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Investor Realization and Response to Climate Change

A study of the local warming effect on investors at the Stockholm stock exchange

Master's Thesis
MSc Finance & Strategic Management
90 pages/ 172 758 Characters

Supervisor: Søren Ulrik Plesner

Copenhagen Business School
June 15th, 2020

“Climate change is the defining challenge of our time. Time is fast running out for us to avert the worst impacts of climate disruption and protect our societies from the inevitable impacts to come”

- António Guterres, UN Secretary-General, cited in WMO (2020, p. 4)

Abstract

Combining data from the Swedish financial market with abnormal temperatures in Stockholm from 2004 to 2019, we study the causal impact of temperature shocks on investor behavior. More specifically, we first examine whether abnormal temperatures affect investors' attention to climate change as proxied by Google Search Volume Index. Then, we study the stock performance of carbon-intensive firms in relation to firms with low carbon emissions during abnormal temperatures. Finally, we identify investors as either retail investors, blockholders, or institutional investors and examine their trading behavior during abnormal temperatures. Combining data from several sources, we do not find evidence that temperature exposures significantly affect local investors' attention, stock prices, nor trading activities. The thesis shed light on the national differentiation of investors' realization and response to climate change, an important contribution to climate finance research.

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1. Introduction

Our global climate is changing, and there is overwhelming scientific evidence that the cause is anthropogenic (Intergovernmental Panel on Climate Change [IPCC], 2018a). Beside the severe impact human actions could have on the environment, the changing climate could also become one of the most economically disrupting occurrences of the century with a loss of five to twenty percent of global annual GDP depending on the trajectory (Stern, 2007). Even so, perceptions and beliefs in climate change vary at large. In August of 2018, the Swedish high-school student Greta Thunberg initiated a global movement of millions striking for policymakers to do more on the issue (BBC News, 2020a). On the other side of the Atlantic, President Donald Trump dismisses the climate “prophets of doom” as alarmist (BBC News, 2020b).

Since the nature of the climate change issue requires it to be effectively tackled in a unified response, understanding what causes these differences in the perceptions of climate change becomes crucial. The public beliefs carry weight, not only for understanding the responses to climate change on a policy level, but also in the pricing of climate-sensitive assets in financial markets. Correctly pricing these assets today is key to lowering the possibility of extreme price movements in the future. As investors trade on their beliefs, the understanding of what impacts the climate change beliefs of investors is an essential contribution, not only to the efficient markets debate, but also to mitigate the possibility of future financial shocks.

For these reasons, the understanding of climate belief formation has in recent years gained academic attention (Hong, Karolyi, & Scheinkman, 2020). Interestingly, many studies find that personally experiencing temperature abnormalities carries large weight in determining our perceptions and beliefs about climate change (Choi, Gao, & Jiang, 2020; Zaval et al., 2014; Deryugina, 2013). Even though local weather carries insignificant information about the trajectory of the global climate, it is more discernible on a personal level than the global climate trend (Choi, Gao, & Jiang, 2020). Therefore, there seems to be a common mis-association between the experienced local temperatures and the health of the climate at large. On an international level, Choi, Gao, and Jiang (2020) find that local temperature shocks affect both investor attention and belief formation toward climate change. Specifically, they find that the pricing of climate-sensitive stocks and Google searches are systematically altered in these periods. The international perspective of Choi, Gao, and Jiang (2020) enables generalized conclusions. However, in order to draw conclusions on the country-specific impact of local abnormal temperatures on aggregate beliefs, complementary national studies are required. Therefore, this thesis aims to extend the findings of Choi, Gao, and Jiang (2020). We will do so by examining how investors in the Swedish market realize and respond to climate change through the experience of abnormal temperatures. More specifically, through objective proxies and financial data, we quantitatively examine whether local temperature abnormalities impact investor attention, investor beliefs, and different investors' trading activity on the Stockholm stock exchange.

Because of individuals' inherent limits to attention, experiencing abnormal temperatures may cause investors to be more attentive toward climate change (Choi, Gao & Jiang, 2020). Our thesis tests this idea by first examining whether the experience of abnormal temperatures affects retail investor attention to climate change as proxied by Google Search Volume Index. In the second set of analyses, we extend the limited attention perspective by looking at the closely related area of personal experience and belief-formation. Given that Swedish investors revise their climate change beliefs when experiencing abnormal temperatures, prices on the local exchange may be impacted due to the home bias. In the same manner as Choi, Gao, and Jiang (2020), we theorize that if the experience of temperature abnormalities causes Swedish investors to update their beliefs about climate change, they might choose to buy stock with lower sensitivity to the climate and sell stocks with higher sensitivity. This trading behavior could occur to the extent that the lower-sensitivity stocks outperform the others. Moreover, once belief in climate change is revised, there is also a possibility that stocks of companies that have a negative impact on the climate will be avoided for conscience reasons. We test whether these behaviors are present in the Swedish market in two consecutive steps. First, we examine whether abnormal temperatures systematically affect the returns of carbon-intensive firms. We do so by categorizing firms based on their respective industry emission levels according to the Intergovernmental Panel on Climate Change (IPCC). The stocks belonging to the highest emitting industries were grouped into a high-emission category, and the others were considered low emitting. Going long in the first and short in the latter, we studied the combined portfolio returns in relation to abnormal temperature. Additionally, the portfolio returns of each separate category were analyzed. Secondly, we assess whether the local temperature impacts investor trading activity on the Stockholm stock exchange in the same firms. We do so by examining the trading behavior of retail investors, blockholders, and institutional investors. Local investors are distinguished from foreign ones, as only local investors are experiencing the local temperatures. The change in ownership-levels at each quarter for the respective groups is analyzed in relation to temperatures abnormalities.

In our comprehensive study, we do not find evidence that temperature exposures significantly affect investors' attention, stock prices, or trading activities on the Stockholm stock exchange. More specifically, we do not find a relationship between abnormal temperature and Swedish investors' attention to climate change. Furthermore, neither the prices of low emitting firms nor high emitting firms are visibly impacted by temperature abnormalities. This finding is also robust in a control-period stretching through the 1990s, which indicates that no such relationship exists. Finally, we find that none of our determined investor groups systematically respond to abnormal temperatures.

Our study presents novel results on the impacts of abnormal temperature on investor behavior in the Swedish market. Existing research on climate change beliefs in Sweden has, to our knowledge, solely been conducted through survey-data. Our study combines these previous findings with quantitative evidence to get closer in understanding the nature of Swedish investors' response to climate change. Our study primarily contributes to the body of research within the new field of Climate finance. We add to the current research on climate change beliefs in Sweden by examining the local warming effect. Additionally, we contribute to the same field by narrowing the scope toward the under-researched area of investors' climate response in the Swedish market. Finally, our research contributes to the larger purpose of disentangling the climate change issue by looking at the important mechanisms at work in the financial market. While our combined analysis of the relationship between abnormal temperatures and investor behavior displays a consistent set of non-results, our tests construct a point of departure for further review. The exclusion of a systematic abnormal temperature impact can guide future research in the important task of identifying the drivers of investors' realization and response to climate change in the Swedish market.

1.2 Research Question

Motivated by the necessity of examining investors' realization and response to climate change and guided by the existing research, our thesis aims to answer the following research question:

> ***"To what extent, if at all, does abnormal temperatures affect equity investors' realization and response to climate change in Sweden?"***

Additionally, to further narrow the contribution of the thesis to the existing research, the three interrelated sub-questions will be answered throughout the analysis:

(i) What is the international evidence on temperature influence on investors' attention and beliefs towards climate change?

(ii) What is the evidence from Sweden on temperature influence on investors' attention and beliefs towards climate change?

(iii) If these differ, what could be the explanation between the diverse findings?

1.3 Delimitations

During the work with this thesis, several delimitations have been made. First of all, we narrow the scope toward the under-researched area of investors' climate response in a high-belief country. More specifically, this thesis focuses on exploring whether the local abnormal temperature in Stockholm impacts investors' realization and response to climate change on the Stockholm stock exchange.

The first delimitation regards the choice of abnormal temperatures, as a whole nation does not experience the same temperature abnormalities. The data sources applied in the research enabled us to separate domestic investors from foreign investors. However, we were unable to distinguish domestic investor location on a city level. Therefore, the temperature had to be collected from a location that most closely responded to the majority of local investors' experience. The capital of Sweden, which is also the city of the exchange, has the highest population density in the country, concentrated capital, and is also substantially covered by the media. Moreover, Sweden is a relatively small country. Even though the temperatures in the north and the south may vary, we argue that the small size of the country leads to monthly abnormal temperatures often being experienced simultaneously across the whole nation. Thus, we argue that any monthly temperature abnormalities in Stockholm are highly related to the experience of the majority of investors on a national level. Consequently, we deemed it reasonable to apply the temperatures measured at the closest weather station to the Stockholm stock exchange as a proxy for investor temperature experience in Sweden.

Moreover, we chose to limit our research to examining only monthly intervals. One could argue that the unexplored territory of a local warming effect on Swedish investors could require an examination of different time intervals to exclude or confirm its existence. However, due to the scope of the thesis, an elaborate choice of one interval frequency had to be made. According to Deryugina (2013), only temperature fluctuations of a month up to a year will predict climate change beliefs. Additionally, Choi, Gao, and Jiang (2020) found that the local warming effect on investor attention and beliefs was strongest at a monthly frequency, when examining daily, weekly, monthly, and quarterly frequencies. Since this previous research suggests that the likelihood of a temperature effect being present but undetectable at a monthly interval should be low, we deemed the monthly frequency most appropriate to examine.

In the first groups of tests, we focus on using the well-established proxy for retail investor attention; Google Search Volume Index (SVI). Thus, attention proxies for the other two investor groups were not examined. We planned to also proxy institutional investor attention by following Ben-Rephael, Da, and Israelsen (2017) approach of using Bloomberg data on the Daily Max Readership score, which measures the search frequency and articles read of a specific stock. Unfortunately, we were unable to collect the data before the COVID-19 lockdown.

In the later tests, when identifying high emission firms in our portfolio construction, we applied IPCC identification of major emission industries. These industries were then hand-matched with the stocks industry code given by DataStream. Other identifications of high emission firms, such as environmental scoring from ESG providers, could have substituted or complemented the IPCC definitions. Additionally, we do not directly measure a firm's specific climate sensitivity through its emission levels. For example, specific physical risks of climate change have not been examined. We do, however, argue that high emission levels are related to other risks of climate change, such as regulatory risks, which implies collective sensitivity for these firms. The reason we focus on the IPCC classification of high emission sources specifically is that it is considered a highly reliable source, accessible for everyone, and eases the comparability of our results with the study of Choi, Gao, and Jiang (2020).

Furthermore, we calculated size-adjusted return by dividing all companies into different size quintiles and then removing the average return of each quintile. Other models of calculating adjusted returns, such as factor models, could also have been used. However, when considering these adjustments for the return calculation, we encountered a significantly reduced sample when obtaining other company information. Therefore, it was considered most appropriate to adjust returns according to the market capitalization data that had better coverage for our sample.

1.4 Overview of the Thesis

To answer the research question specified above, the paper follows a five-section structure. More specifically, it covers the literature on the topic, the analytical approach, the result of the study, and a discussion of the result. The paper finishes up with a conclusion of the results that give rise to recommendations for future studies as well as a perspective of the paper. A more detailed description and purpose of each section are presented below.

Section 1: In the first section of the paper, we provide an introduction to the overall topic, its relevance, and the motivation behind the study. This creates the basis for the specific research question and relevant sub-questions that are then specified. Additionally, the delimitations of the paper are presented to uncover the boundaries of the study.

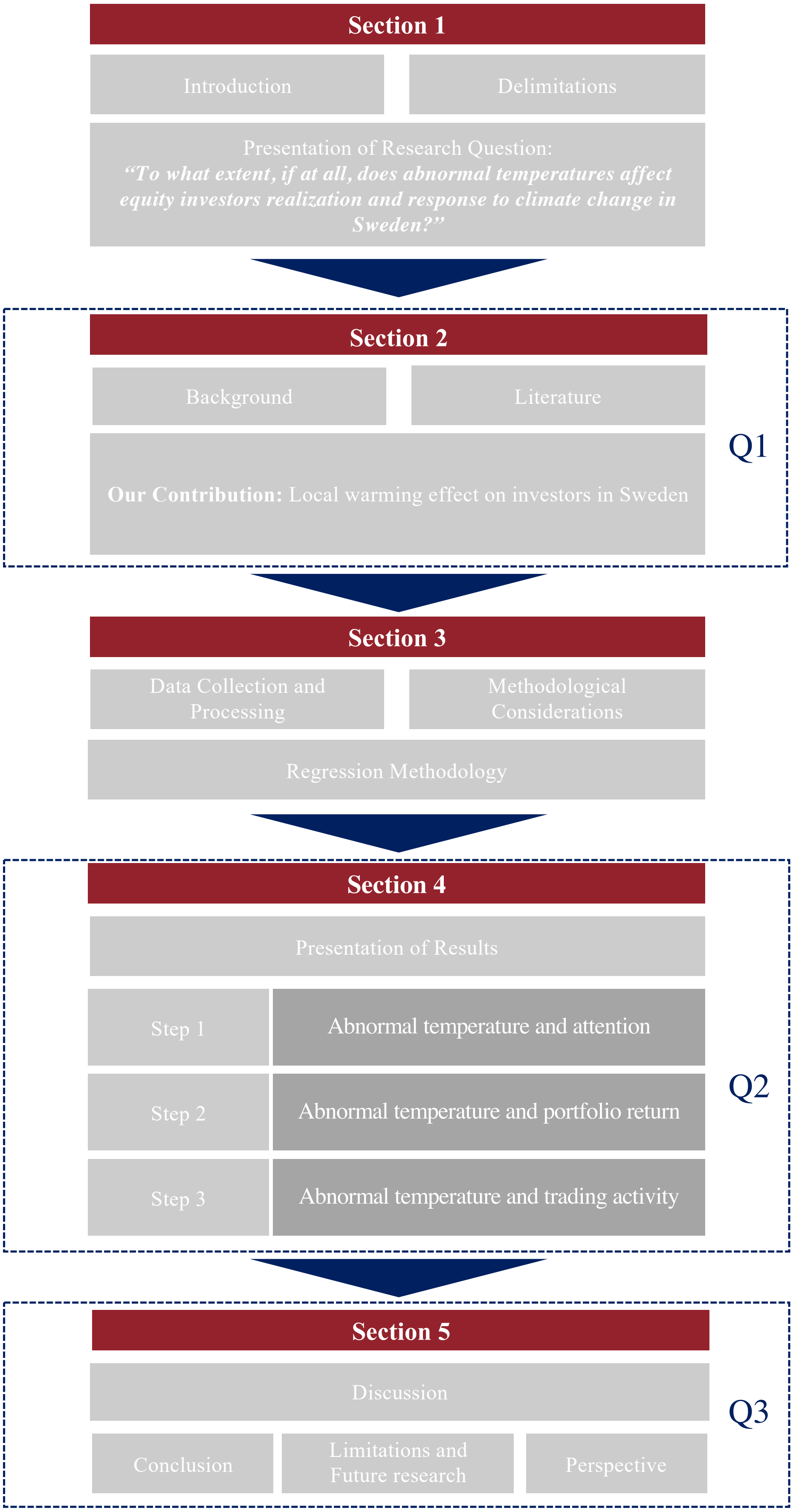
Section 2: In the second section, we aim to both present the theoretical foundation on which this thesis relies and answer the first sub-question of the research. The intention is to equip the reader with the theoretical foundation for the thesis by presenting both the concepts and theories that formed the research. This implies offering an introduction to Climate science and Climate finance, which provides definition to the matter at hand. Further, the behavioral theories which underpin and frames the research are provided. The focus is then narrowed toward the existing research on climate change beliefs and their formation in order to answer the first sub-question of our research. Similarly, we aim to provide the foundation for the third sub-question by introducing nationwide survey studies of citizens' climate change beliefs in Sweden. Finally, we offer the specific contributions of our study in relation to the existing literature presented.

Section 3: The third section presents the methodological approach of the paper. Specifically, we introduce the research design that lays the foundation for the methodological approach. This is followed by a formulation of the hypotheses development that underpins the research. Then, we will describe the data collection and processing, which culminates in the regression methodology that the thesis has applied and the limitations of the same.

Section 4: In the fourth section, we aim to answer the second sub-question by presenting and interpreting the results of our study. First, we provide the results and interpretation of the regressions examining abnormal temperature influence on Swedish investors' attention.

Secondly, the results and interpretation of the regressions examining abnormal temperature influence on stock returns on the Stockholm stock exchange are presented. Finally, we provide the results and interpretation of abnormal temperatures influence on retail investors, blockholders, and institutional investors' trading activity. In each subsection, the results are compared to the international findings of Choi, Gao, and Jiang (2020) to lay the foundation for the following discussion.

Section 5: Finally, in section five, we first answer the third sub-question by interpreting the results from the Swedish market in relation to the theories presented in the literature review. Then, we reach a conclusion where we answer our overall research question and present the relevant findings. The thesis is finalized by putting the results in perspective. First, the limitations of the research and future recommendations are evaluated. Secondly, we comment on the potential implications of the worldwide pandemic COVID-19.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2. Climate Science

In this section, we will provide a brief background to the thesis by defining climate change, and explaining the broader picture of the causes and effects of the changing climate.

The climate of the earth is the long-term regional or global average patterns of temperature, humidity, and rainfall throughout seasons and years National Aeronautics and Space Administration [NASA], n.d.). The change in climate is referred to as climate change and defined by the Nobel Peace Prize awarded IPCC (2018b, p. 544) as:

> "*The change in the state of the climate that can be identified (e.g., by using statistical tests) by changes in the mean and/or the variability of its properties and that persists for an extended period, typically decades or longer. Climate change may be due to natural internal processes or external forcing such as modulations of the solar cycles, volcanic eruptions and persistent anthropogenic changes in the composition of the atmosphere or in land use.*"

Scientists have in recent years reported of a rapid rise in the average global temperature. The increasing long-term temperature trend is one of the most consistent and extensive evidence of a warming earth (United States Global Change Research Program [USGCRP], 2018). According to the National Centers for Environmental Information (NCEI, 2019), the combined land and ocean temperature has, on average, risen with 0.07°C per decade since 1880 and 0.18°C since 1981. This trend has been accompanied by melting glaciers and ice sheets, shrinking snow cover, rising sea level, extreme weather events, and other indicators consistent with a warmer earth (USGCRP, 2018).

In 2019, the global mean surface temperature was 0.95°C warmer than the average temperature between 1901 and 2000 (NCEI, 2019). This makes 2019 to the second warmest year on record after 2016 globally. However, 2016 was characterized by a very strong El Niño, a phenomenon that gives a high global average temperature (World Meteorological Organization [WMO], 2020). Further, the average temperature of 2010 to 2019 makes it the warmest decade on record, as illustrated in figure 1.

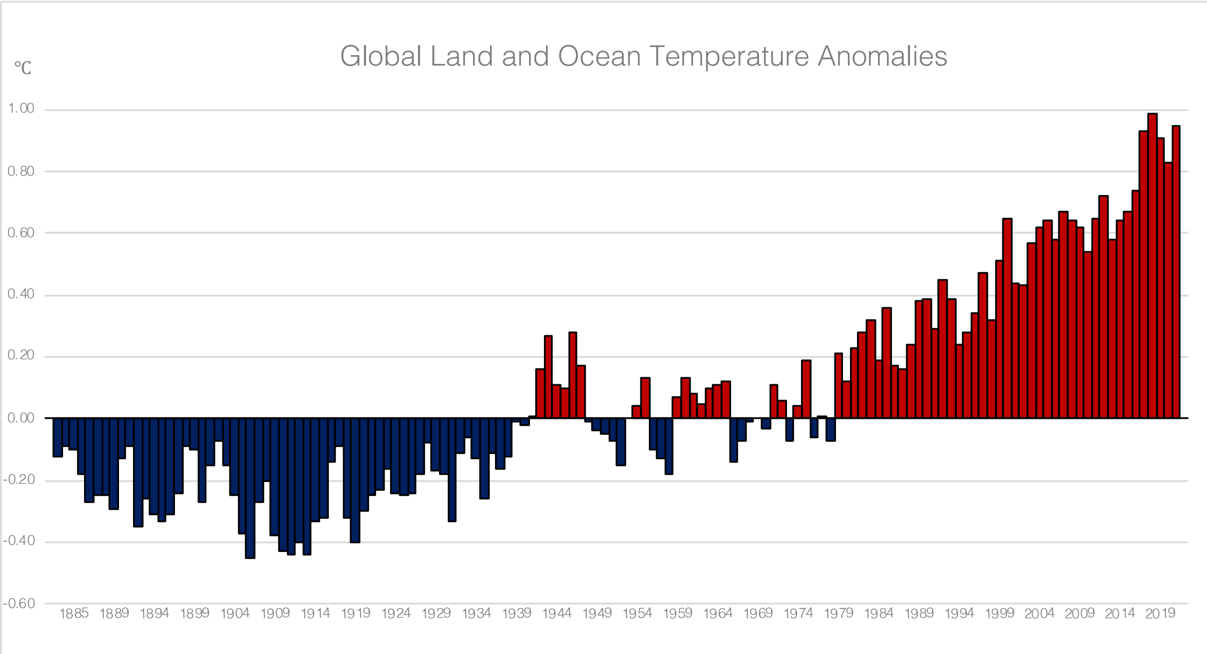

Figure 1: The average annual global temperature compared to the long-term average (1901- 2000), from 1885 to 2019. Data source: Lindsey and Dahlman, 2020.

The changes in the climate since the 20th century is mainly driven by human activities (NASA n.d.). The fossil fuel burning is the primary cause, since it increases the greenhouse gas levels in the atmosphere and raises the average surface temperature (NASA, n.d..).

Climate scientists have concluded that if we continue on the current path, emissions of greenhouse gases will lead to warming of 1.5°C above the pre-industrial levels between 2030 and 2052 (IPCC, 2018a). This would result in long-lasting changes in all components of the climate system and increase the probability of severe and irreversible impacts for people and ecosystems (IPCC, 2018a).

However, climate change is not only a scientific concern but also a severe economic threat (Kelly et al., 2015). It will have significant impacts on the price of energy, availability of resources, the vulnerability of infrastructure, and the valuation of companies (Kelly et al., 2015). Consequently, it poses a major risk to the global economy. This is illustrated by Stern (2007) that estimates that climate change, if not tackled early, could cost between five and twenty percent of annual global GDP. Clearly, the financial impact of such a large reduction in global productivity is severe. However, there still remain several possible future scenarios if mitigation efforts are accelerated, and low-carbon solutions are established at scale (Kelly et al., 2015). It is up to human endeavor to change the path of emission and mitigate against climate change. Thus, it is individuals' efforts, innovations, investments, and policy changes that can shift the path (IPCC, 2014). These efforts can be categorized into two strategies:

1) Adaptation is the process of change to actual or expected climate to limit the negative impacts of climate change.
2) Mitigation is the process of reducing (or preventing) emissions of greenhouse gases to limit future climate change.

Therefore, choices and investments which are made in the short, medium, and long term in both adaption and mitigation will determine how much climate will change throughout the century (United Nations Framework Convention on Climate Change [UNFCCC], n.d.)

3. Literature Survey

Our thesis is resting on the foundation of behavioral theories about individuals' limited attention and processing power. More specifically, the consequences that limited attention seemingly has on individuals' perceptions and beliefs about climate change. When this is combined with an existing home bias, it is possible that local heuristic belief updating does not only have impacts on beliefs but could also shift stock prices. It is within this frame our thesis is embedded. Therefore, our research relies on the combination of four strands of literature: Climate finance, Limited attention, Climate research on belief-formation, and Home bias. The chosen literature within each field is presented in this section in order to provide the necessary building blocks for the later analysis. Furthermore, the review of international evidence aims to answer the first sub-question of our research, which is concerned with the international findings on temperature influence on investors' attention and beliefs toward climate change. Moreover, our third sub-question requires a review of the current findings of climate change beliefs in Sweden, which is also presented within this section. We finalize the section by placing our study in relation to the chosen body of literature and presenting our contribution to the same.

3.1 Climate Finance

Climate finance is defined by the UNFCCC (n.d.., para. 1) to be: "*local, national or transnational financing—drawn from public, private and alternative sources of financing—that seeks to support mitigation and adaptation actions that will address climate change*".

In other words, it is about investments that households, governments, and corporations must undertake to change the path to a low-carbon economy and to build resilience to climate change (Hong, Karolyi, & Scheinkman, 2020). The European Commission estimates that to achieve a net-zero greenhouse gas emissions by mid-century in the European Union, the energy systems and its related infrastructure would have to rise to two-point eight percent of GDP from two percent today. This would require additional investments between €175 and 290 billion a year (European Union, 2019). Estimations for the U.S. are comparable (Hong, Karolyi, & Scheinkman, 2020). In the absence of both mitigation and adaption, a report issued by USGCRP (2018) forecast that this would reduce up to ten percent of the American economy by the end of the century. These large estimations illustrate the significant risks of climate change for companies, capital markets, and in turn, investors (Hong, Karolyi, & Scheinkman, 2020). For example, a study by Kelly et al. (2015) concluded that investors could offset approximately half of the negative impacts of climate change. This can be achieved by investing in assets that exhibit low climate change risk and, including different asset classes in the portfolio, and diversifying internationally. As summarized by at the UN Investor Summit on Climate Risk in January 2016 by the UN secretary-general, Ban Ki-Moon (United Nations, 2016, para. 39):

" . . . Investors need to know how the impacts of climate change can affect specific companies, sectors and financial markets as a whole."

The central questions that underline these concerns is how the damages from climate change should be distributed and in what way societies should price and mitigate risk from global emission. The next question is if capital markets can assess the price of the climate risk and raise the capital that possibly could help households and institutions to hedge the risks (Hong, Karolyi, & Scheinkman, 2020). The answers to these questions are subject to the beliefs and expectations that agents in the economy hold. For instance, characterizing the beliefs of investors is vital to the efficient market debate that concerns the pricing of climate risk (Hong, Karolyi, & Scheinkman, 2020).

3.2 Limited Attention

The standard models of asset pricing rely on the assumption that an investor's decisions are made by utilizing all available information and incorporating new information instantly (Shleifer, 2000). Thus, the price changes of tomorrow reflect solely tomorrow's news and are not dependent on today's price fluctuations. News are unpredictable, and therefore, the price change of tomorrow must be random. Hence, price changes should be as unpredictable as the information content itself (Malkiel, 2003).

This assumption contradicts findings in a large body of the behavioral economics literature, which suggests that individuals often overlook and do not incorporate all relevant information when making decisions (Lim & Teoh, 2010; Barber & Odean, 2008; Kahneman & Tversky, 1972). The failure to incorporate all relevant information in decision making can be ascribed to our cognitive constraints and the immense amount of information available to us (Lim & Teoh, 2010). Attention requires effort, and because of our limited attentive resources, we must be selective in our allocation of attention. As expressed by Nobel Laureate in Economics, Herbert A. Simon (1971, p.40-41):

"What information consumes is rather obvious: it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it."

Hence, limits to attention can bare consequences to asset pricing, as investors only use a subset of available information both when valuing a stock and in the portfolio choice (Lim & Teoh, 2010; Barber & Odean, 2008). Studies have found that when faced with the choice of an immense amount of stocks, the individual investors will, due to their limits to attention, narrow their choice set to stocks that recently caught their attention (Barber & Odean, 2008; Odean, 1999). Barber and Odean (2008, p. 786) rationalize that: *"Investors do not buy all stocks that catch their attention; however, for the most part, they only buy stocks that* do so". In contrast, individual investors do not engage in short selling to the same degree as institutional investors and will only tend to sell stock they already own. As a consequence, Barber and Odean (2008) found that individual investors become net-buyers of attention-grabbing stocks, which generates attention-driven buying pressure, resulting in higher stock prices in the short-run followed by long-run reversals.

Furthermore, Hirshleifer and Teoh (2003) argue that the amount of attention we allocate toward an aspect does not need to be correspondent with its actual importance for the task at hand. In other words, attention can be misdirected. For example, agents tend to underweight abstract and statistical information (Hirshleifer & Teoh, 2003; Tversky & Kahneman, 1973). This tendency can lead to a neglect of relevant information, which impacts asset prices. An example is found in a study by Peng and Xiong (2006), who consider the impact of limited attention on asset price dynamics. They find that an investor with limited attention tends to allocate more attention to market level and sector level factors than to firm-specific factors.

Attention allocation

Because limited attention puts constraints on what we can be attentive towards and might result in misdirected attention, it is central to understand what captures our attention. According to Lim and Teoh (2010), the attention allocation of an individual is largely dependent on the characteristic of the information, i.e., some stimuli are more easily perceived and processed than others. More specifically, the salience of a stimulus is an important denominator for our attention to be captured by it. The salience effect is evident in multiple studies performed on financial markets. For example, Huberman and Regev (2001) find that the salience of a New York Times article on advances in cancer research caused the stock price of the company with drug-licensing rights to soar. The dramatic impact occurred despite the fact that other journals and newspapers had reported the story months earlier. Similarly, Klibanoff, Lamont, and Wizman (1998) find that the price-elasticity of closed-end country funds temporarily rises when country-specific news appears on the front page of the New York Times. They conclude that the salience of the news story causes investors to react more to fundamentals. The salience of certain stimuli is also linked to narrow framing by investors (Lim & Teoh, 2010). For example, studies find that individual decision-making differs between problems framed as losses contra problems framed as gains (Kahneman & Tversky, 1979). This framing bias naturally extends to financial decision-making and risk perceptions, as investors will focus more on loss rather than other risk-measures, such as variance (Lim & Teoh, 2010).

Furthermore, DellaVigna and Pollet (2007) find that investors are often inattentive to less salient and less accessible long-term effects, but attentive to the more salient short-term effects. By forecasting future demand through demographic data and lagged consumption in age-sensitive sectors, they find that the demand changes for five to ten years into the future predicted annual industry stock returns. In contrast, shorter forecasts did not (DellaVigna & Pollet, 2007). The finding is similar to the frog-in-the-pan anecdote, which was hypothesized by Da, Gurun, and Warachka (2014). Specifically, the frog-in-the-pan anecdote entails that a frog will instantly react and jump out of a pan of boiling water. However, if the frog is put in a pan with cold water that is slowly heated to a boiling point, the frog won't react (Da, Gurun, & Warachka, 2014). By hypothesizing the same tendencies with investors and continuous- contra discrete information Da, Gurun, and Warachka (2014) find that, consistent with the frog in the pan, investors seem to underreact to continuous information.

Finally, as attention to one task requires a substitution from other tasks, information may be lost in the noise of competing information (Lim & Teoh, 2010). Therefore, attention allocation is also dependent on the characteristics and number of competing stimuli in the environment (Lim & Teoh, 2010). This is evident in the findings of Hirshleifer, Lim, and Teoh (2009). They examine investor reaction to earnings news when distracted by a large amount of other companies' earnings announcements on the same day. When doing so, they find that when competing announcements are made, there is a weaker same-day price and volume reaction to the own firm's announcement (Hirshleifer, Lim, & Teoh, 2009).

Attention allocations influence on judgment

As described above, Lim and Teoh (2010) argue that attention allocation is affected by the ease with which an individual can access and process information. Further, accessibility and processing ease is connected to the salience of a stimulus. Hirshleifer and Teoh (2003) argue that the salience of an event impacts both judgments of the importance of a stimulus and causality. This is also found in the several studies presented above. Limits to attention and processing power can also impact decision-making due to heuristics, which will be elaborated on in the following paragraphs. More specifically, we will move from the focus on what captures individuals' attention to how limited attention impacts individual judgments through the heuristics. Kliger and Kudryavtsev (2010) explain that when people make decisions, they tend to search for rules (heuristics) that simplify the process of solving a problem and, simultaneously, take the relevant information into account. These heuristics often result in a simplification of the problem and irrational behavior. For instance, people overvalue some information while disregarding others (Kliger & Kudryavtsev, 2010).

The first heuristic that we will consider is the availability heuristic. This heuristic implies that individuals evaluate the likelihood or frequency of an event by the ease with which they can access corroborative memories of similar events (Tversky & Kahneman, 1973). Thus, when making decisions, people tend to consider past experiences, even when it is irrelevant for the present and future (Kliger & Kudryavtsev, 2010). In other words, people estimate the likelihood of an event based on how easy it is to imagine. This can be exemplified with the event of a car accident: an individual who has observed a terrible car accident will judge the likelihood of such an event higher than a person who has not, even if they both have access to the same statistical information. Moreover, recent memories are more available than older memories (Deryugina, 2013). Another exemplification of the heuristic is found by Kliger and Kudryavtsev (2010). In their study, they find that the stock market reacts positively and stronger to recommendation upgrades when accompanied by positive stock market index returns. While they react negatively and stronger to recommendation downgrades when it is accompanied by negative stock market index returns.

The second heuristic is similar to the first and is the representativeness heuristic. An individual that follows this heuristic will judge a probability of an event (or object) by how representative it is in relation to other events (or objects). In other words, the likelihood of an event is determined by the extent it: *"(i) is similar in essential characteristics to its parent population; and (ii) reflect the salient features of the process by which it is generated*" (Kahneman & Tversky, 1972, p. 431). For example, the probability of an event A will be judged more in relation to event B if A appears more representative than B (Kahneman & Tversky, 1972). Thus, an error in judgment is made since representativeness does not imply that the event A is more probable than B.

The third relevant heuristic of this thesis is attribute substitution. This entails that individuals use less relevant but more easily accessible information rather than more diagnostic but less available information (Duan & Li, 2019). This heuristic implies that when people are confronted with a difficult question, they often answer a simpler one instead, without realizing that a substitution has taken place (Kahneman & Frederick, 2002). Thus, the substitution that occurs introduces systematic biases in the decision-making process where an attribute is influenced by how difficult (or easy) the information is accessible (Koutsobinas, 2014). Kahneman & Frederick (2002) exemplifies the heuristic with an illustrative example of a study by Strack, Martin, and Schwarz. In their research, college students were asked two questions. The first question was, "*How happy are you with your life in general?*" and the second was, "*How many dates did you have last month?"* (Strack, Martin, and Schwarz, as cited in Kahneman & Frederick, 2002, p. 53). The relationship between the questions is insignificant when asked in this order. However, the correlation rose by 0.66 when the dating question was asked first. Thus, the answer to how happy a person is about their life is influenced by their dating life if the latter is asked first, i.e., general happiness is substituted by the attributes of the individuals dating life.

Measurements of attention

Until now, we have gone through what limited attention is and how it influences individuals. Another important consideration is how to measure attention, as the psychological findings on individual attention are not necessarily easy to capture empirically. More specifically, due to the lack of an unequivocal measure of investor attention, the attention of investors must be indirectly proxied by some existing measures. Naturally, this has presented some challenges to research and, as a consequence, proxies vary across studies. For example, the earlier mentioned study by Klibanoff, Lamont, and Wizman (1998) uses media coverage as a proxy for investor attention. This is also done by Choi, Gao, and Jiang (2020) who, among other proxies, uses the Raven Pack News Analytics scoring of company-specific news stories to proxy for attention. In a criticizing article, Da, Engelberg, and Gao (2011) mention additional attention proxies ranging from extreme returns and trading volume to advertising expenses. In response to the indirect nature of all of these attention proxies, Da, Engelberg, and Gao (2011) instead propose a more direct measure of attention: Google SVI on Google trends. Through their findings of Google SVI's impact on asset prices, they argue that Google searches are different from, but correlates with other attention proxies. Moreover, they argue that the measure primarily captures retail investor attention. As an extension to the endeavor of finding direct attention measures for other investor groups, Ben-Rephael, Da, and Israelsen (2017) propose the use of reading activity and news searching scores provided for Bloomberg terminal news as a proxy for institutional investor attention.

Main findings of the sub-section

The salience, accessibility, and competing stimuli are important determinants for the allocation of individuals' attention. Furthermore, this is argued to have an influence on investor judgment through related heuristics. Because of these attention-tendencies, investors will only impound information into prices when its relevance for the valuation becomes more salient and easy to process and/or when there are less competing stimuli in the environment (Lim & Teoh, 2010). This could bare consequences for the way investors form their beliefs on climate change and the subsequent pricing of climate-sensitive assets. Therefore, the next section will review climate change research on both the mechanisms behind climate change belief-formation and the pricing effects of the same.

3.3 Evidence from Climate Change Research

Recent studies within Climate Finance argue that beliefs regarding climate change affect asset pricing (Hong, Karolyi, & Scheinkman, 2020; Baldauf, Garlappi, & Yannelis, 2020; Choi, Gao, & Jiang, 2020). Hong, Karolyi, and Scheinkman (2020) emphasize that the perceptions and beliefs regarding climate change are vital denominators for an individual's potential to assess the price of climate risk. Similarly, Krueger, Sautner, and Starks (2019) survey global institutional investors on climate risk perception. They find that institutional investors believe that climate risks have important financial implications for their portfolio firms. Further, institutional investors believe climate risks, especially those related to regulation, have already begun to materialize. In addition, many investors report that they do take actions related to climate risks. They also found that these institutional investors believe that equity valuations in some sectors do not fully reflect the climate risks (Krueger, Sautner, & Starks, 2019).

The proposition that beliefs about climate change affect prices is also confirmed by Baldauf, Garlappi, and Yannelis (2020). They found that real estate prices are influenced by the differences in beliefs regarding climate risks. More specifically, houses that were projected to be underwater as a consequence of climate change sell at a discount in areas where people believe in climate change compared to houses with the same projected future in climate change denier areas. A simple conclusion explains the result: prices will only be affected when we believe in the occurrence and effects of climate change (Baldauf, Garlappi, & Yannelis, 2020). Finally, in relation to the topic of climate risk, the findings by Addoum, Ng, and Ortiz-Bobea (2020) are worth mentioning. They examine how climate risks impact the performance of U.S. companies. More specifically, they examine the impact of increased temperatures on sales and productivity. They find that neither abnormally warm nor abnormally cold weather affects establishment sales or productivity. They conclude that the only evidence of a sales effect caused by abnormal temperatures in the U.S. market is found in the energy industry, while temperatures are abnormally cold.

