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Does green sentiment really exist?

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Abstract

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I set out to explore if market-wide investor sentiment, as defined by (Baker & Wurgler, 2006) can be used as a partial explanation for green sentiment. Recent literature concludes that investors have a preference for greener investments when there is heightened attention to climate change topics, and that this has been one of the main drivers of the outperformance of greener stocks in recent years. I find that green sentiment, as proxied through Google search volume and media intensity, has a significant and positive correlation with investor sentiment. I also find that when controlled for investor sentiment, the contribution of green sentiment towards the outperformance of greener stocks is reduced. This means that market-wide sentiment serves as a partial explanation to green sentiment and the outperformance of greener stocks. However, it does not completely exclude the existence of the former.

Keywords: Investor Sentiment, Green sentiment, Sustainable investing, Climate Change, Global warming

Abstrato

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O meu objetivo é explorar se o sentimento de investidor, tal como definido por (Baker & Wurgler, 2006), pode ser utilizado como uma explicação parcial para o conceito de sentimento verde. Literatura recente conclui que os investidores têm preferência por investimentos mais ecológicos quando há uma maior atenção a temas relativos a alterações climáticas, e que este tem sido um dos principais fatores do superior desempenho das ações consideradas mais ecológicas nos últimos anos. Verifico que o sentimento verde, quantificado através do volume de pesquisa do Google e da intensidade dos media, tem uma correlação significativa e positiva com o sentimento de investidor. Também concluo que, quando se controla pelo sentimento de investidor, a contribuição do sentimento verde para o desempenho superior das ações de empresas mais ecológicas é significativamente reduzida. Isto significa que o sentimento de mercado serve de explicação parcial para o sentimento verde e para o desempenho superior das ações mais ecológicas. No entanto, não exclui completamente a existência do último.

Palavras-chave: Sentimento de investidor, Sentimento verde, Investimentos sustentáveis Mudanças climáticas, Aquecimento global

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1. Introduction

Sustainable investing has rapidly emerged in the past decades. It considers more than just financial performance, like for example environmental, social, and governance criteria. Inside the scope of sustainable investing, the environmental component is said to be the most important one and hence the one we should focus on. According to a recent survey from BlackRock, 88% of their clients ranked the environment component as "the priority most in focus", when asked about sustainable investing (BlackRock, 2020). Investment products with a focus on sustainability have been very appealing to investors, as showcased by Assets Under Management (AUM) of ESG-related assets at the end of 2021 exceeding $35 trillion[1] (Kishan, 2022) and high returns delivered by stocks of more sustainable firms. This seems in line with the findings of (Fama & French, 2007) and (Pástor, et al., 2021). They come to the conclusion that investors care about more than just returns, and derive utility from owning assets that are aligned with their values. However, it does go against other views and literature, where more carbon-intensive firms should deliver better returns (Bolton & Kacperczyk, 2021).

More recent studies tried to dissect these high returns of stocks of more sustainable firms (green stocks). They found that one potential reason for these higher returns is increased public awareness on the topics of climate change and global warming. This is what has come to be known as green sentiment.

However, if we look at the backdrop of most samples used in these studies, the period from 2008 to 2020, was a very unique time in capital markets. After the fallout of the Subprime Crisis of 2008, Central Banks, like the US Federal Reserve (FED) and the European Central Bank (ECB) performed unprecedented levels of Quantitative Easing (QE) and slashed interest rates to zero percent (in the case of the ECB even going as far as to have negative policy rates). This meant, that capital for investments has been readily available at almost no cost, and as such has led to one of the longest bull markets in financial markets history. It was only "briefly" interrupted in 2018 and 2019 as a result of the US and China trade war[2] and in 2020 due to the COVID-19 pandemic[3]. The latter sparked an even more aggressive QE policy from Central

[1] AUM of ESG related assets have risen from around $15 Trillion in 2014 to $35 Trillion at the end of 2021, a 133% increase in seven years. According to Global Sustainable Investment Association one in three dollars managed globally are ESG related.

[2] In 2018 Donald Trump, the US president at the time, imposed severe trade tariffs on Chinese imported goods valued at over $360Bn. This triggered very negative reactions from the markets and forced the US FED to cut interest rates by 75 basis points (Politi, 2019). This was of course a reversal of the prior three years' monetary policy, where it raised the benchmark policy rates from 0% to 2.25% (Refinitiv Eikon).

[3] In 2012 and 2013 there was also the European sovereign debt crisis.

Banks around the world, which sparked massive rallies in equity markets worldwide (Armstrong, 2022). This bull market came to an end in 2022 as Central Banks around the world reversed their aggressive QE policies by lifting interest rates and began performing quantitative tightening in the face of decades-high inflation (Martin & Agnew, 2022).

Considering this particular period in financial markets, (Bansal, et al., 2021) found that highly rated S*ocially Responsible Stocks* (SRI), such as green stocks (stocks of less polluting firms), outperformed less-rated SRI stocks, such as brown stocks (stocks of more polluting firms). In general, SRI stocks overperform during good economic times and in periods of high market valuations but underperform outside those periods. Prior studies such as the one by (Stambaugh, et al., 2012) document that the profits of known asset pricing anomalies are significantly higher following periods of high market-wide investor sentiment, which are usually associated with periods of high market valuations. This means investor sentiment plays a pervasive role in the degree of overpricing. These findings beg the question of whether the high returns of green stocks were really a reflection of increased appetite of investors for greener assets, given an environment that has been very accommodative for most asset classes.

This question should be explored because it is at the core of the "supposed" shift in financial markets and investing. If green sentiment and appetite for green investments is a proxy for or an extension of market-wide investor sentiment, then it could indicate that it was nothing more than greenwashing. Investors were just allocating capital to where they thought it could be more profitable, and not necessarily allocating for the sake of sustainability. In general, climate change is a worldwide crucial societal problem, as it has the potential to impact the well-being of every person and species on the planet. According to (Crutzen & Stoermer, 2000), which coined the term "Anthropocene", we live in the "Age of Human", where we, the human species, have such an impact on the biosphere that we have become a major geological force. From an economical perspective, climate change also poses a significant threat to the global economy and financial markets (Litterman, et al., 2020) (Bansal, et al., 2016).

The question I therefore set out to explore is whether green sentiment is an actual phenomenon or whether it is just a proxy for or an extension of the regular market-wide investor . In short the research question is whether market-wide investor sentiment serves as a partial explanation for green sentiment and its supposed link to the outperformance of greener stocks.

I use three different variables to measure green sentiment as a way to diversify the channels that capture investors‘ attention towards climate change topics. As mentioned by (Ouadghiri, et al., 2021), not all investors use the same sources for acquiring information about climate change. Some investors may actively search for it, for example on Google, while others may just read the newspapers articles. One of the measures is based on the Google Search Volume Index for the topics of "climate change" and "pollution" (see (Choi, et al., 2020) and (Ouadghiri, et al., 2021)). My two other measures are media-based ones. The first of which is a Media Climate Change (MCC) index, which is heavily based on the concept of the MCCC index of (Ardia, et al., 2020) and the Economic Policy Uncertainty (EPU) index of (Baker, et al., 2016). This index tracks the media intensity on the topic of climate change and global warming, through number of articles published on the topics. The second and final one, is the unexpected shock component of the MCC index, given by the prediction error of a autoregressive model of order one applied to the index. To proxy for market-wide investor sentiment, I use the investor sentiment index of (Baker & Wurgler, 2006), as used by (Stambaugh, et al., 2012).

The first performed test is to look for significant correlations between green and market-wide investor sentiment. It shows that all green sentiment measures, with the exception of the MCC index have significant and positive correlations with investor sentiment, in particular the unexpected shock component of the MCC index.

The second test, a complement of the first one, is a regression of green sentiment on investor sentiment. The result are significant and show positive coefficients. I find that all the green sentiment variables, including the MCC index, have a positive linear relationship with investor sentiment.

The last analysis is to examine what impact investor sentiment has on the supposed outperformance of greener stocks when there is heightened green sentiment. To sort stocks into green and brown categories I use an approach, which mimics that of (Choi, et al., 2020). I categorize stocks based on the Intergovernmental Panel on Climate Change (IPCC) classifications of high emission industries. The inclusion of investor sentiment, reduces the impact that green sentiment has on contributing to the outperformance of greener firms. Additionally, this relationship is even more significant and stronger with previous month's investor sentiment. However, despite the statistically significant findings, the introduction of investor sentiment does not have such materially significant results. This leads me to conclude that green sentiment does indeed exist, but market-wide serves only as a partial explanation for its existence. Behind investors supposed preference for greener investments, there is a component of market-wide sentiment that contributes to it.

Most findings around green sentiment are very similar to each other. I contribute to this growing literature by attempting to provide a partial explanation for this phenomenon, in the form of market-wide sentiment. Additionally, my paper contributes to the extensive literature on market-wide investor sentiment by exploring another way through which investor sentiment can play a role in asset pricing. Finally, as a robustness check to check for the persistency of green sentiment in a more recent time sample, I extend the sample period by including two very rich and contrasting years, 2021 and 2022. The former can be characterized as a period of very high valuations, one where the S&P 500 reached all-time highs (Miao, 2023), and overall market euphoria[4] (Lex, 2021), two indicators of high-investor sentiment. On the other hand, 2022 was a reversal of that, marked by a year of great market turmoil, high volatility, and recession fears (Martin & Agnew, 2022) as central banks around the world embarked on an aggressive campaign of Quantitative Tightening (QT) and large interest rate rises, in the face of very high inflation.

This paper is structured as follows: Section 1.2 provides an overview of the current Literature, Section 1.3 and 1.4 explains the Methodology and the Data used respectively, Section 2 presents and discusses the Results, and Section 3 concludes.

1.1.Literature Review

The question of whether investor sentiment affects asset prices as been put forward as early as 1936 by Keynes (Keynes, 1936), which argued that markets can fluctuate with the influence of investors' "animal spirits". In contemporary literature, it was first formalized by (Long, et al., 1990), who demonstrated that uninformed traders, coined "noise" traders, base their trading decisions on sentiment. When sentiment changes, there is greater "noise" trading, which drives greater mispricing. However, the most influential and subsequently most cited work on the effect of investor sentiment on cross-sectional returns of stock was by (Baker & Wurgler, 2006). To my knowledge, they were the first to construct a market-wide index to proxy for investor sentiment, based on six underlying proxies for investor sentiment (e.g., NYSE Share Turnover, number of IPOs, and first-day returns). When the sentiment is low (high) at the

[4] At the beginning of 2021 capital markets were met with a new wave and mania of retail trading frenzy that pushed up the prices of heavily shorted firms, coined "meme-stocks", to extremely high valuations.

beginning of the observing period, subsequent stock returns are particularly high (low), especially for younger, less profitable stocks and for growth stocks.

Subsequent work explored further ways to proxy for Investor Sentiment and to quantify its effects on asset prices. Recently, three novel approaches have emerged in the academic world for investor behavior and sentiment analysis.

Under the first approach, media-based, researchers proxy investor sentiment through media coverage of mainstream media sources, for example, *The Wall Street Journal*. The intuition is that an investor's psychology and sociology are linked to the content and tone of news about the stock market, see (Fang & Peress, 2009) (Tetlock, 2007) (Engle, et al., 2020) (Bessec & Fouquau, 2022) (Ardia, et al., 2020). The latter provides evidence of how media coverage serves as a proxy for investor sentiment and that a high degree of pessimism in media coverage is linked to downward pressure on stock returns.

The second approach to investor sentiment is through internet search volume, in particular *Google Search Volume Index* (GSVI). (Da, et al., 2014) construct an investor sentiment index through GSVI, based on negative words like "recession", "Gold", or "bankruptcy". Their findings, similar to the ones of (Tetlock, 2007), suggest that a high degree of pessimism is linked to negative contemporaneous market returns, which are followed by a reversal in the following days (see also (Vozlyublennaia, 2014) (Choi, et al., 2020) (Ouadghiri, et al., 2021). This approach is widely used because of the availability of daily data, which is publicly available. It reveals attitudes and has a very broad coverage (Da, et al., 2014).

The third and most recent approach to investor sentiment focuses on identifying behavior/sentiment through the existence of arbitrage opportunities in *Exchange Traded Funds* (ETF). (Brown, et al., 2020) argued that the issuance or redemption of ETF shares provides signals of non-fundamental shocks to investors' beliefs, and these signals offer a predictability of cross-sectional returns. According to (Ben-David, et al., 2021), ETFs, and particularly specialized products such as green ETFs, are more appealing to retail and sentiment investors. (Davies, 2022) uses these findings to build a speculation sentiment index, based on the arbitrage activity of leveraged ETFs, which negatively predicts returns.

