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Essays on Investor Sentiment in Capital Markets: Predictability, Comovements, and Trading Behavior.

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Essays on Investor Sentiment in Capital Markets: Predictability, Comovements, and Trading Behavior.

Abstract

This dissertation investigates three main research questions. First, I[1] examine numerous variables in the market forecasting literature, such as investor sentiment proxies, business cycle variables, and valuation ratios, and test whether their limited predictive power is due to their limitation in capturing the full range of market dynamics or, in the case of sentiment metrics, their limitation in focusing primarily on upside sentiment. I find that a downside sentiment index outperforms other variables in in-sample and out-of-sample tests at the monthly frequency. Second, I examine stock-bond daily correlations in 14 countries and test whether investor sentiment captures the comovement dynamics, controlling for several other determinants in the literature. I also analyze the impact of cultural factors and their relevance in explaining cross-country differences. I find that when investors are pessimistic, this predicts a decline in daily correlations, followed by a reversal in 3 days. Fluctuations in sentiment are associated with decoupling episodes, and sentiment effects are more pronounced in periods of extreme negative correlations. Moreover, cultural factors play a limited but relevant role in explaining cross-country differences. Third, to explore how sentiment affects retail investor behavior and to address currently mixed evidence on which group of investors is behind the well-documented sentiment effects, I study the impact of changes in retail investor sentiment on retail ownership of stocks, focusing on the cross-section of stocks. As expected, retail investors are inclined to buy high-volatility stocks when sentiment increases. However, this correlation is influenced by past performance, as I first disentangle the momentum from the volatility effect. Doing so, I find that retail investors buy stocks that are past winners. This further emphasizes the complex relationship between investor sentiment and retail investor behavior.

[1] In this dissertation, I use the term "I" in the introduction and conclusion. It does not necessarily refer to me directly since the third essay is based on joint work with my co-author.

Betreuer: Prof. Dr. Christoph Kaserer Noorhan Elkhayat

Aufsätze zur Anlegerstimmung auf den Kapitalmärkten: Vorhersagbarkeit, Gleichlauf und Handelsverhalten.

Kurzfassung

In dieser Dissertation werden drei Hauptforschungsfragen untersucht. Erstens untersuche ich zahlreiche Variablen aus der Marktprognoseliteratur, wie z.B. Anlegerstimmung-Indikatoren, Konjunkturvariablen und Bewertungskennzahlen, und prüfe, ob ihre begrenzte Vorhersagekraft liegt an, dass sie nicht die gesamte Bandbreite der Marktdynamik erfassen können oder, im Falle der Anlegerstimmung-Indikatoren, dass sie sich fokussieren auf die Aufwärtsseite der Anlegerstimmung. Ich stelle fest, dass ein Index, der sich auf die Abwärtsseite der Stimmung konzentriert, übertrifft herkömmliche Prognosevariablen in In-Sample- und Out-of-Sample-Tests. Zweitens untersuche ich die Korrelationen zwischen Aktien- und Anleiherenditen in 14 Ländern und teste, ob die Anlegerstimmung die Dynamik der Korrelation erfasst, wobei ich mehrere andere Determinanten kontrolliere. Außerdem analysiere ich den Einfluss kultureller Faktoren auf die Stimmungshypothese und ihre Bedeutung für die Erklärung länderspezifischer Unterschiede. Die wichtigsten Ergebnisse sind: Wenn Anleger pessimistisch sind, sagt dies einen Rückgang der täglichen Korrelationen voraus, gefolgt von einer Umkehrung nach drei Tagen. Stimmungsschwankungen sind verbunden mit Decoupling-Episoden, und Stimmungseffekte sind in Zeiten extrem negativer Korrelationen stärker ausgeprägt. Darüber hinaus scheinen kulturelle Faktoren eine begrenzte, aber relevante Rolle zu spielen. Drittens: Um die derzeit uneinheitlichen Erkenntnisse darüber zu klären, welche Gruppe von Anlegern hinter die gut dokumentierten Stimmungseffekte, untersuche ich Nachfrageschocks bei Kleinanlegern im Vergleich zu institutionellen Anlegern und die Auswirkung des Ersten auf Veränderungen im Aktienbesitzes. Ich stelle fest, dass Kleinanleger Aktienkäufer sind, wenn ihre Stimmung steigt. Außerdem kaufen Kleinanleger Aktien, die in der Vergangenheit zu den Gewinnern gehörten. Dies unterstreicht die komplexe Beziehung zwischen Anlegerstimmung und Verhalten der Kleinanleger.

Overview

Contents

List of Tables

List of Figures

List of Abbreviations

AR	Autoregressive
ARMA	Autoregressive Moving Average
BW sentiment index	Baker and Wurgler (2006) sentiment index
CPI	Consumer Price Index
CRSP	Center for Research in Security Prices
DS.SENT	Monthly downside sentiment index (Chapter 1)
DCC	Dynamic Conditional Correlation
E-GARCH	Exponential General Autoregressive Conditional Heteroskedastic model
e.g.	For example
etc.	And so forth (Latin: et cetera)
FE	Fixed Effect(s)
FEARS	Financial and Economic Attitudes Revealed by Search (from Da, Engelberg and Gao (2015)
FRED	Federal Reserve Economic Data
GARCH	General Autoregressive Conditional Heteroskedastic model
GDP	Gross Domestic Product
i.e.	That is (Latin: id est)
IPO	Initial Public Offering
ISIN	International Securities Identification Number
JEL	Journal of Economic Literature classification system
LHS	Left-hand Side
net_sent	Net sentiment index (Chapter 3)
OECD	Organization for Economic Co-operation and Development

PLS	Partial Least Squares regression
RHS	Right-hand Side
sent	Daily downside sentiment index (Chapter 2)
SVI	Search Volume Index from Google Trends
TDS	Thomson Datastream
UK / U.K.	United Kingdom
US / U.S.	United States
VIF	Variance Inflation Factor
VIX	Volatility Index (from Chicago Board Options Exchange)
vs.	versus

Contribution to Essays

Essay 1: A more predictive sentiment index? Forecasting market returns using Google search behavior

Authors: Noorhan Elkhayat

Noorhan Elkhayat reviewed the literature, developed the research design, collected all the data, conducted all analyses, interpreted the results, and prepared and revised the manuscript.

Noorhan Elkhayat

Essay 2: Investor sentiment, flights to quality, and the stock-bond return comovements

Authors: Noorhan Elkhayat

Noorhan Elkhayat reviewed the literature, developed the research design, collected all the data, conducted all analyses, interpreted the results, and prepared and revised the manuscript.

Noorhan Elkhayat

Essay 3: Sentiment Trading, Stock Ownership and Investor Demand

Authors: Christoph Kaserer, Noorhan Elkhayat

Noorhan Elkhayat constructed the sample, conducted all analyses, and drafted the manuscript. Christoph Kaserer and Noorhan Elkhayat were jointly involved in formulating the research question, reviewing the literature, developing the research design, and revising the manuscript.

Christoph Kaserer Noorhan Elkhayat

To my beloved daughter.

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0 Introduction

In his 1936 book "The General Theory of Employment, Interest and Money", Keynes (1936) introduced the concept of "animal spirits" to describe movements in financial markets and macroeconomic activity that are not related to fundamentals. Decades later, Black (1986) coins the term "noise" as a causal factor for market inefficiencies. Since then, the impact of noise traders on financial markets has become a crucial part of economics, and its role is formalized by De Long et al. (1990a). De Long et al. (1990a) address the impact of noise traders in financial markets and suggest that they base their investment choices on sentiment. Investor sentiment would drive prices away from their fundamental value, leading to temporary episodes of sentiment-induced mispricing in the market. Excessive fluctuations in sentiment lead to excessive mispricing and volatility, which are especially detected in the short term. Nowadays, the effect of sentiment is no longer debated, and researchers devote substantial attention to properly quantifying its effect on asset prices and understanding its channels.

Various aspects of the impact of investor sentiment has been investigated in the literature. For example, Baker and Wurgler (2006) construct a monthly investor sentiment index in the U.S. and investigate its effect on the cross-sections of stocks. Baker, Wurgler and Yuan (2012) examine the effect of global and local sentiment on country-level returns of six major stock markets. Stambaugh and Yuan (2017) find that investor sentiment predicts mispricing factors. Da, Engelberg and Gao (2015) construct a daily sentiment index that explains short-term return fluctuations. Many other studies further attempt to dissect the complex relationship between investor sentiment, retail investors, institutions, and capital markets. In spite of the substantial attention given to gauging sentiment and its impact on asset prices and trading decisions, there is still a lack of consensus on several aspects of investor sentiment.

First, the long-run effect of investor sentiment is still debated (e.g., Da, Engelberg and Gao (2015); Kogan et al. (2006)). Second, it is not entirely clear what drives proneness to sentiment compared from one country to another. This points to the importance of considering various country-specific factors and implications derived from cross-country analyses. Third, the state of the art in behavioral finance research is overwhelmingly focused on the U.S. and is largely based on the well-known investor sentiment index constructed by Baker and Wurgler (2006). Although the sentiment patterns widely documented in the literature are attributed to retail investors, new controversial evidence (Devault, Sias and Starks (2019)) suggests that these sentiment findings are rather attributed to institutional investors because prominent sentiment measures do not capture retail investor behavior as previously thought.

In this dissertation, I address these concerns and attempt to further unravel the mechanism of sentiment in financial markets. The dissertation consists of three essays. In the first essay, I construct a monthly investor sentiment index that captures negative individual investor behavior, and I investigate its ability to predict stock market returns. In the second essay, I examine the dynamics of the stock-bond return relation and study the effect of investor sentiment and cultural factors as behavioral biases that drive this time variation. In the third essay, I investigate the relationship between investor sentiment and retail investor behavior.

0.1 Research questions

In the following subsections, I outline three research questions that I investigate in the three essays of my dissertation. For each research question, I summarize the motivation, data, sample, and methods implemented. Furthermore, I report a summary of the key findings.

0.1.1 A more predictive sentiment index? Forecasting market returns using Google search behavior

A growing literature uses sentiment extracted from online media sources (e.g., Tetlock (2007); Da, Engelberg and Gao (2015); Renault (2017)). Because of the accessibility of this data and its availability at high frequencies and for many countries, measures that rely on textual data are becoming increasingly popular. I follow the methodology of Da, Engelberg and Gao (2015) and construct an investor sentiment index based on negative Google search behavior. In this essay, I rely on a monthly measure, which deviates away from the typical daily frequency of these measures, in order to test its predictability power on aggregate U.S. stock market returns at the usual monthly frequency. Moreover, I focus on the downside of sentiment and argue that upside sentiment measures are more relevant in the longer term, while downside sentiment is relevant in the shorter term. I next run a "horse race" between this sentiment index and a set of traditional forecasting variables such as other popular sentiment proxies, valuation ratios, and business cycle variables.

In this essay, I focus on the United States stock market for the period of January 1, 2001 to September 30, 2018. I obtain stock return data from Thomson Datastream (TDS)[1], accounting data (e.g., book value of common equity, common dividends, fiscal year-end dates) from Worldscope. To construct the downside sentiment index, I obtain search data from Google Trends. To compute valuation ratios and business cycle variables (e.g., dividend yield, earnings yield, book-to-market ratio, default spread), I obtain data such as the long-term yield, AAA- and BAA-rated corporate bond yields from the Federal Reserve Economic Data (FRED). Moreover, I obtain the market volatility index (VIX) historical price from the Chicago Board Options Exchange to compute stock market volatility. Other variables include sentiment proxies from Baker and Wurgler (2006) and Huang et al. (2015).

I first run univariate and bivariate forecasting regressions for all the main variables in the study, including the main explanatory variable 'downside sentiment'. I next separate forecasting regressions into high and low sentiment periods. To control for other market forecasting variables, I run regressions with downside sentiment and other traditional

[1] At the time of this particular study, I did not have access to CRSP/COMPUSTAT data. However, afterward, I find a correlation of approximately 99% between TDS and CRSP returns.

forecasting variables as controls. I then combine both upside and downside sentiment measured in one index using the Partial Least Squares (PLS) method used in Huang et al. (2015), and test the predictive power of this combined sentiment index. Lastly, I run out-of-sample tests using different constraints on the out-of-sample forecasts, followed by several robustness tests.

I find that the downside sentiment index predicts market returns in forecast horizons of up to two months. The index outperforms other forecasting variables in both in-sample and out-of-sample tests, and it reports an out-of-sample R^2 of 4.9%. Another interesting finding is that the downside sentiment index is relevant in the short term, while other sentiment proxies, such as the Baker and Wurgler (2006) sentiment index, are relevant in the long term. Moreover, I find that the downside sentiment index performs better alone (rather than in a combined sentiment index), perhaps because the incorporated sentiment proxies are orthogonal to each other. The results suggest that a potential reason for the low predictive power of several sentiment proxies is that they focus on upside sentiment estimates. Upside sentiment measures may take longer to be incorporated into prices due to short-sale constraints. Finally, the findings imply that downside sentiment is an important dimension to understand the relationship between investor sentiment and stock returns.

0.1.2 Investor sentiment, flights to quality, and the stock-bond return comovements

Financial market integration comprises several aspects related to the complex inter-relation across various financial markets (Baele et al. (2004); Kim, Moshirian and Wu (2006)). Many international studies investigate integration *within* specific asset markets (e.g., Neal (1987); Bekaert et al. (2017)), whilst fewer studies investigate financial integration *across* these different markets. Historically, stock and bond returns display a positive correlation, particularly in the Uited States. By the early 2000s, the correlation levels sharply declined to as low as -60% (Baele, Bekaert and Inghelbrecht (2010)). Overall, the stock-bond return correlation displays an asymmetric and dynamic pattern, albeit a modest positive correlation over long time horizons. Baele, Bekaert and Inghelbrecht (2010)) identify various economic sources driving these comovements. They conclude that macroeconomic fundamentals contribute little to explaining these time variations. The authors draw attention to other proxies, such as liquidity, and suggest that non-traditional proxies may play a more important role. In this essay, I examine the role of investor sentiment as a driver of stock-bond return correlations in a large international sample. More specifically, I disentangle the effect of macroeconomic fundamentals from investor sentiment channels at the index level of these correlations. Moreover, I investigate the role of cultural characteristics as a behavioral bias, which may moderate the effect of sentiment or may explain cross-country differences.

In this essay, I examine 14 countries that constitute the largest economies ranked by GDP according to the World Bank, including the U.S. I collect daily bond and stock data from Datastream for this international sample and compute market-level returns. For the U.S. stock data, I use CRSP data. To ensure that the bonds represent a "safe haven" for investors, I obtain the 10-year Treasury notes for each country. The sample period is from 3 January 2000 to 15 November 2018. To measure daily sentiment for each country, I follow the FEARS methodology in Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019). To measure cultural characteristics, I use the Hofstede "Individualism" and "Uncertainty avoidance" cultural indices (see Hofstede (2001)). Finally, to construct the fundamental variables (CPI inflation, short-term interest rate, dividend yield, output growth, sovereign bond rating, and expected inflation), I use data from various sources such as the OECD Database, Worldscope, CRSP/COMPUSTAT, and Moody's Sovereign and Supranational Rating List.

To model the time-varying conditional correlations of stock and bond market returns, I use a bivariate DCC-EGARCH model. After obtaining the conditional correlation series, I then use them as the dependent variable in this essay. I then run several variations of panel regressions of daily stock-bond return correlations on the investor sentiment index in period t-1 and a set of controls. In other analyses, I incorporate cultural factors either as a predictor variable or as a moderating variable in interaction terms with sentiment. Finally, I run robustness tests in which I use liquidity as a control and attempt to disentangle the liquidity effect from the "flight-to-quality" story.

The main findings are summarized as follows. I find that investor sentiment contributes to explaining flights to quality. And beyond flight-to-quality episodes, investor sentiment is able to predict stock-bond return correlations in forecast horizons of up to 2 days. Furthermore, investor cultural characteristics play a limited but important role in moderating the sentiment effect. More specifically, the "uncertainty avoidance" cultural index is positively related to stock-bond correlations, suggesting that investors with more conservative risk perceptions may have more balanced portfolios and thus may suffer fewer losses when stock and bond markets decouple. The evidence points to the role of sentiment and cultural factors as important behavioral factors in examining financial market integration.

0.1.3 Sentiment Trading, Stock Ownership and Investor Demand

It is generally known that retail investors are less sophisticated compared to institutional investors. For instance, they may rely more on personal analysis because they have more limited access to information. This is why the prevalent view in the behavioral finance literature tends to suggest that retail investors are more prone to acting upon their sentiment. Based on Stambaugh, Yu and Yuan (2012), who look at investor sentiment as a main explanatory variable in several of their prominent papers, markets would become more efficient if retail investors' stock ownership shifted from self-managed to professionally managed. Baker and Wurgler (2006)'s influential investor sentiment index is attributed to retail investors. Devault, Sias and Starks (2019) argue otherwise. They find that the widely adopted investor sentiment indices (the Baker and Wurgler (2006) investor sentiment index, the Michigan Consumer Sentiment Index (MSCI), among others) capture institutional investors' demand shocks rather than individual investors. This has important implications that are worthy of investigating further: Their findings point to the possibility that institutions are sentiment traders rather than retail investors. This potentially disrupts our traditional understanding that retail investors are the drivers of the return patterns documented in the sentiment literature and, hence, should be further researched. In this essay, I examine this recent evidence more closely and investigate whether/how retail investor sentiment explains retail investor demand shocks. Moreover, I investigate how this relation is influenced by stock volatility and past stock performance.

This study focuses on the U.S. equity market for the period from January 2004 to December 2019. I rely on equity return data from CRSP of firms listed on NYSE, AMEX, or NASDAQ. I obtain the quarterly fraction of institutional (and retail) ownership (Fraction of shares owned relative to the total number of shares outstanding) from FACTSET. I end up with 7,847 unique firms in the CRSP-FACTSET merged dataset. Moreover, I use, once more, Google Trends to construct an individual investor sentiment index based on search data (following Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019)). This index captures the net sentiment effect on the market as in Gao, Ren and Zhang (2019), to be consistent with the study of Devault, Sias and Starks (2019) in which they investigate a quarterly total investor sentiment index. I end up with the following main variables in the quarterly dataset: retail stock ownership, total volatility, individual investor sentiment, an indicator for past performance, and an indicator for winner stocks (with superior past performance).

First, I sort stocks into deciles using stock volatility, forming 10 volatility portfolios. I compute the cross-sectional average retail investor demand shocks for all the stocks within each volatility decile and sort the 68 quarters into high (low) sentiment periods using the above (below) median value. This correlation test allows me to test in a preliminary manner the relationship between the quarterly sentiment metric and individual investor demand shocks. It also evaluates whether the net sentiment index is a good proxy of individual investor sentiment. Next, to test whether the net sentiment index is able to explain individual investor demand shocks, I run panel regressions of change in retail ownership on net sentiment and a set of controls, including fixed effects. In several variants of the panel regressions, I explore the drivers of the main findings and examine potential sentiment channels.

The main findings in this essay are: When sentiment goes up, retail demand increases. Therefore, retail investors are net buyers of stocks. In the first place, it seems that retail demand increases more for low volatility stocks when sentiment increases. I further investigate this result, as it seems rather counterintuitive, given that preliminary findings point otherwise. I find that when sentiment increases, retail investors are, in fact, buying stocks that were winners over the past weeks or months. Such stocks with high past performance tend to have below-average volatility. In other words, if I disentangle the pure volatility effect from past performance, retail investor demand goes up for high-volatility stocks when net sentiment increases (consistent with the sentiment literature). Therefore, the underlying mechanism is that the relation of sentiment to stock demand is moderated by past performance effects (which in turn affect volatility). I conclude that retail investors do not move opposite to the direction hypothesized in the literature, but the underlying mechanism of retail investor sentiment in the market is more complex than previously thought.

0.2 Contributions

The dissertation's three essays contribute to several standards of the literature. In this section, I summarize the contributions of each essay.

The *first* essay contributes to the literature on behavioral finance and empirical asset pricing. Welch and Goyal (2008) and Cochrane (2008a) argue that although many return-forecasting variables in the literature are able to predict returns in-sample, almost all variables perform worse in out-of-sample forecasts and are not able to beat a simple forecast based on the historical average of stock market returns. Among these variables are several prominent investor sentiment indices. News-based, search-based, and social media-based measures of investor sentiment are mostly tested in shorter time horizons (intra-day, daily, or weekly). Local sentiment does not predict market returns in the long run (e.g., Baker, Wurgler and Yuan (2012)). These findings reconcile with the literature on the poor power of long-horizon return forecasts. In the first essay, I construct a novel downside sentiment index based on the research of Da, Engelberg and Gao (2015) and find that increased pessimistic sentiment predicts higher returns in the next 2 months. I argue that prominent forecasting variables fail out-of-sample tests because they are mostly focused on upside estimates of sentiment. I propose a variable that has a stronger, broader, and more consistent effect on stock market returns compared to other traditional return-forecasting variables, including, for example, valuation ratios, business cycle variables, and market-based investor sentiment indices.

In the *second* essay, I contribute to the literature examining behavioral biases and the literature examining the economic and non-economic sources of the time-variation in bond and stock returns. The international finance literature does not commonly focus on behavioral factors and investigates explanatory variables, which mostly fall under the category of traditional stock price determinants, bond price determinants, or macroeconomic fundamentals (e.g., Baele, Bekaert and Inghelbrecht (2010)). I suggest that investor sentiment is a driver of stock-bond return correlations in a large international sample of 14 countries. Moreover, disentangling the effect of macroeconomic fundamentals and investor sentiment channels at the index level of these correlations remains to be unaddressed. I argue that sentiment has the following mechanism in these two fundamental asset markets: When sentiment is pessimistic, investors trade away from risky stocks into safe treasury bonds "flight to quality", and during this phenomenon, the stock and bond markets decouple. I also find that investor sentiment has a prominent effect on stock-bond return comovements in periods with positive correlation (non-decoupling-episodes). Another main contribution is the inclusion of cultural factors in the study of bond and return comovements. This essay supports the relatively scarce findings in the literature, which suggest that cultural factors are relevant for asset pricing and behavioral finance studies, among others (for e.g., Chui, Titman and Wei (2010)). Building on the sentiment hypothesis, I suggest that one of Hofstede (2001)'s cultural indices, "uncertainty avoidance", moderates the sentiment effect on stock-bond return correlations and may contribute to explaining cross-country differences.

In the *third* essay, I contribute to the literature that uses investor sentiment as a main explanatory variable (For e.g., to explain the value premium, momentum, analyst forecast errors, corporate investment decisions (Devault, Sias and Starks (2019)). Motivated by findings in the research of Devault, Sias and Starks (2019), I focus on a relatively newer sentiment metric, which is becoming more adopted in the literature, and suggest that it captures better retail investor sentiment and retail demand. I also examine the main economic mechanisms of retail investor sentiment in the market and find intriguing patterns. Moreover, I build on the literature documenting the cross-sectional return patterns in relation to sentiment, as well as retail investor trading (e.g., Kostopoulos, Meyer and Uhr (2020a)), which has been shown to be inconsistent by Devault, Sias and Starks (2019).

0.3 Outline

The subsequent sections of this dissertation are structured as follows. In Chapter 1, I forecast market returns using a downside sentiment index. In Chapter 2, I examine the dynamics of stock and bond return correlations in relation to investor sentiment and Hofstede's cultural factors. In Chapter 3, I dissect the relationship between retail sentiment trading and investor demand for different types of stocks. In Chapter 4, I summarize the key findings of this dissertation and outline the main implications, limitations, and suggestions for future research.

1 A more predictive sentiment index? Forecasting market returns using Google search behavior

Abstract

The predictability power of investor sentiment on the aggregate stock market is still an ongoing debate. I investigate whether the reason for the low predictability power of different sentiment proxies is driven by these measures' limitation in focusing on upside estimates of sentiment. I propose a monthly proxy for downside investor sentiment based on negative search behavior extracted from Google. I find that this proxy outperforms the predictability power of other investor sentiment proxies, valuation ratios, and business cycle variables in the short term. Unlike other proxies of investor sentiment that have very low out-of-sample R^2, the proxy for downside sentiment reports 4.9%. The results suggest that downside sentiment is an essential dimension to understanding the relation between investor sentiment and stock returns. It also emphasizes the importance of the newer sentiment measures, which seem to capture individual investor behavior more precisely.

Key words:	Investor Sentiment, Market Predictability, Household Concerns, Google Search Behavior
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1.1 Introduction[1]

The issue of trading away from fundamentals "noise trading" and its impact on return predictability has been a great interest in the scientific community since the role of investor sentiment has been first formalized approximately three decades ago (De Long et al., 1990b). Whether sentiment-driven noise trading has a substantial role in the market is no longer debated, but rather how to quantify the short-run, long-run, and contagious effect of investor sentiment among various asset classes (Baker and Wurgler, 2007; Baker, Wurgler and Yuan, 2012). The cross-sectional effects of investor sentiment seem to be well established in the literature. Baker and Wurgler (2006) show that there is an inverse correlation between the level of investor sentiment and the subsequent returns of small stocks, young stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks, and distressed stocks. Furthermore, Stambaugh, Yu and Yuan (2012) find that anomalies tend to have abnormal returns more pronounced following periods with a high level of investor sentiment. However, the impact of investor sentiment on subsequent returns of the aggregate market return is still an open debate.

Baker, Wurgler and Yuan (2012) analyze the predictability power of local and global sentiment on the aggregate stock market return of six developed countries. They regress the yearly average of monthly country-level value- and equal-weighted returns on the beginning of the year sentiment and document a contrarian effect of sentiment on returns. In line with Baker and Wurgler (2006), the return forecasting results are only significant for high-volatility stocks and stocks of small, distressed, and growth companies.[2] As they study a time span of 25 years (1980-2005), whether the predictability power of the investor sentiment index extends beyond the post-financial crisis period remains debatable. More importantly, the time-series regressions reveal that country-level results are mainly driven by global sentiment. In other words, the effect of local sentiment on return predictability is insignificant. Huang et al. (2015) contribute to the debate by proposing an adjustment

[1] I thank Christoph Kaserer, Rachel Koh (FMA discussant), Laurens Swinkels, Robert Heigermoser, anonymous reviewers, and participants at the FMA annual meeting 2020 and TUM School of Management, Finance Department, summer workshop 2019 for insightful discussions and helpful comments. I thank Theo Beffart and Arda Keskiner for their research assistance. I also thank the Deutscher Akademischer Austauschdienst (DAAD) for financial support, which included a research scholarship.

[2] The relatively weaker sentiment effect on the time series of value-weighted returns, in contrast to equal-weighted returns, shows that smaller or younger stocks - being harder to value and arbitrage due to spottier information and higher costs, are more prone to sentiment.

to the Baker and Wurgler (2006, 2007) investor sentiment, where only information correlated to return is used to estimate investor sentiment. The results show an increase in the predictability power with an R-squared out-of-sample of 1.7%, but the R-squared is positive only in periods with a high level of sentiment. Furthermore, Novy-Marx (2016) argues that strategies based on multiple signals might suffer severe overfitting biases since underlying signals are typically signed such that each predicts positive in-sample returns. Finally, these proxies focus on variables that represent mainly upside sentiment, such as the number of IPOs and first-day returns, but they overlook the downside part of investor sentiment.

Recently, there is a growing literature on sentiment based on social media and search behavior (e.g., Tetlock, 2007; Siganos, Vagenas-Nanos and Verwijmeren, 2014; Da, Engelberg and Gao, 2015; Renault, 2017; Gao, Ren and Zhang, 2019). These studies use textual analysis to directly extract opinions and attitudes about financial markets from publicly available high-frequency data (e.g., Twitter, Facebook, or Google). It is argued that data from online media sources are more reliable as it is transparent, readily available, and based on direct sentiment. Direct sentiment measures are becoming increasingly important as new evidence points to the fact that market-based indices such as Baker and Wurgler (2006)'s investor sentiment index do not truly capture individual investor demand (Devault, Sias and Starks (2019)). Due to how the media-based sentiment is estimated, a common criticism that the traditional measures of sentiment reflect the equilibrium outcome of many economic forces other than investor sentiment itself does not apply.

Although media-based sentiment proxies have many advantages over the traditional proxies of investor sentiment and can better capture the downside sentiment (e.g., Da, Engelberg and Gao, 2015), the debate of the predictability power of these proxies on aggregate market return in (usual) monthly periods remain unaddressed. Previous literature based on online sentiment is limited to short-horizon tests (intra-day, daily, or weekly data), and due to trading costs in high-frequency strategies, it becomes difficult to analyze whether trading strategies would be profitable after transaction costs. Furthermore, the literature mainly analyzes predictability power in-sample. Welch and Goyal (2008) argue that several return-forecasting variables perform worse in out-of-sample forecasts, and are not able to beat a simple forecast based on the historical average of the stock market return. Finally, most of the literature does not focus exclusively on downside measures; for instance, Gao, Ren and Zhang (2019) include in their measure both groups of search terms, which are positively or negatively associated with market returns. Thus, it raises the question of whether a downside sentiment metric based on directly extracted online data predicts aggregate stock market returns at the usual monthly frequency. If so, does the predictability power hold out-of-sample?

In this study, I aim to analyze the predictability power of downside and upside sentiment in the aggregate market returns. Motivated by Da, Engelberg and Gao (2015), I propose a measure of downside sentiment based on Google search behavior of negative words. The choice of Google search is based on evidence that the platform makes the majority of US desktop search traffic. Due to the enormous volume of search traffic from Google, I expect to capture the household concerns with high precision.

The paper's results show that downside sentiment (DS.SENT) estimated with negative google search behavior can better predict returns following periods of high investor sentiment. In addition, this proxy for downside sentiment predicts subsequent positive returns up to a two-month horizon. The results are consistent after controlling for the Baker-Wurgler sentiment index, and alternative proxies for investor sentiment.

Furthermore, the predictive power of DS.SENT remains significant in out-of-sample return predictions, with an out-of-sample R^2 of 4.9% (8.7%) based on a rolling window of 72 (60) months. By comparing the out-of-sample R-squared, I find that DS.SENT subsumes all business cycle variables, valuation ratios, and other proxies for investor sentiment. The implications of these results show that search-based sentiment seems to be a more precise measure of investor sentiment by detecting household concerns.

By comparing the upside and downside proxies of investor sentiment, we can see that downside sentiment outperforms the predictability power of upside sentiment in up to a two-month horizon. In longer periods, the traditional Baker-Wurgler sentiment index shows a more pronounced statistical significance. Finally, I show that combining upside and downside sentiment in the same index does not improve predictability, which indicates that the information of downside and upside sentiment are orthogonal and cannot be condensed in one measure.

This study contributes to the finance and economics literature in several ways. First, I show strong evidence that household concerns measured by negative search behavior impact subsequent stock returns. The findings contribute to the literature that analyzes whether investor sentiment has predictability power. Second, I show that DS.SENT measured monthly seems to have a substantial effect on returns after controlling for several important variables in the literature. Moreover, this effect is more persistent compared to daily and weakly indices. For instance, Da, Engelberg and Gao (2015) find significant predictability power of daily DS.SENT over the two subsequent days, and that the predictability power is insignificant afterward, while monthly DS.SENT shows predictability power even in two-month subsequent returns. This suggests that this sentiment index can be extended to longer frequencies and still remain relevant. Third, I show that DS.SENT has predictability power on returns also in periods with a low level of investor sentiment, which is a shortcoming of traditional measures of investor sentiment (e.g., Huang et al., 2015) and valuation ratios (e.g., Fama and French, 1989). Finally, I show that the predictability power of DS.SENT is more pronounced in a horizon up to two months, while the upside sentiment is stronger in longer time-horizons. This result is evidence that upside sentiment takes longer to be incorporated into prices, which can be a consequence of short-sale constraints or because investors seem to overlook that the stock prices are disconnected from the fundamentals.

The structure of the remaining parts of this paper is as follows. Section 1.2 presents the data used in this research. Section 1.3 presents the results from in-sample predictions. In section 1.4, I propose a combined index, which incorporates upside and downside sentiment. Section 1.5 shows the out-of-sample results. Section 1.6 concludes.

1.2 Data description

This study focuses on the United States equity market from January 1, 2001, to September 30, 2018. I obtain individual equity return data and market capitalization data of firms listed on NYSE, AMEX, or NASDAQ from Thomson Datastream (TDS), accounting data such as book value of common equity, deferred taxes, common dividends, and fiscal year-end date from Worldscope, the long-term treasury yield, AAA- and BAA-rated corporate bond yields from the Federal Reserve Economic Data (FRED), market volatility index

(VIX) historical price data from the Chicago Board Options Exchange, the one-month T-bill rate from Kenneth French's,[3] the Baker-Wurgler investor sentiment index data from Jeffrey Wurgler's website,[4] and the *aligned* investor sentiment index data from Guofo Zhou's website.[5]

I construct the DS.SENT index using search volume extracted from Google Trends and the social media index using online tweets from Twitter. To eliminate common TDS errors and to ensure compatible data quality to the Center for Research in Security Prices (CRSP), I exclude non-common equity securities and apply static and dynamic screens (See Appendix A) as suggested by Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017). I run several data quality checks and construct market-level value-weighted returns for a more extended period from December 31, 1979, to September 30, 2018, in order to match with data from CRSP.[6]

1.2.1 Dependent variables: market capitalization and return data

The empirical tests attempt to explain and measure the variation in value-weighted excess returns across forecast horizons K of 1 month, 2, 4, 6, and 12 months. Similar to Fama and French (1989) and Li, Ng and Swaminathan (2013), I measure continuously compounded excess returns per month, defined as the difference between the continuously compounded return on a value-weighted stock portfolio and the continuously compounded one-month T-bill rate. Li, Ng and Swaminathan (2013) report a correlation of 0.9989 between continuously compounded value-weighted returns and non-continuously compounded value-weighted returns, indicating that results are robust to using either. Excess returns for the 2, 4, 6, and 12 months holding periods are obtained by cumulating monthly excess returns, whereas the 1-month excess return is non-overlapping.[7]

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] http://people.stern.nyu.edu/jwurgler/
[5] http://apps.olin.wustl.edu/faculty/zhou/zpublications.html
[6] I report a correlation of 98.65% between CRSP aggregate returns and aggregate returns constructed from TDS data. Similarly, over the study sample period from January 31, 2000, to September 30, 2018, TDS returns correlate at 99.07% with CRSP returns. See Appendix A. 1.
[7] In unreported results, I conduct preliminary tests using yearly non-overlapping observations. In yearly regressions of excess returns on beginning-of-period sentiment, I report a loss of 70% of observations. This increases the margin of error and decreases the explanatory power, deeming the test meaningless.

1.2.2 Online search behavior measured by DS.SENT

In this section, I first explain why a search-based proxy "DS.SENT" is a good proxy for expected returns. I then describe the extraction of data from Google Trends and the construction of the DS.SENT index.[8]

1.2.2.1 DS.SENT as a measure of expected return

The main explanatory variable in this study is the DS.SENT index, defined as downside sentiment measured by negative search volume generated by households. I differentiate between upside and downside sentiment. Upside sentiment is a wave of optimism and investor overconfidence in the market, which bids up prices of stocks and drives them away from fundamentals. Due to short-sale constraints, overconfident investors are less prone to selling short as they usually are, which creates more limits to the effectiveness of the arbitrage process. As a result, it would take longer for upside sentiment measures to dissipate over time and, in fact, could be more relevant in the long term. On the contrary, downside sentiment is a wave of household concerns or pessimism towards the market, representing fears that economic conditions may deteriorate.

Negative shocks to noise traders' beliefs lead to increased pessimism and risk aversion, which puts downward pressure on prices and subsequently leads to higher future returns. Although the literature suggests that sentiment has a disproportionate effect on the cross-sections of stock returns (e.g., the sentiment effect is more pronounced on difficult-to-value and difficult-to-arbitrage stocks (e.g., Baker and Wurgler, 2006), more recent studies (e.g., Baker, Wurgler and Yuan, 2012; Da, Engelberg and Gao, 2015; Gao, Ren and Zhang, 2019) find that sentiment is a contrarian predictor of country-level returns. Waves of optimistic sentiment lead to subsequent lower future returns. Hence, the downside sentiment index predicts higher future returns.

I mostly refer to the methodology introduced by Da, Engelberg and Gao (2015), where

Harri and Brorsen (2009) and Britten-Jones, Neuberger and Nolte (2011) suggest that more efficient parameter estimates are produced in time-series regressions that deal with overlapping observations. I, therefore, do not report these empirical results and use monthly observations instead. As the values in the time-series regressions may exhibit autocorrelation and heteroskedasticity, the standard errors may be inaccurate. I account for this issue by using a Newey-West correction on the standard errors.

[8] I thank Theo Beffart from the Technical University of Munich for the research assistance in the extraction of Google search data and Arda Keskiner from the Technical University of Munich for the extraction of Twitter data.

they construct a novel FEARS (Financial and Economic Attitudes Revealed by Search) index based on aggregating millions of search queries via Google Trends[9] to reveal market-level sentiment in the United States. As of April 2019, Google remains the leading search engine worldwide and in the US, responsible for 62.7% of the US desktop search traffic. Approximately 3.8 million search queries are being generated via Google per Internet minute, making it an attractive platform to directly measure the Internet search behavior of millions of US households.[10] Several international studies using search data (e.g., Gao, Ren and Zhang (2019) for a large international sample, Kim et al. (2019) for the Norwegian market, Kostopoulos, Meyer and Uhr (2020a) for the German market) has also followed a similar approach to Da, Engelberg and Gao (2015). Figure 1.1 depicts the distribution of online search queries in the US, advocating Google as the primary source of online search volume.

Evidence from Da, Engelberg and Gao (2015) also shows a clear association between their FEARS index and historical returns in the period 2004-2011. They find that high FEARS is associated with low returns today and high returns over the following two days. However, the predictive power is insignificant following the second day, suggesting that daily search behavior has short-term effects on daily returns with a limited window of only a few days. More recent evidence from Kostopoulos, Meyer and Uhr (2020a) documents similar patterns, in which the effect of FEARS on daily market returns is temporary, as it reverses over the following days. Moreover, Gao, Ren and Zhang (2019) show that between 2004 and 2014, a weekly search-based sentiment is a contrarian predictor of country-level market returns, whereas its predictive power is stronger in periods of high sentiment. The findings of these studies are consistent with well-documented stylized facts in the investor sentiment literature, which is largely dominated by indirect market-based sentiment metrics (e.g., Baker and Wurgler, 2006; Baker, Wurgler and Yuan, 2012; Huang et al., 2015). The contrarian effect of sentiment on returns suggests that overly optimistic investor beliefs cannot be justified by market fundamentals, and the increased return expectations are followed by low stock market returns.

[9] The Search Volume Index (SVI) is available to the public on the website of Google Trends (https://trends.google.com/trends/?geo=US), a product of Google.

[10] Source: Statista Database, which provides access to statistical data by industry. Their sources of information include market research, government databases, trade publications, and scientific journals.

The selection of the DS.SENT index in this paper as the primary explanatory variable for excess returns is motivated by the evidence that this estimate can capture household concerns with high precision. In addition, the index exploits the massive Internet search traffic reported on Google Trends to extrapolate beliefs about market trends.

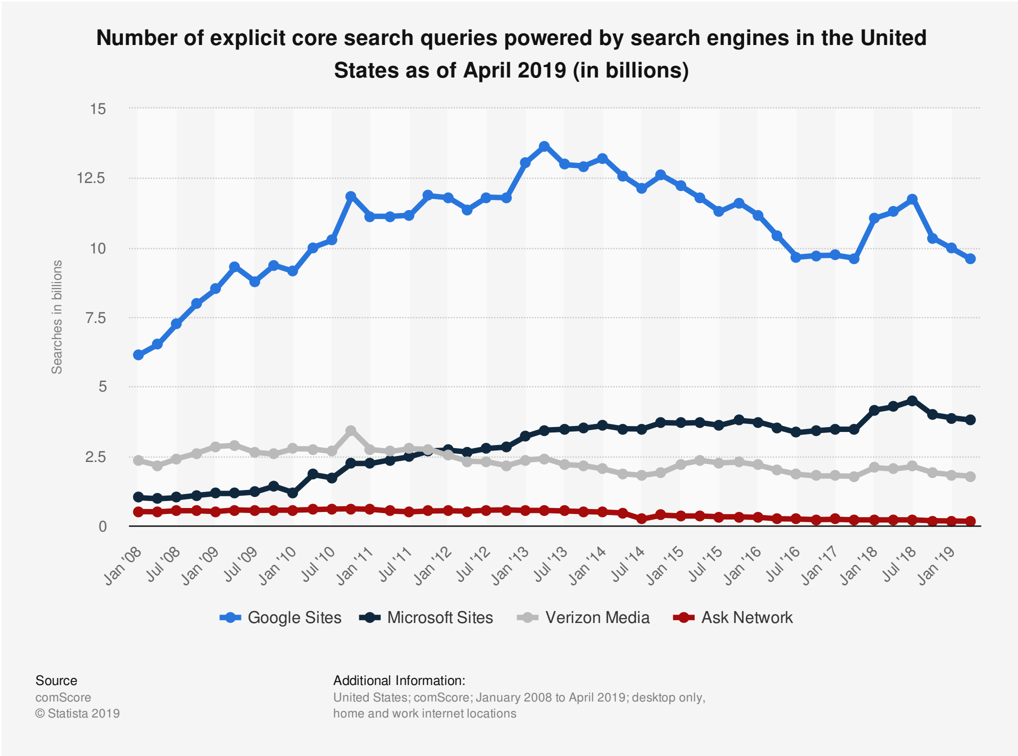

Figure 1.1
Aggregate search volume. This figure depicts the online search traffic on several search engines in the United States. Google processed 9.57 billion search queries as of April 2019, approximately three times as much as search volume processed by Microsoft sites in the second place. Source: Statista Database.

1.2.2.2 Construction of the aggregate DS.SENT index

This methodology aims to create a list of search terms that are good indicators of individual sentiment. First, I decide on the list of search terms. Then, I use as an initial list the positive and negative sentiment words from the "Loughran and McDonald Sentiment Word Lists",[11] which is a dictionary of sentiment words by category, developed specifically for textual analysis in financial applications. Loughran and McDonald (2011) develop this

[11] https://sraf.nd.edu/textual-analysis/resources/

sentiment word list because other word lists often include non-financial words misclassified in financial text. The dictionary contains positive, neutral, and negative word lists, of which 2,709 words are classified into positive and negative sentiment words such as "profitability," "outperform," "stability," "illiquidity," "crisis," and "recession." I do not use neutral sentiment words in the development of the index.

Second, to understand the use of sentiment word lists as search terms, I collect data from Google Trends using positive and negative words. I request the Search Volume Index (SVI) for each word, and the response data would be the monthly Google Trends score, or the Search Volume Index (SVI) of each search term, between January 2004-October 2018. Because the request includes a large time frame, the data is already in monthly intervals, and therefore, there is no need for further intermediate steps to obtain the raw SVI data.[12] Next, the raw data is converted from google trends into an easily readable format for data processing and analysis, and then the monthly SVI data is processed to address words with low search volume and make the SVI values comparable across different search terms.

