CO_2 Emissions and the Pricing of Climate Risk

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October 4, 2017

We provide evidence that firms with higher carbon exposure earn lower future returns in asset pricing context in U.S. stock markets for a 41-year period from January 1976 to December 2016. The quintile hedging strategy buying the lowest CO_2 emission beta portfolio and selling the highest emission beta portfolio earns 3.6-5.3% average annual returns (4.3-6.2% on decile). The negative relation between carbon exposure and future returns is consistent with the view that CO_2 emissions are indicative of perceived deterioration of investment opportunities by investors. Our evidence is also consistent with the view that asset prices have an optimistic bias because investors with low value expectations stay on the sideline without trading. Notably, our result is not consistent with a risk premium view that carbon exposure proxies for market risk nor with a view that no trading profits are possible on the basis of publicly available information on CO_2 emissions. Our preliminary additional tests suggest, however, that our main results are more supportive of the investment opportunities explanation than the Miller's optimistic pricing view.

JEL codes: G12, Q54, G11, G32

Keywords: Climate finance, climate change, carbon emission exposure, asset pricing, risk management

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Although climate finance plays a critical role in global efforts to tackle climate change, it can be a complex and confusing one. The Standing Committee on Finance (2014) of the United Nations Framework Convention on Climate Change (UNFCCC) defines the purpose of climate finance as follows: "Climate finance aims at reducing emissions, and enhancing sinks of greenhouse gases (GHG) and aims at reducing vulnerability of, and maintaining and increasing the resilience of, human and ecological systems to negative climate change impacts." (p.5). This definition, reached out of convergence of differing views across nations, represents climate finance in its broadest form. In this broad form, the achievement of targets laid out in the Paris Agreement of 2016 and scaling up of efforts to keep global warming under control below 2ºC will be directly contingent on the amount of finance that is accessible and how it is used (Buchner, Trabacchi, Mazza, Abramskiehn, and Wang, 2015).

Carbon emissions contribute to air pollution and climate change, which can have serious consequences for humans, environments, and capital markets. There is a scientific consensus that global warming is indeed caused by the emission of greenhouse gases (Lal, 2004; Siegenthaler, 2005; Rohrer, 2007; Jacobson, 2008; Lüthi et al, 2008; Solomon, Plattner, Knutti, and Friedlingstein, 2009). Chief among the greenhouse gases (GHG) is carbon emissions as 72% of the total emitted GHG is carbon dioxide (CO_2), followed by 18% methane and 9% nitrous oxide. CO_2 is inevitably created by burning fuels such as oil, natural gas, diesel, organic-diesel, petrol, organic-petrol, and ethanol. The emissions of CO_2 have increased dramatically in the past 50 years and are still increasing by almost 3% every year (Rohrer, 2007). In fact, global warming is primarily a problem of too much CO_2 in the atmosphere. Although there are other heat-trapping gases (from methane to water vapor), CO_2 stands out and puts us at the greatest risk of irreversible climate changes because it continues to accumulate unabated in the atmosphere (Siegenthaler, 2005; Lüthi et al., 2008). Lemoine and Rudik (2017) suggest that one year's temperature is determined not just by the contemporary quantity of CO_2 in the atmosphere but also by the past trajectory of CO_2, and claim that the climate system displays substantial inertia, warming slowly in response to additional CO_2.

According to the U.S. Environmental Protection Agency (EPA), carbon emissions make up more than 80% of the GHG emitted in the United States (Consequences of Carbon Emissions for Humans, 2017). The burning of fossil fuels releases carbon dioxide and other GHGs. A consensus view in climate science is that these carbon emissions raise global temperatures by trapping solar energy in the atmosphere, alter water supplies and weather patterns, and change the growing seasons for food crops and threaten coastal communities with increasing sea levels (Lal, 2004; Jacobson, 2008; Solomon, Plattner, Knutti, and Friedlingstein, 2009). Jacobson (2008) estimates that an increase of one degree Celsius in air temperature – due to carbon dioxide and the resulting air pollution - is associated with a thousand additional human deaths and many more cases of respiratory illness and asthma in the United States. Worldwide, the human toll is in the upward of 20,000 air-pollution-related deaths per year for each increase in one degree Celsius due to this greenhouse gas. Deschênes, Greenstone, and Shapiro (2017) also provide evidence on how air pollution affects mortality and hospitalizations.

Economically, it is clear that, if it continues, the CO_2 emissions and their consequences through both human and environmental channels would have far-reaching economic consequences, raising the risks and affecting the profitability of firms and industries as well as the sustainability of our economic and environmental systems. Capitalizing on the notion of externality in environmental economics that the private and social costs and benefits of carbon emissions differ between firms and nations, the cap-and-trade has been implemented in

Europe.[1] However, the finance literature has largely ignored the pricing of climate risk in the asset pricing context.

In this paper, we provide evidence on the market effects of climate risk in U.S. stock market. Specifically, we examine the pricing of portfolios investing in "climate risk" stocks, i.e., publicly traded companies involved in CO_2 emissions. Because CO_2 continues to accumulate unabated in the atmosphere, it is insufficient to understand the effect of carbon emissions on future stock returns only based on each firm's CO_2 emissions alone. In addition, Deschênes, Greenstone, and Shapiro (2017) claim that investors' willingness to pay (WTP) for air quality improvements depends on direct investments that might be available from investment opportunities that help to determine factors that enter the utility function directly (Grossman, 1972). It is critical to understand each firm's sensitivity to aggregate atmospheric CO_2 (hereafter we call it carbon exposure). Our main objective is, therefore, to analyze the role of a firm's carbon exposure in predicting the cross section of future stock returns from the viewpoint of future investment opportunities. We believe this study on how carbon exposure influences asset pricing is new.

We focus on asset-pricing portfolio approach for stocks of all U.S. manufacturing firms traded in the New York Stock Exchange, American Exchange, and the NASDAQ for the 41-year period from January 1976 to December 2016. We regress one-month ahead of monthly excess firm returns on the CAPM, Fama-French (1993) three factor model, the Carhart (1997) four factor model, and the Fama-French (2015) five factor model, supplemented by Hou, Xue and Zhang (2015) Q4 factors, and Stambaugh and Yuan (2017) mispricing factors. To our knowledge, this is the first attempt to investigate the investment performance of climate risk stocks within asset pricing and portfolio contexts in the U.S.

[1] Laing, Sato, Grubb and Comberti (2013) assess the effectiveness of the emission trading scheme in the European Union. They conclude that the lack of flexibility of the scheme and the inability to adjust to altered economic conditions threatens to undermine the efficacy of the system.

Our preliminary results suggest that stocks with higher carbon exposure earn significantly lower future returns than otherwise similar stocks. This is clearly inconsistent of familiar risk premium hypothesis (Merton, 1987; Goyal and Santa-Clara, 2003; Fu, 2009), as the relation between carbon exposure and future returns is negative. Furthermore, we present evidence that standard risk-based multifactor models cannot account for this relation. Rather we suggest an investment opportunity hypothesis that carbon exposure is indicative of a deteriorating investment opportunity; we adapted this from Ang, Hodrick, Xing, and Zhang (2006) who advocated a similar relation between increasing market volatility and decreasing investment opportunity and Deschênes, Greenstone, and Shapiro (2017) who supported the relation between investors' willingness to pay for well-being and investment opportunities. Our results are also consistent with the Miller's (1977) view that asset prices have an optimistic bias in that pessimistic investors with low value expectations do not trade given high short-sale costs. In the present context, the implication is that pessimistic investors stay on the sideline without trading when the perceived costs of carbon emissions are high. Our preliminary additional tests suggest, however, that our main results are closer to the investment opportunities explanation than the Miller's optimistic pricing view.

Our study is remotely related to papers that document the effect of weather on worker mood and productivity (DeHassan, Madsen, and Piotrosk, 2015), and on behavioral biases of managers and investors (Goetzmann, Kim, Kumar, and Wang, 2014; Agnes, Xie, and Zhang, 2017; Li, Massa, Zhang, and Zhang, 2017). Our work differs from these studies in several ways. First, we focus on the relation between carbon exposure and future stock returns in asset pricing context. Second, we take the asset-pricing portfolio approach partly because stock returns are less susceptible to reverse causality and endogeneity concerns compared to corporate financial performance measures. Third, our work builds on the work on assessing the performance of socially responsible mutual funds (Hamilton, Jo, and Statman, 1993; Renneboog, Ter Horst, and Zhang, 2009), or on more general work that indicates the pricing of idiosyncratic or residual risk (Merton, 1987; Goyal and Santa-Clara, 2003; Fu, 2009), the idiosyncrasy of the firm being exposed to climate risk. Our paper on carbon exposure is also related, in spirit, to the work of Hong and Kacperczyk (2009) who examine the investment in "sin" companies engaged in alcohol, tobacco, and gaming vice. We examine the predictability of the effect of carbon exposure on future cross-sectional stock returns using several asset pricing models.

Closely related to our work is a "small sample" study of the Euopean Union's carbon trading scheme by Oestreich and Tsiakas (2015), who examined the effect of carbon allowances received by 24 German firms on their stock returns vs. 41 firms who did not. They interpreted the receipt of carbon allowances as carbon emissions by each firm, although there is no net increase in new carbons released into the atmosphere by carbon trading. We investigate the effect of a firm's sensitivity to aggregate atmospheric CO_2 (*carbon exposure* or carbon beta) to future stock returns using a large comprehensive panel data in the U.S. for 41-year period. Our finding of a negative association between carbon exposure and stock return contrasts with their conclusion that "carbon emissions" (in fact, carbon allowances) are associated with higher stock returns.[2]

The paper is organized as follows. In Section 1, we discussed competing hypotheses concerning the relation between a firm's carbon exposure and stock return. Section 2 present data and method, and Section 3 discusses research design. Section 4 present empirical results, and Section 5 concludes including the summary of our research and the plan for additional work with the timeline for the delivery.

[2] Our untabulated result from carbon *reduction* data by firms (obtained from Thomposon Reuter ASSET4 database) that lower carbon *reduction* is associated with higher return is inconsistent with their result, indicating that carbon reduction by the firm, or carbon trading that enables it, is not positively rewarded by the market.

1. Competing Hypotheses

We test three competing hypotheses about the relation between carbon exposure and future stock returns. First, the investment opportunity hypothesis views carbon exposure as a proxy for an indication of deteriorating investment opportunity sets, similar to Ang, Hodrick, Xing, and Zhang (2006) who examined the increased stock market volatility as indicative of deteriorating investment opportunities. From a different angle, Deschênes, Greenstone, and Shapiro (2017) suggest that the empirical evidence on WTP has almost exclusively focused on the factors that enter the utility function directly. The resulting measures of WTP are thus generally underestimated and the extent of this underestimation is unknown. They demonstrate that defensive investments are an important part of WTP for air quality. Thus, we suspect that firms' compensatory behavior of reducing air pollution, i.e., low carbon exposure and resulting defensive investments from expanded investment opportunities set account for certain fraction of WTP. Together, we expect an inverse relation between carbon exposure and stock returns of the firm: the higher the firm's level of carbon exposure, the smaller its investment opportunity sets and hence the lower its future returns.

Alternatively, Miller (1977) argues that asset prices will err on the side of optimistic valuation if pessimistic investors are kept out of the market by high short-sale costs. In Miller's model, optimists hold the stock because they have a higher valuation for the firm than an average market expectation. This price-optimism model suggests that the bigger the disagreement about a true value of the firm, the higher the market price relative to the true value of the stock, and the lower its future returns. Thus, both of these models predict the negative relation between observed carbon exposure and future stock returns.

Second, the unbiasedness hypothesis views that market prices will be unbiased even when CO_2 emission levels diverge across firms, and future returns will be independent of the current level of carbon exposure. The key assumption in this hypothesis is similar to that of

Diamond and Verrecchia (1987) who assume that the market-maker has perfect knowledge of his economic environment and can perform Bayesian updating in the short time between consecutive trades. Hong and Stein (2003), similarly, achieve unbiased pricing by introducing competitive, risk-neutral, and perfectly rational arbitrageurs who can correctly infer the expected asset prices. Both of these models predict that no excess trading profits can be made based on publicly available information, and that there is no relation between observed carbon exposure and future returns.

