scaled capital. Nonetheless, many investors and business leaders continue to resist managing climate risks because they are uncertain whether traditional financial objectives can accommodate the inclusion of environmental factors. In this regard, before calling for investors, business leaders, and policymakers to take series action about climate change, it is necessary to first understand what it means to invest in firms that are "being green."

A growing number of investors are looking at "impact investing" (interchangeably described as environmental, social and governance [ESG] investing, socially responsible investing [SRI], and value-based investing), which is a form of investing that seeks to overlay non-traditional investment criteria alongside the traditional pursuit of financial returns. Yet, impact investing has not resolved the question of whether it is possible to maximize risk-adjusted returns while integrating environmental factors in investment decisions. Therefore, most mainstream investors, especially those with fiduciary obligations to maximize profit, continue to lack confidence in this form of investing, with the result that the $53 trillion funding gap remains unresolved.

Although voluminous research has studied the compatibility of a firm's environmental performance (EP) and financial performance (FP), the debate has been inconclusive both theoretically and empirically. In principle, a theoretical argument about the relationship between EP and FP can go either direction. Some researchers claim that a firm's environmental improvement may not be compatible with profit maximization (e.g., Friedman 1970; Aupperle et al. 1985; Luken 1997; McWilliams and Siegel 1997, Clift and Wright 2000; Jensen 2002). On the contrary, others see environmental improvements as a cost-saving instrument and potential source of a firm's competitiveness in a rapidly changing world and climate (e.g., Schmidheiny 1992; Porter and Linde 1995). Empirical evidence is also mixed. While Hart and Ahuja (1996), Russo

[1] Note all dollar signs in this paper indicate US dollars unless otherwise indicated.

and Fouts (1997), Dowell et al. (2000), King and Lenox (2002), and Konar and Cohen (2001) suggest that EP is positively related to FP, other studies still find a negative or insignificant relationship between the two (e.g., Filbeck and Gorman 2004; Telle 2006; Ziegler and Nogareda 2009). A lack of consensus on reliable EP measures, along with different methodologies and data, also contribute to this discrepancy in empirical studies.

Using the data based on firm-level greenhouse gas (GHG) emissions, this research provides novel empirical evidence among firms' carbon efficiency, stock market performance and other characteristics in order to clarify the risk-return relationship of low-carbon investment. Specifically, we use portfolio analysis to investigate if carbon-efficient firms outperform carbon-inefficient firms, and we conduct regression analysis to identify the characteristics of carbon-efficient firms. Our key research questions thus include:

(1) Do investors achieve higher returns on their low-carbon investment portfolios?;
(2) If so, are they abnormal returns ("alpha") or compensation for bearing additional risk?; and
(3) What are the sources of the observed abnormal returns?

Our main data set consists of 74,486 observations of 736 US firms during the period of January 2005 to December 2015. We basically merge four databases: Trucost for firm-level GHG-related data, MSCI ESG (formerly KLD's) Stats for measures on ESG performance, Compustat for financial variables, and CRSP for stock returns.[2] Our key variable is a firm-level "carbon efficiency" (or "carbon intensity") from Trucost: it is the actual amount of GHG emissions of a firm divided by that firm's revenue.[3] The carbon efficiency can thus be interpreted as the amount of GHG a firm needs to emit in order to make $1 million in revenue. Unlike prior studies that use a firm's EP rating based on self-reported surveys or reputational indices to quantify social and environmental performance (Cohen et al. 1995), we use a quantitative and standardized EP measure so that we can compare across firms and industries.

As to our first question of whether carbon-efficient firms outperform carbon-inefficient firms, we form portfolios by carbon-intensity tertiles and construct a carbon efficient-minus-inefficient (EMI) portfolio. It is a zero-cost portfolio, which can be interpreted as an investment strategy that

[2] A majority of previous literature uses ESG data provided by Kinder, Lydenberg and Domini and Company Research & Analytics, Inc. (KLD). But, from 2010, MSCI ESG Research is the successor to KLD, Innovest and IRRC, which were acquired through MSCI's acquisition of RiskMetrics in 2009. The MSCI ESG Stats was created by KLD in 1991.

[3] Hereafter, we use the terms carbon (emissions) intensity, carbon efficiency, and carbon inefficiency interchangeably as a measure of environmental performance. High carbon efficiency corresponds to low carbon inefficiency, low carbon intensity, and low carbon emissions per revenue.

takes a long position in carbon-efficient stocks and a short position in carbon-inefficient stocks. We also double-sort stocks in two ways and construct EMI portfolios: by book-to-market (B/M) ratio carbon efficiency, and by firm-size (market capitalization) and carbon efficiency. Our EMI portfolio earns a positive cumulative return from 2010, implying carbon-efficient firms do in fact outperform carbon-inefficient firms. The only exception is found in very small firms.

As to the second question, we find that the observed extra returns on our single-sorted EMI portfolio is alpha that cannot be fully explained by the well-known risk factors, such as market, size, value, momentum, operating profitability and investment. And the magnitude of the alpha amounts to the annualized abnormal returns of 3.5–5.4%. Furthermore, we confirm that those double-sorted EMI portfolios earn positive alphas in similar magnitudes. While our EMI portfolio shares some characteristics of growth stocks and short-term winners, it still has its own characteristics that cannot be fully explained by well-known factor-mimicking portfolios after 2009.

As to the third question, we find that carbon-efficient firms are those with higher firm value measured in Tobin's *q*, higher net income relative to invested capital (i.e. ROI), lower ROA, higher cash flow, and higher coverage ratio. We also find that firms with better governance tend to be carbon-efficient. And the statistical association of carbon efficiency with ROA, cash flow, and coverage ratio increases after 2009.

We also examine whether investors explicitly consider firms' efforts to improve carbon efficiency by using the portfolios formed on *changes* in carbon efficiency. Our findings suggest that investors may not closely and directly monitor firms' decarbonization efforts, so these factors are not explicitly considered in their investment decisions.

For robustness, we examine whether other macroeconomic factors, such as fluctuations in oil price or unconventional monetary policy, may affect the performance of our EMI portfolio. We confirm that changes in oil price do not drive EMI portfolio performance. Also, we check whether unconventional monetary policy has any impact on performance of the EMI portfolio. Due to extremely low interest rates after the 2008 global financial crisis (GFC), bond investors have moved their funds to equity markets and are looking for stable and high-dividend-paying industries, such as utilities, telecommunication, and consumer durables. We construct the same EMI portfolio without these industries and find that it tracks the benchmark EMI portfolio closely, suggesting that a change in investor preference caused by unconventional monetary policy cannot explain our findings.

Our study makes unique contributions in several respects. First, we form portfolios using revenue-adjusted GHG emissions at the firm-level, which is a more objective and easily comparable EP measure. Second, we consider intrinsically different levels of GHG emissions across industries when forming portfolios, in contrast to some prior studies that do not consider industry effect. Third, our measure of EP covers a firm's entire value chain and thus considers emissions from supply chains, which has been increasingly important. Fourth, our analysis goes beyond determining the sign of the empirical link between EP and FP, and investigates a more general question of how well carbon-efficient firms perform compared to carbon-inefficient firms in the stock market with accounting for risks they face.

We expect that our empirical findings will help investor and policymakers understand how decarbonization and related firm characteristics are perceived in financial markets. While we acknowledge that the observation of the abnormal return is relatively short, our research strongly indicates the outperformance of carbon-efficient firms may be a long-term sustainable trend. Because the variables that we measure to identify the characteristics of "clean firms" are relatively low-frequency variables, we anticipate that the trend of carbon-efficient firms' outperforming carbon-inefficient firms may persist over longer time periods.

The rest of the paper is structured as follows. Section 2 reviews related empirical studies. Section 3 explains our data and key variables, while providing summary statistics on carbon efficiency. We also explain the advantage of using the Trucost database, compared to other EP-related measures used in the previous literature. In Section 4, we construct EMI portfolios in various ways and examine whether they can be priced by well-known risk factors (or styles) and whether they can earn positive alphas. We also examine the firm-level characteristics of carbon-efficient firms and perform various robustness tests. Section 5 discusses the implication for climate finance and future research agenda along with several unanswered questions that warrant future research direction. Section 6 concludes.

2 Literature Review

While early empirical studies focus on determining the sign of the relationship of a firm's EP and FP, recent studies expand to investigating mechanisms through which EP can positively impact FP. We have identified at least three strands of empirical research: (1) event studies, (2) regression analysis, and (3) portfolio analysis. In addition, we refer to the literature on corporate social responsibility (CSR) and firm characteristics because firms' environmental actions are often integrated into CSR discussions. Incorporating this additional literature will help us understand what kinds of firms are carbon-efficient and carbon-inefficient, which is the main topic of section 4.2.

2.1 Event Studies

Researchers use event study methodology to gauge the impact of an exogenous event on a firm's FP. A typical event study finds a discrete event related to a firm's EP and compares the variables of interest, mostly stock price because it is a high-frequency measure, over a short time period before and after the event. The selected events include macroeconomic events such as new environmental data releases or regulation enactment, and firm-specific news such as new data release or (either voluntarily or involuntarily) joining an environmental program. Researchers are interested in whether and why the selected event might have a positive (or negative) impact on firms' FP. A related literature shows that investors are concerned because a firm would be subject to: (1) an environmental penalty; (2) a potential gain or loss in revenue; and (3) a governance issue, and thus react to the event.

First, investors react to news when they believe a firm's environmental activities are directly related to liability, compliance, and regulatory risks, thereby affecting the cost and value of the firm. For instance, Hamilton (1995) tracks the stock value of 436 publicly traded firms from the New York and American Stock exchange before and after the day that the Environmental Protection Agency (EPA) first released the Toxics Release Inventory (TRI) in 1989, and finds that high polluting firms experience abnormal negative stock returns. The pollution figures are measured by a company's waste generation and reduction activities, and the author argues that the investors take TRI data as news because it may relate to the costs of environmental laws, leading to a higher cost of operation and loss of reputation and goodwill. Similarly, Jones and Rubin (2001) find that, even among 73 negative environmental news reports by the Wall Street Journal, the market only reacts to the firms that would be subject to penalty. Lott and Karpoff (1999) find that the magnitude of market value losses of the firms that violate environmental laws is closely correlated to the legal penalties imposed.

Second, some event studies argue that an "event" need not necessarily relate to environmental penalties but to sales and revenue. More recently, Bushnell et al. (2013) analyze the stock value of 552 stocks in the EURO STOXX index over a three-day window when the EU CO_2 allowance price dropped 50% in late April 2006. Despite the carbon price drop, which may have lead to a reduction of environmental costs, they observed a sharp stock price drop in carbon- and electricity-intensive firms. The authors point out that investors consider the declining carbon price in terms of its product price impacts (e.g., lower carbon price would also lower electricity prices). The finding that the market pays close attention to subsequent changes in firms' revenues due to the release of the news is also consistent with the event studies joining an environmental program. Cañón-de-Francia and Garcés-Ayerbe (2009) find that, among the 80 Spanish firms that voluntarily adopted ISO 14001, only less-polluting and less internationalized firms experienced a drop in their stock prices. This implies that investors do not expect a profit gain from adopting ISO 14001 to compensate the extra cost of this action.

Third, other event studies suggest that investors are also concerned with corporate governance issues in reacting to the event. Fisher-Vanden and Thorburn (2011) examine the effect of membership in a voluntary environmental program on firms' stock returns. They find that companies announcing membership in EPA's Climate Leaders, a program targeting reductions in GHG emissions, experience significantly negative abnormal stock returns. Interestingly, the authors find that firms facing climate-related shareholder resolutions or firms with weak corporate governance standards are more likely to join Climate Leaders, suggesting the endogeneity of such actions. Krüger (2015) demonstrates that investors react negatively not only to negative news about firms' CSR performance, but also—in weaker and less systematic ways—to positive news as well, because investors assume it can result from agency problems inside the firm.

The event-study approach may mitigate the endogeneity problem (i.e., doing well by doing good vs. doing good by doing well) by looking at short time windows around an event. However, the findings of event studies are somewhat limited, which makes it difficult to generalize. Because the event-study approach is based on one-time events, it is hard to analyze long-term trends or consistent measures of a firm's EP that are not tied to a particular date (Konar and Cohen 2001). Moreover, it is also difficult to find an exogenous event. If the event is not fully exogenous, a study using that event may involve endogeneity issues.

2.2 Regression Analysis

Regression studies examine the relationship between key explanatory variables (typically, EP, governance, etc.) and dependent variables (firm value, profitability etc.), while controlling for other variables. This form of analysis examines long-term effects, but the empirical findings of existing studies are not consistent with one another: The full body of research has found positive, negative and not-significant empirical relationship between EP and FP. Even the large-scale meta studies (e.g., Margolis et al. 2009; Fulton et al. 2012; Mercer 2009) that examine the results of over 100 academic studies report mixed results on the empirical link between EP and FP. We find two significant challenges in regression studies in this field. First, studies have not reached a consensus on the right measure for EP and have suffered from the lack of such data. Second, there remains the endogeneity issue of determining whether the observed correlation is causal or not.

It is challenging to find a large enough data sample that effectively represents the market, and, at the same time, has consistent EP measures across the sample period. Most early regression studies use the pollution database generated by the Council on Economic Priorities (CEP). Bragdon and Marlin (1972) examine 17 CEP firms during 1965–1970 and find a strong positive correlation between firm's pollution control and financial performance, such as profitability and earnings per share. On the contrary, Mahapatra (1984) finds a negative association between these variables when he expands the study sample to 67 firms in six industries—chemical, iron and steel, paper, petroleum refining, metal, and textile—from 1967 to1978. As such, because the CEP database has a small sample size, studies based on the CEP data fail to deliver a level of confidence that is acceptable to a large population.

To address this problem, Konar and Cohen (2001) examine a large sample from S&P, and two environmental performance measures from the Investor Responsibility Research Center, which includes the aggregate pounds of toxic chemicals per dollar of revenue of the firm and the environmental lawsuits pending against the firm. However, due to the limited availability of EP data, their sample mostly consists of manufacturing firms and is not suitable for cross-industry analysis.

Furthermore, another aspect of the empirical limitation is lack of standardization of EP measures. For example, Konar and Cohen (2001) criticize previous empirical analysis for "relying upon subjective or anecdotal analysis to characterize environmental performance." As a result, the non-standardized EP disclosure practices may result in a misunderstanding of the relationship between EP and FP, as the empirical results can differ depending on what EP measurement the study uses (e.g., Chatterji et al. 2009; Sharfman 1996; Szwajkowski and Figlewicz 1999). We discuss the issues regarding EP measures in 3.2.

The second limitation of regression analysis, as mentioned earlier, is that findings of simple regression studies do not strictly differentiate between correlation and causality (Krüger 2015). For example, studies that simply regress the annual CSR ratings on the annual values of a firm cannot address the question of whether the firm does well because it does good or vice versa. Prior studies, such as Cohen et al. (1995) and Porter and Linde (1995), attempt to demonstrate that corporate environmental actions have a causal impact on economic success and thus firm value. They find that firms with superior EP do not always generate high FP. Rather, outcomes depend on external and internal factors (e.g., Karagozoglu and Lindell 2000; Christmann 2000; King and Lenox 2002).

Thus, the empirical literature has evolved away from determining the positive or negative link between EP and FP, and toward an examination of the pay-off mechanism of corporate environmental actions. Some studies explain their findings in terms of a trade-off between environmental costs and current/future cash flows (e.g., Gregory et al. 2014). Some recent studies suggest that the financial benefits of environmental actions are from mitigating liability, compliance and regulatory risks (e.g., Godfrey, et al. 2008; Jo and Na 2012; Oikonomou et al. 2012). Others point to operating efficiency and management capability gains. The financial advantages of a firm's EP are also tied to non-environmental factors that happened to deliver EP alongside other external and internal outputs (e.g., Barnett 2007; Christmann 2000; Cohen et al. 1995; Karagozoglu and Lindell 2000; Schaltegger and Synnestvedt 2002; Schaltegger and Figge 2000; Servaes and Tamayo 2013).

In addition to studies that investigate how EP is related to FP, CSR literature has also long discussed the issue of endogeneity. Since CSR has broader criteria that also contains social and governance criteria in addition to the environmental factor, empirical discrepancies in determining the relationship between CSR and its financial returns are also pervasive. Some researchers note that CSR can affect a firm's FP through intermediate variables, such as stakeholder management or customer satisfaction, and the omission of these confounding variables may mislead the empirical results (McWilliams et al. 2006; Orlitzky 2009). Servaes and Tamayo (2013) use models with firm fixed effects to examine the firm-level cross-sectional difference, and they find the link between CSR and firm value is significantly positive only for firms with high customer awareness. Barnett (2007) makes a similar argument that the financial merit of CSR resembles one's own investments in intangible assets such as R&D and marketing.

Some studies on CSR use an instrumental variable (IV) to address potential endogeneity concerns or correlated omitted variables issues. Cheng et al. (2014) find that firms with better CSR performance have significantly lower capital constraints, and these firms have better stakeholder engagement and transparency around CSR performance. Ferrell et al. (2016) also use the IV approach and demonstrate that well-governed firms that suffer less from agency concerns (proxied by less cash abundance, positive pay-for-performance, small control wedge, and strong minority protection) engage more in CSR. They also show that a positive relation exists between CSR and firm value, and that CSR attenuates the negative relation between managerial entrenchment and firm value.