Some search terms do not have sufficient search volume, and their SVIs are reported as missing by Google Trends. To eliminate search terms that do not have sufficient search data available for analysis, similar to Da, Engelberg and Gao (2015), I also filter out such terms. Words where the monthly SVI is reported as 0 for more than 20% of the monthly observations are discarded. I then take the first difference of the data since I am interested in relative changes in search volume and standardize the keywords by calculating the z-scores. To eliminate potential forward-looking bias, I use a 12-month backward-rolling standardization rather than full-sample standardization.[13] That is, I compute the z-scores based on the 12-month rolling mean and standard deviation.[14] I end up with a list of 2457 words prior to the following step.

The focus of the next step lies in identifying significant search terms capable of extrapolating pessimistic beliefs or concerns regarding stock market trends. Since not all words

[12] Due to Google's restriction to perform multiple downloads for the same word, the google trend score is based on the entire time-series of each word. Although the absolute value of the score could be different by using ex-ante data instead of ex-post data, the results should not be driven by the use of ex-post data because the $DS.SENT$ index is based on the first difference of the score and not on the absolute value. Calculating changes in scores from one period to the next therefore eliminates concerns related to Google Trends altering the scaling value of raw scores based on the requested period.

[13] I thank an anonymous reviewer for this suggestion.

[14] In order not to exclude many observations from the sample period, I apply this setting from January 2005.

are strongly associated with returns, in the next step, I analyze the relationship between market returns and each search term as suggested by Da, Engelberg and Gao (2015) (following the approach of Kogan et al. (2006) and eliminate any words that are not related to returns. I use the monthly value-weighted market return (weighted using market capitalization) to determine how each word is historically related to returns. Using an expanding window of 36 months and a minimum window of 6 months, I run backward-rolling regressions for each search term's monthly changes in SVI on contemporaneous market returns and extract the t-values from the regression to determine the most relevant keywords that are historically related to market returns. Given that the index is at monthly intervals, I choose a longer rolling window (relative to a six-month window used in Da, Engelberg and Gao (2015) for the regressions in which the top search terms are determined. I only keep search terms with a strong negative relation to market returns, as I am interested in words that are good proxies for household concerns. The resulting output of this regression is a dynamic list of the top 30 keywords per month with the largest negative t-statistic.[15] The z-scores of those 30 keywords are then averaged to create the DS.SENT index for August 2004 as shown in equation 1.1,

$$DS.SENT_t = \sum_{i=1}^{30} \triangle Z^i \left(SVI_t\right) \tag{1.1}$$

where $Z^i\left(SVI_t\right)$ is the z-score for the search term that had a negative t-statistic rank of i, where ranks start from the largest magnitude negative t-static at $i = 1$ to the smallest at $i = 30$. This process eliminates six months of the dataset, so the final sample of the aggregate DS.SENT index starts in August 2004.[16] Only negative search terms are kept as they are relevant to downside sentiment, and are the most useful for identifying public sentiment (e.g., Tetlock, 2007; Da, Engelberg and Gao, 2015).

Moreover, I exclude irrelevant search terms which may be correlated with non-financial trends. For instance, I eliminate the term "impossible" from searches that took place between June 2015 and December 2015 as it coincides with the release of the movie "Mission Impossible: Rogue Nation" in August 2015, during which the US stock market suffered a

[15] I choose the top 30 keywords to stay consistent with the cutoff number in Da, Engelberg and Gao (2015). The choice of cutoff number is not a concern, as the authors test the robustness of results using alternative cutoff numbers and find no meaningful differences.

[16] I also initially lose 1 month after computing first differences.

substantial and rapid drop. For example, the Dow Jones Industrial Average (DJIA) fell by approximately 1300 points in just three days. I exclude the search term "impossible" (in case they appear in searches) for six months to be conservative.[17]

Table 1.1 shows an example of 15 search terms that are most frequently searched in the full sample, sorted by the count of their appearance in the dynamic list of top 30 keywords most negatively correlated with market returns. Since these terms rank among the top 30 search terms by largest negative t-statistic, they appear to be most frequently searched in times of increased investor pessimism. For example, "incompetents" appear approximately 40% of the time in Google searches. Thus, an increase in the search volume of "incompetents" could indicate an increased concern for lack of adequacy, quality, or perhaps trust in times of uncertainty. This is why it could be strongly negatively related to aggregate returns. Moreover, among the search terms that are not as frequently searched but have the largest correlation with market returns include: "predatory" with a t-statistic of -6.80, "undermine" with a t-statistic of -6.37, and "insurrections" with a t-statistic of -6.03.

The resulting DS.SENT index is meaningful in determining individual sentiment related to financial markets, as it is based on those search terms that are both related to finance and have been historically correlated to returns. Higher DS.SENT means higher negative search volume, which I hypothesize predicts higher market returns in the following month. This would be in line with Da, Engelberg and Gao (2015), where they find that FEARS predicts higher CRSP value-weighted index returns over the following 2 days. In line with evidence in the sentiment literature, I expect the pricing effect to be temporary, as prices revert back to fundamentals and the effect of sentiment subsequently disappears. Figure 1.2 illustrates how DS.SENT moves over time, with peaks and troughs highlighting periods of financial distress and recovery.

1.2.3 Investor sentiment proxies

Most of the empirical tests in this study are carried out at the aggregate market level. We control for several investor sentiment proxies in the multivariate regressions: the Baker

[17] I thank an anonymous reviewer for bringing this to my attention, as well as suggesting a longer window to compute the contemporaneous correlations for determining the top words.

Table 1.1
Most frequently searched terms in the full sample

	Search Term	Count
1	incompetents	54
2	evicted	50
3	impedes	49
4	overcharges	48
5	downgraded	45
6	fatally	44
7	accident	42
8	disappointment	40
9	vulnerabilities	40
10	renegotiating	38
11	overturns	36
12	confrontation	35
13	hampers	35
14	colluding	34
15	downgrades	34

This table reports the 15 most frequently searched terms in the full sample. Search terms are based on the Loughran and McDonald Sentiment Word Lists as described in the index construction. The search terms are ranked according to the frequency of their appearance (*count*) in the monthly dynamic list of top 30 keywords with the most negative t-statistic.

and Wurgler (2006) sentiment index, the Huang et al. (2015) sentiment index, and the University of Michigan Consumer Sentiment Index. Investor sentiment data span from January 2001 to September 2018.

1.2.3.1 Baker-Wurgler Investor Sentiment Index

We use the sentiment index developed by Baker and Wurgler (2006) to control for (institutional) investor sentiment (SENT_{BW}, thereafter).[18] The index is initially based on the first principal component of six standardized proxies, but as of the 2016 update of their published data on investor sentiment, NYSE turnover has been dropped. Similarly, I include only the index based on five sentiment proxies: number of IPOs, first-day returns

[18] Devault, Sias and Starks (2019) provide evidence that commonly used sentiment metrics, among them the popular Baker-Wurgler Investor Sentiment Index, capture demand shocks of institutional investors rather than individual investors. Although the authors suggest that their findings do not necessarily establish causality, they unfold the more complex nature of the relations between sentiment measures, individual investors, and institutional investors. I do not attempt to formally investigate this as it is beyond the scope of this paper.

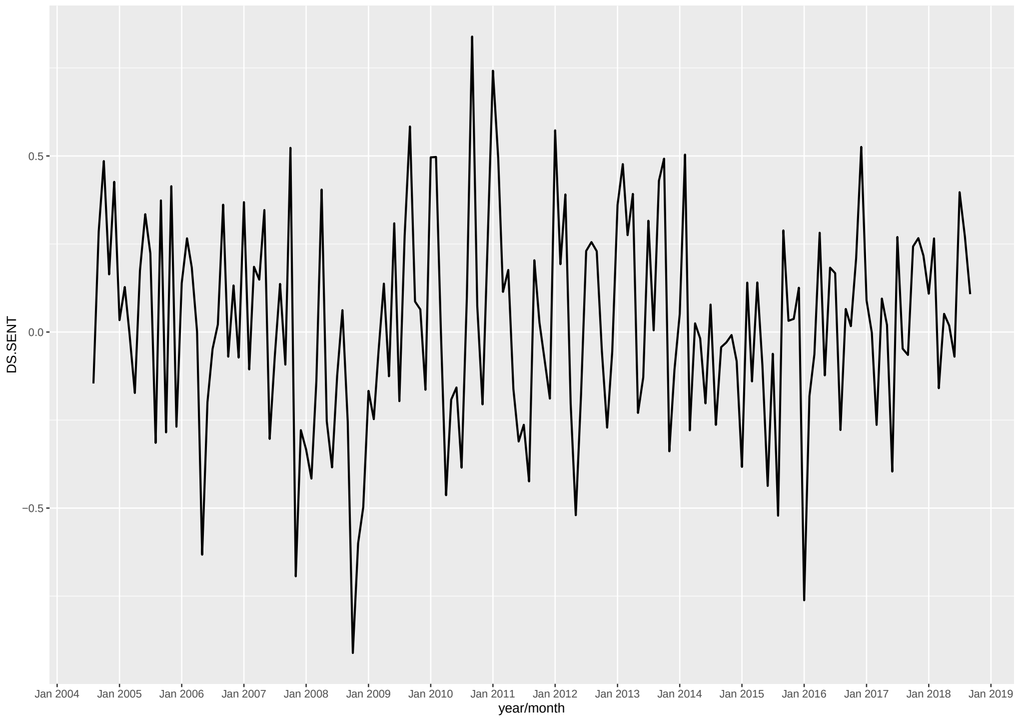

Figure 1.2
DS.SENT over time. This figure depicts the monthly change in DS.SENT over the period of August 2004-October 2018. Sudden peaks and drops in public sentiment reflect a response to events through search behavior. DS.SENT drops and then shoots up significantly in the second half of 2008 till early 2009, possibly in association with the policy response to the subprime crisis in this period and the subsequent market uncertainty gauged by search behavior.

on IPOs, the equity share in new issues, the value-weighted dividend premium, and the closed-end fund discount. The data on SENT_{BW} sentiment is taken from Jeffrey Wurgler's website.

1.2.3.2 Aligned Investor Sentiment Index

The *aligned* investor sentiment index is developed by Huang et al. (2015) and uses the partial least squares (PLS) method to incorporate all relevant forecasting information from the sentiment proxies. Unlike the principal component analysis (PCA) method used by Baker and Wurgler (2006), which extracts the first principal component of the sentiment proxies, Huang et al. (2015) exploit the SENT_{BW} proxies and use the PLS method to take out the information contained in the proxies that are relevant to expected stock market returns from the error or noise. The results of the study show that the aligned investor sentiment index (SENT$_{HJTZ}$, thereafter) can predict aggregate stock market returns with a relatively higher R^2 in the OLS predictive regressions (1.7% in-sample and 1.23% out-of-sample). Data from Huang et al. (2015) is obtained from Guofu Zhou's website (as of the authors' update in November 2015).

1.2.3.3 University of Michigan Consumer Sentiment Index

Empiricists often also use survey-based measures of sentiment, such as the widely known University of Michigan Consumer Sentiment Index ($SENT_{MCSI}$, thereafter). This index surveys households about their economic outlook. I include $SENT_{MCSI}$ as a control in predictive regressions. The index data is obtained from the research database of the Federal Reserve Bank in St. Louis (Federal Reserve Economic Data, FRED).

1.2.4 Valuation ratios and business cycle variables

I compare the performance of the aggregate DS.SENT index with several forecasting variables that are fundamentally related to stock prices and have been commonly used in the literature as return predictors (following Li, Ng and Swaminathan (2013)). The first group of forecasting variables includes the traditional valuation ratios: Dividend yield (DP), Earnings yield (EP), and Book-to-market ratio (BM). The second group includes some commonly used business cycle variables: Default spread, Term spread, Long-term treasury yield, and T-Bill rate. All the monthly forecasting variables are calculated as of the end of the month.

Following Fama and French (1992), I match the accounting data for all fiscal year ends in the calendar year t-1 with the returns for July of year t to June of t+1. Moreover, I use the market equity as of December in the calculation of the DP, EP, and BM ratios. All variables span from January 2001 to September 2018.

1.2.4.1 Dividend yield

The firm-level dividend yield (%) or the dividend-to-price (DP) ratio per month is calculated as the total dividends[19] from the previous fiscal year-end divided by market capitalization at the previous month-end. The market-level DP is the value-weighted average of the firm-level D/P ratios of the US firms in the sample.

1.2.4.2 Earnings yield

The firm-level earnings yield (%) or the earnings-to-price (EP) ratio per month is calculated as the total earnings[20] from the previous fiscal year-end divided by market capitalization at the previous month-end. The market-level EP is the value-weighted average of the firm-level EP ratios of the US firms in the sample.

1.2.4.3 Book-to-market ratio

The firm-level monthly book-to-market (BM) ratio is calculated as the book value (common equity + deferred taxes) from the most recent fiscal year-end divided by market capitalization at the previous month-end. The market-level BM is the value-weighted average of the firm-level BM ratios of the US firms in the sample.

1.2.4.4 Default spread

The difference between Moody's BAA and AAA-rated corporate bond yields is obtained from the research database of the Federal Reserve Bank in St. Louis (Federal Reserve Economic Data, FRED).

1.2.4.5 Term spread

The difference between Moody's AAA-rated corporate bond yields obtained from FRED and the one-month T-bill rate obtained from Kenneth French's website.

1.2.4.6 Long-term treasury yield

It is the 10-year government bond yield obtained from FRED.

[19] Total dividends are equal to the dividends per share multiplied by the number of shares outstanding.
[20] Total earnings are equal to the earnings per share multiplied by the number of shares outstanding.

1.2.5 Other controls

We additionally control for news sentiment (news tone, economic policy uncertainty), a Twitter-based sentiment measure, and changes in VIX in the in-sample return predictions.

1.2.5.1 News sentiment

To control for uncertainty related to economic policies, I use the economic policy uncertainty measure constructed by Baker, Bloom and Davis (2016) (EPU_{BBD}, thereafter). This measure is based on the volume of news articles related to economic policy uncertainty in ten leading US newspapers (USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the New York Times, and the Wall Street Journal). A news article is included if it includes at least one term from each of the following three groups: (a) "economic" or "economy"; (b) "uncertain" or "uncertainty"; (c) "congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". I obtain this data from the FRED database.[21]

Moreover, to examine the robustness of the results to alternative news-based measures, I include the news sentiment measure from Buckman et al. (2020) ($news.tone$, thereafter). Using computational text analysis, the authors capture news sentiment from economic and financial news articles in 16 large newspapers.

1.2.5.2 Twitter-based sentiment measure

Several studies document sentiment-driven noise trading, where sentiment is measured using tweets posted on the social media website Twitter. I construct a simple measure of social media sentiment (*tweets*, thereafter) based only on negative tweets. Tweets were scraped using the Twitterscraper package from Python. For the US, I use 480,915 tweets from January 2010 to September 2018.[22]

I extract negative tweets using words from the McDonald-Loughran sentiment word lists and calculate a monthly *tweets* sentiment score using the proportion of negative tweets

[21] The data is also maintained and available on the authors' website: http://www.policyuncertainty.com/us_monthly.html

[22] There are not enough tweets prior to 2010.

relative to all tweets. For the scoring process, the Valence Aware Dictionary for sEntiment Reasoning (Vader) is used, which is an open-source python tool developed by Hutto and Gilbert (2014) for analyzing and scoring the sentiment in text. Vader is a particularly useful sentiment textual analysis tool that is sensitive to both polarity (positive, negative) and intensity (strength) of emotion.

For each tweet, a sentiment score between +1 and -1 is assigned. These sentiment scores which fall between +1 and -1 are converted to positive, negative, and neutral using thresholds that was advised by the developers of the Vader library. That is, a tweet is 'positive' if the sentiment score > 0.5, 'negative' if the sentiment score is $<$-0.5, and 'neutral' otherwise. Monthly sentiment scores for the '*tweets*' index are then calculated using the fraction of negative tweets as shown in 1.2,

$$\text{score}_t = \frac{\text{number of negative tweets}_t}{\text{number of all tweets}_t} \cdot -1 \tag{1.2}$$

The monthly *tweets* index is then standardized by calculating z-scores, similar to the *DS.SENT* index. However, I construct a simple measure for the Twitter-based sentiment, which does not filter for tweets particularly related to the stock market.

1.2.5.3 Changes in VIX

The Chicago Board Options Exchange (CBOE) market volatility index (VIX) measures the implied volatility of options on the S&P 500. The VIX options were introduced in 2006 as another tool to manage and hedge volatility risk following the successful launch of VIX futures. The VIX index is commonly known as an "investor fear gauge" by practitioners as it measures the market's expectation of future volatility. Empiricists also use it as one of the traditional measures of market sentiment. I obtain VIX historical price data from the CBOE and measure its fluctuations over time. In most specifications, the VIX index is used as a control variable (e.g., Da, Engelberg and Gao, 2015; Gao, Ren and Zhang, 2019); additionally, since there is a positive correlation between VIX and downside sentiment, I similarly include VIX as a control variable in multivariate forecasting regressions.

1.2.6 Descriptive Statistics

Table 1.2 reports univariate summary statistics for all forecasting variables in the paper. The first-order autocorrelation of *DS.SENT* is 0.12, which declines to -0.11 after ten months and increases slightly to -0.07 after 20 months.[23] The *DS.SENT* index exhibits a stationary time series with the autocorrelation approaching zero fairly quickly, in contrast to other forecasting variables with first-order autocorrelations ranging from 0.47 to 0.86 and falling gradually to still as high as 0.60.

Table 1.2
Summary of forecasting variables

						Autocorrelation at lag			
Variable	Mean	Std. dev.	25% pctl	Median	75% pctl	5	10	15	20
DS.SENT	0.02	0.30	-0.17	0.02	0.23	0.12	-0.11	-0.10	-0.07
SENT_{BW}	0.08	0.66	-0.22	-0.01	0.23	0.66	0.28	0.00	-0.18
SENT_{HJTZ}	-0.12	0.73	-0.55	-0.33	0.03	0.47	0.22	0.17	0.08
SENT_{MCSI}	0.16	5.21	-2.64	-0.22	3.47	-0.01	-0.10	-0.10	0.00
BM	0.42	0.08	0.37	0.41	0.46	0.65	0.39	0.27	0.15
DP	1.68	0.37	1.45	1.62	1.81	0.75	0.50	0.27	0.06
EP	4.03	1.44	3.29	4.09	4.92	0.62	0.37	0.22	0.10
Term	4.85	0.95	3.94	4.99	5.42	0.85	0.72	0.62	0.53
Default	1.06	0.44	0.83	0.93	1.21	0.60	0.19	-0.01	-0.10
Tbill	0.11	0.14	0.00	0.07	0.16	0.86	0.70	0.53	0.35
LTyield	3.36	1.11	2.33	3.40	4.28	0.86	0.78	0.68	0.60
xs.vwret	0.28	3.01	-1.51	0.71	2.15	0.04	-0.06	0.04	-0.13

This table shows the mean, standard deviation, 25% percentile, median, 75% percentile, and autocorrelations of the forecasting variables used in the study. The sentiment index from Baker and Wurgler (2006) ($SENT_{BW}$), sentiment index from Huang et al. (2015) ($SENT_{HJTZ}$), University of Michigan Consumer Sentiment Index ($SENT_{MCSI}$), book-to-market ratio (*BM*), dividend-to-price ratio (*DP*), earnings-to-price ratio (*EP*), term spread (*Term*), default spread (*Default*), T-bill rate (*Tbill*), 10-year Treasury yield (*LTyield*), and value-weighted market excess returns (*xs.vwret*) are all monthly data from January 2001 to September 2018, DS.SENT index (*DS.SENT*) is monthly data from July 2004 to September 2018. The autocorrelations for all variables are at the specific lag.

[23] Refer also to Figure 1.2, which shows how downside sentiment moves over time.

1.3 In-sample return predictions

I begin with the multiperiod forecasting regression test in Fama and French (1988) and Fama and French (1989), where they predict market returns over increasing forecast horizons using overlapping and non-overlapping returns:[24]

$$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + bX_t + e_{t+K,t}, \tag{1.3}$$

where K is the forecast horizon, r_{t+k} is the continuously compounded value-weighted excess return per month (scaled by K). X_t is a $1 \times k$ row vector of explanatory variables, b is a $k \times 1$ vector of slope coefficients, and $e_{t+K,t}$ is the residual from the regression.

I conduct the multiperiod forecasting regressions for $K = 1$, 2, 4, 6, and 12 months. An issue with this regression test is that it includes overlapping return observations in tests where $K > 1$, which means that the residuals of the regression are likely autocorrelated and conditionally heteroskedastic; for example, in forecasting r_{t+12}, there are 11 months of overlapping observations. I use OLS standard errors with Newey-West correction with K-1 moving average lags to correct for serial correlation and heteroskedasticity (e.g., Newey and West, 1987).

1.3.1 Univariate forecasting regression results

I first report the univariate regression results, where I examine the forecasting power of *DS.SENT*, which is the main forecasting variable in the paper, and compare its performance with the traditional return forecasting variables in the literature (BM, DP, EP, $Term$, $Default$, $Tbill$, $LTyield$), and other main sentiment indices ($SENT_{BW}$ from Baker and Wurgler (2006), $SENT_{HJTZ}$ from Huang et al. (2015), and $SENT_{MCSI}$ from the University of Michigan Consumer Sentiment Index) across expanding forecast horizons. I then test whether the results are consistent with stylized facts about sentiment and whether they are consistent with predictions in Baker and Wurgler (2006, 2007); Da, Engelberg and Gao (2015). Da, Engelberg and Gao (2015) find that although their daily $FEARS$ index has a high predictive power on returns within a time span of three days, their predictions

[24] Some of the forecasting exercises in this paper are also inspired by Li, Ng and Swaminathan (2013).

are in line with the traditional interpretation of sentiment-induced temporary mispricing, in which they find an almost complete return reversal after two days. An increase in $FEARS$ corresponds with a decrease in contemporaneous stock market returns at day = 0 and predicts an increase in returns in the following two days. Consistent with findings in Baker and Wurgler (2006, 2007), Da, Engelberg and Gao (2015) find the most significant return reversal patterns among higher volatility and higher beta stocks. I, therefore, set X = $DS.SENT$, $SENT_{BW}$, $SENT_{HJTZ}$, $SENT_{MCSI}$, BM, DP, EP, $Term$, $Default$, $Tbill$, $LTyield$ in equation 1.3.

Table 1.3 shows that an increase in negative search volume measured by $DS.SENT$ predicts an increase in stock market returns up to 2 months ahead. When investors are pessimistic, they demand a higher return / risk premium to invest in riskier assets. At K = 0, the positive and significant coefficient on $DS.SENT$ suggests that it is strongly related to contemporaneous market returns. It is rather expected that the strongest correlation with returns and highest explanatory power takes place contemporaneously, in comparison with increasing forecast horizons, as this suggests that searches are quickly reflected in the index performance. In the following two months, the downside sentiment effect is still positive and highly significant, suggesting that the index has a strong return forecasting power. Nevertheless, the coefficient on $DS.SENT$ decays over time, and the explanatory power decreases as indicated by the reduction in R^2 in subsequent months. For example, a one standard deviation increase in $DS.SENT$ is associated with a 1.50% increase in contemporaneous returns at $K = 0$ (significant at the 1% level). At $K = 1$, a one standard deviation increase in $DS.SENT$ leads to a 0.75% increase in future excess returns (significant at the 1% level), followed by a 0.43% increase in excess returns in the second month[25].

The positive coefficient on $DS.SENT$ in forecast horizons ¿ 0 is consistent with findings in Da, Engelberg and Gao (2015), in which sentiment measured by $FEARS$ predicts high returns over the following two days. Surprisingly, unlike Da, Engelberg and Gao (2015), I do not find a negative contemporaneous relation at day = 0. This may be because this is

[25] A one standard deviation change in $DS.SENT$ is equal to 0.30 (refer to table 1.2). While in the construction of $DS.SENT$, each search term has been standardized using z-scores to have a mean = 0 and standard deviation = 1, the average across all search terms will not have a standard deviation = 1, given that there is a correlation among the search terms. A one standard deviation change in $DS.SENT$ leads to a 0.30*b_1 change in the dependent variable.

Table 1.3
Univariate forecasting regressions for the DS.SENT, other sentiment indices, business cycle variables, and valuation ratios.

	K					
	0	1	2	4	6	12
(a) *DS.SENT*	4.989***	2.503***	1.447***	0.688	0.249	0.219
	(0.745)	(0.670)	(0.542)	(0.502)	(0.319)	(0.358)
Observations	170	170	169	167	165	159
Adjusted R^2	0.286	0.065	0.036	0.012	-0.003	-0.002
(b) $SENT_{BW}$		-0.722	-0.828	-0.917*	-1.046**	-1.256***
		(0.679)	(0.641)	(0.493)	(0.415)	(0.379)
Observations		170	169	167	165	159
Adjusted R^2		0.002	0.012	0.037	0.068	0.208
(c) $SENT_{HJTZ}$		-1.135*	-0.812	-0.392	-0.013	0.200
		(0.670)	(0.584)	(0.556)	(0.428)	(0.211)
Observations		125	125	125	125	125
Adjusted R^2		0.038	0.032	0.009	-0.008	0.003
(d) $SENT_{MCSI}$		0.013	0.015	0.014	0.009	-0.0003
		(0.023)	(0.022)	(0.025)	(0.025)	(0.015)
Observations		170	169	167	165	159
Adjusted R^2		-0.003	0.001	0.005	0.001	-0.006
(e) *BM*		4.053	3.960	4.768**	5.035***	4.724***
		(3.256)	(2.974)	(1.907)	(1.324)	(1.271)
Observations		170	169	167	165	159
Adjusted R^2		0.008	0.018	0.060	0.090	0.156
(f) *DP*		0.594	0.540	0.807	0.893**	0.893***
		(0.742)	(0.709)	(0.492)	(0.351)	(0.246)
Observations		170	169	167	165	159
Adjusted R^2		0.0001	0.003	0.031	0.055	0.116
(g) *EP*		0.022	0.037	0.040	0.031	-0.021
		(0.229)	(0.209)	(0.190)	(0.194)	(0.173)
Observations		170	169	167	165	159
Adjusted R^2		-0.006	-0.006	-0.005	-0.005	-0.006
(h) *Term*		-0.517*	-0.550*	-0.609*	-0.565*	-0.429
		(0.305)	(0.299)	(0.327)	(0.312)	(0.284)
Observations		170	169	167	165	159
Adjusted R^2		0.012	0.030	0.077	0.088	0.096
(i) *Default*		-0.443	-0.300	0.037	0.222	0.349*
		(0.682)	(0.681)	(0.602)	(0.457)	(0.208)
Observations		170	169	167	165	159
Adjusted R^2		-0.00000	-0.001	-0.006	0.001	0.026
(j) *Tbill*		-1.812	-1.942*	-2.198**	-2.461**	-2.955**
		(1.225)	(1.151)	(1.096)	(1.210)	(1.460)
Observations		170	169	167	165	159
Adjusted R^2		0.002	0.011	0.034	0.061	0.189
(k) *LTyield*		-0.337*	-0.354**	-0.408**	-0.417**	-0.377**
		(0.172)	(0.156)	(0.164)	(0.169)	(0.177)
Observations		170	169	167	165	159
Adjusted R^2		0.009	0.024	0.069	0.099	0.164

This table summarizes the univariate regression results for the different forecasting variables in equation 1.3 for the period 2004-2018. The dependent variable in these regressions is the continuously compounded value-weighted excess returns per month at different forecast horizons K, scaled by $1/K$; b is the slope coefficient; regressions in which $K > 1$ use overlapping observations. The first column in which $K = 0$ reports the contemporaneous relation between $DS.SENT$ and monthly returns. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression.***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

a monthly index, rather than daily, and I therefore do not capture a rapid return reversal as observed in Da, Engelberg and Gao (2015).[26] In contrast to $DS.SENT$, an increase in $SENT_{BW}$, $SENT_{HJTZ}$ and $SENT_{MCSI}$ respectively predicts a decrease in subsequent stock market returns, which is consistent with findings from Baker and Wurgler (2006, 2007) and Huang et al. (2015). Moreover, the sign on $DS.SENT$ is opposite to the sign on the prominent $SENT_{BW}$ index, suggesting that the former is picking up downside sentiment and the latter predominantly upside sentiment. Another potential reason is that the market-based indices such as $SENT_{BW}$ capture institutional investor demand, as found in Devault, Sias and Starks (2019), while direct public sentiment measures such as the searches-based sentiment index capture individual investor demand more precisely. This highlights the importance of future research dissecting this complex relation between institutions, retail investors, and sentiment. This also highlights the importance of the newer sentiment indices, which could be a potential answer to the questions raised in Devault, Sias and Starks (2019).

Another interesting finding is that, while $DS.SENT$ shows the strongest R^2 predicting one-month returns, the R^2 monotonically decreases as the forecast horizon gets longer. We have the opposite pattern to $SENT_{BW}$, where the highest R-squared is achieved predicting 12-month cumulative returns. The downside sentiment index reports an R^2 of 28.6% explaining returns in the same month, and 6.5% (3.6%) predicting one-month (two-month) ahead stock market returns. On the other hand, the Baker-Wurgler sentiment index shows an intriguing opposite pattern, in which it explains future returns at longer forecast horizons when downside sentiment is no longer relevant. These results are evidence that the effect of $DS.SENT$ is stronger in the short-term (which is what would be expected when discussing retail investor effects on the market), but it is dissipated with time, while $SENT_{BW}$ seems to take a longer horizon to be incorporated into market prices.[27] In other words, the results show evidence that household concerns are quickly incorporated into prices, while upside investor sentiment takes a longer horizon, perhaps because of short-sale

[26] In future research, it would be worthwhile to look at a lagged version of this index or incorporate longer forecast horizons to see whether I deduct such a reversal. Another potential avenue would be to run sensitivity tests.

[27] In unreported results, I find similar patterns and results for the predictors when choosing a longer sample period that starts from January 2001 (except $DS.SENT$, which due to data availability starts from August 2004).

constraints or because investors seem to overlook that the stock prices are disconnected from the fundamentals.

I observe in panels f-g of Table 1.3, as expected, the valuation ratios have a positive slope coefficient. BM is statistically significant in forecast horizons from 4 to 12 months, and it outperforms DP and EP. Besides EP and $Default$, the valuation ratios and business cycle variables in panels f-k seem to perform well in univariate regressions,[28] where their forecast t-statistic and adjusted R^2 tend to increase with the forecast period. Following Cochrane (2008b), this is due to the persistence of the regressors over the forecast horizon, which maximizes the advantages of long-horizon return regressions. I find a consistent pattern with Fama and French (1989), where they regress monthly, quarterly, and annual returns on measures of business conditions, e.g., term spread, default spread, and dividend yield. For more extended horizon tests on returns, the beta coefficient cumulates the information contained in the independent variables over time.

I look for evidence of gradual return reversal patterns in return forecastability. Therefore, I expand the forecast horizons in the univariate regressions up to 12 months and find that after two months, the coefficient on $DS.SENT$ is no longer statistically significant and is quickly decreasing towards zero. Eventually, return reversal may be observed in longer horizons beyond 12 months. This finding is evident of sentiment-induced temporary mispricing (e.g., overreaction) in asset return, which is a central element in theories on investor sentiment. This pattern is consistent with Tetlock (2007), who examines media pessimism through content published in the Wall Street Journal and documents a negative effect on market prices followed by a reversion to fundamentals.

Univariate regressions using individual return predictors may not be the best representation of return forecastability and, therefore, non-conclusive. I instead use these univariate results to understand how the regressors behave in a simple setting and to analyze patterns in the data. In the following tables, I test return predictability under more stringent specifications with control variables.

[28] Even though I limit the univariate regressions to the period 2004-2018 to stay consistent with $DD.SENT$.

1.3.2 High and low sentiment periods

Evidence from Baker and Wurgler (2006), Shen, Yu and Zhao (2017), and Huang et al. (2015) shows that high sentiment predicts negative returns in subsequent periods. The return predictability of low sentiment is, however, not statistically significant. For instance, Baker and Wurgler (2006, 2007) show that in high sentiment periods, an orthogonalized investor sentiment index based on six proxies strongly predicts subsequent low returns for particular kinds of stocks, such as stocks that are small, young, highly volatile, and hard-to-arbitrage. In low sentiment periods, the R^2 is negative. Huang et al. (2015) similarly find evidence that their *aligned* sentiment index predicts low returns in periods of high sentiment. They report a slightly negative R^2 during low sentiment periods.

In Table 1.4, I divide the sample into high and low sentiment periods.[29] Similar to Stambaugh, Yu and Yuan (2012), I classify months where sentiment is high (low) if the level of sentiment is above (below) the median. To stay consistent in comparisons between optimistic and pessimistic periods, I define high and low periods in the case of negative search volume measured by $DS.SENT$ as follows: high (low) $DS.SENT$ periods mean that the changes in SVIs of negative words are below (above) the median value, indicating less (more) pessimistic episodes of downside sentiment where household concerns are decreased (increased). For instance, in optimistic periods, $DS.SENT\dagger$ has a higher explanatory power (0.062) in comparison with $SENT_{HJTZ}$ (0.033), $SENT_{BW}$ (-0.012), and $SENT_{MCSI}$ (-0.004). In pessimistic periods, $DS.SENT\dagger$ still has a positive R^2 (0.003) that is higher than the other sentiment indices, which suggests that downside sentiment may be extracting the behavior of sentiment signals with higher precision. I find that an increase in negative sentiment predicts higher returns in the following month during both high and low sentiment periods. Since I report a positive R^2 in both periods, this suggests that downside sentiment outperforms other existing sentiment measures at the one-month frequency, and is relevant in both high and low sentiment periods.

As a robustness check, I use the $SENT_{BW}$ median cutoff value to define the high and low $DS.SENT$ periods, as indicated by $DS.SENT\ddagger$. The results show that the predictability power of $DS.SENT$ is robust to using other cutoff values. This is indicated

[29] I restrict the sample of all sentiment indices from 2004-2018 before conducting the high/low sentiment regressions.

by the positive R^2 in both high and low sentiment periods. Moreover, the predictability power of *DS.SENT* is more pronounced in high sentiment periods, suggesting that the predictability power is not only relevant during low sentiment periods or periods of market downturns, which are generally much less common than expansion periods. Therefore, the return predictability of *DS.SENT* is not concentrated in the bad state of the stock market.[30]

Furthermore, given that the R^2 is higher even in predictive regressions following periods of more optimistic sentiment, this indicates that negative searches are more sensitive to fluctuations in public sentiment, even more so than upside sentiment measures.

Table 1.4
High and low sentiment periods

Predicting forward returns during high (optimistic) and low (pessimistic) periods, 2004-2018

Variable	ß	R^2	R^2_{High}	R^2_{Low}
DS.SENT†	2.503***	0.065	0.062	0.003
DS.SENT‡	2.503***	0.065	0.055	0.002
SENT_{BW}	-0.910**	0.035	-0.012	-0.005
SENT_{HJTZ}	-1.068**	0.054	0.033	-0.015
SENT_{MCSI}	-0.007	-0.004	-0.004	-0.004

This table shows the univariate regression results for *DS.SENT*, $SENT_{BW}$, $SENT_{HJTZ}$, and $SENT_{MCSI}$. The dependent variable in the regression is the continuously compounded value-weighted excess returns per month at $t+1$. R^2 is the adjusted R^2 for the regression with the entire sample period, R^2_{high} for the regression with the sample of sentiment above the median value (optimistic periods), R^2_{low} for the regression with the sample of sentiment below the median value (pessimistic periods). *DS.SENT*† uses the *DS.SENT* cutoff values, while *DS.SENT*‡ uses the $SENT_{BW}$ median cutoff value to define the high and low sentiment periods. Since *DS.SENT* is a pessimism index, R^2_{high} (R^2_{low}) is for the sample of sentiment below (above) the median value. Newey-West standard errors are reported for coefficients estimated by OLS regression. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

1.3.3 Bivariate forecasting regression results

To test whether different economic predictors drive downside sentiment, I analyze the incremental forecasting power of *DS.SENT* in bivariate regressions and test its return predictability in the presence of other traditional forecasting variables. Similar to Li, Ng and Swaminathan (2013), I find a high correlation among several valuation ratios and business cycle variables (going as high as approximately 0.90). Therefore, I include each

[30] I do not use NBER recession periods for the sample split because the observations of the recession periods during my sample period are extremely low.

of the other variables as a second predictor with the main forecasting variable ($DS.SENT$) in the bivariate regressions. Table 1.5 presents the bivariate regression results.

In panels A-D of table 1.5, I find that $DS.SENT$ predicts future excess returns in the presence of other measures of (upside) sentiment such as the sentiment indices from Baker and Wurgler (2006) and Huang et al. (2015), and the University on Michigan Consumer Sentiment Index.[31] The predictive power remains strong over time and in the presence of valuation ratios and business cycle variables. Because this measure of downside sentiment is more relevant in the shorter term, the regression R^2 dissipates across increasing forecast periods.

This result is not valid for $SENT_{BW}$ from Baker and Wurgler (2006), where the regression R^2 increases with the forecast period. Empirical results in the literature support the notion that investor sentiment could be more relevant in longer periods. For example, Brown and Cliff (2005) find significant results when testing their investor sentiment measure at the one-year horizon and longer. Furthermore, although Baker and Wurgler (2006) investigate the effect of investor sentiment at shorter periods on the cross-sectional level, in their more recent paper (e.g., Baker, Wurgler and Yuan, 2012), they test the return forecasting power of investor sentiment at one-year forecast horizons on the country level and find less statistical evidence.

Huang et al. (2015) finds that investor sentiment extracted using the PLS method predicts better the aggregate stock market returns at the usual monthly frequency, compared with existing sentiment indices up till so far. In the bivariate regression results, I show that $DS.SENT$ outperforms the sentiment index from Huang et al. (2015) at the monthly frequency and at longer time horizons. This evidence suggests that downside sentiment is a better measure of aggregate sentiment and is able to strongly predict future returns.

1.3.4 Downside sentiment and other controls

In previous sections, I compare the performance of $DS.SENT$ with traditional stock return predictors that are directly related to economic fundamentals. In this section, I test the forecasting power of $DS.SENT$ when controlling for other sentiment indices as well as

[31] An increase in concerns related to the economy would expectantly be adjusted for in both survey-based and search-based measures of household sentiment. One concern is that the predictive power of $DS.SENT$ may not be robust when controlling for the survey-based sentiment measure.

Table 1.5
Bivariate forecasting regressions for the DS.SENT, other sentiment indices, business cycle variables, and valuation ratios.

	K				
	1	2	4	6	12
Panel A:					
DS.SENT	2.521***	1.469***	0.715	0.278	0.255
	(0.670)	(0.549)	(0.534)	(0.335)	(0.338)
$SENT_{BW}$	-0.768	-0.856	-0.932*	-1.052**	-1.262***
	(0.631)	(0.589)	(0.487)	(0.421)	(0.387)
Observations	170	169	167	165	159
Adjusted R^2	0.069	0.05	0.05	0.066	0.21
Panel B:					
DS.SENT	2.632***	1.643***	0.823*	0.364	0.393
	(0.702)	(0.493)	(0.438)	(0.301)	(0.427)
$SENT_{HJTZ}$	-0.773	-0.586	-0.279	0.037	0.254
	(0.630)	(0.535)	(0.515)	(0.415)	(0.205)
Observations	125	125	125	125	125
Adjusted R^2	0.105	0.074	0.022	-0.011	0.008
Panel C:					
DS.SENT	2.484***	1.389***	0.623	0.198	0.224
	(0.643)	(0.500)	(0.407)	(0.253)	(0.313)
$SENT_{MCSI}$	0.003	0.009	0.011	0.009	-0.001
	(0.021)	(0.020)	(0.024)	(0.025)	(0.015)
Observations	170	169	167	165	159
Adjusted R^2	0.060	0.033	0.014	-0.003	-0.008
Panel D:					
DS.SENT	2.580***	1.517***	0.751	0.316	0.262
	(0.673)	(0.554)	(0.550)	(0.349)	(0.357)
BM	4.613	4.280	4.893***	5.091***	4.757***
	(3.052)	(2.728)	(1.763)	(1.285)	(1.293)
Observations	170	169	167	165	159
Adjusted R^2	0.078	0.059	0.075	0.090	0.157
Panel E:					
DS.SENT	2.580***	1.511***	0.773	0.34	0.304
	(0.670)	(0.536)	(0.528)	(0.331)	(0.358)
DP	0.766	0.64	0.857*	0.915***	0.912***
	(0.701)	(0.649)	(0.458)	(0.344)	(0.261)
Observations	170	169	167	165	159
Adjusted R^2	0.070	0.043	0.048	0.055	0.120
Panel F:					
DS.SENT	2.571***	1.501***	0.725	0.272	0.211
	(0.668)	(0.531)	(0.479)	(0.286)	(0.313)
EP	0.114	0.09	0.064	0.04	-0.014
	(0.215)	(0.192)	(0.182)	(0.192)	(0.169)
Observations	170	169	167	165	159
Adjusted R^2	0.062	0.033	0.008	-0.008	-0.008
Panel G:					
DS.SENT	2.393***	1.318***	0.553	0.117	0.138
	(0.640)	(0.491)	(0.381)	(0.255)	(0.314)
$Term$	-0.410	-0.492*	-0.587*	-0.560*	-0.424
	(0.291)	(0.283)	(0.310)	(0.308)	(0.277)
Observations	170	169	167	165	159
Adjusted R^2	0.071	0.059	0.083	0.083	0.092
Panel H:					
DS.SENT	2.472***	1.411***	0.746*	0.357	0.371
	(0.648)	(0.497)	(0.435)	(0.296)	(0.355)
$Default$	-0.078	-0.092	0.146	0.274	0.401**
	(0.649)	(0.637)	(0.552)	(0.443)	(0.194)
Observations	170	169	167	165	159
Adjusted R^2	0.060	0.031	0.008	0.001	0.033

Table 1.5 (continued)

Table Continued

	K				
	1	2	4	6	12
Panel I:					
DS.SENT	2.504***	1.448***	0.683	0.243	0.213
	(0.668)	(0.538)	(0.507)	(0.317)	(0.327)
Tbill	-1.818	-1.944*	-2.191**	-2.459**	-2.953**
	(1.227)	(1.100)	(1.080)	(1.206)	(1.455)
Observations	170	169	167	165	159
Adjusted R^2	0.068	0.047	0.046	0.059	0.189
Panel J:					
DS.SENT	2.508***	1.453***	0.699	0.258	0.238
	(0.656)	(0.522)	(0.473)	(0.293)	(0.332)
LTyield	-0.341**	-0.356**	-0.410**	-0.417**	-0.378**
	(0.173)	(0.152)	(0.163)	(0.168)	(0.176)
Observations	170	169	167	165	159
Adjusted R^2	0.075	0.061	0.082	0.096	0.165

This table summarizes the bivariate regression results for the different forecasting variables in equation 1.3. The dependent variable in these regressions is the continuously compounded value-weighted excess returns per month at different forecast horizons K, scaled by $1/K$; b is the slope coefficient; regressions in which $K > 1$ use overlapping observations. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression.***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

proxies for economic policy uncertainty, news media content and social media content. I also control for changes in the CBOE volatility index as it is positively correlated to $DS.SENT$. These controls are widely used in sentiment papers particularly dealing with Google Trends (e.g., Da, Engelberg and Gao, 2015; Gao, Ren and Zhang, 2019): the sentiment index from Baker and Wurgler (2006) '$SENT_{BW}$', its PLS variant from Huang et al. (2015) '$SENT_{HJTZ}$', the survey-based University of Michigan Consumer Sentiment Index pessimism '$SENT_{MCSI}$', a measure for news sentiment from Buckman et al. (2020) '$news.tone$', a measure for negative social media posts via Twitter '$tweets$', changes in the economic policy uncertainty index from Baker, Bloom and Davis (2016) 'EPU_{BBD}', and changes in the CBOE volatility index 'VIX'. Based on equation 1.3, I set X as the following set of seven regressors: $DS.SENT$, $SENT_{BW}$, $SENT_{HJTZ}$, $SENT_{MCSI}$, $news.tone$, EPU_{BBD}, VIX.