The third is the familiar risk premium hypothesis, which considers carbon exposure as a proxy for the firm's non-diversifiable risk. Or investors who are not well diversified will demand compensation for the idiosyncratic risk of the securities they hold (Merton, 1987; Goyal and Santa-Clara, 2003; Fu, 2009). Since higher carbon exposure likely indicates a more volatile and less predictable earnings stream, stocks with higher carbon exposure should earn higher expected returns.

In sum, the investment opportunity hypothesis and Miller's optimistic pricing hypothesis predict a negative relation between carbon exposure and future returns. The unbiasedness hypothesis predicts no relation. And the third risk premium hypothesis predicts a positive relation between the two.

2. Data and Methodology

This section introduces the data set and methodology used to estimate the firm-level CO_2 emission factor loadings ($\beta^{i}_{\ln\_co2}$) in cross-sectional context.

2.1. Data

The total U.S. energy CO_2 emissions data are from the U.S. Energy Information Administration (EIA) webpage (https://www.eia.gov/totalenergy/data/browser/?tbl=T12.01). EIA estimates these data from carbon dioxide (CO_2) emissions from energy consumption, including the nonfuel use of fossil fuels. The data provides carbon dioxide emissions in million metric tons from energy consumptions of 12 different energy products; coal (including coal coke net imports), natural gas (excluding supplemental gaseous fuels), aviation gasoline, distillate fuel oil (excluding biodiesel), jet fuel, kerosene, LPG, lubricants, motor gasoline (excluding ethanol), petroleum coke, residual fuel oil, and other petroleum products (excluding biofuels). These data cover the period from January 1, 1976 to December 31, 2016.[3]

We also obtained alternative carbon emissions data from fossil fuel combustion from Carbon Dioxide Information Analysis Center (CDIAC) webpage (http://cdiac.ornl.gov/trends/emis_mon/emis_mon_co2.html). These data were estimated from the values of fuels consumed: in billions of cubic feet for natural gas, in millions of barrels for petroleum products, and in thousands of short tons for coal.[4] We use this CDIAC data only for robustness check because this dataset only covers from January 1981 to December 2003.

Our daily and monthly stock sample includes all common stocks (shrcd in 10 or 11) traded on NYSE (exchcd=1), Amex (exchcd=2), and NASDAQ (exchcd=3) from January 1, 1976 through December 31, 2016. We require at least 12 monthly observations for inclusion in the monthly stock return dataset. Accounting data was obtained from Compustat. Fama-French market factors $[R_M - R_f]$, small minus big firm size premium (*SMB*), and high minus low book-to-market ratios (*HML*), and the momentum factor (*UMD*), robust minus weak factor (*RMW*) and conservative minus aggressive factor (*CMA*) were obtained from Kenneth French's data library.[5] Hou, Xue and Zhang (2015) Q-4 factors of the market factor (*MKT*), a size factor (*ME*), an investment factor (I/A) and a profitability factor (*ROE*) are provided by Zhang.

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[3] For details of procedures for estimating carbon dioxide emissions, see the U.S. Energy Information Administration (EIA), *Monthly Energy Review*, June 2017 (https://www.eia.gov/totalenergy/data/monthly/pdf/sec12.pdf).

[4] The emission estimates are expressed as teragrams of carbons. One teragram is 1012 grams, or 106 metric tons. To convert from carbon to carbon dioxide, multiply by 44/12 (=3.67).

[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Regarding mispricing factors of *MGMT* and *PERF*, Stambaugh and Yuan (2017) construct the first cluster of anomalies including net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. These six anomaly variables all represent quantities that firms' managements can affect directly. Following Stambaugh and Yuan (2017), we denote the factor arising from this cluster as MGMT (see factor construction in Stambaugh and Yuan (2017)). The second cluster includes distress, O-score, momentum, gross profitability, and return on assets. These five anomaly variables are related more to performance and less directly controlled by management, so following Stambaugh and Yuan (2017), we denote the factor arising from this cluster as PERF. We obtain mispricing factors of Stambaugh and Yuan (2017), *MKT, SMB, MGMT* and *PERF*, from Yuan's website.[6]

We also computed the industry- and characteristic-matched portfolio returns. Industry-matched portfolio returns are constructed based on 49-industry classification by Fama and French (1997). Characteristic-adjusted portfolio benchmarks are constructed following Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2004), which matches each stock to a portfolio of stocks with similar size, book-market ratio, and momentum.[7]

2.2. CO2 emission factor loadings ($\boldsymbol{\beta^{i}_{\ln\_co2}}$) and cross-sectional return predictors

For each stock and for each month, we estimate the CO_2 energy emission factor loadings (β_{ln_co2}) by running the monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the CO_2 emissions in natural log (*ln_co2)* and the market factor in eq. (1) over a 36-month time window. Alternatively, CO_2 emission factor loadings are estimated using the Fama and French

6 http://www.saif.sjtu.edu.cn/facultylist/yyuan/
7 The benchmark data are available in 'http://terpconnect.umd.edu/~wermers/ftpsite/Dgtw/coverpage.htm' for the period 1975-2012.

(1993) three-factor model with the market (*MKT*), size (*SMB*), book-to-market (*HML*) factors in eq. (2):

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t} \quad (1)$$

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t} \quad (2)$$

Following Fama and French (1992), Market betas (β_{MKT}^i) of individual stocks are estimated with rolling regressions using the previous 60 monthly returns available up to month t-1 given by eq. (3):

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{i,t} \quad (3)$$

We define a firm's size (*Size*) as the natural logarithm of the market capitalization (prc×shrout×1000), which is computed at the end of each month using CRSP data. Following Fama and French (1992, 1993, 2000), when computing book-to-market ratios (*BTM*), we match the yearly book value of equity or BE [book value of common equity plus deferred taxes and investment tax credit (txditc)] for all fiscal years ending in June 30 at year t to returns starting in July 1 of year t-1, and dividing this BE by the market capitalization at month t-1. The book-to-market ratio is computed on a monthly basis.

The excess returns of individual stocks over the past 30 days are regressed on Fama and French's (1993, 1996) three factors daily in eq. (4), or are estimated by Carhart four-factor model with the addition of the momentum factor monthly.

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i\left(R_{m,t} - R_{f,t}\right) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \varepsilon_{i,t} \quad (4)$$

Idiosyncratic volatility is computed as the standard deviation of the regression residuals every month. To reduce the impact of infrequent trading on idiosyncratic volatility estimates, we required a minimum of 15 trading days in a month for which CRSP reports, and both a daily return and non-zero trading volume was required for inclusion in the estimation.

3. Research Design

To investigate whether the carbon exposure, i.e., CO_2 emission factor loadings (β_{ln_co2}) explains the cross-sectional variation of expected stock returns, quintile or decile portfolios are formed each month by sorting individual stocks based on the CO_2 emission factor loadings (β_{ln_co2}). After portfolio formation, we record the next-month returns of each quintile (decile) portfolio over the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time.

We estimate the equally-weighted average monthly returns of quintile (decile) portfolios formed based on β_{ln_co2}. We form five (or ten depending on the classification scheme) portfolios according to the β_{ln_co2} in each month. Quintile 1 is composed of stocks with the lowest β_{ln_co2} while quintile 5 is composed of stocks with the highest β_{ln_co2} (and similarly for decile 1 to decile 10 portfolios). These portfolios are rebalanced every month, and held for the subsequent month. Besides average monthly returns of portfolios, we also report Jensen alphas of each quintile (decile) portfolio with respect to the CAPM, Fama-French 3 factor model, Carhart four-factor model, Fama-French five factor model, Hou, Xue and Zhang (2015) model with Q4 factors, and mispricing factors of Stambaugh and Yuan (2017).

To examine whether the β_{ln_co2} can predict stock returns, we also conduct Fama and MacBeth (1973) and other cross-sectional regressions at the firm level. Specifically, we consider market betas (β_{MKT}), size (*SIZE*), book-to-market (*BTM*), momentum (*MOM*), idiosyncratic risk (*IVOL*), illiquidity (*ILLIQ*), reversal (*REV*), co-skewness (*COSKEW*) as common measures of risks that explain stock returns. We run the monthly cross-sectional regression of individual returns of the subsequent month on β_{ln_co2} with other stock-specific control variables discussed above.

Following Jegadeesh and Titman (1993), we compute momentum (*MOM*) factor using cumulative returns over the past 11 months ending one month prior to the portfolio formation period. Short-term reversal (*ST REV*) is estimated based on the past one-month return as in Jegadeesh (1990) and Lehmann (1990) to control for liquidity and microstructure effects. Long-term reversal (*LT REV*) is the cumulative return from t-36 to t-13 and is included to capture the three- to five-year reversal effect documented by DeBont and Thaler (1985). Motivated by Amihud (2002) and Hasbrouck (2009), we define illiquidity (*ILLIQ*) as the ratio of the daily absolute value of the stock return to the daily trading volume of the stock in thousand US$ averaged for the month:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i.d}}\right] \quad (5)$$

where $R_{i,d}$ and $VOLD_{i.d}$ are the daily return and dollar trading volume for stock i on day d, respectively. We require at least 15 daily return observations in month *t*. As Amihud's illiquidity measure is too small, we multiplied it by 10^6.

Following Harvey and Siddique (2000), we also run the regression on daily excess returns of individual stocks on the daily market excess return and the daily squared market excess return using a rolling-window approach with a window size of one year (365 days). Specifically, we re-estimate the regression model at each month-end, where the regression specification is given by:

$$R_{i,t} - R_{f,t} = \beta_0^i + \beta_1^i\left(R_{m,t} - R_{f,t}\right) + \beta_2^i\left(R_{m,t} - R_{f,t}\right)^2 + \varepsilon_{i,t} \quad (6)$$

In this context, the co-skewness (*COSKEW*) of a stock is defined as the coefficient of the squared excess market return. We require at least 225 trading days in a year to reduce the impact of infrequent trading on the co-skewness estimates.

Idiosyncratic volatility is computed using daily returns as per Ang, Hodrick, Xing, and Zhang (2006). The average slopes provide standard Fama-Macbeth tests for determining which explanatory variables on average have non-zero premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof;

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{ln\_co2} + \lambda_{2,t}\beta_{i,t}^{MKT} + \lambda_{3,t}X_{i,t} + \varepsilon_{i,t+1} \tag{7}$$

where $R_{i,t+1}$ is the realized excess return on stock *i* in month t+1, β_{ln_co2} is the CO2 emission factor loadings of stock *i* in month t, $X_{i,t}$ is a collection of stock-specific control variables observable at time *t* for stock *i* (market betas (β_{MKT}), size (*SIZE*), book-to-market (*BTM*), momentum (*MOM*), idiosyncratic risk (*IVOL*), illiquidity (ILLIQ), reversal (REV), co-skewness (*COSKEW*)). The cross-sectional regressions are run at a monthly frequency.

4. Empirical Results

4.1. Descriptive Statistics

First, we present the sample distribution of unique number of firms by year and industry in Table 1. Panel A reports the summary statistics of the climate related variables, total energy CO_2 emissions and the standard pricing factors, $R_m - R_f$, *SMB*, *HML* and *UMD*. The ln_CO_2 is computed as $\log\left(\frac{Total\ Energy\ CO2\ Emissions_t}{Total\ Energy\ CO2\ Emissions_{t-1}}\right)$. Panel B present the correlation matrix among monthly ln_CO_2 and the standard pricing factors mentioned. We obtain total energy CO_2 emissions data from EIA's (U.S. Energy Information Administration) webpage. The sample period covers January 1, 1976 to December 31, 2016. As both the average and standard deviation of ln_CO_2, $R_M - R_f$, *SMB, HML*, and *UMD* are widely dispersed, we can conduct various regression tests.

[Table 1 about here]

4.2. Baseline Portfolio Regression Results

As discussed in section 2.2, for each stock and for each month, we estimate carbon exposure using the CO_2 emission factor loadings (β_{ln_co2}) by running the monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2* over a 36-month window after controlling for the market (*MKT*) in the market-climate two factor model as per eq. (1), or by estimating the augmented Fama and French (1993) three-factor model (the market (*MKT*), size (*SMB*), or book-to-market (*HML*)) as per eq. (2). For each month, decile portfolios are then formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where decile 1 contains stocks with the lowest (and decile 10 the highest) $\beta_{\ln\_co2}$. After portfolio formation, we record the next-month returns of each decile portfolio over the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. Similarly, quintile portfolios are formed with quintile 1 containing the lowest CO_2 emission factor loadings.

