Three Essays in Climate Finance

by

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Thesis

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Declarations

I declare that any material contained in this thesis has not been submitted for a degree to any other university. I further declare that Chapter 2 of the thesis, *Temperature Sensitivity and Predictable Returns*, is co-authored with Alok Kumar and Chendi Zhang. Chapter 3 of the thesis *Climate Change, Analyst Forecasts, and Market Behavior* is a product of joint work with Carina Cuculiza, Alok Kumar and Chendi Zhang. Furthermore, the paper titled *Temperature Sensitivity and Institutional Investor*, drawn from Chapter 4 of this thesis, is co-authored with Carina Cuculiza, Alok Kumar and Chendi Zhang.

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Abstract

This thesis consists of three essays that study the impact of climate risk on financial markets and participants. In the second chapter, we find that firms' exposure to temperature changes predicts stock returns. We use the sensitivity of stock returns to abnormal temperature changes to measure firm-level climate sensitivity. Stocks with higher climate sensitivity forecast lower stock returns. A trading strategy that exploits return predictability generates risk-adjusted returns of 4% per year from 1968 to 2019. Such abnormal returns disappear after one year. Further, climate sensitivity predicts lower earnings, sales and margin profits. Firms with high climate sensitivity also perform worse in ESG scores. Overall, these findings are consistent with stock markets underreacting to firms' climate sensitivity.

In the third chapter, we examine whether sell-side equity analysts help the market assimilate information contained in global climate change. Using a new measure of firm sensitivity to climate change, we show that analysts located in states where firms exhibit greater sensitivity to abnormal temperature changes issue relatively more accurate forecasts in periods following large temperature increases. These effects are stronger for firms that are more sensitive to temperature changes. High temperature sensitivity firms also have lower consensus forecasts and higher earnings surprises,

which generate higher stock market reactions following earnings announcements. Collectively, the evidence suggests that certain sell-side equity analysts incorporate news about climate change in their earnings forecasts and, consequently, earnings information is incorporated into prices quicker.

The fourth chapter document how climate risk affects institutional investors by investigating if they change their holding strategy according to firm-level climate sensitivity. We find that institutional investors ownership of high climate sensitivity stocks is lower. Institutional investors show better skill in high climate sensitivity stocks holding, and low abnormal stock returns of high climate sensitivity stocks are mostly generated from retail investors. Besides, several types of institutional investors have different preferences for high climate sensitivity stocks than others. Aggressive institutional investors react to climate risk better than conservative institutional investors do. We also find that the location of institutional investors does not affect their holding strategy on high climate sensitivity stocks. Collectively, our findings suggest that part of the institutional investors realize the climate risk and react to it.

Chapter 1

Introduction

The effect of climate change has become stronger in the past decades. Emerging climate finance literature has shown that climate risk imposes a large impact on the financial market and participants. For example, Lesk et al. (2016) show that extreme weather disasters affect global crop production. Workers become less productive when temperatures are extremely high (Huntington, 1915). Zivin and Neidell (2014) also find that hot temperatures reduce hours worked in industries with high climate exposure. Evidence from existing studies also suggests that temperature increases can lead to lower productivity levels (Huntington, 1915) and fewer hours worked in climate-sensitive industries (Zivin and Neidell, 2014). If sell-side analysts become less productive or more distracted after an event, then it is possible for them to spend less time on their forecast issues (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hong and Stein, 2007; DellaVigna and Pollet, 2009; Han et al., 2020) and, as a result, become less accurate (Dong and Heo, 2016). Further, Krueger, Sautner and Starks (2020) provide evidence that institutional investors believe that climate risks have financial implications for their portfolios. Ilhan et al. 2021 show that institutional investors value and demand climate risk disclosures. "Big Three" (BlackRock, Vanguard, and

State Street) is found to focus its engagement effort on large firms with high CO2 emissions in which these investors hold a significant stake (Azar et al. 2020).

In this thesis, we are interested in how climate risk impacts the financial market in several areas. First, we investigate how climate risk affects stock price using a novel method to identify ex-ante stocks that are more likely to be influenced by abnormal changes in temperature. Our analysis shows that stock-level temperature sensitivity predicts future returns and firm performance. Second, we examine whether sell-side equity analysts help the market assimilate information contained in global climate change. Using the measurement of location temperature sensitivity, we find that a specific group of analysts react to climate risk, which improves forecast accuracy. Finally, we study whether institutional investors are affected by climate risks.

In chapter two, we propose a novel measurement of climate risk on stock level. Temperature change is one of the most direct and widely used measures of climate change (see Brohe and Greenstone, 2007; Fisher et al., 2012), as climate change leads to more extreme and volatile temperatures. Therefore, we measure firm-level temperature sensitivity as the return sensitivity of stocks to abnormal changes in temperature.

Empirically, we find that firms' temperature sensitivity forecasts stock returns. Portfolios sorted by firm-level temperature sensitivity forecast decreasing risk-adjusted returns from 1960 to 2019. Stocks with the lowest (highest) temperature sensitivity earn an average monthly characteristic-adjusted return of 0.02% (-0.26%). We also show that firm-level temperature sensitivity is also associated with lower future firm performance. Our results show that the Return on Asset (ROA), earnings and profit margin of firms with high temperature sensitivity are significantly lower than other firms. Our longevity test results indicate that it takes about one year for the investors to adjust their expectations on climate risk. Finally, we find that the measurement of temperature sensitivity captures the difference among stocks better than the ESG score does. Our findings provide a new way to measure stock level climate risk and show that climate change affects the financial market significantly.

In chapter three, we explore how sell-side analysts understand climate risk. We first find that analysts in the area where climate changes have a large impact on the local economy react to climate risk more than analysts in other areas. Specifically, these analysts issue more accurate forecasts towards firms after a large temperature increase. Further, we show that the improvement of the accuracy of the forecast is concentrated on stocks with higher temperature sensitivity and can not be explained by analysts' private information.

Besides, we show that our findings are consistent with the common belief that Democrats care more about climate risk than Republicans. Our findings are also robust when using different ways to separate analysts into subgroups. Using the quarterly earning announcement data for firms, we further show that the market reaction to the forecasts issued by these analysts is significant after earning announcement date, although these forecasts are not generally treated to be more accurate in general.

In chapter four, we examine whether institutional investors consider climate risk in their portfolio holding constructions. Specifically, we study institutional investors holdings on stocks with different levels of temperature sensitivity. Our results show that the institutional holding weight decreases almost monotonically from the lowest temperature sensitivity portfolio to the highest temperature sensitivity portfolio from 57.33% to 47.72%. The difference of institutional holding between the lowest and the highest temperature sensitivity is 9.62%, with *t*-statistics of 5.05. Our finding indicates that institutional investors tend to hold less stocks with high temperature sensitivity to avoid low returns.

We then show that different types of institutions show distinct preferences for high temperature sensitivity stocks. Specifically, investment companies, pension funds, and endowments have significantly lower high temperature sensitivity stocks holding weight (0.12% and 0.18%, respectively). In contrast, hedge funds and venture capital hold a higher weight for stocks in the same temperature sensitivity portfolio of 0.15%. On the other hand, banks and insurance companies do not show a clear preference for high temperature sensitivity stocks to other stocks.

Further, we examine whether institutional investors could use their knowledge and skills to find and hold those stocks that perform better than others in the same climate portfolio. We find that institutional investors could pick and hold stocks with better performance than others from the same temperature sensitivity portfolio and such ability benefits them more in higher temperature sensitivity portfolios.

Chapter 2

Temperature Sensitivity and Predictable Returns

2.1 Introduction

Climate change has important implications for the economy and financial markets. For example, Lesk et al. (2016) show that extreme weather disasters affect global crop production. Workers become less productive when temperatures are extremely high (Huntington, 1915). Carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather (Choi et al., 2020). Hong, Li, and Xu (2019) find that droughts predict the stock returns of the food industry. Climate risk has also been shown to affect the long-run discount rates in real estate (Giglio et al., 2015). In addition, institutional investors believe that climate risks have financial implications which are not fully reflected in equity valuation (Krueger et al., 2018). However, the literature on climate finance has focused on the effect of climate-related shocks, such as droughts and heatwaves, on specific industries. Little is known on the effect of systematic differences across firms in terms of their exposures to climate risk. In this paper, we study if firms' exposure to climate change affects stock prices.

We propose a novel method to identify ex-ante stocks that are more likely to be influenced by abnormal changes in temperature. Temperature change is one of the most direct and widely used measures of climate change (see Brohe and Greenstone, 2007; Fisher et al., 2012), as climate change leads to more extreme and volatile temperatures. Therefore, we measure firm-level temperature sensitivity as the return sensitivity of stocks to abnormal changes in temperature. A stock has greater temperature sensitivity if its returns are more sensitive to abnormal temperature changes (either positive or negative).

We posit that temperature sensitivity may affect future stock returns. There are several channels through which extreme temperature influences stock returns. First, extreme temperature events have an impact on firm fundamentals. For example, Addoum et al. (2020) show evidence that extremely hot temperatures impact firm earnings. Investors will react to the low firm earnings after temperature shocks and induce a lower stock return. The second channel is investors' attention and concern to the climate issue. Choi, Gao and Jiang (2020) show that people update their belief on climate issues after unusual warm climates in their area and carbon-intensive stocks underperform after hot temperature events. Specifically, we conjecture that stocks with higher climate sensitivities are likely to be underreacted by the market. Consequently, the return of these stocks may be predictable in the short run. In addition, a firm's profitability could also be affected by temperature sensitivity.

We find that firms' temperature sensitivity forecasts stock returns. Portfolios sorted by firm-level temperature sensitivity forecast decreasing risk-adjusted returns from 1960 to 2019. Stocks with the lowest (highest) temperature sensitivity earn an average monthly characteristic-adjusted return of 0.02% (-0.26%). The factor model estimates also show similar results. The monthly four-factor alpha estimates for the lowest and highest temperature sensitivity portfolios are 0.01% and -0.33%, respectively. A trading strategy that goes long (short) portfolio with the lowest (highest) temperature sensitivity yields a risk-adjusted return of 4.0% p.a., which is statistically significant. The results using the six-factor model are quantitatively similar. The result is robust when we control for macroeconomic factors or use conditional factor models. Results from Fama-MacBeth regressions of stock returns on temperature sensitivity also shows a similar result: higher stock-level temperature sensitivity predicts lower future stock returns.

Further, firm-level temperature sensitivity is also associated with lower future firm performance. We conduct a series of Fama-MacBeth regression using different firm performance variables. Our results show that the Return on Asset (ROA), earnings and profit margin of firms with high temperature sensitivity are significantly lower than other firms.

Next, we conduct a longevity test of return predictability. As the lag between portfolio formation and temperature sensitivity estimation increases from 1 month to 13 months, the abnormal return becomes statistically insignificant. It shows that the abnormal returns are likely to be generated by mispricing, which disappears as information contained in temperature sensitivity becomes staler. Our finding also indicates that it takes a relatively long period for investors to react to climate risk.

In additional tests, we use alternative measures of temperature sensitivity that allow for different sensitivities to positive and negative abnormal temperatures. We find that the temperature sensitivity to both positive and negative temperature contributes similarly to the return predictability. Overall, our results suggest that stock markets misprice stocks with high temperature sensitivity.

In the final test, we show the relation between our measurement of temperature sensitivity and a set of ESG scores from Refinitiv. We find a negative correlation between the temperature sensitivity and the ESG scores for stocks. The average ESG scores of firms in high temperature sensitivity portfolios are significantly lower than those in low-temperature sensitivity portfolios. Besides, we find that portfolios sorted using ESG scores do not have a significant return difference, indicating that our temperature sensitivity measurement captures the stock return difference better than the ESG score does.

Our findings contribute to the emerging finance literature that examines the relationship between climate change and financial markets. Hong, Li, and Xu (2019) find that droughts forecast food stock returns. Addoum et al. (2020) show that analysts and investors do not immediately react to observable temperature shocks. Addoum et al (2020) mainly focus on the establishment-level sales of firms after extreme temperature shocks. They investigate how firms' performance is affected by temperature shock events and only mention analysts and investors reactions a little in the short-run period, while our paper focuses on the firm-level stock return in a 60 years period. We find that investors tend to underreact temperature sensitivity because it affects a firm's performance in the long run. Institutional investors believe that climate risks have financial implications for their portfolio firms, but the risks have not been fully priced into equity valuation (Krueger et al., 2018). Daniel et al. (2018) and Giglio et al. (2015) analyse how climate risk influences real estate prices. Further, banks have begun to price in climate policy exposure in recent years (Delis et al., 2019). Recent empirical studies show that better environmental policies lead to lower downside and overall portfolio risk (Hoepner et al., 2019; Brandon and Krueger, 2018). Ilhan, Sautner, and Vilkov (2018) study the effect of carbon emissions on firms' downside risk using options data. While previous studies focus on specific industries, we examine the systematic effect of temperature sensitivity on stock returns across stocks and industries. To do so, we develop a novel measure of firms' exposure to climate risk and show that climate sensitivities generate mispricing in certain stock market segments, especially in stocks with the highest temperature sensitivity.

Beyond the literature on climate and finance, our finding is related to the literature showing that intangible assets are not fully priced by the stock market. Firms with superior governance (Gompers et al., 2003; Giroud and Mueller, 2011), customer satisfaction (Fornell et al., 2006), environmental efficiency (Derwall et al., 2005), employee satisfaction (Edmans et al., 2014), and high R&D and advertising expenditure (Chan et al., 2001) all earn higher long-run returns. Our paper reports return predictability from temperature sensitivity to the cross-section of stock returns.

The paper is organised as follows. Section 2 introduces data and methodology. The evidence of predictable returns is discussed in Section 3. Section 4 shows robustness checks and further tests, and Section 5 concludes.

2.2 Data and Method

We describe the data sets used in the empirical analysis in this section. We also summarise the methods used for measuring the temperature sensitivity of stocks.

2.2.1 Main Data Sources

We use data from multiple sources. We obtain monthly stock returns, stock prices, and Standard Industry Classification (SIC) codes from the Center for Research on Security Prices (CRSP).

The monthly Fama-French factor returns, historical book equity data, forty-eight SIC industry classifications, and forty-eight industries daily and monthly value-weighted portfolio returns are from Kenneth French's data library. We also use the data from 48 Fama and French industry portfolio returns to get the industry level book-to-market ratio and average firm size for each industry.

We use data from Compustat to compute book-to-market ratios for each listed US firm in our sample. The book-to-market ratio is calculated as the ratio of year-end book equity plus balance sheet deferred taxes to year-end market equity.

We obtain the Daniel, Grinblatt, Titman, and Wermers (1997) characteristic-based benchmark returns from Russ Wermers' website. We calculate the Daniel, Grinblatt, Titman, and Wermers (1997) method to generate a stock assignment and benchmark portfolio returns from 1963 to 2019. We use these stock assignments, and benchmark portfolio returns to calculate characteristic-adjusted returns at the stock level.

In our factor model estimation, we use the Fama-French three-factor (RM-RF, SMB and HML), momentum factor (MOM), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). Data for all the factors except liquidity factor (LIQ) is from Kenneth French's data library. The data for the liquidity factor is from Lubos Pastor's Research.

In our robustness tests, we employ several interaction variables (INT). INT is one of the following: the NBER recession indicator (REC), the Lettau-Luvigson's (2004) *cay* measure, the dividend yield of the CRSP value-weighted index (DIV), the yield on the three-month T-BILL (YLD), or the term spread (TERM). These indicator data are from FRED economic data and Lettau's website. The data period is from June 1939 to December 2019 for REC and YLD, January 1952 to September 2019 for *cay*, June 1939 to December 2016 for DIV, and April 1953 to December 2019 for TERM.

Our temperature data for the US comes from the National Centers for Environmental Information (NCEI) of the US National Oceanic and Atmospheric Administration (NOAA). The temperature record is updated monthly on the NOAA's website, and the data extends back to January 1895. There are two temperature values in this database, i.e. monthly temperature value and the monthly temperature anomaly. More specifically, the monthly temperature anomaly is the difference between the monthly temperature value and the monthly reference temperature value. The reference temperature of a specific month is the average monthly temperature between 1895 and 2019 for the same month. A positive (negative) temperature anomaly implies that the temperature in that month is higher (lower) than the benchmark average temperature. We use the temperature anomaly as the measurement of climate change, which has also been used in previous studies (see Cao and Wei, 2005).

Figure 2.1 shows the trend of temperature anomaly from NCDC. The black dot trend line shows that the temperature is becoming higher in the past century. As a consequence, climate risk has had a more crucial effect on the financial market these years.

2.2.2 Estimating temperature Sensitivity

Each month, for each stock, we regress the excess stock returns during the past 5 years (60 months) on the excess market return and the abnormal temperature. Specifically, we estimate the following time-series regression for stock *i*:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{mkt,t} - r_{f,t}) + \theta_i Temperature\ Anomaly_t + \epsilon_{i,t} \quad (1)$$

where $r_{i,t}$ is the stock return for stock *i* in month t, $r_{f,t}$ is the T-bill rate in month *y*, $r_{mkt,t}$ is the return of CRSP value-weighted index in month *t* and $Temperature\ Anomaly_t$ is the temperature anomaly in month *t*. We calculate $Temperature\ Anomaly$ as the difference between the current temperature at time *t* and the average temperature between 1895 and 2019 in the same month. Since COMPUSTAT data is only available from 1960, we drop all our θ_i measures before 1960.

θ_i captures the return sensitivity to temperature anomaly for stock *i* in month *t*. A positive (negative) θ_i indicates that the stock returns increase (decrease) with temperature anomaly. We report the top and bottom 10 industries in terms of industry return sensitivity to temperature anomaly (θ) using industry-level returns in Panel A of Table 2.1. Interestingly, coal and oil are among the bottom 10 industries, as they earn high (low) returns during low (high) abnormal temperature periods. However, a firm may benefit from both abnormally high and abnormally low temperatures. For example, the profit of clothing firms could increase during both extremely hot summers and extremely cold winters. Hence we aim to identify ex-ante stocks that are more sensitive to abnormal temperature change, either positive or negative.

Therefore, our key variable of interest, temperature sensitivity θ_i^c, is the absolute value of θ_i. Specifically, $\theta_i^c = |\theta_i|$. This transformation ensures that stocks that benefit more from abnormal temperature changes (either positive or negative) have higher temperature sensitivity. To avoid the influence of the outliers, we winsorise θ_i^c at 1% level on both sides. Panel B reports the top and bottom industries in terms of temperature sensitivity (θ_i^c), where we calculate the industry-level temperature sensitivity using the industry-level returns and temperature anomaly.

Using the θ_i^c estimates as our measure of temperature sensitivity, we sort stocks to form portfolios each month. We use the top quintile of stocks to form the High-temperature sensitivity portfolio (High-TS portfolio) and the bottom quintile of stocks to form the Low-temperature sensitivity portfolio (Low-TS portfolio. The High portfolio contains stocks that are most sensitive to temperature changes, while the Low portfolio contains stocks that are least sensitive. The remaining stocks are split equally into portfolios 2, 3, and 4. Portfolios are value-weighted using market capitalisation at the beginning of each month. We rebalance portfolios every month. The portfolio characteristics, including mean temperature sensitivity, log market capitalisation and book-to-market ratio, are presented in Panel C. The average size and book-to-market ratio across the portfolios are similar.

2.3 Evidence on Predictable Returns

2.3.1 Portfolio-Sorting Results

To assess the relationship between temperature sensitivity and stock returns, we first perform univariate portfolio sorts using temperature sensitivity. We report the performance of the following five portfolios: (i) the Low-TS portfolio, which is a value-weighted portfolio of the bottom quintile stocks with the lowest temperature sensitivity estimates, (ii) the High-TS portfolio, which is a value-weighted portfolio of the top quintile stocks with highest temperature sensitivity estimates, (iii) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining stocks sorted into terciles.

Panel A of Table 2.2 shows that the Sharpe ratio decreases monotonically. The pattern is similar for the full sample period and the later sub-period, indicating that climate risk's effect on stocks is becoming larger, especially in recent decades. In Panel B, we report the average monthly market capitalisation for the quintile portfolios. High and Low portfolios cover an economically significant segment of the market (35%-42%).

The portfolio performance estimates are presented in Panel C. We report the raw returns and characteristics-adjusted portfolio returns for the period from January 1960 to December 2019 and two sub-periods of approximately equal length, which span from January 1960 to December 1989 and January 1990 to December 2019. The *t*-statistics computed using Newey and West

(1987) adjusted standard errors with 6 lags are reported in parentheses below the estimates.

We find that portfolio returns decrease with temperature sensitivity. Portfolio Low (High) with the lowest (highest) temperature sensitivity stocks earn an average monthly characteristic-adjusted return of 0.02% (-0.26%). The monthly return difference of Low minus High is 0.28%, which is significant both statistically (*t*-statistic = 2.69) and economically. This is very similar when we use the equal split sub-sample periods to measure performance. The annualised characteristic-adjusted performance differential is 0.32%*12= 3.84% in the 1963-1990 sample period, which is statistically significant. But during the more recent 1991 to 2016 sub-period, the Low-High performance differential decreases to 0.25%*12 = 3%.

When we vary the number of stocks in the extreme portfolios, we find quantitively similar results. As expected, the performance of the Low-High portfolio weakens when we increase the number of stocks in the extreme portfolios (see Panel D). The Low-High return remains economically and statistically significant when we have 1/16 or 1/7 of all the stocks in the extreme portfolios but drop down when we contain a quarter of the stocks.

2.3.2 Factor Model Estimates

To better account for differences in the riskiness of climate-sensitivity portfolios, we examine the risk-adjusted performance of climate-sensitivity-based portfolios using various unconditional and conditional factor models.

These factor models allow us to control for the effects of additional factors that may affect stock returns.

The unconditional factor model estimates are reported in Table 2.3. The unconditional factor models contain the market factor, the size factor (SMB), the value factor (HML), the momentum factor (MOM), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1968 to 2019 because the data for the liquidity factor (LIQ) is only available in the period starting from 1968.

We find that the performance of climate-sensitivity-based stock portfolios remain economically and statistically significant even when we include an extended range of factors in the stock return models. For example, the monthly four-factor alpha (*t*-statistic) estimates for Low and High portfolios are 0.01% (0.29) and -0.33% (-3.72), respectively. A trading strategy that goes long in the Low portfolio and short in the High portfolio yields a risk-adjusted return of 4% p.a. (0.33%*12=4%) [1], which is statistically significant. The results for the six-factor model are quantitively similar (0.32%*12=3.84% p.a.).[2]

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[1] The average bid-ask spread for all firms across 1968 to 2019 is about 0.08%, which means the factor adjusted return difference between the Low and High portfolio is still statistically and economically significant after considering transaction costs ((0.33%-0.08%)*12=3% p.a.)
[2] We do similar tests using Fama-Frech 5 factor and Q5 factor (Hou, Xue and Zhang 2014) in untablucated results. The difference between the low and high portfolio is qualitatively similar.

To allow for time-varying exposures to systematic risks, we account for portfolio risk using various conditional factor models, including a number of conditional macroeconomic factors that vary with the US business cycle. Specifically, we interact each return factor with the following variables: an NBER Recession indicator (REC), the Lettau and Ludvigson's (2001) *cay* measure, the dividend yield of the CRSP value-weighted index (DIV), the term spread (TERM), and the yield on the three-month T-bill (YLD). The *cay* residual is defined as the difference between current consumption (*c*) and its long-term value based on assets (*a*) and income (*y*). The term spread is defined as the 1-year treasury constant maturity rate. The estimation period for each regression is indicated at the top of each column.[3]

We report the conditional alpha estimates and factor exposures for the Low-TS portfolio, High-TS portfolio and Low-High portfolio in Table 2.4. All the conditional models are reported in the full sample period. These results indicate that controlling for other conditional factors do not affect the conclusion that portfolio returns decrease with temperature sensitivity. For example, the alpha of the Low-High portfolio when we use the conditional model with the NBER Recession interaction and the term spread conditional models are 0.32% and 0.35%, respectively (Panel C column (1) and (4)). These estimates are similar to the unconditional four-factor model alpha

[3] REC, YLD, TERM factors finish at December 2019, *cay* data finishes at September 2019 and DIV finishes at December 2016. Therefore, the number of observations varies across models.

estimate of 0.34%. Panel C shows the results of the Low-High portfolios. The alphas are statistically significant when we use conditional models. Taking together, these conditional factor model estimates are similar to results from unconditional models.

To further illustrate the different performances of the temperature sensitivity sorted portfolio, we show a figure of buy and hold return for the Low-TS and High-TS portfolio in Figure 2.2. The monthly rebalanced High-TS portfolio significantly underperform that of the Low-TS portfolio in the sample period. Consistent with our previous finding, the return difference between Low-TS and High-TS portfolios is mainly contributed by the underperformance of the High-TS portfolio.

2.3.3 Fama-MacBeth Regression Estimates

To further control for cross-sectional differences across firms, we make sorting analysis by running Fama and MacBeth (1973) regressions. One of the advantages of Fama-MacBeth regression is that it could rule out the correlation between cross-sectional stock returns and further justify the causality relationship between temperature sensitivity and the future return on stock level by controlling a series of firm level characteristics. To further control the time-series correlation, we calculate the t-statistics using the Newey-West 1987 method with six lags in our regression. In each month t, we run a cross-sectional regression with the future 1-month return as our dependent variable:

$$r_{i,t+1} = \alpha + \beta Temperature\ Sensitivity_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1} \qquad (1)$$

Our key independent variable $Temperature\ Sensitivity_{i,t}$ is our main measurement θ_i^c of the stock i in the previous month. X is a set of additional controls, and ϵ is the error item. The control variables in X are Fama and French (1992) three-factor beta of the stock over the previous month measured using daily stock return and factor data, total returns over six months returns, log market capitalisation of firms at the beginning of the previous month, and book-to-market ratio available six months prior. The estimation period is from January 1968 to December 2019 to be consistent with the portfolio sorting results. The time-series average of coefficients is reported in Table 2.5 Panel A. The t-statistics are calculated using Newey-West (1987) adjusted standard errors. Across all specifications, the coefficients of $Temperature\ Sensitivity$ are significantly negative, which means firms with higher temperature sensitivity earn lower returns. This evidence is consistent with our main conjecture and indicates that differences in temperature sensitivity are associated with differences in stock returns.

Based on the previous finding that the difference in factor adjusted returns are mainly from the High-TS portfolio, we further perform a Fama-MacBeth regression using a *High-TS* dummy instead of *Temperature Sensitivity* in the regression above. Specifically, we define our main independent variable, *High-TS*, as a dummy variable equals one if a stock is in the High-TS portfolio in the previous month, and zero otherwise. The results are shown in Table 2.5 Panel B. Similar to what we find before, the coefficients of the High-TS dummy in all columns are negatively significant, which indicates that the portfolio return of High-TS stocks are significantly lower than stocks in other temperature sensitivity portfolios.