In Table 1.7, I examine the effect of $DS.SENT$ on the continuously compounded value-weighted excess returns at expanding forecast horizons up to two monthly only.[32] For each

[32] I no longer consider horizons beyond two months because the predictability power of $DS.SENT$ is not statistically significant from $K = 3$ onwards (See tables 1.3 and 1.5).

forecast horizon 'K,' I consider either economic policy uncertainty (in the first column) or the news tone index (in the second column). As both measures capture news sentiment, I do not include them in the same regressions as they are highly correlated (at -70% approximately). When $K = 1$, the positive and significant coefficient on $DS.SENT$ suggests that it predicts positive stock market returns the following month. A one standard deviation increase in downside sentiment predicts an increase of 0.80% (0.79%) in market returns (significant at the 1% level), followed by a further increase of 0.33% (0.31%) in the second month (significant at the 10% level).

Table 1.7
Predictive regressions of future excess market returns on DS.SENT and a set of controls

	K					
	0		1		2	
$DS.SENT$	2.060***	2.048***	2.680***	2.620***	1.096*	1.025*
	(0.684)	(0.676)	(0.751)	(0.765)	(0.587)	(0.607)
$SENT_{BW}$	0.367	0.415	-0.370	-0.397	-0.790	-0.850
	(0.964)	(0.932)	(1.253)	(1.235)	(1.150)	(1.153)
$news.tone$		1.633		0.363		-0.349
		(1.005)		(1.714)		(1.108)
EPU_{BBD}	-0.006		0.008		0.013**	
	(0.007)		(0.009)		(0.006)	
VIX	-0.064***	-0.064***	0.003	0.004	0.003	0.004
	(0.013)	(0.013)	(0.011)	(0.011)	(0.007)	(0.008)
$tweets$	-0.040	-0.210	-0.205	-0.238	-0.020	0.024
	(0.185)	(0.170)	(0.298)	(0.348)	(0.235)	(0.252)
$SENT_{MCSI}$	-0.008	-0.019	0.041	0.032	0.048	0.043
	(0.037)	(0.037)	(0.062)	(0.063)	(0.039)	(0.039)
Observations	106	106	106	106	105	105
Adjusted R^2	0.516	0.528	0.045	0.041	0.024	-0.002

$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + bDS.SENT_t + \beta_i CONTROLS_t + e_{t+K,t}$
This table shows the forecasting regression results using a wide set of control variables as regressors. $DS.SENT$ is the main explanatory variable. In the first column, I set CONTROLS = $SENT_{BW}$, $SENT_{MCSI}$, EPU_{BBD}, VIX, $tweets$ in the equation shown above. In the second column, I use the news tone index $news.tone$ from Buckman et al. (2020) instead of EPU_{BBD}. The dependent variable in the time-series regression is the continuously compounded value-weighted excess returns per month at different forecast horizons, scaled by 1 divided by the forecasting horizon K; b is the slope coefficient; regressions in which $K > 1$ use overlapping observations. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

The results indicate that when household concerns are high, investors require a higher risk premium to invest in the stock market, which may temporarily exert downward pressure on prices and subsequently lead to high future returns. Although I do not observe a negative month 0 effect that reverses in the following month, I suspect that return reversal patterns may be either observable at early daily intervals (see, e.g., Da, Engelberg and

Gao, 2015) or at longer monthly intervals when the initial effect completely dissipates. Backing the latter hypothesis, the theoretical predictions in Daniel and Hirshleifer (1998) suggest that the role of investor overconfidence may have a substantial role in the market. If investors overestimate the accuracy of their private signals, this might generate momentum in stock prices, which only first partially corrects as noisy public information arrives. Subsequently, as more public information signals arrive, stock prices eventually correct, and thus, the effect of sentiment disappears.

Traditional sentiment indices have been tested in one-month and longer periods. Brown and Cliff (2005) rely on survey data and find that in periods longer than one year, investor sentiment has a statistically significant predictive power. They do not find significant results in shorter periods. Baker, Wurgler and Yuan (2012) show that the previous year-end global sentiment index (formed from a PCA of six local investor sentiment indices) can predict subsequent 12-month returns on the country level. Huang et al. (2015) show that their sentiment index predicts future excess returns up to 12 months. In this study, I show evidence that the downside sentiment index significantly predicts returns even after controlling for other sentiment indices in forecasting exercises (particularly in forecast horizons up till two months) and outperforms the sentiment index from Huang et al. (2015) at the usual monthly frequency in both in-sample and out-of-sample tests.

While the forecasting power of downside sentiment is strongest in shorter forecast horizons, the opposite is true for measures of upside sentiment, as shown in table 1.5. A possible explanation is a difference in the effects of upside and downside sentiment on temporary mispricing episodes. In periods of high sentiment, investors are more optimistic and are overconfident, which bids up prices of stocks. Moreover, due to short-sale constraints in this arbitrage process, prices shift further away from fundamentals (e.g., Stambaugh, Yu and Yuan, 2012). Therefore, it could take substantially longer for those traditional sentiment measures' effect on the aggregate market to dissipate over time.

In periods of low sentiment or when there is a negative shock to noise traders' beliefs, investors are more pessimistic and risk-averse. Therefore, they simultaneously exert downward pressure on prices. Intuitively, more extreme changes in downside sentiment would generate high volume, which further induces market-wide effects of sentiment (see, e.g., Tetlock, 2007). Therefore, these stocks could simultaneously become underpriced and earn higher subsequent returns. Another possible explanation is that investors reacting to negative sentiment signals would have a higher perceived risk of the market and would require a higher risk premium to invest in the market. Following the model of De Long et al. (1990b), investors who trade on non-fundamental information are still compensated for the risk that they generate. Since shocks are stationary, and there are fewer limits to the effectiveness of arbitrage in eliminating asset mispricings in periods of increased downside sentiment, returns rebound faster to fundamentals in subsequent periods.[33]

Up to my knowledge, this is the first study to conduct a comprehensive return predictability analysis of downside sentiment using Google Trends data at the monthly frequency. The evidence in this study suggests that the SVI-based measure for downside sentiment outperforms traditional sentiment measures at the usual monthly frequency, as well as other traditional market forecasting variables in the literature. And so far, empirical tests using daily and weekly Google search volume perform well (see, e.g., Da, Engelberg and Gao, 2015; Gao, Ren and Zhang, 2019; Kostopoulos, Meyer and Uhr, 2020a; Birru and Young, 2020), which further shows that this data is widely available, easily accessible, and can be used at most data frequencies.

1.3.5 Downside sentiment and market volatility

In line with Black (1986, p. 533), "Anything that changes the amount or character of noise trading will change the volatility of the price." Sentiment theories predict that during sentiment episodes, the resulting noise trading affects stock market volatility. For example, in periods of high sentiment, stocks tend to become overpriced. More extreme changes in absolute sentiment will exert more pressure on prices and generate higher trading volume, which is unjustified by fundamentals. Excessive noise trading leads to excessive volatility, and as the effect of sentiment dissipates over time, so does its effect on stock market volatility.

I use a straightforward market index to measure the changing levels of risk in the market. I examine the returns from VIX options traded on the CBOE, calculated as the change of log monthly closing prices. In table 1.8, I find that an increase in the downside sentiment

[33] Tetlock (2007) find that unusually high media pessimism generates high trading volume. In addition, the author rejects the hypothesis that pessimism is a proxy for information about fundamental asset values.

measure is contemporaneously negatively associated with returns on VIX options. A one standard deviation increase in $DS.SENT$ is associated with a contemporaneous decrease by 2.43% in VIX options return. Huang et al. (2015) find that their PLS-sentiment index is positively related to future volatility. This is consistent with the opposite signs on the coefficients on upside and downside sentiment measures in predictive regressions. In the second column at $K = 0$, the coefficient on $DS.SENT$ remains negative and statistically significant after adding a set of controls, including the comprehensive news coverage measure $news.tone$, the Baker-Wurgler investor sentiment index, the University of Michigan consumer sentiment index, and $tweets$. This effect is, however, temporary. I find a return reversal pattern in the next two months (although $DS.SENT$ is negatively associated with VIX today, it is positively associated with VIX in the next two months). This is consistent with findings in multivariate regressions including VIX (e.g, Tables 1.7 and 1.12). Therefore, the index has a temporary effect on stock market volatility, consistent with the evidence of sentiment-induced temporary mispricing.

Table 1.8
Downside sentiment and volatility

Dependent variable: Returns from VIX options traded on the CBOE at different time horizons, scaled by 'K'

	K					
	0		1		2	
$DS.SENT$	-8.096***	-8.957***	0.203	-2.358	0.798	0.354
	(1.864)	(2.618)	(1.649)	(2.469)	(1.086)	(1.551)
$SENT_{BW}$		2.517		0.584		1.724
		(3.143)		(3.370)		(3.071)
$SENT_{MCSI}$		-0.173		-0.042		0.047
		(0.151)		(0.191)		(0.105)
$news.tone$		6.772		1.064		-1.408
		(5.891)		(7.291)		(4.357)
$tweets$		1.354		0.850		0.053
		(1.166)		(1.703)		(1.087)
Observations	171	106	171	106	171	106
Adjusted R^2	0.103	0.072	-0.006	-0.038	-0.003	-0.033

This table relates $DS.SENT$ to changes in the market volatility. The dependent variable is the returns on the CBOE volatility index per month at different forecast horizons 'K' (calculated as the change of log monthly prices), scaled by 1 divided by the forecasting horizon K, since regressions in which $K > 1$ use overlapping observations. The first column under K is the univariate regression result with $DS.SENT$ as the only predictor variable, and the second column shows the effect on volatility after controlling for $SENT_{BW}$, $SENT_{MCSI}$, EPU_{BBD}, $news$, $tweets$. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

French, Schwert and Stambaugh (1987) provide evidence of a positive relation between expected risk premium and volatility. An increase in sentiment should lead to a decrease in market volatility and a subsequent decrease in the expected market risk premium.

Although the results provide evidence of the behavioral explanation of noise trading,[34] I do not find evidence that a risk-based explanation drives the return forecasting power of our measure. An increase in downside sentiment is associated with a decrease in VIX options return and an increase in excess market return. Therefore, I reject the volatility hypothesis as a possible driver of the index forecasting power.

1.4 A combined sentiment index

Baker and Wurgler (2006, 2007) develop the investor sentiment index by extracting the first principal component of the cross-section of the sentiment proxies. The first principal component is a linear combination of the original variables (sentiment proxies) that account for the largest fraction of variance in the data.[35] The eigenvectors, which are comprised of coefficients corresponding to each sentiment proxy, are used to calculate the principal component scores. The coefficients indicate the relative weight of each variable in the component. The issue with Principal Component Analysis (PCA) is its inability to disentangle the common approximation error in the components, which might negatively influence the predictability of the index.[36] Huang et al. (2015) find that eliminating a common noise component in the proxies of the Baker-Wurgler sentiment index improves its return forecasting power substantially. This is achieved by applying a Partial Least Squares (PLS) method to extract the common sentiment component in each of the proxies while at the same time eliminating the common approximation error component, which is not related to returns, and the idiosyncratic noise related to each individual proxy.[37]

Motivated by Huang et al. (2015), I include the proxies from Baker and Wurgler (2006) as a measure of upside sentiment, and $DS.SENT$ as a measure of downside sentiment, to develop a *combined* sentiment index using the PLS approach applied in their paper. I will then test its forecasting power against the downside sentiment index alone ($DS.SENT$)

[34] The model of De Long et al. (1990b) predicts that noise trading could explain the excess volatility and mean reversion in prices. Investors would react to sentiment signals, which leads to temporary shifts of asset prices away from fundamentals. De Long et al. (1990b, p. 735) state that noise traders, such as investors that trade on sentiment signals, “may be compensated for bearing the risk that they themselves create and so earn higher returns than sophisticated investors even though they distort prices.”
[35] In Baker and Wurgler (2006), the first principal component explains 49% of the variability in the data.
[36] See Huang et al. (2015) for a detailed comparison between the PCA and PLS approach.
[37] The PLS approach is first introduced to the finance literature by Kelly and Pruitt (2013, 2015).

and $SENT_{HJTZ}$ from Huang et al. (2015). In the first step, I run N time-series regressions of each sentiment proxy in period t on market returns in $t+1$ as estimated in 1.4, where N is the number of sentiment proxies and T is the number of time periods.

$$x_{i,t} = a_i + b_i ret_{i,t+1} + e_{i,t}, t = 1, ..., T. \tag{1.4}$$

The loading on $ret_{i,t+1}$ (expected market returns) is the beta coefficient for each sentiment proxy, which measures the covariance of each proxy with expected market returns. The coefficients are the weights of each sentiment proxy in the *combined* sentiment index, as it measures the sensitivity of each proxy to the true investor sentiment, instrumented by expected market returns.

In the second step, I run T cross-sectional regressions of each sentiment proxy in period t on the beta-loadings in period t from the first-stage time-series regression, as estimated in 1.5,

$$x_{i,t} = a_i + b_i S_{i,t} + e_{i,t}, N = 1, ..., N. \tag{1.5}$$

The estimated regression slope S is the *combined* sentiment index. I then standardize the index to have a standard deviation equal to 1, and a mean of 0. In figure 1.3, I look at how the *combined* sentiment index moves over time. Drops in the index indicate periods of financial distress, and increases indicate recovery.

In the first column of table 1.9, I show the results of univariate regressions of market returns on the combined sentiment index. In the second column of the table, I show the forecasting results when controlling for the set of usual controls. A one standard deviation increase in $SENT_{COMB}$ corresponds with a 0.64% increase in market returns in the same month. The beta-coefficient decreases over time in the univariate regressions. The story remains the same when adding controls. The forecasting power of the *combined* sentiment index disappears when adding more controls to the regression.[38]

In unreported results, I find that the combined sentiment index has a strong effect after the first year, despite a decreasing coefficient. In forecast horizons after 12 months,

[38] I address concerns about multicollinearity issues, as the decreasing and later negative R^2 seems to penalize adding more regressors heavily. I run pair-wise correlation tests and estimate the variance inflation factor (VIF) after running the regressions, and I find no signs of a multicollinearity problem in the model.

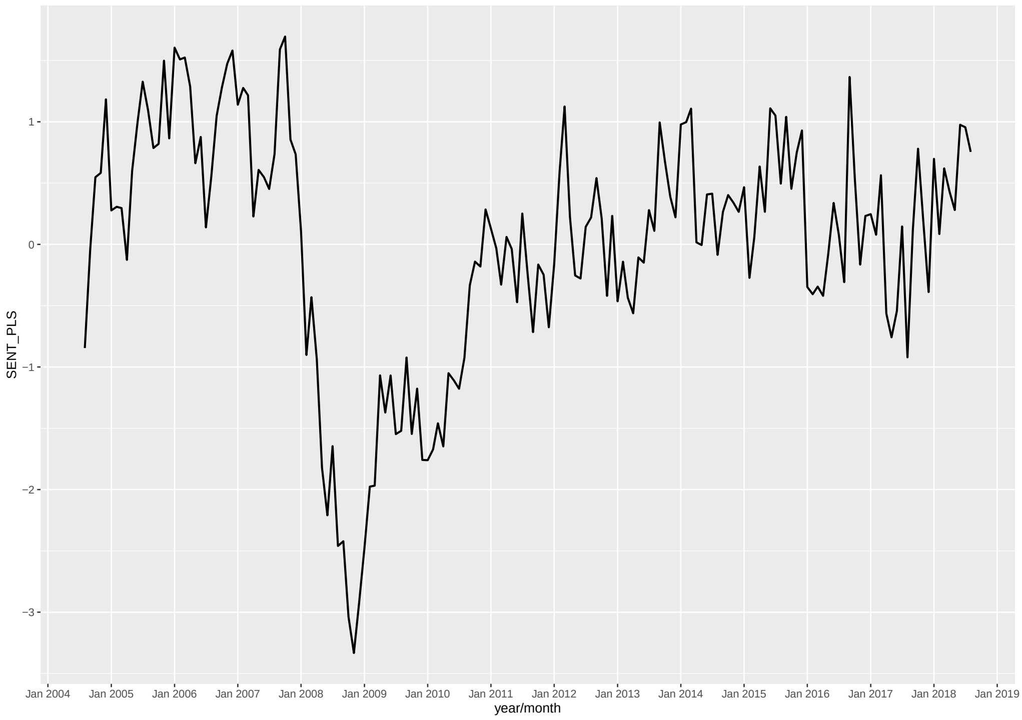

Figure 1.3
Combined sentiment index over time. This figure depicts the monthly changes in the combined sentiment index over the period of August 2004-September 2018. The largest drop in the index could be associated to the decreased U.S. public sentiment during the acute phase of the subprime mortgage crisis, in which global credit markets were dealing with contracted liquidity and financial institutions were subjected to insolvency threats.

the R^2 in the univariate regressions temporarily increases again before falling, showing that the index (which now includes both measures of upside and downside sentiment) is relatively more relevant in the longer term. For example, at $K = 18$, the coefficient on $SENT_{COMB}$ is negative and statistically significant at the 10% level, followed by an even stronger return reversal in which the coefficient improves in both economic magnitude and statistical significance (significant at the 5% level). Therefore, the *combined* index seems to perform better at longer forecast horizons. This could be due to the higher combined absolute weights of the five sentiment proxies relative to the weight of downside sentiment, in determining the sensitivity of each sentiment proxy to the combined sentiment index. I conclude from the PLS approach that the downside sentiment index performs better alone, particularly in shorter horizons. It seems that downside and upside sentiment could not be

Table 1.9
Predictive regressions of future excess market returns on the *combined* sentiment index

	K					
	0		1		2	
$SENT_{COMB}$	0.645**	0.268	0.337	-0.158	0.251	-0.317
	(0.308)	(0.300)	(0.320)	(0.487)	(0.333)	(0.426)
$SENT_{MCSI}$		-0.007		0.059		0.042
		(0.035)		(0.068)		(0.041)
$news.tone$		1.541		0.030		-0.072
		(1.024)		(1.711)		(1.184)
VIX		-0.072***		-0.008		-0.0002
		(0.012)		(0.011)		(0.008)
$tweets$		-0.144		0.120		0.078
		(0.205)		(0.285)		(0.253)
Observations	169	105	169	105	169	105
Adjusted R^2	0.049	0.482	0.009	-0.030	0.008	-0.023

This table shows the forecasting regression results using a wide set of control variables as regressors. The *combined* sentiment index '$SENT_{COMB}$' is the main explanatory variable. In the second column, I add a set of controls (Michigan Consumer Sentiment Index '$SENT_{MCSI}$', news tone index '$news.tone$', changes in the CBOE VIX 'VIX', standardized tweets score '$tweets$'. The dependent variable in the time-series regression is the continuously compounded value-weighted excess returns per month at different forecast horizons, scaled by 1 divided by the forecasting horizon K; b is the slope coefficient; regressions in which $K > 1$ use overlapping observations. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

combined in one measure, because they appear to be orthogonal to each other.[39] In section 1.5 of the empirical analysis, I estimate out-of-sample forecasts of the combined sentiment index against each of the downside sentiment and upside sentiment indices alone.

1.5 Out-of-sample return predictions

Cochrane (2008b) and Welch and Goyal (2008) argue that although many return-forecasting variables in the literature can predict returns in-sample, almost all variables perform worse in out-of-sample forecasts and cannot beat a simple forecast based on the historical average of stock market returns. In this section, I evaluate the out-of-sample performance of $DS.SENT$ to see whether it is able to deliver a superior out-of-sample forecast of the US equity premium relative to commonly used valuation ratios and the business cycle variables.

[39] Perhaps it could be worthwhile to construct a net sentiment index using both positive and negative search terms as done in Gao, Ren and Zhang (2019). This would then be an alternative method to test the predictive power of an index that incorporates both upside and downside measures of sentiment. This avenue could be explored in future research.

I begin with the main predictive regression model:

$$r_{t+1} = a_i + b_i x_{i,t} + e_{i,t+1}, \tag{1.6}$$

where r_{t+1} is the continuously compounded value-weighted excess return per month in period t+1, $x_{i,t}$ is the ith monthly forecasting variable ($DS.SENT_t$, $SENT_{PLS}$, $SENT_{BW}$, $SENT_{HJTZ}$, $SENT_{MCSI}$, BM_t, DP_t, EP_t, $Term_t$, $Default_t$, $Tbill_t$, $LTyield_t$), $e_{i,t+1}$ is the error term.

I divide the sample into two periods: an estimation period of (m) observations and an out-of-sample period of ($q = T - m$). Short estimations periods may lead to spurious rejections, while long estimation periods may improve forecast evaluation (e.g., Hansen and Timmermann, 2012). I choose different sample splits to check whether the out-of-sample performance holds robustly. Moreover, since some variables have more historical data available (such as book-to-market ratio, dividend yield, earnings yield, the Baker-Wurgler sentiment index, among others), I choose a longer sample period for these predictors. I choose an estimation period m of 60 months and 72 months.[40] For example, using a fixed rolling window of m=60, I predict r_{m+1} using the ith forecasting variable, i.e., using a window from t=1 to t=60 to predict returns of out-of-sample period t=61, then from t=2 to t=61 to predict returns of out-of-sample period t=62, and proceeding in this manner through the end of the period. The number of out-of-sample forecast periods in which m = 60 is equal to 153 months for all forecasting variables,[41] except for $DS.SENT$; since $DS.SENT$ data starts from 2004, there are 110 out-of-sample forecast periods. Using base regression coefficients estimated using OLS, I obtain a time series of predicted market returns $\{\hat{r}_{i,t+1}\}_{t=m+1}^{T-m}$ for each predictor variable x_i.

Following Campbell and Thompson (2007) and Welch and Goyal (2008), I use the historical average of excess stock market returns $\bar{r}_{t+1}$ as the benchmark forecasting variable, where I also use a fixed rolling window of the previous m months to estimate the historical average return. If the regression of excess returns on the predictor variable x_i predicts future excess market return better than the historical average forecast, then the predictor

[40] In robustness tests, I also apply different constraints and windows for the out-of-sample forecasts of the main predictor variable $DS.SENT$.

[41] Data $SENT_{HJTZ}$ is also only available up till December 2014. Therefore, it has an out-of-sample forecast period equal to 108 months.

variable x_i is a good predictor of the equity premium.

1.5.1 Out-of-sample estimation

To evaluate the out-of-sample forecast of alternative predictive variables, I use the out-of-sample R^2 statistic, R^2_{oss}:

$$R^2_{oss} = 1 - \frac{\text{MSPE}_X}{\text{MSPE}_H} = 1 - \frac{\sum_{k=1}^{q} \left(r_{m+k} - \hat{r}_{i,m+k}\right)^2}{\sum_{k=1}^{q} \left(r_{m+k} - \bar{r}_{m+k}\right)^2}, \tag{1.7}$$

where MSPE_X is the mean squared prediction error for the OLS model, in which $\hat{r}_{i,m+k}$ are the predicted excess market returns out-of-sample using a particular forecasting variable x_i, MSPE_H is the mean squared prediction error for the historical average forecast, in which $\bar{r}_{m+k}$ are the historical average excess market returns, r_{m+k} are the true excess market returns. If a forecasting variable beats the historical average forecast, $\text{MSPE}_X < \text{MSPE}_H$, then $R^2_{oss} > 0$. A forecasting variable that has a higher R^2_{oss} performs better in out-of-sample forecasts.

1.5.2 Out-of-sample forecast results

I choose an out-of-sample forecast period from January 2001 to September 2018, except for $DS.SENT$, which starts from July 2004 to September 2018.[42] The results in this paper are likely different from earlier articles addressing the predictability power of BM, DP, EP, $Term$, $Default$, $Tbill$, $LTyield$, as I use more recent data in the selection of the sample period. In in-sample return predictions, I find that $DS.SENT$ has a strong predictive power in the first two months. In out-of-sample return predictions, I consider only the return in period $t + 1$ (e.g., Li, Ng and Swaminathan, 2013), in which regressions do not use overlapping observations ($K = 1$).

I first plot in Figures 1.4 and 1.5 the differences over time between the cumulative squared prediction errors of the historical average forecast minus the cumulative squared prediction error of the forecasting models using different forecasting variables x_i. The

[42] As previously noted, Google Trends data starts from January 2004, and since I calculate first differences and use the first six months in the process of selecting words that are historically correlated with market returns, the in-sample and out-of-sample estimation periods for $DS.SENT$ start in August 2004.

figures depict how each variable performs over the forecasting period. Here, I plot figures for which the estimation period (rolling window) is 60 months.[43] The units on the plots are non-intuitive, and the performance of each forecasting variable is determined by whether the slope is positive or negative. A positive slope indicates that the named model beats the historical average model, and a negative slope indicates the opposite. Figure 1.4 shows that $DS.SENT$ starts with a negative slope for a very short time, which then becomes positive for the entire remaining period. $DS.SENT$ stays above zero and has a positive slope that is increasing over time, while the valuation ratios and business cycle variables in figure 1.5 start with a positive slope for only a very short period and are then negative. This indicates that $DS.SENT$ beats the historical average and outperforms the traditional forecasting variables.

In comparison with other alternative sentiment indices, $DS.SENT$ outperforms all of them in out-of-sample tests. The cumulative mean squared prediction error of $SENT_{BW}$ exceeds that of the historical benchmark average throughout most of the period. Although $SENT_{HJTZ}$ looks less persistent, a similar pattern of prediction errors is observed in $SENT_{HJTZ}$. Interestingly, all three alternative sentiment indices ($SENT_{BW}$, $SENT_{HJTZ}$, $SENT_{MCSI}$) seem to have a weaker performance, particularly after 2008 in the aftermath of the financial crisis. Although these indices might have performed well in the past, they show no significant predictive capability in the post-financial crisis period.

The combined sentiment index, which combines the downside sentiment measure $DS.SENT$ with the Baker-Wurgler sentiment proxies (number of IPOs, first-day returns on IPOs, the equity shares in new issues, the value-weighted dividend premium, and the closed-end fund discount) using the PLS approach in Huang et al. (2015), performs surprisingly similar to the Baker-Wurgler index in the out-of-sample tests.[44] It seems that the downside and upside measures of sentiment are not efficiently combined in the process, and they could be orthogonal to each other.

Following Welch and Goyal (2008), there are several diagnostics a reliable model should pass in order to inspire confidence in a potential investor: significant in-sample and reasonably good out-of-sample performance, a generally upward drift that remains positive

[43] Figures for windows of 72 months or 48 months could also be provided upon request.
[44] This appears to be the case in in-sample tests, as well.

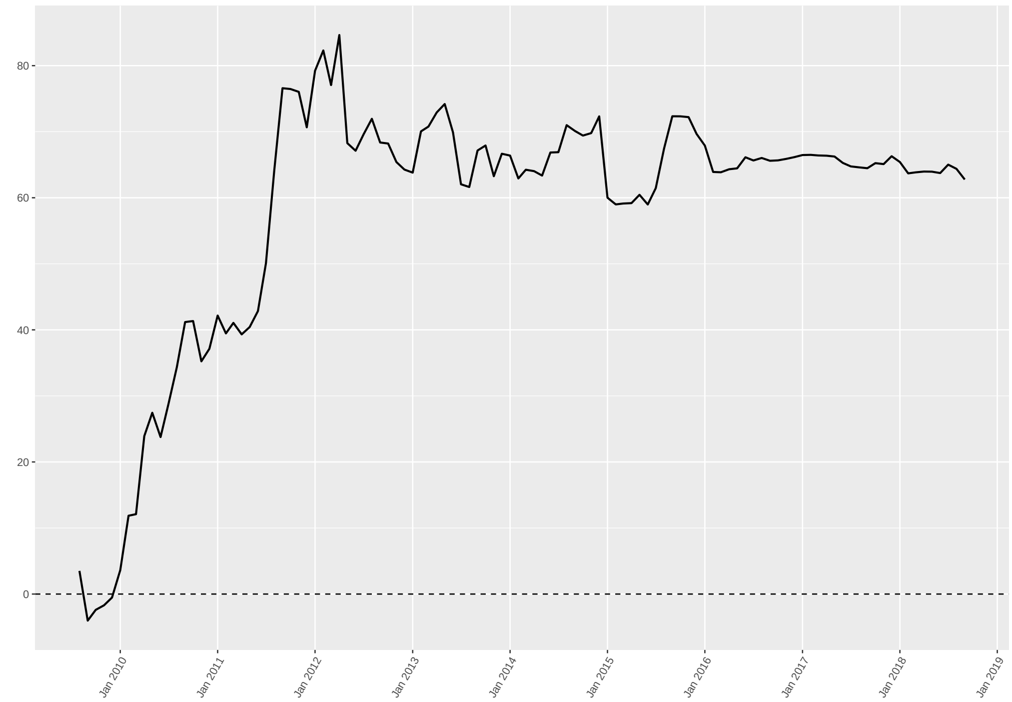

Figure 1.4
This figure depicts the cumulative squared prediction errors for the historical average benchmark forecasting model minus the cumulative squared prediction errors for the forecasting model using downside sentiment ($DS.SENT$). The dotted line in each figure goes through zero. An increase in a line indicates better out-of-sample performance than the historical average.

over the majority of the period, an upward drift that does not just occur around irregular events or shocks. I therefore secondly compare the in-sample R^2 (R^2_{IS}) and out-of-sample R^2 (R^2_{OOS}) in table 1.10 to evaluate the overall performance of forecasting variables.

Table 1.10 presents the performance of monthly predictions in-sample and out-of-sample. Several variables have positive in-sample performance, as shown in the second column of the table. Similar to findings in Li, Ng and Swaminathan (2013), I find that all forecasting models during the study's sample period, other than $DS.SENT$, are unstable and not good enough for investing, given that they do not pass essential diagnostics as suggested by Welch and Goyal (2008). Besides the lack of return predictability in out-of-sample tests, whether their in-sample significance is reliable is uncertain. The results, however, suggest that $DS.SENT$ is more informative than the traditional forecasting variables and the prominent variables in the sentiment literature in forecasting excess returns, in-

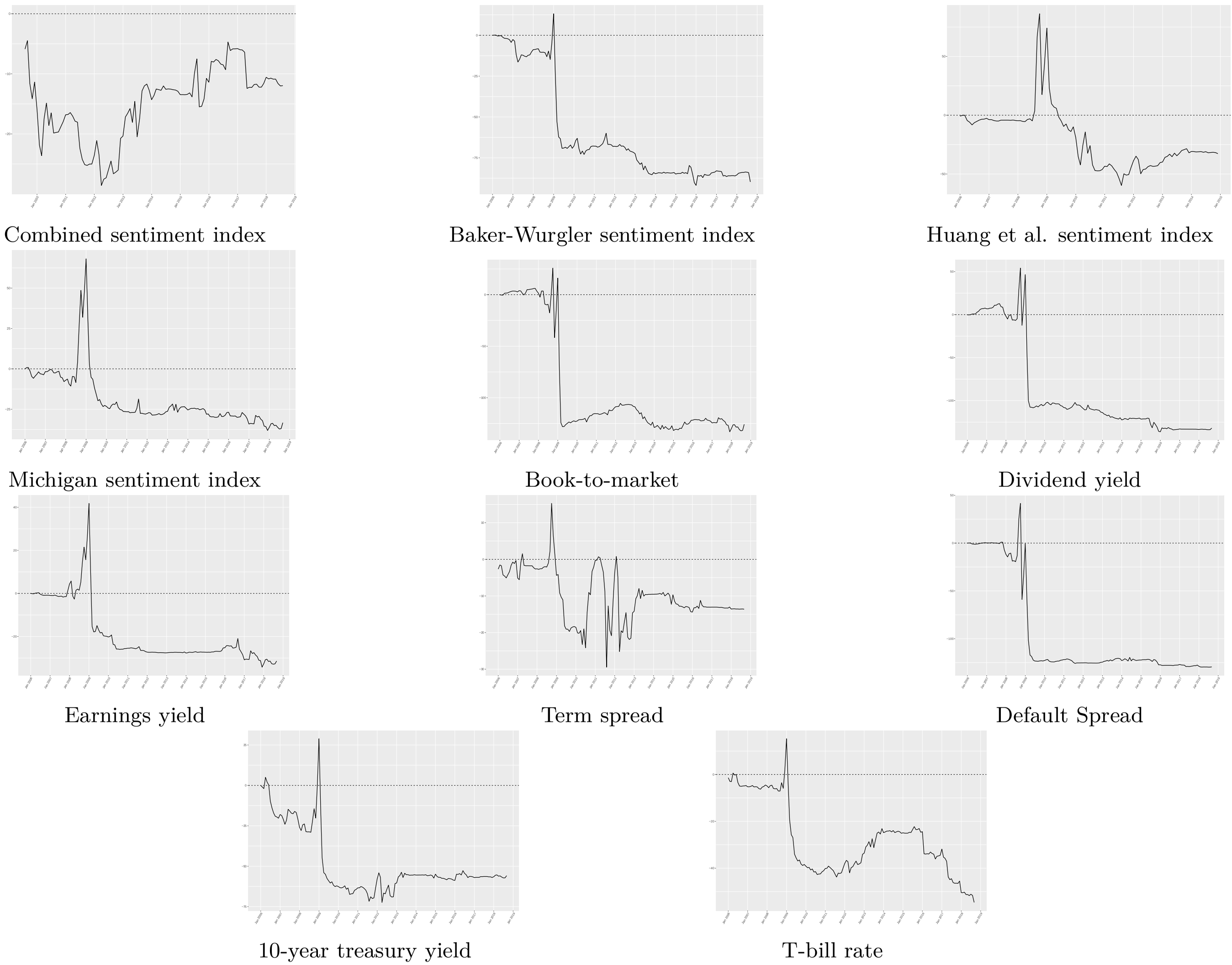

Figure 1.5

This figure depicts the cumulative squared prediction errors for the historical average benchmark forecasting model minus the forecasting model using the alternative forecasting variables: Combined sentiment index ($SENT_{COMB}$), Baker-Wurgler sentiment ($SENT_{BW}$), Huang et al. sentiment index ($SENT_{HJTZ}$), Book-to-market (BM), Dividend yield (DP), Earnings yield (EP), Term spread ($Term$), Default spread ($Default$), 10-year treasury yield ($LTyield$), and T-bill rate ($Tbill$) respectively. The dotted line in each figure goes through zero. An increase in a line indicates better out-of-sample performance of the named model.

Table 1.10
R^2 of in-sample and out-of-sample forecasts for each forecasting variable

Variable	ß	t-stat	R^2_{IS}	$R^2_{OOS}(72)$	$R^2_{OOS}(60)$
DS.SENT	2.503	3.736	0.065	0.049	0.087
SENT_{COMB}	0.337	1.053	0.009	-0.015	-0.017
SENT_{BW}	-0.910	-1.991	0.035	-0.038	-0.069
SENT_{HJTZ}	-1.068	-2.144	0.054	-0.051	-0.031
SENT_{MCSI}	-0.007	-0.318	-0.004	-0.074	-0.025
BM	6.647	2.157	0.028	-0.103	-0.096
DP	1.192	1.738	0.017	-0.140	-0.101
EP	0.086	0.483	-0.003	-0.070	-0.024
Term	-0.625	-2.648	0.034	-0.040	-0.010
Default	-0.370	-0.557	-0.002	-0.102	-0.099
LTyield	-0.525	-3.000	0.032	-0.066	-0.043
Tbill	-3.307	-2.071	0.017	-0.046	-0.042

This table summarizes the R^2_{IS} and R^2_{OOS} for each forecasting variable. The R^2_{IS} statistic is the adjusted R^2 estimated from the univariate regressions of each forecasting variable in which *K=1*. β is the beta-coefficient on the forecasting variable from the in-sample tests, and the *t-stat* is the in-sample t-statistic. For all variables other than $DS.SENT$ and $SENT_{COMB}$, I re-estimate the univariate regressions from table 1.3 to reflect the sample period which starts from January 2001. $R^2_{OOS}(72)$ is for an estimation period (fixed rolling window) of 72 months, while $R^2_{OOS}(60)$ is for an estimation period of 60 months. Newey-West standard errors with a K-1 (zero) lag correction are reported for coefficients estimated by OLS regression.

cluding the combined sentiment index ($SENT_{COMB}$). It performs better in in-sample return predictions over multiple periods (both in univariate regressions and multivariate regressions with several controls) and beats other variables in out-of-sample predictions. I conclude that $DS.SENT$ is a more robust predictor of market returns by outperforming all other analyzed sentiment proxies and traditional market predictors. I further apply some constraints on the R^2_{OOS} for $Ds.SENT$ in robustness tests.

1.5.3 Robustness tests

In this section, I examine the robustness of the main results to different constraints and model specifications.

1.5.3.1 Sign restrictions on forecasts

Campbell and Thompson (2007) and Welch and Goyal (2008) assume that investors would rule out a model which forecasts a negative equity premium, and they explore the impact of imposing a set of economically motivated restrictions on return forecasts out-of-sample. For instance, they truncate such negative return forecasts at zero. Since the $DS.SENT$

time-series could be more volatile or less stable than other sentiment measures, such as $SENT_BW$ and $SENT_Huang$, there is a possibility that $DS.SENT$ outperforms these variables in in-sample and out-of-sample tests because it fits better the highly volatile market return (which often takes negative values).[45] Therefore, applying some constraints on the out-of-sample forecast could help determine whether the R^2_{OOS} for $DS.SENT$ can hold robustly.

In table 1.11, I report the out-of-sample R^2 for return predictions by $DS.SENT$ using sign restrictions on the forecasts like Campbell and Thompson (2007) and Welch and Goyal (2008). As an estimation window of 72 months delivers a relatively modest out-of-sample R^2 relative to 60 and 42 months, I apply the sign restriction on forecasts using 72 months as an estimation window. The first restriction requires that the return forecast of $DS.SENT$ be positive. Otherwise, I set this forecast to zero when calculating the out-of-sample R^2. In another variation, I completely remove the observation which contains a negative forecast and calculate the out-of-sample R^2 accordingly. The results in table 1.11 show that the sign restriction delivers a positive out-of-sample performance. Like Campbell and Thompson (2007), I also find that imposing sign restrictions enhances the out-of-sample forecast of the predictive regression.

Table 1.11
Excess return forecasts with different constraints

Condition	Estimation Window	R-squared
In-sample		0.065
OOS - Unconstrained	72 months	0.049
OOS - Unconstrained	60 months	0.087
OOS - Unconstrained	48 months	0.079
OOS - Constrained, Pos. Forecast	72 months	0.073
OOS - Constrained, Pos. Forecast (T)	72 months	0.106

This table reports the R^2_{IS} (in-sample), unconstrained R^2_{OOS} (out-of-sample), and constrained R^2_{OOS} (out-of-sample) for $DS.SENT$. The R^2_{IS} statistic is the adjusted R^2 estimated from the univariate regression at *K=1*. β is the beta-coefficient on $DS.SENT$, and the *t-stat* is the in-sample t-statistic. $R^2_{OOS}(72)$ is for as estimation period (fixed rolling window) of 72 months, $R^2_{OOS}(60)$ is for an estimation period of 60 months, and $R^2_{OOS}(48)$ is for an estimation period of 48 months. "Pos. Forecast" applies a non-negativity constraint to the out-of-sample forecast. That is, it requires the forecast to be positive, otherwise I set zero as the forecast. The "Pos. Forecast (T)" variation suggests that the forecast is completely removed from the out-of-sample estimation whenever it is negative.

[45] I thank an anonymous reviewer for this important suggestion.

Another potential concern is that shorter estimation windows may be correlated with lower out-of-sample performance, and the choice of estimation windows may influence out-of-sample performance. Therefore, I report the out-of-sample R^2 for an additional estimation period of 48 months to check whether it is robust to different window specifications. As reported in table 1.11, the out-of-sample R^2 remains positive.[46]

1.5.3.2 Alternative sample period and control variable

Since $SENT_{HJTZ}$ find that their method improves the return forecasting power of the Baker-Wurgler sentiment index, in table 1.12, I examine whether the results are robust to the inclusion of $SENT_{HJTZ}$ as an alternative index to $SENT_{BW}$ in the equation of table 1.7. Moreover, since the data availability of $SENT_{HJTZ}$ is restricted to December 2014, I also report the results in this table for a shorter sample period from August 2004 to December 2014. In spite of the short sample period used in this regression, I show that the results are robust to the inclusion of other prominent sentiment indices as control variables. The positive and significant coefficient of $DS.SENT_t$ shows that it subsumes all analyzed proxies of investor sentiment, media sentiment, and economic policy uncertainty at predicting market returns for forecasting horizons from one-month to two-months. The direct extraction of household concerns, or individual sentiment, from Google searches possibly makes $DS.SENT$ is a superior measure of household sentiment and downside sentiment.

The novel results of this paper highlight the different characteristics of upside and downside sentiment. A critical aspect of this study's findings is timing. While downside sentiment has the strongest predictability in shorter time horizons up to 2 months ahead, upside sentiment has a strong predictability power in longer time horizons. Following periods of downside sentiment, it takes faster for prices to revert to fundamentals, which makes downside sentiment more relevant in the shorter term. As investors overreact to negative sentiment signals, they may bid down stock prices. These stocks become underpriced and more attractive, leading to higher subsequent returns. Investors arbitrage away the noisy price movements, eliminating asset mispricings more effectively. Subsequently, in aggregate, these temporary mispricing episodes are shorter, especially during extreme

[46] Also, the out-of-sample R^2 remains positive using a shorter estimation period of 24 months.

sentiment periods.

