Essays in Financial Economics

Anna Kruglova

A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington
2023

Reading Committee:
Thomas Gilbert, Chair
Philip Bond
Yang Song

Program Authorized to Offer Degree:
Business

University of Washington

Abstract

Essays in Financial Economics

Anna Kruglova

Chair of the Supervisory Committee:

Professor Thomas Gilbert

Foster School of Business

This thesis consists of four empirical essays in financial economics, and the central theme is learning in financial markets. The first essay delves into retail investors' learning within an information market, which is comprised of information providers that produce approximately half a million reports on firms' future earnings. The study reveals that the most active information produvers have a significant effect on the subjective beliefs of retail investors. The second essay discusses how investors learn from medical data pertaining to individual COVID-19 cases to navigate a new source of uncertainty. The study reveals that the influence of economic news on prices varies depending on the level of health uncertainty. In the third essay, the focus is on sophisticated investors who gather specific information from individual oil tanker shipments and leverage this data for futures market speculations. It establishes that acquiring access to primary information provides a tangible benefit to sophisticated investors. Lastly, the fourth essay shows that domestic lending by Russian banks exposed to dollar deposits is affected by U.S. monetary policy shocks. Employing diverse research methodologies, these essays aim to provide empirical evidence on the interconnections between learning, belief formation, and economic activity.

Acknowledgements

The journey of writing this thesis has been an endeavor marked by insights and invaluable learning experiences. Along this journey, I've been profoundly fortunate to have an incredible group of mentors, peers, and loved ones at my side. Their unwavering support, endless wisdom, and countless acts of kindness have been instrumental in bringing this work to fruition.

At the very forefront of this group is my advisor, Professor Thomas Gilbert, to whom I owe my deepest gratitude. His ceaseless guidance, insight, and encouragement throughout the research and writing process have been an invaluable asset. He has been not just an advisor, but a mentor, constantly providing moral support and nurturing my development with unparalleled care and dedication.

To Professor Philip Bond, I owe a debt of gratitude for continually inspiring me to delve deeper into the unknown and pushing the boundaries of my knowledge. His sharp, objective eye on my research findings and consistent presence throughout this journey have been a source of immense reassurance. Similarly, I am thankful to Professor Yang Song for his unwavering support and for being a steadfast advocate for me in all circumstances.

My heartfelt gratitude extends to Professor Mark Westerfield, the Head of the PhD program, for his invaluable guidance throughout the program process. I also owe a great deal of appreciation to Professor Jarrad Harford, whose outstanding leadership and remarkable teaching methods set an example I continually aspire to emulate.

One cannot forget Professor Andrei Kirilenko, a key figure in shaping my academic path. His keen eye spotted me at MIT Sloan and led me into a world of thrilling research. He believed in me when I needed it the most and his confidence in my potential led him to recommend me to the PhD program. His faith in me has been both a great honor and a responsibility, and I am immensely grateful for his trust.

My appreciation goes out to Yao Zeng, Christopher Hrdlicka, Avraham Kamara, Lukas Kremens, Ye Li, Stephan Siegel, Jonathan Karpoff, Jennifer Koski, Doron Levit, Kevin Boeh, Edward Rice, Léa Stern, and Felix Feng. Their wisdom, their willingness to engage in discussions, and their support have been critical to my intellectual growth and development.

On a more personal note, I want to express my immense gratitude to my mother, Liya. Her nurturing influence has been instrumental in shaping my independent thinking. To my partner, Kevin, who has been an unwavering pillar of support, love, and stability when the academic pressure loomed large. Lastly, my heartfelt thanks to my 8-year-old research associate, Adelaide. Her curiosity, infectious joy, and fresh perspective have brought a delightful innocence to this process. Yes, my 3d reparameterization plot did indeed resemble a fresh Dorito chip, and the daily S&P 500 return is quite the artistic squiggle! To my mother, Kevin, and Adelaide, I dedicate this thesis. Your love, support, and influence have left an indelible imprint on this work and on me, and for that, I am eternally grateful.

DEDICATION

To Liya, Kevin & Adelaide

Contents

List of Figures

List of Tables

Chapter 1

Introduction

This thesis consists of four empirical essays in financial economics. The topics include the subjective expectations of retail investors and analyst reports, the impact of geographical COVID-19 uncertainty on the market in reaction to initial jobless claims news, the impact of arbitrageurs' activities in crude oil markets, and the transmission of foreign monetary policy shocks under structural instability. Using diverse research approaches, the essays seek to provide empirical evidence on the relationships between learning, belief formation, and economic activity.

These essays centrally focus on learning within the realm of financial markets. The first essay explores the ways in which retail investors learn within an information market that consists of information providers generating roughly half a million future earnings reports over the span of twenty years. The second essay delves into investors using individual COVID-19 case data to learn in real time about a novel source of uncertainty. The third essay centers on savvy investors who accumulate specific data from individual oil tanker shipments to speculate in the futures market. The final essay scrutinizes the learning methodology of a 'benevolent planner,' or policy maker, who scrutinizes individual cross-border lending transactions to understand the repercussions of foreign fiscal policy.

The first essay is "Subjective Equity Premium & Analyst Reports". Survey data on expectations of stock market returns shows that thesubjective equity premium varies highly over time. In order to understand the observed dynamics, I examine the market for information. Data on the sentiment of analyst reports shows that, when learning about aggregate market dynamics, a retail investor weighs equity reports based on the reporting activities of information providers. The data also shows that trading strategies based on information from less active information providers outperform the S&P 500 Index and strategies based on information from more active providers. Since the investor follows the news consistent with the point of view of more active information providers, her subjective expectations are distorted. The distortion stems from reduced use of information from less active information providers, which decreases the information set that the investor uses to form her expectations about asset markets. As this learning is persistent, it leads to the formation of an equilibrium cointegrating relationship between selected signals about earnings and subjective beliefs, and it introduces a persistent time-varying component into the subjective equity premium.

The second essay is "Geographical COVID-19 Uncertainty and The Market Impact of Initial Jobless Claims News", joint with Thomas Gilbert. We investigate whether health uncertainty affects the stock market's reaction to macroeconomic news. We construct a daily measure of health uncertainty as the dispersion in the change in new COVID-19 cases across all 50 U.S. states. If, over a given week, the number of new cases goes down in some states but up in others, investors will be more uncertain about the future path of the pandemic compared to a week when the number of new cases goes up (or down) in all states. We show that the marginal effect of uncertainty is strongly negative during the pandemic. As health uncertainty increases, the release of higher than expected initial jobless claims has an increasingly negative impact on high-frequency E-mini S&P500 futures announcement returns.

The third essay is "Impact of Arbitrageurs' Activities in Crude Oil Markets", joint with Solene Collot and Andrei Kirilenko. We build a partial equilibrium asset pricing model in which we develop a limits to arbitrage extension by introducing cash-and-carry traders' activities in a speculative storage framework. Our model overcomes important issues found in the literature. First, we propose a closed form pricing equation for the termstructure of commodity futures prices with a critical nonlinearity parameter that captures the nonnegativity of speculative storage. Second, we recover a proxy for speculative seaborne inventory of crude oil using a new data set collecting granular information on every tanker that delivered seaborne crude oil into the United States during 2008-2012. As predicted by the model, we find that in equilibrium, cash-and-carry traders' activities are non-linearly linked to the risk premium in commodity prices and the cost of floating storage. We show that, not only our model is capable to incorporate first-order features of the data but also that, arbitrageurs have the ability to send a powerful signal about the state of the market and alertmarket participants as well as policy-makers to potential supply disruptions.

The fourth essay is "The Transmission of Foreign Monetary Policy Shocks Under Structural Instability: The Case of Russia", joint with Konstantin Styrin and Yulia Ushakova. We study the transmission of monetary policy shocks in the U.S. to a small open economy by estimating their effect on lending based on bank-level balance sheet data of Russian banks for 2000-2018. To identify the causal effect at the bank level we exploit heterogeneity across banks in terms of their reliance on cross-border funding. We find evidence that the effect of U.S. monetary policy shocks has been statistically and economically significant. Surprisingly, the magnitude of the effect remained roughly the same even after the monetary policy in Russia transited from exchange rate to inflation targeting. This finding suggests that a free floating regime does not attenuate the effect of foreign monetary policy shocks on domestic lending.

In conclusion, this thesis sheds light in how learning from primary and secondary data shapes financial and economic activities. The essays expose the subjective nature of retail investors' learning from analyst reports, highlighting the potential for bias and distortion. The exploration of investors' learning about novel, pandemic-induced uncertainties reveals the influence of primary health data on market reactions to macroeconomic news. The study of arbitrageurs' activities underscores the sophistication of learning in commodity markets, where granular data about individual shipments informs speculation and can signal potential supply disruptions. Finally, the investigation into the transmission of foreign monetary policy shocks suggests that the impact of systemic changes in economic policy may be quantified from the learning from micro-level cross-border activities. Collectively, these essays demonstrate that learning - whether from secondary sources, like analyst reports, or from primary sources, like health data, shipping information, or cross-border lending - is a key determinant of investor behavior and market dynamics.

Chapter 2

Literature Review on Information Used to Form Expectations

Investor's subjective expectations play a critical role in economic decision-making and are significantly influenced by the information utilized. Literature has delved into both the process of how these expectations are formed and the impact of information sources on this process.

The formation of subjective expectations by investors is traditionally explained through models of Bayesian learning, where investors update their beliefs by using new information to adjust their prior beliefs (Barberis et al. (1998)). This is in line with rational expectations theory, which posits that investors use all available information to form their expectations and that these expectations will, on average, be accurate (Muth (1961)).

We know that the same facts or events are disseminated through two distinct information markets, namely the primary and secondary information markets. Primary information, such as company financial reports, statistical data, data on stock prices, trading volume, offers direct insights about a company's financial health. Secondary information, however, includes analyses and interpretations of primary data, such as financial news, analyst reports, blogs and stock recommendations.

There is substantial evidence that both primary and secondary information influence subjective expectations. Vuolteenaho (2002) shows that primary sources such as company earnings reports or macroeconomic data can significantly impact investors' beliefs about future stock returns. Literature on financial market responses to earnings announcements, such as the works of Bernanke and Gertler (1995), provides evidence that primary information significantly impacts investor sentiment and expectations. Furthermore, the research of Kothari (2001) shows that mandatory financial disclosures, a prime source of primary information, critically influence market expectations, underscoring the role of regulatory policies in shaping information markets. On the other hand, secondary sources, such as financial news media, analyst reports, and social networks, are also powerful influencers of investor sentiment and expectations (Boudoukh et al. (2013)). Research such as Tetlock (2007) demonstrates how media sentiment significantly influences investor expectations and market dynamics. Meanwhile, studies like Hong and Kubik (2003) show that analyst forecast biases can impact investor expectations. Moreover, recent research by Chen et al. (2014) indicates that the rise of social media and digital platforms as secondary information providers is transforming the landscape of information markets, influencing investors' market return expectations in new ways.

Interestingly, the influence of different information sources is not uniform among all types of investors. The upcoming subsections will delve into the scholarly works that discuss how primary and secondary information sources impact learning for investors at varying income levels and those with diverse amounts invested in stocks.

2.1 Sophisticated Investors and Primary and Secondary Information

Investors with larger income and higher investment amounts are generally more active in secondary information markets, frequently accessing analyst reports, earnings forecasts, and other forms of processed information (Barber and Odean (2001)). They often have better access to professional investment advice and sophisticated investment tools, which allow them to integrate and interpret this information more effectively (Guiso and Jappelli (2006)) . Thus, they may form expectations that are more aligned with the consensus view in these markets.

The literature points out to several reasons. First, secondary sources of information, such as analyst reports, news articles, and investment blogs, provide condensed and interpreted information that's easier to digest and act upon (Brennan et al. (2016)) Second, research by **?** found that secondary sources, particularly financial news, can not only help predict market volatility but also offer significant predictive power for stock returns. This further boosts their appeal for sophisticated investors, as they often leverage this kind of sentiment analysis in their trading strategies. Third, another reason comes from the study by Cohen et al. (2012) which found that the market tends to underreact to the information contained in sell-side analyst reports, suggesting that there might be profitable trading opportunities for sophisticated investors who can correctly interpret this information. Lastly, secondary sources also allow sophisticated investors to consider the opinions and sentiment of others, which can be valuable in predicting market movements. For example, Antweiler and Frank (2004) found that the bullishness or bearishness of online investment message boards could predict market returns.

However, another strand of literature suggests that sophisticated investors tend to use primary sources of information. There are several reasons. Firstly, primary information allows for a deeper understanding of the data or event (Cohen et al. (2012)). Sophisticated investors often use primary data to investigate an investment opportunity thoroughly, exploring all available data directly related to the company, the industry, and the market. It provides unfiltered insights into the business environment, financial health, and potential risk factors of the investment target. Secondly, primary information offers the advantage of timing. For instance, in the case of earnings announcements or other company-specific news, having access to this information as it becomes available can provide a competitive edge. This advantage could potentially lead to superior investment performance (Fedyk (2015)). Thirdly, primary information is often more reliable and accurate than secondary sources as it is less prone to distortion, manipulation, or interpretation (Brennan et al. (1993)). This can be particularly important in complex and fast-moving markets where misinterpretations can lead to significant financial losses.

Studies show that accessing and interpreting primary information can be challenging and resource-intensive, requiring substantial expertise and experience (Cohen et al. (2012)). Thus, it's a strategy more often utilized by institutional investors or high-net-worth individuals who can afford the time and resources required. For example, Bushee et al. (2010) found that institutional investors, particularly those with long-term horizons, tend to use primary sources of information more than other types of investors.

In conclusion, while both primary and secondary sources of information have their advantages, the current body of literature suggests that secondary sources, due to their interpreted and often sentiment-inclusive nature, are often preferred by sophisticated investors.

In my thesis, three of the four chapters demonstrate the benefits of utilizing primary information by sophisticated investors. In Chapter 4, I delve into how investors use individual COVID health data to create a nowcasting measure, assisting them in understanding the novel uncertainty. Chapter 5 explores the strategies of commodity traders who operate in multiple markets, such as the oil market, oil transportation market, and oil futures market. Here, traders gather private information about oil inventories to speculate effectively on the futures market. Lastly, Chapter 6 investigates the role of a regulator using granular cross-border lending data to assess the impact of foreign monetary policy. Each of these chapters serves to highlight the importance and advantages of leveraging primary information in different aspects of economic activity.

2.2 Retail Investors and Primary and Secondary Information

Retail investors have often been depicted as the less sophisticated participants in the market, largely due to their reliance on digestible information sources as opposed to the complex financial analyses utilized by institutional investors. This tendency can be traced back to the information asymmetry that exists between these two classes of market participants.

Mainstream literature suggests that retail investors often prefer secondary sources of information, such as analyst reports, financial news media, and online forums, over primary sources like corporate financial statements or economic data releases. This preference is underpinned by several factors. First, secondary sources often provide interpretation, summarization, and contextualization of primary information, making it more accessible to retail investors. Barber and Odean (2001) argue that these investors often lack the expertise to fully comprehend the complex financial data presented in primary sources, making secondary sources a more digestible and convenient alternative. Second, secondary sources like analyst reports often provide forward-looking estimates and opinions that primary sources do not offer. Guiso and Jappelli (2006) note that such forward-looking analysis can help retail investors make informed decisions about future market developments. Third, in the digital age, secondary information sources have expanded rapidly, especially with the rise of financial social media. Chen et al. (2014) suggest that these platforms enable retail investors to share and consume opinion-based, interpretive content that they value more than raw data from primary sources. Fourth, secondary sources can aid retail investors in processing large volumes of information. Tetlock (2007) proposes that retail investors are subject to information overload and cognitive biases, hence secondary sources help them focus on the most salient information. Finally, the behavioral finance literature, as highlighted by Shleifer and Summers (1990), indicates that retail investors may be guided more by sentiment and noise, often prominent in secondary sources, rather than by rational processing of primary information. In summary, the literature shows that retail investors tend to favor secondary information sources due to their interpretative nature, forward-looking analysis, wide availability, ability to cope with information overload, and alignment with investor sentiment and behavioral biases.

While the traditional assumption has been that retail investors lack the capability to interpret complex financial information from primary sources, more recent research has started to challenge this view. The advent of technology and the Internet have facilitated access to a vast array of primary information sources, including company financial statements, regulatory filings, press releases, and real-time financial market data. Retail investors are increasingly seen as being able to handle this raw data, aided by user-friendly financial software and online platforms, and free financial education resources.

Goetzmann et al. (2015) examined the decision-making process of retail investors and concluded that primary information sources have a significant influence on investment decisions, particularly when making stock selections. They observed that the increased availability and accessibility of primary information on the Internet have made retail investors more confident in their ability to make informed decisions. Similarly, Haliassos et al. (2016) found that retail investors place a substantial weight on primary information when forming expectations about future stock returns. They concluded that these investors rely on a mix of public news and personal information, such as their own understanding of the company's industry, to form their investment decisions.

In an interesting twist, Veldkamp (2011) argued that sophisticated retail investors might not only use primary information but actively seek it out. She contended that these investors view primary information as a valuable input into their decision-making process, as it allows them to establish unique investment views and avoid herd behaviour. This research suggests that the preference for primary information might not be universal among retail investors, but a distinguishing trait of the more sophisticated ones. However, more research is needed to confirm this hypothesis and understand its implications.

Although the academic research is still evolving, it is clear that the role of primary information in the investment process of retail investors is gaining recognition, which has important implications for financial education, investor protection, and the design of financial markets.

In Chapter 3 of my dissertation, I provide evidence which indicates that investors, irrespective of their income or the size of their stock investments, seem to depend on secondary information. This is despite having access to primary information, such as stock returns. My analysis underscores that retail investors with a lower income and smaller stock investments tend to depend on TV stock shows. They use the information from stock market reports primarily to enhance their grasp of the market sentiment conveyed in these shows. On the other hand, retail investors who have higher incomes and invest larger amounts in stocks appear to actively utilize analyst reports for their investment decisions.

2.3 Information Aggregation

How do investors process all this information? In the domain of financial decision-making, the concept of information aggregation, particularly the weighting of individual signals, is paramount (O'Hara (1995)). Investors are constantly bombarded with various forms of information or signals, such as primary information from financial reports, or secondary information suchas market trends, and analyst recommendations. It is essential for these investors to interpret, weight, and aggregate these signals to make informed investment decisions (Hellwig (1980)).

The way investors weight signals often depends on various factors, such as their investment strategy, risk tolerance, cognitive biases, and the timeliness and reliability of the information (Shefrin (2008)). For instance, some investors may place greater weight on financial statements, viewing them as more reliable for long-term decisions (**?**). Others may lean more heavily on recent news or analyst recommendations, when making short-term trading decisions (**?**).

Investors also adjust the weights they assign to different signals based on their past experiences and the perceived usefulness of the signal (Daniel et al. (1998)). A positive outcome following an analyst's recommendation might increase the investor's trust in that analyst, leading to greater weight being assigned to their future recommendations (Malmendier and Shanthikumar (2007)).

The advent of big data and machine learning has introduced more advanced ways of aggregating and weighting information. Sophisticated investors and financial institutions now use statistical models and machine learning algorithms to better weigh and aggregate signals (Sirignano and Cont (2019)). These methods can account for the historical accuracy and predictive power of different information sources, enhancing the effectiveness of the decision-making process (Gârleanu and Pedersen (2018)).

However, the process of information aggregation is not devoid of complexity. It is often influenced by various cognitive biases and constraints (Barberis (2018)).

Chpater 3 shows that retail investors show a tendency to disregard reports from less active information providers, and instead, lean towards those who are most active. This finding underscores the critical role of activity level among information providers in the landscape of financial decision-making and underlines the need for further examination of its impact on investors' actions.

2.4 Conclusion

Investors' subjective expectations, a critical component of economic decision-making, are heavily shaped by the information they consume, be it primary or secondary. The literature comprehensively explores this dynamic, revealing the complex interplay between various sources of information, the sophistication level of investors, and their corresponding investment behavior. For sophisticated investors, a propensity for secondary information sources, such as analyst reports and financial news, was found due to the digestible, forward-looking nature of these sources. However, this class of investors also appreciates primary sources for the direct, accurate, and timely insights they offer.

In contrast, retail investors, traditionally seen as less sophisticated, tend to favor secondary sources, largely due to their interpretative and easy-to-understand nature. This preference is enhanced by the information asymmetry between retail and institutional investors, and the prevalence of sentiment and noise trading. Interestingly, recent literature reveals an emerging trend among sophisticated retail investors seeking out primary information to form unique investment perspectives and avoid herd behavior.

Information aggregation is an indispensable step in investors' decision-making process. The weighting of different signals, driven by various factors such as investor strategy, cognitive biases, and reliability of information, plays a crucial role. The review concludes that the information source preference varies among investors based on their sophistication.

Chapter 3

Subjective Equity Premium & Analyst Reports

3.1 Introduction

Do subjective expectations of a retail investor about stock market risk premium vary over time? Does the information market affect the subjective expectations?

The studies by Greenwood and Shleifer (2014) and Nagel and Xu (2019) provide valuable insights into the formation of investors' expectations of future market returns. While Greenwood and Shleifer (2014) find that investors tend to extrapolate recent market performance into the future, leading to time-varying expectations, Nagel and Xu (2019) study suggests that investors' expectations of future market excess returns are "virtually constant." This apparent contradiction highlights the complexity of investors' subjective expectations and the need for further research to better understand the factors that influence these expectations.

I start with examining surveys of individual retail investors from three sources used in Greenwood and Shleifer (2014) and Nagel and Xu (2019) , Gallup, the Survey Research Center at the University of Michigan, and the Conference Board, and analyze subjective expectations of annual stock market returns and the risk-free rate from June 2002 to December 2019. I find that subjective expectations of market risk premium 12 months ahead is a non-stationary, persistent process.

To understand this dynamics, I delve into the market for information and collect granular meta data of

0.5 mln equity reports on 45 U.S. blue-chip companies from InvesText. I find that the aggregated monthly sentiment of 545 information providers displays a persistent pattern over time and has cointegrated relationships with retail investors' subjective expectations of stock market risk premium.

I test four hypothesis

Hypothesis 1. If every report has equal weight or equivalently, the sentiment of information providers is weighted by the reporting activity of information providers, there is an association between subjective expected excess return and sentiment about the growth of companies' earnings.

Hypothesis 2. The association between subjective expected excess return and sentiment about earnings growth is stronger for reports of information providers with higher reporting activity.

Hypothesis 3 Information from less active providers is not related to the temporal fluctuations of aggregate stock market return.

Hypothesis 4 There is no effect of income and stock investement amount on the learning pattern of retail investors.

To test the relationship between the aggregated monthly sentiment of information providers and subjective expectations of market risk premium, I utilize a vector error correction model. This model is based on the theory of cointegrated processes developed by Johansen (1991) and Engle and Granger (1987) and is commonly used in asset pricing research (Campbell and Shiller (1988a), Campbell and Shiller (1988c) [1] and many others).

First, I show that the association between subjective expected excess return and sentiment about earnings growth is present if every report has equal weight or equivalently, the sentiment of information providers is weighted by the reporting activity of information providers.

Second, I show that the association between subjective expected excess return and sentiment about earnings growth is strong for reports written by information providers with higher reporting activity, and absent for reports written by information providers with lower reporting activity. Moreover, my findings show that shock to provider-weighted sentiment of earnings reports is a permanent disturbance that has a long-run effect on subjective expectations. A positive value for this shock raises subjective expectations to

[1] Campbell and Shiller (1988a) and Campbell and Shiller (1988c) use vector autoregression to forecast returns (or dividend growth) with other variables including the log dividend-price ratio. Since they calculated expected returns from an econometric forecasting model, they were estimating the discount rates that would be applied to cash flow by an investor with rational expectations.

a new level in three months and accounts for fifteen percent of its fluctuations (the rest of the impact is the impact of the previous month's subjective expectations that propagate shock even further).

Third, I also demonstrate that a trading strategy based on past-month information from less active information providers may provide valuable insights. To test this, I use two types of analysis. Firstly, I conduct a predictive regression as in Cochrane (2006). The results show that the change in sentiment of active information providers is highly significant, while the change in sentiment of less active information providers is not significant. Secondly, I analyze the profitability of a sentiment-based trading strategy constructed using information from more and less active information providers, following the methodology of Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). The results show that the trading strategy based on information from less active providers is profitable and outperforms the returns of the S&P 500 Index. These findings suggest that information from less active information providers may not be noise, but rather a valuable addition to an investor's information set.

Fourth, I show that retail investors' learning patterns are shaped by their income level and the magnitude of their stock investments. Lower-income investors typically form their subjective expectations of stock market returns from insights gleaned from popular sources, like Jim Cramer's show, as well as provider-weghted sentiment. Conversely, higher-income investors with below-average stock investments seem to gravitate more towards the insights presented on 'Squawk on the Street' that are related to past stock market returns. Meanwhile, investors that boast both high incomes and considerable stock investments generally make their decisions based on information from provider-weghted sentiment of equity reports.

This finding suggests that lower-income retail investors may be more vulnerable to biased or incomplete information, and may be influenced more by the popularity of certain sources than the quality or accuracy of those sources. The fact that income level is a significant factor in this learning pattern also raises important questions about equity and access to information. Lower-income investors may face greater barriers to accessing information or resources that can help them make informed investment decisions. This can perpetuate inequalities in wealth and financial outcomes.

The chapter points out on the importance of information interpretation and dissemination: the perception of events' sentiment can be strongly influenced by the reporting activity of information providers, leading to disparities in expected sentiment values. The straightforward example provided below illustrates the mechanism. Initially, without the influence of reporting activity, the expected sentiment of two contrasting events, one positive (+1) and the other negative (-1), is neutral or zero, as the positive and negative sentiments offset each other. However, when I introduce information providers, as infomration intermediaries, with varying reporting activities into the equation, the expected sentiment score can change dramatically. Consider a scenario where one provider issues a single report for each event, while another issues two reports for the positive event and none for the negative. To calculate the new expected sentiment score, it's crucial to consider not only the sentiment scores themselves but also the frequency of reports by each provider. In our example, the denominator becomes the total number of reports (4), and the numerator is the sum of each sentiment score multiplied by its reporting frequency. This calculation yields a new expected sentiment score of 0.5, a substantial deviation from the original expectation of zero. This deviation can be attributed to differences in the Data Generating Process (DGP) of events and reported events. The DGP of events reflects the raw sentiment frequency, whereas the DGP of reported events captures the frequency of sentiment as shaped by reporting activity. As a result, the positive sentiment, which is overemphasized from the DGP of events perspective, appears accurately weighted from the DGP of reported events perspective. Whether in the financial market, media industry, or social behavior studies, such dynamics can influence public perception, decision-making, and overall sentiment toward certain events or phenomena.

The innovation of this chapter is documenting that the reporting activity of information providers has a significant impact on investors' expectations. In particular, the study shows that more active information providers have a stronger influence on investor sentiment than less active providers. As a result, investors may have distorted expectations of the asset market. This perspective is an important contribution to the existing literature on subjective expectations, which has traditionally focused on the role of past market returns and other macroeconomic variables. By emphasizing the role of information providers in shaping investors' expectations, this study provides a more nuanced view of the mechanisms underlying the formation of subjective expectations. Additionally, this perspective sheds light on the potential biases that can arise in investors' expectations. If investors rely too heavily on a subset of information providers, they may be more susceptible to biases and errors in their expectations. This finding has important implications for policymakers and market participants who seek to improve the accuracy and efficiency of asset prices.

Overall, linking the activity of information providers on the information market to investors' subjective expectations on the stock market provides a valuable contribution to the literature on financial markets and information processing. It highlights the importance of considering the role of information providers in shaping financial market outcomes and suggests new avenues for future research in this area.

Related Literature This chapter makes contribution to three areas of literature. Firstly, this chapter contributes to the literature examining subjective expectations by further investigating and refining our understanding of the temporal nature of retail investors' subjective expectations. While aligning with Greenwood and Shleifer (2014) finding that these expectations are time-varying, my results demonstrate that these expectations are also a non-stationary and persistent process, nuanced by the aggregated monthly sentiment of information providers. This adds a new dimension to the studies of Malmendier and Nagel (2011) and Nagel and Xu (2019), revealing that the information market's dynamics and the sentiment of its participants are instrumental in shaping the trajectory of these time-varying subjective expectations.

Secondly, this chapter has a strong connection to the literature that employs cointegration analysis to pinpoint the primary factors driving fluctuations in financial markets. Within the context of asset pricing, Bansal and Yaron (2004) utilize cointegration to illustrate how long-run risks can contribute to risk premia. Similarly, Bansal et al. (2005) apply cointegration to analyze the term structure of interest rates and its relationship with macroeconomic variables. Other scholars like Hansen et al. (2005) and Bansal et al. (2007) have used cointegration to investigate the relationship between expected returns and dividend growth rates, and the relationship between asset prices, economic activity, and news shocks, respectively.

Engle and Granger (1987) seminal work underscores the importance of cointegration in forecasting. They argue that if two time series are cointegrated, then the deviation of one series from the other, termed as the error-correction variable, is stationary and can be used to forecast future movements in both series. Within the context of this chapter, focusing on subjective expectations and sentiment of earnings reports, this theorem implies that the deviation of the level of subjective expectations from the sentiment of earnings reports can significantly influence both the prediction of future subjective expectations growth rates and the innovations in subjective expectations. Therefore, the application of cointegration analysis in this chapter enables a more profound understanding of the relationship between subjective expectations and sentiment of earnings reports.

My research augments this strand of literature that applies cointegration techniques in financial markets.

I do this by applying a vector error correction model to demonstrate a cointegrated relationship between the aggregated monthly sentiment of information providers and retail investors' subjective expectations of stock market risk premium. This approach reveals a new facet of how the information market impacts investor behavior.

Finally, the chapter contributes to the growing body of literature investigating the relationship between asset markets and information markets, particularly from the perspective of retail investors. Over the past few decades, an increasing number of studies have been dedicated to understanding the nuances of this relationship. The pioneering works of empirical finance, such as Roll (1988), proposed that news is an exogenous process influencing asset prices. This theory suggests that asset markets are reactive, responding to the flow of information as it occurs. However, as the field evolved, it became evident that this relationship is more complex.

Barber and Odean (2001) shifted the focus to the individual investor's perspective, examining how investors trade based on the information from their personal experiences and the impact of this on their portfolio performance. This work emphasizes the importance of personal interpretation and the individual's capacity to process information. Veldkamp (2005) further advanced our understanding by highlighting the endogenous nature of news and its interaction with asset markets. Rather than simply reacting to information, asset markets, through the actions of their participants, play a role in shaping the flow and interpretation of news. The role of information providers or intermediaries has also been a topic of interest. Fishman and Hagerty (2019) explored the influence of news on stock prices, illustrating that both the tone and content of news can have a significant impact on stock returns. This work underscores the importance of information quality and the role of media in the financial market ecosystem. Meanwhile, Tetlock (2011) scrutinized the accuracy of financial analysts' predictions. The study found that analysts with more expertise are better able to predict future stock prices, highlighting the importance of expert knowledge and experience in the realm of financial forecasting. The advent of digital platforms has brought a new dimension to the information-asset market nexus. Eaton and Wu (2021) illustrated how social media can increase the flow of information to retail investors while simultaneously leading to an increase in market "noise" from retail investor trading. This insight suggests that modern communication platforms can both enhance and distort the information environment for retail investors.