2.3.4 Temperature Sensitivity and Firm Performance

So far, our evidence indicates that temperature sensitivity has an economically meaningful impact on asset price. Next, we examine whether temperature sensitivity predicts firm profitability. In Table 2.6, we run Fama-MacBeth regression of a set of firm performance variables on temperature sensitivity:

$$Firm\ Performance_{i,t+1} = \alpha + \beta HighTS_{i,t} + \gamma X_{i,t} + \epsilon_{i,t+1} \qquad (2)$$

The dependent variable $Firm\ Performance_{i,t+1}$ is one of the following measurements of firm performance in year t+1: Return on Asset (ROA), earnings, and marginal profit. To find out whether the performance of firms in the High-TS portfolio is lower than others, we use $HighTS$ as our main independent variable in Fama-MacBeth regression. $HighTS$ is a dummy variable equal to 1 if the annual average temperature sensitivity of a stock is in the High portfolio in the previous year and zero otherwise. X is a set of additional controls, and ϵ is the error term.

We control the following factors in our regression: the one-year-lagged performance variable, lagged market value on the previous year, lagged book-to-market ratio available last year, lagged leverage ratio, loss indicator equals one if the firm made a loss in the last year and zero otherwise, the value of the dividend yield last year, no dividend yield indicator which equals one if the firm did not have a dividend yield in the previous year and zero otherwise, and the GDP of the state in which the firm is located. Fama-French 48 industries are used to control for industry fixed effect in the regression. We repeat regressions for each year of the sample period from 1962 to 2017 and report the time-series average of this coefficient following Fama and MacBeth (1973). The *t*-statistics are calculated using Newey-West (1987) adjusted standard errors.

Table 2.6 shows the regression results for firm performance. In Panel A, we report the results for return on asset (ROA). Panel B shows the estimation of earnings, and the profit margin test is presented in Panel C. All the coefficients of the High-TS dummy across three panels are significantly negative, which indicates that the ROA, earnings and profit margin of firms in the High-TS group are significantly lower than those of other firms. For example, the High-TS firms have a ROA of 0.025 (*t*-statistics=-4.79) lower than that of other firms, and their earnings are 0.017(*t*-statistics=-4.73) less. Besides, the profit margin of High-TS firms is also 0.058(*t*-statistics=-3.95) lower than that of firms in other portfolios. These results suggest that the temperature sensitivity contains information on firms' performance: Higher temperature sensitivity predicts lower future performance, which supports our findings in the stock returns. High-TS stocks have both lower returns and lower firm performance.

2.3.5 Longevity Test of Return Predictability

In this section, we examine the performance of the High-Low portfolio as the lag between portfolio formation and climate-sensitivity estimation increases. If the abnormal performance of the High-Low portfolio reflects temperature sensitivity induced mispricing that eventually gets corrected, the performance estimates will become weaker as the lag increases. Table 2.7 shows the effect of varying portfolio formation from 1 to 13 months on monthly six-factor abnormal returns. A positive shift in the portfolio formation period corresponds to the delayed formation of the High-Low portfolios. The baseline result in Table 2.7 is equivalent to the baseline portfolio formation procedure, and the coefficients are the same as those reported in Panel B Column (6) of Table 2.3. As the lag increases to 12 months, the abnormal return becomes statistically insignificant. This evidence shows that the market corrects the abnormal return of high temperature sensitivity stocks after 1 year, which indicates that the effect of climate on investors lasts for a relatively long period.

2.4 Further Tests

2.4.1 Asymmetric Temperature Sensitivity Results

So far, we find that the firms that are more sensitive to extreme temperature (either positive or negative) are more likely to be overpriced by the stock market. To study whether the return sensitivity to positive or negative abnormal temperature drives the results, we use other different methods to allow for asymmetric temperature sensitivity. First, we set all the negative (positive) temperature anomalies to 0 and keep the positive (negative) ones unchanged. Using this *Positive (Negative) Temperature Anomaly*, we then calculate the firm's sensitivity to positive (negative) abnormal temperatures. Finally, we construct our parameters of interest, θ_i^p and θ_i^n using the absolute value of the θ_i^1 and θ_i^2. Specifically, $\theta_i^p = |\theta_i^1|$ and $\theta_i^n = |\theta_i^2|$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{mkt,t} - r_{f,t}) + \theta_i^1 PositiveTemperatureAnomaly_t + \epsilon_{i,t} \quad (3)$$

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i(r_{mkt,t} - r_{f,t}) + \theta_i^2 NegativeTemperatureAnomaly_t + \epsilon_{i,t} \quad (4)$$

There are two advantages of setting negative (positive) temperature anomalies to 0. First, we could obtain more observations when calculating θ_i^p and θ_i^n using a consecutive of tempearture anomaly. Second, setting the negative (positive) of temperature anomaly to 0 limits the magnitude of changings in temperature anomaly. In this way, the results contains the changes in temperature but eliminates the effect of the temperature sensitivity from the other side. In Table 2.A1, we show the top and bottom 10 industries in terms of average sensitivity to these two measurements of temperature sensitivity across firms in the industry. Specifically, Panel A shows the results for θ_i^p and Panel B shows the results for θ_i^n. The descriptive characteristics for θ_i^p and θ_i^n are shown in Panel C and Panel D, respectively.

In Panel A of Table 2.A2, we report the raw return and characteristic adjusted return of five portfolios constructed using θ_i^p in the period from January 1960 to December 2019. The results of portfolios constructed by θ_i^n are reported in Table 2.A2 Panel B. The findings from two different measurements of temperature sensitivity support our main conclusion that stocks with higher temperature sensitivities have lower returns.

In Table 2.A3, we show the factor model estimates of the two new measurements of temperature sensitivity. Similar to Table 2.3, we conduct four-factor and six-factor unconditional factor model estimates. The result for θ_i^p is shown in Panel A and Panel B shows the estimates for θ_i^n.

We find that the Low-High alpha are both statistically significant for θ_i^p and θ_i^n, which support our main conclusion that higher temperature sensitivity generates a lower future return. The similar alphas indicate that firms' different loadings on the temperature sensitivity to positive and negative abnormal temperature contribute similarly to the abnormal returns.

Second, we measure these different sensitivities simultaneously. In the spirit of Henriksson and Merton (1981), we consider both θ_i^p and θ_i^n at the same time to find out whether our conclusions are still held and which temperature sensitivity dominants the result. Specifically, we measure the temperature sensitivity as:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{mkt,t} - r_{f,t}\right) + \theta_i^1 PositiveTemperatureAnomaly_t$$
$$+\theta_i^2 NegativeTemperatureAnomaly_t + \epsilon_{i,t} \qquad (5)$$

We use the absolute value of θ_i^1 and θ_i^2 as $\theta_i^{p\prime}$ and $\theta_i^{n\prime}$ in this new measurement respectively. The factor model estimates using four factors and six factors for both two types of climate sensitivities are reported in Table 2.8. Specifically, Panel A shows the results for $\theta_i^{p\prime}$ and Panel B shows the results for $\theta_i^{n\prime}$. We find that the return differences in Low and High portfolios based on $\theta_i^{p\prime}$ are higher, which implies that stock returns are relatively more predictable in positive temperature anomaly periods.

2.4.2 Temperature Sensitivity and ESG Score

To better understand our temperature sensitivity measurement, we further show the relationship between our measurement and the firm ESG score, which is also treated as an essential measurement of the firms' risk related to the environmental (E), social (S) and governance (G).

There are varieties of ESG raters that provide ESG scores with firms. As our measurement is only related to the climate risk aspect, we use the ESG score from Refinitiv(Asset4) as a comparison because Refinitiv ESG provides more detailed category scores under the environment group. Specifically, the data set show *Emission, Resource*, and *Innovation* subscores under the E group with a sample period start from 2002.

We show the Pearson correlation between our measurement of temperature sensitivity with Refinitiv ESG score and a group of the subscores in Table 2.9 Panel A. Specifically, we consider the following scores in our test: ESG total score, E score, S score, G score, Emission score, resource score, and innovation score. The last three scores are subscores of the environment score of a firm. The coefficients in Table 2.9 show that our measurement is generally negatively correlated with the ESG scores, which indicates that high temperature sensitivity stocks tend to have lower ESG scores. According to the principle of Refinitiv ESG measurement, they provide a higher score to a firm with better performance in a specific area. Thus, the negative correlation between ESG scores and temperature sensitivity indicates that stocks with high temperature sensitivity do not perform well in ESG related risk.

Panel B of Table 2.9 shows the average ESG scores of the five temperature sensitivity sorted portfolios. All types of ESG scores in Panel B decrease monotonically from Low-TS stocks to High-TS stocks. The difference of ESG scores between High-TS and Low-TS portfolios is negatively significant. For example, the ESG total score for the High-TS portfolio is 27.93, while the Low-TS portfolio has an average ESG total score of 39.72. The difference between the two portfolios is -11.80, with a *t*-statistics of -30.00. Consistent with the correlation results, we find that higher temperature sensitivity stocks have significantly lower ESG scores.

To further determine whether our measurement captures stock return difference better than ESG score, we show the factor adjusted returns of ESG score sorted portfolio in Table 2.10. The alpha difference between High-ESG and Low-ESG portfolios are insignificant across all columns using the four-factor model and six-factor model[4], indicating that ESG scores of Refinitiv do not capture significant stock return differences. These findings are consistent with the previous literature showing that ESG scores do not generally capture stock return differences (see, for example, Bansal et al., 2021).

Overall, our temperature sensitivity has a negative correlation with firms ESG scores. High-TS stocks have a significantly lower ESG score than others. Further, our temperature sensitivity measurement captures stock return differences better than the ESG score does.

2.5. Conclusion

In this paper, we show that firms' exposure to temperature change predicts stock returns. We propose a novel method to identify stocks that are more likely to be influenced by abnormal changes in temperature. Stocks with higher temperature sensitivity have lower future returns. A trading strategy that exploits return predictability generates risk-adjusted returns of 4% per

[4] In untabulated results, we also conduct tests using one-factor and seven-factor model following our main tests. The results are quantitively similar.

year from 1960 to 2019. This result is robust when we control for some macroeconomic factors or use conditional factor models.

Next, we show that higher firm-level temperature sensitivity is also associated with lower firm performance in the future. Specifically, the return on assets, earnings and profit margin of firms in the high temperature sensitivity portfolios are significantly lower than others. Furthermore, as the lag between portfolio formation and climate-sensitivity estimation increases, the abnormal return becomes statistically insignificant, which shows that the abnormal returns are likely to be generated by mispricing. The results are robust when we allow for asymmetric return sensitivity to positive and negative temperature anomalies. At last, we show that our temperature sensitivity measurement is negatively correlated with the ESG scores: higher temperature sensitivity stocks have lower ESG score performance. However, our measurement captures the stock return difference better than the ESG score does. Overall, our results suggest that climate risk have a significant impact on the financial market.

It would be interesting to investigate whether other financial market participants, such as sell-side analysts, institutional investors, and corporate managers, consider climate risk in further research. How their reactions towards climate risk affect themselves and the financial market will also help us better understand the importance of climate risk.

Figure 2.1 Monthly Temperature Anomaly from 1960 to 2019

This figure shows the monthly temperature anomaly from January 1960 to June 2019. The data is from the National Centers for Environmental Information (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). Temperature anomaly is calculated as the difference between the absolute monthly temperature value and the monthly reference temperature value, which is the difference between the temperature of a month and the average monthly temperature of the past 30 years for the same month.

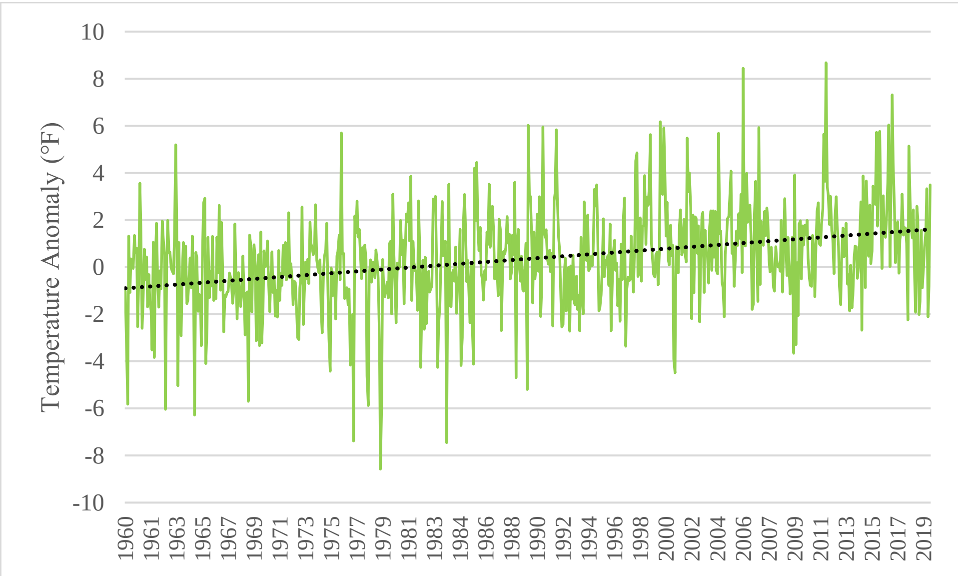

Figure 2.2 Performance of High-TS and Low-TS Portfolios

This figure shows the buy and hold return of the Low-TS portfolio and the High-TS portfolio from 1960 to 2019. Low-TS(High-TS) portfolios are constructed by stocks with temperature sensitivities in the lowest (highest) quintile each month. Both portfolios are rebalanced each month.

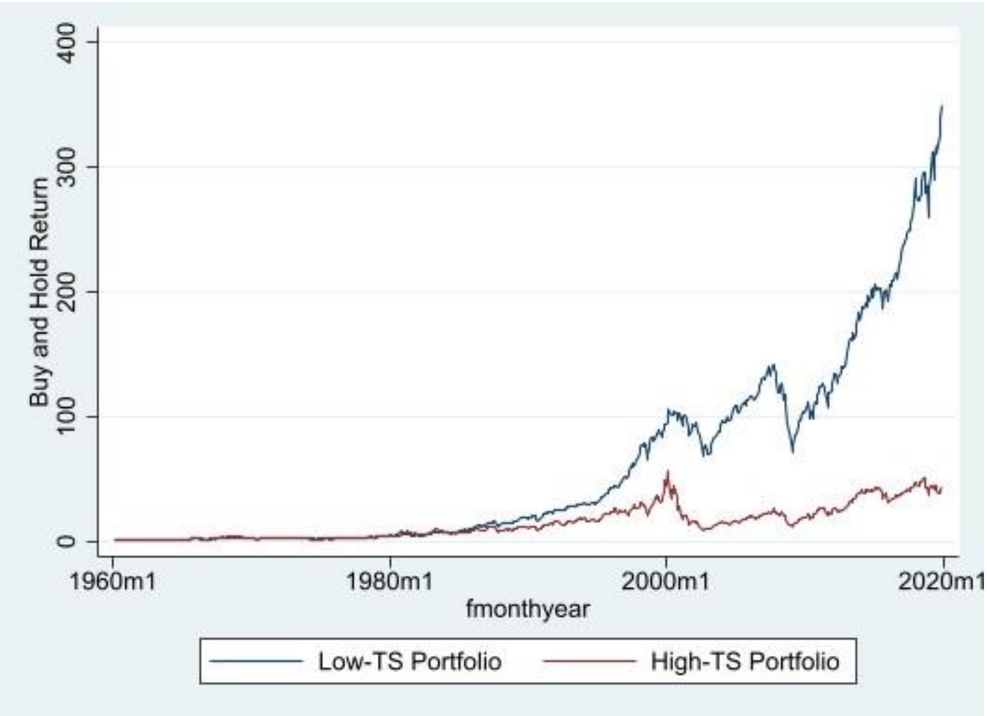

Table 2.1 Descriptive Characteristics

This table reports descriptive characteristics for portfolios defined using the temperature sensitivity model. Panel A reports industries with the top and bottom 10 raw industry-level return sensitivity to temperature anomaly (θ). Panel B reports the top and bottom 10 industries by the absolute value of average temperature sensitivity (θ_i^c). Panel C reports mean temperature sensitivity, size (log market capitalisation), and book-to-market ratio. The estimation period for industries is from January 1960 to December 2019. We report the characteristics of five stock portfolios: (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimate, (ii) the "High" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates.

Panel A: Top and Bottom 10 Industries by Unconditional Temperature Sensitivity (θ)		
Ranking	Positive	Negative
1	Gold	Hlth
2	Medeq	Coal
3	Mines	Clths
4	Steel	Util
5	Fabpr	Persv
6	Beer	Food
7	Fun	Ships
8	Comps	Txtls
9	Meals	Rubbr
10	Mach	Guns
Panel B: Top and Bottom 10 Industries by Conditional Temperature Sensitivity (θ_i^c)		
Ranking	High	Low
1	Gold	Fin
2	Coal	Whlsl
3	Hlth	Bussv
4	Agric	Rtail
5	Guns	Hshld
6	Toys	Meals
7	RlEst	Insur
8	Fun	Trans
9	Soda	Bldmt
10	Txtls	Telcm

Table 2.1 Descriptive Characteristics-Continued

Panel C: Portfolio Characteristics			
Portfolio	Temperature Sensitivity	Size	B/M Ratio
1 (Low)	0.183	12.148	0.838
2	0.292	12.083	0.844
3	0.535	11.844	0.859
4	0.912	11.375	0.885
5 (High)	2.719	10.808	0.811
High-Low	2.536	-1.340	-0.027

Table 2.2 Temperature sensitivity Sorted Portfolios: Performance Estimates

This table reports performance estimates of portfolios defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US stocks during the sample period. We report the performance of five portfolios: (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and are predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates. In Panel A, we report the standard deviation and Sharpe ratio for each portfolio over the three time periods. In Panel B, we report the average monthly market shares across portfolios. In Panel C, we report excess and characteristic-adjusted portfolio returns over three time periods: January 1963 - December 2019, January 1963 - December 1989, and January 1990 - December 2019. Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. In Panel D, we report raw and characteristic-adjusted portfolio returns as in Panel C, but with a varying number of stocks in the High and Low portfolios, i.e. 1/16, 1/7 and 1/4 of all firms. The estimation period in Panel D is from January 1960 to December 2019. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Portfolio Performance Characteristics

	Sample Periods					
	1960-2019		1960-1989		1990-2019	
Portfolio	Std Dev	Sharpe Ratio	Std Dev	Sharpe Ratio	Std Dev	Sharpe Ratio
1(Low)	4.080	0.131	3.952	0.065	4.270	0.200
2	4.362	0.118	4.357	0.050	4.417	0.215
3	4.543	0.111	4.735	0.053	4.529	0.166
4	5.323	0.110	5.414	0.088	5.567	0.134
5(High)	6.811	0.056	6.141	0.072	6.968	0.090

Table 2.2 Temperature sensitivity Sorted Portfolios: Performance Estimates-Continued

Panel B: Average Monthly Portfolio Market Shares (%)			
	Sample Periods		
Portfolio	1960-2019	1960-1989	1990-2019
1(Low)	34.39	37.19	31.59
2	28.79	28.75	28.83
3	21.24	20.05	22.43
4	11.13	10.17	12.07
5(High)	4.46	3.84	5.08
High+Low	38.85	41.03	36.67
High-Low	-30.69***	-33.35***	-26.51***
	(-37.66)	(-25.81)	(-28.87)

Table 2.2 Temperature sensitivity Sorted Portfolios: Performance Estimates-Continued

	Panel C: Portfolio Performance Estimates					
	Sample Periods					
	1963-2019		1963-1989		1990-2019	
Portfolio	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return
1(Low)	0.508**	0.023	0.348	0.001	0.669**	0.044
	(3.14)	(0.81)	(1.47)	(0.04)	(3.04)	(0.90)
2	0.536**	0.033	0.468	0.069*	0.605*	-0.002
	(3.15)	(1.33)	(1.92)	(2.33)	(2.54)	(-0.06)
3	0.495**	0.018	0.389	0.008	0.601*	0.027
	(2.85)	(0.60)	(1.51)	(0.21)	(2.57)	(0.60)
4	0.538**	-0.019	0.441	-0.034	0.635*	-0.005
	(2.71)	(-0.43)	(1.48)	(-0.69)	(2.43)	(-0.07)
5(High)	0.450	-0.26**	0.285	-0.317**	0.616	-0.202
	(1.57)	(-2.87)	(0.77)	(-3.30)	(1.41)	(-1.32)
Low-High	0.0583	0.282**	0.063	0.318**	0.054	0.245
	(0.32)	(2.69)	(0.31)	(2.91)	(0.18)	(1.37)
N months	696	696	336	336	360	360

Table 2.2 Temperature sensitivity Sorted Portfolios: Performance Estimates-Continued

	Panel D: Estimates Using Alternative Extreme Portfolio Sizes					
	Extreme Portfolio Size					
	1/16 Firms		1/7 Firms		1/4 Firms	
Portfolio	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return	Raw Return	Char-Adj Return
1(Low)	0.507**	-0.009	0.522**	0.026	0.494**	0.018
2	0.502**	0.0204	0.482**	0.012	0.544**	0.038
3	0.514**	0.0335	0.510**	0.023	0.490**	0.016
4	0.516*	-0.050	0.515**	-0.021	0.534**	-0.010
5(High)	0.103	-0.802***	0.491	-0.284**	0.479	-0.150*
Low-High	0.404	0.793***	0.032	0.310**	0.015	0.167

Table 2.3 Temperature sensitivity Based Portfolios: Factor Model Estimates

This table reports factor model risk-adjusted-performance estimates of portfolio defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US stocks during the sample period. We consider the estimates of (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and are predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates. (vi) the "Low-High" portfolio, which captures the difference in the returns of the Low and High portfolios. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (MOM), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1968 to December 2019 due to the data availability of the liquidity factor. In Panel A, we report the result of the one-factor model and the four-factor model. in Panel B, we report the result of the six-factor model and the seven-factor model. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.3 Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel A: One Factor and Four Factors Model of 5 Temperature Sensitivity Portfolio												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.038	-0.008	-0.071	-0.054	-0.468***	0.506***	0.010	-0.006	-0.030	-0.021	-0.326***	0.337***
	(0.92)	(-0.22)	(-1.59)	(-0.80)	(-3.39)	(3.08)	(0.29)	(-0.15)	(-0.66)	(-0.36)	(-3.72)	(3.18)
RMRF	0.906***	0.971***	1.006***	1.161***	1.382***	-0.476***	0.945***	0.986***	0.993***	1.092***	1.181***	-0.236***
	(61.64)	(108.49)	(75.26)	(53.27)	(28.84)	(-8.08)	(88.98)	(92.27)	(76.46)	(54.35)	(36.81)	(-6.11)
SMB							-0.131***	-0.073***	-0.000	0.260***	0.661***	-0.792***
							(-7.90)	(-2.77)	(-0.00)	(7.21)	(13.05)	(-13.09)
HML							0.071***	0.011	-0.050**	-0.114***	-0.434***	0.505***
							(2.63)	(0.64)	(-1.99)	(-2.91)	(-9.17)	(7.46)
MOM							0.000	-0.009	-0.030	0.015	0.042	-0.042
							(0.03)	(-0.63)	(-1.35)	(0.74)	(1.18)	(-0.97)
Adj. Rsq.	0.943	0.959	0.946	0.908	0.786	0.234	0.954	0.961	0.947	0.933	0.907	0.663
N months	624	624	624	624	624	624	624	624	624	624	624	624

Table 2.3 Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel B: Six Factor and Seven Factors Model of 5 Temperature Sensitivity Portfolio												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.008	-0.025	-0.032	-0.012	-0.308***	0.316***	0.010	-0.025	-0.027	-0.019	-0.284***	0.294***
	(0.20)	(-0.61)	(-0.67)	(-0.21)	(-3.36)	(2.83)	(0.26)	(-0.61)	(-0.56)	(-0.34)	(-3.13)	(2.64)
RMRF	0.944***	0.979***	0.993***	1.094***	1.187***	-0.243***	0.944***	0.979***	0.992***	1.095***	1.185***	-0.241***
	(81.24)	(104.67)	(74.82)	(53.02)	(36.34)	(-6.09)	(81.21)	(104.62)	(75.41)	(53.69)	(36.02)	(-6.02)
SMB	-0.131***	-0.079***	0.002	0.261***	0.656***	-0.788***	-0.131***	-0.079***	0.003	0.261***	0.658***	-0.789***
	(-8.01)	(-3.43)	(0.08)	(7.44)	(13.84)	(-14.06)	(-8.00)	(-3.43)	(0.09)	(7.36)	(13.92)	(-14.09)
HML	0.071**	0.006	-0.045	-0.115***	-0.446***	0.516***	0.071**	0.006	-0.044	-0.116***	-0.440***	0.511***
	(2.20)	(0.28)	(-1.34)	(-2.72)	(-8.27)	(6.68)	(2.22)	(0.28)	(-1.30)	(-2.74)	(-8.21)	(6.67)
MOM	0.001	-0.002	-0.029	0.012	0.035	-0.033	0.001	-0.002	-0.029	0.012	0.034	-0.033
	(0.08)	(-0.11)	(-1.36)	(0.58)	(0.92)	(-0.71)	(0.08)	(-0.12)	(-1.36)	(0.59)	(0.91)	(-0.70)
STR	0.006	0.040**	0.004	-0.017	-0.037	0.043	0.006	0.040**	0.005	-0.018	-0.033	0.039
	(0.30)	(2.39)	(0.17)	(-0.62)	(-0.93)	(0.81)	(0.33)	(2.38)	(0.22)	(-0.67)	(-0.82)	(0.73)
LTR	-0.000	0.006	-0.009	0.003	0.027	-0.027	-0.001	0.006	-0.011	0.005	0.022	-0.022
	(-0.01)	(0.27)	(-0.31)	(0.09)	(0.53)	(-0.44)	(-0.03)	(0.27)	(-0.35)	(0.13)	(0.43)	(-0.36)
LIQ							-0.711	-0.053	-1.625	1.944	-7.008**	6.297*
							(-0.58)	(-0.05)	(-1.19)	(0.82)	(-2.49)	(1.94)
Adj. Rsq.	0.954	0.962	0.947	0.933	0.907	0.663	0.954	0.962	0.947	0.933	0.908	0.665
N months	624	624	624	624	624	624	624	624	624	624	624	624

Table 2.4 Temperature sensitivity-Based Portfolios: Robustness of Factor Model Estimates

This table reports factor model risk-adjusted-performance estimates of High and Low portfolios defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US firms during the period. In columns (1) through (5), we report estimates from conditional factor models in which each of the factors interacts with an interaction variable (INT). INT is one of the following: an NBER recession indicator (REC), the Lettau-Ludvigson (2004) *cay* measure, the dividend yield of the CRSP value-weighted index (DIV), the yield on the three-month T-bill (YLD), and the term spread (TERM). The interaction variable used in each regression is indicated at the top of each column. In column (6), we include interactions between all the factors and interaction variables. We suppressed all the coefficients for interaction variables in all columns for brevity. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period for each regression is indicated at the top of each column. We report result of High portfolio in Panel A, result of Low portfolio in Panel B and result of Low-High portfolio in Panel C. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.4 Temperature sensitivity-Based Portfolios: Robustness of Factor Model Estimates-Continued