Table 2 Panel A reports the average pre-ranking beta and post-ranking return for each decile portfolio. We also compute the Jensen alpha of each decile portfolio with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on market return or $R_m - R_f$ or the Fama-French three-factors plus momentum factors. “D1-D10” denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (D1) and sells a high $\beta_{\ln\_co2}$ portfolio (D10).

Monthly stock returns are obtained from Center for Research in Security Prices (CRSP) with stocks traded on the NYSE (exchcd=1), Amex (exchcd=2) and NASDAQ (exchcd=3). We use only common shares. The results suggest that the unadjusted raw returns, CAPM alphas, FF3 alphas, and Carhart-4 alphas of the lowest $\beta_{\ln\_co2}$ portfolio (D1) are all greater than those of the highest $\beta_{\ln\_co2}$ portfolio (D10), all at the 1% significance level. In particular, the D1 – D10 long-short strategy for the $\beta_{\ln\_co2}$ portfolio earn a 4.32 percent annual return on average. These results are supportive of our first hypothesis that carbon emissions are indicative of declining investment opportunities and hence are associated with lower future stock returns.

Panel B reports the Jensen's alpha of each decile portfolio with respect to the Fama-French five factor, Hou, Xue and Zhang's (2015) Q4 factors, and Stambaugh and Yuan's (2017) mispricing factor models. Fama-French five factors of $[R_M - R_f]$, *SMB, HML, RMW* and *CMA* are obtained from Kenneth French's website. Hou, Xue and Zhang's (2015) Q-4 factors of MKT, ME, I/A, and ROE factors are provided by Zhang, and we obtain Stambaugh and Yuan's (2017) mispricing factors of *MKT, SMB, MGMT* and *PERF* from Yuan's website. "D1-D10" denotes an arbitrage portfolio that buys a low β_{ln_co2} portfolio (D1) and sells a high β_{ln_co2} portfolio (D10). The results show that the D1 – D10 long-short strategy for the $\beta_{\ln\_co2}$ portfolio earn a 6.16 percent annual return on average.

[Table 2 about here]

We repeat the same portfolio analysis based on quintile portfolio. As before, besides the average raw returns of portfolios, we also report CAPM alphas, FF-3 alphas and Carhart-4 alphas in Table 3. The results are similar to the case of decile portfolios. In Panel A, both returns and alphas of the lowest $\beta_{\ln\_co2}$ index portfolio (Q1) are greater than those of the highest $\beta_{\ln\_co2}$ index portfolio (Q5) in the CAPM model, the Fama-French three-factor model and Carhart four-factor models, again supporting H1. In particular, the Q1 – Q5 strategy that buys the lowest $\beta_{\ln\_co2}$ index portfolio (Q1) and sells the highest $\beta_{\ln\_co2}$ index portfolio (Q5) earn a 3.63 percent annual return on the average.

Panel B reports the Jensen's alpha of each quintile portfolio with respect to the Fama-French five-factor, Hou, Xue and Zhang's (2015) Q4 factors, and Stambaugh and Yuan's (2017) mispricing factor models. The Q1 – Q5 strategy earn a 5.3 percent annual return on average.

[Table 3 about here]

4.3. Fama-MacBeth regressions of future returns on carbon exposure based on CO_2 emission beta

To show the relation between carbon exposure (CO_2 emission beta), various fundamentals and future returns, we run a series of the time-series averages of month-by–month Fama and Macbeth (1973) cross-sectional regressions by regressing monthly excess returns on the *ln_co2* factor loading ($\beta^{i}_{\ln\_co2}$) and other fundamental control variables. The goal is to reassess the role of carbon exposure in asset pricing. Monthly cross-sectional regressions are run for the following specification and nested versions thereof:

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{ln\_co2} + \lambda_{2,t}\beta^{MKT}_{i,t} + \lambda_{3,t}X_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t+1}$ is the realized excess return on stock *i* in month t+1, β_{ln_co2} is the CO_2 emission factor loadings of stock *i* in month t, $X_{i,t}$ is a collection of stock-specific control variables observable at time *t* for stock *i*.

Specifically, we attempt to disentangle the effect of CO_2 emission beta from stock fundamentals and measures of risk by performing a series of monthly cross-sectional regressions of the realized excess return on various lagged firm characteristics. We follow Bali, Brown, and Tang (2016) and explore how *ln_co2* factor loading ($\beta^{i}_{\ln\_co2}$) is distinct from other measures of risk suggested in existing asset pricing models, such as market β (β^{MKT}), size (*SIZE*), book-to-market (*BTM*), momentum (*MOM*), idiosyncratic risk (*IVOL*), illiquidity (*ILLIQ*), short-term reversal (*ST REV*), long-term reversal (*LT REV*), and co-skewness (*COSKEW*).

The results, reported in Table 4, cast doubt on the interpretation of carbon exposure (CO_2 emission beta) as a proxy for non-diversifiable systematic risk. Future stock returns are negatively related to *ln_co2* factor loading ($\beta^i_{\ln\_co2}$) at 1% level.[8] If the *ln_co2* factor loading ($\beta^i_{\ln\_co2}$) is a systematic risk commanding a risk premium, we would expect it to be positively related to returns. Hence, the negative relation between *ln_co2* factor loading ($\beta^i_{\ln\_co2}$) and future returns is not compatible with traditional risk-based asset pricing models. Based on these results, we are inclined to believe that the correct interpretation of CO_2 emission beta is as a proxy for an indication of perceptions of deteriorating investment opportunities among investors. This is consistent with the view of Ang, Hodrick, Xing, and Zhang (2006) who examined the increased stock market volatility as an indication of deteriorating investment opportunity sets *à la* Merton's (1973) intertemporal asset pricing model. Although our adjusted R^2 of 1.6%-4.7% seems a bit low, they are comparable to those (0.31%-6.23%) of Bali, Brown, and Tang (2016).

[Table 4 about here]

4.4. Industry-matched and characteristic-matched portfolio returns

In this section, we report average returns for the $\beta^i_{\ln\_CO2}$ portfolios matched by industry or asset characteristics. $\beta^i_{\ln\_CO2}$ is estimated by running the rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2* over a 36-month window after controlling for the market (*MKT*), size (*SMB*), book-to-market (*HML*) factors of Fama and French (1993) for each month. Industry-matched portfolio returns are constructed based on 49-industry classification of Fama French (1997). Characteristic-adjusted benchmark are constructed following Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2004), which matches each stock to a portfolio of stocks with similar size, book-market ratio, and momentum.

[8] In addition, future returns are negatively associated with size, idiosyncratic risk, and short- and long-term reversal, while positively associated with book-to-market, momentum, and illiquidity.

We report both raw return and the risk-adjusted (using FF-3, FF-4, FF-5 factor, Q-4, M-5 models) monthly returns. Fama-French factors, $[R_M - R_f]$, *SMB, HML, UMD, RMW* and *CMA* are obtained from Kenneth French's website. Hou, Xue and Zhang's (2015) Q-4 factors of *MKT, ME, I/A*, and *ROE* factors are provided by Zhang and we obtain mispricing factors of Stambaugh and Yuan (2017), *MKT, SMB, MGMT* and *PERF*, from Yuan's website. Table 5 Panel A shows that the Q1 – Q5 long-short strategy for the industry-matched portfolio $\beta_{\ln\_co2}$ portfolio earns a 3.87 percent annual return on average, while Panel B indicates that the Q1 – Q5 strategy for the characteristics-matched portfolio $\beta_{\ln\_co2}$ portfolio earns a 3.74 percent annual return on average.

[Table 5 about here]

4.5. Sub-period analysis

To check the robustness of our results, we now calculate mean monthly returns for the CO_2 emission beta portfolio for the sub-periods 1976-1994 and 1995-2016 in Table 6, Panel A.[9] Alternatively, we sub-divided the entire sample period into financial crisis periods (2008-2009) and the periods excluding the 2008-2009 financial crisis. For each stock and for each month, we estimate the β_{ln_co2} by running the rolling regressions of excess stock returns $(\mathrm{R_{i,t}} - \mathrm{R_{f,t}})$ on the *ln_co2* over a 36-month window after controlling for the market (*MKT*), size (*SMB)*, book-to-market (*HML*) factors of Fama and French (1993). As before, for each month, quintile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where quintile 1 (Q1) contains stocks with the lowest $\beta_{\ln\_co2}$ and quintile 5 (Q5) the highest. After portfolio formation, we record the next-month returns of each quintile portfolio during the estimation period. We repeat the procedure by rolling the

[9] When we use the first half period of 1976-1990 and the second half of 1991-2016, the main results remain the same qualitatively.

estimation window forward by one month.

Table 6 reports the average pre-ranking beta and post-ranking return for each quintile portfolio. We also compute the Jensen alpha of each quintile portfolio with respect to the CAPM, Fama French three-factor model, and Carhart four-factor model by running a time series regression of the post-ranking excess returns on factors in each asset pricing model. "Q1-Q5" denotes an arbitrage portfolio that buys a lowest $\beta_{\ln\_co2}$ portfolio (Q1) and sells a highest $\beta_{\ln\_co2}$ portfolio (Q5).

[Table 6 about here]

Panel A shows that the Q1-Q5 portfolio return differential is significant for all models for both sub-periods of 1976-1994 and 1995-2016. As can be seen from the second part of the panel, the average portfolio return differential has increased from 3.00% in the earlier time period (1976-1994) to 3.63 percent in the latter period (1995-2016). A similar pattern of an increase in CO_2 emissions over time are shown in Figures 1 and 2. The amount of the CO_2 emissions per Q1-Q5 return differential increased over time, because of the overall increase in CO_2 emissions in the latter period. Alternatively, reduction in trading costs and greater availability of firm-specific information due to technology and regulation may also have contributed to these results.[10]

Since the U.S. Environmental Protection Agency (EPA) released a final rule to limit greenhouse gas emissions from new power plants on August 3, 2015, it established New Source Performance Standards (NSPS) under the Clean Air Act to limit emissions of carbon dioxide (CO_2) from coal- and natural gas-fired power plants. Thus, we report the effect of NSPS on the relation between carbon exposure and future returns in Table 6 Panel B. The results suggest

[10] Our untabulated results suggest that the Q1-Q5 portfolio return differential is not statistically significant during the recent financial crisis period of 2008-2009. However, the same strong return differential of 3.90 percent annual return is shown out of the financial crisis period.

that while the return differential of 3.19 percent annual return is shown up to the before-NSPS adoption period, the return differential becomes insignificant after the adoption of NSPS.

4.6. Alternative CO_2 emission data

We also obtain the alternative carbon emissions data from the Fossil-Fuel Combustion of USA database from the CDIAC (Carbon Dioxide Information Analysis Center) webpage. This alternative dataset only covers the period of January 1981 to December 2003. As before, for each stock and for each month, we estimate the $\beta_{ln\_co2(CDIAC)}$ estimated using alternative CO_2 emission data by running the monthly rolling regressions of excess stock returns $(R_{i,t} - R_{f,t})$ on the *ln_co2 (CDIAC)* over a 36-month fixed window after controlling for the CAPM or the Fama and French (1993) three-factor model, augmented by CO_2 remission factor. Then, quintile portfolios are formed for each month by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2(CDIAC)}$, and we record the next-month returns of each quintile portfolio following the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time, as before.

Table 7 reports the average pre-ranking beta and post-ranking return for each quintile portfolio. We also compute the Jensen alpha of each quintile portfolio with respect to the CAPM, Fama-French three-factor model, and Carhart four-factor model, augmented by CO_2 emission factor. The results suggest that the Q1 – Q5 strategy for the $\beta_{\ln\_co2(CDIAC)}$ portfolio earn a 5.34 percent annual return on average during the period of 1981-2003.

[Table 7 about here]

4.7. Other climate variables

Although the CO_2 emission is perhaps most critical for climate changes and global warming, other climate related variables could also be important (Agnes, Xie, and Zhang, 2017;

Li, Massa, Zhang, and Zhang, 2017). In this section, we examine the cross-sectional relation between future returns and other climate related variables such as precipitation, temperature, and drought at the firm level.