Table 1.12
Predictive regressions of future excess market returns on DS.SENT and a set of controls - $SENT_{HJTZ}$ as an alternative investor sentiment index to $SENT_{BW}$

	K					
	0		1		2	
$DS.SENT$	1.395*	1.396*	3.580***	3.654***	1.490**	1.441**
	(0.844)	(0.758)	(0.881)	(0.915)	(0.591)	(0.600)
$SENT_{HJTZ}$	-0.089	-0.188	-0.211	-0.262	0.168	0.235
	(0.565)	(0.542)	(0.781)	(0.750)	(0.707)	(0.668)
$news.tone$		2.677**		0.006		-0.888
		(1.326)		(2.518)		(1.520)
EPU_{BBD}	-0.012		-0.013		0.013	
	(0.014)		(0.021)		(0.014)	
VIX	-0.090***	-0.088***	0.015	0.014	-0.002	-0.002
	(0.012)	(0.012)	(0.018)	(0.018)	(0.012)	(0.012)
$tweets$	0.263	-0.462	-0.125	-0.156	0.663	0.923
	(0.505)	(0.507)	(0.807)	(0.945)	(0.619)	(0.602)
$SENT_{MCSI}$	-0.030	-0.046	0.036	0.051	0.067	0.062
	(0.046)	(0.043)	(0.078)	(0.077)	(0.050)	(0.052)
Observations	61	61	61	61	61	61
Adjusted R^2	0.601	0.626	0.105	0.099	0.036	0.031

$\sum_{k=1}^{K} \frac{r_{t+k}}{K} = a + bDS.SENT_t + \beta_i CONTROLS_t + e_{t+K,t}$
This table shows the forecasting regression results using a wide set of control variables as regressors. $DS.SENT$ is the main explanatory variable. In the first column, I set CONTROLS = $SENT_{HJTZ}$, $SENT_{MCSI}$, EPU_{BBD}, VIX, $tweets$ in the equation shown above. In the second column, I use the news tone index $news.tone$ from Buckman et al. (2020) instead of EPU_{BBD}. The dependent variable in the time-series regression is the continuously compounded value-weighted excess returns per month at different forecast horizons, scaled by 1 divided by the forecasting horizon K; b is the slope coefficient; regressions in which $K > 1$ use overlapping observations. Newey-West standard errors with a K-1 lag correction are reported for coefficients estimated by OLS regression. ***, **, and * denote significance at 0.01, 0.05, and 0.10 level, respectively.

A second important aspect of the $DS.SENT$ measure is the investor/trader. It is more likely that this measure captures individual investors rather than institutional investors' demand shocks. In a novel study of sentiment metrics and investor demand, Devault, Sias and Starks (2019) argue that the influential Baker and Wurgler (2006) sentiment index captures the institutional investors' demand shocks because of how it is measured. Moreover, Kostopoulos, Meyer and Uhr (2020a) match their daily $FEARS$ data for the German market with individual investor data from a major German broker and finds that $FEARS$ gauges individual investor trading behavior well. The authors suggest that when household concerns are high, investors sell risky assets in an attempt to reduce their portfolio exposure to the risky asset market.

Given that $DS.SENT$ is also based on household searches, it is more likely that it is associated with individual investors rather than institutional investors. If individual investors are more likely to own a disproportionate fraction of stocks that are more difficult to value, stocks that fall into this category would be more prone to downside sentiment.

1.6 Conclusion

John Maynard Keynes (1923) famously once said, “In the long run, we are all dead”, as a criticism towards economists solely fixating on long-term outcomes at the price of effectively addressing immediate economic challenges. This remark has been heavily debated, even though it triggered a massive impact on economic thought and public policy. Just over a decade later, Keynes (1936) introduced the notion of “animal spirits”. This gave rise to investor sentiment theory, which suggests that investor sentiment drives stock prices away from fundamentals (De Long et al. (1990a)). Several studies examine the long-term effect of sentiment measured through upside financial market-based measures, but, to my knowledge, none of those studies observe the predictability power of downside sentiment on monthly stock returns. This paper introduces a household sentiment measured through media- and online-based methods on the aggregate market. The proposed proxy for downside sentiment ($DS.SENT$) predicts market returns on the medium- and longer-term and beats other traditional forecasting variables, such as the commonly used dividend yield, in addition to the commonly used investor sentiment measure by Baker and Wurgler (2006) in horizons from one- to two-month ahead.

The results indicate that the predictive power of $DS.SENT$ remains significant in out-of-sample return predictions, with an out-of-sample R^2 of 4.9%. This result is even more striking considering that all other proxies analyzed in this study had a negative out-of-sample R-squared. Thus, while the predictability power of other proxies seems to be marginal and conditional on sampling specification, downside sentiment measure has a strong and robust predictability power.

However, the strong predictability power seems to be limited to a period of up to two months ahead, since in longer periods, the traditional Baker-Wurgler sentiment index shows a stronger statistical significance. This result is evidence that downside sentiment is quickly incorporated into prices, while upside sentiment takes longer, likely as a consequence of short-sale constraints or because investors seem to overlook that the stock prices are disconnected to the fundamentals.

The paper's results have implications for academics and practitioners. For academics, I show that investors seem to have a delayed response (or an overreaction) to household concerns that take up to two months to be fully incorporated into prices. This result could be interpreted as evidence that investors are not fully rational, and the level of household concerns can influence subsequent market returns. For practitioners, I propose a proxy for downside sentiment that outperforms the predictability power of the traditional valuation ratios and other proxies for investor sentiment. However, a limitation to this study is that I have a relatively small sample period that starts in 2004 due to a lack of data availability from Google Trends. Thus, further studies are recommended in the future to analyze how robust these results are over time.

2 Investor sentiment, flights to quality, and the stock-bond return comovements

Abstract

This paper examines the dynamics of stock-bond return comovements in an international sample. I disentangle the effect of common economic sources driving this time-variation, such as inflation and interest rates, and show that when investor sentiment is pessimistic, stock-bond return correlations decrease in the following two days, thereby exhibiting a flight-to-quality phenomenon. Therefore, stock and bond market decouplings may be more pronounced in countries where investors are more prone to negative sentiment signals. Cultural characteristics play a limited but important role. Uncertainty avoidance contributes to explaining stock-bond return correlations and may moderate the effect of sentiment, while individualism plays a weak role.

Key words:	Investor Sentiment, Flight-to-Quality, Hofstede Cultural Index, Stock-Bond Return Correlation
JEL Codes:	C58, G01, G15, G19, G40, G41

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Current Status:	Working Paper

2.1 Introduction[1]

Academic research shows that there is a substantial time variation between stock and bond market returns. Baele, Bekaert and Inghelbrecht (2010) document daily correlation levels as high as +0.60 during the mid-1990s, which drop to as low as -0.60 by the early 2000s. Over the last few decades, a negative correlation between the stock index and the government bond index acted as a hedge during stock market downturns. For instance, in response to increased stock market uncertainty, many investors tend to trade away from risky stocks into safe assets like Treasury bonds (see for e.g. Connolly, Stivers and Sun (2005)). This is also known as the "flight to quality" phenomenon, which first gained attention approximately 20 years ago. During these so-called decoupling episodes, investors seek the flight-to-quality benefits of Treasury bonds, which are often perceived as safe havens Baele, Bekaert and Inghelbrecht (2010).

A shock in one market may create cross-market rebalancing, which would induce volatility spillovers between markets (Chordia, Sarkar and Subrahmanyam (2005); Kim, Moshirian and Wu (2006)). Most literature has taken a traditional approach to joint stock and bond pricing[2]. For example, Colacito, Engle and Ghysels (2011) estimate quarterly stock-bond return correlations from daily data using a DCC-MIDAS model. Moreover, Scruggs and Glabadanidis (2003) reject symmetric models of conditional second moments for stock and bond returns. Kim, Moshirian and Wu (2006) model the time-varying conditional correlations of stock and bond returns using a bivariate exponential generalized conditional heteroskedasticity (EGARCH) model. Although substantial empirical work has been dedicated to modeling the asymmetric and dynamic nature of time-varying stock and bond returns, studies attempting to disentangle the sources of these variations seem surprisingly limited.

Baele, Bekaert and Inghelbrecht (2010) investigate many factors driving stock-bond return comovements in a dynamic factor model. They find that macroeconomic fundamentals, such as inflation and interest rates, explain only a small fraction of the correlation.

[1] I thank seminar participants at the Finance Brownbag Seminar 2020 of the TUM School of Management, conference participants at the 2021 JIFMIM-CCPF Symposium, Qian Guo (discussant), and Christoph Kaserer for insightful discussions and useful comments. I thank Theo Beffart for research assistance. I thank the Deutscher Akademischer Austauschdienst (DAAD) for financial support.

[2] See Campbell and Ammer (1993), Campbell, Sunderam and Viceira (2009), among others.

The authors conclude that other proxies related to market liquidity and uncertainty may be stronger determinants of the conditional correlation. There is still an open debate on which economic variables could induce sudden drops in stock-bond return correlations. Moreover, Connolly, Stivers and Sun (2005) suggest that stock market uncertainty measured by the VIX could partially explain those prolonged periods of negative correlations in the United States. Furthermore, Baker and Wurgler (2012) study comovements between bonds and bond-like stocks and document strong comovement patterns. They find that a solely risk-based explanation fails to provide a complete explanation of the magnitude of predictability, and they suggest that investor sentiment is a possible link between bonds and bond-like stocks. Unlike in Baker and Wurgler (2006), they find that the sentiment effect is rather occasional. That is, when sentiment is high, the most risky stocks deliver the lowest returns.

Investor sentiment, which is a predictor of the cross-section of stock returns, also predicts bond returns (Laborda and Olmo, 2014; Bethke, Gehde-Trapp and Kempf, 2015). Low market sentiment signals future increases in interest rates that depress ex-post returns on long-term maturity bonds versus the one-year bond. So, we already know from the literature that there is a robust predictability power of sentiment in the cross-sections of stock returns, as well as in the aggregate stock market. At least in the U.S., this has been well-documented (For e.g., Huang et al. (2015); Baker and Wurgler (2006); Baker, Wurgler and Yuan (2012), among others). Moreover, considerable evidence exists of the sentiment effect on the bond market (For e.g., Laborda and Olmo (2014); Çepni et al. (2020), among others). Given that there is substantial comovement between stocks and bonds, it would be interesting to examine how changes in investor sentiment generate stock and bond return comovements.

In this article, I look at these two fundamental markets from a behavioral perspective. Using daily data on an international sample, I examine the extent to which stock-bond return correlations are driven by investor behavior. More specifically, I focus on the effect of investor sentiment as a driver of stock-bond return correlations. Declining sentiment would induce a flight to quality into Treasury bonds, which would raise bond prices and decrease equity prices, and balanced portfolios would suffer smaller losses compared to stocks alone. More pessimistic periods may witness more dramatic decoupling episodes than less pessimistic ones, showing that more extreme sentiment would drive investors to be more dramatic in their asset re-allocation decisions. This could potentially explain sudden drops in stock-bond return correlations.

Furthermore, there are several psychological biases discussed in the behavioral finance literature. For instance, Chui, Titman and Wei (2010) consider how cultural differences influence momentum returns. They first analyze the impact of individualism, one of Hofstede (2001)'s six cultural factors, on stock returns. They find that individualism positively correlates with momentum profits, trading volume, and volatility. Additionally, including other variables (e.g. analyst forecast dispersion, familiarity of the market to foreigners) does not weaken this correlation. Interestingly, the authors suggest that investors in less individualistic countries, such as countries in East Asia, are less prone to overconfidence and self-attribution bias as described by Daniel, Hirshleifer and Subrahmanyam (2001). Consequently, these investors may be less prone to making investment choices based on momentum strategies. Since Chui, Titman and Wei (2010) do not link cultural factors to sentiment, it would be interesting to exploit cross-country differences in Hofstede (2001)'s cultural factors and how they interact with sentiment in a panel setting. In particular, I consider how cultural factors may moderate the effect of sentiment on stock-bond return correlations. To my knowledge, this paper is the first to analyze how sentiment affects index-level return correlations between stocks and bonds, as well as how sentiment interacts with cultural factors. And in doing so, the paper expands our understanding of how behavioral biases may contribute to explaining stock-bond return comovements, and particularly the observed decoupling between the stock and bond markets in times of uncertainty. Moreover, since the literature on investor sentiment mainly focuses on the U.S. stock market, it would be interesting to exploit daily sentiment extracted from Google Trends in a broad international setting.

To this end, I investigate three hypotheses. The first hypothesis is that decreased investor sentiment, or an increase in the pessimistic sentiment index I use in this paper[3], predicts a decrease in daily correlations. I find that this is rather true, and increased household concerns are associated with decoupling episodes. Particularly, the sentiment

[3] I use a daily investor sentiment index, which focuses on downside sentiment as in Elkhayat (2024). In this paper, I closely follow the daily sentiment methodology in Da, Engelberg and Gao (2015).

effect is strongest following 2 days, with a reversal pattern occurring from day 3 and onwards. This is consistent with the sentiment literature, which suggests that there is sentiment-induced temporary mispricing followed by strong reversal patterns. This result is robust to controlling for macro factors and uncertainty measures. Additionally, even beyond decoupling episodes, I find evidence of shifts in stock-bond correlations due to sentiment. Although the effect is more pronounced during extremely pessimistic periods, sentiment appears to have a general effect on index-level correlations.

The second hypothesis is that cultural factors related to risk-taking behavior have a considerable effect on stock-bond comovements, and this effect exists because cultural background influences investor behavior and, hence, it is relevant to the "sentiment story". In panel regressions examining the independent effect of each of Hofstede's cultural indices, the results indicate that uncertainty avoidance is significantly related to stock-bond return comovements. On the contrary, individualism has no pronounced effect in the panel analysis, as it does not necessarily tell us whether overconfidence and self-attribution bias directly translate into increased proneness to hedging the risk of investment during times of uncertainty. It seems that only uncertainty avoidance is relevant to the flight-to-quality story. Hence, countries that score high on uncertainty avoidance tend to be more prone to sentiment. On the other hand, countries that rank particularly high or low on individualism may not necessarily be more prone to sentiment. Therefore, I exclude individualism from the rest of the analysis.

The third hypothesis builds on the first two and examines whether the level of uncertainty avoidance moderates the effect of sentiment in panel regressions. The results suggest that uncertainty avoidance moderates the effect of sentiment, although the moderating effect decreases in regressions with sentiment lagged by 2 days and when adding all controls. The effect of uncertainty avoidance is more pronounced at higher levels. Therefore, the effect of the sentiment proxy is not subsumed by conditioning on the level of uncertainty avoidance, although it plays a role in driving stock-bond return correlations.

The structure of the remaining parts of this paper is as follows. Section 2.2 presents the data used in this research. Section 2.3 presents the econometric model. Section 2.4 reports the results from panel regressions. Section 2.5 reports robustness tests. Section 2.6 concludes.

2.2 Data description and statistics

To characterize how returns on treasury bonds comove with stock market returns, the study examines a broad range of countries. The sample includes 14 countries that constitute the largest economies around the world, ranked by GDP in the World Bank Database. I include U.S. and Japan as they are the world's two largest economies, Euro zone members that have the largest financial markets and rank within the top 25 world economies by GDP (Germany, France, Italy, Spain, Netherlands, Switzerland, Poland, Sweden, Belgium), Non-Euro zone countries which include the U.K., and additionally Canada and Australia. I do not include China in the sample because Google has an extremely low search engine market share of less than 4% in China (Source: Statista, 2024[4]), and it is censored. Therefore, the sentiment measured by Google search volume would not truly represent the Chinese individual investor's sentiment.

2.2.1 Bond and stock data

For the bond sample, I obtain daily bond return data from Datastream's Total Return Government Bond Indices, similar to Connolly, Stivers and Sun (2005). In particular, I analyze the 10-year Treasury notes for each country. I use longer-term maturities because they are considered long-term investments equivalent to stocks. Additionally, total return on bonds captures coupon payments that are reinvested back into the bonds, which form the index, as well as capture bond price changes. This is similar to the return on stocks, which captures the stock price changes and dividend reinvestments. I choose 10-year Treasury notes instead of 30-year Treasury bonds because the trading activity related to the 10-year securities is substantially higher than that of 30-year securities (Fleming, Kirby and Ostdiek (1998)). Hereafter, I refer to 10-year Treasury notes simply as "bonds". The bond series are in local currency units with a daily frequency from 3 January 2000 to 15 November 2018[5].

For the stock sample, I collect stock data for the U.S. from the Center for Research in

[4] https://www.statista.com/statistics/1365179/china-market-share-of-desktop-search-engines-by-pageview

[5] Upon inclusion of sentiment, the sample is shortened to start from 1 July 2004 to 15 November 2018. I use the longer sample period to compute the time-varying conditional correlations using more substantial historical data. In panel regressions, the sample shortens because the sentiment index starts from July 2004, which is the first available date for Google Trends data.

Security Prices (CRSP) database. The sample includes the common stock (share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ for the period from 3 January 2000 to 13 March 2020[6]. For the non-US (international) sample, I use equity return data and market capitalization data of firms listed on NYSE, AMEX or NASDAQ from Thomson Reuters Datastream (TDS). To first identify the stocks, I use TDS constituent lists. These lists include Worldscope lists, research lists, as well as dead lists to eliminate survivorship bias. To eliminate common TDS errors and ensure high data quality, I restrict the sample of stocks using static screens, generic keyword filters, country-specific keyword filters, and dynamic screens as mainly suggested by Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017)[7]. These screens have become a standard in the literature dealing with international equity markets. The final sample of stocks includes those that pass the screens. For each country, I then construct the daily value-weighted market returns (using market capitalization weights).

Table 2.1 reports the summary statistics of continuously compounded daily bond and stock returns for the entire sample period. On average, bonds are less volatile than stocks. The returns have a fat-tailed distribution (leptokurtosis). We observe these fat tails because the conditional mean and volatility are time-varying, and the conditional distribution of the actual returns depends on some market state or economic state. The skewed returns may suggest that declines in asset prices are more severe than increases. This suggests a time-varying asymmetric distribution in the return series. The table also presents the results of the Ljung-box test for serial correlation up to the 20th lag in the return series and squared return series (to identify heteroskedasticity), similar to Ljung-Box test specifications in Connolly, Stivers and Sun (2005), Kim, Moshirian and Wu (2006), and Lowry, Officer and Schwert (2010). The $Q(20)$ and $Q^2 0$ test statistics in both univariate (stock and bond returns separately) and bivariate i.i.d[8] tests (joint tests) are highly significant in almost all of the countries. The significance of the tests suggest that the first and second moments of the two return series move closely together. Therefore, the choice of model

[6] Upon inclusion of sentiment, the sample is shortened to start from 1 July 2004 to 13 March 2020. Particularly for the US, I have a longer time-series available because stock market returns from December 2018 to March 2020 are publicly available from Kenneth French's data library.

[7] Keyword filters are used to exclude non-common equity securities from the Datastream sample. The constituent lists and the list of screens applied are available in the Appendix.

[8] The term "i.i.d" stands for independently and identically distributed.

should address the bivariate and fat-tailed nature of the return series (Kim, Moshirian and Wu (2006)). To address this, I use a bivariate DCC-EGARCH model (Engle (2002)). I elaborate on this methodology in the Econometric model section.

2.2.2 Sentiment data

2.2.2.1 Market-wide sentiment and expected returns

The literature dealing with investor sentiment is vast, and the role of sentiment-driven noise trading is no longer debated in the market, but rather, empirical work currently focuses on investor sentiment's effect on various asset classes and its contagious effect across markets, on both the short-run and long-run Baker, Wurgler and Yuan (2012). One well-known measure of investor sentiment is constructed by Baker and Wurgler (2006) in their 2006 paper. They extract sentiment using Principal Component Analysis from a set of proxies, in particular, the closed-end fund discount, the number and average first-day returns on IPOs, the dividend premium, and the equity share in new issues[9]. However, the Baker and Wurgler (2006)'s investor sentiment index is constructed from indirect market-based measures, and recent evidence by Devault, Sias and Starks (2019) debates whether the index captures individual investor sentiment. Additionally, it is based on US market data and is available at a monthly frequency.

For the purpose of this study, I focus on a direct measure of investor sentiment that is based on publicly available data at a daily frequency. I follow the methodology of Da, Engelberg and Gao (2015), where they construct a novel FEARS (Financial and Economic Attitudes Revealed by Search) index based on aggregating millions of search queries generated on Google Trends. An important advantage of the search-based measure is its ability to capture household concerns with high precision (for e.g., Da, Engelberg and Gao (2015); Gao, Ren and Zhang (2019); Kostopoulos, Meyer and Uhr (2020b), as it takes advantage of the massive Internet search traffic on the Google search engine. Also, it is available at high frequencies, which is an important feature when dealing with phenomena in which investors rapidly shift their domestic asset allocation. In Elkhayat (2024), I focus on a monthly U.S. measure and therefore, slightly deviate from the methodology in Da,

[9] See Baker and Wurgler (2007) for a detailed discussion on these variables and their definitions.

Table 2.1
Descriptive statistics (I)

	Stock market return				Univariate iid (S)		Bond market return				Univariate iid (B)		Bivariate iid (S,B)	
Country	Mean	Std. dev.	Skew	Kurt	Q(20)	$Q^2(20)$	Mean	Std. dev.	Skew	Kurt	Q(20)	$Q^2(20)$	Q(20)	$Q^2(20)$
USA	0.03	1.19	-0.52	14.65	74.12***	6119.80***	0.02	0.46	0.07	6.38	25.173	991.22***	205.74***	7110.14***
BEL	0.02	1.12	-0.34	8.92	64.45***	4960.00***	0.02	0.36	-0.04	9.70	118.24***	2501.70***	266.46***	7455.60***
CHE	0.02	1.03	-0.35	12.15	70.57***	4609.00***	0.01	0.28	0.18	9.82	46.73***	422.75***	191.73***	5223.51***
DEU	0.03	1.12	0.37	19.07	49.12***	2049.30***	0.02	0.34	-0.13	5.17	38.17***	823.83***	137.09***	3084.01***
ESP	0.01	1.29	-0.19	10.16	52.75***	1663.00***	0.02	0.47	0.89	17.62	219.43***	642.17***	357.19***	2269.11***
FRA	0.03	1.15	-0.13	10.23	59.97***	3785.50***	0.02	0.34	-0.20	5.81	38.62***	1375.00***	169.91***	5135.01***
GBR	0.03	1.06	-0.25	11.48	83.89***	5453.80***	0.02	0.39	0.14	5.32	44.11***	790.75***	213.36***	6083.10***
ITA	0.01	1.33	-0.26	9.35	61.52***	2488.20***	0.02	0.49	0.38	17.76	135.96***	1354.40***	273.43***	3796.18***
NLD	0.03	1.07	-0.36	8.59	69.21***	5023.30***	0.02	0.33	-0.19	4.87	29.52***	758.32***	157.68***	5618.46***
POL	0.02	1.13	-0.48	7.41	38.65***	2116.20***	0.03	0.42	-0.13	14.12	82.22***	525.27***	210.05***	3252.00***
SWE	0.04	1.22	-0.22	8.88	35.96***	3755.70***	0.02	0.32	-0.09	7.26	86.41***	394.56***	164.42***	4062.50***
AUS	0.03	0.99	-0.55	9.10	18.72	5030.00***	0.02	0.46	-0.04	6.70	55.83***	828.09***	138.77***	6137.90***
CAN	0.03	1.00	-0.68	15.32	57.44***	5724.80***	0.02	0.35	-0.03	4.2	28.21	491.53***	141.41***	6192.34***
JPN	0.02	1.28	-0.48	11.45	22.01	3596.80***	0.01	0.19	-0.14	6.03	56.30***	1658.30***	125.46***	5266.01***

This table shows the mean, standard deviation, skewness and kurtosis for the stock and bond market return. Additionally, it reports the tests for univariate i.i.d for stock and bond returns as well as the test for bivariate i.i.d. $Q(20)$ and $Q^2(20)$ stand for the Ljung-Box test statistic for autocorrelation up to the 20th lag in the return series and squared return series (to identify persistent heteroskedasticity) respectively. The null hypothesis is that the data are independently and identically distributed, i.e. any observed correlations are white noise. The alternate hypothesis is that the data are not independently and identically distributed, and they exhibit serial correlation. In bivariate i.i.d tests, rejecting the null hypothesis indicates bond and stock market returns show dependence on each other. The US stock and 10-year government bond return data starts from 1 July 2004 till 13 March 2020 (i.e. takes into account the Covid-19 pandemic effects), while the non-US return data starts from 1 July 2004 till 15 November 2018 (for data availability reasons). ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Engelberg and Gao (2015). In this study, I am interested in daily international data, which is more useful for examining stock-bond return correlations (and in line with papers such as Connolly, Stivers and Sun (2005, 2007)).

Da, Engelberg and Gao (2015) find that high FEARS today is contemporaneously associated with low returns and predicts high returns in the next two days. However, their findings are limited to the United States market. In a more recent paper, Gao, Ren and Zhang (2019) show that a weekly search-based sentiment index is a contrarian predictor of aggregate market returns in an international sample. Consistent with Stambaugh, Yu and Yuan (2012), they find that the sentiment effect is more pronounced during periods with high sentiment levels. Stambaugh, Yu and Yuan (2012) suggest that when sentiment is high, investors are more optimistic and may bid up stock prices, which leads to overpricing. Overpricing may be more prevalent than underpricing due to short-sale constraints, following Miller (1977)'s argument that overconfident investors may be less prone to selling short, which restricts the effectiveness of the arbitrage process. On the contrary, increased waves of pessimism lead to a downward pressure on stock prices.

2.2.2.2 Construction of the sentiment measure

The objective of this methodology is to build a list of search terms that capture household concerns with high precision. I largely follow and extend the methodology of Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019); and since daily international data might be noisier, a more sophisticated pre-processing pipeline is needed[10].

First, to determine the search terms, I take positive and negative sentiment words labeled with ECON or @ECON from the Harvard General Inquirer dictionary word list[11]. This initial list contains 151 words that are labeled as related to economics, and are assigned a positive or negative sentiment. I then translate the word lists to each country's native language in order to accurately reflect the behavior of households in that country. For that purpose, I use Google Translate, which provides free and reliable translations for all the required languages. To understand how households use these words in Google searches, queries from Google Trends are used to identify the top ten related search terms.

[10] I thank Theo Beffart for the valuable research assistance in this section.
[11] http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm

Google Trends describes the returned search queries as ".....terms that are most frequently searched with the term you entered in the same search session, within the chosen category, country, or region". Therefore, this step allows us to augment the word list with related, naturally occurring search terms for each country. Starting with 151 words for each country separately, the top ten related search terms for each word are queried. Therefore, for each of the 14 countries the list would be unique. Each list contains 600-1400 search terms per country, according to the number of related queries that are returned per word.

Since the augmented lists with the related search terms are in each respective country's native language, some words may, in fact, be"lost in translation". For instance, it would be easy to spot an incorrect translation when looking at English-speaking countries. As an example, I find that "gum recession" is one of the top 8 related queries for "recession" in Australia, which is clearly not related to finance and economics and could be related to a completely irrelevant phenomenon at that time. For English-speaking countries, I remove such irrelevant search terms, but for non-English speaking countries, this requires additional effort. To overcome this issue in non-English speaking countries, re-translating all search terms to English is necessary for additional inspection. I filter out any search terms that are not related to finance and economics. The remaining search terms are then kept in the word lists in their original language. This step ensures that all related terms are once again relevant. Following Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019), I remove search terms with insufficient data. Only search terms that have at least 2000 daily observations are kept, given the relatively long time period of the dataset. I end up with 166-363 words per country. Countries with multiple predominant or official languages have a separate word list per language, but I only use the ones that provide the most daily observations of search terms[12].

Next, to process the raw SVI data, the daily SVI for each of these search terms is downloaded over the sample period of January 2004 to March 2020. I calculate the first differences (i.e., change from day to day) of the natural logarithm of the daily SVI values[13].

[12] The final word lists per country are available in the Appendix.

[13] Only requests spanning less than 270 days are answered with daily data. Therefore, the raw daily SVI data is downloaded in chunks of 269 days. Raw SVI values fall in the range from 0 to 100, and hence, they cannot be compared across chunks. Therefore, calculating *changes* in SVIs means I no longer rely on the absolute scale of these values, and I could now combine these chunks to form an uninterrupted series for the entire time period.

This ensures that I use ex-post data because the index is now based on changes, or relative values, rather than absolute values. To address any concerns related to the seasonality and heteroskedasticity in the SVI data, I follow Da, Engelberg and Gao (2015) and first winsorize the series with 2.5% in each tail (by setting all outliers to the boundary value). Then, I deseasonalize the SVI changes by regressing the log-first differences of SVI on weekday and month dummies. This removes any fluctuations in the SVI values that could be attributed to the day of the week or the time of the year to ensure that the deseasonalized log-first differences of SVI cannot be explained by seasonal effects. Lastly, I calculate the z-scores and end up with a series of daily z-scores for each word.

Finally, to generate the index, I run backward rolling regressions for each search term on contemporaneous market returns using an expanding 6-month rolling window, starting at 1 Jan 2004 and expanding by 6 months. I use here the value-weighted market returns for each country. The window here always starts in January 2004 and expands by 6 months each step. For each of those windows, I record the top 30 words with the most negative t-statistic in the regression. The purpose of this step is to identify the historical relationship between search terms and market returns and to construct the index using words that are most important for returns. Hence, the output from the regression is a dynamic list of the top 30 keywords per day with the largest negative t-statistic. The index at any given day is simply the average of the top 30 words' z-scores in that day, as shown in equation 2.1,

$$sent_t = \sum_{i=1}^{30} \triangle Z^i \left(SVI_t\right) \tag{2.1}$$

where $Z^i \left(SVI_t\right)$ is the z-score for the search term that had a negative t-statistic rank of i, where ranks start from the largest magnitude of negative t-static at $i = 1$ to the smallest at $i = 396$. The index starts in July 2004 since I lose the first 6 months of observations from the sample as I require a minimum window from t-6 to t in order to extract the first set of t-values. I only keep words that are strongly negatively related to market returns because the purpose of this methodology is to construct a pessimism index as established in Da, Engelberg and Gao (2015).[14] Additionally, negative words are most useful in identifying sentiment Tetlock (2007). I choose a cutoff of 30 words similar to Da, Engelberg and Gao

[14] see discussion in Elkhayat (2024) about downside sentiment

(2015) because, as the authors suggest, 30 words is the minimum number of observations needed to diverse away idiosyncratic noise. The authors also use several cutoff values in robustness tests and find that alternative cutoff values produce no meaningful differences in results.

Table 2.2 shows an example of the top 5 search terms in the U.S., U.K., Germany, France, and Italy. [15] The words are in the respective country's official and most searched language. The top search words are the most strongly correlated with monthly stock market returns in the full sample, sorted by the most negative t-statistic. Those search terms do not necessarily fall into the negative word lists from the financial dictionary. This is because positive words may be searched in negative Google searches, and the index, after all, captures negative search behavior. For example, similar to Da, Engelberg and Gao (2015), I also find that "gold" and "gold price" are some of the top words in the U.S. sample. Although "gold" falls into the positive sentiment word list of the Harvard General Inquirer dictionary, individual investors most likely associate gold with being a "safe haven" during crisis periods (Da, Engelberg and Gao, 2015; Baur and Lucey, 2009).

As an example of how the index moves over time, figure 2.1 depicts the *dsent* index for the period of July 2004-September 2018 for the U.K. and Germany, and July 2004-February 2020 for the U.S. (for which I have more recent data)[16]. A particularly large peak is commonly observed across the countries in November 2004. This reflects concerns around the 2004 U.S. presidential elections. Interestingly, it seems that sentiment in non-US countries are in line with US-related sentiment. Baker, Wurgler and Yuan (2012) suggest that U.S. sentiment may affect stock prices in other countries, surpassing the effect of these countries' local sentiment itself, provided that private capital flows from the US into such countries. Perhaps even U.S. sentiment influences non-US sentiment (contagious sentiment).

2.2.3 Cultural index data

In this section, I discuss the role of behavioral biases and how they influence the extent to which stock and bond markets are integrated. Moreover, I discuss how cultural differences,

[15] For the sake of brevity, the top search terms for the rest of the countries are not reported. However, they are available upon request.
[16] For the sake of brevity, the plots for the rest of the countries are available upon request.

Table 2.2
Top words in the sample

Country	#	Search term	T-stat.
United States	1	gold	-5.50
	2	gold price	-5.16
	3	business partnership	-3.45
	4	deficit	-3.41
	5	domination	-3.34
United Kingdom	1	hustler	-3.28
	2	liquidation uk	-3.26
	3	creditor	-3.03
	4	debtor	-3.03
	5	compensation	-3.01
Germany	1	vorteil	-3.75
	2	sterbegeldversicherung	-3.73
	3	defizit	-2.86
	4	korrupt	-2.84
	5	deutschland inflation	-2.83
France	1	recession	-3.19
	2	productif	-3.18
	3	epargne	-3.14
	4	faillite	-3.10
	5	bon affaire	-2.90
Italy	1	inoccupato	-3.88
	2	boom economico	-3.69
	3	ricchezze	-3.28
	4	cittadino comune	-3.01
	5	ricatto	-2.96

This table shows the top 5 words and their t-statistics for 4 countries out of the international sample used in the paper. The countries in the table are the United States (USA), the United Kingdom (GBR), Germany (DEU), France (FRA), and Italy (ITA). The top words are in each country's official and most searched language. The top words are words which have the most negative t-statistic, implying that those words are most negatively related to market returns in backward rolling regressions which determine the words constituting the sentiment index. The top 20 word lists for all 14 countries are in the Appendix.

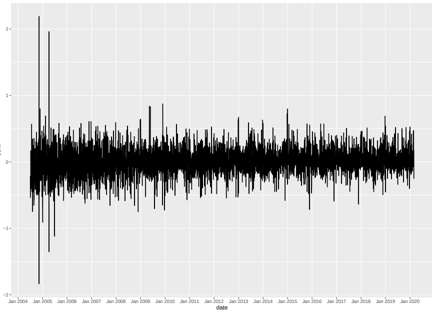
in particular, may moderate the effect of sentiment. Finally, I present the country-level measures for uncertainty avoidance and individualism, respectively.

2.2.3.1 The role of cross-country cultural differences

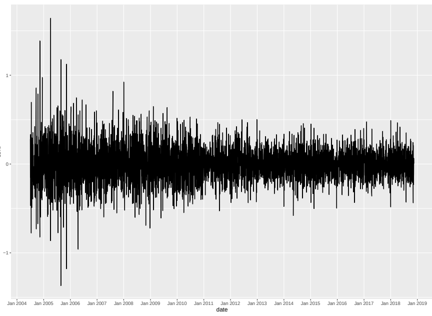
To my knowledge, little work has been done in the finance literature on cultural factors, although cultural background might largely influence the individual proneness to sentiment and subjective evaluation of asset characteristics. A few prominent studies in the finance discipline investigate this cultural aspect.[17]. In the forefront, Chui, Titman and Wei (2010)

[17] In other business disciplines, examples of such papers are Franke, Hofstede and Bond (1991) (economics), Weber, Shenkar and Raveh (1996) (economics), Kachelmeier and Shehata (1997) (accounting), among

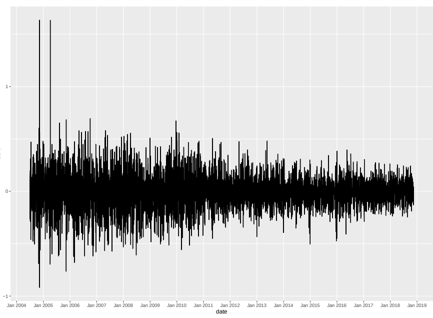
Figure 2.1
The pessimistic sentiment index over time



United States



United Kingdom



Germany

This figure depicts the daily fluctuations in the pessimistic sentiment index *sent* over the period July 2004-September 2018 for the UK and Germany, and over the period of July 2004-February 2020 for the US. A particularly large increase in negative searches is observed in November 2004 in all three figures. This coincides with rising concerns around the 2004 US presidential elections.

examine how individualism is related to overconfidence and self-attribution bias. The authors first analyze the impact of individualism on stock returns, although they do not

others.

link culture to sentiment. Their findings show that individualism is positively associated with momentum profits, trading volume, and volatility. Additionally, they find that other variables, such as analyst forecast dispersion and familiarity of the market to foreigners, do not weaken this association. Interestingly, they find that Asian countries are an exception to those findings. Hence, they argue that cultural differences could be the reason why momentum strategies are not profitable in Asia. Furthermore, the increased popularity of past return-based investment strategies since the momentum strategy by Jegadeesh and Titman (1993) emerged in the asset pricing literature has shed light on both the role of behavioral biases (for e.g., investors' overconfidence[18]) and their heterogeneity across countries. For instance, the so-called empirical failure of momentum is observed in East Asian countries such as Japan, which is attributed to the historically low momentum returns in Japan (Asness (2011)).

In 1967 and 1973, Geert Hofstede conducted a cross-country psychological survey on IBM employees in 72 countries, accumulating 88,000 survey respondents. An index was then developed based on work-goal questions on four cultural dimensions. A fifth dimension was afterward added, and as of 2010, Hofstede added a sixth dimension. Hofstede (2001) identify these cultural dimensions as: Power distance, Individualism vs. Collectivism, Masculinity vs. Femininity, Uncertainty avoidance, Long- and Short-term orientation, and Indulgence vs. Restraint. This study focuses on two cultural factors: "uncertainty avoidance" and "individualism." Although "uncertainty avoidance" does not directly translate into risk aversion, it is directly linked to individuals' perceptions of uncertainty and risk. Moreover, I do not claim that cultural beliefs necessarily measure behavioral biases; I suggest that they are likely to be correlated with investor beliefs and investor perceptions of the market. In particular, I examine the extent to which uncertainty avoidance and individualism moderate the effect of investor sentiment on the stock and bond market and, additionally, their independent role from investor sentiment.

2.2.3.2 Uncertainty Avoidance

Hofstede (2011) describes uncertainty avoidance as "related to the level of stress in a society in the face of an unknown future". Uncertainty avoidance is associated with risk aversion,

[18] See Daniel, Hirshleifer and Subrahmanyam (1998).

in which individuals prefer choices that lead to low-uncertainty outcomes, irrespective of whether a safer choice rewards them with a lower or the same monetary value as a riskier choice. Investors who come from cultures that score high on uncertainty avoidance are more likely to be risk-averse in the choice of their portfolio investments. Independent from sentiment, uncertainty avoidance would positively correlate with returns on Treasury bonds, as they are perceived as safe investments, particularly during uncertain times when they are perceived as safe havens. In contrast, uncertainty avoidance would correlate negatively with stock market returns, as the stock market is generally more volatile. Furthermore, if we are to observe a strong negative correlation, this would suggest that uncertainty is highly related to flight-to-safety episodes, in which investors flee stock markets in favor of bond markets Baele et al. (2020). Hence, uncertainty avoidance may have a moderating effect on sentiment, which is more pronounced during decoupling episodes. The uncertainty avoidance index is obtained from Hofstede Insights[19].

2.2.3.3 Individualism

Individualism is "related to the integration of individuals into primary groups" (Hofstede (2011)). Although Hofstede (2001) relates Individualism vs. Collectivism to society rather than an individual characteristic, many research papers directly link it to individuals' peer-comparison overconfidence and exaggeration of one's abilities. As a result, individuals tend to overestimate the precision of their estimates and the control over their outcomes (Van den Steen (2004). Chui, Titman and Wei (2010) suggest that individualism, to the extent to which it is related to overconfidence and self-attribution bias, is more prominent in Western cultures than in the more collectivistic Eastern cultures. The preliminary findings suggest that individualism correlates positively with both stock and bond market returns, and it negatively correlates with uncertainty avoidance. This implies that more individualistic countries score lower on uncertainty avoidance, which leads to the belief that Western cultures may be more individualistic and more tolerant of risky behavior. Although individualism may be strongly related to the profitability of certain investment strategies, whether it has a direct moderating effect on sentiment, and whether it is linked to stock and bond return comovements remains ambiguous. Although sentiment may be

[19] https://www.hofstede-insights.com/country-comparison/

linked to overconfidence, to the extent to which sentiment reflects flight-to-quality benefits, particularly during decoupling episodes, it is not clear whether individualism moderates this effect at all, as it is not clearly linked to risk aversion. The individualism index is obtained from Hofstede Insights.

Table 2.3 reports univariate summary statistics for the main variables in the empirical analysis (*sent*, cor_{sb}, *uncert* and *indiv*).A positive value of *sent* indicates increases in negative search volume, which indicates “concerns” or “fear.” Although the mean sentiment value is close to zero in all countries, household concerns in the US are particularly the highest compared with the rest of the countries in the sample. As depicted in figure 2.1, *sent* exhibits a stationary time-series[20]. Also, sentiment and the conditional correlation series are volatile, which is consistent with stylized facts in the literature. The most individualistic country in the sample is the US, while the least individualistic country is Japan. The country most prone to uncertainty avoidance is Belgium, while the country least prone to uncertainty avoidance is Sweden.

2.2.4 Fundamental variables

Following Baele, Bekaert and Inghelbrecht (2010), I control for other explanatory variables, such as: inflation, short-term interest rate, dividend yield, output growth, and stock and bond market returns in the previous day.[21] Moreover, I control for Moody’s sovereign bond rating and expected inflation. For the variable computation, I obtain non-US accounting data, such as the book value of common equity and, common dividends, from Worldscope. The US accounting data is obtained from CRSP/COMPUSTAT.

2.2.4.1 CPI inflation

Inflation is measured by the consumer price index (CPI) as an annual growth rate. It is obtained for all the countries from the OECD Database[22] at the monthly frequency.

[20] The stationarity of the sentiment series for each country is confirmed with an Augmented Dickey-Fuller (ADF) test for stationarity in time-series.

[21] See Baele, Bekaert and Inghelbrecht (2010) for a detailed discussion of the traditional stock and bond determinants.

[22] https://data.oecd.org/price/inflation-cpi.htm

Table 2.3
Descriptive statistics (II)

	sent				cor_sb				Hofstede's index	
Country	Mean	Std. dev.	Skew	Kurt	Mean	Std. dev.	Skew	Kurt	uncert	indiv
USA	0.008	0.213	0.180	9.830	-0.334	0.206	0.729	3.057	46	91
BEL	0.000	0.203	0.094	3.236	-0.116	0.176	0.274	3.002	94	75
CHE	-0.001	0.195	-0.009	3.051	-0.240	0.113	0.497	3.870	58	68
DEU	-0.001	0.189	0.239	6.596	-0.304	0.202	0.464	2.942	65	67
ESP	0.002	0.199	0.217	5.003	0.098	0.297	-0.493	2.312	86	51
FRA	0.001	0.198	0.170	4.198	-0.209	0.195	0.144	2.551	86	71
GBR	0.004	0.209	0.205	6.376	-0.286	0.169	0.234	2.686	35	89
ITA	0.003	0.213	-0.008	3.592	0.161	0.331	-0.264	2.196	75	76
NLD	0.002	0.193	0.100	4.643	-0.270	0.160	0.267	2.763	53	80
POL	-0.001	0.184	-0.017	4.080	0.113	0.088	0.209	3.028	93	60
SWE	0.002	0.198	-0.008	3.935	-0.281	0.156	0.339	3.091	29	71
AUS	0.000	0.189	-0.028	4.141	-0.229	0.184	0.094	2.389	51	90
CAN	-0.002	0.187	0.038	3.593	-0.245	0.152	0.186	2.455	48	80
JPN	0.000	0.207	-0.041	5.584	-0.333	0.113	0.586	3.666	92	46

This table shows the mean, standard deviation, skewness and kurtosis for the pessimistic sentiment index, the conditional correlation series, and Hofstede's uncertainty avoidance and indivualism indices. The US data starts from 1 July 2004 till 13 March 2020 (i.e. takes into account the Covid-19 pandemic effects), while the non-US data starts from 1 July 2004 till 15 November 2018 (for data availability reasons).