2.3 Portfolio Analysis

Different from an event study or a regression analysis, the portfolio approach has the advantage of explicitly considering the risk-return relationship. A typical portfolio analysis approach is to form portfolios sorted on an EP measure and then compare the average returns of those portfolios, testing if differences in average returns can be explained by risk factors. For instance, Cohen et al. (1995) construct two portfolios based on environmental performance, naming "environmental leaders" and "environmental laggards," and they show that the former outperform the latter in the stock market between 1987–1990.[4]

However, different EP measures result in different outcomes as well. Derwall et al. (2005) construct two portfolios in terms of the eco-efficiency scores published by Innovest Strategic Value Advisors, and they demonstrate that the high eco-efficient portfolio provides substantially

[4] They create a single EP measure based on nine different measures from government data and 10-K filings such as number of environmental litigation proceedings, superfund sites, number of noncompliance penalties, TRI, number of chemical spills, number and volume of oil spills.

higher average returns than its low eco-efficient one over the 1995–2003 period.[5] Puopolo et al. (2015), on the other hand, find no linear relationship between EP and FP when they use Green Score (GS) by Newsweek as their EP proxy.[6]

To address this inconsistent EP measurement issue, ET Index (2015a) measures a firm's EP based on the absolute amount of carbon emission. It defines firm-level carbon intensity as firm-level GHG emission, in tons of CO2 equivalent (tCO2e), divided by revenue.[7] ET Index (2015b) analyzes 2,267 stocks available from the ET GHG emissions database between January 2009 and March 2015. It double-sorts the stocks by carbon intensity and size, and it constructs a carbon efficient-minus-intensive (EMI) portfolio in a similar way to the Fama-French procedure used for the construction of small-minus-big (SMB) and high-minus-low (HML) factors. It finds that their EMI factor exhibits positive returns and is not related to the standard risk factors, size, value, and momentum. Although ET Index provides evidence that portfolios of low carbon intensity stocks outperform portfolios of high carbon intensity stocks, their Fama-MacBeth test result shows that all the factors in the model have statistically insignificant and very weak explanatory powers. We are not able to confirm whether this limitation results from their methodology or their sample because the ET Index does not report how the sample is constituted in this report. In addition, as it does not control for industry effects, it is possible that several outlier industries may drive the result.

Oestreich and Tsiakas (2015) construct a dirty-minus-clean (DMC) portfolio using 65 German stocks from November 2003 to December 2012. The dirty portfolio is a portfolio of firms that received a high number of free carbon emission allowances granted under the EU Emissions Trading System during its Phase I and II.[8] The clean portfolio includes all firms that did not receive any allowances. They define the carbon premium as the excess return of the DMC portfolio. They

[5] Innovest evaluates a firm's eco-efficiency relative to its industry peers via an analytical matrix. Firms are evaluated along approximately 60 dimensions, which jointly constitute the final rating. For each of these factors, each firm receives a score between 1 and 10. The criteria can be grouped into five broad categories, which address five fundamental types of environmental factor.

[6] GS is based on three components: an environmental impact score, an environmental management score, and an environmental disclosure score, weighted at 45%, 45%, and 10%, respectively. To form the sample, the authors surveyed 500 biggest publicly traded US firms belonging to the 2009–2014 Newsweek Green Rankings, and 31.5% of them disclose the requested data on their environmental impact.

[7] ET Index is a private research company that specializes in low-carbon investment.

[8] During the EU ETS Phase I and II (2005–2007 and 2008–2012 respectively), most allowances were allocated for free to participants whereas each EU country previously decided on the allocation of their emission allowances. The amount of allowances each installation received was decided via National Allocation Plans (NAPs). Each member state would prepare and publish, in a document called a NAP, the proposed number of allowances to be allocated for its installations over the duration of the trading period. These NAPs would then be assessed by the Commission, who would approve or amend the total number of allowances to be allocated, based on criteria set in the annex of the (original) 2003 EU ETS Directive.

show that the dirty portfolio outperforms the clean portfolio during Phase I and II, but not before or after. However, the observed carbon premium is more about the cash flow effect, not about the risk-return relationship. Firms receiving free allowances can reduce their production costs or increase revenue by selling them.[9]

3 Data and Summary Statistics

3.1 Data Description and its Market Representativeness

Our main data set is merged from four databases: Trucost for carbon emission measures; Compustat for financial variables; CRSP for stock prices and returns; and MSCI ESG Stats for ESG indices. The first three databases are yearly data and the stock return data is monthly. In this study, we focus on the US stock market because the US case provides the largest sample, and there is a relatively well-established consensus on risk factors such as market, size, value, operating profitability, investment, and momentum effects.[10] We exclude the financial sector and the observations that do not report firm size and B/M.

The final sample thus consists of 736 publicly traded US firms and the total number of observations is 74,486 from January 2005 to December 2015. Panel (a) in Table 1 shows the number of total observations and distinct firms in our sample.

Prior to the main analysis, we confirm that there are no severe selection biases due to forming our study sample based on Trucost's dataset. In order to check whether our sample well represents the stock universe, we categorize firms in our sample based on Fama-French breakpoints for size and B/M and compare our sample's distribution to Fama-French breakpoints result using all NYSE stocks. According to the breakpoints, the top 50% firms in terms of market capitalization in the stock universe are big firms and the bottom 50% firms are small firms. Also, the top 33% firms in terms of B/M are value firms, the middle 33% are neutral and the bottom 33% are growth firms. Panel (b) in Table 1 shows that our sample is tilted toward large and growth firms; in our sample,

[9] Related to our research, a more interesting observation is that clean portfolios have outperformed dirty portfolios since 2009 when the EU announced that free allowances would be no longer be available beginning in 2013. The DMC portfolio has generated positive returns in Germany from 2009 onward. However, they focus on the period of 2003-2009 to see if free allowances affect the prices of dirty stocks.

[10] From 2005 to 2015, the number of observation in the United State available in Trucost database is 9,510 while those for Japan, the United Kingdom, China, South Korea, France, Germany, and China are 4,516, 3,586, 2,335, 2,119, 1,203, and 1,009, respectively. In et al. (2017a) take the same approach of this paper and analyze the advanced and emerging economies in Europe and East Asian countries.

there are 63,196 big firms (84.8% of the total sample) relative to 11,290 small firms (15.2% of the total sample), and 37,341 growth firms relative to 26,186 neutral firms and 10,959 value firms (50.1%, 35.2% and 14.7% of the total sample, respectively).

There may be concerns that our sample is tilted toward big and growth firms, but this is consistent with findings of other studies that use different US stock samples. For instance, Guerard (1997), Kurtz (1997), Bauer et al. (2005), and Derwall et al. (2005) find that environmentally and socially screened portfolios in the US tend to be biased toward big and growth stocks. In addition, while this bias toward large and growth firms may affect the average returns, it will not affect alpha because we include SMB and HML factors as regressors in the following analysis and portfolios consisting of those large and growth firms will exhibit large coefficients (in absolute values) on SMB and HML factors.

Furthermore, we compare the returns of industry portfolios from Trucost and Fama-French in five directly comparable industries: energy, finance, health, telecommunication, and utilities.[11] Panel (c) in Table 1 shows the correlation coefficients of industry portfolio returns in these five comparable industries. It shows that, except for the telecommunications sector, all correlation coefficients are close to one, suggesting that returns of industry portfolios based on our sample track very well those of all NYSE stocks.

3.2 Issues with EP Measures

While investors and financial intermediaries have begun to integrate ESG data in their valuation models, the availability of reliable corporate carbon emission data is still limited today. This is primarily due to several factors: low disclosure rates, weak transparency and accuracy of the data, inconsistent reporting criteria, and the lack of reporting standards.

First, a number of firms partially disclose or do not disclose at all of their carbon data. Trucost (2015) indicates that only 44% of firms in the five major global indices, including MSCI World, MSCI Europe, S&P 500, MSCI ACWI and MSCI Emerging Market, disclose GHG data, and evidences that disclosing firms are likely be the ones proactively involved in environmental

[11] Trucost and Fama-French industry portfolios use different industry classification; the former uses Global Industrial Classification Standard (GICS) and the latter uses Standard Industrial Classification (SIC). We find that these five industries are directly comparable.

improvement and have lower carbon intensities.[12] An increasing number of countries have begun to mandate the disclosure of ESG information, either through laws and regulations or through stock exchange listing requirements (Ioannou and Serafeim, 2017). In the US, for example, Securities and Exchange Commission (SEC) issued a concept release in 2016 soliciting public input on modernizing the disclosure requirements in Regulation S-K. SEC includes a limited discussion about ESG disclosure, but sustainability reporting on ESG issues remains voluntary in the US.

Second, the transparency and accuracy of sustainability reporting is important as well. Even if firms disclose their carbon data, they often make reporting errors and there is no rigorous validation process for firm-disclosed data. The most common reporting error is that the reported GHG data is not aligned with the GHG Protocol accounting and reporting standard on carbon-emission disclosures. It is categorized into three scopes in term of emission source: direct emissions from operations (Scope 1), indirect emissions from purchased electricity by the owned or controlled equipment or operations of the firm (Scope 2), and other supply chain emissions (Scope 3). Significant data discrepancies are found in Scope 1 (tCO2e) disclosures because, for many firms, this is the largest area of carbon exposure (Trucost, 2015). More importantly, firms could be in a position to game their ESG ratings so they can gain access to increasingly available SRI investors and potentially lower cost of capital (Chatterji et al., 2009; Cheng et al., 2017).

Third, setting consistent reporting criteria is another issue. Current practices of corporate carbon assessment generally do not consider carbon exposure throughout a firm's entire value chain, which may underestimate the firm's real carbon risk. Trucost (2015) finds that the greatest carbon exposure is concealed in their supply chain—part of Scope 3. Only in the transportation and utilities sectors, Scope 3 is insignificant because the high portion of fossil fuel consumption is included in direct operation—part of Scope 1. We also show evidence from our sample that the presence of Scope 3 is not negligible, and discuss this in 3.3.

Fourth, there is a lack of reporting standards to disclose a firm's EP. Companies start to disclose their ESG performance as in a quantifiable form using a single rating or reputational indices (Cohen, et al., 1995). But a single-dimensional ESG or CSR performance measure may mislead its evaluation. Waddock and Graves (1997) argue that CSR performance is a

[12] The MSCI World Index captures large- and mid-cap representation across 23 Developed Markets (DM) countries. The MSCI Europe Index captures large- and mid-cap representation across 15 DM countries in Europe. The MSCI ACWI captures large- and mid-cap representation across 23 DM and 24 Emerging Markets (EM) countries. The MSCI Emerging Markets Index captures large- and mid-cap representation across 24 EM countries.

multidimensional construct that includes a wide variety of inputs (e.g., investment in pollution control equipment, other environmental strategies, nature of products, customer relationship, community relations etc.), and thus an aggregated ranking or score cannot address wide variation across companies and industries. Some recent studies use the weight or volume of a single type of emission as the basis for pollution performance (Jaggi and Freedman, 2014).

Third-party rating agencies have emerged to provide more advanced corporate EP measures, such as MSCI's ESG ratings, ASSET4 from Thomson Reuters, and Sustainalytics. They set consistent standards to apply across firms, industry and countries. Thus, these datasets do a better job of aggregating companies' multidimensional ESG measures than a single proxy measure, thereby providing more credible and easily comparable ESG metrics. However, the currently available ESG ratings are still limited by information omissions and convergence issues.

The aggregation processes associated with ESG metrics often lose track of important information about a firm's actual EP and FP. For example, it is a common practice to subtract the scores of concerns or weaknesses from that of strengths to arrive at a single net environmental score (e.g., Graves and Waddock 1994; Griffin and Mahon 1997; Johnson and Greening 1999; Ruf et al. 2001; Waddock and Graves 1997). But the aggregation process may drop important information as each score can represent distinct constructs (Mattingly and Berman, 2006). In fact, Chatterji, et al., (2009) examine the validity of KLD (now merged as MSCI) ESG ratings, one of most widely used EP measures in recent empirical studies, with a company's EP. They find that its environmental concern ratings constitute fairly good summaries of past EP, but its environmental strength ratings do not accurately predict future EP.

Furthermore, Lee and Faff (2009) argue that the ratings often involve transparency issues and are inconsistent across different rating agencies. Semenova and Hassel (2015) investigate the convergent validity of environmental rating of three major global agencies, KLD, Thomson Reuters, and Global Engagement Services (GES). They find that those ratings have common dimensions, but on aggregate they do not converge.

The above discussion on the drawbacks of today's EP measures underscores the advantage of using Trucost carbon emission data in this study. Trucost assesses the carbon footprint of approximately 13,000 publicly listed companies worldwide by compiling corporate and supplier emission data on the seven GHGs covered by the Kyoto Protocol and measuring them as carbon dioxide equivalents (CO2e).[13] We consider Trucost data as a unique carbon data source based on the following points: First, it provides firm-level carbon exposure based on actual GHG emissions in metric units. This approach can minimize the information asymmetry due to inconsistent evaluation criteria and reporting standards by different rating agencies. Second, Trucost's GHG emission data includes GHG emissions throughout a firm's entire value chain.[14] Third, Trucost validates firms' disclosed data by using the input-output modeling methodology.[15] Trucost validates firm-disclosed data using these estimates from the model, minimizing inaccurately reported outliers. Therefore, our measure of EP is more comparable across industries and relatively free from measurement error.

3.3 Definition of Variables

We use four carbon emission measures: (1) firm-level absolute amounts of GHG emissions, (2) carbon intensity, (3) external costs, and (4) impact ratio provided by Trucost. Carbon intensity is defined by Trucost as the amount of GHG emissions (tCO2e, tonnes of CO2e) divided by one million USD of revenue.[16] It is thus estimated in metric units of (tCO2e/$m), allowing us to compare firm-level carbon efficiency in all firm sizes and across industries. External cost is the total cost that a firm incurs directly and indirectly on the environment through its own activities and supply chains. Impact ratio is the external cost divided by a firm's revenue.

From here, we denote the absolute GHG emission of Scope 1, Scope 2 and Scope 3 as Scope 1 (tCO2e), Scope 2 (tCO2e) and Scope 3 (tCO2e), respectively. We also denote carbon intensity based on Scope 1, Scope 2 and Scope 3 GHG emissions divided by revenue as Scope 1, Scope 2

[13] Globally, collaborative actions have been taken to address inconsistent, incomplete and incomparable EP measurement issue. Thus, the Kyoto Protocol introduced carbon dioxide equivalents (CO2e) as a standard unit for measuring corporations' carbon footprint. It compiled emission data on seven GHGs including carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydro fluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3).

[14] In reporting GHG emission measures, Trucost follows the GHG Protocol Standard – the internationally recognized corporate accounting and reporting standard. That is, Scope 3 thus covers all other indirect GHG emissions from both upstream (supply chain) and downstream (in-use) of the firm's operations. For example, it includes the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the firm, electricity-related activities (e.g. transmission and distribution losses) not covered in Scope 2, outsourced activities, waste disposal, etc.

[15] Its input-output model estimates the amount of resources required to produce a unit of output, and the related level of pollutants. Trucost compiles the environmental impacts of 464 industries. The sector classification used is the North American Industrial Classification System (NAICS). Trucost constructs the prices of 700 environmental indicators per unit of output, and this classification is consistent with the United Nations Millennium Ecosystem Assessment. This input-output model identifies segmental revenue data for each firm primarily using FactSet along with company statements. Trucost then creates company profiles by mapping each firm to a set of industries, inputs and outputs. It then integrates a company profile to the library of environmental impact, and it calculates GHG emission per unit of output.

[16] While Trucost's formula for carbon intensity is identical to that of ET Index, their numerators—firms' carbon emission—are estimated differently. Trucost considers a firm's carbon emission not only from its direct operations but also from purchased electricity and other supply chain inputs.

and Scope 3, respectively. Carbon intensity based on the partial sum of scopes, such as Scope 1 and 2 or Scope 2 and 3, will be denoted as Scope 12 and Scope 23, respectively. And carbon intensity based on the sum of all three scopes will be denoted as "Scope" hereafter.

We find that Scope 3 should be included in Scope, our primary measure of carbon intensity, and this distinguishes our findings from other studies that rely on the volume of a single type of emissions from operation. Panel (a) in Table 2 reports the average value of Scope 1, Scope 2, Scope 3, Scope, external cost, and impact ratio by industry. Column (3) shows that the average values of Scope 3, which reflect value chain emissions, are not small relative to those of Scope 1 and 2. Also, Figure 1 clearly shows that the relative shares of Scope 3 are very large in some industries. While relative shares of Scope 3 are less than 40% in industries that are generally known for being carbon intense, they are higher than 50% of total carbon exposure in other industries, such as consumer staples, consumer discretionary, health care and IT.

It is also important to examine carbon emission measures with varying scopes because it can provide different information. Panel (b) in Table 2 reports the correlation coefficients among measures of carbon intensity. As one can see from the patterns in Panel (a) in Table 2, columns (1)-(3), the correlation coefficients of Scope 1, Scope 2, and Scope 3 are low. The correlation of external cost with Scope 1 is higher compared to those with Scope 2 and Scope 3. And the correlation coefficients of impact ratio with Scope 1 and Scope are close to one.[17]

Figure 2 shows the time trends of carbon intensity over time. It clearly shows Scope and Scope 12 have been declining over time, suggesting that firm-level carbon efficiency has improved. It also suggests that we need to consider time fixed effects when we examine the relationship between carbon efficiency and firm characteristics in Section 4.2.