Panel A: Low-TS Portfolio						
Interaction Variable(INT)	REC	*cay*	DIV	TERM	YLD	All
Sample	1968-2019	1968-2019	1968-2016	1968-2019	1968-2019	1968-2016
Factor	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.007	0.000	-0.002	-0.001	0.012	-0.016
	(0.20)	(0.00)	(-0.06)	(-0.03)	(0.31)	(-0.44)
RMRF	0.937***	0.947***	0.914***	0.960***	0.911***	0.905***
	(75.50)	(81.94)	(50.30)	(53.48)	(51.35)	(22.72)
SMB	-0.130***	-0.125***	-0.113***	-0.155***	-0.074***	-0.070
	(-7.11)	(-7.45)	(-3.56)	(-6.57)	(-3.05)	(-1.18)
HML	0.081**	0.074**	0.119*	0.129***	0.033	0.216***
	(2.27)	(2.50)	(1.89)	(3.28)	(0.86)	(2.77)
MOM	0.001	-0.002	0.003	0.002	-0.005	-0.031
	(0.08)	(-0.14)	(0.13)	(0.09)	(-0.17)	(-0.78)
STR	-0.004	0.005	0.009	-0.008	0.018	-0.035
	(-0.20)	(0.34)	(0.36)	(-0.49)	(0.63)	(-0.88)
LTR	-0.014	0.005	0.007	-0.022	0.038	0.049
	(-0.56)	(0.22)	(0.15)	(-0.69)	(1.17)	(0.66)
Adj R-square	0.955	0.954	0.954	0.956	0.955	0.957
N months	624	621	588	624	624	588
Interaction Variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4 Temperature sensitivity-Based Portfolios: Robustness of Factor Model Estimates-Continued

Panel B: High-TS Portfolio						
Interaction Variable(INT)	REC	*cay*	DIV	TERM	YLD	All
Sample	1968-2019	1968-2019	1968-2016	1968-2019	1968-2019	1968-2016
Factor	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	-0.317***	-0.283***	-0.256***	-0.353***	-0.368***	-0.282***
	(-3.39)	(-3.13)	(-2.91)	(-3.96)	(-3.97)	(-3.03)
RMRF	1.207***	1.187***	1.313***	1.118***	1.300***	1.365***
	(33.30)	(37.96)	(27.41)	(25.43)	(26.33)	(14.22)
SMB	0.653***	0.663***	0.565***	0.693***	0.470***	0.310*
	(12.75)	(14.68)	(6.79)	(11.98)	(6.40)	(1.78)
HML	-0.456***	-0.408***	-0.630***	-0.482***	-0.460***	-0.555***
	(-8.17)	(-9.52)	(-7.71)	(-7.11)	(-5.69)	(-3.90)
MOM	0.045	0.034	0.006	0.136***	-0.060	0.170
	(0.99)	(1.00)	(0.10)	(2.85)	(-1.59)	(1.51)
STR	-0.022	-0.045	-0.065	0.015	-0.043	0.046
	(-0.45)	(-1.26)	(-1.05)	(0.31)	(-0.95)	(0.40)
LTR	0.070	-0.025	0.105	0.032	0.062	0.042
	(1.33)	(-0.50)	(1.13)	(0.47)	(0.73)	(0.26)
Adj R-square	0.908	0.910	0.913	0.911	0.912	0.920
N months	624	621	588	624	624	588
Interaction Variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.4 Temperature sensitivity-Based Portfolios: Robustness of Factor Model Estimates-Continued

Panel C: Low-High TS Portfolio						
Interaction Variable(INT)	REC	*cay*	DIV	TERM	YLD	All
Sample	1968-2019	1968-2019	1968-2016	1968-2019	1968-2019	1968-2016
Factor	(1)	(2)	(3)	(4)	(5)	(6)
Alpha	0.324***	0.283***	0.254**	0.352***	0.381***	0.266**
	(2.96)	(2.62)	(2.39)	(3.36)	(3.44)	(2.47)
RMRF	-0.270***	-0.240***	-0.398***	-0.158***	-0.389***	-0.461***
	(-6.37)	(-6.29)	(-6.99)	(-2.75)	(-6.75)	(-3.95)
SMB	-0.783***	-0.788***	-0.678***	-0.849***	-0.544***	-0.380*
	(-12.85)	(-14.26)	(-6.67)	(-11.47)	(-6.47)	(-1.86)
HML	0.537***	0.482***	0.749***	0.610***	0.493***	0.771***
	(6.56)	(7.71)	(6.12)	(6.10)	(4.97)	(4.25)
MOM	-0.044	-0.036	-0.003	-0.135**	0.055	-0.201
	(-0.81)	(-0.86)	(-0.04)	(-2.17)	(1.37)	(-1.62)
STR	0.019	0.051	0.074	-0.023	0.061	-0.082
	(0.30)	(1.08)	(0.92)	(-0.38)	(1.03)	(-0.62)
LTR	-0.084	0.030	-0.098	-0.053	-0.024	0.007
	(-1.25)	(0.49)	(-0.86)	(-0.61)	(-0.24)	(0.04)
Adj R-square	0.672	0.674	0.688	0.681	0.681	0.714
N months	624	621	588	624	624	588
Interaction Variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 2.5 Temperature sensitivity and Expected Returns: Fama-MacBeth Regression Estimates

This table reports estimates from Fama-MacBeth (1973) regressions. In Panel A, we regress monthly stock return on the following regressors: temperature sensitivity θ_i^c, lagged Fama and French three-factor beta in the previous month measured using daily data, total stock return over the previous six months, log market capitalisation of firms at the beginning of the previous month, the book-to-market ratio of firms six months prior, and industry fixed effect using Fama-French 48 industry portfolio. Stock returns are winsorised at a 1% level on both sides. We change the main dependent variable to a High-TS dummy in Panel B, a dummy variable that equals one if a stock is in the highest quintile of temperature sensitivity sorted portfolio (High-TS portfolio) in the previous month. We report the time-series average of cross-sectional adjusted R^2. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1931 to 2017 in column (1) and from 1960 to 2019 in column (2) and (3). (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Temperature Sensitivity and Future Returns: Fama-MacBeth Regression Estimates

Factor	(1)	(2)	(3)	(4)
Temperature Sensivity	-0.015	-0.131***	-0.147***	-0.126***
	(-1.58)	(-4.46)	(-3.74)	(-5.33)
Beta-RMRF		0.104	0.124	0.103
		(0.81)	(0.91)	(0.73)
Beta-SMB		-0.054	-0.055	-0.045
		(-0.56)	(-0.51)	(-0.49)
Beta-HML		0.125	0.122	0.090
		(1.44)	(1.38)	(1.04)
Lagged 6mRet			-1.180***	-1.293***
			(-2.76)	(-2.85)
Size				0.016
				(0.36)
BM Ratio				0.138***
				(3.66)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Avg Adj Rsq.	0.006	0.009	0.013	0.015
N months	624	624	624	624
N Observations	2261298	2149898	2138748	2051002

Table 2.5 Temperature sensitivity and Expected Returns: Fama-MacBeth Regression Estimates-Continued

Panel B: High-TS stocks and Future Returns: Fama-MacBeth Regression Estimates				
Factor	(1)	(2)	(3)	(4)
High TS	-0.354***	-0.359***	-0.340***	-0.249***
	(-4.00)	(-5.71)	(-5.06)	(-6.31)
Beta-RMRF		0.105	0.127	0.096
		(0.80)	(0.92)	(0.68)
Beta-SMB		-0.062	-0.067	-0.050
		(-0.63)	(-0.61)	(-0.53)
Beta-HML		0.126	0.127	0.095
		(1.44)	(1.41)	(1.08)
Lagged 6mRet			-1.179***	-1.292***
			(-2.78)	(-2.86)
Size				0.022
				(0.48)
BM Ratio				0.139***
				(3.68)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Avg Adj Rsq.	0.007	0.010	0.014	0.015
N months	624	624	624	624
N Observations	2261298	2149898	2138748	2051002

Table 2.6 High TS firms' performance: Fama-MacBeth Regression Estimates

This table reports estimates from Fama-MacBeth (1973) regressions. We regress a series of firm performance variables on the following regressors: a lagged dummy variable (High TS) for stocks ranked in the highest quintile by temperature sensitivity (High-TS portfolio), lagged firm performance, average log market capitalisation of firms across all months last year, the book-to-market ratio of firms last year, leverage last year, a loss indicator equals one if the firm experienced a loss last year and zero otherwise, dividend yield of a firm last year, no dividend yield indicator equals one if the firm did not issue dividend last year, and the GDP of the state in which the firm is located. Industry fixed effect using Fama-French 48 industry portfolio is controlled in the model. In Panel A, we report the ROA results. Panel B presents the estimates of earnings, and Panel C shows the profit margin. We report the time-series average of cross-sectional adjusted R^2. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1968 to 2019. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.6 High TS firms' performance: Fama-MacBeth Regression Estimates-Continued

Panel A: Dependent Variable: Return on Asset				
Factor	(1)	(2)	(3)	(4)
High TS	-0.037***	-0.030***	-0.025***	-0.025***
	(-5.08)	(-4.85)	(-4.78)	(-4.79)
Lagged ROA	0.651***	0.625***	0.539***	0.538***
	(35.75)	(39.50)	(26.78)	(26.94)
Size		0.009***	0.006***	0.006***
		(5.19)	(5.62)	(5.65)
BM Ratio		-0.004**	-0.004*	-0.004*
		(-2.62)	(-1.78)	(-1.78)
Leverage			-0.005	-0.005
			(-0.44)	(-0.48)
Loss			-0.072***	-0.072***
			(-6.92)	(-6.93)
Dividend Yield			0.033	0.033
			(1.03)	(1.03)
No Dividend			0.013***	0.013***
			(5.60)	(5.59)
State GDP				-0.003***
				(-2.97)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Avg Adj Rsq.	0.434	0.434	0.460	0.460
N months	52	52	52	52
N Obs	177668	175122	175093	175042

Table 2.6 High TS firms' performance: Fama-MacBeth Regression Estimates-Continued

Panel B: Dependent Variable: Earnings (EPS/Lagged Price)				
Factor	(1)	(2)	(3)	(4)
High TS	-0.036***	-0.027***	-0.017***	-0.017***
	(-5.25)	(-5.06)	(-4.74)	(-4.73)
Lagged ROA	0.519***	0.496***	0.393***	0.393***
	(35.11)	(30.49)	(18.87)	(18.72)
Size		0.009***	0.006***	0.006***
		(3.98)	(2.98)	(3.03)
BM Ratio		-0.010**	-0.011**	-0.011**
		(-2.12)	(-2.13)	(-2.12)
Leverage			-0.083***	-0.083***
			(-5.53)	(-5.53)
Loss			-0.109***	-0.108***
			(-9.08)	(-9.10)
Dividend Yield			-0.117*	-0.119*
			(-1.78)	(-1.78)
No Dividend			0.016***	0.016***
			(2.90)	(2.89)
State GDP				-0.004***
				(-4.26)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Avg Adj Rsq.	0.250	0.265	0.291	0.291
N months	52	52	52	52
N Obs	157522	156506	156486	156437

Table 2.6 High TS firms' performance: Fama-MacBeth Regression Estimates-Continued

Panel C: Dependent Variable: Profit Margin (Net Income/Sale)				
Factor	(1)	(2)	(3)	(4)
High TS	-0.111***	-0.074***	-0.059***	-0.058***
	(-5.06)	(-4.32)	(-3.96)	(-3.95)
Lagged ROA	0.637***	0.626***	0.614***	0.614***
	(16.74)	(15.58)	(14.71)	(14.72)
Size		0.033***	0.019***	0.019***
		(5.32)	(4.90)	(4.95)
BM Ratio		-0.004	0.003	0.003
		(-1.08)	(0.63)	(0.64)
Leverage			0.087**	0.087**
			(2.60)	(2.60)
Loss			-0.207***	-0.206***
			(-5.51)	(-5.52)
Dividend Yield			0.017	0.019
			(0.10)	(0.11)
No Dividend			0.024***	0.024***
			(3.56)	(3.58)
State GDP				-0.005
				(-1.10)
Industry Fixed Effect	Yes	Yes	Yes	Yes
Avg Adj Rsq.	0.499	0.504	0.511	0.511
N months	52	52	52	52
N Obs	174833	172733	172709	172658

Table 2.7 Longevity of return predictability

This table reports the effect of varying portfolio formation periods on average monthly six-factor adjusted abnormal return to of portfolios sorted by temperature sensitivity. We focus on the performance difference between Low and High portfolios (Low-High). The Low (High) portfolio is a value-weighted portfolio of the quintile stocks with the lowest (highest) temperature sensitivity. We report the monthly six-factor alpha when we positively shift the portfolio formation period by 1-20 months. A positive shift in the portfolio formation period corresponds to the delayed formation of the Low and High portfolios. A shift of zero is equivalent to the baseline portfolio formation procedure, and the coefficients are the same as those reported in Panel B Column (6) of Table 3. The sample period is from January 1968 to December 2019. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	Longevity of Return Predictability						
	Baseline	Shift 2 months	Shift 4 months	Shift 6 months	Shift 8 months	Shift 10 months	Shift 12 months
Alpha	0.316***	0.332***	0.331***	0.290***	0.207**	0.211**	0.161*
	(2.83)	(3.07)	(3.02)	(2.65)	(2.04)	(2.21)	(1.70)
N Months	624	624	624	624	624	624	624
	Shift 13 months	Shift 14 months	Shift 15 months	Shift 16 months	Shift 17 months	Shift 18 months	Shift 20 months
Alpha	0.130	0.074	0.080	0.090	0.083	0.105	0.142
	(1.43)	(0.83)	(0.92)	(0.97)	(0.90)	(1.09)	(1.35)
N Months	624	624	624	624	624	624	624

Table 2.8 Alternative Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates

This table reports factor model risk-adjusted-performance estimates of portfolio defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US stocks during the sample period. We consider the estimates of (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and are predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates, (vi) the "Low-High" portfolio, which captures the difference in the returns of the Low and High portfolios. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (MOM), and two reversal factors (short-term reversal (STR) and long-term reversal (LTR)). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from July 1931 to June 2017. In Panel A, we report the result of the four-factor model and the six-factor model for $\theta_i^{p\prime}$ sorted portfolio. In Panel B, we report the result of $\theta_i^{n\prime}$ based portfolio of the same models. $\theta_i^{p\prime}$ and $\theta_i^{n\prime}$ are measured simultaneously. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.8 Alternative Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel A: Four Factor and Six Factors Model of 5 Climate Risk Portfolio $(\theta_i^{p'})$												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.090***	0.035	0.010	-0.011	-0.216**	0.306***	0.074**	0.052	-0.012	0.026	-0.298***	0.373***
	(2.59)	(1.00)	(0.30)	(-0.23)	(-2.20)	(2.66)	(2.04)	(1.25)	(-0.32)	(0.48)	(-2.66)	(2.89)
RMRF	0.923***	0.974***	1.019***	1.099***	1.238***	-0.316***	0.921***	0.976***	1.017***	1.102***	1.229***	-0.308***
	(94.74)	(100.22)	(111.08)	(69.81)	(43.77)	(-9.09)	(97.78)	(98.03)	(111.23)	(73.67)	(42.15)	(-8.78)
SMB	-0.129***	-0.104***	-0.068***	0.106***	0.367***	-0.496***	-0.130***	-0.101***	-0.060***	0.098***	0.341***	-0.471***
	(-5.89)	(-5.42)	(-3.69)	(4.22)	(5.20)	(-5.75)	(-6.59)	(-5.12)	(-3.42)	(3.32)	(4.64)	(-5.43)
HML	0.023	0.068***	0.038**	0.162***	0.055	-0.032	0.027	0.066***	0.058***	0.135***	0.040	-0.013
	(1.13)	(3.47)	(2.26)	(5.85)	(0.75)	(-0.36)	(1.14)	(2.95)	(2.95)	(4.32)	(0.41)	(-0.11)
MOM	-0.001	-0.013	-0.007	-0.043*	-0.033	0.032	0.001	-0.015	-0.002	-0.050**	-0.024	0.025
	(-0.07)	(-0.68)	(-0.46)	(-1.94)	(-0.73)	(0.62)	(0.08)	(-0.80)	(-0.18)	(-2.30)	(-0.56)	(0.51)
STR							-0.004	0.000	-0.030*	0.039	0.038	-0.042
							(-0.20)	(0.02)	(-1.70)	(1.13)	(0.69)	(-0.65)
LTR							0.020	-0.022	0.026	-0.044	0.111	-0.091
							(1.30)	(-1.06)	(1.46)	(-1.25)	(1.41)	(-1.11)
Adj. Rsq.	0.962	0.965	0.965	0.946	0.857	0.397	0.963	0.966	0.966	0.947	0.859	0.401
N months	624	624	624	624	624	624	624	624	624	624	624	624

Table 2.8 Alternative Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel B: Four Factor and Six Factors Model of 5 Climate Risk Portfolio $(\theta_i^{n\prime})$												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.036	0.055*	0.089**	-0.043	-0.220***	0.256**	0.040	0.045	0.069*	-0.049	-0.266***	0.306**
	(1.08)	(1.65)	(2.46)	(-0.92)	(-2.60)	(2.43)	(1.11)	(1.24)	(1.72)	(-0.93)	(-2.78)	(2.57)
RMRF	0.935***	0.969***	1.005***	1.068***	1.266***	-0.331***	0.936***	0.968***	1.004***	1.066***	1.261***	-0.325***
	(62.31)	(81.30)	(88.88)	(44.89)	(54.62)	(-10.09)	(65.98)	(80.59)	(100.67)	(46.92)	(51.68)	(-9.69)
SMB	-0.137***	-0.128***	-0.054**	0.089**	0.469***	-0.607***	-0.122***	-0.132***	-0.036	0.062	0.456***	-0.578***
	(-6.32)	(-4.99)	(-2.12)	(2.22)	(8.64)	(-8.92)	(-4.87)	(-5.70)	(-1.56)	(1.27)	(8.40)	(-8.19)
HML	0.058***	0.035**	0.044***	0.013	0.085*	-0.027	0.084***	0.031	0.080***	-0.030	0.079	0.005
	(2.79)	(1.97)	(2.71)	(0.55)	(1.76)	(-0.43)	(3.34)	(1.38)	(3.55)	(-0.93)	(1.22)	(0.06)
MOM	-0.015	-0.004	-0.032**	0.025	-0.057	0.042	-0.014	-0.003	-0.027**	0.022	-0.052	0.038
	(-1.04)	(-0.27)	(-2.54)	(1.29)	(-1.63)	(0.94)	(-0.94)	(-0.23)	(-2.19)	(1.12)	(-1.61)	(0.90)
STR							-0.043*	0.008	-0.057***	0.072	0.018	-0.060
							(-1.70)	(0.26)	(-2.63)	(1.45)	(0.40)	(-1.02)
LTR							-0.010	0.013	0.019	0.016	0.061	-0.070
							(-0.63)	(0.67)	(1.08)	(0.54)	(1.10)	(-1.09)
Adj. Rsq.	0.958	0.964	0.965	0.941	0.902	0.516	0.959	0.964	0.966	0.942	0.902	0.519
N months	624	624	624	624	624	624	624	624	624	624	624	624

Table 2.12 Temperature Sensitivity and ESG Score

This table reports the coefficients between temperature sensitivity and ESG Score in Panel A. Following ESG Scores and subscores are presented in this table: Environmental Score (Escore), Social Score (Sscore), Governance Score(Gscore), Emission Score, Resource Score, Innovation Score, and ESG total Score. Panel B shows the value-weighted average ESG Scores for each temperature sensitivity based portfolio. We consider the estimates of (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and are predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates, (vi) the "Low-High" portfolio, which captures the difference in the ESG Scores of the Low and High portfolios. The estimation period is from 2002 to June 2019 due to the availability of ESG data. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Correlation between Temperature Sensitivity and ESG Scores 2002-2019

Variables	Temperature_Beta	Escore	Sscore	Gscore	Emission	Resource	Innovation	ESGScore
Temperature_Beta	1							
Escore	-0.065	1						
Sscore	-0.053	0.714	1					
Gscore	-0.088	0.502	0.429	1				
Emission	-0.056	0.902	0.698	0.513	1			
Resource	-0.058	0.909	0.743	0.5	0.846	1		
Innovation	-0.043	0.749	0.451	0.327	0.502	0.508	1	
ESGScore	-0.082	0.898	0.842	0.766	0.848	0.862	0.618	1

Table 2.9 Temperature Sensitivity and ESG Score-Continued

Panel B: Temperature Sensitivity Sorted Portfolio Average ESG Score							
Portfolio	Escore	Sscore	Gscore	Emission	Resource	Innovation	ESGScore
1(Low)	26.16	41.78	50.80	28.07	29.84	20.05	39.73
2	23.83	40.46	49.42	25.48	27.24	17.74	38.44
3	21.85	39.02	47.37	23.28	24.90	16.67	36.34
4	17.70	36.17	43.61	19.02	20.65	13.04	32.84
5(High)	13.21	33.47	36.87	13.87	15.10	10.79	27.93
Low -High	12.95***	8.310***	13.92***	14.20***	14.73***	9.262***	11.80***
	(26.43)	(28.72)	(20.05)	(26.85)	(21.54)	(24.64)	(30.00)

Table 2.13 ESG Score Based Portfolios: Factor Model Estimates

This table reports factor model risk-adjusted-performance estimates of portfolio defined using the ESG Scores. Component returns are those of all the listed US stocks during the sample period. We consider the estimates of the "High-Low" portfolio, which captures the difference in the returns of the High and Low portfolios based on one of the following ESG Scores: Environmental Score (Escore), Social Score (Sscore), Governance Score(Gscore), Emission Score, Resource Score, Innovation Score, and ESG total Score. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (MOM), two reversal factors (short-term reversal (STR) and long-term reversal (LTR)), and the liquidity factor (LIQ). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1968 to December 2019 due to the data availability of the liquidity factor. In Panel A, we report the result of the four-factor model and. in Panel B, we report the result of the six-factor model. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.10 ESG Score Based Portfolios: Factor Model Estimates-Continued

High-Low ESG Portfolio Factor-Adjusted Return (Value-Weighted)							
Panel A: Four-Factor Model of High-Low ESG Portfolio							
	Escore	Sscore	Gscore	ESG Score	Emission	Resource	Innovation
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	-0.057	0.131	0.202	0.105	0.016	0.071	-0.063
	(-0.34)	(0.60)	(1.30)	(0.55)	(0.10)	(0.42)	(-0.47)
RMRF	-0.103**	-0.139**	-0.180***	-0.195***	-0.072*	-0.097*	-0.028
	(-2.23)	(-2.04)	(-3.76)	(-3.06)	(-1.89)	(-1.67)	(-1.02)
SMB	-0.423***	-0.560***	-0.490***	-0.504***	-0.416***	-0.453***	-0.195**
	(-4.87)	(-7.66)	(-7.11)	(-6.29)	(-4.62)	(-6.14)	(-2.45)
HML	0.192***	0.204*	0.268***	0.250***	0.178***	0.129*	0.128*
	(2.82)	(1.77)	(3.84)	(2.99)	(3.20)	(1.75)	(1.66)
MOM	0.057	0.021	0.129***	0.057	0.115**	0.046	0.018
	(1.42)	(0.38)	(2.75)	(1.49)	(2.36)	(0.77)	(0.42)
Adj Rsq	0.266	0.336	0.389	0.390	0.272	0.290	0.065
N months	204	204	204	204	204	204	204

Table 2.10 ESG Score Based Portfolios: Factor Model Estimates-Continued

High-Low ESG Portfolio Factor-Adjusted Return (Value-Weighted)							
Panel B: Six-Factor Model of High-Low ESG Portfolio							
	Escore	Sscore	Gscore	ESG Score	Emission	Resource	Innovation
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Alpha	0.002	0.166	0.215	0.128	0.050	0.159	-0.001
	(0.01)	(0.74)	(1.34)	(0.65)	(0.30)	(0.92)	(-0.01)
RMRF	-0.090**	-0.138*	-0.168***	-0.183***	-0.079**	-0.113**	-0.041
	(-2.24)	(-1.97)	(-3.61)	(-3.10)	(-2.13)	(-2.49)	(-1.30)
SMB	-0.463***	-0.584***	-0.498***	-0.519***	-0.441***	-0.516***	-0.241***
	(-5.98)	(-9.56)	(-7.46)	(-7.27)	(-5.32)	(-7.92)	(-3.03)
HML	0.105	0.149	0.253***	0.219**	0.121*	-0.017	0.025
	(1.22)	(1.57)	(2.97)	(2.45)	(1.73)	(-0.25)	(0.26)
MOM	0.058	0.022	0.129**	0.057	0.116**	0.049	0.021
	(1.40)	(0.40)	(2.48)	(1.36)	(2.51)	(0.98)	(0.56)
STR	-0.107*	-0.037	-0.064	-0.068	0.000	-0.009	-0.004
	(-1.74)	(-0.43)	(-0.75)	(-0.85)	(0.00)	(-0.12)	(-0.08)
LTR	0.212**	0.122	0.053	0.086	0.115	0.294***	0.208**
	(2.20)	(0.84)	(0.67)	(0.87)	(1.39)	(3.42)	(2.23)
Adj Rsq.	0.297	0.338	0.387	0.391	0.274	0.340	0.097
N months	204	204	204	204	204	204	204

Table 2.A1 Descriptive Characteristics for $\boldsymbol{\theta_i^p}$ and $\boldsymbol{\theta_i^n}$ Sorted Portfolios

This table reports descriptive characteristics for portfolios defined using the temperature sensitivity θ_i^p and θ_i^n. Panel A reports the top and bottom 10 industries by firms' temperature sensitivity based on positive anomaly temperature (θ_i^p) across firms in an industry. Panel B reports the top and bottom 10 industries by firms' temperature sensitivity based on negative anomaly temperature (θ_i^n) across firms in an industry. Panel C and Panel D reports mean temperature sensitivity, size (log market capitalisation), and book-to-market ratio for portfolios defined using the temperature sensitivity θ_i^p and θ_i^n, respectively. The estimation period for industries is from January 1960 to December 2019. We report the characteristics of five stock portfolios: (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimate, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates.