Despite more recent work, the index of (Baker & Wurgler, 2006) remains one of the most widely used measures to quantify market-wide investor sentiment, with the GSVI being ever more adopted given its accessibility, data frequency, and broad coverage.

There is a nascent and growing literature providing empirical evidence that investors should expand their horizons and consider more than traditional economical and financial risks, but other sources of risks, in particular climate change and pollution risks, as part of their decision process. These risks have been identified as an emerging long-run risk factor (Bansal, et al., 2016) (Ilhan, et al., 2020) (Litterman, et al., 2020). (Krueger, et al., 2020) document with their survey-based approach that climate risks have a growing importance for institutional investors on their selection of portfolio companies[5]. Their conclusions are in line with the findings of (Fama & French, 2007), meaning that investors care about more than just returns. Investors have preferences and tastes for assets aligned with their values, such as sustainability, and those tastes affect asset prices.

More traditional literature has demonstrated that because of investors' tastes, stocks of more carbon-intensive firms ("brown" stocks), outperform stocks of less pollutant firms ("green" stocks). For example, (Bolton & Kacperczyk, 2021)[6] show that firms with higher CO2 emissions earn higher returns. (Hong & Kacperczyk, 2009) found that because investors demand compensation to hold stocks that go against societal norms, so-called "sin" stocks, stocks of companies involved in producing alcohol, tobacco, or gaming, outperform "non-sin" stocks. However, in recent years we have seen that green stocks generated very high returns, and indeed several studies report superior historical returns of sustainable strategies (Nagy, et al., 2016) (In, et al., 2019). These findings go against current literature on the topic of sustainable investing, such as (Pástor, et al., 2021)[7], which report that in equilibrium, "green" stocks should have lower expected returns than "brown" stocks as investors with tastes for ESG are willing to forgo better returns in order to hold their desired green portfolios. Similar findings can be seen in the bond market, where on average, green bonds trade at lower yields than equivalent bonds without green features (Zerbib, 2019) and (Baker, et al., 2018).

However, as pointed out by (Pástor, et al., 2022) the high returns of green assets have been

[5] They surveyed over 400 of investment managers to study how institutional investors consider climate risk in their investment decisions. They found that 38% of fund managers analyze a firm's carbon footprints and risks of stranded assets. In their survey, they also found that 25% of managers try to hedge climate risk

[6] They study whether carbon emissions impact cross-section returns of US stocks and found that stocks of firms with higher CO_2 earn higher returns. Carbon emissions and environmental pollution appear to have an influence on cross-sectional stock returns

[7] (Pástor, et al., 2021) developed an asset pricing model based on the Capital Asset Pricing Model (CAPM) that also takes into account ESG criteria as a new risk factor. They discovered that in equilibrium "green" stocks have lower expected returns, because investors like holding them and they can hedge climate risk, and therefore bid-up the price of ESG assets . Another novel insight of their research is that the size of the ESG investment industry depends positively on the dispersion in investor's ESG tastes.

due to unexpectedly high increases in concerns and awareness for climate change. When the performance is controlled for these shocks and earnings, green stocks should have in fact underperformed. For a more in-depth review of current research around climate and sustainable investing see (Giglio, et al., 2021).

This ever growing interest in the debate of whether “green” stocks really outperform “brown” stocks, and sustainable investing offers superior returns, has led researchers to explore which channels could lead to an outperformance of greener stocks. The current most prominent cause is the link between public attention’s to climate change and asset prices, coined green sentiment, which relies on the principles of earlier literature on market-wide investor sentiment.

One of the most influential papers on this topic is (Engle, et al., 2020), where they propose a measure for quantifying investors’ awareness of climate risks through textual analysis of *The Wall Street Journal* newspaper, coined the *Wall Street Journal Climate Change News Index* (WSJ Climate Change News Index). It is based on the idea that climate change coverage rises to the media’s attention when there is cause for concern. In their study, they found that when there is significant increase in the media attention on climate change, as proxied by the index, it is possible to build a portfolio that hedges climate risks, by building long-short portfolios that go long on higher-rated ESG stocks and short on lower-rated ones[8]. Despite the focus of this paper being on trying to hedge climate change risks, which are very difficult to insure with traditional financial instruments, it did produce a method to quantify investors’ attention to climate change. As such, this index has been extensively used in other topics as a proxy of public attention to climate change, such as (Ilhan, et al., 2020) which used it to demonstrate that the cost of option protection against downside tail risks, for carbon-intensive firms is magnified at times when public’s attention to climate change spikes.

Subsequently, there has been extensive work on Green Sentiment. However, as seen in the work performed in the topic of market-wide investor sentiment, the research conducted in green sentiment has been on developing new ways of measuring it, as opposed to redefining the conclusions. Also similar, are the approaches that are being deployed. (Ardia, et al., 2020) uses a media-based measure, the Media Climate Change Concern index, which is inspired by

[8] Their strategy is similar in spirit to the one of (Jegadeesh & Titman, 1993), in which they seek to explore the stocks that performed well and which performed poorly when news about climate change materializes. In essence, they are long previous winners and short past losers and implement it on ESG sorted portfolios.

(Engle, et al., 2020) but available at a daily frequency (see also (Bessec & Fouquau, 2022)[9]. (Briere & Ramelli, 2021)[10] use an ETF arbitrage approach, which they argue is better suited at capturing non-fundamental changes in expectations regarding climate risks. (Choi, et al., 2020) and (Ouadghiri, et al., 2021) use GSVI as the main measure of investor's attention to climate change and green topics, but the latter uses both, media coverage of climate change and GSVI measure. They argue that some investors do not actively search about climate change on Google and others do not necessarily read the corresponding newspaper articles, hence these measures complement each other.

Despite using different approaches to quantifying green sentiment, the findings are similar to each other. Whenever there is a spike in awareness for climate change related risks, green stocks tend to outperform brown stocks. (Pástor, et al., 2021)[11] and (Ardia, et al., 2020), both document that when there are positive shocks to the ESG factor, green stocks tend to outperform. (Briere & Ramelli, 2021) show that an increase in the green sentiment index anticipates an outperformance of greener stocks. In periods of abnormally high local temperatures, (Choi, et al., 2020) found a spike in the local volume of Google Searches for the topic "climate change" and "global warming", which is subsequently followed by the underperformance of stocks of more carbon-intensive firms.

One important test / aspect that is taken for granted in the current literature on green sentiment, is that green sentiment is an actual "anomaly" in itself and is not a proxy for other risk-factors. The previous studies mentioned in the topic of sustainable investing, point to investors tastes leading them to hold assets they like, such as green stocks, and hence bidding their prices higher. This can be seen as some form of overpricing. (Stambaugh, et al., 2012)[12] found that market-wide investor sentiment, using the index of (Baker & Wurgler, 2006), plays a pervasive role in the degree of overpricing in equity markets and that the profits of known anomalies are significantly stronger following levels of high sentiment. Following the same

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[9] (Bessec & Fouquau, 2022) went one step further by using a dictionary-based approach and measuring the frequency and tone of environmental terms in business newspapers.
[10] (Briere & Ramelli, 2021) propose a novel way of measuring Green sentiment based on the abnormal flows of capital into Green ETFs. The reason for their approach is that it isolates true investor appetite and is not moved by changes in individual firm expectations, as well as the more retail investor base of (specialized) ETFs.
[11] In their study they measure the concerns regarding climate change using the Media Climate Change Concerns of (Ardia, et al., 2020), which in itself is based on the original media-based method of (Engle, et al., 2020)
[12] They set out to explore the role of investor sentiment in the degree of profitability of known market anomalies, such as momentum. They argue that investor sentiment has a market-wide component that influences prices of different securities in the same direction and at the same time, and that when combined with the existence of short-selling restrictions creates an environment conducive to overpricing.

logic we can raise the question of whether green sentiment is not actually a proxy or an extension of market-wide investor sentiment. I want to fill this gap with my study.

1.2.Hypothesis development

I want to study whether market-wide investor sentiment, as described by (Baker & Wurgler, 2006), affects green sentiment; this means whether green sentiment is a risk factor in itself or is, to some degree, a proxy for market-wide investor sentiment. The recent literature on the topic of public and/or investors' attention to climate change and its effect on asset prices supports the existence of a green sentiment as a standalone effect. During periods of elevated attention to climate change topics, greener firms' stocks outperform the ones of more polluting firms (see (Ardia, et al., 2020), (Choi, et al., 2020), (Engle, et al., 2020), (Briere & Ramelli, 2021), (Pástor, et al., 2021), (Ouadghiri, et al., 2021), (Bessec & Fouquau, 2022), and (Pástor, et al., 2022)). Given this, green sentiment could be considered an anomaly, similar to market-wide investor sentiment.

However, as (Stambaugh, et al., 2012) found out, investor sentiment has a significant and positive relationship with the profits of long-short anomalies. This means that investor sentiment plays an important role in the profits of several known market anomalies. They point out that due to limits on short-selling and arbitrage activity overpricing becomes prevalent in the market during periods of high sentiment. Regarding socially responsible investing (Bansal, et al., 2021) suggest that stocks of more socially responsible firms (SRI) outperform those of less socially responsible firms during periods of high market valuations, which are associated with periods of high investor sentiment. However, outside these periods, SRI stocks tend to underperform. This could mean that the outperformance of SRI stocks is linked to investor sentiment, by overpricing them during periods of rising sentiment.

This potential explanation does raise the question, if the overperformance of greener stocks, that has been linked to rising green sentiment, could to a certain degree, be linked to investor sentiment. To test if this is, I propose the following hypothesis.

H1: Is green sentiment independent of investor sentiment?

To test my hypothesis, I will be first checking for correlation between green sentiment (GS) and investor sentiment (INV) and second regressing green sentiment on investor sentiment (1). If green sentiment is not independent of market-wide investor sentiment, then I expect a correlation between the two, either positive or negative as well as a significant coefficient.

$$GS_t = \alpha + \beta * INV_t + \varepsilon_t \tag{1}$$

$$GS_t = \alpha + \beta * INV_{t-1} + \varepsilon_t \tag{2}$$

Additionally, and most importantly I will assess the impact that market-wide investor sentiment (INV) has on the influence between green sentiment and the returns of greener stocks relative to brown firms. If investor sentiment plays a role in the degree of outperformance of greener stocks, I expect a less significant effect of green sentiment on the returns of greener stocks. To check this I will regress the returns of the green-minus-brown portfolio (GMB) on contemporary green sentiment and investor sentiment measures.

1.3.Methodology

1.3.1. Measuring green sentiment

To quantify green sentiment, I split my approach in two, the first one being based on Google Search Volume Index (GSVI) data and the second one being media-based. The first one simply uses GSVI data for “Climate Change” and ”Pollution” to look for changes in attitude towards these topics. This approach / data has the advantage of being readily available, easy to use and reflects actual actions taken. Additionally, as demonstrated by (Choi, et al., 2020), (Ouadghiri, et al., 2021) it can generate significant results. The second approach, which is still the most common in the field of green sentiment is to use focus on media attention and or intensity. The approach I chose closely follows the one of (Ardia, et al., 2020). Their method as also been used by (Pástor, et al., 2022) where they obtained similar results and thereby giving it credibility. I construct a Media Climate Change index and then use it to retrieve the unexpected changes in sentiment.

1.3.2. Google Search Volume Index

To calculate the public’s attention to climate change through GSVI data, I utilize the approach of (Choi, et al., 2020). First, I calculate the logarithm of monthly changes in the GSVI ($Ln(\frac{GSVI_t}{GSVI_{t-1}})$). However, as pointed out by the authors, GSVI data suffers from seasonality effects. Therefore it requires adjustment for seasonality. The variable of interest, the delta in search volume index ($DSVI$), is defined as the residuals of the regression of the log change in the monthly GSVI on month-of-the-year dummy variables (3). The residuals ($DSVI$) are winsorized at the 2.5% level.

$$GSVI_t = \alpha + \beta * Month + \varepsilon_t \tag{3}$$

1.3.3. Media Climate Change Index – MCC Index

To capture investors' and the public's attention to climate change topics through media, I utilize the approach of (Ardia, et al., 2020). I use this approach because of its tractable method and the fact that it has been used by (Pástor, et al., 2022). They obtained similar results to the original authors and thereby gave more credibility to the method. The basis for this approach is to calculate a *concerns score* that captures both – the number of articles of climate change and the concerns expressed in each article. The index I use focuses simply on the number of articles. Following the authors, this method still represents a valid measure of media attention and intensity as it resembles one of the most influential media-based sentiment time-series in economics. The Economic Policy Uncertainty index (EPU)[13] developed by (Baker, et al., 2016).