4 Main Analysis

This study consists of three parts: (1) carbon intensity and stock returns, (2) carbon intensity and firm characteristics, and (3) robustness tests. First, we construct portfolios based on carbon intensity (single-sorted), carbon intensity and B/M (double-sorted), and carbon intensity and firm

[17] Initially, we expect to calculate the cost incurred by negative externality using impact ratio. However, we find that the correlation between impact ratio and Scope is over 0.9, and it does not provide additional information.

size (double-sorted). We examine whether there are differences in average returns across carbon-efficient and carbon-inefficient portfolios and, if there are any, whether they can be explained by well-known risk factors. Second, we examine the empirical relationship of carbon intensity with a set of firm-level characteristics. We conduct regression analysis to investigate what types of firms are more likely to be carbon-efficient. Finally, we conduct robustness checks to ensure that our findings are not driven by a small set of industries, variations in oil price, or changing preferences of bond investors caused by the low interest rate regime starting with the 2008 financial crisis.

4.1 Carbon Efficiency and Stock Returns

Prior to our main analysis, we assess whether there are a sufficient number of stocks in each portfolio for diversification and then check the effect of the most and least carbon-intensive industries. We refer to the existing literature on the number of stocks and risk reduction. Campbell et al. (2001) claim that a larger number of stocks are needed to achieve a certain level of diversification because the volatility of individual stocks has been increasing over time. They find that a portfolio of 20 stocks reduced annualized excess standard deviation to about 5% during 1963–1985. However, this level of excess standard deviation requires almost 50 stocks during 1985–1997. Domian and Louton (2007) claim that risk reduction continues even after portfolio size is increased above 100 stocks. Since we have 424–679 firms each month, we are very cautious in increasing the number of portfolios and thus reducing the number of stocks in each portfolio. Increasing the number of portfolios may result in poorly diversified portfolios, in which idiosyncratic returns could drive our results. We thus decided to include at least 50–100 firms for all of our univariate-sort portfolios, if possible.

We also check whether certain industries or fluctuations in energy prices dominate a firm's environmental performance and returns. We choose three industries with the highest Scope (utilities, materials, energy) and three industries with the lowest Scope (health, IT, telecommunications). Figure 3 shows the cumulative returns of selected industry portfolios. It shows that all carbon-efficient industries do not necessary outperform carbon-inefficient industries and vice versa. The other is that, not all industries are negatively affected by a sharp drop in oil price, such as the one that took place in mid 2014. It seems that only the energy industry was negatively hit by the shock.

4.1.1 Constructing the Efficient-Minus-Inefficient (EMI) Portfolios

We form three portfolios sorted on single characteristics: carbon intensity based on all three scopes (denoted as Scope). As mentioned above, we define Scope as:

$$\text{Scope} = \frac{\text{Scope1(tCO2e)} + \text{Scope2(tCO2e)} + \text{Scope3(tCO2e)}}{\text{revenue(\$mil)}}$$

Since the variable of Scope can be interpreted as "how much tCO2e a firm needs to emit in order to generate one million dollars of revenue", a lower value of Scope corresponds to lower carbon intensity or higher carbon efficiency. We divide firms in each industry into three groups in terms of the previous year's carbon intensity level, updating portfolio formation annually.[18] The top 33% of the portfolio consists of firms that are the top 33% carbon-efficient firms in *each* industry and *each* year. These portfolios are value-weighted based on market capitalization. Given very different levels of carbon intensity across industries, as shown in column (4) in Table 2, picking up carbon-efficient and carbon-inefficient firms in each industry prevents particular industries that are extremely carbon-intensive (or carbon-efficient) from driving empirical results.

With the three single-sorted portfolios, we construct an EMI portfolio based on carbon intensity (EMI1), which is our first benchmark portfolio:

$$\text{EMI1} = \text{top 33\% efficient} - \text{bottom 33\% efficient} \qquad (1)$$

Panel (a) in Table 3 displays the average monthly returns of three portfolios sorted on carbon intensity and EMI1 portfolio.[19] It shows that, in terms of average stock returns, the carbon-efficient portfolio outperforms the carbon-inefficient one during the period of January 2006–December 2015. The difference in average returns of the first and third tertile, 0.20 percentage point, is not statistically significant. However, during the period of January 2010–December 2015, the average monthly return of carbon-efficient firms is 1.73%, which is far higher than 1.23% of carbon-inefficient firms. The difference in average monthly returns of top and bottom 33% portfolios,

[18] To minimize the look-ahead bias, we form portfolios using the information also available to investors. Different from other datasets, such as MSCI, Trucost database does not release its data at one date; it releases on a rolling basis throughout the year. Due to this reason, we assume that investors form portfolios using the previous year's data.

[19] When we calculate average portfolio returns, we also use stock returns that are winsorized at 1% and 99%, and 2% and 98% levels. We find that winsorizing does not change our result much. In fact, winsoring makes the average returns of carbon-efficient stocks a little higher.

which is the average return of EMI1 portfolio, is 0.50 percentage points and is statistically significant.

As Fama and French (2015) emphasize, value-weighted portfolios from univariate sorts on variables other than size are typically dominated by big stocks. To address this issue, we examine the return patterns when portfolios are sorted on two characteristics, carbon intensity and B/M or carbon intensity and size. We form nine portfolios sorted on B/M and carbon intensity to see if B/M, carbon efficiency, and stock returns are related to each other. We divide firms into three groups based on B/M. Top 33%, middle 34%, and bottom 33% firms are value, neutral, and growth firms, respectively. We divide firms based on carbon intensity in the same manner. We construct our second EMI portfolio (EMI2) in a similar way to the Fama-French procedure used for the construction of SMB and HML factors.[20]:

$$\mathrm{EMI2} = 0.5(\text{growth efficient} + \text{value efficient}) - 0.5(\text{growth inefficient} + \text{value inefficient}) \tag{2}$$

The portfolio of 'growth efficient' firms consists of growth firms whose carbon efficiency is in the top 33%. Likewise, the portfolio of "value inefficient" firms consists of value firms whose carbon efficiency is in bottom 33%. Panel (b) in Table 3 shows the average returns of the nine portfolios along with the EMI2 portfolio. During the period of 2005–2015, carbon-efficient firms outperform carbon-inefficient firm in case of growth firms. However, the average return difference of neutral firms is close to zero, and the one for value firms is even negative. For the later period of 2010–2015, efficient firms outperform inefficient firms in the case of growth and neutral firms. For growth firms and neutral firms, the differences in monthly average returns amount to 0.95 and 0.43 percent points respectively and they are statistically different.[21]

We also form nine portfolios on size and carbon intensity. Similar to the EMI2 portfolio, we divide firms into three groups based on market capitalization, which can be interpreted as top 33%, middle 34%, and bottom 33% firms are big, medium, and small firms, respectively. We also divide

[20] For example, see the description of Fama-French size and value factors (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html)

[21] This pattern holds also for the case of 2*3, 3*2, 3*5, 5*3, and 4*4. However, the pattern of monotonically increasing or decreasing returns tends to be less robust as we increase the number of portfolios (for example, 7*7, 10*10). As discussed above, given the not-that-large sample size, reducing the number of firms in each portfolio may undermine the benefit of using well-diversified portfolios.

firms based on carbon intensity in the same manner. We initially construct the EMI portfolio by size and carbon intensity as following:

$$\mathrm{EMI3} = 0.5(\text{big efficient} + \text{small efficient}) - 0.5(\text{big inefficient} + \text{small inefficient})$$

We find that small efficient firms underperform small inefficient firms during the period of 2010–2015, and thus including them in the EMI portfolio does not contribute to larger differences in returns of two portfolios—(big efficient + small efficient) and (big inefficient + small inefficient). Panel (c) in Table 3 shows the average returns of nine portfolios. While carbon-efficient firms outperform carbon-inefficient firms during the period of 2005–2015 for medium and big firms, small efficient firms underperform small inefficient firms. However, the return differences are not statistically significant. For the later period of 2010–2015, big efficient firms outperform big inefficient firms while small efficient firms underperform small inefficient firms. The differences in monthly average returns amount to 0.62 and -0.36 percent point, respectively. Due to this pattern, we construct our third EMI portfolio excluding small firms (EMI3)[22],[23]:

$$\mathrm{EMI3} = (\text{big efficient}) - (\text{big inefficient}) \qquad (3)$$

Figure 4 displays the cumulative returns of EMI1, EMI2, and EMI3 portfolios. As we have seen that efficient firms outperform inefficient firms after 2009, the cumulative returns of all EMI portfolios start to rise around 2009 or 2010. Note that all three cumulative returns based on different sorting exhibit similar patterns.

Since it is well known that ESG activities are sector- or industry-biased, we compare the cumulative returns of EMI1, EMI2, and EMI3 including all industries in our sample and excluding most carbon-inefficient and most carbon-efficient industries, which are utilities and telecommunication respectively. All three figures in Figure 5 show that the two industries that are extreme in terms of carbon intensity do not significantly affect the performance of our EMI portfolios.

4.1.2 Pricing EMI Portfolios

[22] We also use the following portfolio and find that the main results are not changed:
$\mathrm{EMI3} = 0.5(\text{big efficient} + \text{medim efficient}) - 0.5(\text{big inefficient} + \text{medium inefficient})$

[23] We also calculate the average returns after controlling for microcaps. Following Hou, Xue, and Zhang (2015), we drop microcaps (stocks with market equity below the 20th percentile at New York Stock Exchange) and calculate the average returns of portfolios in Table 3. We find that the values and patterns are similar.

Having discovered that our EMI portfolios exhibit noticeable positive returns, especially after 2009, we then test if these are the result of taking risks or if they are pure alpha. For this purpose, we price our EMI portfolios with the well-known risk factors. We perform GRS test to see if the well-known risk factors can price the EMI portfolio. We consider four models: (1) CAPM, (2) Fama-French three-factor (FF 3 factor) model, (3) Fama-French three-factor model with momentum factor, and (4) Fama-French five-factor (FF 5 factor) model:

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{Mt} - r_{ft}) + e_{it}, \tag{4}$$

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{Mt} - r_{ft}) + s_i SMB_t + h_i HML_t + e_{it}, \tag{5}$$

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{Mt} - r_{ft}) + s_i SMB_t + h_i HML_t + m_i WML_t + e_{it}, \tag{6}$$

$$r_{it} - r_{ft} = \alpha_i + b_i(r_{Mt} - r_{ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}, \tag{7}$$

where r_{it} is the return of portfolio formed on carbon efficiency, r_{ft} is the risk-free rate, and $(r_{Mt} - r_{ft})$ is the monthly value-weighted market return minus the risk-free rate. The terms SMB_t (small minus big), HML_t (high minus low), WML_t (winner minus loser), RMW_t (robust minus weak), and CMA_t (conservative minus aggressive) are the monthly returns on zero-investment factor-mimicking portfolios designed to capture size, B/M, momentum, operating profitability, and investment, respectively. Figure 6 shows the cumulative returns of these factor-mimicking portfolios. Note that the cumulative return of market risk factor $(r_{Mt} - r_{ft})$ has increased from 2009 and its pattern is similar to those of EMI portfolios in Figure 5. By applying GRS tests including market risk factor, we can separate its effect from the performance of EMI portfolios.

For single-sorted portfolios, the null hypothesis of GRS test is H_0: $\alpha_1 = \alpha_2 = \alpha_3 = 0$ where α_i is the intercept of portfolio *i*. If the intercepts (α) in the above time-series regressions turn out to be positive and statistically significant, it suggests that the return on the EMI portfolio cannot be priced with the standard risk factors and one can earn extra returns without taking further risks. If one interprets the above factors as "styles" and factor models as a method of performance attribution, a positive alpha implies the abnormal return in excess of what could have been achieved by passive investments in those factors.

Before pricing portfolios, we examine the statistical properties of EMI and factor-mimicking portfolios during the sample period. Table 4 reports the average returns, standard deviations, and

Sharpe ratios of EMI portfolios along with other well-known factor-mimicking portfolios used as risk factors. During January 2005–December 2015, the average returns of all portfolios except HML are positive, suggesting that growth stocks outperform value stocks during this period. The average monthly return of EMI1 portfolio is 0.19%, which is not high relative to other portfolios. Also note that the market portfolio earns the highest average return of 0.61%. The Sharpe ratios of the EMI portfolio are 0.12, which is not that high compared to others. However, if we examine the period after 2009, EMI portfolios become quite attractive with relatively high returns and relative low standard deviations. Consequently, their Sharpe ratios are highest at 0.35–0.41, attesting to the attractiveness of EMI portfolios.

Panel (b) in Table 4 shows the correlation coefficients of EMI portfolios with other portfolios. Looking at the statistically significant correlation coefficients for the period of 2005–2015, it shows that EMI portfolios move with the market and behave like firms with weak operating profitability. However, after the onset of the GFC, EMI portfolios behave like growth firms and short-term winners. And EMI1 and EMI3 move like firms with more aggressive investment.

We now examine whether the positive cumulative return of our EMI portfolio can be explained by other risk factors. We run four models on three portfolios sorted on carbon intensity and test if the EMI1 portfolio can be priced. It is equivalent to testing whether a strategy of "short inefficient firms and long efficient firms" earns alpha, and whether it is an abnormal return that cannot be explained by the standard risk factors. Table 5 shows the result of the GRS test on the three single-sorted portfolios by Scope and the EMI1 portfolio. Panel (a) is for the period of January 2006–December 2015, and Panel (b) is for the period of January 2010–December 2015.

According to Panel (a) in Table 5, all three portfolios sorted on carbon intensity earns positive alphas even after accounting for various risk factors. For example, after considering Fama-French 3 factors, the average monthly abnormal returns are amount to 0.62% for efficient portfolio and 0.48% for inefficient portfolio. Even after accounting for Fama-French 5 factors, those returns are 0.59% and 0.37%, respectively. In all four models, the *p*-values of our GRS test statistics are virtually zero, thereby rejecting the null hypothesis of $\alpha_1 = \alpha_2 = \alpha_3 = 0$. Also note that we obtain high R^2s in all specifications. This suggests that, while risk factors explain the returns of portfolios sorted by carbon intensity quite well, there are also positive alphas that cannot be explained by the factors. Column (4) in Panel (a) shows that the estimated alpha of the EMI portfolio is not statistically significant, implying that a strategy of "short inefficient firms and long efficient firms" does not produce statistically significant positive alpha. It is mainly because all three portfolios sorted on carbon intensity produce positive alphas that are of similar magnitudes. For example, if we look at the Fama-French three-factor model with momentum factor, the efficient portfolio produces 0.62% of alpha while the inefficient portfolio produces 0.47%. As a result, the EMI1 portfolio produces 0.15% of alpha, which is not significant. Since alphas of efficient and inefficient portfolios are similar in magnitude and both are statistically significant, it turns out that their difference (i.e. the alpha of EMI1 portfolio) is not statistically different from zero.

When we run the same test on the later sample period, January 2010–December 2015, we find a very different and interesting result. A major difference between Panel (a) and Panel (b) in Table 5 is that, during January 2010 and December 2015, alphas of inefficient portfolios become smaller and their statistical significance becomes weaker, while alphas of efficient portfolios are not much affected. As a result, alphas of EMI1 portfolios become positive and statistically significant, suggesting that a strategy of "long efficient firms and short inefficient firms" is rewarding even after accounting for the well-known factors. Note that efficient firms behave like growth firms and winner firms from 2010. In the case of the top 33% of efficient firms, the factor loadings on HML and WML are negative and positive, respectively. Given the negative average return of HML in our sample, as shown in Panel (a) in Table 4, negative factor loading on HML implies a positive extra return. This pattern is also found in EMI1 portfolio. Column (4) shows that factor loadings on HML and WML are negative and positive, respectively, contributing to higher returns of the EMI portfolio.

This comparison reveals the source of alphas. While all three portfolios sorted on carbon intensity cannot be fully explained by risk factors and thus produces positive alphas, only the top 33% efficient portfolios earn positive and statistically significant alphas from 2010. Thus, the positive alphas of the EMI portfolio come from positive alphas of efficient firms after 2010, not those of inefficient firms. Note that these alphas are equivalent to annualized extra returns of 3.5–5.4%, which are quite large.

Table 6 shows the result of the GRS test on double-sorted portfolios by Scope and B/M. It shows that, for the period of 2006–2015, the EMI2 portfolio is priced by risk factors and it does not earn a positive alpha. However, for the period of 2010–2015, the EMI portfolio produces a positive alpha, which is statistically significant. For example, for the case of the Fama-French 3 factor model and 5 factor model, EMI2 earns 0.38% of alpha. Note that this is equivalent to an annualized return of 4.56% for the EMI portfolio, which is large. Column (6) shows that, when momentum factor is considered, our EMI portfolio does not earn a positive alpha. Factor loadings suggests that WML subsumes some explanatory power of HML. However, even in this case, we find that the efficient portfolio earns statistically significant positive alpha of 0.58%. It suggests that, while a zero-cost investment strategy of "long efficient firms and short inefficient firms" may not earn statistically significant positive alpha when the momentum factor is considered, investing in efficient firms still earns positive abnormal returns.