Research within climate change has examined how beliefs are formed on the topic. In a study by Zaval et al. (2014), it was found that personally experiencing temperature abnormalities increases the perception of climate risks due to attribute substitution. As mentioned in the previous section, attribute substitution entails that individuals use less relevant but more easily accessible information rather than more diagnostic but less available information (Duan & Li, 2019). In other words, Zaval et al. (2014) find that the experience of abnormal temperatures is more accessible than, for example, the more diagnostic climate science, which leads people to substitute the latter for the former. Moreover, Zaval et al. (2014) argue that current temperature abnormalities cause an overestimation of the weight and frequency of similar past events. This conclusion can be linked to the earlier mentioned availability heuristic, where individuals evaluate the probability or frequency of an event by the ease with which they can access corroborative memories of similar events (Tversky & Kahneman, 1973). The presence of heuristic belief updating connected to temperature fluctuations is also found in a study performed by Deryugina (2013). While there seem to be parts of the updating process that are consistent with rationality, Deryugina (2013) finds evidence of both representativeness and availability heuristics in climate change belief formation. In addition, it is found that only longer temperature fluctuations of a month up to a year will predict beliefs, while shorter fluctuations have no effect.

In a similar quest, Konisky, Hughes, and Kaylor (2016) examine the effects of experiencing extreme weather events and concern about climate change. They find that there is a relationship between the two, given that the weather event is recent. Contradictory to the finding of Deryugina (2013), they find that weather activity that has occurred over longer time horizons than one month does not affect public opinion (Konisky, Hughes, & Kaylor, 2016). The tendency to be inattentive toward longer-term weather events has similarities to many of the previously mentioned limited attention findings. For instance, the findings of Da, Gurun & Warachka (2014) where investors seem to underreact to continuous information and the findings of DellaVigna and Pollet (2007) who conclude that investors are often inattentive to less salient and less accessible long-term effects, but attentive to the more salient short-term effects. The impact of salience on climate change risk perception is confirmed by Alok, Kumar, and Wermers (2020). They find that professional money managers overreact to large climatic disasters that happen close to them. These local investors make wrongful estimates of the climate risks and underweight disaster zone stock to a larger degree than distant mutual fund managers. Another related perspective to people's belief updating process is the media coverage on the topic. It has been found that it is a central factor in people's understanding of the issue

(Boykoff & Roberts, 2007). Interestingly, Schmidt (2015) finds that media coverage of climate change appears to be higher in years that are warmer than in previous years.

One can argue that observing and experiencing climate change would be difficult considering its long-term trending nature. However, a large proportion of research has found support for the claim (Borick & Rabe, 2014; Akerlof et al., 2013; Howe et al., 2013). In a survey study in Michigan performed by Akerlof et al. (2013), it was stated by 27 percent of the respondents that they had experienced climate change (Akerlof et al., 2013). The most frequently mentioned perceived personal experiences of climate change were "Seasons" and "Weather." Moreover, Akerlof et al. (2013) argued that these experiences affected beliefs of climate change and increase risk perception, presumably through a combination of direct experience, vicarious experience, and social construction (Akerlof et al., 2013).

Furthermore, in an international survey, Howe et al. (2013) also study when individuals recognize that they have experienced climate change. Consistent with the findings of Akerlof et al. (2013), they find that individuals who experience an increase in local average temperatures are more likely than others to recognize local warming (Howe et al., 2013). Their findings suggest that personally experiencing an increased average local temperature may shift the perception of climate change. Similarly, Borick and Rabe (2014) found that weather-related factors are, by individuals, frequently used as an explanation for their belief that the planet is either warming or not warming.

Recent literate has also examined how these experience-based beliefs regarding climate change impact individuals' actions. Accordingly, Li, Johnson, and Zaval (2011) find that both belief-formation and action is likely to be influenced by heuristics. Through surveys performed in the U.S. and Australia, they find that respondents who considered the survey day warmer than usual believed more in global warming and had greater concern about it than others. Furthermore, respondents were also more likely to donate larger amounts of money to a global warming charity when perceiving deviations from normal temperature. Hence, they find that climate change beliefs and actions incorporate irrelevant but salient information about temperature. A similar pattern is found by Broomell, Budescu, and Por (2015). Through an international survey, they measure the willingness to engage in or endorse specific climate change mitigation actions. They find that personal experience of climate change is strongly related to the willingness of engagement and a driver of climate mitigation actions.

Finally, a very relevant study for this thesis is, as previously mentioned, the study by Choi, Gao, and Jiang (2020). Therefore, we will provide an extensive explanation of their climate change research in the following paragraphs. Choi, Gao, and Jiang's (2020) study is based on the concept of limited attention. Accordingly, they find that people pay more attention to climate change and revise their beliefs upward when experiencing high local temperatures. Using data from 74 exchange cities, they document that attention to global warming increases when the local temperature is abnormally high.

Furthermore, Choi, Gao, and Jiang (2020) also find that stocks classified as low emitting outperform stocks classified as high emitting in abnormally warm weather. This occurrence is further analyzed by looking at reactions to abnormal temperatures in different investor groups. They argue that retail investors are more prone to individual biases than institutional investors and blockholders. Consequently, these three investors group is examined in the article. They find that local retail investors sell high-emission firms and buy low-emission firms when experiencing these conditions. Through a series of robustness tests, they conclude that this occurrence is unlikely to be motivated by changes in firms' fundamental value. Further, local blockholders trade in the opposite direction of retail investors, while local institutional investors do not respond systematically to abnormal temperatures. The outperformance by low emitting stocks is by Choi, Gao, and Jiang (2020) explained by the retail investors' upward revision of beliefs caused by the perceived personal experience of global warming. However, Choi, Gao, and Jiang (2020) open up for the possibility that when collective beliefs are close to the scientific consensus, the relationship between attention, stock prices, and local abnormal temperatures could be weakened. Further, they argue that the equity home bias explains the reason why abnormally warm temperatures impact local investors and stock prices. Therefore, this theory will be further reviewed in the next section.

3.4 Home Bias

Modern portfolio theory assumes that investors aim to maximize their expected utility and thus optimize the expected return for a given amount of risk. Further, in the financial literature, it is well known that there exists a benefit of international diversification of equity portfolios. Since there is a positive correlation within an economy, one could reduce the portfolio risk by diversifying internationally (Solnik, 1974). The optimal risk-return profile is referred to as the world-market portfolio of securities and consists of securities that are diversified internationally, with proportion to their market share of the global economy (Eldor, Pines, & Schwartz, 1998; Tesar & Werner, 1995; Solnik, 1974). Therefore, globally diversifying generates a better risk-return profile in relation to a domestic portfolio since the global capital market bears less systematic risk than a country's internal capital market (Solnik, 1974).

In this context, the tendency of investors to allocate a greater share of their portfolio to domestic securities rather than foreign ones is contrary to the modern portfolio theory. This is known as the "home bias", and this phenomenon is costly after considering the higher risk of the under-diversified portfolio implied by the overweighting of domestic shares (French & Poterba, 1991). One of the first studies of the home bias was conducted by French and Poterba (1991). They revealed that investors worldwide exhibit a strong bias toward domestic shares. For example, American equity traders invest around 94 percent in national securities, even if the U.S equity market covers below 48 percent of the global equity market. More recently, Sercu and Vanpée (2008) illustrate that home bias is present worldwide by measuring the intensity of the ratio of domestic equity relative to the market capitalization. For instance, the study found that in Sweden, more than 60 percent of the equity portfolio is invested in domestic securities. Thus, even if markets have become more integrated and barriers to international investments have fallen in comparison to the pioneer study by French and Poterba (1991), countries still continue to hold significantly biased equity portfolios (Kang & Stulz, 1997). As stated by Kang and Stulz (1997, p. 4):

"*Financial Economists have noticed that even though the barriers to international investment have fallen dramatically, foreign ownership of shares is still extremely limited and much smaller than one would expect in the absence of barriers to international investment*."

Over time the financial literature has provided different explanations for why investors seem to neglect the so-called "free lunch" of diversification. However, academia has far from agreed whether the phenomenon is driven by rational or behavioral reasons. For example, Huberman

(2001) argues that the reason for the home bias is that people feel comfortable to invest their money in the familiar and often overlook the principles of portfolio theory. Coval and Moskowitz (1999) found that in the U.S., investment managers favor investments in locally headquartered firms. They argue that this bias is motivated by informational advantage instead of familiarity after discovering that the local holdings tend to be in small firms with a high degree of leverage. Consistent with the belief, Bae, Stulz, and Tan (2008) investigate if distance impacts the quality of the information held by analysts. Using an international sample of 32 countries and controlling for both firm and analyst features, they find a local analyst advantage. Thus, the result suggests that local analysts have better information in relation to foreign ones since local analysts generate more accurate forecasts.

Regardless of the underlying motives, investors' preference for domestic securities is found to create an overrepresentation of local investors in financial markets globally. As a result, the prices of securities are affected by these local investors. For example, Shive (2012) finds that during power blackouts, when trading is probably prevented for those in the affected area, firms with headquarters in the area are affected. Specifically, the share turnover of these firms decreases by three to seven percent in addition to a price volatility drop on days of blackouts. This is in line with the argument that local investors own a greater number of shares in local stocks and influence stock prices. Another example is a study by Chan, Hameed, and Lau (2003). In their study, they find that prices of securities are impacted by country-specific investors' sentiment. More specifically, they find that the Jardine Group stock, after moving the trading activity to Singapore from Hong Kong, correlated less with the Hong Kong market and more with Singapore's market after the move. The core business was still in Hong Kong and Mainland China, while the stock was traded in Singapore. If markets were integrated, the trading location should not influence the stocks trading behavior (Chan, Hameed, & Lau, 2003).

3.5 Sweden and Climate Change

The thesis is based on the Swedish market and, therefore, this section introduces the Swedish citizens' beliefs on the topic. Ultimately, the section functions as a complement to our study in order to enable a deeper interpretation of results in the Swedish market compared to international findings. First, we will shortly describe the changing climate in the country. Then, we will introduce the media coverage on the topic in recent years. Finally, we will present nationwide surveys conducted on climate change beliefs.

The poles are warming at a faster speed than the rest of the planet. As a result, the yearly change in the average temperature is higher in Sweden than the average change of the rest of the world Swedish Meteorological and Hydrological Institute (SMHI, 2020a). This occurrence is exemplified in the figure 2, by comparing the average annual temperature in 2019 to the long-term average (1901- 2000).

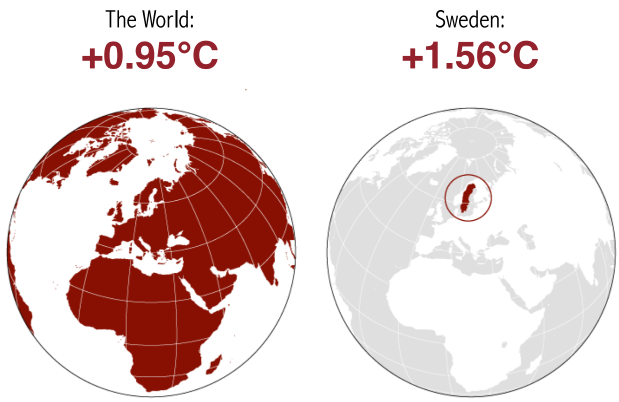

Figure 2: The average annual temperature in Sweden compared to the world. Data sources: Globe illustration from (Dagens Nyheter, 2020), climate data from Lindsey and Dahlman (2020), and SMHI (2020b).

As shown in the illustration, the surface temperature in Sweden has risen with 1.56°C, while the global land and ocean surface temperature increased with 0.95°C in 2019. This increasingly changing climate has, in recent years, been heavily covered by the Swedish media. Retriever (2020) has, in the six most recent years, examined the media coverage of climate change in Sweden. As illustrated in table 1, the total number of articles on climate change has increased considerably in from 2014 to 2019.

Year	Total no. of articles		Business newspapers	
	No. of articles	Trend	No. of articles	Trend
2014	41,875	-	877	-
2015	53,852	29%	1,497	71%
2016	52,426	-3%	1,892	26%
2017	61,121	17%	2,282	21%
2018	84,647	38%	2,678	17%
2019	145,824	72%	4,610	72%

Table 1: Climate change articles published between 2014 and 2019. Data source: Retriever (2020).

As shown in the figure above, the number of articles on the topic of climate change has increased by 72 percent from 2018 to 2019. The total number of articles on the topic was 150,000, and 4,610 articles were published in business newspapers. This makes the climate change, by far, the biggest news topic in the Swedish media in 2019 (Retriever, 2020), Additionally, the climate activist Greta Thunberg is the most mentioned person in the media, including in business newspapers headlines, in 2019. The year before, when she started to strike for the climate, she was on place eleven (Retriever, 2020).

Nationwide Surveys

The following paragraphs will complement our empirical study with three nationwide surveys conducted by institutional organizations on how the population views climate change. This enables us to deepen the understanding of people's beliefs in the country.

First, a nationwide survey is carried out by the SOM Institute every year in the form of a mail questionnaire to randomly selected people in the age group between 16 to 85 that live in Sweden. The survey consists of several sub-surveys, which comprise of approximately 3,500 respondents per survey. Since 2001, a survey regarding the concern about climate change has been conducted (SOM Institute, 2019).

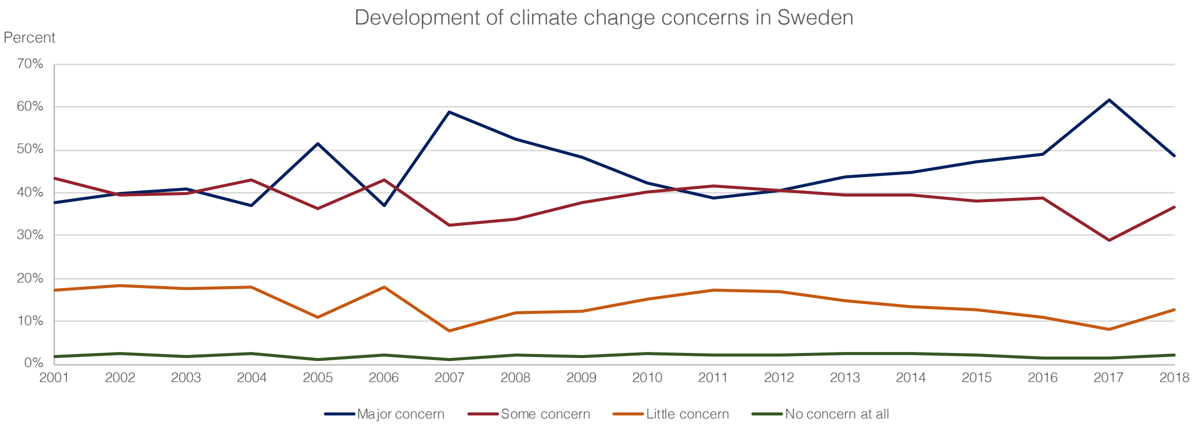

Figure 3: Development of respondents' concern about climate change from 2001 to 2018 in Sweden. Own creation. Data source: University of Gothenburg, SOM Institute (2020).

As shown in figure 3 above, since the survey started in 2001, more than 30 percent of the respondents have stated that they are very concerned about climate change. In 2017, more than

60 percent stated the same, representing the highest level in the survey period. In 2018 there where drought, forest fires, and Greta Thunberg initiated school strikes for the climate. However, as shown in figure 3, the proportion of very concerned respondents decreased by 20 percentage points in the same year. Nevertheless, the proportion of very concerned respondents is still the second-highest in the decade.

The second nationwide survey that covers climate change is conducted by Kantar Sifo, and the results are presented in a report by Wennö and Söderpalm (2020). The web survey includes randomly selected people in the age group between 18 to 79 that live in Sweden. The number of respondents was 2,101. There are several interesting findings in the survey related to the topic of this thesis. First, the survey finds that those who do not believe in climate change, the so-called "climate deniers", are only three percent of the respondents. Furthermore, less than 40 percent of the respondents knew what the two largest emitters in Sweden were (Wennö & Söderpalm, 2020). Another interesting finding in the survey is illustrated in figure 4. The respondents were asked to what degree they were concerned about several climate change effects. The percentages of the respondents that answered that they were highly concerned about the listed effects of climate change are displayed in the figure below.

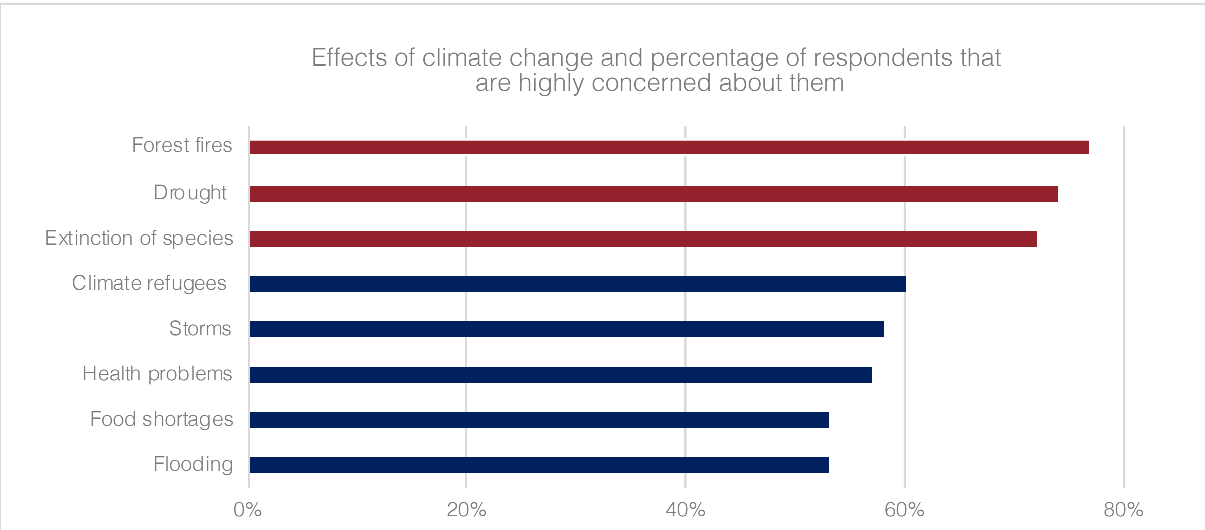

Figure 4: Effects of climate change and percentage of respondents that are highly concerned about them in 2019. Data source: Wennö and Söderpalm (2020).

As shown in the figure, the respondents are most worried about wildfires, drought, and extinction of species. Wennö and Söderpalm (2020) argue that it is most likely explained by the drought and forest fires in the country the year before and the intensive media surveillance on the topics. The high level of fear of extinction of species is also a topic that has been discussed extensively in the media in Sweden in the past year. The effects that the public is least worried about is flooding and food shortages. Common to these two topics is that there are effects that are more likely to occur elsewhere in the world than in Sweden.

The last survey that this thesis will cover is conducted by the European Social Survey (2018) that examines public views towards climate change in European countries. The fieldwork was conducted between 2016 to 2017, and it consisted of 44,387 respondents from 23 different countries. The respondents were asked whether they think the world's climate is changing. The percentages of the respondents that answered that climate is probably or definitely changing are displayed in figure 5.

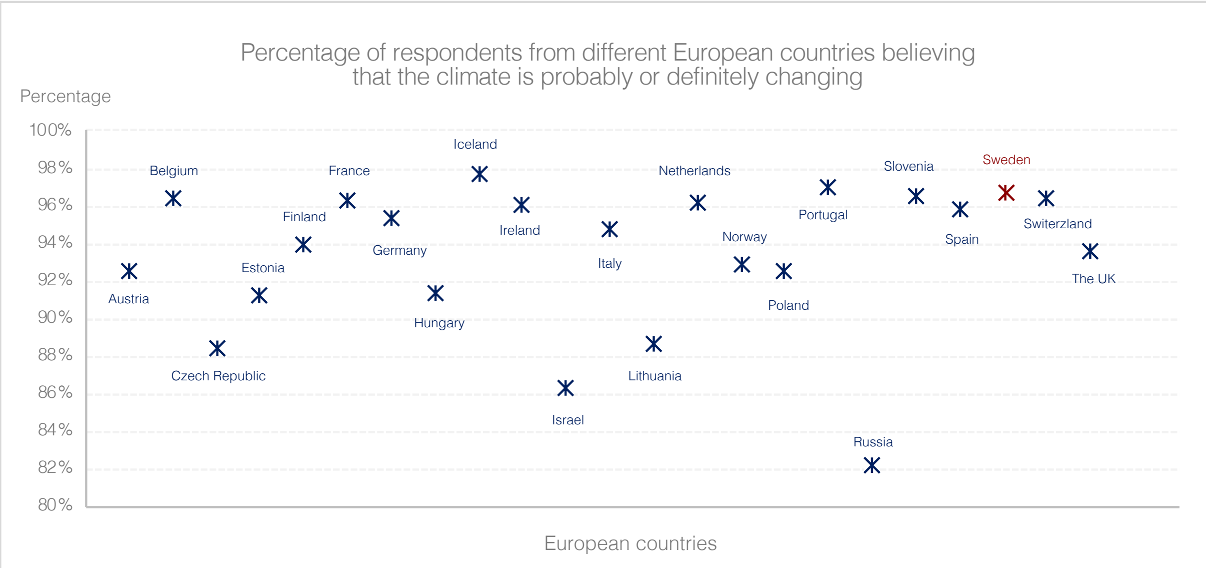

Figure 5:Percentage of respondents from different European countries believing that the climate is probably or definitely changing between 2016 and 2017. Own creation. Data source: European Social Survey (2018).

As shown in figure 5, 96.80 percent of the respondents in Sweden believe that the climate is probably or definitely changing. That makes the country one of the top three European countries believing that the climate is changing in the years 2016 to 2017. The average percentage of the respondents believing in climate change was 93.40 percent, and the answers vary from 82.20 percent in Russia to 97.70 percent in Iceland. Furthermore, the same question was asked in a different nationwide survey study (n>18.000) on the other side of the Atlantic by Marlon et al.

(2016). They found that in the U.S, only 70 percent of the respondents believed that climate change was occurring in 2016.

3.6 Contribution

The climate science is clear: humans are causing an increase in global temperature, and it has severe consequences (IPCC, 2018a; Kelly et al., 2015). As the increasing temperature poses risks to all layers of society, not least the financial, the phenomenon has given rise to the research field of Climate finance (Hong, Karolyi, & Scheinkman, 2020). A crucial part of the field is the study on how individuals form their perceptions and beliefs about climate change. This is not only important to policymakers in order to efficiently drive political processes toward mitigation, but also to the stability of our financial markets. In the year 2020, Choi, Gao, and Jiang released an acknowledged study on investor belief formation when it comes to climate change. Their international study suggests that the experience of local abnormal temperatures caused investors to pay more attention to climate change and to revise their beliefs about climate change. They find that the local investor belief-revision impacted the prices of local stock because of the home bias. However, the specific impact on individual countries is still unknown. Therefore, this thesis aims to fill this research gap in Climate finance by studying how investors realize and respond to climate change in Sweden. Up until now, studies on climate change beliefs in Sweden has, to our knowledge, only been conducted through surveys. Furthermore, Sweden is unique in many aspects with regard to climate change. First, the temperatures around the poles increase faster than the rest of the world (SMHI, 2020a). Secondly, concerns and beliefs about climate change are higher in Sweden than in many other countries (European Social Survey, 2018).

By examining the tendencies found by Choi, Gao, and Jiang (2020) in Sweden, we contribute to many research aspects. First, we add to the current research on climate change beliefs in Sweden by examining the local warming effect, which, to our knowledge, is domestically unexplored. Second, we contribute to the same field by narrowing the scope toward the under-researched area of investors' climate response in the Swedish market. Third, we extend the international findings of Choi, Gao, and Jiang (2020) with our in-depth analysis of a specific country, which enables complementary conclusions on the country-specific impact of local abnormal temperatures. Finally, our research contributes to the larger purpose of disentangling the climate change issue by looking at the important mechanisms at work in the financial market. Thus, as presented in our introductory section, this thesis aims to answer the following research question and following sub-questions:

> *"To what extent, if at all, does abnormal temperatures affect equity investors' realization and response to climate change in Sweden?"*

(i) What is the international evidence on temperature influence on investors' attention and beliefs towards climate change?

(ii) What is the evidence from Sweden on temperature influence on investors' attention and beliefs towards climate change?

(iii) If these differ, what could be the explanation between the diverse findings?

4. Methodology

The following section will describe the data collection process, as well as our methodological approach. The starting point will be a concise description of the research design. This is followed by a formulation of the hypotheses that guide the empirical research. Then, we will describe the data collection process, which culminates in the regression methodology that the thesis has applied.

4.1 Research Design

With a basis in positivist philosophy, we set out a three-part analysis and aim to investigate the relationships between abnormal temperature and investor realization and response to climate change in Sweden. At the core, we are testing the recent findings of Choi, Gao, and Jiang (2020) on a national level and in a more recent time setting. Our approach is consistent with the positivist philosophy, as we apply an objective lens in our evaluation of reality, assuming that observable data can fully portray the phenomenon. In doing so, we follow a deductive approach that allows for hypothesis development and discussions in light of previous findings and enables comparability between our national findings and the international findings of Choi, Gao, and Jiang (2020). The quantitative form of our research method is based on an extensive data sample, where we evaluate our hypotheses by examining links between abnormal temperature and investor attention, stock returns, and different investors' trading activity.

To ensure the internal validity of our research, we have conducted a well-designed research that carefully measures the phenomena. We based our study on data from high-quality data providers FactSet, Thomson Reuters, Google Trends, and Swedish Meteorological and Hydrological Institute. Our study sample size is also large, and we apply established proxies based on research published in top journals. This ensures that our observed findings represent the population that we are examining and ensure internal validity (Druckman et al., 2011). Further, our study is not set up for a generalized conclusion, this would require a global sample. Thus, external validity is not a goal of the research. Finally, by following a strict methodological approach, we can ensure that the results are replicable for the Swedish market in the same time horizon, which confirms reliability.

4.2 Hypothesis Development

Our overall research question is grounded in the idea that abnormal temperatures could affect investor realization and response to climate change. This assumption is nested in existing theory on limited attention, biased belief updating processes, and home bias.

Because of human's limited attention, Lim and Teoh (2010) argue that attention allocation is affected by the ease with which an individual can access and process information. Accessibility and processing ease are primarily determined by the salience of the information and the characteristics and number of competing stimuli in the environment (Lim & Teoh, 2010). DellaVigna and Pollet (2007) find that investors are often inattentive to less salient and less accessible long-term effects, but attentive to the more salient short-term effects. Incorporating this tendency into a climate change setting, the finding suggests that there may be inattentiveness toward the long-term trending effect of climate change. Further, the experienced short-term effects of climate change, such as abnormal temperatures, could grant more attention. Howe et al. (2013) find that individuals who experience an increase in local average temperatures are more likely than others to recognize climate change. Hence, people are prone to mis-associate abnormal temperatures with the climate at large. Therefore, experiencing salient abnormal temperatures could increase investor attention toward climate change. This form the first hypothesis:

(i) H_A: Abnormal temperatures impact Swedish investors' attention towards climate change.

Further, Choi, Gao, and Jiang (2020) found that the highest level of abnormal temperatures increased investor attention. Thus, a higher level of abnormal temperature might be the most salient. This leads to our second hypothesis:

(ii) H_A: The highest level of abnormal temperatures does impact Swedish investors' attention towards climate change to a larger degree than the other temperature levels.

Moreover, our limited attention can give rise to cognitive biases that influence beliefs and decision-making. Existing climate research suggests that temperature abnormalities influence our risk perceptions and beliefs about climate change (Choi, Gao, & Jiang, 2020; Zaval et al., 2014; Li, Johnson & Zaval, 2011). Since abnormal temperatures seemingly affect climate change beliefs and investors trade on their beliefs, abnormal temperatures could also impact stock prices. It is important to note that only local investors would experience the temperature shocks that could influence beliefs and actions. However, due to the home-bias, local investors influence the prices of local stock (Shive, 2012; Chan, Hameed & Lau, 2003). If local investors adjust their beliefs when experiencing temperature abnormalities, they may choose to sell stocks that are sensitive to climate change and buy stocks with lower sensitivity to climate change (Choi, Gao & Jiang, 2020). Moreover, Choi, Gao, and Jiang (2020) claim that this could occur to the extent that the latter outperforms the former. Similarly, Li, Johnson, and Zaval (2011) claim that experiencing abnormal temperatures increase the willingness to engage in mitigation action. This suggests that abnormal temperature could also lead investors to avoid stocks that they perceive as harmful to the climate. This forms the third hypothesis:

(iii) H_A: Abnormal temperatures impact stock return in high and/or low emission firms.

In conformity with the reasoning in the second hypothesis, we also examine whether a potential effect is nonlinear. Our fourth hypothesis is the following:

(iv) H_A: The highest level of abnormal temperatures does impact stock returns in high and/or low emission firms to a larger degree than the other temperature levels.

Furthermore, there are reasons to believe that different investor groups would react differently to the experience of abnormal temperature. Choi, Gao, and Jiang (2020) argue that retail investors are more prone to individual biases than institutional investors and blockholders. Therefore, to gain a deeper understanding of whether abnormal temperatures influence different investor types' trading behavior in high and low emission firms, three hypotheses are formed:

(v) H_A: Abnormal temperatures impact local retail investors' average net buy of high and/or low emission firms.

(vi) H_A: Abnormal temperatures impact local institutional investors' average net buy of high and/or low emission firms.

(vii) H_A: Abnormal temperatures impact local blockholders' average net buy of high and/or low emission firms.

In conformity with previous hypotheses, we test whether the potential effect is nonlinear with our last hypotheses:

(viii) H_A: The highest level of abnormal temperatures has a larger impact on local retail investors' average net buy of high and/or low emission firms than the other temperature levels.

(ix) H_A: The highest level of abnormal temperatures has a larger impact on local institutional investors' average net buy of high and/or low emission firms than the other temperature levels.

(x) H_A: The highest level of abnormal temperatures has a larger impact on local blockholders' average net buy of high and/or low emission firms than the other temperature levels.

4.3 Data collection and Processing

In accordance with the hypothesis development of the thesis, we attempt to uncover the three subsequent areas in order to answer our overall research question:

i) The relationship between abnormal temperature and investor attention

ii) The relationship between abnormal temperature and stock returns

iii) The relationship between abnormal temperature and trading activity of different investor types.

The examination of the three areas requires market data, long-term weather data, and proxies for investor attention from different data sources. A more specific description of the data sources and processing are found in each subsection. Finally, to analyze the data, we run several regressions as described in section 4.5 Regression Methodology.

Sample size

The main testing period for our analysis stretches from 31 December 2003 to 31 December 2019. The choice of our main testing period is based on several considerations: (i) firstly, we wished to obtain data from a period when climate change was a phenomenon in Sweden as that is essential for capturing any of the proposed effects (ii) secondly, we wish to generate a sample with sufficient overlap to previous studies to ease comparability (iii) thirdly, for more reliable comparability with the international results we also wanted to apply the same time horizon for the sample. We chose our control period, 30 December 1983 to 31 December 1999, because at this period in time, fewer people recognized climate change as a phenomenon. This is based on the conclusion that the major public concern for the human causation of climate change occurred after this period. For instance, in the IPCC report in 2001, it is stated that at the period of the report's release, there existed new and more powerful evidence that climate change has an anthropogenic cause.

As mentioned in the previous section, we have had to utilize a variety of data sources as one data-provider could not supply the necessary information. The combination of the data from different sources has caused some decreases in our samples due to the provider limitations. Because of the limits to the availability of Google Trends data, which is key in our first sets of hypotheses testing, the first analysis is conducted with a sample stretching from the earliest time that Google provided search data, January 2004, to December 2019. Further, FactSet and Thomson Reuters DataStream does not provide data on all the same firms. Therefore, the datasets were matched by the individual tickers, resulting in a smaller final sample of stocks than the individual samples from both suppliers. The obtained market data has monthly intervals, with the exception of the FactSet ownership data, which could only be collected at quarterly intervals. The obtained weather data has intra-daily frequencies that are later transformed into monthly averages. The monthly interval was chosen based on the previous findings by Deryugina (2013) and Choi, Gao, and Jiang (2020) as earlier described in the delimitations, section 1.3. After all data-processing, which is further elaborated on in the following sections, the final sample sizes are presented in table 2.

Final Sample size			
SMHI *Temperature data*	**Google Trends** *Google search data*	**FactSet** *Institutional investor data*	**Thomson Reuters DataStream** *Market data (Blockholder data)*
Monthly frequency December 1979 - December 2019 480 observations	Monthly frequency January 2004 - December 2019 192 observations	Quarterly frequency December 2003 - December 2019 65 observations of 498 stocks	Monthly frequency (Quarterly frequency) Control period: December 1983 - December 1999 Main period: December 2003 - December 2019 386 (65) observations of 498 (498) stocks

Table 2: Final Sample size. Own creation. Data sources: SMHI (2020b), Google Tends (2020), FactSet (2020), and Thomson Reuters (2020).

Weather Data

Daily weather data was obtained from the Swedish Meteorological and Hydrological Institute from 31 December 1979 to 31 December 2019. The closest weather station to Stockholm Stock Exchange that has been active in the sample period was selected. Following Choi, Gao, and Jiang (2020), we decomposed the local temperatures into three components: average temperature, monthly temperature, and abnormal temperature.

$$Temperature_t = Avg\_temp_t + Mon\_temp_t + Ab\_temp_t \tag{1}$$

To estimate the three temperature components, the temperature for each month in our sample period was found by first calculating the average of intra-daily temperatures between 06:00-18:00 and then finding the average of the daily temperatures within each month. Then, we found the average temperature ($Aver\_temp_t$), which is the average monthly temperature (in Celsius degrees) in Stockholm over the previous 120 months. We calculated the monthly temperature (Mon_temp_t) as the average temperature in the same month over the previous ten years, minus the average temperature ($Aver\_temp_t$). Hence, we find how much each month, on average, deviates from the yearly average. Finally, we calculated the abnormal temperature (Ab_temp_t) in month t by subtracting $Aver\_temp_t$ and Mon_temp_t from the observed temperature. In the figure below, the abnormal temperature development in the main sample period is displayed.

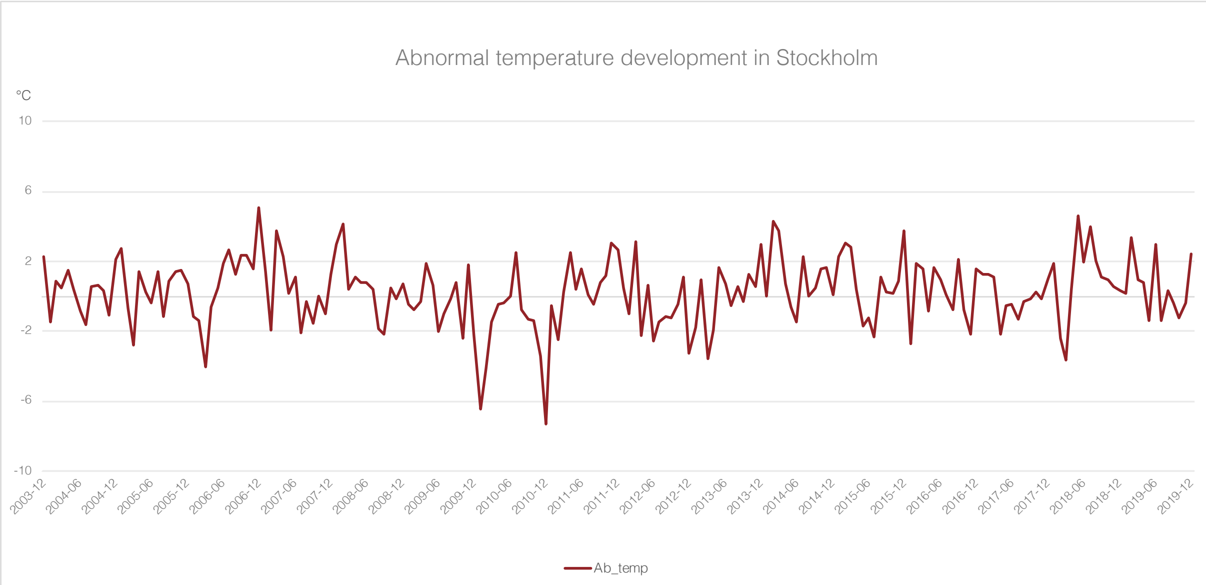

Figure 6: Abnormal temperature development in Stockholm between December 2003 and December 2019. Own creation. Data source: SMHI (2020b).

As shown in figure 6, the temperature in Stockholm has risen in recent years as the abnormal temperature display. For example, the abnormal temperature in December 2004 was 2.14°C compared to 2.42°C in December 2019. Furthermore, there are more months that are abnormally warm than abnormally cold in the main testing period.

Proxy for Investor Attention

As noted in the literature review, investors' attention is not necessarily easy to capture empirically. More specifically, due to the lack of an unequivocal measure of investor attention, it must be indirectly proxied by some existing measures. Google has since 2004 offered the Google Search Volume Index (SVI) through the product Google Trends. The Google SVI provides the possibility to explore the popularity of a topic or search term in a specific location and period. Da, Engelberg, and Gao (2011) argue that Google SVI data captures retail investors' attention very well. This proxy is also used by Choi, Gao, and Jiang (2020) to measure retail investors' attention to climate change. Another proxy is applied in the research of Klibanoff, Lamont, and Wizman (1998). Specifically, they use media coverage of companies as a proxy for investor attention. Thus, potentially, one alternative to our study could be to proxy climate change attention as the number of articles on the topic. However, we do not have access to platforms that provide the number of articles in our whole time period. Thus, we graph the two proxies to examine whether Google SVI incorporate the media effect, or if they differ greatly in recent years.

