Do Investors Care about Carbon Risk?[1]

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Abstract: This paper explores whether carbon emissions affect the cross-section of U.S. stock returns. We find that stocks of firms with higher CO2 emissions earn higher returns, after controlling for size, book-to-market, momentum, and other factors that predict returns. We cannot explain this carbon premium through differences in unexpected profitability or other known risk factors. We also find that institutional investors implement exclusionary screening based on scope 1 emissions in a few salient industries. These results are consistent with an interpretation that investors are demanding compensation for their exposure to carbon risk.

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1 Introduction

A large asset-pricing literature seeks to explain the cross-sectional pattern of stock returns based on exposures to aggregate risk factors such as size and book-to-market ratios, or firm-specific risk linked to observable firm characteristics. One variable that has so far been missing from the analysis is corporate carbon emissions. This omission may be for historical reasons, as concerns over global warming linked to CO2 emissions from human activity have only recently become salient. But, both the evidence of rising temperatures and the renewed policy efforts to curb CO2 emissions raise the question whether carbon emissions represent a material risk today for investors that is reflected in the cross-section of stock returns and portfolio holdings.

Two major recent developments, in particular, suggest that this may be the case. First, the Paris COP 21 climate agreement of December 2015, with 195 signatories committing to limit global warming to well below 2°C above pre-industrial levels. Second, the rising engagement of the finance industry with climate change, largely as a result of the call to non-governmental actors to join the fight against climate change at the COP 21. Institutional investors are more and more focused on environmental, social, and governance (ESG) aspects of firm conduct, and are increasingly tracking the greenhouse gas emissions of listed companies. More and more asset owners are following the lead of the Church of England Pension Fund, whose stated goal is "to demonstrate transparently that it has delivered on its commitment to be aligned to the Paris Agreement".[2] By some recent estimates, the total global assets under management of funds with some ESG tilt represented $30.7 trillion in 2018.[3]

Even if the U.S. has since pulled out of the Paris agreement, and even if the commitments of the other remaining signatories are only partially credible, major curbs in CO2 emissions are likely to be introduced over the next decade. Primarily affected by these curbs are the companies with operations generating high CO2 emissions, or with activities linked to companies in the value chain that have high CO2 emissions. In light of these developments, one would expect to see the risk with respect to carbon emissions to be reflected in the cross-section of stock returns. Yet, considerable skepticism remains, not least in the U.S. where the current administration has vowed to upend the

[2] Statement made by Adam Matthews, the fund's director of ethics and engagement. The Church of England Pension Fund is co-chairing the IIGCC initiative.
[3] See the Global Sustainable Investment Review 2018, http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf

regulations introduced in recent years that limit CO2 emissions. As Eccles and Klimenko (2019) observe "The impression among [US] business leaders is that ESG just hasn't gone mainstream in the investment community". They further note that "It is one thing for the CEO or chief investment officer of a major investment firm to espouse sustainable investing and quite another for it to be practiced by the analysts and portfolio managers who make the day-to-day investment decisions. Historically, the ESG group at investment firms was separate from portfolio managers and sector analysts (on both the buy side and the sell side) in much the same way that corporate social responsibility groups were historically separate from business units." [Eccles and Klimenko, 2019]

This lack of integration of ESG with financial analysis, and lack of consensus among institutional investors around climate change, raises the possibility that carbon risk may not yet be reflected in asset prices. To find out, this paper systematically explores whether investors demand a carbon risk premium by looking at how stock returns vary with CO2 emissions across firms and industries. We undertake a standard cross-sectional analysis, asking whether a carbon risk factor or carbon-emission characteristics affect cross-sectional U.S. stock returns.

There are several ways in which one might expect CO2 emissions to affect stock returns. First, since CO2 emissions are tied to fossil-fuel energy use, returns are affected by fossil-fuel energy prices and commodity price risk. Relatedly, firms with disproportionately high CO2 emissions may be exposed to carbon pricing risk and other regulatory interventions to limit emissions. Forward-looking investors may seek compensation for holding the stocks of disproportionately high CO2 emitters and the associated higher carbon risk they expose themselves to, giving rise to a positive relation in the cross-section between a firm's own CO2 emissions and its stock returns. We refer to this as *the carbon risk premium hypothesis*. An interesting question is whether carbon is perceived as a systematic risk factor and whether the carbon risk premium is tied to loadings on this risk factor.

Second, an alternative possibility is that stock returns tied to carbon emissions reflect earnings surprises. Khan, Serafeim, and Yoon (2016) have shown that firms with better sustainability performance indicators generate both higher future stock returns and returns on sales. They suggest an explanation based on the greater efficiency of firms with better sustainability scores. By their logic firms with lower carbon emissions could thus also generate higher returns because their greater efficiency results in better than expected earnings. To be sure, a recent study by Garvey, Iyer, and

Nash (2018) finds some evidence suggesting that firms with lower carbon emissions generate stronger returns on assets and higher stock returns. We refer to this explanation as *the unexpected profitability hypothesis*.

A third hypothesis is that financial markets are pricing carbon risk inefficiently and the risk associated with carbon emissions is underpriced. Consistent with Eccles and Klimenko's observations, carbon risk may not be fully integrated by most investors, who by force or habit look at future cash-flow projections through local thinking à la Gennaioli and Shleifer (2010), ignoring unrepresentative information about global warming and its attendant risks. Indeed, the cash-flow scenarios commonly used by financial analysts exclude any direct reference to carbon emissions and their possible future repricing. A recent study by In, Park, and Monk (2019) suggests that this is the case and concludes that a portfolio that is long stocks of companies with low carbon emissions and short stocks of companies with high emissions generates positive abnormal returns. We refer to this hypothesis as *the market inefficiency, or carbon alpha, hypothesis*. An important question we will explore is whether financial markets systematically underprice carbon risk, after controlling for all other known risk factors and firm characteristics, and whether responsible investors, who care about carbon emissions and climate change, can "do well by doing good".

A fourth hypothesis is that stocks of firms with high emissions are like other "sin stocks"; they are shunned by socially responsible, or ethical, investors to such an extent that the spurned firms present higher stock returns. A key question in this respect is how investors identify the firms to be divested from. Do they look at carbon emissions at the firm level, or do they pigeonhole firms into broader categories such as the industry they operate in? Even socially responsible investors that care about climate change may use sparse models (à la Gabaix, 2014) and not look much beyond industry categorizations, such as the energy and electric utility sectors, which produce a disproportionate share of CO2 emissions. Indeed, prominent divestors like the Rockefeller Brothers Fund that have pledged to divest from fossil fuel companies, largely focus on energy companies that extract coal and tar sands.[4] We refer to this as *the divestment hypothesis*.

[4] See https://www.rbf.org/mission-aligned-investing/divestment

A pioneer in producing company-level CO2 emissions data is the carbon disclosure project (CDP).[5] More recently it has been joined by other leading providers of carbon data, including MSCI ESG Research and Trucost, among others.[6] While more and more institutional investors make use of these data it is not known how much individual companies' stock returns are actually affected by the availability of these more granular CO2 emissions data to financial analysts. Our study relies on the Trucost EDX data, which cover around 1,000 listed companies since fiscal year 2005, and over 2,900 listed companies in the U.S. since fiscal year 2016. We match these data with the FactSet returns and balance-sheet data for all U.S.-listed companies from 2005 to 2017.

Carbon emissions from a company's operations and economic activity are typically grouped into three different categories: direct emissions from production (scope 1), indirect emissions from consumption of purchased electricity, heat, or steam (scope 2), and other indirect emissions from the production of purchased materials, product use, waste disposal, outsourced activities, etc. (scope 3). The scope 3 category in turn is separated into upstream and downstream indirect emissions. The data on scope 1 and scope 2 emissions have been more systematically reported. Although scope 3 emissions are the most important component of companies' emissions in a number of industries (e.g., automobile manufacturing) they have not been reported by companies until recently. This is why portfolio and index construction strategies using a carbon filter have relied on mostly scope 1 and 2 emissions measures (see Andersson, Bolton, and Samama, 2016). However, several providers, in particular Trucost, use an input-output model to estimate firms' upstream scope 3 emissions.

In this paper, we undertake a systematic exploration of how corporate carbon emissions affect stock returns in the cross-section of U.S. listed firms and investigate which, if any, of the four hypotheses outlined above best explains the impact of carbon emissions on stock returns. Our main broad finding is that carbon emissions significantly affect stock returns. For all three categories of emissions we find a positive and statistically significant effect on firms' stock returns. The effect is also economically significant: A one-standard-deviation increase in respectively the level and change of scope 1 emissions leads to a 18-bps and 27-bps increase in stock returns, or respectively a 2.1% and 3.2% annualized increase. In addition, a one-standard-deviation increase in respectively the level and change of scope 2 emissions leads to respectively a 28-bps and 19-bps increase in stock returns,

[5] See http://www.cdp.net/en-US/Pages/About-Us.aspx
[6] See https://www.msci.com/climate-change-solutions and https://www.trucost.com/policy-academic-research.

or a 3.4% and 2.3% annualized increase. Finally, a corresponding one-standard-deviation increase in the level and change of scope 3 emissions increases stock returns by 39 bps and 31 bps per month, or 4.6% and 3.8% on an annual basis. Importantly, firms with higher emissions generate higher returns, after controlling for size, book-to-market, momentum, other well-recognized variables that predict returns, and firm characteristics such as the value of property, plant & equipment (PPE) and investment over assets.

This finding is surprising in light of the received wisdom that firms with high carbon emissions are overvalued, and that a portfolio that underweights high-emission firms and overweighs low-emission firms generates abnormal returns. It also contradicts the hypothesis that the carbon premium is due to unexpected persistent positive earnings shocks. Indeed, we find that higher levels of emissions either have no significant effect on unexpected earnings or have a negative effect. Basically, our main finding is largely consistent with the view that investors are pricing in a carbon risk premium at the firm level. What explains our different finding from earlier studies? Partly the data coverage is different, both in the cross-section and over time, but more to the point, unlike in our analysis, the study by In, Park and Monk (2019), which is closest in design to ours, omits industry controls and firm characteristics, such as PPE and investment, that are highly related to both emissions and stock returns.

If the doing-well-by-doing-good hypothesis cannot explain the carbon premium in the cross-section, and if the carbon premium appears to reflect a compensation for risk, which of the other main hypotheses best explains how stock returns are affected by carbon emissions? We first explore whether exposure to an aggregate carbon risk factor could explain cross-sectional returns and apply a cross-sectional test similar to that of Bollerslev, Tauchen, and Zhou (2009). Although we find limited support for this hypothesis, especially for upstream scope 3 emissions, we conclude overall that the carbon premium is best explained by idiosyncratic risk exposures tied to carbon emissions.

Following Hong and Kacperczyk (2009), we also explore whether the carbon premium could be explained as a premium on "sin stocks". A first finding is that, in aggregate, institutional investors hold a smaller fraction of companies with high scope 1 emissions. When we disaggregate by investor categories (mutual funds, insurance companies, banks, pension funds, and hedge funds) we further find that insurance companies, pension and mutual funds are underweight scope 1 carbon emissions.

The negative ownership effect of moving from high to low scope 1 emission firms is economically large and accounts for about 15-20% of the cross-sectional variation in the ownership variable. This finding is in line with the rise in the sustainable investment movement and the popular negative exclusionary screening investment strategy followed by funds with an ESG tilt.[7] A more surprising finding, however, is that institutional investors are not underweight scope 2 and scope 3 emissions. This is true in aggregate and when we break down institutional investors by categories. It is as if institutional investors have been applying exclusionary screens (or not) solely on the basis of scope 1 emissions and have not paid attention to scope 2 or scope 3 emissions. Even more striking, we find that when we exclude the industries with the highest CO2 emissions (oil & gas, utilities, and motor industries) then institutional investors are also not excluding firms with high scope 1 emissions. In other words, the exclusionary screening is done entirely in these industries, and in all other industries the carbon premium at the firm level cannot be explained in terms of a "sin stock" phenomenon.

Another striking finding is the jump in the carbon premium post 2015. The year 2015 is a breaking point for two separate reasons. First, it is the year when the Paris agreement was signed, signaling a greater global policy commitment to fighting climate change. Second, it is also the year when Trucost significantly expanded the coverage of firms. Interestingly, we find that there is a jump in the carbon premium post 2015, especially for scope 1 and scope 2 emissions, suggesting that investors became more concerned about carbon risk following the Paris agreement. In another test, we show that applying the same cross-sectional distribution of emissions to the 1990s does not result in a significant carbon premium, consistent with the view that investors at that time likely did not pay as much attention to carbon emissions.

To summarize, investors seem to take a somewhat schizophrenic attitude to carbon emissions. On the one hand, institutional investors clearly want to take a proactive approach by divesting from industries with high CO2 emissions. On the other hand, they also recognize that this categorical exclusionary screening approach only partially addresses the carbon risk issue. Indeed, investors also price in a carbon emission risk premium at the firm level in all industries outside the industries with the highest CO2 emissions (oil & gas, utilities, and motor industries). The challenge with carbon risk

[7] See Krueger, Sautner, and Starks (2019). Also, according to the Global Sustainable Investment Review 2018, negative/exclusionary screening is the largest sustainable investment strategy globally, representing $19.8 trillion of assets under management. http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf

is that it cannot just be reduced to a fossil fuel supply problem. As with recreational drugs, part of the problem lies also with the demand for energy. Once one factors in both supply and demand aspects, all companies are sinners to various degrees when it comes to carbon emissions. A coarse exclusionary approach focusing only on the energy and utility sectors misses the full extent of the CO2 emissions problem. Accounting for carbon risk is also required on the demand side, so to speak, which inevitably involves the careful tracking of emissions at the firm level.

Our study is related to a rapidly growing literature on climate change and financial markets. An early study by Matsumura, Prakash, and Vera-Munoz (2014) finds that higher emissions are associated with lower firm values. Relatedly, Chava (2014) finds that firms with higher carbon emissions have higher costs of capital. Andersson, Bolton, and Samama (2016) propose a carbon risk hedging strategy for passive investors based on low carbon indexes. More recently, Ilhan, Sautner, and Vilkov (2019) have found that carbon emissions increase downside risk as reflected in out-of-the-money put option prices. Hsu, Li, and Tsou (2019) look at the effects of environmental pollution on the cross-section of stock returns. They find that highly polluting firms are more exposed to environmental regulation risk and command higher average returns. Engle, Giglio, Lee, Kelly, and Stroebel (2019) have constructed an index of climate news through textual analysis of the Wall Street Journal and other media and show how a dynamic portfolio strategy can be implemented that hedges risk with respect to climate change news. Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2019) construct a carbon-risk factor and estimate a carbon beta for firms. Monasterolo and De Angelis (2019) explore whether investors demand higher risk premia for carbon-intensive assets following the COP 21 agreement. Garvey, Iyer, and Nash (2018) study the effect of changes in scope 1 and 2 emissions on stock returns.

Other related studies have explored the asset pricing consequences of greater material risks linked to climate events and global warming. Hong, Li, and Xu (2019) have found that the rising drought risk caused by climate change is not efficiently priced by stock markets. Several studies have looked at climate change and real estate prices. Baldauf, Garlappi, and Yannelis (2019) find little evidence of declining prices as a result of greater flood risk due to sea level rise. Bakkensen and Barrage (2017) find that climate risk beliefs in coastal areas are highly heterogeneous and that rising flood risk due to climate change is not fully reflected in coastal house prices. Bernstein, Gustafson, and Lewis (2019) find that coastal homes vulnerable to sea level rise are priced at a 6.6% discount relative to similar homes at higher elevations. Giglio, Maggiori, Rao, Stroebel, and Weber (2018) use real estate pricing data to infer long-run discount rates for valuing investments in climate change abatement.

The remainder of the paper is organized as follows. Section 2 describes the data and provides summary statistics. Section 3 discusses the results. Section 4 concludes.

2 Data and Sample

Our primary database covers the period 2005-2017 and is largely a result of matching two data sets by Trucost and FactSet. Trucost provides information on corporate carbon and other greenhouse gas emissions. FactSet provides data on stock returns, corporate fundamentals, and institutional ownership. We performed the matching using ISIN as a main identifier. In some instances, in which ISIN was not available to create a perfect match, we relied on matching based on company names.[8] Finally, when there are multiple subsidiaries of a given company, we used the primary location as a matching entity. The ultimate matching produced 3221 unique companies out of 3281 companies available in Trucost. Among the 60 companies we were not able to match, more than half are not exchange listed and the remaining ones are small. Hence, we believe our data cover almost the entire universe of companies with available emission data.

2.1 Data on Corporate Carbon Emissions

Firm-level carbon emissions data are assembled by seven main providers, CDP, Trucost, MSCI, Sustainalytics, Thomson Reuters, Bloomberg, and ISS. All these providers follow the Greenhouse Gas Protocol that sets the standards for measuring corporate emissions.[9] More and more companies disclose their greenhouse gas emissions, and most large corporations report their emissions to CDP. Other providers rely on the CDP data and supplement it with other sources. Emissions can be measured directly at source or more commonly by applying conversion factors to energy use. The Greenhouse Gas Protocol distinguishes between three different sources of emissions: scope 1 emissions, which cover direct emissions over one year from establishments that are owned or

[8] After standardizing the company names in FactSet and Trucost, respectively, we choose companies whose names have a similarity score of one based on the standardized company names.

[9] See https://ghgprotocol.org.

controlled by the company; these include all emissions from fossil fuel used in production. Scope 2 emissions come from the generation of purchased heat, steam, and electricity consumed by the company. Scope 3 emissions are caused by the operations and products of the company but occur from sources not owned or controlled by the company. These include emissions from the production of purchased materials, product use, waste disposal, and outsourced activities.

In some sectors, like automobile manufacturing, and for many companies, by far the most important component of their emissions is the aggregation of all their scope 3 emissions. The Greenhouse Gas Protocol distinguishes between 15 different categories of scope 3 emissions, including purchased goods and services, capital goods, upstream & downstream transportation and distribution, waste generated in operations, business travel, employee commuting, processing & use of sold products, and end-of-life treatment of sold products.[10] According to CDP's 2016 Climate Change Report, most scope 3 emissions are concentrated in two categories, purchased goods and services (around 44%) and use of sold products (around 48%).[11] The Greenhouse Gas Protocol provides detailed guidance on how to identify a company's most important sources of scope 3 emissions and how to calculate them. For purchased goods and services, this basically involves measuring inputs, or "activity data", and applying emission factors to these purchased inputs that convert activity data into emissions data. The upstream scope 3 data from Trucost that we use is constructed using an input-output model that provides the fraction of expenditures from one sector across all other sectors of the economy. This model is extended to include sector-level emission factors, so that an upstream scope 3 emissions estimate can be determined from each firm's expenditures across all sectors from which it obtains its inputs (see Trucost, 2019).[12]

Because they are easier to measure, and because disclosure requirements are stricter, data on scope 1 and scope 2 have been more systematically reported and accurately estimated. As Busch, Johnson, Pioch, and Kopp (2018) have shown, there is very little variation in the reported scope 1 and 2 emissions data across the data providers. Correlations in the reported scope 1 data average 0.99, and 0.98 for scope 2, across the five providers CDP, Trucost, MSCI, Sustainalytics, and Thomson

[10] See http://ghgprotocol.org/standards/scope-3-standard

[11] See CDP 2016 Climate Change Report "Tracking Progress on Corporate Climate Action"

[12] Downstream scope 3 emissions, caused by the use of sold products, can also be estimated and are increasingly reported by companies. Trucost has recently started assembling this data (see Trucost, 2019); however, we do not include this data in our study.