My work bridges several areas of existing scholarship and presents new insights into how the information market influences retail investors' subjective expectations. While Greenwood and Shleifer (2014) and Nagel and Xu (2019) provide critical starting points, highlighting the time-varying nature of retail investors' expectations and their tendency to extrapolate recent market performances, their analyses do not fully explain the mechanisms underlying these patterns. In response to this gap in the literature, my research delves deeper into the dynamics of these subjective expectations, revealing them as a non-stationary, persistent process.

Further, I extend our understanding of the information market by scrutinizing a large corpus of equity reports from InvesText. The analysis of this granular data demonstrates that the aggregated monthly sentiment of information providers follows a persistent pattern over time and, importantly, shares a cointegrated relationship with retail investors' subjective expectations of stock market risk premiums. This finding expands the existing knowledge, providing empirical support for the endogeneity of news to asset markets as suggested by Veldkamp (2005).

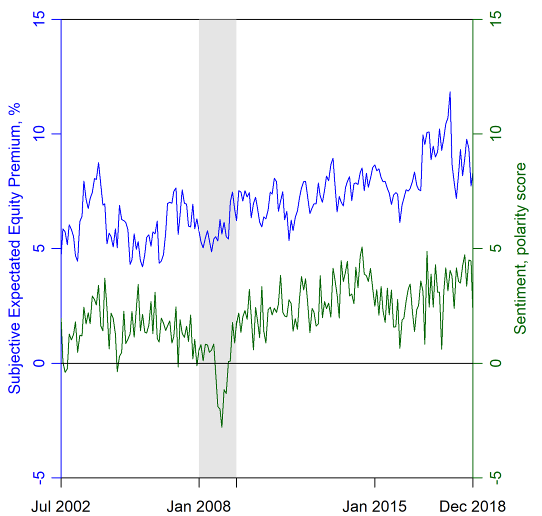
My research also advances our understanding of the differential impact of information providers based on their activity level, a topic not extensively addressed in existing literature. I show that retail investors' subjective expectations are more strongly influenced by information providers with higher reporting activity, underscoring the importance of information source prominence in shaping market perceptions. Moreover, my findings illuminate the potential value of less active information providers, suggesting that their contributions may not be mere noise but a valuable addition to an investor's information set, an insight that could have important implications for the design of investor strategies.

Moreover, I explore the socioeconomic dimensions of information processing in the asset market. My work reveals that income level plays a significant role in shaping the learning patterns of retail investors, with lower-income investors being more susceptible to the influences of highly active information providers. This finding sheds light on potential inequities in the access to and utilization of information in the asset market, prompting important questions about the distribution of resources and opportunities in financial markets.

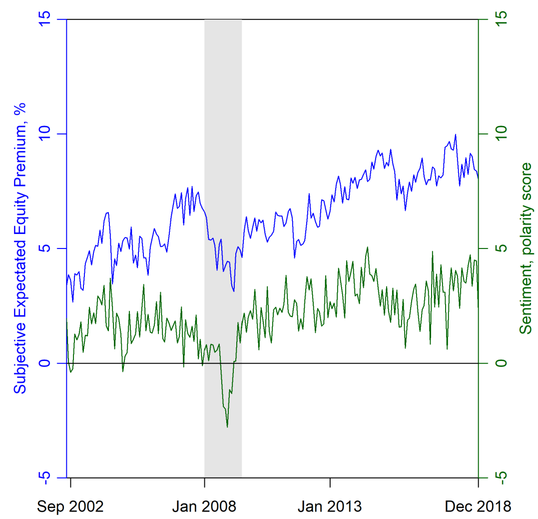
In sum, this chapter extends our understanding of the interplay between the asset and information markets. It uncovers new dimensions of this relationship, and raises critical questions about equity and access in

Figure 3.1: Subjective Equity Premium From Surveys & Provider-Weighted Aggregated Sentiment Of Analyst Reports

Green lines and green right y-axes on both plot correspond to aggregated sentiment of equity reports about 45 US blue-chip companies. Blue line and blue y-axis on the left plot show subjective equity premium from CCS survey. Blue line and blue y-axis on the right plot show subjective equity premium from MSC survey. Gray area is NBER recession.



(a) CCS Subjective Expected Equity Premium & s_t^w Sentiment



(b) MSC Subjective Expected Equity Premium & s_t^w Sentiment

financial markets. This work paves the way for future research exploring the dynamics of investor behavior in the increasingly complex and digitized world of finance.

3.2 Empirical Regularity

In this section, I illustrate an empirical regularity, a link between the retail investor's subjective expected equity premium and the aggregated sentiment reflected in equity reports about US blue-chip companies. The subsequent analysis brings into focus the potential role of sentiment expressed in these reports as an influencing factor in shaping retail investors' expectations about the equity premium.

Figure 3.1 shows the relationship between a retail investor's subjective expected equity premium and aggregated sentiment of 0.5 mln equity reports about 45 US blue-chip companies. The monthly subjective expected equity premium of a representative retail investor is obtained from CCS and MSC surveys, while the aggregated sentiment of equity reports is calculated from reports from 565 information providers.

The figure illustrates a strong co-movement between the monthly subjective expected equity premium of a representative retail investor and the aggregated sentiment of the equity reports. It implies that the retail investor's expected equity premium could potentially be influenced by the collective sentiment of the equity reports.

This observation prompts further exploration and deeper understanding of the role of information providers in shaping retail investors' expectations and the mechanisms through which these sentiments are communicated and assimilated by retail investors.

3.3 Data And Measures

In this section, I present survey data on a retail investor's subjective expected equity premium, as well as a measure of expected equity premium from surveys. Additionally, I provide information on the reporting activity of information providers and outline measures of sentiment regarding earnings growth.

3.3.1 Asset Market: Subjective Expectations of Representative Retail Investor

In this subsection, I describe surveys employed to measure the subjective expected market risk premium. The primary resources for this purpose are two well-established surveys, the Michigan Survey of Consumers[2] and the Conference Board Consumer Confidence Survey[3]. These surveys are not only the most enduring monthly investigations in this field, but they are also widely recognized in economic and financial literature[4]. For additional context, I have added an Appendix that outlines eight other surveys, initiated by a range of central banks, the Federal Reserve system, and Vanguard. However, a notable limitation of these surveys is that they span a maximum period of ten years.

The Conference Board has been administering the Consumer Confidence Survey (CCS) consistently since 1967. Each month, roughly 5,000 individuals are selected to participate in the survey through mail. The response rate averages around 70%, yielding a substantial volume of completed questionnaires. The selection process for the sample adopts a balanced-quota design, where households are chosen based on distinct characteristics with the goal of making the sample representative of the broader population. The CCS primarily seeks respondents' opinions on expected changes in stock prices and interest rates for the

[2] https://data.sca.isr.umich.edu/

[3] https://conference-board.org/data/consumerdata.cfm

[4] The surveys are used in Barsky and Sims (2012); Souleles (2004); Baker and Fradkin (2017); Ludvigson (2004); Throop (2010); Carroll et al. (1994); Lemmon and Portniaguina (2006); Acemoglu and Scott (1994); Bram and Ludvigson (1998); Souleles (2001); Matsusaka and Sbordone (1995); Dees and Brinca (2011) among amny others.

upcoming twelve-month period. This set of questions has been incorporated since June 1987 and continues to this day. The collected responses to these questions are compiled in the Consumer Confidence Survey report, which can be accessed through a paid subscription.

The University of Michigan Surveys of Consumers (MSC) have been conducted consistently since 1958. It is monthly nationally representative survey based on approximately 500 telephone interviews of US households. The sample is randomly selected from a list of household telephone numbers, with about 70 percent of households responding. Responses are weighted based on Census strata to adjust for variation in the age and income distributions observed in monthly samples. Questionnaires focus on demographics, financial prospects for respondents, and the economy in general. I use questions covering the latter. To measure subjective expectations of market return, I focus on a survey question that asks respondents about the percent chance that a one thousand dollar investment in the stock market will increase in value in the year ahead. The question is available from June 2002 to current date. Answers are reported as a mean probability of increase in stock market in next year. The aggregated response data can be found in Table 20 “Probability of Increase in Stock Market in Next Year” in the Saving and Retirement section of the survey.[5] To measure subjective expectations of risk-free rate, I use a survey question that asks about expected direction of the change of interest rates for borrowing money a year ahead. The question is available from January 2008 to current date. The response data can be found in Table 31 “Expected Change in Interest Rates During The Next Year” in the Unemployment, Interest Rates, Prices, Government Expectations section of the survey.[6]

The CCS survey aims to gauge expectations among the US population. Meanwhile, the MSC survey gathers responses from individuals who have invested over $10,000 in the stock market. In MSC samples, respondents with less than $10,000 in stock market investments or with no investments at all make up roughly 5% of the respondents each month.

To transform coarse probability estimates to point estimates of subjective expectation of market return, I follow Greenwood and Shleifer (2014) and Nagel and Xu (2019) methodology. They use UBS/Gallup

[5]Table 20 also contains and a coarse answers' distribution with brackets $\{0\%,\ 1-24\%,\ 25-49\%,\ 50\%,\ 51-74\%,\ 75-99\%,\ 100\%\}$ and number of "Do not Know" and "NA" responses. The SDA Customized Subset of Variables/Cases gives access to individual data and stratification weights. The name of the variable is $PSTK$ variable "Percent chance of investment increase in 1 year".

[6]Table 20 also contains index, calculated as share of respondents who expect rate to go down minus share of respondents who expect rates to go up plus 100, and number of "Do not Know" and "NA" responses. The SDA Customized Subset of Variables/Cases gives access to individual data and stratification weights. The name of the variable is $RATEX$ variable "Interest Rates Up/Down Next Year".

surveys that contains point estimates of monthly subjective expectations of market return for the period between January 2000 and April 2003 and portfolio return expectations in percents from January 2000 to October 2007. The UBS/Gallup data is used to infer relationships between subjective expected probability of return growth and subjective return expectation on the UBS/Gallaup sample, and to impute the MSC and CCS percent return expectations in the longer sample from January 2000 to December 2019. The detailed description of the survey and the methodology is provided in Appendices A and B. In the case of risk-free rate, I use the Survey of Professional Forecasters[7], point estimates[8] as a benchmark for imputation of subjective expected risk-free rate[9] Appendix describes imputation procedure in details.

The subjective estimation of an equity risk premium $\tilde{r}_t$ a year ahead as the difference between a subjective expected return on the stock market a year ahead $E_t[\tilde{r}_{t\to t+12}]$ and a subjective expected risk-free rate over the next year $\tilde{y}_{t+1}$

$$\tilde{r}_t \equiv E_t[\tilde{r}_{t\to t+12} - \tilde{y}_{t\to t+12}] \tag{3.1}$$

In summary, this subsection outlins the approach employed for assessing the subjective expected market risk premium, focusing on two well-established surveys - the Michigan Survey of Consumers and the Conference Board Consumer Confidence Survey.

3.3.2 Market For Information: Monthly Sentiment About Earnings Growth

In this subsection, I provide a detailed overview of the data and the measurement techniques employed to gauge the sentiment of equity reports. I also show on how sentiment, captured from individual reports, are consolidated into an aggregated monthly time series.

I utilize the Thomson Reuters Embargoed Research Collection (InvesText) on the Mergent Online platform for this analysis. Mergent is part of the London Stock Exchange Group's Information Services Di-

[7] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters

[8] For my analysis, I use the cross-sectional averages provided by the Federal Reserve Bank of Philadelphia. Specifically, I use the average of one, two, three and four quarter ahead forecast for the three-month Treasury bill rate. $(TBILL2 + TBILL3 + TBILL4 + TBILL5)/4$ The respondents fill in these forecasts monthly. For the period from June 1987 to October 2020, average quarterly estimates are $\overline{TBILL2} = 3.03$, $\overline{TBILL3} = 3.10$, $\overline{TBILL4} = 3.17$, $\overline{TBILL5} = 3.28$ percent point.

[9] The correlation between SPF estimates and realized Market Yield on U.S. Treasury Securities at 1-Year Constant Maturity, Quoted on an Investment Basis, $GS1$, from Board of Governors of the Federal Reserve System (US), https://fred.stlouisfed.org/series/GS1 is 0.9935 in the sample from Jun 1987 to October 2020.

vision. InvesText provides a vast, global repository of investment reports. This comprehensive collection includes both current and historical research reports on various companies, industries, products, and countries. These reports have been curated from over 1,700 brokerages, investment banks, and independent research firms. The database, starting from 1982, comprises more than 18 million reports.

I focus on equity reports[10] about 45 US blue-chip companies. These include diverse industry leaders such as Apple, recognized globally for its innovation in consumer electronics; JP Morgan Chase, a pillar of the financial sector; and the pharmaceutical giant Pfizer. Other renowned names on the list are IBM, a key player in technology services, and Exxon Mobil, one of the largest publicly traded oil and gas companies.[11]

The choice of 45 companies is based on their presence in the Dow Jones Industrial Average Index from January 1, 2000, to December 31, 2019. The chosen 45 companies effectively represent the market. A synthetic market index, constructed as a weighted average of stock prices of these companies (weighted by their market capitalization), shares a three-year rolling correlation of about 80 percent with the S&P 500. This high correlation supports the assertion that these companies adequately represent the aggregate market dynamics.

My sample consists of meta data of 511,302 equity reports. Table 3.1 shows an example of a meta data of a report $\#$ BA_01012007-02282009. It consists of a document date, name of an analyst, name of the information provider, headline, language, number of pages, tickers, company names, category of report, countries, industries, report styles and a report ID in the InvesText.

Consider a report represented as $e_{d,f,c,ev}$, where $e \in \Theta$ symbolizes the text of a headline (editorial), $d \in D$ signifies a date, $f \in F$ denotes an information provider, $c \in C$ refers to a company listed in the Dow

[10] These reports are "COMPANY (EQUITY) REPORTS" type of reports in InvesText data base.

[11] The complete list of the companies is Alcoa, Apple, American International Group, Amgen, American Express, Boeing, Bank of America, Citigroup, Caterpillar, Salesforce, Cisco Systems, Chevron, Dow, DuPont, Walt Disney, General Electric, General Motors, Goldman Sachs, Home Depot, AlliedSignal (Honeywell), Hewlett Packard, IBM, Intel, International Paper Company, Johnson & Johnson, J.P. Morgan (JPMorgan Chase), Coca-Cola, Eastman Kodak, McDonald's, 3M Company (Minnesota Mining & Manufacturing), Merck, Microsoft, Nike, Pfizer, Proctor & Gamble, Philip Morris, Raytheon (United Technologies), AT&T (SBC Communications), Travelers, UnitedHealth, Visa, Verizon, Walgreens Boots, Walmart, Exxon Mobil

Table 3.1: InvesText. Meta Data Of Investment Report # BA_01012007-02282009

id	BA_01012007-02282009
Document Date	9/9/2008
Author	Suzanne H. Betts / Argus Research
information provider (Contributor)	Argus Research Corporation
Headline	BA: Machinist strike could cost Boeing $3 billion in sales
Language	English
Pages	6
Tickers	BA
Company Names	Boeing Co
Category	EQUITY
Countries	United States
Industries	Industrial Materials / Defense / Aerospace
Regions	North America
Subjects	
Report Styles	COMPANY (EQUITY) REPORTS

index, and ev stands for an event. Thus, the full set of reports, Θ, can be defined as:

$$\Theta = \{e_{d,f,c,ev} = (d, f, c, ev) : d = \{\text{Dates}\}, \tag{3.2}$$

$$f = \{\text{Information Providers}\}, \tag{3.3}$$

$$c = \{\text{Companies}\}, \tag{3.4}$$

$$ev = \{\text{Events}\}\} \tag{3.5}$$

The set of dates D contains 6,945 dates d. There are 565 information providers f in the set F, 45 Dow companies c in the set C and up to 325,066 unique headlines (events) are in the set of event Ev. Table A.8 in the Appendix presents the top ten information providers. The list includes top investment banks with strong think tanks (for example, the Credit Suisse with the Credit Suisse Research Institute) and online platforms (for example, the Refinitiv StreetEvents that publishes verbatim representations of corporate and institutional events, the Trefis, an interactive financial online community structured around trends, forecasts and insights related to popular stocks in the US[12]).

Table 3.2 shows an example of set of reports $\Theta(\text{Nike, Oct 2019})$ about Nike at October 2019. First three columns is the information form the data set, while Events section of the table illustrates a break down of

[12]The start-up was founded in 2007 and joined the Thompson and Reuters platform later.

Table 3.2: Example of Event Coverage: Headlines of Equity Reports About Nike Published at October 2019

The table presents headlines of equity reports regarding Nike that were published on weekdays in October 2019 and assigned non-zero sentiment scores. Five significant events are highlighted in the Events section of the table. These events include the issuance of a new 10-Q financial statement, the implementation of a new methodology for Return On Invested Capital (ROIC), the unfolding of the US-China trade dispute and associated tariffs, Nike's acquisition of TraceMe, and the appointment of a new CEO.

information provider, f	Date, d	Headline, e	Events, $Ev(Nike)$				
			10-Q	ROIC	Tariffs	M&A	CEO
Macquarie Research	Oct 7	Macquarie: NIKE (NKE US) (Outperform) - Oh I See… Your New ROIC		x			
	Oct 11	Macquarie: NIKE (NKE US) (Outperform) - 10Q: The Chessmaster	x				
	Oct 17	Macquarie: NIKE (NKE US) (Outperform) - Tracing the Digital Acquisitions				x	
	Oct 22	Macquarie: NIKE (NKE US) (Outperform) - Another "Digital Acquisition"					x
Oppenheimer	Oct 10	Product Innovation Still Fueling NKE	x				
	Oct 21	Trade Risks Abound, Leading Chains and Brands Still Managing Well			x		
Susquehanna Financial Group	Oct 8	Buy the Pullback; Adverse Impact on NKE from China's Battle with NBA Overblown			x		
Stock Traders Daily Research	Oct 15	Comprehensive Technical and Fundamental Analysis for NKE. This reports includes The Investment Rate, a macroeconomic leading indicator, and Market Analysis.	x				
Corporate Watchdog Reports	Oct 18	Watchdog Report: NKE - Red Flags and Warning Signs	x				
JPMorgan	Oct 22	NIKE, Inc. : "Win/Win" Hire w/ "Accelerate" > Overhaul Opportunity; Mgmt Follow-Up Takes; Overweight					x
Piper Sandler Companies	Oct 23	Nike CEO Rotation Rounds Out Trifecta Of Athletic Leadership Changes This Week					x
Wedbush Securities	Oct 23	New CEO Has Large Sneakers to Fill as Company Dominates Consumer, Innovation					x

events covered by information providers.

Table 3.2 show that panel of reports is sparse. No single information provider consistently publishes daily reports or reports about all listed events. Each provider, as shown in the example, exercises selectivity in their coverage. It's also noteworthy that the "10Q" event, which represents the issuance of a new 10-Q financial statement, is cumulative by nature. This means it potentially encompasses the other four events – the adoption of a new methodology for Return On Invested Capital ("ROIC"), the implications of the US-China trade dispute ("Tariffs"), Nike's acquisition of TraceMe ("M&A"), and the appointment of a new CEO ("CEO") – either in its current or subsequent reporting cycle. Therefore, the information landscape is not uniformly distributed, but instead varies significantly between different providers and across distinct events, emphasizing the complexity of interpreting and aggregating sentiment data.

Table 3.2 also shows that the headline of the report highlights the main event of the report and contains information about a information provider's sentiment on direction and strength of change in future earnings. For example, *"Macquarie: NIKE (NKE US) (Outperform) - Oh I See... Your New ROIC"* headline from Macquarie Research could be interpreted as positive, considering the optimistic language ('Outperform') and the mention of a new ROIC methodology, while *"New CEO Has Large Sneakers to Fill as Company Dominates Consumer, Innovation"* headline from Wedbush Securities suggests mixed sentiments. It implies a challenge for the incoming CEO to meet high expectations but also emphasizes Nike's strong position in the market.

To measure the sentiment embedded in an editorial, I utilize the headline's textual sentiment. This involves the use of a polarity score to gauge the sentiment present in the headlines produced by information providers. Polarity, in this context, assesses the extent to which a text is negative or positive. For instance, a negative polarity score in an earnings report corresponds to declining earnings or negative earnings growth. Conversely, a positive polarity score in the same report signifies increasing earnings or positive earnings growth.

The usage of textual polarity is a common practice in behavioral finance, serving as a tool to examine the influence of sentiment on decision-making processes and market behaviors. Predominantly, two forms of sentiment are explored. The first is investor sentiment, defined as assumptions about future cash flows and investment risks unsupported by the current facts (Baker and Wurgler (2007)). The second is textual sentiment, which denotes the positivity or negativity level within texts. While investor sentiment encapsulates subjective judgments and behavioral attributes of investors, textual sentiment can encompass these aspects but also extends to the more objective reflections of circumstances within information providers and markets.

Measure of Sentiment of Headlines of Individual Reports I utilize the sentiment score calculation methodology outlined by Rinker (2021), as described in their study. This method employs the Stanford Natural Language Processing (NLP) coreNLP annotation pipeline framework developed by Manning et al. (2014). The algorithm considers both the relative positions of words within a sentence and their context. This is achieved through a set of rules that were established based on a comprehensive training set of sentences, effectively making the algorithm pre-trained. To maintain objectivity in my analysis and prevent any potential bias, I have opted not to train the algorithm on my own dataset. Instead, I rely on the initial pre-training to ensure the accurate quantification of sentiment scores in headlines[13]. Rinker (2021) mephodology delivers fast, interpretable and accurate results. The algorithm $J : e_{d,f,c} \rightarrow s_{d,f,c}$ maps text of an editorial $e_{d,f,c}$ into a polarity score $s_{d,f,c} \in \mathbb{R}$

$$\forall e \in \Theta,\ J : e_{d,f,c,ev} \rightarrow s_{d,f,c,ev},\ \text{ such that } \forall e \in \Theta, \exists s \in \mathbb{R},\ J(s) = e \tag{3.6}$$

$J(\cdot)$ considers relations among words and accounts for relative position of words in a sentence.

$$s(e) = \frac{\sum_j f(w_j^+, w_j^-, \delta_j)}{\sqrt{n}} * 100 \tag{3.7}$$

where $f(\cdot)$ is a function of positions and scores of positive words w_j^+, negative words w_j^-, δ_j is a vector of polarity shifters (words-negators, words-amplifiers, words-deamplifiers and words that are adversative conjunctions), and n is a number of words and some punctuation signs in a headline.

Figure 3.2 shows an example of mapping from editorial $e_{d,f,c,ev}$ = *"Coca - Cola Co. : 2013 Should Be Better, But Not That Much Better; Lowering Estimates"* to a sentiment score $s_{d,f,c,ev} = -0.12$ using Rinker (2018) algorithm $J : e_{d,f,c,ev} \rightarrow s_{d,f,c,ev}$. In the first step, the algorithm finds positive and negative polarized words based on Loughran and McDonald (2016) financial dictionary. The sentence contains two positive words "better" that weight one point $P = 1$ each. Simplistic text processing stops here by assigning positive two as the sentiment score of the sentence. The Rinker (2021) algorithm takes clusters that are formed around polarized words "better", cl_1 and cl_2, and utilises position and influence of polarity shifters (words-negators, words-amplifiers, words-deamplifiers and words that are adversative conjunctions) to tune the sentiment of polarized words. The first cluster cl_1, *"Co : Should Be Better"*, does not contain polarity shifters. Sentiment score of the first polarized words "better" is 1. The second cluster cl_2, *", But Not That*

[13]Based on Wankhade et al. (2022), there are three approaches to measure polarity. The simplest one is a pre-trained rule-based model that uses a dictionary that assigns a predetermined sentiment score to each word and sums scores up. The rule-based solutions are fast, but has low accuracy. The naive bayes classifier uses conditional probabilities of each lexical feature occurring in either positive or negative text in the training data to arrive at the outcome. Naive Bayes model is used only if there is available complete data for training the model. As in my case, writing style is information provider type-specific, I have smaller training set for less active providers and bigger set for more active providers. The difference in size of the sets would affect the sentiment, so I don't use this method. A Deep Learning allows for processing data in a complex manner. A Long Short-Term Memory model, a type of Recurrent Neural Network, maps words positions in the sentence and polarity scores according to custom neural network (unsupervised learning) models. The method has high accuracy, but lacking interpretability, as the algorithm utilizes a set of hidden layers of cascading classification problems.

Figure 3.2: Simplified Example Of Polarity Score Calculation Based On Rinker (2018) Algorithm
Figure illustrates how Rinker (2021) utilizes clusters of words around positive and negatives words to tune sentiment of a sentience. There are two polarized words in the sentence - "better" and "better". The polarized words are positive and have score $P = 1$ per word. Rinker (2021) algorithm considers polarized words within clusters. A cluster consists of 5 words before a polarized word and two words after it. Underscored words shows words in clusters. A cluster score corrects P considering effect of amplifiers A, de-amplifiers D, negators neg and adversative conjunctions, b. A polarity score of a sentance is a sum of polarity scores of its clusters, $s_{d,f,c,ev}$

$$s_{d,f,c,ev} = cl_1 + cl_2, \text{ where } \quad cl_l = \frac{(1 + (A_l + D_l)) * P_l(-1)^{(2 + \text{\# of negators}_l)}}{\sqrt{n}}$$

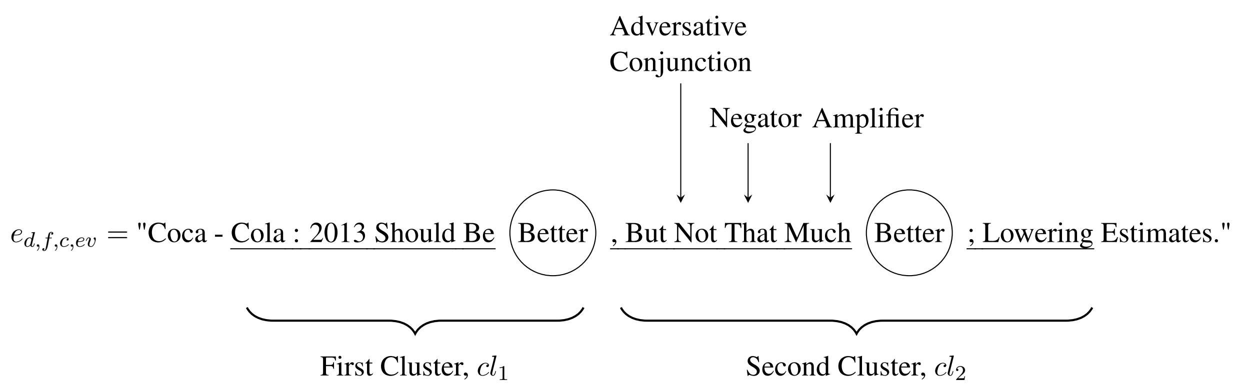
and $A = 0.8 * (1 - \text{\# of negators}_l) * \text{\# of amplifires}_l + \mathbf{1}_{\text{\# of adversative conjunctions}_l > 0}(1 + 0.25 * \text{\# of adversative conjunctions}_l)$, $D = -0.8(\text{\# of negators}_l * \text{\# of amplifires}_l)$, n is a number of words in the sentence, including punctuation. So sentiment scores of the first and the second clusters are

$$s_{d,f,c,ev} = 0.28 - 0.40 = -0.12, \text{ where}$$

$$cl_1 = \frac{(1 + (0 + 0)) * P(-1)^{(2+0)}}{\sqrt{13}} = \frac{1}{\sqrt{13}} = 0.28, \text{ where } \quad A_1 = 0.8 * (1 - 0) * 0 = 0$$
$$D_1 = -0.8 * (0 * 0 + 0) = 0$$

$$cl_2 = \frac{(1 + (1.25 - 0.8)) * P(-1)^{(2+1)}}{\sqrt{13}} = \frac{-1.45}{\sqrt{13}} = -0.40, \text{ where } \quad A_2 = 0.8 * (1 - 1) * 1 + 1 + 0.25 * 1 = 1.25$$
$$D_2 = -0.8(1 * 1 + 0) = -0.8$$

The sentiment score for a sentence is a sum of scores of its clusters $s_{d,f,c,ev} = 0.28 - 0.40 = -0.12$



Much Better; Lowering", contains one adversative conjunction "but", one negator "not" and one amplifier "much" after the polarized word. Sentiment score of the second polarized words "better" is -1.45.

Figure 3.2 provides an illustration of how the editorial $e_{d,f,c,ev}$ = *"Coca - Cola Co. : 2013 Should Be Better, But Not That Much Better; Lowering Estimates"* is translated into a sentiment score $s_{d,f,c,ev} = -0.12$ using Rinker (2021) algorithm $J : e_{d,f,c,ev} \rightarrow s_{d,f,c,ev}$. The initial step of the algorithm identifies words with positive and negative connotations, relying on Loughran and McDonald (2016) financial dictionary. In this sentence, there are two positive words: "better," each contributing a point $P = 1$. A simple text analysis would conclude at this juncture, assigning a sentiment score of positive two to the sentence.

However, Rinker (2021) algorithm delves deeper by identifying clusters formed around these polarized words, "better" - referred to as cl_1 and cl_2. It then adjusts the sentiment of these polarized words based on the position and impact of polarity shifters, which include negating words, amplifying words, de-amplifying words, and adversative conjunctions. The first cluster, cl_1 or *"Co : Should Be Better"*, does not have any polarity shifters, hence the sentiment score of the first occurrence of "better" remains as 1. The second cluster cl_2, *", But Not That Much Better; Lowering"*, includes an adversative conjunction "but", a negator "not", and an amplifier "much" following the polarized word. Therefore, the sentiment score of the second "better" is adjusted to -1.45.

When text is short and in form of sentences, Rinker (2021) offers significant improvements over the more traditional "bag of words" approach[14] when mapping text to numerical values. On the sentence level, it provides a 4.6-fold increase in granularity of polarity score, with 2,281 unique polarity scores assigned using the Rinker's algorithm as compared to 495 unique scores using the "bag of words" approach. The detailed description of Rinker (2021) algorithm is provided in the Appendix.

Measure of Expected Aggregate Market Earnings Growth. Given that the subjective expected equity premium of a representative investor is a monthly time series, and sentiment is a four-dimensional panel with day-information provider-company-event as the unit of observation, the sentiment data can be aggregated in various ways to test their association with the subjective equity premium of a retail investor.