The first step in this method is to normalize the number of articles published on climate change (4) in each source (s). To calculate the average and standard-deviation, I use a 36-month rolling window[14], as done by (Ardia, et al., 2020). The normalization of scores reflects that some sources, on average, publish fewer articles on climate change. Therefore, if these sources start publishing more articles, it sends a stronger signal that a relevant climate-change event has likely happened. The aggregation is then achieved through the average of normalized scores of each source.

$$normalized\ articles = \frac{\overline{articles_s}}{\sigma_s} \tag{4}$$

As pointed out by (Doyle, et al., 2016) and (Flaxman, et al., 2016), there is a non-linear relationship between the exposure to an opinion or topic (such as number of articles read) and

[13] The EPU index is available at: https://www.policyuncertainty.com/index.html. Accessed on March 18, 2023.
[14] The MeCCC data starts from January 2004, this means that to apply the 36 month rolling window, the formation period for the normalization of scores starts in January 2007.

the increase in concerns. For example: reading 20 articles on climate change versus reading just one, is unlikely to raise concerns by twenty times. To account for the decreasing marginal rate at which media attention increases concerns regarding climate change, I apply a square root function to the average of normalized scores of each source (5).

$$MCC_t = \sqrt{\frac{1}{s}\sum_{s=1}^{s} normalized\ articles} \tag{5}$$

The methodology so far constructs the Media Climate Change index (MCC), and can be considered a proxy for media climate change attention / intensity. As mentioned by (Ardia, et al., 2020) and (Gentzkow, et al., 2019), one of the most influential media-based time series in economics is the EPU index developed by (Baker, et al., 2016). The index is the simple average of the normalized count of articles that contain at least one keyword for the topics of economy, policy, and uncertainty across several newspapers. The construction of the MCC index therefore follows very closely the EPU approach, but for the topic of Climate Change and Global Warming[15] and without a focus on political uncertainty.

The final stage of the media-based approach for measuring green sentiment is to capture *unexpected* changes (or innovations) in climate concerns. The argument is that investors expect some news (e.g., planned international conferences) or the presence of stale news (articles with only minor modifications of the content). Therefore, to capture the shock component in the MCC index I use an autoregressive time series model, as proposed by the authors and as commonly used in literature, e.g., (Engle, et al., 2020). The shock component is the prediction error[16] (ε) from the autoregressive model (6), and I refer to it as Unexpected Media Changes (UMC). This autoregressive model and UMC are computed on an Out-of-sample basis, using a rolling-window of 36-months.

[15] (Gavriilidis, 2021) has developed the Climate Policy Uncertainty (CPU) index, following the same approach of the EPU index. The author searches for articles in eight leading US newspapers containing the terms {"uncertainty" or "uncertain"} and {"carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental"} and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy"}, etc.)

[16] The residuals are winsorized at the 2.5% level, keeping in line with the approach for GSVI.

$$MCC_t = \alpha + \beta * MCC_{t-1} + \varepsilon_t \tag{6}$$

1.3.4. Constructing green-minus-brown portfolio

The practical purpose of this research is to check what influence investor sentiment has on the returns of green firms, in the presence of green sentiment. To track the returns of greener firms, I follow the most used approach in literature, using a long-short portfolio. This portfolio goes long on green stocks – shares of publicly traded low-emitting firms, and short on brown stocks – shares of publicly traded high-emitting firms. This long-short portfolio is called green-minus-brown (GMB).

The construction of this portfolio requires the identification of green and brown firms. Brown firms are those that belong to the industries identified by the IPCC as being high-emitters, and the green firms are all of those that fall outside (see Section 1.4.3 for more information). I calculate GMB using both – equal-weighted and value-weighted (by market capitalization) returns.

1.3.5. Impact of Green sentiment on GMB's returns

To get a baseline figure on the influence of Green Sentiment (GS) on the returns of GMB, I regress GMB's returns (GMB_t) – my independent variable, on the contemporary green sentiment (GS_t) measure (7). Additionally, as (Pástor, et al., 2022) demonstrated, there is a delayed stock price reaction to climate news. Therefore I also included the previous month's green sentiment variable[17]. The three-factor model of (Fama & French, 1992) is introduced as a control factor. I use this model because it is the most widely used and accepted in asset-pricing studies. Additionally, the existing research on green sentiment uses the three-factor as a control factor for stock returns. The three-factor model consists of the Market excess returns (MKT_t), the High-Minus-Low factor (HML_t) and the Small-Minus-Big (SMB_t) factor:

$$GMB_t = \alpha + \beta * MKT_t + \beta * HML_t + \beta * SMB_t + \boldsymbol{\beta} * \boldsymbol{GS_t} + \boldsymbol{\beta} * \boldsymbol{GS_{t-1}} + \varepsilon_t \tag{7}$$

Next, and the crucial part of my analysis is where I analyze the impact that market-wide

[17] (Pástor, et al., 2022) demonstrated that stocks react slowly to climate news. This effect, as is expected, it's more pronounced for smaller stocks, as they react more slowly in general. By separating the analysis into Green and Brown stocks they also found that the delay comes mostly from Brown stocks.

investor sentiment (INV) has on the influence of green sentiment on the returns of GMB. I run the same regression as (7), but now I introduce the contemporary investor sentiment (INV_t):

$$GMB_t = \alpha + \beta * MKT_t + \beta * HML_t + \beta * SMB_t + \boldsymbol{\beta} * \boldsymbol{GS_t} + \boldsymbol{\beta} * \boldsymbol{GS_{t-1}} + \boldsymbol{\beta} * \boldsymbol{INV_t} + \varepsilon_t \tag{8}$$

GS takes the form of one of the three measures: Google Search Volume index - $DSVI_t$; Media Climate Change media - MCC_t; and the unexpected shocks to the MCC index - UMC_t. The different forms are used to validate the internal validity of the obtained results and check for their robustness.

1.4.Data

1.4.1. Google Search Volume Index

The data source for the Google Search Volume Index ($GSVI$), is Google Trends, which provides search volume index for any desired topic. I use the approach of (Choi, et al., 2020) to measure the public's attention to climate change. I downloaded the monthly search volume index for the topic of "Climate Change" and "Pollution"[18], in the United States. The data downloaded spans from January 2004 to December 2022.

Table 1 shows summary statistics for $DSVI_t$, UMC_t, MCC_t, and INV_t. The mean and median of $DSVI_t$ are both 0.00. The high value of excess kurtosis (2.17) indicates that $DSVI_t$ may not be that normally distributed. Moreover, in Panel A of Figure 1, where the distribution of $DSVI_t$ and UMC_t are plotted, we can observe that both variables have fat tails and leptokurtic distributions.

[18] In their paper, they also attempted to use search data for the topic of "global warming", but the search traffic for it is much lower than that of both "Climate Change" or "Pollution".

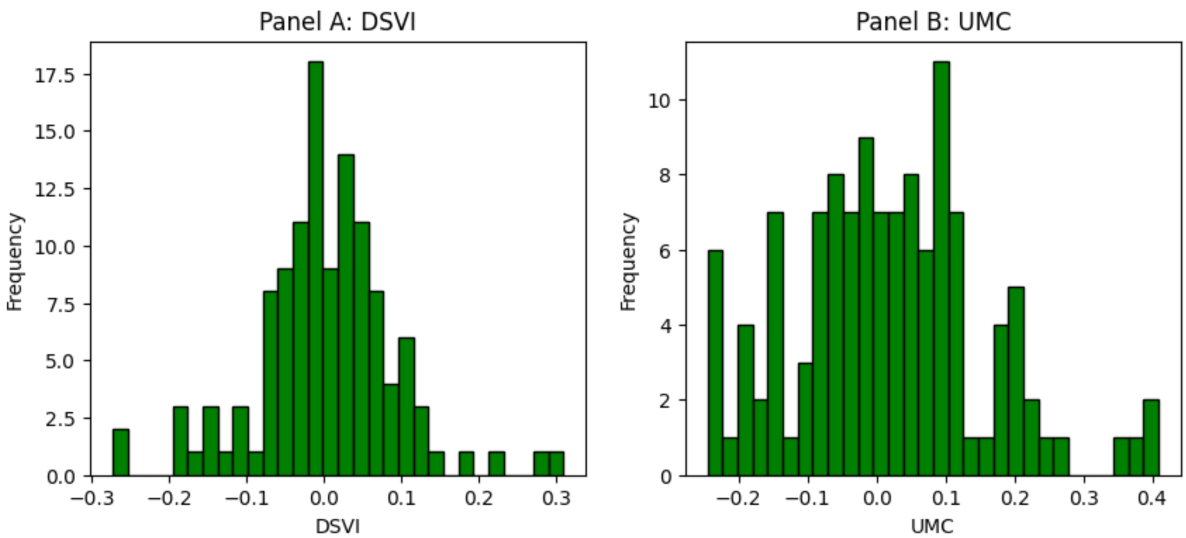
Table 1: Summary statistics for green sentiment and investor sentiment variables

This table shows summary statistics for 4 sentiment capturing variables: 1) DSVI – the residuals of the regression of the log change in the monthly GSVI on month-of-the-year dummy variables, 2) UMC – the unexpected shock component of the MCC index, which is defined as the residuals of an AR1 model on MCC, 3) MCC – The Media Climate Change news index is the average of the normalized number of articles published each month on climate change or global warming in five US newspapers, 4) INV – (Baker & Wurgler, 2006) investors sentiment index. The time sample is January 2010 to December 2019

	DSVI	UMC	MCC	INV
Obs	120	120	120	120
Mean	0.00	0.02	1.42	-0.16
SD	0.09	0.14	0.26	0.22
Min	-0.27	-0.24	0.95	-0.92
P25	-0.04	-0.07	1.19	-0.25
P50	0.00	0.01	1.43	-0.16
P75	0.05	0.09	1.61	-0.04
Max	0.31	0.41	2.07	0.25
Skew	0.07	0.37	0.22	-0.90
Kurt	2.17	0.29	-0.69	1.68

Figure 1: Distribution of DSVI and UMC

This figure plots the distribution of DSVI and UMC for the period of January 2010 to December 2019. Panel A represents the histogram of DSVI values and Panel B represents the histogram of UMC values.



1.4.2. Media Climate Change Index

I proxy the public's and investors' attention to Climate Change through Media Intensity. The approach I follow is linked to the one of (Ardia, et al., 2020)[19], which has been used as well by (Pástor, et al., 2022) as a proxy for unexpected changes in climate change concerns. To gauge the intensity of media attention on climate change, I use the number of articles posted on the subject. I use a time series on the number of articles on Climate change from the Media and Climate Change Observatory (MeCCO)[20]. MeCCO is a multi-university collaboration that monitors 130 mainstream sources in 59 countries around the world for media coverage of "Climate Change" and "Global Warming". They compile the number of newspaper articles that cover these topics per source on a monthly basis. The data accessed spans from January 2004 to January 2023.

As specified in the Methodology section, the construction of the MCC index requires a 36 month window to calculate source-specific (s) standard-deviation to obtain the standardized source-specific number of articles (4). This means that the MCC index is only computed from January 2007 onwards. On top of this, the extrapolation of UMC_t is done on an out-of-sample basis with also a 36-month (rolling) window. The latter implies that it is only available from January 2010 onwards, which means that my analyzed period begins January 2010, when all measures are available.

As my research is focused on US stock markets, I selected all the United States newspapers available in the MeCCO dataset. The five newspapers available in the MeCCO dataset are: the Los Angeles Times, New York Times, USA Today, The Wall Street Journal, and Washington Post. Table 2 reports the number of articles published on all newspaper sources used for the construction of the MCC index during the sample period. The New York Times publishes the most about climate change. Across the whole time period (January 2010 to December 2019) it published 17,430 articles discussing climate change topics representing an average of 145 articles per month. On the other hand, USA Today and Wall Street Journal publish the lowest amount[21], with just 14 and 17 articles per month respectively.

[19] The MCCC index is available at https://sentometrics-research.com/. In my paper I decided not use their index for the main analysis as the available data only goes until 2018. Instead I used their index as a robustness check against my results.
[20] The data is available at https://sciencepolicy.colorado.edu/icecaps/research/media_coverage/index.html. Accessed on January 30 2023.
[21] It's important to consider that these numbers refer only to absolute values. Newspapers like the New York

Table 2: Sources of climate change news

This table reports for each newspaper source the number of articles (N) discussing climate change and their weight on the total number of articles (%) from January 2010 to December 2019. The table also reports summary statistics on the number of articles.