Reuters.[13] However, when it comes to estimated scope 1 and scope 2 emissions (when reported data are missing), the correlations drop to respectively 0.79 and 0.63 for the three providers, Trucost, MSCI, and Sustainalytics, that offer these estimates. Finally, only two data providers, Trucost and ISS ESG, provide estimates of scope 3 emissions. The Trucost EDX database we use in our main analysis reports all three scopes of carbon emissions in units of tons of CO2 emitted in a year. We report the summary statistics of these variables in Panel A of Table 1.

The average firm in our sample produces 1.95 million tons of scope 1 emissions, and is tied to 1.7 million tons of scope 3 emissions. The quantity of scope 2 emissions is relatively smaller, at 339,000 tons of CO2 equivalent. Notably, the median number is the largest for scope 3 emissions, as almost all companies in our sample are tied to a significant quantity of such emissions. The scope 1, 2, and 3 measures are in units of tons of CO2 and normalized using the natural log scale. We further report annual growth rates in each emission measure. To mitigate the impact of outliers we winsorize all growth measures at the 2.5% level.

The total quantity of emissions may be hard to interpret at an individual firm level, as companies may differ in the size and scope of their operations. We therefore also look at the carbon intensity of a company expressed as tons of CO2 equivalent divided by the company's revenues in million U.S. dollar units, also winsorized at the 2.5% level. The average scope 1 intensity in our sample equals 263.38 tons/million, while the respective intensities for scope 2 and scope 3 are 39.58 tons/million and 163.34 tons/million. We further analyze the average values of all three emission sources over time. Figure 1 and Table 2 present the results. As one might expect, there is a steady decline in scope 1 and scope 3 emissions over time as a result of energy efficiency improvements, technological innovations, and the increased reliance on renewable energy sources. At the same time, however, the average carbon intensity of scope 2 emissions is relatively unchanged. While the individual quantities of emissions have been going down over time, we note that the aggregate value of each emission source has been steady. This observation underscores the economic importance of the problem faced by society and regulators.

We also look at alternative measures Trucost provides, in particular: i) *CARBON DIRECT*, which adds three additional greenhouse gases to the GHG Protocol scope 1 measures; ii) *CARBON INDIRECT*, which covers a slightly broader set of emissions by the direct suppliers to a company

[13] More than 6,300 companies worldwide answered CDP's climate change questionnaire in 2018. Of these, 76% disclosed scope 1 emissions, 68% scope 2 emissions, and 38% scope 3 emissions (see https://www.cdp.net).

than scope 2; iii) *GHG DIRECT*, measured in U.S. dollars, which covers all direct external environmental impacts of a company. Trucost applies a monetary value to GHG emissions quantities, which represents the global average damage of each environmental impact; and iv) *GHG INDIRECT*, which covers indirect supply chain environmental impacts. These are estimated impacts based on Trucost's environmental impact models. Again, these are reported in U.S. dollars and represent the global average damages of each environmental impact.

We also note that firms with significant emissions are represented in a wide range of industries. In Table 3, we present the distribution of firms in our sample with respect to the six-digit Global Industry Classification (GIC 6). Banks, biotech, and oil & gas are the most represented industries, with each one having more than 150 firms. In Table 4, we provide a list of industries with the highest and the lowest intensity of emissions. Power, electric, and multi-utility industries produce the most scope 1 emissions, while consumer finance, thrifts and mortgages, and capital markets are the cleanest. The ranking is somewhat different when we classify industries with respect to their scope 2 and scope 3 emissions. Metals and mining, electric utilities, and construction materials are the three most scope 2 emission intensive industries (the cleanest industries mimic those based on scope 1 classification). In turn, food products, metals and mining, and construction materials are the three most scope 3 emission intensive industries. Internet software and services, health care technologies, and software are the three least intensive industries.

Finally, we observe not only substantial variation in the growth rates of emissions across different industries, but also significant variation in the rates of all three categories of emissions across firms within the same industry, as can be seen in Figure 3, which displays the time-series plots of the average cross-sectional standard deviations of emission growth rates across all firms (Panel A) and across all firms within a given GIC 6 industry (Panel B). Even though the scale of the variation in Panel A is larger than that in Panel B there is still a significant dispersion in emissions in Panel B.

2.2 Variables in Cross-sectional Return Regressions

Our empirical analysis of stock returns employs a monthly measure of returns as a dependent variable. In our cross-sectional return regressions, the dependent variable $RET_{i,t}$ is the monthly return of an individual stock i in month t. Our return data primarily comes from FactSet, but for a small subset of delisted companies we replace the return data using delisting-adjusted values from Compustat. Finally, we remove observations with returns greater than 100% to mitigate the impact of outliers.[14]

Our control variables are defined as follows: $LOGSIZE_{i,t}$ is the natural logarithm of firm *i*'s market capitalization (price times shares outstanding) at the end of year *t*; $B/M_{i,t}$ is firm *i*'s book value divided by its market cap at the end of year *t*; *LEVERAGE* is the book leverage of the company; $MOM_{i,t}$ is the average of the most recent 12 months' returns on stock *i*, leading up to and including month *t-1*; *INVEST/A* represents the firm's capital expenditures divided by the book value of its assets; *HHI* is the Herfindahl concentration index of firms with respect to different business segments, based on each segment's revenues; *LOGPPE* is the natural logarithm, of the firm's property, plant, and equipment; $BETA_{i,t}$ is the market beta of firm *i* in year *t*, calculated over the one year period using daily data; finally, $VOLAT_{i,t}$ is the standard deviation of returns based on past 12 months of monthly returns. To eliminate the impact of outliers we winsorize *B/M, LEVERAGE,* and *INVEST/A* at the 2.5% level, and *MOM* and *VOLAT* at the 0.5% level. We report the summary statistics of these variables in Panel B of Table 1.

The average firm's monthly stock return equals 1.16%, with a standard deviation of 11.01%. The average firm has a market capitalization of $2.1 billion. That is also the size of a median firm in the sample. The average book-to-market ratio equals 0.48, while the average book leverage equals 25%. The average market beta equals 1.10, slightly more than that of the market.

2.3 Variables in Time-series Return Regressions

The variables for our time-series regressions are defined as follows: $MKTRF_t$ is the monthly return of the CRSP value-weighted portfolio in month *t*, net of the risk- free rate; SMB_t, HML_t, MOM_t, and CMA_t are well-known portfolio return series downloaded from Ken French's Web site: *SMB* is the monthly return of a portfolio that is long on small stocks and short on large stocks; *HML* is the monthly return of a portfolio that is long on high book-to-market stocks and short on low book-to-market stocks; *MOM* is the monthly return of a portfolio that is long on past one-year return winners and short on past one-year return losers; *CMA* is the monthly return of a portfolio that is long on

[14] The number of excluded firm/month observations is 109 and its exclusion does not materially affect our results. However, using unrestricted returns data would be problematic as the data, for example, include four observations with monthly returns greater than 10000%.

conservative investment stocks and short on aggressive investment stocks. *BAB* is the monthly return of a portfolio that is long on low-beta stocks and short on high-beta stocks; *LIQ* is the liquidity factor of Pastor and Stambaugh; *NET ISSUANCE* is the monthly return of a portfolio that is long on high-net-issuance stocks and short on low-net-issuance stocks. Net issuance for year *t* is the change in the natural log of split-adjusted shares outstanding from the fiscal yearend in *t-2* to the fiscal yearend in *t-1*; *IDIO VOL* is the monthly return of a portfolio that is long on low idiosyncratic volatility stocks and short on high idiosyncratic volatility stocks. We present the summary statistics for the various portfolio returns in Panel C of Table 1.

The average market risk premium in our sample is 0.7% per month. Other factors with relatively high risk premia are net issuance and *BAB*. Somewhat atypically, the value factor return in our sample is equal to 0%. Similarly, the momentum factor generates a mere 0.07% per month, and the volatility factor has a negative return of -0.18% per month.

2.4 Variables in Business-cycle Regressions

Our variables reflecting the business cycle are: *INF* for inflation measured through the consumer price index (CPI); *TERM* which is the term spread measured as the difference between the 10-year and 1-year Treasury constant maturity rates; *GDPGR* which is the quarterly GDP growth rate; *GDP1YR* which is the growth rate a year later; *DEFAULT* which is the default spread measured as the difference between BAA and AAA corporate bond rates. All variables are obtained from the Federal Reserve Bank of St. Louis. We present the summary statistics for the variables in Panel D of Table 1.

2.5 Variables in Profitability Regressions

Our profitability regression variables are: *E/A* which is the firm's earnings scaled by total assets; *V/A* which is the ratio of the market value to the book value of assets; *DD* which is an indicator variable for non-dividend-paying firms; and, *D/B* which is the ratio of dividend payments to book equity. We also report the summary statistics for unexpected profitability (*UP*) in Panel E of Table 1. Unexpected profitability is the residual of the expected profitability regression given in equation (3) below.

2.6 Variables in Divestment Regressions

Our institutional ownership regression variables are: $IO_{i,t}$ which is the fraction of the shares of company *i* held by institutions in the FactSet Database at the end of year *t*. *IO* is calculated by aggregating the shares held by all types of institutions at the end of the year, and then dividing this amount by number of shares outstanding at the end of the year. We further decompose the institutional ownership with respect to subgroups of owners. *IO_BANKS* is the ownership by banks; *IO_INSURANCE* is the ownership by insurance companies; *IO_INVESTCOS* is the ownership by investment companies (e.g., mutual funds); *IO_ADVISERS* is the ownership by independent investment advisers; *IO_PENSIONS* is the ownership by pension funds; *IO_HFS* is the ownership by hedge funds. Even though the total institutional ownership captures the intensive margin only, the range of disaggregated ownership variables varies from 0% to 100% (as long as the total institutional ownership in the data has a positive value).

The control variables in the ownership regressions include $PRINV_{i,t}$, which is the inverse of firm *i*'s share price at the end of year *t*; $VOLAT_{i,t}$ is the standard deviation of monthly stock returns for company *i* over the one-year period; $VOLUME_{i,t}$ is the average daily trading volume (in $million) of stock *i* over the calendar year *t*. $NASDAQ_{i,t}$ is an indicator variable equal to one if a stock *i* is listed on NASDAQ in year *t*, and zero otherwise; $SP500_{i,t}$ is an indicator variable equal to one if a stock *i* is part of the S&P 500 index in year *t*, and zero otherwise. We report the summary statistics for these variables in Panel F of Table 1.

The average *IO* is 0.76, and the cross-sectional standard deviation of *IO* is 0.23. In other words, in a typical year, a typical firm has about 76% of its shares held by institutions, and the standard deviation of institutional ownership in a typical cross-section is 23%. Among the different institutional owners, independent advisers are the biggest holders with an average stock's ownership equal to 43.5%, followed by investment companies with an average 18. % ownership. Banks and insurance companies, in turn, are the smallest institutional owners. The average stock return volatility in our sample is 9.5% or annualized 150.8%. The average daily stock volume is $440,000. Finally, about 29% of stock-month observations are companies listed on NASDAQ, and 36% observations are companies from the S&P 500 index.

3 Results

We begin our analysis by investigating the determinants of scope 1, scope 2, and scope 3 emissions. We then turn to the evaluation of the carbon return premium in the cross-section of stocks. Our main finding is that stocks of companies with high levels and growth rates of emissions have higher returns than those of companies with low levels of emissions for all three emission categories. This result contradicts the market inefficiency hypothesis that high carbon emission stocks are overvalued relative to low carbon emissions stocks. We next explore which of the three remaining hypotheses described above provides the most compelling explanation of this finding. First, we examine whether the premium can be explained by differences in unexpected profitability or discount rates. Second, we study the time-series properties of the cross-sectional carbon premium with respect to well-known risk factors and business cycle components. Third, we consider the divestment hypothesis by looking at institutional ownership patterns.

3.1 Determinants of Carbon Emission Intensities

Since emissions are not reported by all companies, one basic issue to explore first is how emissions of companies that report compare with imputed emissions of non-reporting companies. To assess the quantitative differences on the extensive margin we compare various firm-level characteristics for the reporting and non-reporting firms. We describe basic summary statistics of the two categories of firms in Table A.1 of the Appendix. As one might expect, we find that larger firms are more likely to report their emissions. Also, firms with lower book-to-market ratios and higher book leverage are more likely to report emissions. At the same time, the two groups of firms do not differ significantly in terms of their stock returns or investment levels.

Next, we assess the differences in emission intensities (emissions divided by sales) across firms using a regression framework. Our dependent variables are *SCOPE 1*, *SCOPE 2*, and *SCOPE 3*. Since there is little theory that can guide us on what determines the level of carbon emissions, especially with regard to their different sources, we include a host of firm-level variables, comprising *LOGSIZE, B/M, ROE, LEVERAGE, INVEST/A, HHI,* and *LOGPPE*. In columns (4)-(6), we also include industry fixed effects. To reflect the possibility that firm-level emissions could concentrate across firms and in time, we cluster standard errors at the firm and year levels.[15] We present the results in Table 5.

Our results from the specification without industry fixed effects indicate that all three categories of emission intensities are significantly negatively related to *LOGSIZE*, and both *SCOPE 1* and *3* are significantly negatively related to *HHI*. The size result is particularly interesting as it suggests that larger companies are either more efficient in their use of fossil fuels or are better able to diversify away from high-emission operations. It could be that firms strategically choose to operate in different segments to reduce the risk of carbon policies, which would also explain why *HHI*, which measures the diversification of a company's operations across different sectors, has a negative impact on emissions. At the same time, *LOGPPE* is the strongest positive predictor of all three types of emissions. Among other predictors, *B/M* is a strong negative predictor of *SCOPE 2* and *3*, but its predictive ability disappears once we include industry fixed effects, and *INVEST/A*, in turn, negatively predicts *SCOPE 3*. *ROE* is positively related to *SCOPE 3,* but it has no significant effect on *SCOPE 1* and *2*. Further, the effect on *SCOPE 3* becomes insignificant once we include industry fixed effects. Finally, leverage only affects *SCOPE 3* emissions significantly, with a negative sign.

3.2 Cross-sectional Evidence on Returns

Next, we relate companies' emissions to their corresponding stock returns in the cross-section. We consider two measures: the total level of emissions (*TOT Emissions*) and the growth rate of emissions (*ΔTOT Emissions*). We first estimate the following cross-sectional regression model using pooled OLS:

$$RET_{i,t} = a_0 + a_1 LOG\ (TOT\ Emissions)_{i,t} + a_2 Controls_{i,t-1} + \mu_t + \varepsilon_{i,t} \qquad (1)$$

where $RET_{i,t}$ measures the stock return of company *i* in month *t* and *Emissions* is a generic term alternately standing for *SCOPE 1, SCOPE 2,* and *SCOPE 3* emissions. The vector of controls includes a host of firm-specific variables known to predict returns, such as *LOGSIZE, B/M, LEVERAGE, MOM, INVEST/A, HHI, LOGPPE, BETA,* and *VOLAT*. Our model also includes year/month fixed effects. We cluster standard errors at the firm and year levels. Our coefficient of interest is a_1.

[15] Standard errors in all panel regressions become significantly smaller in alternative specifications that cluster at the firm, industry, time, or industry and time levels.

We report the results in Table 6, Panel A. Column (1) shows the results for *SCOPE 1*; column (2) for *SCOPE 2*, and column (3) for *SCOPE 3*. For all three categories of emissions we find a positive and statistically significant effect on firms' stock returns. The effect is also economically significant: A one-standard-deviation increase in *SCOPE 1* leads to an 18-bps increase in stock returns, or 2.1% annualized, and a one-standard-deviation increase in *SCOPE 2* leads to a 28-bps increase in stock returns, or 3.4% annualized. Finally, a one-standard-deviation increase in *SCOPE 3* increases stock returns by 39 bps per month, or 4.6% on an annual basis.

Since emissions tend to cluster significantly within specific industries a question of interest is whether the firm-specific differences can be attributed to industry-specific effects. To examine this possibility, we additionally include industry-fixed effects using the Trucost industry classification. The results presented in columns (4) to (6) are quite striking. Including industry effects significantly strengthens the cross-sectional dispersion of returns due to carbon emissions. In fact, the economic significance increases by anywhere between 60% and 200% relative to the model without industry effects.

We further plot the time series of the cumulative values of the unadjusted and industry-adjusted carbon premia in Figure 4. As can be seen in the figure, there are large positive cumulative returns for all measures of total emissions. The economic magnitudes of the effect become even larger once we factor in differences in industry exposures.

Even though we control for size, one limitation with specification (1) is that we have not normalized emissions by sales, which would better reflect how wasteful with (or dependent on) its fossil fuel energy consumption a firm is. In addition, it is not obvious a priori what size controls for. Does it control for a risk characteristic, or does it reflect the effect of the size of a firm's operations on its carbon emissions? Accordingly, a better specification might be to replace the total level of emissions (TOT Emissions) with *Emission Intensity*, the normalized emissions variable (by sales), which captures how much CO2 is emitted to produce one dollar of sales. However, we cannot simply estimate the same specification as (1) by replacing contemporaneous *Emissions* with contemporaneous *Emission Intensity*, as this risks introducing a look-ahead bias; indeed we would then be dividing emissions by a contemporaneous sales variable. Also, sales may be correlated with market equity, which could introduce an additional bias. To address these concerns, we consider percentage *change*s in total emissions, which has the additional benefit of removing the ambiguity associated with the size variable in model (1). Therefore, we estimate the following cross-sectional regression model:[16]

$$RET_{i,t} = a_0 + a_1\Delta(TOT\ Emission)_{i,t} + a_2 Controls_{i,t-1} + \mu_t + \varepsilon_{i,t} \qquad (2)$$

We report the results in Table 6, Panel B. Again, we find a positive and statistically significant effect of changes in total emissions on firms' stock returns for all three categories of emissions. Interestingly, unlike for the previous specification reported in Panel A, including industry effects makes essentially no difference to the cross-sectional dispersion of returns. In terms of economic magnitudes, the monthly carbon premia vary between 19 bps (*SCOPE 2*) and 31 bps (*SCOPE 3*), which is comparable to the results in Panel A.[17]

Overall, these results suggest that investors assign a return premium to stocks with higher emissions. The question remains, whether this premium is explained by unexpected profitability, a systematic carbon risk factor, or divestment from high carbon stocks and compensation for holding undiversified idiosyncratic risk. We explore each of these hypotheses in the following sections.