I employ three strategies that use weighted averages to aggregate sentiments derived from individual reports. For the first strategy, the sentiment aggregation from individual reports is weighted according to each company's market capitalization. This means the sentiments linked to companies with larger market capitalizations carry more significance in the overall sentiment analysis. The second strategy involves placing equal emphasis on every information provider. This is achieved by calculating the average sentiment from each information provider and then deriving the arithmetic mean of these averages. Therefore, each information provider, regardless of their activity levels or the volume of reports they generate, is given equal weight. The third strategy involves calculating the arithmetic average of sentiments across all individual reports, thereby giving each report equal weight. This approach ensures that each report contributes equally

[14] The traditional "bag of words" approach calculates sentiment by summing the scores of positive and negative words, normalized by the square root of the total number of words and certain punctuation marks in a headline.

to the overall sentiment, irrespective of the associated company or information provider. It is worth noting that this third aggregation strategy is mathematically equivalent to the process of weighting the average sentiment from each information provider by the number of reports they have produced. In other words, it is a weighted average where the weights correspond to the number of reports generated by each information provider.

For the first way of aggregation, I hypothesize that a signal about a company with a higher market capitalization, like Apple, will provide more information regarding the direction in which the aggregate stock market is moving than a signal about a company with a lower market capitalization, such as 3M Company. Indeed, the weighted average of the realized stock prices of 45 companies weighted by their market capitalization has 80 % three-year rolling correlation with the S&P 500. To aggregate the sentiment data according to this hypothesis, I weight sentiment of by-company reports by number of report written about each company $\mathbf{e_{t,c}} \equiv \mathbf{s}^{'}_{\mathbf{t,c}}\mathbf{n_{t,c}}$ for every company $c = \{c_1, c_2 \ldots, \}$ at month t. They form a vector $\mathbf{S_t^{w}}' = [e_{t,c_1},\ e_{t,c_2}, \ldots]$ at size $[1 \times m_t]$ of expected cross-news sentiment given a company, where m_t is a number of companies at time t. To aggregate the vector to one number, I use a vector of market capitalization of the companies $\mathbf{w}_t^C$ as weights

$$s_t^m \equiv \mathbf{S_t^{w}}'\mathbf{w_t^C} = \begin{bmatrix} e_{t,c_1} & e_{t,c_2} & \ldots \end{bmatrix} \begin{bmatrix} w_t^1 \\ w_t^2 \\ \ldots \end{bmatrix} \tag{3.8}$$

to get monthly time series s_t^m of company-weighted aggregate sentiment scores, the measure that captures an economic structure of the market.

In the second way of aggregation, I hypothesize that if the market for information is populated by many atomistic information providers that deliver a homogeneous product, a random signal about the aggregate market performance, expectations over all by-information provider signals is equally important and should be informative. In this case, first, I look at the space of the reports through the lens of information providers, and next treat by-information provider signals as equally weighted. To aggregate the data according to this hypothesis, I weight sentiment of individual by-provider reports $\mathbf{e_{t,f}} \equiv \mathbf{s}^{'}_{\mathbf{t,f}}\mathbf{n_{t,f}}$ for every information providers $f = \{f_1, f_2 \ldots, \}$ at month t, $\mathbf{S}_t^{'} = [e_{t,f_1},\ e_{t,f_2}, \ldots]$, with n_t is a number of reporting providers at month t. To aggregate the vector to one number, I average the by-information provider sentiment scores,

$$s_t \equiv \frac{1}{n_t}\mathbf{S}_t^{'}\mathbf{1} = \frac{1}{n_t}\begin{bmatrix} e_{t,f_1} & e_{t,f_2} & \dots \end{bmatrix}\begin{bmatrix} 1 \\ 1 \\ \dots \end{bmatrix} \tag{3.9}$$

to get monthly time series s_t of equally information provider-weighted aggregate sentiment scores.

In the third way of aggregation, I hypothesize that if the market for information is populated by information providers with different activity levels that deliver heterogeneous products, a random signal about the aggregate market performance multiplied by an activity level of a information provider, expectations over aggregated by-information provider market signals weighted by the activity level should be informative. In this case, first, I look at the space of the reports through the lens of information providers, and then weight by-information provider signals by information providers' activity level. To aggregate the data according to this hypothesis, I weight sentiment of individual by-provider reports $\mathbf{S}_t^{'} = [e_{t,f_1},\ e_{t,f_2},\dots]$ for every $f = \{f_1, f_2 \dots, \}$ at month t and weight these signals by the share of reports published by each information provider f in a given month t, $\mathbf{w_t^{f}}^{'} = [n_t^{f_1}\ \ n_t^{f_2},\dots]$

$$s_t^w = \mathbf{S}_t^{'}\mathbf{w_t^{f}}^{'} = \begin{bmatrix} e_{t,f_1} & e_{t,f_2} & \dots \end{bmatrix}\begin{bmatrix} n_t^{f_1} \\ n_t^{f_2} \\ \dots \end{bmatrix} \tag{3.10}$$

As shares of reports published are probabilities of a randomly picked report is published by a information provider f, $\mathbf{w_t^{f}}^{'} = [p(f_1)\ \ p(f_2),\dots]$, the measure is equivalent to $E_F[E_{S|F}[p_{S|F}(s|f)]] = E[s]$ per month t, according to the data generating process on the market for information.

Table 3.3 offers a simplified example to explain how sentiment data is processed. This "toy" dataset represents the number of reports per sentiment score (-1, 0, 1), information provider, and company, within a specific month. In this example, two information providers, J.P. Morgan and Credit Suisse, are considered, covering two companies, Apple and Visa. The specific breakdown of the reports is as follows: J.P. Morgan issues one report on Apple with a sentiment score of -1 and one on Visa with a sentiment score of 0. Credit Suisse, on the other hand, releases two reports on Apple with a sentiment score of 0 and one on Visa with a

Table 3.3: Toy Example of Sentiment Data

The table shows the number of reports per sentiment score, information provider and company per one month.

Company, c	information provider, f	Sentiment Score, s			Share of Reports
		-1	0	1	
Apple	J.P. Morgan	1			$1/5$
	Credit Suisse		2		$2/5$
Visa	J.P. Morgan		1		$1/5$
	Credit Suisse			1	$1/5$
Share of Reports		$1/5$	$3/5$	$1/5$	1

sentiment score of 1.

Before proceeding with the aggregation, let's calculate sentiment conditional on companies $e_{t,c}$ and sentiment conditional on information providers, $e_{t,f}$

$$e_{t,c_1}(\text{Apple}) = (-1) * \frac{1/5}{3/5} + 0 * \frac{2/5}{3/5} = -\frac{1}{3} \tag{3.11}$$

$$e_{t,c_2}(\text{Visa}) = 0 * \frac{1/5}{2/5} + 1 * \frac{1/5}{2/5} = \frac{1}{2} \tag{3.12}$$

$$e_{t,f_1}(\text{JPM}) = (-1) * \frac{1/5}{2/5} + 0 * \frac{1/5}{2/5} = -\frac{1}{2} \tag{3.13}$$

$$e_{t,f_2}(\text{CS}) = 0 * \frac{2/5}{3/5} + 1 * \frac{1/5}{3/5} = \frac{1}{3} \tag{3.14}$$

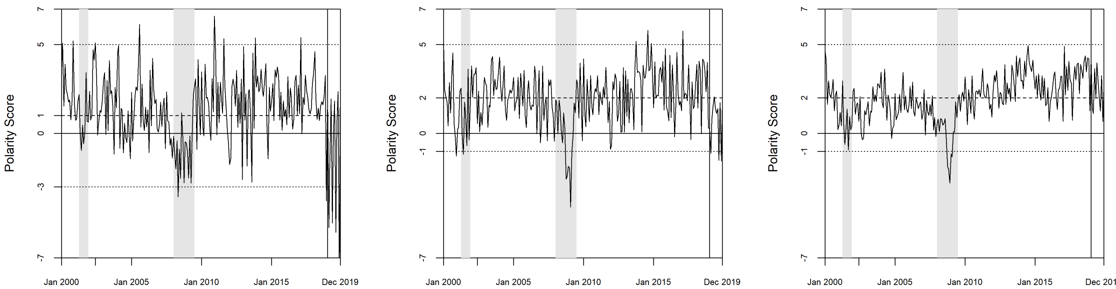
For the first aggregation approach, I calculate s_t^m as a weighted mean using the normalized market capitalization of companies as weights. Assuming that normalized market capitalization of Apple and Visa is $\mathbf{w}' = [w(\text{Apple}), w(\text{Visa})] = [2/3, 1/3]$ in a given month, $s_t^m = e_{t,c_1}(\text{Apple}) * w(\text{Apple}) + e_{t,c_2}(\text{Visa}) * w(\text{Visa})$,

$$s_t^m = \begin{bmatrix} e_{t,c_1}(\text{Apple}) & e_{t,c_2}(\text{Visa}) \end{bmatrix} \begin{bmatrix} w_t(\text{Apple}) \\ w_t(\text{Visa}) \end{bmatrix} = (-\frac{1}{3}) * \frac{2}{3} + \frac{1}{2} * \frac{1}{3} = -\frac{1}{18} \tag{3.15}$$

For the second aggregation approach, I calculate s_t, as ariphmetic average with of average information

Figure 3.3: Aggregated Sentiment Score

Plot (a) shows company-weighted sentiment score, s_t^m. Plot (b) shows equally weighted by-information provider sentiment score, s_t . Plot (c) shows information provider-weighted by-information provider sentiment score, s_t^w per month. Dashed line on a plot is the mean of corresponding time series of sentiment scores, dotted lines are two standard deviations around the mean. Gray areas are NBER recessions.



(a) Company-Weighted **(b)** Equally-Weighted **(c)** Provider-Weighted

providers' sentiment, $s_t = \frac{1}{2}\left(E[s|f{=}\text{JPM}] + E[s|f{=}\text{CS}]\right)$:

$$s_t = \frac{1}{n_t}\begin{bmatrix} e_{t,c_1}(JMP) & e_{t,c_2}(\text{CS}) \end{bmatrix} = \frac{1}{2}(-\frac{1}{2} + \frac{1}{3}) = -\frac{1}{12} \tag{3.16}$$

For the third aggregation approach, I calculate s_t^w as a weighted average using the percentage of published reports of an information provider as weights, $s_t^w = E\left[s|f{=}\text{JPM}\right] * p(f{=}\text{JMP}) + E\left[s|f{=}\text{CS}\right] * p(f{=}\text{CS})$

$$s_t^w \equiv \begin{bmatrix} e_{t,c_1}(\text{JMP}) & e_{t,c_1}(\text{CS}) \end{bmatrix} \begin{bmatrix} n_t^{\text{JMP}} \\ n_t^{\text{CS}} \end{bmatrix} = (-\frac{1}{2}) * \frac{2}{5} + \frac{1}{3} * \frac{3}{5} = 0 \tag{3.17}$$

Note that if partition $p(f = \text{JMP})$ and $p(f = \text{CS})$ is observed, the third case is equivalent to application of the law of total expectations and recovering expected value of sentiment[15].

[15]Let the random variables X and Y, defined on the same probability space, assume a finite or countably infinite set of finite values. Assume that $E[X]$ is defined, that is, $\min(E[X_+], E[X_-]) < \infty$ $\min(E[X_+], E[X_-]) < \infty$. If $\{A_i\}$ is a partition of the probability space Ω, then

$$E(X) = \sum_i E(X \mid A_i)P(A_i)$$

$$\begin{aligned} E(E(X \mid Y)) &= E\left[\sum_x x \cdot P(X{=}x \mid Y)\right] = \sum_y \left[\sum_x x \cdot P(X{=}x \mid Y{=}y)\right] \cdot P(Y{=}y) \\ &= \sum_y \sum_x x \cdot P(X{=}x, Y{=}y) = E(X) \end{aligned}$$

Table 3.4: Descriptive Statistics

The table shows descriptive statistics of subjective expected equity premium over the next 12 months from MSC, $\tilde{r}_t^M$, and CCS, $\tilde{r}_t^C$, surveys, in percents. The realized and CCS data are from January 2000 to December 2019 and contain 240 observations. The MSC data is from June 2002 to January 2019 and contains 210 observations. The table also shows descriptive statistics of aggregate polarity score as company-weighted and information provider-weighted average with equal aggregation weights and number of published reports per information provider as an aggregation weight, scaled by 100, from January 2000 to December 2019. Sentiment scores are scaled by 100.

Variables	Mean	St. Dev.	Min	Max
Subjective Expected Equity Premium				
$\tilde{r}_t^M$	6.67	1.76	2.66	10.50
$\tilde{r}_t^C$	6.98	1.47	4.20	11.84
Sentiment Measures				
s_t^m	1.36	2.07	-8.05	6.60
s_t	1.93	1.60	-4.14	5.79
s_t^w	2.00	1.31	-2.78	4.94

Figure 3.3 shows the time series of the monthly aggregated sentiment score scores.

3.3.3 Descriptive Statistics

Table (3.4) provides descriptive statistics of subjective equity premium from the Michigan Survey of Consumers (MSC) and the Conference Board Consumer Survey (CCS). There is a sampling error of mean of subjective expected equity premium is 2.1 and 2.3 the MSC and CCS surveys. It indicates that mean of subjective expected annual equity premiums is statistically different from zero.

While mean subjective expected annualized equity premium is similar for MSC and CCS surveys, 6.67 % and 6.98 % per year, mean sentiment weighted by different weightings schemes differs. Mean sentiment weighted by number of providers reports is the highest, 2.00, while mean sentiment weighted by companies market capitalization s_t^m, is the lowest, 1.36.

Though mean subjective annualized equity premium is similar, subjective market price of risk in the sample, $\frac{\text{Mean}}{\text{St.Dev.}}$, differs. It is lower for MSC survey, 3.79, and higher for CCS survey expectations 4.51. Different standard deviation causes this difference.

I report two dispersion measures, standard deviation and values of maximum and minimum of variables.

While standard deviation of subjective expectations time series is close, 1.76 versus 1.47, for MSC and CCS surveys, standard deviation of sentiment measures drops from 2.07 for sentiment weighted by companies market capitalization s_t^m to 1.31 for sentiment weighted by information providers activity s_t^m. Values of maximum and minimum values are olny positive for survey expectations. Sentiment weighted by companies market capitalization s_t^m has bigger in absolute value minimum, -8.05, than maximum, 6.60, while sentiment weighted by number of providers reports has the opposite, its minimum of -2.78 is almost two times lower in absolute value than maximum of 4.94.

3.4 Empirical Strategy

In this section I describe results of stationarity tests, Elliott et al. (1996) and Zivot and Andrews (1992) univariate unit root tests, as well as Johansen (1988, 1991) cointegration test. Considering test results, I introduce a vector error correction model that builds on the time series properties of the system of variables, aggregate sentiment scores of equity report headlines and subjective expectation of equity premium over the next 12 months.

3.4.1 Stationarity Tests

Figure (3.1) on page 42 shows that there is a visual upward drift in the monthly subjective expected equity premium and aggregated sentiment scores, so I start with stationarity tests.

As my sample includes one and a half business cycles[16] and contains noisy monthly data, I use Elliott et al. (1996), ERS, stationarity test that has high asymptotic power for samples with a slow evolving trend and dominating random component. To account for a potential break in the trend function under the alternative hypothesis, I use Zivot and Andrews (1992) , ZA, stationarity test.

Table (3.5) shows the values of the ERS statistics, τ_μ and the ZA statistics t_α for realized return and subjective expected premia from the MSC and CCS surveys, and sentiment time series. The τ_τ statistics of ERS test tests trend stationarity[17]. The statistics is more than 5 % critical value of -2.89 for all time series except aggregated provider-weighted and equally-weighted sentiment score, so I cannot reject the null that

[16]Recession of 2008.

[17]Critical values for ERS test are taken fromElliott et al. (1996) and equal to 3.48, -2.89 and -2.57 for 1%, 5% and 10% significance level. Decision rule is to reject $H0$ if tests statistics $<$ critical value.

Table 3.5: Elliott, Rothenberg and Stock (1996) and Zivot and Andrews (1992) Stationarity Tests
The Elliott et al. (1996) test tests level stationarity and has a regression specification

$$\Delta r_t^{e,d} = \pi r_{t-1}^{e,d} + \sum_1^p \phi_j \Delta r_{t-j}^{e,d} + \varepsilon_t$$

where $r_t^{e,d} = r_t^e - \beta_\phi^0 - \beta_\phi^1 t$ is GLS-detrended equity premium. The τ_τ is conventional t-statistics for the coefficient π testing the null hypothesis $H_0 : \pi = 0$ that series are non-stationary $I(1)$ with drift, versus an alternative $H_1 : |\pi| < 1$ is that time series are $I(0)$ with deterministic time trend. I use Schwert (1988) to determine a number of lags.
The t_α statistics of Zivot and Andrews (1992) tests trend stationarity with endogenous break λ and has a regression specification

$$r_t = \hat{\mu} + \hat{\alpha} r_{t-1} + \hat{\beta} t + \theta DT_t(\lambda) + \sum_i^p c_i \Delta r_{t-i} + \epsilon_t$$

where $DT_t(\lambda) = t - T(\lambda)$ if $t > T$ and 0 otherwise, and $p = 2$. The test has null hypothesis that the series has a unit root $I(1)$ without an exogenous structural break, against the alternative hypothesis that it is trend-stationary process with a one-time break in the trend occurring at an unknown point in time. The test statistics t_α estimates a break point that gives the most weight to the trend-stationary alternative.

	Test Statistics	
	τ_τ	t_α
	Realized Return	
r_t^{1m}	-2.48	
	Expected Subjective Equity Premium	
$\tilde{r}_t^M$	-2.38	
$\tilde{r}_t^C$	-2.39	
	Sentiment Measures	
s_t^w	-3.14	-3.78
s_t^m	-2.62	
s_t	-3.16	-3.87

they follow $I(1)$ process with drift[18] [19] For aggregated provider-weighted and equally-weighted sentiment score time series, I can reject the null and accept on an alternative that the variables are stationary $I(0)$

[18]The functional form of $I(1)$ time series with drift is

$$x_t = a + bt + x_{t-1} + \epsilon_t \tag{3.18}$$

[19]The persistence of realized return time series aligns with existing research and contributes to the ongoing debate about return predictability. Some scholars assert that expected returns contain a time-varying component, implying future return predictability (Fama and French (1988); Campbell and Shiller (1988b); Cochrane (1991); Goetzmann and Jorion (1993); Hodrick (1992); Lewellen (2004); Lettau and Ludvigson (2001); Lustig and Van Nieuwerburgh (2005); Menzly et al. (2004)). However, others contend that such conclusions are debatable. They highlight that the relationship between financial ratios and future stock returns exhibits disconcerting features, including problematic inference due to extreme persistence of financial ratios (Nelson and Kim (1993); Stambaugh (1999); Ang and Bekaert (2001); Ferson et al. (2003); Valkanov (2003)) and poor out-of-sample forecasting power (Bossaerts and Hillion (1999); Goyal and Welch (2003, 2004); Viceira (1996); Paye and Timmermann (2003)).

Table 3.6: Trace Statistics of Johansen Cointegration Test

The Trace test statistic is likelihood ratio test of the null hypothesis that the number of distinct cointegrating vectors is less than or equal to r against the alternative hypothesis of more than r cointegrating relations. The Trace test statistic, denoted $\lambda_{\text{trace}}(r)$, is given by

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{n} \ln(1 - \hat{\lambda}_i) \tag{3.20}$$

where T is the number of usable observations, $\hat{\lambda}_i$ is the ith largest canonical correlation between the $I(1)$ variables and their lagged first differences, and n is the number of variables in the system. The larger values of the test statistic provide stronger evidence against the null hypothesis.

	Variables	Test Statistics $\lambda_{\text{trace}}(r)$	
		$r = 0$	$r = 1$
CCS Survey	$(s_t^w, \tilde{r}_t^C)$	42.64	9.44
	$(s_t, \tilde{r}_t^C)$	64.21	10.88
	$(s_t^m, \tilde{r}_t^C)$	54.36	10.60
MSC Survey	$(s_t^w, \tilde{r}_t^M)$	37.36	5.56
	$(s_t, \tilde{r}_t^M)$	59.34	5.89
	$(s_t^m, \tilde{r}_t^M)$	47.06	5.88

with deterministic trend[20]. The t_α statistics of ZA test test trend stationarity with an endogenous break in alternative hypothesis. The statistics is more than 5 % critical value of -4.42[21] for two sentiment measures. So, I cannot reject the null that the time series are $I(1)$ processes at 5% significance level. The potential break is at September 2000. As my MSC data starts at July 2002, I exclude the beginning of the sample from regressions, so the potential break does not affect the inference.

As I have persistent $I(1)$ variables in the sample, there might exist linearly independent vectors such that their linear combination is stationary, $I(0)$. To diagnose the presence of cointegrating relationships among variable, I run Johansen (1991) test. The test shows that there exist one linearly independent vector.

In Tables 3.6, the results of the Johansen test for two set of variables, with subjective expectations from MSC survey $\{s_t^w,\ \tilde{r}_t^M\}$ and with subjective expectations from CCS survey $\{s_t^w,\ \tilde{r}_t^C\}$, are given. Considering the statistic, the hypothesis of no cointegration can be rejected at the 1 % level for both sets. While the set with CCS survey expectations have one cointegration vector (tests statistics for rank $r = 1$, 9.44, is more

[20]The functional form of $I(0)$ time series with deterministic time trend is

$$x_t = a + bt + \pi x_{t-1} + \epsilon_t, \quad \text{where} \quad |\pi| < 1 \tag{3.19}$$

[21]Critical values for a test specification with four lags in error correction term are $0.01 = -4.934$ $0.05 = -4.42$ $0.1 = -4.11$. Decision rule is to reject $H0$ if tests statistics $<$ critical value.

that critical value of 8.18) for all sentiment measures at the 5 % level, tests for the set with MSC survey expectations yield contradictory conclusions about the cointegration rank. For this case, following Johansen and Juselius (1992), I study loading weights matrix of a cointegration vector, matrix α[22] The authors argued that if the values of $\alpha_{i,c}$ for $i = 1, 2$ at column c are close to zero, it is not significant. For systems with different surveys' expectations and aggregated sentiment scores, α matrices have elements in the second column (loading of the second cointegration vector) are close to zero (Table A.9 with loading matrices is provided in Appendix). I conclude that there is one cointegration vector for systems with subjective expectations from both surveys.

3.4.2 Timing

Based on the survey methodology provided by the MSC and the CCS, subjective expectations issued at month t reflect expectations of respondents at month t. The MSC conducts its survey by phone throughout most of the month. Final figures for the full sample are subsequently made available at the end of the month and are not subject to further revision. The CCS mails questionnaires. The mailing is scheduled so that the questionnaires reach sample households on or about the first of each month. Returns flow in throughout the collection period, from first to last days of the month t, with the sample close-out for preliminary estimates occurring around the eighteenth of the month. Any returns received after then are used to produce the final estimates for the month, which are published with the release of the following month's data. The preliminary figures of subjective expectations from CCS are released on last Tuesday of month. Final figures are released with next month's release. I use final figures in my analysis.

As described in Data section, the sentiment s_t at month t is a weighted average of sentiments of individual reports published by information providers at month t. I estimate that about 40 % of equity reports discuss financial statements[23] issued at month t, and about 60 % analyse impact of events on earnings. As events are randomly distributed within a month, the ones that occur at the end of the month might be reported at the beginning of the next month.

[22]Test is performed on an unrestricted VECM model of the form

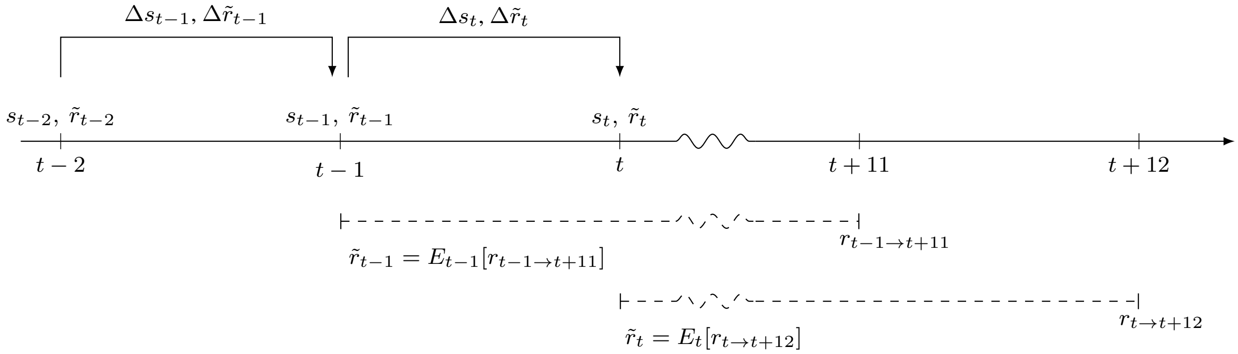
$$\mathbf{\Delta Y_t} = \Gamma \mathbf{\Delta Y_{t-1}} + \alpha\beta^i \mathbf{\Delta Y_{t-2}} + \Phi D + \varepsilon_\mathbf{t} \quad (3.21)$$

where β is a matrix of coefficients of cointegration vectors and α is a matrix of the loading weights of cointegration vectors.

[23]The headlines that contain quarter number or a fiscal year.

Figure 3.4: Timing of Variables

This figure shows the timing of variables at month t. s_t is an average sentiment score of equity reports published at month t. $\tilde{r}_t$ is a subjective expected equity premium from surveys sampled during month t about expected return 12 months ahead $\tilde{r}_t = E_t[r_{t\to t+12}]$.



3.4.3 Misspecified Approach

This section presents a specification that ignore existence of cointegrating relationships between subjective expected equity premium,sentiment score and realized equity premium in the sample.

The OLS regression of subjective expected equity premium and sentiment score in differences is

$$\Delta\tilde{r}_t = a + b\Delta s_t + \epsilon_t \tag{3.22}$$

where $\Delta\tilde{r}_t$ is the difference in subjective expected equity premium calculated as $\tilde{r}_t - \tilde{r}_{t-1}$, and Δs_t is the difference in aggregated sentiment score calculated as $s_t - s_{t-1}$.

Table 3.7 shows that no coefficient has statistical significance. Is this an indication that aggregate sentiment scores of equity report headlines are unrelated to subjective expectations of investors?

The Granger representation theorem of Engle and Granger (1987) tells that if the levels are cointegrated then the data generation process has a representation as an error correction model (VECM). The VECM includes a lagged levels term but a regression 3.7 in differences omits this term. This constrains the estimated coefficient on the lagged levels to be zero and also forces the estimated coefficients on the differenced regressors away from the values they would take if the model were correctly specified as VECM.

As the stationarity tests 3.5 and 3.6 show that sentiment score s_t and realized equity premium r_t^e time series form cointegrating relationships, to account for the stochastic long-run equilibrium relation among variables, I use vector error correction model.

Table 3.7: OLS Regression Specification
The regression specification is

$$\Delta\tilde{r}_t = a + b\Delta s_t + \epsilon_t \tag{3.23}$$

where $\Delta\tilde{r}_t$ is the difference in subjective expected equity premium calculated as $\tilde{r}_t - \tilde{r}_{t-1}$, and Δs_t is the difference in aggregated sentiment score calculated as $s_t - s_{t-1}$. I use three types of sentiment scores, equally weighted Δs_t, company-weighted Δs_t^m and provider-weighted Δs_t^w. I report standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:					
	$\Delta\tilde{r}_t^M$	$\Delta\tilde{r}_t^C$	$\Delta\tilde{r}_t^M$	$\Delta\tilde{r}_t^C$	$\Delta\tilde{r}_t^M$	$\Delta\tilde{r}_t^C$
	(1)	(2)	(3)	(4)	(5)	(6)
Δs_t	0.01	−0.02				
	(0.02)	(0.03)				
Δs_t^m			0.004	0.01		
			(0.02)	(0.02)		
Δs_t^w					0.01	0.06
					(0.04)	(0.05)
Constant	0.02	0.01	0.02	0.02	0.02	0.01
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Observations	198	198	198	198	198	198
R^2	0.0003	0.002	0.0002	0.001	0.0005	0.01

3.4.4 Vector Error Correction Model

In this section I describe mechanics of a vector error correction model. As my focus is not on particular contemporaneous coefficient estimates, but rather on how the variables respond to shocks dynamically, I also outline computing orthogonal impulse responses.

The VECM model specification is

$$\begin{cases} \Delta s_t = \underbrace{\alpha_1(s_{t-1} + \beta_1\tilde{r}_{t-1})}_{\text{long-term dynamics}} + \underbrace{\gamma_{ss}\Delta s_{t-1} + \gamma_{s\tilde{r}}\Delta\tilde{r}_{t-1}}_{\text{short-term dynamics}} + \phi_1 D + \varepsilon_{st} \\ \Delta\tilde{r}_t = \underbrace{\alpha_2(s_{t-1} + \beta_1\tilde{r}_{t-1})}_{\text{long-term dynamics}} + \underbrace{\gamma_{\tilde{r}s}\Delta s_{t-1} + \gamma_{\tilde{r}\tilde{r}}\Delta\tilde{r}_{t-1}}_{\text{short-term dynamics}} + \phi_2 D + \varepsilon_{\tilde{r}t} \end{cases} \tag{3.24}$$

To write the system in matrix form, let $\mathbf{\Delta Y}_t \equiv \begin{bmatrix} \Delta s_t & \Delta \tilde{r}_t \end{bmatrix}$, so

$$\mathbf{\Delta Y}_t = \alpha\beta^{'}\mathbf{Y}_{t-1} + \mathbf{\Gamma}\mathbf{\Delta Y}_{t-1} + \Phi D + \varepsilon_t \tag{3.25}$$

where $\alpha\beta^{'} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} 1 & \beta_1 \end{bmatrix}$ captures long-run dynamics, while $\mathbf{\Gamma}$ is $\begin{bmatrix} \gamma_{ss} & \gamma_{s\tilde{r}} \\ \gamma_{\tilde{r}s} & \gamma_{\tilde{r}\tilde{r}} \end{bmatrix}$ matrix of coefficients that captures short-run effects. ΦD is a vector of constant terms, and $\varepsilon_t = [\varepsilon_{st}, \quad \varepsilon_{\tilde{r}t}]^{'}$ is a vector of stationary innovations, forecast errors of a variable conditional on observing its past values and the past values of sentiment and subjective expectations variables. $\varepsilon_{st} \sim N(0, \sigma_s^2)$ and $\varepsilon_{\tilde{r}t} \sim N(0, \sigma_{\tilde{r}}^2)$. As a general matter, ε_{st} and $\varepsilon_{\tilde{r}t}$ are correlated and its variance-covariance matrix of the system 3.25 Ω_ε has non-zero off-diagonal elements

$$\Omega_\varepsilon = E[\varepsilon_t \varepsilon_t^{'}] = \begin{bmatrix} \sigma_s^2 & \rho\sigma_s\sigma_{\tilde{r}} \\ \rho\sigma_s\sigma_{\tilde{r}} & \sigma_{\tilde{r}}^2 \end{bmatrix} \tag{3.26}$$

where ρ is a correlation between ε_{st} and $\varepsilon_{\tilde{r}t}$.

Whatever causes sentiment to rise (say a positive ε_{st}) would probably cause subjective expected equity premium to rise, too (so $\varepsilon_{\tilde{r}t}$ would also go up). Therefore, these innovations do not have a 'structural' interpretation[24].