Table 8 presents the results from firm and year fixed effects regression for the one-month ahead stock return and climate related variables. Standard errors are corrected for clustered at firm-level. In addition to CO_2 emission (*ln_CO2*), climate related variables including precipitation *(ln_PCP),* temperature *(ln_TAVG)* and drought (*ln_PDSI)* are all computed as a natural log of the respective index at time t over t-1.

Consistent with the negative relation between CO_2 emissions and future stock returns, temperature and drought severity are also seen negatively associated with future stock returns (and statistically significant at 1%) in Table 8. The results reiterate our earlier finding and consistency with our first hypothesis indicating a negative association between carbon exposure and future stock returns. Remarkably, when we include all the risk factor models of the CAPM (unreported), Fama-French 3 factor model, Carhart four-factor model, Fama-French five factor, Hou, Xue and Zhang (2015) Q4 factors, and mispricing factors of Stambaugh and Yuan (2017), the result of a negative relation between one-month ahead stock return and climate variable of temperature remain intact across all asset pricing models. However, the results of precipitation and drought variables are somewhat mixed. In particular, drought variable is negatively associated with future returns in 10 out of 15 models, while precipitation variable is positively associated with future returns in 8 out of 15 models.

[Table 8 about here]

4.8. Investment opportunity or optimistic pricing?

In the above, we discussed that our main result of a negative relation between carbon exposure and future stock returns is consistent with either deteriorating investment opportunities or with Miller's (1977) optimistic pricing view, adapted to carbon exposure. In this section, we will attempt to sort these alternative explanations out to deepen our understanding of the nature of the relation between carbon exposure and stock returns. If the investment opportunity hypothesis is correct, our intuition is that we should observe that cumulative CO_2 emissions will further aggravate future investment opportunities as time goes by. In contrast, if the Miller's optimistic pricing explanation is more valid, to the extent that the stock market incorporates public information of CO_2 emissions, we would expect that the effect of carbon exposure (and other climate related variables) on future stock returns would decrease over time, reaching a point when we would observe no relation between the two. Notably, our preliminary results indicate that the negative relation between future stock returns and carbon exposure (and other climate related variables such as temperature and drought) continue to be significant over time for three years forward, i.e., t+1, t+2, and t+3 in most empirical models. Thus, tentatively we are leaning toward an interpretation that our finding of a negative relation between climate variables and future stock returns is supportive of the investment opportunity hypothesis rather than the Miller's optimistic pricing view.

For deeper understanding, we still must explore more. Given that high short-sale costs are the main impediment to the revelation of negative information, Miller's (1977) optimistic bias should be more pronounced for stocks that are difficult to short-sell. In this respect, using dispersion in analyst earnings forecasts as a proxy for disagreement, Diether, Malloy, and Scherbina (2002) argue that high-dispersion stocks in the S&P 500 index should not earn lower returns, because these stocks should be very cheap to short-sell.

If we find that stocks in lowest carbon exposure quintile of the S&P 500 index outperform stocks in the highest carbon exposure quintile, then that evidence should be considered as more direct evidence against the Miller effect. Consistent with the above conjecture, we find that stocks in lowest carbon exposure quintile of the S&P 500 index outperform stocks in the highest carbon exposure quintile of the S&P 500 index, further supporting the investment opportunities explanation, but not the Miller's optimistic pricing view.

[Table 9 about here]

In addition, to examine the effect of carbon exposure (CO_2 emissions) and other climate related variables on investment opportunities directly, we use two proxies of investment opportunities. Adam and Goyal (2008) find that, on a relative scale, the market-to-book assets (*MBA*) ratio has the highest information content with respect to investment opportunities. They also find that although both the market-to-book equity and the earnings–price ratios are related to investment opportunities, the latter does not contain information that is not already contained in the former. Thus, following Adam and Goyal (2008), we measure investment opportunities using the market-to-book assets ratio (*M/B*). *M/B* is computed as (share price × shares outstanding + preferred stock + debt in current liabilities + long term debt deferred taxes and investment tax credit) divided by book value of asset. They also used capital expenditures divided by net plant, property, and equipment (*CAPX/PPE*) as another proxy for investment opportunities. Thus, we use both *CAPX/PPE* and *M/B* variables for investment opportunities.

To this end, we follow Agnes, Xie, and Zhang (2017) and include firm size using *Log (Asset)*, *ROA, leverage*, as firm controls. *Log (Asset)* is the natural logarithm of book asset. *ROA* is computed by net income divided by total asset. Leverage is computed by total debt divided by total asset. We also add additional control variables, PPE, Log(sales), R&D intensity, and Sales growth, that seem to explain investment opportunities.

Table 10 suggests that carbon exposure (i.e., carbon beta) decreases a quarter-ahead *CAPX/PPE* and *M/B* for all four models during the period, January 1976 to December 2016. The results of precipitation, temperature, and drought variables are neither significant nor consistent. Thus, it seems that carbon exposure (out of the four climate-related variables) seems to be the most significant in decreasing future investment opportunities. This supports the investment opportunity explanation discussed above.

[Table 10 about here]

5. Summary and Conclusions

In this paper, we provide evidence that stocks with higher carbon exposure (i.e., carbon beta) earn significantly lower future returns than otherwise comparable stocks. Our results reject the notion that carbon exposure is a proxy for non-diversifiable risk commanding risk premium, since the relation between carbon exposure and future returns is negative. Further, we present evidence that standard multifactor risk-based explanations cannot account for this relation. The results are consistent with a view that carbon exposure is an indication of deteriorating investment opportunities in the future. Our results are also consistent with the hypothesis that prices will reflect the optimistic view when investors with the lowest valuations do not trade. While Miller (1977) theorizes on short-sale costs as the reason why investors with the lower firm valuations may not trade, we believe that such reasoning can be generalized to a situation of any frictions that can prevent the revelation of negative opinions. If so, such theory can explain the negative relation between carbon exposure and future returns that we document in this paper.

Our tests suggest, however, that our main result of an inverse relation between carbon exposure and future stock returns over time is leaning toward the investment opportunities explanation than the Miller's optimistic pricing explanation.

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Appendix A. Variable definitions and data sources

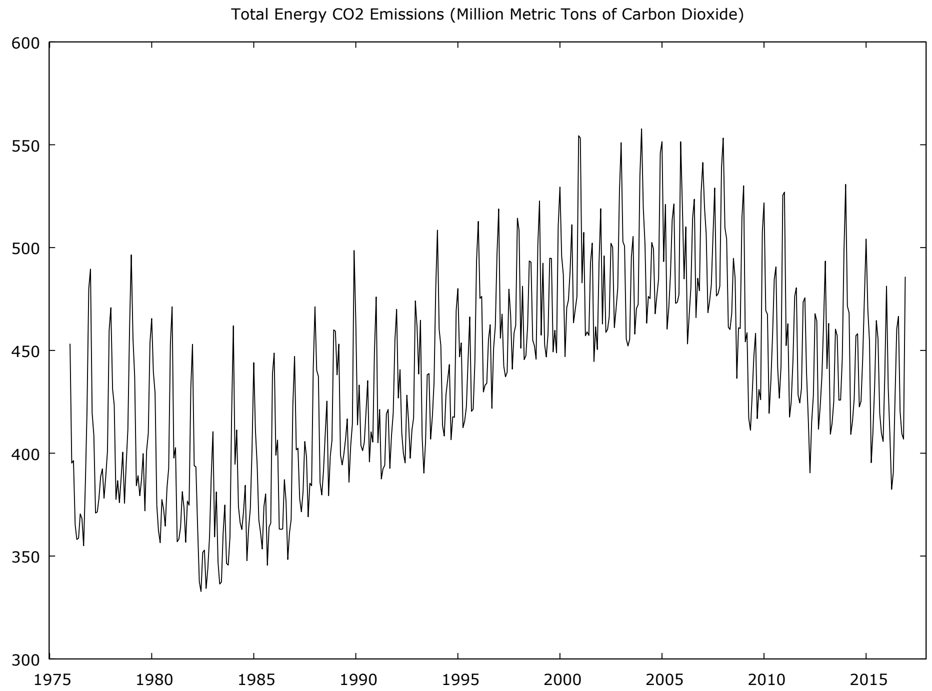
Category	Variable	Definition	Data Source
Climate related variables	*ln_CO2*	$\log\left(\frac{Total\ \ Energe\ \ CO2\ \ Emission_t}{Total\ \ Energe\ \ CO2\ \ Emission_{t-1}}\right)$	https://www.eia.gov/totalenergy/data/browser/?tbl=T12.01
	ln_PCP	$\log\left(\frac{Precipitation\ \ Index_t}{Precipitation\ \ Index_{t-1}}\right)$	https://www7.ncdc.noaa.gov/CDO/CDODivisionalSelect.jsp#
	ln_TAVG	$\log\left(\frac{Temperature\ \ Index_t}{Temperature\ \ Index_{t-1}}\right)$	
	ln_PDSI	$\log\left(\frac{Palmer\ \ Drought\ \ Severity\ \ Index_t}{Palmer\ \ Drought\ \ Severity\ \ Index_{t-1}}\right)$	
Factors	FF3, FF4, FF5 Factors	$R_M - R_f$, SMB, HML, UMD, RMW and CMA	http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
	Q4 factors	MKT, ME, I/A and ROE	Lu Zhang
	M4 factors	MKT, SMB, MGMT and PERF	http://www.saif.sjtu.edu.cn/facultylist/yyuan/
Investment Opportunity proxies	CAPX/PPE	Capital Expenditures / Net Plant, Property, and Equipment	CSRP & COMPUSTAT
	MBA	(share price × shares outstanding + preferred stock + debt in current liabilities + long term debt deffered taxes and investment tax credit)/ book value of asset.	
Accounting Variables	*Log (Asset)*	$log(Asset_t)$	CSRP & COMPUSTAT
	ROA	$Net\ \ income_t/Asset_t$	
	Leverage	$Debt_t/Asset_t$	
	PPE	$Property\ \ Plant\ \ and\ \ Equipment_t/Asset_t$	
	Log (Sales)	$log(Sales_t)$	
	R&D Intensity	$Research\ \ and\ \ Development\ \ Expense_t/Sales_t$	
	ROA	$Net\ \ income_t/Revenue_t$	
	Growth (Sales)	$(Sales_t - Sales_{t-1})/sales_{t-1}$	

Note. Fama and French (1993) three-factor model with the market (*MKT*), size (*SMB*), book-to-market (*HML*) factors. The momentum factor (*UMD*), robust minus weak factor (*RMW*) and conservative minus aggressive factor (*CMA*) were obtained from Kenneth French's data library. Hou, Xue and Zhang (2015) Q-4 factors of the market factor (*MKT*), a size factor (*ME*), an investment factor (I/A) and a profitability factor (*ROE*) are provided by Zhang. Regarding mispricing factors of *MGMT* and *PERF*, Stambaugh and Yuan (2017) construct the first cluster of anomalies including net stock issues, composite equity issues, accruals, net operating assets, asset growth, and investment to assets. These six anomaly variables all represent quantities that firms' managements can affect directly. Following Stambaugh and Yuan (2017), we denote the factor arising from this cluster as MGMT (see factor construction in Stambaugh and Yuan (2017)). The second cluster includes distress, O-score, momentum, gross profitability, and return on assets. These five anomaly variables are related more to performance and less directly controlled by management, so following Stambaugh and Yuan (2017), we denote the factor arising from this cluster as PERF. We obtain mispricing factors of Stambaugh and Yuan (2017), *MKT, SMB, MGMT* and *PERF*, from Yuan's website.