3.3 The Unexpected Return Hypothesis

Our results could be explained by the fact that firms with higher emissions have also been exposed to unexpected positive value shocks. We explore this hypothesis by analyzing returns that strip out the effect of earnings surprises. Specifically, we subtract from the monthly stock returns the component that is realized on earnings announcement days and re-estimate the regression models in (1) and (2) with the adjusted returns. We report the results in Table 7 for the level of total emissions (Panel A) and for the growth rate of emissions (Panel B).

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[16] In the Online Appendix, we also report results from estimating a cross-sectional regression using emission intensity, lagged by one year. Although this specification avoids any look-ahead bias it suffers from the fact that the main explanatory variable of interest, depending on the month when we observe returns, is nearly one year old.

[17] To allay any concern that our results may be driven by the correlation between emissions and size, we provide additional robustness tests in which we estimate univariate regression models with respective emission variables only, and regressions with emissions and size only. The results, reported in Table A.10 of the Online Appendix indicate that size is an important control when one considers the level of total emissions as a regressor but it is not as important in the model with growth rate of emissions, which further underscores the relevance to use the latter model as an alternative.

We find no significant differential effect of earnings announcements on the carbon premium. Stocks with higher levels and growth rates of emissions still have higher returns. This result is both economically and statistically significant.

3.4. The Unexpected Profitability Hypothesis

It is also possible that firms with high levels of emissions may have higher returns due to unexpectedly high profitability. We test this hypothesis formally by looking at the relation between emissions and unexpected profitability. To obtain the profitability surprises, we extend the Fama and French (2000) profitability model by adding lagged profitability, following Vuolteenaho (2002). Specifically, we estimate the following model each year using a cross-section of firms in our sample:

$$(E/A)_{i,t} = b_0 + b_1(V/A)_{i,t} + b_2 DD_{i,t} + b_3(D/B)_{i,t} + b_4(E/A)_{i,t-1} + \varepsilon_{i,t} \qquad (3)$$

Expected profitability at the firm level is the fitted value from this regression, and unexpected profitability (*UP*) is the regression error.

Next, we relate *UP* to respectively contemporaneous total emissions and the growth in total emissions, using a pooled linear regression model with year-month fixed effects and *LOGSIZE*. In some specifications, we also include industry fixed effects. We estimate the model using a regression framework with standard errors clustered by firm and year. We present the results in Table 8.

If our results were driven by differences in cash-flow shocks, then we would expect to see large positive profitability shocks for high-emission companies. But, as the results in Panel A show, the opposite is true for contemporaneous total emissions, in all three categories, when we adjust for industry. Interestingly, however, in Panel B we observe that unexpected profitability is positively related to the growth in total emissions, whether or not we adjust for industry. These results make perfect economic sense: unexpected profitability must be associated with unexpected sales shocks, which, in turn, translate into (unexpected) changes in total emissions. Thus, Table 8 captures in a succinct way a basic intertemporal tradeoff with respect to carbon emissions. In the long run, companies with lower total emissions have greater values (or lower returns) other things equal, but in the short run companies with higher realized profits are more valuable. Since higher realized profits are partially obtained through higher sales, it follows that companies with higher realized sales, and therefore also higher realized growth in emissions, are more valuable.

3.5 The Carbon Risk Factor Hypothesis

3.5.1 Carbon Return Premium and Risk Factors

Is there a carbon risk factor that is not subsumed by traditional risk factors? To answer this question, we estimate the following time-series regression model using monthly data:

$$a_{1,t} = c_0 + \boldsymbol{cF_t} + \varepsilon_t \tag{4}$$

where $a_{1,t}$ is the carbon return premium estimated from the cross-sectional Fama-MacBeth regression in equation (1); $\boldsymbol{F}$ is a set of factor-mimicking portfolios that includes *MKTRF, HML, SMB, MOM, CMA, BAB, LIQ, NET ISSUANCE,* and *IDIO VOL.* We calculate standard errors of the coefficients using the Newey-West procedure with 12 lags to account for autocorrelation in error terms. Our coefficient of interest is c_0, which measures the residual carbon premium controlling for other risk/style factors. We present the results in Table 9.

Panel A shows the results for the carbon premium related to contemporaneous total emissions. In the odd columns, we report the unconditional carbon premium as a benchmark. In the even columns, we add various factors *MKTRF, HML, SMB, MOM*, *CMA*, *BAB, LIQ, NET ISSUANCE,* and *IDIO VOL*. Comparing the odd and even columns for the respective scope categories of emissions, we find that the carbon premium remains statistically and economically significant after we adjust for differential factor exposures. However, the economic size of the premium is about 10%-20% smaller in magnitude. Overall, the regression intercepts from the cross-sectional return regressions are both economically and statistically significant in the presence of various risk factors.

Panel B shows the results for the carbon premium related to the growth rate in total emissions. We find again that the set of standard risk factors cannot explain the average value of the carbon premium for any of the emissions categories. This time, however, the difference in magnitudes across specifications is much smaller.

Overall, our time-series regressions show that the carbon premium cannot be explained by known risk factors, which reinforces the finding in Section 3.2 that carbon emissions contain independent information about the cross section of average returns.

3.5.2 Business-Cycle Effects

If the carbon premium captures risk compensation, one should expect that the premium becomes larger in times of economic downturns. We test this hypothesis by relating the time series of carbon premium, as defined in Panel A of Table 8, to a host of variables that are known to capture business cycle variation: *INF, TERM, GDPGR, GDP1YR,* and *DEFAULT*. We present the results in Table 10.

In Panel A, we look at pairwise correlations between the carbon premia for the three emission categories and these business-cycle variables. The results suggesting that carbon premia are higher in economic downturns are mixed. While the correlation is negative with *INF* and positive with *DEFAULT*, the results for other variables are not consistent across the three emission variables. In particular, we observe a positive correlation with *TERM* for scope 1 and scope 2, and a positive correlation with *GDP* for scope 2 and scope 3.

Next, we assess the statistical significance of the relationships using a time-series regression framework, with standard errors adjusted for autocorrelation of up to 12 lags. As with our findings in Panel A, the statistical evidence for each individual business cycle proxy is mixed. In Panel C, we further analyse the relationship with business cycle variables for the growth rate of emissions. Again, we do not find a strong effect of business cycles on the carbon premium.

Overall, we do find some evidence (though statistically not very strong) that the carbon premium increases in economic downturns, which is consistent with the risk-based explanation of our findings. To shed more light on this interpretation we turn next to a direct evaluation of the hypothesis that carbon risk is a systematic risk factor.

3.5.3 Is Carbon Risk a Systematic Risk Factor?

The evidence reported so far suggests that the carbon premium has properties consistent with the presence of an underlying systematic carbon risk factor. The carbon premium cannot be explained by traditional risk factors, it cannot entirely be explained by differences in unexpected profitability, and it exhibits some degree of countercyclical variation. Therefore, we examine next if it actually reflects a systematic risk factor.

In order to answer this question, we create a tradable hedge portfolio that every month takes a long position in a portfolio of stocks with high levels of total emissions, and a short position in a portfolio of stocks with low levels of total emissions. The former portfolio is made up of the top 20% distribution of the highest-emission firms, and the latter portfolio is created of the bottom 20% of the distribution. We create this zero-investment strategy separately for our three categories of emissions. If carbon risk is priced, we should observe that the risk premium on the carbon factor be positively related to the average return of the test assets. Our test assets are 25 size-book-to-market portfolios of Fama and French.

To obtain the risk premia on the carbon factor, we estimate the following time-series regression for each test asset:

$$FF25_{i,t} = d_0 + d_1 CR_{j,t} + \varepsilon_{i,t} \tag{5}$$

where, $FF25_{i,t}$ is the return on the *i*-th test portfolio of Fama and French, and $\mathrm{CR}_{\mathrm{j,t}}$ is the carbon risk portfolio based on sort *j*, with *j* being defined by the relevant emission category (*SCOPE 1, 2, or 3*). We present the coefficients d_1 from estimating the 25 regressions in Table 11. In Panel A, we report the results for *SCOPE 1*, in Panel B for *SCOPE 2*, and in Panel C for *SCOPE 3*.

Our results indicate a statistically strong relationship between the test assets and the CR factors for respectively *SCOPE 1* and *SCOPE 3*, further evidence against the market inefficiency hypothesis that high carbon emission stocks are overpriced. All risk premia are statistically significant. However, for *SCOPE 2* emissions, we find that only one out of 25 loadings is statistically significant. Also, the magnitudes of the coefficients display considerable variation across different portfolios, especially for *SCOPE 3*. The spread for *SCOPE 3* varies between -1.128 and -0.298. Similarly, for *SCOPE 1*, the spread is between -0.858 and -0.311. Based on these results, one would conclude that carbon is a systematic risk factor for at least *SCOPE 1* and *SCOPE 3* emissions.

To test this hypothesis more formally, we further look at risk premia obtained by regressing average returns of Fama-French assets on the estimated carbon risk loadings. We present the results in Panel D. Consistent with *SCOPE 1* and *SCOPE 3* carbon emissions being a priced risk factor, we find a positive relationship between *FF25* returns and factor loadings. However, the relationship is statistically significant only at the 10% level.

We next explore the conditional nature of the relationship. To this end, we estimate the cross-sectional regression of average *FF25* returns on the estimated loadings for each year/month cross-section, and aggregate the estimates using the time-series variation, as in Fama and MacBeth (1973). We present the results in Panel E. Although the coefficients in the time-series regression remain positive, their statistical significance drops, which would indicate that there is no systematic carbon risk factor. The lack of a strong positive relationship between average returns and factor loadings indicates that it is unlikely that other, more demanding, tests would reverse this conclusion.

3.6 The Divestment Hypothesis

Another possible explanation for the observed carbon premium could be under-diversification as a result of divestment and exclusionary screening of stocks with high carbon emissions by institutional investors implementing a sustainable investment policy. To the extent that some investors may shun companies with high carbon emissions, risk sharing would be limited, and idiosyncratic risk could be priced (e.g., Merton, 1987; Hong and Kacperczyk, 2009). If the extent of such divestment is high, one would expect to see significant pricing effects.

We test this possibility by looking at the portfolio holdings of institutional investors. Formally, we estimate the following pooled regression model:

$$IO_{i,t} = d_0 + d_1 Emission_{j,t} + d_2 Controls_{j,t} + \varepsilon_{i,t} \qquad (6)$$

We consider ownership effects based on carbon intensity, the measure which is most aligned with explicit mandates imposed by socially sensitive asset managers.[18] The vector of controls includes *LOGSIZE, PRINV, B/M, MOM, BETA, VOLAT, VOLUME, NASDAQ*, and *SP50*0. All regressions include year/month fixed effects. Also, carbon emissions tend to vary geographically, due to resource-driven firm locations. It is thus possible that the geographic location may also interact with ownership incentives. We test this idea by including in the ownership regression state fixed effects

[18] In the Online Appendix, we also present the results for the less used measures of total emissions and changes in emissions.

determined by the firm headquarters' locations (in even numbered columns). Our coefficient of interest is d_1, which measures the degree of avoidance of firms with greater carbon emissions. We cluster standard errors at the industry and year levels. We present the results in Table 12.

In Panel A, we report the results for the aggregate institutional ownership measure. Columns (1) and (2), show the results for *SCOPE 1*, respectively without and with state fixed effects. Both coefficients are negative and statistically significant at the 5% and 1% levels, respectively. The economic effect of the divestment is relatively modest: A one-standard-deviation increase in *SCOPE 1* leads to approximately a 1.3-percentage-point decrease in aggregate institutional ownership, which is about 6.3% of the cross-sectional standard deviation in ownership. In contrast, the coefficients are statistically insignificant for *SCOPE 2* and *SCOPE 3* emissions, indicating that the exclusionary screens institutional investors apply in constructing their portfolios are entirely based on *SCOPE 1* emissions.

The institutional investor world pools a number of different constituencies with possibly different investor pressures. We conjecture that certain institutions, such as insurance companies, investment advisers, or pension funds, are more likely to avoid high-emission companies, as opposed to mutual funds and hedge funds who are natural arbitrageurs. We test this hypothesis formally by dividing the institutional investors' universe into six categories: banks, insurance companies, investment companies, independent advisers, pension funds, and hedge funds. For each category, we obtain their stock-level institutional ownership and estimate the regression model in (6) for each of them separately.

In Panel B, we report the results for *SCOPE 1*. We observe a strong cross-sectional variation in the ownership patterns. Insurance companies, investment advisers, and pension funds tend to hold less of the high-emission companies. At the same time, we observe positive, though weaker, ownership effects for banks, investment companies, and hedge funds, consistent with these groups being natural arbitrageurs. The divestment effects are economically large. A movement in *SCOPE 1* from one standard deviation below the mean to one standard deviation above the mean, corresponding to a spread between low and high-emission firms leads to a reduction in ownership by 21%, 5%, and 4% of the cross-sectional standard deviation of ownership for investment advisers, insurance companies, and pension funds, respectively. In particular, given its large aggregate shares of stock holdings, the effect through investment advisers could lead to significant pricing effects.

In Panels C and D, we report the results for respectively *SCOPE 2* and *SCOPE 3*. In sharp contrast to the results in Panel B, we observe that (with the exception of Banks loading up on *SCOPE 3*) all coefficients for the different investor types are small and statistically insignificant, which suggests that institutional investors do not seem to discriminate between stocks with regard to their scope 2 and scope 3 emission levels.

Overall, limited risk sharing could explain why we observe a return premium for companies with higher scope 1 emissions. As with other sin stocks, it may simply be a compensation for bearing idiosyncratic risk. At the same time, we do not find much support for this hypothesis with respect to scope 2 and scope 3 emissions.

3.6.1 Categorical Divestment

It is often pointed out that only a handful of industries produce the most significant fraction of carbon emissions.[19] The typical industries that are mentioned are the oil & gas (GIC = 2), utilities (GIC = 65-69), and motor (GIC = 19, 20, and 23). It is therefore natural to wonder whether our results are disproportionately driven by these sectors, and whether our cross-sectional carbon premium would become significantly smaller once we exclude these industries from our analysis.

In Table 13, we report the results for the subset of firms, excluding the sectors mentioned above. Panel A reports the results for contemporaneous total emissions and Panel B the results for the growth rate in total emissions. Compared with the results in Table 6, we observe that, if anything, excluding these salient sectors strengthens the results on the firm-level carbon premium, especially for scope 1 and scope 2.

These findings suggest that the coarse categorization of companies within a given industry is particularly important in industries that many market participants would consider as strong polluters. In turn, firm-level carbon emissions play a more important role when we exclude the focal industries from our analysis.

[19] For instance, in a 2016 report the International Energy Agency estimates that 39% of CO2 emissions come from electricity and heat production, 30% from transport, and 11% from industrial production (see https://www.iea.org/media/statistics/Energy_and_CO2_Emissions_in_the_OECD.pdf).

In Table 14, we report the results on carbon emissions and institutional ownership when we exclude the salient high-CO2 industries. Consistent with Gabaix (2014), we find that coarse industry-level categorization drives some of our key results. For the remaining industries the exclusionary screening results for institutional investors are much smaller and statistically insignificant. This is true for the aggregate ownership effect as well as for the disaggregated effect by the separate institutional investor categories.

3.7. Investor Awareness and the Carbon Premium

The carbon premium in stock returns could also be affected by the changing awareness of investors about carbon risk. In particular, one would expect that periods with greater climate change awareness could also be characterized by a higher carbon premium. In this section, we evaluate this hypothesis by looking at two different episodes of changing market awareness, the repercussions of the Paris Agreement in the years 2016 and 2017, and a period before climate change was on investors' radar screens, the decade of the 1990s.

The Paris Agreement raised both the awareness of risks tied to carbon emissions and the prospect of regulatory interventions to limit carbon emissions. One would therefore expect that the carbon risk premium would increase after 2015 following the Paris Agreement. We test this hypothesis by estimating the regression model in (1) on the two sub-periods: 2005-2015, and 2016-2017. We report the results in Table 15. We find that indeed the premium associated with all three categories of emissions is larger during the 2016-2017 subperiod. What precisely caused this increase, whether it is the anticipation of tighter regulations, accelerating technological improvements in renewable energy, greater investor aversion to carbon emissions we, of course, cannot say. But the fact that the premium has significantly increased is consistent with the view that investors care more about carbon risk following the Paris Agreement.

An auxiliary prediction of a growing market awareness of carbon risk can be formulated in terms of investors' divestment. One would expect that the growing awareness of carbon risk should lead to more shunning of high-emission companies after the Paris Agreement. We test this hypothesis by looking at the group of institutions most sensitive to carbon risk: investment advisors. Specifically, we estimate the ownership regression in equation (6) for each cross-section between 2005 and 2017. We plot the coefficient from these regressions in Figure 6, Panel A. Surprisingly, we find that although investors do divest companies based on their scope 1 emissions, divestment is not increasing over time. It is actually weakening. In contrast, we find that although the divestment effect is significantly weaker for scope 2 and scope 3 emissions, there is a more pronounced divestment towards the end of our sample period, especially for scope 2. We further investigate whether these divestment results are driven by a few salient industries in our sample and re-estimate the divestment rate excluding these salient industries. We find, of course, that the overall negative divestment effect is significantly weaker when we exclude the salient industries. The decline in divestment over time is smaller, but still positive for scope 1. In turn, the results for scope 2 and scope 3 emissions are only marginally different.

In another test, we add another dimension driving investors' awareness which is information dissemination. We hypothesize that firms that report their emissions over a longer time span are more likely to be on their radar screen. These firms may therefore be more sensitive to changes in investor perceptions of carbon risk. We evaluate this hypothesis by only considering firms that have been in the sample prior to 2015, while also excluding salient industries. We report the results in Panel C. Compared to our previous findings we observe one significant difference, namely that the shunning intensity increases in the post 2015 period for these firms, in particular for scope 2 and scope 3 emissions. This result is consistent with the view that the Paris Accord has raised investors' awareness about carbon risk especially with regard to scope 3 emissions.

Climate change and carbon emissions were not yet salient issues in the 1990s. It is only in the last two decades, with the accumulation of CO2 in the atmosphere and the repeated record-breaking temperatures that climate change has turned into a widespread concern. Public attention and investor focus on corporate carbon emissions were much smaller in the 1990s. This naturally raises the question whether stock returns were already affected by corporate carbon emissions in the 1990s. If information about firm-level emissions was scarce and/or investors did not pay attention to carbon risk one would expect that the pricing effects we have identified between 2005 and 2017 would be much smaller back then. Given that our carbon emissions data begins in 2005 we cannot evaluate this hypothesis directly. However, we can impute back the unobserved emissions data for each firm in the 1990s from the values we observe later on. In other words, since the cross-sectional variation in emissions is very stable over time (see Figure 3) it seems reasonable, as a first pass, to assume that the cross-sectional variation of emissions in the 1990s tracks closely that observed in our data.

Specifically, we assume that each firm with stocks trading during the 1990s has an emission intensity equal to the first officially reported value in the 2005-2017 period. Next, we collect the time-series information on each company's revenues for the period 1990-1999 and impute the total value of emissions for each firm by taking the product of the emission intensity coefficient and the firm's time-varying sales. We thus obtain a panel of imputed total corporate emissions for the period 1990-1999.