Structural approach to the analysis presumes that the underlying driving forces of innovations are rooted in fundamental structural shocks. Let $u_t = [u_{st}, \quad u_{\tilde{r}t}]$ be "structural shocks", which are, by definition, uncorrelated with one another. Assume that there is a linear mapping between these structural shocks and the VECM system's 3.24 innovations:

$$\varepsilon_t = Bu_t \tag{3.27}$$

[24] Structural in the econometric sense means that they are mean zero and are uncorrelated with one another. Each is drawn from some distribution with known variance.

Taking the expectation of the outer product of the error vector with its transpose gives

$$E[\varepsilon_t \varepsilon_t^{'}] = BE[u_t u_t^{'}]B^{'} \tag{3.28}$$

Because structural shocks are uncorrelated, the off-diagonal elements of $E[u_t u_t^{'}]$ are zero. I can normalize the variance of each structural shock to be unity, which means that $E[u_t u_t^{'}] = I$. The above equation then becomes

$$\Omega_\varepsilon = BB^{'} \tag{3.29}$$

This is a system of equations that, without some assumptions, is under-determined. Indeed, there are four unique elements of B, but there are only three unique elements of Ω_ε, since a variance covariance matrix is symmetric. Hence, without imposing restrictions on B, it cannot be identified.

I use the most common restrictions - recursive restrictions, introduced by Sims (1980). They impose timing assumptions - some shocks only affect some variables with a delay. Put differently, some of the elements of B are zero. Following macroeconomic literature, I employ a Cholesky decomposition of variance-covariance matrix as B.

Assume that to form subjective expectations, an investor reads reports published by information providers at time t about events that move the stock market.

$$s \rightarrow \tilde{r} \tag{3.30}$$

This would mean that the (1,2) element of B would be restricted to be zero. Given this restriction, the remaining elements of B is identified from the variance-covariance matrix of residuals[25]

$$B = \begin{bmatrix} \sigma_s & 0 \\ \rho\sigma_{\tilde{r}} & \sigma_{\tilde{r}}\sqrt{1-\rho^2} \end{bmatrix} \tag{3.31}$$

where σ_s^2 is variance of ε_{st}, $\sigma_{\tilde{r}}^2$ is variance of $\varepsilon_{\tilde{r}t}$ and ρ is correlation of ε_{st} and $\varepsilon_{\tilde{r}t}$.

While $B(1,1)$ element of matrix B gives the standard deviation of the errors in equations explaining aggregated sentiment score dynamics, element $B(2,2)$ gives the conditional standard deviation of errors in the equation explaining subjective expected equity premium when the sentiment score errors are constant[26].

To calculate orthogonal responses of variables to shocks, I follow a standard two step procedure. First, I use Wold representation theorem, as in Wold (1954), to write my VECM as vector moving average[27] model $MA(\infty)$. This step transform the model into a linear combination of shocks.

$$\mathbf{Y_t} = \mathbf{D_0}\varepsilon_\mathbf{t} + \mathbf{D_1}\varepsilon_\mathbf{t-1} + \mathbf{D_2}\varepsilon_\mathbf{t-2} + \dots \tag{3.32}$$

25

$$\Omega_\varepsilon = \begin{bmatrix} \sigma_s^2 & \rho\sigma_s\sigma_{\tilde{r}} \\ \rho\sigma_s\sigma_{\tilde{r}} & \sigma_{\tilde{r}}^2 \end{bmatrix} = \begin{bmatrix} \sigma_s^2 & \rho\sigma_s\sigma_{\tilde{r}} \\ \rho\sigma_s\sigma_{\tilde{r}} & \rho^2\sigma_{\tilde{r}}^2 + (1-\rho^2)\sigma_{\tilde{r}}^2 \end{bmatrix} = \underbrace{\begin{bmatrix} \sigma_s & 0 \\ \rho\sigma_{\tilde{r}} & \sigma_{\tilde{r}}\sqrt{1-\rho^2} \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} \sigma_s & \rho\sigma_{\tilde{r}} \\ 0 & \sigma_{\tilde{r}}\sqrt{1-\rho^2} \end{bmatrix}}_{B'}$$

[26] What exactly the Cholesky decomposition does? if there is a one standard deviation shock to the sentiment, $\boldsymbol{\epsilon}_t = \begin{bmatrix} \sigma_s & 0 \end{bmatrix}'$, then $\mathbf{B}^{-1}$ will convert this shock into a vector

$$\mathbf{u_t} = \mathbf{B}^{-1}\boldsymbol{\epsilon}_t = \begin{bmatrix} \sigma_s^{-1} & 0 \\ -\rho(1-\rho^2)^{-\frac{1}{2}}\sigma_s^{-1} & (1-\rho^2)^{-\frac{1}{2}}\sigma_{\tilde{r}}^{-1} \end{bmatrix} \begin{bmatrix} \sigma_s \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ -\rho\cdot(1-\rho^2)^{-\frac{1}{2}} \end{bmatrix}$$

The matrix $\mathbf{B}^{-1}$ rescales $\boldsymbol{\varepsilon}_t$ to have unit norm, $\mathrm{E}\big[\mathbf{B}^{-1}\,\boldsymbol{\varepsilon}_t\,\boldsymbol{\varepsilon}_t^\top(\mathbf{B}^{-1})^\top\big] = \mathbf{I}$, and rotates the vector to account for the correlation ρ between ε_{st} and $\varepsilon_{\tilde{r}t}$. The rotation takes into account the correlation between ε_{st} and $\varepsilon_{\tilde{r}t}$, as matrix $\mathbf{B}^{-1}$ turns the shock $\boldsymbol{\varepsilon}_t = \begin{bmatrix} \sigma_s & 0 \end{bmatrix}^\top$ into a vector that is pointing 1 standard deviation in the s direction and $-\rho\cdot(1-\rho^2)^{-\frac{1}{2}}$ in the $\tilde{r}$ direction.

If there is a one standard deviation shock to the subjective expectaions, $\boldsymbol{\epsilon}_t = \begin{bmatrix} 0 & \sigma_{\tilde{r}} \end{bmatrix}'$, there is no response in the s direction and $(1-\rho^2)^{-\frac{1}{2}}$ response in $\tilde{r}$ direction

$$\mathbf{u_t} = \mathbf{B}^{-1}\boldsymbol{\epsilon}_t = \begin{bmatrix} \sigma_s^{-1} & 0 \\ -\rho(1-\rho^2)^{-\frac{1}{2}}\sigma_s^{-1} & (1-\rho^2)^{-\frac{1}{2}}\sigma_{\tilde{r}}^{-1} \end{bmatrix} \begin{bmatrix} 0 \\ \sigma_{\tilde{r}} \end{bmatrix} = \begin{bmatrix} 0 \\ (1-\rho^2)^{-\frac{1}{2}} \end{bmatrix}$$

[27] "Moving average" term is also used for the procedure of smoothing data with a running mean. A footnote in Pankratz (1983), on page 48, says: "The label "moving average" is technically incorrect since the MA coefficients may be negative and may not sum to unity. This label is used by convention." Box and Jenkins (1976) also says on page 10: "The name "moving average" is somewhat misleading because the weights . . . need not total unity nor need that be positive. However, this nomenclature is in common use, and therefore we employ it."

where where $\mathbf{D_0}$, $\mathbf{D_1}$, $\mathbf{D_2}$ are coefficients of MA(∞). If I let $\mathbf{A}_1 = \mathbf{I} + \alpha\beta^{'} + \mathbf{\Gamma}$ and $\mathbf{A}_2 = -\mathbf{\Gamma}$,

$$\mathbf{D_0} = \mathbf{I} \tag{3.33}$$

$$\mathbf{D_1} = \mathbf{D_0 A_1} \tag{3.34}$$

$$\mathbf{D_2} = \mathbf{D_1 A_1} + \mathbf{D_0 A_2} \tag{3.35}$$

$$\dots \tag{3.36}$$

$$\mathbf{D_t} = \sum_{j=1}^{2} \mathbf{D_{t-j} A_j} \quad for\ t = 1, 2, \dots \tag{3.37}$$

Second, following Sims (1980) I use matrix B to orthgonalize the shocks in the MA(∞)[28]:

$$\mathbf{Y_t} = \mathbf{D_0 B B^{-1}} \varepsilon_\mathbf{t} + \mathbf{D_1 B B^{-1}} \varepsilon_\mathbf{t-1} + \mathbf{D_2 B B^{-1}} \varepsilon_\mathbf{t-2} + \dots \tag{3.39}$$

$$\equiv \mathbf{C_0 u_t} + \mathbf{C_1 u_{t-1}} + \mathbf{C_2 u_{t-2}} + \dots \tag{3.40}$$

where $u_t, u_{t-1}, u_{t-1}, \dots$ are i.i.d.

To find the impulse response function of $\tilde{r}_t$ to $u_{\tilde{s}t}$ over time, I set $u_{\tilde{s}t} = 1$. The impulse response on impact at $t = 0$ would be $C_0(2, 1)$, the response after one period, at $t = 1$, would be $C_1(2, 1)$, and so on. For example, orthonogalized impulse responses of $\tilde{r}_t$ to u_{st} in VECM with provider-weighted aggregated

[28]I denote a vector of variables as $\boldsymbol{Y}_t \equiv [s_t,\ \ \tilde{r}_t]$, and write the VECM system as VAR(2) model

$$\mathbf{\Delta Y}_t = \Gamma \mathbf{\Delta Y}_{t-1} + \alpha\beta^{'} \mathbf{Y}_{t-1} + \Phi D + \varepsilon_t \ \ \Leftrightarrow \ \ \mathbf{Y}_t = A_1 \mathbf{Y}_{t-1} + A_2 \mathbf{Y}_{t-2} + \Phi D + \varepsilon_t \tag{3.38}$$

where $A_1 \equiv \mathbf{I} + \Gamma + \alpha\beta^{'}$ and $A_2 \equiv -\Gamma$

sentiment and CCS survey expectations is 0.14 at time $t = 0$, 0.17 at $t = 1$, 0.20 at $t = 2$

$$\mathbf{C_0} = \mathbf{D_0B} = \begin{bmatrix} 0.92 & 0.00 \\ \textcircled{0.14} & 0.72 \end{bmatrix}$$

$$\mathbf{C_1} = \mathbf{D_1B} = \begin{bmatrix} 0.30 & 0.11 \\ \textcircled{0.17} & 0.55 \end{bmatrix}$$

$$\mathbf{C_2} = \mathbf{D_2B} = \begin{bmatrix} 0.44 & 0.21 \\ \textcircled{0.20} & 0.54 \end{bmatrix}$$

Mathematically $\mathbf{C_i}(2, 1)$ elements of $\mathbf{C_i}$ matrices are:

$$\mathbf{C_0}(2, 1) = \rho\sigma_{\tilde{r}} \tag{3.41}$$

$$\mathbf{C_1}(2, 1) = \sigma_s(\alpha_2 + \gamma_{\tilde{r}s}) + \rho\sigma_{\tilde{r}}(\alpha_2\beta_1 + 1 + \gamma_{\tilde{r}\tilde{r}}) \tag{3.42}$$

$$\mathbf{C_2}(2, 1) = \sigma_s\Big((\alpha_2 + \gamma_{\tilde{r}s})(\alpha_2\beta_1 + 1 + \gamma_{\tilde{r}\tilde{r}}) - \gamma_{\tilde{r}s} + (\alpha_2 + \gamma_{\tilde{r}s})(\alpha_1 + \gamma_{ss} + 1)\Big) + \tag{3.43}$$

$$+ \rho\sigma_{\tilde{r}}\Big((\alpha_2\beta_1 + 1 + \gamma_{\tilde{r}\tilde{r}})^2 - \gamma_{\tilde{r}\tilde{r}} + (\alpha_2 + \gamma_{\tilde{r}s})(\gamma_{s\tilde{r}} + \alpha_1\beta_1)\Big) \tag{3.44}$$

Dynamic orthogonal impulse responses $\mathbf{C_i}(2, 1)$ are weighted sums of standard deviation of innovations in VECM subjective expectation equation, $\sigma_{\tilde{r}}$ and standard deviation of innovations in VECM sentiment equation, σ_s. Both, coefficeints that account for long-run dynamics, α_1, α_2, β_1 and short-term fluctuations, γ_{ss}, $\gamma_{s\tilde{r}}$, $\gamma_{\tilde{r}s}$, $\gamma_{\tilde{r}\tilde{r}}$, contributes to orphogonal impulse response of $\tilde{r}$ to shock in s_t.

3.4.5 Intuition

For illustarative purposes, following Stock and Watson (1993), I can write the cointegrated system (3.24) with restrictions (3.31) in block triangular form. Following Stock and Watson (1993), I focus only on long-term relationships betwenn variables, and ignore short-tern dinamics,

$$\tilde{r}_t = \beta_1 s_t + e_{\tilde{r}t}, \quad \text{where } e_{\tilde{r}t} = \alpha_2 e_{st} + \varepsilon_{\tilde{r}t} \tag{3.45}$$

$$\Delta s_t = e_{st}, \quad \text{where } e_{st} = \sum_{j=0}^{\infty} \theta_0 \varepsilon_{st-1} + \theta_{t-2}\varepsilon_{st-2} + \theta_{t-3}\varepsilon_{st-3} + \dots \tag{3.46}$$

where innovations $\varepsilon_{\tilde{r}t} \sim I(0)$ and $\varepsilon_{st} \sim I(0)$ are from VECM model (3.24) without short-term dynamics, β_1 is a coefficient of conintegration vector in (3.24), and α_2 is a coeffitient of equilibrium adjustment vector in (3.24).

The first equation is $\tilde{r}_t = \beta_1 s_t + e_{\tilde{r}t}$ describes the long-term equilibrium relationship between $\tilde{r}_t$ and s_t. The parameter β_1 is the cointegration coefficient and measures how changes in s_t are associated with changes in $\tilde{r}_t$ in the long run. The term $e_{\tilde{r}t}$ is a disturbance term that captures short-term deviations from the long-term equilibrium. It is composed of two parts: $\alpha_2 e_{st}$ and $\varepsilon_{\tilde{r}t}$. The first part, $\alpha_2 e_{st}$, represents the error correction mechanism that adjusts $\tilde{r}$ towards its long-term equilibrium relationship with s_t. If e_{st} is positive, it means s_t is above its equilibrium value given $\tilde{r}$, and hence $\tilde{r}$ needs to increase to restore equilibrium. The adjustment is proportional to α_2. The second part, $\varepsilon_{\tilde{r}t}$ is an independent shock to $\tilde{r}$ that has nothing to do with s_t.

The second equation is $\Delta s_t = e_{st}$, which represents the change in s_t as a function of the disturbance term e_{st}. The disturbance term e_{st} is given by a sum of the past innovations ε_{st-j} weighted by the parameters θ_{t-j}. This equation captures the dynamics of s_t and how its changes are influenced by past shocks.

It's important to note that $\varepsilon_{\tilde{r}t}$ depends on β_1 and, if β_1 is not equal to zero, so does e_{st}. This means that the short-term dynamics and the long-term equilibrium of the system are interconnected. A change in sentiment s_t (for example, due to an innovation ε_{st}) not only directly affects s_t itself but also induces a change in the subjective expectations $\tilde{r}_t$ to restore the long-term equilibrium relationship.

The main economic intuition behind this model is that there are both long-term and short-term forces at work in this economic system. The long-term forces maintain a stable relationship between $\tilde{r}_t$ and s_t, while the short-term forces cause temporary deviations from this equilibrium. The system constantly adjusts to these deviations, moving towards the long-term equilibrium.

3.5 Findings

In this section I discuss the tests conducted and the evidence garnered in support of the four hypotheses that are stated in the introduction section.

Hypothesis 1 If every report has equal weight or equivalently, the sentiment of information providers is weighted by the reporting activity of information providers, there is an association between subjective expected excess return and sentiment about the growth of companies' earnings.

Utilizing the findings from the VECM specifications presented in Tables A.10 and A.11, Figure 3.5 displays the orthogonal impulse response functions (OIRFs) along with confidence intervals[29]. These functions illustrate the effect of a one standard deviation shock in sentiment on the subjective expected equity premium. This is demonstrated across three sentiment score categories: information provider-weighted (s_t^w), equally-weighted (s_t), and company-weighted (s_t^m) sentiment scores.

Figure 3.5 demonstrates that the information provider-weighted sentiment score has a significant impact on the subjective expected equity premium. The top two plots, (a) and (b), indicate that the adjustment of subjective expectations in response to a provider-weighted sentiment shock is both immediate and persistent. At the time of impact, $t = 0$, of one standard deviation shock in sentiment, subjective expectations grows 10 (MSC survey) to 15 basis points (CCS survey). The impact reaches 20-23 basis points in three months after the shock.

However, when subjective expectations are weighted by a company's market capitalization, there is no discernible reaction to the aggregated sentiment score shock, as evidenced by plots (e) and (f).

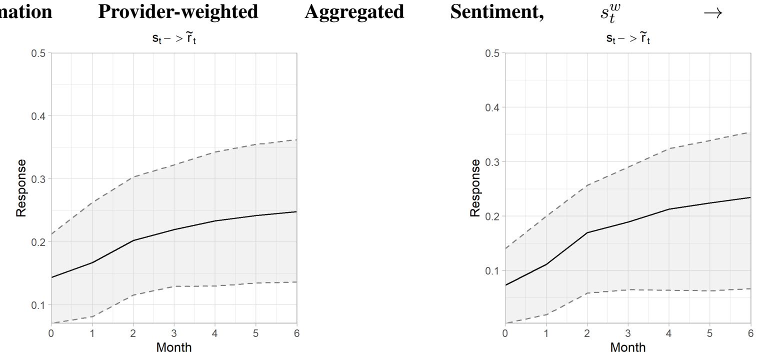
Are there mixed aggregation schemes that dominate by-information provider weighting? To answer the question, I construct 5,027 convex combinations of equally weighted $s_t = \frac{1}{n_t}\mathbf{1}\mathbf{S_t}'$, where $\mathbf{S_t}'$ is a vector of average sentiment of n_t information providers at month t, information provider-weighted $s_t^w = \mathbf{w_t^f}\mathbf{S_t}'$

[29]Confidence intervals are represented as $CI_s = [s_{a/2}, s_{1-a/2}]$, where $s_{a/2}$ and $s_{1-a/2}$ correspond to the $a/2$ and $1 - a/2$ quantiles of the bootstrap distribution of orthogonalized coefficients C_τ in the MA(∞) representation of the VECM.

Figure 3.5: Hypothesis 1. Orthogonal Impulse Responses, in %

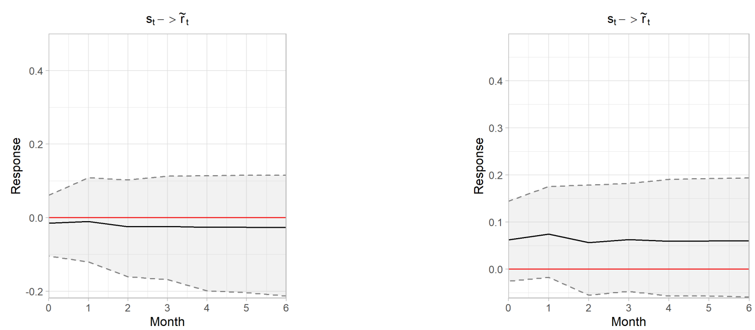
OIR of one standard deviation sentiment shock, s_t to subjective sxpectations, $\tilde{r}_t$ The sentiment score s_t is scaled by 100. 95 % confidence interval for the bootstrapped errors bands. 100 runs. Confidence intervals are represented as $CI_s = [s_{a/2}, s_{1-a/2}]$, where $s_{a/2}$ and $s_{1-a/2}$ correspond to the $a/2$ and $1-a/2$ quantiles of the bootstrap distribution of orthogonalized coefficients C_τ in the MA(∞) representation of the VECM.

Information Provider-weighted Aggregated Sentiment, $s_t^w \rightarrow \tilde{r}_t$



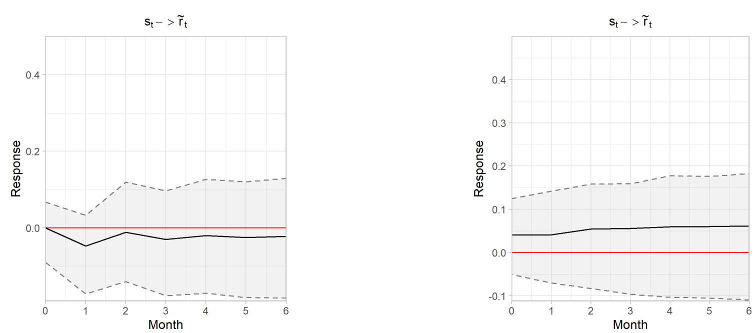
(a) CCS Survey **(b)** MSC Survey

Equally-weighted Aggregated Sentiment, $s_t \rightarrow \tilde{r}_t$



(c) CCS Survey **(d)** MSC Survey

Company-weighted Aggregated Sentiment, $s_t^m \rightarrow \tilde{r}_t$



(e) CCS Survey **(f)** MSC Survey

and company-weighted $s_t^m = \mathbf{w_t^c}\mathbf{S_t}^{c,'} = \mathbf{w_t^{c,adj}}\mathbf{S_t}'$ sentiment measures, S_t^c,

$$S_t^c = \alpha s_t + \beta s_t^w + \gamma s_t^m = \mathbf{W_t^c}\mathbf{S_t}' \tag{3.47}$$

$$\text{such that } \alpha + \beta + \gamma = 1, \tag{3.48}$$

$$\mathbf{W_t^c} = \alpha \frac{1}{n_t}\mathbf{1} + \beta \mathbf{w_t^f} + \gamma \mathbf{w_t^{c,adj}} \tag{3.49}$$

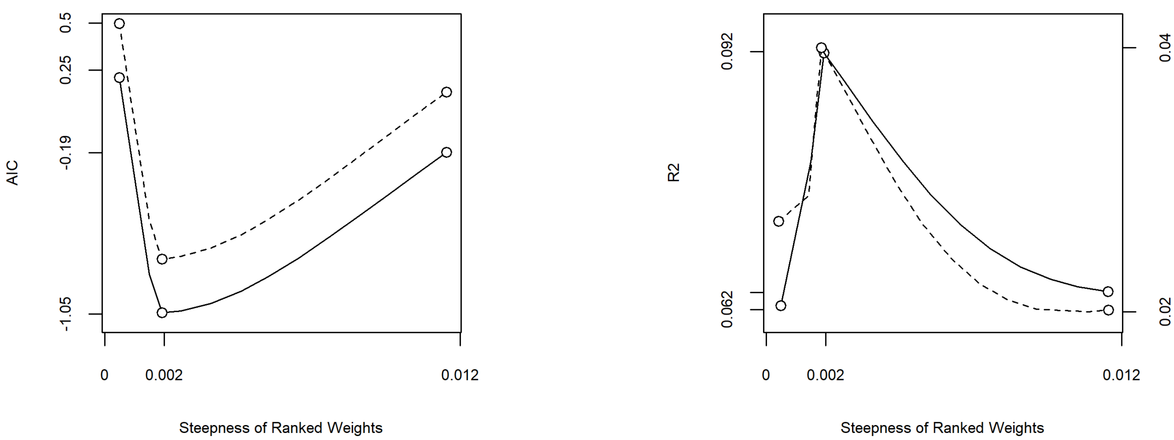
$$0 \leq \alpha \leq 1,\ 0 \leq \beta \leq 1,\ 0 \leq \gamma \leq 1 \tag{3.50}$$

Figure 3.6: Steepness of Weighting $\mathbf{W_t^c}$ Vs. Lower Boundary of VECM AIC and Steepness of Weighting $\mathbf{W_t^c}$ Vs. Adjusted R^2 of Subjective Expectations Equation in VECM($S_t, \tilde{r}_t$)

The X-axis represents the 'steepness' of a reparametrization scheme's weights. It's calculated as $\bar{sl} = \alpha sl(\bar{s_t}) + \beta sl(\bar{s_t^w}) + \gamma sl(\bar{s_t^e})$, where $sl(\bar{s_t})$, $sl(\bar{s_t^w})$, and $sl(\bar{s_t^e})$ are the slopes of individual weighting schemes. Each slope is determined by the formula $sl = \frac{1}{n_t}(\max w_t - \min w_t)$, where $\max w_t$ is the maximum weight in the scheme, $\min w_t$ is the minimum weight in the scheme, and n_t is the number of news items per month t.

The right plot visualizes the lowest values within the set of AIC (Akaike Information Criterion) of VECM (Vector Error Correction Model) models. In contrast, the left plot displays the highest values within the set of adjusted R^2 for the subjective expectations equation in VECM($S_t^e, \tilde{r}_t$). The solid black line represents specifications with subjective expectations from the MSC survey, while the dashed black line indicates those from the CBS survey. The left y-axis corresponds to the AIC of the subjective expectations equation from the MSC survey, whereas the right y-axis pertains to the AIC of the subjective expectations equation from the CBS survey.

A 'steepness' of 0 denotes an "equally-weighted" scheme. A 'steepness' of 0.002 signifies a weighting scheme that allocates 100% of the weight to provider-weighted sentiment. Lastly, a 'steepness' of 0.008 refers to a weighting scheme that gives 100% of the weight to exponentially-weighted sentiment.



(a) AIC

(b) Adj. R^2 of Subj.Exp. Equation

where α, β and γ are shares that form the convex combination of sentiment weighting schemes[30] [31]

[30] A total of 5,027 convex combinations are created using the following method. First, I generate three grids of weights, α, β, and γ, which range from 0 to 1 in increments of 0.01.

$$\alpha = 0, 0.01, 0.02, ..., 1 \; \beta = 0, 0.01, 0.02, ..., 1 \; \gamma = 0, 0.01, 0.02, ..., 1$$

Next, I create a data frame containing all possible combinations of these values and retain only those combinations where the sum of α, β, and γ is equal to one.

$$\alpha + \beta + \gamma = 1$$

[31] As my data is in news-information provider-company-date granularity, I can map company-driven weights $\mathbf{w_t^c}$ to company-driven weights per information provider, $\mathbf{w_t^{c,adj}}$, $s_t^m = \mathbf{w_t^{c,adj}} \mathbf{S_t}'$.

To illustrate the transformation, let's look at information providers A and B that both write reports news about companies 1 and 2. Information provider A writes three news articles about company 1 and four news acticles about company 2, $3s_1^A$, $4s_2^A$, while information provider B writes one news article about company1 and one news article about company 2, s_1^B, s_2^B. Market capitalization of company 1 is X and company 2 is Y, in percents of total market capitalization. Company-weighted sentiment is $s_t^c = \mathbf{w_t^c} \mathbf{S_t}^{c,'} = (3s_1^A + s_1^B)\frac{1}{4}X + (4s_2^A + s_2^B)\frac{1}{5}Y$. If I want to map company-weighted weights per information provider, I can rearrange the equation as follows $s_t^m = \frac{7}{7}(3s_1^A\frac{1}{4}X + 4s_2^A\frac{1}{5}Y) + \frac{2}{2}(s_1^B\frac{1}{4}X + s_2^B\frac{1}{5}Y)$, where 7 is a number of reports written by information provider A and 2 is a number of reports written by information provider B.

Table 3.8: Descriptive Statistics: Monthly Provider-Weighted Average Sentiment Score By Type of Provider

The table shows descriptive statistics of individual and aggregate polarity score, scaled by 100, from January 2000 to December 2019.

Variables	N	Mean	St. Dev.	Min	Max
Cross-News Panel					
Sentiment of Less Active Providers	21,120	0.35	19.40	-170.05	161.00
Sentiment of More Active Providers	489,360	1.99	20.10	-203.52	192.43
Aggregated Monthly Time Series					
Sentiment of Less Active Providers	240	0.58	3.3	-13.57	11.24
Sentiment of More Active Providers	240	2.09	1.37	-3.1	5.16

To characterize these big vectors of weights $\mathbf{W_t^c}$ for the ease of illustration of the results, I use "steepness of weights" $\bar{sl}$ of weighting schemes $\mathbf{W_t^c}$ to display results. "Steepness of weights" refers to the degree of disparity or differentiation between the weights assigned to different information providers within each weighting scheme $\mathbf{W_t^c}$. A steep weighting scheme assigns much higher weights to some information providers or companies and much lower weights to another ones. In contrast, a flat weighting scheme would assign similar weights to all information providers or companies. The steepness of a weighting scheme implicitly tracks the degree of bias towards the observations that are given higher weights.

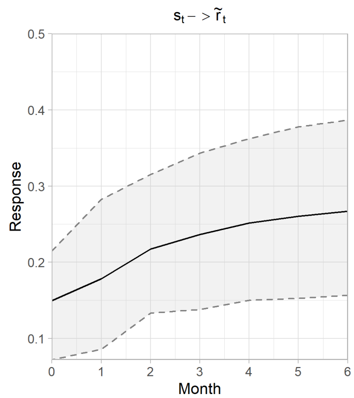
Figure 3.6 shows "steepness of weights" $\bar{sl}$ of $\mathbf{W_t^c}$ versus lower convex hull of AIC of VECM($S_t^c, \tilde{r}_t$) and upper boundary of the set of adjusted R^2 of subjective expectations equation in VECM($S_t^c, \tilde{r}_t$). Plots illustrate that specification with the minimum AIC information criterion and maximum adjusted R^2 of subjective expectation equation corresponds to the weighting scheme with steepness of weights $\bar{sl} = 0.002$. This steepness corresponds to the convex combination $\{\alpha, \beta, \gamma\} = \{0, 1, 0\}$ or 100 % provider-weighted sentiment.

Hypothesis 2 The association between subjective expected excess return and sentiment about earnings growth is stronger for reports of information providers with higher reporting activity.

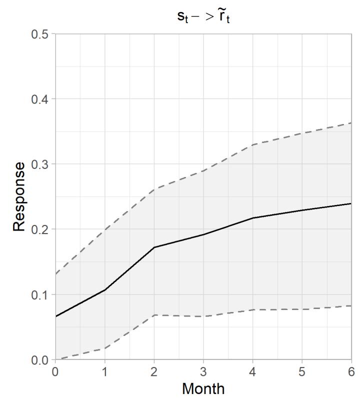
To test the hypothesis, I sort information providers by number of published reports over the sample period, use the top fifth quantile (top 20%) as more active information providers and first to forth quantiles as less active information providers. As information provider-weighted sentiment has the highest association with the subjective expected equity premium, I use information provider-weighted sentiment for building

Figure 3.7: Orthogonal Impulse Response Functions of VECM With Sentiment of More and Less Active Providers
The sentiment score s_t is scaled by 100. 95 % confidence interval for the bootstrapped errors bands. 100 runs.