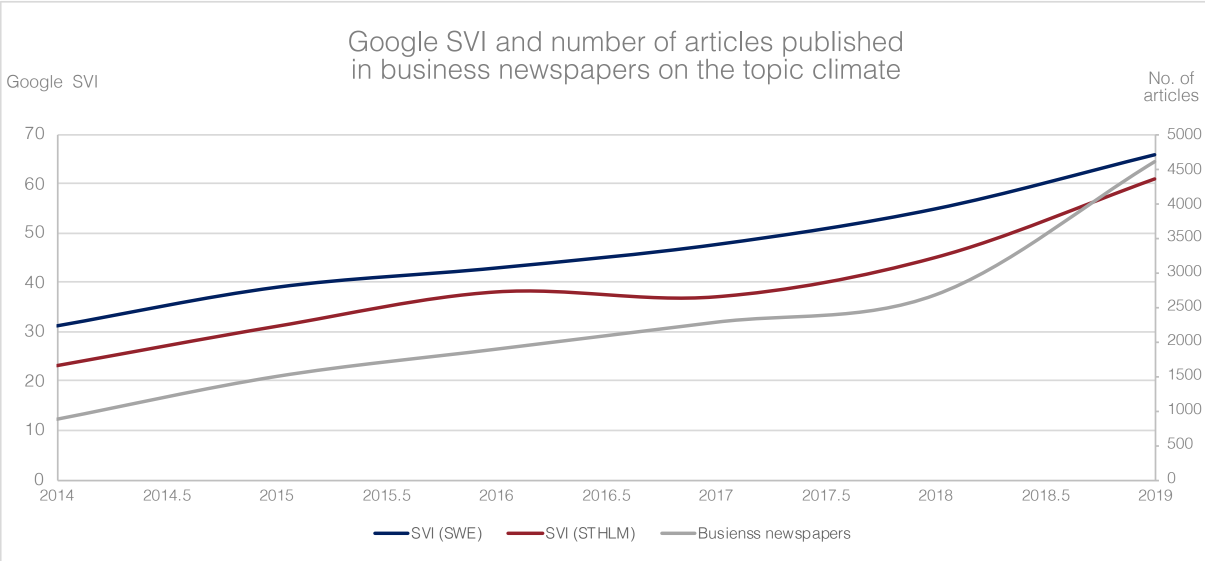

Figure 7: Google SVI and number of articles published in business newspapers on the topic climate change. Time period between January 2014 and December 2019. Own illustration. Data sources: Google Trends (2020) and Retriever (2020).

As shown above, the two proxies seem to be highly correlated. This is also in accordance with the Da, Engelberg, and Gao (2011) findings, that Google searches are different from, but correlates with other attention proxies. Thus, Google SVI is also assumed to capture media attention as well as the retail investor attention. The utilization of this proxy also eases the comparability of the study of Choi, Gao, and Jiang (2020). Furthermore, the action of actively searching for a specific search term indicates that the attention of the agent is definitely upon that topic. Moreover, as the attention theories and heuristics tested in this paper is closely linked to the behavior of individual investors, we find this proxy especially appropriate for this study.

Google Search Volume Index (SVI)

Google SVI uses a standardized scale from 0 to 100, where 0 is the lowest search volume and 100 the highest search volume for a given time horizon. Thus, Google SVI is a relative measure of the search volume for the chosen period. Narrowing the Google SVI to “search terms” would imply an exclusion of possible misspellings and searches in different languages. Therefore, we chose to collect data by "topic" to get a comprehensive measure of the attention to "Climate change".

In accordance with recent studies within climate finance, we explore the two topics: "Climate change" and "Global warming" as a proxy for the attention to climate change (Choi, Gao, & Jiang, 2020). However, we do not exclude the possibility that other search topics may capture investor attention to climate change and encourage future research to explore this further.

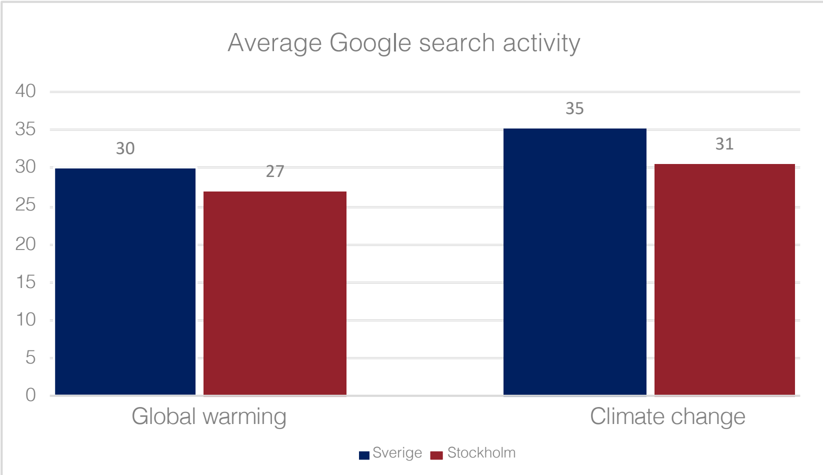

Figure 8: Average Google search activity for the topics "Global warming" and "Climate change" between January 2004 and December 2019. Own creation. Data source: Google Trends (2020).

The two topics, "Climate change" and "Global warming", are highly correlated, but we apply the latter in our research since the search traffic is slightly higher throughout the time period, as shown in figure 8. Thus, we argue that the topic "Climate change" captures investor attention towards climate change better than the topic "Global warming". Therefore, we retrieve monthly Google SVI data for the topic "Climate change" in Stockholm and Sweden over the time series January 2004 to December 2019.

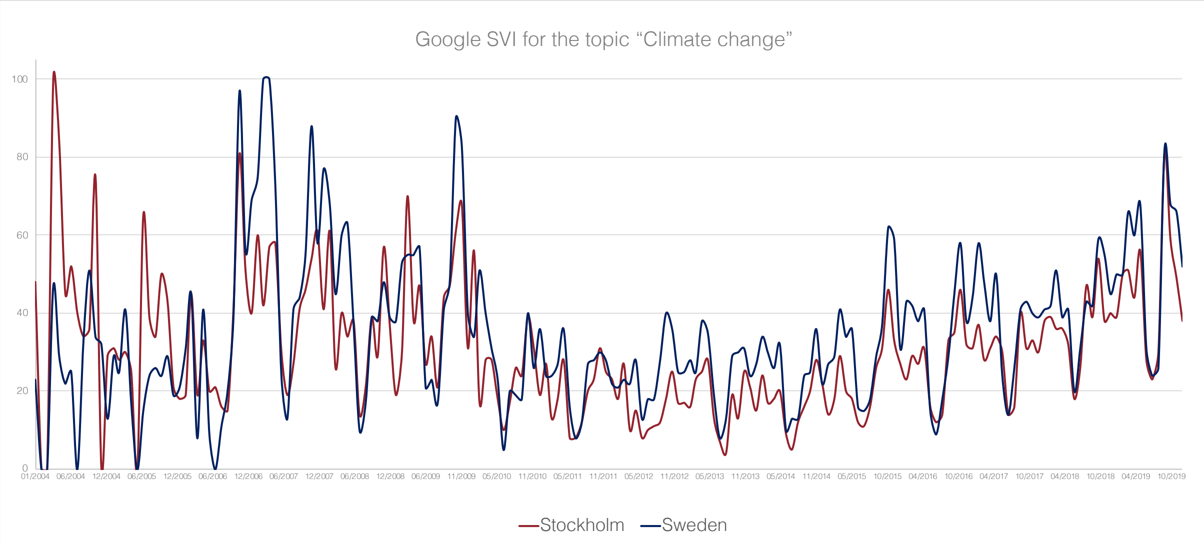

Figure 9: Google SVI for the topic "Climate change" in Sweden and Stockholm. Stretching from January 2004 to December 2019. Own creation. Data source: Google Trends (2020).

As shown in figure 9, the search traffic for "Climate change", between January 2004 and December 2019, is generally higher at the beginning of the period, then reduced in 2010 and finally increased in recent years. To capture the change in Google SVI, we apply the following formula:

$$Log\ Change\ in\ SVI = LnSVI_t - LnSVI_{t-1} \qquad (2)$$

Thus, the change in Google SVI towards climate change is defined as the natural log change in Google SVI. However, the time series have a few undefined values due to the characteristics of Google SVI. For example, two percent of the values are missing for the log change in Google SVI Sweden. Since the natural log of zero is undefined, we followed Pratama et al. (2016) and replaced these missing values with the mean of the observation sample.

There are reasons to believe that Google search data may display seasonality; in other words, periodic fluctuations. For example, some search terms such as "tax" may be trending around the tax season every year. When plotting the seasonal subseries with their respective means, shown in figure 10, it is evident that Google SVI for "Climate change" displays a seasonal trend.

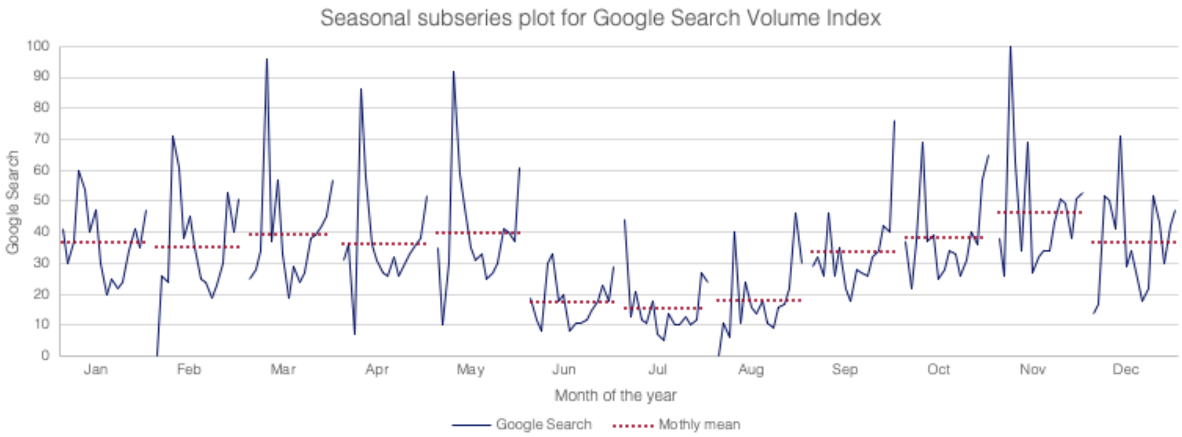

Figure 10: Illustration of seasonal subseries plot of Google SVI for "Climate change" in Sweden stretching from 2004 to 2019. Own creation. Data source: Google Trends (2020).

As shown in figure 10, a seasonal trend is visible. For example, in the summer months from June to August, the search volume is considerably lower compared to the rest of the months. As a consequence, the SVI was adjusted for seasonality. Following Choi, Gao, and Jiang (2020), the log change in Google SVI was regressed on month-of-the-year dummy variables. The residuals from this regression are the DSVI used in further regressions. Thus, DSVI is the seasonally adjusted monthly log change of SVI on the topic of "Climate Change" in Stockholm or Sweden.

Market Data

All utilized market data has been retrieved at Thomson Reuters DataStream (DataStream) and FactSet, where the latter covers institutional ownership data. Data collected from DataStream include stock returns, market capitalization, firm-specific information, and ownership data on blockholders.

Stock and firm-specific information

The utilized market data, excluding the institutional ownership data, has been retrieved at DataStream. Our sample construction began with all major listings of common stock on the Stockholm Stock Exchange (Nasdaq OMX Stockholm and First North Stockholm), thereby excluding exchange-traded funds, preferred stock, closed-end funds, and warrants. To avoid survival bias, both dead and active companies within the sample period have been included, i.e. companies that have defaulted, merged, or been delisted for other reasons within the period of observation are included in the sample. As a result of lack of data, our sample only consist of primary listings, because all secondary listings were missing key data points for further testing. The market data retrieved for this sample is market capitalization, total return indexes, total percentage of outstanding shares held by blockholders, and percentage of outstanding shares held by foreign blockholders. In addition to the time-series data, static data on the Industry Classification Benchmark (ICB) of industry subsectors for each company was retrieved. More information on the codes and definitions of the utilized data can be found in the appendix B. All stocks that were lacking data on one of the acquired market data variables in the whole sample period were removed.

Subsequent to the first treatment of the raw data, the monthly returns were calculated according to the changes in the Return Index, which takes capital gains and dividends into account as well as adjusts for subsequent capital actions such as stock splits. Hence, the calculated changes in the Return Index is the return of holding the stock in each month, including capital gains and dividends.

DataStream may suffer from further data errors and needs to be treated according to the found errors. Therefore, we screen the calculated return data according to the findings by Ince and Porter (2006). More specifically, DataStream reports data on firms that are no longer traded by repeating the last valid data point in consecutive months for the entire time period. Consequently, we trim the data on delisted firms by removing all monthly observations of zero returns at the end of the sample period to the first record of a non-zero return. Consecutively, due to research observations of occasional DataStream pricing errors (Choi, Gao, & Jiang, 2020; Hou, Karolyi & Kho, 2011; Ince & Porter, 2006), we follow the suggested procedure of removing any monthly return above 300 percent that is reversed within one month. The removal is determined by the following rule suggested by Ince and Porter (2006), specified as:

$$\text{if } (\mathrm{R_t} > 300 \text{ percent}) \text{ or } (\mathrm{R_t} - 1 > 300 \text{ percent}), \text{ and}$$
$$((1 + \mathrm{R_t})\ (1 + \mathrm{R_{t-1}}) - 1 > 50 \text{ percent}), \text{ then both } \mathrm{R_t} \text{ and } \mathrm{R_{t-1}} \text{ are treated as missing.}$$

Further consideration was taken in accordance with observations of DataStream rounding practice for low price stock. According to Ince and Porter (2006), a minimum stock price of $1 should be required to avoid non-trivial observation errors. Therefore, we require a minimum stock price of 10 SEK at the end of the previous month for an observation to be included in the analysis. This also minimizes potential biases arising from illiquid stock.

Size-adjusted returns

Banz (1981) finds that there is a size effect present in stock return movements. Specifically, it is found that there is a negative relationship between the firm's market capitalization and the return. In accordance with these findings, initial return calculations were size-adjusted. All companies were divided into quintiles based on their market values. Subsequently, the average return of each quintile was removed from the return of each stock in that specific quintile in the same month, i.e. the size-adjusted return of a stock in quintile one is equal to the actual return of the stock in month t minus the average return of quintile one in month t.

This return adjustment enables us to draw conclusions on whether any observed effect in the regressions is robust to adjustments for size premiums. Other models, such as factor models, were considered for the calculation of adjusted returns. For example, Hou, Karolyi, and Kho (2011) have found that factors driving global stock returns are momentum and cashflow-to-price. However, when considering adjusting returns based on these variables, we encountered large difficulties in easily obtaining the cashflow-to-price data for all stocks in our sample. Therefore, it was considered most appropriate to follow Choi, Gao, and Jiang (2020) method and adjust returns according to the market capitalization data that had better coverage for our sample.

Ownership data

Choi, Gao, and Jiang (2020) found that market behavior differs between investor types. We apply this theory to our research and examine the potential influence of abnormal weather on trading behavior among three investor types. The three investor types of interest to our thesis are retail investors, blockholders, and institutional investors. In order to examine investor trading behavior, we collect ownership data for blockholders and institutional investors and create a proxy for retail investors.

Blockholders and Institutional Investors

Ownership data on the sample was collected from two sources, DataStream and FactSet. DataStream provides data on the percentage of outstanding shares held by foreign and domestic blockholders (owning more than five percent of shares outstanding). FactSet provides data on quarterly institutional ownership in the form of time series. In FactSet, tickers for stocks listed in Stockholm were obtained and later used to build specified institutional ownership sheets in the FactSet Download Builder. The request was specified to present the percentage of outstanding shares owned by institutional investors in each stock, grouped by foreign investors and domestic investors. This resulted in a detailed sheet, presenting the name of each institutional owner and their ownership stake in each quarter. Ownership data for active and inactive stocks was retrieved in 102 separate excel sheets due to the limitations of the builder. These were subsequently merged with the help of macros to present full ownership time-series for all stocks. The merged sheet was further used to separate institutional blockholders (owning more than five percent) from institutional investors that are not blockholders. Both categories were also grouped by their foreign or domestic origin.

Proxy for Retail Investors

Since retail ownership cannot be directly measured for each of the sample stocks, we apply a proxy for retail ownership. To enable the proxy to be calculated, the final sheet of FactSet's data on institutional investors explained in the previous section, was subsequently matched with the DataStream sheet on blockholders by the stocks' individual tickers and names. Finally, this data was used in the following formula developed by Choi, Gao, and Jiang (2020) to proxy for retail ownership:

$$Retail\ own. = 100\% - Blockholder\ own. - Institutional\ own. (excl. blockholders) \quad (2)$$

Where the data on blockholder ownership originates from DataStream and institutional ownership from FactSet. Naturally, retail ownership is not an exact measurement and is, therefore, prone to errors.

Portfolio construction

For the subsequent testing, we construct portfolios with the final stock return data and ownership data from DataStream and FactSet. This section will go through the process of the portfolio constructions. First, the construction method for portfolios based on stocks climate sensitivity will be presented. Secondly, the construction of ownership portfolios for the same stocks will be introduced.

Climate portfolios

The paper hypothesizes that investors might increase their attention toward climate change when they experience abnormal temperatures. As a result, they might revise their beliefs on the topic and subsequently buy stocks less sensitive to the climate and sell stocks with higher sensitivities to the climate. We, therefore, construct portfolios based on this assumption. Firms with high emission levels are generally more sensitive to climate change because of the risk of adverse cash-flow effects (Choi, Gao, & Jiang, 2020). These could stem from the possibility of increasing production costs through the price of carbon and increasingly strict regulations. Moreover, they inhabit the possibility that investors avoid them for social conscience reasons. Therefore, the stocks are categorized by their emission levels as a proxy for their sensitivity to the climate. The high emission firms are identified with the aid of the Intergovernmental Panel on Climate Change (IPCC).

The IPCC assesses the science related to climate change for the United Nations (IPCC, 2020). In doing so, they also provide yearly reports summarizing the scientific findings on the drivers of climate change (IPCC, 2020). These reports are by science academies viewed to represent the consensus of the international scientific community on climate change science (Science, 2001). Due to the accessibility of these reports for all types of investors and the fact that they are considered to represent the scientific consensus, we consider it a reasonable measurement for firms viewed to have high climate sensitivity. Therefore, firms that belong to an industry sector that is identified as a major emission source by the IPCC were considered to belong in the higher sensitivity category.

To categorize all firms in our sample according to IPCC's definitions, the industry sub-sectors provided by DataStream were hand-matched with the IPCC industry sub-categories. The full list of IPCC sub-categories are found in IPCC (1996) and Krey et al. (2014). For our sample, the matched DataStream industries together with their respective IPCC sub-category code are shown in table 3 below.

TRD industry name	IPCC industry name(s)	IPCC category code
Conventional Electricity	Public electrucity and Heat production	1A1a
Oil: Crude Producers	Manufacture of Solid Fuels and other Energy Industries, Oil	1A1bc, 1B2a
Iron and Steel	Iron and steel, Iron and steel production	1A2a, 2C1
Aluminum	Non-ferrous metals, Aluminum production	1A2b, 2C3
Chemicals: Diversified	Chemicals, Chemical industry	1A2c, 2B
Paper	Pulp and paper, Other production: Pulp and paper	1A2d, 2D1
Tobacco	Food processing, beverages and Tobacco	1A2e
Food Products	Food processing, beverages and Tobacco, Other production: Food and drink	1A2e, 2D2
Farming, Fishing, Ranching and Plantations	Agriculture/Forestry fishing, Enteric Fermentation,Manure management, Agricultural soils	1A4c 4A, 4B, 4Dr
Transportation Services	Transport equipment, Road transportation	1A2f2, 1A3b
Commercial Vehicles and Parts	Transport equipment	1A2f2
Machinery: Construction and Handling	Transport equipment, Machinery	1A2f2, 1A2f3
Machinery: Industrial	Machinery	1A2f3
Machinery: Tools	Machinery	1A2f3
General Mining	Mining and quarrying	1A2f4
Gold Mining	Mining and quarrying	1A2f4
Construction	Construction	1A2f6
Home Construction	Construction, Residential	1A2f6, 1A4b
Airlines	Civil aviation, International aviation	1A3a, 1C1
Trucking	Road transport (includes evaporation) (fossil)	1A3b
Marine Transportation	Navigation	1A3d, 1C2

Table 3: Mapped Emission industries in accordance with IPCC and DataStream ICB subsectors. Own creation. Data sources: Thomson Reuters(2020), Krey et al. (2014), and IPCC (1996).

Further, the matching was purposefully restrictive in order to avoid bias. A firm was only included in the high-emission category if the DataStream industry name could unambiguously be matched to one or more of the IPCC codes. To ensure robustness in a Swedish setting, the categorized sample was further analyzed in relation to the National Inventory Report Sweden which covers the greenhouse gas emission inventories from 1990 to 2017 (Swedish Environmental Protection Agency, 2019). The report is submitted under the IPCC framework and gives insight into which of the IPCC industries are the most polluting in Sweden. Hence, by examining the IPCC industries in a Swedish context, it was established that the chosen emission industries were not only polluting in an international context, but also sources of high emission in Sweden. The final proportion of the matched industries within the high-emission category is presented in figure 11.

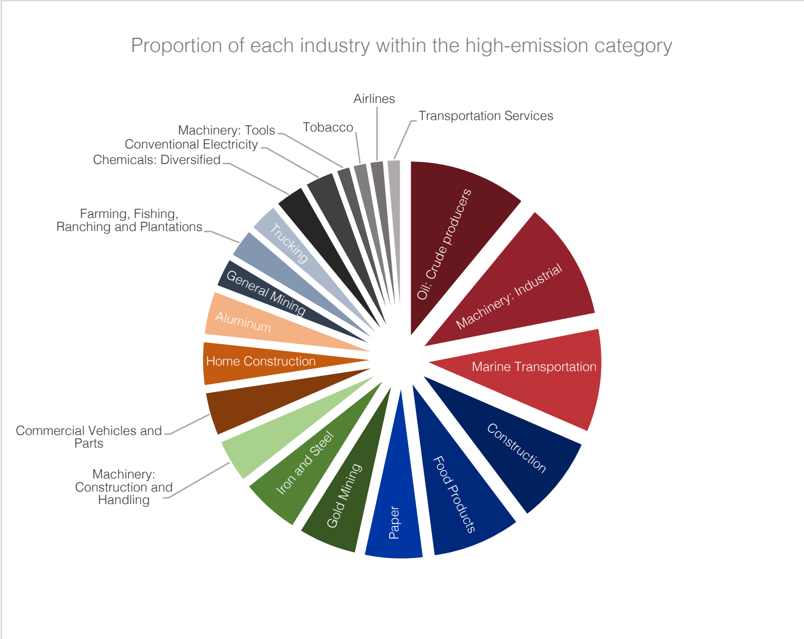

Figure 11: Proportion of each industry within the high-emission category in our sample. Own creation.

Once the matched firms had been categorized as high-emission, the remaining firms were categorized as low-emission firms. The high-emission- and low-emission grouping of firms will further be referred to as Clean and Emission, respectively. In order to be able to further robust any consecutive findings, both value-weighted and equal-weighted returns for the Clean and Emission portfolios were calculated.

Subsequent to the grouping, a long-short portfolio was constructed. The portfolio was constructed to take a long position in the Emission firms and short the Clean firms. The returns of the EMC ("Emission Minus Clean") portfolio were both equal-weighted and value-weighted.

Trading Activity Portfolios

As mentioned in the ownership section, three investor types were considered in this study: retail investors, blockholders, and institutional investors. In accordance with Choi, Gao, and Jiang (2020), we deem the trading activity for each investor group to be the change in ownership from one quarter to another. For instance, if institutional investors decreased their holding in a stock from 24 percent to 20 percent of total shares outstanding, it is concluded that institutional investors sold four percent of the shares in this quarter. The same sample of firms and the same firm-categorization, as described in the previous section, is utilized for these portfolios. For each type of investor, the average net buy across all Clean firms was calculated for each quarter (ΔClean), as well as the average net buy across all Emission firms (ΔEmission). Successively, separate "long-short"-portfolios for each investor type were created taking ΔEmission minus ΔClean. These portfolios will further be referred to as EMCΔRetail, EMCΔInstitutional, and EMCΔBlockholders. Moreover, only local investors experience the abnormal temperatures that could affect their trading behavior. Therefore, separate portfolios for foreign institutional investors, local institutional investors, foreign blockholders, and local blockholders were constructed. These portfolios will further be referred to as EMCΔLocInstitutional, EMCΔForInstitutional, EMCΔLocBlockholders, and EMCΔForBlockholders. As no data on the origin of retail investors could be obtained, all are assumed to be local. This assumption is based on the reviewed theory on the home bias, which implies that at least a majority of these investors should be domestic.

4.5 Regression Methodology

In order to answer the research questions, "*To what extent, if at all, do abnormal temperatures affect equity investors' realization and response to climate change in Sweden?*" the paper runs several regressions that are divided into three categories. First, we will go through how the test for attention towards climate change will be conducted. Then, the tests related to portfolio returns will be explained. Further, we will go through the last test category that comprises the trading behavior in high versus low emission stocks among different investor types. Then, the descriptive statistics and considerations related to the regressions are presented. Finally, we acknowledge the methodological limitations that we consider important for further interpretation of our results.

Abnormal temperatures and attention to climate change

This thesis examines whether abnormal temperatures experienced over the recent 16 years in Stockholm explain the changes in attention towards climate change. The paper applies the log change in Google SVI for the topic "Climate change" as a proxy for investor attention to climate change. The log change in Google SVI is then seasonally adjusted and termed DSVI. To examine the relationship between investor attention and abnormal temperatures, the following regression is run:

$$DSVI_t = \alpha + B_1 Ab\_temp_t + \varepsilon_t \quad (3)$$

In order to assess whether the change in attention is dependent on the level of abnormal temperatures, the regression is run on quintile dummies based on Ab_temp. Specifically, Ab_temp Q1 is the 20 percent lowest abnormal temperatures and Ab_temp Q5 is the 20 percent warmest abnormal temperatures. Finally, the study repeats all regressions by replacing DSVI in Stockholm with DSVI in Sweden to capture the attention of investors on a national level.

Abnormal Temperatures and Portfolio Return

If investors realize the effect of climate change by experiencing abnormal temperatures, they may update their beliefs about the value of firms or avoid climate-unfriendly stocks. Therefore, the thesis examines whether abnormal temperatures affect stock returns on the Stockholm Stock Exchange. To do so, we utilize a series of linear regressions directly between the stock returns and abnormal temperatures. Where, EMC_t is the value-weighted or equal-weighted, size-adjusted or unadjusted return of the EMC portfolio in month t (from December 2003 to December 2019), and Ab_temp is the abnormal temperature, yielding the following return regression:

$$EMC_t = \alpha + B_1 Ab\_temp_t + \varepsilon_t \quad (4)$$

In the same manner as the first regression, we run the regression on quintile dummies based on Ab_temp. Specifically, Ab_temp Q1 is the 20 percent lowest abnormal temperatures and Ab_temp Q5 is the 20 percent warmest abnormal temperatures. Further, to robust any potential findings, the regression is run on a control test period stretching from December 1983 to December 1999. This is the same time horizon as the original test period, with the exception that fewer people are assumed to have recognized climate change as a phenomenon and its link to human greenhouse gas emissions in these years (Intergovernmental Panel on Climate Change, 2001).

Abnormal Temperatures and Trading Activity

In order to examine how different investors react to abnormal temperatures, we study the relationship between the trading activity of different investor types and abnormal temperatures.

The link between abnormal temperature and change in ownership of blockholders (owning more than five percent of shares outstanding), institutional investors and retail investors are analyzed. For each investor group, the EMC portfolio is defined as the average net buy across all high-emission firms minus the average net buy across all low-emission firms in quarter t. The following regression is run for each type of investor:

$$EMC\_\Delta_t = \alpha + B_1 Ab\_temp_t + \varepsilon_t \quad (5)$$

Where EMCΔ is the change in ownership for either investor group, further defined as EMCΔRetail, EMCΔInstitutional, and EMCΔBlockholder. Similar to regression one and two, these regressions are then run on quintile dummies based on Ab_temp to examine whether the level of temperature has an impact on investor behavior.

Finally, since only local investors are experiencing the local abnormal temperature, we run the regressions on portfolios divided by investor location. Specifically, domestic blockholders, foreign blockholders, domestic institutional owners, and foreign institutional owners. This enables us to conclude whether the potential effect can, in fact, be derived from the experience of local temperature.

4.5.1 Descriptive Statistics and Diagnostic Testing

In this section, we will present the statistical properties of the time series for our main testing period. To avoid unnecessary repetition, but still allow for considerations to be presented, some variables will be presented in this section whilst others will be found in the appendix. We will first describe our approach for the handling of outliers, which is applied through all testing. Then the considerations will be divided into the three test groups; abnormal temperatures influence on investor attention, portfolio returns, and trading activity.

It is important to identify extreme values within the sample to ensure robustness of the regression. If extreme values in the sample can be characterized as genuine outliers, they are typically treated in one of the following ways: keeping the outlier, winsorizing it, or eliminating it (Ghosh & Vogt, 2012). However, each of these methods has potential drawbacks. The first method, keeping the outlier, may overvalue it and cause the estimate to vary drastically from the true population value. The second and third treatment, winsorize or eliminate the outlier, may introduce statistical bias and may undervalue the outlier (Ghosh & Vogt, 2012). The method chosen for this thesis for dealing with outliers is winsorization. All variables, except Ab_temp, are winsorized at the top and bottom 2.5 percent tails to mitigate the impact of outliers. However, the known drawbacks are important to consider when interpreting the regression results. Therefore, the winsorized results will be considered with respect to non-winsorized results.

Abnormal Temperatures and Attention

In the first sets of tests, we study whether abnormal temperature impact attention towards climate change. The variables DSVI (STHLM) and DSVI (SWE) are the seasonally adjusted monthly log change of Google SVI on the topic climate change in Stockholm and Sweden, respectively. The variable Aver_temp is the average monthly temperature (in Celsius degrees) in Stockholm over the previous 120 months. The variable Mon_temp is the average temperature in the same month of the year over the past ten years, minus Aver_temp. The variable Ab_temp is the average temperature in a particular month minus Aver_temp and Mon_temp. The variables applied in the regressions is Ab_temp, DSVI(STHLM), and DSVI(SWE).

			Percentiles						
Variable	Mean	SD	10%	25%	50%	75%	90%	Skewness	Kurtosis
DSVI (STHLM)	0.016	40.306	-50.520	-21.931	0.689	26.313	52.991	-0.070	2.861
DSVI (SWE)	0.550	35.945	-44.031	-17.095	1.644	21.362	39.767	0.068	3.691
Aver_temp	8.265	0.166	7.955	8.184	8.302	8.386	8.448	-0.904	3.027
Mon_temp	0.033	7.414	-9.311	-7.201	-0.687	8.028	10.412	0.154	1.565
Ab_temp	0.230	1.902	-2.182	-0.985	0.371	1.431	2.527	-0.446	4.281

Table 4: Descriptive statistics of Google DSVI and Ab_temp in the sample period stretching from December 2003 to December 2019. Own creation. Data Source: SMHI (2020b) and Google Trends (2020).

In table 4, the descriptive statistics are presented. As shown in the skewness column, the variable Aver_temp is moderately skewed to the left, while the rest of the variables are approximately symmetric. However, as stated earlier, the variable Aver_temp is only used to calculate Ab_temp and is not applied in any regression. Furthermore, the skewness is not surprising given the nature of the variable. As described in section 3.5, the long-term average temperature has increased as a consequence of climate change. Hence, we would expect this variable to be slightly skewed. Looking at the kurtosis, we see that DSVI (STHLM) and

Ab_temp exhibit some fat tails, while DSVI(SWE) is slightly more light-tailed than the normal distribution. However, this rather small deviation from the normal distribution, and all variables are argued to be acceptable.

An illustration of the distribution of regression residuals in both a histogram and Q-Q plot is found in figure 12 for DSVI (STHLM) and in appendix C.12 for DSVI (SWE). The residuals of both DSVI (STHLM) and DSVI (SWE) on Ab_temp is approximately normally distributed. Moreover, it is important to consider possible heteroskedasticity and autocorrelation when dealing with time-series data (Wooldridge, 2013). Therefore, the Breusch Pagan's test on the residuals is used to check for heteroscedasticity. Further, we test for no serial correlation by using the Breusch-Godfrey test of autocorrelation. The results are presented in appendix C and remedied by the utilization of Newey-West standard errors when applicable.

Histogram and Q-Q plot of residuals of DSVI (STHLM) and Ab_temp

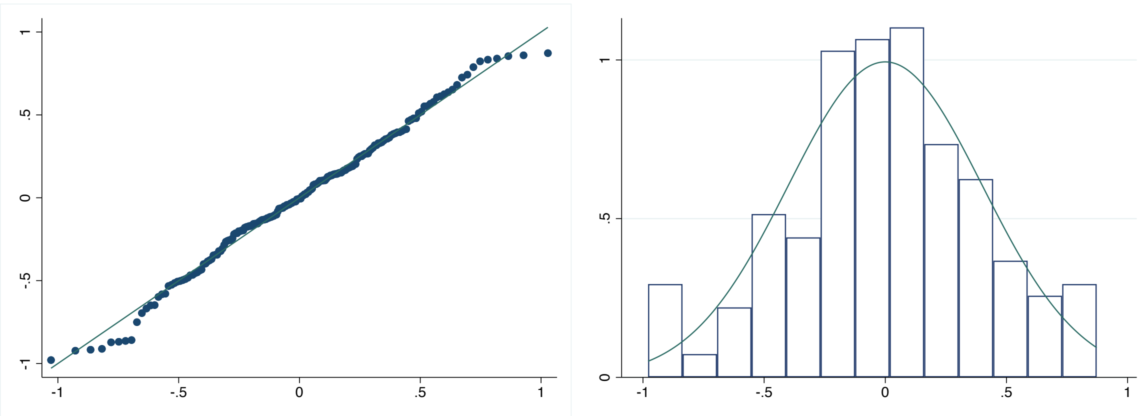

Figure 12: Distribution of the residuals of DSVI (STHLM) and Ab_temp stretching from December 2004 and December 2019. Own creation. Data sources: SMHI (2020b) and Google Trends (2020).

Abnormal temperatures and portfolio returns

In the second group of tests, we form three portfolios based on the IPCC definitions of high emission industries, as described in section 4.3. The portfolio of high emission firms is entitled Emission while the low emission firms comprise the Clean portfolio. Furthermore, a long-short portfolio is formed and equals Emission minus Clean (EMC). EMC (Unadjusted) is the only portfolio presented in unadjusted returns. The other portfolios are presented in size-adjusted returns as described in section 4.3. Finally, as illustrated below, we apply both equal-weighted and value-weighted returns.

Variable	Mean	SD	Percentiles 10%	25%	50%	75%	90%	Skewness	Kurtosis
Equal Weighted									
EMC (Unadjusted)	-1.078	3.209	-5.231	-3.403	-1.412	1.085	2.676	0.288	2.836
EMC	-0.074	0.461	-0.653	-0.383	-0.045	0.195	0.528	-0.040	2.957
Emission	-0.273	1.735	-2.445	-1.508	-0.216	0.848	2.152	-0.042	2.647
Clean	0.042	0.266	-0.299	-0.112	0.025	0.222	0.378	0.025	2.989
Value Weighted									
EMC (Unadjusted)	-0.789	2.264	-3.704	-2.267	-0.824	0.699	1.846	0.135	3.106
EMC	0.143	1.519	-1.770	-0.867	0.182	1.073	1.887	-0.247	3.362
Emission	0.100	2.414	-3.262	-1.516	0.058	1.689	3.404	-0.033	2.443
Clean	-0.148	1.495	-1.951	-1.077	-0.239	0.682	1.691	0.428	3.368
Ab_temp	0.232	1.902	-2.182	-0.985	0.371	1.431	2.527	-0.442	4.252

Table 5: Descriptive statistics of portfolio return and Ab_temp in the sample period stretching from December 2003 to December 2019. Own creation. Data Source: SMHI (2020b) and Thomson Reuters (2020).

In table 5, the descriptive statistics are presented. Looking at descriptive statistics, we find that all variables are approximately symmetric, except for value-weighted EMC and Clean portfolio that is moderately skewed to the left and the right, respectively. The result implies the EMC portfolio earns slightly more frequent small gains and has fewer extreme losses than the normal distribution, while the CLEAN portfolio has more frequent small losses and fewer extreme gains compared to the normal distribution.

As for the previous group of tests, the distribution of the residuals for the equal-weighted EMC portfolio and Ab_temp is presented in both a histogram and Q-Q plot while the others are found in their respective section within appendix D. As shown in figure 13 below, the residuals of the equal-weighted EMC portfolio are approximately normally distributed. Further, none of the other portfolios display serious violations of normality. The tests for heteroskedasticity and autocorrelation are found in appendix D, and treated with Newey-West (HAC) standard errors when applicable.

Histogram and Q-Q plot of residuals of equal-weighted EMC portfolio and Ab_temp

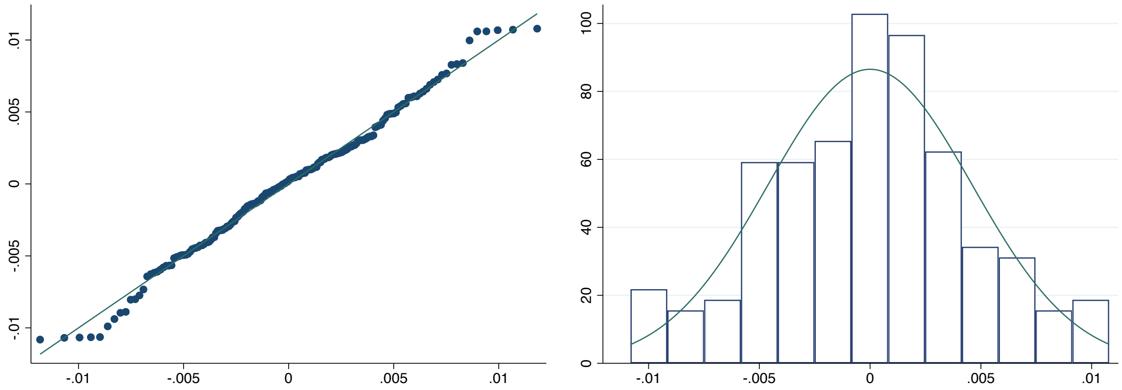

Figure 13: Distribution of the residuals of the equal-weighted EMC portfolio and Ab_temp stretching from December 2004 to December 2019. Own creation. Data sources: SMHI (2020b) and Thomson Reuters (2020).