Next, we estimate the regression model in (1) using the imputed emission values and report the results in Table 16.[20] Our results indicate no significant carbon premium both for the regression models with and without industry fixed effects. This result is consistent with our hypothesis that investors did not yet internalize carbon risk over this time period.

3.9 Robustness

We have explored a number of alternative tests that shed additional light on the effects we document. We report specific figures and tables in the Online Appendix. Below, we briefly summarize the main findings.

First, we explore whether there is also a carbon premium with respect to (one-year) lagged emission intensity. We report the results in Table A.2. Basically, we find that there is no premium for lagged *SCOPE* 1 and *SCOPE* 2 emission intensities, but there is a statistically significant premium for *SCOPE* 3 emission intensity. As we discussed above, the absence of a carbon premium for lagged *SCOPE* 1 and *SCOPE* 2 emission intensities could be due to the fact that information becomes stale as we move the conditioning information one year back. This is less of an issue for *SCOPE* 3 emissions, which are indirect emissions determined through an input-output model.

Second, we explore whether unexpected profitability is associated with higher lagged emission intensity. We report the results in Table A.3. We find that, if anything, lagged emission intensity tends to reduce unexpected profitability.

Third, we explore whether the variation in carbon premium based on lagged emission intensity is captured by traditional risk factors and perform a similar estimation as in Table 9. The results in Table A.4 show that there is no robust conclusion to be obtained from this exercise.

[20] The process of imputation is not suitable to obtain the variation in emission growth rates since changes in emissions would vary one to one with changes in revenues. We considered an alternative model in which we fixed the growth rates at the first available reported value and used it for all dates in the 1990-1999 period. The results from this estimation, available upon request, indicate that the carbon premium is insignificant.

Fourth, in Table A.5 we explore how institutional investors' exclusionary screening policies affect their exposure to total contemporaneous emissions. Remarkably, we find that, if anything, the effect of these policies is to load up institutional investor portfolios on *SCOPE 2* and *SCOPE 3* emissions. One possible reason for this outcome is that divestment from the oil & gas and utility industries, which concentrate a major part of *SCOPE 1* emissions, necessarily translates into greater portfolio weights being put on the other industries and firms, which together are disproportionately responsible for *SCOPE 2* and *SCOPE 3* emissions. The irony is that the very effort to reduce exposure to *SCOPE 1* emissions leads to greater exposures to *SCOPE 2* and *SCOPE 3* emissions. Divestment from fossil fuel companies is not guaranteed to shield investors from carbon risk, as other companies may be dependent on fossil fuels for their operations. Hence, categorical divestment policies may simply displace exposure from *SCOPE 1* emissions to *SCOPE 2* and *SCOPE 3* emissions

4 Conclusion

How is climate change affecting stock returns? This is a fundamental question for the burgeoning field of climate change and finance. It is also a fundamental question for policy makers who are seeking to enlist investors in the fight against climate change. We address this question by undertaking a cross-sectional stock returns analysis with carbon emissions as a firm characteristic, and find robust evidence that carbon emissions significantly and positively affect stock returns. There is a straightforward link between climate change mitigation and the reduction in carbon emissions. Whether through the production of their goods and services or through the use of their products firms are differentially affected by policies to curb carbon emissions and renewable-energy technology shocks. Our evidence is that investors are discerning these cross-sectional differences and are pricing in carbon risk. We also find that the carbon premium cannot be explained through a *sin stock* divestment effect. Divestment takes place in a coarse way in a few industries such as oil & gas, utilities, and automobiles and is entirely based on scope 1 emission screens. However, outside these few industries we find a robust, persistent, and significant carbon premium at the firm level for all three categories of emissions.

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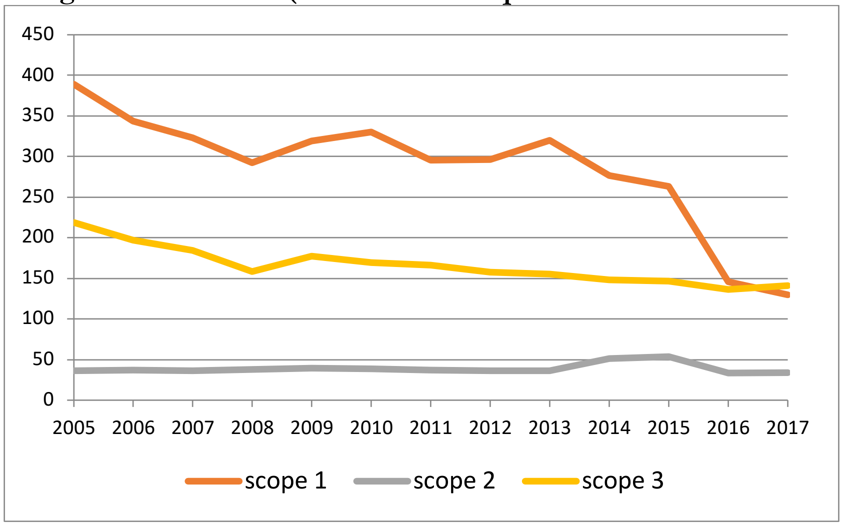
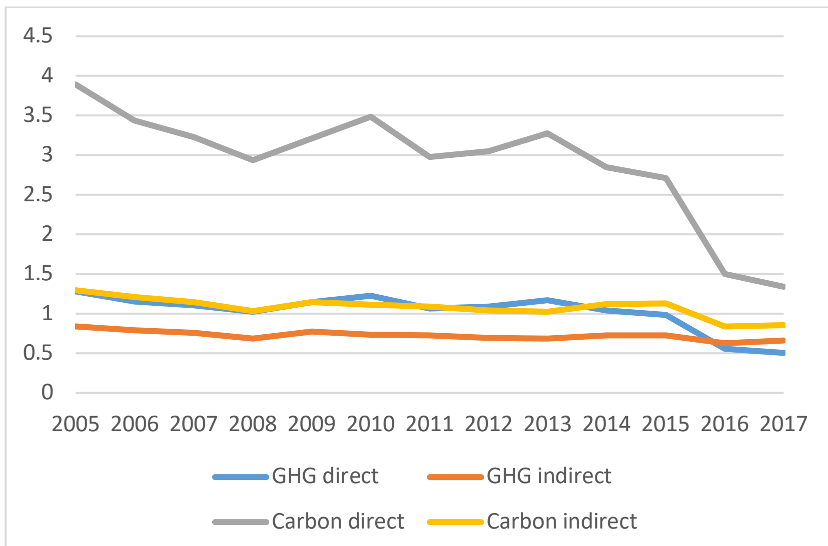
Figure 1. Carbon Emissions: Time-Series Summary

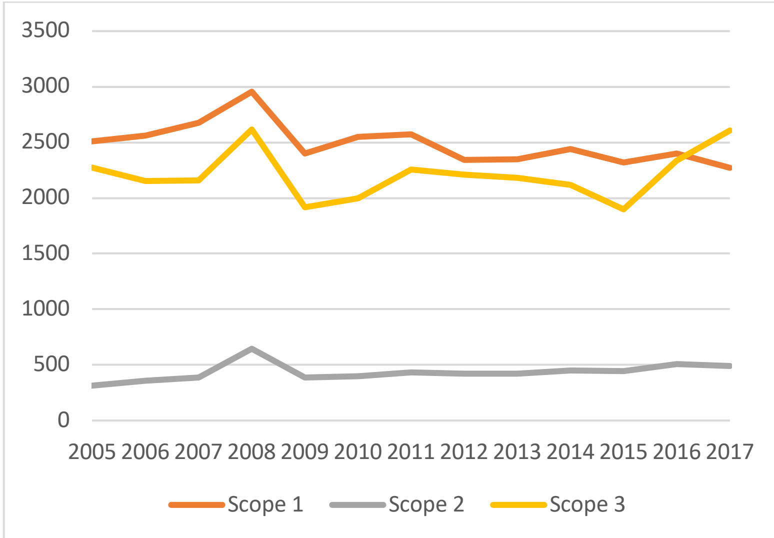
a) Average firm emissions (Tons of CO2 equivalent to revenues in $ million)

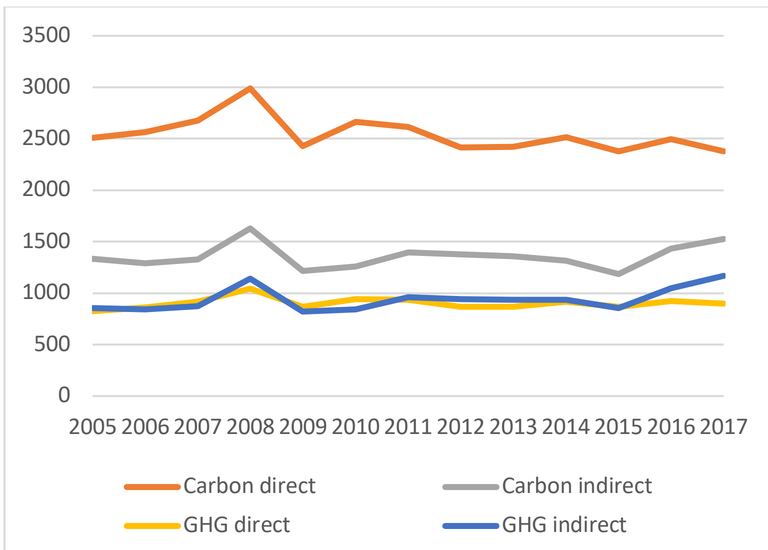




Note: GHG Direct and GHG Indirect are impact ratios expressed as a percentage of costs in revenues (in $ m.). Carbon direct and Carbon indirect are intensities expressed in tons of CO2 equivalent to revenues in $ million.

b) Total emissions





Note: All emissions are in tons of CO2 equivalent.

Figure 2. Carbon Emissions: Sample Selection

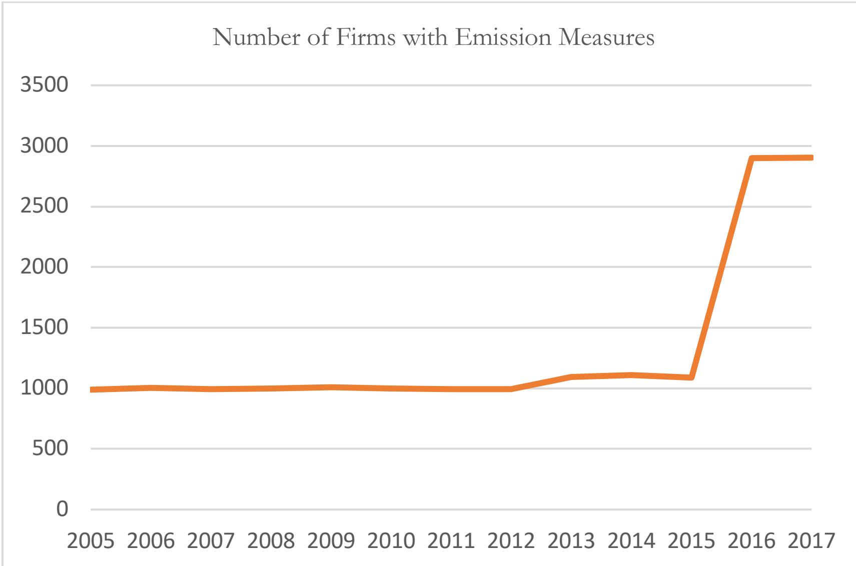
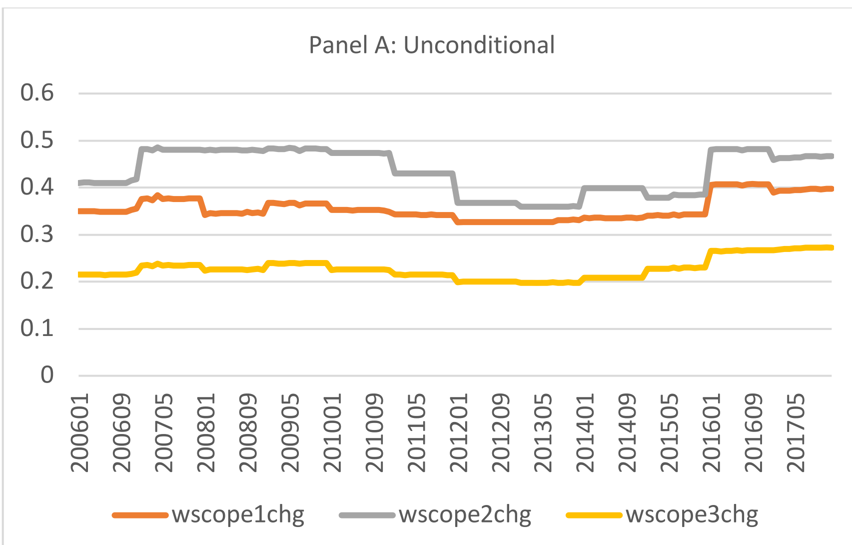


Figure 3. Standard Deviation of Carbon Emission Growth Rates



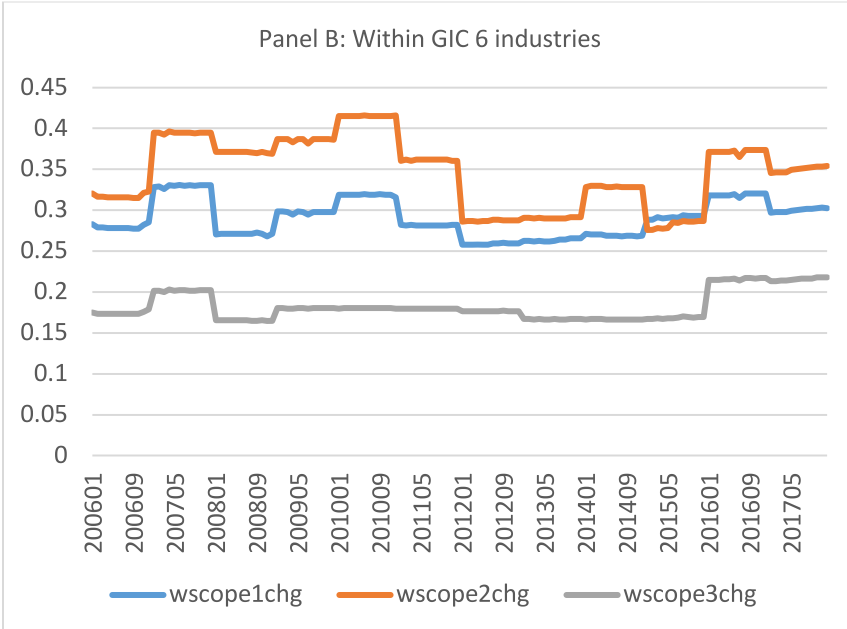
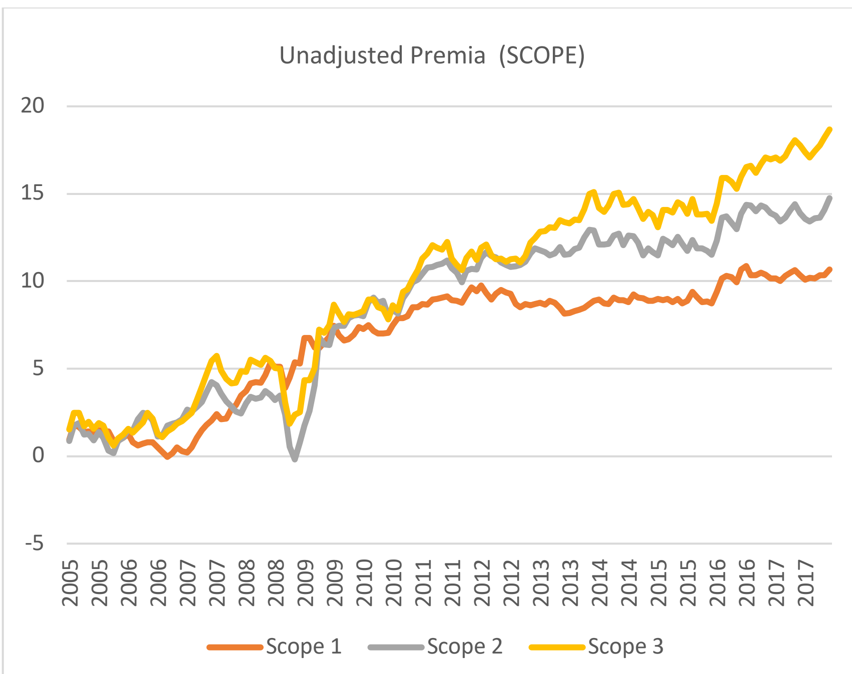
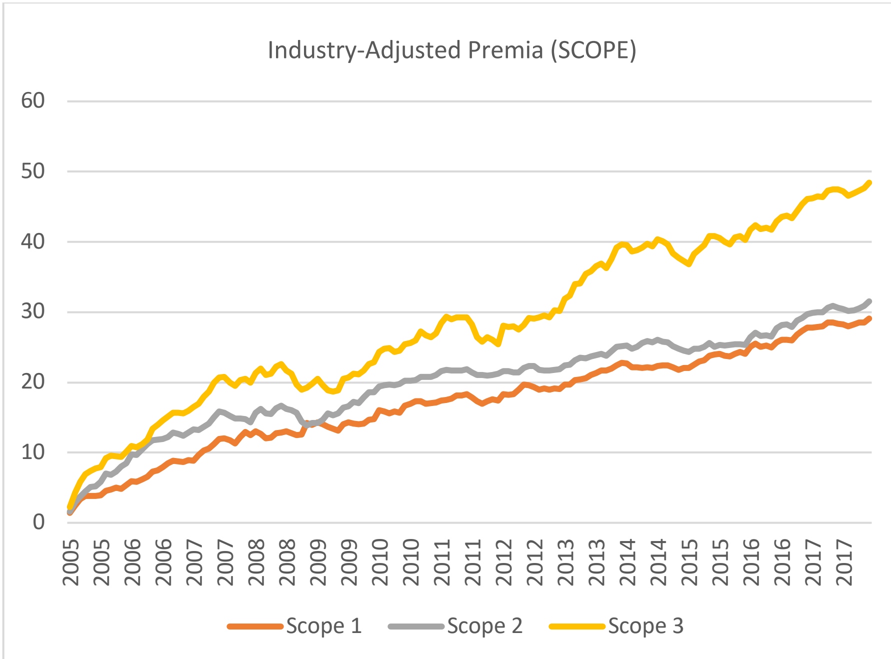


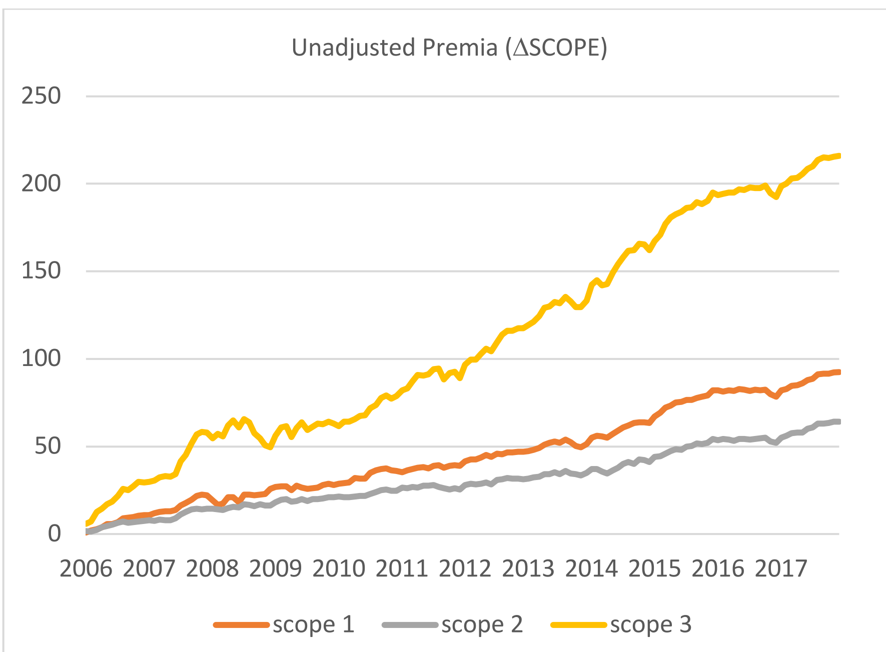
Figure 4. Carbon Cumulative Return Premia: Level Effect





Note: Figures plot cumulative carbon premia with and without industry fixed effects.