	Articles				
Source	*N*	%	Mean	Max	Min
Los Angeles Times (US)	5,909	17%	49	119	8
New York Times (US)	17,430	51%	145	524	45
USA Today (US)	1,703	5%	14	41	3
Wall Street Journal (US)	1,982	6%	17	50	3
Washington Post (US)	7,407	22%	62	146	8
Total	34,431	100%			

Figure 2: Media Climate Change (MCC) Index

This figure plots the Media Climate Change (MCC) Index from January 2010 to December 2019. The MCC index is constructed based on the average of five mainstream US newspapers' normalized number of articles published each month on climate change or global warming. It follows a modified approach of (Ardia, et al., 2020) MCC index, and the EPU index of (Baker, et al., 2016).

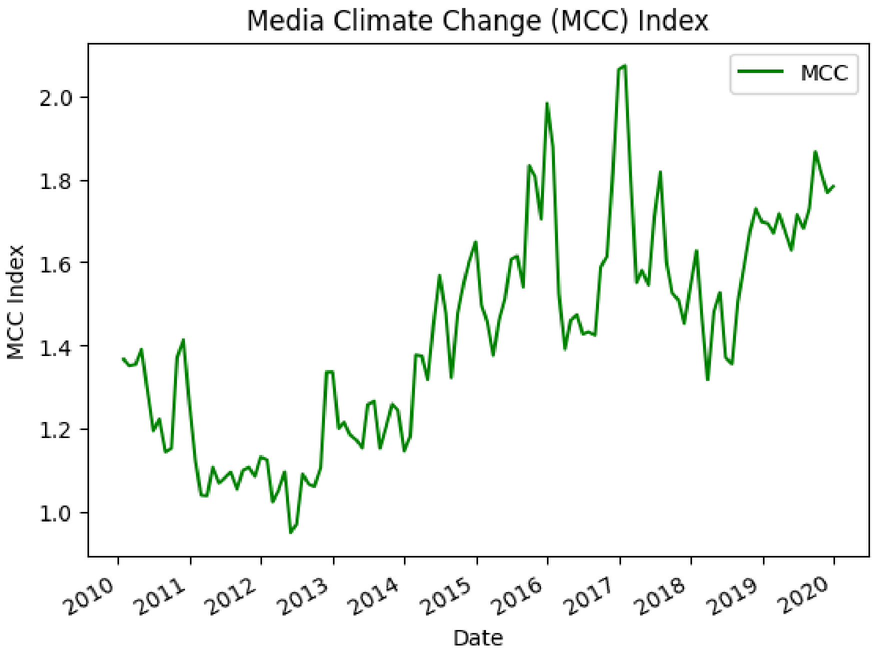


Figure 2 displays the monthly evolution of the MCC index from January 2010 to December 2019. It seems to capture major events related to climate change. At the end of 2012, there was

Times and Washington Post may just publish more articles discussing climate change, because they publish more articles on all topics. Without data on the total number of articles published by each newspapers, it's not possible to define which one publishes more on relative terms. (Ardia, et al., 2020) reports that in their sample, the Wall Street Journal had the highest relative publishing on climate change (0.26%), and USA Today the least (0.08%).

the UN Doha Climate Change Conference where the Doha Climate Gateway and a roadmap for the 2015 Paris Agreement were signed (United Nations, 2012). In November 2013 a devastating cyclone hit the Philippines, causing around 5% losses to the country's GDP (UNICEF, 2013). Around and up until the 2015 Paris Agreement was sealed, the MCC spikes up and remains very elevated. This supports the argument that major climate events are expected by investors and are accompanied by prior intensified media coverage. However, after the agreement was signed on December 2015, there is a noticeable reduction in the media coverage of climate change topics, with the index dropping 25% to its mean value (1.42). At the end of 2016, as the Paris Agreement entered into force, the same pattern happened, with the MCC surging to 2.07 and then crashing 33% to 1.55. A few months later, in 2017, then former US president Donald Trump announced the intention to withdraw the US from the Paris agreement (FT, 2017). Then in 2019, the Amazon rainforest, was hit by a devastating wave of wildfires, causing the destruction of vast areas of forest and sparking widespread protests on climate protection (Nasa Earth Observatory, 2019).These observations suggest that this index can capture significant events that correlate with anecdotal evidence of heightened increases in climate change concerns.

Since UMC_t is extrapolated from the MCC through an autoregressive model using the ordinary least squares (OLS) method (6), it has a mean very close to zero (0.02). However, due to its positive excess kurtosis (0.29), visible in Panel B of Figure 1, UMC exhibits a probability of extreme (or tail) events greater than predicted by the standard normal distribution. The histogram of UMC also showcases a left-sided distribution, which is coherent with the overall positive evolution of the MCC index.

1.4.3. Emissions data

The construction of the GMB portfolio requires the identification of high- and low-emission firms. For this, I adopt the classification provided by the Intergovernmental Panel on Climate Change (IPCC). The IPCC identifies five major industry sectors as major emission sources: Energy; Transport; Buildings; Industry (such as chemicals and metals); and Agriculture, Forestry and Other Land Uses (AFOLU). Each of these sectors is further broken down into subcategories (e.g., Domestic Air Transport, International Aviation as part of Transport). As there is no official mapping of these subsectors into standardized industry classifications, such as the North America Industry Classification System (NAICS), I use the mapping,

Table 3, done by (Choi, et al., 2020). In their research, they hand-matched the IPCC subcategories with the Industry Classification Benchmark (ICB) provided by DataStream[22]. The firms identified by the IPCC are classified as high-emission firms (brown).

One common alternative to this approach, is to use carbon emissions or Environmental Scores provided by independent data providers, such as MSCI ESG Ratings or Refinitiv. One of the major drawback of these scores is that they are industry adjusted, making cross industry comparisons difficult. Additionally, these ratings cover only a subset of firms, and not the whole range of listed firms. As a result, these methods can produce significantly different classifications of firms[23]. This is why the focus of my research is using the IPCC definitions.

[22] The ICB is a globally recognized standard system managed by FTSE Russel for categorizing companies and securities across four levels of classification. In 2021 the ICB was revised to include more granularity and is no longer compatible with the one used by (Choi, et al., 2020). Therefore, I first had to covert the old system to the existing one, as is available in DataStream..

[23] e.g., (Choi, et al., 2020) report that there are a few cases where these methods provide substantially different conclusions. For example, Toyota Motor Corporation is mapped to the Transport Equipment industry (IPCC code = 1A2f2), and therefore a high-emission industry. The ratings method would classify Toyota Motor Corporation as a low-emission firm.

Table 3: Summary of IPCC Categories to ICB codes mapping

This table provides the mapping between the IPCC high-emission categories and the ICB codes as provided by Datastream. The Industry Classification Benchmark (ICB) code refers to the sub-sector code available in DataStream.

ICB Code	DataStream industry name	IPCC category code	IPCC industry name
Energy			
60101040	Coal	1A2f4	Mining and quarrying
65101015	Conventional Electricity	1A1a	Power and Heat Generation
60101010	Oil: Crude Producers	1B2	Flaring and fugitive emissions from oil and natural gas
65102020	Gas Distribution	1A3e, 1B2	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
60101000	Integrated Oil and Gas	1A1bc	Other Energy Industries
60101030	Oil Equipment and Services	1A1bc	Other Energy Industries
Transport			
40501010	Airlines	1A3a, 1C1	Domestic air transport, International aviation
50206030	Marine Transportation	1A3d, 1C2	Inland shipping (fossil), International navigation
50206020	Railroads	1A3c	Rail transport
50206060	Transportation Services	1A2f2, 1A3b	Transport equipment, Road transport (includes evaporation) (fossil)
50206010	Trucking	1A3b	Road transport (includes evaporation) (fossil)
Buildings			
50101035	Building Materials: Other	1A4a, 2A1	Commercial and public services (fossil), Cement production
50101010	Construction	1A2f6	Construction
40202010	Home Construction	1A4b	Residential (fossil)
Industry			
55102035	Aluminum	1A2b, 2C3	Non-ferrous metals, Aluminium production (primary),
40101020	Automobiles	1A2f2	Transport equipment
50206015	Commercial Vehicles and Parts	1A2f2	Transport equipment
55201000	Chemicals: Diversified	1A2c	Chemicals
10102015	Electronic Components	2F7a, 2F8a	Semiconductor Manufacture, Electrical
50202025	Electronic Equipment: Gauges and Meters	2F7a, 2F8a	Equipment Manufacture Semiconductor Manufacture, Electrical Equipment Manufacture
45102020	Food Products	1A2e	Food and tobacco
55102000	General Mining	1A2f4	Mining and quarrying
55103025	Gold Mining	1A2f4	Mining and quarrying
50204000	Machinery: Industrial	1A2f3	Machinery
55102010	Iron and Steel	1A2a	Iron and steel
65102000	Multi-utilities	1A1a, 1A2f	Power and Heat Generation, Other industries (stationary) (fossil)
55102050	Nonferrous Metals	1A2b	Non-ferrous metals
55101015	Paper	1A2d	Pulp and paper
55103030	Platinum and Precious Metals	2Cr	Non-ferrous metals production
10102010	Semiconductors	2F7a	Semiconductor Manufacture
55201020	Specialty Chemicals	1A2c	Chemicals
45103010	Tobacco	1A2e	Food and tobacco
65103035	Waste and Disposal Services	6A	Solid waste disposal on land
AFOLU			
45102010	Farming, Fishing, Ranching and Plantations	1A4c3, 4A, 4B, 4C, 4Dr	Fishing (fossil), Enteric Fermentation, Manure management, Rice cultivation, Agricultural soils (direct)

1.4.4. Investor sentiment

As mentioned in section 1.1, there are many ways to measure market-wide investor sentiment, but despite the more recent contributions, the market based investor sentiment measure of (Baker & Wurgler, 2006) (BW) remains the most popular. In this paper I measure prevailing investor sentiment, through the BW index. I download the index from the author's webpage[24], where they regularly update the data.

The entire sentiment index spans from July 1965 until August 2022. The BW index is formed by taking the first principal component of six measures of investor sentiment. The six measures are: closed-end fund discount, number and the first-day returns of IPOs, NYSE turnover[25], equity share in total new issues, and dividend premium.

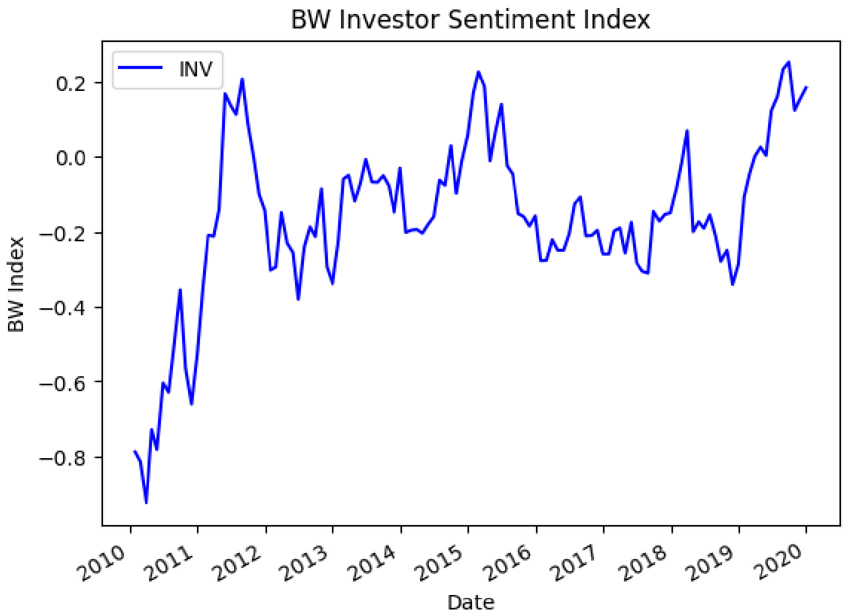
Figure 3 plots the (Baker & Wurgler, 2006) investor sentiment index for my sample period from January 2010 to December 2019. Visual inspection of the graph reveals several distinct periods. The first one 2010-2011, consists of the years immediately after the Great Financial Crisis of 2008 (GFC) where financial markets were very depressed. In the fallout of the GFC, Central Banks around the world adopted unprecedented QE policies, such as cutting interest rates to 0% (The New York Times, 2019). These actions contributed to a strong economic recovery and one of the longest bull markets in financial history. Despite this, the BW index remained relatively stable between 2012 and 2019 apart from 2015 and 2019. At the end of 2014, the US Federal Reserve (FED) announced the first policy rate increases since the unprecedent cut following the financial crisis of 2008. This rate hike cycle lasted until the end of 2018 and lifted rates from 0% to range between 2.25% and 2.5%. Then in 2019, in response to risks over the US-China trade war, the FED again cut the policy rates, which helped boost stock markets (The New York Times, 2019).