Panel A: Top and Bottom 10 Industries by Temperature sensitivity Based on θ_i^p		
Ranking	High	Low
1	RlEst	Food
2	ElcEq	Insur
3	Txtls	Telcm
4	Cnstr	Rtail
5	Gold	Guns
6	Toys	Aero
7	BusSv	Books
8	Agric	Banks
9	Drugs	PerSv
10	LabEq	Coal
Panel B: Top and Bottom 10 Industries by Temperature sensitivity Based on θ_i^n		
Ranking	High	Low
1	RlEst	Other
2	Whlsl	Cnstr
3	Rtail	Comps
4	Drugs	Insur
5	BusSv	Autos
6	Banks	Aero
7	Guns	Chems
8	Coal	Hshld
9	Clths	Mines
10	Meals	Food

Table 2.A1 Descriptive Characteristics for $\boldsymbol{\theta_i^p}$ and $\boldsymbol{\theta_i^n}$ Sorted

Portfolios-Continue

	Panel C: θ_i^p Sorted Porfolio Characteristics		
Portfolio	Temperature Sensitivity	Size	B/M Ratio
1 (Low)	0.145	12.43	0.489
2	0.380	12.35	0.458
3	0.686	12.14	0.466
4	1.128	11.67	0.476
5 (High)	2.155	10.78	0.465
	Panel D: θ_i^n Sorted Porfolio Characteristics		
Portfolio	Temperature Sensitivity	Size	B/M Ratio
1 (Low)	0.281	12.46	0.472
2	0.753	12.36	0.485
3	1.373	12.14	0.455
4	2.195	11.64	0.461
5 (High)	4.116	10.79	0.507

Table 2.A2 Asymmetric Temperature sensitivity Sorted Portfolios: Performance Estimates

This table reports performance estimates of portfolios defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US stocks during the sample period. We report the performance of six portfolios: (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and is predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates, (vi) the "Low-High" portfolio, which captures the difference in the returns of the Low and High portfolios. In Panel A, we report excess and characteristic-adjusted portfolio returns constructed by θ_i^p over three time periods: January 1963 - December 2019, January 1963 - December 1989, and January 1990 - December 2019. Characteristic-adjusted returns are computed using the method of Daniel, Grinblatt, Titman, and Wermers (1997). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. Similar results of characteristic-adjusted portfolio return constructed by θ_i^n are reported in Panel B. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.A2 Asymmetric Temperature sensitivity Sorted Portfolios: Performance Estimates-Continued

Panel A: Portfolio Performance Estimates (θ_i^p)						
	Sample Periods					
	1963-2019		1963-1989		1990-2019	
Portfolio	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return
1(Low)	0.534**	0.0172	0.390	-0.00394	0.677**	0.0384
	(3.29)	(0.69)	(1.67)	(-0.13)	(3.03)	(0.96)
2	0.527**	0.0402	0.436	0.0590	0.619**	0.0214
	(3.15)	(1.62)	(1.77)	(1.72)	(2.73)	(0.60)
3	0.477**	0.0162	0.396	0.0408	0.558*	-0.00852
	(2.68)	(0.57)	(1.53)	(1.13)	(2.29)	(-0.20)
4	0.528**	-0.0166	0.438	-0.0163	0.618*	-0.0168
	(2.67)	(-0.39)	(1.51)	(-0.36)	(2.30)	(-0.23)
5(High)	0.458	-0.214*	0.275	-0.327***	0.641	-0.101
	(1.66)	(-2.43)	(0.77)	(-3.57)	(1.53)	(-0.67)
Low-High	0.076	0.231*	0.116	0.323**	0.036	0.139
	(0.44)	(2.32)	(0.59)	(3.05)	(0.13)	(0.83)
N months	696	696	336	336	360	360

Table 2.A2 Asymmetric Temperature sensitivity Sorted Portfolios: Performance Estimates-Continued

Panel A: Portfolio Performance Estimates (θ_i^n)						
	Sample Periods					
	1963-2019		1963-1989		1990-2019	
Portfolio	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return	Excess Return	Char-Adj Return
1(Low)	0.512**	0.0391	0.352	0.0261	0.672**	0.052
	-3.13	-1.77	-1.48	-0.98	-3.02	-1.48
2	0.471**	-0.000172	0.408	0.0124	0.533*	-0.0128
	-2.84	(-0.01)	-1.66	-0.45	-2.41	(-0.29)
3	0.535**	0.017	0.488	0.0531	0.583*	-0.0191
	-2.95	-0.56	-1.89	-1.64	-2.29	(-0.37)
4	0.523**	-0.0199	0.364	-0.0785	0.684*	0.0388
	-2.63	(-0.51)	-1.29	(-1.65)	-2.45	-0.63
5(High)	0.432	-0.258**	0.286	-0.262**	0.578	-0.254
	-1.53	(-2.90)	-0.76	(-2.81)	-1.38	(-1.67)
Low-High	-0.0799	-0.297**	-0.0662	-0.288**	-0.0935	-0.306
	(-0.46)	(-2.99)	(-0.32)	(-2.75)	(-0.34)	(-1.81)
N months	696	696	336	336	360	360

Table 2.A3 Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates

This table reports factor model risk-adjusted-performance estimates of portfolio defined using the temperature sensitivity return prediction model. Component returns are those of all the listed US stocks during the sample period. We consider the estimates of (i) the "Low-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with the lowest temperature sensitivity estimates and are predicted to have the highest returns in the next month, (ii) the "High-TS" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates and predicted to have the lowest returns in the next month, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates, (vi) the "Low-High" portfolio, which captures the difference in the returns of the Low and High portfolios. The factor models contain some combination of the following factors: the market excess return (RMRF), the size factor (SMB), the value factor (HML), the momentum factor (MOM), and two reversal factors (short-term reversal (STR) and long-term reversal (LTR)). The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from January 1968 to December 2019. In Panel A, we report the result of the four-factor model and the six-factor model for θ_i^p sorted portfolio. In Panel B, we report the result of θ_i^n based portfolio of the same models. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Table 2.A3 Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel A: Four Factor and Six Factors Model of 5 Climate Risk Portfolio (θ_i^p)												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.090***	0.031	-0.019	-0.000	-0.245***	0.335***	0.052	0.038	-0.017	0.029	-0.264**	0.317**
	(2.70)	(0.90)	(-0.56)	(-0.01)	(-2.62)	(2.98)	(1.50)	(0.97)	(-0.47)	(0.47)	(-2.46)	(2.54)
RMRF	0.922***	0.969***	1.028***	1.100***	1.231***	-0.309***	0.919***	0.969***	1.028***	1.103***	1.228***	-0.310***
	(66.63)	(74.52)	(105.14)	(66.16)	(36.06)	(-7.66)	(77.91)	(77.72)	(105.96)	(66.76)	(35.96)	(-7.87)
SMB	-0.098***	-0.135***	-0.071***	0.108***	0.395***	-0.493***	-0.088***	-0.146***	-0.070***	0.103***	0.386***	-0.474***
	(-4.14)	(-5.90)	(-3.43)	(4.33)	(5.28)	(-5.55)	(-3.48)	(-5.92)	(-3.37)	(3.45)	(5.12)	(-5.41)
HML	0.032	0.060***	0.070***	0.122***	0.049	-0.016	0.061**	0.039	0.072***	0.104***	0.040	0.022
	(1.45)	(3.07)	(4.09)	(4.37)	(0.57)	(-0.16)	(2.43)	(1.40)	(3.60)	(3.44)	(0.40)	(0.18)
MOM	0.006	-0.008	-0.010	-0.050**	-0.042	0.048	0.013	-0.010	-0.010	-0.055**	-0.040	0.053
	(0.41)	(-0.60)	(-0.72)	(-2.29)	(-0.88)	(0.85)	(0.98)	(-0.81)	(-0.75)	(-2.44)	(-0.87)	(0.99)
STR							-0.042*	0.034	-0.004	0.025	0.018	-0.060
							(-1.77)	(1.07)	(-0.20)	(0.66)	(0.34)	(-0.98)
LTR							0.045***	-0.006	-0.003	-0.035	0.027	0.018
							(2.72)	(-0.29)	(-0.17)	(-0.97)	(0.46)	(0.28)
Adj. Rsq.	0.957	0.963	0.967	0.942	0.871	0.413	0.958	0.963	0.966	0.942	0.871	0.413
N months	624	624	624	624	624	624	624	624	624	624	624	624

Table 2.A3 Asymmetric Temperature sensitivity Based Portfolios: Factor Model Estimates-Continued

Panel B: Four Factor and Six Factors Model of 5 Climate Risk Portfolio (θ_i^n)												
	Low	2	3	4	High	L-H	Low	2	3	4	High	L-H
Factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.031	0.049	0.070**	-0.070	-0.206***	0.237***	0.021	0.051	0.047	-0.085	-0.221**	0.242**
	(0.95)	(1.55)	(2.04)	(-1.25)	(-2.60)	(2.58)	(0.58)	(1.40)	(1.33)	(-1.24)	(-2.51)	(2.39)
RMRF	0.953***	0.947***	1.002***	1.076***	1.276***	-0.323***	0.953***	0.948***	1.000***	1.074***	1.275***	-0.322***
	(63.60)	(74.63)	(136.07)	(75.67)	(47.23)	(-8.83)	(68.75)	(74.30)	(141.52)	(77.76)	(45.38)	(-8.71)
SMB	-0.123***	-0.156***	-0.036	0.064*	0.478***	-0.600***	-0.108***	-0.154***	-0.036*	0.051	0.475***	-0.583***
	(-5.19)	(-7.45)	(-1.64)	(1.90)	(7.84)	(-8.00)	(-3.99)	(-7.72)	(-1.84)	(1.35)	(7.56)	(-7.19)
HML	0.038**	0.049**	0.050***	0.048*	0.066	-0.029	0.066***	0.052*	0.057***	0.031	0.067	0.000
	(1.98)	(2.37)	(3.41)	(1.74)	(1.17)	(-0.44)	(2.93)	(1.76)	(3.12)	(1.00)	(0.84)	(0.00)
MOM	-0.021	-0.004	-0.002	0.002	-0.090**	0.069*	-0.018	-0.004	0.001	0.003	-0.088**	0.070*
	(-1.55)	(-0.30)	(-0.24)	(0.10)	(-2.48)	(1.75)	(-1.30)	(-0.32)	(0.11)	(0.13)	(-2.56)	(1.85)
STR							-0.046*	-0.005	-0.008	0.030	0.002	-0.047
							(-1.66)	(-0.18)	(-0.50)	(1.12)	(0.03)	(-0.63)
LTR							0.009	-0.003	0.029**	0.022	0.020	-0.011
							(0.50)	(-0.16)	(2.24)	(0.73)	(0.40)	(-0.18)
Adj. Rsq.	0.956	0.952	0.967	0.939	0.865	0.339	0.963	0.961	0.968	0.940	0.903	0.530
N months	624	624	624	624	624	624	624	624	624	624	624	624

Chapter 3

Climate Change, Analyst Forecasts, and Market Behavior

3.1 Introduction

An emerging literature in economics and finance examines whether climate change affects firm performance and whether firms are able to manage climate-related risks effectively. Sell-side equity analysts play a crucial role in financial markets as they gather, analyze, and disseminate information about public companies to market participants. As information intermediaries, analysts should provide earnings forecasts that reflect the potential impact of global climate change on firm performance. But do they? In this study, we examine whether sell-side equity analysts successfully incorporate the impact of climate change in their earnings forecasts.

Clearly, not all analysts are likely to see the link between climate change and firm performance. In fact, it is not even obvious which firms are directly or indirectly affected by climate change and to what degree. We posit that analysts located in areas where firms are more affected by climate change are more likely to understand how climate change affects firm performance. This conjecture is based on the premise that these analysts are in a unique position to observe and experience the economic effects of large temperature changes. Further, the expertise that analysts may gather by being in areas where firms are more sensitive to climate change can help them better identify which companies could be more affected by climate-related risks, regardless of the location of firms.

Our main conjecture is that, following large increases in temperature (i.e., temperature "shocks"), analysts located in areas where firms have higher sensitivities to climate change will issue relatively more accurate forecasts. This hypothesis builds upon two strands of recent literature. First, a group of literature debates on ex-ante whether analysts would become more or less accurate following the temperature events. On the one hand, evidence from existing studies suggests that temperature increases can lead to lower productivity levels (Huntington, 1915) and fewer hours worked in climate-sensitive industries (Zivin and Neidell, 2014). If analysts become less productive or more distracted after an event, then it is possible for them to spend less time in their forecast issues (Hirshleifer and Teoh, 2003; Peng and Xiong, 2006; Hong and Stein, 2007; DellaVigna and Pollet, 2009; Han et al., 2020) and, as a result, become less accurate (Dong and Heo, 2016).

On the other hand, according to Cuculiza et al. (2021), external shock may make analysts more pessimistic, which will as a result lead to lower forecast issue. Since the average forecast level made by analysts are always tend to be higher than the actual value (see, for example, Easterwood et al. (1999), Hong and Kubil (2003)). These findings indicates that analysts may be systemetically more accurate after the shock. This evidence would be consistent with prior analyst studies, which find that relatively more conservative analysts issue more efficient forecasts (Hugon and Muslu, 2010; Jiang et al., 2016).

Our hypothesis also builds upon a small but growing accounting and finance literature that examines how climate changes affect financial markets and the economy. Existing studies show that countries with higher average temperatures have lower per capita income (Gallup, Sachs, and Mellinger, 1999; Dell, Jones, and Olken 2009, 2012) and greater reduction in national output (Hsiang, 2010). Recent evidence also suggests that abnormally warm temperatures can affect firm performance. For example, Hugon and Law (2019) find that an increase in temperature is associated with lower firm earnings.

Based on this collective evidence, we posit that analysts in areas where firms exhibit greater sensitivity to climate changes would be more aware and sensitive to large temperature changes. Consequently, they are more likely to issue relatively more accurate forecasts following periods of abnormally warm temperatures, as firm earnings could be adversely affected. This effect could be amplified for firms that are more sensitive to climate change.

To test these hypotheses, we obtain data from the National Centers for Environmental Information (NCEI), a division of the National Oceanic and Atmospheric Administration (NOAA). Our temperature anomaly variable is measured as the difference between the average monthly temperature and the average monthly temperature from 1895 to 2019. Consistent with previous global warming estimates, we find that temperatures have been rising through time, as the anomaly variable has a monthly mean of 1.2°F and a positivity rate of 73% during our sample period.

To measure the average firm sensitivity to temperature changes in a state, we estimate a 5-year rolling regression of each firm's excess stock return on the market excess return and the temperature anomaly variable. Then, for each state, we find the monthly value-weighted average of temperate change sensitivity of firms located in the state. We define states in the top tercile (i.e., the 3rd tercile) as high temperature-sensitivity states (i.e., "High-TS states"). Our assumption is that analysts in High-TS states are likely to better understand how climate change affects firm performance, as firms in these areas would potentially be more affected by temperature changes.

We test our conjecture using a Diff-in-Diff method, specifically, we regress our dependent variable, *PMAFE*, on our main independent variable, *High-Temperature Sensitivity Area* (*HTSA*). *PMAFE* is the proportional median absolute forecast error. *HTSA* is an indicator variable equal to one if an analyst is located in a High-TS state and issues a forecast during the month of the event or during the following three months. We define a month as experiencing a large temperature increase (decrease) if the temperature anomaly for month *t* is greater (less) than the sample average temperature anomaly plus (minus) 1.96 times the standard deviation of the temperature anomaly.[5] The treatment group are analysts in High-TS states and the control group are analysts in other area. We define the pre-event window as the three

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[5] The choice of using this method to identify large changes in temperature is motivated by the distinction between climate change and local weather conditions. Specifically, global warming is a trend that persists over a long period of time and is typically unobservable at a personal level. However, local weather conditions are usually more noticeable and could be driven by several factors, such as ocean oscillations, in addition to global warming. Therefore, we capture changes in temperature due to climate change as extreme changes in the temperature anomaly variable.

months before the large temperature increase month (t=[-3,0)) and the post-event wiondow as the event month and the following three months (t=[0,3]). Our key prediction is that the coefficient on *HTSA* will be positive and statistically significant, indicating that following a large temperature increase, analysts in areas where firms are more sensitive to temperature changes will issue more accurate forecasts relative to the consensus[6].

In our regression specifications, we control for a large number of analyst-level covariates and also include various fixed effects. The analyst-level fixed effects rule out the possibility that our results are driven by analysts who systematically issue more accurate forecasts. The time (year-quarter) fixed effects absorb time trends, and the firm-level fixed effects control for both time-varying information about a firm's earnings that could be available to all analysts and time-invariant firm characteristics.

The empirical results are consistent with our hypothesis. We find that analysts in high temperature-sensitive areas are more likely to issue more accurate forecasts than the consensus during the three months following a large increase in temperature (the coefficient of *HSTA* is 0.07 with a *t*-statistics of 2.40). Conversely, large decreases in temperature do not affect their forecast

[6] Since we multiply the PMAFE variable by negative one, positive values of PMAFE indicate a better than average accuracy and negative values suggest a worse than average accuracy.

accuracy. This evidence is consistent with the findings in climate change studies, which suggest that abnormally warmer climates have a larger economic impact than unusually colder temperatures (Gallup, Sachs, and Mellinger, 1999; Dell, Jones, and Olken 2009, 2012; Hsiang, 2010; Hugon and Law, 2019; Choi, Gao, and Jiang, 2020). People are found more likely to revise their beliefs upward when local tempearture is abnormally warm and carbon-intensive firms underperform in the month in which the exchange city is warmer than usual.

To establish a causal relationship between the large increases in temperature and the forecasts of treated analysts, we first examine whether our empirical set-up meets the parallel trends assumption. That is, we investigate whether prior to the abnormally warmer climates, treated and control analysts have a similar trend in forecasts. This is important since treated analysts may be more likely to issue more accurate forecasts before the events due to other factors. Thus, the effect may not be driven by the large increases in temperature.

The evidence in Figure 1 indicates that the forecast trends only differ following the unusually hot climates. Specifically, prior to the events, the graph shows that analysts in the control group have slightly higher forecasts accuracy levels. Importantly, the trends in the forecasts between the control and treated groups prior to the events are parallel (i.e., the difference is not statistically significant), suggesting that it is highly unlikely that a pre-existing trend in forecast accuracy could explain our findings.

Next, we extend this analysis to further examine whether treated analysts have a better understanding of climate-related effects. Specifically, we examine whether analysts issue relatively more accurate forecasts for firms that have a higher sensitivity to temperature changes, i.e., climate-sensitive firms.

For this test, we sort firms into quintiles based on their return sensitivity to abnormal temperature changes. Firms in the top quintile (i.e., 5th quintile) are classified as high temperature-sensitive firms (i.e., "High-TS firms"), while the remaining firms are in the "other firms" subgroup. Suppose treated analysts' relatively more accurate forecasts are driven by their ability to better assess how abnormal climate changes can negatively affect firm earnings. In that case, we expect the effect to be stronger for firms with higher temperature sensitivity (High-TS firms).

The results show that analysts in areas where firms are more sensitive to changes in temperature issue relatively more accurate forecasts for High-TS firms during the three months following a large increase in temperature. The results are weaker for the other firms subgroup. This evidence indicates that analysts adjust their forecasts accordingly, as High-TS firms are more likely to be affected by unusually warmer climates.

It is important to note that High-TS firms are not necessarily to be headquartered in the same state as the analyst. Thus, these results suggest that being in a High-TS state provides analysts with valuable experiences that allow them to better comprehend the effects of climate change on firm performance. As a result, they are better able to discriminate between firms that are more or less likely to be affected by the large increases in temperature.

To provide additional evidence of analysts' ability to discriminate, we determine whether our finding could be explained by the local bias, which indicates that analysts tend to issue more accurate forecasts on the local firms relative to others. Consistent with this conjecture, we find that treated analysts' accuracy increase after the large increases in temperature is not affected by the local bias of analysts.

We perform additional tests to confirm our core finding that a certain subset of sell-side equity analysts is better able to assess the impact of climate change on firm earnings. The first additional test is motivated by the observation that political affiliation is correlated with views about climate change. Namely, Democrats are more concerned about climate change than Republicans (McCright and Dunlap, 2011). Therefore, local political values may influence analysts' perception and awareness about climate-related risks to firms. Consistent with this conjecture, we find that forecasts made by analysts whose political affiliation is predominantly Democrat are more accurate than the forecasts of analysts that are predominantly Republican.

Our next additional test investigates whether treated analysts' forecast accuracy is higher because they systematically issue bold forecasts, regardless of the direction, as these forecasts have greater private information and greater accuracy (Clement and Tse, 2005). If the increased accuracy of treated analysts is driven by their superior comprehension of climate-related risks for firms, then we would expect them to exhibit a greater propensity to issue downward bold forecast revisions for High-TS firms and a lower propensity to issue more optimistic upward-bold forecast revisions for those firms. We find support for this hypothesis. Our evidence indicates that treated analysts are more likely to issue less upward bold revision forecasts (but not downward bold revision forecasts) for High-TS firms.

To show that our treatment group definition does not dominate our results, we further perform a set of robustness tests using a different way to separate the treatment group. Specifically, we redefine the treatment group using state-level energy efficiency policy data. Our findings show that those analysts in states with decoupling policies in energy use show similar reactions to a large increase in temperature as analysts in the treatment group defined in our main tests. According to Center for Climate and Energy Solutions (C2ES) website, decoupling policy on electric is a policy that changes in power reguation that base utility revenue on factors other than volume of electricity sold, which is a way to promote energy sector efficiency. We also show that our results are unlikely to be driven by local beliefs about climate change. The local belief measurement is derived from Yale Program on Climate Change Communication (YPCCC).

In the last part of the paper, we examine the market's reaction to forecast revisions. Since previous studies suggest that analysts' earnings forecasts contain useful information for investors, we examine whether investors are aware of the higher forecast accuracy of treated analysts. We find that investors do not anticipate treated analyst forecasts to be more accurate, as their forecast revisions do not generate stronger market reactions.

In the last empirical test, we analyze the stock market reaction to earnings announcements. We find that High-TS firms covered by more analysts in High-TS states tend to have higher post earning announcement drifts (PEAD) after earnings announcements following a large temperature increase, suggesting that earnings information is not incorporated into prices immediately.

These findings contribute to several strands of literature in finance, accounting and economics. First, our study contributes to the growing finance literature that examines how climate change affects financial outcomes. Recent papers suggest that extreme temperatures affect agricultural production, aggregate industrial output, labour supply and establishments (Fisher et al., 2012; Graff-Zivin and Neidell, 2014; Jones and Olken, 2010; Hsiang, 2010; Addoum, Ng, and Ortiz-Bobea, 2020). Investors use environmental information in investment decisions (Amel-Zadeh and Serafeim, 2018) and believe that some equity valuations do not fully reflect climate risks (Krueger et al., 2020). Climate change and carbon-transition risk affect stock returns (Hong et al., 2019; Bolton and Kacperczyk, 2020). In a related paper, Hugon and Law (2019) show that an unusually warm climate negatively affects firm earnings. We contribute to this research area by showing that analysts forecasts are affected by climate changes.

We also contribute to the literature that examines the factors that affect analyst forecasts. Previous studies suggest that analysts are subject to various biases, including representativeness (De Bondt and Thaler, 1990), conservatism (Zhang, 2006), availability (Bourveau and Law, 2016), and overconfidence (Hilary and Menzly, 2006) biases. Analysts could also be affected by depression (Dehaan et al., 2017), limited attention (Dong and Heo, 2016), and extreme negative events (Cuculiza et al., 2020). We complement this analyst literature by establishing that large increases in temperature affect analyst forecast and accuracy.

In a related paper, Addoum, Ng, and Ortiz-Bobea (2019) examine how extreme temperatures affect earnings expectations and find that analysts anticipate part of the earnings shocks associated with temperature extremes. We complement these findings by further investigating how analysts come to understand the effects of climate change on firms and if they adjust their forecasts accordingly. Our economic setting allows us to compare the forecasts issued by analysts in areas that are more sensitive to climate change with the forecasts of analysts who are in areas that are less sensitive to temperature changes. We find that analysts in states where firms are more sensitive to changes in temperature issue relatively more accurate forecasts.

Beyond the analyst literature, our paper complements studies that examine how political beliefs affect financial decisions. Recent studies suggest that political views affect mutual fund managers' asset allocations (Hong and Kostovetsky, 2012), retail investors' stock market participation decisions (Ke, 2020), and firms' corporate social responsibility policies (Di Giuli and Kostovetsky, 2014). They also affect individuals' attitudes towards climate change (McCright and Dunlap, 2011; Howe et al., 2015; Addoum, Ng, and Ortiz-Bobea, 2019). Our results show that local political beliefs are associated with analysts' ability to assess the relation between climate change and firm earnings.

The rest of the paper is organized as follows. In Section 2, we describe the data sources and the empirical method. In Section 3, we examine how large changes in temperature affect analyst forecasts, and in Section 4, we perform several robustness tests. In Section 5, we analyze the reaction of the market to analysts' forecasts. Section 6 concludes with a brief summary.

3.2 Data and Methods

We use several data sources, including the National Centers for Environment Information (NCEI), Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S), the Center for Research in Security Prices (CRSP) and COMPUSTAT.

3.2.1 Temperature Data

We collect temperature data from the National Centers for Environmental Information (NCEI), a division of the National Oceanic and Atmospheric Administration (NOAA). The temperature record is available starting in January 1895 and is updated on a monthly basis. The database provides each month's average temperature value and anomaly temperature. The monthly temperature anomaly variable is measured as the difference between the average monthly temperature and the average monthly temperature from 1895 to 2019 for the same month of a year. A positive (negative) temperature anomaly implies that the average temperature for a given month is higher (lower) than the average temperature of the benchmark.[7] Following prior literature, our main measure of climate change is the temperature anomaly variable (Cao and Wei, 2005).

3.2.2 Analyst Forecasts

[7] Historically, all periods have had positive average monthly temperatures.

We obtain annual forecast values on earnings per share (EPS) and actual values from Thomson Reuters' Institutional Brokers Estimate System (I/B/E/S) guidance database. Our sample period is from 1996 to 2017. Even though analyst forecasts are available prior to this period, coverage in the early years is sparse (Easton and Sommers, 2007; Malmendier and Shanthikumar, 2014; Jiang et al., 2016), and thus, we exclude them from our analysis.

We follow the analyst literature and impose several restrictions on our sample to filter for potential entry errors and mitigate the influence of outliers. First, we exclude forecasts with an absolute forecast error greater than one (Lim, 2001; Bernhardt et al., 2006). Second, we restrict our sample to forecasts issued for firms with an average share price greater than $1 (Chen and Jiang, 2006; Cen et al., 2013; Malmendier and Shanthikumar, 2014). To ensure that our consensus measurement is not biased by firms followed by a few analysts, we only include forecasts for firms covered by at least five analysts (Hilary and Hsu, 2013). Further, we keep forecasts with a maximum horizon of six months and a minimum horizon of one month from the earnings announcement date. This choice decreases the potential noise that could be introduced by stale forecasts and information leakage (Jegadeesh et al., 2004; Jackson, 2005).

To identify the location of each analyst, we follow Jianget al (2016) and use the coordinates of the city center in which the analysts' branch office is based as the analyst location. The latitude and longitude coordinate information of analysts are available from Gazetteer Files in U.S. Census Bureau.

3.2.3 Equity Data

We use stock-level data from the Center for Research on Security Prices (CRSP) and COMPUSTAT. From CRSP, we obtain the daily and monthly stock returns, stock prices, and Standard Industry Classification (SIC) codes. We restrict our sample to common stocks (share codes of 10 and 11). We use COMPUSTAT to obtain various firm characteristics. In addition, we obtain the forty-eight SIC industry classifications from Professor Kenneth French's data library.

3.2.4 Estimating Firm-Level Temperature Sensitivity

To measure a firm's average sensitivity to temperature changes, we estimate each firm's sensitivity to temperature changes by performing a set of rolling regressions of a company's excess stock return on the excess market return, as well as the abnormal temperature variable. The regression specification is as follows:

$$r_{j,t} - r_{f,t} = \alpha_j + \beta_j(r_{mkt,t} - r_{f,t}) + \theta_j Temperature\ Anomaly_t + \epsilon_{j,t}, \qquad (1)$$

where *j* denotes firm and *t* denotes month. $r_{j,t}$ is the stock return for stock *j* in month *t*. $r_{f,,t}$ is the Treasury bill rate in month *t*. $r_{mkt,t}$ is the Fama-French market factor in month *t*. The *Temperature Anomaly*$_t$ variable is the difference between the average temperature in month *t* and the average monthly return of the period from 1895 to 2019. The estimation time window is 5 years, or 60 months, and we require a minimum of 3 years (36 months).[8] Since the COMPUSTAT data is only available starting in January 1960, we estimate θ_j from January 1963 onwards.