Table 7 shows the result of the GRS test with the double-sorted portfolios by Scope and size. It shows the EMI3 portfolio earns a large positive alpha for the later period of 2010–2015. In particular, the EMI3 portfolio earns 0.45% and 0.49% of alpha for Fama-French 3 and 5 factor models, respectively. When we include the momentum effect (WML) in addition to Fama-French 3 factors, it is 0.38%. These alphas then translate into the annualized extra returns of 4.6–7.0%, which are quite large.

Here is a summary of our empirical results: (1) Based on 75,638 observations of US firms from January 2005 to December 2015, we form portfolios based on carbon intensity measured as (sum of Scope 1, 2, and 3/revenue [CO2e/$mil]) and construct a zero-cost portfolio of the EMI ("efficient-minus-inefficient") portfolio. (2) From 2010, carbon-efficient firms outperform carbon-inefficient firms, implying that the costless EMI portfolio earns a positive cumulative return. (3) Using the CAPM, the Fama-French 3 factor model, the Fama-French 3 factor model with momentum factor, and the Fama-French 5 factor model, we test if the EMI portfolio earns a positive abnormal return ("alpha") and find that our EMI portfolio produces a positive and statistically significant alpha. The magnitudes of alpha suggest that an investment strategy that purchases shares of carbon-efficient firms and sells shares of carbon-inefficient firms earns abnormal returns of 3.5–5.4%. (4) We also consider a double-sort strategy based on firm size and carbon intensity, and B/M and carbon intensity. We confirm that EMI portfolios earn a positive alpha of similar magnitudes. The only exception is that small efficient firms do not outperform small inefficient firms. (5) We find that, while our EMI portfolio shares some characteristics of HML and WML, it still has its own characteristics that cannot be fully explained by these factors during the period after 2009.

4.2 Carbon Efficiency and Firm Characteristics

We examine the relationship of carbon intensity with a set of firm-level characteristics to examine the sources of alpha we observe in section 4.1. Based on previous literature that investigates the financial implications (i.e. firm value and stock performance) of ESG activities, we deliberately choose variables that reflect firm-level characteristics. For variables related to financial performance, we use market capitalization, B/M, Tobin's q, ROA, ROI, EPS, PER, cash flow, free cash flow, cash holdings, coverage ratio, dividend payout ratio, leverage ratio, share of tangible assets, capital intensity, operating profitability, and cost of capital. We also use the ratings of environmental strength and concern, and governance strength and concern from the MSCI ESG Stats. The construction of these variables is described in Appendix A.

Table 8 reports the average values of firm characteristic variables for the top 33% efficient portfolio and the bottom 33% efficient portfolio, the differences in these average values and their statistical significance. It shows that firms in the top 33% efficient portfolio, compared to firms in the bottom 33% efficient portfolio, are firms of smaller size, lower B/M, higher firm value measured in Tobin's q, and higher ROI. However, a simple comparison of the average values may not control for industry fixed effects and any time trends in carbon efficiency. Table 2 clearly documents that levels of carbon intensity are very different for each industry and Figure 2 shows that our measures of carbon intensity, Scope and Scope12, are declining over time, suggesting that firms emit less and less carbon to generate the same amount of revenue over time.

To consider fixed effects related to industry and time more explicitly, we use a regression approach based on the following specification[24]:

$$ln(\text{Scope}_{it}) = \alpha + x_{it}\beta + \alpha_j + \alpha_t + \alpha_{jt} + u_{it}$$

The dependent variable is log of Scope firm i at year t and x_{it} includes a set of firm-level characteristics for firm i at year t. α_j denotes the fixed effect of industry j and α_t denotes year fixed effect. We also consider industry-year fixed effect α_{jt}. While a variable is defined as ratios, we take logs if it is not well nested within zero and one. For example, we take logs in coverage ratio. Note that we do not attempt to uncover the causal relationship between carbon intensity and a set

[24] Another way to control for industry and time effect is to use z-scores. We perform the same analysis using z-scores constructed for each time period and within each industry. We find that the main result is not changed.

of firm characteristics in order to specify the exact source of positive abnormal returns. Rather, this pooled OLS examines what kinds of firms are carbon-efficient or carbon-inefficient on average after controlling for industry and time fixed effects.

In addition, we run a logit model to see what kinds of firms are in the top 33% efficient portfolio or the bottom 33% efficient portfolio. We estimate the following logit regression equation:

$$\Pr\,(y_{it} = 1|x_{it}, \alpha_j, \alpha_t, \alpha_{jt}) = \alpha + x_{it}\beta + \alpha_j + \alpha_t + \alpha_{jt} + u_{it}$$

The dependent variable y_{it} is a dummy variable that takes a value of one if firm *i* at year *t* is in the top 33% efficient portfolio in each industry and zero if it is in the bottom 33% efficient portfolio in each industry.

The estimation results of pooled OLS and logit regression show that carbon-efficient firms are "good firms" in terms of financial performance (Tobin's q, ROI, cash flow and coverage ratio) and corporate governance.[25] Carbon-inefficient firms have more tangible assets with higher ROA. The statistical association of carbon efficiency with Tobin's q, ROA, cash flow, and coverage ratio increases after 2009. Columns (1)–(4) in Table 9 show the results of pooled OLS based on different sets of x_{it} and column (5) shows the result of the logit regression. Comparing the results in columns (1)–(4), we find that the signs and statistical significances of estimated coefficients are quite robust across specifications, except for firm size. The result from logit regression in column (5) is largely consistent with the results of pooled OLS in columns (1)–(4). Based on Panel (a) in Table 9 for the period of 2005-2015, carbon-efficient firms are those of higher firm value measured in Tobin's q, higher net income relative to invested capital (higher ROI), higher cash flow, lower free cash flow and cash holdings, lower share of tangible assets, higher capital expenditure relative to total assets (higher capital intensity), and lower coverage ratio. Panel (b) shows the result for the period of 2010-2015, when carbon-efficient firms outperform carbon-inefficient firms.

The characteristics of these carbon-efficient firms contrast with those of carbon-inefficient firms. Specifically, they have higher Tobin's q, ROI, cash flow and coverage ratio. And they have less amount of tangible assets with lower ROA. Interestingly, variables that include stock prices or number of shares (PER, EPS), or dividend payout (payout ratio) are not closely related to carbon efficiency. One thing to note is that the estimated coefficients on ROA. They are all positive,

[25] We find that carbon-efficient firms exhibit higher operating profitability. Since correlation between ROI and operating profitability is quite high, we do not include both variables in regression equations.

suggesting that carbon-inefficient firms have higher ROAs. However, higher ROA is not always better (e.g, Gallo, 2016). A firm may increase its ROA through "denominator management," by which it sets up separate entities and sell its assets to them. Or higher ROA may simply suggest that the company is not renewing its asset and not investing in new machinery, sacrificing its long-term prospect. In our context, a firm that is reluctant to invest in more carbon-efficient equipment may exhibit higher ROA.[26] When we compare the results of the two sample periods, 2005–2015 in Panel (a) and 2010–2015 in Panel (b), the estimated coefficients of cash flow and (log of) coverage ratio become larger in absolute values during the latter period.

Our findings are consistent with previous studies and complement them. The positive sign of environmental concern ratings implies that carbon-efficient firms tend to have a smaller number of environmental concerns. Chava (2014), who also uses the same MSCI database for environmental concern ratings, shows that lenders charge a significantly higher interest rate on the bank loans issued to firms with environmental concerns, and this environmental profile of a firm is not a proxy for an omitted component of default risk.[27,28] Regarding measures of corporate governance, Servaes and Tamayo (2013) point out that managerial agency problems can be acute when a firm generates substantial free cash flows. Ferrell, et al. (2016) suggest that high values of free cash flow and cash holdings can be an indication of agency problems. We obtain the positive signs of coefficients both for free cash flow and cash holdings, suggesting that carbon-efficient firms may suffer less from agency problems.

As to the signs and statistical significance of variables from the MSCI, we have an interesting result. While we expect the opposite signs of estimated coefficients for ratings of environmental strength and environmental concern, both turn out to be positive. Chatterji, et al. (2009) suggest that environmental concern ratings are likely to be consistent with firms' past environmental performance, but environmental strength ratings are not. Semenova and Hassel (2015) show that MSCI environmental concerns converge with the GES environmental industry risk and company emissions from the ASSET4 database. In et al. (2017b) examine the endogeneity of environmental

[26] We also run the same regressions with adding ROE (return on equity) and find that the estimated coefficients of ROE are not statistically significant and other estimates are not much affected.

[27] However, we find that cost of capital is not statistically different between carbon-efficient and carbon-inefficient firms in our sample. Note that, while Chava (2014) focuses on bank loan rates, our measure is the overall cost of debts.

[28] Cole et al. (2005) find that, based on UK data, pollution intensity is a positive function of energy use and physical and human capital intensity while it is a negative function of the size of the average firm in an industry, the productivity of an industry and the industry's expenditure on capital and research and development (R&D). We do not include R&D expenditure as a regressor because we have only about 1,000 non-zero observations for R&D expenditure.

strength ratings. According to them, a firm with more environmental concerns may invest more to improve its environmental performance or take more environmentally-friendly corporate actions to avoid regulatory penalties or to raise its reputation, leading to a higher rating of environmental strength. If we regard the ratings of environmental concern as a better measure of a firm's environmental performance, following Chatterji, et al. (2009) and Semenova and Hassel (2015), our results suggest that firms with lower ratings of environmental concern tend to be carbon-efficient.

We also check the possibility that some "outlier" industries may drive our results, by re-estimating the specification of columns (3) and (5) in Table 9 with or without three most and least carbon-intensive industries. From Table 2, we identify the three most carbon-inefficient industries in terms of Scope as utilities, energy and materials, and the three most carbon-efficient industries as telecommunication, health and IT. Panel (a) and (b) in Table 10 show that many of the signs and statistical significances are maintained regardless of whether we exclude the three most carbon-efficient industries or three most carbon-inefficient industries. Panel (a) is for the period of 2005–2015 and Panel (b) is for the period of 2010–2015. One thing to note is that the coefficient of Tobin's *q* becomes larger when the three most carbon-inefficient industries are excluded. For the period of 2005-2015, the estimate becomes larger from -0.050 to -0.071 when we exclude three most carbon-inefficient industries. It implies that the relationship between carbon efficiency and firm value are more pronounced among carbon-efficient industries. Similar to Table 9, we also compare two sample periods in Table 10. Interestingly, we observe the similar pattern that emerges in Table 9 when we compare the results of the two sample periods, 2005–2015 in Panel (a) and 2010–2015 in Panel (b). The estimated coefficients of ROA, cash flow, and coverage ratio become larger in absolute values during the later period.

4.3 Robustness Tests

In this section, we perform some robustness checks. Having already found that carbon-efficient firms outperform carbon-inefficient firms, we not investigate whether investors consider firm-level carbon-efficiency when making investment decisions. we assess if fluctuations in oil price and unconventional monetary policy can explain our empirical findings.

4.3.1 Investors' Perceptions of Decarbonization Efforts

It is natural to ask whether market participants evaluate the carbon efficiency of firms and invest accordingly. To test if investors make their investment decision based on carbon efficiency, we sort by *changes* in carbon intensity in each industry at each date and form portfolios in the same manner as we did for the EMI1 portfolio. Our conjecture is that, if investors monitor firms' carbon efficiency and value decarbonization effort in their portfolio selection, we should observe statistically significant differences in the average returns of those portfolios formed not only on levels of carbon intensity, but also on changes in carbon intensity.

Similar to the univariate-sort portfolios based on carbon intensity, we form portfolios based on changes in carbon intensity. We measure a firm's effort in improving carbon efficiency as follows:

$$\mathrm{gScope}^{j} \equiv \frac{\mathrm{Scope}_{i,t-1} - \mathrm{Scope}_{i,t-1-j}}{\mathrm{Scope}_{i,t-1-j}}$$

where $\mathrm{Scope}_{i,t-1-j}$ is the firm i's Scope at year $(t-1-j)$. We use $\mathrm{Scope}_{i,t-1-j}$, not $\mathrm{Scope}_{i,t-j}$, to minimize the look-ahead bias. The variable of gScope^{j} measures how much a firm has improved its carbon efficiency for the past j year. We use $j=1$ and 2. That is, we consider portfolios formed on change in carbon intensity for the past one year ($j=1$) and two years ($j=2$), denoted as gScope^{1} and gScope^{2}, respectively.

We first calculate the average monthly returns on three portfolios sorted by gScope^{j}. For $j=1$ case, the average returns of three portfolios formed on gScope^{1} are 1.19% (top 33% carbon-efficient), 1.12%, and 1.07% (bottom 33% carbon-efficient) for the period of 2006–2015. For the later period of 2010–2015, they are 1.47%, 1.37%, and 1.29%. The top 33% portfolio earns the highest return, and we observe a monotonically decreasing pattern in average returns. However, the difference between the top 33% and bottom 33% portfolios turns out to be not statistically significant. For $j=2$ case, the average returns for the period of 2007–2015 are 1.09% (top 33% carbon-efficient), 1.08%, and 1.13% (bottom 33% carbon-efficient). And they are 1.29%, 1.51%, and 1.43% for the later period of 2010–2015. In the case when $j=2$, we do not find any monotonic patterns in average returns on portfolios, and the difference in average returns is not statistically significant.

Figure 7 shows the cumulative returns of our benchmark EMI portfolio single-sorted by Scope (EMI1), the EMI portfolio formed by gScope^{1} (EMI (change, 1-year)) and the EMI portfolio formed by $gScope^2$ (EMI (change, 2-year)). It clearly shows that the performance of EMI portfolios formed on change in carbon intensity is not rewarding as much as the benchmark EMI1. While the EMI portfolio formed on $gScope^1$ earns a positive cumulative return, the increasing pattern is less steep compared to that of EMI1. And the cumulative return of the EMI portfolio formed on $gScope^2$ is rather close to zero or negative. We perform the GRS tests on these two portfolios and find that they do not earn positive abnormal returns. We also estimate the same logit model in section 4.2 and find that few covariates are statistically significant.

Evidence from the average returns and Figure 7 illustrates that improvement or deterioration in carbon efficiency is not closely related to stock market performance, suggesting that investors may not closely and directly monitor firms' decarbonization efforts in their investment decisions.[29]

4.3.2 Effect of Oil Price

Since oil price is closely related to energy use and efficiency, changes in oil price may affect our measure of carbon intensity differently across firms and industries. For example, a sharp increase in oil price may affect carbon-inefficient firms more negatively compared to carbon-efficient firms even in the same industry. This possibility suggests that fluctuations in oil price may affect the formation of carbon-efficient and carbon-inefficient portfolios and thus the performance of the EMI portfolio.

We find that our empirical results on the behavior of EMI portfolios are not mainly driven by changes in oil price. Panel (a) in Figure 8 shows the time-series of oil price and the cumulative return of our benchmark EMI1 portfolio. The impression from Panel (a) is that the relationship between oil price and EMI1 is volatile. Sometimes the performance of EMI1 and oil price move in the same direction, sometimes in opposite directions. Panel (b) shows the time-series of a rolling correlation coefficient between oil price and the cumulative return of EMI1 portfolio.[30] As the

[29] Considering the possibility of diminishing returns in a firm's effort to improve its EP, this result should be interpreted with caution. Suppose that a firm makes huge investment to improve its EP at year t and obtains a relatively higher value of $gScope^1$ between t and $t+1$. In year $t+2$, this firm will be in the top 33% portfolio. However, if the return of a firm's investment for better EP diminishes, it is very hard for this firm to stay in the top 33% portfolio for long time. It implies that, different from the case of Scope, turnover of firms will happen more frequently in portfolios formed on $gScope^1$ and heterogeneous firms in many aspects would be included in the same portfolio. We find that firms move across three portfolios more frequently when portfolios are formed on $gScope^1$. In case of EMI1 formed on Scope, a firm that is included in the most carbon-efficient portfolio at least once stays in that portfolio for 77.7% of the sample period on average. For medium 34% and bottom 33% portfolio groups, a firm stays 62.7% and 75.8% respectively. In contrast, in case of the EMI portfolio formed on $gScope^1$, a firm in efficient, medium and inefficient portfolios stays 39.9%, 38.3% and 35.3% respectively. It suggests that carbon-efficient firms tend to stay carbon-efficient during the sample period and vice versa. However, the rankings in terms of $gScope^1$ change frequently within each industry over time, making it difficult to find spreads in average returns of portfolios formed on $gScope^1$.

[30] We also calculate the rolling correlation coefficient between oil price and the return of EMI portfolio. We find that there is no stable relationship between the two.

rolling correlation coefficient swings between positive and negative values as shown in Panel (b), we confirm our impression from Panel (a). The average of rolling correlation coefficient is quite small at 0.08, suggesting that there is no relationship between the two during our sample period.

4.3.3 Effect of Unconventional Monetary Policy

We also confirm that our empirical results are not driven by a change in bond investors' investment style caused by unconventional monetary policy. Due to the prolonged period of extremely low interest rates caused by unconventional monetary policy during and after the 2008 GFC, bond investors moved their funds into equity markets. Following the risk appetite of typical bond investors, they preferred stable and high-dividend-paying industries. We thus check whether this increased investment shifting from the bond market toward these industries and if this affects our empirical results.