2.2.4.2 Short-term interest rate

The short-term interest rate is the 1-month risk-free rate from Datastream. For countries in which the 1-month rate is missing, I use the 3-month rate from Datastream. The rates are at the daily frequency.

2.2.4.3 Dividend yield

The firm-level dividend yield (%) is calculated as the total dividends[23] from the previous year-end divided by market capitalization at the previous day-end. The country-level dividend yield is the value-weighted average of the firm-level dividend yields of the firms in each country's stock market.

[23] For Datastream data, I calculate total dividends from the dividends per share value. Total dividends are equal to the dividends per share multiplied by the number of shares outstanding.

2.2.4.4 Output growth

It is the quarterly Gross Domestic Product (GDP) from OECD[24], measured as the percentage change from the previous year's same period.

2.2.4.5 Sovereign bond rating

To control for financial market development, I exploit the within-country and cross-country variation in my international sample. I use Moody's local-currency government bond ratings from Moody's Sovereign and Supranational Rating List. This is an indicator of financial development, which also tells us whether the government has the capacity to repay its local currency bonds in a timely manner. It also serves as a proxy of sovereign credit risk (De Santis (2012)). For instance, the European sovereign debt crisis that started in 2008 left many European countries unable to repay or refinance their government debt. Consequently, during the peak of the crisis, several European countries received downgrades in their government bond ratings and were no longer perceived as safe havens for investors. For example, in the period of 2008-2011, Italy received a negative credit outlook while Spain suffered from several credit rating downgrades (De Santis (2012)).

2.2.4.6 Expected inflation

Expected inflation is the quarterly inflation forecast expressed in annual growth rates obtained from the OECD Database. The inflation forecast is based on the assessment of the economic climate of the individual country and the global economy by the OECD[25].

2.3 Econometric model

This study examines whether shifts in individual investor sentiment induce changes in stock-bond comovement by making inferences from the behavior of the daily conditional volatility interdependencies and time-varying conditional correlations. Considerable anecdotal evidence suggests that volatility is persistent (e.g., Schwert (1990)). For instance, volatility may spike during uncertain periods and stay high for a while, and then it would

[24] https://data.oecd.org/gdp/quarterly-gdp.htm
[25] https://data.oecd.org/price/inflation-forecast.htm

dampen down to its original, long-term level. Generalized autoregressive conditional heteroskedasticity (GARCH, hereafter) models pick up such sort of variations or volatility clusterings very well. GARCH models are popular stochastic volatility models and are successful at modeling serial correlations in the second-order moment of the return series. Hence, they are widely used in the literature (e.g., Baur and Lucey (2009); Colacito, Engle and Ghysels (2011); Christoffersen, Jacobs and Ornthanalai (2012)).

Since symmetric models of conditional second moments for stock and bond returns have been rejected, for e.g., in Scruggs and Glabadanidis (2003), I model the join return generating process of stock and bond markets in each country using a bivariate exponential GARCH (EGARCH) model. EGARCH models overcome the need for non-negativity constraints (Fleming, Kirby and Ostdiek (1998); Kim, Moshirian and Wu (2006). For example, negative news tends to impact volatility more than positive news. This also follows the approach in the paper by Kim, Moshirian and Wu (2006), in which they examine the influence of the European Monetary Union on inter-stock-bond market integration dynamics. I also use the student's t-distribution in fitting the EGARCH model to account for positive and negative shocks and leptokurtic returns. While the bivariate EGARCH model generates volatility series,[26] to compute the time-varying conditional correlations, I use the dynamic conditional correlation (DCC) extension from Engle (1982). This variation allows the conditional correlation matrix to be time-varying.

The bivariate DCC-EGARCH model involves a two-step approach based on the likelihood function; first, I estimate the univariate EGARCH model for each of the bond and stock market return series (for each country), and second, I estimate the conditional correlation using the transformed residuals from the first step. Separating the univariate specs from the dynamic conditional correlation specification makes the estimation more robust (Engle (2002)). The univariate EGARCH model has a conditional first moment or mean equation of ARMA(1,1)[27] and a conditional second moment or variance equation of EGARCH(1,1), where AR captures the effect of regressing Y_t on Y_{t-1} i.e., its own

[26] I assess the validity of the model using model diagnostics for different specifications (for e.g., standard versus exponential GARCH, normal versus student's t-distribution). The Schwartz Information Criterion (Schwartz IC) is one of the factors to evaluate GARCH models. The model with the lowest Schwartz IC is preferred because it penalizes less for the number of parameters added.

[27] the ARMA order of (1,1) stands for the number of autoregressive terms and moving average terms which are needed to eliminate the univariate serial correlations in standardized residuals.

lagged values or the respective asset Y's past performance, and the MA term is the linear combination of error terms occurring simultaneously and at various points in the past. Following Engle (2002), the DCC class of bivariate GARCH estimators is a generalization of Bollerslev (1990)'s constant conditional correlation (CCC) estimator. The DCC estimator differs in allowing the correlation matrix R containing the conditional correlations to be time-varying, such that:

$$H_t = D_t R_t D_t, \quad \text{where} \quad D_t = \text{diag}\left\{\sqrt{h_{i,t}}\right\} \tag{2.2}$$

where R_t is the time-varying correlation matrix, h contains the univariate (E)GARCH models, D is a diagonal matrix with the conditional volatilities (using the GARCH models). The detailed derivations are outlined in Engle (2002). Moreover, the bivariate EGARCH model estimation using a bivariate ARMA and the conditional covariance equation estimation are outlined in Kim, Moshirian and Wu (2006). The specification of the correlation matrix from the bivariate DCC-EGARCH model can be simply described as follows (from Kim, Moshirian and Wu (2006)):

$$\rho_{BS,t} = \frac{\sigma_{BS,t}}{\sqrt{\sigma_{B,t}\sigma_{S,t}}} \quad \text{where} \quad \sigma_{BS,t} = \delta_0 + \delta_1\sqrt{\sigma_{B,t}\sigma_{S,t}} + \delta_2\sigma_{BS,t-1} \tag{2.3}$$

where $\sigma_{BS,t}$ is the conditional covariance equation that varies over time and is formulated based on the cross-product of standard errors of the stock and bond market returns as well as the past conditional covariance. $\rho_{BS,t}$ is the time-varying conditional correlation, which represents the contemporaneous correlation between the bond and stock return series and reflects the pricing of common information at any point. The bivariate DCC-EGARCH model captures correlation clustering, which is a stylized fact in financial time series (e.g., Connolly, Stivers and Sun (2005)). For instance, a shock in period t-1 may also impact the correlation in period t. Correlation and volatility clustering are typical reasons for using GARCH models (e.g., Kim, Moshirian and Wu (2006)). In plots of the squared residuals from the ARMA(1,1) model (i.e., the residuals from regressing the asset return on its lagged values), they exhibit typical GARCH-like patterns, where they suddenly rise then dampen to a near-average level. This again confirms such stylized facts in this study's sample. The extracted dynamic conditional correlation series is the dependent variable in the main analysis of this study.

Table 2.4 reports the bivariate DCC-EGARCH model estimates of the conditional volatility spillovers between bond and stock returns. First, I report the estimates of the mean and variance equation (from fitting a univariate EGARCH with student's t-distribution) for stock and bond market returns, respectively. Then, in the last panel of table 2.4 I report the DCC estimates for the conditional correlation and covariance part.

In all countries, a negative significant *alpha*1 indicates a leverage effect, which suggests that the volatility of the time series is more sensitive to negative shocks than positive shocks. The *shape* parameters are all significant, confirming that the student's t-distribution is appropriate for the model. In the case of joint insignificance of the *alpha*1 and *beta*1 terms, this indicates that the EGARCH(1,1) does not make sense for the given bond or stock series. This is not the case, as reported in the table. In most countries and both bond and stock specifications, the two terms are jointly significant[28]. Moreover, the DCC estimates *dcca*1 and *dccb*1 are highly significant in all countries, which suggests DCC(1,1) is the correct choice for the model.

Figure 2.2 plots the time-varying conditional correlations for stock and bond returns over the period of July 2004-September 2018 for the UK and Germany, and July 2004-February 2020 for the US (for which I have more recent data)[29]. The largest drop in correlations (< -0.70) is seen during June 2016 in the aftermath of the Brexit vote. As a result of the vote, stock market crashes occurred around the world, with many investors fleeing into "safe havens". A particularly dramatic drop in correlations is seen in the United Kingdom after the Brexit vote (correlations dropped by approximately 0.77 or 77%). Moreover, a large drop in correlations occurred on November 2nd, 2004, in all three countries following large increases in pessimistic sentiment on the previous day. This coincides with a rise in investor concerns around the U.S. 2004 presidential election. This example provides a simple illustration of how *sent* and cor_{sb} are related.

[28] In a few exceptional cases, *alpha*1 is insignificant in spite of a significant *beta*1. This indicates there is no sign effect, but the coefficient on the EGARCH term is significant.

[29] For the sake of brevity, the plots for the rest of the countries are available upon request.

Table 2.4
Bivariate DCC-EGARCH model estimates of the conditional volatility spillovers between bond and stock returns

Parameter	USA	BEL	CHE	DEU	ESP	FRA	GBR
Mean (S):							
mu	0.056***	0.048***	0.040***	0.055***	0.028*	0.042**	0.033*
	(0.011)	(0.011)	(0.009)	(0.017)	(0.015)	(0.019)	(0.018)
*ar*1	0.310***	-0.847***	-0.198***	0.296***	-0.325***	-0.254***	0.540***
	(0.006)	(0.011)	(0.010)	(0.007)	(0.007)	(0.007)	(0.006)
*ma*1	-0.350***	0.868***	0.231***	-0.258***	0.340***	0.260***	-0.549***
	(0.008)	(0.011)	(0.010)	(0.007)	(0.006)	(0.007)	(0.007)
Variance (S):							
omega	-0.008**	-0.007**	-0.011***	-0.005	0.002	-0.004	-0.008**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.005)	(0.004)
*alpha*1	-0.155***	-0.105***	-0.149***	-0.127***	-0.104***	-0.143***	-0.128***
	(0.011)	(0.009)	(0.010)	(0.013)	(0.008)	(0.010)	(0.019)
*beta*1	0.979***	0.978***	0.974***	0.979***	0.981***	0.978***	0.983***
	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)	(0.002)	(0.004)
*gamma*1	0.144***	0.182***	0.139***	0.135***	0.120***	0.130***	0.132***
	(0.024)	(0.019)	(0.001)	(0.045)	(0.012)	(0.029)	(0.053)
shape	7.655***	7.433***	7.782***	7.184***	8.271***	9.327***	9.186***
	(0.800)	(0.691)	(0.901)	(0.779)	(0.933)	(1.214)	(1.238)
Mean (B):							
mu	0.023***	0.029***	0.020***	0.027***	0.021***	0.029***	0.023***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
*ar*1	0.644***	-0.132***	0.579***	-0.267***	-0.151***	-0.242***	-0.408***
	(0.035)	(0.006)	(0.013)	(0.022)	(0.013)	(0.007)	(0.010)
*ma*1	-0.661***	0.189***	-0.545***	0.312***	0.222***	0.269***	0.432***
	(0.034)	(0.009)	(0.014)	(0.022)	(0.014)	(0.008)	(0.010)
Variance (B):							
omega	-0.011*	-0.047**	-0.040***	-0.020***	-0.017***	-0.028*	-0.010***
	(0.006)	(0.024)	(0.012)	(0.005)	(0.006)	(0.016)	(0.001)
*alpha*1	0.021***	-0.017*	0.010	0.005	-0.031***	0.002	0.008
	(0.006)	(0.010)	(0.009)	(0.006)	(0.008)	(0.007)	(0.006)
*beta*1	0.993***	0.980***	0.984***	0.991***	0.991***	0.988***	0.995***
	(0.003(	(0.010)	(0.004)	(0.002)	(0.003)	(0.007)	(0.000)
*gamma*1	0.091***	0.134***	0.133***	0.081***	0.116***	0.102***	0.062***
	(0.012)	(0.027)	(0.017)	(0.007)	(0.014)	(0.014)	(0.001)
shape	11.062***	7.027***	4.597***	7.939***	0.956***	7.447***	9.429***
	(1.533)	(0.626)	(0.291)	(0.780)	(0.018)	(0.695)	(1.189)
DCC fit (Covariance):							
*dcca*1	0.049***	0.028***	0.030***	0.040***	0.021***	0.032***	0.037***
	(0.010)	(0.005)	(0.006)	(0.009)	(0.005)	(0.007)	(0.009)
*dccb*1	0.928***	0.960***	0.936***	0.940***	0.976***	0.954***	0.938***
	(0.017)	(0.009)	(0.014)	(0.016)	(0.007)	(0.011)	(0.018)
mshape	8.557***	7.439***	6.184***	7.280***	7.534***	7.870***	8.729***
	(0.582)	(0.446)	(0.332)	(0.479)	(0.500)	(0.515)	(0.662)
Diagnostics:							
Log-Likelihood	-9316	-7559	-6168	-7658	-9042	-7919	-7778
Schwartz IC	3.701	3.105	2.540	3.145	3.711	3.251	3.194

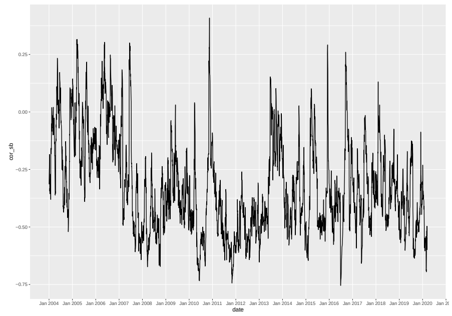
Table continued next page.

Table 2.4 (continued)

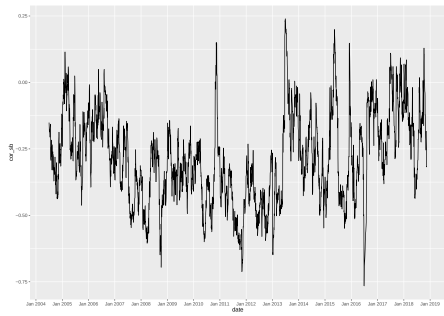
Parameter	ITA	NLD	POL	SWE	AUS	CAN	JPN
Mean (S):							
mu	0.020	0.039***	0.036*	0.057***	0.036*	0.060***	0.043***
	(0.020)	(0.008)	(0.019)	(0.012)	(0.020)	(0.009)	(0.015)
*ar*1	0.955***	0.137***	-0.195***	-0.889***	0.980***	0.047***	0.451***
	(0.003)	(0.007)	(0.049)	(0.017)	(0.005)	(0.010)	(0.007)
*ma*1	-0.931***	-0.091***	0.249***	0.895***	-0.965***	-0.008	-0.410***
	(0.003)	(0.005)	(0.054)	(0.017)	(0.000)	(0.012)	(0.008)
Variance (S):							
omega	-0.002	-0.001	0.002	0.000	-0.009***	-0.009***	0.006
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)
*alpha*1	-0.139***	-0.118***	-0.043***	-0.112***	-0.115***	-0.087***	-0.132***
	(0.013)	(0.009)	(0.008)	(0.009)	(0.013)	(0.009)	(0.018)
*beta*1	0.987***	0.982***	0.986***	0.985***	0.988***	0.987***	0.962***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.007)
*gamma*1	0.108***	0.137***	0.126***	0.137***	0.107***	0.139***	0.173***
	(0.016)	(0.012)	(0.014)	(0.014)	(0.014)	(0.013)	(0.015)
shape	7.506***	9.501***	6.154***	8.273***	9.191***	7.437***	6.628***
	(0.782)	(1.145)	(0.651)	(0.904)	(0.186)	(0.719)	(0.606)
Mean (B):							
mu	0.027***	0.028***	0.023***	0.027***	0.024***	0.024***	0.011***
	(0.005)	(0.004)	(0.002)	(0.004)	(0.006)	(0.004)	(0.002)
*ar*1	-0.350***	-0.191***	-0.634***	0.033***	0.489*	0.679***	0.472***
	(0.010)	(0.041)	(0.003)	(0.009)	(0.266)	(0.005)	(0.021)
*ma*1	0.401***	0.233***	0.640***	0.062***	-0.545**	-0.692***	-0.508***
	(0.009)	(0.038)	(0.003)	(0.011)	(0.253)	(0.006)	(0.019)
Variance (B):							
omega	-0.020***	-0.025	0.008***	-0.040	-0.006***	-0.036***	-0.017***
	(0.006)	(0.024)	(0.003)	(0.056)	(0.001)	(0.008)	(0.005)
*alpha*1	-0.039***	0.002	-0.124***	0.015*	0.011*	0.008	-0.013
	(0.009)	(0.007)	(0.031)	(0.008)	(0.006)	(0.007)	(0.009)
*beta*1	0.990***	0.989***	0.988***	0.983***	0.997***	0.982***	0.995**
	(0.003)	(0.009)	(0.00)	(0.023)	(0.000)	(0.004)	(0.002)
*gamma*1	0.128***	0.090***	0.385***	0.103***	0.060***	9.686***	0.168***
	(0.015)	(0.023)	(0.046)	(0.030)	(0.002)	(1.118)	(0.021)
shape	6.248***	8.435***	2.100***	7.440***	8.088***	0.029***	4.566***
	(0.513)	(0.890)	(0.002)	(0.794)	(0.848)	(0.007)	(0.283)
DCC fit (Covariance):							
*dcca*1	0.033***	0.026***	0.014***	0.029***	0.027***	0.029***	0.016***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.009)	(0.007)	(0.005)
*dccb*1	0.963***	0.959***	0.976***	0.950***	0.964***	0.955***	0.976***
	(0.007)	(0.011)	(0.009)	(0.011)	(0.015)	(0.014)	(0.009)
mshape	7.166***	8.074***	4.000***	7.800***	8.500***	8.028***	5.321***
	(0.444)	(0.554)	(0.098)	(0.521)	(0.586)	(0.520)	(0.240)
Diagnostics:							
Log-Likelihood	-8860	-7773	-10415	-8258	-8107	-7257	-5515
Schwartz IC	3.633	3.192	4.501	3.389	3.327	2.982	2.275

This table reports estimates of the mean and variance equations (univariate GARCH), followed by the DCC estimates and the model diagnostics. *mu* denotes the coefficient on the constant term, *ar*1 the coefficient on the AR term, and *ma*1 the coefficient on the MA term. *omega* denotes the coefficient on the constant term, *alpha*1 denotes the coefficient on the asymmetry term capturing the sign effect, *beta*1 the coefficient on the EGARCH term referring to past variance, *gamma*1 the coefficient on the ARCH term capturing the size effect, and *shape* denotes the approximate degrees of freedom of the t-distribution. The *dcca*1 and *dccb*1 coefficients test the appropriateness of the DCC model, and *mshape* indicates the appropriateness of the student-t distribution. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

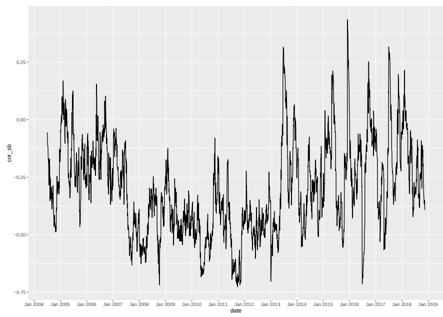
Figure 2.2
Time-varying conditional correlations - Stock-bond return comovement over time



United States



United Kingdom



Germany

This figure depicts the estimated time-varying daily conditional correlations between stock and bond returns cor_{sb} over the period July 2004-September 2018 for the UK and Germany, and over the period of July 2004-February 2020 for the US.

2.4 Panel regressions

Panel regressions allow us to exploit potential drivers of stock-bond return comovements, beyond the traditional set of stock and bond determinants. In fact, the Hofstede cultural factors could only be exploited in panel regressions, rather than time-series regressions, as they are time-invariant country-specific characteristics. I, therefore, run panel regressions of daily stock-bond return correlations on the main predictor variable in period t-1 and a set of controls. The following are the mainline specifications for the regressions with sentiment, uncertainty avoidance, and individualism respectively:

$$\rho_{BSi,t} = \alpha_{1i} + \alpha_{2i} S_{i,t-1} + \alpha_{Ci} C_{i,t-1} + \varepsilon_{it} \tag{2.4}$$

$$\rho_{BSi,t} = \alpha_{1i} + \alpha_{2i} U_{i} + \alpha_{Ci} C_{i,t-1} + \varepsilon_{it} \tag{2.5}$$

$$\rho_{BSi,t} = \alpha_{1i} + \alpha_{2i} I_{i} + \alpha_{Ci} C_{i,t-1} + \varepsilon_{it} \tag{2.6}$$

where the subscript i and t represent country i and day t, respectively. The independent variables $S_{i,t-1}$, U_i and I_i represent the time-varying pessimistic sentiment index, the time-invariant uncertainty avoidance index, and the time-invariant individualism index, respectively. Since the conditional correlation series are based on highly persistent conditional volatility patterns[30], I cluster the residuals by both country and time. Also, because the sentiment effect is more pronounced during decoupling episodes, and those episodes are not synchronized across countries, I use country*year fixed effects to separate this decoupling issue in regressions with sentiment as in equation 2.4 (See Petersen (2009) for a detailed discussion on robust t-statistics in similar panel settings)[31]. Also, since decoupling episodes may be closely related to periods of recessions and growths, which tend to vary on a year-to-year basis rather than a month-to-month or day-to-day basis, country*year fixed effects help separate this issue. In addition to country*year fixed effects,

[30] A spike in conditional volatility would stay high for a while, then it dampens down to its long-term level (Schwert (1990)). Spikes appear to occur on almost a year-to-year basis, in line with decoupling episodes.

[31] In line with the discussion in Petersen (2009), I test variants of these regressions. In robustness checks, I also use day and month fixed effects. The day and month dummies are insignificant and do not convey added value to the results.

I also use country fixed effects to control for time-invariant characteristics across countries (e.g., geography, local market size, local market accessibility, and other local market conditions). The panel regression results show that both country and country*dummies contribute to explaining stock and bond comovements. In regressions with uncertainty avoidance or individualism, I follow Chui, Titman and Wei (2010) and only cluster the residuals by country and time.

2.4.1 Sentiment and flights to quality

Table 2.6 reports the basic sentiment and stock-bond comovement results. The table includes the panel regressions of the estimated conditional correlation between bond and stock returns on the pessimism index and a set of controls. Columns (1), (2) and (3) include the univariate regressions with the pessimism index in periods t-1, t-2 and t-3 respectively. An increase in investor pessimism predicts a decrease in stock-bond correlations. A one-standard-deviation leads to approximately 0.30%[32] decrease in the conditional correlation the following day and an even further decrease by 0.42% the second day[33]. The increase in economic magnitude and statistical significance of the beta coefficient on sentiment in period t-2 suggests that the effect of sentiment is more pronounced on the second day. Perhaps this suggests that there is a gradual response to sentiment signals in terms of asset reallocation.

In line with evidence of temporary sentiment-induced effects in the market, on the third day, the effect of sentiment dissipates. Increased investor pessimism measured by *sent* suggests that investors have less confidence in the stock market performance, which exerts downward pressure on stock prices. Investors flee into the safety of treasury bonds (which are perceived as safe havens), and this bids up the prices of treasury bonds (flight

[32] The exact value is equal to 0.30 multiplied by the value of one standard deviation of the sentiment index. Although in the construction of *sent*, each search term has been standardized using z-scores to have a mean = 0 and a standard deviation = 1, the average across all search terms does not, in fact, have a standard deviation = 1 because there is a correlation among search terms (Da, Engelberg and Gao (2015)). Therefore, a one standard deviation change in *sent* leads to a $\sigma * \alpha_{2i}$ change in the dependent variable, whereas α_{2i} is the beta coefficient on *sent*.

[33] In unreported results, also test other variants of these regressions in line with suggestions in Petersen (2009). I first cluster at the country level. However, in regressions (4), (5), and (6), I double cluster the standard errors by both county and time to further ensure that standard errors would not be correlated across countries in crisis periods or in decoupling episodes. Although this inflates the standard errors, the results remain robust. In the rest of the regressions, I double cluster standard errors.

to quality). This leads to negative correlations. The temporary effect of sentiment and the relatively fast reversal patterns may be due to the fact that pessimistic periods are associated with less substantial underpricing than optimistic periods in which investors bid up stock prices and induce substantial overpricing in the stock market (Miller short-sale argument[34]). That is, in the presence of short-sale constraints, when sentiment is optimistic, its effect may take longer to disappear from the market (Stambaugh, Yu and Yuan (2012)). This is not the case in pessimistic periods, in which we see fast reversal patterns.

Columns (4) and (5) in Table 2.6 report the results of multivariate regressions controlling for a set of lagged controls (at t-1): consumer price index (CPI) inflation, dividend yield, short-term interest rate, GDP growth, expected inflation (inflation forecast), the overall stock and bond market return, in addition to controlling for financial development and sovereign credit rating represented by the interaction term $moody.rating * sent$. Once more, the effect of sentiment in period t-2 is stronger than in period t-1. After controlling for a set of fundamental factors, inflation uncertainty and growth uncertainty, as well as financial development, the results are still significant at the 5% level, as shown in column 5. Adding the interaction term $moodys.rating*sent$ changes the values of the beta-coefficient on *sent*. For example, in column (4), the effect of one unit increase in pessimistic investor sentiment leads to a decrease by 1.23% (-0.005544-0.00681) in stock bond-correlations the following day if a country has a high credit rating (AAA), i.e., high credit rating, increases the coefficient on sentiment. Therefore, credit rating is positively related to sentiment and moderates its effect to a certain extent. A similar pattern is observed in column (5).

Column 6 in Table 2.6 looks at whether market condition matters to the predictability of sentiment (for e.g., Baker, Wurgler and Yuan (2012); Connolly, Stivers and Sun (2005)). Whether the predictive power of sentiment with respect to stock-bond correlations is strictly limited to periods of decoupling episodes or bad states of the market is an important question. Following the definition in Baker and Wurgler (2012), *decoup.dummy* takes 1 when there is a decoupling episode (days in which stock and bond market returns move in opposite directions), and 0 otherwise. The regression of stock-bond return cor-

[34] See Stambaugh, Yu and Yuan (2012) for a detailed discussion of Miller's argument and sentiment-related mispricing.

Table 2.6
The effect of sentiment on estimated conditional correlations

	Dependent variable: cor_sb					
	(1)	(2)	(3)	(4)	(5)	(6)
$sent_{t-1}$	-0.00300**			-0.00554*		-0.00312*
	(0.00133)			(0.00280)		(0.00171)
$sent_{t-2}$		-0.00416***			-0.00470**	
		(0.00127)			(0.00208)	
$sent_{t-3}$			-0.00180			
			(0.00131)			
$cpi.inflation_{t-1}$				0.0248	0.0247	
				(0.0187)	(0.0187)	
dy_{t-1}				-0.00590	-0.00592	
				(0.0133)	(0.0133)	
$stir_{t-1}$				0.00773	0.00776	
				(0.00579)	(0.00579)	
$gdp.growth_{t-1}$				0.00725	0.00723	
				(0.0106)	(0.0106)	
$exp.inflation_{t-1}$				-0.0213	-0.0212	
				(0.0207)	(0.0207)	
$mretc_{t-1}$				-0.00163	-0.00161	
				(0.000963)	(0.000960)	
$b10retc_{t-1}$				-0.00987*	-0.00986*	
				(0.00468)	(0.00467)	
$moodys.rating * sent$						
$A3$				-0.0182***	-0.0168***	
				(0.00389)	(0.00428)	
Aaa				-0.00681*	-0.00476	
				(0.00338)	(0.00291)	
$Baa1$				-0.0472***	-0.0466***	
				(0.00200)	(0.00194)	
$decoup.dummy$						-0.0425***
						(0.00468)
Constant	5.76e-05***	-0.000546***	-0.00109***	-0.300***	-0.302***	0.0208***
	(7.74e-06)	(1.03e-05)	(1.25e-05)	(0.0698)	(0.0698)	(0.00228)
Observations	52,694	52,681	52,668	41,980	41,972	52,694
R-squared	0.750	0.750	0.751	0.749	0.749	0.757
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	C	C	C	CT	CT	CT

This table presents results from panel regressions of the pessimistic sentiment index on the estimated conditional correlations between stock and bond returns. The dependent variable cor_sb is the estimated conditional correlation series. Columns (1), (2) and (3) report the univariate regressions with *sent* at different lags as the only predictor variable. Columns (4) and (5) show the effect of sent in period $t-1$ and $t-2$ respectively after controlling for CPI inflation $cpi.inflation_{t-1}$, dividend yield dy_{t-1}, short-term interest rate $stir_{t-1}$, GDP growth $gdp.growtht-1$, inflation expectations $exp.inflation_{t-1}$, previous day stock market return $mretc_{t-1}$, previous day treasury bond market return $b10retc_{t-1}$, and an interaction term between Moody's sovereign rating for each country and the investor sentiment for each county $moodys.rating * sent$. I report in the table the significant $moodys.rating * sent$ interactions for the sake of brevity. I use country and country*year fixed effects, and use country clustered or double clustered standard errors at the country and year level and report them in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

relations on sentiment lagged by 1 day and the decoupling episodes' dummy shows that sentiment is still related to stock/bond correlations beyond periods of decoupling episodes. This is in spite of the pessimistic sentiment index being more useful in predicting stock and bond market decoupling. The decoupling dummy is highly significant and is, as expected, negatively strongly related to stock-bond comovements.

Contemporaneously, pessimistic investor sentiment is most strongly associated with cor_{sb} in univariate tests. In a forecast horizon of one day, the effect relatively weakens but is strongest in forecast horizons of 2 days[35]. This is consistent in most of the regression specifications in the paper. This suggests that effect of fear is more powerful in countries that are most prone to herding behavior (For instance, Japan, as the Japanese culture is highly regarded as a collectivistic culture and rank quite high on uncertainty avoidance). This is, in fact, true. In unreported results, time-series regressions in Japan show an extremely significant and large negative coefficient on *sent* during periods of high investor pessimism. A one unit increase in investor pessimism decrease stock-bond correlations by approximately 12%. In the following sections, I examine the effect of investor cultural factors in more detail.

Lastly, I recognize the limitations of these results. In table 2.6, the R-squared values from the panel regressions are quite high. One potential reason could be that the macroeconomic variables have high collinearity with the year dummies. In future versions of this paper, the omission of either time dummies or macro variables could be tested. Another potential solution to address the high R-squared values would be to use the first differences of the dependent variables.

2.4.2 Cultural characteristics and conditional correlations

Table 2.7 reports the independent effects of the investor's cultural background on the stock-bond comovements. The cultural baseline results show that uncertainty avoidance is strongly related to stock-bond correlations in both univariate and multivariate regressions. This is not the case for individualism, which is insignificant in univariate regressions in the first place. The uncertainty avoidance index *uncert* implies that the more conservative investors are in their risk perceptions and risk appetite, the more likely they are

[35] For the sake of brevity, contemporaneous univariate regression results are available upon request.

to have well-diversified portfolios that consist of relatively safe investments, regardless of local conditions (since *uncert* as a characteristic of individual investor behavior is time-invariant). The positive coefficient on *uncert* intuitively implies that investors may be more likely to invest in safe assets if the local stock and bond markets move in the same direction. The rationale behind this is that increased hedging behavior may serve as a safety cushion when country-specific or global shocks impact local financial markets. Controlling for fundamental and uncertainty-related variables as well as a country's financial development and treasury bond quality does not dampen down the relation between *uncert* and cor_{sb}.

Table 2.7
The effect of cultural characteristics on estimated conditional correlations

	Dependent variable: cor_sb			
	(1)	(2)	(3)	(4)
$uncert$	0.00420**		0.00608***	
	(0.00174)		(0.00166)	
$indiv$		-0.00399		-0.00654*
		(0.00366)		(0.00366)
$cpi.inflation_{t-1}$			0.0247	0.0151
			(0.0256)	(0.0349)
dy_{t-1}			0.0340*	0.0277
			(0.0157)	(0.0215)
$stir_{t-1}$			0.00678	0.00478
			(0.0131)	(0.0136)
$gdp.growth_{t-1}$			0.0171	0.00920
			(0.0106)	(0.0150)
$exp.inflation_{t-1}$			-0.0364	-0.0170
			(0.0248)	(0.0330)
$moodys.rating$			0.0259	0.00294
			(0.0229)	(0.0251)
$mretc_{t-1}$			-0.000509	-0.000501
			(0.00194)	(0.00221)
$b10retc_{t-1}$			-0.0135	-0.0125
			(0.00804)	(0.00840)
Constant	-0.450***	0.113	-0.823***	0.201
	(0.0889)	(0.291)	(0.216)	(0.318)
Observations	52,841	52,841	42,042	42,042
R-squared	0.128	0.043	0.259	0.122
Cluster	CT	CT	CT	CT

This table presents results from panel regressions of uncertainty avoidance *uncert* and individualism *indiv* on the estimated conditional correlations between stock and bond returns. The dependent variable $cor_s b$ is the estimated conditional correlation series. Columns (1) and (2) report the univariate regressions with *uncert* and *indiv* as the only predictor variable. Columns (3) and (4) show the effect of each of the cultural indices after controlling for CPI inflation $cpi.inflation_{t-1}$, dividend yield dy_{t-1}, short-term interest rate $stir_{t-1}$, GDP growth $gdp.growtht-1$, inflation expectations $exp.inflation_{t-1}$, previous day stock market return $mretc_{t-1}$, previous day treasury bond market return $b10retc_{t-1}$, and Moody's sovereign rating for each country to control for financial development and sovereign credit quality. I use double clustered standard errors at the country and year level and report them in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Although individualism seems to have no relationship with stock-bond correlations, it is negatively associated with the conditional correlations in multivariate regressions. Following the rationale of Chui, Titman and Wei (2010) in explaining individualism, it is related to overconfidence about information signals and self-attribution bias. Additionally, individualism is positively related to volatility. Therefore, investors in highly individualistic countries such as the United States tend to make investment choices that generate high returns. Individualism may not be directly related to cor_{sb}, but it moves opposite to *uncert*. Interestingly, in approximately half of the sample, highly individualistic countries rank lower on uncertainty avoidance (e.g., the US), and vice versa (e.g., Japan)[36]. Although individualism has an effect on the stock market (e.g., Chui, Titman and Wei (2010); Daniel, Hirshleifer and Subrahmanyam (2001)), it is unclear whether it affects the comovement between the two fundamental markets. In unreported results, the interaction term between individualism and sentiment is insignificant. Since individualism does not pass univariate regressions and does not seem to have a role in moderating the effect of sentiment, I focus solely on the former cultural index *uncert* in the remaining empirical analysis.

2.4.3 The effect of sentiment conditional on the uncertainty avoidance factor

Table 2.8 reports the results of sentiment conditional on Hofstede's uncertainty avoidance index. Table 2.7 already explains how investors' cultural backgrounds may influence stock and bond markets. Contrary to Chui, Titman and Wei (2010), in the specific setting of this study, the effect of individualism is not substantial. However, as uncertainty avoidance has a considerable effect on the stock-bond return correlation, in this table, I test whether *uncert* moderates the effect of sentiment in a cross-country analysis. The addition of country- and (country*time)-fixed effects panel regressions eliminates the time-invariant cultural index from the regressions. Therefore, I do not test the effect of sentiment controlling for culture as it is not possible to do so in this setting. However, I test how sentiment for different levels of uncertainty avoidance may influence stock and bond markets. The *uncert* index ranks countries on several uncertainty avoidance levels. For the

[36] Refer to Table 2.3.

sake of brevity, I report the interaction term $uncert * sent$ for low L, medium M, and high H levels. I include the two highest levels of uncertainty avoidance in the table because the extremely high levels of uncertainty avoidance, in particular, exhibit the strongest effects worth further analyzing.

Columns (1) and (2) in table 2.8 report the effect of *sent* at lags of 1 and 2 days conditional on uncertainty avoidance. In comparison with table 2.7, the coefficient on $sent_{t-1}$ and $sent_{t-2}$ is larger and is statistically significant at the 1% level after 1 and 2 days. Adding the interaction term $uncert * sent$ changes the values of the beta-coefficient on *sent*. For example, in column (1), when the level of uncertainty avoidance is highest, the effect of one unit increase in pessimistic investor sentiment leads to an increase of 0.163% (-0.00604+0.00767) in stock bond-correlations the following day. Controlling for a country's financial development and treasury bond quality in columns (3) and (4), in addition to the rest of the controls in columns (5) and (6), the results remain significant. However, it seems that when adding all the other controls to the panel regressions, the effect of *uncert* weakens, suggesting that the effect of cultural factors on sentiment may be subsumed by other variables.

Therefore, although cultural characteristics affect proneness to investor sentiment, it does so to a limited extent, and it is mainly the independent effect of sentiment that drives stock-bond correlations. The results highlight the complex relation between sentiment, cultural factors, and stock-bond correlations. Therefore, it would be interesting for more studies in the behavioral finance literature to address these interactions, especially since sentiment is a widely used explanatory variable in the literature, and sentiment dynamics are still widely researched and debated (For e.g., Devault, Sias and Starks (2019); Birru and Young (2022)).

2.5 Robustness tests: Disentangling liquidity

In a study of various determinants of stock and bond comovements, Baele, Bekaert and Inghelbrecht (2010) conclude that factors other than macroeconomic fundamentals play a more important role in explaining these time-variations. One important factor includes

Table 2.8
The effect of sentiment conditional on cultural characteristics

	Dependent variable: cor_sb					
	(1)	(2)	(3)	(4)	(5)	(6)
$sent_{t-1}$	-0.00604***		-0.00839***		-0.00834**	
	(0.00165)		(0.00238)		(0.00323)	
$sent_{t-2}$		-0.00785***		-0.00792***		-0.00773***
		(0.00158)		(0.00162)		(0.00222)
uncert*sent$_{t-k}$:						
$L.uncert * sent_{t-k}$	0.00647*	0.00989***	0.00692*	0.00993**	0.00662	0.00962*
	(0.00307)	(0.00287)	(0.00367)	(0.00358)	(0.00443)	(0.00485)
$M.uncert * sent_{t-k}$	0.00928**	0.00823**	0.00897**	0.00845**	0.00386	0.00554
	(0.00381)	(0.00297)	(0.00361)	(0.00362)	(0.00415)	(0.00533)
$H1.uncert * sent_{t-k}$	0.00778**	0.00881**	0.00949*	0.00886**	0.00921	0.00739
	(0.00338)	(0.00333)	(0.00491)	(0.00341)	(0.00604)	(0.00482)
$H2.uncert * sent_{t-k}$	0.00767**	0.00682*	0.0104**	0.00688*	0.00947*	0.00640
	(0.00303)	(0.00338)	(0.00436)	(0.00333)	(0.00494)	(0.00414)
Constant	4.01e-05	-0.000616***	-2.55e-05	-0.000652***	-0.300***	-0.302***
	(2.42e-05)	(2.85e-05)	(5.44e-05)	(4.28e-05)	(0.0698)	(0.0698)
Control variables	None	None	Fin Dvlpmt	Fin Dvlpmt	All	All
Observations	52,694	52,681	52,693	52,679	41,980	41,972
R-squared	0.750	0.750	0.750	0.750	0.749	0.749
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Country*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	CT	CT	CT	CT	CT	CT

This table presents results from fixed effects panel regressions of the pessimistic sentiment index conditional on cross-country cultural differences. I include in this table the interaction effects between sentiment and uncertainty avoidance. The dependent variable $cor_s b$ is the estimated conditional correlation series between stock and bond returns. Columns (1) and (2) report the regressions with sentiment moderated by the role of uncertainty avoidance *uncert*. $sent_{t-1}$ is the sentiment index in period $t-1$, and $sent_{t-2}$ is the sentiment index in period $t-2$. I report several levels of uncertainty avoidance, with L being the lowest level of uncertainty avoidance, M being the medium level of uncertainty avoidance, $H1$ and $H2$ being the highest and second highest levels of uncertainty avoidance. k stands for the number of sentiment lags in days; k=1 in columns (1), (3) and (5), and k=2 in columns (2), (4) and (6). Columns (3) and (4) include the control for financial development. Columns (5) and (6) include all control variables (CPI inflation, dividend yield, short-term interest rate, GDP growth, inflation expectations, previous day stock market return, previous day treasury bond market return, and the control for financial development ($moodys.rating * sent$). I use country and country*year fixed effects, and use double clustered standard errors at the country and year level and report them in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

liquidity[37], which they suggest may affect stock-movements in several ways. From a policy-making perspective, De Santis (2012) discusses the importance of disentangling the liquidity explanation from the flight-to-safety motive.

First, return comovements may be affected by how liquidity shocks comove across countries. For example, if there is a shock that improves liquidity, it may simply encourage trading activity in the more liquid market. Depending on how related are financial markets, this affects return comovements. Second, in crisis periods such as stock market crashes, investors may move away from stocks into highly liquid treasury bonds, which may lead

[37] See also Karolyi, Lee and Van Dijk (2012) which discusses commonality in liquidity across countries.

to negative comovements (see for e.g. De Santis (2012); Karolyi, Lee and Van Dijk (2012) for a discussion on the effect of liquidity). Of course, this is most likely to happen in countries in which treasury bonds are perceived as safe havens[38]. Therefore, illiquidity in stock markets may correlate with the flight-to-quality phenomenon, which is represented by shifts in the pessimistic sentiment index. This motivates the use of liquidity as a control variable in the following robustness test.

I rely on a price impact liquidity measure following Amihud (2002) and use firm-level data to construct a market illiquidity proxy. I initially apply the dynamic screens mentioned in section 2.2, which are in line with Ince and Porter (2006); Schmidt et al. (2017), and apply some additional screens to establish a minimum standard of data quality for the liquidity variable, such as: 1) If the price is equal to zero, the observation is set to missing, 2) If either price or volume is missing, the observation is set to missing, 3) Observations with suspiciously high returns are removed (Griffin, Kelly and Nardari (2010)). The illiquidity measure for each stock is calculated as follows:

$$illiq_{i,t} = log\left(1 + \frac{|R_{i,t}|}{P_{i,t}VO_{i,t}}\right), \tag{2.7}$$

where the subscript i and t represent firm i and day t, $|R_{i,t}|$ is the absolute return in local currency, $P_{i,t}$ is the stock price in local currency, $VO_{i,t}$ is the trading volume of stock i in day d, $illiq_{i,t}$ is the Amihud illiquidity proxy. I add a constant to the measure and take logs to reduce the impact of outliers (following Karolyi, Lee and Van Dijk (2012)). To calculate the daily market illiquidity proxy, I take the simple average per day.