Following Kumar, Xin and Zhang (2019), we take the absolute value of θ_j, $\theta_j^c = |\theta_j|$, as stock *j*'s sensitivity to the temperature anomaly variable in month *t*. A higher (lower) θ_j^c indicates that the stock return tends to be more (less) sensitive to abnormal changes in temperature. We define firms in the top quintile of θ_j^c (i.e., the 5th quintile) as high temperature-sensitivity firms, i.e., High-TS firms, in month *t*.

[8] The main results of the paper are not sensitive to increasing or decreasing the minimum requirement for data availability.

We use θ_j^c to create the average sensitivity of firms to temperature changes in a state. Specifically, for each state, we calculate the value-weighted average of local firms' sensitivity to temperature changes. We then take the time-series average of the state-level temperature sensitivity starting in 1963 up until the current month *t*. We use the average temperature sensitivity values of U.S. states (i.e., the value-weighted and time-series average of $\theta_j^c, \bar{\theta}$) to sort them into terciles each month. We define states in the top tercile of $\bar{\theta}$ (i.e., the 3rd quintile) as high temperature-sensitivity (TS) states.

3.2.5 Forecast Accuracy Regression Specification

Our main goal is to examine whether equity analysts understand the impact of climate-related risks on firm performance. Specifically, we expect analysts in High-TS states to issue relatively more accurate forecasts since large temperature increases are more likely to remind analysts of climate risk in these states.

To examine this conjecture, we use a difference-in-differences (DID) method. Our experimental setting uses extreme changes in temperature as an exogenous event. We define a month as experiencing a large temperature increase if the temperature anomaly for month *t* is greater than the average temperature anomaly plus 1.96 times the standard deviation of the temperature anomaly. Similarly, a month is defined as experiencing a large temperature decrease if the temperature anomaly for month t is less than the average temperature anomaly minus 1.96 times the standard deviation of the temperature anomaly. We require the time lag between each event to be at least seven months to avoid overlapping windows.

For each event, we define the pre-treatment period as the three months prior to the event. The post-treatment period includes the event month and the following three months. We restrict our sample to only include observations in the pre- and post- time periods. To determine the treatment and control groups, we use the average temperature sensitivity values of states. Specifically, analysts who reside in High-TS states are classified into the treatment group, while the remaining analysts constitute the control group.[9]

Our DID regression specification is as follows:

$$PMAFE_{i,j,t} = \alpha + \beta HTSA_{i,t} + \gamma X_{i,j,t} + \delta_{analyst} + \iota_{firm} + \varsigma_{time} + \varepsilon_{i,j,t}. \quad (2)$$

$PMAFE_{i,j,t}$ is the proportional median absolute forecast error to compare an analyst's absolute forecast error to the median absolute forecast error of

[9] In Section 4.1, we show that the results are robust to using different definition of the treatment group.

other analysts that cover the same firm at the same time. The measure is as follows:

$$PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}}, \tag{3}$$

for analyst *i*, firm *j*, at time *t*. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ value_{i,j,t} - Actual\ value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm *j* at time *t*. An advantage of using this measure is that it accounts for firm × time fixed effects (Clement, 1999). We multiply the PMAFE variable by negative one, such that positive values of PMAFE indicate a better than average performance and negative values suggest a worse than average performance.

$High\ Temperature\ Sensitivity\ Area_{i,t}$, ($HTSA_{i,t}$) is our main independent variable, which is a dummy variable equal to one if an analyst is located in a High-TS state and issues a forecast during the month of the event or in the following three months (i.e., *t* = [0,3]).

We control for several analyst-level characteristics denoted by $X_{i,j,t}$. This set includes *Forecast Horizon*, which is the number of months between the forecast date and the actual earnings announcement date. It controls for potential time trends in forecasts such as "walk-downs" to beatable forecasts before earnings announcements (Richardson et al., 2004). *No. Companies* is the number of firms an analyst follows during a year. *Firm Experience* is the number of years an analyst has covered a firm. *General Experience* is the number of years between the forecast issued for a company and the first forecast of the analyst in the I/B/E/S database. *Broker Size* is the number of analysts who are employed at an analyst's brokerage firm. *All Star* is a dummy variable equal to one if the analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. It captures an analyst's ability and reputation. *No. Industries* is the number of Fama-French 48 Industries that an analyst follows. *Lagged AFE (LAFE)* is an analyst's absolute forecast error for a firm during the previous period.

We also include analyst, firm, and time (i.e., year-quarter) fixed effects. The analyst fixed effects control for the possibility that our results are driven by analysts who systematically issue lower forecasts. The firm fixed effects absorb firm-specific characteristics that may affect analysts' forecasts. The time fixed effects absorb any time trends.

3.2.6 Summary Statistics

We report summary statistics for our sample in Table 3.1. It shows that analysts in our sample have about 7.80 years of general experience and 4.05

years of firm-specific experience. On average, they follow 16 companies and 6 industries. Also, 14% of analysts in our sample are *All Star*.

3.3 Main Empirical Results

In this section, we test our main conjectures. Specifically, we analyze whether analysts in High-TS states are more likely to issue relatively more accurate forecasts following an abnormally warm climate. To establish a causal relation, we show that treated and control analysts have a similar trend in their forecasts prior to the events. In addition, we investigate whether these effects are stronger for firms with higher sensitivity to changes in temperature.

3.3.1 Large Changes in Temperature and Analyst Forecasts

In this section, we examine if the large increases in temperature affect analyst accuracy. Specifically, we calculate a performance measure similar to Clement (1999). In particular, we use the proportional median absolute forecast error (PMAFE) to compare an analyst's absolute forecast error to the median absolute forecast error of other analysts that cover the same firm at the same time. We multiply the *PMAFE* variable by negative one, such that positive values of PMAFE indicate a better than average performance and negative values suggest a worse than average performance.

We present our main findings in Table 3.2. We report the results for extreme-hot temperature changes in columns (1) to (3) and the findings for extreme-cold temperature changes in columns (4) to (6). Consistent with our main hypothesis, we find that analysts in temperature-sensitive areas issue relatively more accurate forecasts following unusually hot temperatures. The estimates in column (1) show that the coefficient on *HTSA* is positive and statistically significant. This result is robust to including analyst, firm, and time fixed effects.

For instance, the results in column (3) suggest that treated analysts' proportional median absolute forecast error is 7% lower following a large temperature increase than untreated analysts. Further, the *All Star* coefficient in column (3) indicates that all-star analysts issue forecasts with a 9.5% higher accuracy level than others.

The results in columns (4) to (6) show that analysts who are in areas that are sensitive to temperature changes do not issue more accurate forecasts after a large decrease in temperature. These findings are consistent with prior evidence, which suggests that abnormally hot temperatures have stronger economic effects than unusually cold temperatures (Gallup, Sachs, and

Mellinger, 1999; Dell, Jones, and Olken 2009, 2012; Hsiang, 2010; Hugon and Law, 2019; Choi, Gao, and Jiang, 2020).

Further, these results also provide suggestive evidence that our findings are unlikely to be explained by analysts' lower productivity levels or limited attention. For instance, it could be possible that after an abnormally hot temperature, analysts have a more difficult time concentrating when issuing their forecasts. However, this potential alternative explanation suggests that analysts would issue forecasts that are farther away from the consensus and become less accurate.

3.3.2 Time Trend in Analyst Forecasts

To establish a causal relationship between large increases in temperature and analyst forecast accuracy, we need to establish that treated and control analysts have a similar trend in their forecasts prior to the events. It is possible that treated analysts already exhibit a greater propensity to issue lower forecasts before the events. This potential endogeneity concern would suggest that we are capturing a pre-existing trend in analysts' likelihood of issuing better forecasts.

Figure 3.1 provides a visual representation of analysts' average *PMAFE* three months before the events to three months after the events. The graph shows that treated and control analyst forecasts have a parallel trend prior to the large increases in temperature. Moreover, the figure suggests that control analysts issue better forecasts than treated analysts—the *t*-statistics for the differences in the mean range between -1.98 and -0.74 for the pre-event periods. However, this trend begins to change from the event date. The forecast accuracy of treated analysts increases to a level higher than that of control analysts in the three months after the large temperature increase event, as the latter's trend remains mostly unchanged.

Importantly, during the three-month period following the large increases in temperature, the forecasts of treated and control analysts continue to diverge. That is, treated analysts issue more accurate forecasts as time progresses, while the forecasts of analysts in the control group do not experience any major changes following the events. The difference becomes statistically significant in the third month (*t*-statistic = 1.86), indicating that it takes a couple of months for the effect to be fully reflected in analysts' forecasts.

Overall, the results in this section suggest that the differences in forecasts only exist following the events. The evidence is consistent with analysts having parallel trends prior to the large increases in temperature. Thus, it is highly unlikely that our findings could be explained by pre-existing trends in analysts' likelihood of issuing more accurate forecasts.

3.3.3 Temperature Changes and High-TS Firms

The results so far indicate that in states where firms are more sensitive to temperature changes, analysts better comprehend the effects of climate-related risks since they issue relatively more accurate forecasts. To further pin down this mechanism, we now examine if treated analysts issue relatively more accurate forecasts for high-temperature sensitivity firms. We perform this test by sorting firms into quintiles based on their sensitivity to temperature anomaly θ_j . We classify firms in the 5th quintile as high temperature-sensitivity firms ("High-TS firms"), and the remaining firms are categorized into the "other firms" group.

Panel A of Table 3.3 reports the regression estimates where *PMAFE* is the dependent variable. As conjectured, the coefficient on *HTSA* for High-TS firms is positive and statistically significant. The estimates in column (2) suggest that following a large increase in temperature, the accuracy level of treated analysts is 14.6% higher for firms that have high sensitivities to temperature changes than other analysts. These results are robust to the inclusion of analyst, firm, and time fixed effects. Conversely, the coefficient on *HTSA* is insignificant for the other firms' subsample. This evidence suggests that treated analysts issue more accurate forecasts for High-TS firms as these are more likely to be affected by abnormally warm temperatures.

An alternative explanation for our findings above is that treated analysts could be located in the same state as the High-TS Firms do so that the higher accuracy level of their forecasts could be generated from local bias since analysts may have more information about their local firms than others. To further address this problem, we conduct tests and show our results in Table 3.4. Our key independent variable of interest is an interaction dummy between *Local Dummy* and *Temperature Event Dummy*. *Local Dummy* is a dummy variable if the analyst i is in the same state of the firm j which she issues forecasts on, and zero otherwise. *Temperature Event Dummy* equals one if the forecast is made during the large temperature increase month or three months following. Panel A of Table 3.4 presents the results for the full sample of all analysts and all firms. The insignificant coefficients of interaction dummy show that analysts do not issue more accurate forecasts on their local firms after large temperature increase events.

We further divide the sample into different subgroups based on the analysts' location. The subsample results for analysts in High-TS states and other states are shown in Panel B Table 3.4. The coefficients of interaction variables in subsamples indicate that the treated analysts in our main tests are not affected by local bias. Their accuracy forecasts for local firms do not significantly increase after large temperature increases, which indicates that the previous finding that treated analysts have better forecasts for High-TS firms after events can not be explained by local bias. The firms' subsample results are further presented in Panel C. Similar to analyst subsample results, local bias does not play a significant role in forecast accuracy improvement after a large temperature increase for both firms located in High-TS states and other states.

Overall, these results provide evidence that treated analysts issue more accurate forecasts following a temperature increase event. Importantly, the results are mostly driven by firm-level temperature sensitivity, as these companies are more likely to be affected by the unusually hot climates. Firms' and analysts' locations, on the other hand, is not crucial to the forecast accuracy after large temperature increase events.

3.4 Alternative Explanations and Robustness Tests

Our baseline results indicate that following large increases in temperature, analysts in areas where firms are more sensitive to changes in temperature issue relatively more accurate forecasts. In this section, we entertain alternative explanations and further examine the robustness of these results.

3.4.1 Large Temperature Increases and State-Level Political Affiliations

Recent evidence suggests that political affiliations can affect individuals' views about climate change. For instance, McCright and Dunlap (2011) show that liberals and Democrats are more likely to express concern about climate change than conservatives and Republicans. Building upon these insights, we examine whether analysts that lean toward the Democrat Party are more likely to issue relatively more accurate forecasts following a large temperature increase than analysts that lean toward the Republican Party.

We use the analysts' donation data to define their political affiliations. Specifically, we classify an analyst as *Democrat* if her total donation amount to the Democratic Party exceeds that to the Republican Party. We obtained analysts' political orientation from Jiang et al. 2016. We further interact this variable with *Shock*, which is an indicator variable equal to one if analysts' forecasts are issued within the month of large temperature increases or three months after.

The results for our earning forecasts are presented in Table 3.5. The estimates suggest that analysts with a Democratic tilt issue relatively more accurate forecasts than analysts who donate more to Republicans. For instance, the coefficient of the interaction term is positive and statistically significant in column (1) (estimate = 0.130, *t*-statistic = 2.30). As shown in column (5), this result is robust when we include time, analyst, and firm fixed effects.

3.4.2 Large Changes in Temperature and Bold Forecasts

A possible alternative explanation for the forecast accuracy results is that analysts systematically issue bold forecasts, regardless of the direction, as these tend to incorporate analysts' private information (Clement and Tse, 2005). Specifically, this hypothesis suggests that treated analysts would be more likely to issue both downward and upward bold forecasts for High-TS firms. However, if their understanding of firms' sensitivities drives treated analysts' more accurate forecasts to abnormally warmer climates, then the downward and upward bold should not exist simultaneously.

We test this possibility by examining whether treated analysts are less likely to issue bold forecasts after a large increase in temperature. Our dependent variable, *Bold Revision,* is a dummy variable equal to one if the analyst issues a forecast above or below the prior consensus and her/his previous forecast, and zero otherwise. As in the previous empirical analysis, we sort firms into quintiles to create the High-TS firms and the other-firms subgroups.

We regress *Bold Revision* on a vector of control variables. These include *Forecast Horizon*, *No. Companies*, *Firm Experience*, *General Experience, Broker Size*, *All Star*, *No. Industries*, and *LAFE*. We also incorporate analyst, firm, and time fixed effects as in equation (2). The estimates in Table 3.6, columns (1) and (2) show that the coefficient on *HTSA* is statistically insignificant for both High-TS firms and companies in the lower sensitivity subsample. This evidence suggests that analysts in High-TS states do not exhibit a greater propensity to issue bold forecasts following a large increase in temperature.

We now extend this analysis and examine downward and upward bold forecasts separately. The dependent variable in columns (3) and (4) is *Downward Bold Revision*, an indicator variable equal to one if the analyst issues a forecast below the prior consensus and her/his previous forecast, and zero otherwise. Conversely, the dependent variable in columns (5) and (6) is *Upward Bold Revision,* a dummy variable equal to one if the analyst issues a forecast above the prior consensus and her/his previous forecast, and zero otherwise.

Consistent with our hypothesis, our results show that treated analysts are more likely to issue bold revisions more upward but not downwards for High-TS firms. For instance, the *HTSA* coefficient in column (5) is 0.036 (*t*-statistic =1.76), while the *HTSA* coefficient in column (3) is -0.045 (*t*-statistic = -1.70). In contrast, when the dependent variable is *Downward Bold Revision*, we find the coefficients of *HTSA* are insignificant. We find that estimate for *HTSA* in the two subsamples of firms is statistically insignificant for both upward and downward bold revision.

Collectively, the bold regression estimates suggest that unusually hot temperatures do not affect treated analysts' overall likelihood of issuing bold forecasts. However, analysts in areas where firms are more sensitive to changes in temperature are more likely to issue less upward bold forecast revisions after a large increase in temperature. The coefficients on *HTSA* for firm subsamples are statistically insignificant across all specifications. This evidence rules out the potential alternative explanation for our findings that analysts are more accurate because they systematically issue bold forecasts.

3.4.3 Robustness Tests

In this subsection, we examine the robustness of our results using alternative measures of treated analysts. We also examine if the effects are driven by analysts' pre-existing awareness of climate change.

3.4.3.1 Alternative Definition for Treated Analysts

In our DiD methodology, we classify analysts who reside in High-TS states into the treatment group, while the remaining analysts constitute the control group. Our findings indicate that analysts who observe and experience more economic effects of climate are more likely to understand how climate change affects firm performance. To make sure our results are not driven by a particular classification of treatment and control group. In this section, we redefine our treatment group using state policy data. Specifically, we create *Decoupling Policy Area* (*DPA)*, an indicator variable equal to one if the analyst is located in a state with a decoupling policy on electricity, which is a policy aim to promote energy sector efficiency, and issues a forecast during the month of the event or during the following three months. Our results generated from decoupling policy data instead of temperature sensitivity to determine treatment and control group further strengthen our findings by ruling out the possibility that our main results are driven by the specification of the treatment group. The High-TS states and Decoupling Policy States are listed in Appendix A2.

The forecast accuracy results are in Panel A of Table 3.A3. Consistent with our main test, we examine whether treated analysts are more likely to issue more accurate forecasts following a large temperature increase. We find that the coefficient on *DPA* is positive and statistically significant throughout the specifications, indicating that analysts in states with decoupling policy issue relatively more accurate forecasts following large increases in temperature.

In Panel B, we investigate whether treated analysts issue relatively more accurate forecasts for High-TS firms following the events. The estimates show that the coefficient on *DPA* is positive and statistically significant in columns (1) and (2) for High-TS firms but not for other firms, suggesting that treated analysts improve their forecasts accuracy by accounting firms' different climate risk levels.

We further perform the bold test using decoupling policy as the specification of treatment group and control group of analysts in Table 3.A3 Panel C. Our results find the same conclusion as before: the increase in forecast accuracy is not generated from incorporating treated analysts' private information as they do not tend to issue more bold forecasts after a large increase in temperature.

3.4.3.2 Local Climate Change Beliefs

It is possible that the overall local awareness of climate change in High-TS states is higher than in other states. This would suggest that our results are driven by analysts' pre-existing beliefs about climate change rather than by experiencing firms' higher sensitivities to changes in temperature. To examine this possibility, we collect data from the Yale Program on Climate Change Communication (YPCCC), which provides climate change opinions at the county level. We create the variable, *High Belief State,* an indicator equal to one if the analyst is in a high belief state, i.e., a top tertile state for the "*Estimated percentage who think that global warming is happening*" in YPCCC, and the forecast is issued during the event month or within three months after the event.

The results in Table 3.A4 show that analysts located in states where individuals believe that climate change is occurring do not issue relatively more accurate forecasts following large increases in temperatures. These findings suggest that treated analysts' more accurate forecasts are unlikely to be driven by their pre-existing beliefs about climate change. This finding is not contridict to our main findings. The explanation is that only belief in climate change is not enough to improve the analysts' forecasts. The awareness on how climate change affects the financial market is more closely related to analysts forecasting. This is the key difference bewteen the analysts in High-TS states and in other states- these group of analysts have more opportunities to observe how climate risk affects local stock returns.

3.5 Large Temperature Increases and Market Reaction

Building upon our results so far, we now examine the reaction of the market to treated analysts' relatively more accurate forecasts. We first investigate if investors regard it as probable that analysts exposed to the large increases in temperature are more accurate. We also examine the market response to earnings announcements.

3.5.1 Market Reaction to Forecast Revisions

Since the forecasts of treated analysts are more accurate and can provide valuable information for investors, we investigate if investors anticipate for these analysts to be more accurate. To test this conjecture, we follow Hirshleifer et al. (2019) and regress a firm's return on *Forecast Revision* × *HTSA*. As a measure of a firm's return, we use its three-day market-adjusted excess return centred on the revision date. *Forecast Revision* is defined as the difference between analyst *i*'s current forecast for firm *j* at time *t* and the forecast issued immediately before the current forecast, scaled by the standard deviation of forecasts of all analysts who follow firm *j* in time *t*. In addition to the covariates in equation (2), we also include controls for Friday and fourth-quarter effects.

The results in Table 3.7 show that the coefficient on *Forecast Revision* is positive and statistically significant across all specifications, except when we include controls interacted with *Forecast Revision*. Consistent with prior findings in the analyst literature, this result shows that the market reaction around forecast revisions is correlated with the signed magnitude of the revision. However, the interaction term *Forecast Revision* × *HTSA* is not statistically significant, which suggests that the forecast revisions of treated analysts do not generate a stronger market reaction. Thus, investors do not consider analysts in High-TS states as more accurate when they issue forecasts following a large increase in temperature.

3.5.2 Large Temperature Increases and Unexpected Earnings

Our results so far suggest that after unusually hot temperatures, treated analysts issue relatively more accurate forecasts. We now examine if High-TS firms that are followed by more analysts in High-TS states have higher unexpected earnings following an event. Since analysts issue relatively more optimistic forecasts in general and treated analysts have more accurate forecasts after large temperature increases, we expect firms covered more by treated analysts have relatively higher unexpected earnings.

To test this conjecture, we need to determine which firms are covered by a greater number of analysts in High-TS states. Therefore, for each firm-quarter, we create a weighted average of analysts' local (i.e., state-level) temperature sensitivity across analysts covering the firm.[10] We then sort firms based on this aggregated value. We construct the firm-level variable, *HTSA(F)*, which equals one if the firm belongs to the highest quintile and the earnings announcement occurs within three months after the temperature event, and zero otherwise.

The dependent variable, *Unexpected Earning* (*UE*), is the difference between the actual announced earning and the median of the forecasts in the past quarter, scaled by the lagged stock price. To be consistent with the analyst literature, we use quarterly earnings announcements and forecasts. For this analysis, we include covariates that control for Friday and fourth-quarter

[10] An analyst's local temperature sensitivity is the average temperature sensitivity of firms in the analyst's state (i.e., $\bar{\theta}$ in Section 2.4). For each firm-quarter, we use the number of forecasts issued by each analyst as weights for the firm-level measure.

effects, as well as control for several firm-level characteristics. These include *Log(ME), Log(BM), RepLag, Busy,* and *Loss.* These variables are defined in Table 3.A1.

We interact *HTSA(F)* with *High TS*, an indicator variable equal to one if the firm is a High-TS firm, and zero otherwise. Since we expect High-TS firms that are followed by more analysts in High-TS states to have a lower consensus forecast, we conjecture that the coefficient on the interaction term, *HTSA(F)* × *High TS,* would be positive and statistically significant. Consistent with this hypothesis, the results in Table 3.8 show that the coefficient for the interaction term in the first column is 0.147 (*t*-statistic = 3.26). The interaction coefficient remains positive and statistically significant when we include a vector of control variables, as shown in column (2).

Overall, these findings suggest that when more treated analysts follow a High-TS firm, their more accurate forecasts generate higher unexpected earnings.

3.5.3 Market Reaction to Earnings Announcements

In the last set of tests, we examine how the stock market reacts to earnings announcements. We create two variables to measure the stock market reaction. The first measure *CAR* is the cumulative abnormal return for the three days centred around the earnings announcement [-1, 1]. The second measure is the post-earnings announcement drift (PEAD), which is the cumulative abnormal return for the [2, 60] trading days following the earnings announcement. We expect that firms with a lower consensus, as a result of the higher number of lower forecasts, will have a higher PEAD because the market would be able to incorporate the information contained in the earnings announcements in a short period after. That is, we expect our triple interaction, *HTSA(F)* × *High TS* × *UE*, to be positive and statistically significant.

The dependent variable in columns (1) and (2) of Table 3.9 is *PEAD*. The coefficient on the triple interaction term in column (1) is positive and statistically significant (estimate = 2.83, *t*-statistic = 1.67). The finding is similar in column (2). Conversely, the coefficient for the triple interaction in columns (3) and (4), when the dependent variable is *CAR*, is statistically insignificant.

These findings suggest that climate-sensitive firms followed by more analysts in High-TS states have higher unexpected earnings. This generates stronger *PEAD* as stock prices react to the earning announcements following the large temperature increases in a short period after but not immediately. Thus, the market takes time to incorporate the information contained in the earnings announcement, and as a result, the cumulative abnormal return is not significant.

3.6 Summary and Conclusions

This paper examines whether sell-side equity analysts understand the effects of climate change on firm performance. We conjecture that analysts in areas where firms are more sensitive to changes in temperature are in a better position to assess climate-related effects and better able to comprehend them. Consistent with this conjecture, we find that analysts who are located in high-temperature sensitivity states in the U.S. issue relatively more forecasts in the period following a large increase in temperature.

We perform additional analyses to further examine analysts' understanding of the impact of climate change on firm performance. Specifically, we use the cross-sectional variation in firms' sensitivities to temperature changes and find that our results are mostly concentrated in firms with the highest sensitivities to temperature changes (i.e., "High-TS firms"). We further show that this finding is not driven by the local bias of analysts and the location of firms and analysts.

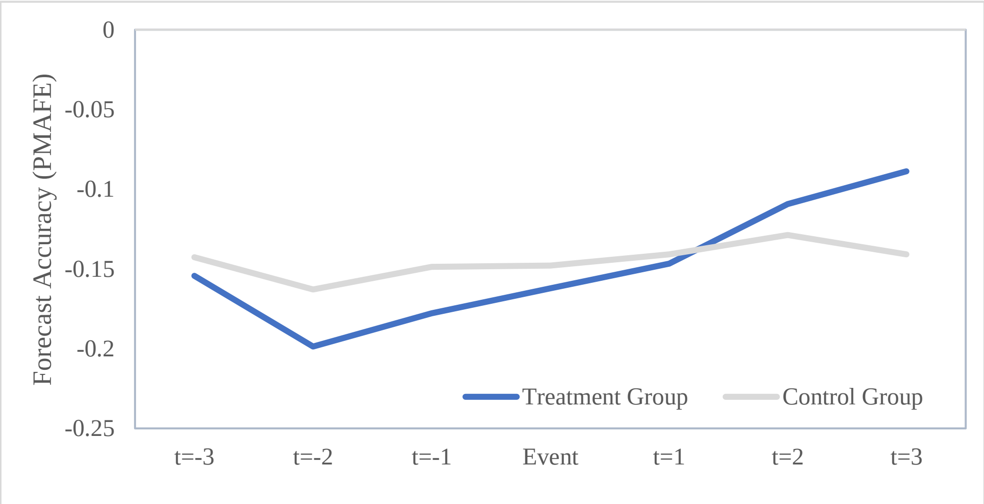
Our market reaction tests show that investors do not anticipate treated analysts to be more accurate, as there is no differential market reaction following their forecast revisions. Conversely, we find that High-TS firms that more analysts in High-TS states follow have a higher unexpected earning following unusually hot climates. This generates a higher stock market reaction to the earnings announcements of climate-sensitive firms after large temperature increases in a short period.

These results complement the evidence from a growing literature that examines market participants' understanding of climate-related risks. Our main contribution in this paper is to show that analysts in areas that are more sensitive to temperature changes issue relatively more accurate forecasts following abnormally warm temperatures. This affects the information dissemination process in financial markets as the market reacts more strongly to earnings surprises after large temperature increases.

In future research, it would be interesting to examine whether corporate managers, investors, or other market participants are also aware of climate-related risks. It would also be useful to examine whether equity analysts are skillful in incorporating information from other non-traditional sources (e.g., gambling or dividend sentiment) into their earnings forecasts.

Figure 3.1 Forecast Accuracy Around Large Temperature Increases

This figure presents the average forecast accuracy level for treatment and control analysts before and after large temperature increases. The y-axis displays the average PMAFE of treatment and control analysts[11]. The x-axis displays the time period (month) in relation to when analysts experience a large temperature increase (event).