By comparing the average dividend payout ratios of each industry, we identify four high-dividend-paying industries in our sample: utilities, telecommunication, IT, and consumer goods.[31] Also, by estimating the betas of value-weighted industry portfolios based on our sample, we identify four low-beta industries: utilities, telecommunications, consumer staples, health care. In addition, mass media coverage on this issue typically recommends utilities, telecommunications, and consumer durables to investors who prefer stable dividend payout.[32]

We find that, with or without these four industries, the performance of our EMI portfolio does not change much. Figure 9 shows the cumulative returns of our benchmark EMI1 portfolio, EMI1 portfolios constructed without four industries of utilities, telecommunications, IT, and consumer staples and the EMI portfolio without IT industry, which is to check the effect of tech stocks. We also apply GRS test to the EMI portfolio excluding the four industries and confirm that it earns positive abnormal returns, which is statistically significant.

[31] We find that real estate industry also pays relatively more dividends. However, we do not include this industry because its sample size is too small, less than 400 observations during the period of 2005-2015. Low-dividend-paying industries in our sample are energy and materials.

[32] For example, see https://www.cnbc.com/2014/07/20/what-stock-sectors-offer-the-best-dividends.html.

5 Discussion

The findings from our main analysis demonstrate robust empirical evidence that carbon-efficient firms outperform carbon-inefficient firms after 2009 and low-carbon portfolios generate positive abnormal returns. These findings on low-carbon investment performance evaluation may be limited due to a relatively short sample period—from 2005 to 2015; therefore, follow-up studies will need to verify our results over longer periods with accumulative time and data. Nevertheless, our initial findings are promising enough to help policymakers develop environmental investment programs and inform some investors who are willing to start entering this market.

This section discusses the implications of our findings for both academic research and investment practices, as well as proposing several questions for further examination in future research.

5.1 Implication for Climate Finance

Our research has important implications for investors, business leaders and policymakers because it clarifies the risk-return relationship of low-carbon investment. For too long, the global community of fiduciary bound investors, representing today over $100 trillion in assets under management, have seen carbon as a non-financial risk; one to be considered and utilized in investment decision-making only with extreme caution. In fact, investors often see the risks related to the environment as "extra-financial" in nature, and not relevant to their purest commercial pursuits.

In this regard, this study, with a growing body of research in this field, helps understand market incentives on low-carbon investment. As our findings demonstrate that an investment strategy of "long carbon-efficient firms and short carbon-inefficient firms" would earn abnormal returns of 3.5–5.4% per year, this study indeed indicates that investing in carbon-efficient firms can be profitable even without government incentives. Such rigorous academic study will directly affect investor behavior to invest more confidently in clean firms with reduced uncertainty.

The world's large fiduciary investors, such as pension funds, endowments, foundations, sovereign funds and insurance companies, often are required to generate high risk-adjusted returns in order to live up to their promise and meet their fiduciary obligations. Many have adopted a strict interpretation of fiduciary duty, which has led investors to consider only those risk factors that have been explicitly shown to drive corporate and project returns, unequivocally. Any risks that were not explicitly linked to profit were deemed "extra-financial" and considering them in an investment could be a breach of fiduciary duty if it was shown an investor gave up commercial return for some other non-commercial return.

In the context of the environment, the risks to assets and companies are intuitively real and of financial nature, but they are long-term. As such, it has been very difficult to convince investors of the financial legitimacy of climate and environmental risks, relegating them to the underappreciated pile of all "extra-financial". Indeed, there is a still a widespread perception among investors today that explicitly managing environmental risks could and likely would reduce investment returns, because traditional finance theory instructs us that anything that arbitrarily limits the investible universe of companies and opportunities would reduce risk-adjusted returns.

This dynamic of long-term fiduciaries ignoring environmental risks is particularly nefarious, as it places in direct contradiction the solutions of one of our society's biggest challenges (i.e., funding the retirement and healthcare of a rapidly aging population) with the solution of another of society's biggest challenges (unlocking the financial capital required to prevent the most catastrophic consequences of climate change). This contradiction exists today, and its persistence is something we should all be concerned about.

And yet, if we could show that carbon-efficient firms do outperform carbon-inefficient firms, then we could actually flip this negative dynamic into a combination of mutual reinforcing solutions in which the path to secure the retirements of our aging population explicitly encourages the transformation of our economy into one that is carbon efficient. That is precisely what we attempt to test in this paper and why we believe the implications of our findings are so profound.

By showing that our carbon-efficient portfolios dramatically outperform our carbon-inefficient portfolios, we will free investment organizations to consider environmental risks, and, we acknowledge with some satisfaction, potentially obligate them to do so. Just as we now see clearly that financial markets are not efficient and financial actors are not rational, we too hope that readers and investors will see that environmental factors clearly have a place among the traditional risk factors that drive investments and returns.

In addition, our clarification on the low-carbon investment's risk-return relationship will also benefit policymakers by helping them understand how much the risk-return relationship observed in the current financial market is (in)consistent with social optimum in terms of externality. This clarification will also help policymakers design policies that can reduce negative externality associated with carbon emissions and induce private investors to reallocate their capital on the basis of environmental impact.

5.2 Suggested Research Topics

In order to validate our proposed implications, it is worthwhile to examine whether our empirical results will hold in the future as we accumulate more data. If alpha we find is simply a result of mispricing, then it will be gone with arbitragers' trading for a short-term period. However, if this alpha reflects some characteristics – we have already shown that carbon-efficient firms are "good" firms within our sample period – or risks that are not currently captured by well-known risk factors or investment styles, then it will persist for the time being.

First, will this alpha (or at least higher return) of 'being green' persist? If our estimated abnormal returns are the result of mispricing, they should disappear out-of-sample as the sophisticated investors and traders learn about this mispricing and invest accordingly. In this regard, Mclean and Pontiff (2016) study the out-of-sample and post-publication return predictability of 97 variables and find that portfolio returns are 26% lower out-of-sample and 58% lower post-publication. Their finding strongly suggests that investors are informed by academic publications.[33] Meanwhile, if the cross-sectional relationship between our EP measure (Scope) and portfolio returns reflects risk that is not fully captured by well-known risk factors, then there is no reason for this pattern to decay. In a related study, Edmans (2011) finds that the stock market does not fully value intangibles such as employee satisfaction and thus certain SRI screens may improve investment returns. While we do not uncover the direct and causal relationship on the outperformance of carbon-efficient stocks, we show that those firms share the characteristics of higher firm value, higher ROI, higher cash flow, and better governance. Since these variables are expected not to change rapidly compared to stock returns, it is still possible to see this alpha to persist unless those characteristics are not fully exploited by investors' decision-making. For the time being, it would be best to sit back and wait for more data to accumulate in order to answer this question.

[33] In addition, they show that post-publication declines are greater for predictors with higher in-sample returns, and returns are higher for portfolios concentrated in stocks with high idiosyncratic risk and low liquidity.

Second, why do carbon-efficient firms start to outperform from 2009 or 2010, as shown in Figure 4 and Figure 5?[34] While the cumulative returns of industry portfolios (Figure 3) and market excess return (Figure 6) has increased from 2009 like our EMI portfolio, a key difference between industry portfolios and the EMI portfolio is that the latter is a zero-cost portfolio, showing the relative performance of carbon-efficient stocks relative to carbon-inefficient stocks. Moreover, the patterns of these cumulative returns are different from ones before 2009. The cumulative returns of industry portfolios and market excess return has increased until 2008, but carbon-efficient firms underperform until 2009. MSCI (2017) reports the similar patterns. It performs a monthly rebalancing of five portfolios based on ESG ratings and show that higher ESG-rated companies outperform those with lower ratings both in the US and global market. More interestingly, the period of outperformance in MSCI (2017) starts around 2009 or 2010 as well. At this juncture, it is crucial to ask what makes carbon-efficient firms or firms with higher ESG-rated firm start to outperform around 2009. One way to answer is to check if any changes favorable to these firms take place around this time. In this regard, we examine if a change in bond investors' strategy precipitated by unconventional monetary policy that started in the late 2008 affect the performance of carbon-efficient portfolio. We find that fund shifting from bond market to equity market does not affect our empirical results much. However, we admit that our robustness check is not sufficient to answer this question and future research toward this direction is warranted.

Third, does our EP measure (Scope) fully capture how much a firm care about the environment? Although we believe that our EP measure is a better measure in explaining a firm's EP, compared to self-reported surveys or one-digit summaries that attempt to reflect multi-faceted aspects of a firm's environmental actions and governance, our variable may at least partially capture business strategy rather than the extent to which it cares about the environment. To address this problem, we need to examine how a firm's intention toward the environment can be translated into our measure of EP, Scope. Alternatively, we need direct evidence of linking a firm's intention and its carbon efficiency.

[34] While we report our empirical results for the period of 2010-2015, our main results still hold for the period of 2009-2015.

6 Conclusion

Today, the threat of climate change could potentially have devastating impacts to economies around the world. The International Energy Agency (2014) estimates that $53 trillion is needed by 2035 to combat these impacts. However, investment has been hampered by the unclear relationship between corporate EP and FP. This study empirically investigates the risk-return relationship of low-carbon investment, and characteristics of carbon-efficient firms. The underlying objective of this study is to provide reliable evidence on the market evaluation of low-carbon investment.

Based on 74,486 observations of U.S. firms from January 2005 to December 2015, we construct a carbon efficient-minus-inefficient (EMI) portfolio by carbon intensity, revenue-adjusted GHG emissions at firm-level. We find that our EMI portfolio generates positive abnormal returns since 2010, which cannot be explained by well-known risk factors. The findings demonstrate that an investment strategy of "long carbon-efficient firms and short carbon-inefficient firms" would earn abnormal returns of 3.5–5.4% per year. We also confirm that our double-sorted EMI portfolios also earn a positive alpha of similar magnitudes. The only exception is that small carbon-efficient firms do not outperform small carbon-inefficient firms. We also investigate the source of EMI portfolio's abnormal returns by examining the relationship between carbon intensity and firm-level characteristics. We find that carbon-efficient firms are likely to be "good firms" in terms of financial performance (measured by Tobin'q, ROI, cash flow, coverage ratio) and corporate governance. However, we do not find strong evidence that investors explicitly consider carbon efficiency in their investment decision. Our findings are not driven by a small set of industries and other macroeconomic factors. Although we acknowledge that the observation of the abnormal return is relatively short, we nevertheless assert that our findings are promising enough to encourage investors, business leaders and policymakers to modify their approach to low-carbon investment.

Appendix

A. Variable Description

Variables	Description and Data Source
a) Firm-level Carbon Data	
Scope 1 (tCO2e)	Greenhouse gas emissions generated from burning fossil fuels and production processes which are owned or controlled by the company (reference: GHG Protocol), unit: tCO2e. Source: Trucost
Scope 2 (tCO2e)	Greenhouse gas emissions from consumption of purchased electricity, heat or steam by the company (reference: GHG Protocol), unit: tCO2e. Source: Trucost
Scope 3 (tCO2e)	Other indirect Greenhouse gas emissions, such as from the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities (e.g. T&D losses) not covered in Scope 2, outsourced activities, waste disposal, etc (reference: GHG Protocol), unit: tCO2e. Source: Trucost
Scope 1	Scope 1 emissions divided by a firm's revenue (million), unit: tCO2e/$mil Source: Trucost
Scope 2	Scope 2 emissions divided by a firm's revenue, unit: tCO2e/$mil Source: Trucost
Scope 3	Scope 3 emissions divided by a firm's revenue, unit: tCO2e/$mil Source: Trucost
Scope 12	Sum of Scope 1 and Scope 2 divided by a firm's revenue, unit: tCO2e/$mil Source: Trucost
Scope	Sum of Scope 1, Scope 2 and Scope 3 divided by a firm's revenue, unit: tCO2e/$mil Source: Trucost
External direct cost	Cost that a company incur directly on the environment through its own activities, unit: USD million. Source: Trucost
External indirect cost	Cost that arises when a firm purchases goods and services or through supply chains, unit: USD million. Source: Trucost
External cost	Sum of external direct and indirect cost, unit: USD million. Source: Trucost

Direct impact ratio	External direct cost/revenue. Source: Trucost
Indirect impact ratio	External indirect cost/revenue. Source: Trucost
Impact ratio	Sum of direct and indirect impact. Source: Trucost
b) Variables Related to Firms' Financial Performance and Corporate Governance	
Firm size (Size)	Total assets (AT). Source: CRSP/Compustat Merged (CCM)
Book-to-market ratio (B/M)	Book value (AT-LT) to market value (MKVALT). Alternatively, book value can be defined as the number of shares (CSHO) multiplied by book value per share (BKVLPS). Source: CCM
Tobin's *q*	Ratio of the market value of a company's assets (as measured by the market value of its outstanding stock and debt) divided by the replacement cost of the company's assets (book value). (AT+(CSHO*PRCC_F)-CEQ)/AT. Source: CCM
Return on Assets (ROA)	Return on assets, net income (NI) divided by total assets (AT). Source: CCM
Return on Equity (ROE)	Return on equity; net income (NI) divided by market value of equity (MKVALT or CSHO*PRCC_F). Source: CCM
Return on Investment (ROI)	Return on investment; net income (NI) divided by invested capital (ICAPT). Source: CCM
Earnings per share (EPS)	Net income (NI) divided by the number of common shares outstanding. Source: CCM
PER	Price-earnings ratio; closing price (PRCC_F) divided by net income (NI) Source: CCM
Cash flow	Sum of income before extraordinary items (IBC) and depreciation and amortization (DP), scaled by total assets (AT). Source: CCM
Free cash flow	Earnings before interest and taxes (EBIT) multiplied by (1-tax rate), plus depreciation & amortization (DPC), minus change in working capital (WCAPCH), scaled by total assets (AT). Tax rate is calculated as the ratio of income taxes (TXT) to pretax income (PI). Zero observation for WCAPCH. Source: CCM

Cash holdings	Amount of cash and short-term investment (CHE), scaled by total assets (AT). Source: CCM
Coverage ratio	Earnings before interest and taxes (EBIT) divided by total interest and expense (XINT) Source: CCM
Payout ratio	Dividend-payout ratio; sum of preferred dividend (DVP), common/ordinary dividend (DVC), purchases of preferred and common stocks (PRSTKC), divided by income before extraordinary items (IB) Source: CCM
Leverage ratio	Sum of long-term debt (DLTT) and current debt (DLC), scaled by stockholders' equity (SEQ). Source: CCM
Tangible assets	Net amount of property, plant, and equipment (PPENT) scaled by total assets (AT). Source: CCM
Capital intensity	Capital expenditure (CAPX) divided by total assets (AT). Source: CCM
Operating profitability	(revenue (REVT) - cost of goods sold (COGS) – interest and related expenses (XINT) – sales, general and administrative expenses (XSGA)), divided by total assets (AT). Source: CCM
Cost of capital	Interest and related expenses (XINT), divided by debt in current liabilities (DLC). Source: CCM
R&D intensity	R&D expenditures divided by total assets (AT). Source: CCM
c) Variables Related to Firms' Environmental Performance and Governance (from MSCI)	
Environmental strength	Number of "yes" on 6 categories on a firm's strengths in environmental issues (env_str_num). Source: MSCI
Environmental concern	Number of "yes" on 6 categories on a firm's concerns in environmental issues (env_con_num). Source: MSCI
Governance strength	Number of "yes" on 6 categories on a firm's strengths in corporate governance issues (cgov_str_num). Source: MSCI

Governance concern	Number of “yes” on 6 categories on a firm’s concerns in corporate governance issues (cgov_con_num). Source: MSCI

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Table 1. Sample Properties

(a) Numbers of total observations and distinct firms

		Number of observations	
	Sample period	Total	Distinct
Trucost	2005-2015	9,510	1,124
merged with Compustat	2005-2015	8,607	975
meged with MSCI	2005-2015	8,124	903
merged with CRSP	Jan 2005-Dec 2015	87,609	851
excluding financial industry	Jan 2005-Dec 2015	75,638	739
Applying exclusion criteria	Jan 2005-Dec 2015	74,486	736

(b) Number of firms by Fama-French breakpoints (size and B/M 2*3 breakpoints)

	Small			Big			
Year	Growth	Neutral	Value	Growth	Neutral	Value	total
2005	413	388	130	2,740	1,730	678	6,079
2006	426	301	119	2,800	1,861	669	6,176
2007	294	258	315	2,985	1,658	795	6,305
2008	379	386	798	1,825	1,874	1,265	6,527
2009	325	278	124	3,754	2,098	200	6,527
2010	302	340	143	3,286	2,330	565	6,779
2011	323	434	461	2,746	2,064	1,048	7,076
2012	313	465	266	3,451	2,177	646	7,318
2013	464	569	196	4,181	2,138	464	8,012
2014	386	601	548	3,428	2,327	839	8,129
2015	135	222	188	2,385	1,687	502	5,119
Total	3,760	4,242	3,288	33,581	21,944	7,671	74,486

(c) Correlation coefficients of selected industry portfolios with Fama-French industry portfolios

Industry	Jan 2005 - Dec 2015	Jan 2010 - Dec 2015
Energy	0.99	0.99
Finance	0.95	0.97
Health	0.98	0.98
Telecommunication	0.80	0.75
Utilities	0.96	0.94

Table 2. Summary Statistics of Carbon Emissions and Intensity, by Industry

Panel (a) shows the average values of carbon intensity defined in terms of Scope 1, 2, and 3 (tCO2e/$mil), external cost, and impact ratio (external cost/revenue) by eleven GICS industry sectors. Panel (b) reports the correlation coefficients.