Figure 1. The time-series of total energy CO2 emission and carbon beta

This figure shows the time-series of Total Energy CO2 Emission and *ln_CO2* from January 1976 through December 2016. Panel A plots the time-series Total Energy CO2 Emissions (Million Metric Tons of Carbon Dioxide) obtain from EIA's (U.S. Energy Information Administration) webpage. Panel B plots the time-series of *ln_CO2*. The *ln_CO2* is computed as $\log\left(\frac{Total\ Energe\ CO2\ Emission_t}{Total\ Energe\ CO2\ Emission_{t-1}}\right)$

Panel A. Total Energy CO2 Emissions (Million Metric Tons of Carbon Dioxide)



Panel B. *ln_CO2*

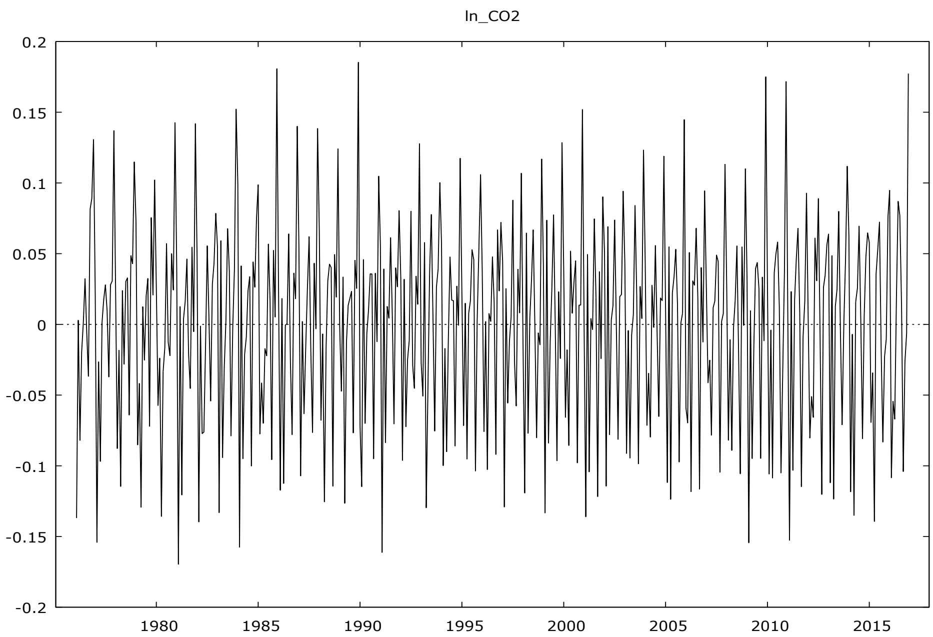


Figure 2. The time-series behavior of the average carbon beta, $\boldsymbol{\beta_{ln\_co2}}$, of each quintile portfolio

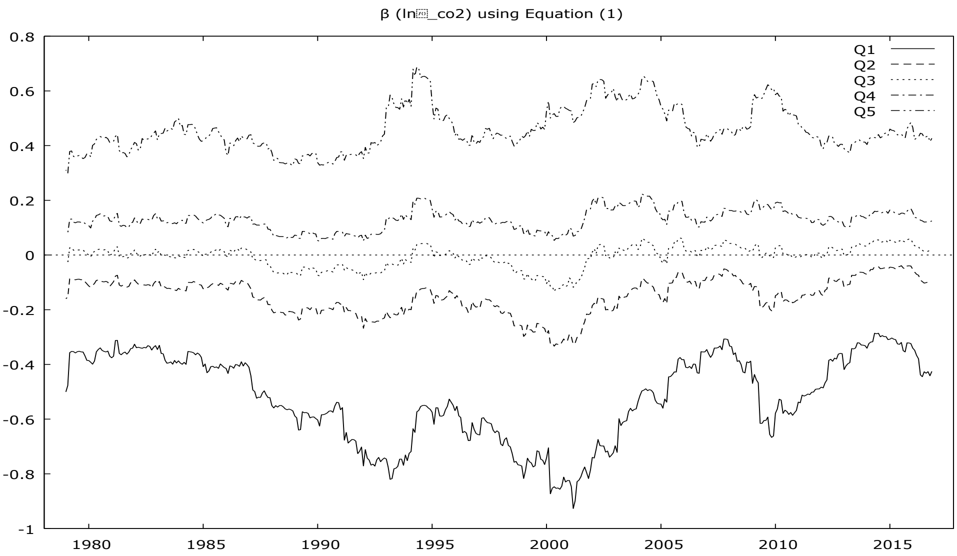
This figure shows the time-series behavior of the average β_{ln_co2} of quintile portfolios. For each stock and for each month, the β_{ln_co2} are estimated by running the following monthly rolling regressions of excess stock returns $(R_{i,t} - R_{f,t})$ on the *ln_co2* over a 36-month fixed window after controlling for the market (MKT) (or the market (MKT), size (SMB), book-to-market (HML)) factors of Fama and French (1993):

(1) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$

(2) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$

For each month, quintile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$. Panel A plots the time-series of monthly average β_{ln_co2} estimated from Equation (1). Panel B plots the time-series of monthly average β_{ln_co2} estimated from Equation (2).

Panel A. Time-series of monthly average β_{ln_co2} estimated from Equation (1)



Panel B. Time-series of monthly average β_{ln_co2} estimated from Equation (2)

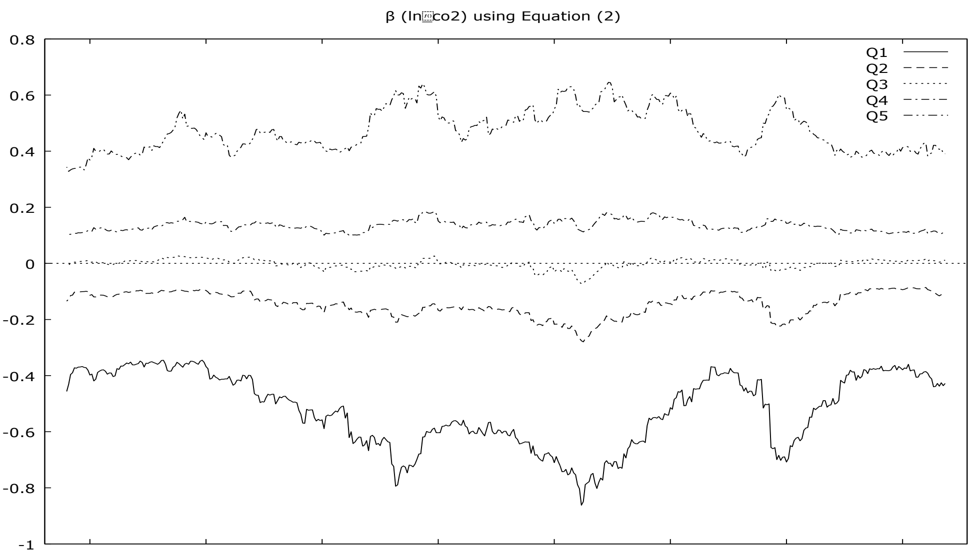


Table 1. Descriptive statistics

Panel A reports the summary statistics of the climate related variables, total energy CO2 emissions and the standard pricing factors, $R_m - R_f$, SMB, HML and UMD. The *ln_CO2* is computed as $\log\left(\frac{Total\ Energy\ CO2\ Emission_t}{Total\ Energy\ CO2\ Emission_{t-1}}\right)$. Panel B reports the correlation between monthly *ln_CO2* and the standard pricing factors, $\mathrm{R_M} - \mathrm{R_f}$, SMB, HML, and UMD. We obtain total energy CO2 emissions data from EIA's (U.S. Energy Information Administration) webpage. Fama-French factors [$\mathrm{R_M} - \mathrm{R_f}$], small market capitalization minus big (SMB), and high book-to-market ratio minus low (HML), and momentum factor (UMD)] are obtained from Kenneth French's website. The sample period covers Jan 1976 to Dec 2016.

Panel A. Summary Statistics

Variables	Mean	Std Dev	Max.	Quintile 1	Median	Quintile 3	Minimum
Total Energy CO2 Emissions (Million Metric Tons of Carbon Dioxide)	433.944	49.864	557.722	394.324	434.236	468.272	332.76
ln_CO2	0	0.068	0.185	-0.047	0.01	0.043	-0.17
$R_m - R_f$	0.005	0.046	0.161	-0.021	0.009	0.035	-0.232
SMB	0.002	0.031	0.221	-0.015	0.001	0.02	-0.172
HML	0.004	0.029	0.129	-0.012	0.003	0.019	-0.113
UMD	0.007	0.044	0.184	-0.008	0.007	0.029	-0.346

Panel B. Correlations

	ln_CO2	$R_m - R_f$	SMB	HML	UMD
ln_CO2	1	0.047	-0.011	-0.042	0.064
		(0.280)	(0.799)	(0.338)	(0.139)
$R_m - R_f$	0.047	1	0.265	-0.279	-0.144
	(0.280)		(<.0001)	(<.0001)	(0.001)
SMB	-0.011	0.265	1	-0.206	-0.002
	(0.799)	(<.0001)		(<.0001)	(0.956)
HML	-0.042	-0.279	-0.206	1	-0.181
	(0.338)	(<.0001)	(<.0001)		(<.0001)
UMD	0.064	-0.144	-0.002	-0.181	1
	(0.139)	(0.001)	(0.956)	(<.0001)	

Table 2. Decile portfolio returns

For each stock and for each month, we estimate the β_{ln_co2} by running the following monthly rolling regressions of excess stock returns $(R_{i,t} - R_{f,t})$ on the *ln_co2* over a 36-month fixed window after controlling for the market (MKT) in the market-climate two factor model, or the market (MKT), size (SMB), or book-to-market (HML)) in the Fama and French (1993):

(1) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$

(2) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$

For each month, decile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where decile 1 (10) contains stocks with the lowest (highest) $\beta_{\ln\_co2}$. After portfolio formation, we record the next month returns of each decile portfolio following the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. Panel A reports the average pre-ranking beta and post-ranking return for each decile portfolio. We also compute the Jensen alpha of each decile portfolio with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on $R_m - R_f$, (SMB, HML, and UMD). "D1-D5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (D1) and sells a high $\beta_{\ln\_co2}$ portfolio (D10). Panel B reports the Jensen alpha of each decile portfolio with respect to the Fama-French five factor, Hou, Xue and Zhang's (2015) Q4 factors, and Stambaugh and Yuan's (2017) mispricing factor models. Fama-French five factors of $[\mathrm{R_M} - \mathrm{R_f}]$, SMB, HML, RMW and CMA are obtained from Kenneth French's website. Hou, Xue and Zhang's (2015) Q-4 factors of MKT, ME, I/A, ROE factors are provided by Zhang and we obtain mispricing factors of Stambaugh & Yuan (2017) of MKT, SMB, MGMT and PERF from Yuan's website. "D1-D10" denotes an arbitrage portfolio that buys a low β_{ln_co2} portfolio (D1) and sells a high β_{ln_co2} portfolio (D10). Newey-West adjusted *t-statistics* are given in parentheses. The sample period covers January 1976 to December 2016.