In the third group of tests, we follow the definition of the IPCC of the carbon emission industries, as described in section 4.3. The EMC portfolio is formed based on different owners to examine different trading activities. The three ownership groups are retail investors, blockholders (owning more than five percent of shares outstanding), and institutional investors. We assumed that the retail investors are mainly local and divided the blockholders and the institutional investors into local and foreign investor categories. The change in ownership is defined as the percentage average change in respective ownership groups over the quarter between the Emission and Clean portfolio.

			Percentiles						
Variable	Mean	SD	10%	25%	50%	75%	90%	Skewness	Kurtosis
EMC ΔInstitutional	-0.068	0.558	-0.805	-0.400	-0.068	0.296	0.654	-0.124	2.712
EMC ΔBlockholders	-0.093	0.996	-1.223	-0.567	-0.115	0.417	1.216	0.021	3.835
EMC ΔRetail	0.067	1.438	-1.994	-0.820	0.060	1.027	1.899	0.067	2.650
EMC ΔForInstitutional	-0.023	0.385	-0.408	-0.207	0.018	0.220	0.471	-0.521	3.482
EMC ΔForBlockholders	-0.021	0.771	-0.629	-0.405	-0.114	0.129	1.242	0.433	3.920
EMC ΔLocInstitutional	-0.073	0.456	-0.640	-0.338	-0.048	0.215	0.442	-0.248	3.020
EMC ΔLocBlockholders	-0.078	0.619	-0.908	-0.426	0.023	0.287	0.551	-0.709	3.507
Ab_temp	0.227	1.386	-1.290	-0.502	0.270	1.055	2.280	-0.549	4.260

Table 6: Descriptive statistics of trading activity and Ab_temp in the sample period stretching from December 2003 to December 2019. Own creation. Data sources: SMHI (2020b), Thomson Reuters (2020) and FactSet (2020).

Looking at the descriptive statistics in table 6, we find that most of the variables are approximately symmetric. However, some variables are moderately skewed, including the quarterly abnormal temperature, EMC portfolio of foreign institutional investors, and local blockholders. The portfolio returns of foreign intuitional investors and quarterly abnormal temperatures are slightly skewed to the left and, therefore, argued to be satisfactory. The EMC portfolio of local blockholders is moderately skewed to the left, meaning that it has slightly more positive net-buys and have fewer extreme negative net-buys than the normal distribution. As the ownership portfolio is constructed with average net-buy in Emission firms minus the average net buy in Clean firms, the interpretation would be that there are more frequent buys in the Emission portfolio and fewer instances of extreme net buys in the Clean portfolio. Since the variables are only moderately skewed, we argue that it is satisfactory. Looking at the kurtosis, we see that all variables approximately follow the normal distribution.

Abnormal Temperatures and Trading Activity

The residuals for the third group of tests are displayed ~~in~~ both a histogram and Q-Q plot. The EMC portfolio of retail investors and Ab_temp is presented below, while the rest of the portfolios are found in their respective appendix. As shown below, the portfolio is approximately normally distributed. The residuals of the Blockholder portfolio in this group of tests seem to violate normality. The limitation of apparent non-normality will, therefore, be considered in the coming section. As for previous tests, any presence heteroskedasticity and autocorrelation is remedied by Newey West standard errors.

Histogram and Q-Q plot of residuals of EMCΔRetail and Ab_temp

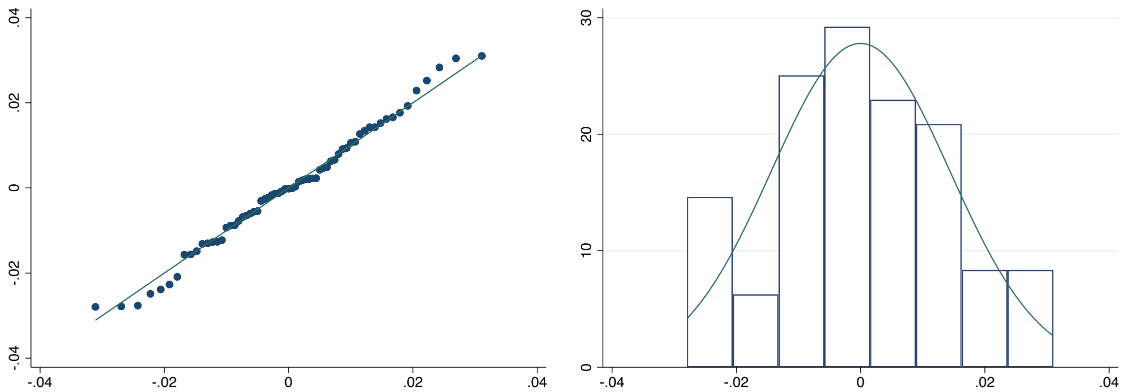

Figure 14: Distribution of the residuals of the EMCΔRetail and Ab_temp stretching from December 2004 to December 2019. Own creation. Data sources: SMHI (2020b), Thomson Reuters (2020), and FactSet (2020).

Limitations to Regression Methodology

In this section, we wish to acknowledge the methodological limitations that we consider important for further interpretation of our results. More specifically, we will discuss the limitations in light of possible Type I and Type II errors. A Type I error, also called a "False Positive", would mean that the null hypothesis is falsely rejected and a Type II error, a "False Negative", would mean that a false null hypothesis is not rejected.

In our model, we have, for some of the utilized variables, identified violations of the zero-conditional mean assumption. More specifically, when performing the Ramsey Reset test, we identified that when introducing the ownership portfolio of Institutional investors, the model exhibited indications of omitted variable bias and is therefore mis-specified (appendix E.1). Furthermore, the value-weighted Emission portfolio in the control period (appendix D.24), as well as the equal-weighted unadjusted EMC portfolio in the main testing period (appendix D.1), exhibit similar test results. As all of the other variables fulfill the assumptions to an acceptable degree, we chose to keep the model. However, the interpretations of the results of these specific regressions should be considered with caution. The possible omitted variables in the model mean that the model will attribute the effect of the left-out variables to the included variables (Kumar, 2020). This creates biased estimates and could increase the possibility of errors. As described in the previous section, our residuals are argued to be approximately normally distributed, even if blockholders exhibit some tendencies of non-normality. According to Pallant (2013), violations of normality should not cause major problems given that a large enough sample size (>30) is used. However, we wish to acknowledge that extra caution is taken with regards to any significant results as non-normality could increase the possibility of Type I errors (Mellenbergh, 2019). Thus, to decrease the possibility of false positives, we choose to be conservative in our result interpretations.

5. Presentation of Results

In this section, the results of the regressions are presented and interpreted. The regression output will be interpreted in relation to non-winsorized results in all of the three test groups. In the second test, the result will also be interpreted in relation to a control test period when, as previously argued, fewer people are assumed to recognize climate change as a phenomenon. The empirical findings will be compared with the results of Choi, Gao, and Jiang (2020) that was presented in the literature review.

Regression Outputs 1: Abnormal Temperatures and Attention to Climate Change

In the first group of regressions, we test the first hypotheses, if Swedish investors' attention towards climate change varies with abnormal temperatures. A change in the attention toward climate change is measured by the DSVI, which is the seasonally adjusted monthly log change of Google searches. The final regression results are reported in table 7.

	DSVI (STHLM)	DSVI (STHLM)	DSVI (SWE)	DSVI (SWE)
	(1)	(2)	(3)	(4)
Ab_temp	0.553		1.365	
	(0,44)		(1,17)	
Ab_temp Q2		10.903		12.006
		(1,44)		(1,43)
Ab_temp Q3		-12.751		-6.840
		(-0,13)		(-0,88)
Ab_temp Q4		0.813		4.109
		(0,09)		(0,60)
Ab_temp Q5		10.006		11.417
		(1,23)		(1,53)
Observations	191	191	191	191
R^2	0.001	0.017	0.005	0.039

*Table 7: Regression output of DSVI and Ab_temp with coefficients in percentage. The t-statistics are reported in parentheses. The statistical significance of the coefficients is reported by *p<0.10; **p<0.05; ***p<0.01.*

In the first test, column one and three, the coefficient of interest is B1, the slope of the abnormal temperature variable. The coefficients' significance is reported in parenthesis. The coefficient estimates of Ab_temp are not significant, which suggests that neither people in Stockholm (t-stat = 0.44) nor Sweden (t-stat=1.17) pay more attention to climate change when they are experiencing abnormal temperatures. A low R-squared is expected given that a lot of variables other than temperatures can have predictive power of the variance of people's attention toward climate change.

As a second step, we test our second hypothesis. More specifically, if Swedish investors' attention towards climate change varies more with the highest level of abnormal temperatures than with other temperature levels. To do so, we rank all months into quintiles based on Ab_temp in order to examine whether a change in attention varies with the level of abnormal temperatures. This is done by using quintile dummies in the regression instead of Ab_temp. Specifically, Ab_temp Q1 is the 20 percent lowest abnormal temperatures and Ab_temp Q5 is the 20 percent warmest abnormal temperatures. As shown in columns two and four, none of the coefficients of the quintile dummies are significant. The findings contradict the results of Choi, Gao, and Jiang (2020), who identifies that abnormal temperature is significantly positive at a 95 percent confidence level. Furthermore, they find that the relationship is nonlinear, as the highest abnormal local temperature in quintile five has the only coefficient significantly different from zero.

As explained in section 4.3, the Google DSVI is winsorized at the top and bottom 2.5 percent tails to mitigate the impact of outliers. However, such winsorizing can result in statistical bias by undervaluing the outliers. Therefore, in table 8, the non-winsorized results are also presented to allow considerations in relation to the winsorized. As seen in table 8, the non-winsorized results are similar to the winsorized results in table 7, and neither show significance.

	DSVI (STHLM)	DSVI (STHLM)	DSVI (SWE)	DSVI (SWE)
	(1)	(2)	(3)	(4)
Ab_temp	0.620		1.410	
	(0,49)		(1,20)	
Ab_temp Q2		11.050		10.288
		(1,40)		(1,12)
Ab_temp Q3		-0.590		-7.354
		(-0,06)		(-0,84)
Ab_temp Q4		1.371		2.195
		(0,14)		(0,28)
Ab_temp Q5		10.371		11.753
		(1,24)		(1,53)
Observations	191	191	191	191
R^2	0.001	0.016	0.005	0.031

*Table 8: Regression output of non-winsorized DSVI and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.10; **p<0.05; ***p<0.01.*

Sub-Conclusion

Based on the evidence in table 7 and 8, this thesis does not find support for the first and second hypothesis that Swedish investor attention towards climate change, by means of google search, is impacted by abnormal temperature. Hence, the tests fail to reject the first and second null hypothesis, indicating that neither abnormal temperature nor the level of abnormal temperature increases the attention toward climate change. The results contradict the findings of Choi, Gao, and Jiang (2020), who find that abnormal temperature results in an increase in attention and that the impact is nonlinear.

Regression Output 2. Abnormal Temperatures and Portfolio Returns

In the third hypothesis, the relationship between abnormal temperature and stock returns on the Stockholm Stock exchange are examined. If people in Sweden revise their beliefs about climate change when experiencing abnormal temperatures, they might assess the climate risks differently or simply avoid climate unfriendly stocks. As described in the methodology section (4.3), portfolios were formed according to the IPCC definitions to distinguish climate-unfriendly stocks (Emission) from the others (Clean). All portfolios have been formed using both equal-weights and value-weights to further robust any findings and ease compatibility with previous findings by Choi, Gao, and Jiang (2020).

Table 9, columns one to eight and nine to sixteen provides the results for the four portfolios of interest in equal weights and value weights, respectively. The long-short portfolio Emission Minus Clean (EMC) is presented both in unadjusted returns and size-adjusted returns. The separate displays of the Emission and Clean portfolios are presented in size-adjusted returns. By examining a long-short portfolio, going long the Emission stocks and short the Clean stocks, a conclusion can be drawn regarding a potential systematic relationship between the performance of Emission and Clean stocks and abnormal temperatures. Subsequently, by studying the Emission and Clean portfolios separately, their individual contributions to the returns of the EMC portfolio can be assessed.

	Equal-weighted portfolios								Value-weighted portfolios							
	EMC		EMC (unadjusted)		Emission		Clean		EMC		EMC (unadjusted)		Emission		Clean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Ab_temp	0.035		-0.160		0.060		-0.022		0.068		-0.067		0.004		-0.085	
	(0,20)		(-1,24)		(0,09)		(-0,22)		(1,19)		(-0,77)		(0,05)		(-1,51)	
Ab_temp Q2		0.134		2.296		0.547		-0.077		0.040		0.244		0.515		0.058
		(1,28)		(0,30)		(1,39)		(-1,28)		(0,12)		(0,44)		(0,94)		(0,17)
Ab_temp Q3		0.089		0.459		0.384		-0.051		0.303		0.614		0.186		-0.354
		(0,84)		(0,61)		(0,97)		(-0,83)		(0,87)		(1,25)		(0,34)		(-1,04)
Ab_temp Q4		-0.006		-0.038		-0.265		0.003		0.112		0.192		0.817		-0.128
		(-0,06)		(-0,06)		(-0,07)		(0,06)		(0,32)		(0,39)		(0,15)		(-0,38)
Ab_temp Q5		0.115		-1.047		0.418		-0.067		0.481		-0.479		0.384		-0.493
		(1,09)		(-1,53)		(1,05)		(-1,10)		(1,39)		(-0,93)		(0,69)		(-1,45)
Obs.	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193
R^2	0.000	0.016	0.009	0.026	0.000	0.018	0.002	0.016	0.007	0.014	0.003	0.025	0.000	0.006	0.012	0.020

*Table 9: Regression output of equal-weighted and value-weighted portfolio returns and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.10; **p<0.05; ***p<0.01.*

In table 9, columns one, three, five, and seven, are part of the equal-weighted portfolio and show no support for a relationship between abnormal temperature and portfolio returns. This also holds true for the value-weighted portfolio in columns nine, eleven, thirteen, and fifteen in the table. This is consistent with our findings regarding the relationship between attention and abnormal temperatures. Further, even though no statistically significant conclusions can be drawn, it is noteworthy that the coefficients of the size-adjusted returns seem to behave in the opposite manner of Choi, Gao, and Jiang (2020). For example, we find that the return of the EMC and Emission portfolios is slightly positive in months of abnormal temperature. At the same time, the Clean portfolios have a slightly negative return in the same months. Hence, if significant, the coefficients would imply that Emission stocks systematically receive a positive adjusted return in months with abnormal temperatures while Clean stocks underperform in the same months.

As argued in the previous section, the winsorized result must be considered in relation to the non-winsorized result. Therefore, in table 10, the non-winsorized results are presented and will be considered in relation to the winsorized results in table 9.

	Equal-weighted portfolios								Value-weighted portfolios							
	EMC		EMC (unadjusted)		Emission		Clean		EMC		EMC (unadjusted)		Emission		Clean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Ab_temp	0.016		-0.192		0.054		-0.097		0.078		-0.086		-0.097		-0.098	
	(0,68)		(-1,39)		(0,59)		(-0,70)		(1,28)		(-0,94)		(-1,10)		(-1,57)	
Ab_temp Q2		1.128		0.191		0.474		-0.064		0.021		0.177		0.578		-0.118
		(0,79)		(0,24)		(0,88)		(-0,77)		(0,06)		(0,31)		(0,99)		(0,31)
Ab_temp Q3		0.701		0.491		0.315		-0.040		0.312		0.594		0.135		-0.036
		(0,49)		(0,62)		(0,58)		(-0,48)		(0,85)		(1,17)		(0,23)		(-0,97)
Ab_temp Q4		-0.022		-0.807		-0.085		0.012		0.046		0.139		0.076		-0.022
		(-0,15)		(-0,11)		(-0,16)		(0,15)		(0,13)		(0,26)		(0,13)		(-0,06)
Ab_temp Q5		0,245*		-1,333*		0,915*		-0,142*		0.558		-0.664		0.368		-0.590
		(1,70)		(-1,73)		(1,68)		(-1,71)		(1,51)		(-1,15)		(0,63)		(-1,57)
Obs.	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193
R^2	0.002	0.023	0.011	0.031	0.002	0.023	0.003	0.023	0.009	0.018	0.004	0.028	0.000	0.007	0.013	0.025

*Table 10: Regression output of non-winsorized equal-weighted and value-weighted portfolio returns and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.1; **p<0.05; ***p<0.01.*

Table 10 and 9 show no systematic relationship between abnormal temperature and portfolio returns. However, there is a noteworthy difference between the equal-weighted portfolios in the two tables when temperature quintiles are considered. As stated earlier, we do not find any significant relationships between the level of abnormal temperature and the winsorized estimates. This is in contrast to the non-winsorized results where the warmest temperature quintile and returns on all equal-weighted portfolios are significant at a ten percent level. Furthermore, this is in line with Choi, Gao, and Jiang (2020), who find that the warmest temperature quintile had the statistically strongest relationship with returns. However, in contrast to Choi, Gao, and Jiang (2020), the economic impact of our results is inverse for all portfolios with size-adjusted returns. The coefficients of EMC and Emission at the warmest temperature quintile are positive and the coefficient of Clean is negative, indicating an overperformance by Emission stocks in abnormally warm weather. Consequently, a change from the coldest temperature quintile (one) to the warmest quintile (five) would imply an increase of 25 basis points (t-stat = 1.70) in size-adjusted return of the equal-weighted portfolio. However, these findings are only significant at the lowest level (90 percent) and not supported by a presence in the value-weighted portfolios, nor in any shown systematic relationship with the Ab_temp variable. The difference between the winsorized and non-winsorized results in the equal-weighted portfolio is therefore assumed to be caused by the outliers that are biased since they create a significant association that is not present. Hence, the evidence is claimed contingent.

Finally, in table 11, all of the regressions are repeated in the control test period when climate change was less publicly recognized. The regressions are not significant, and the model has even lower explanatory power than the original test period. The same holds true for the non-winsorized results that are shown in appendix D.17.

	Equal-weighted portfolios								Value-weighted portfolios							
	EMC		EMC (unadjusted)		Emission		Clean		EMC		EMC (unadjusted)		Emission		Clean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Ab_temp	0.008		-0.007		0.016		-0.005		0.010		0.003		0.069		0.015	
	(0,25)		(-0,09)		(0,29)		(-0,22)		(0,15)		(0,02)		(0,97)		(0,21)	
Ab_temp Q2		0.018		0.223		0.073		-0.004		-0.165		0.021		-0.303		0.102
		(0,07)		(0,37)		(0,17)		(-0,03)		(-0,33)		(0,02)		(-0,56)		(0,18)
Ab_temp Q3		0.028		0.233		0.010		-0.023		-0.207		-0.548		-0.341		0.142
		(0,12)		(0,36)		(0,02)		(-0,14)		(-0,42)		(-0,57)		(-0,63)		(0,25)
Ab_temp Q4		-0.040		-0.055		-0.051		0.033		0.180		0.633		0.219		-0.084
		(-0,17)		(-0,08)		(-0,12)		(0,20)		(0,36)		(0,66)		(0,41)		(-0,15)
Ab_temp Q5		-0.101		0.086		-0.121		0.081		-0.228		-0.416		0.267		0.374
		(-0,42)		(0,16)		(-0,28)		(0,48)		(-0,46)		(-0,45)		(0,49)		(0,67)
Obs.	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193
R^2	0.000	0.002	0.000	0.002	0.000	0.001	0.000	0.003	0.000	0.005	0.000	0.010	0.005	0.012	0.000	0.004

*Table 11: Regression output of control period (December 1983 to December 1999), equal-weighted and value-weighted portfolio returns and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.1; **p<0.05; ***p<0.01.*

Sub-conclusion

This thesis finds no evidence of a relationship between abnormal temperatures and monthly stock returns on the Stockholm Stock exchange. Hence, we found no support for the third and fourth alternative hypothesis that abnormal temperature affect stock return. This is in line with the previous findings of this thesis that show no statistically significant effect of abnormal temperature on attention. In contrast to the findings by Choi, Gao, and Jiang (2020), this thesis finds no evidence that people in Sweden revise their beliefs about climate change when experiencing abnormal temperatures.

Regression Output Test 3: Abnormal Temperatures and Trading Activity

In the fifth, sixth, and seventh hypothesis, the relationship between different investor types and their average net buy of high and low emission firms during abnormal temperatures are examined. More specifically, the investor types are grouped as retail investors, blockholders, and institutional investors. Average net buy for each investor group is defined as the average change in ownership between two quarters in the Emission firms minus the average ownership change in Clean firms. Table 12 provides the results for the three portfolios of interest. By examining the different investor groups' trading activity in the EMC portfolio, a conclusion can be drawn regarding a potential systematic relationship between the investor types trading activity and abnormal weather.

	EMC ΔRetail		EMC ΔInstitutional		EMC ΔBlockholders	
	(1)	(2)	(3)	(4)	(5)	(6)
Ab_temp	-0.055		0,782*		0.038	
	(-0,42)		(1,72)		(0,36)	
Ab_temp Q2		-0.374		0.013		0.535
		(-0,67)		(0,06)		(1,17)
Ab_temp Q3		0.869		0.008		-0.458
		(1,57)		(0,04)		(-1,07)
Ab_temp Q4		-0.169		0.225		0.217
		(-0,30)		(1,18)		(0,56)
Ab_temp Q5		-0.146		0,444**		-0.009
		(-0,26)		(2,45)		(-0,03)
Observations	65	65	65	65	65	65
R^2	0.003	0.092	0.038	0.100	0.003	0.108

*Table 12: Regression output of trading activity and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.1; **p<0.05; ***p<0.01.*

As shown in table 12 columns one and five, neither retail investors nor blockholders show systematic trading behavior during abnormal temperatures. However, at the lowest significance level, 90 percent, institutional investors systematically increase their holdings in Emission firms under abnormal temperatures (t-stat =1.72). Thus, a 1-standard-deviation increase in Ab_temp would correspond to an increase in the average net buy of 1.08 percent (=0.782*1.386) in the EMC portfolio of institutional investors. Further, even though no statistically significant conclusions can be drawn regarding the retail investors and blockholders trading activity, it is noteworthy that the coefficients of interest in these tests seem to behave in the same manner as in Choi, Gao, and Jiang (2020) findings. The retail investor coefficient is slightly negative, while the blockholders coefficient is slightly positive. Hence, if significant, the coefficients would imply that retail investors decrease their holdings while blockholders increase their holdings in abnormal temperatures. We also examine the eighth, ninth, and tenth hypothesis, that is whether the highest level of abnormal temperature impact the respective investor group. Column four shows that institutional investors increase their EMC holdings by 0.78 percent in the warmest temperature quintile compared (five) to the coldest quintile (one). Similar to the result above, no significant trading behavior is found for the blockholders nor retail investors.

It is important to note that one of our methodological limitations concerned the institutional investor variable. The possibility of Type I errors in this regression was elaborated on in the regression methodology limitations (section 4.5). Hence, we are conservative in the interpretation of the above significance and rely on the following test for conclusions regarding institutional investors.

In table 13, we examine whether the behavior differs among foreign and local investors to test our hypotheses. Since only local investors will experience the temperature in Sweden, the potential behavioral effect of experiencing abnormal temperature will only apply to local investors. Thus, the differentiation between foreign and local investors simultaneously functions as an indication of the robustness of the findings in table 12.

	EMC ΔLocInstitutional		EMC ΔForInstitutional		EMC ΔLocBlockholders		EMC ΔForBlockholders	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ab_temp	0.032		0.047		-0.006		-0.004	
	(0,86)		(1,37)		(-0,11)		(-0,06)	
Ab_temp Q2		-0.046		0.092		0.255		-0.277
		(-0,24)		(0,61)		(1,10)		(-0,91)
Ab_temp Q3		-0.144		0.179		-0,459*		-0.393
		(-1,04)		(1,18)		(-1,98)		(-1,29)
Ab_temp Q4		0.017		0,274*		-0.008		0.013
		(0,11)		(1,81)		(-0,03)		(0,04)
Ab_temp Q5		0.234		0.204		0.011		-0.164
		(1,56)		(1,35)		(0,05)		(-0,54)
Observations	65	65	65	65	65	65	65	65
R^2	0.010	0.075	0.029	0.061	0.000	0.142	0.000	0.042

*Table 13; Regression output of trading activity of foreign and local investors and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.1; **p<0.05; ***p<0.01.*

As shown in table 13, columns one and three, the previously systematic relationship between abnormal temperature and trading behavior vanishes when dividing the institutional investors based on their geographical origin. Hence, instead of further supporting the weak relationship found in the previous test, these findings indicate that no systematic relationship, in fact, exists. Since this test provides no significant result, the relationship found in table 12 is concluded to be obsolete. Further, as shown in columns five and seven, there is, as expected, no relationship presents for blockholders.

As explained earlier, it is important to evaluate the winsorized result in relation to non-winsorized estimates. Therefore, in table 14, the non-winsorized results are presented and these will be considered in relation to the winsorized results in table 13 and 12.

	EMC ΔRetail		EMC ΔInstitutional		EMC ΔBlockholders	
	(1)	(2)	(3)	(4)	(5)	(6)
Ab_temp	-0.070		0,083*		0.037	
	(-0,51)		(1,78)		(0,35)	
Ab_temp Q2		-0.278		0.013		0.569
		(-0,47)		(0,06)		(1,21)
Ab_temp Q3		0.869		-0.008		-0.501
		(1,46)		(-0,04)		(-1,12)
Ab_temp Q4		-0.254		0.302		0.217
		(-0,43)		(1,25)		(0,56)
Ab_temp Q5		-0.146		0,444**		-0.009
		(-0,25)		(2,45)		(-0,03)
Observations	65	65	65	65	65	65
R^2	0.004	0.079	0.036	0.097	0.002	0.114

*Table 14: Regression output of non-winsorized trading activity and Ab_temp with coefficients in percentage. The statistical significance of the coefficients is reported by *p<0.1; **p<0.05; ***p<0.01.*

In table 14, columns one, three, and five similar results between abnormal temperatures and trading behavior as in the winsorized tests are shown. In the same manner as in the winsorized tests, no support is found when dividing the investor groups based on their geographical origin, as shown in appendix E.8.

Sub-conclusion

This thesis finds no evidence of a systematic relationship between the trading activity of any investor group and abnormal temperature. The weak relationship found between institutional investors and abnormal temperatures was not supported when the group was geographically divided and therefore deemed obsolete. Thus, there is no support for the hypotheses that experiencing abnormal temperatures affects the trading behavior of the different investor groups. This is in contrast to Choi, Gao, and Jiang (2020), who find that local retail investors systematically sell high emission stocks while blockholders buy high emission stocks in abnormal temperatures.

6. Discussion

This section aims to provide a fuller discussion of the empirical results in relation to the underlying theory of the thesis and depict the result in relation to the national surveys conducted by institutional parties that were presented in the 3.5 section of the thesis. This will be done in three interrelated sections. First, a discussion regarding attention to climate change and abnormal temperature will be performed. Secondly, the discussion will focus on investor beliefs in light of the literature on the topic and surveys conducted in Sweden. Finally, building on the findings in the first two sections, the discussion emerges in a depiction of the ownership impact on stock prices.

Abnormal Temperatures and Attention to Climate Change

The first sets of hypotheses examine whether abnormal temperature impacts Swedish investors' realization about climate change. More specifically, whether the experience of abnormal temperatures causes Swedish investors to pay more attention to climate change. As argued in the literature chapter, limited attention puts constraints on what we can be attentive towards and might result in a misdirected attention (Lim & Teoh, 2010; Hishleifer & Teoh, 2003). Furthermore, DellaVigna and Pollet (2007) argue investors are often inattentive to less salient and less accessible long-term effects, but attentive to the more salient short-term effects. Since the local weather is people's direct experience, it could affect people's attention towards climate change (Choi, Gao, & Jiang, 2020), even if the short-term abnormal temperatures say nothing about the long-term trend (IPCC, 2018b; Zaval et al., 2014).

In the paper of Choi, Gao, and Jiang (2020), it is concluded that abnormal temperatures in an international setting result in an increase in attention towards climate change. This thesis tests whether the same effect is visible when focused solely on the Swedish market and in a more recent time period. However, the thesis does not find support for the set-out hypotheses. Hence, the findings contradict Choi, Gao, and Jiang's (2020) result, and the potential reasons and implications will now be discussed.

According to Lim & Teoh (2010), the salience of a stimulus is an important denominator for our attention to be captured by it. Therefore, our insignificant result causes a question of the salience of abnormal temperatures to rise. One could argue that a reason for the non-result is that abnormal temperatures are not salient for people in Sweden. However, the substantial findings of abnormal temperature impact on an international level suggest that the stimuli are perceived as salient in many nations. As a consequence, one must turn to what might offset the salience of abnormal temperatures in Sweden. We argue that a likely explanation could be found in the perception, characteristics, and the number of competing stimuli in the environment as these are likely to differ across borders. This line of reasoning stems from the description of attention allocation by Lim and Teoh (2010). They argue that attention allocation is not only dependent on the salience of the stimulus in question, but also on the characteristics and number of competing stimuli in the environment. This is derived from the premise that attention to one task requires substitution from another task (Lim & Teoh, 2010). Thus, we argue that the insignificant result of the first test could be explained by the argument that competing stimuli in the area of climate change might be more salient than the abnormal temperatures in Sweden. Hence, the stimulus abnormal temperature might be offset by other competing stimuli towards climate change. Accordingly, we graph several relevant climate change events in recent years, that could be competing stimulus, and compare it to Google SVI for the topic "Climate change" in Sweden.

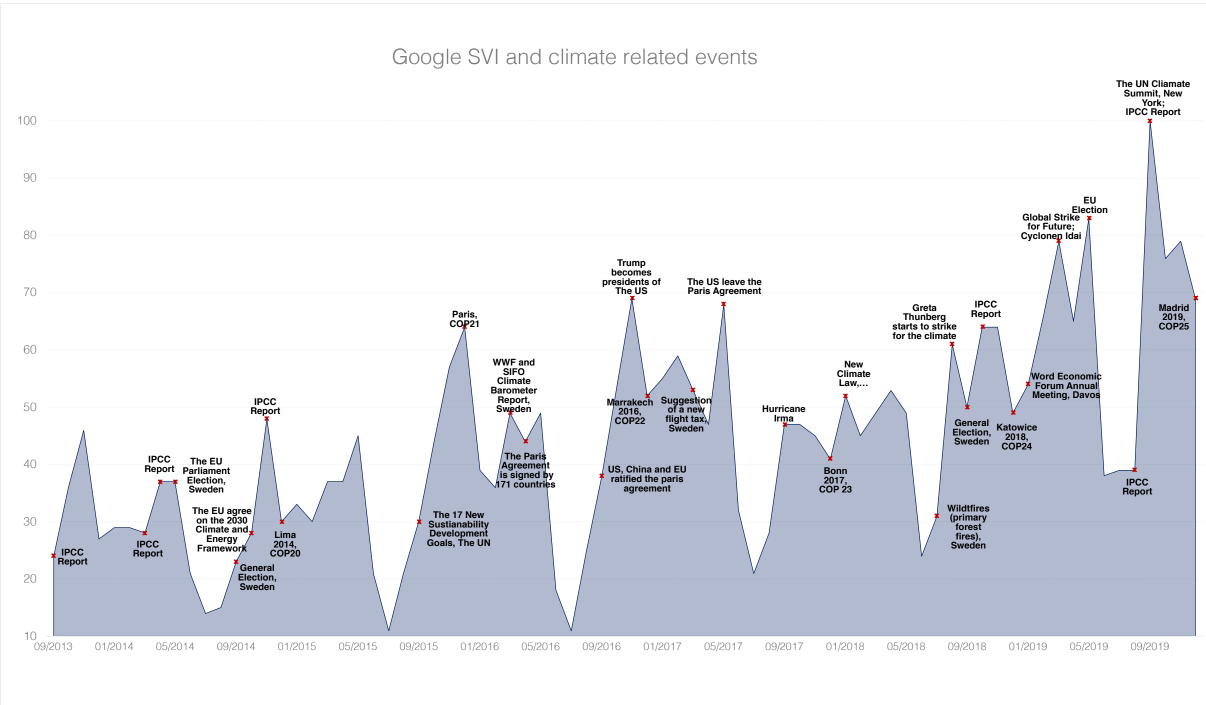

Figure 15: Google search volume and climate related events. Time period stretching from 2013 to 2019. Own illustration. Data source: Google Trends (2020).

As shown in figure 15, some potential competing stimuli seem to correlate with attention toward climate change. Notably, some events seem to repeatedly result in increased attention toward climate change, such as IPCC reports and the United Nations Climate Change Conference (COP).

Schmidt (2015) claims that media coverage of climate change appears to be higher in years that are warmer than previous years; in other words, years that break the records. Thus, the attention effect of local weather could be enhanced by the media. If the media systematically cover the topic of climate change in abnormal temperatures, the local warming effect on attention found in other studies, such as Choi, Gao, and Jiang (2020), could partly be ascribed to increased media coverage. The salience of media coverage has been found in many of the studies covered in our thesis. Klibanoff, Lamont, and Wizman (1998) and Huberman and Regev (2001) both found that the salience of New York Times articles impacted investors. Moreover, Boykoff and Roberts (2007) found that media coverage was a central factor in people's understanding of climate change.

In Sweden, record-breaking years, such as 2019, seem to increase media attention. For instance, in Swedish business newspapers, the number of articles related to the topic of climate change increased by 72 percent in relation to the previous year (Retriever, 2020). We also see an increase in Google SVI in these years. This indicates that media coverage could be related to abnormal temperatures. However, by looking at the yearly tendencies, we cannot identify whether the increase in media coverage is related to specific months of abnormal temperatures or if the increased media attention is coincidental. Consequently, we cannot rule out the possibility that Sweden exhibits a weaker relationship between abnormal temperatures and attention due to the media coverage being unrelated to abnormal temperatures. As argued in the previous section, it seems as the potential salience of abnormal temperatures is offset by competing stimuli. Since media coverage is often perceived as salient, it could potentially reveal which these competing stimuli are. For instance, Greta Thunberg is one of the most mentioned in the business newspaper headlines in recent years (Retriever, 2020) and seems to attract google searches, as shown in figure 15.

Abnormal Temperatures and Portfolio Returns

The combination of the third and fourth sets of hypotheses examines whether abnormal temperature impacts Swedish investors' response to climate change. The results from the hypothesis testing will be elaborated on in this section. The result will be discussed in relation to studies presented in the literature chapter on how personal experience can affect the belief regarding climate change and people's adopted actions. These will further be applied to the Swedish context for answers regarding the apparent difference in our findings compared to international studies. The result will also be depicted in relation to the first analysis to develop the discussion further of the interrelated results.

According to the efficient market hypothesis, beliefs are supposed to be revised when new value implicating information reaches the market (Malkiel, 2003). As abnormal temperatures carry no new information about the climate at large, beliefs about climate cash-flow implications and the following prices should not be revised. However, existing climate research suggests that temperature abnormalities do influence our risk perceptions and beliefs about climate change (Choi, Gao, & Jiang, 2020; Zaval et al., 2014; Li, Johnson, & Zaval, 2011). In an international setting, Choi, Gao, and Jiang (2020) concluded that abnormal temperature affects investors' beliefs and stock prices of climate sensitive stock. Heuristic belief-updating and collective market actions lay the foundation for this effect to be present, as temperature abnormalities are, as previously argued, non-information with regards to the climate at large. As concluded in the regression output section 4.5, we find contradicting results in the Swedish market. In Sweden, we find no evidence of a systematic relationship between abnormal temperature and EMC returns in Sweden. Because of this, we do not find support for the hypothesis that Swedish investors systematically update their beliefs regarding climate change when experiencing abnormal temperatures. Our finding, therefore, supports a conclusion where belief updating with regards to climate change does not seem to be heuristic in the Swedish market and does not give support to conclusions about market inefficiency. However, the potential underlying reasons for our non-result need to be elaborated on further. Therefore, the following discussion will evaluate the potential reasons behind the non-result in contrast to the underlying theory of the thesis and opposing result of Choi, Gao, and Jiang (2020).

One potential reason for the non-result could be that Swedish investors have not, to a large extent, updated their belief regarding climate change when experiencing abnormal temperatures. In order for a price-effect to be visible within the means of our method, it would require either a continuous updating or a reversal of beliefs about climate change related to abnormal temperature periods. In a yearly survey by the SOM Institute, approximately 20,000 Swedes are asked about the level of concern they have about climate change, which gives some indications on the belief-updating process in Sweden.

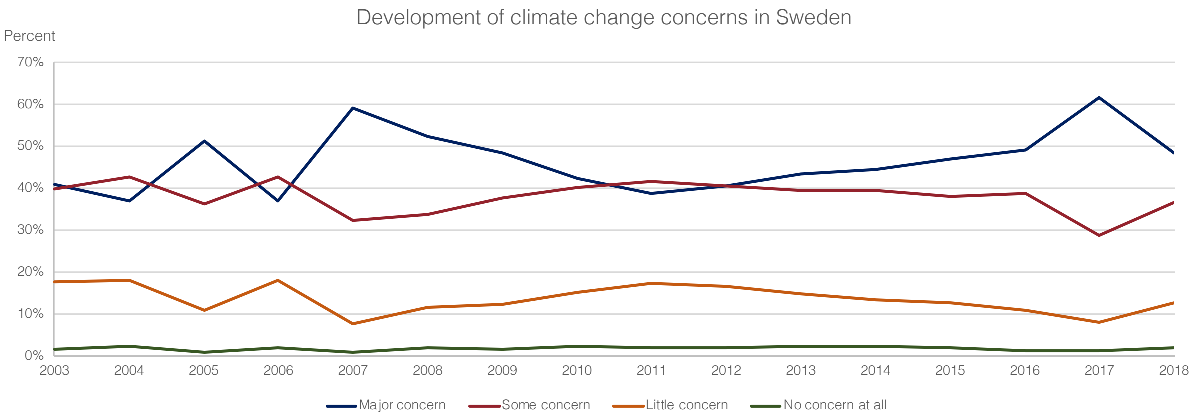

Figure 16: Development of respondents' concern about climate change from 2003 to 2018 in Sweden. Own creation. Data source: University of Gothenburg, SOM Institute (2020).