Table 2.9 illustrates the results of a simple panel regression with the sentiment index and the liquidity measure and examines whether liquidity subsumes the effect of sentiment. The results show that this is not the case. Controlling for stock market liquidity, sentiment is still able to negatively influence stock-bond correlations, documenting flight to quality effects. As reported in table 2.9, a one-unit increase in pessimistic investor sentiment is followed by a decrease of approximately 0.304% on the first day and 0.528% on the second

[38] Therefore, I include in my sample the top world economies, which also comprise, to a large extent, developing countries. Hence, I additionally control for financial development and bond credit quality in panel regressions.

day. Perhaps investors flee into the safety of treasury bonds simply because investors are seeking downside protection, rather than demanding liquidity. In fact, the effect is stronger in the second day which suggests that this may be some sort of an "information cascade". Similar to information cascades, the effect may be sequential as investors exhibit herding behavior (Borensztein and Gelos (2003)). Perhaps future research could shed further light on sentiment vs. liquidity as it is beyond the study's research focus. For instance, it would be interesting to examine flights to quality vs. flights to liquidity effects in more detail (as highlighted by De Santis (2012)), even including a bond market liquidity measure for a large sample of countries and examining whether sentiment is able to predict stock and bond market liquidity or illiquidity.

Table 2.9
Sentiment and liquidity

	Dependent variable: cor_sb	
	(1)	(2)
$sent_{t-1}$	-0.00317*	
	(0.00165)	
$sent_{t-2}$		-0.00465**
		(0.00179)
illiquidity	-0.00533	-0.00532
	(0.00465)	(0.00465)
Constant	0.00212	0.00151
	(0.00125)	(0.00125)
Observations	51,185	51,171
R-squared	0.750	0.750
Country FE	Yes	Yes
Country*Year FE	Yes	Yes
Cluster	CT	CT

This table presents results from bivariate tests of sentiment while controlling for illiquidity. The dependent variable $cor_s b$ is the estimated conditional correlation series between stock and bond returns. $sent_{t-1}$ is the sentiment index in period $t-1$, and $sent_{t-2}$ is the sentiment index in period $t-2$. I use country and country*year fixed effects, and use double clustered standard errors at the country and year level and report them in the parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

2.6 Conclusion

Several studies examine the effect of sentiment on the aggregate stock market, the cross-section of stock returns, and less often, on the bond market. Bond prices and equity prices tend to move in opposite directions during crisis periods or periods of increased stock market uncertainty, which leads to smaller losses in balanced portfolios that comprise stocks and bonds. Investors turn to treasury bonds for downside protection, as they are often perceived as safe havens. In the U.S. over the last two decades, negative stock-bond return correlations were often observed and consequently examined in several papers (e.g., Baele, Bekaert and Inghelbrecht (2010); Connolly, Stivers and Sun (2005)). Although several papers investigate the comovement relationship in general, particular attention is paid to decoupling episodes, in which the correlation between bond and stock markets drops to a negative level. Recent evidence points to the importance of non-fundamental variables that drive this time variation, such as uncertainty (e.g., Connolly, Stivers and Sun (2005)) and investor sentiment (e.g., Baker and Wurgler (2012)), among other variables.

In this study, I use Google search volume (following the methodology of Da, Engelberg and Gao (2015)) to measure daily sentiment and construct a sentiment index based on negative household search behavior. Direct measures of sentiment (extracted from online search behavior, news media, or social media) may estimate investor sentiment more precisely, are available at a higher frequency, could be measured for most countries, and are becoming widely popular in the literature. Examining a broad sample of 14 countries and controlling for a wide set of variables, the results indicate that increased investor pessimism negatively affects stock-bond return correlations in the 2 following days. Increased individual investor concerns contribute to explaining flights to quality as well as the stock-bond return comovements beyond decoupling episodes. Additionally, it seems that investors may flee to the safety of treasury bonds ultimately because they seek downside protection, rather than access to liquidity.

Moreover, the role of investor characteristics (particularly cultural factors) may play an important role in moderating the effect of sentiment. For instance, Kostopoulos, Meyer and Uhr (2020b) consider the effect of individual investor sentiment (measured also using Google search volume) conditional on investor characteristics (such as age, academic title, and gender) in Germany. They find that less sophisticated investors are more prone to sentiment. In another study, Chui, Titman and Wei (2010) show that individualism (one of Hofstede (2001)'s cultural factors) has an important effect on stock return patterns. However, they do not link culture to sentiment in the study. This paper exploits cross-country cultural differences measured with Hofstede (2001)'s uncertainty avoidance index and individualism index, and examines the the effect of investor sentiment conditional on cultural factors, as well as the independent effect of cultural factors on return comovement. This second part of the analysis extends and builds on growing evidence in the literature suggesting that investors are influenced by their cultural backgrounds, which leads them to interpret information in a different manner and make different investment choices (i.e. they are influenced by cultural biases). To my knowledge, no other study looks at the role of investor sentiment and cultural factors in driving return comovement. This may potentially contribute to explaining stock and bond return comovement, beyond the role of common economic sources such as inflation, interest rates, and output growth.

The results indicate that uncertainty avoidance plays an important role. It is positively related to bond-stock return correlations, suggesting that, in general, investors in countries that have higher conservatism in risk assessment tend to have more balanced portfolios in the first place and, therefore, may suffer fewer losses when stock and bond markets decouple. Finally, in spite of the role of individualism in the behavioral finance literature (e.g., Chui, Titman and Wei (2010); Corredor, Ferrer and Santamaria (2013); Schneider, Fehrenbacher and Weber (2017), findings in this paper indicate that it does not play a significant role in this context, or is subsumed by other variable in my analysis. Moreover, conditioning on the investor's cultural background, the effect of sentiment is more pronounced (in line with explanations in Schmeling (2009)). I observe a positive moderating effect of uncertainty avoidance, suggesting that investors in countries that rank highest on uncertainty avoidance are more conservative in general and subsequently more influenced by pessimistic sentiment, perhaps because they are more influenced by behavioral biases.

3 Sentiment Trading, Stock Ownership and Investor Demand

Abstract

This paper investigates how retail investor sentiment affects stock demand in the cross-section, focusing on the U.S. equity market. Employing panel regressions for a sample period of 2004-2020, we find that when sentiment goes up, retail demand increases. Our findings unfold a nuanced relationship; in the first place, it seems that retail investors buy low volatility stocks when sentiment increases. When disentangling the momentum from the volatility effect, we find that retail investors are, in fact, buying stocks that were past winners. Similarly, when controlling for past performance effects, retail demand increases for high volatility stocks when sentiment increases. The results are largely consistent with theories of investor sentiment and offer a deeper understanding of retail investors' investment choices in response to sentiment changes.

Key words:	Retail Investors, Institutional Investors, Demand Shocks, Share Ownership, Investor Sentiment, Cross-Section of Stocks
JEL Codes:	G11, G23, G40, G59

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Current Status:	Working Paper
Note:	In this chapter I use the first-person plural narrative.

3.1 Introduction[1]

Up until the mid-2000s, there was no empirical consensus on the effect of sentiment in the market. Baker and Wurgler (2006) first construct an investor sentiment index consisting of five main sentiment proxies based on market-based measures, such as closed-end fund discount and number of IPOs per year, and demonstrate that this index effectively forecasts market returns. Thereafter, a large number of studies have adopted this index and shown evidence of its effect on the cross-section of stocks, on the aggregate market level, as well as in relation to market anomalies (e.g., Baker, Wurgler and Yuan (2012); Stambaugh, Yu and Yuan (2012); Huang et al. (2015)). For instance, when investor sentiment decreases, it leads to a downward pressure on asset prices. The sentiment effect is temporary, and therefore, we typically observe a return reversal over the following periods. Looking at the cross-section of stocks, in particular, we would observe that when sentiment increases, the propensity to speculate increases and investors shift from lower volatility to higher volatility stocks (e.g., Baker and Wurgler (2006); Tetlock (2007)).

It is widely assumed in the literature that these sentiment-induced shifts in investor demand are attributed to individual investors, who are more prone to sentiment (e.g., Lee, Shleifer and Thaler (1991); Lemmon and Portniaguina (2006); Kumar and Lee (2006); Renault (2017); Kostopoulos, Meyer and Uhr (2020b)). The trading behaviors of individual investors, driven by bullish or bearish sentiment, would impact market prices and efficiency. Devault, Sias and Starks (2019) argue otherwise. The authors find that the widely adopted Baker and Wurgler (2006) investor sentiment index captures institutional investors' demand shocks rather than individual investors' demand shocks. This has important implications worth further investigation: Their findings suggest that institutions are sentiment traders rather than retail investors. Their research further sheds light on the complexity of the relationship between institutions, individuals, and sentiment metrics. It also disrupts our traditional understanding that individual investors are the drivers of the return patterns documented in the sentiment literature and, hence, should be further researched.

[1] We thank participants at the TUM School of Management, Finance Department, 2023 PhD Workshop for helpful comments and suggestions. We thank Daniel Schmidt for providing institutional ownership data, and Theo Beffart for help in data collection. We thank the Deutscher Akademischer Austauschdienst (DAAD) for financial support, which included a research scholarship.

Retail sentiment is prone to noise and bias, and therefore, a large significance is placed on the methods by which sentiment is measured. Acknowledging the evolving nature of sentiment analysis techniques, researchers are able to extract vast textual data from online platforms or rely on advanced sentiment lexicons to gain a deeper understanding of sentiment dynamics. This gave rise to several other investor sentiment indices, which rely on direct estimates of sentiment. Da, Engelberg and Gao (2015) construct an investor sentiment index based on household concerns extracted from Google search data and argue that this measure serves as an important indicator of market sentiment, influencing market returns, excess volatility, and investment choices. Therefore, this paper focuses on this newer sentiment metric based on Da, Engelberg and Gao (2015) and investigates whether it serves as a better gauge for retail investor sentiment. We also propose that due to the way this metric is constructed, it appears to capture the individual investor demand shocks better. Moreover, we examine in our empirical analysis the main economic mechanisms that explain the relation between investors, sentiment, and trading decisions.

The paper also extends on the research of Devault, Sias and Starks (2019). It builds on the literature documenting the cross-sectional return patterns in relation to sentiment, as well as retail investor trading, which has been shown to be inconsistent by Devault, Sias and Starks (2019). Since investor sentiment has been used as a main explanatory variable in the literature (for instance, to explain value premium, momentum, anomalies, analyst forecast errors, etc.), and its role analyzed in various domains of the literature, it is essential to address the current lack of consensus on which group of investors is behind the documented effects of sentiment in the literature, and to further analyze the potential sentiment channels in the market.

We focus on the United States equity market for the period from January 2004 to December 2019. To build our main dataset, we extract equity return data from CRSP, the quarterly fraction of institutional and retail ownership from FACTSET (as the FACTSET database includes quarterly stock holdings data), as well as search data from Google Trends. We then construct a market-wide investor sentiment index following closely Da, Engelberg and Gao (2015)[2], and measure our main retail ownership variable, as well as

[2] We also follow Gao, Ren and Zhang (2019), and use both negative and positive search terms to form a net sentiment index. We elaborate on this methodology in the Data section.

volatility variables. Next, using different specifications in the model variants, we run panel regressions of change in retail ownership on the net sentiment index and a set of controls, including fixed effects.

The main findings of this paper can be summarized as follows. When sentiment goes up, retail demand increases. Retail investors are now net buyers of stocks. In other words, if sentiment increases, we observe an increased propensity to buy stocks. This is intuitive and similar to what we find in the general sentiment literature (e.g., Kostopoulos, Meyer and Uhr (2020b)). We further validate this result by dividing the sample into high and low sentiment periods in the first panel regressions. We find that in high-sentiment periods, retail investors are net buyers, while in low-sentiment periods, retail investors are net sellers of stocks. This reinforces our primary finding. In the first place, it seems that retail demand increases more for low-volatility stocks when investor sentiment increases. We further investigate this result as it seems rather counter-intuitive, especially since our preliminary findings and cross-sectional correlation tests point to otherwise. We test whether this result is in fact driven by volatility or past stock performance. It is well-known in the literature that contemporaneous returns are negatively related to changes in volatility (e.g., Black (1993), Falkenstein (1994), among others)). Therefore, we next substitute in our analysis volatility with past stock performance. We find that if we disentangle the pure volatility effect from past performance, retail investor demand goes up more for high volatility stocks when net sentiment increases. This suggests that when sentiment increases, retail investors are buying stocks which were winners over the past weeks or months. Such stocks with high past performance tend to have below average volatility. Consequently, the underlying mechanism is that the relation of sentiment to stock demand is moderated by past performance effects (which in turn affect volatility).

These striking patterns suggest that retail investors do not move opposite to the direction hypothesized in the literature, but rather that the underlying mechanism of retail investor sentiment in the market is more complex than previously thought. Moreover, whilst the Baker and Wurgler (2006) investor sentiment index appears to capture institutional investor demand (as suggested by Devault, Sias and Starks (2019)), our results imply that a more direct measure of individual investor sentiment such as the sentiment metric we use in this paper, captures retail investor behavior with higher precision.

Since we focus on a quarterly sentiment index to match the stock ownership data which is available on a quarterly basis, we run a preliminary test to explore the predictive power of the quarterly net sentiment index.[3] In contemporaneous regressions of the quarterly net sentiment index of the quarterly mean of stock returns, we find that a one standard deviation increase in the net sentiment index is correlated with a 0.02% decrease in the quarterly average of stock returns. This is followed by a return reversal over a forecast horizon of two quarters. This is in line with evidence of temporary sentiment-induced effects attributed to retail investors.

In robustness checks, we first use a lagged volatility indicator instead of current volatility. We find that our results are robust to the choice of quarter in which the stock volatility is calculated. Next, we measure relative volatility, i.e., the difference between stock volatility and market volatility, and find that our findings remain unaffected by using relative volatility. Finally, we challenge our last main finding related to the potential sentiment channel. We use the previous quarter to measure stock performance and compute our winner stocks' indicator. In line with return reversal patterns attributed to the temporary effects of retail investor sentiment, we should expect to see a reversal in retail trading behavior over the next quarter. The result of our last robustness test confirms these patterns, as we observe a reversed effect when looking into the preceding quarter.

In short, our results show that retail investor demand shocks are meaningfully related to stock returns, consistent with a large body of prior research and general interpretations of retail sentiment. However, our findings are also partially in line with the paper of Devault, Sias and Starks (2019), as we point out that a different sentiment metric from Baker and Wurgler (2006) may capture retail investor demand shocks more precisely. We suggest that sentiment channels may be more complex than previously thought.

The paper is organized as follows. We discuss the data in section 3.2. Section 3.3 presents time-series correlation tests between the net sentiment index and the cross-sectional average retail investor demand shocks by volatility decile. Section 3.4 examines in panel regressions the relationship between sentiment and individual investors' demand shocks. Section 3.5 presents the robustness tests. Section 3.6 concludes.

[3] Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019) extensively analyze the predictive power of the daily and weekly version of this index, respectively. Since we do not position our paper as a return predictability paper in the first place, we do not run extensive analyses in this direction.

3.2 Data description and statistics

3.2.1 Data

We use data collected from various sources in this study. First, we obtain US equity data from the Center for Research on Security Prices (CRSP) for the period from January 1st, 2004 to December 31st, 2019. We restrict the sample to ordinary securities (share codes 10 and 11) listed on NYSE, AMEX, and NASDAQ within the CRSP universe[4].

Next, using data on all quarterly holdings per institution from the FactSet database, we obtain the fraction of institutional and retail ownership in quarterly stock holdings. We then match this data with our stock data from CRSP and end up with a final sample of 7,847 unique firms.

To construct a proxy for individual investor sentiment, we rely on data from Google Trends[5]. We largely follow the methodology in the paper of Da, Engelberg and Gao (2015), in which they construct a novel FEARS (Financial and Economic Attitudes Reveal by Search) index based on aggregating millions of daily search queries generated by the Google Trends website. We elaborate on this methodology and the construction of our market-wide sentiment measure in the following section.

3.2.2 Main variables construction

To examine the relationship between retail ownership, institutional ownership, investor sentiment metrics, and stock characteristics, we construct a range of variables from various data sources. In this section, we describe the construction of the sentiment metric, quarterly retail ownership, institutional ownership variables, and volatility (for the construction of volatility portfolios).

3.2.2.1 Investor sentiment

One prominent investor sentiment metric is constructed by Baker and Wurgler (2006) (BW sentiment index, hereafter), which has been widely adopted in the literature. The BW

[4] We apply the standard filters in the literature (exclude penny stocks, remove returns for stocks that are off-exchange, and adjust for delisted returns).
[5] http://trends.google.com/trends/

sentiment index is based on the first principal component of a set of standardized sentiment proxies, which have been first orthogonalized with respect to a set of macroeconomic variables. The sentiment proxies include the number and average of first-day returns on IPOs, the dividend premium, the closed-end fund discount, and the equity share in new issues. Higher (lower) values of the BW sentiment index indicate more investor optimism (pessimism) in the market. Huang et al. (2015) adopt a different version of the Baker and Wurgler (2006) index, mainly by using the partial least squares method rather than principal component analysis. The authors claim that this alternative investor sentiment index performs better in out-of-sample tests.

It has been widely assumed in the literature that market-based sentiment measures, due to the way they are constructed, capture individual investors' sentiment. In return, the sentiment literature suggests that sentiment-induced mispricing is driven by individual investors. Interestingly, Devault, Sias and Starks (2019) find striking results that suggest otherwise. Their findings show that the popular BW sentiment index captures institutional investors' demand shocks rather than individual investors' demand shocks.

The underlying mechanism behind investor sentiment indices is that investors (or sentiment traders) shift to more speculative stocks when their propensity to speculate increases, bidding up the prices of these stocks, and they eventually earn lower subsequent returns. According to Devault, Sias and Starks (2019), their main findings are based on the market-clearing condition, in which changes in investor demand (in response to changes in sentiment) are offset by the supply of traders who are less prone to changes in sentiment. They emphasize that changes in investor sentiment should be positively related to changes in investor demand (that is, sentiment traders' demand shocks) for speculative stocks and inversely related to investor traders' demand for safe stocks. Particularly, they find that an increase in the BW sentiment index is associated with an increase in institutional investors' demand for speculative stocks and, following the market clearing condition, a decrease in individual investors' demand for safe stocks.

Whether these results imply that sentiment metrics, in general, capture institutional investors' demand shocks remains an open question. This is because Devault, Sias and Starks (2019) consider sentiment metrics, such as the BW sentiment index, the individual components of the BW sentiment index, mutual fund flows, survey-based measures of consumer confidence, among other similar variables. Most of these measures estimate investor sentiment gauged through surveys, market-based, or indirect sentiment proxies. Other newer sentiment metrics are assumed to be more *direct* measures of investor sentiment. One particularly interesting metric is a market-wide sentiment measure extracted from Google searches. Da, Engelberg and Gao (2015) construct a FEARS (Financial and Economic Attitudes Revealed by Search) index based on daily internet search volume in the United States extracted from Google Trends.[6] Since then, their methodology and research have been cited in many papers in the areas of behavioral finance and asset pricing, among others (for e.g., Smales (2017), Gao, Ren and Zhang (2019), Kostopoulos, Meyer and Uhr (2020b), and Zechner, Pagano and Wagner (2020)). Da, Engelberg and Gao (2015) find a significant and powerful predictive power of daily FEARS on stock market returns over two consecutive days in the period from 2004 to 2011. Their findings show that high FEARS (or investor pessimism) is associated with low returns today and low returns over the following two days. Therefore, their results document strong return prediction patterns followed by a strong reversal effect consistent with evidence of sentiment-induced temporary mispricing in the market.

The objective of our sentiment methodology is to build a list of search terms that are good indicators of individual investor sentiment. By doing so, we are able to construct a measure that *directly* captures aggregate sentiment in the market with high precision. We closely follow and extend the methodology of Da, Engelberg and Gao (2015), who employ an extensive pre-processing pipeline to deal with relatively noisy daily data.

First, we start with positive and negative economics-related words labeled with ECON and @ECON from the Harvard General Inquirer dictionary word list[7]. To understand how households employ these words in Google searches, we augment this initial list of words with the top ten related search terms. Starting with the 151 "seed words", we query Google Trends for the top ten related search terms for each of those words for the entire timeframe of January 2004 until March 2020. We further filter out any related search terms not attributed to finance or economics.[8]

[6] See also Da, Engelberg and Gao (2011) for an overview and discussion of the Search Volume Index (SVI) as a robust predictor of stock prices.

[7] http://www.wjh.harvard.edu/~inquirer/spreadsheet_guide.htm

[8] We include in Appendix C. 1 a list of search terms for the U.S., prior to data processing and index calculation.

Next, we download the daily SVI for each of the search terms over the sample period of January 2004 to March 2020. We then calculate the first differences (changes from day to day) of the natural logarithms of the daily SVI.[9] Computing *changes* ensures that we use ex-post data, as the index is based on relative values rather than the absolute scale of these values. Then, to address seasonality and heteroskedasticity concerns, we winsorize the series with 2.5% in each tail. After that, we deseasonalize the series to remove seasonal effects on SVI changes. We regress log-first differences of SVI on weekday and month dummies. Subsequently, we calculate z-scores of the deseasonalized log-first differences. This is the last step in preparing the SVI data for index generation.

For the index generation, we first discard any words with less than 2,000 observations. To identify the historical relationship between search terms and contemporaneous US market returns[10], we run backward-looking rolling regressions expanding every June and December by 6 months. Similar to Gao, Ren and Zhang (2019), we also find significant historical correlations with both positive and negative words. Therefore, we follow Gao, Ren and Zhang (2019) here and choose the top 30 negative and the top 30 positive keywords by the largest t-statistic. Table 3.1 shows 30 search terms that have the largest time-series correlation with the US stock market over our entire sample period. We report the top 15 terms with the largest negative t-statistic from the contemporaneous regressions, as well as the top 15 terms with the largest positive t-statistic from the contemporaneous regressions. Search terms include “gold” and “gold price” with a t-statistic of -5.361 and -4.960, respectively. Those are also the top two most negatively associated search terms with the market as of December 2011, as reported by Da, Engelberg and Gao (2015). This indicates how these search terms capture heightened pessimism or periods of market distress, where individual investors shift their investments to gold, which is perceived as a “safe haven”. Furthermore, positively associated search terms ”prosperous year” or ”economic prosperity” may signal more positive market conditions. The terms displayed in the table indicate that this data-driven methodology captures direct market sentiment

[9] Requests spanning less than 270 days are answered with daily data. Therefore, raw daily SVI data is downloaded in chunks of 269 days. Since raw SVI values fall in the range from 0 to 100, they would not be compared across chunks. Therefore, calculating first differences in SVIs means we rather rely on the *changes* in these values, and we could now combine these chunks to form an uninterrupted series for the entire time period.

[10] Taken from the Kenneth French Data Library: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

with a high degree of precision.

Lastly, following Gao, Ren and Zhang (2019), we generate our sentiment index by averaging the z-scores of the top 30 positive and top 30 negative search terms and calculating the difference between these two averages, as shown in equation 1:

$$net\_sent_t = \sum_{i=1}^{30} R_+^i \left(\Delta ASVI_i\right) - \sum_{i=1}^{30} R_-^i \left(\Delta ASVI_i\right) \tag{3.1}$$

where $\sum_{i=1}^{30} R_\pm^i \left(\Delta ASVI_i\right)$ is the simple average of the top 30 positive (negative) search terms' z-scores by largest magnitude positive (negative) t-statistic. By taking the simple average and computing the difference between positive and negative words, we construct a net sentiment index. This index takes into account the dispersion of investor beliefs and measures the net effect of sentiment in the market.

Finally, because our stock holdings variables are based on quarterly FactSet data, we construct a quarterly sentiment measure. We take the sum of daily net sentiment over the quarter and calculate change from quarter to quarter, as shown in equation 2:

$$\Delta net\_sent_{qt} = \Delta \sum_{q=1}^{3} net\_sent_t \tag{3.2}$$

where $\Delta \sum_{q=1}^{3} net\_sent_t$ is the quarterly change in the sum of daily net sentiment over quarter qt.

3.2.2.2 Retail ownership

We obtain data from FactSet[11], which details the fraction of institutional ownership in quarterly stock holdings. Similar to the approach in the paper of Devault, Sias and Starks (2019), we then compute the remaining fraction of retail ownership, such that total ownership amounts to 100%. In addition to computing institutional and individual investor ownership levels, we also calculate investor demand shocks. Investor demand shocks are equal to changes in institutional (individual) ownership for each stock-quarter. Following the same rationale in Devault, Sias and Starks (2019), individual investors' demand shocks

[11] We thank Daniel Schmidt for providing us with the institutional ownership variables.

Table 3.1
Search terms with the highest market correlations from the full sample

Rank	Search term	T-Statistic
Top negative correlations		
1	gold	-5.361
2	gold price	-4.960
3	jobless benefits	-3.849
4	price of gold	-3.555
5	business partnership	-3.454
6	deficit	-3.415
7	domination	-3.343
8	depression	-3.183
9	entrepreneurial business	-2.901
10	bankrupt	-2.851
11	crisis	-2.826
12	cost of living	-2.777
13	riches	-2.770
14	recession	-2.727
15	jobless rate	-2.684
Top positive correlations		
1	prosperous year	3.525
2	entrepreneurship	3.501
3	economize	3.471
4	economic prosperity	3.359
5	affluent neighborhoods	3.321
6	savings bonds	3.163
7	generosity	3.066
8	endow	2.934
9	backwardness	2.93
10	recession	2.889
11	affluence	2.703
12	rewards	2.624
13	fixed cost	2.559
14	uneconomical	2.545
15	tax expense	2.544

This table reports the top 15 search terms with the largest negative (positive) correlations with the stock market. The search terms are initially derived from the Harvard General Inquirer dictionary, as described in section 3.2.1.

(ΔRO_{qt}) are equal to the negative of institutional demand shocks (ΔIO_{qt}), as shown in the equation below (the quarterly change is measured in %).

$$RO_{qt} = 1 - IO_{qt} \tag{3.3}$$

$$\Delta RO_{qt} = -(\Delta IO_{qt}) \tag{3.4}$$

We merge the FACTSET and CRSP datasets using the FactSet-CRSP Linking Table by WRDS, which includes the historical matching between the CRSP firm identifier "PERMNO" and several FactSet firm identifiers.

3.2.2.3 Total Volatility

To measure within-month total volatility, we compute the standard deviation of periodic returns, in addition to annualized volatility. We follow the standard method in the literture[12], and apply the following formula:

$$\mathrm{Vol_i} = \sqrt{\frac{\sum_{\mathrm{t=1}}^{\mathrm{n}} (\mathrm{R_{i,t}} - \mathrm{R_i})^2}{\mathrm{n} - 1}} \sqrt{m} \tag{3.5}$$

where $R_{i,t}$ is the return of stock i in day t, R_i is the mean return of stock i taken over the respective month, n is the number of tradings days within the month of observation for stock i, n is the number of trading days in one year. Multiplying by $\sqrt{m}$ converts the standard deviation of returns into Vol_i, which is an annualized value. We then use the standard deviation of returns to construct and sort portfolios, which we elaborate on in section 3.3. To compute quarterly volatility variables, we take the mean of volatility for each stock-quarter.[13]

3.2.3 Descriptive statistics

Table 3.2 presents descriptive statistics for the input and output parameters in our main model. Specifically, Table 3.2 reports the mean, standard deviation, 25% percentile, me-

[12] See Bali, Engle and Murray (2016), for example.

[13] We also adjust volatility for skewness by taking $log(1+Vol_{Qly})$ and then we re-run our main regressions - we do not find that it influences the results.

dian, and 75% percentile for the net sentiment index *net_sent*, institutional demand shocks *IO_change*, individual investor demand shocks *RO_change*, the volatility variables *sd_qly* and *avol_qly*, and the quarterly stock returns *ret_qly*, calculated as the mean of daily returns over the stock-quarter.

Table 3.2
Summary statistics of variables

Variable	Mean	SD	25%-percentile	Median	75%-percentile
Δnet_sent	-0.16	2.39	-1.72	0.13	1.66
ΔRO	-0.40	5.43	-1.54	-0.01	0.94
sd_qly	2.10	1.02	1.35	1.98	2.71
avol_qly	4.61	1.20	3.82	4.58	5.36
ret_qly	0.12	1.84	-0.14	0.06	0.25

This table provides the mean, standard deviation, 25%-percentile, median, and 75%-percentile of the main variables in the paper. The net sentiment index *net_sent*, individual investor demand shocks *RO_change*, the volatility variables *sd_qly* and *avol_qly*, and the quarterly mean of stock returns *ret_qly* are quarterly data from January 2004 to December 2020 (*net_sent* starts from the 4th quarter in 2004, as we lose the first 6 months of sentiment data in the backward-rolling regressions to compute top words for the index construction, and we lose one additional quarter to compute *changes* in quarterly sentiment). *ret_qly* is calculated as the mean of daily returns over the stock-quarter. Detailed descriptions of the variables are provided in section 3.2. *RO_change* and *ret_qly* are expressed in percent. We report the *sd_qly* and *avol_qly* volatility values adjusted for skewness by taking log (1 + volatility).

The average quarterly change in the net sentiment index is -0.16, and its standard deviation is 2.39. The mean and median are close to zero, which indicates that we measure changes in sentiment rather than levels. As shown in the table, there is great variability in the sentiment and retail ownership data. This is not surprising since the sample includes periods of market upturns and downturns, for e.g., the 2007-2008 financial crisis. These periods would be reflected in positive (negative) sentiment among investors, as well as shifts in ownership of different stock classes among retail investors.

3.3 Correlation tests

We first run correlation tests to examine the relationship between the quarterly sentiment metric and individual investor demand shocks. Since we know that the Baker-Wurgler sentiment metric captures institutional investor demand shocks, as shown in extensive tests in the paper of Devault, Sias and Starks (2019), we expect our sentiment metric, which relies on households' Google search behavior, to follow a different pattern. In a similar test in Devault, Sias and Starks (2019), the authors show that when the Baker-Wurlger sentiment metric increases, institutions tend to net buy high volatility stocks from retail investors and sell low volatility stocks to retail investors.[14] Therefore, if our sentiment metric captures individual investor demand shocks, we should see an opposite pattern.

Table 3.3
Correlation tests - Investor demand and investor sentiment by volatility decile

	r	High sent	Low sent	High – Low sent
Low vol. stocks	0.440	0.293	0.402	-0.109
2	0.280	0.217	0.433	-0.216
3	0.290	0.235	0.386	-0.151
4	0.243	0.244	0.280	-0.036
5	0.208	0.211	0.235	-0.024
6	0.173	0.213	0.186	0.027
7	0.201	0.301	0.181	0.120
8	0.145	0.161	0.182	-0.021
9	0.040	0.170	-0.024	0.194
High vol. stocks	0.016	0.065	0.010	0.055
High vol - Low vol	-0.424	-0.228	-0.392	0.164

This table reports time-series correlation test results for retail investor demand and investor sentiment by volatility decile. Column 1 reports the time-series correlation between the quarterly net sentiment index (Net_{Sent}) and cross-sectional average retail investor demand shocks (RO_{change}) for stocks within each volatility decile (where volatility is estimated using the standard deviations of periodic returns). The bottom row in column 1 reports the the difference in individual demand shocks for high versus low volatility stocks. We sort the 68 quarters (from January 2004 to December 2020) into high (above median value) and low (below median value) sentiment periods and report the time-series mean of the cross-sectional average individual ownership shocks for stocks within each volatility decile for high sentiment periods (column 2), low sentiment periods (column 3), and their difference (last column). The last row in columns 2 and 3 reports the difference in RO_{change} for the high volatility portfolio and the low volatility portfolio. The last row in the last column reports the difference between high and low sentiment periods.

In Table 3.3, we report the time-series correlation between quarterly changes in net sentiment and cross-sectional average individual investor demand shocks for stocks within each volatility decile.[15] The market-clearing condition requires that individual investors offset trades by institutional investors whose propensity to speculate increases when their

[14] In the Appendix table C. 3, we replicate a similar correlation test following Devault, Sias and Starks (2019), using the Baker-Wurgler sentiment metric and institutional demand shocks calculated from FactSet data. Similarly, we find that the Baker-Wurgler sentiment index captures institutional investor demand shocks.

[15] For the sake of brevity, we report results for volatility deciles where volatility is estimated using standard deviation of periodic returns. Similar results are reported using annualized volatility.

sentiment increases, based on the sentiment hypothesis and based on the general findings in the research by Devault, Sias and Starks (2019). In Table 3.3, we sort stocks into deciles, forming 10 volatility portfolios. The first column in the table shows that the correlation coefficient monotonically decreases going from low to high volatility stocks. If institutional investors, in aggregate and on average, net buy high volatility stocks, then the coefficient in the last row of column 1 shows that individual investors, on average, net sell high volatility stocks to institutional investors.

Columns 2 and 3 sort our sample period into high (above median value) and low (below median value) sentiment periods and report the time-series mean of the cross-sectional average individual ownership shocks for stocks within each volatility decile for high sentiment periods, low sentiment periods, and their difference. We see a similar pattern when we limit our sample period to high sentiment periods, indicated by the negative difference in mean individual ownership shocks between high and low volatility stocks. However, the last row in the third and last column shows that although our sentiment metric, in aggregate, captures individual investor demand shocks, individual investors do not necessarily behave opposite to institutional investors. There are many possibilities as to why we see such a pattern. To broaden our results and to further understand the mechanism behind how individual investors behave in the market alongside institutional investors, and the role of sentiment trading, we run panel regressions in section 5.

3.4 Panel regressions

Panel regressions allow us to exploit firm-level data and control for other factors that may be potential drivers of investor demand shocks. Therefore, to test whether the net sentiment index is able to explain individual investor demand shocks, we run panel regressions of change in retail ownership on net sentiment. We report results from variants of the following regression model:

$$\Delta RO_{i,t} = \alpha_{1i} + \alpha_{2i}\Delta net\_sent_t + \alpha_{Ci}C_{i,t} + \varepsilon_{it} \tag{3.6}$$

where $\Delta RO_{i,t}$ is the quarterly change in retail ownership (or retail investor demand shocks), Δnet_sent_t is the net sentiment index based on quarterly changes, $C_{i,t}$ is a set of controls, including fixed effects. In line with the discussion on robust t-statistics in panel settings in the paper of Petersen (2009), we define four regression models with different specifications in Table 3.4 to learn further about the forms of dependence within our analysis. All model variants in this paper are estimated using ordinary least squares (OLS).

3.4.1 Basics regressions: Explaining investor demand shocks

Based on sentiment definitions in Baker and Wurgler (2006) and findings in the literature (See, for e.g., the study by Kostopoulos, Meyer and Uhr (2020b) on German retail investor behavior), if our sentiment metric captures retail investor sentiment, then we should see that retail investors buy if sentiment goes up. Table 3.4 reports the basic regression results. In the first column, we focus on the most basic OLS regression. In the second, third, and fourth columns, we report regressions with firm, quarter, and year fixed effects, respectively. We add firm fixed effects to control for time-invariant firm-specific variables which might influence retail investment. For example, firms that operate within a specific industry might attract more institutional investors vs. retail investors on average. We add time (quarter and year) fixed effects to control for macroeconomic factors or general conditions that would affect the firms within our sample (such as term structure, interest rates, or an economic crisis). We then cluster standard errors at the firm level in column 5[16]. This table documents the robustness of our baseline regression result in column 5 with respect to the econometrics. We see the same pattern of results whether we drop or add fixed effects in columns 1-4 or cluster standard errors.

We document positive coefficients across the regressions, consistent with our hypothesis that a positive correlation exists between the sentiment index and individual investor demand shocks. This indicates that this sentiment index captures well or is able to explain retail demand shocks after controlling for time-invariant firm characteristics in the firm fixed effects. We do not include a time fixed effect because it would absorb the net sentiment index, which is a market-wide variable that does not vary across firms. [17] Moreover,

[16] Following Cameron, Gelbach and Miller (2011), at least 30-50 clusters are needed in order to avoid unnecessarily inflated standard errors. In the spirit of Devault, Sias and Starks (2019), we also cluster standard errors at the firm level.

[17] In other regressions with institutional demand shocks as the dependent variable, we see a negative

Table 3.4
Panel regressions - Can net sentiment explain individual investor demand shocks?

	ΔRO			
	(1)	(2)	(3)	(4)
Δnet_sent	0.0553***	0.0653***	0.0330***	0.0653***
	(10.57)	(12.51)	(5.508)	(12.29)
Observations	188,327	188,327	188,327	188,327
R^2	0.00059	0.05200	0.03041	0.01874
Firm FE	No	Yes	Yes	Yes
Year FE	No	No	Yes	No
Estimator	OLS	OLS	OLS	OLS
Clustered SE	No	No	No	Firm

This table reports coefficients from firm-level panel regressions of retail investor demand shocks (ΔRO) on the changes in net sentiment index (Δnet_sent). Both variables are calculated quarterly. The sample period is from January 2004 to December 2020. Column 1 reports regressions without fixed effects. Column 2 reports regressions with firm fixed effects, and column 3 reports regressions with both firm and year fixed effects. Finally, in column 5, we additionally cluster standards at the firm level. *t-statistics* are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

the positive coefficient indicates that, on average, retail investors are net buyers of stocks when the sentiment index increases. In line with traditional sentiment interpretations (see Baker and Wurgler (2006, 2007) for elaborate definitions), high investor sentiment, as measured by Δnet_sent, indicates that investors are more optimistic about future asset prices and cash flows, and therefore, they are more likely to place buy rather than sell orders.

3.4.2 Retail trading and volatility

Our main finding so far is that retail investors are more likely to be net buyers of stocks when their sentiment increases. First, to further test the validity of this finding, we divide the same into high and low sentiment periods. We create an indicator "*up_sent*" which takes 1 when sentiment is in the top 30%, and 0 otherwise. We similarly create an indicator "*down_sent*" which takes 1 when sentiment is in the bottom 30%, and 0

coefficient across the regressions. This is rather intuitive, as changes in institutional and individual stock ownership are obviously related. In aggregate, a reduction in institutional ownership should be met by an increase in retail ownership and vice versa.

otherwise. We then repeat the baseline regression in column 4 of Table 3.4 using *up_sent* and *down_sent*. Column 1 in Table 3.5 reinforces our main result and shows that when sentiment is up, retail investors tend to be net buyers of stocks. This is indicated by the positive and statistically significant coefficient on *up_sent*. Intuitively, column 2 of Table 3.5 shows that when sentiment is down, retail investors tend to be net sellers of stocks. Hence, we document stronger results during up-sentiment quarters, in which investors tend to net buy stocks. During pessimistic episodes, investors would tend to net sell, but the results (compared to up episodes) are less powerful because the impact of pessimistic investors may be more dissipated in capital markets due to short-selling constraints (Miller (1977); Gao, Ren and Zhang (2019)). Therefore, up-sentiment episodes (or periods of high sentiment) may play a more important role in the market.

Next, to learn about the degree of risk proneness in response to increased sentiment, we are interested in adding an interaction term of $up\_sent * sd\_qly$. Looking at the interaction between high sentiment and volatility allows us to examine the relation between retail sentiment trading and volatility, and determine what kinds of stocks retail investors flow into. In column 3 of Table 3.5, we see a significant and negative coefficient on the interaction term between sentiment and volatility. This suggests that, although retail investors tend to be net buyers when the sentiment index increases, they are less likely to buy risky stocks. In other words, when sentiment increases, retail ownership increases, and this would be the case when volatility has a below-average value. Moreover, this negative interaction effect is even larger in magnitude when we look at extremely volatile stocks in column 4. This further suggests that retail investors may be less likely to be net buyers of highly volatile stocks. In column 5, we test the robustness of this finding by limiting the sample to low volatility stocks only (stocks with their annualized volatility in the bottom 30%) and re-running the main regression with sentiment as the only RHS variable. This further confirms our finding that retail investors tend to be net buyers of low volatility stocks. Moreover, we find that sentiment is significant in all regressions, and adding volatility does not weaken its effect in any of the regressions. During high sentiment periods or when looking at high volatility stocks, there are interaction effects besides the main effects.

However, we consider the drivers of this result and question whether this is, in fact,

Table 3.5
Panel regressions - Retail sentiment trading and volatility

	All stocks				*Low volatility stocks only*
	ΔRO				
	(1)	(2)	(3)	(4)	(5)
up_sent	0.4404***				
	(16.540)				
down_sent		-0.2257***			
		(-8.499)			
Δnet_sent			0.0817***	0.0718***	0.0704***
			(13.630)	(13.320)	(7.437)
up_avol			0.9053***		
			(22.820)		
Δnet_sent*up_avol			-0.0568***		
			(-4.679)		
extreme_up_avol				1.987***	
				(27.280)	
Δnet_sent*extreme_up_avol				-0.0811***	
				(-3.997)	
Observations	188,327	188,327	188,043	188,043	55,923
R^2	0.05258	0.05154	0.05614	0.06113	0.08534
Firm FE	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	OLS	OLS
Clustered SE	Firm	Firm	Firm	Firm	Firm

This table reports coefficients from firm-level quarterly panel regressions of retail investor demand shocks (ΔRO) on the changes in net sentiment index (Δnet_sent) and an interaction term between sentiment and volatility. The sample period is from January 2004 to December 2020. up_sent is an indicator that takes 1 when sentiment is in the top 30% (otherwise 0), $down_sent$ is an indicator that takes 1 when sentiment is in the bottom 30% (otherwise 0), up_avol is an indicator that takes 1 when volatility is in the top 30%, otherwise 0, and $extreme_up_avol$ is an indicator which takes 1 when volatility is in the top 10%, otherwise 0. All regressions include firm fixed effects. Standard errors are clustered standards at the firm level in all regressions. *t-statistics* are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

driven by volatility or past performance. It is known in the literature that contemporaneous returns are negatively related to changes in volatility, e.g., Black (1993); Falkenstein (1994); Van Vliet, Blitz and van der Grient (2011)). Given that, it is possible that when sentiment increases, retail investors are buying stocks that were winners over the past weeks or months (which would be in line with empirical findings from behavioral finance). Such stocks with high past performance tend to have below-average volatility. In unreported results, we study interaction terms between sentiment and indicators of low (and extremely low) volatility and find that the effect of sentiment remains large and significant, but the interaction term is insignificant. The fact that we see a significant and negative interaction between sentiment and high volatility but no significant interaction between sentiment and low volatility further motivates us to pursue this hypothesis. In Table 3.6, we test the drivers of this behavior, focusing on the possibility that we may be capturing past performance instead of volatility.