Panel A: Sorted by β_{ln_co2}

ln_co2 factor loadings ($\beta_{\ln\_co2}^i$)	Decile Portfolio										
Sorting Statistic	D1(low)	D2	D3	D4	D5	D6	D7	D8	D9	D10(high)	D1-D10
Beta estimation using equation (1)											
β_{ln_co2}	-0.747	-0.338	-0.203	-0.114	-0.043	0.021	0.088	0.167	0.285	0.638	
Average return	1.49	1.42	1.30	1.37	1.35	1.27	1.28	1.26	1.20	1.17	0.31***
	(3.78)	(4.53)	(4.77)	(5.69)	(5.54)	(5.31)	(5.28)	(4.84)	(4.10)	(3.05)	(2.77)
CAPM Alpha	0.31	0.33	0.27	0.38	0.38	0.31	0.30	0.26	0.14	-0.00	0.31***
	(1.16)	(1.62)	(1.60)	(2.47)	(2.51)	(1.88)	(1.88)	(1.65)	(0.77)	(-0.02)	(2.87)
FF3 Alpha	0.20	0.16	0.11	0.23	0.21	0.15	0.14	0.11	-0.01	-0.09	0.29***
	(1.24)	(1.52)	(1.28)	(2.86)	(2.79)	(1.77)	(1.70)	(1.39)	(-0.07)	(-0.58)	(2.71)
FF4 Alpha	0.56	0.42	0.28	0.37	0.33	0.24	0.24	0.22	0.14	0.11	0.45***
	(2.66)	(3.05)	(2.84)	(4.34)	(4.42)	(2.81)	(3.11)	(2.93)	(1.37)	(0.63)	(2.99)
Beta estimation using equation (2)											
β_{ln_co2}	-0.741	-0.328	-0.193	-0.105	-0.035	0.029	0.096	0.177	0.298	0.665	
Average ret	1.51	1.43	1.36	1.38	1.29	1.26	1.28	1.28	1.16	1.15	0.36***
	(3.73)	(4.63)	(5.12)	(5.52)	(5.46)	(5.35)	(5.23)	(4.86)	(4.01)	(3.04)	(3.25)
CAPM Alpha	0.32	0.34	0.34	0.38	0.32	0.30	0.31	0.28	0.09	-0.03	0.35***
	(1.20)	(1.71)	(2.07)	(2.39)	(2.16)	(1.95)	(1.93)	(1.68)	(0.51)	(-0.11)	(3.28)
FF3 Alpha	0.22	0.19	0.17	0.22	0.16	0.16	0.15	0.12	-0.06	-0.12	0.34***
	(1.29)	(1.85)	(2.26)	(2.61)	(2.16)	(1.97)	(1.81)	(1.46)	(-0.61)	(-0.79)	(3.02)
FF4 Alpha	0.56	0.42	0.34	0.38	0.26	0.26	0.25	0.25	0.09	0.09	0.47***
	(2.59)	(3.09)	(3.61)	(4.07)	(3.63)	(3.19)	(3.31)	(3.16)	(0.90)	(0.57)	(2.97)

Panel B: Decile β_{ln_co2} portfolio alphas using FF5, M4, Q4 factor models

ln_co2 factor loadings ($\beta^{i}_{\ln\_co2}$)	Decile Portfolio										
Sorting Statistic	D1(low)	D2	D3	D4	D5	D6	D7	D8	D9	D10(high)	D1-D10
Beta estimation using equation (1)											
FF5 Alpha	0.97	0.72	0.57	0.65	0.60	0.51	0.50	0.49	0.45	0.59	0.39**
	(4.17)	(4.57)	(4.85)	(6.68)	(7.45)	(5.75)	(6.52)	(6.37)	(4.35)	(3.56)	(2.38)
M4 Alpha	1.23	0.91	0.72	0.71	0.67	0.56	0.52	0.55	0.54	0.67	0.56***
	(4.58)	(5.74)	(6.18)	(7.78)	(8.60)	(6.28)	(6.22)	(6.69)	(4.86)	(3.58)	(2.98)
Q4 Alpha	1.31	0.96	0.71	0.76	0.68	0.57	0.58	0.58	0.57	0.80	0.51***
	(4.36)	(4.62)	(4.11)	(5.60)	(5.94)	(4.55)	(5.61)	(5.87)	(4.99)	(4.41)	(2.60)
Beta estimation using equation (2)											
FF5 Alpha	1.01	0.74	0.61	0.62	0.54	0.55	0.51	0.51	0.41	0.55	0.45***
	(4.33)	(4.93)	(5.85)	(6.11)	(6.82)	(6.58)	(5.94)	(5.96)	(4.11)	(3.44)	(2.90)
M4 Alpha	1.23	0.92	0.74	0.72	0.60	0.60	0.55	0.58	0.48	0.67	0.57***
	(4.45)	(5.84)	(6.75)	(7.49)	(8.16)	(6.60)	(6.56)	(6.84)	(4.55)	(3.66)	(2.90)
Q4 Alpha	1.35	0.95	0.75	0.75	0.61	0.63	0.58	0.61	0.53	0.75	0.60***
	(4.46)	(4.67)	(4.85)	(5.13)	(5.34)	(5.72)	(5.01)	(5.33)	(5.09)	(4.22)	(3.06)

Table 3. Quintile portfolio returns

For each stock and for each month, we estimate the β_{ln_co2} by running the following monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2* over a 36-month fixed window after controlling for the market (MKT) (or the market (MKT), size (SMB), book-to-market (HML)) factors of Fama and French (1993):

(1) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$
(2) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{ln\_co2}^i ln\_co2 + \varepsilon_{i,t}$

For each month, decile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where quintile 1 contains stocks with the lowest (quintile 5 the highest) $\beta_{\ln\_co2}$. After portfolio formation, we record the next-month returns of each quintile portfolio over the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. Panel A reports the average pre-ranking beta and post-ranking return for each quintile portfolio. We also compute the Jensen alpha of each decile portfolio with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on $R_m - R_f$, (SMB, HML, and UMD). "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2}$ portfolio (Q5).

Panel B reports the Jensen alpha of each quintile portfolio with respect to the Fama-French five factor, Hou, Xue and Zhang (2015) Q4 factors, Mispricing factor models. Fama-French five factors, $[R_M - R_f]$, SMB, HML, RMW and CMA are obtained from Kenneth French's website. Hou, Xue and Zhang (2015) Q-4 factors, MKT, ME, I/A, ROE factors are provided by Zhang and we obtain Mispricing factors of Stambaugh & Yuan (2017), MKT, SMB, MGMT and PERF, from Yuan's website. "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2}$ portfolio (Q5). Newey-West adjusted *t-statistics* are given in parentheses. The sample period covers January 1976 to December 2016.

Panel A: Sorted by β_{ln_co2}

ln_co2 factor loadings ($\beta_{\ln\_co2}^i$)	Quintile portfolio					
Sorting Statistic	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Beta estimation using equation (1)						
β_{ln_co2}	-0.542	-0.158	-0.011	0.128	0.461	
Average return	1.45	1.34	1.31	1.27	1.18	0.27***
	(4.16)	(5.23)	(5.45)	(5.07)	(3.55)	(2.72)
CAPM Alpha	0.32	0.32	0.34	0.28	0.07	0.25***
	(1.40)	(2.04)	(2.20)	(1.79)	(0.32)	(2.66)
FF3 Alpha	0.18	0.17	0.18	0.12	-0.05	0.23**
	(1.43)	(2.17)	(2.35)	(1.63)	(-0.40)	(2.48)
FF4 Alpha	0.49	0.33	0.29	0.23	0.12	0.36***
	(2.90)	(3.74)	(3.72)	(3.20)	(0.96)	(2.90)
Beta estimation using equation (2)						
β_{ln_co2}	-0.534	-0.149	-0.003	0.136	0.481	
Average return	1.47	1.37	1.28	1.28	1.15	0.32***
	(4.16)	(5.33)	(5.43)	(5.06)	(3.50)	(3.69)
CAPM Alpha	0.33	0.36	0.31	0.29	0.03	0.30***
	(1.45)	(2.25)	(2.08)	(1.82)	(0.15)	(3.63)
FF3 Alpha	0.20	0.20	0.16	0.13	-0.09	0.29***
	(1.57)	(2.56)	(2.15)	(1.70)	(-0.75)	(3.43)
FF4 Alpha	0.49	0.36	0.26	0.25	0.09	0.40***
	(2.85)	(4.01)	(3.57)	(3.39)	(0.73)	(3.18)

Panel B: Quintile β_{ln_co2} portfolio alphas using FF5, M4, Q4 factor models

ln_co2 factor loadings ($\beta^{i}_{\ln\_co2}$)	Quintile portfolio					
Sorting Statistic	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Beta estimation using equation (1)						
FF5 Alpha	0.85	0.61	0.55	0.50	0.52	0.33**
	(4.42)	(5.91)	(6.82)	(6.77)	(4.08)	(2.40)
M4 Alpha	1.07	0.72	0.61	0.54	0.60	0.46***
	(5.12)	(7.26)	(7.75)	(6.79)	(4.24)	(2.97)
Q4 Alpha	1.13	0.73	0.63	0.58	0.69	0.45***
	(4.59)	(4.85)	(5.33)	(5.92)	(4.98)	(2.72)
Beta estimation using equation (2)						
FF5 Alpha	0.87	0.62	0.54	0.51	0.48	0.39***
	(4.64)	(6.17)	(7.04)	(6.24)	(3.83)	(3.06)
M4 Alpha	1.08	0.73	0.60	0.57	0.57	0.51***
	(5.05)	(7.43)	(7.78)	(7.04)	(4.17)	(3.21)
Q4 Alpha	1.15	0.75	0.62	0.59	0.64	0.51***
	(4.65)	(5.07)	(5.68)	(5.30)	(4.83)	(3.10)

Table 4. Fama-MacBeth regressions

This reports the time-series averages of month-by–month Fama and Macbeth (1973) cross-sectional regression coefficient estimates from regressing monthly excess returns on the *ln_co2* factor loading ($\beta^{i}_{\ln\_co2}$) and control variables. Control variables include market β (β^{MKT}), size (*SIZE*), book-to-market (*BTM*), momentum (*MOM*), idiosyncratic risk (*IVOL*), illiquidity (*ILLIQ*), short-term reversal (*ST REV*), long-term reversal (*LT REV*), co-skewness (COSKEW). Monthly cross-sectional regressions are run for the following econometric specification and nested versions thereof;

$$R_{i,t+1} = \lambda_{0,t} + \lambda_{1,t}\beta_{ln\_co2} + \lambda_{2,t}\beta^{MKT}_{i,t} + \lambda_{3,t}X_{i,t} + \varepsilon_{i,t+1}$$

where $R_{i,t+1}$ is the realized excess return on stock *i* in month t+1, β_{ln_co2} is the CO2 energy emission factor loadings of stock *i* in month t, $X_{i,t}$ is a collection of stock-specific control variables observable at time *t* for stock *i.* Newey-west adjusted t-statistics for the time-series average of coefficients using lag 12 are reported. Numbers in parentheses indicate t -statistics. The sample period covers January 1976 to December 2016.

Variable	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5	MODEL6	MODEL7	MODEL8	MODEL9	MODEL10	MODEL12	MODEL13	MODEL14	MODEL15
$\boldsymbol{\beta_{ln\_co2,CAPM}}$	**-.00242****	**-.00161***	**-.00184****	**-.00177****	**-.00206****	**-.00194****	**-.00188****							
.	**(-2.53)**	**(-1.74)**	**(-2.17)**	**(-2.10)**	**(-2.45)**	**(-2.37)**	**(-2.32)**							
$\boldsymbol{\beta_{ln\_co2,FF3}}$								**-.00265*****	**-.00191****	**-.00205*****	**-.00198*****	**-.00222*****	**-.00214*****	**-.00207*****
.								**(-3.25)**	**(-2.45)**	**(-2.70)**	**(-2.63)**	**(-2.92)**	**(-2.83)**	**(-2.76)**
β^{MKT}	-.00011	0.00028	0.00076	0.00101	0.00091	0.00105	0.00109	-.00010	0.00028	0.00076	0.00101	0.00090	0.00104	0.00108
.	(-0.07)	(0.17)	(0.57)	(0.76)	(0.68)	(0.82)	(0.85)	(-0.06)	(0.17)	(0.57)	(0.76)	(0.68)	(0.81)	(0.85)
SIZE		-.00117***	-.00164***	-.00151***	-.00152***	-.00136***	-.00138***		-.00118***	-.00165***	-.00152***	-.00153***	-.00137***	-.00139***
.		(-2.63)	(-4.55)	(-4.17)	(-4.18)	(-3.92)	(-3.96)		(-2.64)	(-4.57)	(-4.20)	(-4.22)	(-3.95)	(-3.99)
BTM		0.00167***	0.00191***	0.00171***	0.00169***	0.00164***	0.00163***		0.00167***	0.00191***	0.00171***	0.00170***	0.00164***	0.00164***
.		(5.17)	(6.28)	(5.76)	(5.72)	(5.66)	(5.63)		(5.16)	(6.29)	(5.76)	(5.74)	(5.67)	(5.65)
MOM			0.00329**	0.00337**	0.00389**	0.00373**	0.00378**			0.00332**	0.00339**	0.00389**	0.00373**	0.00377**
.			(2.08)	(2.14)	(2.53)	(2.41)	(2.47)			(2.08)	(2.14)	(2.52)	(2.40)	(2.45)
IVOL			-.12001***	-.13676***	-.13477***	-.13789***	-.13515***			-.12086***	-.13761***	-.13553***	-.13862***	-.13588***
.			(-3.36)	(-3.84)	(-3.75)	(-3.91)	(-3.89)			(-3.39)	(-3.86)	(-3.78)	(-3.94)	(-3.91)
ILLIQ				0.04243***	0.04199***	0.04224***	0.04210***				0.04239***	0.04199***	0.04224***	0.04210***
.				(3.30)	(3.32)	(3.32)	(3.30)				(3.31)	(3.32)	(3.33)	(3.30)
ST REV					-.00756***	-.00774***	-.00819***					-.00743***	-.00758***	-.00803***
.					(-3.24)	(-3.37)	(-3.53)					(-3.17)	(-3.29)	(-3.44)
LT REV						-.00156***	-.00153***						-.00157***	-.00155***
.						(-3.22)	(-3.20)						(-3.25)	(-3.22)
COSKEW							0.00003							0.00003
.							(0.79)							(0.78)
$\overline{Adj}\ R^2$	0.0168	0.0300	0.0404	0.0426	0.0439	0.0455	0.0467	0.0163	0.0297	0.0401	0.0424	0.0437	0.0453	0.0465