Figure 5. Carbon Cumulative Return Premia: Growth Effect



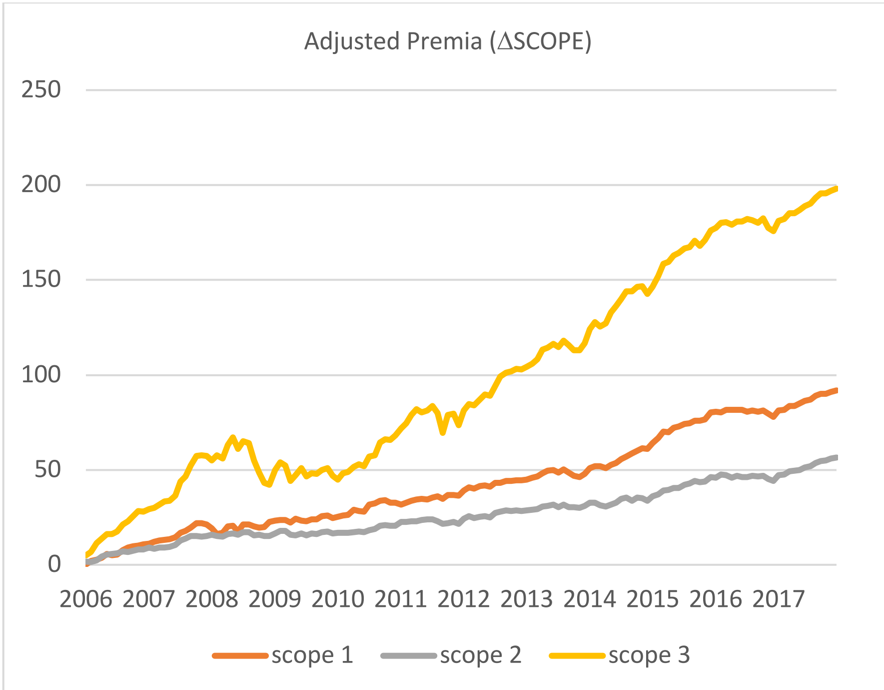
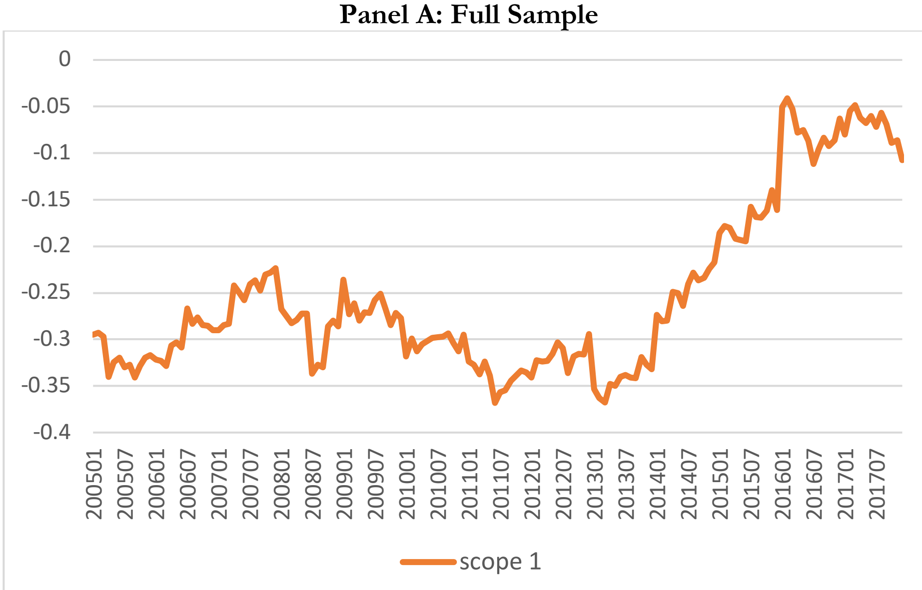
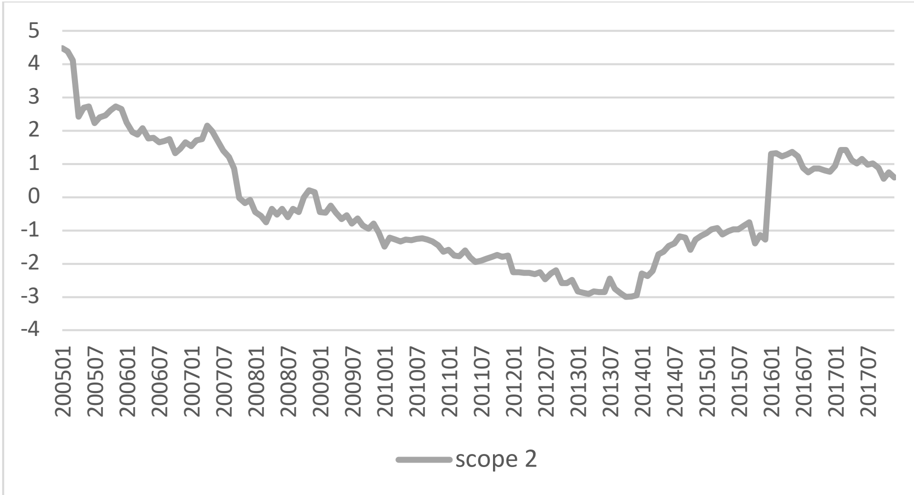
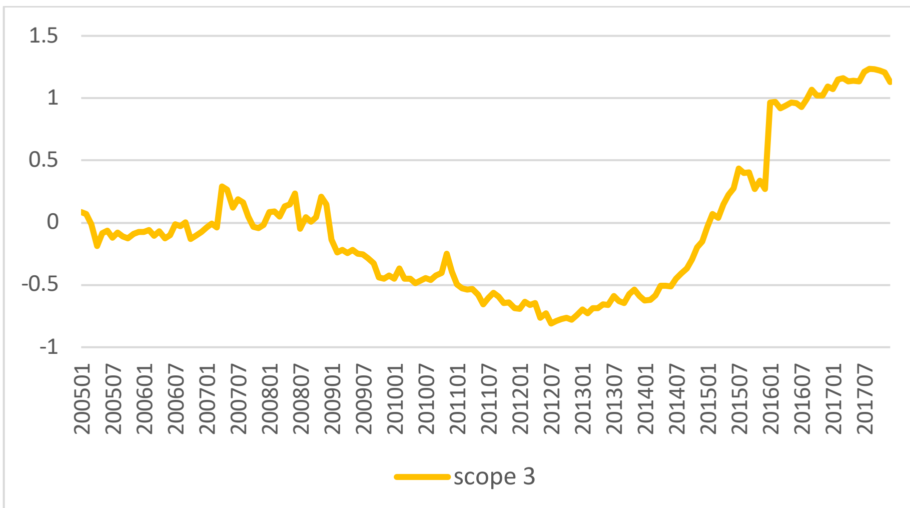


Figure 6. Carbon Intensity and Financial Adviser Ownership

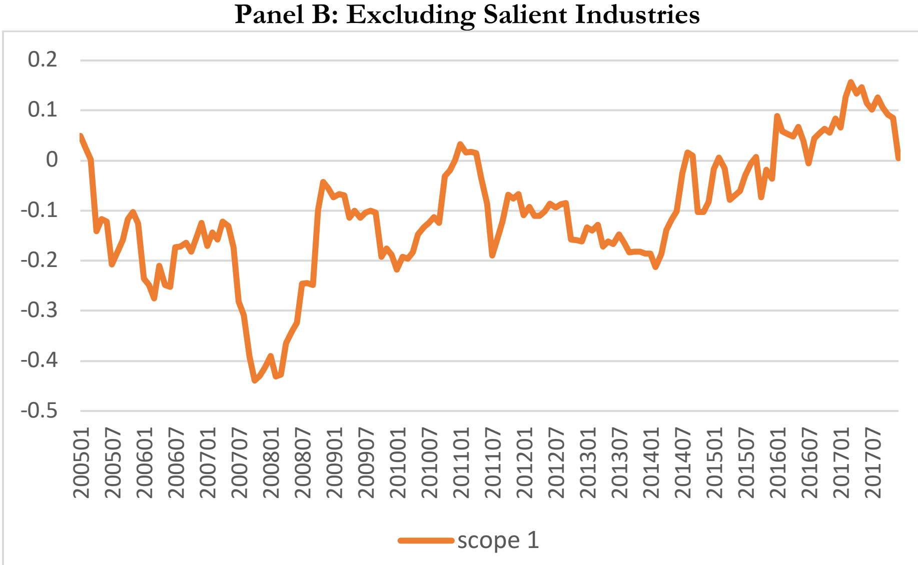
Panel A: Full Sample

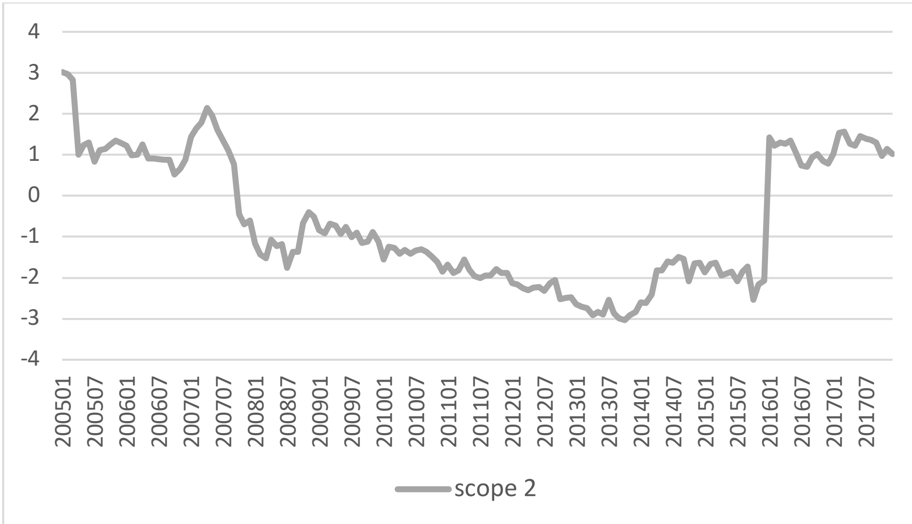


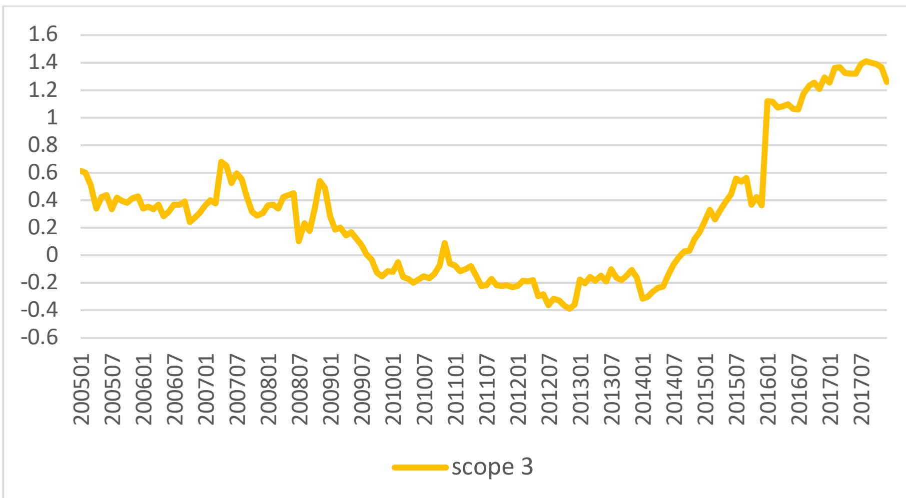




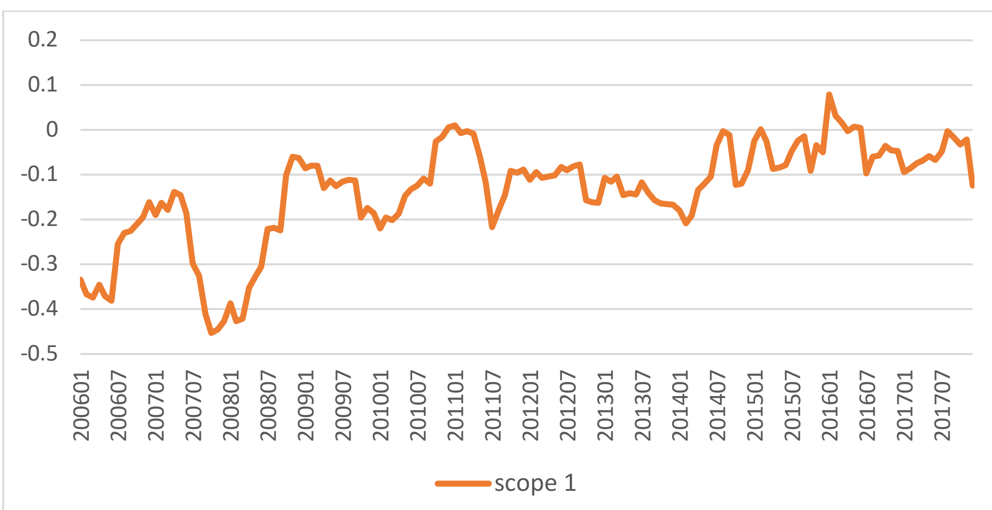
Panel B: Excluding Salient Industries

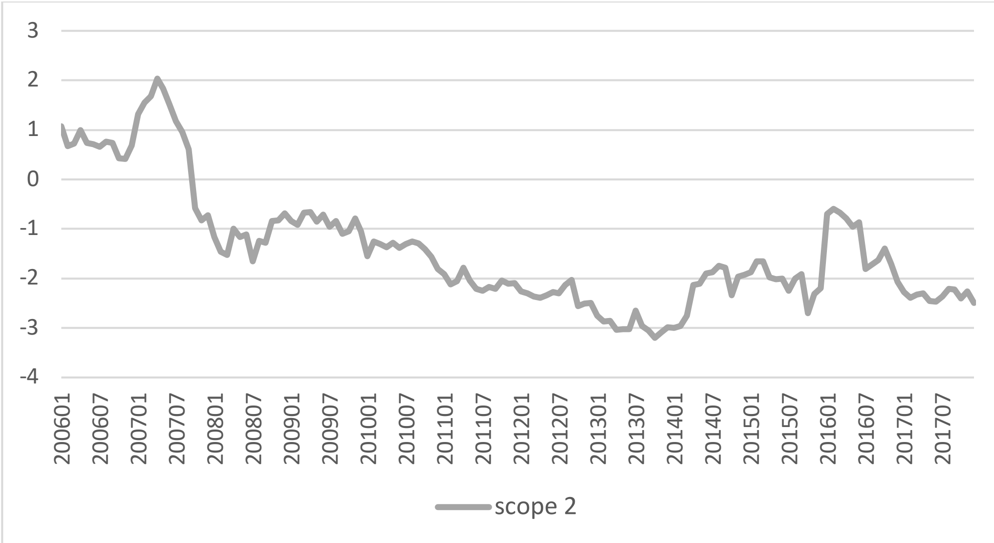






Panel C: Excluding Salient Industries and New Companies

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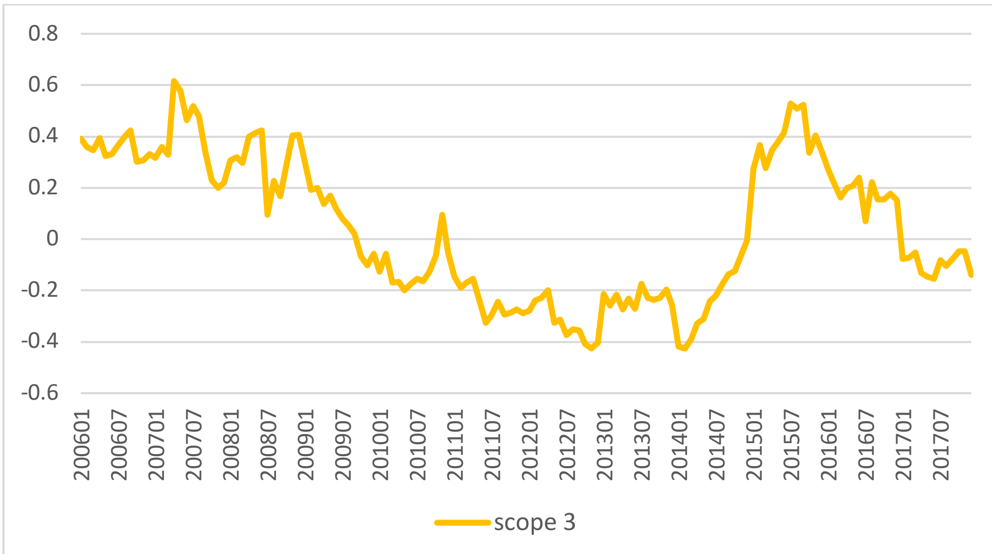
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Table 1: Summary Statistics