As shown in figure 16, there are some indications of a continuous belief-updating process in Sweden. In the period from 2003 to 2018, we see a decrease in respondents with little- to no concern from 19.4 percent to 15.0 percent and an increase in respondents with some- to major concern from 80.6 percent to 84.9 percent. The same holds for potential belief reversals, where the figure indicates that concerns do vary across the years. For example, in 2006 and 2011, it is visible that the respondents with major concern decreases and little- to some concern increases. As argued earlier, a detectable price-effect would require either a continuous updating or a reversal of beliefs about climate change related to abnormal temperature periods. Given that the SOM Institute survey could mirror investor beliefs, it indicates that beliefs are continuously revised and reversed. These indications imply that in relation to our result, it is not that belief-updating and reversals are not occurring, which are implicating our results, but rather that abnormal temperatures do not seem to drive the beliefs. However, it is still uncertain whether the small proportion of people with varying concerns would be enough to implicate stock prices.

With that in mind, it is important to consider Swedish people's climate change beliefs in relation to other countries since the current literature on the topic is covering international data and larger markets such as the U.S. In a U.S. survey from 2016, only 70 percent of the respondents believe that climate change is occurring (Marlon et al., 2016). In the same year, European Social Survey (2018) finds that 96.8 percent of Swedes believe that climate is changing. Furthermore, compared to other European countries, Sweden scores second-highest on the question. Additionally, as shown in figure 16, a large proportion of Swedes are concerned about climate change as early as in 2003, which in itself indicates a belief in a changing climate. As argued in the previous paragraph, the development of concerns is also rather small. This is also indicated in a survey by Kantar Sifo, where only three percent of the respondents in 2019 do not believe in climate change (Wennö & Söderpalm, 2020). Hence, the non-result of our study compared to other international studies could potentially be explained by the evidence suggesting that such a large proportion of Swedes already believe that climate change is happening. When collective beliefs are so close to the scientific consensus, the relationship between stock prices and local abnormal temperatures is expected to be weakened (Choi, Gao, & Jiang, 2020). Thus, the belief-updating process, which can be identified in an international setting, might be too small to detect in a Swedish setting given that beliefs are not adequately reversed within the testing period.

Another important consideration is to evaluate the second set of discussions in relation to the first discussion on Attention to climate change. As argued in the literature review, limited attention cannot only cause heuristics which implicate beliefs, but also create attention-driven buying pressure (Barber & Oden, 2008). According to Barber and Odean (2008), individual investors can become net-buyers of attention-grabbing stocks, which generates attention-driven buying pressure, resulting in higher stock prices in the short-run followed by long-run reversals. As abnormal temperature does not systematically increase Swedish attention toward climate change, the possibility of this type of price pressure was excluded in our first analysis. Thus, the result from our second analysis is in conjunction with our first. In figure 17 below, attention toward climate change, as proxied by Google SVI, abnormal temperature and major concern about climate change are presented.

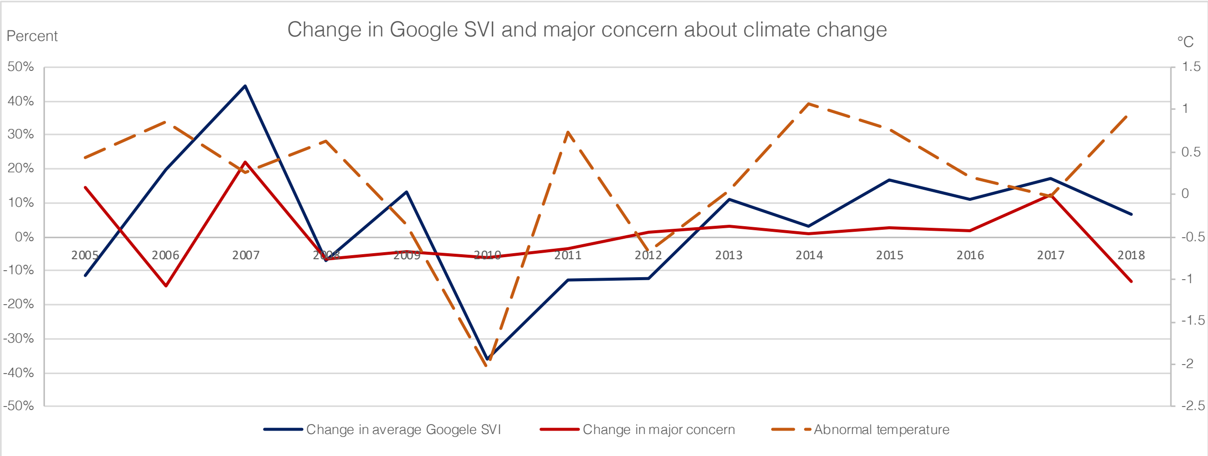

Figure 17: Percentage change in yearly average Google SVI, percentage change in major concerns of climate change, and yearly average abnormal temperature. Own creation. Data soures: Google Trends (2020), University of Gothenburg, SOM Institute (2020), and SMHI (2020b).

As shown in figure 17, the change in the two factors, attention and major concern about climate change, seem to continuously correlate while abnormal temperature does not. This further establishes that the identification of what factors drives these processes might have attention-driven pricing implications, but that the determining factor in the Swedish market does not seem to be abnormal temperature.

As argued in the literature review, many studies have found that personal experience is important for the belief process when it comes to climate change (Baldauf, Garlappi, & Yannelis, 2020; Keenan, Johnson, & Weber, 2014; Zaval et al., 2014). In a survey by Kantar Sifo in 2019, the importance of personal experience is, to some degree, visible in the responses from Swedish people when they elaborate on what concerns them most about climate change (Wennö & Söderpalm, 2020). The potential of wildfires and droughts are the most worrying scenarios, which are connected to recent experiences of the incidents. This indicates that availability heuristic, where individuals evaluate the likelihood or frequency of an event by the ease with which they can access corroborative memories, could be present in the belief-process of Swedes. One could argue that both worrying scenarios are closely connected to warm local temperatures. Thus, it seems that any potential pricing effect due to an increase in attention and/or heuristic belief revision could be correlated with the warmest quintile of abnormal temperature. However, we did not find this systematic pattern in our study, even if the population in the Kantar Sifo survey seem to demonstrate these behavioral patterns. Hence, we could not find supporting evidence of a heuristic belief formation related to abnormal temperatures in Sweden. However, in relation to this argumentation, it could be considered whether a combination of experiences and social construction could be explanatory for the non-result of our study. In an article by Akerlof et al. (2013), it is argued that an increased risk perception of climate change is caused, presumably, through a combination of the direct experience, the vicarious experience, and the social construction. Therefore, the direct experience of abnormal temperatures might not in itself be enough to explain the formation of beliefs, but a combination of experiences and social construction could have explanatory power.

Even though the above arguments suggest that other factors than abnormal temperatures drive climate change beliefs and attention in the Swedish market, one cannot completely exclude the factor as a driver. It is important to consider whether the IPCC classification of high emission firms captures the general beliefs of investors. In a survey by Kantar Sifo in 2019, less than 40 percent of the respondents knew what the two largest emitters in Sweden were (Wennö & Söderpalm, 2020). Hence, this indicates that more than the majority of the respondents demonstrate some degree of incompetence on the major emitters in the society. If these results can be translated to the majority of investors, any potential price effect for the Emission and Clean stocks may not be detectable with our IPCC classifications. This indication of public ignorance surrounding the issue is interesting for future classifications. However, the assumption of undetectability due to ignorance is a rather strong one to make. The conclusion that a proportion of Swedes are unable to identify the two largest emission sources does not directly imply that they are unable to identify which sources that generate high emissions. Hence, we argue that the categorization where the largest emission industries are grouped into one unit should have the ability to capture the public perception.

Furthermore, it is important to consider whether the IPCC classification could suffer from actual cash-flow effects in abnormal temperatures. For example, if a multitude of industries in the Clean grouping of stocks experience a negative earnings effect in abnormally warm weather while the Emission stocks do not, a potential price-effect due to belief revision could be canceled out. However, since the Emission and Clean portfolios are examined separately, we would still be able to detect a systematic effect in the respective portfolios. Furthermore, Addoum, Ng, and Ortiz-Bobea (2020) find that in the U.S. market, neither abnormally warm nor abnormally cold weather affects establishment sales or productivity. They conclude that the only evidence of a sales effect caused by abnormal temperatures in the U.S. market is found in the energy industry, while temperatures are abnormally cold. The IPCC definitions of our thesis classify all energy companies as high emission firms. Thus, if the result of the study by Addoum, Ng, and Ortiz-Bobea (2020) can be translated to the Swedish market, the non-existing relationship of our study between abnormal temperatures and returns is in line with earnings expectations. Hence, a cash-flow effect that cancels out a present price effect caused by belief-updates is unlikely in our study.

Abnormal Temperatures and Trading Activity

In the third set of hypotheses, the abnormal temperature impact on Swedish investor response to climate change was further examined. More specifically, the relationship between abnormal temperature and different investors' trading behavior on the Stockholm Stock exchange was studied. The result will primarily be viewed in light of our previous findings. Further, it will be an extension to the previous discussion on stock prices and abnormal temperature by taking a point of departure in the ownership impact on stock prices.

The results from the first sets of hypotheses indicate that there should be no systematic trading behavior based on abnormal temperatures. At least, any potential systematic trading behavior does not affect the pricing mechanism. The results from the last sets of hypotheses confirm this conjecture, and no systematic relationship between abnormal temperature and trading activity of retail investors, blockholders, or institutional investors is found. However, we must consider the importance of a home bias presence in the matter. Research has found that investors tend to allocate a greater share of their portfolio to domestic securities rather than foreign ones (French & Poterba, 1991). As a result, the prices of local stocks are affected by local investors' trading behavior (Chan, Hameed, & Lau, 2003). Thus, if our sample does not exhibit this unbalance between local and foreign investors, local investors would not be able to move prices to the same degree. In the results of hypothesis two, ownership proportions are unknown. Therefore, as an extension to the previous discussion, an estimation of the sample proportion of local and foreign investors is presented.

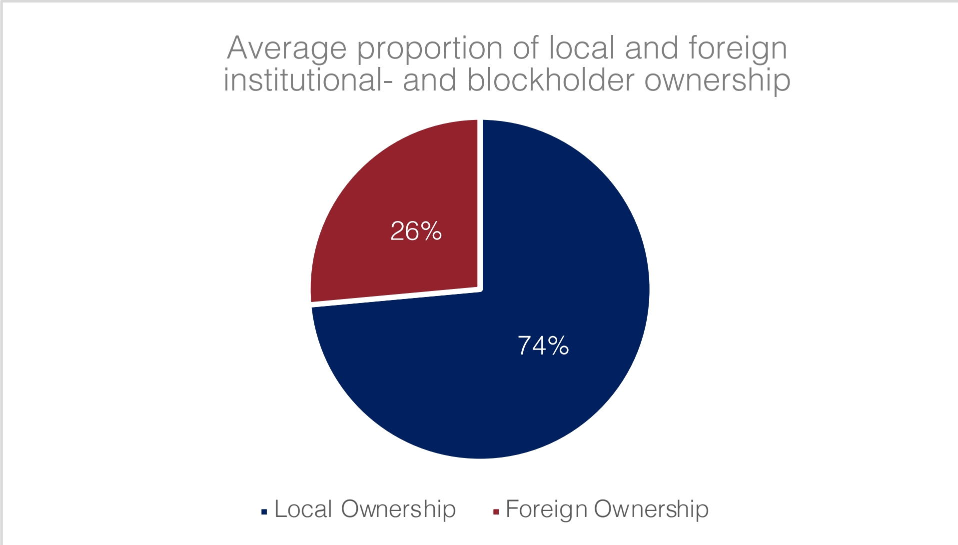

Figure 18: Average proportion of local and foreign institutional investors and blockholders. Time period stretching from December 2003 to December 2019. Own creation. Data sources: Thomson Reuters (2020) and FactSet (2020).

As shown in the pie chart above, the average local institutional ownership and blockholders ownership in our sample is 74 percent, while 26 percent is foreign. Further, all retail investors are assumed to be local. Hence, we can see that the sample exhibits an overrepresentation of local ownership. Consequently, we would expect to see a price movement if the local abnormal temperatures would be a determining factor for local investors' valuation of stocks. However, since no such relationship is present, it is not the proportion of local and foreign investors that is explanatory for the non-result, but rather that abnormal temperature is not the determining factor.

Further, Choi, Gao, and Jiang (2020) argue that retail investors are more prone to individual biases than institutional investors and blockholders. The findings of Choi, Gao, and Jiang (2020) also support the claim, where retail investors systematically avoid the Emission stocks once their beliefs are updated. Therefore, we would expect that trading activity based on heuristic belief-formation in abnormal temperatures would primarily, in case of its presence, be visible in the retail investor segment. Consequently, the non-relationship between abnormal temperatures and all investor trading activity further supports the conclusion that belief-formation in Sweden does not seem to stem from experiencing temperature abnormalities. However, in line with the arguments formed in the previous discussion, we cannot ultimately exclude the factor as a driver. The result is prone to some of the same potential diluting mechanisms as discussed in the previous section. In particular, if the IPCC classifications do not reflect the public perception, the test of investor trading activity would also be prone to the same dilution of the result as argued earlier. Nevertheless, the combined results in all our hypotheses testing strongly suggest that abnormal temperature is not influencing investor behavior on the Stockholm stock exchange.

7. Conclusion

This thesis studies to what extent, if at all, exposure to abnormal temperature in Sweden affects equity investors' realization and response to climate change. The aim of the thesis is to contribute to the limited research made by financial economists on the effect of abnormal temperature exposures on investor behavior in regard to climate change. Inspired by international studies, we contribute with novel insight from the Swedish stock market.

Our study was conducted in three interrelated sections starting off by showing a non-significant relationship between abnormal temperature and increased attention by means of Google searches on the topic "Climate change". We argue that the stimulus abnormal temperature might be offset by other competing stimuli toward climate change. Thus, we could not find that abnormal temperature influenced investors' realization of the climate change issue.

Further, we turned to the Stockholm stock market by identifying industries as either high or low emission and constructed a long-short portfolio defined as Emission Minus Clean (EMC). At a monthly frequency, we find that the effects of temperature abnormalities on stock prices are statistically insignificant. Thus, we could not find support for our hypotheses that abnormal temperature impact investor beliefs, and the market as a whole do not react to abnormal temperature. We argue that the high level of climate change believers in Sweden makes the link between abnormal temperature and stock prices weaker. The updating of beliefs as a consequence of abnormal temperatures might be too small to impact prices or not exist at all on the Stockholm stock exchange. Consistent with these results, we find similar non-results at the ownership level, where we document that temperature exposures are unrelated to trading activities among retail investors, blockholders, and institutional investors.

The consistent set of non-results strongly suggests that abnormal temperatures do not influence equity investors' realization and response to climate change in Sweden. This provides a starting point for further examination that will be expressed in the next section.

8. Limitations and Future Research

While our combined analysis of the relationship between abnormal temperatures and investor behavior displays a consistent set of non-results, our tests construct a point of departure for further review. In this section, we will therefore extend the previous discussion and present limitations combined with suggestions for future research.

From our combined analysis, it is clear that some questions remain to be answered for an ultimate conclusion of what drives investor attention, beliefs, and ultimately actions with regards to climate change in the Swedish market. In our discussion regarding abnormal temperatures and stock returns, we identified some indications of availability heuristics when it comes to climate change concerns in Sweden. We elaborated on the argument by linking the worrying scenarios of wildfire and drought to abnormally warm temperatures. These scenarios specifically correlate with warm summers. However, the variable of abnormal temperature used in our research will pick up abnormality in all seasons. For example, many of our abnormally warm months occur in the wintertime. Consequently, while our results suggest that abnormal temperatures in general do not seem to impact investor behavior, it remains unsolved whether, for example, abnormally warm summers do. Given the indications of a potential behavioral effect linked to certain seasons of abnormal temperatures, it would be valuable for future research to examine seasonality or other temperature measures further.

Our previous discussions also mentioned the potential of not capturing the public perception with the IPCC categorization. More specifically, a survey by Kantar Sifo in 2019 indicates some incompetence on emission sources among the Swedish respondents (Wennö & Söderpalm, 2020). In spite of this indicated incompetence, we argue it unlikely that the IPCC categorization would fail to capture the public perception. However, a survey study on investor perception regarding emitting industries or specific companies could help to create a more precise categorization to capture investor belief. Further, the IPCC categorization might inherit some industry effects. By employing different categorization measures, such as the one described above, or other already available environmental classifications, researchers could further exclude potential industry effects. Therefore, we encourage further research to explore other types of firm-categorization in order to gain a deeper understanding of the belief mechanisms on the Swedish market.

Further, the chosen proxy to capture attention toward climate change in the Swedish market is not necessarily exhaustive. While Google SVI is often occurring in later research as a comprehensive measure of attention, other proxies are also utilized. As a starting point for future studying of Swedish investor attention to climate change it could therefore be of interest to examine other proxies more closely. Furthermore, as beliefs and attention seem to correlate in the Swedish market, research on the relationship between stock prices and the attention-variable itself could be of interest. In our research we have also been limited to using a proxy for the ownership proportion of retail investors. This proxy is susceptible to measurement errors. Further, the amount of local- contra foreign retail investors is unknown. Instead, all retail investors are assumed to be local. Therefore, a study allowing a precise measure on, not only the institutional investors and blockholders, but also retail investors would be a valuable contribution to the research field.

It is also important to mention that stock returns are affected by many factors. The market impact of the current worldwide outbreak of COVID-19 is an excellent example of an event that could dominate other potential factors such as abnormal temperature. Hence, market-disrupting events and other price implicating factors can potentially create too much noise for a detection to be possible within the means of our chosen method. Over the length of the main sample period, 16 years, many such price-implicating events have taken place, which could dilute results. Further, our method is unable to capture whether any effect might have been present in some years, but not in others. Hence, a suggestion for further establishment of the abnormal temperature effect would be to study it in different time horizons. It is also important to note that while our monthly and quarterly time series' does not exhibit a significant relationship, it cannot be excluded that other time intervals do. It could, therefore, be of interest to further study the effect of abnormal temperatures on attention and beliefs in other intervals. Another limitation of our study in comparison to Choi, Gao, and Jiang (2020) is that it does not exhibit the same identification advantage as one based on international data. In an international setting, beliefs will naturally vary across countries and will most likely not be revised or updated simultaneously. This will clearly facilitate an identification of any abnormal temperature effect.

To conclude, future research efforts may be dedicated to further investigate these concepts. Notwithstanding, we are confident that our thesis advances existing knowledge on the Swedish investor realization and response to climate change.

8.1 Perspective

While writing this thesis, the global COVID-19 pandemic has rippled through our societies and created devastating effects for people across the globe. Moreover, the virus has a dramatic impact on financial markets all over the world. The combination of the two has caused an economic crisis in which our thesis must be viewed in relation to. Since our thesis examines data from a period prior to these events, the potential effect of the crisis will be taken into consideration. The consideration requires the atypical approach of introducing additional information. However, due to the significance of the events, we do not wish to leave it un-commented.

The outbreak of the COVID-19, is in many ways resembling a future climate crisis. Watching the pandemic develop is like looking into a crystal ball where the climate crisis unfolds. The two crises are both global challenges that are not at all concerned with borders. Furthermore, these challenges call for governments' actions on a global scale, which have practically never before been seen during peacetime (The Economist, 2020). However, no matter how uncanny the resemblance might be, the perhaps less obvious interaction between the two is even more noteworthy for the field of climate finance in general, and our research in particular. These interactions will, therefore, be reviewed in relation to our research area.

Visibility of the Climate Change Magnitude

The basis for our thesis is the limited attention of individuals, which inherently requires that attention to one task is conditioned with less attention to other tasks. In light of this, it is interesting to observe whether the attention to the global pandemic causes attention to climate change to decrease. The Swedish media-coverage implies that this might be the case. In 2019 the top-subject in Swedish media was the climate (Retriever, 2020). When comparing the number of climate articles in 2019 with COVID-19 articles in only the first four months of 2020, the COVID-19 coverage is more than double the climate amount (Retriever, 2020). The effect of COVID-19 on investor attention to climate change would, therefore, be of interest to further investigate. Moreover, if COVID-19 causes attention to climate change to decrease, further studying the effects of abnormal temperatures on attention to climate change internationally could serve a purpose. Our results indicate that this would not be manifested in Sweden since climate change attention is unrelated to abnormal temperatures prior to the crisis

On the other hand, the global pandemic could also shed light on the magnitude of the challenges of climate change. Since the pandemic has caused complete shutdowns of parts of the economy, it has also resulted in enormous reductions of greenhouse-gas emissions. The International Energy Agency (IEA, 2020). forecasts a reduction of global industrial greenhouse-gas emissions of eight percent in 2020 compared to 2019. This would make the reduction six times bigger than what was achieved in the aftermath of the 2008 financial crisis (IEA, 2020). Even so, the shutdowns and significant limitations to people's daily lives have proven far too small to be able to reach the goal of a climate only being 1.5°C warmer than pre-industrial levels. According to The Economist (2020) we would need to decarbonize 90 percent more than we have done during COVID-19 lockdowns in order to reach the goal. The insufficiency of the reductions, even when such dramatic limitations to daily life are imposed, paints a very vivid picture of the magnitude of the climate change challenge. Even though the necessary de-carbonization levels could be argued to be incorporated into investor forecasts and risk-assumptions, this very vivid realization could have impact on the way investors approach emission industries going forward. More specifically, when applying the concept of heuristics, the salient personal experience of limits to daily lives and realizations of its insufficiency could have an impact on risk judgments. The question remains whether our attention will be framed toward the risks of a future pandemic or whether it could create the argued realization of climate change magnitude. Another factor to consider is whether the influence of such a realization causes inaction rather than action i.e., whether the magnitude creates feelings of helplessness. Our thesis deals with investors' realization and response to climate change as a consequence of abnormal temperature, but these new potential impacts on the subject matter remain unsolved. Therefore, studying the post COVID-19 realization of the climate change magnitude and the response of investors would be an interesting extension to the subject area.

The EMC Portfolios

During the global pandemic outbreak, there has been a crash in the prices of risk assets and a spike in volatility. Due to the wide-reaching lockdowns, the demand for energy has also decreased significantly in the period. IEA (2020) states that global energy demand declined by 3.8 percent in the first quarter of 2020. The demand for coal and oil was mostly affected, whereas renewables was the only source with an increased demand. The decreased demand in oil and subsequent OPEC+ failure to agree on output cuts caused spot prices to plummet in March (International Monetary Fund, 2020). Moreover, investors seem to expect the prices to stay low for a long time as the oil futures curve shifted down. What kind of extended effects these tendencies of low demand in the carbon-intensive energy sectors combined with increased demand in the renewables sector will have post-crisis is hard to tell. However, the carbon-intensive energy sector is largely represented on the Emission side of our portfolios. Thus, special caution in portfolio considerations should be applied in future studies, even if we see no reason to believe that the crisis will affect the systematic relationship of abnormal temperature on stock prices in Sweden. The crisis also poses implications for sectors that could alleviate the investors' physical climate-risks. More specifically, the impact of insurance companies and governments being strained by COVID-19 could also impact investor perceptions of risks associated with climate change as the alleviating parties may have less coverage. Having said that, a potential relationship might vanish in other countries or in an international study, due to the salient competing stimuli COVID-19. Hence, a multitude of interactions between the pandemic and the climate change issue gives reason for additional portfolio considerations and rise to future research areas.

In conclusion, the disruptive nature of the global pandemic poses several scenarios where the climate change issue might be perceived and tackled differently than before. Even though we do not believe that the COVID-19 crisis will affect the level of climate change believers in Sweden, the crisis could affect attention toward it. Furthermore, the significant impact on numerous sectors has disruptive impacts, which gives reason to believe that new considerations must be accounted for in future climate finance research.

9. Final Remark

The climate change issue requires it to be effectively tackled in a unified response. We believe that more research on the topic is critical to make that possible. As of today, research conducted by financial economists is rather limited, even if many questions, such as investors' behavior, are naturally suited for the field. Thus, we hope that this thesis can inspire other researchers in finance to address questions related to the changing climate, which is one of the most critical challenges of our time.

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Appendix

Appendix Overview

Appendix A: Glossary

Term	Description
Ab_temp	Abnormal monthly temperature at a temperature station located closest to the Stockholm Stock exchange.
Ab_temp quintiles	Abnormal monthly temperature including abnormal monthly temperature divided into quintiles, where Q1 is the 20 percent lowest abnormal temperatures and Q5 is the 20 percent warmest abnormal temperatures.
Clean	Portfolio consisting of the remaining stocks in the sample when Emission stocks had been removed.
DSVI(STHLM)	Seasonally adjusted log change in Google SVI on the topic "Climate change" in Stockholm. Winsorized at 2.5 percent tails.
DSVI(SWE)	Seasonal adjusted log change in Google SVI on the topic "Climate change" in Sweden Winsorized at 2.5 percent tails.
EMC	Long-short portfolio defined as going long in the Emission portfolio and short in the Clean portfolio.
EMCΔBlockholders	Net average quarterly ownership change between Emission and Clean firms for blockholders (owning more than five percent of outstanding shares). Winsorized at 2.5 percent tails.
EMCΔForBlockholders	Net average quarterly ownership change between Emission and Clean firms for foreign blockholders (owning more than five percent of shares outstanding). Winsorized at 2.5 percent tails.
EMCΔForInstitutional	Net average quarterly ownership change between Emission and Clean firms for foreign institutional investors (excluding foreign institutional blockholders). Winsorized at 2.5 percent tails.
EMCΔInstitutional	Net average quarterly ownership change between Emission and Clean firms for institutional investors (excluding institutional blockholders). Winsorized at 2.5 percent tails.

EMCΔLocInstitutional	Net average quarterly ownership change between Emission and Clean firms for domestic institutional investors (excluding domestic institutional blockholders). Winsorized at 2.5 percent tails.
EMCΔLocBlockholders	Net average quarterly ownership change between Emission and Clean firms for domestic blockholders (owning more than five percent of shares outstanding). Winsorized at 2.5 percent tails.
EMCΔRetail	Net average quarterly ownership change between Emission and Clean firms for retail investors. Winsorized at 2.5 percent tails.
Emission	Portfolio consisting of the sample stocks defined as high-emission industries.
Equal-weighted Clean	Portfolio size-adjusted return of the Clean portfolio where the same weight is given in all stocks in the Clean portfolio. Winsorized at 2.5 percent tails.
Equal-weighted EMC	Size-adjusted return of the EMC portfolio where the same weight is given in all stocks in the EMC portfolio. Winsorized at 2.5 percent tails.
Equal-weighted EMC (Unadjusted)	Unadjusted return of the EMC portfolio where the same weight is given in all stocks in the EMC portfolio. Unadjusted returns defined as the monthly change in Thomson Reuters DataStream Return Index. Winsorized at 2.5 percent tails.
Equal-weighted Emission	Size-adjusted return of the Emission portfolio where the same weight is given in all stocks in the Emission portfolio. Winsorized at 2.5 percent tails.
Non-winsorized	Non-winsorized versions of all of the above variables are presented as (Non-winsorized).
Value-weighted Clean	Size-adjusted return of the Clean portfolio weighted according to the monthly market capitalization of each firm. Winsorized at 2.5 percent tails.
Value-weighted EMC	Size-adjusted return of the EMC portfolio weighted according to the monthly market capitalization of each firm. Winorized at 2.5 percent tails.

Value-weighted EMC (unadjusted)	Unadjusted return of the EMC portfolio weighted according to the monthly market capitalization of each firm. Unadjusted returns defined as the monthly change in Thomson Reuters DataStream Return Index. Winsorized at 2.5 percent tails.
Value-weighted Emission	Size-adjusted return of the Emission portfolio weighted according to the monthly market capitalization of each firm. Winsorized at 2.5 percent tails.

B: DataStream Mnemonics

DataStream Mnemonics	Description
ICBSUN	Industry Classification Benchmark (ICB) Level: Subsector.
MV	Market value. Share price multiplied with the number of ordinary shares in issue.
RI	Return Index. The change in Return index is the stock return of the holder (including capital gains and dividends).
NOSHST	Strategic Holdings. Percentage of company shares outstanding (of five percent or more) that is not available to ordinary investors.
NOSHFR	Foreign Strategic Holdings. Percentage of company shares outstanding (of five percent or more) that is owned by foreign institutions.
UP	Unadjusted Price. The quoted closing price at date t.

Appendix C: Google DSVI and Ab_temp

C.1 DSVI (SHLM) and Ab_temp quintiles

```
Ramsey RESET test using powers of the fitted values of dsvi_sthlm
       Ho:  model has no omitted variables
                 F(3, 186) =      0.49
                  Prob > F =      0.6896


Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: ab_temp

        F(1 , 189)   =     0.98
        Prob > F     =   0.3238


Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
2	40.555	2	0.0000

H0: no serial correlation

Source	SS	df	MS
Model	.021035899	1	.021035899
Residual	30.8464818	189	.163208899
Total	30.8675177	190	.16246062

Number of obs	=	191
F(1, 189)	=	0.13
Prob > F	=	0.7200
R-squared	=	0.0007
Adj R-squared	=	-0.0046
Root MSE	=	.40399

dsvi_sthlm	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0055308	.0154057	0.36	0.720	-.0248584	.03592
_cons	-.0011131	.0294458	-0.04	0.970	-.0591978	.0569715

```
Regression with Newey-West standard errors       Number of obs     =        191
maximum lag: 2                                   F(  1,       189) =       0.19
                                                 Prob > F          =     0.6622
```

dsvi_sthlm	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0055308	.0126393	0.44	0.662	-.0194013	.0304629
_cons	-.0011131	.0194133	-0.06	0.954	-.0394077	.0371815

Appendix C: Google DSVI and Ab_temp

Source	SS	df	MS			
				Number of obs	=	191
				F(4, 186)	=	0.80
Model	.524805896	4	.131201474	Prob > F	=	0.5239
Residual	30.3427118	186	.163132859	R-squared	=	0.0170
				Adj R-squared	=	-0.0041
Total	30.8675177	190	.16246062	Root MSE	=	.4039

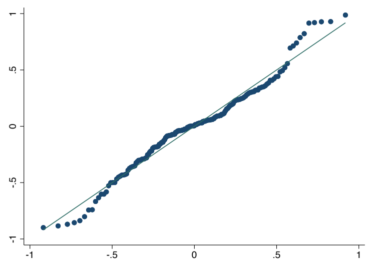
dsvi_sthlm	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1090309	.0920645	1.18	0.238	-.0725939	.2906556
ab_temp_q3	-.0127513	.0920645	-0.14	0.890	-.1943761	.1688734
ab_temp_q4	.0081275	.0920645	0.09	0.930	-.1734973	.1897522
ab_temp_q5	.1000589	.0920645	1.09	0.279	-.0815659	.2816837
_cons	-.0405199	.0646753	-0.63	0.532	-.1681114	.0870715

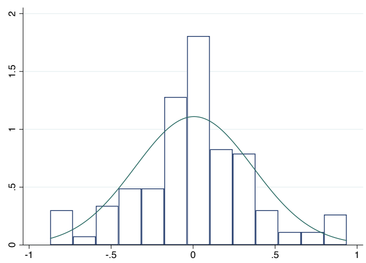
```
Regression with Newey-West standard errors          Number of obs     =        191
maximum lag: 2                                      F(  4,        186) =       0.95
                                                    Prob > F          =     0.4337
```

dsvi_sthlm	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1090309	.0757389	1.44	0.152	-.0403868	.2584486
ab_temp_q3	-.0127513	.0946888	-0.13	0.893	-.1995535	.1740508
ab_temp_q4	.0081275	.0920582	0.09	0.930	-.1734851	.18974
ab_temp_q5	.1000589	.0815597	1.23	0.221	-.0608421	.2609598
_cons	-.0405199	.0542558	-0.75	0.456	-.1475558	.066516

C.2 DSVI (SWE) and Ab_temp quintiles

Histogram of Q-Q plot of residuals






```
Ramsey RESET test using powers of the fitted values of dsvi_swe
       Ho:  model has no omitted variables
                 F(3, 186) =      0.14
                  Prob > F =      0.9363
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 189)    =      0.75
         Prob > F      =    0.3885
```

Appendix C: Google DSVI and Ab_temp

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
2	8.075	2	0.0176

H0: no serial correlation

Source	SS	df	MS			
				Number of obs	=	191
				F(1, 189)	=	0.99
Model	.128149054	1	.128149054	Prob > F	=	0.3206
Residual	24.4204752	189	.129208864	R-squared	=	0.0052
				Adj R-squared	=	-0.0000
Total	24.5486243	190	.129203286	Root MSE	=	.35946

dsvi_swe	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0136511	.0137074	1.00	0.321	-.0133881	.0406903
_cons	.0023593	.0261998	0.09	0.928	-.0493223	.0540408

Regression with Newey-West standard errors
maximum lag: 2

Number of obs	=	191
F(1, 189)	=	1.38
Prob > F	=	0.2421

dsvi_swe	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0136511	.0116345	1.17	0.242	-.009299	.0366012
_cons	.0023593	.0174821	0.13	0.893	-.0321258	.0368444

Source	SS	df	MS			
				Number of obs	=	191
				F(4, 186)	=	1.90
Model	.961342978	4	.240335744	Prob > F	=	0.1130
Residual	23.5872813	186	.12681334	R-squared	=	0.0392
				Adj R-squared	=	0.0185
Total	24.5486243	190	.129203286	Root MSE	=	.35611

dsvi_swe	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1200601	.0811715	1.48	0.141	-.0400751	.2801953
ab_temp_q3	-.0684011	.0811715	-0.84	0.400	-.2285363	.0917341
ab_temp_q4	.0410902	.0811715	0.51	0.613	-.119045	.2012254
ab_temp_q5	.1141731	.0811715	1.41	0.161	-.0459622	.2743083
_cons	-.0356683	.057023	-0.63	0.532	-.1481634	.0768267

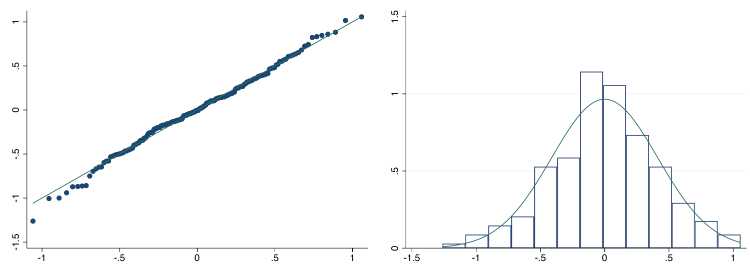
Appendix C: Google DSVI and Ab_temp

```
Regression with Newey-West standard errors          Number of obs     =        191
maximum lag: 2                                      F(  4,        186) =       1.47
                                                    Prob > F          =     0.2119
```

dsvi_swe	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1200601	.0842074	1.43	0.156	-.0460643	.2861844
ab_temp_q3	-.0684011	.0779291	-0.88	0.381	-.2221397	.0853375
ab_temp_q4	.0410902	.0689894	0.60	0.552	-.0950121	.1771926
ab_temp_q5	.1141731	.0745854	1.53	0.128	-.0329691	.2613152
_cons	-.0356683	.0479015	-0.74	0.457	-.1301684	.0588317

C.3 DSVI (STHLM, non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of not_winsor_dsvi_sthlm
       Ho:  model has no omitted variables
                  F(3, 186) =      0.50
                   Prob > F =      0.6857
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 189)    =     0.28
         Prob > F      =   0.5992
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
2	38.245	2	0.0000

H0: no serial correlation

Appendix C: Google DSVI and Ab_temp

Source	SS	df	MS			
				Number of obs	=	191
				F(1, 189)	=	0.15
Model	.026396946	1	.026396946	Prob > F	=	0.6964
Residual	32.6769377	189	.17289385	R-squared	=	0.0008
				Adj R-squared	=	-0.0045
Total	32.7033347	190	.172122814	Root MSE	=	.41581

not_winsor~m	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0061956	.0158562	0.39	0.696	-.0250822	.0374735
_cons	-.0014252	.0303069	-0.05	0.963	-.0612084	.058358

Regression with Newey-West standard errors — maximum lag: 2

Number of obs	=	191
F(1, 189)	=	0.24
Prob > F	=	0.6272

not_winsor~m	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0061956	.0127365	0.49	0.627	-.0189283	.0313196
_cons	-.0014252	.0203816	-0.07	0.944	-.0416299	.0387795

Source	SS	df	MS			
				Number of obs	=	191
				F(4, 186)	=	0.73
Model	.508514709	4	.127128677	Prob > F	=	0.5695
Residual	32.19482	186	.17309043	R-squared	=	0.0155
				Adj R-squared	=	-0.0056
Total	32.7033347	190	.172122814	Root MSE	=	.41604

not_winsor~m	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1105016	.0948326	1.17	0.245	-.0765842	.2975874
ab_temp_q3	-.0059006	.0948326	-0.06	0.950	-.1929864	.1811853
ab_temp_q4	.0137174	.0948326	0.14	0.885	-.1733684	.2008032
ab_temp_q5	.1037127	.0948326	1.09	0.276	-.0833731	.2907985
_cons	-.0441737	.0666199	-0.66	0.508	-.1756016	.0872541

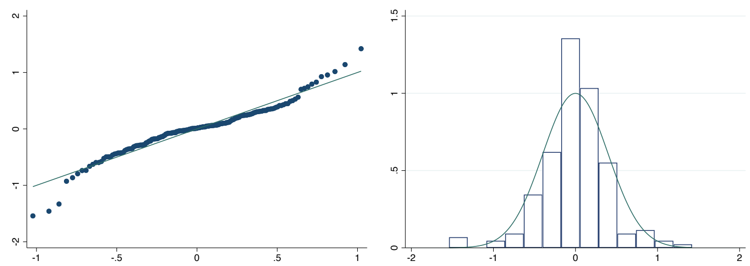
Regression with Newey-West standard errors — maximum lag: 2

Number of obs	=	191
F(4, 186)	=	0.88
Prob > F	=	0.4775

not_winsor~m	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1105016	.0787087	1.40	0.162	-.044775	.2657782
ab_temp_q3	-.0059006	.0963477	-0.06	0.951	-.1959752	.1841741
ab_temp_q4	.0137174	.0951008	0.14	0.885	-.1738974	.2013322
ab_temp_q5	.1037127	.0835076	1.24	0.216	-.0610311	.2684565
_cons	-.0441737	.0571515	-0.77	0.441	-.1569222	.0685748

C.4 DSVI (SWE, non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of not_winsor_dsvi_swe
       Ho:  model has no omitted variables
                 F(3, 186) =      0.13
                  Prob > F =      0.9444
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 189)    =     0.45
         Prob > F      =   0.5055
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
2	54.283	2	0.0000

H0: no serial correlation

Source	SS	df	MS
Model	.13674346	1	.13674346
Residual	30.2425538	189	.160013512
Total	30.3792973	190	.159891038

Number of obs	=	191
F(1, 189)	=	0.85
Prob > F	=	0.3564
R-squared	=	0.0045
Adj R-squared	=	-0.0008
Root MSE	=	.40002

not_winsor~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0141014	.0152541	0.92	0.356	-.0159888	.0441917
_cons	-.0032438	.0291561	-0.11	0.912	-.060757	.0542695

Appendix C: Google DSVI and Ab_temp