(a) Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	
GICS industry sectors	Scope 1	Scope 2	Scope 3	Scope	External cost	Impact ratio	*N*
Consumer Discretionary	19.9	36.4	142.4	198.7	78.4	0.7	15,306
Consumer Staples	40.5	41.4	447.7	529.6	430.0	1.86	4,884
Energy	447.4	59.8	216.3	723.5	602.0	2.55	6,451
Financials	3.3	7.0	42.7	53.0	19.2	0.19	7,186
Health Care	17.2	18.9	103.8	139.9	59.8	0.49	7,911
Industrials	160.9	22.9	216.0	399.7	141.4	1.42	13,964
Information Tech	15.2	23.2	101.7	140.1	40.5	0.49	12,070
Materials	497.7	174.5	425.1	1,097.2	327.6	4.01	6,699
Real Estate	116.7	51.1	154.6	322.4	76.6	1.12	385
Telecommunication	8.0	30.5	54.5	93.0	96.3	0.33	1,357
Utilities	3,780.9	96.4	319.2	4,196.6	1,096.7	14.73	5,663
Total	375.9	45.5	194.5	615.8	229.9	2.18	81,876

(b) Correlation coefficients. * and ** denote p-value<0.10 and p-value<0.01, respectively.

	Scope 1	Scope 2	Scope 3	Scope	External cost	Impact Ratio
Scope 1	1					
Scope 2	0.088**	1				
Scope 3	0.26**	0.071**	1			
Scope	0.97**	0.26**	0.40**	1		
External cost	0.45**	0.047**	0.30**	0.47**	1	
Impact ratio	0.97**	0.27**	0.39**	0.99**	0.47**	1

Table 3. Average Returns of Portfolios, by Different Portfolio Formation

This table displays the average returns of value-weighted portfolios formed on Scope only, Scope and book-to-market ratio, and Scope and firm size. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

(a) Average returns, single-sorted on carbon intensity

	1 (Efficient)	2	3 (Inefficient)	total	differences
2005m1-2015m12	1.33	1.15	1.13	1.20	0.20
2010m1-2015m12	1.73	1.28	1.23	1.41	0.50***

(b) Average returns, double-sorted on carbon intensity and book-to-market (3×3)

	Sample period: 2005m1-2015m12				
	Efficient	2	Inefficient	total	difference
Growth	1.65	1.26	1.01	1.31	0.64***
2	1.04	1.01	1.03	1.03	0.01
Value	1.30	1.15	1.53	1.32	-0.23
Total	1.33	1.14	1.19	1.22	0.14
	Sample period: 2010m1-2015m12				
	Efficient	2	Inefficient	total	difference
Growth	2.13	1.34	1.18	1.55	0.95***
2	1.52	1.17	1.09	1.26	0.43*
Value	1.54	1.23	1.51	1.43	0.03
Total	1.73	1.25	1.26	1.41	0.47

(c) Average returns, double-sorted on carbon intensity and size (3× 3)

	Sample period: 2005m1-2015m12				
	Efficient	2	Inefficient	total	difference
Big	1.26	1.07	1.02	1.12	0.24
2	1.48	1.44	1.37	1.43	0.11
Small	1.73	1.76	1.99	1.83	-0.26
Total	1.49	1.42	1.46	1.46	0.03
	Sample period: 2010m1-2015m12				
	Efficient	2	Inefficient	total	difference
Big	1.73	1.20	1.11	1.35	0.62***
2	1.72	1.68	1.57	1.66	0.15
Small	1.59	1.67	1.95	1.74	-0.36**
Total	1.68	1.52	1.54	1.58	0.14

Table 4. Summary Statistics of EMI's and Other Factor Portfolios

This table shows the average returns, standard deviations, and Sharpe ratios of EMI (efficient-minus-inefficient) portfolios, market excess return, portfolios of SMB (small-minus-big), HML (high-minus-low), RMW (robust-minus-weak), CMA (conservative-minus-aggressive), and WML (winner-minus-loser). EMI portfolio is defined as (top 25% carbon-efficient – bottom 25% carbon-efficient).

(a) Summary statistics

statistics	EMI1	EMI2	EMI3	mktrf	SMB	HML	RMW	CMA	WML
Sample period: 2006:1-2015:12									
Average returns	0.19	0.21	0.24	0.61	0.09	-0.14	0.26	0.08	0.09
Standard deviation	1.62	1.77	2.01	4.46	2.38	2.61	1.56	1.33	4.98
Sharpe ratios	0.12	0.12	0.12	0.14	0.04	-0.05	0.17	0.06	0.02
Sample period: 2010:1-2015:12									
Average returns	0.47	0.49	0.62	1.09	0.02	-0.19	0.03	0.09	0.57
Standard deviation	1.27	1.40	1.51	3.91	2.23	1.92	1.50	1.25	3.00
Sharpe ratios	0.37	0.35	0.41	0.28	0.01	-0.10	0.02	0.07	0.19

(b) Correlation coefficients. * and ** denote p-value<0.10 and p-value<0.01, respectively.

	EMI	EMI2	EMI3	mktrf	SMB	HML	RMW	CMA	WML
Sample period: 2006m1-2015m12									
EMI1	1								
EMI2	0.80**	1							
EMI3	0.98**	0.77**	1						
mktrf	0.21*	0.16*	0.19*	1					
SMB	0.13	0.05	0.14	0.40**	1				
HML	0.00	0.05	0.04	0.33**	0.29**	1			
RMW	-0.26**	-0.22*	-0.27**	-0.51**	-0.40**	-0.27**	1		
CMA	-0.07	0.05	-0.04	-0.01	0.07	0.50**	0.03	1	
WML	-0.23*	-0.06	-0.22*	-0.35**	-0.17*	-0.44**	0.25**	-0.07	1
Sample period: 2010m1-2015m12									
EMI1	1								
EMI2	0.78**	1							
EMI3	0.97**	0.75**	1						
mktrf	0.14	0.10	0.08	1					
SMB	-0.08	-0.10	-0.09	0.39**	1				
HML	-0.48**	-0.22*	-0.47**	0.21*	0.19	1			
RMW	-0.11	-0.05	-0.12	-0.40**	-0.46**	-0.22*	1		
CMA	-0.39**	-0.12	-0.37**	0.16	0.10	0.65**	0.01	1	
WML	0.30**	0.34**	0.31**	-0.08	0.09	-0.26*	0.13	-0.03	1

Table 5. GRS Test on 3 Portfolios Sorted on Carbon Intensity

This table shows the GRS tests based on equation (4), (5), (6), and (7). There are three portfolios formed on Scope. EMI1 portfolios is "efficient-minus-inefficient" portfolio. The null hypothesis of GRS test is $\alpha_1 = \alpha_2 = \alpha_3 = 0$. *P*-values based on GRS test statistics are provided.

(a) Sample period: 2006m1-2015m12

	(1) Efficient	(2) 2	(3) Inefficient	(4) EMI1
		CAPM		
mktrf	0.95***	0.92***	0.88***	0.08*
alpha	0.65***	0.50***	0.50***	0.15
R^2	0.96	0.94	0.91	0.04
	average alpha = 0.55, p-value =0.00			
		Fama-French 3 factor model		
mktrf	0.98***	0.95***	0.90***	0.08*
SMB	-0.01	-0.11**	-0.05	0.05
HML	-0.12***	-0.07	-0.07	-0.05
alpha	0.62***	0.48***	0.48***	0.14
R^2	0.96	0.95	0.92	0.05
	average alpha = 0.53, p-value =0.00			
		Fama-French 3 factor model + momentum		
mktrf	0.98***	0.93***	0.92***	0.06
SMB	-0.01	-0.11**	-0.06	0.05
HML	-0.12***	-0.12**	-0.01	-0.11
WML	0.00	-0.07***	0.08**	-0.08*
alpha	0.62***	0.49***	0.47***	0.15
R^2	0.96	0.95	0.92	0.10
	average alpha = 0.53, p-value =0.00			
		Fama-French 5 factor model		
mktrf	0.99***	0.98***	0.95***	0.04
SMB	0.00	-0.08*	-0.01	0.01
HML	-0.13***	-0.07	-0.08	-0.06
RMW	0.07	0.19**	0.29***	-0.22*
CMA	0.06	0.05	0.07	-0.02
alpha	0.59***	0.41***	0.37***	0.22
R^2	0.96	0.95	0.93	0.09
	average alpha = 0.46, p-value =0.00			

(b) Sample period: 2010m1-2015m12

	(1) Efficient	(2) 2	(3) Inefficient	(4) EMI1
	CAPM			
mktrf	0.97***	0.92***	0.93***	0.04
alpha	0.66***	0.27*	0.22*	0.45**
R^2	0.95	0.94	0.95	0.02
	average alpha = 0.39, p-value =0.00			
	Fama-French 3 factor model			
mktrf	1.01***	0.98***	0.93***	0.09*
SMB	-0.07	-0.24***	-0.02	-0.05
HML	-0.25***	-0.09	0.08	-0.33***
alpha	0.57***	0.19	0.24*	0.34*
R^2	0.96	0.96	0.96	0.30
	average alpha = 0.33, p-value =0.00			
	Fama-French 3 factor model + momentum			
mktrf	1.02***	0.98***	0.93***	0.09**
SMB	-0.10*	-0.23***	-0.03	-0.07
HML	-0.20***	-0.11*	0.09	-0.29***
WML	0.12***	-0.05	0.03	0.09*
alpha	0.51***	0.22*	0.22*	0.29*
R^2	0.97	0.96	0.96	0.34
	average alpha = 0.32, p-value =0.00			
	Fama-French 5 factor model			
mktrf	1.01***	1.01***	0.93***	0.07*
SMB	-0.07	-0.17***	0.01	-0.08
HML	-0.32***	-0.04	-0.02	-0.30***
RMW	-0.02	0.30***	0.13	-0.15
CMA	0.17	-0.06	0.27**	-0.10
alpha	0.55***	0.16	0.18	0.37**
R^2	0.96	0.97	0.96	0.34
	average alpha = 0.30, p-value =0.00			

Table 6. GRS Test on EMI2 Portfolio, Sorted on B/M and Carbon Intensity

This table shows the results of GRS test, based on two sample periods, January 2006-December 2015 and January 2010-December 2015. We use four well-known factor models (CAPM, Fama-French 3-factor model, 4-factor models with momentum, Fama-French 5-factor model) to see if they can price EMI portfolio. EMI portfolio is based on 3*3 B/M-carbon intensity portfolio. Scope is used for carbon intensity. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

	2006m1-2015m12			2010m1-2015m12		
	(1) Efficient	(2) Inefficient	(3) EMI2	(4) Efficient	(5) Inefficient	(6) EMI2
	CAPM			CAPM		
mktrf	1.04***	0.97***	0.07	1.03***	0.99***	0.04
alpha	0.75***	0.58***	0.07	0.71***	0.26*	0.45*
R^2	0.95	0.89	0.03	0.94	0.95	0.01
	Fama-French 3 factor			Fama-French 3 factor		
mktrf	1.04***	0.97***	0.07	1.06***	0.98***	0.07
SMB	0.06	0.07	-0.02	-0.05	0.03	-0.08
HML	-0.07	-0.07	0.00	-0.15*	0.02	-0.18*
alpha	0.74***	0.57***	0.07	0.65***	0.27*	0.38*
R^2	0.95	0.9	0.03	0.95	0.95	0.09
	Fama-French 3 factor + momentum			Fama-French 3 factor + momentum		
mktrf	1.03***	0.96***	0.07	1.07***	0.98***	0.08
SMB	0.06	0.08	-0.02	-0.08	0.04	-0.12
HML	-0.09	-0.09	-0.01	-0.10	0.01	-0.11
WML	-0.03	-0.03	0.00	0.12**	-0.03	0.16**
alpha	0.74***	0.57***	0.07	0.58***	0.29*	0.29
R^2	0.95	0.9	0.03	0.96	0.95	0.19
	Fama-French 5 factor			Fama-French 5 factor		
mktrf	1.06***	1.02***	0.04	1.05***	0.99***	0.06
SMB	0.07	0.12	-0.05	-0.06	0.05	-0.11
HML	-0.08	-0.04	-0.05	-0.29***	-0.07	-0.22
RMW	0.12	0.36***	-0.24	-0.05	0.08	-0.12
CMA	0.07	-0.05	0.13	0.31*	0.24*	0.07
alpha	0.69***	0.45**	0.14	0.61***	0.23*	0.38*
R^2	0.95	0.91	0.06	0.95	0.96	0.10

Table 7. GRS Test on EMI3 Portfolio, Sorted on Size and Carbon Intensity

This table shows the results of GRS test, based on two sample periods, January 2006-December 2015 and January 2010-December 2015. We use four well-known factor models (CAPM, Fama-French 3-factor model, 4-factor models with momentum, Fama-French 5-factor model) to see if they can price EMI portfolio. EMI portfolio is based on 3*3 size-carbon intensity portfolio. Scope is used for carbon intensity. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

	2006m1-2015m12			2010m1-2015m12		
	(1) Efficient	(2) Inefficient	(3) EMI3	(4) Efficient	(5) Inefficient	(6) EMI3
	CAPM			CAPM		
mktrf	0.92***	0.83***	0.09*	0.93***	0.89***	0.03
alpha	0.61***	0.43**	0.09	0.72***	0.14	0.58**
R^2	0.93	0.87	0.04	0.90	0.92	0.01
	Fama-French 3 factor			Fama-French 3 factor		
mktrf	0.96***	0.88***	0.08	1.00***	0.91***	0.09
SMB	-0.10*	-0.17**	0.07	-0.20***	-0.14*	-0.06
HML	-0.10*	-0.07	-0.04	-0.28***	0.11	-0.39***
alpha	0.58***	0.40**	0.08	0.59***	0.14	0.45**
R^2	0.94	0.88	0.04	0.94	0.93	0.26
	Fama-French 3 factor + momentum			Fama-French 3 factor + momentum		
mktrf	0.96***	0.91***	0.06	1.01***	0.92***	0.10*
SMB	-0.11*	-0.18**	0.08	-0.24***	-0.15*	-0.09
HML	-0.09*	0.00	-0.10	-0.21***	0.13*	-0.34***
WML	0.02	0.11***	-0.09*	0.17***	0.05	0.11*
alpha	0.58***	0.39**	0.1	0.50***	0.11	0.38*
R^2	0.94	0.89	0.08	0.95	0.93	0.31
	Fama-French 5 factor			Fama-French 5 factor		
mktrf	0.98***	0.94***	0.04	0.99***	0.93***	0.07
SMB	-0.09	-0.12*	0.02	-0.19**	-0.08	-0.12
HML	-0.14**	-0.09	-0.05	-0.39***	-0.01	-0.38**
RMW	0.07	0.38***	-0.32*	-0.02	0.21*	-0.23
CMA	0.13	0.13	0.00	0.26*	0.34**	-0.08
alpha	0.54***	0.25	0.19	0.55***	0.06	0.49**
R^2	0.94	0.90	0.08	0.94	0.95	0.30

Table 8. Comparison of Firm Characteristics, Efficient and Inefficient Portfolios

This table shows the average values of firm characteristics variables for top 33% carbon-efficient portfolio and bottom 33% carbon-efficient portfolio, along with their differences during the period of 2005-2015 and 2010-2015. Variables are winsorized at 2% and 98%. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

	2005-2015			2010-2015		
	efficient	inefficient	difference	efficient	inefficient	difference
Size	12,611	15,452	-2841***	13,560	16,587	-3027***
B/M	0.403	0.465	-0.062***	0.398	0.452	-0.054***
Tobin's q	2.135	1.942	0.194***	2.127	1.939	0.188***
ROA	0.061	0.059	0.002	0.061	0.058	0.002
ROI	0.102	0.092	0.009***	0.100	0.091	0.009**
EPS	2.266	2.407	-0.141*	2.56	2.576	-0.016
PER	0.178	0.171	0.007	0.184	0.174	0.011
Cash flow	0.103	0.099	0.004*	0.103	0.099	0.004
Free cash flow	0.061	0.064	-0.003	0.064	0.064	0
Cash holdings	0.129	0.132	-0.004	0.13	0.134	-0.004
Coverage ratio	32.9	28.7	4.2*	34.2	25.5	8.7***
Payout ratio	0.742	0.726	0.016	0.761	0.731	0.03
Leverage ratio	0.883	0.911	-0.028	0.941	0.968	-0.027
Tangible assets	0.28	0.346	-0.066***	0.272	0.345	-0.073***
Capital intensity	0.057	0.054	0.003*	0.053	0.054	0
Environmental strength	0.472	0.872	-0.400***	0.761	1.194	-0.432***
Environmental concern	0.241	0.734	-0.492***	0.196	0.543	-0.347***
Governance strength	0.149	0.223	-0.075***	0.169	0.2	-0.031
Governance concern	0.611	0.605	0.006	0.428	0.367	0.061**

Table 9. Carbon Intensity and Firm Characteristics, Pooled OLS and Logit Regressions