This tables reports summary statistics (averages, medians, and standard deviations) for the variables used for the six sets of regressions. The sample period is 2005-2017. **Panel A** reports the emission variables. **Panel B** reports the cross-sectional return variables. *RET* is the monthly stock return; *LOGSIZE* is the natural logarithm of market capitalization (in $ million); *B/M* is the book value of equity divided by market value of equity; *ROE* is the return on equity; *LEVERAGE* is the book value of leverage defined as the book value of debt divided by the book value of assets; *MOM* is the cumulative stock return over the one-year period; *INVEST/A* is the CAPEX divided by book value of assets; *HHI* is the Herfindahl index of the business segments of a company with weights proportional to revenues; *LOGPPE* is the natural logarithm of plant, property & equipment (in $ million); *BETA* is the CAPM beta calculated over the one year period; *VOLAT* is the monthly stock return volatility calculated over the one year period. **Panel C** reports the time-series variables. *MKTRF* is the monthly return on the value-weighted stock market net of the risk free rate; *HML* is the monthly return on the portfolio long value stocks and short growth stocks; *SMB* is the monthly return on the portfolio long small-cap stocks and short large-cap stocks; *MOM* is the monthly return on the portfolio long 12-month stock winners and short 12-month past losers; *CMA* is the monthly return of a portfolio that is long on conservative investment stocks and short on aggressive investment stocks; *BAB* is the monthly return of a portfolio that is long on low-beta stocks and short on high-beta stocks; *LIQ* is the liquidity factor of Pastor and Stambaugh; *NET ISSUANCE* is the monthly return of a portfolio that is long on high-net-issuance stocks and short on low-net-issuance stocks. Net issuance for year *t* is the change in the natural log of split-adjusted shares outstanding from the fiscal yearend in *t-2* to the fiscal yearend in *t-1*; *IDIO VOL* is the monthly return of a portfolio that is long on low idiosyncratic volatility stocks and short on high idiosyncratic volatility stocks. **Panel D** reports the business-cycle variables. *INF* is inflation rate, measured as the consumer price index (CPI); *TERM* is the term spread measured as the difference between the 10-year and 1-year Treasury constant maturity rates; *GDPGR* is the quarterly GDP growth rate; *GDP1YR* is the growth rate a year later; *DEFAULT* is the default spread measured as the difference between BAA and AAA corporate bond rates. **Panel E** reports the unexpected profitability variable, calculated using the methodology in Vuolteenaho (2002). **Panel F** reports the ownership variables. $IO_{i,t}$ is the fraction of the shares of company *i* held by institutions in the FactSet Database at the end of year *t*. *IO* is calculated by aggregating the shares held by all types of institutions at the end of the year, and then dividing this amount by shares outstanding at the end of the year. *IO_BANKS* is the ownership by banks; *IO_INSURANCE* is the ownership by insurance companies; *IO_INVESTCOS* is the ownership by investment companies (e.g., mutual funds); *IO_ADVISERS* is the ownership by independent investment advisers; *IO_PENSIONS* is the ownership by pension funds; *IO_HFS* is the ownership by hedge funds. $PRINV_{i,t}$ is the inverse of firm *i*'s share price at the end of year *t*; $TOT\ VOLAT_{i,t}$ is the standard deviation of daily stock returns for company *i* over the one-year period; $VOLUME_{i,t}$ is the average daily trading volume (in $million) of stock *i* over the calendar year *t*; $NASDAQ_{i,t}$ is an indicator variable equal to one if a stock *i* is listed on NASDAQ in year *t*, and zero otherwise; $SP500_{i,t}$ is an indicator variable equal to one if a stock *i* is part of the S&P 500 index in year *t*, and zero otherwise.

Variable	Mean	Median	St. Dev.
Panel A: Emission variables			
Log (Carbon Emissions Scope 1 (tons CO2e))	10.55	10.47	2.94
Log (Carbon Emissions Scope 2 (tons CO2e))	10.52	10.66	2.35
Log (Carbon Emissions Scope 3 (tons CO2e))	12.30	12.45	2.25
Growth Rate in Carbon Emissions Scope 1 (winsorized at 2.5%)	0.08	0.03	0.37
Growth Rate in Carbon Emissions Scope 2 (winsorized at 2.5%)	0.14	0.05	0.45
Growth Rate in Carbon Emissions Scope 3 (winsorized at 2.5%)	0.09	0.06	0.24
Carbon Intensity Scope 1 (tons CO2e/USD m.)/100 (winsorized at 2.5%)	1.91	0.15	5.86
Carbon Intensity Scope 2 (tons CO2e/USD m.)/100 (winsorized at 2.5%)	0.34	0.18	0.46
Carbon Intensity Scope 3 (tons CO2e/USD m.) /100 (winsorized at 2.5%)	1.57	0.97	1.58
Carbon Intensity Direct (winsorized at 2.5%)/100	2.12	0.16	6.45
Carbon Intensity Indirect (winsorized at 2.5%)/100	1.03	0.58	1.31
GHG Direct Impact Ratio (winsorized at 2.5%)	0.75	0.06	2.29
GHG Indirect Impact Ratio (winsorized at 2.5%)	0.71	0.46	0.68
Panel B: Cross-sectional return variables			
RET (%)	1.16	1.08	11.01
LOGSIZE	8.22	8.23	1.59
B/M (winsorized at 2.5%)	0.48	0.38	0.42
LEVERAGE (winsorized at 2.5%)	0.25	0.23	0.19
MOM (winsorized at 0.5%)	0.15	0.11	0.46
INVEST/A (winsorized at 2.5%)	0.05	0.03	0.05
HHI	0.83	1	0.24
LOGPPE	6.20	6.33	2.28
BETA	1.10	1.05	0.44
VOLAT (winsorized at 0.5%)	0.10	0.08	0.06

Panel C: Time-series variables			
MKTRF (in %)	0.70	1.06	4.08
HML (in %)	0.00	-0.22	2.57
SMB (in %)	0.07	0.04	2.26
MOM (in %)	0.07	0.36	4.53
CMA (in %)	0.02	-0.06	1.39
BAB (in %)	0.49	0.74	2.66
LIQ (in %)	0.15	0.38	3.59
NET ISSUANCE (in %)	0.51	0.55	1.65
IDIO VOL (in %)	-0.18	0.03	5.27
Panel D: Business-cycle variables			
INF (in %)	2.23	2.25	0.15
TERM (in %)	1.43	1.47	0.86
GDPGR (in %)	1.74	2.05	2.40
DEFAULT (in %)	1.10	0.95	0.50
Panel E: Profitability variables			
UP (in %)	0	0.77	65.94
Panel F: Ownership variables			
IO	0.76	0.83	0.23
IO_BANKS (in %)	0.10	0.07	0.16
IO_INSURANCE (in %)	0.34	0.13	3.04
IO_INVESTCOS. (in %)	18.05	18.26	8.74
IO_ADVISERS (in %)	43.53	45.85	15.69
IO_PENSIONS (in %)	3.37	3.47	2.38
IO_HFS (in %)	11.08	7.80	10.39
PRINV (winsorized at 0.5%)	0.06	0.03	0.16
VOLAT (winsorized at 0.5%)	0.10	0.08	0.06
VOLUME (in $million) (winsorized at 2.5%)	0.44	0.21	0.56
NASDAQ	0.29	0	0.46
SP500	0.36	0	0.48

Table 2: Carbon Emissions Intensity over Time

The table reports the cross-sectional averages of scope 1, scope 2, and scope 3 intensity variables over the period 2005-2017.

Year	Scope 1	Scope 2	Scope 3
2005	394.07	36.37	219.39
2006	349.89	38.59	197.45
2007	324.05	38.73	185.76
2008	293.57	40.31	158.57
2009	316.88	41.00	176.70
2010	325.97	40.26	168.71
2011	292.79	39.36	165.03

2012	294.19	38.21	156.38
2013	315.34	37.99	154.12
2014	274.83	51.90	147.48
2015	266.51	54.94	146.06
2016	151.10	33.90	135.72
2017	139.86	34.15	140.76

Table 3: Industry Representation by Number of Firms

The table reports the distribution of unique firms in our sample with regard to GIC 6 industry classification. *Total* represents the total number of firms in our sample. The sample period is 2005-2017.

GIC 6	Industry Name	# of Firms
1	Energy Equipment & Services	75
2	Oil, Gas & Consumable Fuels	164
3	Chemicals	81
4	Construction Materials	17
5	Containers & Packaging	21
6	Metals & Mining	47
7	Paper & Forest Products	12
8	Aerospace & Defense	46
9	Building Products	32
10	Construction & Engineering	36
11	Electrical Equipment	54
12	Industrial Conglomerates	16
13	Machinery	118
14	Trading Companies & Distributors	40
15	Commercial Services & Supplies	69
16	Professional Services	42
17	Air Freight & Logistics	15
18	Airlines	13
19	Marine	27
20	Road & Rail	31
21	Transportation Infrastructure	5
22	Auto Components	43
23	Automobiles	8
24	Household Durables	64
25	Leisure Products	21
26	Textiles, Apparel & Luxury Goods	41
27	Hotels, Restaurants & Leisure	95
28	Diversified Consumer Services	38
29	Media	83
30	Distributors	8
31	Internet & Direct Marketing Retail	45
32	Multiline Retail	17

33	Specialty Retail	110
34	Food & Staples Retailing	27
35	Beverages	17
36	Food Products	57
37	Tobacco	9
38	Household Products	12
39	Personal Products	15
40	Health Care Equipment & Supplies	109
41	Health Care Providers & Services	77
42	Health Care Technology	20
43	Biotechnology	203
44	Pharmaceuticals	87
45	Life Sciences Tools & Services	34
46	Banks	260
47	Thrifts & Mortgage Finance	61
48	Diversified Financial Services	28
49	Consumer Finance	37
50	Capital Markets	92
51	Mortgage Real Estate Investment Trusts (REITs)	22
52	Insurance	111
53	Internet Software & Services	100
54	IT Services	102
55	Software	150
56	Communications Equipment	47
57	Technology Hardware, Storage & Peripherals	34
58	Electronic Equipment, Instruments & Components	82
59	Semiconductors & Semiconductor Equipment	103
60	Diversified Telecommunication Services	34
61	Wireless Telecommunication Services	15
62	Media	49
63	Entertainment	22
64	Interactive Media & Services	29
65	Electric Utilities	42
66	Gas Utilities	17
67	Multi-Utilities	30
68	Water Utilities	13
69	Independent Power and Renewable Electricity Producers	17
70	Equity Real Estate Investment Trusts (REITs)	184
71	Real Estate Management & Development	35
Total		3917

Table 4: Carbon Emission Intensity by Industry

Top panel reports the top 10 of GIC 6 industries in terms of average emission intensity (scope 1, scope 2, scope 3). Bottom panel reports the bottom 10 of GIC 6 industries in terms of average emission intensity (scope 1, scope 2, scope 3). The sample period is 2005-2017. The emission variables are expressed in tons of CO2e per million dollars of revenues.

Largest Emissions (Avg.)					
GIC 6	**Scope 1**	**GIC 6**	**Scope 2**	**GIC 6**	**Scope 3**
69	5399.0	6	206.2	36	825.8
65	4265.0	65	178.3	6	507.2
67	2748.4	4	167.8	4	453.9
4	1367.0	3	166.7	5	402.3
19	1220.2	7	152.6	35	371.0
18	1041.0	5	104.6	22	365.9
6	803.7	27	73.5	3	359.4
2	648.3	2	69.6	13	338.0
7	442.7	70	64.7	23	329.2
66	422.5	38	58.4	67	318.5

Smallest Emissions (Avg.)					
GIC 6	**Scope 1**	**GIC 6**	**Scope 2**	**GIC 6**	**Scope 3**
47	1.1	47	2.5	47	25.8
49	1.3	52	3.2	46	27.1
46	2.0	46	3.8	52	30.3
62	3.3	18	5.0	49	31.3
64	3.4	50	7.3	51	32.6
29	4.0	42	7.6	50	32.7
52	4.4	49	8.2	16	40.7
53	4.5	55	8.5	55	42.6
55	4.5	69	9.4	42	45.8
61	5.0	16	9.7	54	47.1

Table 5: Determinants of Carbon Emission Intensities

The sample period is 2005-2017. The dependent variables are carbon intensities *SCOPE 1*, *SCOPE 2*, and *SCOPE 3*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm level and year. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	SCOPE 1	SCOPE 2	SCOPE 3	SCOPE 1	SCOPE 2	SCOPE 3
LOGSIZE	-0.977***	-0.071***	-0.353***	-0.119*	0.002	-0.021**
	(0.263)	(0.016)	(0.061)	(0.062)	(0.006)	(0.009)
B/M	0.240	-0.126***	-0.535***	0.007	0.004	-0.000
	(0.321)	(0.027)	(0.080)	(0.106)	(0.009)	(0.013)

ROE	-0.007	-0.000	0.005***	-0.002	-0.000	0.000
	(0.005)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)
LEVERAGE	0.645	0.045	-0.386**	0.364	0.004	-0.056*
	(0.463)	(0.068)	(0.176)	(0.228)	(0.030)	(0.030)
INVEST/A	4.008	0.432*	-1.403*	-0.651	-0.072	-0.456**
	(2.863)	(0.212)	(0.785)	(1.140)	(0.152)	(0.203)
HHI	-6.237***	-0.047	-1.895***	-2.176***	0.009	-0.256***
	(0.924)	(0.047)	(0.174)	(0.494)	(0.031)	(0.062)
LOGPPE	1.045***	0.087***	0.290***	0.127***	0.025***	0.026***
	(0.207)	(0.015)	(0.036)	(0.041)	(0.007)	(0.007)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	190,379	190,379	190,379	190,379	190,379	190,379
R-squared	0.217	0.116	0.200	0.787	0.649	0.935

Table 6: Carbon Emissions and Stock Returns

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon total emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.060**			0.193***		
	(0.022)			(0.044)		
LOG (TOT SCOPE 2)		0.120**			0.199***	
		(0.044)			(0.057)	
LOG (TOT SCOPE 3)			0.172***			0.358***
			(0.049)			(0.084)
LOGSIZE	-0.114	-0.171	-0.186	-0.287*	-0.317*	-0.409**
	(0.162)	(0.173)	(0.172)	(0.151)	(0.161)	(0.175)
B/M	0.263	0.284	0.270	0.398	0.384	0.322
	(0.231)	(0.244)	(0.234)	(0.245)	(0.241)	(0.241)
LEVERAGE	-0.332	-0.356	-0.260	-0.398**	-0.413**	-0.499**
	(0.223)	(0.232)	(0.219)	(0.182)	(0.175)	(0.165)
MOM	0.397	0.430	0.417	0.352	0.364	0.371
	(0.269)	(0.266)	(0.269)	(0.290)	(0.290)	(0.290)
INVEST/A	-2.461	-2.073	-1.649	0.351	0.345	0.812

	(1.682)	(1.695)	(1.707)	(2.011)	(2.032)	(1.947)
HHI	0.135*	0.045	0.248**	0.241***	0.156*	0.213**
	(0.075)	(0.098)	(0.086)	(0.075)	(0.072)	(0.073)
LOGPPE	-0.034	-0.043	-0.068	-0.003	-0.004	-0.046
	(0.100)	(0.089)	(0.087)	(0.052)	(0.050)	(0.046)
BETA	0.045	0.006	0.037	0.038	0.032	0.059
	(0.128)	(0.130)	(0.128)	(0.151)	(0.150)	(0.148)
VOLAT	-0.219	-0.431	-0.265	-0.108	-0.251	-0.112
	(3.577)	(3.463)	(3.510)	(3.277)	(3.276)	(3.256)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	190,548	190,476	190,644	190,548	190,476	190,644
R-squared	0.197	0.197	0.197	0.200	0.200	0.200

Panel B: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.721***			0.725***		
	(0.211)			(0.195)		
ΔSCOPE 2		0.429**			0.424**	
		(0.181)			(0.179)	
ΔSCOPE 3			1.305***			1.329***
			(0.419)			(0.419)
LOGSIZE	0.016	0.026	0.002	-0.071	-0.063	-0.088
	(0.111)	(0.113)	(0.112)	(0.111)	(0.113)	(0.115)
B/M	0.248	0.241	0.286	0.570*	0.559*	0.613**
	(0.236)	(0.237)	(0.223)	(0.278)	(0.277)	(0.262)
LEVERAGE	-0.207	-0.196	-0.201	-0.439*	-0.438*	-0.429*
	(0.209)	(0.207)	(0.211)	(0.220)	(0.222)	(0.221)
MOM	0.257	0.274	0.207	0.207	0.224	0.157
	(0.263)	(0.269)	(0.256)	(0.260)	(0.264)	(0.254)
INVEST/A	-2.536	-2.252	-2.658	-0.375	-0.209	-0.557
	(1.704)	(1.723)	(1.756)	(2.201)	(2.155)	(2.223)
HHI	-0.110	-0.072	-0.133	-0.018	0.001	-0.040
	(0.150)	(0.150)	(0.147)	(0.083)	(0.088)	(0.088)
LOGPPE	-0.023	-0.032	-0.009	0.035	0.026	0.051
	(0.059)	(0.058)	(0.060)	(0.040)	(0.040)	(0.042)
BETA	0.102	0.118	0.094	0.154	0.169	0.137

	(0.160)	(0.160)	(0.160)	(0.161)	(0.161)	(0.162)
VOLAT	0.707	0.832	0.774	0.553	0.660	0.631
	(4.326)	(4.306)	(4.357)	(4.147)	(4.140)	(4.171)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	158,096	158,000	158,168	158,096	158,000	158,168
R-squared	0.212	0.212	0.212	0.215	0.215	0.215

Table 7: Carbon Emissions and Stock Returns Net of Earnings Returns

The sample period is 2005-2017. The dependent variable is *RET* net of daily return realized on the earnings announcement day. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon total emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.059**			0.175***		
	(0.023)			(0.040)		
LOG (TOT SCOPE 2)		0.108**			0.176***	
		(0.043)			(0.052)	
LOG (TOT SCOPE 3)			0.153**			0.316***
			(0.051)			(0.078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	190,548	190,476	190,644	190,548	190,476	190,644
R-squared	0.213	0.214	0.214	0.216	0.216	0.216

Panel B: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.594**			0.588***		
	(0.200)			(0.185)		
ΔSCOPE 2		0.348**			0.340**	
		(0.164)			(0.164)	
ΔSCOPE 3			0.952**			0.966**
			(0.407)			(0.413)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	158,096	158,000	158,168	158,096	158,000	158,168
R-squared	0.229	0.229	0.229	0.232	0.232	0.232

Table 8: Carbon Emissions and Unexpected Profitability

The sample period is 2005-2017. The dependent variable is *UP*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry level. All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	-0.008**			-0.027***		
	(0.003)			(0.007)		
LOG (TOT SCOPE 2)		-0.007			-0.032***	
		(0.005)			(0.008)	
LOG (TOT SCOPE 3)			-0.011*			-0.044***
			(0.006)			(0.013)
LOGSIZE	0.022***	0.022***	0.025***	0.035***	0.043***	0.052***
	(0.005)	(0.007)	(0.007)	(0.007)	(0.008)	(0.012)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry adj.	No	No	No	Yes	Yes	Yes
Observations	133,627	133,567	133,675	133,627	133,567	133,675
R-squared	0.084	0.079	0.082	0.349	0.357	0.361

Panel B: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.061***			0.042***		
	(0.014)			(0.008)		
ΔSCOPE 2		0.043***			0.035***	
		(0.011)			(0.008)	
ΔSCOPE 3			0.164***			0.124***
			(0.042)			(0.025)
LOGSIZE	0.016***	0.016***	0.015***	0.014***	0.014***	0.013***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry adj.	No	No	No	Yes	Yes	Yes
Observations	111,932	111,848	111,968	111,932	111,848	111,968
R-squared	0.086	0.082	0.112	0.372	0.371	0.387

Table 9: Can the Carbon Premium be explained by Risk Factors?