```
Regression with Newey-West standard errors      Number of obs     =        191
maximum lag: 2                                  F(  1,       189) =       1.44
                                                Prob > F          =     0.2321
```

not_winsor~e	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0141014	.0117634	1.20	0.232	-.0091031	.0373059
_cons	-.0032438	.0188603	-0.17	0.864	-.0404475	.03396

Source	SS	df	MS
Model	.935438442	4	.233859611
Residual	29.4438589	186	.158300316
Total	30.3792973	190	.159891038

```
Number of obs     =        191
F(4, 186)         =       1.48
Prob > F          =     0.2108
R-squared         =     0.0308
Adj R-squared     =     0.0099
Root MSE          =     .39787
```

not_winsor~e	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1028816	.0906906	1.13	0.258	-.0760328	.281796
ab_temp_q3	-.0735391	.0906906	-0.81	0.418	-.2524535	.1053753
ab_temp_q4	.0219454	.0906906	0.24	0.809	-.156969	.2008598
ab_temp_q5	.117526	.0906906	1.30	0.197	-.0613884	.2964404
_cons	-.033586	.0637101	-0.53	0.599	-.1592734	.0921014

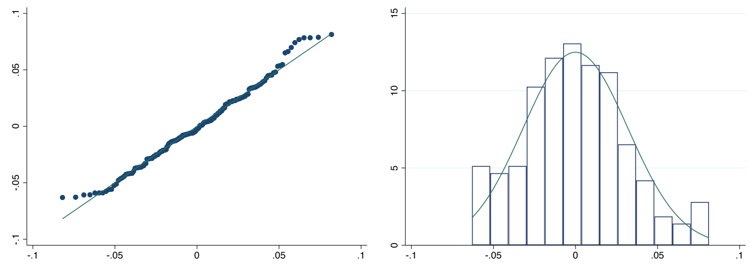
```
Regression with Newey-West standard errors      Number of obs     =        191
maximum lag: 2                                  F(  4,       186) =       1.15
                                                Prob > F          =     0.3356
```

not_winsor~e	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp_q2	.1028816	.0915427	1.12	0.263	-.0777139	.2834771
ab_temp_q3	-.0735391	.0876998	-0.84	0.403	-.2465533	.0994751
ab_temp_q4	.0219454	.0774546	0.28	0.777	-.130857	.1747478
ab_temp_q5	.117526	.0767952	1.53	0.128	-.0339756	.2690276
_cons	-.033586	.0490506	-0.68	0.494	-.130353	.063181

Appendix D: Change in portfolio return and Ab_temp

D.1 Equal-weighted EMC (unadjusted) and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_raw_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      3.60
                  Prob > F =      0.0146
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     0.83
         Prob > F      =   0.3622
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	5.603	1	0.0179

H0: no serial correlation

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	1.73
Model	.001774522	1	.001774522	Prob > F	=	0.1900
Residual	.195963864	191	.001025989	R-squared	=	0.0090
				Adj R-squared	=	0.0038
Total	.197738387	192	.001029887	Root MSE	=	.03203

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ab_temp	-.0015985	.0012154	-1.32	0.190	-.0039959	.0007989
_cons	-.0104068	.0023228	-4.48	0.000	-.0149884	-.0058252

Appendix D: Change in portfolio returns and Ab_temp

Regression with Newey-West standard errors — Number of obs = 193
maximum lag: 1 — F(1, 191) = 1.53
Prob > F = 0.2180

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0015985	.0012934	-1.24	0.218	-.0041497	.0009528
_cons	-.0104068	.0025442	-4.09	0.000	-.0154251	-.0053884

Source	SS	df	MS
Model	.005058918	4	.00126473
Residual	.192679468	188	.001024891
Total	.197738387	192	.001029887

Number of obs	=	193
F(4, 188)	=	1.23
Prob > F	=	0.2979
R-squared	=	0.0256
Adj R-squared	=	0.0049
Root MSE	=	.03201

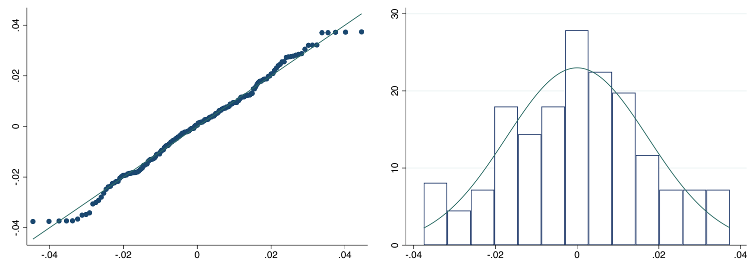
emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0022958	.0072497	0.32	0.752	-.0120054	.0165971
q3	.0045865	.0072973	0.63	0.530	-.0098086	.0189815
q4	-.0003775	.0072497	-0.05	0.959	-.0146787	.0139238
q5	-.0104666	.0072973	-1.43	0.153	-.0248617	.0039284
_cons	-.0100072	.0051263	-1.95	0.052	-.0201197	.0001053

Regression with Newey-West standard errors — Number of obs = 193
maximum lag: 1 — F(4, 188) = 1.48
Prob > F = 0.2113

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0022958	.0076406	0.30	0.764	-.0127765	.0173682
q3	.0045865	.0074991	0.61	0.542	-.0102067	.0193796
q4	-.0003775	.0068029	-0.06	0.956	-.0137973	.0130424
q5	-.0104666	.0068414	-1.53	0.128	-.0239623	.0030291
_cons	-.0100072	.0052252	-1.92	0.057	-.0203148	.0003004

D.2 Equal-weighted Emission and Ab_temp quintiles

Histogram of Q-Q plot of residuals



Appendix D: Change in portfolio returns and Ab_temp

```
Ramsey RESET test using powers of the fitted values of emc_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      0.77
                  Prob > F =      0.5133
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     0.36
         Prob > F      =   0.5503
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.01
Model	2.4765e-06	1	2.4765e-06	Prob > F	=	0.9280
Residual	.057812435	191	.000302683	R-squared	=	0.0000
				Adj R-squared	=	-0.0052
Total	.057814912	192	.000301119	Root MSE	=	.0174

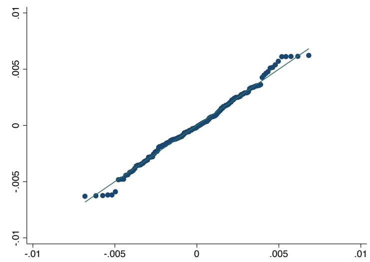
emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000597	.0006602	0.09	0.928	-.0012425	.0013619
_cons	-.0027469	.0012616	-2.18	0.031	-.0052354	-.0002584

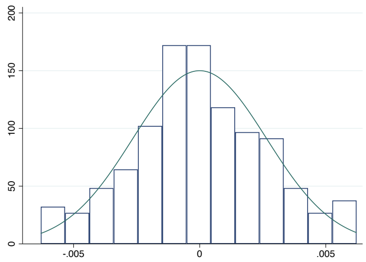
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.88
Model	.001056824	4	.000264206	Prob > F	=	0.4799
Residual	.056758087	188	.000301905	R-squared	=	0.0183
				Adj R-squared	=	-0.0026
Total	.057814912	192	.000301119	Root MSE	=	.01738

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0054675	.0039348	1.39	0.166	-.0022944	.0132295
q3	.0038358	.0039606	0.97	0.334	-.003977	.0116487
q4	-.0002654	.0039348	-0.07	0.946	-.0080273	.0074966
q5	.0041763	.0039606	1.05	0.293	-.0036366	.0119891
_cons	-.0053618	.0027823	-1.93	0.055	-.0108503	.0001268

D.3 Equal-weighted Clean and Ab_temp quintiles

Histogram of Q-Q plot of residuals





Appendix D: Change in portfolio returns and Ab_temp

```
Ramsey RESET test using powers of the fitted values of clean_equal
       Ho:  model has no omitted variables
                F(3, 188) =      0.75
                 Prob > F =      0.5213
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     0.20
         Prob > F      =   0.6544
```

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.05
       Model |  3.3177e-07         1  3.3177e-07   Prob > F        =    0.8292
    Residual |  .001358154       191  7.1108e-06   R-squared       =    0.0002
-------------+----------------------------------   Adj R-squared   =   -0.0050
       Total |  .001358485       192  7.0754e-06   Root MSE        =    .00267

------------------------------------------------------------------------------
       clean |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |  -.0000219   .0001012    -0.22   0.829    -.0002214    .0001777
       _cons |   .0004288   .0001934     2.22   0.028     .0000474    .0008102
------------------------------------------------------------------------------
```

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(4, 188)       =      0.78
       Model |  .000022149         4  5.5373e-06   Prob > F        =    0.5401
    Residual |  .001336336       188  7.1082e-06   R-squared       =    0.0163
-------------+----------------------------------   Adj R-squared   =   -0.0046
       Total |  .001358485       192  7.0754e-06   Root MSE        =    .00267

------------------------------------------------------------------------------
       clean |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |  -.0007726   .0006038    -1.28   0.202    -.0019636    .0004185
          q3 |   -.000506   .0006077    -0.83   0.406    -.0017048    .0006928
          q4 |   .0000338   .0006038     0.06   0.955    -.0011572    .0012248
          q5 |  -.0006714   .0006077    -1.10   0.271    -.0018702    .0005274
       _cons |   .0008048   .0004269     1.89   0.061    -.0000374     .001647
------------------------------------------------------------------------------
```

D.4 Equal-weighted EMC and Ab_temp quintiles

```
Ramsey RESET test using powers of the fitted values of emc_equal
       Ho:  model has no omitted variables
                F(3, 188) =      0.77
                 Prob > F =      0.5133
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     0.21
         Prob > F      =   0.6445
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
Model	8.4700e-07	1	8.4700e-07	Number of obs	=	193
Residual	.004082265	191	.000021373	F(1, 191)	=	0.04
				Prob > F	=	0.8424
Total	.004083112	192	.000021266	R-squared	=	0.0002
				Adj R-squared	=	-0.0050
				Root MSE	=	.00462

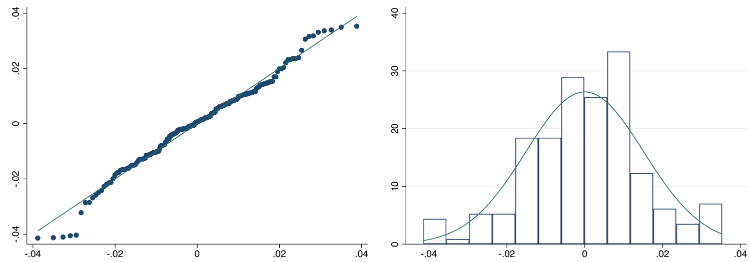
emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000349	.0001754	0.20	0.842	-.0003111	.0003809
_cons	-.0007455	.0003353	-2.22	0.027	-.0014068	-.0000843

Source	SS	df	MS			
Model	.000066333	4	.000016583	Number of obs	=	193
Residual	.004016779	188	.000021366	F(4, 188)	=	0.78
				Prob > F	=	0.5420
Total	.004083112	192	.000021266	R-squared	=	0.0162
				Adj R-squared	=	-0.0047
				Root MSE	=	.00462

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0013392	.0010467	1.28	0.202	-.0007257	.0034041
q3	.0008887	.0010536	0.84	0.400	-.0011898	.0029671
q4	-.00006	.0010467	-0.06	0.954	-.0021249	.0020049
q5	.0011507	.0010536	1.09	0.276	-.0009277	.0032291
_cons	-.0013974	.0007402	-1.89	0.061	-.0028575	.0000626

D.5 Value-weighted EMC (unadjusted) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emc_raw_value
       Ho:  model has no omitted variables
                 F(3, 188) =      0.67
                  Prob > F =      0.5708
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.61
Model	.000310666	1	.000310666	Prob > F	=	0.4376
Residual	.098061	191	.000513408	R-squared	=	0.0032
				Adj R-squared	=	-0.0021
Total	.098371666	192	.000512352	Root MSE	=	.02266

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0006688	.0008598	-0.78	0.438	-.0023647	.0010271
_cons	-.0077342	.0016431	-4.71	0.000	-.0109752	-.0044932

Regression with Newey-West standard errors — Number of obs = 193
maximum lag: 1 — F(1, 191) = 0.59
Prob > F = 0.4421

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0006688	.0008684	-0.77	0.442	-.0023817	.001044
_cons	-.0077342	.0016822	-4.60	0.000	-.0110522	-.0044161

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	1.19
Model	.002427216	4	.000606804	Prob > F	=	0.3171
Residual	.09594445	188	.000510343	R-squared	=	0.0247
				Adj R-squared	=	0.0039
Total	.098371666	192	.000512352	Root MSE	=	.02259

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0024368	.0051158	0.48	0.634	-.0076549	.0125286
q3	.0061398	.0051493	1.19	0.235	-.0040181	.0162977
q4	.0019241	.0051158	0.38	0.707	-.0081676	.0120159
q5	-.0047917	.0051493	-0.93	0.353	-.0149497	.0053662
_cons	-.0090358	.0036174	-2.50	0.013	-.0161718	-.0018999

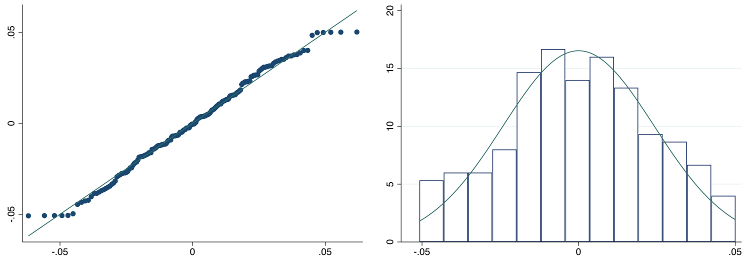
Regression with Newey-West standard errors — Number of obs = 193
maximum lag: 1 — F(4, 188) = 1.24
Prob > F = 0.2958

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0024368	.0054862	0.44	0.657	-.0083857	.0132593
q3	.0061398	.0049245	1.25	0.214	-.0035746	.0158542
q4	.0019241	.0048933	0.39	0.695	-.0077288	.011577
q5	-.0047917	.0051616	-0.93	0.354	-.0149738	.0053903
_cons	-.0090358	.003766	-2.40	0.017	-.0164649	-.0016068

Appendix D: Change in portfolio returns and Ab_temp

D.6 Value-weighted Emission and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emission_value
       Ho:  model has no omitted variables
                 F(3, 188) =      0.20
                  Prob > F =      0.8994
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.00
Model	1.2808e-06	1	1.2808e-06	Prob > F	=	0.9627
Residual	.111855075	191	.000585629	R-squared	=	0.0000
				Adj R-squared	=	-0.0052
Total	.111856356	192	.000582585	Root MSE	=	.0242

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000429	.0009183	0.05	0.963	-.0017683	.0018542
_cons	.0009861	.0017549	0.56	0.575	-.0024753	.0044476

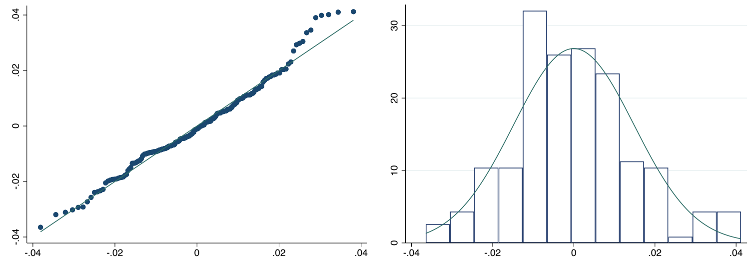
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.30
Model	.00070651	4	.000176627	Prob > F	=	0.8785
Residual	.111149846	188	.000591223	R-squared	=	0.0063
				Adj R-squared	=	-0.0148
Total	.111856356	192	.000582585	Root MSE	=	.02432

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0051508	.0055063	0.94	0.351	-.0057113	.0160128
q3	.0018637	.0055424	0.34	0.737	-.0090696	.0127969
q4	.0008171	.0055063	0.15	0.882	-.010045	.0116791
q5	.0038426	.0055424	0.69	0.489	-.0070907	.0147758
_cons	-.0013334	.0038935	-0.34	0.732	-.009014	.0063472

Appendix D: Change in portfolio returns and Ab_temp

D.7 Value-weighted Clean and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of clean_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.81
                  Prob > F =      0.1470
```

Source	SS	df	MS			
Model	.000506169	1	.000506169	Number of obs	=	193
Residual	.04242946	191	.000222144	F(1, 191)	=	2.28
				Prob > F	=	0.1328
				R-squared	=	0.0118
				Adj R-squared	=	0.0066
Total	.042935629	192	.000223623	Root MSE	=	.0149

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0008537	.0005656	-1.51	0.133	-.0019693	.0002618
_cons	-.0012851	.0010808	-1.19	0.236	-.003417	.0008468

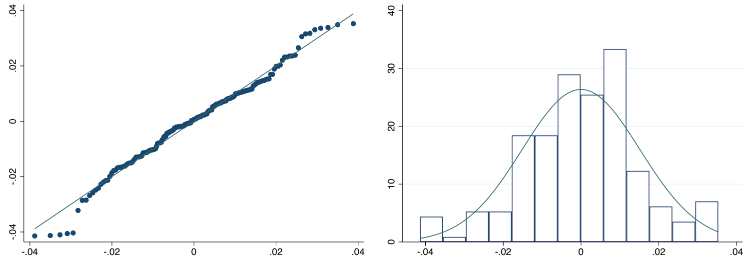
Source	SS	df	MS			
Model	.000844384	4	.000211096	Number of obs	=	193
Residual	.042091245	188	.00022389	F(4, 188)	=	0.94
				Prob > F	=	0.4403
				R-squared	=	0.0197
				Adj R-squared	=	-0.0012
Total	.042935629	192	.000223623	Root MSE	=	.01496

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0005767	.0033884	0.17	0.865	-.0061075	.007261
q3	-.0035364	.0034107	-1.04	0.301	-.0102645	.0031917
q4	-.001282	.0033884	-0.38	0.706	-.0079663	.0054022
q5	-.0049318	.0034107	-1.45	0.150	-.0116598	.0017963
_cons	.0003268	.002396	0.14	0.892	-.0043996	.0050533

Appendix D: Change in portfolio returns and Ab_temp

D.8 Value-weighted EMC and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.29
                  Prob > F =      0.2790
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	1.41
Model	.000324283	1	.000324283	Prob > F	=	0.2368
Residual	.043969006	191	.000230204	R-squared	=	0.0073
				Adj R-squared	=	0.0021
Total	.044293289	192	.000230694	Root MSE	=	.01517

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0006833	.0005757	1.19	0.237	-.0004523	.0018189
_cons	.001272	.0011003	1.16	0.249	-.0008982	.0034423

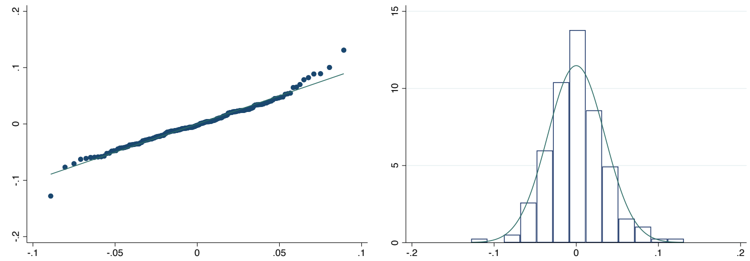
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.67
Model	.000623037	4	.000155759	Prob > F	=	0.6132
Residual	.043670252	188	.000232289	R-squared	=	0.0141
				Adj R-squared	=	-0.0069
Total	.044293289	192	.000230694	Root MSE	=	.01524

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0003991	.0034514	0.12	0.908	-.0064094	.0072075
q3	.0030293	.003474	0.87	0.384	-.0038238	.0098824
q4	.0011215	.0034514	0.32	0.746	-.005687	.00793
q5	.0048143	.003474	1.39	0.167	-.0020388	.0116674
_cons	-.0004212	.0024405	-0.17	0.863	-.0052355	.0043931

Appendix D: Change in portfolio returns and Ab_temp

D.9 Equal-weighted EMC (unadjusted, non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emc_raw_euqal_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      3.16
                  Prob > F =      0.0259
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =      0.11
         Prob > F      =    0.7358
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	8.239	1	0.0041

H0: no serial correlation

Source	SS	df	MS
Model	.002548322	1	.002548322
Residual	.232010075	191	.001214712
Total	.234558397	192	.001221658

Number of obs	=	193
F(1, 191)	=	2.10
Prob > F	=	0.1491
R-squared	=	0.0109
Adj R-squared	=	0.0057
Root MSE	=	.03485

emc_raw_no~n	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0019155	.0013225	-1.45	0.149	-.0045242	.0006931
_cons	-.0103051	.0025274	-4.08	0.000	-.0152903	-.0053199

Regression with Newey-West standard errors
maximum lag: 1

Number of obs	=	193
F(1, 191)	=	1.94
Prob > F	=	0.1651

emc_raw_no~n	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0019155	.0013746	-1.39	0.165	-.004627	.0007959
_cons	-.0103051	.0027989	-3.68	0.000	-.0158257	-.0047844

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
Model	.007446793	4	.001861698	Number of obs	=	193
Residual	.227111603	188	.00120804	F(4, 188)	=	1.54
				Prob > F	=	0.1920
Total	.234558397	192	.001221658	R-squared	=	0.0317
				Adj R-squared	=	0.0111
				Root MSE	=	.03476

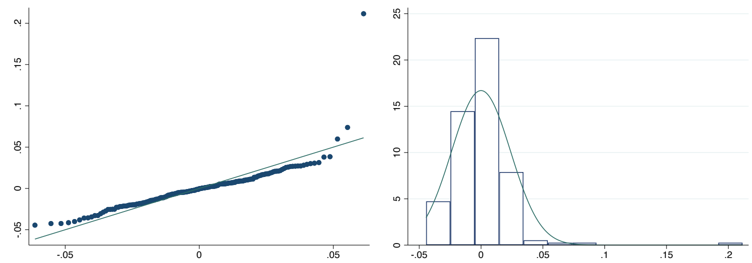
emc_raw_no~n	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0019134	.0078709	0.24	0.808	-.0136132	.01744
q3	.004914	.0079225	0.62	0.536	-.0107144	.0205424
q4	-.0008071	.0078709	-0.10	0.918	-.0163337	.0147195
q5	-.013336	.0079225	-1.68	0.094	-.0289644	.0022924
_cons	-.0093144	.0055656	-1.67	0.096	-.0202934	.0016646

Regression with Newey-West standard errors — Number of obs = 193
maximum lag: 1 — F(4, 188) = 1.57
Prob > F = 0.1846

emc_raw_no~n	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0019134	.0079392	0.24	0.810	-.013748	.0175749
q3	.004914	.0079634	0.62	0.538	-.0107951	.0206231
q4	-.0008071	.0071112	-0.11	0.910	-.014835	.0132209
q5	-.013336	.0077123	-1.73	0.085	-.0285497	.0018778
_cons	-.0093144	.0055283	-1.68	0.094	-.0202198	.001591

D.10 Equal-weighted Emission (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emission_euqal_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      0.85
                  Prob > F =      0.4676
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     1.13
         Prob > F      =   0.2890
```

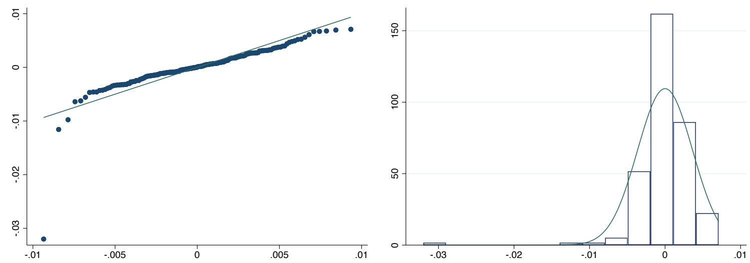
Appendix D: Change in portfolio returns and Ab_temp

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.35
       Model |  .000200128         1  .000200128   Prob > F        =    0.5555
    Residual |  .109607146       191  .000573859   R-squared       =    0.0018
-------------+----------------------------------   Adj R-squared   =   -0.0034
       Total |  .109807274       192  .000571913   Root MSE        =    .02396

------------------------------------------------------------------------------
emission_n~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   .0005368    .000909     0.59   0.556    -.0012562    .0023298
       _cons |  -.0016924   .0017372    -0.97   0.331    -.0051189    .0017341
------------------------------------------------------------------------------
```

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(4, 188)       =      1.08
       Model |  .002477495         4  .000619374   Prob > F        =    0.3653
    Residual |  .107329779       188  .000570903   R-squared       =    0.0226
-------------+----------------------------------   Adj R-squared   =    0.0018
       Total |  .109807274       192  .000571913   Root MSE        =    .02389

------------------------------------------------------------------------------
emission_n~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |   .0047378   .0054108     0.88   0.382    -.0059359    .0154116
          q3 |   .0031463   .0054463     0.58   0.564    -.0075974      .01389
          q4 |  -.0008533   .0054108    -0.16   0.875     -.011527    .0098205
          q5 |   .0091495   .0054463     1.68   0.095    -.0015942    .0198932
       _cons |  -.0047739    .003826    -1.25   0.214    -.0123213    .0027736
------------------------------------------------------------------------------
```

D.11 Equal-weighted Clean (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of clean_euqal_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      0.77
                  Prob > F =      0.5132
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     1.04
         Prob > F      =   0.3093
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
Model	6.4687e-06	1	6.4687e-06	Number of obs	=	193
Residual	.002548796	191	.000013344	F(1, 191)	=	0.48
				Prob > F	=	0.4871
Total	.002555264	192	.000013309	R-squared	=	0.0025
				Adj R-squared	=	-0.0027
				Root MSE	=	.00365

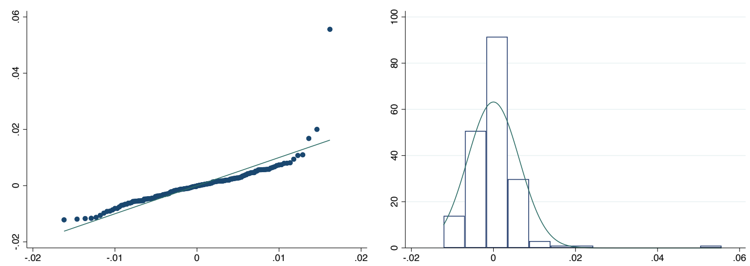
clean_no_win	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000965	.0001386	-0.70	0.487	-.0003699	.0001769
_cons	.0002752	.0002649	1.04	0.300	-.0002473	.0007977

Source	SS	df	MS			
Model	.000057873	4	.000014468	Number of obs	=	193
Residual	.002497391	188	.000013284	F(4, 188)	=	1.09
				Prob > F	=	0.3632
Total	.002555264	192	.000013309	R-squared	=	0.0226
				Adj R-squared	=	0.0019
				Root MSE	=	.00364

clean_no_win	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0006393	.0008254	-0.77	0.440	-.0022675	.0009889
q3	-.000395	.0008308	-0.48	0.635	-.0020339	.0012438
q4	.0001249	.0008254	0.15	0.880	-.0015033	.001753
q5	-.0014179	.0008308	-1.71	0.090	-.0030567	.000221
_cons	.0007137	.0005836	1.22	0.223	-.0004375	.001865

D.12 Equal-weighted EMC (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_euqal_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      0.78
                  Prob > F =      0.5078
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 191)    =     1.05
         Prob > F      =   0.3065
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.47
Model	.000018699	1	.000018699	Prob > F	=	0.4954
Residual	.007655451	191	.000040081	R-squared	=	0.0024
				Adj R-squared	=	-0.0028
Total	.00767415	192	.00003997	Root MSE	=	.00633

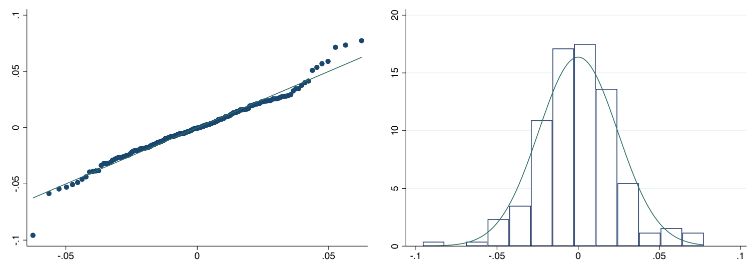
emc_no_win	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0001641	.0002402	0.68	0.495	-.0003098	.0006379
_cons	-.0004729	.0004591	-1.03	0.304	-.0013784	.0004327

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	1.09
Model	.000173734	4	.000043433	Prob > F	=	0.3635
Residual	.007500416	188	.000039896	R-squared	=	0.0226
				Adj R-squared	=	0.0018
Total	.00767415	192	.00003997	Root MSE	=	.00632

emc_no_win	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0011275	.0014304	0.79	0.432	-.0016941	.0039491
q3	.0007012	.0014397	0.49	0.627	-.0021389	.0035413
q4	-.0002178	.0014304	-0.15	0.879	-.0030394	.0026038
q5	.0024529	.0014397	1.70	0.090	-.0003872	.0052931
_cons	-.0012397	.0010114	-1.23	0.222	-.0032349	.0007555

D.13 Value-weighted EMC (unadjusted, non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emc_raw_value_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      0.58
                  Prob > F =      0.6295
```

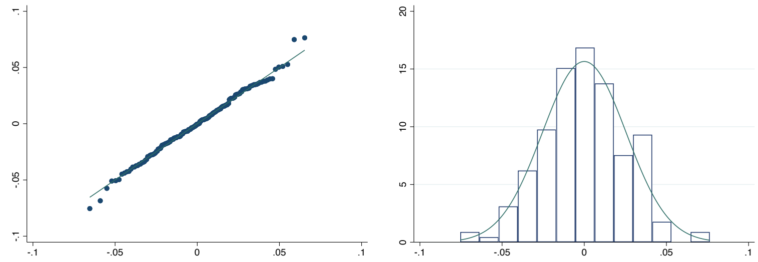
Appendix D: Change in portfolio returns and Ab_temp

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.85
       Model |  .000507718         1  .000507718   Prob > F        =    0.3577
    Residual |  .114063669       191  .000597192   R-squared       =    0.0044
-------------+----------------------------------   Adj R-squared   =   -0.0008
       Total |  .114571387       192  .000596726   Root MSE        =    .02444

------------------------------------------------------------------------------
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   -.000855   .0009273    -0.92   0.358    -.0026841    .0009741
       _cons |  -.0077521   .0017721    -4.37   0.000    -.0112475   -.0042566
------------------------------------------------------------------------------

Regression with Newey-West standard errors      Number of obs     =        193
maximum lag: 1                                  F(  1,        191) =      0.87
                                                Prob > F          =     0.3508

------------------------------------------------------------------------------
             |             Newey-West
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   -.000855   .0009142    -0.94   0.351    -.0026583    .0009482
       _cons |  -.0077521   .0018212    -4.26   0.000    -.0113444   -.0041597
------------------------------------------------------------------------------

      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(4, 188)       =      1.34
       Model |  .003165122         4   .00079128   Prob > F        =    0.2584
    Residual |  .111406265       188  .000592587   R-squared       =    0.0276
-------------+----------------------------------   Adj R-squared   =    0.0069
       Total |  .114571387       192  .000596726   Root MSE        =    .02434

------------------------------------------------------------------------------
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |    .001767   .0055126     0.32   0.749    -.0091076    .0126415
          q3 |   .0059394   .0055488     1.07   0.286    -.0050065    .0168852
          q4 |    .001388   .0055126     0.25   0.801    -.0094865    .0122626
          q5 |  -.0066409   .0055488    -1.20   0.233    -.0175868     .004305
       _cons |  -.0084496    .003898    -2.17   0.031    -.0161391   -.0007602
------------------------------------------------------------------------------

Regression with Newey-West standard errors      Number of obs     =        193
maximum lag: 1                                  F(  4,        188) =      1.33
                                                Prob > F          =     0.2590

------------------------------------------------------------------------------
             |             Newey-West
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |    .001767   .0057013     0.31   0.757    -.0094798    .0130137
          q3 |   .0059394   .0050894     1.17   0.245    -.0041002     .015979
          q4 |    .001388   .0053015     0.26   0.794    -.0090701    .0118461
          q5 |  -.0066409   .0057566    -1.15   0.250    -.0179966    .0047148
       _cons |  -.0084496   .0040225    -2.10   0.037    -.0163847   -.0005145
------------------------------------------------------------------------------
```

Appendix D: Change in portfolio returns and Ab_temp

D.14 Value-weighted Emission (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emission_value_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      0.13
                  Prob > F =      0.9432
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.01
Model	6.5144e-06	1	6.5144e-06	Prob > F	=	0.9206
Residual	.124755964	191	.000653173	R-squared	=	0.0001
				Adj R-squared	=	-0.0052
Total	.124762479	192	.000649805	Root MSE	=	.02556

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000969	.0009698	-0.10	0.921	-.0020097	.001816
_cons	.0010488	.0018533	0.57	0.572	-.0026068	.0047044

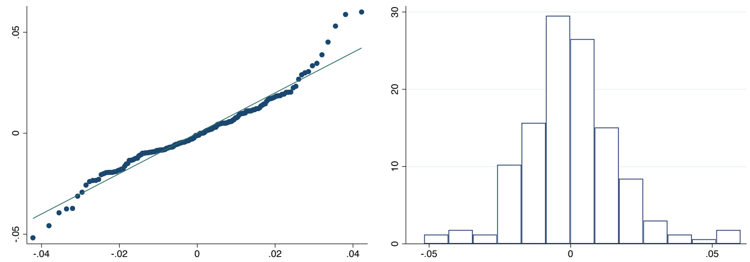
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.33
Model	.000877869	4	.000219467	Prob > F	=	0.8555
Residual	.123884609	188	.000658961	R-squared	=	0.0070
				Adj R-squared	=	-0.0141
Total	.124762479	192	.000649805	Root MSE	=	.02567

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0057818	.0058132	0.99	0.321	-.0056856	.0172492
q3	.0013465	.0058513	0.23	0.818	-.0101961	.0128891
q4	.0007612	.0058132	0.13	0.896	-.0107062	.0122286
q5	.0036755	.0058513	0.63	0.531	-.0078671	.0152181
_cons	-.0012846	.0041105	-0.31	0.755	-.0093933	.0068241

Appendix D: Change in portfolio returns and Ab_temp

D.15 Value-weighted Clean (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of clean_value_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      1.76
                  Prob > F =      0.1555
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	2.47
Model	.000672025	1	.000672025	Prob > F	=	0.1178
Residual	.051983275	191	.000272164	R-squared	=	0.0128
				Adj R-squared	=	0.0076
Total	.0526553	192	.000274246	Root MSE	=	.0165

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0009837	.000626	-1.57	0.118	-.0022185	.0002511
_cons	-.0012626	.0011963	-1.06	0.293	-.0036224	.0010971

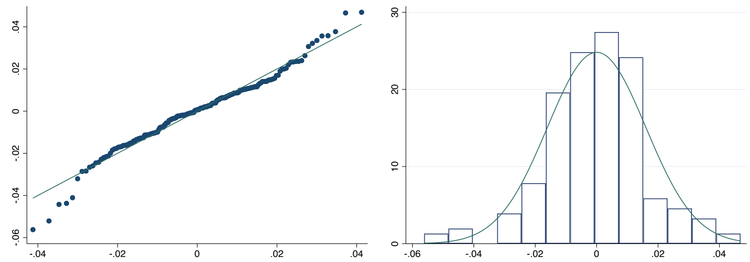
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	1.22
Model	.001336175	4	.000334044	Prob > F	=	0.3022
Residual	.051319125	188	.000272974	R-squared	=	0.0254
				Adj R-squared	=	0.0046
Total	.0526553	192	.000274246	Root MSE	=	.01652

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0011771	.0037415	0.31	0.753	-.0062036	.0085577
q3	-.0036491	.003766	-0.97	0.334	-.0110782	.0037799
q4	-.0002183	.0037415	-0.06	0.954	-.0075989	.0071624
q5	-.0059011	.003766	-1.57	0.119	-.0133302	.0015279
_cons	.000196	.0026456	0.07	0.941	-.0050229	.0054149

Appendix D: Change in portfolio returns and Ab_temp

D.16 Value-weighted EMC (Non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emc_value_nonwinsor
       Ho:  model has no omitted variables
                 F(3, 188) =      1.35
                  Prob > F =      0.2607
```

Source	SS	df	MS			
Model	.000426624	1	.000426624	Number of obs	=	193
Residual	.049630363	191	.000259845	F(1, 191)	=	1.64
				Prob > F	=	0.2016
Total	.050056988	192	.000260713	R-squared	=	0.0085
				Adj R-squared	=	0.0033
				Root MSE	=	.01612

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0007838	.0006117	1.28	0.202	-.0004227	.0019903
_cons	.0012543	.001169	1.07	0.285	-.0010514	.00356

Source	SS	df	MS			
Model	.000903709	4	.000225927	Number of obs	=	193
Residual	.049153279	188	.000261454	F(4, 188)	=	0.86
				Prob > F	=	0.4866
Total	.050056988	192	.000260713	R-squared	=	0.0181
				Adj R-squared	=	-0.0028
				Root MSE	=	.01617

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0002072	.0036617	0.06	0.955	-.0070161	.0074304
q3	.0031221	.0036857	0.85	0.398	-.0041485	.0103927
q4	.0004611	.0036617	0.13	0.900	-.0067621	.0076844
q5	.0055785	.0036857	1.51	0.132	-.0016922	.0128491
_cons	-.0004122	.0025892	-0.16	0.874	-.0055198	.0046954

Appendix D: Change in portfolio returns and Ab_temp

Control Period (December 1983 to December 1999)

D.17 Non-winsorized summary statistics portfolio return and abnormal temperature (control period)

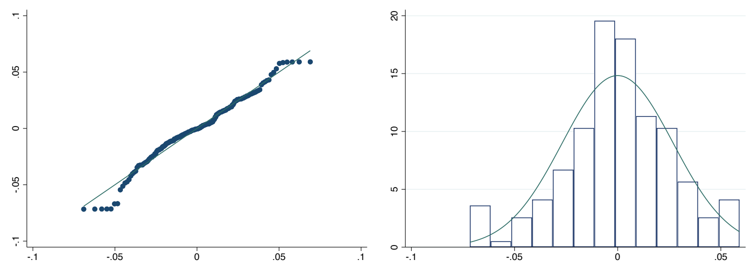
	Equal-weighted portfolios								Value-weighted portfolios							
	EMC		EMC (unadjusted)		Emission		Clean		EMC		EMC (unadjusted)		Emission		Clean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Ab_temp	0.003		-0.023		0.003		0.002		0.007		0.006		0.061		0.020	
	(0,09)		(-0,28)		(0,04)		(-0,09)		(0,10)		(0,05)		(0,81)		(0,24)	
Ab_temp Q2		-0.075		-0.006		-0.185		0.049		-0.152		0.041		-0.379		0.054
		(-0,29)		(-0,01)		(-0,37)		(0,28)		(-0,28)		(0,04)		(-0,67)		(0,09)
Ab_temp Q3		-0.006		0.169		-0.048		0.000		-0.164		-0.727		-0.381		0.094
		(-0,02)		(0,25)		(-0,09)		(-0,00)		(-0,30)		(-0,70)		(-0,67)		(0,15)
Ab_temp Q4		-0.086		-0.096		-0.124		0.064		0.098		0.774		0.225		0.020
		(-0,33)		(-0,14)		(-0,25)		(0,36)		(0,18)		(0,77)		(0,40)		(0,03)
Ab_temp Q5		-0.175		-0.175		-0.340		0.123		-0.197		-0.425		0.139		0.326
		(-0,67)		(-0,26)		(-0,67)		(0,68)		(-0,36)		(-0,45)		(0,24)		(0,52)
Obs.	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193	193
R^2	0.000	0.003	0.000	0.001	0.000	0.003	0.000	0.003	0.000	0.002	0.000	0.012	0.003	0.011	0.000	0.002

Regression output of equal-weighted and value-weighted portfolio returns with coefficients in percentage.