This table reports the results of pooled OLS and logit regression. The dependent variable is log of Scope (sum of Scope 1,2, and 3, divided by revenue). Columns (1)-(4) report the coeffiicients based on pooled OLS and column (5) reports the logit regression result with the dependent variable taking a value of one when a firm is carbon-inefficient and zero when a firm is carbon-efficient. All regressions include industry fixed effects, year fixed effects, and industry-year fixed effects. Variables are winsorized at 2% and 98%. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

(a) Sample period: 2005-2015

	(1)	(2)	(3)	(4)	(5)
	sample period: 2006-2015				
log(size)	0.007	-0.099***	0.018	-0.099***	-0.438***
Tobinq	-0.054***	-0.067***	-0.050***	-0.056***	-0.237***
ROA	4.149***	5.017***	5.440***	6.221***	23.262***
ROI	-1.498***	-1.899***	-1.666***	-2.249***	-6.557***
EPS	0.006	0.008	0.001	0.008	0.076**
PER	-0.025	-0.016	0.018	-0.019	-0.06
Cash flow	-2.392***	-2.784***	-2.557***	-2.877***	-15.465***
Free cash flow	0.722**	0.811**	0.877**	0.835**	4.804***
Cash holdings	0.490***	0.336***	0.431***	0.339**	2.029***
Leverage ratio	0.008	0.01	0.004	0.004	-0.048
Tangible assets	1.513***	1.425***	1.431***	1.333***	5.133***
Capital intensity	-2.158***	-1.599***	-2.063***	-1.507**	-5.383*
Environmental strength		0.110***		0.098***	0.474***
Environmental concern		0.253***		0.251***	1.031***
Governance strength		-0.062*		-0.015	-0.036
Governance concern		-0.033*		-0.048**	-0.178*
log(coverage ratio)			-0.040***	-0.042***	-0.126**
Payout ratio			-0.004	-0.001	-0.025
R^2	0.617	0.651	0.620	0.654	
N	6,154	5,056	5,317	4,358	2,951

(b) Sample period: 2010-2015

	(1)	(2)	(3)	(4)	(5)
	sample period: 2010-2015				
log(size)	0.010	-0.073***	0.023	-0.072***	-0.351***
Tobinq	-0.054***	-0.060***	-0.060**	-0.053*	-0.275**
ROA	5.082***	6.059***	6.214***	7.313***	28.328***
ROI	-1.366***	-1.874***	-1.371***	-2.056***	-4.737*
EPS	-0.002	0.005	-0.01	-0.001	-0.004
PER	-0.028	0.011	0.036	0.029	0.148
Cash flow	-3.449***	-3.840***	-3.474***	-3.813***	-19.577***
Free cash flow	0.823*	0.812	0.984*	0.885	4.712**
Cash holdings	0.369**	0.207	0.348*	0.263	2.121**
Leverage ratio	0.008	0.010	-0.001	-0.003	-0.076
Tangible assets	1.522***	1.387***	1.427***	1.264***	4.721***
Capital intensity	-1.390*	-0.829	-1.221	-0.634	-1.932
Environmental strength		0.092***		0.090***	0.456***
Environmental concern		0.227***		0.231***	0.945***
Governance strength		-0.077		-0.055	-0.329
Governance concern		-0.077**		-0.096**	-0.379**
log(coverage ratio)			-0.050***	-0.067***	-0.242***
Payout ratio			-0.001	-0.001	-0.077
R^2	0.607	0.631	0.610	0.635	
N	3,526	2,428	3,082	2,123	1,431

Table 10. Carbon Intensity and Firm Characteristics, with or without Most Carbon-Efficient and Carbon-Inefficient Industries

This table reports the results of pooled OLS regressions. Columns of 'w/o efficient' reports the estimated coefficients without 3 most carbon-intensive industries (utilities, energy, materials) and columns of 'w/o inefficient' reports the coefficients without 3 least carbon-intensive industries (telecommunication, health, IT). All regressions include industry fixed effects, year fixed effects, and industry-year fixed effects. Variables are winsorized at 2% and 98%. *, **, *** denote p-value<0.10, p-value<0.05, and p-value<0.01, respectively.

(a) Sample period: 2005-2015

	Specification 1			Specification 2		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	w/o efficient	w/o inefficient	all	w/o efficient	w/o inefficient
log(size)	0.018	0.012	-0.027**	-0.438***	-0.577***	-0.504***
Tobinq	-0.050***	-0.042*	-0.071***	-0.237***	-0.157	-0.271***
ROA	5.440***	4.858***	6.399***	23.262***	21.521***	24.297***
ROI	-1.666***	-1.198**	-1.527***	-6.557***	-6.339**	-6.127**
EPS	0.001	0.016*	-0.003	0.076**	0.173***	0.034
PER	0.018	0.006	0.008	-0.06	-0.267	-0.034
Cash flow	-2.557***	-2.582***	-3.636***	-15.465***	-15.690***	-16.315***
Free cash flow	0.877**	-0.001	1.079**	4.804***	1.829	4.574**
Cash holdings	0.431***	0.284	0.314**	2.029***	1.582*	1.383**
Leverage ratio	0.004	0.016	0.004	-0.048	0.024	-0.044
Tangible assets	1.431***	1.388***	1.276***	5.133***	4.678***	3.848***
Capital intensity	-2.063***	-3.107***	-0.56	-5.383*	-9.065***	0.407
log(coverage ratio)	-0.040***	-0.043**	-0.037**	-0.126**	-0.143*	-0.157**
Payout ratio	-0.004	0.002	-0.013	-0.025	0.012	-0.029
Environmental strength				0.474***	0.358***	0.566***
Environmental concern				1.031***	1.067***	0.840***
Governance strength				-0.036	-0.086	0.108
Governance concern				-0.178*	-0.228*	-0.318***
R^2	0.62	0.56	0.35			
N	5,317	3,920	3,929	2,951	2,180	2,141

(b) Sample period: 2010-2015

	Specification 1			Specification 2		
	(1)	(2)	(3)	(4)	(5)	(6)
	all	w/o efficient	w/o inefficient	all	w/o efficient	w/o inefficient
log(size)	0.023	0.027	-0.02	-0.351***	-0.388***	-0.520***
Tobinq	-0.060**	-0.052	-0.081***	-0.275**	-0.161	-0.320**
ROA	6.214***	6.487***	6.862***	28.328***	30.808***	29.890***
ROI	-1.371***	-0.997*	-1.068**	-4.737*	-4.419*	-3.774*
EPS	-0.01	0.003	-0.012	-0.004	0.072	-0.024
PER	0.036	0.063	0.003	0.148	0.246	0.087
Cash flow	-3.474***	-4.230***	-4.470***	-19.577***	-23.648***	-22.295***
Free cash flow	0.984*	0.303	1.094*	4.712**	2.014	4.736*
Cash holdings	0.348*	0.107	0.354*	2.121**	1.463	1.773**
Leverage ratio	-0.001	0.01	0.001	-0.076	-0.011	-0.06
Tangible assets	1.427***	1.384***	1.297***	4.721***	3.999***	3.487***
Capital intensity	-1.221	-1.924*	0.527	-1.932	-4.054	6.304
log(coverage ratio)	-0.050***	-0.053**	-0.044**	-0.242***	-0.251***	-0.284***
Payout ratio	-0.001	0.015	-0.015	-0.077	-0.038	-0.093
Environmental strength				0.456***	0.401***	0.559***
Environmental concern				0.945***	1.004***	0.852***
Governance strength				-0.329	-0.569**	-0.145
Governance concern				-0.379**	-0.644***	-0.519***
R^2	0.61	0.55	0.34			
N	3,082	2,248	2,308	1,431	1,051	1,052

Figure 1. Carbon Intensity by Scope Measures and Industry

This figure shows the relative shares of carbon intensity in terms of Scope 1, Scope 2, and Scope 3 by each industry in the sample. The relative shares are obtained from the average values of each Scope measure for each industry from 2005 to 2015.

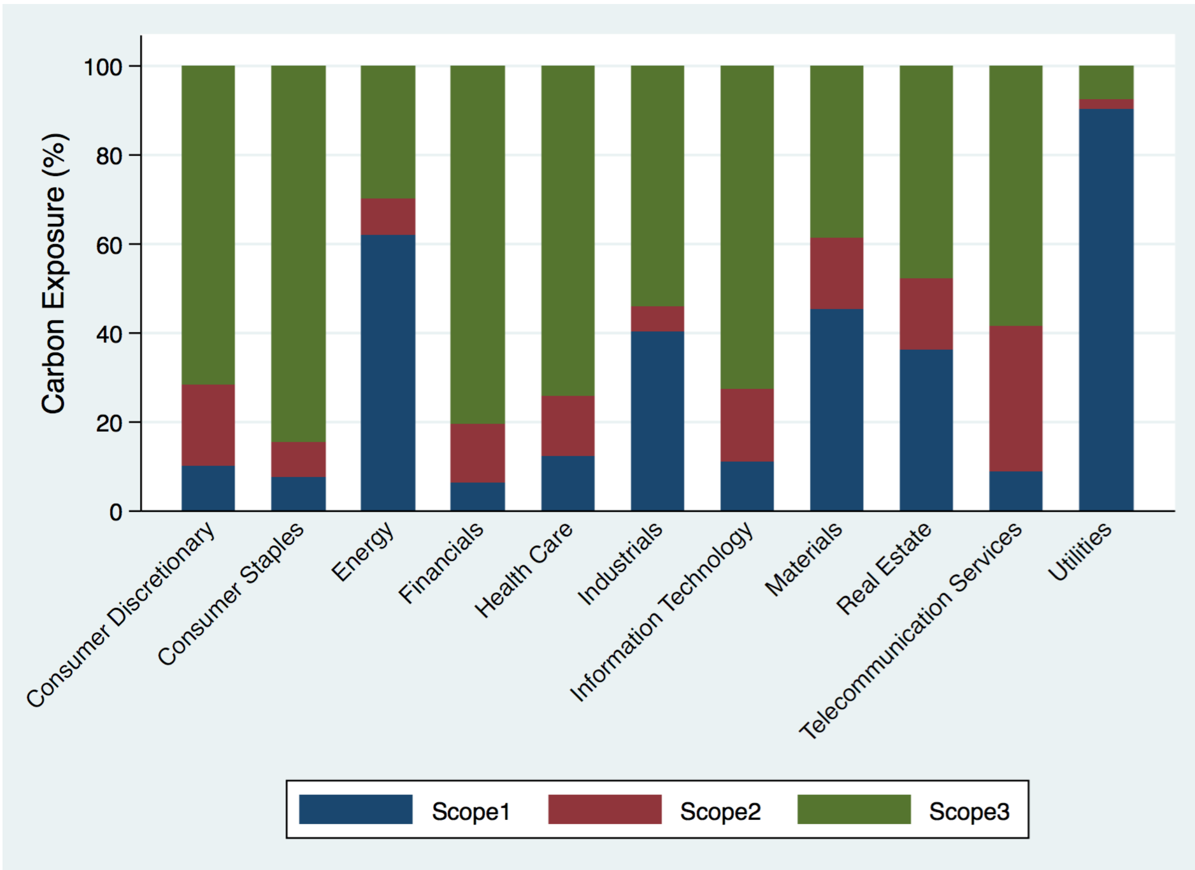


Figure 2. Trends in Carbon Intensity

This graph shows the average values of our Scope measures over time. 'Scope' is the sum of Scope 1, 2, and 3, divided by a firm's revenue. 'Scope (11 yrs)' is the average values of Scope based on firms that exist in the sample from 2005 to 2015. 'Scope (10 yrs)' is based on firms that stays in the sample for at least 10 years. 'Scope12' is the sum of Scope 1 and 2, divided by a firm's revenue.

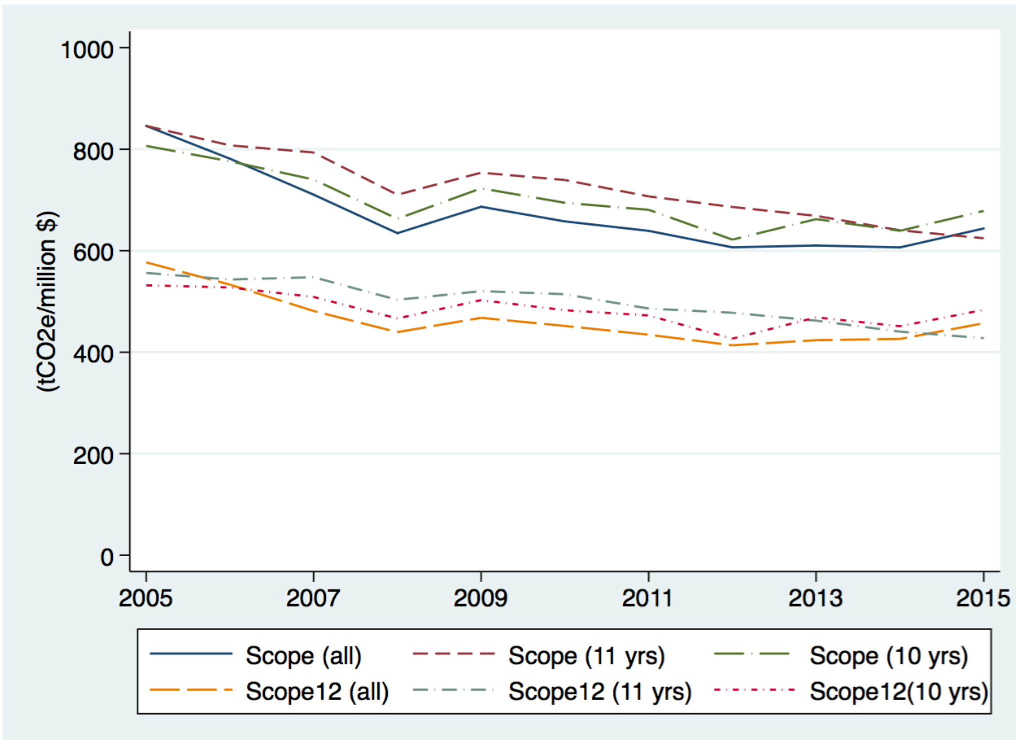


Figure 3. Cumulative Returns of Selected Industry Portfolios

This figure shows the cumulative returns of selected industry portfolios. Among 11 GICS industries, we choose 3 industries with highest carbon emissions intensity (utilities, materials, energy) and 3 industries with lowest carbon emissions intensity (health, IT, telecommunication). We use the sum of Scope 1, 2, and 3, divided by revenue for carbon emissions intensity.

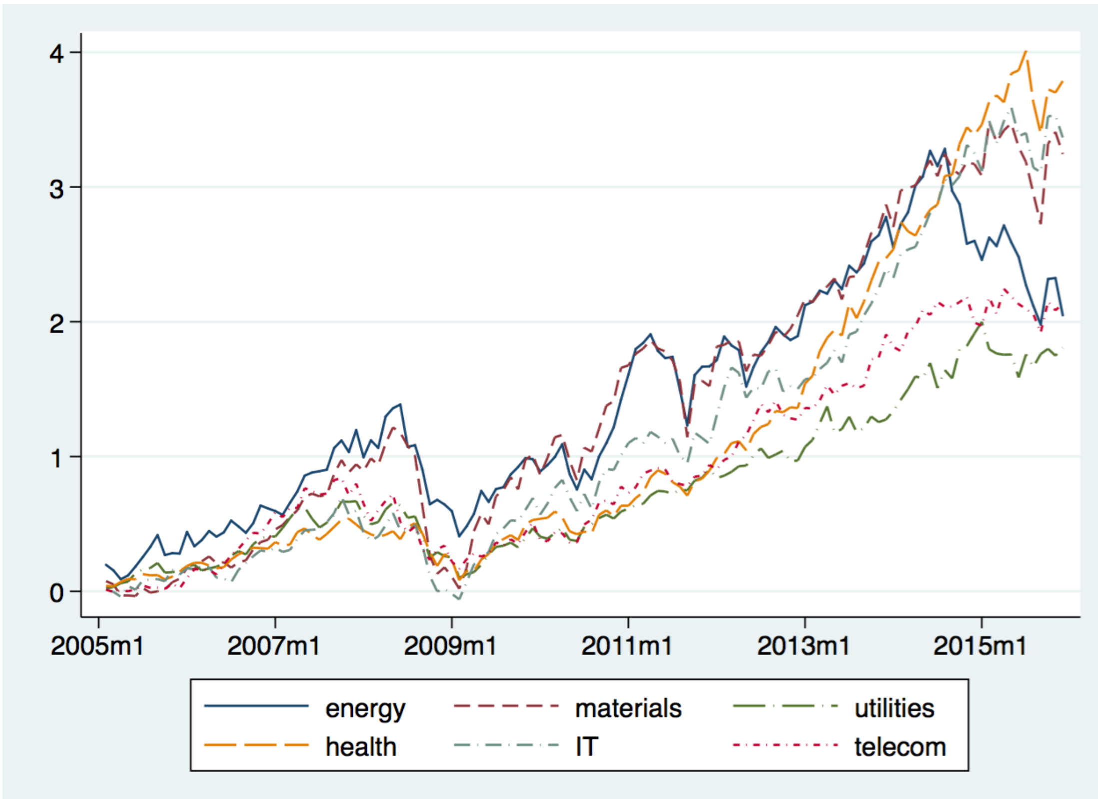


Figure 4. Cumulative Returns of EMI 1, EMI2, and EMI3 Portfolios

This figure shows the cumulative returns of EMI portfolios, defined in various ways. EMI1 is the single-sorted portfolio based on Scope. EMI2 and EMI3 are the double-sorted portfolios based on Scope and book-to-market ratio and Scope and size, respectively.