Information Provider-weighted Sentiment, More Active Providers, $s_t^{w,5} \rightarrow \tilde{r}_t$

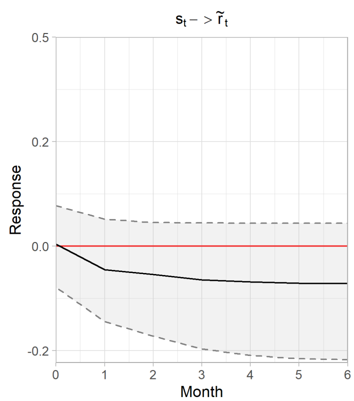


(a) CCS Survey

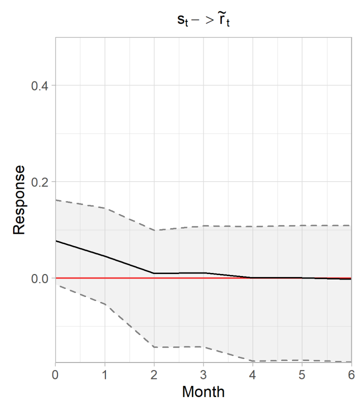


(b) MSC Survey

Information Provider-weighted Sentiment, Less Active Providers $s_t^{w,1:4} \rightarrow \tilde{r}_t$



(c) CCS Survey



(d) MSC Survey

the two sentiment time series. The description of quantiles is provided in Appendix.

Table 3.8 shows descriptive statistics for individual and monthly time-series of aggregated provider-weighted sentiment for two types of information providers. The more active providers have 3.6 times higher monthly mean sentiment score and 2.4 lower standard deviatin.

I run the same VECM model using sentiment of more and less active providers weighted by information provider's activity, $s_t^{w,5}$ and $s_t^{w,1:4}$.

Tables A.13 and A.12 show sentiment of less active providers $s_t^{w,1:4}$ has no association with subjective

Table 3.9: AIC of VECM With Sentiment Of More and Less Active Information Providers and Adjusted R^2 of Equation for Subjective Expectations in VECM

Subjective Expectations	Sentiment	Models		
		VECM($s_t^w, \tilde{r}_t$)	VECM($r_{t-1}, s_t^w, \tilde{r}_t$)	VECM($r_{t-1}, \tilde{r}_t$)
		AIC		
$\tilde{r}_t^M$	More Active Providers $s_t^{w,5}$	-0.72	1.57	1.62
	Less Active Providers $s_t^{w,1-4}$	1.48	3.92	
$\tilde{r}_t^C$	More Active Providers $s_t^{w,5}$	-1.01	1.87	1.91
	Less Active Providers $s_t^{w,1-4}$	1.16	4.22	
		Adjusted R^2 of VECM Equation for Subjective Expectations		
$\tilde{r}_t^M$	More Active Providers $s_t^{w,5}$	0.10	0.08	0.07
	Less Active Providers $s_t^{w,1-4}$	0.07	0.07	
$\tilde{r}_t^C$	More Active Providers $s_t^{w,5}$	0.04	0.08	0.06
	Less Active Providers $s_t^{w,1-4}$	0.03	0.05	

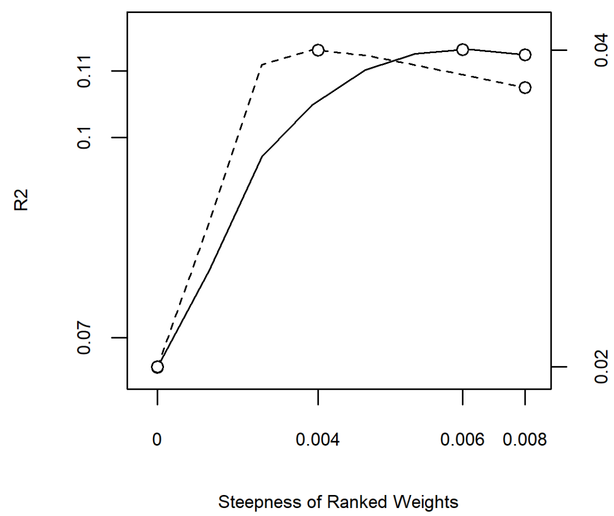
expected equity premium for both surveys. Sentiment of more active providers $s_t^{w,5}$ has highly significant long-term impact though cointegration vector and weakly significant short-term impact on subjective expected equity premium.

Table 3.9 shows that adding lagged realized return increases AIC of VECM considerably.

What if I add even more weight to the sentiment of more active information providers? Before delving into the main question, note that VECM specifications A.10, A.11, A.13, and A.12 indicate that the equation representing sentiment consistently exhibits a higher goodness of fit than the equation representing subjective expectations (approximately 30-40% compared to 4-10%). Furthermore, the coefficient of lagged sentiment in the sentiment equation is highly significant across all specifications. Given these observations, to answer the question I focus on the goodness of fit measures for the subjective expectations equation of VECM. Relying on the information criteria of the entire VECM system could lead to selection of a sentiment measure with the highest autoregressive component.

For test purposes, I introduce a new mesure, the average sentiment of the top 3 information providers. This metric allocates all weight to the average sentiment of the three most active information providers and assigns zero weight to all others. The choice of the top 3 providers serves as a straightforward, "rule of thumb" measure that can represent the concept of selective attention without necessitating any behavioral

Figure 3.8: Steepness of Weighting Scheme, $\bar{S}^e$, Vs. Upper Convex Hull of Set of Adjusted R^2 of Subjective Expectations Equation in VECM($S_t^e, \tilde{r}_t$)
X-axis shows "steepness" of weights of a reparametrization scheme, calculated as $\bar{sl} = \alpha \bar{sl(s_t)} + \beta \bar{sl(s_t^w)} + \gamma \bar{sl(s_t^e)}$, where $\bar{sl(s_t)}$, $\bar{sl(s_t^w)}$, $\bar{sl(s_t^e)}$ are slopes of invdividual weightening schemes with a slope $sl = \frac{1}{n_t}(\max w_t - \min w_t)$, where $\max w_t$ is the maximum weight in the scheme, $\min w_t$ is the minimum weight in the scheme and n_t is the number of news per month t. The plot shows upper convex hull of adjusted R^2 of subjective expectations equation in VECM($S_t^e, \tilde{r}_t$) with subjective expectations with MSC survey (solid black line) and CBS survey (dashed black line) versus the steepness of sentiment weighting scheme. Left y-axis corresponds to AIC of subjective expectations equation from MSC survey. Right y-axis corresponds to AIC of subjective expectations equation from CBS survey. 0 steepness corresponds to "equally-weighted" scheme; 0.042 steepness corresponds to weighting scheme that puts 100% of weight on $s_t^{w,5}$ sentiment, and 0.008 steepness corresponds to weighting scheme that puts 100% of weight on sentiment of top 3 information providers.



assumption about retail investors' limited attention span.

To construct the measure, every month I sort information providers from the most active to the least active ones using number of written reports in a given month. Let's denote the ordering as $1, 2, \ldots, n_t$, which sorts information providers from the most active one (1) to the least active one (n_t) within a month t. Next, I calculate average sentiment of top three information providers. So, weights in this "top-weighting" scheme are $\mathbf{w_t^e} = \{0.33, 0.33, 0.33, 0, 0 \ldots\}$.

Next, I construct 5,027 convex combinations of equally weighted $s_t = \frac{1}{n_t}\mathbf{1}\mathbf{S_t}'$, information provider-weighted $s_t^w = \mathbf{w_t^f}\mathbf{S_t}'$ and top-weighted $s_t^e = \mathbf{w_t^e}\mathbf{S_t}'$ sentiment measures

$$S_t^e = \mathbf{W_t^e}\mathbf{S_t}' \tag{3.51}$$

$$\text{such that } \alpha + \beta + \gamma = 1, \tag{3.52}$$

$$\mathbf{W_t^e} = \alpha \frac{1}{n_t}\mathbf{1} + \beta \mathbf{w_t^f} + \gamma \mathbf{w_t^e} \tag{3.53}$$

$$0 \leq \alpha \leq 1,\ 0 \leq \beta \leq 1,\ 0 \leq \gamma \leq 1 \tag{3.54}$$

where α, β and γ are shares that form the convex combination of sentiment weighting schemes.

Figure 3.8 depicts the adjusted R^2 of the subjective expectation equation of the VECM in relation to the average steepness of the generated weighting scheme. The graph reveals that the peak adjusted R^2 for the subjective expectations equation in the VECM($S_t^e, \tilde{r}_t$), with expectations $\tilde{r}_t$ derived from the CBS survey (represented by the dashed line and right y-axis), tops out at $R^2 = 0.04$. This peak corresponds to a weighting scheme steepness of 0.004, which is made up of 73% provider-weighted sentiment and 27% top-weighted sentiment, hence $\alpha, \beta, \gamma = 0, 0.73, 0.27$. The sentiment measure $s_t^{w,5}$, which includes the 20% most active information providers, also exhibits an average weighting scheme steepness of 0.004 and a corresponding $R^2 = 0.04$. Therefore, for the CBS survey, the sentiment of the 20% most active providers, represented by $s_t^{w,5}$, could be the most representative of the "true" weighting scheme.

The graph also shows that the maximum adjusted $R^2 = 0.11$ for the subjective expectations equation of the VECM($S_t^e, \tilde{r}_t$), with expectations $\tilde{r}_t$ derived from the MSC survey (indicated by the solid line and left y-axis), reaches a peak at a steepness of 0.006. Since this steepness is higher than the 0.004 steepness of $s_t^{w,5}$ and higher than the $R^2 = 0.10$ of the subjective expectation equation in VECM($s_t^{w,5}, \tilde{r}_t$) with $s_t^{w,5}$, it can be inferred that investors from the MSC survey might lean towards learning from a set of providers with an even steeper weighting scheme. To avoid mechanical curve fitting, the precise determination of weighting for MSC survey expectations should be informed by behavioral research studies. This would provide a more accurate reflection of how individuals weigh different sources of information, factoring in human cognitive biases and decision-making patterns.

Hypothesis 3 Information from less active providers is not related to the temporal fluctuations of aggregate stock market return.

First, I examine whether total annual return of the CRSP value-weighted portfolio[32] R_t is associated with the change in annual aggregated weighted sentiment of reports about 45 blue-chip companies. To study whether the sentiment of the reports contribute to time variations of aggregate stock market returns, or predictability of aggregate stock market return, I run a standard predictability regression as in Cochrane (2006) with and without the change in the sentiment and examine whether sentiment measures have statistical significance.

Table 3.10 presents specifications for the following predictability regressions

$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \epsilon_t \tag{3.55}$$

$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_2 \Delta s^{w,1-4}_{t-12\to t-1} + \epsilon_t \tag{3.56}$$

$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_3 \Delta s^{w,5}_{t-12\to t-1} + \epsilon_t \tag{3.57}$$

$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_2 \Delta s^{w,1-4}_{t-12\to t-1} + \beta_3 \Delta s^{w,5}_{t-12\to t-1} + \epsilon_t \tag{3.58}$$

where $R_{t\to t+11}$ is the annual real total return of the CRSP value-weighted index at month t deflated by the CPI[33], $(D/P)_{t-11\to t}$ is the dividend-price ratio[34], $\Delta s^{w,5}_{t-12\to t-1}$ is the change in the average weighted lagged sentiment of more active information providers and $\Delta s^{w,1-4}_{t-12\to t-1}$ is the change in the lagged weighted sentiment of less active information providers.

As in Cochrane (2006), I use Hansen and Hodrick (1980) standard errors to account for serially corre-

[32] vwretd variable from CRSP

[33] The real monthly total return of CRSP value-weighted Index is calculated as

$$R_t = \frac{vwretd_t + 1}{cpi_t + 1} - 1 \tag{3.59}$$

where cpi_t is $CPIAUCSL_CH$ is the percent change in Consumer Price Index for All Urban Consumers divided by 100 from U.S. Bureau of Labor Statistics, https://fred.stlouisfed.org/series/CPIAUCSL and annual return $R_{t\to t+11}$ is equal to

$$R_{t\to t+11} = \Pi_t^{t+11}(R_t + 1) - 1 \tag{3.60}$$

where R_t is the annual real total return of the CRSP value-weighted index at month t.

[34] The dividend-price ratio is calculated as

$$(D/P)_{t-11\to t} = \Pi_{t-11}^{t} \frac{vwretd_t + 1}{vwretx_t + 1} - 1 \tag{3.61}$$

where $vwretd_t$ is the annual real total return on the CRSP value weighted portfolio and $vwretx_t$ is the return on the CRSP value weighted portfolio excluding dividends at month t

Table 3.10: Predictive Regression: Overlapping Regression Specification
The regression specifications are

$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \epsilon_t$$
$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_2 \Delta s^{w,1-4}_{t-12\to t-1} + \epsilon_t$$
$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_3 \Delta s^{w,5}_{t-12\to t-1} + \epsilon_t$$
$$R_{t\to t+11} = \alpha + \beta_1 (D/P)_{t-11\to t} + \beta_2 \Delta s^{w,1-4}_{t-12\to t-1} + \beta_3 \Delta s^{w,5}_{t-12\to t-1} + \epsilon_t$$

where $R_{t\to t+11}$ is an annual return of value-weighted market index with dividends $r_{t\to t+11} = \Pi_t^{t+11}(vwretd_t + 1)/(\pi_t + 1) - 1$ adjusted for monthly inflation π_t, $(D/P)_{t-11\to t}$ is annual dividend-price ratio calculated from monthly $vwretd_t$ and $vwretx_t$ as $\Pi^t_{t-11}(vwretd_t + 1)/(vwretx_t + 1) - 1$. $s_t^{w,1-4}$, $\Delta s^{w,1-4}_{t-12\to t-1}$ and $\Delta s^{w,5}_{t-12\to t-1}$ are average annual sentiment of less and more active information providers. I report Hansen-Hodrick (1980) standard errors with 12 month window in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:			
	$R_{t\to t+11}$			
	(1)	(2)	(3)	(4)
$(D/P)_{t-11\to t}$	17.98***	17.55***	17.43***	17.14***
	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta s^{w,1-4}_{t-12\to t-1}$		0.03		0.03
		(0.06)		(0.06)
$\Delta s^{w,5}_{t-12\to t-1}$			0.10***	0.09***
			(0.02)	(0.02)
Constant	0.71	0.72	0.72*	0.72*
	(0.45)	(0.44)	(0.43)	(0.43)
Observations	197	197	197	197
R^2	0.09	0.09	0.09	0.10
Adjusted R^2	0.08	0.08	0.08	0.08

lated errors in the overlapping regression.

The first regression specification Table 3.10 replicates Cochrane (2006) predictive regression. Second, third, and fourth regression specifications also include the average lagged weighted sentiment of more and less active information providers. It is shown in Table 3.10 that the change in the average sentiment of more active information providers ishighly statistically significant.

To explore non-overlapping predictive regression, I employ quarterly real return, quarterly dividend-price ratio, and quarterly change in sentiment to evaluate the statistical significance of sentiment measures. Table 3.9 shows that quartely sentiment of more active providers remains not only weakly statistically significant, but also increase adjusted R^2 from -0.01 to 0.03.

Table 3.11: Predictive Regression Specification: Non-overlapping Regression Specification
The regression specifications are

$$R_q = \alpha + \beta_1 (D/P)_{q-1} + \epsilon_q$$
$$R_q = \alpha + \beta_1 (D/P)_{q-1} + \beta_2 \Delta s_{q-1}^{w,1-4} + \epsilon_q$$
$$R_q = \alpha + \beta_1 (D/P)_{q-1} + \beta_3 \Delta s_{q-1}^{w,5} + \epsilon_q$$
$$R_q = \alpha + \beta_1 (D/P)_{q-1} + \beta_2 \Delta s_{q-1}^{w,1-4} + \beta_3 \Delta s_{q-1}^{w,5} + \epsilon_q$$

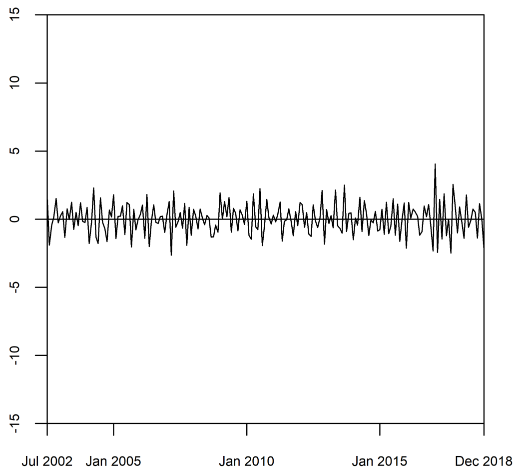
where R_q is a real return of CRSP value-weighted portfolio, $(D/P)_{q-1}$ is quarterly dividend-price ratio calculated from monthly $vwretd_t$ and $vwretx_t$ as $\Pi_t^{t+2}(vwretd_t + 1)/(vwretx_t + 1) - 1$. I use quarterly change in sentiment $\Delta s_q^{w,1-4}$ and $\Delta s_q^{w,5}$. I report heteroscedasticity-consistent standard errors (with HC3 adjustment for small sample size) in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:			
	sprtrn.x			
	(1)	(2)	(3)	(4)
$(D/P)_{q-1}$	3.26	4.37	9.93	9.73
	(17.84)	(18.08)	(13.79)	(13.84)
$\Delta s_{q-1}^{w,1-4}$		−0.14		−0.08
		(0.43)		(0.44)
$\Delta s_{q-1}^{w,5}$			2.15*	2.14*
			(1.21)	(1.24)
Constant	0.003	−0.004	−0.03	−0.03
	(0.09)	(0.09)	(0.07)	(0.07)
Observations	65	64	64	64
R^2	0.001	0.004	0.06	0.06
Adjusted R^2	−0.01	−0.03	0.03	0.02

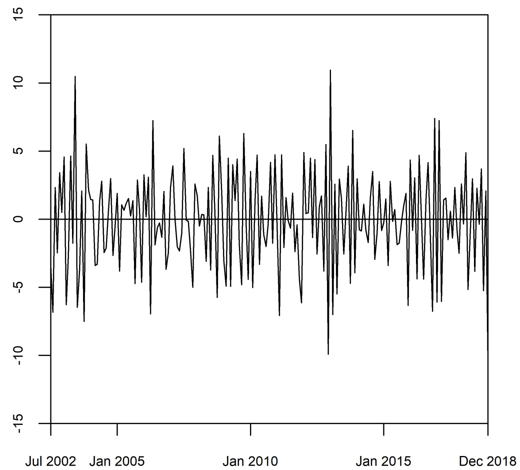
Second, I investigate the link between stock returns in a given month t and the sentiment change in reports in the previous month $t - 1$. To achieve this, I use a cross-sectional return analysis. This process includes the development of a momentum trading strategy, which is based on sentiments conveyed in reports from both highly active and less active information providers. By juxtaposing the cumulative returns from strategie, I assess the impact that change in sentiment of active and less active information providers has on stock returns.

The momentum strategy I utilize is based on the sentiment of report headlines from information providers in the previous month. Every month, this strategy ranks 45 stocks according to the sentiment about the company in the preceding month's reports and then assigns these stocks to portfolios. The portfolios are held for

Figure 3.9: Time Series of Change in Sentiment of More and Less Active Information Providers



(a) Change in Sentiment of More Active Providers, $\Delta s_t^{w,5}$



(b) Change in Sentiment of Less Active Providers, $\Delta s_t^{w,1:4}$

one month.

In particular, I use the sentiment-based momentum strategy as in Jegadeesh and Titman (1993) and Moskowitz and Grinblatt (1999). However, instead of using past returns to sort stocks into portfolios, I use sentiment from the previous month's reports. The strategy involves investing equally in the stocks with the most and least pessimistic sentiment.

I use two datasets of monthly reports — one for active providers and another for less active providers. Both datasets are structured with the month, PERMNO of the company, monthly sentiment, and monthly return. In each dataset, every month, companies are sorted based on their sentiment from the previous month and assigned a quintile number (from 1 to 5) for the current month. This creates a sentiment-driven quintile. The average return for each month-quintile is then calculated. To ensure equal numbers of companies in each quintile, only the top 8 companies are retained for each month-quintile. The new dataset now contains the month, sentiment-driven quintile, and average return at time t. Next, a long-short portfolio is created by going long on the 5th quintile and shorting the 1st quintile. This is the equivalent of subtracting the return of the 1st quintile from the return of the 5th quintile at time 't', yielding a new dataset with the month and portfolio return for that month. Finally, I calculate the average return and standard deviation of the portfolio returns, providing the sentiment-based trading strategy's average return and standard deviation for portfolios formed based on more active and less active information providers.

Table 3.12: Monthly Return of Return-based and Sentiment-based Trading Strategies

Sorting based on previous month aggregated sentiment of information provider's type. One month strategy formation period. Holding period is 1 month. Trading strategy based on information from less active information providers is to long stocks with the most pessimistic report headlines and short stocks with the most optimistic report headlines. Trading strategy based on information from more active information providers is to long stocks with the most optimistic report headlines and short stocks with the most pessimistic report headlines. 240 months.

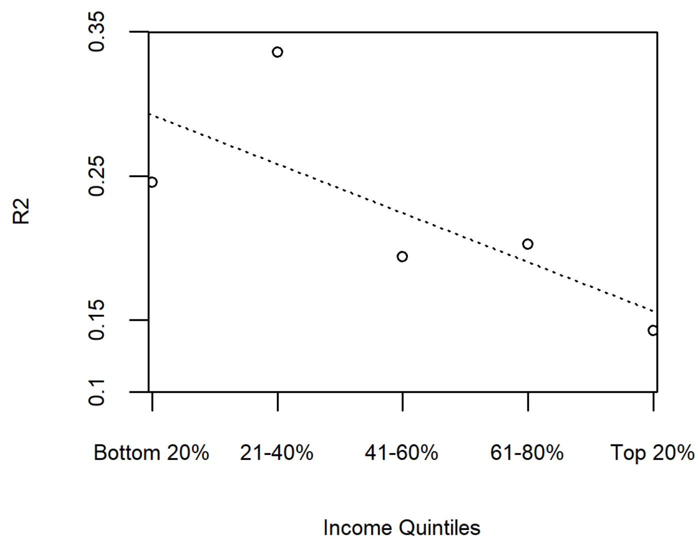
Strategy	Average Return	St.Dev.	Sharpe Ratio
Return-Based Strategies			
S&P 500	0.28	0.49	0.31
	(0.03)		
Momentum based on r_{t-1}	-0.11	0.58	-0.40
	(0.04)		
Sentiment-Based Strategies			
Based on less active providers $s_{t-1}^{w,1:4}$	0.30	0.36	0.50
	(0.02)		
Based on more active providers $s_{t-1}^{w,5}$	0.16	0.46	0.08
	(0.03)		

Table 3.12 indicates that a trading strategy that relies on the sentiment of less active information providers generates a higher expected return than a strategy based on the sentiment of more active providers. Interestingly, these results from the cross-sectional analysis seems to contradict the outcomes of the predictive time-series regression.

Table 3.12 indicates that the sentiment from less active information providers in the previous month (month $t-1$) could be a better predictor of stock returns in the current month (month t) compared to the sentiment from more active information providers. This observation emphasizes the potential importance of recent data from less active providers in analyzing the stock market.

Note that the trading strategies based on information from less active and more active providers follow opposite directions. A strategy that utilizes data from less active providers would involve buying stocks with the most pessimistic report headlines from the previous month and selling those with the most optimistic headlines. Conversely, a strategy that relies on data from more active providers would involve buying stocks with the most optimistic report headlines from the previous month and selling those with the most pessimistic headlines. This trend aligns with the negative sign of information from less active providers in the non-overlapping predictability regression (3.11), as well as with the descriptive statistics of sentiments from both types of providers.

Figure 3.10: Average Goodness of Fit of Expectations Equation Of VECM($s_t^w, \tilde{r}_t$) With Subjective Expectations of Investors With Different Income and Stock Investment Amount Quintiles
The plot displays the average adjusted R^2 values of the subjective expectations equation in the VECM($s_t^w, \tilde{r}_t$), where $\tilde{r}_t$ represents the subjective expectations of investors from different income brackets across quintiles of stock investment amounts within each income quintile, according to data from the MSC. The X-axis represents income quintiles, while the Y-axis represents the adjusted R^2 of the subjective expectations equation in the VECM. A dotted line is included to depict the regression of the R^2 values on income quintiles for visual reference. These computations are based on monthly data from June 2002 through December 2018.



Descriptive statistics presented in Table 3.8 shows that less active providers tend to be more conservative in their reports (mean sentiment of individual reports is 0.35) and publish less frequently (21,120 reports in sample), compared to more active providers who generally express more optimism (mean sentiment of individual reports is 1.99) and publish more often (489,360 reports in sample). Hence, when less active providers issue positive equity reports, they are typically more pessimistic and published relatively later than those from more active providers. Consequently, the stock market return tends to decrease in response to positive news from less active providers. For instance, if more active providers issue 10 reports predicting a 20% growth in Apple's stock, a subsequent single report from a less active provider forecasting a 10% growth may be associated with a decrease in the stock market return.

Hypothesis 4 There is no effect of income on the learning pattern of retail investors.

I examine whether investors' income and stock investment amount affect the relationship between the aggregated polarity of earnings reports and investors' subjective expectations. As the MSC provides microdata on income and stock investment of all respondents, I construct subjective expectations for investors within MSC quintiles of income[35] and MSC quintiles of stock investment amount[36] . For my analysis, I use 18 combinations of income and stock investment quintiles formed from individual surveys conducted the University of Michigan and accumulated in the University of Michigan's Surveys of Consumers from June 2008 through December 2012.

I employ the data as provided by the University of Michigan, which is adjusted based on random sampling and population adjustment procedures. There are no additional statistical adjustments made on my part. This approach aligns with the standard practices within economics and finance literature that work with the MSC to analyse subjective expectations of individuals regarding the economy (Ludvigson (2004); Souleles (2004); Barsky and Sims (2012); Baker and Wurgler (2007); Brunnermeier et al. (2014)[37] among others).

I run VECM($s_t^w, \tilde{r}_t$) with subjective expectations of investors within income quintiles. Figure 3.10 displays the adjusted R^2 of a subjective expectaions equation of the VECM($s_t^w, \tilde{r}_t$). The VECM($s_t^w, \tilde{r}_t$) with the highest R^2 (25- 35$\%$) corresponds to models with subjective expectations of investors with bottom 20 percentile incomes and 21-40 percentile incomes. Those respondents who belong to the bottom 20% income quintile and the bottom 20% investment quintile earn an average of $18,753 a year and invest an average of $6,919 in stocks. Their stock investments account for 37 percent of their annual income. Those in the 21-40% income quintile with stock investments up to 60% earn on average $35,972 per year, with an average stock investment of $35,573. Their stock investments account for 99 percent of their annual income.

VECM with the lowest R^2 corresponds to models with subjective expectations of investors in the top 20% of the income distribution. On average, they earn $189,888 per year and hold $600,127 in stocks.

[35] Variable YTL5 in MSC database.

[36] Variable STL5 in MSC database.

[37] Ludvigson (2004) made extensive use of the Michigan Survey of Consumers to investigate the predictive power of consumer confidence for consumption growth. The paper concludes that consumer sentiment has significant power in forecasting future consumption growth, especially for non-durable goods and services. Souleles (2004) used the Michigan Survey of Consumers to examine how changes in consumer sentiment affect consumer spending. The study found that changes in consumer confidence have significant and substantial effects on household consumption, with these effects being larger for households that are more likely to be liquidity constrained. Barsky and Sims (2012) used the Michigan Survey of Consumers to study news shocks. They relied on the survey's data about consumer expectations regarding personal and macroeconomic conditions to identify news shocks. They then analyzed how these shocks propagate into macroeconomic quantities. Baker and Wurgler (2007) used the Index of Consumer Sentiment from the Michigan Survey in their study on investor sentiment and its effects on the cross-section of stock returns. Their analysis provides evidence that investor sentiment may indeed affect asset prices. Brunnermeier et al. (2014) utilized the survey data to investigate the role of belief disagreements in financial markets. They used the data on consumer expectations to measure disagreement and its impact on stock price volatility.

There is 316% of annual income attributed to stock holdings.[38]

The data shows that retail investors with lower income, in 0-20% and 21-40% income quintiles, tend to follow provider-weghted equity reports, whereas investors with top 20% incomes are less susceptible to this learning pattern. First, this finding suggest that income level is a significant factor in learning patterns. Second, it suggests simultaneously that lower-income retail investors tend to follow more active providers (and may be influenced more by the popularity of certain sources) and/or lower income investor read equity reports.

There is a consensus in the literature that higher-income retail investors have a greater tendency to read and interpret financial reports. Souleles (2004), found that it is the case as higher-income households have the larger financial stakes involved and the capacity to afford professional financial advice. Similarly, D'Acunto et al. (2019) argued that wealthier individuals are more likely to consume financial news because they have more resources at stake in financial markets. As such, they are more incentivized to stay informed and make optimal decisions. Their study also suggested that wealthy investors have better access to quality information, which might explain their higher consumption of financial reports. Lower-income investors are generally found to be less engaged with financial reports. Hastings and Tejeda-Ashton (2008) found that lower-income investors tend to be less financially literate and are, therefore, less likely to read and understand financial reports. Their study also highlighted that lower-income individuals often face barriers such as lack of time or expertise, which prevent them from effectively utilizing financial reports. Finally, studies like Lusardi and Mitchell (2014) have raised concerns about financial literacy among lower-income individuals, suggesting that they may not consume or interpret financial reports effectively. This could contribute to suboptimal financial decision-making among this demographic. To summarize, literature suggests that higher-income investors are generally more active consumers of financial reports due to larger financial stakes and access to resources, whereas lower-income investors may face barriers preventing them from effectively consuming and understanding financial reports.

Considering the findings in the light of the literature, I propose a hypothesis that lower income investors' behavior may be more driven by their preference for popular information sources, rather than the equity reports these sources publish. To test this hypothesis, I include data from a well-known information source

[38]The respondents have an annual income ranging from $1,000 to $500,000.

and re-examine the learning patterns observed earlier.

What can help to explain the direction of heterogeneity of learning patterns? To further investigate the potential factors that may affect the observed diversity in learning patterns, I will examine whether other prevalent information sources affect retail investors in heterogenious way.

Television shows could be a viable source of information given that several studies, including those by Gershuny & Robinson (1998) and Robinson & Godbey (1997), have identified a negative correlation between television viewing and income levels. Therefore, I hypothesize that popular television shows focusing on stock investing might have different impacts on investors across varying income levels. However, since I lack granular data regarding the television viewing habits of retail investors, this section is speculative.

Using the Moving Image Archive and the Internet Archive TV News at the Internet Archive[39], a non-profit free digital library of Internet sites and cultural artifacts, I collected transcripts of 8,128 episodes of Mad Money show, 2,329 episodes of the Squawk on the Street show and 1,710 episodes on 60 Minutes show that were aired from June 2, 2009 to December 31, 2019 on CNBC, American basic cable business news channel, and 42 local channels, such as KPIX, television station licensed to San Francisco, California, a WUSA, a television station in Washington, D.C., and WBAL, a television station in Baltimore, Maryland. The Internet Archive misses year 2011 for all three shows, so I use only episodes from January 1, 2012 to December 31, 2019 for my analysis. That is 3,668 episodes of Mad Money show, 2,134 episodes of Squawk on the Street show and 1,710 episodes on the 60 Minutes show.