[11] We mutiply PMAFE by negative one so that higher value indicates high forecast accuracy.

Table 3.1 Summary Statistics

This table reports summary statistics for the variables used in the empirical analysis. We use data from Thomson Reuters' Institutional Brokers System (I/B/E/S) during the 1996 to 2017 period. We multiply the coefficient for *AFE* by 100 for readability. The variable definitions are available in Table A1.

	Obs.	Mean	Stdev.	25^{th} Pctl.	Median	75^{th} Pctl.
Earnings	100,448	1.63	2.43	0.46	1.22	2.36
Earnings Forecast	100,448	1.63	2.41	0.47	1.23	2.35
Forecast Errors (%)	100,448	0.89	181.21	-3.51	1.03	5.69
PMAFE	100,448	0.26	1.72	-0.21	0.00	0.23
HTSA	100,448	0.05	0.22	0.00	0.00	0.00
Forecast Horizon	100,448	2.64	1.47	2.00	2.00	4.00
No. Companies	100,448	16.14	7.11	12.00	15.00	20.00
Firm Experience	100,448	4.05	3.57	1.00	3.00	5.00
General Experience	100,448	7.80	5.30	3.00	6.00	11.00
Brokerage Size	100,448	37.62	29.08	15.00	31.00	50.00
No. Industries	100,448	6.38	3.67	4.00	6.00	8.00
All Star	100,448	0.14	0.35	0.00	0.00	0.00
AFE (%)	100,448	0.68	1.24	0.08	0.25	0.69
Local dummy	100,448	0.12	0.33	0.00	0.00	0.00
Bold Revision	101,316	0.77	0.42	1.00	1.00	1.00
Downward Revision	101,316	0.36	0.48	0.00	0.00	1.00
Upward Revision	101,316	0.40	0.49	0.00	0.00	1.00
Forecast Revision	59,784	-0.03	0.21	-0.08	-0.01	0.05
HTSA(F)	35,601	0.11	0.32	0.00	0.00	0.00
High TS	35,601	0.14	0.35	0.00	0.00	0.00
UE (%)	35,601	0.03	0.62	-0.06	0.04	0.17
Log(ME)	35,601	13.83	1.73	12.60	13.70	14.93
Log(BM)	35,601	-0.27	0.85	-0.79	-0.27	0.18
RepLag	35,601	3.36	0.39	3.09	3.33	3.61
Busy	35,601	3.38	1.32	2.00	4.00	5.00
Loss	35,601	0.17	0.38	0.00	0.00	0.00
Q4 Dummy	35,601	0.40	0.49	0.00	0.00	1.00
Friday	35,601	0.06	0.23	0.00	0.00	0.00
DPA	100,448	0.01	0.13	0.00	0.00	0.00

Table 3.2 Large Temperature Increases and Analyst Forecast Accuracy

The table examines whether analysts in High-TS states issue more accurate forecasts. We follow Clement (1999) and create the proportional mean absolute error (PMAFE), where $PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}}$. $AFE_{i,j,t}$ is the absolute forecast error of analyst *i* for firm *j* at time *t*. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ value_{i,j,t} - Actual\ value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm *j* at time *t*. An advantage of using this measure is that it accounts for firm × time fixed effects (Clement, 1999). Since we multiply the PMAFE variable by negative one, positive values of PMAFE indicate a better than average performance and negative values suggest a worse than average performance. *HTSA* is a dummy variable equal to one if the analyst is in a High-TS state and the forecast is issued during the event month or within three months after the event. We multiply the coefficients for *No. Companies* and *Broker Size* by 100 for readability. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter-level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Table 3.2 Large Temperature Increases and Analyst Forecast Accuracy-Continued

	Large Temperature Increase			Large Temperature Decrease		
	(1)	(2)	(3)	(4)	(5)	(6)
HTSA	0.049**	0.069**	0.070**	0.046**	0.008	-0.006
	(2.27)	(2.52)	(2.40)	(2.55)	(0.37)	(-0.16)
Forecast Horizon		-0.032***	-0.032***		-0.025**	-0.011
		(-4.70)	(-5.12)		(-2.60)	(-1.21)
No. Companies		0.018	0.064		-0.492	-0.549
		(0.09)	(0.31)		(-1.50)	(-1.45)
Firm Experience		0.005	-0.007		-0.012	-0.008
		(0.40)	(-0.53)		(-0.87)	(-0.77)
General Experience		-0.003	-0.018		0.089	0.123**
		(-0.10)	(-0.55)		(1.85)	(2.53)
Broker Size		-0.015	-0.039		-0.007	0.035
		(-0.41)	(-1.04)		(-0.10)	(0.53)
No. Industries		-0.005	-0.003		-0.005	-0.007
		(-1.02)	(-0.57)		(-0.66)	(-0.64)
All Star		0.089**	0.095**		-0.029	-0.043
		(2.26)	(2.44)		(-0.67)	(-0.99)
LAFE		3.776***	9.062***		1.135	4.927*
		(4.03)	(5.45)		(1.14)	(2.00)
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	No	Yes	No	No	Yes
N	138689	100825	100448	59819	41344	40898
Adj. Rsq.	0.014	0.020	0.028	0.035	0.040	0.141

Table 3.3 Large Temperature Increases and High-Temperature Sensitivity Firms

We examine if the effects are stronger for firms with higher sensitivities to changes in temperature. We divide the sample into two groups by sorting all the firms by their firm-level sensitivity each month and treating the firms in the top quintile in the previous month as "High-TS Firms" and the rest as other firms. We follow Clement (1999) and create the proportional mean absolute error (PMAFE), where $PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}}$. $AFE_{i,j,t}$ is the absolute forecast error of analyst i for firm j at time t. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ value_{i,j,t} - Actual\ value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm j at time t. Since we multiply the PMAFE variable by negative one, positive values of PMAFE indicate a better than average performance, and negative values suggest a worse than average performance. *HTSA* is a dummy variable equal to one if the analyst is in a High-TS state and the forecast is issued during the event month or within three months after the event. We multiply the coefficients for *No. Companies* and *Broker Size* by 100 for readability. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter-level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Table 3.3 Large Temperature Increases and High-Temperature Sensitivity Firms-Continued

	Dependent Variable: PMAFE			
	High-TS Firms		Other Firms	
	(1)	(2)	(3)	(4)
HTSA	0.201***	0.146*	0.025	0.034
	(2.80)	(1.94)	(1.04)	(1.18)
Forecast Horizon	-0.033**	-0.047**	-0.032***	-0.033***
	(-2.48)	(-2.41)	(-5.52)	(-4.60)
No. Companies	0.085	-0.054	-0.015	0.017
	(0.14)	(-0.10)	(-0.08)	(0.09)
Firm Experience	-0.012	-0.023	0.008	-0.005
	(-0.67)	(-0.81)	(0.52)	(-0.28)
General Experience	0.049	0.058	-0.025	-0.044
	(0.59)	(0.72)	(-0.75)	(-1.22)
Broker Size	-0.064	-0.067	-0.009	-0.037
	(-0.75)	(-0.83)	(-0.22)	(-0.78)
No. Industries	-0.031*	-0.021	0.000	0.004
	(-2.05)	(-1.35)	(0.07)	(0.61)
All Star	-0.099	-0.075	0.127***	0.124***
	(-0.89)	(-0.64)	(3.53)	(3.37)
LAFE	3.961**	12.090***	3.755***	9.138***
	(2.47)	(3.73)	(3.74)	(5.12)
Time Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	No	Yes
N	21708	21273	78404	77996
Adj. Rsq.	0.016	0.046	0.018	0.027

Table 3.4 Large Temperature Increases and Local Bias

This table examines whether the more accurate forecasts made by analysts in High-TS states after large temperature increases are generated from local bias. We construct a *Local Dummy* variable equals one if the analyst and the firm in the forecast are in the same states, and zero otherwise. Our main independent variable is the interaction between *Local Dummy* and *Shock*, which is a dummy variable equals one if the forecast is issued during the large temperature month or in the following three months. The results for forecast accuracy of the full sample are reported in Panel A. We present the subsample results based on the analysts' location in Panel B. Panel C shows the subsample results separated by the location of firms. We suppress the control variables for brevity. The control variables are defined in Table A1. Heteroskedasticity robust *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter-level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Panel A: Full Sample Results for Local Bias after Large Temperature Increase

	Dependent Variable: PMAFE	
	All analysts and firms	
	(1)	(2)
Local dummy*shock	-0.029	-0.030
	(-0.80)	(-0.78)
Shock	-0.017	0.001
	(-0.61)	(0.04)
Local dummy	-0.015	0.015
	(-0.58)	(0.58)
Control Variables	Yes	Yes
Time Fixed Effect	Yes	Yes
Analyst Fixed Effect	Yes	Yes
Firm Fixed Effect	No	Yes
N	100825	100448
Adj. Rsq.	0.019	0.027

Table 3.4 Large Temperature Increases and Local Bias–Continued

Panel B: Subsample Results for Local Bias after Large Temperature Increase on Analysts				
	Dependent Variable: PMAFE			
	High-TS State Analysts		Other Analysts	
	(1)	(2)	(3)	(4)
Local dummy*Shock	-0.013	-0.003	-0.023	-0.012
	(-0.20)	(-0.04)	(-0.47)	(-0.26)
Shock	-0.063**	-0.070*	-0.011	0.014
	(-2.31)	(-1.79)	(-0.34)	(0.38)
Local dummy	0.011	0.140*	-0.034	0.036
	(0.29)	(2.04)	(-0.97)	(1.23)
Control Variables	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	No	Yes
N	15338	14762	85433	85000
Adj. Rsq.	0.021	0.035	0.020	0.029

Panel C: Subsample Results for Local Bias after Large Temperature Increase on Firms				
	Dependent Variable: PMAFE			
	High-TS State Firms		Other State Firms	
	(1)	(2)	(3)	(4)
Local dummy*Shock	-0.124	-0.130	0.009	0.014
	(-1.61)	(-1.56)	(0.21)	(0.38)
Shock	0.005	0.025	-0.021	0.001
	(0.08)	(0.28)	(-1.19)	(0.08)
Local dummy	0.061	0.048	-0.045	0.015
	(1.13)	(0.72)	(-1.17)	(0.62)
Control Variables	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	No	Yes
N	32656	32523	67535	67275
Adj. Rsq.	0.024	0.023	0.020	0.035

Table 3.5 Large Temperature Increases and Analysts Political Views

This table examines whether political views affect analysts' forecasts and accuracy following a large temperature increase. Specifically, we investigate if the forecasts made by analysts whose donation to the Democratic Party is higher than that to the Republican Party are more accurate than other analysts after a large increase in temperature. We follow Clement (1999) and create the proportional mean absolute error (PMAFE), where $PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}}$. $AFE_{i,j,t}$ is the absolute forecast error of analyst *i* for firm *j* at time *t*. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ value_{i,j,t} - Actual\ value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm j at time t. Since we multiply the PMAFE variable by negative one, positive values of PMAFE indicate a better than average performance, and negative values suggest a worse than average performance. To define a state's average political affiliation, we use analysts donation data. Specifically, we classify a state as Democrat if her donation to the Democratic Party is higher than that to the Republican Party. *Shock* is a dummy variable equals one if analysts' forecasts are issued three months after large temperature increases or within that month. The control variables are defined in Table A1 and suppressed for brevity. *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

	Dependent Variable: PMAFE				
	(1)	(2)	(3)	(4)	(5)
Shock*Democrat Dummy	0.130**	0.130**	0.130**	0.128**	0.115**
	(2.30)	(2.30)	(2.27)	(2.26)	(2.15)
Shock	-0.000	-0.006			
	(-0.01)	(-0.22)			
Democrat Dummy	0.031	0.028	0.031	0.028	
	(1.34)	(1.22)	(1.41)	(1.26)	
Control Variables	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effect	No	No	No	No	Yes
N	101168	100918	101168	100918	100448
Adj. Rsq.	0.008	0.011	0.008	0.012	0.027

Table 3.6 Large Temperature Increases and Bold Revisions

This table examines whether affected analysts are more likely to issue bold forecasts for high TS firms. *Bold Revision* is a dummy variable equal to one if the analyst issues a forecast that is above or below the prior consensus and her/his previous forecast, and zero otherwise. *Downward Bold Revision* is a dummy variable equal to one if the analyst issues a forecast below the prior consensus and her/his previous forecast, and zero otherwise. *Upward Bold Revision* is a dummy variable equal to one if the analyst issues a forecast above the prior consensus and her/his previous forecast, and zero otherwise. *HTSA* is a dummy variable equal to one if the analyst is in a High-TS state and the forecast is issued during the event month or within three months after the event. We restrict the sample to three months prior to and three months after the event. We multiply the coefficients for *No. Companies* and *Broker Size* by 100 for readability. The control variables are defined in Table A1 and suppressed for brevity. Heteroskedasticity robust *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter-level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Table 3.6 Large Temperature Increases and Bold Revisions-Continue

	Bold Revision		Downward Bold Revision		Upward Bold Revision	
	High-TS Firms	Other Firms	High-TS Firms	Other Firms	High-TS Firms	Other Firms
	(1)	(2)	(3)	(4)	(5)	(6)
HTSA	-0.009	-0.017	-0.045	-0.004	0.036*	-0.013
	(-0.35)	(-1.37)	(-1.70)	(-0.25)	(1.76)	(-1.05)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	21512	78661	21512	78661	21512	78661
Adj. Rsq.	0.086	0.055	0.295	0.214	0.352	0.244

Table 3.7 Large Temperature Increases and Market Reaction to Forecast Revisions

This table analyzes the market's reaction to treated analysts' forecast revisions. The dependent variable is a firm's three-day market-adjusted excess return centred on the forecast revision date. The independent variable, *Forecast Revision*, is a measure of the difference between analyst *i*'s current forecast for firm *j* at time *t* and the forecast issued immediately before the current forecast, scaled by the standard deviation of forecasts of all analysts who follow firm *j* in time *t*. *HTSA* is a dummy variable equal to one if the location of the analyst is in a High-TS state, and the forecast is made during the event month or within three months after the temperature shock. In addition to the baseline control variables, we include *Friday Dummy* and *Q4*. The set of covariates is constant throughout all the specifications and suppressed for brevity. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the analyst level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

	Dependent Variable:3-day Market Adjusted Return					
	(1)	(2)	(3)	(4)	(5)	(6)
HTSA	-0.001	-0.007	-0.165	-0.132	-0.200	-0.228
	(-0.01)	(-0.04)	(-1.29)	(-0.82)	(-0.79)	(-0.91)
Forecast Revision	7.240***	7.357***	6.779***	6.832***	7.087***	4.978***
	(43.11)	(42.23)	(36.44)	(35.59)	(30.29)	(4.82)
HTSA* Forecast Revision	0.656	0.467	0.901	0.684	0.544	0.659
	(0.99)	(0.70)	(1.53)	(1.11)	(0.61)	(0.74)
Controls Variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	No	Yes	Yes	No	No
Analyst Fixed Effect	No	Yes	No	Yes	No	No
Firm*Analyst Fixed Effect	No	No	No	No	Yes	Yes
Controls* Forecast Revision	No	No	No	No	No	Yes
N	74688	74198	74201	73691	59784	59784
Adj. Rsq.	0.063	0.077	0.202	0.206	0.101	0.105

Table 3.8 Large Temperature Increases and Unexpected Earnings

This table analyzes firms' unexpected earnings (UE) on the earnings announcement date. *Unexpected Earning (UE)* is the difference between the actual announced earning and the median of the forecasts in the past quarter, scaled by the lagged price. We use quarterly earnings announcements and forecasts to be consistent with the past literature. We restrict our sample to be between three months prior and three months after the quarterly announcement. To construct a firm-level *High-Temperature Sensitivity Area (HTSA(F))*, we first create a weighted average of analysts' local (i.e., state-level) temperature sensitivity for each firm-quarter, using the number of forecasts they issue as weights. Then, within each quarter, we sort firms into quintiles based on their temperature sensitivities. *HTSA(F)* is a dummy equal to one if a firm is in the highest quintile and its earnings announcement is in the event month or during three months after the shock, and zero otherwise. *High TS* is an indicator variable equal to one if the firm's TS is in a top quintile in the previous month, and zero otherwise. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the announcement date and firm level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Table 3.8 Large Temperature Increases and Unexpected Earnings-Continued

Dependent Variable: Unexpected Earnings		
	(1)	(2)
HTSA(F)*High TS	0.147***	0.115**
	(3.26)	(2.14)
HTSA(F)	-0.027*	-0.029**
	(-1.96)	(-2.23)
High TS	0.004	0.010
	(0.25)	(0.60)
Log(ME)		0.045***
		(3.96)
Log(BM)		0.109***
		(7.90)
RepLag		-0.023***
		(-4.27)
Busy		-0.622***
		(-24.79)
Loss		0.005
		(0.44)
Q4 dummy		-0.041**
		(-2.31)
Friday		-0.035
		(-1.51)
Time Fixed Effect	Yes	Yes
Firm Fixed Effect	Yes	Yes
N	35792	35601
Adj. Rsq.	0.137	0.210

Table 3.9 Large Temperature Increases and the Market's Reaction to Earning Announcements

This table reports the market reaction to a firm's earnings announcement. *CAR* is the cumulative abnormal return for the time period [-1--,1] around the earnings announcement. The *Post-Earnings Announcement Drift* (*PEAD*) is the cumulative abnormal return for the [2,60] trading days following the earnings announcement. We use quarterly earnings announcements and forecasts to be consistent with the past literature. We restrict our sample to be between three months prior and three months after the quarterly announcement. A firm's unexpected earning (UE) is the difference between the actual announced earning and the median of the forecasts in the past quarter, scaled by the lagged price. To construct a firm-level *High-Temperature Sensitivity Area (HTSA(F))*, we first create a weighted average of analysts' local (i.e., state-level) temperature sensitivity for each firm-quarter, using the number of forecasts they issue as weights. Then, within each quarter, we sort firms into quintiles based on their temperature sensitivities. *HTSA(F)* is a dummy equal to 1 if a firm is in the highest quintile and its earnings announcement is in the event month or during the three months after the shock, and zero otherwise. *High TS* is an indicator variable equal to one if the firm's TS is in a top quintile in the previous month, and zero otherwise. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the announcement date and firm level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Table 3.9 Large Temperature Increases and the Market's Reaction to Earning Announcements – Continued

	Dependent Variable: PEAD		Dependent Variable: CAR	
	(1)	(2)	(3)	(4)
HTSA(F)*High TS* UE	2.834*	3.145*	-0.395	0.328
	(1.67)	(1.87)	(0.75)	(0.62)
HTSA(F)*High TS	-1.102	-0.945	0.704*	0.622
	(-0.95)	(-0.81)	(1.86)	(1.65)
HTSA(F)* UE	-1.233*	-1.404**	-0.661***	-0.607***
	(-1.88)	(-2.14)	(-3.21)	(-2.97)
High TS* UE	-1.195	-1.265	-0.519**	-0.461*
	(-1.37)	(-1.44)	(-2.03)	(-1.81)
HTSA(F)	0.383	0.664	-0.089	-0.084
	(0.69)	(1.27)	(-0.56)	(-0.53)
High TS	-0.013	-0.197	-0.123	-0.048
	(-0.02)	(-0.37)	(-0.75)	(-0.29)
UE	1.501***	1.790***	2.695***	2.606***
	(4.63)	(5.40)	(24.61)	(23.61)
Log(ME)		-4.232***		1.304***
		(-9.87)		(11.84)
Log(BM)		0.612		1.410***
		(1.12)		(8.74)
RepLag		0.672		0.022
		(1.01)		(0.13)
Busy		-0.113		-0.419***
		(-0.53)		(-7.00)
Loss		-0.306		0.327*
		(-0.48)		(1.85)
Q4 dummy		-4.914***		0.005
		(-5.87)		(0.04)
Friday		0.976		-0.280
		(1.25)		(-1.61)
Time Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
N	35792	35601	35792	35601
Adj. Rsq.	0.209	0.226	0.069	0.077

Appendix

Table 3.A1 Variable Definitions

Variable	Definition
PMAFE	The ratio of the difference between an analyst's absolute forecast error and the median absolute forecast error of other analysts that cover the same firm at the same time to the median absolute forecast error. Since we multiply the PMAFE variable by negative one, positive values of PMAFE indicate a better than average performance, and negative values suggest a worse than average performance. Source: I/B/E/S
HTSA	A dummy variable equal to one if the analyst is in a High-TS state and the forecast is issued during the event month or within three months after the event. Source: I/B/E/S
Forecast Horizon	The number of months between the forecast date and the actual value announcement. Source: I/B/E/S
No. Companies	The number of companies an analyst follows during a year. Source: I/B/E/S
Firm Experience	The number of years an analyst has covered a certain firm. Source: I/B/E/S
General Experience	The number of years since an analyst issued a forecast for a firm and her/his first forecast in the I/B/E/S database. Source: I/B/E/S
Broker Size	The number of analysts employed by an analyst's brokerage firm. Source: I/B/E/S
All Star	A dummy variable equals to one if an analyst is ranked as first, second, third, or runner-up in the Institutional Investor magazine in the previous year. Source: Jannati et al. (2020)
No. Industries	The number of Fama-French 48 Industry followed by an analyst. Source: I/B/E/S
Lagged AFE (LAFE)	The absolute forecast error for company j at time t-1. Source: I/B/E/S
Bold Revision	A dummy variable equal to one if the analyst issues a forecast that is above or below the prior consensus and her/his previous forecast, and zero otherwise. Source: I/B/E/S
Downward Bold Revision	An indicator variable equal to one if the analyst issues a forecast below the prior consensus and her/his previous forecast, and zero otherwise. Source: I/B/E/S
Upward Bold Revision	An indicator variable equal to one if the analyst issues a forecast above the prior consensus and her/his previous forecast, and zero otherwise. Source: I/B/E/S
Forecast Revision	The difference between analyst i's current forecast for firm j at time t and the forecast issued immediately before the current forecast, scaled by the standard deviation of forecasts of all analysts who follow firm j in time t. Source: I/B/E/S
HTSA(F)	A dummy equal to 1 if a firm is in the highest quintile sorted by firm-level HTSA aggregated from analysts in the past quarter and its earnings announcement is in the event month or during three months after the event. Source: I/B/E/S
High TS	An indicator variable equal to one if the firm is a High-TS firm. Source: CRSP NOAA

Table 3.A1 Variable Definitions - Continued

Variable	Definition
UE	The difference between the actual announced earning and the median of the forecasts in the past quarter, scaled by the lagged price. Source: I/B/E/S CRSP
Log(ME)	The natural logarithm of the firm's market capitalization last year. Source: CRSP
Log(BM)	The natural log of the firm's book to market ratio last year. Source: CRSP COMPUSTAT
Beta	The firm market beta using the daily stock return in the past quarter. Source: CRSP
RepLag	The number of days between the earnings announcement date and the quarter end date. Source: I/B/E/S
Busy	The annual quintile rankings of the total number of all earnings announcements on the day of the firm's announcement. Source: I/B/E/S
Loss	An indicator equal to one for negative I/B/E/S actual earnings per share, and zero otherwise. Source: I/B/E/S
Q4 dummy	An indicator equal to one for fourth-quarter announcements, and zero otherwise. Source: I/B/E/S
Friday	An indicator equal to one for Friday announcements, and zero otherwise. Source: I/B/E/S
DPA	A dummy variable equal to one if the analyst is in a state with decoupling policy and the forecast is issued during the event month or within three months after the event. Source: I/B/E/S, State Climate Policy Maps
Size	Natural logarithm of total assets. Source: COMPUSTAT
Leverage	The sum of short-term debt and long-term debt, divided by total assets. Source: COMPUSTAT
Dividend Yield	Dividends divided by shareholders' equity. The shareholders' equity is, depending on availability and in the following order, the shareholders' equity, or commons/ordinary equity. If both items are missing, the shareholders' equity is total assets minus total liabilities and minority interests. Source: COMPUSTAT
No-Dividend Indicator	A dummy variable equals one if the dividend is zero, and zero otherwise. Source: COMPUSTAT
Democrat	A dummy variable equals one if the analyst donates more to the Democratic Party than that to the Republican Party. Source: Jiang et al.2016

Table 3.A2 Temperature Changes and State Classifications

This table provides information on the timing of the large temperature changes and state classifications into the high- and low- TS groups. Panel A reports the list of large temperature increases and decreases months and their temperature anomaly. Panel B reports the 10 states with the highest frequency of appearing in the High-TS state group during the sample period 1996-2017. It also reports the states' average temperature sensitivity (TS), the number of analysts, and the number of firm forecasts. Panel C reports the states with the greatest number of forecasts in our sample, and Panel D shows the number of analysts and firms in states with decoupling policies.

Panel A: Extreme Temperature Event		
Event Type	Year-Month	Temperature Anomaly
Increase	1999m2	5.63
	1999m11	6.18
	2001m11	5.48
	2004m3	5.68
	2006m1	8.45
	2007m3	5.93
	2012m1	5.64
	2015m12	5.73
	2016m11	6.04
Decrease	1997m4	-3.36
	2000m11	-3.90
	2009m10	-3.66

Table 3.A2 Temperature Changes and State Classifications – Continued

Panel B: States in the Highest TS Group				
High-TS State	Frequency	Average Beta (%)	No. Analyst	No. Company
California	0.472	0.677	1107	4968
Florida	0.977	0.654	101	927
Tennessee	0.972	0.751	100	986
Colorado	0.838	0.831	67	386
Maine	0.983	0.676	13	136
Nebraska	0.750	0.733	4	11
Kansas	0.968	0.981	3	22
Arizona	0.658	0.649	2	11
Oklahoma	0.953	1.830	2	3
Mississippi	0.867	0.608	2	4

Panel C: Top 5 States with Highest No. of Forecast Observations in T Groups	
States	No. Forecasts in High-TS Group
California	27539
Florida	2185
Tennessee	2643
Colorado	1042
Maine	299
States	No. Forecasts in Other Group
New York	102189
Minnesota	10051
Virginia	8097
Texas	5931
Missouri	6386

Panel D: States with Decoupling Policy			
States	No. Analyst	No. Company	No. Forecasts
Ohio	115	1242	4640
Idaho	95	1108	3328
Colorado	67	386	1042
Maine	13	136	299

Table 3.A3 Robustness Tests for Forecast Accuracy using Alternative Definition

This table presents several robustness tests. We use an alternative definition for treated analysts. Specifically, we define *DPA* as a dummy variable equal to one if the analyst is in a state with decoupling policy and the forecast is issued during the event month or within three months after the event. The results for analysts' forecast accuracy are reported in this table. The control variables are defined in Table A1. *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter-level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

Panel A: DPA and Anlysts Forecast Accuracy

Dependent Variable: PMAFE

	Large Temperature Increase		
	(1)	(2)	(3)
DPA	-0.078*	-0.113**	-0.117**
	(-1.81)	(-2.29)	(-2.24)
Forecast_Horizon		-0.032***	-0.032***
		(-4.68)	(-5.08)
No_Companies		0.018	0.064
		(0.09)	(0.31)
Firm_Experience		0.005	-0.007
		(0.41)	(-0.51)
General_Experience		-0.004	-0.019
		(-0.11)	(-0.56)
Broker_Size		-0.013	-0.037
		(-0.35)	(-0.98)
No_Industries		-0.005	-0.003
		(-1.03)	(-0.58)
All_Star		0.088**	0.095**
		(2.25)	(2.43)
LAFE		3.766***	9.060***
		(4.09)	(5.53)
Time Fixed Effect	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes
Firm Fixed Effect	No	No	Yes
N	138689	100825	100448
Adj. Rsq.	0.014	0.020	0.028

Panel B: Subsample tests on DPA				
	Dependent Variable: PMAFE			
	High-TS Firms		Other Firms	
	(1)	(2)	(3)	(4)
DPA	-0.206**	-0.255**	-0.097	-0.078
	(-2.17)	(-2.31)	(-1.58)	(-1.24)
Control Variables	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes
Firm Fixed Effect	No	Yes	No	Yes
N	21708	21273	78475	78080
Adj. Rsq.	0.054	0.072	0.015	0.024

Panel C: Bold Test on DPA						
	Bold Revision		Downward Bold		Upward Bold	
	High-TS Firms	Other Firms	High-TS Firms	Other Firms	High-TS Firms	Other Firms
	(1)	(2)	(3)	(4)	(5)	(6)
DPA	-0.030	0.008	-0.051	0.018	0.021	-0.010
	(-0.85)	(0.51)	(-1.42)	(0.97)	(0.71)	(-0.58)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Analyst Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	21511	78662	21511	78662	21511	78662
Adj. Rsq.	0.087	0.055	0.295	0.215	0.352	0.244

Table 3.A4 Large Temperature Increases and Local Climate Change Beliefs

The table examines whether analysts in states where climate change beliefs are strong issue more accurate forecasts. We follow Clement (1999) and create the proportional mean absolute error (PMAFE), where $PMAFE_{i,j,t} = \frac{AFE_{i,j,t} - \widehat{AFE}_{j,t}}{\widehat{AFE}_{j,t}}$. $AFE_{i,j,t}$ is the absolute forecast error of analyst *i* for firm *j* at time *t*. $AFE_{i,j,t}$ is defined as $\left|\frac{Forecast\ value_{i,j,t} - Actual\ value_{j,t}}{Price_{j,t-1}}\right|$, where $\widehat{AFE}_{j,t}$ is the median absolute error for firm *j* at time *t*. An advantage of using this measure is that it accounts for firm × time fixed effects (Clement, 1999). *High Belief State* is a dummy variable equal to one if the analyst is in a High-Belief state and the forecast is issued during the event month or within three months after the event. We multiply the coefficients for *No. Companies* and *Broker Size* by 100 for readability. The control variables are defined in Table A1 and suppressed for brevity. *t*-statistics are presented in parentheses and are clustered at the firm and year-quarter level. We denote significance at the 10%, 5%, and 1% levels using *, **, and ***, respectively.