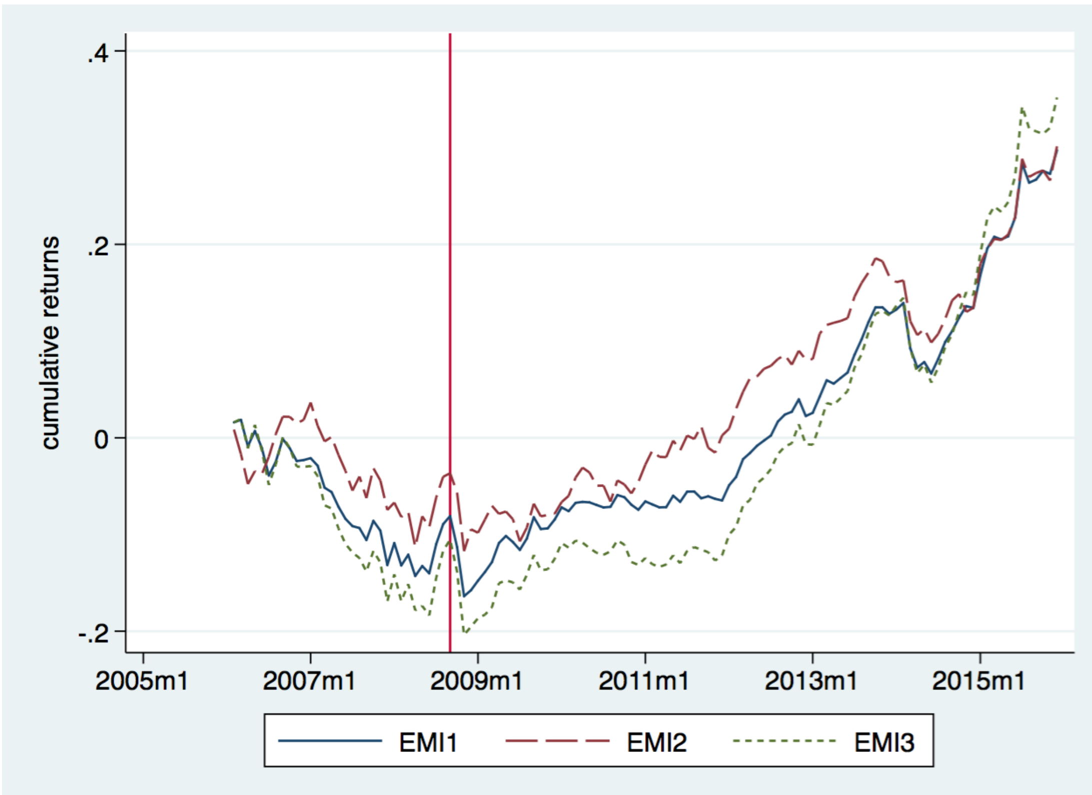


Figure 5. Cumulative Returns of EMI portfolios

This figure shows the cumulative returns of EMI portfolios, defined in various ways. A line of 'w/o utilities sector' is for the cumulative return of value-weighted EMI portfolio formed without utilities sector. A line of 'w/o utilities and telecom' is for the cumulative return of value-weighted EMI portfolio formed without utilities and telecommunication sector.

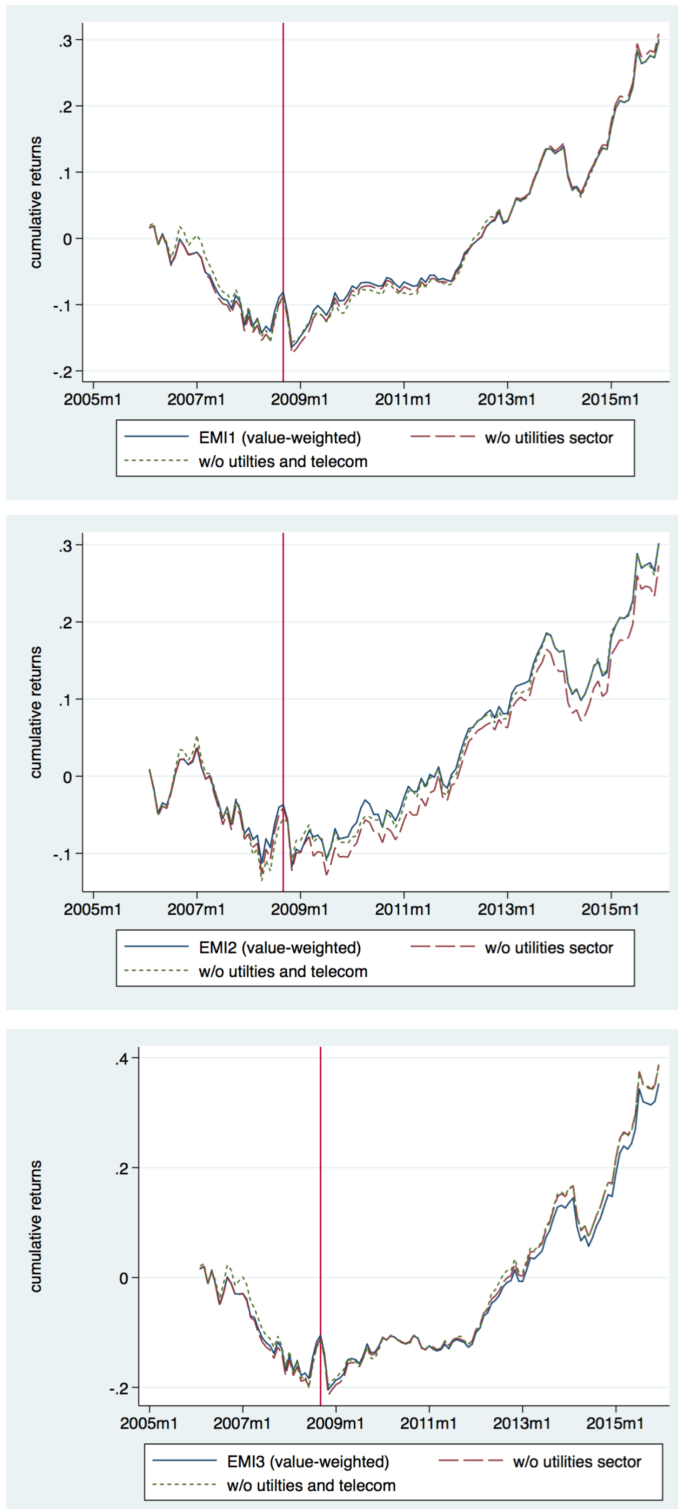


Figure 6. Cumulative Returns of Factor Portfolios

This figure shows the cumulative returns of factor portfolios. We include the market excess returns, SMB (small-minus-big) for size effect, HML (high-minus-low) for value effect, RMW (robust-minus-weak) to capture the effect of operating profitability, CMA (conservative-minus-aggressive) for investment, and WML (winner-minus-loser) for momentum effect.

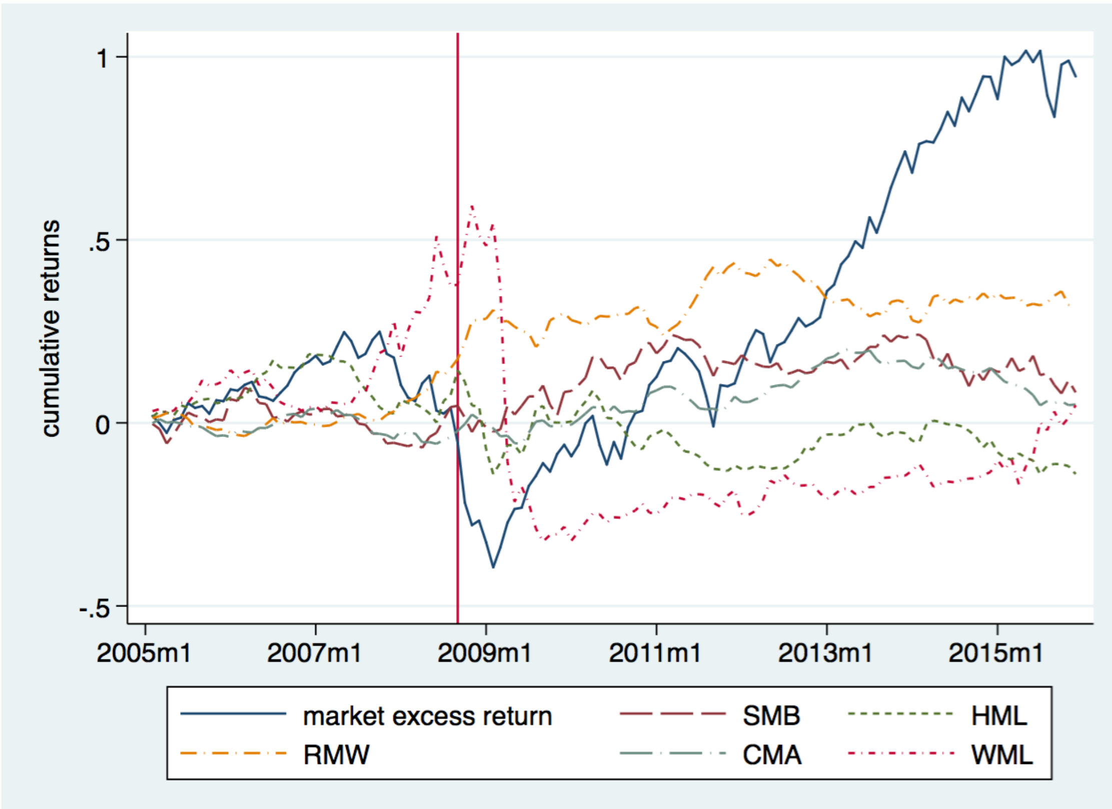


Figure 7. EMI Portfolios Sorted on Changes in Carbon Intensity

This figure shows the cumulative returns of value-weighted EMI portfolios, defined in various ways. A solid line labeled as 'EMI (level)' shows the cumulative return of EMI portfolio sorted on level of carbon intensity. A line of 'EMI (change, 1-year)' shows the cumulative return of EMI portfolio sorted on the changes in carbon intensity for the past 1 year. A line of 'EMI (change, 2-year)' is for the cumulative return of EMI portfolio formed on the changes in carbon intensity for the past 2 year. A red vertical line denotes September 2008, when Lehman Brothers filed for bankruptcy.

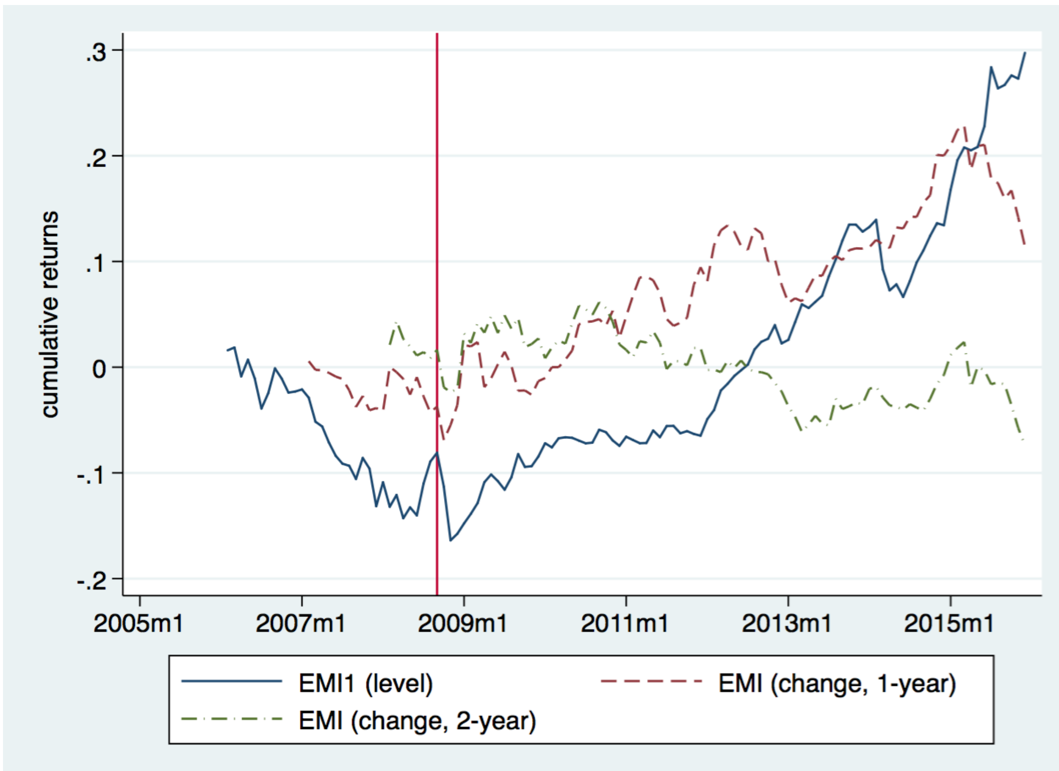
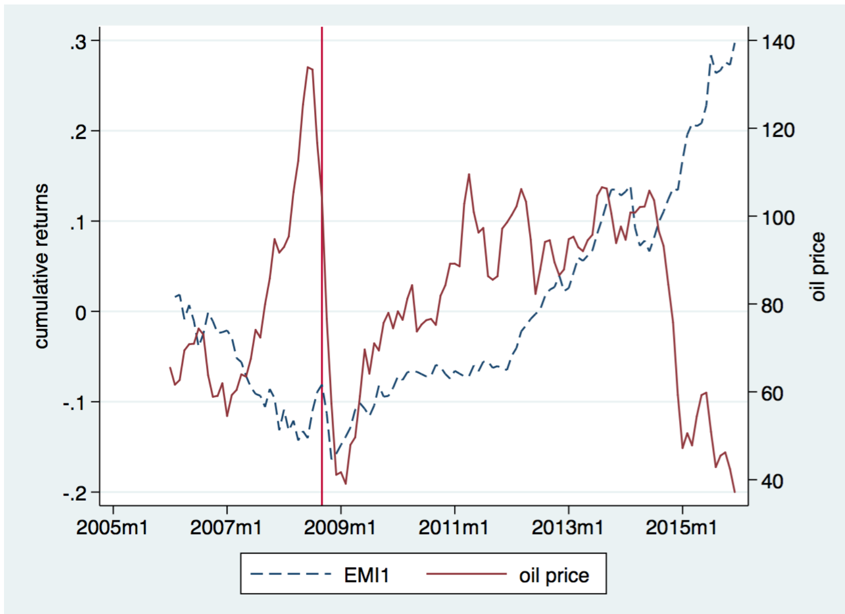


Figure 8. Oil Price and EMI Portfolios

Panel (a) shows the global price index of WTI Crude oil (US dollars per barrel) with the cumulative return of EMI1 portfolios. Panel (b) shows the rolling coefficient between oil price and cumulative returns of EMI1. The rolling window is 18 months.

(a) Oil price and cumulative return of EMI1 portfolio



(b) Rolling correlation coefficient between oil price and cumulative return of EMI, 18-month window

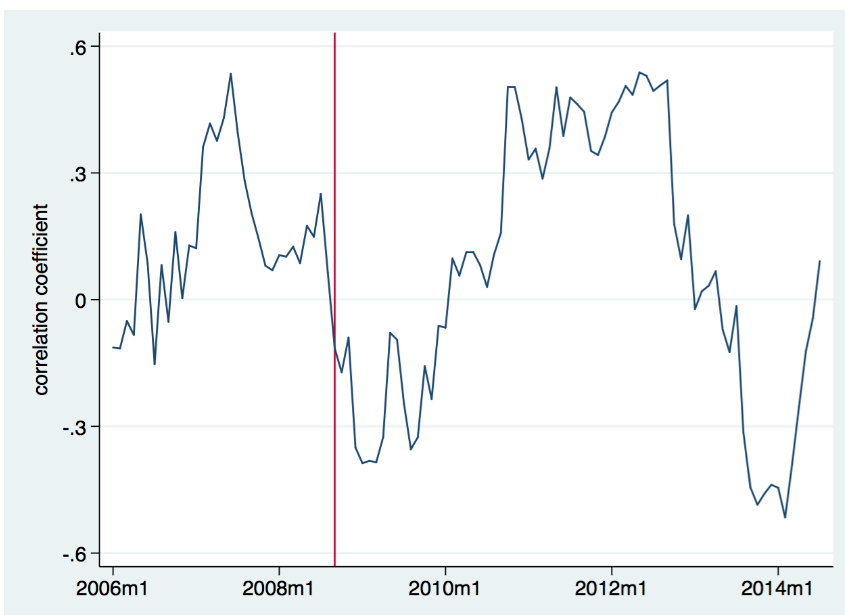


Figure 9. Cumulative Returns of EMI1 Portfolios without Some Industries

This figure shows the cumulative returns of three portfolios. One is EMI1 portfolio (single sort on carbon intensity). 'EMI1 w/o 4 industries' is the cumulative return of EMI portfolio formed without four stable and high-dividend-paying industries (utilities, telecommunication, IT, and consumer staples). 'EMI1 w/o IT' is the cumulative return of EMI portfolio formed without IT industry.