3.4.3 Drivers: Volatility or past performance?

We substitute in our analysis volatility with past performance. Because we have a long frequency (on quarter), we use the mean stock return over the current quarter (t) to measure performance. Moreover, we also create an indicator variable that takes '1' for stocks that belong in the top 30% winner stocks. We re-run the panel regression of retail investor demand on the changes in the net sentiment index (in addition to stock fixed effects, as well as clustering standard errors by stock) and limit the sample to winner stocks only. Table 3.6 indeed confirms our hypothesis that retail trading behavior is driven by return performance rather than volatility. Looking at the first column in Table 3.6, we see that a one-standard-deviation increase in sentiment is associated with an increase of 0.0863% in the fraction of retail ownership of winner stocks in a quarter.

So far, we find that retail investor sentiment, measured by our net sentiment index, is positively associated with retail ownership. That is, retail investors tend to net buy when sentiment goes up. Next, we analyze the channels by showing that retail investors are likely buying past winners. Finally, we now disentangle the winner effect from the volatility effect to determine whether retail investors, given the same performance in the past, would rather buy high or low volatility stocks in periods of high sentiment. This

Table 3.6
Panel regressions - Drivers of retail investor behavior

	Winner stocks only	*All stocks*	
	ΔRO		
	(1)	(2)	(3)
Δnet_sent	0.0863***	0.0584***	0.0609***
	(8.247)	(11.030)	(11.170)
avol_qly		-0.0026***	0.000077263**
		(6.899)	(2.263)
winner		-0.4006***	
		(-5.505)	
Δnet_sent*avol_qly		0.00000311***	0.000007155*
		(2.759)	(1.669)
avol_qly*winner		-0.0026***	
		(-6.844)	
ret_qly			-0.3002***
			(-4.562)
avol_qly*ret_qly			-0.000000127
			(-0.9211)
Observations	55,539	188,043	188,043
R^2	0.15279	0.06913	0.05479
Firm FE	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
Clustered SE	Firm	Firm	Firm

This table reports coefficients from firm-level quarterly panel regressions of retail investor demand shocks (ΔRO) on the changes in net sentiment index (Δ*net_sent*), focusing on winner stocks only. The sample period is from January 2004 to December 2020. *winner* is an indicator that takes 1 when the stock performance is in the top 30% (otherwise 0), *ret_qly* is the mean stock performance over the quarter, and $avol_q ly$ is the quarterly volatility variable. All regressions include firm fixed effects. Standard errors are clustered standards at the firm level in all regressions. *t-statistics* are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

further gives us deeper insights into the effect of sentiment as well as the effect of sentiment conditional on volatility. In column 2 of Table 3.6, we run a panel regression of the change in retail ownership in each stock on sentiment, volatility, an indicator for winner stocks, and an interaction term between volatility and the winner stocks indicator (to disentangle or control for the volatility effect conditional on the winner effect). We find that the coefficient on the interaction term between sentiment and volatility is now positive. This indicates that retail investors would be more likely to buy into riskier stocks when their sentiment increases, given we disentangle the winner effect.

Interestingly, this result is also in line with the paper by Kostopoulos, Meyer and Uhr (2020b) investigating retail investor behavior in Germany, showing that such findings could be extended to international markets.

3.4.4 Testing the predictive power of the index

We build a quarterly panel based on a quarterly sentiment index and quarterly ownership data from FACTSET. Given that previous sentiment indices are often based on a daily, weekly, or monthly basis (For e.g., Baker and Wurgler (2006); Da, Engelberg and Gao (2015); Gao, Ren and Zhang (2019)), we would like to know whether this quarterly measure could predict stock returns in the first place. In Table 3.7, we run a preliminary test on the predictive power of the quarterly net sentiment index.

In column 1 of Table 3.7, we run a contemporaneous regression of the quarterly net sentiment index on the quarterly mean of stock returns. A one standard deviation increase in the net sentiment index is correlated with a 0.02% decrease in the quarterly average of stock returns.[18] In column 2, the coefficient on *net_sent* remains negative and significant in a forecast horizon of one quarter, followed by a return reversal in a forecast horizon of two quarters. Therefore, although the net sentiment index is associated with lower returns in the first two quarters, it predicts higher returns in the third quarter. This return reversal pattern is consistent with theories of investor sentiment as well as stylized facts reported in the literature.

3.5 Robustness tests

In column 3 of Table 3.5, we report one of our main findings, which is the tendency of retail investors to buy low volatility stocks in periods of increased sentiment. This result has motivated us to look closer into the drivers of this behavior. We end up finding that

[18] A one standard deviation change in net_sent is equal to 2.39 (refer to Table 3.2)

Table 3.7
Panel regressions - Preliminary test on return predictability

	ret_qly		
	(1)	(2)	(3)
Δnet_sent	-0.0081***		
	(-3.917)		
Δnet_sent_t-1		-0.0060***	
		(-3.249)	
Δnet_sent_t-2			0.0159***
			(7.900)
Observations	188,367	186,982	183,351
R^2	0.07761	0.08033	0.09013
Firm FE	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
Clustered SE	Firm	Firm	Firm

This table reports coefficients from firm-level quarterly panel regressions of quarterly returns (*ret_qly*) on the changes in net sentiment index (Δ*net_sent*). The sample period is from January 2004 to December 2020. All regressions include firm fixed effects. Standard errors are clustered standards at the firm level in all regressions. *t-statistics* are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

retail investors are, in fact, buying stocks that were winners over the past quarter, and those stocks tend to have below-average volatility. However, we also wonder to what extent the results are influenced by using the volatility of the current quarter. To test the robustness of this important finding, we run a panel regression similar to the one in column 3 of Table 3.5 whilst replacing current volatility with the volatility of the preceding quarter (t-1). Table 3.8 reports this result. We find that using a lagged volatility indicator does not impact our findings. The panel regression in Table 3.8 confirms the important finding that retail investors tend to be less likely to buy risky stocks when their sentiment increases. This finding is robust to the choice of the quarter in which the stock volatility is calculated.

In our mainline specification, we use stock volatility as the volatility indicator. We ask ourselves whether our results would change if we use relative volatility rather than stock volatility. We first measure relative volatility as the difference between stock volatility and market volatility, whereas we compute market volatility as the mean of all stocks'

Table 3.8
Robustness tests

	ΔRO		
	(1)	(2)	(3)
Δnet_sent	0.0827***	0.0758***	0.1376***
	(13.307)	(13.198)	(5.083)
up_lag_avol	0.6609***		
	(16.394)		
Δnet_sent*up_lag_avol	-0.0379***		
	(-3.234)		
relative_up_avol		0.3705***	
		(8.548)	
Δnet_sent*relative_up_avol		-0.0352***	
		(-2.623)	
avol_qly			0.6682***
			(28.039)
winner			2.087***
			(13.100)
Δnet_sent*avol_qly			-0.0145**
			(-2.506)
avol_qly*winner			-0.5939***
			(-16.923)
Observations	188,046	188,043	188,043
R2̂	0.0540	0.0526	0.0642
Firm FE	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
Clustered SE	Firm	Firm	Firm

This table reports the results of robustness tests. The first column shows the results of using current vs. past volatility in the main specifications. The second column shows the results of using relative volatility as the volatility indicator. The third column shows the results of using the stock performance in the preceding quarter as a measure for the *winner* indicator. The table reports coefficients from firm-level quarterly panel regressions of retail investor demand shocks (ΔRO) on a set of explanatory variables. up_lag_avol is an indicator that takes 1 when volatility in the preceding quarter is in the top 30%, otherwise 0. $relative_up_avol$ is an indicator that takes 1 when relative volatility in the current quarter is in the top 30%, otherwise 0 (whereas relative volatility is equal to stock volatility minus market volatility in the respective quarter). *winner* is an indicator that takes 1 when the stock performance in the preceding quarter is in the top 30%, otherwise 0. The sample period is from January 2004 to December 2020. All regressions include firm fixed effects. Standard errors are clustered standards at the firm level in all regressions. *t-statistics* are reported in parentheses. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

volatilities over each quarter. Similar to the setup in Table 3.5, we then measure an *relative_up_avol* indicator using volatility in the top 30% quantile. We finally run panel regressions similar to column 3 of Table 3.5, and report coefficients from firm-level quarterly panel regressions of retail investor demand shocks on the net sentiment index and an interaction term between net sentiment and the high relative volatility indicator. The advantage of this test is that we see how retail demand behaves for those stocks in which volatility has increased more than the average. Column 2 of Table 3.8 reports this result. We see that the significant and negative coefficient on the interaction term, which we are particularly interested in, remains unaffected by using relative volatility.

In the third robustness test, we further look at the major contribution of our paper, which shows that if we disentangle the pure volatility effect from past performance, retail investor demand in the high sentiment period goes up more for high volatility stocks. That is, retail investors would be more likely to buy into riskier stocks when their sentiment increases, given we disentangle the winner effect. In previous tests, we include a *winner* indicator that incorporates the past performance of top stocks. Since we have a relatively long frequency, we use the mean stock return over the current quarter to measure performance. We measure past performance during the same quarter as the *RO_change* variable (our main explanatory variable) because we are interested in the mechanical effect of past performance on measured volatility. However, in this robustness test, we also run a specification by using the preceding quarter's performance. We would expect that, in this case, we might get a different result that would support our finding.

The last column in Table 3.8 reports this test's results. Once again, we are most interested in the interaction term between the net sentiment index and the volatility indicator, given we control for the winner effect. Using the previous quarter to measure performance, we interestingly now find that the coefficient on the interaction term is negative, rather than positive. When sentiment increases, retail investors are buying stocks which were winners over the past weeks or months. Such stocks with high past performance tend to have below-average volatility. This is why when we disentangle the winner effect, we are finally seeing a positive coefficient on $net\_sent * avol\_qly$. This is in line with the main findings in the behavioral finance literature that increased sentiment is associated with higher risk proneness. However, in Table 3.8, when we look into the preceding quarter, we now see a negative interaction term. This highlights the sentiment-induced temporary effect in the market, in which retail investors flow into and out of risky stocks based on these high sentiment episodes. This is also in line with return reversal patterns we see in Table 3.7 and in the general sentiment literature (For e.g., Stambaugh, Yu and Yuan (2012); Da, Engelberg and Gao (2015)).

3.6 Conclusion

In this paper, we have offered a new perspective on how investor sentiment affects retail investor behavior. By closely following the Google Trends-based FEARS index developed by Da, Engelberg and Gao (2015), we first have shown that this index actually measures retail investor sentiment. In fact, for the US equity market over the period 2004 to 2019 we could show that a positive (negative) change in this sentiment index is associated with an increase (decrease) in retail ownership as measured by FACTSET data. More precisely, a one standard deviation change in the sentiment index is associated with a 0.13% change in retail ownership. This result is statistically highly significant, robust to different test choices, and confirms other results from the literature ((e.g., Kostopoulos, Meyer and Uhr (2020b)). The contradiction to the paper of Devault, Sias and Starks (2019) is due to the fact that they use the index developed by Baker and Wurgler (2006). We argue that this index is likely to measure institutional investor sentiment rather than retail investor sentiment.

The more intriguing question is how investor sentiment affects stock demand in the cross-section. It has been argued in the literature that anomalies such as the momentum effect or the idiosyncratic volatility puzzle might be driven by sentiment behavior. This could be used as a starting point for explaining the volatility puzzle. However, in our data, at first glance, it seems that low volatility stocks are most affected by sentiment changes, i.e., their retail holdings are more likely to increase in times of increasing sentiment. This can hardly be matched with a phenomenon like the idiosyncratic volatility puzzle.

However, we were able to reconcile this somewhat counterintuitive result with the literature. For that purpose, we disentangled the momentum from the volatility effect. In fact, once we control for past performance, we were able to show that retail investor demand goes up more for high volatility stocks when net sentiment increases. Taking into account that stocks with high past performance tend to have below average volatility, our results show that retail investors are more inclined to buy past winners in times of increasing sentiment. The same is true for stocks with above average volatility.

Overall, this paper delivers new insights in several dimensions. First, we have shown that a specific variant of the FEARS index delivers a robust correlation between retail investor behavior and sentiment. Of course, there might still be room for improvement for such a retail investor sentiment index. However, our paper has shown that using the FEARS index as a starting point leads in a promising direction.

Second, the paper was also able to reconcile behavioral hypotheses assuming that retail investors have a preference for high-risk (low-risk) or high-volatility (low-volatility) stocks in times of increasing (decreasing) sentiment. In fact, by recognizing that this correlation might be affected by past performance, we can show that this expectation actually holds. Overall, our retail sentiment index can be used as a mechanism to better understand the cross-sectional reaction of retail investors to sentiment changes. This is an important research avenue to better understand some documented anomalies in the asset pricing literature, such as the momentum or the idiosyncratic volatility puzzle.

4 Conclusion

Several empirical and theoretical studies have suggested that behavioral factors systematically affect asset prices (e.g., Kumar and Lee (2006); Baker, Wurgler and Yuan (2012); Daniel, Hirshleifer and Sun (2020). For example, Daniel, Hirshleifer and Sun (2020) propose a theoretically motivated factor model based on behavioral factors alongside the market factor, and suggest that changes in sentiment, alongside expectations related to fundamentals, drive the explanatory power of these behavioral factors. Investors are prone to acting on sentiment signals and expose themselves to behavioral factors, which in turn induce mispricing (Daniel, Hirshleifer and Sun (2020)). Therefore, the role of investor sentiment in asset markets is well-documented. Moreover, given that retail investors are less sophisticated than institutional investors (e.g., Kostopoulos, Meyer and Uhr (2020a)), the sentiment patterns studied in the literature have been mostly attributed to retail investors (e.g. Baker and Wurgler (2006); Kumar and Lee (2006)).

However, recent evidence suggests that prominent sentiment metrics are not truly capturing retail investor demand shocks (e.g., Devault, Sias and Starks (2019)). This further highlights the lack of consensus on how to quantify the short- and long-term sentiment effects. More specifically, there is an increasing necessity in the literature for a robust sentiment index that captures retail investor behavior and is relevant for a wide sample of countries and at different return intervals. In this dissertation, I address this gap and focus on a sentiment metric constructed by Da, Engelberg and Gao (2015). I extend on the index construction methodology and develop a sentiment index that demonstrates to be a robust predictor of country-level returns and an important driver of stock-bond return correlations. I also analyze the role of other behavioral factors, with investor sentiment at the forefront, to examine the dynamics of stock and bond return comovements. Finally, I exploit the cross-section of stocks to examine retail investor behavior and draw conclusions about the potential sentiment channels in the market.

The key findings in the dissertation are as follows. The first essay proposes a novel investor sentiment index that predicts returns at the usual monthly frequency and survives a battery of in-sample, out-of-sample, and robustness tests. In the second essay, investor sentiment has a significant role in explaining the stock-bond market correlation, and its effect is robust to decoupling episodes. Although I support the sentiment hypothesis as the main explanation for the comovement patterns, investor cultural characteristics play a limited but important role. In the third essay, I propose that this investor sentiment index captures retail investor demand shocks more precisely compared to other prominent indices, and document new interesting findings on retail investor behavior.

Nonetheless, I acknowledge that this dissertation still faces some limitations. The limitations can be summarized as follows. First, although the investor sentiment index is robust to a host of checks, the sample period in this dissertation does not study the COVID-19 and post-COVID periods, for example. Therefore, it would be beneficial to further test the robustness of the forecasting power of the sentiment metric in Chapter 1 using a longer sample period. Moreover, looking at decoupling episodes after 2020 (as in Chapter 2) could bring forward additional implications on the sentiment effect on stock-bond correlations in uncertainty periods or decoupling episodes. Second, to further examine retail investor trading in Chapter 3, it could be useful to exploit the trading records of retail investors as in Barber and Odean (2001), for e.g., from a large discount brokerage. However, I argue that relying on data from FACTSET, which is comparable to data used in the study of Devault, Sias and Starks (2019), is sufficient to address the research questions in Chapter 3.

The findings in this dissertation have implications for researchers, practitioners, and policy-makers. First, Chapter 3 sheds light on the importance of further research on retail vs. institutional sentiment trading and their contrasting effects on the market. Second, sentiment extracted from Google search behavior is a more robust proxy for investor sentiment, and it can be measured for many countries and at various frequencies. This can facilitate research that employs investor sentiment variables. For example, it can be used to gain a deeper understanding of some anomalies documented in the asset pricing literature. Third, the dissertation points to the importance of incorporating non-traditional or non-fundamental variables in forecasting the market and analyzing market comovement patterns and spillovers. On one hand, this may influence investment decisions and risk management strategies. On the other hand, from a policy-making perspective, there may be effects on contagion risk, liquidity, credit risk perceptions, credit spreads, and financial market integration.

A Chapter 1

Datastream sample definition

Constituent lists

Datastream constituent lists comprise: (1) research lists, (2) Worldscope lists, and (3) dead lists. I use dead lists to avoid any survivorship bias. For each country, I compile these lists and remove any duplicates. This outputs a list of equities per country, which can then be used in the subsequent static screening process. Table A. 1 provides an overview of the constituent lists used for the U.S. market, which I used in Chapter 1. (In other chapters, I gain access to CRSP/COMPUSTAT for U.S. equity data.) Constituent lists for other countries are reported in the respective Chapter's appendix.

Static screens

I restrict the sample to common equity stocks by applying several static screens. Screens (1) to (7) are commonly applied in the literature. Screen (8) is based on the following work: Ince and Porter (2006); Griffin, Kelly and Nardari (2010); Campbell, Cowan and Salotti (2010); Karolyi, Lee and Van Dijk (2012), among others. This screen provides generic filter rules to eliminate non-common equity securities from Thomson Reuters Datastream. Generic keyword deletions are applied for all countries. For specific countries, Griffin, Kelly and Nardari (2010) provide additional keywords. The identified keywords are matched to security names under the following Datastream items: "NAME", "ENAME", or "EC-NAME". I focus in Chapter 1 on the U.S. market only and, therefore, provide the list of generic filter rules only, as there are no specific filter rules for the U.S. with respect to Screen (8). For countries in other chapters of this dissertation, I provide the specific filter rules in the corresponding chapter's appendix. Tables A. 2 and A. 3 provide the static screens and generic filter rules which I used in Chapter 1.

Dynamic screens

I obtain return and market capitalization data from Datastream and accounting data from Worldscope for the securities that pass the static filters above. In the next step, commonly used dynamic screens are applied to account for data errors, mostly related to return characteristics.

Table A. 1
U.S. Constituent lists

Country	List				
U.S.	DEADUS1	FUSAC	WSUS4	WSUS12	WSUS20
	DEADUS2	FUSAD	WSUS5	WSUS13	WSUS21
	DEADUS3	FUSAE	WSUS6	WSUS14	WSUS22
	DEADUS4	FUSAF	WSUS7	WSUS15	WSUS23
	DEADUS5	FUSAG	WSUS8	WSUS16	WSUS24
	DEADUS6	WSUS1	WSUS9	WSUS17	
	FUSAA	WSUS2	WSUS10	WSUS18	
	FUSAB	WSUS3	WSUS11	WSUS19	

This table contains the Thomson Datastream (TDS) Research lists, Worldscope lists, and Dead lists for the U.S. market.

Table A. 2
Static screens

Nr.	Description	Datastream item involved	Source
(1)	For firms with more than one security, only the one with the largest market capitalization and liquidity is used.	MAJOR = Y	Schmidt et al. (2017)
(2)	The type of security must be equity.	TYPE = EQ	Ince and Porter (2006)
(3)	Only the primary quotations of a security are included.	ISINID = P	Fong, Holden and Trzcinka (2017)
(4)	Firms are located in the respective domestic country.	GEOGN = country shortcut	Ince and Porter (2006)
(5)	Securities are listed in the respective domestic country.	GEOLN = country shortcut	Griffin, Kelly and Nardari (2010)
(6)	Securities with a quoted currency different from the one of the associated country are excluded.	PCUR = currency shortcut of the country	Griffin, Kelly and Nardari (2010)
(7)	Securities with an ISIN country code different from the one of the associated country are excluded.	GGISN = country shortcut	Annaert, De Ceuster and Verstegen (2013)
(8)	Securities whose name fields indicate non-common stock affiliation are excluded.	NAME, ENAME, ECNAME	Ince and Porter (2006), Campbell, Cowan and Salotti (2010), Griffin, Kelly and Nardari (2010) and Karolyi, Lee and Van Dijk (2012)

This table displays the static screens applied in the study, mainly following Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017). Column 3 lists the Datastream items involved (on the left of the "=" sign) and the values they are set to in the screening process (on the right of the "=" sign). Column 4 specifies the source of the screens.

Table A. 3
Generic keyword deletions

Non-common equity	**Keyword**
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository Receipts	ADR, GDR
Preferred Stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit Trusts	.IT, .ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
ETFs	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly based on Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD

This table reports the generic keywords that are searched for in the names of all the stocks in a country. If one or more of these keywords are detected in the stock's name, the respective stock is excluded from the sample.

Table A. 4
Dynamic screens

No.	Description	Reference
(1)	Zero returns at the end of the return time series are deleted, which exist because, in case of delisting, Datastream displays stale prices from the date of delisting until the end of the respective time series. Associated market capitalizations are also deleted.	Ince and Porter (2006)
(2)	Associated returns and market capitalizations in case of abnormal prices (unadjusted prices $>$ 1000000) are deleted.	Schmidt et al. (2017); whereas the screen is applied here to unadjusted prices.
(3)	Monthly returns and the associated market capitalizations are deleted in case returns exceed 990%.	Schmidt et al. (2017)
(4)	Monthly returns and the associated market capitalizations are deleted in case of strong return reversals, defined as follows: R_{t-1} or $R_t >=$ 3.0 and $(1 + R_{t-1})(1 + R_t) - 1 < 0.5$.	Ince and Porter (2006)

This table displays the dynamic screens applied to the monthly stock data following Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017). Column 2 describes the dynamic screen. Column 3 specifies the source of the screens.

Figure A. 1
CRSP vs. TDS U.S. market returns. This figure depicts the correlation between CRSP aggregate returns and aggregate returns constructed from TDS data in the period January 2000-September 2018. TDS returns correlate at 99.07% with CRSP returns.

B Chapter 2

Table B. 1
Constituent lists

Country	List	Country	List	Country	List	Country	List
Australia	DEADAU	**Germany**	FGKURS	**Netherlands**	DEADNL	**U.S.**	DEADUS1
	FAUS		FGERIBIS		FHOL		DEADUS2
	WSCOPEAU		WSCOPEBD		WSCOPENL		DEADUS3
Belgium	FBELAM		DEADBD1	**Poland**	WSCOPEPO		DEADUS4
	FBELCM		DEADBD2		FPOL		DEADUS5
	FBEL		DEADBD3		DEADPO		DEADUS6
	WSCOPEBG		DEADBD4	**Spain**	DEADES		FUSAA
	DEADBG		DEADBD5		WSCOPEES		FUSAB
Canada	DEADCN1		DEADBD6		FSPN		FUSAC
	DEADCN2		FGER1	**Sweden**	WSCOPESD		FUSAD
	DEADCN3		FGER2		FSWD		FUSAE
	DEADCN4	**Italy**	FITA		FAKTSWD		FUSAF
	DEADCN5		DEADIT		DEADSD		FUSAG
	DEADCN6		WSCOPEIT	**Switzerland**	WSCOPESW		WSUS1
	WSCOPECN	**Japan**	WSCOPEJP		FSWS		...
	FVANC		FJASDAQ		FSWA		WSUS24
	FTORO		FOSAKA		FSWUP	**U.K.**	FBRIT
	LTTOCOMP		FTOKYO		DEADSW		WSCOPEUK
France	DEADFR		FFUKUOKA				WSCOPEJE
	WSCOPEFR		JAPOTC				LUKPLUSM
	FFRA		DEADJP				LSETSMM
							LSETSCOS
							DEADUK

This table contains the Thomson Datastream (TDS) Research lists, Worldscope lists, and Dead lists for the following 14 countries: Australia, Belgium, Canada, France, Germany, Italy, Poland, Spain, Sweden, Switzerland, Netherlands, United Kingdom, and the United States.

Table B. 2
Static screens

Nr.	Description	Datastream item involved	Source
(1)	For firms with more than one security, only the one with the largest market capitalization and liquidity is used.	MAJOR = Y	Schmidt et al. (2017)
(2)	The type of security must be equity.	TYPE = EQ	Ince and Porter (2006)
(3)	Only the primary quotations of a security are included.	ISINID = P	Fong, Holden and Trzcinka (2017)
(4)	Firms are located in the respective domestic country.	GEOGN = country shortcut	Ince and Porter (2006)
(5)	Securities are listed in the respective domestic country.	GEOLN = country shortcut	Griffin, Kelly and Nardari (2010)
(6)	Securities with a quoted currency different from the one of the associated country are excluded.	PCUR = currency shortcut of the country	Griffin, Kelly and Nardari (2010)
(7)	Securities with an ISIN country code different from the one of the associated country are excluded.	GGISN = country shortcut	Annaert, De Ceuster and Verstegen (2013)
(8)	Securities whose name fields indicate non-common stock affiliation are excluded.	NAME, ENAME, ECNAME	Ince and Porter (2006), Campbell, Cowan and Salotti (2010), Griffin, Kelly and Nardari (2010) and Karolyi, Lee and Van Dijk (2012)

This table displays the static screens applied in the study, mainly following Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017). Column 3 lists the Datastream items involved (on the left of the "=" sign) and the values they are set to in the screening process (on the right of the "=" sign). Column 4 specifies the source of the screens.

Table B. 3
Generic keyword deletions

Non-common equity	**Keyword**
Duplicates	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa
Depository Receipts	ADR, GDR
Preferred Stock	PF, 'PF', PFD, PREF, PREFERRED, PRF
Warrants	WARR, WARRANT, WARRANTS, WARRT, WTS, WTS2
Debt	%, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT
Unit Trusts	.IT, .ITb, TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT
ETFs	AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR
Expired securities	EXPD, EXPIRED, EXPIRY, EXPY
Miscellaneous (mainly based on Ince and Porter (2006))	ADS, BOND, CAP.SHS, CONV, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD

This table reports the generic keywords that are searched for in the names of all the stocks in a country. If one or more of these keywords are detected in the stock's name, the respective stock is excluded from the sample.

Table B. 4
Country-specific keyword deletions

Country	Keyword
Australia	PART PAID, RTS DEF, DEF SETT, CDI
Belgium	VVPR, CONVERSION, STRIP
Canada	EXCHANGEABLE, SPLIT, SPLITSHARE, VTG\\., SBVTG\\., VOTING, SUB VTG, SERIES
France	ADP, CI, SICAV, \\)SICAV\\), SICAV-
Germany	GENUSSCHEINE
Italy	RNC, RP, PRIVILEGIES
Netherlands	CERTIFICATE, CERTIFICATES, CERTIFICATES\\), CERT, CERTS, STK\\.
Sweden	CONVERTED INTO, USE, CONVERTED-, CONVERTED - SEE
Switzerland	CONVERTED INTO, CONVERSION, CONVERSION SEE
U.K.	PAID, CONVERSION TO, NON VOTING, CONVERSION 'A'

This table displays the country-specific keywords searched for in the names of all the stocks in a country. If one or more of these keywords are detected in the stock's name, the respective stock is excluded from the sample.

Table B. 5
Dynamic screens

No.	Description	Reference
(1)	Zero returns at the end of the return time series are deleted, which exist because, in case of delisting, Datastream displays stale prices from the date of delisting until the end of the respective time series. Associated market capitalizations are also deleted.	Ince and Porter (2006)
(2)	Associated returns and market capitalizations in case of abnormal prices (unadjusted prices > 1000000) are deleted.	Schmidt et al. (2017); whereas the screen is applied here to unadjusted prices.
(3)	Daily returns and the associated market capitalizations are deleted in case returns exceed 200%.	Schmidt et al. (2017)
(4)	Daily returns and the associated market capitalizations are deleted in case of strong return reversals, defined as follows: R_{t-1} or $R_t >= 1.0$ and $(1 + R_{t-1})(1 + R_t) - 1 < 0.2$.	Ince and Porter (2006), Griffin, Kelly and Nardari (2010), Jacobs (2016)

This table reports the dynamic screens applied to the daily stock data following Ince and Porter (2006), Griffin, Kelly and Nardari (2010), and Schmidt et al. (2017). Column 2 displays the dynamic screen, and column 3 cites the source of the screen.

Multilingual Word Lists for Sentiment Index Construction

This subsection includes the word lists used in Chapter 2 for generating the multilingual sentiment index based on individual investor search behavior. The word lists are based on positive and negative sentiment words labeled with ECON or @ECON from the Harvard General Inquirer dictionary. Word lists are used in each country's native language by translating into Google Translate. Word lists for each country are augmented with the top ten related search terms in Google Trends. Search terms are once again checked for relevance to finance and economics. For non-English word lists, an additional manual check is done to ensure multilingual word lists are not incorrectly translated. The exact methodology is explained in Chapter 2.

Moreover, an additional screen is applied to the word lists provided: At least 2000 daily observations are kept (following Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019)). At the end of the methodology described in Chapter 2, I end up with dynamic top-word lists per country for each regression window. For the sake of brevity, Appendix B includes the word lists for the following countries: U.S., Australia, Belgium (french, dutch), Germany, France, U.K., Italy, and Sweden. Word lists for other countries are available upon request.

Table B. 6

U.S. Word List (with related search terms)

abundance	compensate	interest expense	owe	rewards
in abundance	compensation	expense ratio	owe money	rich
accrue	workers compensation	expense report	owe taxes	rich homie
accrue interest	unemployment compensation	expense account	taxes	get rich
student loans	unemployment	expensive	irs	crazy rich
advantage	deferred compensation	extravagant	owe irs	rich people
affluence	compensation plan	fellowship	i owe taxes	big rich
affluent	workers compensation insurance	fine	partner	rich kids
affluent neighborhoods	contribute	fire	business partner	riches
afloat	contribution	frugal	partnership	rags to riches
allowance	cooperative	frugal living	business partnership	richness
tax allowance	cooperative bank	gain	llc	ruin
aristocracy	corrupt	gain capital	llc partnership	savings
government	corrupt government	gamble	partnership agreement	savings account
aristocrat	cost	generosity	patron	savings bonds
aristocratic	cost of living	ghetto	patronage	american savings
associate	cost stock	gift	pollution	savings bond
backer	fixed cost	gold	environmental pollution	security
backward	costliness	gold price	poor	social security benefits
backwardness	costly	white gold	poor people	segregation
bankrupt	crisis	price of gold	poor credit	shortage
go bankrupt	financial crisis	guide	poor man	skill
going bankrupt	economic crisis	hole	poor credit loans	skills
bankrupt companies	debtor	hustle	poverty	skill level
us bankrupt	creditor	side hustle	poverty level	skill set
bankruptcy	debt	hustler	poverty line	squander
bankruptcy court	credit	inexpensive	us poverty	steal
file bankruptcy	default	inflation	poverty income	subsidize
filing bankruptcy	deficit	inflation rate	poverty rate	subsidized
bargain	budget deficit	rate of inflation	federal poverty level	subsidize loan
beggar	budget	us inflation	poverty guidelines	subsidies
benefactor	us deficit	inflation rates	world poverty	subsidize farmers
beneficiary	trade deficit	money inflation	poverty in america	subsidy
insurance beneficiary	depreciation	gdp	precious	child care subsidy
insurance	tax depreciation	inherit	priceless	government subsidy
trust beneficiary	depreciation expense	inheritance	privileged	tax subsidy
life insurance	property depreciation	intervention	privilege	success
benefit	depreciation value	crisis intervention	privileged information	success stories
benefits	depreciation rate	invaluable	productive	business success
security benefit	accumulated depreciation	invaluable auction	productivity	successful
social security benefit	bonus depreciation	jobless	increase productivity	tariff
social security	asset depreciation	jobless claims	labor productivity	us tariff
cost benefit	depreciation method	jobless rate	work productivity	harmonized tariff
unemployment benefit	depression	us jobless	business productivity	trade tariff
benevolence	great depression	jobless benefits	economic productivity	tariff china
benevolent	destitute	weekly jobless claims	profit	thrift
bequeath	domination	jobless report	profit margin	thrifty
betroth	donate	jobs	gross profit	treasure
betrothal	donation	initial jobless claims	profitable	underworld
blackmail	economize	unemployment rate	profitable business	uneconomical
extortion	define economize	laid	profitable businesses	unemployed
bonus	economizer	laid off	most profitable business	unemployed insurance
signing bonus	economy	lay	most profitable businesses	how many unemployed
bonus tax	endow	legal	most profitable companies	unemployed health insurance
boom	endowment	liquidate	profitable franchises	health insurance
breadwinner	entrepreneurial	liquidate assets	prosper	insurance for unemployed
bribe	entrepreneurial business	liquidate funds	prosper loans	loans
bribery	entrepreneur	liquidate inventory	prosperity	unemployed loans
corruption	entrepreneurship	liquidated	prosperity bank	unemployed workers
broke	entrepreneurial management	liquidation	economic prosperity	unprofitable
bum	equity	liquidation sale	prosperous	unprofitable servant
buy	home equity	government liquidation	prosperous year	vagabond
capitalize	private equity	liquidation sales	race	vagrant
capitalized	equity loan	liquidation auction	radical	valuable
charitable	home equity loan	lucrative	recession	valuable coins
charitable foundation	what is equity	lucrative businesses	the recession	valuable pennies
charitable trust	equity capital	luxury	great recession	warfare
charity	equity line of credit	luxury homes	a recession is	
cheap	health equity	luxury rentals	the great recession	
colony	expense	meritorious	us recession	
commoner	tax expense	net worth	economy recession	
community	worth	miser	economic recession	
waste	business expense	nobility	recompense	
community bank	expenses	nobleman	reward	

Table B. 7

Australia Word List (with related search terms)

abundance
accrue
accrue property
advantage
competitive advantage
affluence
affluence funds management
affluent
afloat
allowance
youth allowance
aristocracy
aristocrat
aristocratic
associate
associate director
sales associate
backer
financial backer
backward
backwardness
bankrupt
bankrupt australia
bankruptcy
going bankrupt
america bankrupt
declare bankruptcy
bankruptcy notice
insolvency
declaring bankruptcy
bargain
big bargain
beggar
benefactor
beneficiary
super beneficiary
estate
superannuation
benefit
child benefit
benevolence
benevolent
benevolent society
virtue
public benevolent institution
bequeath
betroth
betrothal
blackmail
extortion
bonus
baby bonus
tax bonus
boom
breadwinner
bread winner
bribe
broke
why im broke
bum
buy
buy house
buy car
buy and sell
buy a house
capitalize
capitalise
charitable
charitable trust
charitable organisations
charity
charity work
charities
cheap
super cheap
cheap accommodation
colony
commoner
community
compensate
compensation
workers compensation
workers compensation insurance
work compensation
contribute
contribution
contribution tax
cooperative
cooperative bank
co-operative
corrupt
corruption
corrupt countries
cost
gold cost
cost of living
costliness
costly
crisis
financial crisis
global crisis
global financial crisis
economic crisis
debt crisis
debtor
creditor
creditors
default
credit default
deficit
australia deficit
budget deficit
current account
trade deficit
depreciation
depreciation tax
property depreciation
depression
great depression
depression australia
destitute
destitute of money
domination
donate
donation
economize
endow
entrepreneurial
entrepreneur
entrepreneurial ideas
entrepreneurial characteristics
entrepreneurial mindset
equity
members equity
private equity
home equity
equity loan
equity investment
return on equity
expense
interest expense
depreciation expense
expense management
income tax expense
expensive
extravagant
fellowship
fine
pay fine
fire
frugal
frugal living
gain
capital gain
capital gain tax
gamble
generosity
generous
ghetto
gift
gold
gold price
rose gold
white gold
guide
hole
hustle
side hustle
hustler
inexpensive
inflation
inflation rate
inflation australia
inflation rate australia
australian inflation
inflation rates
inherit
can you inherit debt
intervention
government intervention
invaluable
invaluable auctions
valuable
jobless
jobless rate
jobless claims
laid
laid off
lay
legal
legal aid
liquidate
liquidation
company liquidation
voluntary liquidation
auctions
liquidation sales
liquidation auctions
companies in liquidation
lucrative
luxury
meritorious
miser
nobility
nobleman
owe
partner
business partner
partnership
business partnership
partnership agreement
limited partnership
sole trader
patron
patronage
nepotism
pollution
environmental pollution
poor
poor people
rich and poor
poor countries
poverty
world poverty
precious
priceless
privileged
privilege
privileged position
productive
productive efficiency
productivity
productivity report
labour productivity
productivity growth
profit
gross profit
margin
profit margin
net profit
profitable
most profitable businesses
prosper
prosperity
peak prosperity
prosperous
race
radical
recession
recession australia
economic recession
global recession
recompense
reward
rich
rich people
riches
rags to riches
richness
ruin
savings
savings account
savings loans
security
security jobs
segregation
shortage
skills shortage
skill shortage
skill
squander
steal
subsidize
subsidy
child subsidy
wage subsidy
government
government subsidy
success
success factors
business success
debit success
successful
successful business
tariff
customs
thrift
thrifty
thrifty rental
budget
treasure
underworld
uneconomical
unemployed
loans
loans for unemployed
cash loans
unemployment
bad credit loans
unprofitable
vagabond
vagrant
warfare
waste
worth
net worth

Table B. 8

Belgium *french* Word List (with related search terms)

abondance	débiteur	prospérer
accumuler	créancier	la prospérité
avantage	défaut	prospère
avantage en nature voiture	déficit	course
richesse	dépréciation	radical
affluent	une dépression	récession
à flot	dépourvu	récession économique
allocation	domination	recession
allocation familiale	faire un don	récompense
allocation chomage	don	riches
chomage	économiser	riches claires
allocation familiale belgique	doter	se ruiner
allocation familiales	entrepreneurial	des économies
allocation de chomage	équité	sécurité
allocation etude	frais	sécurité sociale
allocations familiales	coûteux	pénurie
paiement allocation	extravagant	métier en pénurie
montant allocation familiale	camaraderie	compétence
aristocratie	bien	gaspiller
aristocrate	pari	voler
aristocratique	cadeau	subventionner
associer	or	subvention
bailleur de fonds	or prix	succès
en arrière	or cours	le succès
arriération	achat or	réussi
faillite	guider	tarif
faillite belgique	trou	épargne
vente faillite	bousculer	épargne pension
vente de faillite	arnaqueur	compte épargne
faillite en belgique	peu coûteux	caisse épargne
loi faillite	inflation	caisse d épargne
faillites belgique	inflation belgique	assurance épargne
la faillite	inflation belgique 2018	compte epargne
bonne affaire	inflation belgique 2019	économe
mendiant	hériter	trésor
bienfaiteur	intervention	monde souterrain
bénéficiaire	inestimable	peu rentable
prime bénéficiaire	sans emploi	vagabond
bienveillance	posé	de valeur
bienveillant	allonger	piece de 2 euros valeur
léguer	légal	piece de monnaie
fiancer	cohabitant légal	valeur vénale
fiançailles	liquider	valeur de la livre sterling
chantage	liquidation	guerre
prime	liquidation judiciaire	déchets
boom	réserve de liquidation	vaut
soutien de famille	lucratif	
pot-de-vin	luxe	
cassé	méritoire	
clochard	avare	
acheter	la noblesse	
acheter maison	la capitale	
capitaliser	noble	
charitable	devoir	
charité	partenaire	
pas cher	partenariat	
colonie	partenariat domestique	
roturier	mécène	
communauté	patronage	
compenser	la pollution	
compensation	pauvres	
contribuer	la pauvreté	
contribution	précieux	
coopérative	privilégié	
banque coopérative	productif	
corrompu	productivité	
coût	profit	
cherté	social profit	
cher	profit margin	
crise	gross profit	
la crise	profit stock	
crise économique	social profit sector	
crise financière	rentable	

Table B. 9

Belgium *dutch* Word List (with related search terms)

overvloed	contract onbepaalde duur	tijdelijk werkloos	verlaagd tarief
opbouwen	huurcontract	werkloosheidsuitkering	tarief vennootschapsbelasting
voordeel	arbeidsovereenkomst	gelegd	vennootschapsbelasting
voordeel alle aard	crisis	leggen	spaarzaamheid
fiscaal voordeel	financial crisis	legaal	schat
voordeel in natura	economische crisis	liquideren	onderwereld
welvaart	crisis management	liquidatie	oneconomisch
welzijn	economic crisis	liquidatie vennootschap	onrendabel
welvarend	2008 crisis	lucratief	zwerver
drijven	schuldenaar	luxe	de zwerver
toelage	standaard	luxe appartement	waardevol
studie toelage	tekort	verdienstelijk	oorlogvoering
studietoelage	afschrijving	vrek	verspilling
aristocratie	afschrijvingen	adel	waard
aristocraat	afschrijvingspercentages	edelman	
aristocratisch	depressie	verschuldigd	
associëren	berooid	partner	
steun	overheersing	vennootschap	
achteruit	doneren	commanditaire vennootschap	
achterlijkheid	bezuinigen	naamloze vennootschap	
failliet	schenken	vennootschap oprichten	
bank failliet	successierechten	gewone commanditaire vennootschap	
faillissementen	schenking onroerend goed	vereffening	
faillissement	schenkingsrechten	vereffening vennootschap	
veilingen faillissement	ondernemend	eenmanszaak	
veilingen	ondernemend diest	patroon	
veiling	eigen vermogen	bescherming	
faillissement veiling	extravagant	civiele bescherming	
faillisement	prima	subsidiaire bescherming	
veilingen faillissement belgie	brand	verontreiniging	
koopje	zuinig	arm	
bedelaar	zuinig leven	armoede	
weldoener	krijgen	armoede in belgie	
begunstigde	ontslag krijgen	kansarmoede	
welwillendheid	gokken	armoede in vlaanderen	
welwillend	vrijgevigheid	welzijnszorg	
nalaten	getto	armoedebestrijding	
verloofde	geschenk	kostbaar	
verloving	goud	onbetaalbaar	
chantage	goud prijs	bevoorrecht	
bonus	goud kopen	productief	
boom	wit goud	productiviteit	
kostwinner	goud koers	winst	
steekpenningen	goud verkopen	koers winst verhouding	
kapot gegaan	goudprijs	winst per aandeel	
kont	goud waarde	winstgevend	
kopen	gids	voorspoedig	
huis kopen	gat	ras	
auto kopen	drukte	radicaal	
hoofdletter	hustler	recessie	
liefdadigheid	hustlers	economische recessie	
goedkoop	hustle	vergelden	
kolonie	husler	beloning	
gewoonter	inflatie	rijk	
gemeenschap	inflatie belgie	rijkdom	
compenseren	index	ruïneren	
een vergoeding	ecb	besparingen	
bijdragen	inflatie 2017	besparingen gezondheidszorg	
sociale bijdragen bijberoep	inflatie 2013	veiligheid	
berekening sociale bijdragen	inflatie 2016	maatschappelijke veiligheid	
bijdrage	inflatie 2011	segregatie	
coöperatie	inflatie september 2018	vaardigheid	
corrupt	erven	verkwisten	
kosten	nieuwe erven	stelen	
notaris	erfrecht	subsidiëren	
vaste kosten	erfenisrecht	subsidie	
aftrekbare kosten	erfenisrechten	subsidies	
openbare verkoop kosten	interventie	succes	
openbare verkoop	onschatbaar	succesvol	
huis kopen kosten	werkloos	tarief	
kosten eigen aan de werkgever	technisch werkloos	btw	
kostbaarheid	economisch werkloos	btw tarief	
duur	werkloosheid	sociaal tarief	