	(1)	(2)	(3)
High Belief State	-0.038	-0.048	-0.059
	(-1.52)	(-1.53)	(-1.46)
Control Variables	No	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes
Analyst Fixed Effect	No	No	Yes
N	82,293	60,933	72,734
Adj. Rsq.	0.002	0.002	0.018

Chapter 4

Temperature Sensitivity and Institutional Investor

4.1 Introduction

Climate risks have a large impact on investor's portfolios. Firms with higher carbon risks have higher stock returns (Bolton and Kacperczyk, 2019). Toxic emission intensity is shown to have a great impact on stock returns (Hsu, Li and Tsou, 2019). Kruttli, Tran and Watugala (2019) show that extreme weather is reflected in stock and option market prices. Firms in some specific industries are also significantly affected by climate risks. For example, extreme temperature events impact earnings in over 40% of industries (Addoum, Ng and Ortiz-Bobea, 2019). The food industry is highly affected by the drought disaster (Hong, Li and Xu, 2019). All these findings suggest that it is important for investors to consider climate risk when constructing their portfolios.

Institutional investors are crucial participants in the financial market. Their consideration of climate risk in their investment decisions has a large impact on the stock returns. An emerging literature investigating how institutional investors understand and react to climate risk. For example, Krueger, Sautner and Starks (2020) provide evidence that institutional investors believe that climate risks have financial implications for their portfolios. Ilhan et al. 2021 show that institutional investors value and demand climate risk disclosures. "Big Three" (BlackRock, Vanguard, and State Street) is found to focus its engagement effort on large firms with high CO_2 emissions in which these investors hold a significant stake (Azar et al., 2020). However, although all these findings indicate that institutional investors have begun addressing climate risks, little is known about how institutional investors manage climate risks in their portfolios.

In this study, we study institutional investors holdings on stocks with different levels of temperature sensitivity. There is plenty of research showing that institutional investors have engaged in climate risk management. For example, McCahery, Sautner, and Starks (2016) show that only 16% of institutional investors had not taken any actions over the past five years to mitigate climate risk. Institutional ownership is positively correlated with firms' environmental performance (Dyck et al., 2019). Motivated by this evidence, we first conjecture that the institutional holdings on the portfolio with the highest temperature sensitivity should be lower. Investors in different institution types are also found to show heterogeneous beliefs in climate risk. The motivation and management approach to incorporate climate risk of institutional investors vary across types (Kruger et al. 2020). Investors with longer horizons tend to prefer higher ESG firms significantly more than do short-term investors. Following these previous findings, we develop our second hypothesis that institutions of different types show different preferences on high temperature sensitivity stocks. Since institutional investors are generally more professional and experienced in investment than retail investors, we further conjecture that institutional investors have the skills to find and hold high temperature sensitivity stocks with better performance.

To test the hypotheses above, we first construct five temperature sensitivity based portfolios following Kumar, Xin and Zhang (2019) and then examine the institutional holdings on each portfolio. The institutional holding data is from Thomson Institutional (13f) Holdings, and the sample period is from 1980Q1 to 2017Q4. We aggregate the investor holding on each stock into portfolio level holding using their value-weighted average for each temperature sensitivity portfolio in each quarter. We expect that the institutional holding weight would be lower for higher temperature sensitivity portfolios.

The empirical findings support our hypothesis. The institutional holding weight decreases almost monotonically from the lowest temperature sensitivity portfolio to the highest temperature sensitivity portfolio from 57.33% to 47.72%. The difference of institutional holding between the lowest and the highest temperature sensitivity is 9.62%, with *t*-statistics of 5.05. Our finding indicates that institutional investors tend to hold less stocks with high temperature sensitivity to avoid low returns.

We then investigate the different ownership if high temperature sensitivity portfolios among types of institutions. Based on the findings from past literature, investors in different institutions may have heterogeneous attitudes towards climate risk. The holding strategies in different types of institutions, as a result, may also be different. We suppose that specific types of institutional investors would react to climate risk better than others. Using the firm-level institutional ownership data from FactSet, we test the weight difference between high temperature sensitivity portfolios and other portfolios held by six types of institutions.

Consistent with the previous finding, the total institutional ownership is lower for high temperature sensitivity stocks. However, different types of institutions show distinct preferences for high temperature sensitivity stocks.

Specifically, investment companies, pension funds, and endowments have significantly lower high temperature sensitivity stocks holding weight (0.12% and 0.18%, respectively). In contrast, hedge funds and venture capital hold a higher weight for stocks in the same temperature sensitivity portfolio of 0.15%. On the other hand, banks and insurance companies do not show a clear preference for high temperature sensitivity stocks to other stocks.

Next, we examine whether institutional investors could use their knowledge and skills to find and hold those stocks that perform better than others in the same climate portfolio. In each quarter, we divide the highest temperature sensitivity portfolio into two sub-portfolios: stocks held by institutional investors and those not using institutional holding data. We find that the raw return and factor adjusted return of these two sub-portfolios show that stocks held by institutional investors significantly outperform those that institutional investors do not hold. Specifically, the raw return and six-factor adjusted return differences between the "Held" portfolio and the "Not Held" portfolio is 0.67% (*t*-statistic =4.52) and 0.76% (*t*-statistic =4.90), respectively.

To find out how institutional investors perform in different temperature sensitivity stocks. We further separate the "Held" portfolio above into three parts based on their changes in institutional holding weight and then conduct a double sort test. The results are consistent with our hypothesis that institutional investors could pick and hold stocks with better performance than others from the same temperature sensitivity portfolio. Such ability benefits them more in higher temperature sensitivity portfolios.

Last, we examine whether the investing strategy of institutional investors is affected by their location. As is shown in may psychology literature, people's beliefs in specific areas are updated by the related experience. Motivated by these findings, we conjecture that institutional investors in areas where firms exhibit greater sensitivity to climate changes would be more aware and sensitive to climate risk and holding less high temperature sensitivity stocks to get higher portfolio returns.

Our findings contribute to the emerging finance literature that examines the relationship between climate change and financial markets. Addoum et al. (2019) show that analysts and investors do not react to observable temperature shocks immediately. Trading strategies with higher sustainability can reduce investors' overall portfolio risk (Brandon and Krueger, 2018). Daniel et al. (2016) and Baldauf et al. (2019) analyze how climate risk influences real estate prices. Choi et al. (2020) find that stocks of carbon-intensive firms underperform firms with low carbon emissions in abnormally warm weather. Ilhan, Sautner, and Vilkov (2018) show that the cost of option protection against downside tail risks is higher for firms with high carbon emissions. Barrot and Sauvagnat (2016) study the effect of natural disasters on sales growth and find that disasters negatively affect the sales growth of directly exposed firms and their largest customers. Dessaint and Matray (2017) find that hurricane strikes reduce the market value of firms located in the United States. Brown et al. (2017) study cold spells and the use of credit and find that extreme cold represents a shock to firms cash holdings.

Beyond the literature on the performance implications of environmental conditions, our study is linked to the literature on climate hazards and investor awareness. For instance, Jona et al. (2016) find that corporate disclosures of adverse climate shocks reduce the market value of equity. Anttila-Hughes (2016) finds that NASA announcements of temperature records and ice shelve collapse affect the returns of energy companies. On the same note, Bernstein et al. (2019) find that real estate that is exposed to expected rises in the sea level sells at a discount.

Our findings are consistent with perceptions by institutional investors regarding their portfolio firms (see Ilhan et al. 2020). We add significantly to the emerging literature that studies sustainability at the institutional investor level. Hong and Kostovetsky (2012) show that democratically inclined fund managers hold more sustainable investment portfolios. Relying on proprietary data from one large UK based institutional investor, Dimson, Karakaş, and Li (2015) study private (or behind-the-scene) sustainability-oriented shareholder engagements and show that successful engagements generate shareholder value. Using archival data, Dyck et al. (2019) show that firm-level sustainability is related positively to institutional ownership. They also show this relationship to be strongest for ownership by institutional investors based in countries with strong social norms. Nofsinger, Sulaeman, and Varma (2016) study institutional ownership in firms with good and bad environmental and social performance. Amel-Zadeh and Serafeim (2017) survey senior investment professionals working at institutional investors to examine why and how investors use ESG information in the investment process. Chen, Dong, and Lin (2020) show that higher institutional ownership and more concentrated shareholder attention induce corporate managers to invest more in sustainability activities.

The paper is organized as follows. Section 2 introduces data and methodology. Evidence of predictable returns is provided in Section 3, robustness test results are discussed in Section 4, and Section 5 concludes.

4.2 Data and Method

We describe the data sets used in the empirical analysis in this section. We also summarise the methods used for measuring the climate risk of stocks.

4.2.1 Main Data Sources

We use data from multiple sources. The 13(f) institutional holdings data is from both FactSet and Thomson. FactSet provides the ownership data of different types of institutions from 2000Q1 to 2017Q4. The Thomson Institutional (13f) Holdings shows the stock-level institutional holding data, the sample period of which is from 1980Q1 to 2017Q4. Both data sources provide quarterly snapshots of investor portfolio positions. Additional fields used in the analysis include the stock historical CUSIP number, trade date, trade direction, quantity of shares traded, and trade execution price. We hand-collect the ZIP codes of the institution's headquarters using the *Nelson's Directory of Investment Managers*.

We obtain daily and monthly stock returns, stock prices, and Standard Industry Classification (SIC) codes from the Center for Research on Security Prices (CRSP). Both daily and monthly stock returns from CRSP are available for July 1926 to June 2017 period.

The monthly Fama-French factor returns, historical book equity data, forty-eight SIC industry classifications, and forty-eight industries daily and monthly value-weighted portfolio returns are from Kenneth French's data library. The monthly returns for the 48 Fama and French (1997) industry portfolio returns are available from July 1926 to June 2017. We also use the data from 48 Fama and French industry portfolio returns to get the industry level book-to-market ratio and average firm size for each industry.

We use data from Compustat to compute book-to-market ratios for each listed US firm in our sample. The book-to-market ratio is calculated as the ratio of year-end book equity plus balance sheet deferred taxes to year-end market equity.

In our factor model estimation, we use the Fama-French three-factor (RM-RF, SMB and HML,), momentum factor (MOM), and two reversal factors (short-term reversal (STR) and long-term reversal (LTR)). Data for all the factors is from Kenneth French's data library. The available data periods are from January 1927 to July 2017 for the momentum factor, June 1926 to July 2017 for the short-term reversal factor, January 1931 to July 2017 for the long-term reversal factor and August 1962 to December 2016 for the liquidity factor. The estimates of the NBER recession indicator (REC), mean household income, population and GDP growth are obtained from the FRED economic data. Lettau-Ludvigson's (2004) cay measure is from Lettau's website.

The state-level control variables are from the U.S.Census Bureau. Specifically, we consider the total population of a state, the state-level of education (the proportion of state population above age 25 that has completed a bachelor's degree or higher), the male-female ratio in the state, the proportion of households in the state with a married couple, the median age of the state, minority population (the proportion of the population in the state that is non-white), and the proportion of the state residents who live in urban areas. Similar to Kumar, Page, Spalt (2011), we employ these state characteristics as control variables in our empirical analysis.

Our temperature data for the US comes from the National Centers for Environmental Information (NCEI) of the US National Oceanic and Atmospheric Administration (NOAA). The temperature record is updated monthly on the NOAA's website, and the data extends back to January 1895. This database has two temperature values, i.e., monthly temperature value and the monthly temperature anomaly. More specifically, the monthly temperature anomaly is the difference between the monthly temperature value and the monthly reference temperature value. The reference temperature of a specific month is the average monthly temperature between 1895 and 2019 for the same month. A positive (negative) temperature anomaly implies that the temperature in that month is higher (lower) than the benchmark average temperature. We use the temperature anomaly as the measurement of climate change, which has also been used in previous studies.

4.2.2 Estimating Temperature sensitivity

Following methods in Kumar, Xin and Zhang (2019), we use 5-year rolling window to estimate the return sensitivity to temperature anomaly and then take the absolute value (θ_i^c) to capture the temperature sensitivity of stocks using the following regression:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i\left(r_{mkt,t} - r_{f,t}\right) + \theta_i Temperature\ Anomaly_t + \epsilon_{i,t} \quad (1)$$

$$\theta_i^c = |\theta_i| \quad (2)$$

4.2.3 Institutional Investor Holding Measurement

We construct a measure of investor level portfolio holding based on the institutional holding data (13(f)). First, we aggregate all institutional holdings for one stock across institutional investors in the same quarter. We then capture the stock-level institutional holding weight, which is calculated by dividing each quarter's holding value by market capitalization. Finally, the portfolio holding weight is aggregated from stock level holding weight by taking the value-weighted average. We measure the changes in institutional holding weight of stock *i* as the difference between its current institutional holding weight in quarter *t* and the previous quarter *t-1*.

The institutional type-level portfolio ownership is captured from FactSet data. Specifically, we aggregate the firm-level institutional ownership in each temperature sensitivity portfolio by each type of institution using their value-weighted average in each quarter.

4.2.4 Summary Statistics

The summary statistics are reported in Table 4.1. It shows that stocks in our sample have a mean temperature sensitivity of 1.00 and the mean log of market capitalization is 12.12. On average, institutions hold 54.83% of temperature sensitivity portfolios and change their holdings to 0.21% per quarter.

4.3 Empirical Results

According to the findings from Kumar, Xin and Zhang (2019), the firm's exposures to temperature changes affect its stock returns. In this section, we analyze how institutional investors understand and react to climate risk when they construct their portfolios. Specifically, we show that the institutional holding of portfolios with higher temperature sensitivity is lower. We also test if institutions of different types react differently towards temperature sensitivity. In addition, we investigate whether institutional investors can find and hold stocks that perform better than those in the same temperature sensitivity portfolio. Last, we show evidence on whether the location of an institutional investor impacts his holding strategy regarding climate risk.

4.3.1 Institutional Holding of Temperature sensitivity Portfolios

To determine how institutional investors react to climate risk, we first establish five temperature sensitivity portfolios following Kumar, Xin and Zhang (2019). Then, we calculated the portfolio level institutional holding weight for each portfolio in each quarter by taking the value-weighted average of stock-level institutional holding weight. The stock-level institutional holding weight is the ratio between the institutional investor total holding value and market capitalization of a particular stock each quarter.

We present the institutional holding result in Table 4.2, along with some basic portfolio characteristics. The first column of Table 4.2 shows that with the increase of portfolio temperature sensitivity, the institutional holding of the portfolio decreases monotonically. The Low- and High-temperature sensitivity portfolio institutional holding is 57.33% and 47.72%, respectively. The difference between these two portfolios is 9.62% (*t*-statistics=5.05), showing that institutional investors hold a significantly lower percentage of high temperature sensitivity stocks. The finding is consistent with the stock return findings from Kumar, Xin and Zhang (2019), which indicates that higher temperature sensitivity stocks tend to have lower returns.

Our findings support the hypothesis that institutional investors generally hold less stocks in high temperature sensitivity portfolios because of the lower returns. However, it is still not clear whether investors in different types of institutional react the same toward climate risk. Further, we estimate OLS regression to investigate whether the high temperature sensitivity stocks have low institutional ownership than others using firm-level institutional ownership data from FactSet.

The main independent variable *High TS Stock*, is a dummy variable if a stock is in the high temperature sensitivity portfolio and zero otherwise. We control for a set of macro-control variables in our test, including lagged institutional ownership of stock i by type x on time t, recession indicator (REC), the Lettau-Ludvigson's (2004) cay measure, national population, mean personal income, and GDP growth. The changes in national population and personal income are also controlled in our test. We also include firm and time fixed effects in our estimation. The firm fixed effects absorb firm-specific characteristics that may affect analysts' forecasts. The time fixed effects absorb any time trends.

We report our findings in Table 4.3. Columns (1) and (2) present the results for all institutions. Different types of institutional investors High-TS stock holding results are shown in columns (3) to (10) of Table 4.3.

The estimates of *High TS Stock* in the first two columns indicates that the overall institutional holding weight of high temperature sensitivity stocks is lower than others at 1.86%, which is consistent with our previous finding. The rest coefficients in Table 4.3 show that institutional investors of different types have heterogeneity in understanding the climate risk. For example, the High TS Stock estimates in columns (3) to (6) show that investment companies, pension funds, and endowments hold less high temperature sensitivity stocks on 0.12% and 0.18%, respectively. In contrast, the coefficients of High TS stock in columns (7) and (8) indicates that hedge funds and venture capital investors hold 1.03% more high temperature sensitivity stocks than others relative to the stock market cap.

Further, the insignificant coefficients in columns (9) and (10) suggests that banks do not react to the temperature sensitivity of stocks on their portfolio constructions. Their holdings on high temperature sensitivity stocks are not different from other stocks. These findings indicate that specific types, but not all, of the institutional investors, consider climate risks on portfolio constructions to generate higher portfolio returns.

4.3.2 Performance of Institutional Investor Holding Stocks

So far, we show that the institution holding of stocks with high temperature sensitivity is less than others. The previous research can explain the finding that high temperature sensitivity stocks have lower returns. In this section, we examine the performance of the stocks that institutional investors hold in different temperature sensitivity portfolios.

We show the performance of institutional investors holding stocks in the high temperature sensitivity portfolio in Table 4.4. Since the previous finding show that the high temperature sensitivity portfolios underperform, we focus on whether institutional investors choose and hold the stock in this portfolio that performs better than others. Specifically, in each quarter, we divide the high temperature sensitivity stocks into two parts: i) stocks that the institutional investors hold and ii) stocks that the institutional investors do not hold. We then measure the performance of the *Holding* portfolio and the *Not Holding* portfolio. Table 4.4 shows the monthly raw returns, market-adjusted returns, Carhart-4-factor adjusted returns, and 6-factor adjusted returns (Market premium, size factor, value factor, momentum factor, and short- and long-term reversal) for each portfolio.

The results in Table 4.4 Panel A show that institutional investors hold those high temperature stocks that perform better than others. The raw return and factor adjusted returns for the *Holding* portfolio are higher than those of the *Not Holding* portfolio. Specifically, the institutional investors' holding stocks have a raw return of 0.96% per month, while the rest of the high climate sensitivity portfolio generates only a 0.29% return. The difference between the monthly raw returns of the *Holding* and the *Not Holding* portfolio is 0.67%, with *t*-statistics of 4.52, indicating that institutional investors have the ability to hold stocks that significantly outperform others among the same temperature sensitivity level.

The factor adjusted returns in Table 4.4 support the conclusion above. Although the factor adjusted return of the High-TS portfolio is underperformed, those High-TS stocks held by institutional investors have higher returns than others. For example, the 6-factor adjusted return for the

Holding portfolio is -0.065%, which is not significantly lower than the benchmark, while the *Not Holding* portfolio has a negative monthly return of -0.828%. The difference between these two portfolios returns is 0.763% per month, indicating that institutional investors have a 9.2% return per year higher than retail investors. These finding also suggests that the mispricing of high temperature sensitivity stocks is primarily from retail investors. Institutional investors, on the other hand, are holding stocks with no underperformance to the benchmark.

We further perform a similar split sample analysis based on institution type. Following Kumar, Page and Spalt (2011), we use Bushee's Institutional Investor Classification Data to separate institutions into two groups: "aggressive institutions" (i.e., independent investment advisors, investment companies, and others) and "conservative institutions" (i.e., banks and insurance companies). The results are shown in Panel B and Panel C of Table 4.4. Consistent with our previous finding in institution type, aggressive institutional investors have a better performance in choosing and holding High-TS stocks. For example, aggressive institutional investors' Holding and Not Holding portfolios have an annualized factor adjusted return of 5.11% (0.426%*12=5.11%). In contrast, conservative institutional investors do not show the ability to pick stocks that performs better in High-TS portfolios. There is no significant difference between *Holding* and *Not Holding* portfolio adjusted returns in Panel C.

So far, our findings suggest that institutional investors, especially aggressive ones, can choose and hold High-TS stocks with relatively better performance than others. Next, we examine whether institutional investors show such ability in all temperature sensitivity portfolios.

We double sort all the stocks in each quarter using temperature sensitivity and changes in institutional holding weight. Specifically, we first sort all the stocks each month using their temperature sensitivity into five temperature sensitivity portfolios. Then, within each temperature sensitivity portfolio, we construct a *Not Holding* portfolio using those stocks that are none of the institutional investors hold in that month. Further, for the institutional investors' holding stocks, we sort them into three equally split portfolios (*i.e. Low Holding Changes* portfolio, *Medium Holding Changes* portfolio, and *High Holding Changes* portfolio) using their changes in institutional holding weight. We measure the changes in institutional holding weight of stock i as the difference between its current institutional holding weight in quarter t and in the previous quarter $t-1$.

We report the performance of all 20 double sorted portfolios in columns (1) to (4) in Table 4.5. Column (5) shows the performance difference between column (4) and column (1), and column (6) measures the return difference between column (4) and column (2). Consistent with our previous finding, the raw return of High-TS stocks is significantly positive in column (4), where the institutional increase their holdings the most. The *High Holding Changes* portfolio outperforms others within the High-TS portfolio significantly. (i.e. the raw return difference in column (5) and column (6) of High-TS portfolio is 1.80% and 2.65%, respectively.) However, the outperformance of *High Holding Changes* portfolios become less significant with the decrease of temperature sensitivity. For example, the raw return difference between the *High Holding Changes* and the *Not Holding* is only 0.33 (*t*-statistic=1.85) within the third temperature sensitivity portfolio. It further becomes insignificant in the Low-TS portfolio.

These results show that institutional investors only show the ability to choose and hold better stocks within portfolios with higher temperature sensitivity, indicating that the better performance of stocks held by institutional investors among the High-TS portfolio can not be fully explained by their general skills and experience. Institutional investors' better understanding of climate risk helps them construct portfolios with better performance.

4.3.3 Institutional Investor Location and Portfolio Holdings

Our findings up to now show that different types of institutional investors have different reactions to climate risk. In this section, we further test whether institutional investors' location varies their attitude to climate risk and thus affect their portfolio holdings.

We measure the state-level temperature sensitivity following Cuculiza et al. (2021). Specifically, for each state, we find the monthly value-weighted average of temperate change sensitivity of firms located in the state and then define states in the top tertile (i.e., the 3rd quintile) as high temperature-sensitivity states (i.e., "high-TS states").

To test whether institutional investors in High-TS states tend to hold less High-TS stocks, we first measure the institutional investors' excess weight of the temperature sensitivity portfolios following Coval and Moskowitz (1999). Specifically, we measure the difference between the weight of temperature sensitivity portfolio *s* in investor *i*'s portfolio and the market weight of the High-TS portfolio in time *t* and then normalize the difference by the market weight of the portfolio s as the excess weight of investor *i*'s excess holding weight on portfolio s at time t. $EW_{i,s,t} = (w_{i,s,t} - w_{m,s,t})/w_{m,s,t}$. We then estimate OLS regressions in which the dependent variable is the excess holding weight of the High-TS portfolio in an institutional portfolio at the end of a particular quarter. Two institutional characteristics are also controlled in our model: i) portfolio size, which is defined as the market value of the total institutional portfolio. ii) portfolio concentration, which is defined as the Herfindahl index of the institution's portfolio weights. We further include a set of demographic characteristics of the state in which the institution is located, including the total population of a state, the state-level of education (the proportion of state population above age 25 that has completed a bachelor's degree or higher), the male-female ratio in the state, the proportion of households in the state with a married couple, the median age of the state, minority population (the proportion of the population in the state that is non-white), and the proportion of the state residents who live in urban areas. Time fixed effect and institution type fixed effect are also controlled in our estimation.

Table 4.6 reports the regression results of the High-TS portfolio and Other portfolio holdings of institutional investors located in High-TS states. We show the results for all institutional investors in columns (1) and (2) of

Table 4.6.

The coefficients of the High-TS state dummy are insignificant in all six columns, indicating that institution locations do not have a large impact on the investors' portfolio holding preference regarding temperature sensitivity. We find no evidence supporting that institutional investors climate risk awareness is affected by their working location.

We further extend the analysis and examine aggressive investors and conservative investors separately. The results for aggressive investors are shown in columns (3) and (4). Columns (5) and (6) present the conservative investors' results. Consistent with the results for all investors, neither of the aggressive and conservative investors located in High-TS states show a significantly different temperature sensitivity portfolio holding from other investors, indicating that location is not crucial for institutional investors' climate belief.

Overall, the results in this section provide evidence that institutional investors generally hold less High-TS stocks, especially those investors in investment companies, pension funds and endowments. However, not all institutional investors have the same preference for these stocks. Further, we also find that institutional investors can choose and hold stocks with better performance from High-TS portfolios. This ability can not be fully explained by their general experience and skills. Finally, institution location does not play a crucial role in investors' climate risk awareness. The High-TS portfolio excess holding weight shows no significant difference between institutional investors in High-TS states and other investors.