Table 5. Risk-adjusted quintile portfolio returns: Industry-matched and characteristic-matched portfolio return

This table reports average $\beta^{i}_{\ln\_co2}$ portfolio monthly industry-matched portfolio returns and characteristics-matched portfolio returns. $\beta^{i}_{\ln\_co2}$ is estimated by running the monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2* over a 36-month fixed window after controlling for the market (MKT), size (SMB), book-to-market (HML) factors of Fama and French (1993) for each month. Industry-matched portfolio returns are constructed based on 49-industry classification of Fama French (1997). Characteristic-adjusted benchmark are constructed following Daniel, Grinblatt, Titman and Wermers (1997) and Wermers (2004), which matches each stock to a portfolio of stocks with similar size, book-market ratio, and momentum. We report both raw return and the risk-adjusted (using FF-3, FF-4, FF-5 factor, Q-4, M-5 models) monthly returns. Fama-French factors, $[\mathrm{R_M} - \mathrm{R_f}]$, SMB, HML, UMD, RMW and CMA are obtained from Kenneth French's website. Hou, Xue and Zhang (2015) Q-4 factors, MKT, ME, I/A, ROE factors are provided by Zhang and we obtain Mispricing factors of Stambaugh & Yuan (2017), MKT, SMB, MGMT and PERF, from Yuan's website. "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2}$ portfolio (Q5). Newey-West adjusted *t-statistics* are given in parentheses. The sample period covers January 1976 to December 2016 (December 2012 for Characteristic-adjusted return).

ln_co2 factor loadings ($\beta^{i}_{\ln\_co2}$)	Panel A: Industry-matched portfolio return						Panel B: Characteristics-matched portfolio return					
Sorting Statistic	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Average return	0.25	0.16	0.08	0.10	-0.02	0.27***	0.39	0.19	0.13	0.12	0.14	0.24***
	(3.55)	(2.81)	(1.38)	(2.05)	(-0.34)	(3.98)	(1.20)	(0.76)	(0.55)	(0.50)	(0.45)	(2.90)
CAPM Alpha	-0.17	-0.18	-0.25	-0.25	-0.43	0.26***	-0.35	-0.45	-0.48	-0.50	-0.58	0.23***
	(-2.01)	(-2.38)	(-3.47)	(-3.63)	(-5.42)	(4.05)	(-1.19)	(-1.87)	(-2.08)	(-2.04)	(-1.97)	(2.90)
FF3 Alpha	-0.21	-0.21	-0.26	-0.27	-0.46	0.25***	-0.41	-0.54	-0.56	-0.59	-0.64	0.23***
	(-2.88)	(-2.85)	(-3.84)	(-4.26)	(-6.05)	(3.89)	(-1.51)	(-2.32)	(-2.50)	(-2.46)	(-2.31)	(2.74)
FF4 Alpha	-0.13	-0.22	-0.30	-0.30	-0.46	0.33***	-0.14	-0.37	-0.44	-0.44	-0.45	0.31**
	(-1.39)	(-2.98)	(-4.54)	(-4.77)	(-5.58)	(3.27)	(-0.47)	(-1.53)	(-1.88)	(-1.86)	(-1.59)	(2.59)
FF5 Alpha	-0.13	-0.29	-0.35	-0.36	-0.46	0.32***	-0.12	-0.51	-0.56	-0.60	-0.46	0.34***
	(-1.42)	(-4.12)	(-5.27)	(-5.31)	(-5.17)	(3.12)	(-0.38)	(-1.94)	(-2.24)	(-2.26)	(-1.49)	(2.96)
M4 Alpha	-0.05	-0.30	-0.39	-0.41	-0.47	0.42***	0.07	-0.36	-0.46	-0.47	-0.34	0.42***
	(-0.48)	(-4.14)	(-6.07)	(-5.72)	(-5.03)	(3.18)	(0.20)	(-1.20)	(-1.63)	(-1.65)	(-1.00)	(2.83)
Q4 Alpha	-0.03	-0.28	-0.37	-0.39	-0.44	0.41***	0.08	-0.39	-0.48	-0.51	-0.33	0.41***
	(-0.27)	(-3.87)	(-5.66)	(-5.42)	(-5.33)	(2.97)	(0.22)	(-1.33)	(-1.75)	(-1.79)	(-1.05)	(2.68)

Table 6. Sub-period analysis: Quintile portfolio returns sorted by β_{ln_co2}

This table reports the average returns and the Jensen alpha with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) of the quintile portfolios formed on β_{ln_co2} for subsamples. In Panel A, we check the robustness of our results by dividing the entire sample period into 1976~1994 and 1995~2016 sub-periods. In panel B, we check the robustness of our results by sub-dividing the entire sample period into financial crisis periods (2008-2009) and the periods excluding the 2008-2009 financial crisis. For each stock and for each month, we estimate the β_{ln_co2} by running the following monthly rolling regressions of excess stock returns $(R_{i,t} - R_{f,t})$ on the *ln_co2* over a 36-month fixed window after controlling for the market (MKT), size (SMB), book-to-market (HML) factors of Fama and French (1993). For each month, quintile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where quintile 1 (5) contains stocks with the lowest (highest) $\beta_{\ln\_co2}$. After portfolio formation, we record the next month returns of each quintile portfolio following the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. This table reports the average pre-ranking beta and post-ranking return for each quintile portfolio. We also compute the Jensen alpha of each quintile portfolio with respect to the CAPM (Fama-French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on $R_m - R_f$, (SMB, HML, and UMD). "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2}$ portfolio (Q5). Newey-West adjusted *t-statistics* are given in parentheses.

Panel A. Sub-period 1976~1994 and 1995~2016

Sub-period	1976-1994						1995-2016					
ln_co2 factor loadings ($\beta^i_{\ln\_co2}$)	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Average return	1.39	1.38	1.37	1.36	1.12	0.27**	1.24	1.30	1.22	1.14	0.95	0.29***
	(2.81)	(3.61)	(3.89)	(3.52)	(2.22)	(2.36)	(2.50)	(3.74)	(3.94)	(3.48)	(2.01)	(2.81)
CAPM Alpha	0.09	0.15	0.16	0.12	-0.20	0.29***	0.12	0.39	0.39	0.29	-0.14	0.26***
	(0.29)	(0.70)	(0.88)	(0.57)	(-0.67)	(2.62)	(0.39)	(1.76)	(1.79)	(1.34)	(-0.48)	(2.74)
FF3 Alpha	-0.11	-0.05	0.00	-0.01	-0.28	0.17*	0.08	0.26	0.25	0.15	-0.21	0.28**
	(-0.69)	(-0.75)	(0.08)	(-0.08)	(-1.51)	(1.83)	(0.42)	(2.37)	(2.31)	(1.39)	(-1.23)	(2.54)
FF4 Alpha	-0.04	0.03	0.08	0.06	-0.31	0.27**	0.39	0.43	0.36	0.28	0.02	0.38**
	(-0.28)	(0.34)	(1.34)	(0.70)	(-1.81)	(2.60)	(1.83)	(3.59)	(3.28)	(2.90)	(0.11)	(2.30)

Panel B. Before New Source Performance Standards (NSPS) and After NSPS

Sub-period	Before *New Source Performance Standards (NSPS)*						After *NSPS*					
ln_co2 factor loadings ($\beta^i_{\ln\_co2}$)	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Average return	1.52	1.40	1.30	1.31	1.20	0.32***	1.33	1.43	1.50	1.12	0.69	0.64
	(4.35)	(5.48)	(5.53)	(5.22)	(3.66)	(3.76)	(1.19)	(1.83)	(2.24)	(1.52)	(0.86)	(1.67)
CAPM Alpha	0.37	0.38	0.32	0.31	0.06	0.31***	-0.31	0.17	0.43	-0.02	-0.74	0.43
	(1.61)	(2.33)	(2.11)	(1.92)	(0.28)	(3.73)	(-0.50)	(0.62)	(1.69)	(-0.06)	(-2.81)	(0.92)
FF3 Alpha	0.22	0.20	0.15	0.14	-0.08	0.30***	-0.28	-0.00	0.24	-0.08	-0.38	0.11
	(1.71)	(2.55)	(2.07)	(1.73)	(-0.67)	(3.53)	(-0.60)	(-0.04)	(5.70)	(-0.91)	(-3.03)	(0.25)
FF4 Alpha	0.50	0.36	0.26	0.25	0.10	0.40***	-0.09	0.05	0.23	-0.08	-0.29	0.20
	(2.92)	(3.99)	(3.48)	(3.41)	(0.79)	(3.20)	(-0.24)	(0.86)	(6.10)	(-0.99)	(-2.48)	(0.55)

Table 7. Alternative CO2 emission data: Quintile portfolio returns sorted by $\boldsymbol{\beta_{ln\_co2(CDIAC)}}$

For each stock and for each month, we estimate the $\beta_{ln\_co2(CDIAC)}$ estimated using alternative CO2 emission data by running the following monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2 (CDIAC)* over a 36-month fixed window after controlling for the market (MKT) (or the market (MKT), size (SMB), book-to-market (HML)) factors of Fama and French (1993):

(1) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{ln\_co2(CDIAC)}^i ln\_co2(CDIAC) + \varepsilon_{i,t}$

(2) $R_{i,t} - R_{f,t} = \beta_0^i + \beta_{MKT}^i(R_{m,t} - R_{f,t}) + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + \beta_{ln\_co2(CDIAC)}^i ln\_co2(CDIAC) + \varepsilon_{i,t}$

For each month, quintile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2(CDIAC)}$, where quintile 1 (5) contains stocks with the lowest (highest) $\beta_{\ln\_co2(CDIAC)}$. After portfolio formation, we record the next month returns of each quintile portfolio following the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. This table reports the average pre-ranking beta and post-ranking return for each quintile portfolio. We also compute the Jensen alpha of each quintile portfolio with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on $R_m - R_f$, (SMB, HML, and UMD). "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2(CDIAC)}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2(CDIAC)}$ portfolio (Q5). Carbon emissions data from Fossil-Fuel Combustion of USA are obtained from CDIAC (Carbon Dioxide Information Analysis Center) webpage. Newey-West adjusted *t-statistics* are given in parentheses. The sample period covers January 1981 to December 2003.

Total CO2 emissions from fossil-fuel	Quintile portfolio					
Sorting Statistic	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
Panel A: beta estimation using equation (1)						
$\beta_{ln\_co2(CDIAC)}$	-0.64	-0.20	-0.04	0.11	0.45	
Average return	1.62	1.36	1.37	1.33	1.22	0.40***
	(3.70)	(4.41)	(5.15)	(4.84)	(3.01)	(2.90)
CAPM Alpha	0.44	0.31	0.39	0.34	0.10	0.35***
	(1.21)	(1.22)	(1.54)	(1.33)	(0.30)	(2.66)
FF3 Alpha	0.33	0.08	0.15	0.13	0.04	0.30**
	(1.69)	(0.70)	(1.30)	(1.21)	(0.22)	(2.05)
FF4 Alpha	0.81	0.33	0.30	0.27	0.26	0.55**
	(2.87)	(2.43)	(2.40)	(2.33)	(1.43)	(2.59)
Panel B: beta estimation using equation (2)						
$\beta_{ln\_co2(CDIAC)}$	-0.60	-0.17	-0.01	0.14	0.50	
Average return	1.67	1.37	1.33	1.32	1.21	0.46***
	(3.75)	(4.55)	(5.10)	(4.75)	(2.98)	(3.67)
CAPM Alpha	0.49	0.34	0.36	0.32	0.07	0.42***
	(1.34)	(1.35)	(1.41)	(1.28)	(0.21)	(3.64)
FF3 Alpha	0.41	0.11	0.14	0.10	-0.03	0.44***
	(2.04)	(1.00)	(1.13)	(0.96)	(-0.15)	(3.09)
FF4 Alpha	0.86	0.35	0.27	0.27	0.22	0.64***
	(2.89)	(2.63)	(2.13)	(2.42)	(1.24)	(2.77)

Table 8. Future returns and climate related variables

This table presents the results from firm and year fixed effects regressions of the one (two, three)-month ahead stock returns and climate related variables. The climate related variables, *ln_CO2, ln_PCP, ln_TAVG and ln_PDSI,* are computed as $\log\left(\frac{Total\ Energy\ CO2\ Emission_t}{Total\ Energy\ CO2\ Emission_{t-1}}\right)$, $\log\left(\frac{Precipitation\ Index_t}{Precipitation\ Index_{t-1}}\right)$, $\log\left(\frac{Temperature\ Index_t}{Temperature\ Index_{t-1}}\right)$, $\log\left(\frac{Palmer\ Drought\ Severity\ Index_t}{Palmer\ Drought\ Severity\ Index_{t-1}}\right)$. The constant terms are omitted for the brevity. Standard errors are clustered at the firm level. The sample period covers January 1976 to December 2016.