I picked Mad Money and Squawk on the Street shows as they are both about stock investing, but have different narrative style. I use 60 Minutes show as a control, to check whether a natural text processing algorithm does produce different polarity score for different shows.

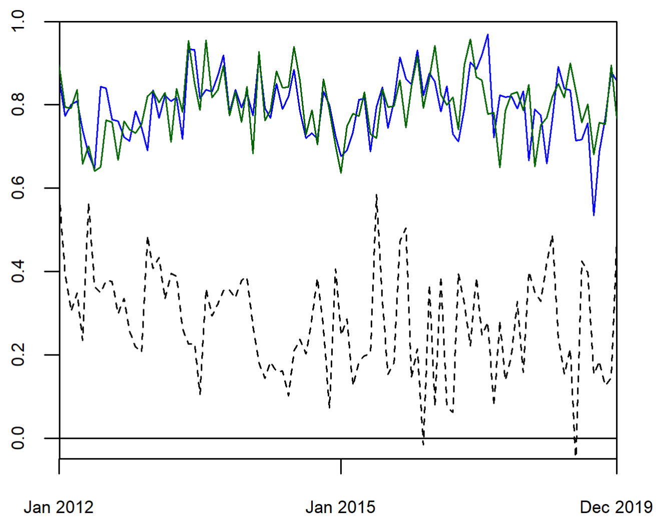
Mad Money is a financial television program that airs weeknights on the CNBC network 6PM ET and 11PM ET. The show began airing on March 14, 2005. It is a 60 minutes show that is hosted by Jim Cramer, a former hedge fund manager and stockbroker. The program is focused on providing stock market analysis, investment advice, and stock recommendations to viewers [40]. The show typically features Cramer discussing

[39] https://archive.org/about/

[40] According to Cramer, the term "mad money" refers to the funds that are available for investing in stocks, but not for retirement purposes, as retirement savings should be placed in more conservative investment options such as a 401K, individual retirement account (IRA), savings account, bonds, or stocks that pay dividends. Source: Cramer, James; Mason, Cliff (2006). Mad Money: Watch TV, Get Rich. New York: Simon & Schuster. p. 45. ISBN 978-1-4165-3790-8.

Figure 3.11: Polarity of Mad Money (Dark Green Solid Line), Squawk on the Street (Blue Solid Line) and 60 Minutes (Back Dashed Line) Shows, Monthly

Plot presents monthly polarity of Mad Money (dark green solid line), Squawk on the Street (blue solid line) and 60 Minutes (back dashed line) shows. Data is from June 2002 to December 2018.



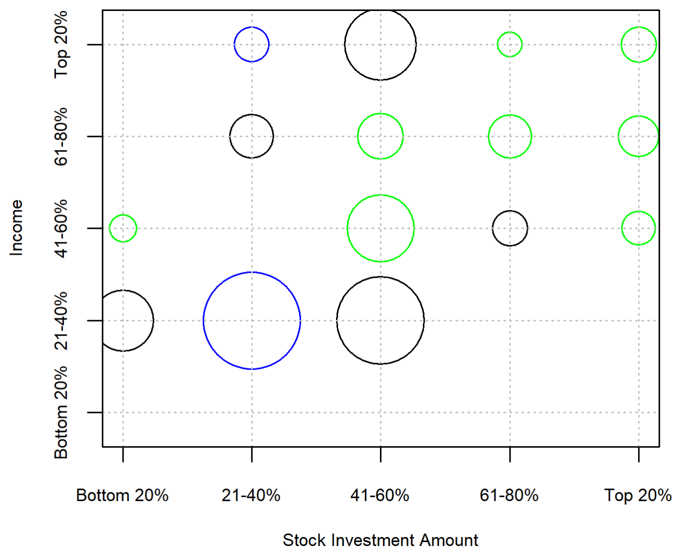
the day's top stock market news and events, as well as interviewing business leaders and market analysts. Cramer also takes calls from viewers, answering their questions about stocks and providing investment advice.

Mad Money is known for its fast-paced and entertaining style, with Cramer often using humorous sound effects and props to illustrate his points. The show also features a "Lightning Round" segment, in which Cramer rapidly gives his opinion on various stocks that viewers ask about. Overall, Mad Money is a popular program in the financial media landscape, providing retail investors with insights and analysis on the stock market.

Squawk on the Street is a financial news television program that airs weekdays on the CNBC network. The show debuted on December 19, 2005. It is two hours show, from 9 am to 11 am ET, that is co-hosted by Carl Quintanilla, David Faber, and Morgan Brennan. Squawk on the Street is known for its coverage of the stock market, business news, and analysis of the day's top stories. The program is broadcast live from the floor of the New York Stock Exchange, and features frequent updates on the markets and trading activity. The hosts interview industry experts and business leaders, providing viewers with insights into the latest trends and developments in the financial world.

Figure 3.12: "Best" VECM Specifications (Color) and Adjuster R^2 of VECM's Subjective Expectations Equations (Size of Circle)

The bubble plot shows adjusted R^2 of the "best" VECM with subjective expectations $\tilde{r}_t$ of investors with different level of investment in stocks and income from MSC survey. X-axis shows Stock Investment Amount quintile. Y-axis shows Income quintiles. The size of a circle is proportional to adjusted R^2 of VECM's subjective expectations equation. The biggest circle is equivalent adjusted $R^2 = 39\%$, the smallest to the $R^2 = 8\%$. Black color corresponds to VECM($jc_t, s_t, \tilde{r}_t$) with the following ordering of variables $jc \rightarrow s \rightarrow \tilde{r}$, where jc is polarity of the Mad Money episodes and s is a sentiment of equity reports. Blue color corresponds to VECM($r_{t-1}, s_t, \tilde{r}_t$) or VECM($r_{t-1}, q_t, \tilde{r}_t$) with ordering $r \rightarrow q \rightarrow \tilde{r}$, where q is polarity of the Squawk on the Street episodes. Green color corresponds to VECM($s_t, \tilde{r}_t$) with ordering $s \rightarrow \tilde{r}$ The calculations are based on monthly data from January 2012 to December 2018.



Squawk on the Street also covers breaking news and events that can impact the stock market and global economy. The program features analysis of corporate earnings reports, economic data releases, and other key indicators that affect the markets. Overall, Squawk on the Street is a viable source of information and analysis for investors and anyone interested in the financial markets.

As a control, I also use 60 Minutes show, an American television news magazine program that has been airing on CBS since 1968. The show has generally kept the Sunday evening format, and starts at 7:00 p.m. ET. It is known for its in-depth investigative journalism and hard-hitting interviews with news makers and public figures. Each episode of 60 Minutes typically consists of several segments, each covering a different news story or topic. The show covers a wide range of issues, including politics, business, science, technology, and entertainment. The segments are usually around 12-15 minutes long, and are presented by veteran correspondents who specialize in the topic being covered. I use this show to check that its polarity differ from episodes of Mad Money and Squawk on the Street.

The Internet Archive transcribes speech into text. As with many transcription algorithms, letter capitalization and punctuation is often lost in the text. For this reason, I employ the "bag of words" text processing method that sums up Loughran and McDonald (2016) scores of positive w_j^+ and negative w_j^- words in every episode's text

$$B(e) = \frac{\sum_{j=1}^{m} h(w_j^+) + \sum_{j=1}^{g} h(w_j^-)}{\sqrt{n}} * 100, \qquad m + g \leq n \tag{3.62}$$

where Loughran and McDonald (2016) scores $h(\cdot)$ of positive words w_j^+, negative words w_j^-, m is a number of positive words in a headline, g is a number of negative words in a sentence, and n is a number of words and some punctuation signs in a headline.

On average, an episode's transcript has 11,705 words, so this method picks the polarity of transcripts well. Taking an average of the polarity of episodes aired within a month, I aggregate the polarity of individual episodes into monthly time series.

Figure 3.11 shows time series of aggregated monthly polarity of three shows. Plot shows that Mad Money, jc_t and Squawk on the Street, q_t time series are highly correlated. Pearson correlation of 0.60^{***} is high and highly significant. As expected, Monthly 60 Minutes polarity, nm_t, is negatively correlated with both financial shows. It has -0.14 correlation with Mad Money and -0.03 with Squawk on the Street polarity scores.

Next, as empirical tests indicate that the time series of TV show polarity has a unit root[41] and are cointegrated with the aggregate subjective expectations and the polarity of equity reports, I proceed with VECM model. I run 42 Johansen (1991) estimation procedures and corresponding VECM or VAR models per quintile expecttaions with two, v_i, v_j, and three variables, v_i, v_j, v_k. The v_i, v_j and v_i, v_j, v_k are combinations of variables from a vector that includes quintile subjective expectations, sentiment measures, stock market return, and TV polarity measures.

If in previous sections I rely on VECM AIC and VECM ordering to compare models, in this section, I use VECM or VAR AIC, models' ordering and, in addition, Granger-type causality tests that pin down impact of polarity of reports and polarity of TV shows on subjective expectations.

[41] Elliott et al. (1996) test statistics for the specification with a constant is -2.21 for Mad Money monthly polarity, jc_t, and -2.53 for Squawk on the Street monthly polarity. Zivot and Andrews (1992) test statistics is -3.28 for Mad Money monthly polarity, jc_t, and -3.38 for for the Squawk on the Street monthly polarity.

I follow Toda and Phillips (1991) to evaluate Granger causality in Johansen-type error correction models. The approach uses Wald statistics with null hypothesis of non-causality and tests whether coefficients in differences and coefficients in error correction vector in VECM equation (3.24) of explanatory variable of interest are zero.

I start with selecting models with p-value of Wald statistics less than 0.125 for every VECM or VAR model of subjective expectations of retail investors within income-stock investment amount quintiles. Next, I select the models with the lowest AIC within the subsets. The detailed table with Wald statsics, AIC and adjusted R^2 of subjective expectations equation within all selected VECMs is provided in Table A.16.

Figure A.10 shows adjusted R^2 of subjective expectations equation of VECM of selected model (size of a bubble) on the grid of retail investors' income quintiles and quintiles of stock investment amount. Colors correspond to different combinations of variables in VECM or VAR.

Black color bubbles lay at the left bottom of the grid, accounts for subjective expectations of retail investors with bottom 20% and 21-40% income quintile and corresponds to VECM with the following ordering of variables

$$jc \rightarrow s^w \rightarrow \tilde{r} \tag{3.63}$$

$$jc \rightarrow s^c \rightarrow \tilde{r} \tag{3.64}$$

where jc is monthly polarity of Mad Money show, s^w is monthly polarity of provider-weighted equity reports, s^c is monthly polarity of company-weighted equity reports, and $\tilde{r}$ is retail investor's subjective expectations of stock market return.

Blue color bubbles lay on the left side of the grid and accounts for subjective expectations of retail investors with income in 21-40%, and top 20% quintiles, who has stock investment amount in 21-40% quintile. Blue color corresponds to VECM models with variables ordering that include past realized stock market return r_{t-1} and the Squawk on the Street sentiment

$$r \rightarrow q \rightarrow \tilde{r} \tag{3.65}$$

where q is monthly polarity of Squawk on the Street show and r is past stock market return.

Green color bubbles lay at the center of the grid, accounts for subjective expectations of retail investors within 41-60% and 61-80% and top 20% income quintiles and 41-60% and 61-80% and top 20% investment amount quintiles. Green color corresponds to VECMs with ordering

$$\begin{bmatrix} s^{w} \\ s^{w,1-4} \\ s^{w,5} \end{bmatrix} \to \tilde{r} \tag{3.66}$$

where s^{w}, $s^{w,1-4}$, $s^{w,5}$ are provider-weighted sentiment, sentiment of 20% more active providers and sentiment of less active providers correspondingly.

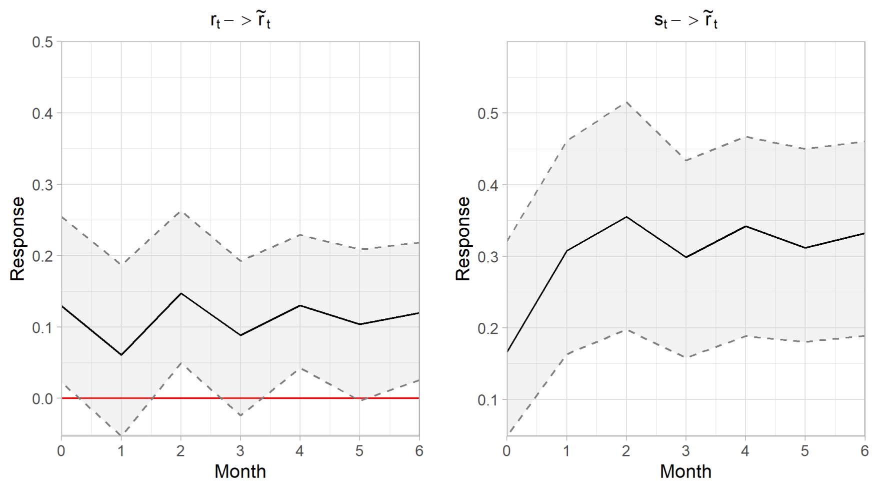
In the Appendix, I included a grid based on VAR models incorporating changes in the sentiment of both reports and TV shows. The objective is to ascertain the factors that influence the rate of change in subjective expectations.

The analysis reveals that the learning patterns of retail investors are influenced by their income level and the size of their stock investments. Investors with lower incomes tend to form their subjective expectations of stock market returns based on insights from Jim Cramer's show. On the other hand, investors with higher incomes but below-average stock investments might lean more towards insights from 'Squawk on the Street'. Meanwhile, investors with both high incomes and substantial stock investments tend to base their decisions on information from equity reports.

The dynamics of the system can be understood through Figure 3.13, which presents examples of orthogonal impulse responses of subjective expectations from investors with low and high incomes, but within the same stock investment amount quintile. The left plot depicts how a sentiment from Jim Cramer's show influences the subjective expectations of retail investors who fall within the 21-40% income quintile. A shock equivalent to one standard deviation that increases the sentiment leads to a direct positive effect on subjective expectations. Furthermore, these expectations remain positive, although they fluctuate around the level of the initial impact. On the right, the plot demonstrates the impact of a positive shock, equivalent to one standard deviation, from provider-weighted reports on the subjective expectations of a retail investor in the top 20% income bracket. Upon impact, subjective expectations surge, they continue to grow in the first and second months, and finally stabilize at the level they achieved after the first month.

Figure 3.13: Orthogonal Impulse Response Functions With Expecttaions of Investors In Low Income Vs High Income Quintiles Within Same Stock Investment Quintile

Orthogonal Impulse Response Functions sentiment to expectations for "best" models for low and high income. 95 % confidence interval for the bootstrapped errors bands. 100 runs.



(a) $jc \rightarrow \tilde{r}$, Expectaions of investors in 21-40% Income Quintile and 41-60% Stocks Investment Quintile

(b) $s^w \rightarrow \tilde{r}$, Expecttaions of investors in top 20% Income Quintile and 41-60% Stocks Investment Quintile

To sum up, the sentiment derived from a popular television show and provider-weighted reports both positively influence the subjective expectations of retail investors. However, the intensity and duration of this impact vary contingent upon the income levels of the investors.

3.5.1 Mechanism

Process in Hand

Suppose there are two events: one is positive with a score of +1, and the other is negative with a score of -1. The expected sentiment of these events is zero. However, when I add information providers with different reporting activity, I get a different result. Let one provider publish one report about the positive event and one report about the negative event, while another provider publish two reports about the positive event and zero reports about the negative event.

To calculate the expected sentiment with this additional information, I need to weight the sentiment scores by the frequency of each event and the frequency of reporting by each provider. So the denominator is $2 + 1 + 1 = 4$. The numerator is the sum of the products of the sentiment scores and the frequency of reporting by each provider. For the positive event, the numerator is $1 * (1 + 2)$, since one provider reports it twice and the other reports it once. For the negative event, the numerator is $-1 * (1 + 0)$, since one provider reports it once and the other reports it zero times. Adding these two products and dividing by the denominator gives us:

$$\frac{1 * (1+2) + (-1) * (1+0)}{2+1+1} = \frac{1}{2} \tag{3.67}$$

This means that the expected sentiment score is now 0.5, which is different from the expected sentiment score of zero without the addition of information providers.

The reason for this difference is that the data generating process (DGP) of events and the DGP of reported events differ. The frequency of sentiment from the DGP of events may not necessarily match the frequency of reported sentiment from the DGP of reported events. In this case, the positive sentiment is overweighted from the perspective of the DGP of events, but the sentiment is correctly weighted from the perspective of the DGP of reported events.

Why would a retail investor ignore information from less active providers?

Firstly, it could be a rational. If there are many information providers available, the weight of sentiment provided by less active providers would be relatively small. Therefore, it may be rational to assign a zero weight to less active providers, as the law of large numbers would suggest that their impact on the overall sentiment calculation would be negligible.

Second, it might be a friction from supply side. Investors may be influenced by analysts' upward earnings forecast bias, driven by compensation and investment-banking incentives, as in Lin and McNichols (1993) and Dugar and Nathan (1993), to believe that fewer neutral or pessimistic reports from less active information providers are less trustworthy than a constant flow of positive reports from more active information providers. Also, reports from more active information providers may be easier to access than those from less active ones. Although another possibility is that high reporting activity may be too overwhelming and may not allow an investor to read all reports of active information provider, so he might prefer to wait for and read an informative report from less active information providers.

Third, it might be a friction from demand side. Excessive coverage of active information providers may increase investor overconfidence by overstating precision of the informational content in analyst reports.

Overconfidence is expected to feed investors' illusion of knowledge resulting in disregarding reports of less active information providers. Investors' judgment biases, as in Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subramanyam (1998), and Hirshleifer and Teoh (2003) can also influence investors' choices.

The test of behavioral supply and demand stories would require granular data on subjective expectations, including data on when and which reports investors read, as well as when and what investor watch.

3.6 Robustness Check

3.6.1 Exclusion of 2019

My company-weighted sentiment measure is highly volatile in 2019, putting it at a disadvantage compared to other more homoskedastic sentiment measures. I exclude 2019 from VECM specifications. Plot A.11 in Appendix A shows effect of exclusion of one year, from 2002 to 2019, on AIC criterion of the VECM $(s_t^w,\ \tilde{r}_t)$. Higher line is AIC of the MSC expectations regression. Lower line is AIC of CCS expectations regression. The plot shows that exclusion of 2019 does not change AIC of VECM dramatically.

3.6.2 Strategy Formation Window

Figure A.12 in Appendix A examines average annualized return and standard deviation of sentiment-based momentum strategies with one-month to twelve months formation period and holding period of one month. Blue line corresponds to the strategy that is built on information of less active information providers, while green line - on information of more active information providers. To eliminated selection, every quantile's portfolio is restricted to contain top eight stocks. Dashed line corresponds to standard momentum strategy restricted to top eight stocks in each standard momentum quantile's portfolios as.

Plots (a) and (c) on Figure A.12 shows that sentiment-based momentum strategies based on information from less active information providers earn higher average return than ones that are based on information from less active information providers over July 2002 to December 2018 sample period. Plots (a) - (d) show that when the strategy formation period is one month (this corresponds to the point $t-1$ on x-axis of every plot), the average return of sentiment-based strategy based on information from more active providers is 1.95% per year with a standard deviation of 15.98%. The corresponding returns of strategy based on information from less active providers earns an average return of 3.66% with standard deviation of 12.38%. The dotted line shows return of standard momentum strategy implemented on the set of 45 blue-chip stocks with the maximum eight stocks in each portfolio.

3.7 Conclusion

This chapter takes a deeper dive into the temporal variability retail investors' subjective expectations regarding stock market risk premium. It establishes a connection between these expectations and the market for information, by examining an extensive dataset of equity reports. The aggregated monthly sentiment derived from these reports illustrates a persistently fluctuating pattern over time and holds a cointegrated relationship with retail investors' subjective expectations of stock market risk premium.

The investigation further strengthens the link between the sentiment about earnings growth, derived from the reports, and the subjective expected excess returns. This association is particularly robust for reports generated by information providers with a higher reporting activity, while it is relatively absent for those written by less active providers. Moreover, it is demonstrated that the sentiment shock from provider-weighted reports has a lasting impact on subjective expectations, adjusting them to a new level in a span of three months, while accounting for a substantial proportion of their fluctuations.

Meanwhile, the chapter also highlights the potential value of information from less active providers. While their change in sentiment might not show statistical significance in a overlapping ammual predictive regression, a sentiment-based trading strategy constructed using their monthly information can outperform the returns of the S&P 500 Index. This suggests that such information should not be readily dismissed as noise, but rather considered a valuable component of an investor's informational set.

Furthermore, the chapter shows that learning patterns of retail investors seem to be significantly influenced by their income levels and their stock investment amounts. Lower-income investors tend to derive their expectations from popular sources and provider-weighted sentiment, while higher-income investors with below-average stock investments rely more on insights related to past stock market returns. On the other hand, high-income investors with substantial stock investments base their decisions on provider-weighted sentiment from equity reports. This suggests a potential vulnerability for lower-income retail investors who may be more susceptible to biased or incomplete information.

This chapter underscores the impact of information providers' reporting activity on shaping investor expectations, thereby contributing significantly to the existing literature on subjective expectations. It provides a more nuanced perspective on the mechanisms underlying the formation of these expectations and potential biases that can arise therein. Moreover, it highlights the role of information providers in shaping financial market outcomes, suggesting new research directions in this area.

By integrating insights from various existing studies and introducing new findings, this research contributes to the literature examining subjective expectations, as well as the relationship between asset and information markets. It highlights the significance of considering the role of information providers in shaping financial market outcomes and paves the way for future research in this area. It calls attention to potential inequities in the access and utilization of information in financial markets, raising questions about the distribution of resources and opportunities therein.

Chapter 4

Geographical COVID-19 Uncertainty and The Market Impact of Initial Jobless Claims News

4.1 Introduction

The goal of this chapter is to investigate how uncertainty about the future propagation of the COVID-19 pandemic affects the stock market's reaction to macroeconomic news. The news event we consider is the U.S. Department of Labor's weekly announcement of initial jobless claims, which reports the number of people filing to receive unemployment insurance benefits for the first time during the past week and which has received considerable media attention since the onset of the pandemic. Our main empirical innovation is the construction of a novel non-financial and time-varying measure of fundamental health uncertainty as the standard deviation of weekly changes in new COVID-19 cases across all 50 U.S. states. We find that the marginal effect of COVID-19 health uncertainty on the stock return impact of the release of initial jobless claims news is strongly negative. During the pandemic economy, investors view bad news (higher than expected initial jobless claims) as bad news for equities when the expected path of the virus is more uncertain. We also show that there is a threshold in the level of our health uncertainty measure that changes the sign of the news impact: following bad news, stock returns fall when uncertainty is high but actually rise if uncertainty is low.

We quantify COVID-19 uncertainty by constructing a daily measure of the expected spread of the disease. Epidemiological studies such as Park et al. (2021) show that there is a lot of uncertainty about the evolution of active infections, in particular before and around the peak of the infection path. As Liu et al. (2021) point out, a key feature of the COVID-19 pandemic is that the outbreaks did not take place simultaneously in all locations. Investors can learn from the spread of the disease and subsequent containment in state A to make inference of what is likely to happen in state B while allowing for heterogeneity across locations. However, investor expectations about the aggregate path of the pandemic, and hence its economic impact, are likely to be more uncertain if the path of the virus across both states is different. This geographical heterogeneity is the metric underlying our measure of health uncertainty.

We use each U.S. state's daily change in new cases over the past week as the sufficient statistic characterizing active infection propagation in that state. In the pandemic economy, a key state variable is the path of the virus since it has a first-order effect on government actions, consumer demand and hence firm behavior. On any given day, if the distribution of these state-level changes in new cases has a large variance, then we label that day's heterogeneity as high uncertainty in the expected evolution of COVID-19 infections at the national level. If instead the distribution has a small variance, then the path of infections is similar across all states, and investors face less uncertainty in predicting the path of the disease at the national level. The cross-sectional distribution of states' changes in new cases is our proxy for investors' beliefs about the country's fundamental health uncertainty.

We do not claim that our measure is better than other measures of uncertainty (see list in Baker et al. (2020) and others) in capturing economic uncertainty. Rather, our measure is unique in that it only utilizes health numbers in its construction and does not rely on financial data or news or surveys. We do assume that the marginal investor pays attention to the path of the virus when forming her expectations. Moreover, we show that our results are robust to the inclusion of the VIX Index and the Baker et al. (2016) economic policy uncertainty index.

We perform our analysis in three steps. First, as a benchmark and following the extensive literature that studies market reaction to macroeconomic news releases, we estimate the announcement impact of surprises in initial jobless claims on the high-frequency returns of the E-mini S&P 500 futures before the pandemic (June 1998 to December 2019). We define surprises as the difference between the announced figure and the market's expectation proxied by the median forecast of surveyed investment professionals (see Chen et al. (1986), McQueen and Roley (1993), Balduzzi et al. (2001), Andersen et al. (2003), and many others). During the pre-COVID-19 sample, we show that surprises in initial jobless claims have a significant negative impact on high-frequency market announcement returns. Moreover, the impact of the news on returns remains significant even after we condition on the stage of the business cycle using the National Bureau of Economic Research (NBER) recession indicator.

Second, using the same methodology, we estimate the relationship between 15-minute announcement returns and surprises in initial jobless claims during the COVID-19 pandemic (April 2020 to June 2021). Contrary to the pre-COVID sample, this analysis shows an insignificant reaction of the announcement returns to surprises in initial jobless claims.

Third, to account for the economy's underlying health uncertainty during the pandemic, we include our novel measure of COVID-19 uncertainty into the analysis as an interaction variable with the surprises in initial jobless claims. We find that the marginal effect of health uncertainty on the impact of macroeconomic news surprises on high-frequency equity returns is strongly negative. This stands in contrast to the insignificant unconditional impact of the news during the pandemic. It shows that the market impact of macroeconomic announcements is context dependent. In a pandemic, a state variable is the path of the virus and as a result, bad news (higher than expected initial jobless claims) matters only when prior health uncertainty is high.

We also find that the magnitude and sign of the relationship between stock market returns and surprises in initial jobless claims change with the level of our COVID-19 uncertainty measure. As COVID-19 uncertainty increases from its 25th to its 75th percentile, the impact of a one standard deviation increase in initial jobless claims surprises on announcement returns falls from 0.07% to -0.26%. This 33 basis basis point drop is economically large in that it is more than one order of magnitude larger than the average 15-minute announcement return of the E-mini S&P 500 futures.

From a theoretical perspective, our findings are consistent with the Bayesian learning model in Kim and Verrecchia (1991), who show that the impact of news is larger when investors' prior information is more dispersed. When investors are more uncertain about the pandemic's future expected propagation (high

COVID-19 uncertainty measure), they learn more from surprises in macroeconomic announcements relative to times when investors are less uncertain about the pandemic's propagation (low COVID-19 uncertainty measure). Our analysis shows that there is a threshold in the level of fundamental health uncertainty around which the sign of the effect changes. When COVID-19 uncertainty is low, the overall impact of bad news (higher than expected initial jobless claims) on returns is positive, but when COVID-19 uncertainty is high, the impact of bad news on returns is negative – bad news is bad news for stocks.

4.2 Related Literature and Hypothesis

We contribute to an extensive literature studying the link between the scheduled release of macroeconomic news and announcement market returns.[1] We use 15-minute returns on E-mini S&P 500 futures around the weekly release of initial jobless claims.[2] We follow the standard approach and define the surprise component of the news as the difference between the announced value and the median analyst forecast.[3] Consistent with the prior literature, we run our tests both unconditionally and also conditional on the stage of the business cycle.[4]

Recent work shows that the state dependence of the stock market's response to macroeconomic news is driven by investors' uncertainty about the future. A key paper that our work is related to is Kurov and Stan (2018), who show that in times of high monetary policy uncertainty proxied by the realized volatility of interest rate futures, macroeconomic indicators have a greater role in shaping investors' expectations about future policy. When monetary policy uncertainty is high, policy expectations become more sensitive to economic news, which affects the response of a variety of markets to such fundamental news.[5] We build on this by constructing a non-financial health-based measure of uncertainty and analyze the stock market's

[1]See Schwert (1981), Pearce and Roley (1985), Chen et al. (1986), Hardouvelis (1987), and Cutler et al. (1989), among many others, for early work establishing the link between monthly macroeconomic news and daily returns.

[2]See Andersen et al. (2003) and Andersen et al. (2007), among others, for early work using high-frequency returns to highlight the impact of macroeconomic news on markets.

[3]A recent alternative approach pioneered by Savor and Wilson (2013) is to look at average returns on announcement days relative to non-announcement days, independent of the actual surprise and the business cycle (see also Ernst et al. (2021)).

[4]McQueen and Roley (1993), Bae (1994), and Boyd et al. (2005), among others, show that bad macroeconomic news has a negative effect on the stock market in bad times (cash flow effect) but a positive effect in good times (expected loosening of monetary policy).

[5]There is a rich literature that studies the stock market's response to FOMC announcements and monetary policy news surprises (some on the day before the announcement) and some relate these findings to uncertainty resolution: Lucca and Moench (2015), Gorodnichenko and Weber (2016), Ozdagli and Weber (2017), Gu et al. (2018), Hu et al. (2018), Boguth et al. (2019), Cieslak et al. (2019), Dor and Rosa (2019), Neuhierl and Weber (2019), Kurov et al. (2021), among others.

response to unemployment news during the pandemic.

These findings refine previous results such as Bloom (2014), who shows that both macro and micro uncertainty appear to rise in recessions and fall in expansions. Veronesi (1999) shows that uncertainty about the state of the economy causes stock market investors to overreact to bad news in good economic times and underreact to good news in bad economic times. From a theoretical Bayesian learning standpoint, Kim and Verrecchia (1991) show that, in equilibrium, when investors' prior information is less precise (more uncertainty), public announcements lead them to revise their beliefs more, leading to larger price impact.

Based on the above literature and analysis, we expect the marginal effect of uncertainty on the impact of news releases on stock returns to be significant. We therefore test the following hypothesis:

Hypothesis: As COVID-19 uncertainty increases, the reaction of stocks to macroeconomic news becomes stronger.

We also contribute to a growing empirical literature on measuring uncertainty. Kozeniauskas et al. (2018) classify uncertainty measures into three groups: macro uncertainty (uncertainty about macro outcomes in the aggregate time series), higher-order uncertainty (disagreement of forecasts), and micro uncertainty (cross-sectional variance of entity-level outcomes). Our fundamental health-based measure belongs in the third group since it is constructed as a cross-state dispersion in the change in new COVID-19 cases. However, we implicitly use it as a proxy for macro uncertainty, i.e., investors' expectation of the future path of the virus and hence the future state of the pandemic economy.