Table B. 10

Germany Word List (with related search terms)

fülle	teuer	legal	landstreicher
in hülle und fülle	krise	kostenlos	krieg
in fülle vorhanden	schuldner	liquidieren	abfall
anfallen	gläubiger	liquidation	wert
vorteil	zwangsvollstreckung	liquidation gmbh	gold wert
geldwerter vorteil	mahnbescheid	lukrativ	münzen wert
wohlstand	standard	konsum	münzen
bip	defizit	luxus	
wahrer wohlstand	strukturelles defizit	verdienstvoll	
wohlhabend	abschreibung	geizhals	
flott	degressive abschreibung	adel	
beihilfe	lineare abschreibung	edelmann	
aristokratie	abschreibung gebäude	verdanken	
oligarchie	depression	partner	
aristokrat	mittellos	business partner	
aristokratisch	herrschaft	partnerschaft	
assoziieren	macht	patron	
unterstützer	spenden	schirmherrschaft	
rückwärts	geld spenden	schirmherr	
rückständigkeit	spende	verschmutzung	
pleite	spende steuer	arm	
insolvenz	spende steuererklärung	armut	
konkurs	sparen	armut deutschland	
pleite konkurs	geld	wertvoll	
konkurs anmelden	geld sparen	unbezahlbar	
insolvenzbekanntmachungen	steuern sparen	privilegiert	
schnäppchen	schenken	priviligiert	
bettler	geld schenken	produktiv	
wohltäter	unternehmerisch	produktivität	
begünstigter	eigenkapital	produktivität wirtschaftlichkeit	
lebensversicherung	baufinanzierung eigenkapital	wirtschaftlichkeit	
überweisung	hauskauf eigenkapital	rentabilität	
sterbegeldversicherung	baufinanzierung	effizienz	
wohlwollen	hauskauf	arbeitsproduktivität	
wohlwollend	kredit	profitabel	
arbeitszeugnis	aufwand	profitable	
vererben	aufwand ertrag	gedeihen	
immobilien vererben	ertrag	der wohlstand	
erbschaftssteuer	auszahlung	rennen	
nießbrauch	extravagant	radikale	
verloben	fein	rezession	
verlobt	feuer	rezession deutschland	
verlobung	sparsam	rezession inflation	
erpressung	sparsam leben	konjunktur	
räuberische erpressung	dazugewinnen	belohnen	
nötigung	zocken	belohnung	
bonus	großzügigkeit	reich	
boom	ghetto	reich werden	
ernährer	geschenk	reichtümer	
bestechung	gold	reichtum	
korruption	silber	geld reichtum	
bestechlichkeit	rose gold	das reichtum	
gammler	gold euro	ruine	
kaufen	leiten	ersparnisse	
haus kaufen	loch	sicherheit	
immobilien kaufen	gedränge	trennung	
profitieren	hustler	mangel	
wohltätig	preiswert	fertigkeit	
nächstenliebe	inflation	fähigkeiten	
billig	deutschland inflation	verschwenden	
kolonie	deflation	stehlen	
bürger	inflationsrate	subventionieren	
gemeinschaft	euro inflation	subventionen	
kompensieren	erben	subvention	
kompensation	haus erben	einstellungstest	
vergütung	erben pflichtteil	erfolg	
tarifvertrag	intervention	erfolgreich	
einen beitrag leisten	von unschätzbarem wert	tarif	
beitrag	arbeitslos	sparsamkeit	
krankenversicherung	arbeitslos melden	schatz	
genossenschaft	arbeitsamt	unterwelt	
korrupt	arbeitslosengeld	unwirtschaftlich	
kosten	gelegt	unrentabel	
kostspieligkeit	legen	vagabund	

Table B. 11

France Word List (with related search terms)

abondance	compensation	guider	profit
accumuler	compensation financière	trou	au profit
avantage	contribuer	bousculer	le profit
richesse	contribution	arnaqueur	rentable
richesse france	contribution solidarité	peu coûteux	investissement
riche	coopérative	inflation	placement rentable
reglage vis de richesse	coopérative agricole	inflation 2018	franchise rentable
affluent	cooperative	inflation en france	rentabilité
à flot	société coopérative	inflation 2011	franchise
allocation	banque coopérative	inflation 2017	business rentable
allocation familiale	corrompu	inflation 2013	investir
allocation logement	coût	inflation 2019	le film le plus rentable
allocation chomage	cout	hériter	prospérer
chomage	coût de la vie	intervention	la prospérité
allocation scolaire	coût de la construction	inestimable	prospère
aristocratie	coût de revient	sans emploi	course
bourgeoisie	cherté	aide sans emploi	radical
oligarchie	cher	recherche emploi	récession
aristocrate	crise	posé	la récession
aristocratique	crise économique	allonger	récession économique
associer	débiteur	légal	recession
bailleur de fonds	compte débiteur	liquider	récession france
bailleurs de fonds	solde débiteur	liquidation	france en récession
en arrière	créancier	liquidation judiciaire	récession dépression
arriération	créditeur	liquidation entreprise	récompense
faillite	débiteur créditeur	la liquidation judiciaire	riches
faillite personnelle	taux débiteur	liquidation société	pays riches
faillite france	debiteur	liquidation judiciaire entreprise	pays les plus riches
faillite banque	défaut	liquidation sarl	se ruiner
entreprise faillite	déficit	entreprise en liquidation	des économies
faire faillite	déficit france	lucratif	économie
france en faillite	déficit public	but lucratif	economie
faillite bancaire	deficit	non lucratif	sécurité
faillite civile	déficit budgétaire	but non lucratif	securite sociale
faillite banques	dette	à but non lucratif	ségrégation
la faillite	déficit sécurité sociale	association à but lucratif	pénurie
faillite de la france	sécurité sociale	association a but lucratif	compétence
la france en faillite	déficit de la france	association à but non lucratif	gaspiller
la faillite personnelle	dépréciation	luxe	voler
la faillite du monde moderne	la dépréciation	méritoire	subventionner
la grece en faillite	amortissement	avare	subvention
faillite de la grece	depreciation	la noblesse	demande subvention
bonne affaire	dépréciation titres de participation	noble	subventions
bon affaire	dépréciation des titres	devoir	succès
mendiant	dépréciation des stocks	partenaire	réussi
un mendiant	dépréciation comptabilité	partenariat	tarif
bienfaiteur	dépréciation de stock	contrat partenariat	épargne
bénéficiaire	une dépression	partenariat entreprise	caisse épargne
assurance vie	la dépression	mécène	caisse d épargne
bénéficiaire assurance vie	depression	patronage	compte épargne
clause bénéficiaire	dépourvu	la pollution	caisse épargne compte
beneficiaire	domination	pauvres	la caisse épargne
bienveillance	faire un don	les pauvres	la caisse d épargne
bienveillant	don	pays pauvres	compte caisse d épargne
léguer	économiser	les pays pauvres	epargne
fiancer	doter	pays les plus pauvres	économe
fiançailles	entrepreneurial	les pays les plus pauvres	trésor
chantage	équité	la pauvreté	monde souterrain
prime	égalité équité	pauvreté en france	peu rentable
boom	equite	la pauvreté en france	vagabond
soutien de famille	frais	la pauvreté dans le monde	de valeur
pot-de-vin	frais reel	pauvreté dans le monde	valeur monnaie
cassé	coûteux	seuil de pauvreté	valeur ajoutée
clochard	extravagant	précieux	chaine de valeur
acheter	camaraderie	privilégié	guerre
acheter maison	bien	créancier privilégié	déchets
capitaliser	feu	privilégier	vaut
charitable	frugal	productif	
charité	gain	système productif	
pas cher	pari	productivité	
colonie	la générosité	productivité du travail	
roturier	ghetto	gains de productivité	
communauté	cadeau	production	
compenser	or	productivité marginale	

Table B. 12

U.K. Word List (with related search terms)

abundance
accrue
accrue capital
accure
advantage
affluence
affluent
afloat
allowance
tax allowance
aristocracy
aristocrat
aristocratic
associate
sales associate
backer
backward
backwardness
bankrupt
go bankrupt
bankrupt stock
going bankrupt
discharged bankrupt
declare yourself bankrupt
bankruptcy
uk bankruptcy
after bankruptcy
bankruptcy court
debt
insolvency
bankruptcy register
bank
bankruptcy advice
bankruptcy scotland
bargain
beggar
benefactor
beneficiary
trustee
benefit
child benefit
housing
housing benefit
benefit uk
benefit calculator
benefits
child tax benefit
benefit fraud
council tax
benevolence
benevolent
benevolent fund
bequeath
betroth
betrothal
blackmail
bonus
boom
breadwinner
bribe
bribery
bribe informally
broke
bum
buy
buy house
home buy
capitalize
capitalise
charitable
charitable trusts
charitable company
charity
cheap
colony
commoner
community
community bank
compensate
compensation
compensation claims
contribute
contribution
pension contribution
pension
national insurance
ni contribution
cooperative
the cooperative
the cooperative bank
cooperative banking
cooperative insurance
corrupt
corruption
corrupt countries
cost
low cost
cost of living
costliness
costly
crisis
crisis loan
financial crisis
crisis uk
debtor
debtor days
creditor debtor
creditor
debtors
creditors
default
deficit
depreciation
depreciation calculator
what is depreciation
straight line depreciation
depreciation calculator car
depreciation definition
depreciation formula
accumulated depreciation
currency depreciation
depression
the depression
depression uk
destitute
domination
donate
donation
charity donation
economize
endow
endowment
entrepreneurial
entrepreneur
entrepreneurship
equity
private equity
equity release
equity fund
equity capital
equity loan
equity investment
equity share
equity calculator
shared equity
expense
global expense
expenses
the expense
expense claim
interest expense
expense management
expense ratio
expensive
extravagant
fellowship
fine
fire
frugal
frugal life
frugal living uk
gain
gain capital
gamble
generosity
ghetto
gift
gold
uk gold
gold price
guide
hole
hustle
hustler
inexpensive
inflation
uk inflation
inflation rate
inflation rate uk
inflation calculator
rate of inflation
inflation rates
current inflation
price inflation
inflation in uk
inherit
inheritance
inheritance tax
intervention
invaluable
invaluable auction
invaluable auctions
jobless
jobless claims
us jobless
jobless claims us
jobless benefits
initial jobless claims
uk jobless claims
uk jobless rate
us jobless figures
us initial jobless claims
laid
laid off
lay
legal
liquidate
how to liquidate a company
liquidation
company liquidation
liquidation uk
voluntary liquidation
stock liquidation
liquidation sale
administration
company in liquidation
auctions
liquidation auctions
lucrative
luxury
meritorious
miser
nobility
nobleman
owe
owe money
i owe you
do i owe tax
student loan
partner
business partner
partnership
business partnership
limited partnership
patron
patronage
pollution
poor
poor credit
poor people
loans
poor credit loans
poverty
poverty uk
child poverty
poverty in uk
world poverty
poverty in the uk
precious
priceless
privileged
productive
productive efficiency
productivity
productivity uk
labour productivity
increase productivity
productivity growth
productivity economics
production
profit
the profit
gross
profit loss
gross profit
profit margin
net
margin
net profit
profit and loss
profitable
profitable business
profitable business ideas
prosper
prosperity
prosperity uk
prosperity wealth
prosperity fund
economic prosperity
prosperous
race
radical
recession
the recession
uk recession
uk in recession
economic recession
recession in the uk
2008 recession
economy
recompense
reward
rich
rich people
riches
richness
ruin
savings
savings account
savings accounts
savings rates
national savings
security
segregation
shortage
skill
squander
steal
subsidize
subsidise
subsidy
government subsidy
fuel subsidy
farm subsidy
housing subsidy
success
business success
successful
successful business
tariff
uk tariff
thrift
thrifty
treasure
underworld
uneconomical
unemployed
uk unemployed
loans for unemployed
unemployed benefits
loan
unemployment
benefits for unemployed
unemployed benefit
loan for unemployed
unprofitable
vagabond
vagrant
valuable
valuable coins
valuable pound coins
warfare
waste
worth
net worth

Table B. 13

Italy Word List (with related search terms)

abbondanza	costoso	hustler	monopolio
maturare	crisi	inflazione	redditizio
vantaggio	crisi economica	tasso inflazione	prosperare
affluenza	crisi governo	inflazione italia	prosperità
affluente	debitore	istat inflazione	prospero
a galla	creditore	tasso di inflazione	gara
indennità	pignoramento presso terzi	deflazione	radicale
indennità disoccupazione	debitore esecutato	calcolo inflazione	recessione
indennità di disoccupazione	cessione del credito	btp inflazione	recessione contratto
aristocrazia	pignoramento mobiliare	inflazione 2013	la recessione
aristocratico	predefinito	ereditare	italia recessione
socio	disavanzo	intervento	recessione economica
sostenitore	disavanzo pubblico	inestimabile	contratto di locazione
arretrato	disavanzo di fusione	senza lavoro	italia in recessione
bollo auto	disavanzo primario	offerte di lavoro	compenso
arretratezza	disavanzo di bilancio	di cui	ricompensa
fallito	debito pubblico	posare	ricco
legge fallimentare	disavanzo commerciale	legale	il ricco
fallimento	disavanzo di cassa	liquidare	ricchezze
istanza fallimento	disavanzo finanziario	liquidazione	ricchezza
fallimento società	disavanzo nel bilancio	in liquidazione	ricchezza e povertà
legge fallimento	ammortamento	la liquidazione	ricchezza vera
istanza di fallimento	piano ammortamento	liquidazione società	ricchezza italia
affare	calcolo ammortamento	liquidazione tfr	rovinare
mendicante	ammortamento mutuo	società in liquidazione	risparmi
benefattore	super ammortamento	srl in liquidazione	cassa dei risparmi
beneficiario	piano di ammortamento	liquidazione coatta	investire risparmi
beneficiario bonifico	mutuo	lucrativo	come investire risparmi
beneficiario polizza vita	ammortamento francese	lusso	sicurezza
assicurazione vita	piano ammortamento mutuo	meritorio	sicurezza lavoro
bonifico bancario	calcolo piano ammortamento	avaro	sicurezza sul lavoro
beneficiare	aliquota ammortamento	nobiltà	segregazione
benevolenza	depressione	nobile	carenza
benevolo	la depressione	dovere	abilità
lasciare per testamento	indigente	compagno	sperperare
fidanzare	dominio	associazione	rubare
fidanzamento	donare	patrono	sovvenzionare
ricatto	donazione	mecenatismo	sussidio
boom	economizzare	inquinamento	sussidio di disoccupazione
boom economico	dotare	povero	sussidio disoccupati
sostegno della famiglia	imprenditoriale	povertà	sussidio per disoccupati
corrompere	piano imprenditoriale	la povertà	sussidio affitto
rotto	equità	povertà italia	sussidio di cittadinanza
culo	equita	povertà in italia	successo
acquistare	spese	soglia povertà	riuscito
capitalizzare	rimborso spese	povertà nel mondo	tariffa
caritatevole	stravagante	istat povertà	tariffa doganale
beneficenza	compagnia	soglia di povertà	parsimonia
economico	la compagnia	poveri	parsimonioso
sviluppo economico	compagnia italiana	poverta	tesoro
conto economico	bene	prezioso	ministero del tesoro
ministero sviluppo economico	fuoco	privilegiato	malavita
trattamento economico	frugale	credito privilegiato	antieconomico
economico sociale	guadagno	creditore privilegiato	disoccupato
bilancio economico	ricavo	credito chirografario	sono disoccupato
colonia	spesa guadagno ricavo	creditore chirografario	inoccupato disoccupato
cittadino comune	mancato guadagno	produttivo	inoccupato
comunità	guadagno e ricavo	processo produttivo	infruttuoso
compensare	margine di guadagno	ciclo produttivo	vagabondo
minusvalenze	giocare	settore produttivo	guerra
compensazione	generosità	fattore produttivo	rifiuto
compensazione crediti	ghetto	decentramento produttivo	di valore
la compensazione	regalo	produttività	valore monete
codice tributo	oro	detassazione produttività	valore assoluto
contribuire	oro quotazione	produttività marginale	prezzo valore
contributo	compro oro	incremento produttività	
contributo affitto	oro prezzo	incremento	
cooperativa	oro usato	produttività del lavoro	
cooperativa di lavoro	valore oro	premio di produttività	
corrotto	oro oggi	profitto	
costo	oro grammo	saggio di profitto	
passaggio di proprietà	guida	massimizzazione del profitto	
costo passaggio di proprietà	buco	profitto economico	
costo eccessivo	spingere	margine	

Table B. 14

Sweden Word List (with related search terms)

överflöd	kooperativ	ärva	låna pengar
tillfalla	kooperativ hyresrätt	ärva skulder	lån med säkerhet
fördel	kooperativet	arv	låna pengar utan säkerhet
välstånd	korrupt	intervention	arbetsmiljö
förmögen	korruption	ovärderlig	segregation
flytande	kosta	arbetslös	brist
ersättning	kostbarhet	arbetslös sjukskriven	skicklighet
ersättning försäkringskassan	kostsam	arbetslös bidrag	slösa
a kassa ersättning	kris	lagd	slösa bort
aristokrati	ekonomisk kris	lägga	stjäla
aristokrat	kris sverige	rättslig	subventionera
aristokratisk	gäldenär	likvidera	framgång
associera	borgenär	likvidera bolag	framgångsrik
hjälpare	standard	likvidation	taxa
bakåt	gold standard	moderat likvidation	sparsamhet
bliv	underskott	likvidation av aktiebolag	skatt
bankrutt	underskott av kapital	likvidation av bolag	skatt lön
bankrupt	skatteverket	likvidation betyder	efter skatt
konkurs	underskott enskild firma	alla bolag	skatt efter lön
konkurs företag	skattereduktion	likviditet	hur mycket skatt
personlig konkurs	skattereduktion underskott av kapital	lukrativ	räkna skatt
konkurser	underskott av näringsverksamhet	lyx	betala skatt
företag i konkurs	avskrivning	förtjänstfull	statlig skatt
konkurs auktion	avskrivning fastighet	girigbuk	räkna ut skatt
auktion	avskrivningar	adel	undre världen
ving konkurs	depression	adelsman	oekonomisk
norwegian konkurs	great depression	skyldig	olönsam
konkurs aktiebolag	utblottad	partner	vagabond
alla bolag konkurs	herravälde	partnerskap	värdefulla
förhandla	donera	beskyddare	krigföring
förhandla ränta	donation	beskydd	avfall
bolån	donationsregistret	förorening	värde
förhandla bolån	hushålla	fattig	mynt
förhandla lön	begåva	fattigdom	värde mynt
förhandla ränta bolån	företagande	fattigdom i sverige	guld värde
tiggare	socialt företagande	relativ fattigdom	
tiggeri	hållbart företagande	absolut fattigdom	
välgörare	ungt företagande	fattiga länder	
förmånstagare	entreprenörskap och företagande	dyrbar	
försäkringskassan	företagarna	privilegierad	
välvilja	rättvisa	priviligerad	
välvillig	justice	produktiv	
testamentera	bekostnad	produktivitet	
testamente	dyr	effektivitet	
arvsrätt	extravagant	vinst	
trolova	bra	skatt på vinst	
trolovning	brand	aktiebolag	
hemgift	sparsam	triss vinst	
utpressning	sparsam skatt	lönsam	
bonus	få	blomstra	
bom	få tillbaka på skatten	välmående	
boom	spela	lopp	
familjeförsörjare	generositet	radikal	
muta	getto	lågkonjunktur	
mutbrott	gåva	lågkonjunktur sverige	
bestickning	guld	lågkonjuktur	
pank	guldfynd	ekonomiska kretsloppet	
pank och fågelfri	pris guld	pris	
luffare	sälja guld	bästa pris	
köpa	gold	rik	
köpa hus	guide	bli rik	
köpa aktier	hål	hur man blir rik	
kapitalisera	liv	aktier	
välgörande	hustler	pengar	
välgörande ändamål	inflation	rika	
välgörenhet	inflation sverige	tjäna pengar	
billig	varför inflation	rikedom	
koloni	deflation	jordisk rikedom	
vanligare	bnp	besatta av rikedom	
gemenskap	inflation rate	ruin	
kompensera	ränta	besparingar	
bidra	hög inflation	säkerhet	
bidrag	inflation i sverige	lån	
söka bidrag	inflation 2018	lån utan säkerhet	

C Chapter 3

Table C. 1

U.S. Word List (with related search terms)

abundance	compensate	interest expense	owe	rewards
in abundance	compensation	expense ratio	owe money	rich
accrue	workers compensation	expense report	owe taxes	rich homie
accrue interest	unemployment compensation	expense account	taxes	get rich
student loans	unemployment	expensive	irs	crazy rich
advantage	deferred compensation	extravagant	owe irs	rich people
affluence	compensation plan	fellowship	i owe taxes	big rich
affluent	workers compensation insurance	fine	partner	rich kids
affluent neighborhoods	contribute	fire	business partner	riches
afloat	contribution	frugal	partnership	rags to riches
allowance	cooperative	frugal living	business partnership	richness
tax allowance	cooperative bank	gain	llc	ruin
aristocracy	corrupt	gain capital	llc partnership	savings
government	corrupt government	gamble	partnership agreement	savings account
aristocrat	cost	generosity	patron	savings bonds
aristocratic	cost of living	ghetto	patronage	american savings
associate	cost stock	gift	pollution	savings bond
backer	fixed cost	gold	environmental pollution	security
backward	costliness	gold price	poor	social security benefits
backwardness	costly	white gold	poor people	segregation
bankrupt	crisis	price of gold	poor credit	shortage
go bankrupt	financial crisis	guide	poor man	skill
going bankrupt	economic crisis	hole	poor credit loans	skills
bankrupt companies	debtor	hustle	poverty	skill level
us bankrupt	creditor	side hustle	poverty level	skill set
bankruptcy	debt	hustler	poverty line	squander
bankruptcy court	credit	inexpensive	us poverty	steal
file bankruptcy	default	inflation	poverty income	subsidize
filing bankruptcy	deficit	inflation rate	poverty rate	subsidized
bargain	budget deficit	rate of inflation	federal poverty level	subsidize loan
beggar	budget	us inflation	poverty guidelines	subsidies
benefactor	us deficit	inflation rates	world poverty	subsidize farmers
beneficiary	trade deficit	money inflation	poverty in america	subsidy
insurance beneficiary	depreciation	gdp	precious	child care subsidy
insurance	tax depreciation	inherit	priceless	government subsidy
trust beneficiary	depreciation expense	inheritance	privileged	tax subsidy
life insurance	property depreciation	intervention	privilege	success
benefit	depreciation value	crisis intervention	privileged information	success stories
benefits	depreciation rate	invaluable	productive	business success
security benefit	accumulated depreciation	invaluable auction	productivity	successful
social security benefit	bonus depreciation	jobless	increase productivity	tariff
social security	asset depreciation	jobless claims	labor productivity	us tariff
cost benefit	depreciation method	jobless rate	work productivity	harmonized tariff
unemployment benefit	depression	us jobless	business productivity	trade tariff
benevolence	great depression	jobless benefits	economic productivity	tariff china
benevolent	destitute	weekly jobless claims	profit	thrift
bequeath	domination	jobless report	profit margin	thrifty
betroth	donate	jobs	gross profit	treasure
betrothal	donation	initial jobless claims	profitable	underworld
blackmail	economize	unemployment rate	profitable business	uneconomical
extortion	define economize	laid	profitable businesses	unemployed
bonus	economizer	laid off	most profitable business	unemployed insurance
signing bonus	economy	lay	most profitable businesses	how many unemployed
bonus tax	endow	legal	most profitable companies	unemployed health insurance
boom	endowment	liquidate	profitable franchises	health insurance
breadwinner	entrepreneurial	liquidate assets	prosper	insurance for unemployed
bribe	entrepreneurial business	liquidate funds	prosper loans	loans
bribery	entrepreneur	liquidate inventory	prosperity	unemployed loans
corruption	entrepreneurship	liquidated	prosperity bank	unemployed workers
broke	entrepreneurial management	liquidation	economic prosperity	unprofitable
bum	equity	liquidation sale	prosperous	unprofitable servant
buy	home equity	government liquidation	prosperous year	vagabond
capitalize	private equity	liquidation sales	race	vagrant
capitalized	equity loan	liquidation auction	radical	valuable
charitable	home equity loan	lucrative	recession	valuable coins
charitable foundation	what is equity	lucrative businesses	the recession	valuable pennies
charitable trust	equity capital	luxury	great recession	warfare
charity	equity line of credit	luxury homes	a recession is	
cheap	health equity	luxury rentals	the great recession	
colony	expense	meritorious	us recession	
commoner	tax expense	net worth	economy recession	
community	worth	miser	economic recession	
waste	business expense	nobility	recompense	
community bank	expenses	nobleman	reward	

This table reports the list of 363 economics- and finance-related search terms used for the US net sentiment index construction. The word lists are filtered afterward to exclude search terms that do not have sufficient observation counts following Da, Engelberg and Gao (2015) and Gao, Ren and Zhang (2019). For a search term to be included in our final world list, we set a minimum number of 2000 daily observations throughout the entire sample period. This ensures that search terms are relevant, and enforces a minimum standard for the sentiment data quality.

Table C. 2
Search terms with the highest observation count during the full sample period

	Search term
1	advantage
2	associate
3	bankruptcy
4	bargain
5	benefits
6	bonus
7	budget
8	compensation
9	cost of living
10	credit
11	crisis
12	debt
13	default
14	donation
15	economy
16	equity
17	expensive
18	gold
19	government
20	health insurance
21	inflation
22	insurance
23	loans
24	profit
25	savings
26	security
27	social security
28	success
29	taxes
30	unemployment

This table reports the search terms with the highest observation count during the full sample period. The search terms are initially derived from the Harvard General Inquirer dictionary, as described in Chapter 3.

Table C. 3
Correlation tests - Institutional demand and institutional investor sentiment by volatility decile

	r	High BW sent	Low BW sent	High sent - Low sent
Low vol. stocks	0.017	-0.237	0.046	-0.283
2	0.171	0.1	0.031	0.069
3	0.309	0.237	0.08	0.157
4	0.234	0.136	0.025	0.111
5	0.253	0.203	0.093	0.11
6	0.301	0.1501	0.073	0.0771
7	0.454	0.366	0.262	0.104
8	0.372	0.306	0.15	0.156
9	0.369	0.183	0.141	0.042
High vol. stocks	0.269	0.049	0.21	-0.161
High vol - Low vol	0.252	0.286	0.164	0.122

This table reports time-series correlation test results for institutional investor demand and the Baker and Wurgler (2006) investor sentiment index by volatility decile. Column 1 reports the time-series correlation between the quarterly Baker-Wurgler sentiment index and the cross-sectional average institutional investor demand shocks (IO_{change}) for stocks within each volatility decile. The bottom row in column 1 reports the difference in institutional demand shocks for high versus low volatility stocks. We sort the 68 quarters (from January 2004 to December 2020) into high (above median value) and low (below median value) sentiment periods and report the time-series mean of the cross-sectional average institutional ownership shocks for stocks within each volatility decile for high sentiment periods (column 2), low sentiment periods (column 3), and their difference (last column). The last row in columns 2 and 3 reports the difference in IO_{change} for the high volatility portfolio and the low volatility portfolio. The last row in the last column reports the difference between high and low sentiment periods.

Bibliography

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5 (1), 31–56.

Annaert, J., De Ceuster, M., Verstegen, K., 2013. Are extreme returns priced in the stock market? european evidence. Journal of Banking & Finance 37 (9), 3401–3411.

Asness, C., 2011. Momentum in japan: The exception that proves the rule. The Journal of Portfolio Management 37 (4), 67–75.

Baele, L., Bekaert, G., Inghelbrecht, K., 2010. The determinants of stock and bond return comovements. Review of Financial Studies 23 (6), 2374–2428.

Baele, L., Bekaert, G., Inghelbrecht, K., Wei, M., 2020. Flights to safety. The Review of Financial Studies 33 (2), 689–746.

Baele, L., Ferrando, A., Hördahl, P., Krylova, E., Monnet, C., 2004. Measuring financial integration in the euro area. Tech. rep., ECB occasional paper.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61 (4), 1645–1680.

Baker, M., Wurgler, J., 2007. Investor sentiment in the stock market. Journal of Economic Perspectives 21 (2), 129–151.

Baker, M., Wurgler, J., 2012. Comovement and predictability relationships between bonds and the cross-section of stocks. Review of Asset Pricing Studies 2 (1), 57–87.

Baker, M., Wurgler, J., Yuan, Y., 2012. Global, local, and contagious investor sentiment. Journal of Financial Economics 104 (2), 272–287.

Baker, S. R., Bloom, N., Davis, S. J., 2016. Measuring economic policy uncertainty. Quarterly Journal of Economics 131 (4), 1593–1636.

Bali, T. G., Engle, R. F., Murray, S., 2016. Empirical asset pricing: The cross section of stock returns. John Wiley & Sons.

Barber, B. M., Odean, T., 2001. Boys will be boys: Gender, overconfidence, and common stock investment. The quarterly journal of economics 116 (1), 261–292.

Baur, D. G., Lucey, B. M., 2009. Flights and contagion—an empirical analysis of stock–bond correlations. Journal of Financial stability 5 (4), 339–352.

Bekaert, G., Harvey, C. R., Lundblad, C. T., Siegel, S., 2017. Economic and financial integration in europe. Duke I&E Research Paper (2017-09), 17–42.

Bethke, S., Gehde-Trapp, M., Kempf, A., 2015. Investor sentiment, flight-to-quality, and corporate bond comovement. Working paper, University of Cologne, Centre for Financial Research (CFR) Working Paper No. 13-06 [rev.3].

Birru, J., Young, T., 2020. Sentiment and uncertainty. Fisher College of Business Working Paper (2020-03), 010.

Birru, J., Young, T., 2022. Sentiment and uncertainty. Journal of Financial Economics 146 (3), 1148–1169.

Black, F., 1986. Noise. Journal of Finance 41 (3), 528–543.

Black, F., 1993. Return and the beta. Journal of Portfolio Management 20 (1), 8–18.

Bollerslev, T., 1990. Modelling the coherence in short-run nominal exchange rates: a multivariate generalized arch model. The Review of Economics and Statistics, 498–

505.

Borensztein, E., Gelos, R. G., 2003. A panic-prone pack? the behavior of emerging market mutual funds. IMF Staff papers 50 (1), 43–63.

Britten-Jones, M., Neuberger, A., Nolte, I., 2011. Improved inference in regression with overlapping observations. Journal of Business Finance and Accounting 38 (5-6), 657–683.

Brown, G. W., Cliff, M. T., 2005. Investor sentiment and asset valuation. Journal of Business 78 (2), 405–440.

Buckman, S. R., Shapiro, A. H., Sudhof, M., Wilson, D. J., et al., 2020. News sentiment in the time of covid-19. FRBSF Economic Letter 8, 1–05.

Cameron, A. C., Gelbach, J. B., Miller, D. L., 2011. Robust inference with multiway clustering. Journal of Business & Economic Statistics 29 (2), 238–249.

Campbell, C. J., Cowan, A. R., Salotti, V., 2010. Multi-country event-study methods. Journal of Banking & Finance 34 (12), 3078–3090.

Campbell, J. Y., Ammer, J., 1993. What moves the stock and bond markets? a variance decomposition for long-term asset returns. Journal of Finance 48 (1), 3–37.

Campbell, J. Y., Sunderam, A., Viceira, L. M., 2009. Inflation bets or deflation hedges? the changing risks of nominal bonds. Working paper, National Bureau of Economic Research.

Campbell, J. Y., Thompson, S. B., 2007. Predicting excess stock returns out of sample: Can anything beat the historical average? Review of Financial Studies 21 (4), 1509–1531.

Çepni, O., Guney, I. E., Gupta, R., Wohar, M. E., 2020. The role of an aligned investor sentiment index in predicting bond risk premia of the us. Journal of Financial Markets

51, 100541.

Chordia, T., Sarkar, A., Subrahmanyam, A., 2005. An empirical analysis of stock and bond market liquidity. Review of Financial Studies 18 (1), 85–129.

Christoffersen, P., Jacobs, K., Ornthanalai, C., 2012. Dynamic jump intensities and risk premiums: Evidence from s&p500 returns and options. Journal of Financial Economics 106 (3), 447–472.

Chui, A. C., Titman, S., Wei, K. J., 2010. Individualism and momentum around the world. Journal of Finance 65 (1), 361–392.

Cochrane, J. H., 2008a. The dog that did not bark: A defense of return predictability. The Review of Financial Studies 21 (4), 1533–1575.

Cochrane, J. H., 2008b. The dog that did not bark: A defense of return predictability. Review of Financial Studies 21 (4), 1533–1575.

Colacito, R., Engle, R. F., Ghysels, E., 2011. A component model for dynamic correlations. Journal of Econometrics 164 (1), 45–59.

Connolly, R., Stivers, C., Sun, L., 2005. Stock market uncertainty and the stock-bond return relation. Journal of Financial and Quantitative Analysis, 161–194.

Connolly, R. A., Stivers, C., Sun, L., 2007. Commonality in the time-variation of stock–stock and stock–bond return comovements. Journal of Financial Markets 10 (2), 192–218.

Corredor, P., Ferrer, E., Santamaria, R., 2013. Value of analysts' consensus recommendations and investor sentiment. Journal of Behavioral Finance 14 (3), 213–229.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. The journal of finance 66 (5), 1461–1499.

Da, Z., Engelberg, J., Gao, P., 2015. The sum of all fears investor sentiment and asset prices. Review of Financial Studies 28 (1), 1–32.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. Journal of Finance 53 (6), 1839–1885.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short-and long-horizon behavioral factors. The review of financial studies 33 (4), 1673–1736.

Daniel, K. D., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance 56 (3), 921–965.

Daniel, K. H., Hirshleifer, D., 1998. D. and subrahmanyam, a.(1998).'investor psychology and security market under-and-overreactions.'. Journal of Finance 53 (6), 1839–1885.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990a. Noise trader risk in financial markets. Journal of Political Economy 98 (4), 703–738.

De Long, J. B., Shleifer, A., Summers, L. H., Waldmann, R. J., 1990b. Noise trader risk in financial markets. Journal of political Economy 98 (4), 703–738.

De Santis, R. A., 2012. The euro area sovereign debt crisis: safe haven, credit rating agencies and the spread of the fever from greece, ireland and portugal.

Devault, L., Sias, R., Starks, L., 2019. Sentiment metrics and investor demand. Journal of Finance 74 (2), 985–1024.

Elkhayat, N., 2024. A more predictive sentiment index? forecasting market returns using google search behavior.

Engle, R., 2002. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business and Economic Statistics 20 (3), 339–350.

Engle, R. F., 1982. Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. Econometrica: Journal of the econometric society, 987–1007.

Falkenstein, E. G., 1994. Mutual funds, idiosyncratic variance, and asset returns. Northwestern University.

Fama, E. F., French, K. R., 1988. Dividend yields and expected stock returns. Journal of Financial Economics 22 (1), 3–25.

Fama, E. F., French, K. R., 1989. Business conditions and expected returns on stocks and bonds. Journal of Financial Economics 25 (1), 23–49.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47 (2), 427–465.

Fleming, J., Kirby, C., Ostdiek, B., 1998. Information and volatility linkages in the stock, bond, and money markets. Journal of Financial Economics 49 (1), 111–137.

Fong, K. Y., Holden, C. W., Trzcinka, C. A., 2017. What are the best liquidity proxies for global research? Review of Finance 21 (4), 1355–1401.

Franke, R. H., Hofstede, G., Bond, M. H., 1991. Cultural roots of economic performance: A research notea. Strategic management journal 12 (S1), 165–173.

French, K. R., Schwert, G. W., Stambaugh, R. F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19 (1), 3.

Gao, Z., Ren, H., Zhang, B., 2019. Googling investor sentiment around the world. Journal of Financial and Quantitative Analysis, 1–66.

Griffin, J. M., Kelly, P. J., Nardari, F., 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets. Review of Financial Studies 23 (8), 3225–3277.

Hansen, P. R., Timmermann, A., 2012. Choice of sample split in out-of-sample forecast evaluation.

Harri, A., Brorsen, B. W., 2009. The overlapping data problem. Quantitative and Qualitative Analysis in Social Sciences 3 (3), 78–115.

Hofstede, G., 2001. Culture's consequences: Comparing values, behaviors, institutions and organizations across nations. Sage publications.

Hofstede, G., 2011. Dimensionalizing cultures: The hofstede model in context. Online readings in psychology and culture 2 (1), 2307–0919.

Huang, D., Jiang, F., Tu, J., Zhou, G., 2015. Investor sentiment aligned: A powerful predictor of stock returns. Review of Financial Studies 28 (3), 791–837.

Hutto, C., Gilbert, E., 2014. Vader: A parsimonious rule-based model for sentiment analysis of social media text. In: Proceedings of the International AAAI Conference on Web and Social Media. Vol. 8.

Ince, O. S., Porter, R. B., 2006. Individual equity return data from thomson datastream: Handle with care! Journal of Financial Research 29 (4), 463–479.

Jacobs, H., 2016. Market maturity and mispricing. Journal of financial economics 122 (2), 270–287.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of finance 48 (1), 65–91.

Kachelmeier, S. J., Shehata, M., 1997. Internal auditing and voluntary cooperation in firms: A cross-cultural experiment. Accounting Review, 407–431.

Karolyi, G. A., Lee, K.-H., Van Dijk, M. A., 2012. Understanding commonality in liquidity around the world. Journal of Financial Economics 105 (1), 82–112.

Kelly, B., Pruitt, S., 2013. Market expectations in the cross-section of present values. Journal of Finance 68 (5), 1721–1756.

Kelly, B., Pruitt, S., 2015. The three-pass regression filter: A new approach to forecasting using many predictors. Journal of Econometrics 186 (2), 294–316.

Keynes, J. M., 1936. The General Theory of Employment, Interest and Money. Macmillan and Company.

Kim, N., Lučivjanská, K., Molnár, P., Villa, R., 2019. Google searches and stock market activity: Evidence from norway. Finance Research Letters 28, 208–220.

Kim, S.-J., Moshirian, F., Wu, E., 2006. Evolution of international stock and bond market integration: Influence of the european monetary union. Journal of Banking and Finance 30 (5), 1507–1534.

Kogan, L., Ross, S. A., Wang, J., Westerfield, M. M., 2006. The price impact and survival of irrational traders. The Journal of Finance 61 (1), 195–229.

Kostopoulos, D., Meyer, S., Uhr, C., 2020a. Google search volume and individual investor trading. Journal of Financial Markets 49, 100544.

Kostopoulos, D., Meyer, S., Uhr, C., 2020b. Google search volume and individual investor trading. Journal of Financial Markets 49, 100544.

Kumar, A., Lee, C. M., 2006. Retail investor sentiment and return comovements. The Journal of Finance 61 (5), 2451–2486.

Laborda, R., Olmo, J., 2014. Investor sentiment and bond risk premia. Journal of Financial Markets 18, 206–233.

Lee, C. M., Shleifer, A., Thaler, R. H., 1991. Investor sentiment and the closed-end fund puzzle. The journal of finance 46 (1), 75–109.

Lemmon, M., Portniaguina, E., 2006. Consumer confidence and asset prices: Some empirical evidence. The Review of Financial Studies 19 (4), 1499–1529.

Li, Y., Ng, D. T., Swaminathan, B., 2013. Predicting market returns using aggregate implied cost of capital. Journal of Financial Economics 110 (2), 419–436.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-ks. Journal of Finance 66 (1), 35–65.

Lowry, M., Officer, M. S., Schwert, G. W., 2010. The variability of ipo initial returns. Journal of Finance 65 (2), 425–465.

Miller, E. M., 1977. Risk, uncertainty, and divergence of opinion. Journal of finance 32 (4), 1151–1168.

Neal, L., 1987. The integration and efficiency of the london and amsterdam stock markets in the eighteenth century. The Journal of Economic History 47 (1), 97–115.

Newey, W. K., West, K. D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708.

Novy-Marx, R., 2016. Testing strategies based on multiple signals. Working Paper.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. Review of Financial Studies 22 (1), 435–480.

Renault, T., 2017. Intraday online investor sentiment and return patterns in the US stock market. Journal of Banking and Finance 84, 25–40.

Schmeling, M., 2009. Investor sentiment and stock returns: Some international evidence. Journal of empirical finance 16 (3), 394–408.

Schmidt, P. S., Von Arx, U., Schrimpf, A., Wagner, A. F., Ziegler, A., 2017. On the construction of common size, value and momentum factors in international stock markets: A guide with applications. Swiss Finance Institute Research Paper (10-58).

Schneider, C. R., Fehrenbacher, D. D., Weber, E. U., 2017. Catch me if i fall: Cross-national differences in willingness to take financial risks as a function of social and state 'cushioning'. International Business Review 26 (6), 1023–1033.

Schwert, G. W., 1990. Stock volatility and the crash of'87. The review of financial studies 3 (1), 77–102.

Scruggs, J. T., Glabadanidis, P., 2003. Risk premia and the dynamic covariance between stock and bond returns. Journal of Financial and Quantitative Analysis, 295–316.

Shen, J., Yu, J., Zhao, S., 2017. Investor sentiment and economic forces. Journal of Monetary Economics 86, 1–21.

Siganos, A., Vagenas-Nanos, E., Verwijmeren, P., 2014. Facebook's daily sentiment and international stock markets. Journal of Economic Behavior and Organization 107, 730–743.

Smales, L. A., 2017. The importance of fear: investor sentiment and stock market returns. Applied Economics 49 (34), 3395–3421.

Stambaugh, R. F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104 (2), 288–302.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing factors. The review of financial studies 30 (4), 1270–1315.

Tetlock, P. C., 2007. Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62 (3), 1139–1168.

Van den Steen, E., 2004. Rational overoptimism (and other biases). American Economic Review 94 (4), 1141–1151.

Van Vliet, P., Blitz, D., van der Grient, B., 2011. Is the relation between volatility and expected stock returns positive, flat or negative? Flat or Negative.

Weber, Y., Shenkar, O., Raveh, A., 1996. National and corporate cultural fit in mergers/acquisitions: An exploratory study. Management science 42 (8), 1215–1227.

Welch, I., Goyal, A., 2008. A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21 (4), 1455–1508.

Zechner, J., Pagano, M., Wagner, C., 2020. Disaster resilience and asset prices. In: Discussion Paper Series Centre for Economic Policy Research, DP14773.