4.4 Robustness Results

In this section, we examine the robustness of our results on institutional ownership among different types. We also examine the performance of double sorting portfolios using various benchmarks.

In our institutional ownership tests, we examine the difference holding preference of investors in different institution types towards High-TS stocks. Our main dependent variable is the High-TS stock dummy, an indicator variable equal to one if the stock is in the High-TS portfolio in time t and zero otherwise. In this section, we examine whether our results hold if we use stock temperature sensitivity. The results in Table 4.7 are consistent with our main findings. Institutional ownership for stocks with higher temperature sensitivity is generally lower. Investment companies, pension funds and endowments hold less stocks with higher temperature sensitivity, while hedge funds and venture capital hold more. Banks portfolio construction is not affected by the temperature sensitivity of stocks.

We test the performance of portfolios double sorted by temperature sensitivity and changes in institutional holding weight in our main result by measuring portfolio raw returns. We estimate the factor-adjusted returns of the double-sorted portfolios for robustness check and see whether our findings still exist. Specifically, we report the market-adjusted return, Carhart-four-factor adjusted returns and six-factor adjusted returns (market premium, size factor, value factor, momentum factor, and short- and long-term reversal) in Table 4.8. Panel A show the result of market-adjusted returns. Carhart-four-factor adjusted returns and six-factor adjusted returns results are presented in Panel B and Panel C, respectively.

The High-TS portfolio's factor-adjusted returns in all columns are significantly negative and lower than those of the Low-TS portfolio, indicating that High-TS portfolios underperform the benchmark and temperature sensitivity significantly influence the stock returns. On the other hand, portfolios with higher holding increases generate higher adjusted returns among portfolios with higher temperature sensitivity, supporting that institutional investors can choose and hold better stocks from higher temperature sensitivity levels. The insignificant difference in the last two columns of Table 4.7 for the lower temperature sensitivity portfolio suggests that institutional investors' general experience and skills can not fully explain why they can hold better stocks. Climate risk awareness and management play a crucial role in their portfolio constructions.

4.5 Summary and Conclusions

In this paper, we study how institutional investors manage climate risk in their portfolio constructions. Motivated by the previous finding that stocks with high temperature sensitivities have lower returns, we conjecture that institutional investors hold less stocks with higher temperature sensitivity. Consistent with our conjecture, we find that the institutional holding weight for stocks with high temperature sensitivity is significantly lower than others. Specifically, the institutional holding weight of the highest temperature sensitivity portfolios is 9.62% lower than that of the lowest. We also find that different types of investors have heterogeneous preferences on stocks with high temperature sensitivity. Investment companies, pension funds and endowments hold a smaller weight of high temperature sensitivity stocks while hedge funds and venture capital hold more. Other institutions such as banks are indifferent towards stocks with temperature sensitivities, indicating that the climate risk awareness and managements among institutional investors are different, which affects their portfolio constructions significantly.

Further, we find that high temperature sensitivity stocks held by institutional investors have a higher annualized return of 9.16% than those not, indicating that institutional investors have the ability to choose and hold better stocks with high temperature sensitivity. Aggressive investors, including independent investment advisors, investment companies, and others, perform better than conservative ones in choosing and holding high temperature sensitivity stocks. To explain our finding, we test whether this ability exists among all temperature sensitivity portfolios. Our results show that Holding stocks outperform the Not Holding stocks in only higher temperature sensitivity levels, suggesting that institutional investors' general experience and skills can not fully explain our finding. Climate risk awareness and management help institutional investors improve their portfolio performance.

Additionally, we test whether the location of the institution affects investors' portfolio construction on temperature sensitivity. We find no evidence supporting that institutional investors in high temperature sensitivity states hold a lower weight of stocks with high temperature sensitivity.

Overall, our results contribute to the literature on how institutional investors understand climate risk by showing that institutional investors, especially in some specific types, manage temperature-related risk in their portfolio constructions. They can find stocks with better performance than others in high temperature sensitivity portfolios, and their general experience and skills can not fully explain such ability.

Further research would be done to investigate the mechanism behind institutional investors' climate risk awareness. For example, it would be interesting to examine whether institutional investors would change their portfolio after external climate shocks such as natural disasters and sudden temperature changes. Besides, it would also be useful to understand how retail investors understand climate risks and how their investment affects the market's asset price.

Table 4.1 Summary Statistics

This table reports summary statistics for the variables used in the empirical analysis. We use data from Thomson Institutional 13(f) Holdings during the 1980Q1 to 2017Q4 period. The state-level data are from FRED and U.S.Census Bureau.

	Mean	Stdev.	25th Pctl.	Median	75th Pctl.
Temperature Sensitivity	1.00	1.44	0.24	0.56	1.56
Size	12.12	2.24	10.45	11.99	13.68
B/M Ratio	0.81	1.80	0.30	0.57	0.97
Institutional Holding Weight	54.83	14.14	45.19	54.81	67.61
Changes in Institutional Holding	0.21	2.62	-1.26	0.34	1.64
State Population	12.35	0.24	12.17	12.36	12.56
State Personal Income	7.75	1.45	6.32	8.00	9.11
State GDP Growth	0.01	0.01	0.00	0.01	0.01
State Education	0.45	0.10	0.15	0.26	0.33
State Male-Female Ratio	0.96	0.37	0.94	0.96	0.98
State Marriage Ratio	0.55	0.71	0.50	0.55	0.60
State Median Age	35.85	4.10	32.00	37.00	40.00
State Minority Percentage	0.22	0.15	0.10	0.19	0.29
State Urbam Ratio	0.62	0.22	0.45	0.67	0.79

Table 4.2 Institutional Holding and Characteristics of Temperature Sensitivity Sorted Portfolios

This table reports the institutional holding weight and other characteristics of five temperature sensitivity portfolios. We report the characteristics of five stock portfolios: (i) the "Low" portfolio, which is a value-weighted portfolio of the quintile stocks with lowest temperature sensitivity estimate, (ii) the "High" portfolio, which is a value-weighted portfolio of the quintile stocks with highest temperature sensitivity estimates, (iii-v) portfolios 2 to 4, which represent the value-weighted portfolios of the remaining industries sorted into terciles based on temperature sensitivity estimates. The estimation period is from 1993Q1 to 2017Q4.

Institutional Ownership and Characteristics of Temperature Sensitivity Sorted Portfolios				
Portfolio	Investor Holding (%)	Climate Sensitivity	Size	B/M Ratio
1(Low)	57.330	0.183	12.148	0.838
2	56.851	0.292	12.083	0.844
3	56.874	0.535	11.844	0.859
4	55.402	0.912	11.375	0.885
5(High)	47.716	2.719	10.808	0.811
Low-High	9.615	-2.536	1.340	0.027

Table 4.3 Temperature sensitivity and Firm-Level Institutional Ownership by Investor Type

This table reports OLS regression model estimates using the quarterly intuitional ownership data as the dependent variable:

$$Institutional\ Ownership\ by\ Type_{x,i,t+1} = \alpha + \beta High\ TS\ stock_{i,t} + \gamma X_{i,j,t} + \delta_{firm} + \iota_{time} + \epsilon_{i,t}$$

x is institution type. It is one of the following: investment companies, pension funds and endowments, hedge fund and venture capital, and banks. $Institutional\ Ownership\ by\ Type_{x,i,t+1}$ is the holding ratio by institution type x of stock i on stock market capitalization on time $t+1$. The main independent variable *High TS Stock* is a dummy variable if a stock is in the high temperature sensitivity portfolio and zero otherwise. $X_{i,j,t}$ include the following control variables: The one quarter lagged holding ratio by institution type x of stock i, NBER recession indicator (REC), the Lettau-Ludvigson's (2004) cay measure, Population is the logarithm of the national-level population. Population Change is the change in Population over the previous quarter. Personal Income is the logarithm of the mean household income. IncomeChange is the change in Income from a quarter earlier. GDP_growth is the percentage change in GDP between t and t-1. Panel A shows the results for all institutional investors, investment companies, and pension funds and endowments. The results for hedge funds and venture capital, and banks are presented in Panel B. The estimation period is from 2000Q1 to 2017Q2. *T*-statistics reported in parentheses below the estimates are clustered at the time- and firm-level. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)[12]

[12] Besides the FactSet institutional type classification in Table 4.3 and Table 4.7, we also use institutional type classification following Brian Bushee at Chicago using Thomson 13F dataset. The results are qualitatively and quantitatively similar.

Table 4.3 Temperature sensitivity and Firm-Level Institutional Ownership by Investor Type-Continued

	All Institutions		Investment Companies		Pension Funds and Endowments		Hedge Funds, Venture Capital		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
High TS Stock	-0.208**	-1.853***	-0.118***	-0.115***	-0.036***	-0.182***	0.101**	1.034***	-0.002	-0.010
	(-2.28)	(-6.10)	(-3.29)	(-3.31)	(-2.85)	(-6.70)	(2.30)	(9.47)	(-0.75)	(-1.10)
Lagged Ownership		0.869***		0.879***		0.855***		0.880***		0.944***
		(171.87)		(224.71)		(40.93)		(151.54)		(22.47)
REC		0.151		-0.113		-0.031		-0.068		0.024**
		(0.11)		(-1.00)		(-0.48)		(-0.16)		(2.54)
cay		59.772		4.595		-2.472		11.574		-1.891***
		(1.30)		(1.06)		(-0.60)		(0.83)		(-3.54)
Population		184.580**		32.955***		2.492		-58.117**		-1.991**
		(2.38)		(4.19)		(0.48)		(-2.62)		(-2.15)
Population Changes		3652.207**		-120.064		-14.171		1585.171***		37.386**
		(2.55)		(-0.63)		(-0.14)		(4.07)		(2.16)
Personal Income		11.610		2.424		-0.620		30.032***		0.376**
		(0.78)		(1.49)		(-0.75)		(6.94)		(2.03)
IncomeChanges		33.330		2.815		-3.203		0.427		-1.199**
		(0.92)		(1.10)		(-0.91)		(0.04)		(-2.42)
GDP Growth		35.292		1.165		2.507		12.308		0.197
		(0.46)		(0.23)		(0.47)		(0.65)		(0.35)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES		YES		YES		YES		YES	
N	243909	243996	243909	243996	243909	243996	243996	243996	243909	243996
Adj. Rsq	0.858	0.075	0.750	0.051	0.630	0.001	0.091	0.091	0.422	0.001

Table 4.4 Investor holdings of High-Temperature Sensitivity Stock

This table reports the performance of two sub-portfolios from the High-temperature sensitivity portfolio. *Holding* portfolio contains those stocks held by institutional investors in quarter t, while *Not Holding* portfolio contains all other stocks. We report raw returns, market-adjusted returns, Carhart-four-factor returns and six-factor-adjusted returns (market premium, size factor, value factor, momentum factor, and short- and longer-term reversal) of portfolios. Panel A report the results from all institutional investors. The portfolio's performance constructed from aggressive institutional investors and conservative investors are shown in Panel B and Panel C, respectively. Following Kumar, Page, and Spalt (2011), we treat independent investment advisors, investment companies, and others as aggressive institutional investors while conservative institutions contain banks and insurance companies. The t-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1980Q1 to 2016Q4 for Panel A. The sample period of Panel B and Panel C is from 1981Q1 to 2016Q4. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: All Institutional Investors			
Returns	Holding	Not Holding	H-NH
	(1)	(2)	(3)
Raw (%)	0.961***	0.687**	0.671***
	(2.65)	(2.35)	(4.52)
CAMP Adj. (%)	-0.315*	-1.014***	0.699***
	(-1.85)	(-4.82)	(4.81)
4 Factor Adj. (%)	-0.080	-0.833***	0.754***
	(-0.74)	(-4.76)	(4.91)
6 Factor Adj. (%)	-0.065	-0.828***	0.763***
	(-0.59)	(-4.60)	(4.90)
Avg No. of Firms	562	361	
No. of Months	444	444	

Table 4.4 Investor holdings of High-Temperature Sensitivity Stock-Continued

Panel B: Aggressive Institutional Investors			
Returns	Holding	Not Holding	H-NH
	(1)	(2)	(3)
Raw (%)	0.910**	0.494	0.416***
	(2.48)	(1.32)	(3.25)
CAMP Adj. (%)	-0.305*	-0.734***	0.430***
	(-1.73)	(-3.96)	(3.39)
4 Factor Adj. (%)	-0.047	-0.462***	0.414***
	(-0.42)	(-3.37)	(3.18)
6 Factor Adj. (%)	-0.032	-0.458***	0.426***
	(-0.29)	(-3.26)	(3.27)
Avg No. of Firms	347	577	
No. of Months	432	432	

Panel C: Conservative Institutional Investors			
Returns	Holding	Not Holding	H-NH
	(1)	(2)	(3)
Raw (%)	0.938***	0.646*	0.292*
	(2.82)	(1.72)	(1.69)
CAMP Adj. (%)	-0.249	-0.578***	0.329**
	(-1.36)	(-3.21)	(1.97)
4 Factor Adj. (%)	-0.036	-0.300***	0.264
	(-0.23)	(-2.62)	(1.53)
6 Factor Adj. (%)	-0.042	-0.288**	0.246
	(-0.26)	(-2.47)	(1.43)
Avg No. of Firms	191	696	
No. of Months	432	432	

Table 4.5 Raw Return of Double-Sorted Portfolios Based on Temperature Sensitivity and Institutional Holding Changes

Table 5 reports the raw return of portfolios double sorted by temperature sensitivity and institutional ownership changes. In each month, we sort all the stocks into five equally split portfolios using their temperature sensitivities. We construct a Not Holding portfolio within each temperature sensitivity portfolio using those stocks with 0 institutional ownership in the current quarter. Based on each stock's institutional ownership changes from the previous quarter, we further equally sort the rest in the same temperature sensitivity portfolio into three sub-groups. The last two columns show the return difference between the different holding groups. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1980Q1 to 2017Q4. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

	Not Holding	Low Holding Changes	Medium Holding Changes	High Holding Changes	High-Not Holding	High-Low Holding
1 (Low TS)	0.732***	1.260***	0.986***	0.957***	0.215	-0.303
	(2.98)	(5.42)	(5.54)	(3.59)	(1.39)	(-1.18)
2	0.974***	1.273***	0.903***	0.869***	-0.115	-0.403
	(3.64)	(5.07)	(4.51)	(2.96)	(-0.60)	(-1.56)
3	0.837***	1.251***	0.899***	1.195***	0.328*	-0.056
	(3.37)	(4.47)	(4.77)	(4.11)	(1.85)	(-0.19)
4	0.810**	0.442	0.806***	1.360***	0.510**	0.918**
	(2.47)	(1.32)	(3.48)	(3.85)	(2.29)	(2.58)
5 (High TS)	0.290	-0.532	0.241	2.120***	1.799***	2.652***
	(0.72)	(-1.16)	(0.64)	(5.06)	(9.56)	(8.45)
High-Low	-0.443	-1.793***	-0.745**	1.163***		
	(-1.61)	(-5.15)	(-2.44)	(4.24)		

Table 4.6 Institution Locations and Portfolio Holding

Table 6 is based on the institutional investor quarter level dataset. Following Coval and Moskowitz (1999), we measure institutional investor excess weight as $EW_{i,s,t} = w_{i,s,t} - w_{m,s,t}$. The excess weight for each institutional investor *i* on a set of stocks *s* on-time *t* equals the weight of the set of stocks *s* in investor *i*'s holding portfolio on time *t* minus the market weight of the set of stocks *s*. *s* is the quintile sorted portfolio based on temperature sensitivity. The dependent variable is the institutional investor excess weight of the High-TS portfolio and Other portfolio in each quarter. *High-TS State* is a dummy variable equals to 1 if the location of the institutional investor is in the high temperature sensitivity state group. We control for a set of institutional investor-level factors and state-level characteristics in the test. *Portfolio Size* is the natural log of each institution *i*'s total portfolio market capitalization in quarter t (Kacper-czyk et al., 2016). *Portfolio Concentration* is defined as the Herfindahl index of the institution's portfolio weights. *Total population* measures the total population of a state, *Education* is the state-level of education (the proportion of state population above age 25 that has completed a bachelor's degree or higher). We also include the *male-female ratio* in the state, the proportion of households in the state with a *married* couple, the median *age* of the state, *minority* population (the proportion of the population in the state that is non-white), and the proportion of the state residents who live in *urban* areas. We control for the time fixed effect and institutional investor type fixed effect in our regression. *t*-statistics presented in parentheses and are clustered at the state level. The estimation period is from 1980Q1 to 2016Q4.

Table 4.6 Institution Locations and Portfolio Holding-Continued

	Dependent Variable: Excess Holding Weight					
	All Investors		Aggressive Investors		Conservative Investors	
	High-TS Portfolio	Other Portfolio	High-TS Portfolio	Other Portfolio	High-TS Portfolio	Other Portfolio
	(1)	(2)	(3)	(4)	(5)	(6)
High-TS State	0.003	-0.001	-0.005	0.002	-0.002	-0.010
	(0.07)	(-0.16)	(-0.10)	(0.28)	(-0.08)	(-0.84)
Portfolio Size	-0.060***	0.005***	-0.059***	0.004***	-0.028***	0.006***
	(-4.50)	(5.70)	(-3.98)	(4.78)	(-4.73)	(3.35)
Portfolio Concentration	0.000***	-0.000***	0.000***	-0.000***	0.000	0.000
	(6.73)	(-3.40)	(8.91)	(-8.33)	(1.54)	(0.06)
Total Population	0.000***	-0.000**	0.000***	-0.000***	0.000**	-0.000
	(3.48)	(-2.49)	(2.95)	(-2.84)	(2.28)	(-0.24)
Education	1.389**	-0.139*	1.661**	-0.053	0.439	-0.270
	(2.10)	(-1.72)	(2.04)	(-0.71)	(1.53)	(-1.48)
Male-female ratio	-0.332	0.282*	-0.054	0.379**	-0.069	-0.121
	(-0.34)	(1.86)	(-0.04)	(2.67)	(-0.12)	(-0.34)
Married	-0.312	-0.235**	-0.381	-0.234*	-0.594	-0.060
	(-0.34)	(-2.31)	(-0.33)	(-1.85)	(-1.21)	(-0.25)
Age	0.005	-0.001	0.008	0.000	-0.001	-0.000
	(0.68)	(-0.60)	(0.84)	(0.04)	(-0.32)	(-0.12)
Minority	0.162	-0.043	0.160	-0.036	0.084	0.011
	(0.67)	(-1.37)	(0.52)	(-1.18)	(0.73)	(0.18)
Urban	0.097	-0.049	0.174	-0.060*	-0.111	-0.039
	(0.48)	(-1.61)	(0.69)	(-1.96)	(-1.10)	(-0.68)
Time Fixed Effect (Year-Quarter)	Yes	Yes	Yes	Yes	Yes	Yes
Institutional Type Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
N	139523	168741	109709	131868	24094	29796
Adj. Rsq.	0.126	0.071	0.092	0.071	0.067	0.118

Table 4.7 Temperature sensitivity and Institutional Ownership by Investor Type

This table reports OLS regression model estimates using the quarterly intuitional ownership data as the dependent variable:

$$Institutional\ Ownership\ by\ Type_{x,i,t+1} = \alpha + \beta Temperature\ Sensitivity_{i,t} + \gamma X_{i,j,t} + \delta_{firm} + \iota_{time} + \epsilon_{i,t}$$

x is institution type. It is one of the following: investment companies, pension funds and endowments, hedge fund and venture capital, and banks. $Institutional\ Ownership\ by\ Type_{x,i,t+1}$ is the holding ratio by institution type x of stock i on stock market capitalization on time t. The main independent variable $Temperature\ Sensitivity_{i,t}$ measures the absolute value of stock i's return sensitivity to temperature anomaly in the past five years. $X_{i,j,t}$ include the following control variables: The one quarter lagged holding ratio by institution type x of stock i, NBER recession indicator (REC), the Lettau-Ludvigson's (2004) cay measure, Population is the logarithm of the national-level population. Population Change is the change in Population over the previous quarter. Personal Income is the logarithm of the mean household income. IncomeChange is the change in Income from a quarter earlier. GDP_growth is the percentage change in GDP between t and t-1. Panel A shows the results for all institutional investors, investment companies, and pension funds and endowments. The results for hedge funds and venture capital, and banks are presented in Panel B. The estimation period is from 2000Q1 to 2017Q2. *T*-statistics reported in parentheses below the estimates are clustered at the time- and firm-level. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$)

Table 4.7 Temperature sensitivity and Institutional Ownership by Investor Type-Continued

	All Institutions		Investment Companies		Pension Funds and Endowments		Hedge Funds, Venture Capital		Banks	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Temperature Sensitivity	-0.181***	-0.689***	-0.042***	-0.198***	-0.010***	-0.047***	0.019***	0.151***	0.000	0.000
	(-4.52)	(-4.75)	(-3.53)	(-4.55)	(-2.92)	(-4.31)	(3.14)	(3.69)	(0.64)	(0.15)
Lagged Ownership		0.865***		0.881***		0.858***		0.869***		0.926***
		(196.15)		(255.30)		(44.71)		(180.10)		(22.45)
REC		0.080		-0.156		-0.041		-0.034		0.024**
		(0.06)		(-1.08)		(-0.66)		(-0.08)		(2.59)
cay		60.369		19.986***		-2.642		11.084		-1.934***
		(1.35)		(3.50)		(-0.65)		(0.79)		(-3.62)
Population		161.541**		71.081***		0.592		-57.632**		-1.932**
		(2.16)		(6.69)		(0.12)		(-2.57)		(-2.07)
Population Changes		3606.620**		-162.092		-23.538		1609.089***		38.469**
		(2.58)		(-0.65)		(-0.24)		(4.11)		(2.21)
Personal Income		16.171		-3.829*		-0.288		29.936***		0.364*
		(1.13)		(-1.77)		(-0.36)		(6.82)		(1.95)
IncomeChanges		36.349		13.004***		-3.129		-1.304		-1.204**
		(1.02)		(2.98)		(-0.91)		(-0.12)		(-2.44)
GDP Growth		37.843		1.772		2.321		14.519		0.208
		(0.52)		(0.23)		(0.45)		(0.76)		(0.38)
Firm Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Time Fixed Effect	YES		YES		YES		YES		YES	
N	239953	240342	239953	240342	239953	240342	239953	240342	239953	240342
Adj. Rsq	0.862	0.080	0.753	0.055	0.631	0.003	0.658	0.092	0.423	0.000

Table 4.8 Performance of Double-Sorted Portfolios Based on Temperature Sensitivity and Institutional Holding Changes

Table 8 reports the factor adjusted return of portfolios double sorted by temperature sensitivity and institutional ownership changes. In each month, we sort all the stocks into five equally split portfolios using their temperature sensitivities. We construct a Not Holding portfolio within each temperature sensitivity portfolio using those stocks with 0 institutional ownership in the current quarter. Based on each stock's institutional ownership changes from the previous quarter, we further equally sort the rest in the same temperature sensitivity portfolio into three sub-groups. The last two columns show the return difference between the different holding groups. In Panel A, we report the market-adjusted returns for double sorted portfolios. Panel B present the Carhart four-factor adjusted returns. Six-factor adjusted returns include market premium, size factor, value factor, momentum factor, and short- and long-term reversal are shown in Panel C. The *t*-statistics computed using Newey-West (1987) adjusted standard errors are reported in parentheses below the estimates. The estimation period is from 1980Q1 to 2017Q4. (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

Panel A: Market Adjusted Return						
	Not Holding	Low Holding Changes	Medium Holding Changes	High Holding Changes	High-Not Holding	High-Low Holding
1 (Low TS)	-0.238**	0.276*	0.100	-0.058	0.193	-0.334
	(-2.03)	(1.78)	(0.96)	(-0.43)	(1.20)	(-1.30)
2	-0.027	0.252*	-0.022	-0.188	-0.151	-0.441
	(-0.21)	(1.68)	(-0.19)	(-1.28)	(-0.75)	(-1.63)
3	-0.200*	0.179	-0.027	0.121	0.313*	-0.058
	(-1.87)	(0.98)	(-0.20)	(0.78)	(1.77)	(-0.20)
4	-0.370**	-0.711***	-0.193	0.160	0.515**	0.871**
	(-2.50)	(-3.07)	(-1.36)	(0.84)	(2.27)	(2.42)
5 (High TS)	-1.014***	-1.904***	-0.967***	0.775***	1.785***	2.679***
	(-4.82)	(-6.71)	(-4.13)	(3.39)	(9.58)	(8.37)
High-Low	-0.776***	-2.180***	-1.068***	0.833***		
	(-2.87)	(-6.80)	(-3.71)	(3.35)		

Table 4.8 Performance of Double-Sorted Portfolios Based on Temperature Sensitivity and Institutional Holding Changes-Continued

	Panel B: Four-factor Adjusted Return					
	Not Holding	Low Holding Changes	Medium Holding Changes	High Holding Changes	High-Not Holding	High-Low Holding
1 (Low TS)	-0.370***	0.281*	0.083	-0.112	0.281*	-0.393
	(-3.37)	(1.86)	(0.75)	(-0.83)	(1.75)	(-1.53)
2	-0.041	0.314*	-0.041	-0.170	-0.122	-0.484*
	(-0.33)	(1.78)	(-0.33)	(-1.19)	(-0.63)	(-1.71)
3	-0.124	0.260	-0.022	0.143	0.263	-0.117
	(-1.10)	(1.31)	(-0.16)	(0.95)	(1.45)	(-0.37)
4	-0.172	-0.701***	-0.221	0.122	0.273	0.823**
	(-1.28)	(-3.14)	(-1.56)	(0.64)	(1.22)	(2.28)
5 (High TS)	-0.833***	-1.525***	-0.732***	0.975***	1.806***	2.501***
	(-4.76)	(-6.46)	(-4.05)	(5.44)	(9.97)	(7.94)
High-Low	-0.463**	-1.807***	-0.815***	1.087***		
	(-2.35)	(-6.55)	(-3.36)	(5.76)		

Table 4.8 Performance of Double-Sorted Portfolios Based on Temperature Sensitivity and Institutional Holding Changes-Continued

Panel C: Six-factor Adjusted Return						
	Not Holding	Low Holding Changes	Medium Holding Changes	High Holding Changes	High-Not Holding	High-Low Holding
1 (Low TS)	-0.382***	0.260*	0.096	-0.119	0.281*	-0.379
	(-3.36)	(1.70)	(0.84)	(-0.87)	(1.68)	(-1.46)
2	-0.040	0.286*	-0.024	-0.175	-0.122	-0.462*
	(-0.32)	(1.71)	(-0.20)	(-1.19)	(-0.62)	(-1.65)
3	-0.153	0.241	-0.017	0.161	0.308*	-0.081
	(-1.29)	(1.20)	(-0.11)	(1.06)	(1.68)	(-0.26)
4	-0.174	-0.689***	-0.172	0.143	0.298	0.832**
	(-1.25)	(-3.12)	(-1.22)	(0.75)	(1.32)	(2.32)
5 (High TS)	-0.828***	-1.535***	-0.736***	1.006***	1.835***	2.541***
	(-4.60)	(-6.51)	(-4.04)	(5.59)	(10.08)	(8.16)
High-Low	-0.447**	-1.795***	-0.832***	1.125***		
	(-2.15)	(-6.42)	(-3.36)	(5.86)		

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