Our uncertainty measure resembles those that use the unconditional cross-sectional dispersion of a firm-level or industry-level variable as a proxy for micro uncertainty Schaal (2011); Christiano et al. (2014); Gilchrist et al. (2014); Arellano et al. (2019). Bloom et al. (2018) and Herskovic et al. (2018) use the cross-sectional dispersion of establishment-level total factor productivity shocks. Kozeniauskas et al. (2018) use the cross-sectional variance of firm growth rates. Hassan et al. (2019) use the cross-sectional standard deviation of firm-level political risk, where political risk is approximated as the share of firm's quarterly earnings conference calls that it devotes to political risks. Our geographical health uncertainty measure is not built using firm-level information and hence is a more direct proxy for the underlying state variable that is driving firm behavior.

Baker et al. (2020) point out that assessing the economic impact of the COVID-19 pandemic is challenging because the crisis has unfolded with extreme speed. They identify (without tests) three indicators – stock market volatility, newspaper coverage frequency, and business expectation surveys - that can provide real-time forward-looking uncertainty measures. We show that our results are robust to the inclusion of the VIX Index as well as the newspaper-based economic policy uncertainty measure of Baker et al. (2016).

4.3 Data

In this section, we first describe our main innovation, which is the creation of a novel cross-state measure of health uncertainty. We then describe the macroeconomic news and returns data used in the subsequent empirical analysis.

4.3.1 Geographical COVID-19 Uncertainty

Our U.S. COVID-19 uncertainty measure is calculated in two steps. First, we obtain the change in new cases $\Delta NC_{i,t,n}$ on day t over the previous n days for state i:

$$\Delta NC_{i,t,n} = \frac{NC_{i,t} - NC_{i,t-n}}{n} \tag{4.1}$$

where $NC_{i,t}$ is the number of new cases on day t for state i and the division by n is done to rescale the n-day change into a daily change. Second, we calculate the sample standard deviation of $\Delta NC_{i,t,n}$ across all 50 states i on each day t:

$$SD\Delta NC_{t,n} = \sqrt{\frac{\sum_{i=1}^{50}(\Delta NC_{i,t,n} - \overline{\Delta NC}_{t,n})^2}{50-1}}. \tag{4.2}$$

The intuition behind our measure is that if there are large differences in the change in new cases across states, the expected growth path of the pandemic is unclear. For instance, if the number of cases is increasing in New York and Florida but decreasing in California and Texas, investors' expectations are more uncertain compared to a week when cases are going down (or up) in all states. When the dispersion across states is high, investors face a higher level of uncertainty in estimating the expected propagation the virus. In turn, this increases the uncertainty in demand and supply forecasting and hence in predicting the associated responses by federal, state and local authorities. Conversely, if new cases are going up (or down) in all states, the geographical health uncertainty is lower, and hence there is less uncertainty about the future growth rate of the economy (up or down).

It is important to note that, compared to other measures of uncertainty used in the literature NBERw26983, our measure does not use any financial or economic data. It is 100% COVID-19 focused and only the number of new cases across all 50 states is used in its calculation. We are making the implicit assumption that investors use the path of the virus to predict its future path and its impact on the economy. In that sense, our measure is trying to capture the unknown exogenous state variable without using financial, economic, surveys, or news variables. We do not claim that our measure is a better measure of overall economic uncertainty – we only assume that the marginal investor uses the geographical spread in changes in new cases across states when processing macroeconomic news during the pandemic.

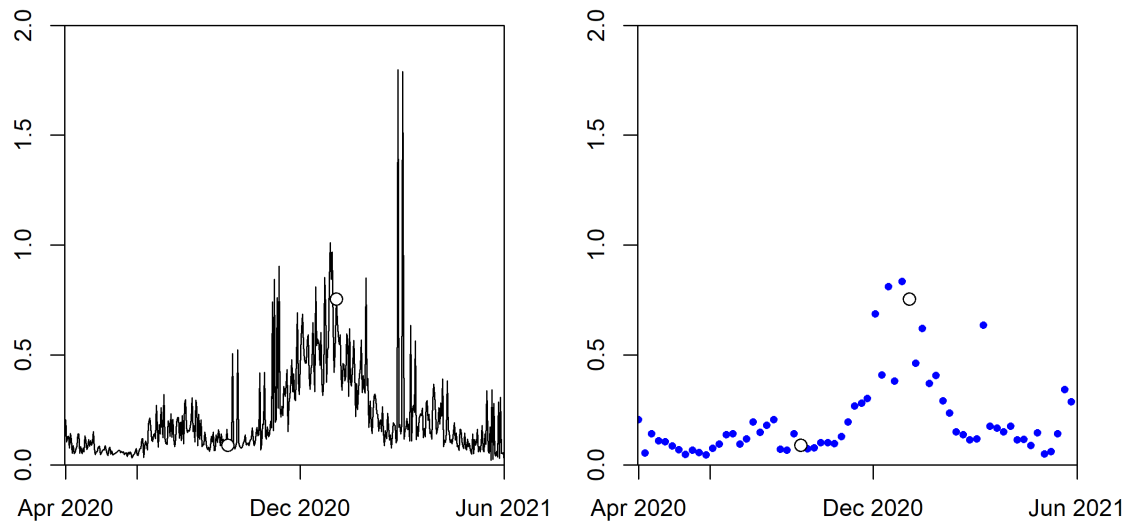
To calculate this measure, we use a panel dataset provided by Johns Hopkins University (JHU) consisting of a daily time-series of new COVID-19 cases for all 50 U.S. states. JHU has been the main aggregator of COVID-19 statistics since the beginning of the pandemic. The first official cases were identified in January 2020 but JHU started accumulating statistics for all states in April. Thus our sample starts on April 2, 2020. The COVID-19 data is updated and released once a day between 04:45 and 05:15 UTC (1:15am EST). It is freely available on a GitHub repository maintained by JHU's Center for Systems Science and Engineering (CSSE).[6] The repository gives access to daily state-level case reports and daily time series summary tables, including confirmed cases, deaths and recovered cases. JHU's CSSE updates the data if new data becomes available and if inaccuracies are identified. We use the data vintage downloaded in July 2021.

Figure 4.1 shows the time series of our COVID-19 uncertainty measure over the April 2020 to June 2021 sample. For the remainder of the chapter, we use $n = 5$, making our lagged measure consistent with the U.S. Center for Disease Control and Prevention (CDC) practice of releasing information about cases and deaths as weekly moving averages and preventing the measure from overlapping with the previous week's macroeconomic announcement. We present robustness checks with $n = 10$ and with population weights in Section 4.4.5. Panel 4.1a presents the time series of $SD\Delta NC_{t,5}$ in calendar time, while Panel 4.1b shows its values only on the days before the release of initial jobless claims news by the U.S. Department

[6] https://github.com/CSSEGISandData/COVID-19/blob/master/csse_covid_19_data/README.md

Figure 4.1: Time Series of Geographical COVID-19 Uncertainty

This figure shows the time series in calendar time of the cross-state standard deviation of the change in new COVID-19 cases over the past five days: $SD\Delta NC_{t,5}$. Weekends are excluded and the measure is in thousands of cases. Panel A presents the measure every day and Panel B presents the measure on the day before every weekly announcement of Initial Jobless Claims (IJC) by the U.S. Department of Labor. The two white dots are example dates for high and low uncertainty. The sample period is from April 2, 2020 to June 30, 2021.



(a) Daily $SD\Delta NC_{t,5}$ in calendar time

(b) $SD\Delta NC_{t,5}$ on days before IJC news

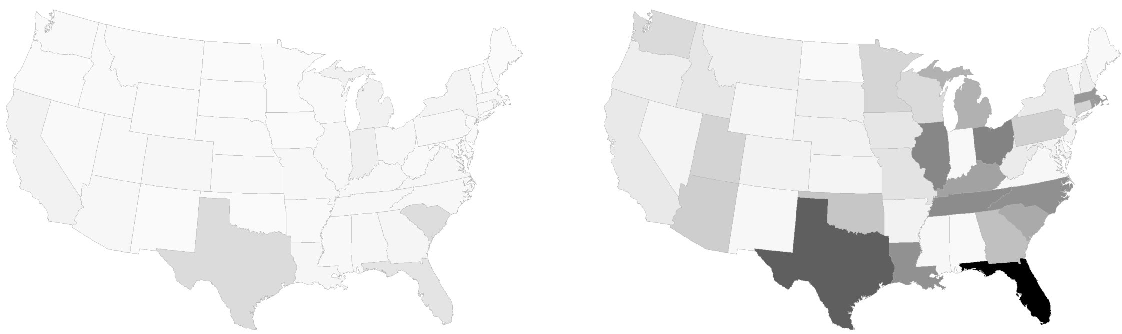
of Labor. The measure is volatile, ranging from 0.04 to over 1.7 thousand cases. The overall trend in our uncertainty measure is correlated with the various waves of the pandemic and a few peaks are due to large states (California and Texas for instance) updating their data all at once.

As examples of high and low health uncertainty, we choose two dates, September 15, 2020 and January 7, 2021, which are shown as white dots on both panels of Figure 4.1. To gain insight into our measure, Figure 4.2 shows these two example dates of low and high values of COVID-19 uncertainty on a map of the U.S., where each state's shading is proportional to its deviation in new cases relative to the national average $\overline{\Delta NC}_{t,5}$. Small deviations $\Delta NC_{i,t,5} - \overline{\Delta NC}_{t,5}$ are in lighter shading while high deviations are in darker shading.

On September 15, 2020, Panel 4.2a shows that all states' shading is relatively light, meaning that the change in new cases is relatively uniform across all 50 states. COVID-19 uncertainty is low and $SD\Delta NC_{t,5} = 0.09$. In contrast, Panel 4.2b shows a much higher dispersion in case growth across states on January 7, 2021. Florida and Texas, for instance, have growth rates far above the national average. The

Figure 4.2: Maps of Geographical COVID-19 Dispersion on Two Days

This figure presents two maps of the 48 contiguous U.S. states where each state's shading is proportional to its change in new COVID-19 cases relative to the national average on two different days (shown as white dots on Figure 4.1). Panel A shows a low uncertainty day (September 15, 2020) when the change in new cases is relatively uniform across all states. Panel B shows a high uncertainty day (January 7, 2021) when there is a high level of dispersion in the change in new cases across states. Darker shading represents higher deviation of $\Delta NC_{i,t,5}$ for state i relative to the national average. Similarly, lighter shading indicates that state i's change in new COVID-19 cases is closer to the national average. For ease of interpretation of the maps, the scale of shading (white as minimum and black as maximum) is set across the union of both days.



(a) Low uncertainty day: September 15, 2020 **(b)** High uncertainty day: January 7, 2021

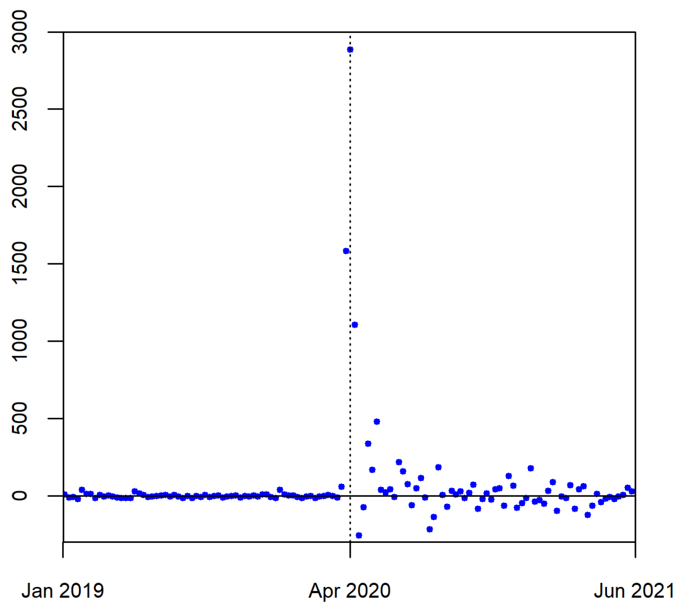
contrast between midwestern states and eastern states points to a high level of COVID-19 uncertainty and $SD\Delta NC_{t,5} = 0.76$.

4.3.2 Weekly Initial Jobless Claims as Macroeconomic News

We use the weekly report of Initial Jobless Claims (IJC) by the U.S. Department of Labor as macroeconomics news.[7] Since the COVID-19 pandemic was a large shock to labor due to significant infection risk and lockdowns, weekly news on the number of initial claims for unemployment insurance became a critical reference point for policy makers and as a result for investors. The Department of Labor releases IJC news weekly on Thursday at 8:30 a.m. Eastern Standard Time. We collect announcement days, the released (and hence unrevised) number of new jobless claims for the week, as well as analyst expectations from Bloomberg over the period from June 1998 to June 2021. Following the literature, we construct the unanticipated (sur-

[7] https://www.dol.gov/ui/data.pdf

Figure 4.3: Surprises in Initial Jobless Claims Before and During the Pandemic
This figure shows the surprise in IJC news from January 1, 2019 to June 30, 2021 in thousands of claims. The dotted vertical line corresponds to the beginning of the COVID-19 sample, April 2, 2020.



prise) component of the news, which is measured as the difference between the actual reported IJC and the market's expectation. Bloomberg surveys about 40 economists before the official announcements and we use the median expectation as our measure of market expectation.

Figure 4.3 shows the time series of the weekly surprise SUR_t in IJC news, calculated as the difference between the actual news IJC_t and the expected news $E_{t-1}[IJC_t]$

$$SUR_t = IJC_t - E_{t-1}[IJC_t] \tag{4.3}$$

on day t. For the remainder of the chapter, we label positive IJC surprises as bad news since higher than expected initial jobless claims were filed. The dotted vertical line corresponds to the beginning of the COVID-19 sample, April 2, 2020, that we use to construct our geographical health uncertainty measure. The line divides the sample into two distinct regimes, pre-COVID-19 and COVID-19. For ease of view, we plot only one year of data prior to the start of the pandemic. To alleviate concerns about the impact of outliers, we show in Section 4.4.5 that our results are robust to removing the first announcement.

Following Balduzzi et al. (2001) and the rest of the literature on the impact of macroeconomic news on returns, we scale IJC surprises by the sample standard deviation of surprises

$$SUR_t^s = \frac{IJC_t - E_{t-1}[IJC_t]}{\sigma_{SUR_t}} \tag{4.4}$$

where σ_{SUR_t} is calculated using all surprises in the given sample period. This scaling does not impact the estimation of standard errors but eases the interpretation of the estimated coefficients as one standard deviation shocks in surprise, and hence facilitates comparisons across samples.

4.3.3 Market Data and Summary Statistics

We use five-minute price data for the E-mini S&P 500 futures and calculate 15-minute returns around IJC macroeconomic announcements as

$$fr_t = \left(\frac{P_t(8:40:00) - P_t(8:25:00)}{P_t(8:25:00)}\right) * 100 \tag{4.5}$$

where $P_t(8:40:00)$ is the price ten minutes after the announcement and $P_t(8:25:00)$ is the price five minutes before the announcement.[8] Since IJC news is released at 8.30am ET when the stock market is closed but the futures market is open, futures market data allows us to use a narrow intraday window around the news announcement.

Table 4.1 reports summary statistics of our main variables during both the pre-pandemic sample and the pandemic sample. We also split the pre-COVID-19 sample into NBER recessions and expansions.[9] Before COVID-19, scaled IJC surprises are on average larger in recessions (0.17) than in expansions (-0.01). During the COVID-19 sample, the IJC surprises are on average (0.20) similar to the recession sample. Our measure of health uncertainty on the day before IJC announcements, $SD\Delta NC_{t-1,5}$, is right skewed but otherwise well behaved. Lastly, average returns are similar across all samples, even though the median return is higher in recessions than in expansions.

[8] We thank Alexander Kurov for the data from Genesis Financial Technologies.

[9] https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

Table 4.1: Descriptive Statistics on Announcement Days
This table presents summary statistics of the variables used in the empirical analysis on IJC announcement dates. The before COVID-19 sample is from June 4, 1998 to December 1, 2019 and the COVID-19 sample is from April 2, 2020 to June 30, 2021. SUR_t^s are the scaled IJC surprises. The five-day change in new cases by state, $\Delta NC_{i,t-1,5}$, and our measure of health uncertainty, the dispersion in the change in new cases across all states, $SD\Delta NC_{t,5}$, are in thousands of new cases. E-mini S&P 500 15-minute futures returns fr_t are in percentage points.

Statistic	n	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Pctl(90)	Pctl(95)	Pctl(99)	Max
					Before COVID-19						
SUR_t^s	1,117	0.01	1.00	-4.81	-0.52	-0.06	0.52	1.16	1.58	3.03	4.64
fr_t	1,117	0.00	0.19	-1.43	-0.07	0.00	0.08	0.17	0.30	0.54	1.70
					Before COVID-19: Expansions						
SUR_t^s	1,004	-0.01	0.93	-4.11	-0.58	-0.06	0.46	1.10	1.51	2.78	4.64
fr_t	1,004	0.00	0.17	-1.43	-0.06	0.00	0.07	0.15	0.25	0.53	1.05
					Before COVID-19: Contractions						
SUR_t^s	113	0.17	1.46	-4.81	-0.46	0.23	0.87	2.02	2.56	3.24	3.59
fr_t	113	-0.01	0.32	-0.97	-0.15	0.00	0.13	0.32	0.46	0.59	1.70
					COVID-19						
SUR_t^s	65	0.20	1.00	-0.65	-0.09	0.03	0.16	0.44	0.80	4.43	7.32
$\Delta NC_{i,t-1,5}$	3,264	24.97	333.55	-5047.60	-13.60	4.40	40.65	138.60	289.18	831.47	12835.40
$SD\Delta NC_{t-1,5}$	65	0.21	0.19	0.04	0.09	0.14	0.27	0.44	0.68	0.82	0.83
fr_t	65	0.01	0.21	-0.85	-0.08	0.00	0.06	0.24	0.28	0.56	0.82

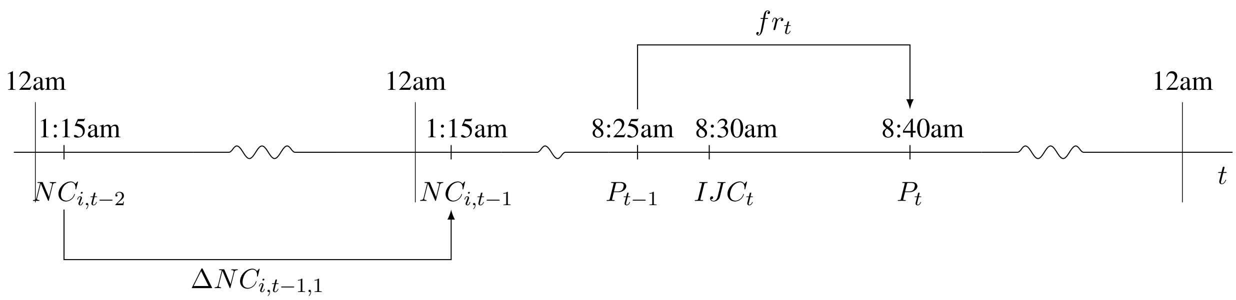
4.4 Empirical Analysis

This section describes our empirical strategy and results. We separate our analysis into two time periods, before the COVID-19 pandemic and during the pandemic. Our main focus is on the effect of the release of IJC news in times of high health uncertainty during the pandemic.

4.4.1 Empirical Design

Figure 4.4 shows the timing of events in our empirical design. The main hypothesis is that market returns fr_t respond differently to the release of macroeconomic news IJC_t in times of high or low health uncertainty, which is measured the day before the announcement as explained in the prior section. As a result, the focus of the chapter is on examining the market response to surprises in IJC news as COVID-19 uncertainty changes and compare these findings to similar tests run before the pandemic and without accounting for health uncertainty.

Figure 4.4: Timeline of Health Uncertainty, News, and Returns
This figure shows the release of initial jobless claims on day t at 8.30am. As an example, the one-day change in new COVID-19 cases in state i before the IJC_t announcement is calculated as the difference between the number of new cases released by Johns Hopkins University, $NC_{i,t-1}$ and $NC_{i,t-2}$. Our measure of health uncertainty is the standard deviation of the seven-day change in new cases across all 50 states on day $t-1$. All times are Eastern Standard Time.



As a benchmark and following the previous literature, we use an ordinary linear regression model to study the relationship between returns and news surprises in the pre-COVID-19 period:

$$fr_t = \alpha + \beta SUR_t^s + \varepsilon_t \tag{4.6}$$

where fr_t is the E-mini S&P 500 15-minute futures return on announcement day t and SUR_t^s is the normalized surprise in initial jobless claims announced on day t.

The prior literature has shown that equity markets respond differently to news across the business cycle and we therefore run a second regression during the pre-pandemic sample to account for that effect:

$$fr_t = \alpha_D + \beta_e(1 - D_t)SUR_t^s + \beta_c D_t SUR_t^s + \varepsilon_t \tag{4.7}$$

where D_t is an economic cycle dummy variable that is zero during NBER expansions and one during NBER contractions.

During the pandemic, we hypothesize that the relationship between macroeconomic news and stock market returns is moderated by the underlying COVID-19 health uncertainty. More specifically, we would expect investors to respond more strongly to bad news when uncertainty is high. As a result, we run a similar regression during our COVID-19 sample without the recession dummy but with our novel COVID-19 health uncertainty measure as an interaction variable to quantify the marginal effect of the change in fundamental

Table 4.2: Pre-COVID-19 Impact of Initial Jobless Claims on High-Frequency Futures Returns
The first regression specification is

$$fr_t = \alpha + \beta SUR_t^s + \varepsilon_t$$

and the second regression specification is

$$fr_t = \alpha_D + \beta_e(1 - D_t)SUR_t^s + \beta_c D_t SUR_t^s + \varepsilon_t$$

where the dependent variable is the high-frequency E-mini S&P 500 futures return and the independent variable is the normalized surprise in IJC announced on day t. The NBER business cycle indicator D_t is equal to one during contractions and zero during expansions. The sample period is from June 4, 1998 to December 1, 2019. We report heteroskedasticity-consistent White standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:	
	fr_t	
	(1)	(2)
SUR_t^s	-0.05^{***}	
	(0.01)	
$(1 - D_t)SUR_t^s$		-0.04^{***}
		(0.01)
$D_t SUR_t^s$		-0.09^{***}
		(0.02)
Constant	0.00	0.00
	(0.01)	(0.01)
Observations	1,115	1,115
R^2	0.07	0.08

health uncertainty on investors' processing of unemployment news.

Our main test during the COVID-19 sample is the following ordinary least squares regression in event time of IJC announcement days:

$$fr_t = \alpha_1 + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5} + \beta_3 SUR_t^s * SD\Delta NC_{t-1,5} + \varepsilon_t \tag{4.8}$$

where $SD\Delta NC_{t-1,5}$ is the cross-sectional standard deviation among the 50 U.S. states of the change in new COVID-19 cases observed on day $t - 1$ over the prior five days. The coefficient of interest to test our hypothesis is β_3 in equation (4.8).

4.4.2 Market Impact of Macroeconomic News Before COVID-19

We begin by looking at the pre-pandemic average effect of IJC surprises on stock market returns. The results are presented in Table 4.2, first unconditionally and then conditional on the business cycle.[10] Regression specification (1) shows that there is a significant negative impact of IJC surprises on stock market futures returns: higher than expected IJC is bad news for stocks. Regression specification (2) shows that the impact of IJC news is stronger in recessions than in expansions, although the effect is negative in both. Consistent with the prior literature, the weekly release of IJC seems to have strong negative impact on high-frequency E-mini S&P 500 returns (Kurov and Stan (2018)).

4.4.3 Market Impact of Macroeconomic News During COVID-19

We repeat the regression analysis of the prior sub-section during our COVID-19 sample from April 2020 to June 2021. Table 4.3 shows that the release of higher than expected IJC, i.e., bad news, has little to no impact on equity futures returns during the pandemic. Compared to Table 4.2, the statistical significance is markedly different from the pre-pandemic sample although the point estimates are also negative. We add the national daily number of new cases the day before the announcement as an independent variable to account for the possibility that announcement returns are impacted by a summary statistic for the level propagation of the virus.[11]

4.4.4 Geographical Health Uncertainty and the Market Impact of Macroeconomic News During COVID-19

Table 4.4 presents our main analysis where we investigate whether COVID-19 uncertainty affects the stock market's reaction to macroeconomic news. We do so by adding our novel measure of geographical heterogeneity in the change in new cases as an interaction variable in the regression model: $SUR_t^s * SD\Delta NC_{t-1,5}$. The coefficient on that interaction variable captures the marginal impact of COVID-19 uncertainty on the market's response to the unanticipated component of IJC news announcements.

[10] To avoid any pollution of the pre-pandemic sample and any possible bias in our regression estimates, we end the pre-COVID-19 sample on December 1, 2019. Even though news of this new virus started emerging in December 2019, JHU's COVID-19 data for all 50 states only starts in April 2020.

[11] Implicitly, our health uncertainty measure captures a cross-sectional second moment of COVID-19 new cases whereas NC_t captures the aggregate first moment.

Table 4.3: COVID-19 Impact of Initial Jobless Claims on Equity Returns

The regression specification is

$$fr_t = \alpha + \beta SUR_t^s + \varepsilon_t$$

where the return on high-frequency E-mini S&P 500 futures is regressed on the normalized surprise in announced IJC on announcement days t. NC_{t-1} is the national number of new cases over the prior week. The sample period is from April 2, 2020 to June 30, 2021. We report heteroskedasticity-consistent White standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:	
	fr_t	
	(1)	(2)
SUR_t	−0.08	−0.08
	(0.05)	(0.05)
NC_{t-1}		0.00
		(0.00)
Constant	0.03	0.05
	(0.02)	(0.03)
Observations	65	65
R^2	0.14	0.15

We see that the marginal effect of COVID-19 health uncertainty on the stock market's response to the release of weekly initial jobless claims is economically large and statistically significant. The negative coefficient on the interaction effect shows that, as uncertainty increases, bad news (higher than expected IJC) is increasingly viewed as bad news by equity investors (prices fall). This result is consistent with our hypothesis that higher COVID-19 uncertainty intensifies the impact of macroeconomic announcements on equity returns. Moreover, this stands in contrast to the insignificant unconditional effect of the news during the pandemic and it shows that the market impact of macroeconomic announcements is context dependent: bad news matters when prior uncertainty is high.

Using the estimates from model (2) in Table 4.4, we can see how the relationship between fr_t and SUR_t^s varies across the range of $SD\Delta NC_{t-1,5}$ (25th and 75th percentiles from Table 4.1). At low values of COVID-19 uncertainty, a one standard deviation increase in macroeconomic news surprise SUR_t^s is associated with a 0.07% increase in high-frequency E-mini S&P 500 returns around the announcement.[12]

[12]We have: $0.02 + 0.21 * 1 - 0.26 * 0.09 - 1.55 * 1 * 0.09 = 0.0671$.

Table 4.4: Market Impact of Macroeconomic News and COVID-19 Health Uncertainty
The regression specification is

$$fr_t = \alpha_1 + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5} + \beta_3 SUR_t^s * SD\Delta NC_{t-1,5} + \varepsilon_t$$

where the dependent variable fr_t is the high-frequency E-mini S& P 500 futures return around the news announcement, SUR_t^s is the normalized surprise in announced weekly IJC, and $SD\Delta NC_{t-1,5}$ is our measure of cross-state standard deviation in the change in new COVID-19 cases over the five working days prior to the announcement. NC_{t-1} is the national number of new cases over the prior week. The sample period is from April 2, 2020 to June 30, 2021. We report heteroskedasticity-consistent White standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:	
	fr_t	
	(1)	(2)
SUR_t^s	0.20	0.21
	(0.16)	(0.16)
$SD\Delta NC_{t-1,5}$	−0.09	−0.26
	(0.09)	(0.20)
$SUR_t^s * SD\Delta NC_{t-1,5}$	−1.49**	−1.55**
	(0.74)	(0.73)
NC_{t-1}		0.00
		(0.00)
Constant	0.04	0.02
	(0.03)	(0.04)
Observations	65	65
R^2	0.35	0.36

At high values of COVID-19 uncertainty, a one standard deviation increase in SUR_t^s is associated with a -0.26% decrease in fr_t.[13]

Kurov and Stan (2018) finds that higher monetary policy uncertainty weakens the impact of IJC news. In our pandemic sample, we find that higher health uncertainty increases the impact of IJC news. One driver of this difference may be that there was little monetary uncertainty during the pandemic as the federal funds rate was at the zero lower bound and enormous fiscal and monetary support was unleashed instantaneously. As a result, our sample contains mostly a direct cash flow effect from news to returns. In the face of high health uncertainty, investors view bad news as really bad news for stocks during the pandemic.

To shed further light on this hypothesis, we look at the marginal effect of unemployment surprises SUR_t^s

[13] We have: $0.02 + 0.21 * 1 - 0.26 * 0.27 - 1.55 * 1 * 0.27 = -0.2587$

on stock returns, which is equal to $\beta_1 + \beta_3 SD\Delta NC_{t-1,5}$. For our pandemic sample, Figure **??** overlays the normalized IJC surprises with shaded areas when the marginal impact of high COVID-19 uncertainty leads to a negative stock response to the release of higher than expected initial jobless claims.

Using model (4) in Table 4.4, we calculate the threshold value of COVID-19 uncertainty that makes the impact of the release of positive IJC surprises on returns change sign. Bad jobless claims news is bad news for stocks if $SD\Delta NC_{t-1,5} > -\frac{0.21}{-1.55} = 0.1355$. However, bad news is good news for stocks if uncertainty is below that threshold. In Figure **??**, the white areas show the former and the gray areas show the latter. These results are consistent with our second hypothesis that high health uncertainty is associated with a cash flow effect (bad news is bad news for stocks) but low health uncertainty is associated with a interest rate effect (bad news is good news for stocks).

4.4.5 Robustness Tests

We investigate two aspects of our novel geographical cross-state measure of COVID-19 health uncertainty. First, while we argue that it captures the fundamental underlying uncertainty of a pandemic economy, how different is it from market-based measures of uncertainty, such as the VIX Index? Second, is there a differential effect based on how the change in new cases is calculated?

We first investigate whether our main result is robust to including the VIX Index as an alternative proxy for uncertainty. Models (1) and (2) in Table 4.5 are regression specifications containing both uncertainty measures, $SD\Delta NC_{t-1,5}$ and VIX_t, and interaction effects of each of them with IJC surprises SUR_t^s. The lack of results on the VIX variables shows that our measure of health uncertainty captures something different from a market-based measure of uncertainty. The interaction term $SUR_t^s * SD\Delta NC_{t-1,5}$ remains statistically significant and preserves its magnitude. We also compare our measure with the Baker et al. (2016) measure of economic policy uncertainty (EPU_t) based on newspaper coverage frequency. Models (3) and (4) show that our health uncertainty measure preserves its significance and magnitude.