	FF3			FF4			FF5			M4			Q4		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
VARIABLES	Ret(+1)	Ret(+2)	Ret(+3)	Ret(+1)	Ret(+2)	Ret(+3)	Ret(+1)	Ret(+2)	Ret(+3)	Ret(+1)	Ret(+2)	Ret(+3)	Ret(+1)	Ret(+2)	Ret(+3)
ln_CO2	**-0.00456****	**-0.0443*****	**-0.0192*****	**-0.00219**	**-0.0453*****	**-0.0152*****	**-0.00926*****	**-0.0387*****	**-0.0242*****	**-0.00727*****	**-0.0408*****	**-0.0199*****	**-0.00943*****	**-0.0436*****	**-0.0181*****
	(-2.064)	**(-21.13)**	**(-9.567)**	**(-0.988)**	**(-21.50)**	**(-7.565)**	**(-4.182)**	**(-18.58)**	**(-11.97)**	**(-3.246)**	**(-19.36)**	**(-9.743)**	**(-4.222)**	**(-20.63)**	**(-8.913)**
ln_PCP	0.00190***	-0.000781*	0.00351***	0.00231***	-0.000949**	0.00422***	-0.00003	-0.00001	0.00223***	0.00120**	-0.000717	0.00272***	-0.000123	0.00005	0.00154***
	(4.042)	(-1.738)	(7.660)	(4.886)	(-2.111)	(9.167)	(-0.0810)	(-0.0400)	(4.867)	(2.516)	(-1.593)	(5.815)	(-0.257)	(0.112)	(3.308)
ln_TAVG	-0.0192***	-0.0307***	-0.0305***	-0.0197***	-0.0305***	-0.0313***	-0.0224***	-0.0283***	-0.0329***	-0.0217***	-0.0287***	-0.0325***	-0.0223***	-0.0315***	-0.0311***
	(-24.27)	(-36.69)	(-37.38)	(-24.88)	(-36.52)	(-38.29)	(-28.21)	(-33.78)	(-39.90)	(-27.38)	(-34.85)	(-39.17)	(-27.96)	(-37.53)	(-37.67)
ln_PDSI	-0.000829***	0.00615***	-0.00279***	-0.00107***	0.00625***	-0.00322***	-0.000399*	0.00594***	-0.00248***	-0.00140***	0.00587***	-0.00150***	-0.000725***	0.00597***	-0.00180***
	(-3.565)	(25.45)	(-11.87)	(-4.616)	(25.85)	(-13.69)	(-1.727)	(24.63)	(-10.49)	(-5.766)	(23.49)	(-6.177)	(-3.008)	(23.88)	(-7.411)
MKT	0.0515***	-0.189***	-0.153***	0.0423***	-0.186***	-0.169***	0.0130***	-0.146***	-0.181***	-0.00186	-0.153***	-0.151***	0.00725**	-0.163***	-0.159***
	(14.28)	(-54.01)	(-45.96)	(11.74)	(-53.11)	(-49.94)	(3.596)	(-42.06)	(-52.44)	(-0.473)	(-39.46)	(-40.13)	(1.970)	(-46.93)	(-45.85)
SMB	0.0581***	-0.118***	-0.288***	0.0635***	-0.120***	-0.279***	0.0912***	-0.0828***	-0.288***	0.0282***	-0.115***	-0.268***			
	(11.27)	(-24.14)	(-50.15)	(12.35)	(-24.49)	(-49.09)	(15.66)	(-15.31)	(-48.93)	(4.768)	(-20.88)	(-43.65)			
HML	-0.0446***	-0.148***	-0.135***	-0.0629***	-0.141***	-0.165***	0.0892***	-0.265***	0.0293***						
	(-8.100)	(-25.83)	(-24.19)	(-11.30)	(-24.42)	(-28.60)	(12.25)	(-34.92)	(4.074)						
UMD				-0.0499***	0.0198***	-0.0817***									
				(-14.45)	(5.872)	(-23.93)									
RMW							-0.0249***	0.161***	-0.0539***						
							(-3.426)	(23.20)	(-7.698)						
CMA							-0.295***	0.231***	-0.237***						
							(-27.57)	(21.61)	(-22.82)						
MGMT										-0.175***	-0.0611***	-0.0223***			
										(-28.31)	(-10.08)	(-3.637)			
PERF										-0.0281***	0.146***	-0.0237***			
										(-7.397)	(32.26)	(-6.277)			
ME													0.121***	-0.0802***	-0.318***
													(22.96)	(-16.48)	(-54.37)
I/A													-0.295***	-0.0925***	-0.146***
													(-36.00)	(-11.23)	(-18.20)
ROE													0.0837***	0.108***	-0.113***
													(14.00)	(17.66)	(-19.26)
Year and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,546,166	1,529,530	1,513,122	1,546,166	1,529,530	1,513,122	1,546,166	1,529,530	1,513,122	1,521,406	1,508,139	1,494,996	1,521,406	1,508,139	1,494,996
R-squared	0.009	0.014	0.014	0.009	0.014	0.015	0.009	0.014	0.014	0.009	0.014	0.013	0.010	0.013	0.015

Table 9. Quintile portfolio returns using S&P 500 listed stocks

This table reports average $\beta^{i}_{\ln\_CO2}$ portfolio monthly portfolio returns using S&P 500 listed stocks. S&P 500 listed constituents are obtained in Compustat. $\beta^{i}_{\ln\_CO2}$ is estimated by running the monthly rolling regressions of excess stock returns ($R_{i,t} - R_{f,t}$) on the *ln_co2* over a 36-month fixed window after controlling for the MKT, SMB, HML factors of Fama and French (1993) for each month. For each month, quintile portfolios are formed by sorting individual stocks based on their regression coefficients, $\beta_{\ln\_co2}$, where quintile 1 contains stocks with the lowest (quintile 5 the highest) $\beta_{\ln\_co2}$. After portfolio formation, we record the next-month returns of each quintile portfolio over the estimation period. We repeat the procedure by rolling the beta estimation window forward by one month at a time. We reports the average return for each quintile portfolio and also compute the Jensen alpha of each decile portfolio with respect to the CAPM (Fama French three-factor model, Carhart four-factor model) by running a time series regression of the post-ranking excess returns on $R_m - R_f$, (SMB, HML, and UMD). "Q1-Q5" denotes an arbitrage portfolio that buys a low $\beta_{\ln\_co2}$ portfolio (Q1) and sells a high $\beta_{\ln\_co2}$ portfolio (Q5). Newey-West adjusted *t-statistics* are given in parentheses. The sample period covers January 1976 to December 2016 (December 2012 for Characteristic-adjusted return).

Sorting Statistic	Q1 (low)	Q2	Q3	Q4	Q5 (High	Q1-Q5
Average ret	1.36	1.28	1.26	1.18	1.14	0.22**
	(5.12)	(5.79)	(6.15)	(5.66)	(4.66)	(2.20)
CAPM Alpha	0.21	0.24	0.26	0.17	0.02	0.18*
	(1.46)	(1.92)	(1.96)	(1.39)	(0.17)	(1.93)
FF3 Alpha	0.06	0.09	0.12	0.03	-0.10	0.17*
	(0.63)	(1.07)	(1.43)	(0.41)	(-1.32)	(1.65)
FF4 Alpha	0.26	0.20	0.21	0.12	0.06	0.21**
	(2.64)	(2.69)	(2.62)	(1.58)	(0.81)	(2.04)

Table 10. Investment opportunity and climate related variables

This table presents the results from firm and year fixed effects regressions of the one-quarter ahead investment opportunity variables and climate related variables. The investment opportunity proxies are constructed following standard definitions. CAPX/PPE is computed as capital expenditures divided by net plant, property, and equipment and market-to-book assets ratio (M/B) is computed as (share price × shares outstanding + preferred stock + debt in current liabilities + long term debt deffered taxes and investment tax credit) divided by book value of asset. The climate related variables, *ln_CO2, ln_PCP, ln_TAVG and ln_PDSI,* are computed as $\log\left(\frac{Total\ Energy\ CO2\ Emission_t}{Total\ Energy\ CO2\ Emission_{t-1}}\right)$, $\log\left(\frac{Precipitation\ Index_t}{Precipitation\ Index_{t-1}}\right)$, $\log\left(\frac{Temperature\ Index_t}{Temperature\ Index_{t-1}}\right)$, $\log\left(\frac{Palmer\ Drought\ Severity\ Index_t}{Palmer\ Drought\ Severity\ Index_{t-1}}\right)$. The control variables, *Log (Asset), ROA, Leverage, PPE, Log (Sales), R&D Intensity, ROS, Growth (Sales)* are computed as $Log\ (Asset) = log(Asset_t)$, $ROA = Net\ income_t/Revenue_t$, $Leverage = Debt_t/Asset_t$, $PPE = Property\ Plant\ and\ Equipment_t/Asset_t$, $Log\ (Sales) = log(Sales_t)$, $R\&D\ Intensity = Research\ and\ Development\ Expense_t/Sales_t$, $Growth\ (Sales)_t = (Sales_t - Sales_{t-1})/sales_{t-1}$. All the accounting variables are winsorized at top 1% and bottom 1%. The constant terms are omitted for the brevity. Standard errors are clustered at the firm level. The sample period covers January 1976 to December 2016.

Variables	CAPX/PPE		M/B	
	(1)	(2)	(3)	(4)
ln_CO2	-0.750***	-1.325***	-0.284***	-0.416**
	(-11.14)	(-7.114)	(-4.497)	(-2.241)
ln_PCP		-0.133***		0.123***
		(-9.286)		(3.000)
ln_TAVG		-0.0936**		-0.0133
		(-2.406)		(-0.371)
ln_PDSI		-0.00346		0.0622***
		(-0.794)		(6.997)
Log (Asset)	-0.0201	-0.0275	-0.926***	-0.900***
	(-1.252)	(-1.487)	(-17.16)	(-17.41)
ROA	0.134**	0.0398	-1.416***	-1.212***
	(2.168)	(0.787)	(-3.976)	(-3.603)
Leverage	-0.110*	-0.158*	-1.035***	-1.109***
	(-1.669)	(-1.938)	(-8.332)	(-9.933)
PPE	-0.280***	-0.291***	-1.776***	-1.593***
	(-4.962)	(-4.913)	(-6.058)	(-6.118)
Log (Sales)	0.00635	0.0168	0.368***	0.372***
	(0.317)	(0.728)	(8.586)	(8.488)
R&D Intensity	-0.00559	-0.00294	0.0275**	0.0274**
	(-1.346)	(-0.786)	(2.406)	(2.472)
ROA	-0.00686	-0.00505	-0.0609***	-0.0554***
	(-0.942)	(-0.622)	(-5.432)	(-5.129)
Growth (Sales)	0.00510	-0.00162	0.174***	0.149***
	(0.661)	(-0.151)	(6.567)	(4.763)
Year and Firm FE	Yes	Yes	Yes	Yes
Observations	264,812	210,390	282,129	223,815
R-squared	0.002	0.002	0.026	0.025