[24] Data is available at: https://pages.stern.nyu.edu/~jwurgler/. Accessed on January 20, 2023

[25] NYSE turnover has been dropped as one of the six sentiment indicators. The sentiment index maintained now is based on five indicators. According to the authors, NYSE turnover does not mean what it once did, given the explosion of institutional high-frequency trading and the migration of trading to a variety of venues.

Figure 3: BW Index 2010-2019

This figure displays the (Baker & Wurgler, 2006) Investor sentiment index from 2010 to 2019. The BW index is formed by taking the first principal component of six measures of investor sentiment. The six measures are: closed-end fund discount, number and the first-day returns of IPOs, NYSE turnover, equity share in total new issues, and dividend premium.



1.4.5. Stock data

I obtained the list of S&P 500 constituents as of December 2019 from Refinitv Eikon DataStream. I also extracted the CUSIP, ISIN codes, Ticker, and the ICB sector and sub-sector code and name. Returns, price and market capitalization data were retrieved from CRSP. For these data I referred to CRSP as (Choi, et al., 2020) pointed out that DataStream is known to suffer from data errors in return data. I used the Tickers and CUSIP codes to match the list of constituents from DataStream to the CRSP Permno code. I do recognize that using the S&P 500 constituents as of December 2019 for the whole sample raises concerns about survivorship bias. However, for the purposes of my study this should not have a material impact on the results.

In Table 4 I report descriptive statistics of the Green, Brown and GMB' returns for both equal-weighted and value-weighted construction. In both configurations, the Green portfolio has outperformed the Brown one on a risk-adjusted basis, as showcased by a substantially higher Sharpe-ratio. The long-short portfolios have an average monthly return of 0.3% and 0.4% respectively. Despite the value-weighted GMB having a higher standard deviation (1.8% vs. 1.5%), the higher return means it still achieves a higher (monthly) Sharpe-ratio of 0.21.

Table 4: Summary Statistics of GMB Returns

This table presents the summary statistics for the Green, Brown and Green-Minus-Brown (GMB) portfolio's returns from January 2010 to December 2019. The brown portfolio corresponds to the companies whose industry code is identified by the IPCC as high-emitter, while the Green portfolio are all the remaining firms. GMB is the portfolio that goes long on the Green portfolio and short on the Brown one. The values reported are on a monthly basis.

	Equal-Weighted			Value-Weighted		
	Green	Brown	GMB	Green	Brown	GMB
Obs.	120	120	120	120	120	120
Mean	1.2%	0.9%	0.3%	1.0%	0.7%	0.4%
Std	3.9%	3.8%	1.5%	3.6%	3.8%	1.8%
Min	-10.8%	-9.9%	-3.5%	-9.5%	-9.9%	-3.6%
P25	-0.8%	-0.8%	-0.6%	-0.8%	-1.3%	-0.9%
P50	1.6%	1.2%	0.2%	1.5%	1.0%	0.4%
P75	3.7%	3.1%	1.0%	3.3%	2.9%	1.5%
Max	12.2%	11.9%	3.4%	9.5%	11.4%	5.0%
Skewness	-0.44	-0.39	0.06	-0.50	-0.45	0.18
Kurtosis	0.84	0.88	-0.15	0.47	0.75	-0.27
Sharpe ratio	0.31	0.24	0.19	0.29	0.17	0.21

Figure 4: GMB cumulative returns

This graph plots the cumulative returns of the equal-weighted and the value-weighted green-minus-brown portfolio from January 2010 to December 2019.

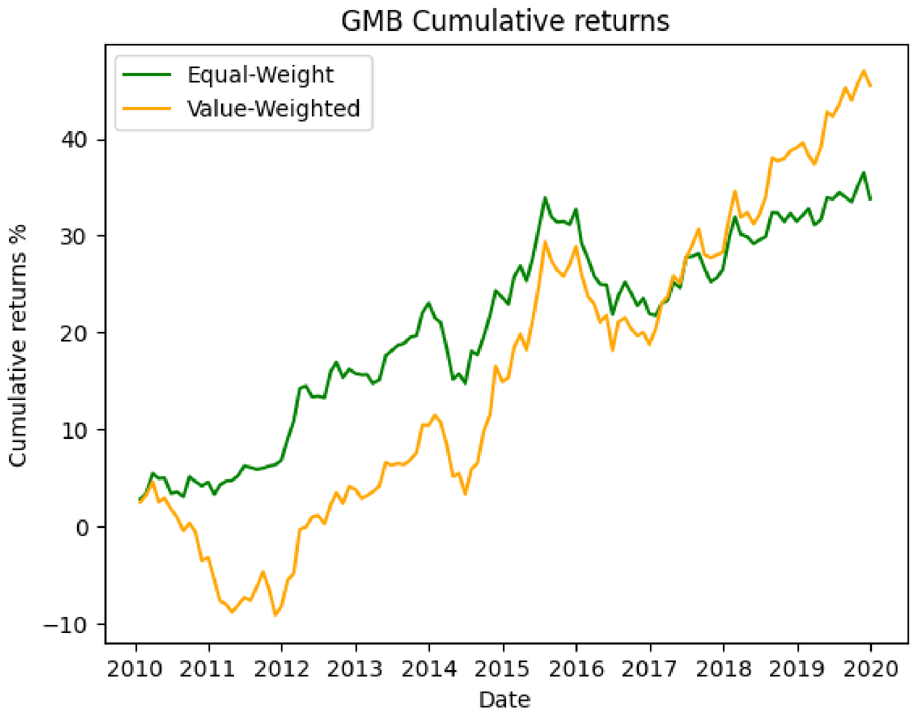


Figure 4 plots the cumulative returns of both the equal and value-weighted GMB returns. From 2010 to 2019, the value-weighted cumulatively returned nearly 50%, whereas the equal-weighted delivered around 35%, despite the former having more crashes. All these numbers showcase that stocks of greener firms have indeed outperformed stocks of more pollutant firms in recent years, especially from 2012 onwards.

1.4.6. Choice of time-frame

My research concentrates on the period from January 2010 to December 2019. This time frame was chosen for two reasons. Firstly, the period subsequent to 2020, which was characterized by the COVID-19 pandemic, was an exceptional time in the history of financial markets. 2020 and 2021, in the midst of the global pandemic and worldwide quarantines the S&P 500 reached all-time highs (Miao, 2023), and there was an overall market euphoria and retail investor frenzy[26] (Lex, 2021). Secondly, and most importantly, most of the research on green sentiment and its influence on stock returns is restricted to periods ending in 2020. Studies such as (Ardia, et al., 2020) and (Pástor, et al., 2022) examine periods up until 2018. By limiting my time sample to the aforementioned time period, I can reduce temporal variance from prior research and thus enhance the comparability of my results.

[26] At the beginning of 2021 capital markets were met with a new wave and mania of retail trading frenzy that pushed up the prices of heavily shorted firms, coined "meme-stocks", to extremely high valuations.

2. Findings

2.1. Correlations: Green sentiment and investor sentiment

First, I estimate the correlations between the different measures of green sentiment: $DSVI$, MCC index and UMC, and the BW investor sentiment index INV. In Table 5 I report the complete correlation matrix.

Table 5: Correlation matrix of sentiment measures

This table presents the correlations between the four sentiment capturing variables: DSVI – the residuals of the regression of the log change in the monthly GSVI on month-of-the-year dummy variables. UMC – the unexpected shock component of the MCC index, which is defined as the residuals of an AR1 model on MCC. MCC – The Media Climate Change news index is the average of the normalized number of articles published each month on climate change or global warming in five US newspapers. INV – (Baker & Wurgler, 2006) investor sentiment index. INV_{t-1} represents the previous month's BW investor sentiment index value. The sample period is from January 2010 to December 2019. *p < .1; **p < .05; ***p < .01.

	DSVI	UMC	MCC	INV	INV_{t-1}
DSVI	1.0***				
UMC	0.32***	1.0***			
MCC	0.19*	0.61***	1.0***		
INV	0.12	0.25**	0.14	1.0***	
INV_{t-1}	0.13	0.35***	0.20*	0.85***	1.0***

As expected, UMC and MCC are highly correlated (0.61) as the former is the prediction error of an AR1 model of the MCC. $DSVI$ and UMC are also significantly correlated, but not to the same extent, with a correlation of 0.32. The weakest correlation, that also has the least statistical significance, is the one between MCC and $DSVI$, having a correlation of 0.2. However, in this table, the variable of interest is investor sentiment. In this front, INV is significantly positively correlated with UMC, having a factor of 0.25. However, INV is not correlated with any of the other green sentiment measures, not even MCC. Interestingly, UMC and MCC have a stronger correlation with the previous month's investor sentiment value (INV_{t-1}), than with the contemporary one. Even for MCC, the correlation is significant (albeit only at 10% significance) although it was not before. Unsurprisingly, given that the construction of the index uses low frequency indicators for its construction[27], during my time sample, the investor sentiment has a very high autocorrelation of order one (0.85).

[27] The BW investor sentiment index is based on six measures (closed-end fund discount, number and the first-day returns of IPOs, NYSE turnover, equity share in total new issues, and dividend premium) that do not tend to have extreme movements from month to month.

In sum, the green sentiment measures are significantly positively correlated. The variables of interest are INV and INV_{t-1}, and both are positively correlated with two of the three green sentiment measures, UMC and MCC, in a very significant manner.

2.2. Sentiment regressions: Green sentiment on Investor sentiment

Next, I regress all the measures of green sentiment, on the BW investor sentiment index, both contemporary (1) and previous month's (2).

Table 6: Green sentiment regressions on investor sentiment

This table reports the results of the effect of investor sentiment - INV - on the measures of green sentiment measures: DSVI, UMC, and MCC. The sample covers January 2010 to December 2019. Panel A reports the results of the regressions of green sentiment on the contemporary BW investor sentiment index. Panel B reports the results of the regression of green sentiment on the previous month's BW investor sentiment index. The BW investor sentiment index is normalized for the time sample so the results can be interpreted as standard deviation moves. *p < .1; **p < .05; ***p < .01.

	DSVI	UMC	MCC
Panel A: Contemporary INV			
Const	0.0025	0.0165	1.4253***
	(0.0081)	(0.0121)	(0.0251)
INV	0.0112*	0.0351***	0.0419**
	(0.0060)	(0.0102)	(0.0198)
R^2	1.6%	6.5%	2.3%
Adjusted R^2	0.7%	5.7%	1.4%

	DSVI	UMC	MCC
Panel B: Lagged INV			
Const	0.0026	0.0171	1.4260***
	(0.0081)	(0.0117)	(0.0249)
INV_{t-1}	0.0121*	0.0495***	0.0560***
	(0.0064)	(0.0094)	(0.0199)
R^2	1.8%	12.6%	4.0%
Adjusted R^2	1.0%	11.9%	3.1%

Table 6 reports the results of these regressions, and as expected based on the correlations in Table 5, INV has a very significantly positive impact on UMC. This means that a one standard deviation increase in the BW investor sentiment index is associated with an increase of 0.035 points in the UMC, with its standard deviation being 0.190 points. A similar story can be found with MCC, albeit with not as strong significance or magnitude. A one standard deviation increase in INV is linked to a 0.042 increase in the MCC, and this compares to a standard deviation of 0.280 points.

Similar to what is observed in the correlations, the relationship between green sentiment, primarily UMC and MCC and the previous month's investor sentiment (INV_{t-1}) is stronger than the one with the contemporary investor sentiment. For both green sentiment variables, the significance and magnitude of the coefficient is even stronger. Additionally, the higher R^2 also signifies that it can explain more of the variation. The coefficient of INV_{t-1} for MCC is 0.056 points, instead of 0.042 for INV, while for UMC it is now 0.05

Based on the correlations and the results from these regressions, it seems that green sentiment, especially as measured through media attention (UMC and MCC), is positively influenced by investor sentiment. This influence is even stronger with the unexpected shock component of the MCC index. Considering as well the fact that this relationship is apparently even stronger with the previous' period investor sentiment makes it clear that green sentiment could be influenced more by market-wide investor sentiment than previously expected.

2.3.GMB regressions

The goal of this section is to analyze the impact that investor sentiment has on the supposed positive relationship between green sentiment and the returns of greener stocks. It is important to understand and breakdown the performance of the GMB portfolio, alongside its long and short leg, through the (Fama & French, 1992) three-factor model. Table 7 reports the results of the regressions of the equal-weighted and value-weighted Green (long leg), Brown (short leg) and the GMB (long-short) portfolios on the three-factor model.