*Control period.The statistical significance of the coefficients is reported by *p<0.10; **p<0.05; ***p<0.01.*

D.18 Equal-weighted EMC (unadjusted) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emc_raw_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      1.63
                  Prob > F =      0.1839
```

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.01
       Model |  5.0162e-06         1  5.0162e-06   Prob > F        =    0.9339
    Residual |  .138962209       191  .000727551   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0052
       Total |  .138967225       192  .000723788   Root MSE        =    .02697

------------------------------------------------------------------------------
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |  -.0000677   .0008149    -0.08   0.934    -.001675    .0015397
       _cons |  -.0083827   .0019447    -4.31   0.000   -.0122186   -.0045468
------------------------------------------------------------------------------
```

Appendix D: Change in portfolio returns and Ab_temp

Regression with Newey-West standard errors   Number of obs = 193
maximum lag: 1   F(1, 191) = 0.01
Prob > F = 0.9316

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000677	.0007874	-0.09	0.932	-.0016208	.0014855
_cons	-.0083827	.0021872	-3.83	0.000	-.0126969	-.0040686

Source	SS	df	MS
Model	.000258853	4	.000064713
Residual	.138708372	188	.00073781
Total	.138967225	192	.000723788

Number of obs = 193
F(4, 188) = 0.09
Prob > F = 0.9862
R-squared = 0.0019
Adj R-squared = -0.0194
Root MSE = .02716

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0022254	.0061511	0.36	0.718	-.0099087	.0143595
q3	.0023319	.0061915	0.38	0.707	-.0098817	.0145456
q4	-.000547	.0061511	-0.09	0.929	-.0126811	.0115871
q5	.0008597	.0061915	0.14	0.890	-.0113539	.0130734
_cons	-.0093595	.0043495	-2.15	0.033	-.0179396	-.0007794

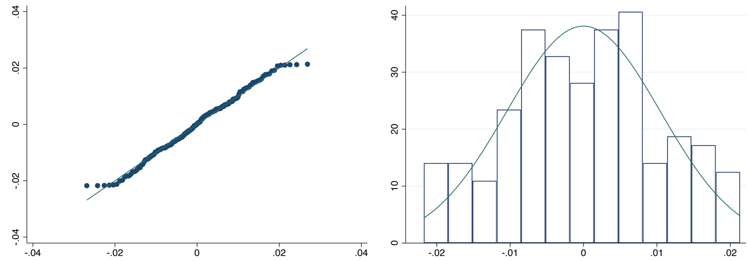
Regression with Newey-West standard errors   Number of obs = 193
maximum lag: 1   F(4, 188) = 0.08
Prob > F = 0.9891

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0022254	.0059768	0.37	0.710	-.0095648	.0140156
q3	.0023319	.0064149	0.36	0.717	-.0103226	.0149865
q4	-.000547	.0065491	-0.08	0.934	-.0134662	.0123722
q5	.0008597	.0055024	0.16	0.876	-.0099946	.0117141
_cons	-.0093595	.0041518	-2.25	0.025	-.0175496	-.0011694

Appendix D: Change in portfolio returns and Ab_temp

D.19 Equal-weighted EMC and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      2.38
                  Prob > F =      0.0709
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.06
Model	7.0523e-06	1	7.0523e-06	Prob > F	=	0.8007
Residual	.021073549	191	.000110333	R-squared	=	0.0003
				Adj R-squared	=	-0.0049
Total	.021080601	192	.000109795	Root MSE	=	.0105

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000802	.0003173	0.25	0.801	-.0005457	.0007062
_cons	-.0015548	.0007573	-2.05	0.041	-.0030486	-.000061

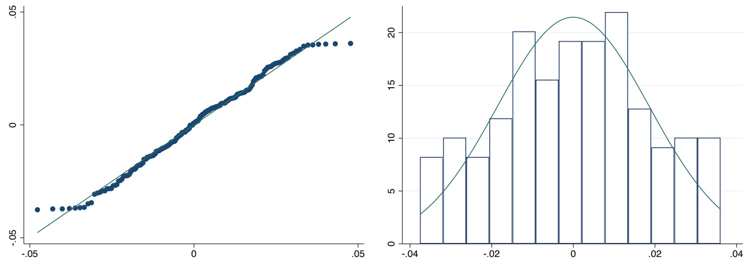
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.09
Model	.000042212	4	.000010553	Prob > F	=	0.9842
Residual	.02103839	188	.000111906	R-squared	=	0.0020
				Adj R-squared	=	-0.0192
Total	.021080601	192	.000109795	Root MSE	=	.01058

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.000179	.0023956	0.07	0.941	-.0045466	.0049047
q3	.0002837	.0024113	0.12	0.906	-.0044729	.0050404
q4	-.0003972	.0023956	-0.17	0.868	-.0051229	.0043285
q5	-.0010058	.0024113	-0.42	0.677	-.0057625	.0037508
_cons	-.0013577	.0016939	-0.80	0.424	-.0046992	.0019839

Appendix D: Change in portfolio returns and Ab_temp

D.20 Equal-weighted Emission and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emission_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      2.20
                  Prob > F =      0.0890
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.09
Model	.000029636	1	.000029636	Prob > F	=	0.7706
Residual	.066385572	191	.000347568	R-squared	=	0.0004
				Adj R-squared	=	-0.0048
Total	.066415208	192	.000345913	Root MSE	=	.01864

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0001645	.0005632	0.29	0.771	-.0009465	.0012754
_cons	-.0030137	.0013442	-2.24	0.026	-.0056649	-.0003624

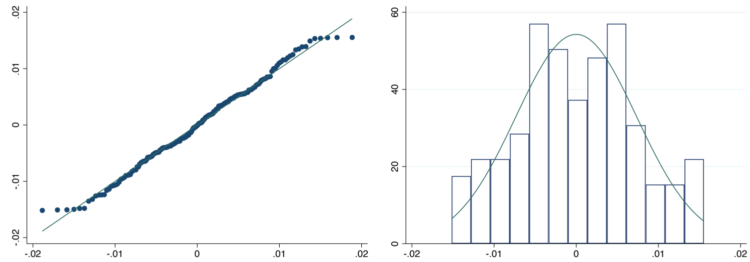
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.06
Model	.00008093	4	.000020233	Prob > F	=	0.9939
Residual	.066334278	188	.000352842	R-squared	=	0.0012
				Adj R-squared	=	-0.0200
Total	.066415208	192	.000345913	Root MSE	=	.01878

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0007304	.0042538	0.17	0.864	-.0076608	.0091217
q3	.0000952	.0042817	0.02	0.982	-.0083511	.0085415
q4	-.0005143	.0042538	-0.12	0.904	-.0089056	.0078769
q5	-.0012074	.0042817	-0.28	0.778	-.0096536	.0072389
_cons	-.002816	.0030079	-0.94	0.350	-.0087495	.0031175

Appendix D: Change in portfolio returns and Ab_temp

D.21 Equal-weighted Clean and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of clean_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      2.44
                  Prob > F =      0.0659
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.05
Model	2.6187e-06	1	2.6187e-06	Prob > F	=	0.8264
Residual	.010374507	191	.000054317	R-squared	=	0.0003
				Adj R-squared	=	-0.0050
Total	.010377125	192	.000054048	Root MSE	=	.00737

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000489	.0002227	-0.22	0.826	-.0004881	.0003903
_cons	.0010542	.0005314	1.98	0.049	6.09e-06	.0021023

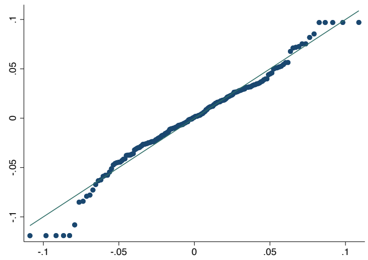
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.12
Model	.000025951	4	6.4877e-06	Prob > F	=	0.9761
Residual	.010351175	188	.000055059	R-squared	=	0.0025
				Adj R-squared	=	-0.0187
Total	.010377125	192	.000054048	Root MSE	=	.00742

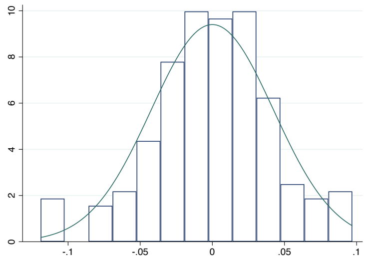
clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0000447	.0016803	-0.03	0.979	-.0033595	.00327
q3	-.0002344	.0016914	-0.14	0.890	-.0035709	.0031021
q4	.0003339	.0016803	0.20	0.843	-.0029808	.0036487
q5	.0008141	.0016914	0.48	0.631	-.0025224	.0041506
_cons	.000875	.0011882	0.74	0.462	-.0014689	.0032189

Appendix D: Change in portfolio returns and Ab_temp

D.22 Value-weighted EMC (unadjusted) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of emc_raw_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.86
                  Prob > F =      0.1377
```

Source	SS	df	MS		
				Number of obs =	193
				F(1, 191) =	0.00
Model	8.0338e-07	1	8.0338e-07	Prob > F =	0.9832
Residual	.345596702	191	.001809407	R-squared =	0.0000
				Adj R-squared =	-0.0052
Total	.345597506	192	.001799987	Root MSE =	.04254

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000271	.0012851	0.02	0.983	-.0025078	.0025619
_cons	-.0138478	.0030669	-4.52	0.000	-.0198971	-.0077985

```
Regression with Newey-West standard errors        Number of obs     =       193
maximum lag: 1                                    F(  1,        191) =      0.00
                                                  Prob > F          =    0.9832
```

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000271	.0012877	0.02	0.983	-.0025129	.002567
_cons	-.0138478	.0033359	-4.15	0.000	-.0204277	-.0072679

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.45
Model	.003297829	4	.000824457	Prob > F	=	0.7703
Residual	.342299677	188	.001820743	R-squared	=	0.0095
				Adj R-squared	=	-0.0115
Total	.345597506	192	.001799987	Root MSE	=	.04267

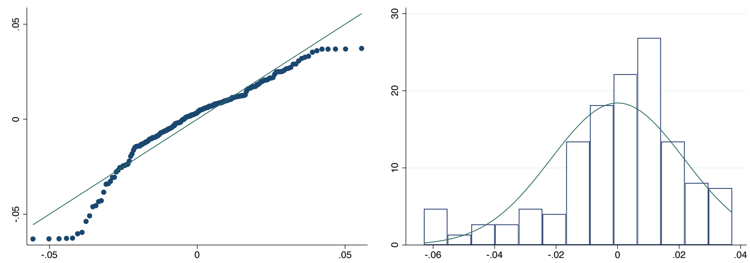
emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0002118	.0096629	0.02	0.983	-.0188498	.0192734
q3	-.005476	.0097263	-0.56	0.574	-.0246626	.0137106
q4	.0063316	.0096629	0.66	0.513	-.01273	.0253933
q5	-.0041574	.0097263	-0.43	0.670	-.023344	.0150292
_cons	-.0132697	.0068327	-1.94	0.054	-.0267483	.0002089

```
Regression with Newey-West standard errors      Number of obs     =        193
maximum lag: 1                                  F(  4,        188) =       0.36
                                                Prob > F          =     0.8367
```

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0002118	.0086026	0.02	0.980	-.0167582	.0171817
q3	-.005476	.0096007	-0.57	0.569	-.024415	.013463
q4	.0063316	.0095412	0.66	0.508	-.0124899	.0251532
q5	-.0041574	.0093189	-0.45	0.656	-.0225404	.0142256
_cons	-.0132697	.0058343	-2.27	0.024	-.0247787	-.0017606

D.23 Value-weighted EMC and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_value
       Ho:  model has no omitted variables
                 F(3, 188) =      2.32
                  Prob > F =      0.0769
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.02
Model	.000010506	1	.000010506	Prob > F	=	0.8816
Residual	.090146425	191	.000471971	R-squared	=	0.0001
				Adj R-squared	=	-0.0051
Total	.090156931	192	.000469567	Root MSE	=	.02172

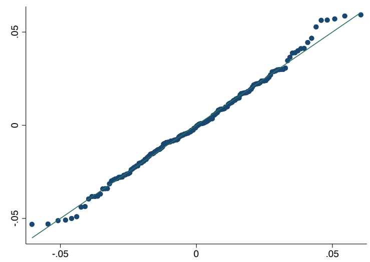
emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000979	.0006563	0.15	0.882	-.0011967	.0013925
_cons	-.0043149	.0015663	-2.75	0.006	-.0074045	-.0012254

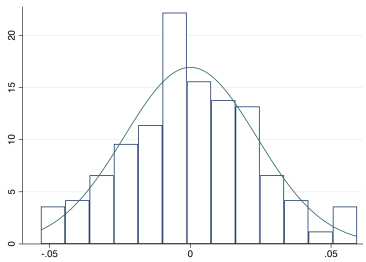
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.24
Model	.000461962	4	.000115491	Prob > F	=	0.9142
Residual	.089694969	188	.000477101	R-squared	=	0.0051
				Adj R-squared	=	-0.0160
Total	.090156931	192	.000469567	Root MSE	=	.02184

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0016471	.0049464	-0.33	0.740	-.0114047	.0081104
q3	-.0020677	.0049788	-0.42	0.678	-.0118892	.0077539
q4	.0018046	.0049464	0.36	0.716	-.0079529	.0115622
q5	-.0022822	.0049788	-0.46	0.647	-.0121038	.0075393
_cons	-.003477	.0034976	-0.99	0.321	-.0103766	.0034227

D.24 Value-weighted Emission and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals






```
Ramsey RESET test using powers of the fitted values of emission_value
       Ho:  model has no omitted variables
                 F(3, 188) =      3.60
                  Prob > F =      0.0145
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.94
Model	.000523372	1	.000523372	Prob > F	=	0.3341
Residual	.106612695	191	.000558182	R-squared	=	0.0049
				Adj R-squared	=	-0.0003
Total	.107136067	192	.000558	Root MSE	=	.02363

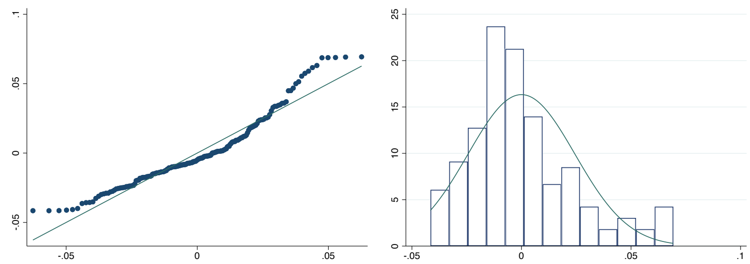
emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0006912	.0007138	0.97	0.334	-.0007167	.0020991
_cons	-.0013661	.0017034	-0.80	0.424	-.004726	.0019938

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.55
Model	.001239904	4	.000309976	Prob > F	=	0.6990
Residual	.105896163	188	.000563277	R-squared	=	0.0116
				Adj R-squared	=	-0.0095
Total	.107136067	192	.000558	Root MSE	=	.02373

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0030345	.0053746	-0.56	0.573	-.0136367	.0075677
q3	-.0034111	.0054098	-0.63	0.529	-.0140828	.0072606
q4	.0021858	.0053746	0.41	0.685	-.0084165	.012788
q5	.0026737	.0054098	0.49	0.622	-.007998	.0133455
_cons	-.0009554	.0038004	-0.25	0.802	-.0084523	.0065415

D.25 Value-weighted Clean and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of clean_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.73
                  Prob > F =      0.1630
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
Model	.000025382	1	.000025382	Number of obs	=	193
Residual	.114561716	191	.0005998	F(1, 191)	=	0.04
				Prob > F	=	0.8372
Total	.114587098	192	.000596808	R-squared	=	0.0002
				Adj R-squared	=	-0.0050
				Root MSE	=	.02449

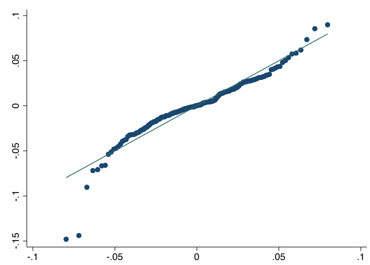
clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0001522	.0007399	0.21	0.837	-.0013072	.0016116
_cons	.0053116	.0017658	3.01	0.003	.0018287	.0087945

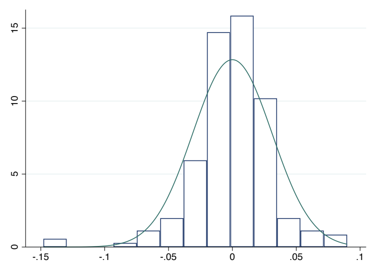
Source	SS	df	MS			
Model	.000461938	4	.000115484	Number of obs	=	193
Residual	.11412516	188	.000607049	F(4, 188)	=	0.19
				Prob > F	=	0.9433
Total	.114587098	192	.000596808	R-squared	=	0.0040
				Adj R-squared	=	-0.0172
				Root MSE	=	.02464

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0010238	.0055795	0.18	0.855	-.0099826	.0120303
q3	.0014191	.0056161	0.25	0.801	-.0096595	.0124978
q4	-.0008357	.0055795	-0.15	0.881	-.0118421	.0101708
q5	.0037404	.0056161	0.67	0.506	-.0073382	.0148191
_cons	.0042784	.0039453	1.08	0.280	-.0035043	.0120611

D.26 Equal-weighted EMC (unadjusted, non-winsorized), and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of emc_raw_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      1.30
                  Prob > F =      0.2773
```

Appendix D: Change in portfolio returns and Ab_temp

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.06
       Model |  .000060477         1  .000060477   Prob > F        =    0.8032
    Residual |  .185388267       191  .000970619   R-squared       =    0.0003
-------------+----------------------------------   Adj R-squared   =   -0.0049
       Total |  .185448743       192  .000965879   Root MSE        =    .03115

------------------------------------------------------------------------------
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |  -.0002349   .0009412    -0.25   0.803    -.0020915    .0016216
       _cons |  -.0088672   .0022462    -3.95   0.000    -.0132978   -.0044366
------------------------------------------------------------------------------
```

```
Regression with Newey-West standard errors      Number of obs     =        193
maximum lag: 1                                  F(  1,        191) =      0.08
                                                Prob > F          =     0.7814

------------------------------------------------------------------------------
             |             Newey-West
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |  -.0002349   .0008456    -0.28   0.781    -.0019028    .0014329
       _cons |  -.0088672   .0025629    -3.46   0.001    -.0139225   -.0038119
------------------------------------------------------------------------------
```

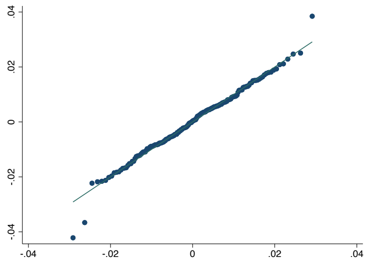
```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(4, 188)       =      0.06
       Model |  .000251658         4  .000062915   Prob > F        =    0.9924
    Residual |  .185197085       188  .000985091   R-squared       =    0.0014
-------------+----------------------------------   Adj R-squared   =   -0.0199
       Total |  .185448743       192  .000965879   Root MSE        =    .03139

------------------------------------------------------------------------------
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |  -.0000615   .0071076    -0.01   0.993    -.0140823    .0139593
          q3 |   .0016865   .0071542     0.24   0.814    -.0124262    .0157993
          q4 |  -.0009615   .0071076    -0.14   0.893    -.0149824    .0130593
          q5 |  -.0017523   .0071542    -0.24   0.807    -.0158651    .0123605
       _cons |  -.0086795   .0050258    -1.73   0.086    -.0185937    .0012347
------------------------------------------------------------------------------
```

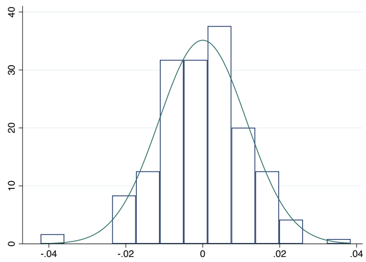
```
Regression with Newey-West standard errors      Number of obs     =        193
maximum lag: 1                                  F(  4,        188) =      0.07
                                                Prob > F          =     0.9904

------------------------------------------------------------------------------
             |             Newey-West
     emc_raw |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |  -.0000615   .0071406    -0.01   0.993    -.0141476    .0140246
          q3 |   .0016865   .0066354     0.25   0.800    -.0114028    .0147759
          q4 |  -.0009615   .0070603    -0.14   0.892    -.0148891     .012966
          q5 |  -.0017523   .0066714    -0.26   0.793    -.0149126    .0114081
       _cons |  -.0086795   .0044591    -1.95   0.053    -.0174758    .0001168
------------------------------------------------------------------------------
```

Appendix D: Change in portfolio returns and Ab_temp

D.27 Equal-weighted EMC (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of emc_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      2.29
                  Prob > F =      0.0801
```

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.01
Model	1.0758e-06	1	1.0758e-06	Prob > F	=	0.9275
Residual	.024757995	191	.000129623	R-squared	=	0.0000
				Adj R-squared	=	-0.0052
Total	.024759071	192	.000128953	Root MSE	=	.01139

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000313	.000344	0.09	0.928	-.0006471	.0007098
_cons	-.0016015	.0008209	-1.95	0.053	-.0032206	.0000176

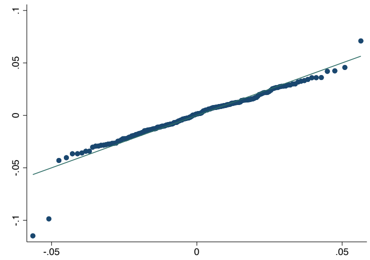
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.15
Model	.0000771	4	.000019275	Prob > F	=	0.9642
Residual	.024681971	188	.000131287	R-squared	=	0.0031
				Adj R-squared	=	-0.0181
Total	.024759071	192	.000128953	Root MSE	=	.01146

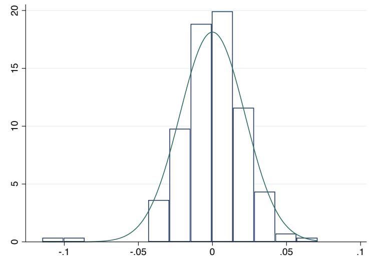
emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0007496	.0025947	-0.29	0.773	-.0058682	.0043689
q3	-.0000622	.0026118	-0.02	0.981	-.0052143	.0050899
q4	-.0008569	.0025947	-0.33	0.742	-.0059754	.0042617
q5	-.0017457	.0026118	-0.67	0.505	-.0068978	.0034064
_cons	-.0009166	.0018348	-0.50	0.618	-.004536	.0027027

Appendix D: Change in portfolio returns and Ab_temp

D.28 Equal-weighted Emission (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of emission_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      1.90
                  Prob > F =      0.1316
```

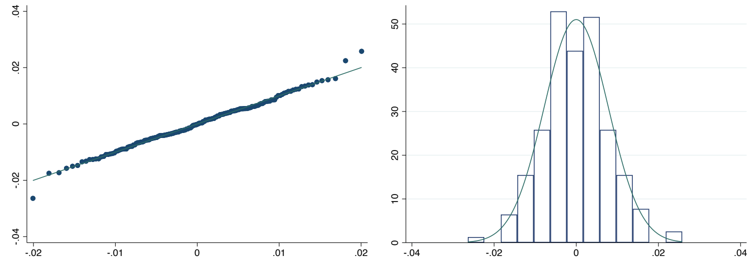
```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(1, 191)       =      0.00
       Model |  9.5214e-07         1  9.5214e-07   Prob > F        =    0.9648
    Residual |  .092946562       191  .000486631   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0052
       Total |  .092947514       192  .000484102   Root MSE        =    .02206

------------------------------------------------------------------------------
    emission |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   .0000295   .0006665     0.04   0.965    -.0012851     .001344
       _cons |  -.0034792   .0015905    -2.19   0.030    -.0066163    -.000342
------------------------------------------------------------------------------
```

```
      Source |       SS           df       MS      Number of obs   =       193
-------------+----------------------------------   F(4, 188)       =      0.14
       Model |  .000268939         4  .000067235   Prob > F        =    0.9687
    Residual |  .092678575       188  .000492971   R-squared       =    0.0029
-------------+----------------------------------   Adj R-squared   =   -0.0183
       Total |  .092947514       192  .000484102   Root MSE        =     .0222

------------------------------------------------------------------------------
    emission |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |  -.0018535    .005028    -0.37   0.713     -.011772     .008065
          q3 |  -.0004784   .0050609    -0.09   0.925     -.010462    .0095051
          q4 |  -.0012437    .005028    -0.25   0.805    -.0111622    .0086748
          q5 |  -.0033952   .0050609    -0.67   0.503    -.0133788    .0065883
       _cons |  -.0020866   .0035553    -0.59   0.558    -.0091001    .0049268
------------------------------------------------------------------------------
```

Appendix D: Change in portfolio returns and Ab_temp

D.29 Equal-weighted Clean (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of clean_equal
       Ho:  model has no omitted variables
                 F(3, 188) =      2.38
                  Prob > F =      0.0709
```

Source	SS	df	MS		
Model	4.9227e-07	1	4.9227e-07	Number of obs =	193
Residual	.011742855	191	.000061481	F(1, 191) =	0.01
				Prob > F =	0.9288
				R-squared =	0.0000
				Adj R-squared =	-0.0052
Total	.011743347	192	.000061163	Root MSE =	.00784

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000212	.0002369	-0.09	0.929	-.0004884	.0004461
_cons	.0010583	.0005653	1.87	0.063	-.0000568	.0021734

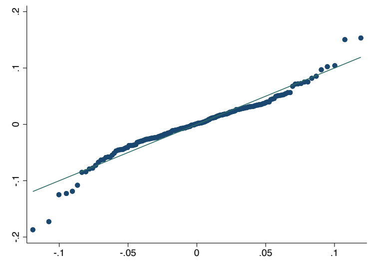
Source	SS	df	MS		
Model	.000040063	4	.000010016	Number of obs =	193
Residual	.011703284	188	.000062252	F(4, 188) =	0.16
				Prob > F =	0.9578
				R-squared =	0.0034
				Adj R-squared =	-0.0178
Total	.011743347	192	.000061163	Root MSE =	.00789

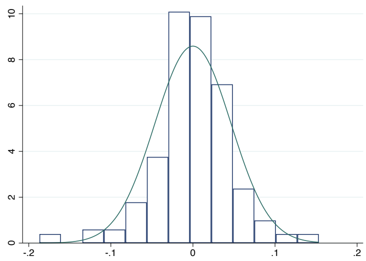
clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0004945	.0017867	0.28	0.782	-.0030302	.0040191
q3	-3.76e-06	.0017984	-0.00	0.998	-.0035515	.003544
q4	.0006407	.0017867	0.36	0.720	-.0028839	.0041653
q5	.0012267	.0017984	0.68	0.496	-.002321	.0047744
_cons	.0005852	.0012634	0.46	0.644	-.001907	.0030775

Appendix D: Change in portfolio returns and Ab_temp

D.30 Value-weighted EMC (unadjusted, non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of emc_raw_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.50
                  Prob > F =      0.2168
```

Source	SS	df	MS
Model	3.9201e-06	1	3.9201e-06
Residual	.414312164	191	.002169174
Total	.414316084	192	.002157896

Number of obs	=	193
F(1, 191)	=	0.00
Prob > F	=	0.9661
R-squared	=	0.0000
Adj R-squared	=	-0.0052
Root MSE	=	.04657

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000598	.0014071	0.04	0.966	-.0027156	.0028352
_cons	-.0138993	.003358	-4.14	0.000	-.0205227	-.0072758

Regression with Newey-West standard errors
maximum lag: 1

Number of obs	=	193
F(1, 191)	=	0.00
Prob > F	=	0.9635

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000598	.0013047	0.05	0.963	-.0025137	.0026334
_cons	-.0138993	.0036737	-3.78	0.000	-.0211455	-.0066531

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS
Model	.0049647	4	.001241175
Residual	.409351385	188	.002177401
Total	.414316084	192	.002157896

Number of obs	=	193
F(4, 188)	=	0.57
Prob > F	=	0.6847
R-squared	=	0.0120
Adj R-squared	=	-0.0090
Root MSE	=	.04666

emc_raw	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0004108	.010567	0.04	0.969	-.0204343	.021256
q3	-.0072697	.0106363	-0.68	0.495	-.0282515	.0137121
q4	.007741	.010567	0.73	0.465	-.0131041	.0285862
q5	-.0042532	.0106363	-0.40	0.690	-.025235	.0167286
_cons	-.0132697	.007472	-1.78	0.077	-.0280094	.0014701

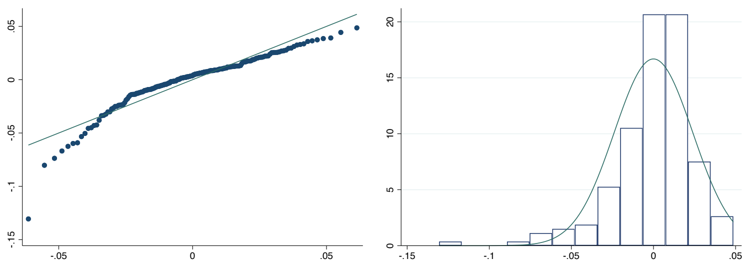
Regression with Newey-West standard errors
maximum lag: 1

Number of obs	=	193
F(4, 188)	=	0.46
Prob > F	=	0.7660

emc_raw	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0004108	.0097367	0.04	0.966	-.0187965	.0196182
q3	-.0072697	.0103126	-0.70	0.482	-.0276131	.0130737
q4	.007741	.0100724	0.77	0.443	-.0121285	.0276105
q5	-.0042532	.0093524	-0.45	0.650	-.0227023	.0141959
_cons	-.0132697	.0058343	-2.27	0.024	-.0247787	-.0017606

D.31 Value-weighted EMC (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of emc_value
       Ho:  model has no omitted variables
                 F(3, 188) =      2.05
                  Prob > F =      0.1083
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.01
Model	6.0842e-06	1	6.0842e-06	Prob > F	=	0.9182
Residual	.109762474	191	.000574673	R-squared	=	0.0001
				Adj R-squared	=	-0.0052
Total	.109768559	192	.000571711	Root MSE	=	.02397

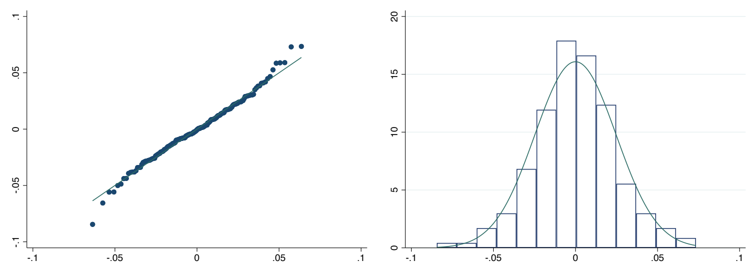
emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0000745	.0007242	0.10	0.918	-.001354	.0015031
_cons	-.0047308	.0017284	-2.74	0.007	-.0081399	-.0013216

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.11
Model	.000247962	4	.00006199	Prob > F	=	0.9802
Residual	.109520597	188	.000582556	R-squared	=	0.0023
				Adj R-squared	=	-0.0190
Total	.109768559	192	.000571711	Root MSE	=	.02414

emc	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0015153	.0054658	-0.28	0.782	-.0122974	.0092669
q3	-.0016433	.0055016	-0.30	0.766	-.0124961	.0092096
q4	.0009828	.0054658	0.18	0.857	-.0097993	.0117649
q5	-.0019714	.0055016	-0.36	0.720	-.0128242	.0088814
_cons	-.0039014	.0038649	-1.01	0.314	-.0115255	.0037228

D.32 Value-weighted Emission (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of emission_value
       Ho:  model has no omitted variables
                 F(3, 188) =      3.33
                  Prob > F =      0.0207
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.65
Model	.000402352	1	.000402352	Prob > F	=	0.4208
Residual	.118080772	191	.000618224	R-squared	=	0.0034
				Adj R-squared	=	-0.0018
Total	.118483123	192	.0006171	Root MSE	=	.02486

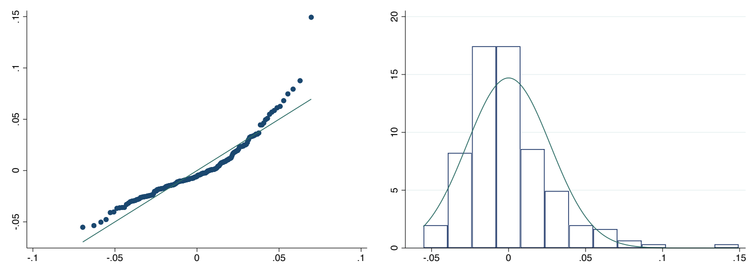
emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.000606	.0007512	0.81	0.421	-.0008757	.0020877
_cons	-.0014537	.0017927	-0.81	0.418	-.0049897	.0020823

Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.51
Model	.001261436	4	.000315359	Prob > F	=	0.7315
Residual	.117221688	188	.00062352	R-squared	=	0.0106
				Adj R-squared	=	-0.0104
Total	.118483123	192	.0006171	Root MSE	=	.02497

emission	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0037854	.0056547	-0.67	0.504	-.0149402	.0073694
q3	-.0038133	.0056918	-0.67	0.504	-.0150412	.0074146
q4	.002248	.0056547	0.40	0.691	-.0089068	.0134027
q5	.0013858	.0056918	0.24	0.808	-.0098421	.0126137
_cons	-.0005827	.0039985	-0.15	0.884	-.0084703	.007305

D.33 Value-weighted Clean (non-winsorized) and Ab_temp quintiles (control period)

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of clean_value
       Ho:  model has no omitted variables
                 F(3, 188) =      1.52
                  Prob > F =      0.2101
```

Appendix D: Change in portfolio returns and Ab_temp

Source	SS	df	MS			
				Number of obs	=	193
				F(1, 191)	=	0.06
Model	.000042109	1	.000042109	Prob > F	=	0.8117
Residual	.141367428	191	.000740144	R-squared	=	0.0003
				Adj R-squared	=	-0.0049
Total	.141409537	192	.000736508	Root MSE	=	.02721

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.000196	.0008219	0.24	0.812	-.0014252	.0018173
_cons	.0057052	.0019615	2.91	0.004	.0018363	.0095742

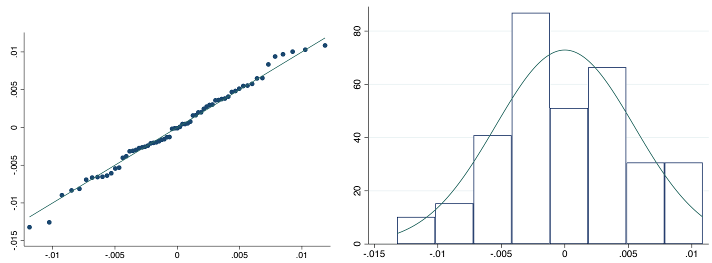
Source	SS	df	MS			
				Number of obs	=	193
				F(4, 188)	=	0.09
Model	.000267246	4	.000066812	Prob > F	=	0.9858
Residual	.141142291	188	.000750757	R-squared	=	0.0019
				Adj R-squared	=	-0.0193
Total	.141409537	192	.000736508	Root MSE	=	.0274

clean	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0005405	.0062049	0.09	0.931	-.0116996	.0127806
q3	.0009436	.0062456	0.15	0.880	-.0113768	.013264
q4	.0001984	.0062049	0.03	0.975	-.0120417	.0124385
q5	.0032649	.0062456	0.52	0.602	-.0090555	.0155852
_cons	.004754	.0043875	1.08	0.280	-.0039011	.013409

Appendix E: Trading activity and Ab_temp

E.1 EMCΔInstitutional and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of delta_emc_institutional
       Ho:  model has no omitted variables
                  F(3, 60) =      2.98
                  Prob > F =      0.0384
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.54
         Prob > F     =   0.4658
```