The sample period is 2005-2017. The dependent variable is the monthly carbon premium estimated each period using a cross-sectional return regression. All variables are defined in Table 1. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using Newey-West test. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

	TOT SCOPE 1		TOT SCOPE 2		TOT SCOPE 3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MKTRF		-1.528*		3.206***		3.124**
		(0.782)		(1.090)		(1.391)
HML		-5.350***		-3.776**		-5.535*
		(1.826)		(1.860)		(3.103)
SMB		-0.230		1.529		1.543
		(0.844)		(2.679)		(1.826)
MOM		0.257		-4.194**		-4.022***
		(0.594)		(1.751)		(1.445)
CMA		0.078**		0.051		0.108***
		(0.031)		(0.035)		(0.041)
BAB		0.887		0.377		2.061
		(0.816)		(1.820)		(1.719)
LIQ		2.805***		1.156		3.475***
		(0.767)		(1.143)		(1.039)
NET ISSUANCE		1.490		-1.166		0.666
		(1.075)		(2.368)		(2.466)
IDIO VOL		1.408*		0.509		-0.085
		(0.818)		(1.338)		(1.587)
Constant	0.068**	0.063**	0.095**	0.076***	0.120***	0.079***
	(0.027)	(0.025)	(0.037)	(0.029)	(0.036)	(0.028)
Industry adj.	No	No	No	No	No	No
Adj. R2	0.001	0.300	0.001	0.307	0.001	0.223
Observations	156	156	156	156	156	156

Panel B: Growth rate in total emissions

	ΔSCOPE 1		ΔSCOPE 2		ΔSCOPE 3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MKTRF		3.317		-4.280		3.798
		(5.682)		(2.666)		(9.391)
HML		-10.131**		-6.114		-19.105**
		(4.671)		(3.823)		(9.076)
SMB		-14.673**		-8.331		-21.996
		(6.640)		(5.714)		(14.095)
MOM		3.686		3.865		9.864
		(4.690)		(2.800)		(9.242)
CMA		-0.138		-0.143***		-0.409**
		(0.088)		(0.054)		(0.180)
BAB		-9.326***		2.230		12.403
		(3.092)		(2.059)		(8.505)
LIQ		2.450		-0.163		10.619***
		(2.170)		(1.908)		(3.975)
NET ISSUANCE		2.985		-0.824		10.204
		(5.327)		(4.669)		(12.739)
IDIO VOL		4.438		6.693*		17.724
		(6.726)		(3.651)		(12.435)
Constant	0.642***	0.665***	0.446***	0.499***	1.500***	1.427***
	(0.095)	(0.130)	(0.068)	(0.068)	(0.238)	(0.247)
Industry adj.	No	No	No	No	No	No
Adj. R2	0.001	0.114	0.001	0.190	0.001	0.279
Observations	144	144	144	144	144	144

Table 10: Carbon Premium: Business-Cycle Variation

The sample period is 2005-2017. Panel A reports the correlation matrix for carbon premiums and a host of business cycle variables. The dependent variable in Panel B is the natural logarithm of contemporaneous total emissions. All variables are defined in Table 1. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using Newey-West test. ***1% significance; **5% significance; *10% significance.

Panel A: Correlation Matrix (Industry Unadjusted)

Variables	Scope 1_premium	Scope 2_premium	Scope 3_premium
INF	-0.104	-0.077	-0.050
TERM	0.030	0.003	-0.012
GDPGR	-0.036	0.047	0.042

GDP1YR	-0.128	0.096	0.059
DEFAULT	0.156	0.201	0.145

Panel B: Contemporaneous total emissions

VARIABLES	(SCOPE 1)	(SCOPE 2)	(SCOPE 3)
INF	-0.002	-0.003	-0.002
	(0.002)	(0.002)	(0.002)
TERM	0.012	0.002	-0.008
	(0.030)	(0.032)	(0.039)
GDPGR	-0.005	0.010	0.010
	(0.013)	(0.023)	(0.019)
GDP1YR	-0.018	0.021	0.014
	(0.012)	(0.013)	(0.015)
DEFAULT	0.105**	0.211	0.163
	(0.042)	(0.139)	(0.107)
Industry adj.	No	No	No
Observations	156	156	156

Panel C: Growth rate in total emissions

VARIABLES	(ΔSCOPE 1)	(ΔSCOPE 2)	(ΔSCOPE 3)
INF	0.001	0.002	-0.005
	(0.007)	(0.005)	(0.017)
TERM	-0.131*	-0.127**	-0.308
	(0.071)	(0.058)	(0.226)
GDPGR	0.032	0.021	0.226**
	(0.048)	(0.021)	(0.092)
GDP1YR	0.012	0.010	-0.052
	(0.047)	(0.024)	(0.079)
DEFAULT	-0.162	-0.145	-0.967***
	(0.168)	(0.100)	(0.369)
Industry adj.	No	No	No
Observations	144	144	144

Table 11: Is Carbon Premium Systematic Risk?

The sample period is 2005-2017. Panel A, Panel B, and Panel C present the coefficients from estimating univariate time-series regressions of monthly returns on 25 Fama-French test assets sorted on book-to-market ratio and size on the portfolio return that takes a long position on companies with 20% highest contemporaneous total emissions and a short position on companies with 20% lowest contemporaneous total emissions. Panel A reports the results for *SCOPE 1*, Panel B reports the results for *SCOPE 2*, and Panel C reports the results for *SCOPE 3*. Standard errors (in parentheses) are adjusted for autocorrelation with 12 lags using the Newey-West procedure. R-squared from each regression are in brackets. Panel D reports the results from the cross-sectional regression of average returns on each of the 25 assets on the premiums reported in Panels A-C. Panel E reports the results from estimating each period the Fama-MacBeth regression of Fama-French assets on the carbon premiums in Panels A-C. *t*-statistics are obtained using the autocorrelation-adjusted standard errors with 12 lags. ***1% significance; **5% significance; *10% significance.

Panel A: SCOPE 1

	Small	Size2	Size3	Size4	Large
Low	-0.557***	-0.481***	-0.458***	-0.378***	-0.338***
	(0.174)	(0.138)	(0.126)	(0.110)	(0.069)
	[0.151]	[0.125]	[0.118]	[0.098]	[0.068]
BM2	-0.515***	-0.440***	-0.373**	-0.368***	-0.311***
	(0.163)	(0.161)	(0.162)	(0.131)	(0.092)
	[0.164]	[0.134]	[0.116]	[0.104]	[0.099]
BM3	-0.553***	-0.437**	-0.379**	-0.334**	-0.341***
	(0.167)	(0.176)	(0.154)	(0.143)	(0.119)
	[0.213]	[0.161]	[0.132]	[0.100]	[0.149]
BM4	-0.534***	-0.461***	-0.346**	-0.362**	-0.549**
	(0.183)	(0.169)	(0.152)	(0.158)	(0.212)
	[0.231]	[0.201]	[0.135]	[0.142]	[0.245]
High	-0.611***	-0.719***	-0.502**	-0.639***	-0.858***
	(0.223)	(0.250)	(0.229)	(0.197)	(0.192)
	[0.240]	[0.262]	[0.199]	[0.285]	[0.416]

Panel B: SCOPE 2

	Small	Size2	Size3	Size4	Large
Low	-0.122	-0.144	-0.055	0.008	-0.157
	(0.243)	(0.226)	(0.208)	(0.176)	(0.113)
	[0.085]	[0.081]	[0.098]	[0.081]	[0.116]
BM2	-0.137	0.008	0.036	0.063	-0.081
	(0.235)	(0.207)	(0.204)	(0.161)	(0.105)
	[0.083]	[0.070]	[0.043]	[0.058]	[0.044]
BM3	-0.163	0.008	0.022	0.135	-0.132
	(0.225)	(0.218)	(0.192)	(0.198)	(0.131)
	[0.096]	[0.052]	[0.047]	[0.031]	[0.051]
BM4	-0.174	-0.066	0.022	0.055	-0.181
	(0.229)	(0.208)	(0.167)	(0.155)	(0.173)

	[0.069]	[0.054]	[0.030]	[0.030]	[0.079]
High	-0.114	-0.278	-0.053	-0.312	-0.526**
	(0.228)	(0.272)	(0.201)	(0.197)	(0.209)
	[0.078]	[0.091]	[0.058]	[0.086]	[0.126]

Panel C: SCOPE 3

	Small	Size2	Size3	Size4	Large
Low	-0.712***	-0.611***	-0.538***	-0.441***	-0.298***
	(0.163)	(0.135)	(0.118)	(0.121)	(0.087)
	[0.085]	[0.081]	[0.098]	[0.081]	[0.116]
BM2	-0.702***	-0.584***	-0.513***	-0.466***	-0.361***
	(0.136)	(0.135)	(0.146)	(0.132)	(0.102)
	[0.083]	[0.070]	[0.043]	[0.058]	[0.044]
BM3	-0.736***	-0.628***	-0.547***	-0.496***	-0.456***
	(0.125)	(0.158)	(0.142)	(0.138)	(0.105)
	[0.096]	[0.052]	[0.047]	[0.031]	[0.051]
BM4	-0.749***	-0.689***	-0.552***	-0.545***	-0.713***
	(0.144)	(0.135)	(0.131)	(0.155)	(0.182)
	[0.069]	[0.054]	[0.030]	[0.030]	[0.079]
High	-0.839***	-0.957***	-0.742***	-0.871***	-1.128***
	(0.170)	(0.189)	(0.188)	(0.177)	(0.196)
	[0.078]	[0.091]	[0.058]	[0.086]	[0.126]

Panel D: C-x evidence

Cross-Section	SCOPE 1	SCOPE 2	SCOPE 3
Risk premium	0.424*	0.438	0.238*
t-statistic	1.77	1.66	1.76

Panel E: Fama-MacBeth evidence

Cross-Section	SCOPE 1	SCOPE 2	SCOPE 3
Risk premium	0.531	0.470	0.351
t-statistic	1.07	1.34	0.89

Table 12: Carbon Emissions and Institutional Ownership

The sample period is 2005-2017. The dependent variable in Panel A is *IO*. The dependent variables in Panel B, Panel C, and Panel D are *IO_BANK, IO_INSURANCE, IO_INVESTCOS, IO_ADVISERS, IO_PENSIONS,* and *IO_HFS*. Panels A-D present the result for contemporaneous measures of emission intensity. Panel B presents the results for *SCOPE 1*, Panel C presents the results for *SCOPE 2*, and Panel D presents the results for *SCOPE 3*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry and year level. All regressions include year-month fixed effects. In Panel A, columns (2), (4), and (6) additionally include state-fixed effects. All regressions in Panels B-D include state fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Aggregate Ownership (Carbon Intensity)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	-0.193**	-0.218***				
	(0.086)	(0.083)				
SCOPE 2			-0.405	-0.381		
			(1.622)	(1.610)		
SCOPE 3					0.088	-0.130
					(0.552)	(0.581)
LOGSIZE	2.071	1.847	2.090	1.859	2.097	1.850
	(1.522)	(1.702)	(1.496)	(1.678)	(1.511)	(1.706)
PRINV	-29.383***	-37.095***	-29.365***	-37.159***	-29.341***	-37.197***
	(5.626)	(6.452)	(5.623)	(6.396)	(5.652)	(6.480)
MOM	-1.456	-1.792*	-1.545	-1.871**	-1.546	-1.858*
	(0.932)	(0.877)	(0.888)	(0.823)	(0.913)	(0.856)
B/M	-1.104	-0.889	-1.471	-1.205	-1.436	-1.215
	(1.429)	(1.601)	(1.372)	(1.540)	(1.345)	(1.548)
BETA	9.141***	9.470***	9.349***	9.705***	9.317***	9.695***
	(1.493)	(1.459)	(1.406)	(1.375)	(1.415)	(1.388)
VOLAT	-8.111	4.126	-7.332	4.776	-7.577	4.538
	(14.364)	(12.829)	(13.630)	(11.943)	(14.120)	(12.569)
VOLUME	-4.365***	-4.613**	-4.317**	-4.568**	-4.328***	-4.583**
	(1.414)	(1.635)	(1.437)	(1.650)	(1.392)	(1.625)
NASDAQ	-1.215	-1.530	-0.936	-1.255	-0.812	-1.292
	(1.463)	(1.700)	(1.430)	(1.639)	(1.301)	(1.506)
SP500	2.430	1.711	2.290	1.508	2.266	1.510
	(2.121)	(2.092)	(2.121)	(2.088)	(2.128)	(2.095)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	170,553	160,394	170,553	160,394	170,553	160,394
R-squared	0.122	0.166	0.119	0.162	0.119	0.162

Panel B: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 1	0.001**	-0.011*	0.026	-0.258***	-0.009*	0.033
	(0.000)	(0.005)	(0.022)	(0.056)	(0.004)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,394	160,394	160,394	160,394	160,394	160,394
R-squared	0.164	0.025	0.210	0.155	0.231	0.177

Panel C: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 2	0.009	-0.253	-0.139	-0.156	0.049	0.108
	(0.006)	(0.144)	(0.406)	(0.992)	(0.097)	(0.441)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,394	160,394	160,394	160,394	160,394	160,394
R-squared	0.164	0.025	0.210	0.144	0.231	0.176

Panel D: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 3	0.004*	-0.021	0.038	0.052	0.028	-0.230
	(0.002)	(0.071)	(0.115)	(0.409)	(0.030)	(0.151)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,394	160,394	160,394	160,394	160,394	160,394
R-squared	0.165	0.024	0.210	0.144	0.231	0.178

Table 13: Carbon Emissions and Stock Returns: Excluding Salient Industries

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry level. The sample excludes companies in the oil & gas (gic=2), utilities (gic=65-69), and motor (gic=18, 19, 23) industries All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.094***			0.221***		
	(0.025)			(0.052)		
LOG (TOT SCOPE 2)		0.132***			0.283***	
		(0.035)			(0.066)	
LOG (TOT SCOPE 3)			0.160**			0.400***
			(0.053)			(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	169,691	169,763	169,787	169,691	169,763	169,787
R-squared	0.207	0.207	0.207	0.209	0.210	0.210

Panel B: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.725***			0.717***		
	(0.232)			(0.214)		
ΔSCOPE 2		0.538**			0.534**	
		(0.181)			(0.176)	
ΔSCOPE 3			1.533***			1.562***
			(0.430)			(0.423)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	139,975	140,023	140,047	139,975	140,023	140,047
R-squared	0.224	0.224	0.224	0.227	0.227	0.227

Table 14: Carbon Emissions and Institutional Ownership: Excluding Salient Industries

The sample excludes companies in the oil & gas (gic=2), utilities (gic=65-69), and motor (gic=18, 19, 23) industries. The sample period is 2005-2017. Panel A presents the results for aggregate ownership for contemporaneous carbon intensity measures, Panel B for disaggregated ownership for Scope 1, Panel C for disaggregated ownership for Scope 2, Panel D for disaggregated ownership for Scope 3. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry and year level. All regressions include year-month fixed effects. In Panel A, columns (2), (4), and (6) additionally include state-fixed effects. All regressions in Panels B-D include state fixed effects. ***1%; **5%; *10% significance.

Panel A: Aggregate Ownership

Variables	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	-0.021	-0.007				
	(0.094)	(0.104)				
SCOPE 2			-0.581	-0.525		
			(1.972)	(2.024)		
SCOPE 3					0.415	0.246
					(0.540)	(0.568)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	152,663	143,325	152,663	143,325	152,663	143,325
R-squared	0.127	0.169	0.127	0.169	0.128	0.169

Panel B: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 1	0.001*	-0.013	-0.059	-0.060	0.009	0.114
	(0.000)	(0.012)	(0.041)	(0.078)	(0.010)	(0.068)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,325	143,325	143,325	143,325	143,325	143,325
R-squared	0.154	0.027	0.212	0.156	0.231	0.165

Panel C: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 2	0.006	-0.298*	-0.320	-0.224	0.051	0.261
	(0.006)	(0.164)	(0.487)	(1.252)	(0.124)	(0.523)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,325	143,325	143,325	143,325	143,325	143,325
R-squared	0.154	0.028	0.212	0.155	0.231	0.164

Panel D: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 3	0.004*	-0.015	0.063	0.436	0.041	-0.282
	(0.002)	(0.077)	(0.125)	(0.376)	(0.031)	(0.170)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,325	143,325	143,325	143,325	143,325	143,325
R-squared	0.155	0.027	0.212	0.157	0.231	0.166

Table 15: Carbon Emissions and Stock Returns: Sub-Periods

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. We report the results for the natural logarithm of contemporaneous total emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

	2005-2015			2016-2017		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.159***			0.218**		
	(0.050)			(0.107)		
LOG (TOT SCOPE 2)		0.155**			0.254**	
		(0.064)			(0.114)	
LOG (TOT SCOPE 3)			0.328**			0.352***
			(0.118)			(0.135)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	124,972	124,900	125,056	65,464	65,464	65,476
R-squared	0.263	0.263	0.263	0.111	0.111	0.111

Panel B: Growth rate in total emissions

	2005-2015			2016-2017		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.692***			0.768		
	(0.186)			(0.701)		
ΔSCOPE 2		0.335**			0.647	
		(0.131)			(0.568)	
ΔSCOPE 3			1.298**			1.306
			(0.551)			(1.067)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,813	111,729	111,873	46,188	46,176	46,200
R-squared	0.274	0.274	0.274	0.087	0.086	0.087

Table 16: Carbon Emissions and Stock Returns (1990-1999)

The sample period is 1990-1999. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. The total level of emissions is imputed using the earliest observed level of emission intensity for each firm and the actual revenue values from the period 1990-1999. ***1% significance; **5% significance; *10% significance.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	-0.037			0.082		
	(0.034)			(0.078)		
LOG (TOT SCOPE 2)		0.033			0.236	
		(0.045)			(0.134)	
LOG (TOT SCOPE 3)			0.005			0.318*
			(0.059)			(0.162)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	59,878	59,878	59,878	59,878	59,878	59,878
R-squared	0.149	0.149	0.149	0.156	0.156	0.156

Online Appendix

Table A.1: Carbon Emissions: Sample Selection

Providing carbon data?	No	Yes
RET	1.222	1.152
SIZE	2645.00	12685.03
B/M	0.598	0.497
LEVERAGE	0.202	0.252
MOM	0.198	0.147
INVEST/A	0.041	0.046
LOGPPE	4.124	6.200
BETA	0.958	1.101
VOLAT	0.131	0.096

Table A.2: Carbon Emissions and Stock Returns

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Lagged emission intensity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	-0.003			0.009		
	(0.011)			(0.008)		
SCOPE 2		0.127			0.095	
		(0.128)			(0.108)	
SCOPE 3			0.085**			0.171**
			(0.035)			(0.075)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	Yes	Yes
Observations	160,592	160,592	160,592	156,082	156,082	156,082
R-squared	0.206	0.206	0.207	0.215	0.215	0.215

Table A.3: Carbon Emissions and Unexpected Profitability

The sample period is 2005-2017. The dependent variable is *UP*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Lagged emission intensity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	-0.004***			-0.001**		
	(0.001)			(0.000)		
SCOPE 2		-0.021*			-0.023***	
		(0.010)			(0.007)	
SCOPE 3			-0.003			0.002
			(0.003)			(0.007)
LOGSIZE	0.016***	0.016***	0.016***	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry adj.	No	No	No	Yes	Yes	Yes
Observations	112,425	112,425	112,425	110,517	110,517	110,517
R-squared	0.091	0.073	0.071	0.367	0.368	0.367

Table A.4: Can the Carbon Premium be Explained by Risk Factors?