In both configurations, the GMB does not achieve a significant alpha. In the value-weighted configuration, both the Green and Brown portfolios have significant and negative alphas, but the Green has the least negative one. Moreover, the green portfolio is more exposed to market-risk than the Brown one, potentially suggesting it achieves some of its higher returns through more risk. However, the most relevant aspect of these regressions is the exposure to the HML factor. In both the equal- and value-weight, the brown portfolio has a significantly positive exposure to this factor, while the Green, albeit only in the value-weight configuration, has a negative exposure. Combined, the GMB has a significant negative exposure to the value factor. This implies that Greener stocks, the ones it goes long on, have higher relative valuations, than less green stocks. These finding are in line with (Pástor, et al., 2021), which suggest that since investors like holding these assets they bid their prices up, leading to higher valuations and as a consequence lower expected returns in equilibrium.

Table 7: GMB regressions

This table reports the results of the regressions of the Green, Brown and GMB portfolios on the (Fama & French, 1992) three-factor model. The Brown portfolio consists of the S&P 500 stocks, as of December 2019, that belong to the industries identified by the IPCC as high-emitters. The Green portfolio are the other S&P 500 stocks that fall outside those industries. The sample cover January 2010 to December 2019. *p < .1; **p < .05; ***p < .01.

	Equal-Weighted GMB			Value-Weighted GMB		
	Green	Brown	GMB	Green	Brown	GMB
Const	0.0006	-0.0008	0.0010	-0.0010***	-0.0037***	0.0023
	(0.0007)	(0.0013)	(0.0014)	(0.0004)	(0.0014)	(0.0016)
MRP	1.0114***	0.9098***	0.1013***	0.9884***	0.9310***	0.0571
	(0.0170)	(0.0369)	(0.0364)	(0.0123)	(0.0367)	(0.0440)
SMB	0.1124***	0.0910	0.0241	-0.1493***	-0.0409	-0.1056
	(0.0353)	(0.0608)	(0.0711)	(0.0197)	(0.0726)	(0.0872)
HML	-0.0067	0.1468***	-0.1507***	-0.0720***	0.1630***	-0.2321***
	(0.0322)	(0.0534)	(0.0545)	(0.0145)	(0.0607)	(0.0679)
R^2	97.1%	88.2%	10.8%	98.6%	86.3%	10.4%
Adj. R^2	97.0%	87.9%	8.5%	98.6%	86.0%	8.1%

Next, I add the green sentiment variables to the GMB regressions. As mentioned in section 1.3.5 I also include the previous month's green sentiment because of delayed stock price reactions to climate news. Table 8 shows the results of the regressions of the GMB returns on the green sentiment variables and investor sentiment.

Regarding $DSVI$, the regressions showcase that the contemporary sentiment has a positive impact on the returns of the GMB, which is in line with the findings of (Choi, et al., 2020). However, the magnitude of the impact is limited, as a one standard deviation movement in $DSVI$ (0.09) only leads to around 0.3% higher returns. When I analyse its interaction with INV and INV_{t-1}, I find that its introduction is meaningful and does indeed reduce the impact of $DSVI$ on the returns of GMB. A one standard deviation increase in the previous month's sentiment value leads to 0.3% higher returns in the value-weighted GMB. On top of that, the introduction of the investor sentiment does also increase the adjusted R^2 of the regression, from 9.7% to 11.8% for the value-weighted GMB. Interestingly, and as previously seen with the correlations, section 2.1, and the sentiment regressions, section 2.2, the impact of the previous month's investor sentiment is more powerful than the contemporary one. INV_{t-1}, in the value-weighted setting, is significant at the 5% level, while INV is not significant at all. This means that investor sentiment indeed is behind some of the $DSVI$'s influence on the returns of greener firms.

Table 8: GMB regressions on green sentiment and BW investor sentiment

This table presents the results of the regressions of the GMB portfolio, both equal- and value-weighted, on the three-factor model of (Fama & French, 1992), the three measures of green sentiment and the (Baker & Wurgler, 2006) investor sentiment index. Panel A reports the results of the regressions for the Google Search Volume Index ($DSVI$). Panel B reports the results of the regressions for the unexpected shock component (UMC) of the Media Climate Change index. Panel C reports the results of the regressions of the Media Climate Change index (MCC). The sample covers January 2010 to December 2019. *p < .1; **p < .05; ***p < .01.

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: DSVI								
Const	0.0023*	0.0009	0.0009	0.0009	0.0033**	0.0022	0.0023	0.0023
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
MRP		0.1014***	0.1016***	0.1039***		0.0519	0.0524	0.0578
		(0.0367)	(0.0368)	(0.0366)		(0.0442)	(0.0443)	(0.0441)
SMB		0.0013	0.0039	0.0052		-0.1123	-0.1041	-0.1030
		(0.0690)	(0.0693)	(0.0688)		(0.0827)	(0.0820)	(0.0802)
HML		-0.1626***	-0.1602***	-0.1580***		-0.2311***	-0.2236***	-0.2202***
		(0.0548)	(0.0545)	(0.0543)		(0.0680)	(0.0673)	(0.0671)
DSVI	0.0357**	0.0343**	0.0337**	0.0325**	0.0316*	0.0370**	0.0350**	0.0327*
	(0.0149)	(0.0142)	(0.0142)	(0.0141)	(0.0181)	(0.0177)	(0.0176)	(0.0171)
$DSVI_{t-1}$	-0.0205	-0.0265	-0.0271	-0.0272	0.0113	-0.0053	-0.0070	-0.0067
	(0.0158)	(0.0168)	(0.0169)	(0.0168)	(0.0205)	(0.0203)	(0.0202)	(0.0199)
INV			0.0006				0.0019	
			(0.0014)				(0.0017)	
INV_{t-1}				0.0013				0.0031**
				(0.0011)				(0.0015)
R^2	3.9%	14.7%	14.8%	15.4%	3.5%	13.4%	14.5%	16.2%
Adj. R^2	2.3%	10.9%	10.3%	10.9%	1.8%	9.7%	10.0%	11.8%

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel B: UMC								
Const	0.0024*	0.0010	0.0010	0.0010	0.0031*	0.0020	0.0021	0.0021
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0016)	(0.0016)	(0.0016)	(0.0016)
MRP		0.0968***	0.0969***	0.0999***		0.0509	0.0512	0.0572
		(0.0354)	(0.0356)	(0.0355)		(0.0432)	(0.0434)	(0.0434)
SMB		0.0269	0.0285	0.0276		-0.0874	-0.0827	-0.0860
		(0.0699)	(0.0700)	(0.0694)		(0.0852)	(0.0839)	(0.0825)
HML		-0.1556***	-0.1520***	-0.1472***		-0.2476***	-0.2371***	-0.2301***
		(0.0546)	(0.0547)	(0.0545)		(0.0676)	(0.0681)	(0.0681)
UMC	0.0128	0.0132	0.0123	0.0096	0.0187	0.0221	0.0195	0.0148
	(0.0116)	(0.0110)	(0.0112)	(0.0114)	(0.0147)	(0.0140)	(0.0139)	(0.0143)
UMC_{t-1}	-0.0147	-0.0105	-0.0109	-0.0108	-0.0032	-0.0039	-0.0050	-0.0045
	(0.0142)	(0.0121)	(0.0120)	(0.0121)	(0.0163)	(0.0144)	(0.0144)	(0.0144)
INV			0.0006				0.0017	
			(0.0014)				(0.0017)	
INV_{t-1}				0.0014				0.0029*
				(0.0011)				(0.0015)
R^2	1.2%	11.7%	11.9%	12.4%	1.7%	12.7%	13.5%	14.8%
Adj. R^2	-0.5%	7.8%	7.2%	7.8%	(0.0%)	8.8%	8.9%	10.2%

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel C: MCC								
Const	0.0113*	0.0093	0.0107*	0.0106*	-0.0005	-0.0007	0.0018	0.0022
	(0.0068)	(0.0061)	(0.0060)	(0.0060)	(0.0083)	(0.0079)	(0.0079)	(0.0079)
MRP		0.1082***	0.1087***	0.1104***		0.0620	0.0628	0.0667
		(0.0346)	(0.0347)	(0.0348)		(0.0434)	(0.0434)	(0.0436)
SMB		0.0123	0.0188	0.0161		-0.1073	-0.0959	-0.0989
		(0.0697)	(0.0694)	(0.0692)		(0.0859)	(0.0836)	(0.0828)
HML		-0.1674***	-0.1612***	-0.1608***		-0.2479***	-0.2371***	-0.2335***
		(0.0541)	(0.0536)	(0.0536)		(0.0670)	(0.0669)	(0.0669)
MCC	0.0122*	0.0158**	0.0168**	0.0142**	0.0161*	0.0201**	0.0217***	0.0165**
	(0.0066)	(0.0064)	(0.0066)	(0.0064)	(0.0082)	(0.0079)	(0.0082)	(0.0079)
MCC $_{t-1}$	-0.0186***	-0.0219***	-0.0239***	-0.0212***	-0.0135**	-0.0182***	-0.0217***	-0.0167***
	(0.0049)	(0.0048)	(0.0051)	(0.0049)	(0.0065)	(0.0060)	(0.0068)	(0.0061)
INV			0.0016				0.0029*	
			(0.0012)				(0.0015)	
INV $_{t-1}$				0.0015				0.0032**
				(0.0011)				(0.0014)
R^2	4.8%	17.0%	18.1%	17.9%	1.8%	13.3%	15.7%	16.2%
Adj. R^2	3.2%	13.3%	13.8%	13.5%	0.1%	9.5%	11.2%	11.8%

In Panel B of Table 8, I present the results of the same regressions, however this time the green sentiment is proxied by the unexpected component of the MCC index, UMC. In none of the settings, UMC is significant, however, it is still possible to analyse the impact of investor sentiment. When it is added, the coefficient of UMC decreases significantly, and similar with $DSVI$, INV_{t-1} is significant and positive, for value-weighted GMB.

Panel C of Table 8 shows the results of the GMB regression on the MCC index. The contemporary variable is significant in all specifications and has a positive impact on the GMB's return. Out of all the three measures, MCC has the largest impact and significance in terms of GMB returns. The impact and significance are particularly strong for the value-weighted GMB, where a one standard deviation movement in the MCC (0.22) leads to 0.4% higher returns. However, what is most interesting, is that the previous month's sentiment has a very significant negative impact on the returns. This indicates that investors anticipate some climate events and that previous month's news were already reflected in the stocks prices. When I add the investor sentiment variables, I find a very similar story. Investor sentiment, and in particular the previous month's value, have a positive and significant impact on the outperformance of greener stocks.

For comparison, I also ran the same regressions using the MCCC index and its unexpected component of (Ardia, et al., 2020) and achieved very similar results. The results of this regressions are shown in Appendix 3. This means that in the presence of investor sentiment, the impact of the green sentiment measures on the outperformance of greener stocks reduces. The adjusted R^2 of the regressions also increases considerably upon the introduction of investor sentiment.

In sum, the fact that both $DSVI$ and MCC are significant and are identified as a having a positive impact on the GMB's returns contributes to the validity of my measures. Whenever there is heightened attention towards climate change topics, green stocks outperform brown ones. However, for my research I find that across all three measures there is a very clear and consistent story that disputes the current literature. The presence of investor sentiment, especially the previous month's one, as measured by the BW investor sentiment index, reduces the relevance of green sentiment in the outperformance of greener stocks. There is more to the current narrative then just increased appetite for greener investments, there is also the fact that market conditions being more favourable and investors wanting more risk promotes this shift. This is similar to the findings of (Bansal, et al., 2021), whereby investors seem to care more about green investments when the economy is doing better than when the economy is not doing as good.

2.4.Robustness checks

2.4.1. Time sample

The period I covered in my main analysis, the post global financial crisis period until the end of 2019, is the one most covered by literature. The existing literature on the topic of green sentiment has not analyzed its perseverance following the COVID-19 pandemic. With my robustness tests I try to explore: first, whether green sentiment is still robust after the COVID-19 shock; and second, if the same conclusions I achieved for the period ending at the end 2019 still hold when the COVID-19 shock is included. For this I expand the time sample until June 2022, the most recent date that the BW Investor sentiment index is available.

Table 9: Correlation matrix of sentiment measures 2022

This table presents the correlations between the four sentiment capturing variables: DSVI – the residuals of the regression of the log change in the monthly GSVI on month-of-the-year dummy variables. UMC – the unexpected shock component of the MCC index, which is defined as the residuals of an AR1 model on MCC. MCC – The Media Climate Change news index is the average of the normalized number of articles published each month on climate change or global warming in five US newspapers. INV – (Baker & Wurgler, 2006) investor sentiment index. INV_{t-1} represents the previous month's BW investor sentiment index value. The sample period is from January 2010 to June 2022. *p < .1; **p < .05; ***p < .01.