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	6.228	1	0.0126

H0: no serial correlation

Source	SS	df	MS
Model	.000075202	1	.000075202
Residual	.001917344	63	.000030434
Total	.001992546	64	.000031134

Number of obs	=	65
F(1, 63)	=	2.47
Prob > F	=	0.1210
R-squared	=	0.0377
Adj R-squared	=	0.0225
Root MSE	=	.00552

delta_emc_~l	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.000782	.0004975	1.57	0.121	-.0002121	.0017761
_cons	-.0008583	.0006935	-1.24	0.220	-.0022441	.0005276

Appendix E: Trading activity and Ab_temp

Regression with Newey-West standard errors		Number of obs =	65
maximum lag: 1		F(1, 63) =	2.97
		Prob > F =	0.0898

W_emc_inst~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.000782	.0004539	1.72	0.090	-.000125	.0016891
_cons	-.0008583	.0006008	-1.43	0.158	-.0020589	.0003423

Source	SS	df	MS		
				Number of obs =	65
				F(4, 60) =	1.66
Model	.000198628	4	.000049657	Prob > F =	0.1709
Residual	.001793918	60	.000029899	R-squared =	0.0997
				Adj R-squared =	0.0397
Total	.001992546	64	.000031134	Root MSE =	.00547

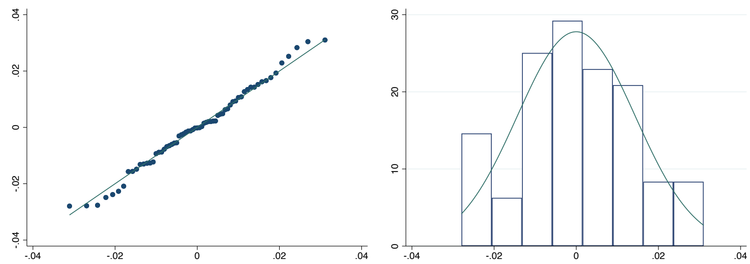
delta_emc_~l	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0001347	.0021447	0.06	0.950	-.0041553	.0044248
q3	.0000825	.0021447	0.04	0.969	-.0042076	.0043726
q4	.0022544	.0021447	1.05	0.297	-.0020357	.0065444
q5	.004442	.0021447	2.07	0.043	.000152	.0087321
_cons	-.0020638	.0015165	-1.36	0.179	-.0050973	.0009697

Regression with Newey-West standard errors		Number of obs =	65
maximum lag: 1		F(4, 60) =	2.13
		Prob > F =	0.0875

W_emc_inst~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0001347	.0023151	0.06	0.954	-.0044961	.0047655
q3	.0000825	.0021893	0.04	0.970	-.0042967	.0044618
q4	.0022544	.0019129	1.18	0.243	-.001572	.0060808
q5	.0044421	.0018157	2.45	0.017	.0008101	.008074
_cons	-.0020638	.0012815	-1.61	0.113	-.0046272	.0004995

E.2 EMCΔRetail and Ab_temp quintiles

Histogram of Q-Q plot of residuals



Appendix E: Trading activity and Ab_temp

```
Ramsey RESET test using powers of the fitted values of delta_emc_retail_investors
       Ho:  model has no omitted variables
                  F(3, 60) =      0.30
                  Prob > F =      0.8229
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.29
         Prob > F     =   0.5897
```

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	0.18
Model	.00003767	1	.00003767	Prob > F	=	0.6729
Residual	.013187814	63	.00020933	R-squared	=	0.0028
				Adj R-squared	=	-0.0130
Total	.013225485	64	.000206648	Root MSE	=	.01447

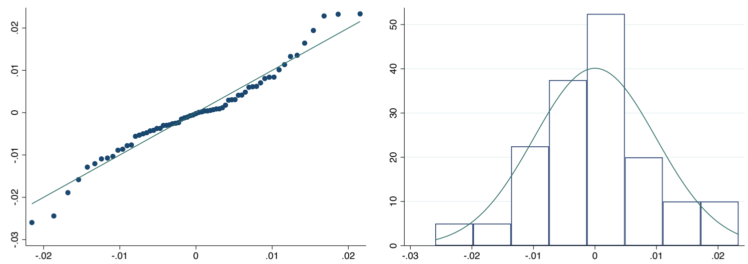
delta_em~ors	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0005535	.0013047	-0.42	0.673	-.0031607	.0020537
_cons	.0007999	.0018187	0.44	0.662	-.0028346	.0044344

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.52
Model	.00121905	4	.000304763	Prob > F	=	0.2069
Residual	.012006434	60	.000200107	R-squared	=	0.0922
				Adj R-squared	=	0.0317
Total	.013225485	64	.000206648	Root MSE	=	.01415

delta_em~ors	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0037362	.0055485	-0.67	0.503	-.0148348	.0073624
q3	.0086866	.0055485	1.57	0.123	-.002412	.0197852
q4	-.0016899	.0055485	-0.30	0.762	-.0127886	.0094087
q5	-.0014648	.0055485	-0.26	0.793	-.0125635	.0096338
_cons	.0003154	.0039234	0.08	0.936	-.0075325	.0081633

E.3 EMCΔBlockholders and Ab_temp quintiles

Histogram of Q-Q plot of residuals



Appendix E: Trading activity and Ab_temp

```
Ramsey RESET test using powers of the fitted values of delta_emc_blockholders
       Ho:  model has no omitted variables
                  F(3, 60) =      0.64
                  Prob > F =      0.5941
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     5.19
         Prob > F     =   0.0261
```

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	0.17
Model	.000017489	1	.000017489	Prob > F	=	0.6779
Residual	.006329292	63	.000100465	R-squared	=	0.0028
				Adj R-squared	=	-0.0131
Total	.006346781	64	.000099168	Root MSE	=	.01002

delta_emc_b~	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003771	.0009039	0.42	0.678	-.0014291	.0021833
_cons	-.0010195	.00126	-0.81	0.421	-.0035373	.0014984

```
Regression with Newey-West standard errors      Number of obs     =         65
maximum lag: 0                                  F(  1,        63) =       0.13
                                                Prob > F          =     0.7224
```

W_emc_bloc~s	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003771	.0010568	0.36	0.722	-.0017348	.0024889
_cons	-.0010195	.0013547	-0.75	0.455	-.0037266	.0016877

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.81
Model	.000685014	4	.000171254	Prob > F	=	0.1378
Residual	.005661767	60	.000094363	R-squared	=	0.1079
				Adj R-squared	=	0.0485
Total	.006346781	64	.000099168	Root MSE	=	.00971

delta_emc_b~	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0053506	.0038102	1.40	0.165	-.0022709	.012972
q3	-.0045801	.0038102	-1.20	0.234	-.0122015	.0030414
q4	.0021694	.0038102	0.57	0.571	-.0054521	.0097909
q5	-.0000882	.0038102	-0.02	0.982	-.0077096	.0075333
_cons	-.0015044	.0026942	-0.56	0.579	-.0068936	.0038848

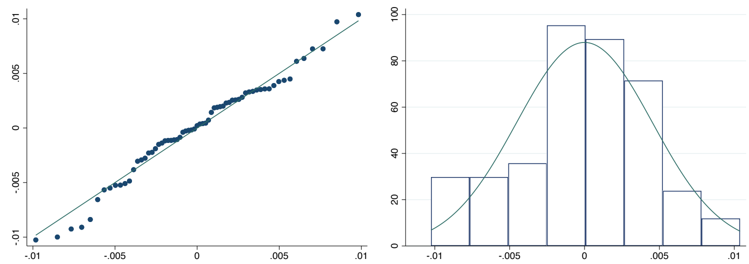
Appendix E: Trading activity and Ab_temp

```
Regression with Newey-West standard errors          Number of obs     =        65
maximum lag: 0                                      F(  4,        60) =      1.50
                                                    Prob > F          =    0.2148
```

W_emc_bloc~s	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0053505	.0045829	1.17	0.248	-.0038166	.0145176
q3	-.0045801	.0042669	-1.07	0.287	-.0131151	.0039549
q4	.0021693	.0039076	0.56	0.581	-.005647	.0099856
q5	-.0000884	.0034439	-0.03	0.980	-.0069773	.0068005
_cons	-.0015043	.0031647	-0.48	0.636	-.0078346	.004826

E.4 EMCΔLocInstitutional and Ab_temp quintiles

Histogram of Q-Q plot of residuals




```
Ramsey RESET test using powers of the fitted values of delta_emc_local_institutional_ex
       Ho:  model has no omitted variables
                  F(3, 60) =      2.88
                  Prob > F =      0.0431
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.00
         Prob > F     =   0.9999
```

```
. estat bgodfrey, lag(1)
```

Breusch-Godfrey LM test for autocorrelation

lags(*p*)	chi2	df	Prob > chi2
1	4.385	1	0.0362

H0: no serial correlation

Appendix E: Trading activity and Ab_temp

Source	SS	df	MS
Model	.000012855	1	.000012855
Residual	.001316495	63	.000020897
Total	.00132935	64	.000020771

Number of obs	=	65
F(1, 63)	=	0.62
Prob > F	=	0.4358
R-squared	=	0.0097
Adj R-squared	=	-0.0060
Root MSE	=	.00457

delta_emc_~x	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003233	.0004122	0.78	0.436	-.0005004	.0011471
_cons	-.0008049	.0005746	-1.40	0.166	-.0019532	.0003434

Regression with Newey-West standard errors
maximum lag: 1

Number of obs	=	65
F(1, 63)	=	0.74
Prob > F	=	0.3938

W_emc_loca~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003233	.0003766	0.86	0.394	-.0004292	.0010759
_cons	-.0008049	.000515	-1.56	0.123	-.001834	.0002242

Source	SS	df	MS
Model	.000099829	4	.000024957
Residual	.001229521	60	.000020492
Total	.00132935	64	.000020771

Number of obs	=	65
F(4, 60)	=	1.22
Prob > F	=	0.3127
R-squared	=	0.0751
Adj R-squared	=	0.0134
Root MSE	=	.00453

delta_emc_~x	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0004589	.0017756	-0.26	0.797	-.0040106	.0030927
q3	-.0014357	.0017756	-0.81	0.422	-.0049874	.0021159
q4	.0001669	.0017756	0.09	0.925	-.0033848	.0037185
q5	.0023352	.0017756	1.32	0.193	-.0012165	.0058868
_cons	-.0008532	.0012555	-0.68	0.499	-.0033646	.0016582

Regression with Newey-West standard errors
maximum lag: 1

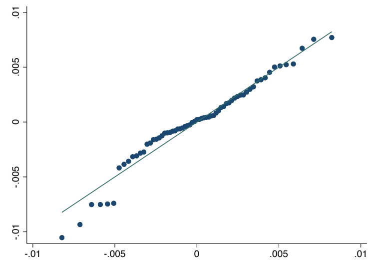
Number of obs	=	65
F(4, 60)	=	1.32
Prob > F	=	0.2729

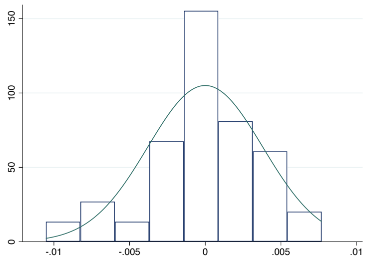
W_emc_loca~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.000459	.0019313	-0.24	0.813	-.0043223	.0034043
q3	-.0014358	.0013778	-1.04	0.302	-.0041917	.0013202
q4	.0001668	.0014815	0.11	0.911	-.0027967	.0031303
q5	.0023353	.0014959	1.56	0.124	-.0006568	.0053275
_cons	-.0008532	.0008871	-0.96	0.340	-.0026277	.0009214

Appendix E: Trading activity and Ab_temp

E.5 EMCΔForInstitutional and Ab_temp quintiles

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of delta_emc_foreign_institutional_
       Ho:  model has no omitted variables
                  F(3, 60) =      0.35
                  Prob > F =      0.7881
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.07
         Prob > F     =   0.7857
```

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	1.88
Model	.000027501	1	.000027501	Prob > F	=	0.1756
Residual	.000923147	63	.000014653	R-squared	=	0.0289
				Adj R-squared	=	0.0135
Total	.000950648	64	.000014854	Root MSE	=	.00383

delta_emc_~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0004729	.0003452	1.37	0.176	-.0002169	.0011627
_cons	-.0003379	.0004812	-0.70	0.485	-.0012995	.0006236

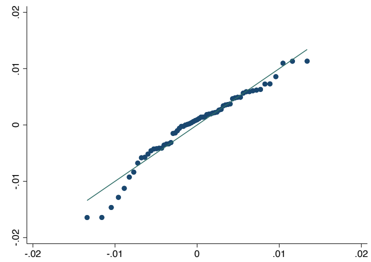
Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	0.98
Model	.00005838	4	.000014595	Prob > F	=	0.4246
Residual	.000892268	60	.000014871	R-squared	=	0.0614
				Adj R-squared	=	-0.0012
Total	.000950648	64	.000014854	Root MSE	=	.00386

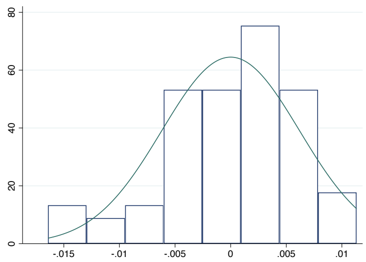
delta_emc_~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0009243	.0015126	0.61	0.543	-.0021013	.0039499
q3	.0017864	.0015126	1.18	0.242	-.0012392	.004812
q4	.0027392	.0015126	1.81	0.075	-.0002864	.0057648
q5	.0020401	.0015126	1.35	0.182	-.0009855	.0050657
_cons	-.0017288	.0010695	-1.62	0.111	-.0038682	.0004106

Appendix E: Trading activity and Ab_temp

E.6 EMCΔLocBlockholders and Ab_temp quintiles

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of delta_emc_local_blockholders
       Ho:  model has no omitted variables
                  F(3, 60) =      0.52
                  Prob > F =      0.6703
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)     =      0.01
         Prob > F      =    0.9195
```

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	0.01
Model	5.0594e-07	1	5.0594e-07	Prob > F	=	0.9095
Residual	.002448908	63	.000038872	R-squared	=	0.0002
				Adj R-squared	=	-0.0157
Total	.002449414	64	.000038272	Root MSE	=	.00623

delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000641	.0005622	-0.11	0.910	-.0011876	.0010594
_cons	-.0007677	.0007837	-0.98	0.331	-.0023339	.0007985

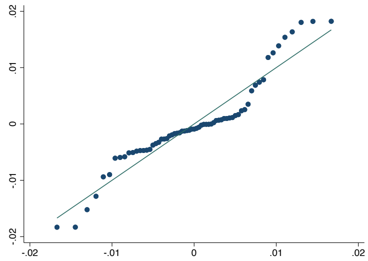
Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	2.48
Model	.000347627	4	.000086907	Prob > F	=	0.0533
Residual	.002101787	60	.00003503	R-squared	=	0.1419
				Adj R-squared	=	0.0847
Total	.002449414	64	.000038272	Root MSE	=	.00592

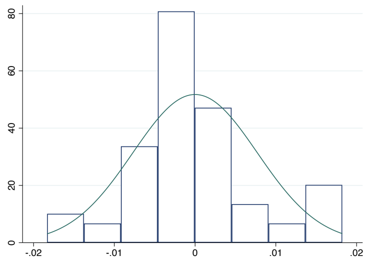
delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0025471	.0023215	1.10	0.277	-.0020965	.0071907
q3	-.0045869	.0023215	-1.98	0.053	-.0092305	.0000567
q4	-.0000779	.0023215	-0.03	0.973	-.0047215	.0045657
q5	.0001112	.0023215	0.05	0.962	-.0045324	.0047548
_cons	-.0003809	.0016415	-0.23	0.817	-.0036645	.0029026

Appendix E: Trading activity and Ab_temp

E.7 EMCΔForBlockholders and Ab_temp quintiles

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of delta_emc_foreign_blockholders
       Ho:  model has no omitted variables
                  F(3, 60) =      0.58
                  Prob > F =      0.6314
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.09
         Prob > F     =   0.7621
```

```
      Source |       SS           df       MS      Number of obs   =        65
-------------+----------------------------------   F(1, 63)        =      0.00
       Model |  2.0831e-07         1  2.0831e-07   Prob > F        =    0.9534
    Residual |  .003804531        63  .000060389   R-squared       =    0.0001
-------------+----------------------------------   Adj R-squared   =   -0.0158
       Total |   .00380474        64  .000059449   Root MSE        =    .00777

------------------------------------------------------------------------------
delta_emc_.. |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |  -.0000412   .0007008    -0.06   0.953    -.0014415    .0013592
       _cons |  -.0002015   .0009769    -0.21   0.837    -.0021536    .0017506
------------------------------------------------------------------------------
```

```
      Source |       SS           df       MS      Number of obs   =        65
-------------+----------------------------------   F(4, 60)        =      0.66
       Model |  .000160897         4  .000040224   Prob > F        =    0.6206
    Residual |  .003643842        60  .000060731   R-squared       =    0.0423
-------------+----------------------------------   Adj R-squared   =   -0.0216
       Total |   .00380474        64  .000059449   Root MSE        =    .00779

------------------------------------------------------------------------------
delta_emc_.. |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
          q2 |  -.0027716   .0030567    -0.91   0.368    -.0088858    .0033427
          q3 |  -.0039329   .0030567    -1.29   0.203    -.0100471    .0021814
          q4 |   .0001347   .0030567     0.04   0.965    -.0059796    .0062489
          q5 |   -.001641   .0030567    -0.54   0.593    -.0077552    .0044732
       _cons |   .0014313   .0021614     0.66   0.510    -.0028921    .0057547
------------------------------------------------------------------------------
```

Appendix E: Trading activity and Ab_temp

E.8 Summary statistics trading activity (non-winsorized) and Ab_temp quintiles

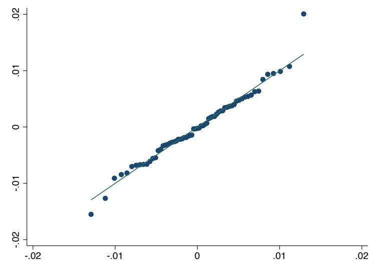
	EMC ΔLocInstitutional		EMC ΔForInstitutional		EMC ΔLocBlockholders		EMC ΔForBlockholders	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ab_temp	0.039		0.054		-0.015		-0.004	
	(0,96)		(1,36)		(-0,22)		(-0,05)	
Ab_temp Q2		-0.058		0.102		0.401		-0.277
		(-0,29)		(0,60)		(1,46)		(-0,90)
Ab_temp Q3		-0.144		0.188		-0,502*		-0.397
		(-1,04)		(1,10)		(-1,83)		(-1,29)
Ab_temp Q4		0.017		0,350**		-0.008		0.021
		(0,11)		(2,11)		(-0,03)		(0,07)
Ab_temp Q5		0.272		0.214		0.011		-0.164
		(1,59)		(1,25)		(0,04)		(-0,53)
Observations	65	65	65	65	65	65	65	65
R^2	0.012	0.084	0.029	0.076	0.001	0.155	0.000	0.043

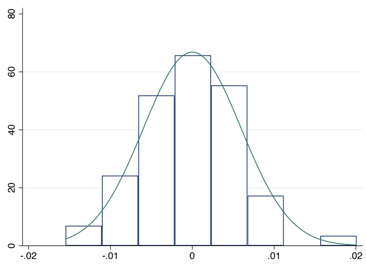
Regression output of trading activity of foreign and local investors and abnormal temperature with coefficients in percentage.

*Non-winsorized. The statistical significance of the coefficients is reported by *p<0.10; **p<0.05; ***p<0.01.*

E.9 EMCΔInstitutional (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals






```
Ramsey RESET test using powers of the fitted values of delta_emc_institutional_nonwinso
       Ho:  model has no omitted variables
                 F(3, 60) =      2.78
                 Prob > F =      0.0490
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =      0.03
         Prob > F     =    0.8525
```

```
Breusch-Godfrey LM test for autocorrelation
```

lags(p)	chi2	df	Prob > chi2
1	5.981	1	0.0145

```
                              H0: no serial correlation
```

Appendix E: Trading activity and Ab_temp

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	2.35
Model	.000085159	1	.000085159	Prob > F	=	0.1301
Residual	.002280854	63	.000036204	R-squared	=	0.0360
				Adj R-squared	=	0.0207
Total	.002366013	64	.000036969	Root MSE	=	.00602

delta_emc_~l	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0008322	.0005426	1.53	0.130	-.0002521	.0019164
_cons	-.00075	.0007564	-0.99	0.325	-.0022615	.0007614

Regression with Newey-West standard errors   Number of obs = 65
maximum lag: 1   F(1, 63) = 3.17
Prob > F = 0.0797

delta_emc_~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0008322	.0004671	1.78	0.080	-.0001013	.0017656
_cons	-.00075	.0006458	-1.16	0.250	-.0020407	.0005406

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.60
Model	.00022856	4	.00005714	Prob > F	=	0.1850
Residual	.002137453	60	.000035624	R-squared	=	0.0966
				Adj R-squared	=	0.0364
Total	.002366013	64	.000036969	Root MSE	=	.00597

delta_emc_~l	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0001347	.0023411	0.06	0.954	-.0045481	.0048176
q3	-.0000834	.0023411	-0.04	0.972	-.0047663	.0045994
q4	.0030181	.0023411	1.29	0.202	-.0016647	.007701
q5	.004442	.0023411	1.90	0.063	-.0002408	.0091249
_cons	-.0020638	.0016554	-1.25	0.217	-.0053751	.0012475

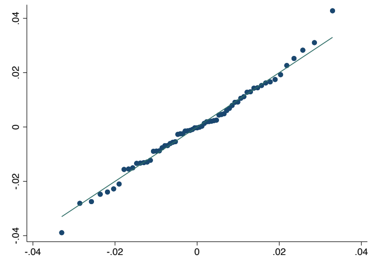
Regression with Newey-West standard errors   Number of obs = 65
maximum lag: 1   F(4, 60) = 2.24
Prob > F = 0.0748

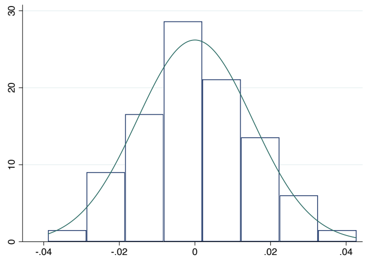
delta_emc_~l	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0001347	.0023151	0.06	0.954	-.0044961	.0047655
q3	-.0000834	.0022717	-0.04	0.971	-.0046276	.0044607
q4	.0030181	.0024082	1.25	0.215	-.0017989	.0078352
q5	.004442	.0018157	2.45	0.017	.0008101	.008074
_cons	-.0020638	.0012815	-1.61	0.113	-.0046272	.0004995

Appendix E: Trading activity and Ab_temp

E.10 EMCΔRetail (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals





```
Ramsey RESET test using powers of the fitted values of delta_emc_retail_investors_nonwi
       Ho:  model has no omitted variables
                  F(3, 60) =      0.35
                  Prob > F =      0.7879
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.18
         Prob > F     =   0.6744
```

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	0.26
Model	.000060328	1	.000060328	Prob > F	=	0.6146
Residual	.014839046	63	.00023554	R-squared	=	0.0040
				Adj R-squared	=	-0.0118
Total	.014899374	64	.000232803	Root MSE	=	.01535

delta_em~ors	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0007004	.001384	-0.51	0.615	-.003466	.0020652
_cons	.0008549	.0019292	0.44	0.659	-.0030004	.0047102

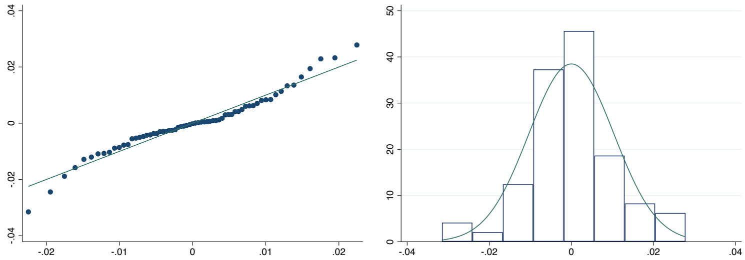
Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.29
Model	.00118357	4	.000295893	Prob > F	=	0.2824
Residual	.013715804	60	.000228597	R-squared	=	0.0794
				Adj R-squared	=	0.0181
Total	.014899374	64	.000232803	Root MSE	=	.01512

delta_em~ors	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0027774	.0059303	-0.47	0.641	-.0146398	.009085
q3	.0086866	.0059303	1.46	0.148	-.0031758	.020549
q4	-.0025401	.0059303	-0.43	0.670	-.0144025	.0093223
q5	-.0014648	.0059303	-0.25	0.806	-.0133272	.0103976
_cons	.0003154	.0041934	0.08	0.940	-.0080726	.0087034

Appendix E: Trading activity and Ab_temp

E.11 EMCΔBlockholders (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of delta_emc_blockholders_nonwinsor
       Ho:  model has no omitted variables
                  F(3, 60) =      0.60
                  Prob > F =      0.6196
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     3.85
         Prob > F     =   0.0541
```

```
      Source |       SS           df       MS      Number of obs   =        65
-------------+----------------------------------   F(1, 63)        =      0.15
       Model |  .000016467         1  .000016467   Prob > F        =    0.6991
    Residual |  .006878765        63  .000109187   R-squared       =    0.0024
-------------+----------------------------------   Adj R-squared   =   -0.0134
       Total |  .006895232        64  .000107738   Root MSE        =    .01045

------------------------------------------------------------------------------
delta_em~ers |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   .0003659   .0009423     0.39   0.699     -.001517    .0022489
       _cons |  -.0010342   .0013135    -0.79   0.434    -.0036591    .0015907
------------------------------------------------------------------------------

Regression with Newey-West standard errors          Number of obs     =        65
maximum lag: 0                                      F(  1,        63) =      0.12
                                                    Prob > F          =    0.7309

------------------------------------------------------------------------------
             |             Newey-West
delta_emc_b~ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     ab_temp |   .0003659   .0010592     0.35   0.731    -.0017508    .0024826
       _cons |  -.0010342   .0014068    -0.74   0.465    -.0038455    .0017772
------------------------------------------------------------------------------
```

Appendix E: Trading activity and Ab_temp

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.94
Model	.000789134	4	.000197284	Prob > F	=	0.1157
Residual	.006106098	60	.000101768	R-squared	=	0.1144
				Adj R-squared	=	0.0554
Total	.006895232	64	.000107738	Root MSE	=	.01009

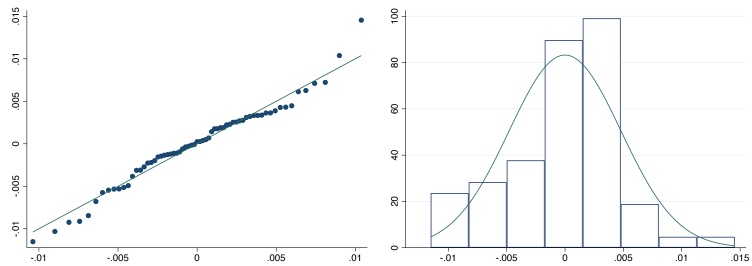
delta_em~ers	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0056939	.0039568	1.44	0.155	-.002221	.0136088
q3	-.0050097	.0039568	-1.27	0.210	-.0129246	.0029052
q4	.0021694	.0039568	0.55	0.586	-.0057455	.0100843
q5	-.0000882	.0039568	-0.02	0.982	-.0080031	.0078267
_cons	-.0015044	.0027979	-0.54	0.593	-.007101	.0040923

Regression with Newey-West standard errors — Number of obs = 65
maximum lag: 0 — F(4, 60) = 1.50
Prob > F = 0.2132

delta_emc_b~	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0056939	.0047088	1.21	0.231	-.003725	.0151128
q3	-.0050097	.0044592	-1.12	0.266	-.0139295	.0039101
q4	.0021694	.0039076	0.56	0.581	-.0056469	.0099857
q5	-.0000882	.0034439	-0.03	0.980	-.006977	.0068007
_cons	-.0015044	.0031646	-0.48	0.636	-.0078346	.0048259

E.12 EMCΔLocInstitutional (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of var40
       Ho:  model has no omitted variables
                 F(3, 60) =      3.13
                 Prob > F =      0.0320
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.09
         Prob > F     =   0.7697
```

Appendix E: Trading activity and Ab_temp

Breusch-Godfrey LM test for autocorrelation

lags(p)	chi2	df	Prob > chi2
1	4.220	1	0.0400

H0: no serial correlation

Source	SS	df	MS			
				Number of obs	=	65
				F(1, 63)	=	0.79
Model	.000018443	1	.000018443	Prob > F	=	0.3773
Residual	.001469447	63	.000023325	R-squared	=	0.0124
				Adj R-squared	=	-0.0033
Total	.00148789	64	.000023248	Root MSE	=	.00483

delta_emc_~x	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003873	.0004355	0.89	0.377	-.000483	.0012576
_cons	-.0007666	.0006071	-1.26	0.211	-.0019798	.0004466

Regression with Newey-West standard errors　　Number of obs = 65
maximum lag: 1　　F(1, 63) = 0.92
Prob > F = 0.3420

delta_emc_~x	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.0003873	.0004044	0.96	0.342	-.000421	.0011955
_cons	-.0007666	.0005386	-1.42	0.160	-.0018428	.0003097

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	1.38
Model	.000125415	4	.000031354	Prob > F	=	0.2514
Residual	.001362475	60	.000022708	R-squared	=	0.0843
				Adj R-squared	=	0.0232
Total	.00148789	64	.000023248	Root MSE	=	.00477

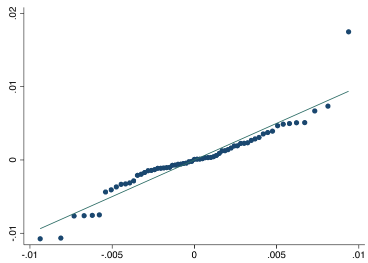
delta_emc_~x	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0005758	.0018691	-0.31	0.759	-.0043146	.0031629
q3	-.0014357	.0018691	-0.77	0.445	-.0051745	.002303
q4	.0001669	.0018691	0.09	0.929	-.0035719	.0039056
q5	.0027163	.0018691	1.45	0.151	-.0010224	.0064551
_cons	-.0008532	.0013217	-0.65	0.521	-.0034969	.0017905

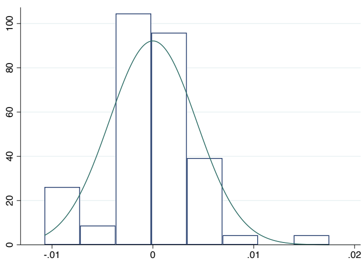
```
Regression with Newey-West standard errors      Number of obs     =         65
maximum lag: 1                                  F(  4,        60) =       1.28
                                                Prob > F          =     0.2872
```

delta_emc_~x	Coef.	Newey-West Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0005758	.0019793	-0.29	0.772	-.0045349	.0033833
q3	-.0014357	.0013777	-1.04	0.302	-.0041916	.0013202
q4	.0001669	.0014815	0.11	0.911	-.0027966	.0031304
q5	.0027163	.0017086	1.59	0.117	-.0007013	.006134
_cons	-.0008532	.0008871	-0.96	0.340	-.0026277	.0009214

E.13 EMCΔForInstitutional (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals






```
Ramsey RESET test using powers of the fitted values of var41
       Ho:  model has no omitted variables
                  F(3, 60) =      0.47
                  Prob > F =      0.7054
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.02
         Prob > F     =   0.9021
```

Source	SS	df	MS
Model	.000035466	1	.000035466
Residual	.001199381	63	.000019038
Total	.001234847	64	.000019294

```
Number of obs   =         65
F(1, 63)        =       1.86
Prob > F        =     0.1771
R-squared       =     0.0287
Adj R-squared   =     0.0133
Root MSE        =     .00436
```

delta_emc_~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	.000537	.0003935	1.36	0.177	-.0002492	.0013233
_cons	-.0002185	.0005485	-0.40	0.692	-.0013146	.0008775

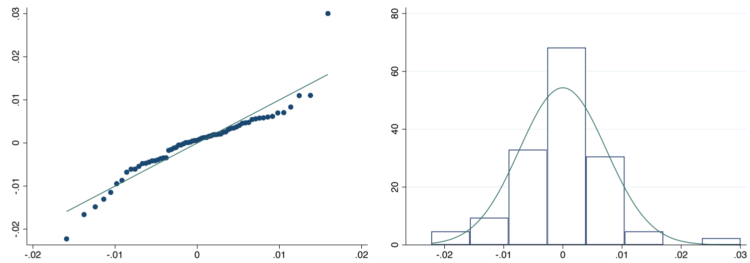
Source	SS	df	MS
Model	.000093496	4	.000023374
Residual	.001141351	60	.000019023
Total	.001234847	64	.000019294

Number of obs	=	65
F(4, 60)	=	1.23
Prob > F	=	0.3083
R-squared	=	0.0757
Adj R-squared	=	0.0141
Root MSE	=	.00436

delta_emc_~_	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
q2	.0010212	.0017107	0.60	0.553	-.0024007	.0044432
q3	.0018833	.0017107	1.10	0.275	-.0015386	.0053053
q4	.0036029	.0017107	2.11	0.039	.0001809	.0070248
q5	.002137	.0017107	1.25	0.216	-.0012849	.005559
_cons	-.0018258	.0012097	-1.51	0.136	-.0042454	.0005939

E.14 EMCΔLocBlockholders (non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals



```
Ramsey RESET test using powers of the fitted values of delta_emc_local_blockholders_non
       Ho:  model has no omitted variables
                  F(3, 60) =      0.43
                  Prob > F =      0.7340
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.07
         Prob > F     =   0.7974
```

Source	SS	df	MS
Model	2.7118e-06	1	2.7118e-06
Residual	.003450497	63	.00005477
Total	.003453209	64	.000053956

Number of obs	=	65
F(1, 63)	=	0.05
Prob > F	=	0.8246
R-squared	=	0.0008
Adj R-squared	=	-0.0151
Root MSE	=	.0074

delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
ab_temp	-.0001485	.0006674	-0.22	0.825	-.0014821	.0011851
_cons	-.000543	.0009303	-0.58	0.562	-.0024021	.0013161

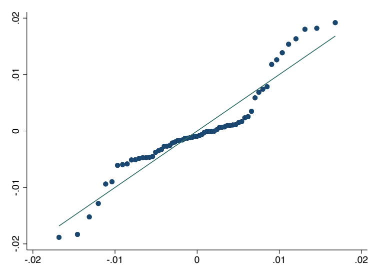
Appendix E: Trading activity and Ab_temp

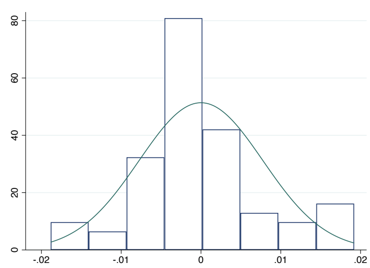
Source	SS	df	MS			
Model	.000533787	4	.000133447	Number of obs	=	65
Residual	.002919422	60	.000048657	F(4, 60)	=	2.74
				Prob > F	=	0.0366
Total	.003453209	64	.000053956	R-squared	=	0.1546
				Adj R-squared	=	0.0982
				Root MSE	=	.00698

delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	.0040064	.002736	1.46	0.148	-.0014664	.0094792
q3	-.0050182	.002736	-1.83	0.072	-.010491	.0004546
q4	-.0000779	.002736	-0.03	0.977	-.0055507	.0053949
q5	.0001112	.002736	0.04	0.968	-.0053616	.005584
_cons	-.0003809	.0019346	-0.20	0.845	-.0042508	.0034889

E.15 EMCΔForBlockholders (Non-winsorized) and Ab_temp quintiles

Histogram of Q-Q plot of residuals






```
Ramsey RESET test using powers of the fitted values of delta_emc_foreign_blockholders_n
       Ho:  model has no omitted variables
                  F(3, 60) =      0.58
                  Prob > F =      0.6335
```

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
         Ho: Constant variance
         Variables: ab_temp

         F(1 , 63)    =     0.09
         Prob > F     =   0.7610
```

Source	SS	df	MS			
Model	1.7671e-07	1	1.7671e-07	Number of obs	=	65
Residual	.003859949	63	.000061269	F(1, 63)	=	0.00
				Prob > F	=	0.9573
Total	.003860125	64	.000060314	R-squared	=	0.0000
				Adj R-squared	=	-0.0158
				Root MSE	=	.00783

delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
ab_temp	-.0000379	.0007058	-0.05	0.957	-.0014484	.0013726
_cons	-.0001949	.000984	-0.20	0.844	-.0021612	.0017714

Appendix E: Trading activity and Ab_temp

Source	SS	df	MS			
				Number of obs	=	65
				F(4, 60)	=	0.68
Model	.000166779	4	.000041695	Prob > F	=	0.6103
Residual	.003693346	60	.000061556	R-squared	=	0.0432
				Adj R-squared	=	-0.0206
Total	.003860125	64	.000060314	Root MSE	=	.00785

delta_emc_..	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
q2	-.0027716	.0030774	-0.90	0.371	-.0089272	.0033841
q3	-.0039716	.0030774	-1.29	0.202	-.0101272	.002184
q4	.0002101	.0030774	0.07	0.946	-.0059455	.0063657
q5	-.001641	.0030774	-0.53	0.596	-.0077966	.0045146
_cons	.0014313	.002176	0.66	0.513	-.0029214	.005784