The sample period is 2005-2017. The dependent variable is the monthly carbon premium based on lagged emission intensity estimated each period using a cross-sectional return regression. All variables are defined in Table 1. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using Newey-West test. ***1% significance; **5% significance; *10% significance.

	Lagged emission intensity					
	SCOPE 1		SCOPE 2		SCOPE 3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MKTRF		-0.836***		0.132		0.268
		(0.182)		(2.937)		(0.836)
HML		-0.567*		-5.317		-4.430**
		(0.311)		(5.006)		(2.180)
SMB		-0.967*		-9.137*		-1.292
		(0.543)		(5.358)		(1.359)
MOM		0.768***		-0.468		-0.854
		(0.247)		(3.053)		(0.670)
CMA		-0.000		0.016		0.052
		(0.007)		(0.089)		(0.037)
BAB		0.456		-5.856		-1.451

		(0.397)		(4.091)		(0.895)
LIQ		0.227		2.384		2.504***
		(0.285)		(2.667)		(0.775)
NET ISSUANCE		0.229		-8.034*		0.942
		(0.402)		(4.390)		(1.278)
IDIO VOL		0.203		8.912***		0.640
		(0.302)		(3.182)		(1.025)
Constant	-0.002	0.002	0.141	0.234***	0.048*	0.042*
	(0.009)	(0.008)	(0.099)	(0.087)	(0.027)	(0.027)
Industry adj.	No	No	No	No	No	No
Adj. R2	0.001	0.400	0.001	0.151	0.001	0.109
Observations	144	144	144	144	144	144

Table A.5: Carbon Emissions and Institutional Ownership

The sample period is 2005-2017. The dependent variable in Panel A is *IO*. The dependent variables in Panel B and Panel C are *IO_BANK, IO_INSURANCE, IO_INVESTCOS, IO_ADVISERS, IO_PENSIONS,* and *IO_HFS*. Panel B presents the results for *SCOPE 3*, and Panel C presents the results for *SCOPE 12*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry level. All regressions include year-month fixed effects. In columns (2) and (4), we additionally include state-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Aggregate Ownership (Total Carbon Emissions)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.580	0.627				
	(0.488)	(0.522)				
LOG (TOT SCOPE 2)			1.621**	1.805***		
			(0.564)	(0.567)		
LOG (TOT SCOPE 3)					1.532**	1.564**
					(0.639)	(0.678)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	170,481	160,322	170,409	160,250	170,553	160,394
R-squared	0.123	0.167	0.137	0.184	0.131	0.174

Panel B: Disaggregate Ownership (Total Emissions SCOPE 1)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
LOG (TOT SCOPE 1)	0.003**	-0.052	0.146*	0.290	0.050**	0.191*
	(0.001)	(0.043)	(0.067)	(0.382)	(0.022)	(0.106)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,322	160,322	160,322	160,322	160,322	160,322
R-squared	0.166	0.026	0.212	0.147	0.233	0.179

Panel C: Disaggregate Ownership (Total Emissions SCOPE 2)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
LOG (TOT SCOPE 2)	0.004***	-0.081	0.102	1.291***	0.125***	0.363**
	(0.001)	(0.060)	(0.114)	(0.349)	(0.023)	(0.151)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,250	160,250	160,250	160,250	160,250	160,250
R-squared	0.166	0.026	0.210	0.166	0.239	0.180

Panel D: Disaggregate Ownership (Total Emissions SCOPE 3)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
LOG (TOT SCOPE 3)	0.006**	-0.054	0.116	1.178**	0.137***	0.181
	(0.002)	(0.063)	(0.112)	(0.458)	(0.029)	(0.188)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,394	160,394	160,394	160,394	160,394	160,394
R-squared	0.166	0.025	0.210	0.158	0.238	0.177

Panel A.2: Aggregate Ownership (Growth Rate in Carbon Emissions)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	-0.669	-0.356				
	(0.594)	(0.612)				
ΔSCOPE 2			-1.375**	-1.270*		
			(0.605)	(0.601)		
ΔSCOPE 3					-1.238	-0.866
					(1.669)	(1.789)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	141,599	133,219	141,503	133,123	141,647	133,267
R-squared	0.090	0.139	0.090	0.139	0.089	0.139

Panel B.2: Disaggregate Ownership (Change in Emissions SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 1	0.000	-0.073	0.241	-0.974*	-0.171	0.621**
	(0.003)	(0.051)	(0.301)	(0.535)	(0.102)	(0.263)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133,219	133,219	133,219	133,219	133,219	133,219
R-squared	0.190	0.026	0.180	0.122	0.192	0.174

Panel C.2: Disaggregate Ownership (Change in Emissions SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 2	-0.006	-0.053	-0.011	-1.383**	-0.223**	0.407*
	(0.004)	(0.035)	(0.261)	(0.448)	(0.072)	(0.225)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133,123	133,123	133,123	133,123	133,123	133,123
R-squared	0.191	0.026	0.180	0.124	0.193	0.173

Panel D2: Disaggregate Ownership (Change in Emissions SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 3	-0.006	-0.088	0.440	-1.733	-0.455***	0.977**
	(0.008)	(0.064)	(0.556)	(1.297)	(0.143)	(0.402)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	133,267	133,267	133,267	133,267	133,267	133,267
R-squared	0.190	0.026	0.180	0.122	0.193	0.174

Table A.6: Carbon Emissions and Stock Returns: Sub-Periods

The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. In columns (1)-(3), the sample period is 2005-2015, and in columns (4)-(6) the sample period is 2016-2017. All regressions include year-month fixed effects and industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Lagged emission intensity

	2005-2015			2016-2017		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	0.009			-0.004		
	(0.010)			(0.005)		
SCOPE 2		0.063			0.106	
		(0.152)			(0.076)	
SCOPE 3			0.197**			0.039
			(0.087)			(0.096)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111,122	111,122	111,122	44,869	44,869	44,869
R-squared	0.273	0.273	0.273	0.084	0.084	0.084

Table A.7: Carbon Emissions and Stock Returns: Excluding Salient Industries

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. The sample excludes companies in the oil & gas (gic=2), utilities (gic=65-69), and motor (gic=18, 19, 23) industries All regressions include year-month fixed effects. In columns (4)-(6), we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Lagged emission intensity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	0.001			0.022		
	(0.023)			(0.022)		
SCOPE 2		0.181			0.138	
		(0.115)			(0.108)	
SCOPE 3			0.075*			0.229**
			(0.039)			(0.091)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	142,775	142,775	142,775	138,272	138,272	138,272
R-squared	0.217	0.217	0.217	0.227	0.227	0.227

Table A.8: Carbon Emissions and Institutional Ownership: Excluding Salient Industries

The sample excludes companies in the oil & gas (gic=2), utilities (gic=65-69), and motor (gic=18, 19, 23) industries. The sample period is 2005-2017. Panel A presents the results for aggregate ownership for total carbon emissions, Panel B for disaggregated ownership for Scope 1, Panel C for disaggregated ownership for Scope 2, Panel D for disaggregated ownership for Scope 3. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry and year level. All regressions include year-month fixed effects. In columns (2), (4), and (6), we include state-fixed effects. ***1%; **5%; *10% significance.

Panel A: Aggregate Ownership (Contemporaneous Total Carbon Emissions)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	1.299**	1.416**				
	(0.496)	(0.515)				
LOG (TOT SCOPE 2)			1.759**	2.006***		
			(0.659)	(0.646)		
LOG (TOT SCOPE 3)					1.922**	2.029***
					(0.633)	(0.661)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	152,591	143,253	152,663	143,325	152,663	143,325
R-squared	0.145	0.190	0.147	0.195	0.146	0.190

Panel B: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 1)	0.004**	-0.046	0.138	0.974**	0.099***	0.248*
	(0.002)	(0.054)	(0.088)	(0.342)	(0.023)	(0.137)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,253	143,253	143,253	143,253	143,253	143,253
R-squared	0.156	0.028	0.213	0.174	0.239	0.167

Panel C: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 2)	0.004***	-0.099	0.134	1.375***	0.143***	0.449**
	(0.001)	(0.073)	(0.124)	(0.412)	(0.024)	(0.162)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,325	143,325	143,325	143,325	143,325	143,325
R-squared	0.156	0.029	0.212	0.179	0.241	0.170

Panel D: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 3)	0.006**	-0.058	0.159	1.554***	0.155***	0.214
	(0.002)	(0.065)	(0.108)	(0.421)	(0.029)	(0.209)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,325	143,325	143,325	143,325	143,325	143,325
R-squared	0.156	0.027	0.212	0.179	0.240	0.165

Panel A.2: Aggregate Ownership (Growth Rate in Carbon Intensity)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	-0.927	-0.679				
	(0.768)	(0.734)				
ΔSCOPE 2			-1.176	-1.032		
			(0.742)	(0.664)		
ΔSCOPE 3					-1.498	-1.212
					(2.028)	(2.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	125,888	118,117	125,936	118,165	125,936	118,165
R-squared	0.094	0.140	0.095	0.140	0.094	0.140

Panel B.2: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 1	0.001	-0.066	0.162	-0.994	-0.177	0.395**
	(0.003)	(0.058)	(0.339)	(0.557)	(0.102)	(0.174)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,117	118,117	118,117	118,117	118,117	118,117
R-squared	0.179	0.029	0.180	0.128	0.195	0.160

Panel C.2: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 2	-0.009*	-0.032	-0.031	-1.106**	-0.248***	0.394*
	(0.005)	(0.036)	(0.304)	(0.478)	(0.079)	(0.201)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,165	118,165	118,165	118,165	118,165	118,165
R-squared	0.179	0.029	0.180	0.128	0.196	0.160

Panel D.2: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
ΔSCOPE 3	-0.009	-0.079	0.547	-1.678	-0.442**	0.449
	(0.010)	(0.071)	(0.659)	(1.272)	(0.155)	(0.489)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,165	118,165	118,165	118,165	118,165	118,165
R-squared	0.179	0.029	0.180	0.128	0.196	0.160

Table A.9: Carbon Emissions and Institutional Ownership: Salient Industries

The sample excludes companies in the oil & gas (gic=2), utilities (gic=65-69), and motor (gic=18, 19, 23) industries. The sample period is 2005-2017. Panel A presents the results for aggregate ownership for total carbon emissions, Panel B for disaggregated ownership for Scope 1, Panel C for disaggregated ownership for Scope 2, Panel D for disaggregated ownership for Scope 3. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry and year level. All regressions include year-month fixed effects. In columns (2), (4), and (6), we include state-fixed effects. ***1%; **5%; *10% significance.

Panel A: Aggregate Ownership (Contemporaneous Total Carbon Emissions)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.340	0.014				
	(1.286)	(0.948)				
LOG (TOT SCOPE 2)			-0.231	-0.686		
			(0.432)	(0.387)		
LOG (TOT SCOPE 3)					-1.690	-2.173**
					(1.722)	(0.723)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	17,892	17,070	17,748	16,926	17,892	17,070
R-squared	0.137	0.340	0.137	0.341	0.146	0.354

Panel B: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 1)	0.003	-0.013*	0.336	-0.895*	0.021	0.563
	(0.003)	(0.007)	(0.371)	(0.482)	(0.036)	(0.427)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,070	17,070	17,070	17,070	17,070	17,070
R-squared	0.377	0.215	0.318	0.316	0.414	0.351

Panel C: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 2)	0.006**	0.013	-0.171	-0.043	0.048	-0.540
	(0.002)	(0.008)	(0.194)	(0.319)	(0.042)	(0.352)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,926	16,926	16,926	16,926	16,926	16,926
R-squared	0.381	0.215	0.316	0.303	0.415	0.350

Panel D: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
LOG (TOT SCOPE 3)	-0.002	-0.003	-0.695**	-1.476***	-0.006	0.009
	(0.004)	(0.004)	(0.313)	(0.415)	(0.068)	(0.515)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,070	17,070	17,070	17,070	17,070	17,070
R-squared	0.377	0.211	0.322	0.320	0.413	0.345

Panel A.2: Aggregate Ownership (Growth Rate in Carbon Intensity)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	2.386	2.280				
	(1.515)	(1.442)				
ΔSCOPE 2			-0.191	0.572		
			(1.162)	(1.068)		
ΔSCOPE 3					2.435	3.055
					(2.318)	(2.100)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	15,713	15,103	15,569	14,959	15,713	15,103
R-squared	0.136	0.369	0.134	0.362	0.134	0.368

Panel B.2: Disaggregate Ownership (SCOPE 1)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
ΔSCOPE 1	0.000	-0.019	0.519	-0.054	0.078	1.756
	(0.006)	(0.019)	(0.553)	(1.050)	(0.119)	(1.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,103	15,103	15,103	15,103	15,103	15,103
R-squared	0.414	0.212	0.316	0.315	0.389	0.355

Panel C.2: Disaggregate Ownership (SCOPE 2)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
ΔSCOPE 2	0.004	-0.019**	0.203	-0.265	0.000	0.650
	(0.006)	(0.008)	(0.524)	(0.646)	(0.039)	(0.467)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,959	14,959	14,959	14,959	14,959	14,959
R-squared	0.413	0.212	0.315	0.310	0.388	0.350

Panel D.2: Disaggregate Ownership (SCOPE 3)

VARIABLES	(1) Banks	(2) Insurance	(3) Invest. Cos.	(4) Advisers	(5) Pensions	(6) Hedge Funds
ΔSCOPE 3	0.011	-0.056**	0.067	-0.191	-0.176*	3.400***
	(0.010)	(0.021)	(1.516)	(1.697)	(0.091)	(0.807)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,103	15,103	15,103	15,103	15,103	15,103
R-squared	0.414	0.213	0.315	0.315	0.389	0.358

Table A.10: Carbon Emissions and Stock Returns (Reduced Controls)

The sample period is 2005-2017. The dependent variable is *RET*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon emissions. ***1% significance; **5% significance; *10% significance.

Panel A: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	-0.007	0.021				
	(0.022)	(0.045)				
LOG (TOT SCOPE 2)			0.005	0.075		
			(0.022)	(0.074)		
LOG (TOT SCOPE 3)					0.023	0.115
					(0.028)	(0.083)
LOGSIZE		-0.127		-0.177		-0.212
		(0.126)		(0.157)		(0.161)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	No	No	No
Observations	203,663	203,525	203,591	203,453	203,759	203,621
R-squared	0.192	0.192	0.192	0.193	0.192	0.193

Panel B: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.735**	0.735**				
	(0.240)	(0.244)				
ΔSCOPE 2			0.459**	0.460**		
			(0.200)	(0.200)		
ΔSCOPE 3					1.298**	1.303**
					(0.516)	(0.501)
LOGSIZE		-0.030		-0.031		-0.038
		(0.111)		(0.112)		(0.111)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	No	No	No
Observations	167,755	167,648	167,659	167,552	167,827	167,720
R-squared	0.208	0.208	0.208	0.208	0.208	0.208

Panel C: Contemporaneous total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	-0.001	0.185**				
	(0.036)	(0.081)				
LOG (TOT SCOPE 2)			-0.015	0.191*		
			(0.036)	(0.100)		
LOG (TOT SCOPE 3)					-0.010	0.300**
					(0.044)	(0.132)
LOGSIZE		-0.311*		-0.337*		-0.421*
		(0.154)		(0.178)		(0.201)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	203,663	203,525	203,591	203,453	203,759	203,621
R-squared	0.195	0.195	0.195	0.196	0.195	0.196

Panel D: Growth rate in total emissions

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
ΔSCOPE 1	0.704***	0.701***				
	(0.217)	(0.221)				
ΔSCOPE 2			0.426**	0.425**		
			(0.190)	(0.191)		
ΔSCOPE 3					1.198**	1.208**
					(0.503)	(0.488)
LOGSIZE		-0.094		-0.095		-0.101
		(0.120)		(0.122)		(0.120)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	167,755	167,648	167,659	167,552	167,827	167,720
R-squared	0.211	0.211	0.211	0.211	0.211	0.211

Table A.11: Carbon Emissions and Institutional Ownership (Logs)

The sample period is 2005-2017. The dependent variable in Panel A is *IO*. The dependent variables in Panel B, Panel C, and Panel D are *IO_BANK, IO_INSURANCE, IO_INVESTCOS, IO_ADVISERS, IO_PENSIONS,* and *IO_HFS*. Panels A-D present the result for contemporaneous measures of emission intensity. Panel B presents the results for *SCOPE 1*, Panel C presents the results for *SCOPE 2*, and Panel D presents the results for *SCOPE 3*. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the industry and year level. All regressions include year-month fixed effects. In Panel A, columns (2), (4), and (6) additionally include state-fixed effects. All regressions in Panels B-D include state fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Aggregate Ownership (Carbon Intensity)

Variables	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1	-0.002*	-0.003**				
	(0.001)	(0.001)				
SCOPE 2			-0.028	-0.033		
			(0.042)	(0.044)		
SCOPE 3					0.006	0.001
					(0.009)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	No	Yes	No	Yes	No	Yes
Observations	170,665	160,493	170,665	160,493	170,665	160,493
R-squared	0.161	0.171	0.160	0.171	0.160	0.170

Panel B: Disaggregate Ownership (SCOPE 1)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 1	0.001**	-0.001**	0.002*	-0.006***	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,493	160,493	160,493	160,493	160,493	160,493
R-squared	0.283	0.079	0.263	0.198	0.423	0.184

Panel C: Disaggregate Ownership (SCOPE 2)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 2	0.008*	-0.023*	-0.018	-0.022	0.010	0.004
	(0.004)	(0.012)	(0.035)	(0.039)	(0.025)	(0.043)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,493	160,493	160,493	160,493	160,493	160,493
R-squared	0.283	0.080	0.263	0.193	0.423	0.184

Panel D: Disaggregate Ownership (SCOPE 3)

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Banks	Insurance	Invest. Cos.	Advisers	Pensions	Hedge Funds
SCOPE 3	0.003*	0.004	0.009	0.005	0.012	-0.016
	(0.001)	(0.006)	(0.007)	(0.011)	(0.007)	(0.013)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	160,493	160,493	160,493	160,493	160,493	160,493
R-squared	0.284	0.079	0.263	0.193	0.424	0.185