	DSVI	UMC	MCC	INV	INV_{t-1}
DSVI	1.0***				
UMC	0.18*	1.0***			
MCC	0.07	0.58***	1.0***		
INV	0.04	0.03	0.33***	1.0***	
INV_{t-1}	0.03	0.07	0.33***	0.96***	1.0***

In Table 9 I report the results of the correlations between the three measures of green sentiment, and contemporary and lagged investor sentiment. Here, I can already observe significant changes versus the main period. First of all, UMC now shares a much lower correlation with $DSVI$ (0.18 vs 0.32), which is also less significant. In top of this, it no longer has a significant correlation with INV and INV_{t-1}. On the other hand, MCC now has a significant and positive correlation with investor sentiment.

Table 10: Green sentiment regressions on investor sentiment 2022

This table reports the results of the effect of investor sentiment - INV - on the measures of green sentiment measures: DSVI, UMC and MCC. The time sample covers January 2010 to June 2022. Panel A represents the results of the regressions of green sentiment on the contemporary BW investor sentiment index. Panel B reports the results of the regression of green sentiment on the previous month BW investor sentiment index. The BW investor sentiment index is normalized for the time sample so the results can be interpreted as standard deviation moves. *p < .1; **p < .05; ***p < .01.

	DSVI	UMC	MCC
Panel A: Contemporary INV			
Const	0.0005	0.0105	1.4567***
	(0.0079)	(0.0110)	(0.0199)
INV	0.0040	0.0046	0.0863***
	(0.0084)	(0.0111)	(0.0160)
R^2	0.2%	0.1%	11.1%
Adjusted R^2	-0.5%	-0.6%	10.5%

	DSVI	UMC	MCC
Panel B: Lagged INV			
Const	0.0005	0.0107	1.4582***
	(0.0079)	(0.0110)	(0.0199)
INV_{t-1}	0.0033	0.0096	0.0880***
	(0.0089)	(0.0120)	(0.0181)
R^2	0.1%	0.5%	11.0%
Adjusted R^2	-0.6%	-0.2%	10.4%

Next, when considering the green sentiment on investor sentiment regressions, showcased in Table 10, I obtain a similar story to the previous test. The previous very significantly positive linear relationship between INV and UMC is now completely gone. Instead, I now achieve an even more significant relationship between investor sentiment and the MCC index. The coefficients for both INV and INV_{t-1} nearly doubled, and are now 0.087 and 0.088 points respectively, whereas in my main time sample they are 0.036 and 0.047.

These two tests combined point to a significant decoupling between the two shock based measures, and brought closer together the MCC index and investor sentiment, in the period of January 2020 to June 2022. Appendix 1 plots the MCC and INV indices together from January 2010 to June 2022. There, we can see that after 2020, the two indices shared a very similar behavior, very radical moves in similar directions. After the COVID-19 pandemic, the investor sentiment rose significantly, from around 1.0 to a peak of 3.7 in late 2021. At the same time, the MCC, after crashing at the onset of the COVID-19 pandemic recovered very sharply. At the beginning of 2022 both indices also crashed considerably.

Finally, when considering the GMB regressions, it is striking that both, INV and INV_{t-1}, lose their significance. For all three measures of green sentiment, investor sentiment is shown to have no impact on either the returns of the GMB or green sentiment. Additionally, green sentiment, with the exception of MCC, appears to have a reduced impact on the GMB returns. When the performance of the BW Investor sentiment (Appendix 1) and the performance of the GMB portfolio (Appendix 2) are visualized it becomes more understandable. During 2020 and 2021, after the COVID-19 shock, green stocks continued their run of outperformance. As US stock markets, such as the S&P 500, crashed significantly during the early stages of 2020, the GMB did not[28]. However, at the same time, and as previously mentioned, the investor sentiment rose dramatically to a peak of around 3.7 in 2021. During 2022, as the S&P 500 tumbled in face of record high inflation, and rising interest rates, so did the GMB, with the equal-weighted setting losing around 11% by June year-to-date. This latter point again demonstrates the results of (Bansal, et al., 2021), when markets deliver negative returns, green stocks also significantly underperform more traditional brown stocks. However, despite the investor sentiment also crashing, it remained very elevated relative to the whole sample.

In conclusion, the years 2020 to 2022, were special years in many aspects. It started with the COVID-19 pandemic causing huge economic turmoil worldwide, and leading to lockdowns all over the world. This fueled unprecedented government stimulus measures, which contributed to a massive rally in equity market worldwide (Armstrong, 2022). In 2021 as the S&P 500 reached its all-time high, markets experienced very high levels of volatility, which are best encapsulated by the retail trading frenzy events, such as the "GameStop short-squeeze" (Lex, 2021). In 2022, markets were hit by record high inflation, reversal of monetary policies, rising interest rates, and large geopolitical tensions that culminated in the war between Russia and Ukraine (Martin & Agnew, 2022). By including this period there is no longer any significant relationship found with either green sentiment, and the returns of the GMB because of the huge disconnect between the other measures and the BW investor sentiment index. However, it is interesting how the green sentiment remains robust and present during this period.

[28] This is assumed to be, as the COVID-19 pandemic was a completely external shock that was not foreseen. This meant that there was a massive generalized selloff in the markets.

3. Conclusion

Contemporary literature on sustainable investing, climate financing, and similar topics have identified the presence of a green sentiment. Green sentiment refers to the prevailing public and investor's attention to climate change topics. The literature has identified that increases in green sentiment are linked to the outperformance of greener stocks relative to stocks of more polluting firms. However, as (Stambaugh, et al., 2012) found out, market-wide investor sentiment plays a pervasive role in the existence of anomalies in financial markets. This is why in my paper I set out to research what effect market-wide investor sentiment, as measured by the index of (Baker & Wurgler, 2006), has on green sentiment and its ability to influence the outperformance of greener stocks.

My findings are in line with those of (Stambaugh, et al., 2012). Investor sentiment does have a positive and significant influence on green sentiment and the outperformance of greener stocks. I find that investor sentiment, both contemporary and especially the previous' month one, have a significantly positive correlation with two out of three of my green sentiment variables. When the green sentiment variables are regressed on investor sentiment, the latter is shown to be significantly positive for all measures. This means, that higher values of green sentiment are associated with higher values market-wide investor sentiment. Next, when I regress returns of the long short green minus brown portfolio on green sentiment I find that increases in investors' attention / awareness for climate change topics are linked to an outperformance of greener firms. However, when I control for market wide investor sentiment, not only does the relationship becomes weaker, but in some cases even loses its significance.

These results point to another partial explanation for green sentiment and how it affects the outperformance of greener stocks. This other partial explanation is market-wide investment sentiment, and as my results show, higher levels of green sentiment are associated with higher levels of investor sentiment, both contemporary and last month's. At the same time, it also reduces the influence that green sentiment has on the outperformance of greener stocks relative to brown stocks. This said, it should be noted, that these results do not dismiss the actual existence of green sentiment. Investor sentiment appears to work only as a partial explanation for this.

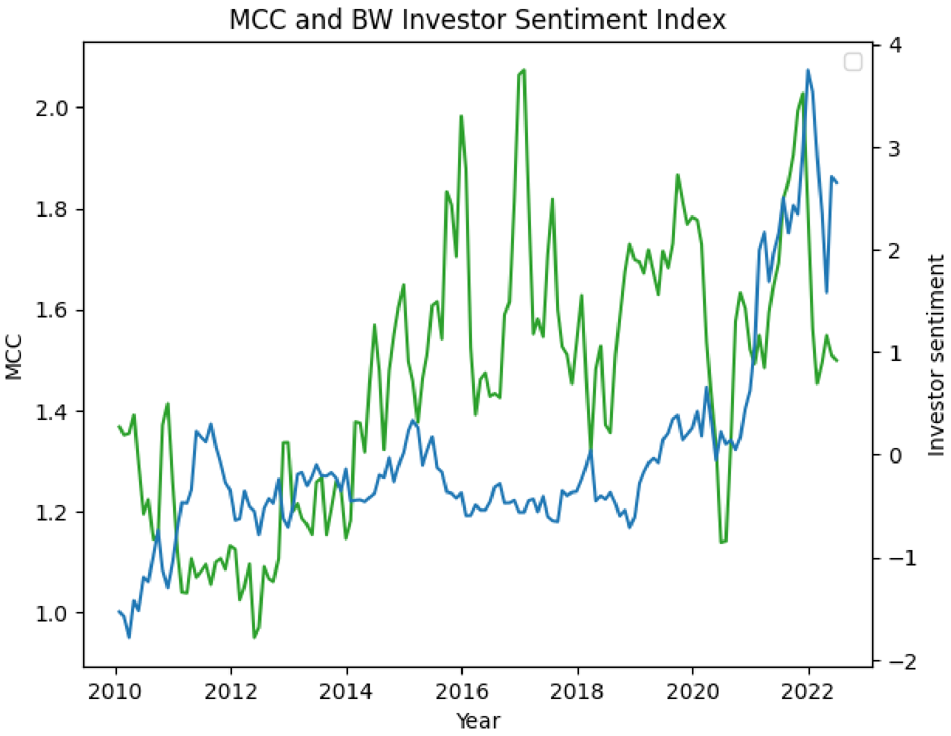
Finally, to come back to my initial question: does green sentiment really exist? Yes, but behind the increased attention and interest for climate change topics and green investments, there is also market-wide sentiment component. This component works in its favor and contributes to its existence, however, I do not attempt to add an explanation as for why exactly. Even though my method reveals this partial explanation, it still has some limitations. First, my approach towards measuring green sentiment is very simplistic, and as the regressions conducted with the $MCCC$ index of (Ardia, et al., 2020) show, it is possible to achieve more significant results. Their method involves analyzing the concerns expressed in every article of each newspaper by using daily data and an extensive textual analysis.

From my primary results onwards, it would be interesting for future research to utilize more comprehensive and complex methods for measuring green sentiment, such as the ETF approach of (Briere & Ramelli, 2021), and to understand and provide explanations for this phenomenon.

4. Appendix

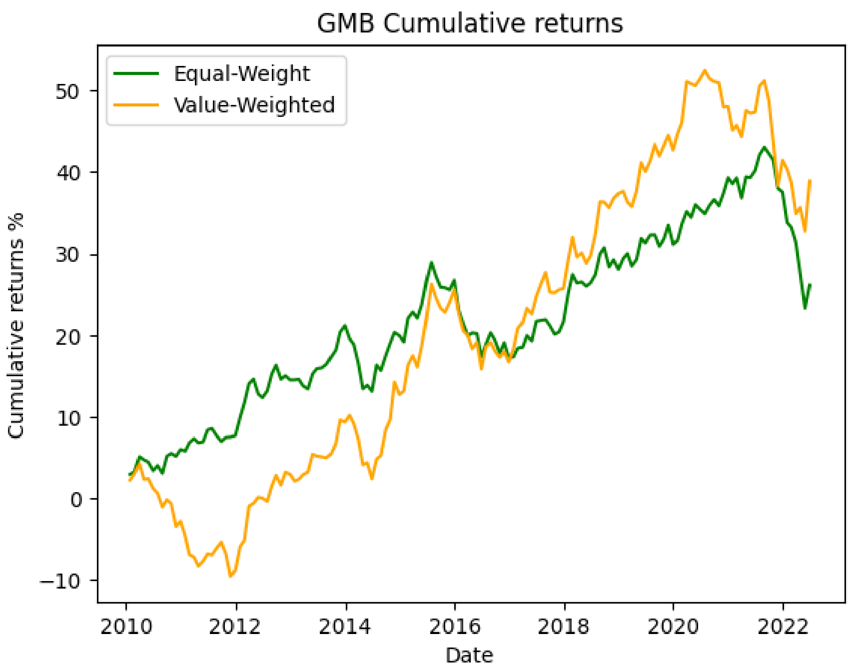
Appendix 1: MCC and BW Investor sentiment index 2010-2022

This figure plots the Media Climate Change (MCC), in green, and (Baker & Wurgler, 2006) Investor sentiment Index, in blue from January 2010 to June 2022.



Appendix 2: GMB Value and Equal weighted cumulative returns 2010-2022

This graph plots the cumulative returns of the equal-weighted and the value-weighted green-minus-brown portfolio from January 2010 to June 2022.



Appendix 3: GMB regressions on MCCC

This table presents the results of the regressions of the GMB portfolio on the three factor model of (Fama & French, 1992), the two green sentiment measures proposed by (Ardia, et al., 2020) and the (Baker & Wurgler, 2006) investor sentiment index. Panel A reports the results of the regressions for the Media Climate Change Concerns (MCCC) index of (Ardia, et al., 2020). Panel B reports the results of the regression on the unexpected shock component (UMC) of the MCCC index. The time sample is from January 2010 to June 2018. The investor sentiment index is normalized for the time sample so the results can be interpreted as standard deviation moves. *p < .1; **p < .05; ***p < .01.

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: MCCC								
Const	0.0043	0.0020	0.0045	0.0040	-0.0040	-0.0050	-0.0005	-0.0003
	(0.0054)	(0.0048)	(0.0050)	(0.0050)	(0.0064)	(0.0063)	(0.0065)	(0.0063)
MRP		0.1372***	0.1408***	0.1433***		0.1028**	0.1094**	0.1168**
		(0.0364)	(0.0372)	(0.0375)		(0.0454)	(0.0466)	(0.0481)
SMB		0.0099	0.0144	0.0131		-0.1104	-0.1022	-0.1030
		(0.0672)	(0.0660)	(0.0664)		(0.0850)	(0.0818)	(0.0813)
HML		-0.1439**	-0.1356**	-0.1352**		-0.2311***	-0.2160***	-0.2112***
		(0.0578)	(0.0565)	(0.0565)		(0.0750)	(0.0722)	(0.0715)
MCCC	0.0331**	0.0374**	0.0391**	0.0347**	0.0311*	0.0412**	0.0443**	0.0350**
	(0.0152)	(0.0150)	(0.0157)	(0.0149)	(0.0173)	(0.0165)	(0.0175)	(0.0160)
MCCC $_{t-1}$	-0.0368**	-0.0401***	-0.0429***	-0.0381***	-0.0198	-0.0305*	-0.0355**	-0.0258*
	(0.0149)	(0.0140)	(0.0150)	(0.0139)	(0.0187)	(0.0158)	(0.0175)	(0.0156)
INV			0.0043				0.0079**	
			(0.0027)				(0.0039)	
INV $_{t-1}$				0.0039*				0.0090**
				(0.0023)				(0.0036)
R^2	5.7%	20.3%	21.8%	21.5%	2.4%	14.1%	17.3%	18.3%
Adj. R^2	3.8%	16.2%	16.9%	16.6%	0.4%	9.6%	12.0%	13.2%

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel B: UMC								
Const	0.0152**	0.0150**	0.0153**	0.0144**	0.0024	0.0115	0.0119	0.0101
	(0.0069)	(0.0065)	(0.0068)	(0.0066)	(0.0018)	(0.0079)	(0.0084)	(0.0080)
MRP		0.1227***	0.1256***	0.1286***		0.0764	0.0817	0.0892*
		(0.0398)	(0.0410)	(0.0412)		(0.0492)	(0.0508)	(0.0518)
SMB		0.0083	0.0110	0.0092		-0.0906	-0.0858	-0.0888
		(0.0748)	(0.0739)	(0.0739)		(0.0895)	(0.0872)	(0.0861)
HML		-0.1883***	-0.1796***	-0.1782***		-0.2731***	-0.2573***	-0.2513***
		(0.0654)	(0.0650)	(0.0643)		(0.0801)	(0.0788)	(0.0774)
UMC	0.0408*	0.0481**	0.0443*	0.0416*	0.0394*	0.0630**	0.0562**	0.0490*
	(0.0228)	(0.0221)	(0.0230)	(0.0227)	(0.0223)	(0.0260)	(0.0268)	(0.0263)
UMC_{t-1}	-0.0227*	-0.0254**	-0.0255**	-0.0240**		-0.0182	-0.0184	-0.0150
	(0.0125)	(0.0115)	(0.0121)	(0.0117)		(0.0137)	(0.0146)	(0.0140)
INV			0.0013				0.0024	
			(0.0014)				(0.0018)	
INV_{t-1}				0.0016				0.0034**
				(0.0012)				(0.0017)
R^2	4.2%	17.0%	17.6%	17.9%	2.7%	15.2%	16.7%	18.0%
Adj. R^2	2.2%	12.6%	12.4%	12.7%	1.7%	10.8%	11.4%	12.8%

Appendix 4: Summary statistics for green sentiment and investor sentiment: 2010-2022

This table shows summary statistics for 4 sentiment capturing variables: 1) DSVI – the residuals of the regression of the log change in the monthly GSVI on month-of-the-year dummy variables, 2) UMC – the unexpected shock component of the MCC index, which is defined as the residuals of an AR1 model on MCC, 3) MCC – The Media Climate Change news index is the average of the normalized number of articles published each month on climate change or global warming in five US newspapers, 4) INV – (Baker & Wurgler, 2006) investors sentiment index. The time sample is January 2010 to June 2022

	DSVI	UMC	MCC	INV
Obs	150	150	150	150
Mean	0.00	0.01	1.46	0.05
SD	0.10	0.14	0.26	0.54
Min	-0.27	-0.31	0.95	-0.92
P25	-0.05	-0.08	1.25	-0.21
P50	0.00	0.01	1.48	-0.10
P75	0.05	0.09	1.63	0.13
Max	0.31	0.41	2.07	2.08
Skew	0.03	0.27	0.10	1.77
Kurt	1.12	0.28	-0.66	3.22

Appendix 5: GMB base regressions 2010 – 2022

This table reports the results of the regressions of the Green, Brown and GMB portfolios on the (Fama & French, 1992) three-factor model. The Brown portfolio consists of the S&P 500 stocks, as of December 2019, that belong to the industries identified by the IPCC as being high-emitters. The Green portfolio are the other S&P 500 stocks that fall outside those industries. The time sample cover January 2010 to June 2022. *p < .1; **p < .05; ***p < .01.

	Equal-Weighted GMB			Value-Weighted GMB		
	Green	Brown	GMB	Green	Brown	GMB
Const	0.0002	-0.0004	0.0003	-0.0013***	-0.0037***	0.0021
	(0.0009)	(0.0013)	(0.0011)	(0.0004)	(0.0013)	(0.0015)
MRP	1.0223***	0.9367***	0.0866***	0.9842***	0.9888***	-0.0037
	(0.0288)	(0.0386)	(0.0290)	(0.0126)	(0.0339)	(0.0399)
SMB	0.1049***	0.0219	0.0850*	-0.1544***	-0.0588	-0.0935
	(0.0390)	(0.0532)	(0.0507)	(0.0184)	(0.0607)	(0.0730)
HML	0.1327***	0.3243***	-0.1881***	-0.0296**	0.1762***	-0.2023***
	(0.0507)	(0.0597)	(0.0311)	(0.0143)	(0.0412)	(0.0420)
R^2	95.7%	89.9%	23.2%	98.6%	89.0%	13.0%
Adjusted R^2	95.6%	89.7%	21.6%	98.6%	88.7%	11.2%

Appendix 6: GMB regressions on green sentiment and BW investor sentiment 2010 – 2022

This table presents the results of the regressions of the GMB portfolio, both equally and value-weighted, on the three-factor model of (Fama & French, 1992), the three measures of green sentiment and the (Baker & Wurgler, 2006) investor sentiment index. Panel A reports the results of the regressions for the Google Search Volume Index ($DSVI$). Panel B reports the results of the regressions for the unexpected shock component (UMC) of the Media Climate Change index. Panel C reports the results of the regressions of the Media Climate Change index (MCC). The time sample cover January 2010 to June 2022. *p < .1; **p < .05; ***p < .01.

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: DSVI								
Const	0.0014	0.0003	0.0003	0.0003	0.0022	0.0021	0.0021	0.0021
	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
MRP		0.0860***	0.0839***	0.0843***		-0.0071	-0.0082	-0.0074
		(0.0294)	(0.0298)	(0.0296)		(0.0399)	(0.0403)	(0.0404)
SMB		0.0777	0.0731	0.0747		-0.0812	-0.0837	-0.0818
		(0.0513)	(0.0519)	(0.0519)		(0.0762)	(0.0758)	(0.0756)
HML		-0.1893***	-0.1823***	-0.1850***		-0.2017***	-0.1979***	-0.2008***
		(0.0312)	(0.0333)	(0.0332)		(0.0417)	(0.0489)	(0.0484)
DSVI	0.0198	0.0178	0.0180	0.0179	0.0290*	0.0326**	0.0327**	0.0326**
	(0.0145)	(0.0119)	(0.0120)	(0.0120)	(0.0159)	(0.0150)	(0.0151)	(0.0151)
$DSVI_{t-1}$	-0.0150	-0.0109	-0.0104	-0.0106	0.0179	0.0090	0.0093	0.0091
	(0.0146)	(0.0136)	(0.0134)	(0.0135)	(0.0184)	(0.0190)	(0.0191)	(0.0192)
INV			-0.0010				-0.0006	
			(0.0014)				(0.0025)	
INV_{t-1}				-0.0007				-0.0001
				(0.0013)				(0.0025)
R^2	1.5%	24.3%	24.7%	24.5%	3.9%	16.3%	16.4%	16.3%
Adj. R^2	0.1%	21.7%	21.6%	21.3%	2.6%	13.4%	12.9%	12.8%

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel B: UMC								
Const	0.0014	0.0003	0.0003	0.0003	0.0021	0.0020	0.0020	0.0020
	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0016)	(0.0015)	(0.0015)	(0.0015)
MRP		0.0809***	0.0790***	0.0790***		-0.0055	-0.0062	-0.0056
		(0.0285)	(0.0288)	(0.0286)		(0.0400)	(0.0405)	(0.0406)
SMB		0.0889*	0.0841*	0.0855*		-0.0882	-0.0900	-0.0884
		(0.0497)	(0.0505)	(0.0504)		(0.0723)	(0.0724)	(0.0720)
HML		-0.1889***	-0.1822***	-0.1842***		-0.2037***	-0.2012***	-0.2035***
		(0.0303)	(0.0323)	(0.0323)		(0.0421)	(0.0485)	(0.0479)
UMC	0.0159	0.0155	0.0154	0.0159*	0.0067	0.0082	0.0082	0.0082
	(0.0109)	(0.0096)	(0.0097)	(0.0096)	(0.0145)	(0.0135)	(0.0136)	(0.0134)
UMC_{t-1}	-0.0197	-0.0129	-0.0127	-0.0131	-0.0001	-0.0017	-0.0016	-0.0017
	(0.0121)	(0.0104)	(0.0105)	(0.0103)	(0.0155)	(0.0144)	(0.0144)	(0.0144)
INV			-0.0010				-0.0004	
			(0.0013)				(0.0025)	
INV_{t-1}				-0.0008				-0.0000
				(0.0013)				(0.0025)
R^2	2.0%	24.4%	24.8%	24.7%	0.2%	13.2%	13.2%	13.2%
Adj. R^2	0.6%	21.8%	21.7%	21.5%	(1.1%)	10.2%	9.6%	9.6%

	Equal-Weighted GMB				Value-Weighted GMB			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel C: MCC								
Const	0.0125**	0.0078	0.0077	0.0075	0.0064	0.0066	0.0069	0.0072
	(0.0063)	(0.0057)	(0.0059)	(0.0059)	(0.0091)	(0.0092)	(0.0085)	(0.0086)
MRP		0.0865***	0.0864***	0.0861***		-0.0038	-0.0035	-0.0030
		(0.0283)	(0.0284)	(0.0284)		(0.0399)	(0.0401)	(0.0402)
SMB		0.0772	0.0771	0.0767		-0.0979	-0.0973	-0.0967
		(0.0496)	(0.0499)	(0.0500)		(0.0720)	(0.0720)	(0.0717)
HML		-0.1909***	-0.1906***	-0.1899***		-0.2034***	-0.2045***	-0.2054***
		(0.0309)	(0.0328)	(0.0329)		(0.0430)	(0.0491)	(0.0483)
MCC	0.0129*	0.0166***	0.0166***	0.0167***	0.0053	0.0073	0.0073	0.0070
	(0.0066)	(0.0060)	(0.0060)	(0.0059)	(0.0093)	(0.0089)	(0.0089)	(0.0086)
MCC_{t-1}	-0.0207***	-0.0219***	-0.0218***	-0.0218***	-0.0083	-0.0104	-0.0106	-0.0106
	(0.0052)	(0.0043)	(0.0048)	(0.0044)	(0.0077)	(0.0069)	(0.0074)	(0.0069)
INV			-0.0001				0.0002	
			(0.0014)				(0.0025)	
INV_{t-1}				-0.0002				0.0004
				(0.0013)				(0.0025)
R^2	5.5%	28.5%	28.5%	28.5%	0.5%	13.7%	13.7%	13.8%
Adj. R^2	4.2%	26.0%	25.5%	25.5%	(0.8%)	10.7%	10.1%	10.1%

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Affidavit

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