In the final robustness checks, we repeat the main test using different versions of our COVID-19 uncertainty measure. First, we calculate a weighted standard deviation of the change in new cases $SD\Delta NC_{t-1,5,w}$

by using each state's pre-pandemic population numbers:

$$SD\Delta NC_{t-1,5,w} = \sqrt{\frac{\sum_{i=1}^{50} w_i(\Delta NC_{i,t,n} - \overline{\Delta NC}_{t,n})^2}{50-1}} \tag{4.9}$$

where w_i is state i's population weight: $w_i \equiv \frac{p_i}{\sum_{i=1}^{N} p_i}$ and p_i is each state's 2019 population estimates from the U.S. Census Bureau..[14] Second, we run our main test without the first announcement date in April 2020, which, per Figure 4.3, could be viewed as an outlier. Third, we increase the window over which the change in new cases is calculated from five to ten days: $\Delta NC_{i,t,10} = \frac{NC_{i,t} - NC_{i,t-10}}{10}$. All three models in Table 4.6 show that our main result is robust to variations in the way our novel health uncertainty measure is calculated.

4.5 Conclusion

In this chapter, we investigate whether the uncertainty surrounding the future path of the COVID-19 pandemic affects the reaction of the stock market to macroeconomic announcements. We first construct a novel measure of fundamental health uncertainty by calculating the daily cross-state standard deviation in the change in new cases. The assumption behind this measure is that investors will be more uncertain if cases are going up in some states and down in others compared to a world where cases are going down (or up) in most states (Liu et al. (2021)). If the state-by-state variability of COVID-19 case changes is low, investors are more certain in their estimate of the future evolution of the virus and hence in their expected path of the pandemic economy. Consistent with Bayesian learning, if the prior uncertainty is high (low quality of the pre-announcement information), then the market impact of a given piece of news should be higher as more updating occurs (Kim and Verrecchia (1991)).

We show that, while the weekly release of initial jobless claims has no unconditional impact on the high-frequency return on the E-mini S&P 500 futures during the pandemic, its release has an increasingly negative impact on equity returns as geographical health uncertainty increases. Higher than expected initial jobless claims is bad news for stocks when health uncertainty is high but it is good news for stocks when health uncertainty is low. Boyd et al. (2005) discuss similar cash flow versus interest rate effects outside of

[14] "CO-EST2019-alldata: Annual Resident Population Estimates, Estimated Components of Resident Population Change, and Rates of the Components of Resident Population Change for States and Counties: April 1, 2010 to July 1, 2019."

the context of a pandemic and health uncertainty. Our notion of geographical dispersion in growth rates as a fundamental measure of uncertainty could be expanded to other domains, such as the standard deviation of local changes in shipping delays as a measure of supply chain uncertainty. We leave this for future research.

Table 4.5: Health Uncertainty Versus Financial Market Uncertainty
The regression specifications are

$$fr_t = \alpha + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5} + \beta_3 VIX_t + \beta_4 SUR_t^s * SD\Delta NC_{t-1,5} + \beta_5 SUR_t^s * VIX_t + \varepsilon_t$$
$$fr_t = \alpha + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5} + \beta_3 EPU_t + \beta_4 SUR_t^s * SD\Delta NC_{t-1,5} + \beta_5 SUR_t^s * EPU_t + \varepsilon_t.$$

The dependent variable is the 15-minutes return on the E-mini S&P 500 futures. SUR_t^s is the normalized surprise in announced weekly IJC. VIX_t is the value of the VIX option-implied market volatility. EPU_t is Baker et al. (2016) measure of economic policy uncertainty based on newspaper coverage frequency. $SD\Delta NC_{t-1,5}$ is our measure of cross-state standard deviation in the change in new COVID-19 cases over the five working days prior to the announcement. NC_{t-1} is the national number of new cases over the prior week. The sample is from April 2, 2020 to June 30, 2021 with outliers. We report heteroskedasticity-consistent White standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:			
	fr_t			
	(1)	(2)	(3)	(4)
SUR_t^s	0.14	0.12	0.30	0.29
	(0.24)	(0.23)	(0.21)	(0.20)
VIX_t	0.01*	0.01		
	(0.00)	(0.00)		
$SUR_t^s * VIX_t$	0.00	0.00		
	(0.00)	(0.00)		
EPU_t			0.00	0.00
			(0.00)	(0.00)
$SUR_t^s * EPU_t$			−0.00	−0.00
			(0.00)	(0.00)
$SD\Delta NC_{t-1,5}$	−0.04	−0.20	−0.07	−0.19
	(0.09)	(0.22)	(0.07)	(0.18)
$SUR_t^s * SD\Delta NC_{t-1,5}$	−1.44*	−1.53**	−1.16**	−1.24**
	(0.76)	(0.76)	(0.59)	(0.62)
NC_{t-1}		0.00		0.00
		(0.00)		(0.00)
Constant	−0.12	−0.12	0.02	0.02
	(0.09)	(0.09)	(0.05)	(0.05)
Observations	65	65	65	65
R^2	0.38	0.39	0.37	0.37

Table 4.6: Alternative Measures of COVID-19 Uncertainty
The regression specifications are

$$fr_t = \alpha + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5,w} + \beta_3 SUR_t^s * SD\Delta NC_{t-1,5,w} + \varepsilon_t$$
$$fr_t = \alpha + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,5} + \beta_3 SUR_t^s * SD\Delta NC_{t-1,5} + \varepsilon_t$$
$$fr_t = \alpha + \beta_1 SUR_t^s + \beta_2 SD\Delta NC_{t-1,10} + \beta_3 SUR_t^s * SD\Delta NC_{t-1,10} + \varepsilon_t$$

where specification (1) uses a population-weighted measure $SD\Delta NC_{t-1,5,w}$, specification (2) uses the standard measure $SD\Delta NC_{t-1,5}$ but without the first observation, and specification (3) uses a measure with 10-day changes in new cases $SD\Delta NC_{t-1,10}$. The dependent variable is the 15-minutes return on the E-mini S&P 500 futures. SUR_t^s is the normalized surprise in announced weekly initial jobless claims. $SD\Delta NC_{t-1,5}$ is our measure of cross-state standard deviation in the change in new COVID-19 cases over the five working days prior to the announcement. NC_{t-1} is the national number of new cases over the prior week. The sample is from April 2, 2020 to June 30, 2021. We report heteroskedasticity-consistent White standard errors in parentheses and the statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

	Dependent variable:		
	fr_t		
	(1)	(2)	(3)
SUR_t^s	0.18	0.20	0.24
	(0.14)	(0.14)	(0.21)
$SD\Delta NC_{t-1,5,w}$	−0.09		
	(0.09)		
$SD\Delta NC_{t-1,5}$		−0.19	
		(0.17)	
$SD\Delta NC_{t-1,10}$			−0.01
			(0.41)
$SUR_t^s * SD\Delta NC_{t-1,5,w}$	-0.85^{**}		
	(0.38)		
$SUR_t^s * SD\Delta NC_{t-1,5}$		-1.20^{**}	
		(0.57)	
$SUR_t^s * SD\Delta NC_{t-1,10}$			-2.48^{*}
			(1.48)
NC_{t-1}	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Constant	0.02	0.02	0.01
	(0.03)	(0.04)	(0.04)
Observations	65	64	65
R^2	0.37	0.13	0.32

Chapter 5

Impact of Arbitrageurs' Activities in Crude Oil Markets

5.1 Introduction

Accounting for the activities of commodity cash-and-carry traders, we provide a limits to arbitrage extension to speculative storage framework shown in the literature. Our empirical results are consistent with the predictions of the model and address important questions of the theoretical and empirical literature on the limits to arbitrage and their impact on equilibrium prices. Because arbitrageurs are capital constrained, arbitrage activities are subject to frictions and limitations that manifest themselves in both market prices and positions of arbitrageurs (Shleifer and Vishny (1997)). Moreover, if arbitrage activities require specialized knowledge, they are delegated to specialized funds operated by asset managers, who extract the entire surplus from these activities subject to leverage constraints — adding to market frictions in the process (Berk and Green (2004)). How can we explain arbitrageurs' activities? Is there an effect of arbitrageurs on equilibrium pricing? If so, how significant is the signal sent by cash-and-carry traders on commodity supply? In this chapter, we investigate the activities of arbitrageurs and examine their role in determining equilibrium prices.

Canonical speculative storage models are able to match a crucial empirical fact of commodity prices. However, these models are known to perform poorly when confronted with the data. This is due to (1) lack of closed form equilibrium solution that mandates use of complex iterative estimation methods; (2) difficulties with identification because data on speculative inventory is hard to come by. The contribution of this chapter is to address both of these problems. First, we develop a limits to arbitrage extension to the speculative storage framework which delivers a closed form pricing equation for the term structure of commodity futures prices with a critical nonlinearity parameter that captures the nonnegativity of speculative storage. Second, we recover a proxy for speculative seaborne inventory of crude oil using a novel dataset with granular information on every tanker that entered into U.S ports during 2008-2012.

To begin with a few facts, during 2008-2012, the term structure of Brent futures prices remained on average distinctly upward sloping, i.e., in contango, with occasional extreme slopes that have been labeled as supercontango. A period of contango, or supercontango, is likely to be noticed by speculators. Indeed, physical commodity traders engage in a commodity carry trade in which they buy physical crude oil at, e.g., $50 per barrel today, store the oil in a suitable storage facility, and simultaneously enter into a short futures contract to sell the oil at $55 per barrel two to three months later. This is illustrated in Figure 5.1.

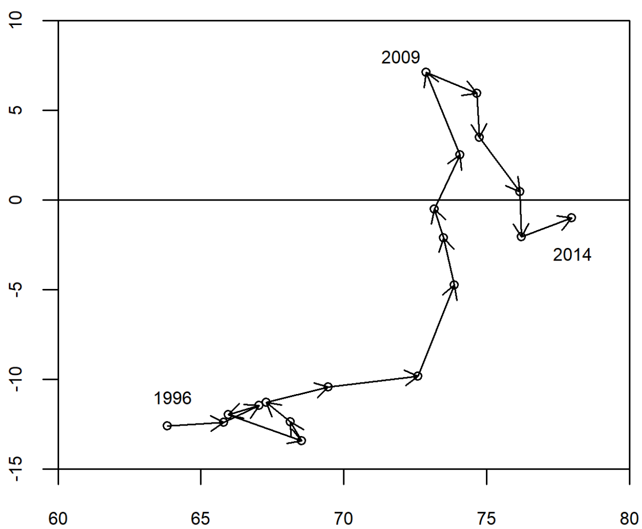
Canonical speculative storage models of Deaton and Laroque (1992, 1996) capture this logic when deriving an equilibrium relationship between prices, inventories, supply and demand for a storable commodity like crude oil. In these models, total supply consists of new production in a given period (assumed for technological reasons to be exogenous) and inventory that was deliberately put into storage in the previous period. Total demand for a commodity in a given period consists of stochastic consumer demand and demand for inventory to be put into storage until the next period. The amount of storage reflects a speculative decision based on the current and expected future prices and storage costs.

In equilibrium, the current price is predicted to be equal to the expected discounted future price minus the cost of storage. If the expected discounted future price is higher than the current price and the premium exceeds the cost of storage, speculators will have a strong motive to buy the physical commodity at the current price, put it in storage, and lock in a futures contract to sell it at the higher price in the future.

However, the reverse is not true. Namely, the current price can be much higher than the expected discounted future price and there is little speculators can do about it because speculative storage cannot be negative i.e., supply cannot be borrowed from future periods for current consumption. The canonical

Figure 5.1: Global Crude Oil Supply and the Slope of the Term Structure of Brent Futures Prices: 1996–2014

This figure presents global crude oil supply and the slope of the term structure of Brent futures prices. Global production is on x-axis and is in millions of barrels per day. The slope of the Brent futures term structure is on y-axis and in dollars per thousand barrels calculated as the difference between the futures contracts three months out and the nearby. Global crude oil supply data is from the U.S. Energy Information Administration. Brent futures prices are from the Intercontinental Exchange. Annual averages are computed from daily term structure prices.



framework for commodity price formation accounting for speculative storage is thus able to match a crucial empirical fact of commodity prices — "long periods of stagnant prices interrupted by sharp upward spikes" (Deaton and Laroque (2003)).

The canonical framework contains a number of shortfalls. First, it fails to match other aspects of the commodity price process, most critically high autocorrelation of prices to the point of nonstationarity and autoregressive heteroscedasticity combined with structural breaks. As Kleppe and Oglend (2017) concisely summarize: "The theoretical foundation of the [speculative storage] model is well established by now. What has proved more difficult is confronting the model with data in order to operationalize it for practical policy analysis and hypothesis testing. Estimation has been limited by two factors: (1) the lack of a closed form solution to the model, necessitating a computationally demanding subroutine to solve a dynamic optimization problem for each parameter evaluation, and (2) lack of reliable quantity data [for speculative inventory]." [1] Second, the models of Deaton and Laroque (1992, 1996) and their extensions assume, according to the

[1]Text in square brackets added.

saying of Dvir and Rogoff (2014), "free entry into the storage sector as well as risk neutrality, implying that the actions of arbitrageurs will raise or lower the current price until it is at a level which renders the strategy unprofitable in expectation". Third, assumption of risk neutrality also implies that the canonical framework has little to say about futures prices as agents do not have a reason to hedge commodity price risks.

The chapter builds on the recent work by Acharya et al. (2013) who develop a two-period equilibrium model of commodity markets that includes frictions due to limits to arbitrage. The model consists of commodity consumers, commodity producers, and asset managers. In each period, commodity consumers demand a certain amount of commodity, e.g., crude oil, in the physical (cash) market. Competitive producing firms supply the physical market with an inelastic supply of the commodity save for an amount that they choose to store as inventory and make available in the next period. Risk averse producers also have access to the futures market where they can hedge their natural long position in the physical commodity by taking a short futures position. The producers' hedging demand in the futures market is accommodated by specialized, capital-constrained commodity asset managers, who provide the long side of the futures trade in return for appropriate compensation and only up to a limited size. The authors show that frictions and limitations imposed on the producers and commodity asset managers help explain how hedging activities in the futures market translate into equilibrium commodity prices as a function of speculative inventory. By assumption, arbitrageurs in Acharya et al. (2013) trade only in the futures market, but not in the cash market. Thus, in order to link cash and futures market prices with speculative inventory decisions, the authors rely on the concept of a convenience yield — an assumed reason to hold inventory for ease of future access or "an embedded timing option" (Routledge et al. (2000)).

The chapter contributes to the asset pricing literature in several ways. First, we propose an extension to the equilibrium model of Acharya et al. (2013) by adding commodity cash-and-carry traders and test implications of the model by using novel, highly disaggregated data for crude oil imports into the United States. Cash-and-carry traders are risk averse arbitrageurs who possess specialized knowledge and technology to arbitrage between the physical (cash) and futures markets. Indeed, they are assumed to have access to a market for off-shore floating storage technology i.e., shipping vessels can be used to store physical commodity bought in one period for delivery in the next period, [2] and to be constrained by the size of their unhedged

[2] On the use of floating storage to speculate in the market for crude oil see, for example, Eric (2016).

arbitrage position. The market for off-shore floating storage technology is assumed to be competitive and solely driven by the demand and supply of vessels suitable for storage and transportation of crude oil. It is further assumed that the floating storage market is only open to cash-and-carry traders at a cost proportional to the amount stored as floating inventory.

Second, we preserve, in equilibrium, the canonical results of Deaton and Laroque (2003), i.e. "long periods of stagnant prices interrupted by sharp upward spikes." In addition, we show that in equilibrium, during the periods of sharp upward spikes in prices in the physical market, futures prices are also in contango or even supercontango. During these periods, equilibrium speculative off-shore inventory of commodity carry traders is positive. In contrast, when the term structure is slightly upward sloping, flat or downward sloping, equilibrium inventory of commodity carry traders is at zero.

Third, our model contains a closed form equilibrium solution. This unique feature acts as a remedy to the use of complex iterative estimation methods. As in Routledge et al. (2000), we do not need to rely on the concept of convenience yield as a primitive input in order to characterize the equilibrium slope of the term structure of futures prices, but derive it as an output of the equilibrium pricing equation. Indeed, our speculative storage framework delivers a closed form pricing equation for the term structure of commodity futures prices with a critical nonlinearity parameter due to the nonnegativity of speculative storage. This parameter as a Lagrange multiplier i.e., endogenous variable retrieved from observed data, links cash and futures market prices with speculative inventory decisions. Therefore, this quantity of interest shadows carry traders' decisions to buy floating commodity inventories hence, the level of carry traders' activities. Empirically, we should expect to see a component of inventories associated with activities of cash-and-carry traders to rise around 2008 until about mid–2010 (when contango is increasing) and then to decline from the second half of 2010 until the end of 2012 (when contango is decreasing). The amounts put into off-shore speculative storage should be of relatively limited size due to frictions and limitations of executing cash-and-carry arbitrage.

Finally, we constitute and analyze in this chapter a unique data set collecting granular data on every tanker that delivered seaborne crude oil into the United States during 10/01/2008–12/31/2012. Thus, we build a proxy for the speculative floating inventory component instead of relying on aggregate inventory data as in Kilian and Murphy (2014) and Kilian and Lee (2014). By delivering a closed form equilibrium solution, our model links cash and futures market prices with speculative inventory decisions in order to shadow the level of carry traders' activities.

Some clear results emerge from our study. First, our findings confirm our model predictions. Not only the cash-and-carry trade business requires entry barriers, in particular specialized knowledge and technology, but also to be profitable. This introduces additional limits to arbitrage translated into the equilibrium arbitrage condition. As predicted by the model, we find that speculative floating inventory is strongly positively related to the slope of Brent futures prices and negatively related to the costs implied by the use of vessels for speculative storage. Second, our findings provide empirical support to the existing literature. Consistent with extensions to the canonical speculative storage framework by Dvir and Rogoff (2009, 2014), speculative floating inventory imported into the U.S. increased during January 2008–August 2010 when the global supply response was constrained. Speculative floating inventory then decreased to zero during the second half of 2010 and in 2011 when the U.S. was increasing its domestic production of crude oil even though the term structure of Brent futures prices remained in contango. We also find that price volatility was lower when the speculative inventory was rising during 2008–mid-2010.

The remainder of the chapter is as follows. Section 5.2 outlines the model. Section 5.3 describes our new data set of disaggregated U.S. crude oil imports and the derivation of the time series for speculative floating oil inventory. Section 5.4 presents our empirical analysis, as we test model predictions by using our data set. Section 5.5 concludes.

5.2 The Baseline Model

We develop a partial equilibrium asset pricing model of commodity prices in the presence of arbitrageurs, cash-and-carry traders who possess specialized knowledge and technology - speculative storage - to arbitrage between the physical and the futures markets for crude oil.

There are four types of agents in the two-period equilibrium model: crude oil consumers, crude oil producers, crude oil fund managers, and cash-and-carry traders. The first three types of agents are modeled in the same way as in Acharya et al. (2013) since we extend their model by adding cash-and-carry traders. For ease of exposition and wherever possible, we preserve the original notation.

5.2.1 Consumers

Consumers maximize the following objective function:

$$u\left(C_0, Q_0\right) + \beta E_0 u\left(C_1, Q_1\right), \tag{5.1}$$

where Q_t is the total quantity of crude oil supplied and C_t is consumption of other goods, respectively in period $t = 0, 1$.

$$u\left(C_t, Q_t\right) = \frac{1}{1-\rho}\left(\left(C_t^{\frac{\epsilon-1}{\epsilon}} + \omega Q_t^{\frac{\epsilon-1}{\epsilon}}\right)^{\frac{\epsilon}{\epsilon-1}}\right)^{1-\rho} \tag{5.2}$$

is assumed to be a constant elasticity of substitution utility function with the elasticity of substitution $\epsilon > 0$, the relative risk aversion $\rho > 0$, and the share parameter $\omega > 0$.

The solution to the first-order optimality condition implies the inverse demand function of the form

$$S_t = \omega\left(\frac{C_t}{Q_t}\right)^{\frac{1}{\epsilon}}, \tag{5.3}$$

where S_t is the price of crude oil in period $t = 0, 1$.

The marginal rate of substitution between periods 0 and 1 in the Euler equation is given by

$$\Lambda = \beta\left(\frac{C_0}{C_1}\right)^{-\rho}\left(\frac{1+\omega(\frac{Q_1}{C_1})^{\frac{\epsilon-1}{\epsilon}}}{1+\omega(\frac{Q_0}{C_0})^{\frac{\epsilon-1}{\epsilon}}}\right)^{\frac{\frac{1}{\rho}-\epsilon}{\frac{\epsilon-1}{\rho}}}. \tag{5.4}$$

For parsimony, demand for other goods, C_t is assumed to be an exogenous random variable with $E(\ln C_t) = \mu$ and $Var(\ln C_t) = \sigma^2$. This assumption together with the functional form of the inverse demand function implies the variance of the spot price is

$$\sigma_s^2 = \omega^2 Q_1^{-\frac{2}{\epsilon}}\left(e^{\frac{\sigma^2}{\epsilon^2}} - 1\right)e^{\frac{2\mu}{\sigma}+\frac{\sigma^2}{\epsilon^2}} = \kappa Q_1^{-\frac{2}{\epsilon}}, \tag{5.5}$$

where $\kappa > 0$ is a constant.

5.2.2 Producers

There is an infinite number of production firms with a mass normalized to unity. Production firms are operated by production managers who have access to three technologies. First, production managers operate a specialized production technology that exogenously generates a deterministic output of g_0 barrels of crude oil in period zero and g_1 barrels in period one.

Second, production managers have access to *on-shore* storage technology for crude oil. This storage technology is available to all production managers on the same terms as they collectively own it. Namely, for i barrels of crude oil put into on-shore storage facility at time zero, a production manager receives $i(1-\delta)$ barrels of crude oil in period one, where $0 < \delta < 1$ denotes depreciation due to storage in physical terms (barrels).

Third, production managers have access to the crude oil futures market where they can hedge against fluctuations in spot crude oil prices.

Production managers are assumed to be risk averse maximizers of the value of their firms (the firms, in turn, are fully owned by consumers) subject to the variance of next period earnings. To do so, in period zero, a production manager sells $g_0 - i$ barrels of crude oil in the physical market at the period-zero spot price of S_0 dollars per barrel. In addition, the production manager sells h_p barrels worth of futures contracts in the futures market at the price of F dollars per barrel (F is known in period zero). In period one, the production manager sells $i(1-\delta) + g_1$ barrels of crude oil at the period-one spot price of S_1 dollars per barrel and cash settles the short futures position, h_p.

The objective function of a representative production manager is formally described as follows:

$$\max_{i,h_p} S_0\left(g_0 - i\right) + h_p F + E\left\{\Lambda S_1\left(i(1-\delta) + g_1 - h_p\right)\right\} \\ -\frac{\gamma_p}{2} Var\left\{S_1\left(i(1-\delta) + g_1\right) + h_p\left(F - S_1\right)\right\} \tag{5.6}$$

$$s.t. \quad i \geq 0,$$

where γ_p denotes a representative production manager's risk aversion coefficient.

The first-order condition with respect to i gives the optimal rule for on-shore inventory:

$$i^{\star}(1-\delta) = \frac{(1-\delta)E\{\Lambda S_1\} - S_0 + \lambda_i}{(1-\delta)\gamma_p \sigma_s^2} - g_1 + h_p, \tag{5.7}$$

where λ_i is the Lagrange multiplier on the on-shore inventory nonnegativity constraint and σ_s^2 is the variance of spot crude oil prices.

Optimal on-shore inventory rises with an increase in the amount hedged by the producer in the futures market and falls with an increase in the risk aversion coefficient of the producer, spot price volatility and production in the next period. In the event of an on-shore inventory stock-out, $\lambda_i > 0$ and the current spot price S_0 can be higher than expected discounted future spot price as in the speculative storage framework of Deaton and Laroque (1992, 1996).

The first-order condition with respect to h_p gives the optimal rule for hedging demand:

$$h_p^{\star} = \frac{F - E\{\Lambda S_1\}}{\gamma_p \sigma_s^2} + i^{\star}(1-\delta) + g_1. \tag{5.8}$$

Notably, if $F = E\{\Lambda S_1\}$ indicating that the futures and spot crude oil markets are free of frictions and limitations, then it is optimal for a representative production manager to be fully hedged, i.e., to set $h_p^{\star} = i^{\star}(1-\delta) + g_1$. In contrast, if $E\{\Lambda S_1\} > F$, then it is optimal for a representative production manager to be less than fully hedged, i.e., to demand a smaller short open position in the futures markets.

5.2.3 Fund Managers

Commodity fund managers are risk-averse long-only speculative investors who possess a specialized knowledge to invest in spot and futures markets for crude oil; they do not have capacity to invest in oil producing firms nor have access to the physical crude oil storage technology of any kind. Their optimization decisions are constrained by the variance of their net speculative position. In period zero, a commodity fund manager goes long h_s barrels of futures contracts in the futures market at a price of F dollars per barrel. In period one, the commodity fund manager cash settles the entire long position at the period-one spot price of S_1

dollars per barrel.

The objective function of a representative commodity fund manager is described as follows:

$$\max_{h_s} h_s \left(E\left\{\Lambda S_1\right\} - F\right) - \frac{\gamma_s}{2} Var\left(h_s\left(S_1 - F\right)\right), \tag{5.9}$$

where γ_s denotes a representative commodity fund manager's risk aversion coefficient.

The first-order condition with respect to h_s gives the optimal rule for the optimal long speculative position in the futures market:

$$h_s^{\star} = \frac{E\left\{\Lambda S_1\right\} - F}{\gamma_s \sigma_s^2}. \tag{5.10}$$

If $E\left\{\Lambda S_1\right\} > F$, commodity fund managers are optimally willing to provide a greater long open interest.

5.2.4 Cash-and-Carry Traders

Cash-and-carry traders are a new type of agent that we introduce into the model of Acharya et al. (2013). These traders possess a specialized knowledge to arbitrage between the cash (physical) and futures markets for crude oil. In the cash market, they are assumed to have access to *off-shore* costly storage technology - shipping vessels that can be used to store physical crude oil in period zero for delivery in period one. The floating storage market is open only to carry traders at a cost proportional to the amount stored as floating inventory. The market for off-shore floating storage technology is assumed to be competitive and driven solely by the demand and supply of vessels suitable for storage and transportation of crude oil. To that end, it is assumed that between period zero and one, the market for floating storage is unaffected by any frictions, limitations, quantities and prices in the physical or futures markets for crude oil. It is further assumed that cash-and-carry traders do not have access to the on-shore storage facilities owned and operated by the producers.

Carry traders are risk averse. Their optimization decisions are constrained by the variance of the value of their speculative position. In period zero, a carry trader buys y barrels of crude oil at the period-zero spot price of S_0 dollars per barrel and puts the entire inventory into floating storage at a cost R_0 dollars per barrel. The carry trader also sells short h_c barrels worth of futures contracts at the price of F dollars per barrel. In period one, the floating inventory is delivered and the carry trader sells the physical inventory and cash settles the short position at the period-one spot price of S_1 dollars per barrel.

The objective function of a representative carry trader is described as follows:

$$\max_{y,h_c} -yS_0 - yR_0 + h_cF + E\left\{\Lambda S_1\right\}(y - h_c) - \frac{\gamma_c}{2}Var\left\{S_1(y - h_c)\right\} \tag{5.11}$$
$$s.t. \quad y \geq 0,$$

where γ_c denotes a representative carry trader's risk aversion coefficient.

The first-order condition with respect to y gives the optimal rule for the optimal floating inventory:

$$y^{\star} = \frac{E\left\{\Lambda S_1\right\} - S_0 - R_0 + \lambda_y}{\gamma_c \sigma_s^2} + h_c, \tag{5.12}$$

where λ_y is the Lagrange multiplier on the off-shore inventory nonnegativity constraint.

Optimal off-shore inventory rises with an increase in the amount hedged by the carry trader in the futures market and falls with the cost of floating storage, an increase in the risk aversion of the carry trader and spot price volatility. In the event of an off-shore inventory stock-out, $\lambda_y > 0$ and the current spot price S_0 can be higher than expected discounted future spot price.

The first-order condition with respect to h_c gives the optimal rule for a carry trader's optimal (short) arbitrage position in the futures market:

$$h_c^{\star} = \frac{F - E\left\{\Lambda S_1\right\}}{\gamma_c \sigma_s^2} + y^{\star}. \tag{5.13}$$

Note that if $E\left\{\Lambda S_1\right\} > F$, then it is optimal for a carry trader to demand a smaller short position. This is in the same direction as the producer (who is also short futures) and in the opposite direction from the asset manager (who is providing the long side).

5.2.5 Equilibrium

The market for physical crude oil clears in the same way as in Acharya et al. (2013) to which we add the speculative floating oil market. Recall that unlike on-shore storage technology that results in a loss of physical oil of size $0 < \delta < 1$ between periods zero and one, floating storage is costly, but does not result in any intertemporal loss of physical oil. Accordingly, in equilibrium, supply in period one,

$$Q_1 = Y^\star + I_0^\star(1-\delta) + G_1, \tag{5.14}$$

where $Y^\star$ is the aggregate optimal off-shore inventory, $I_0^\star$ the aggregate on-shore inventory carried over from period one, and G_1 is the aggregate production in period one.

Futures market clears in accordance under the zero net supply condition

$$h_p^\star + h_c^\star = h_s^\star, \tag{5.15}$$

with long-only positions established by commodity fund managers having to be exactly equal to the sum of short positions demanded by the commodity producers and the carry traders. Note that both commodity carry traders and commodity producers demand a short position in the futures markets against the limited capacity of capital-constrained commodity asset managers to provide the long side. This introduces additional limits to hedging for commodity producing firms and translates into equilibrium prices.

Substituting Eqs.(5.8), (5.10), and (5.13) into Eq.(5.15), and then substituting Eq.(5.14) for the market clearing optimal supply results in

$$E\left\{\Lambda S_1\right\} - F = \gamma\sigma_s^2 Q_1\left(Y^\star, I_0^\star\right), \tag{5.16}$$

where $\gamma > 0$ is defined such that $\frac{1}{\gamma} = \frac{1}{\gamma_p} + \frac{1}{\gamma_s} + \frac{1}{\gamma_c}$. Further substituting Eq.(5.5) for σ_s^2 results in

$$E\left\{\Lambda S_1\right\} - F = \gamma\kappa Q_1^{1-\frac{2}{\epsilon}}\left(Y^\star, I_0^\star\right), \tag{5.17}$$

Substituting out the futures price using the equilibrium arbitrage condition (Eq.(5.19)) and the period one equilibrium supply (Eq.(5.14)) results in

$$E\left\{\Lambda S_1\left(Y^\star, I_0^\star\right)\right\} - S_0\left(Y^\star, I_0^\star\right) - R_0 + \lambda_y\left(Y^\star\right) = \gamma\kappa\left(Y^\star + I_0^\star(1-\delta) + G_1\right)^{1-\frac{2}{\epsilon}}, \tag{5.18}$$

an equation that combines spot prices and aggregate supply as functions of equilibrium on-shore and off-shore inventory.

5.2.6 Model Predictions

Combining the two first-order conditions for the cash-and-carry traders given by Eqs.(5.12) and (5.13) results in an equilibrium arbitrage condition of the form:

$$\frac{F - S_0 - R_0 + \lambda_y\left(y^\star\right)}{\gamma_c \sigma_s^2} = 0 \tag{5.19}$$

Eq.(5.19) gives predictions about the relationship between the slope of the term structure of futures prices, $F - S_0$, speculative floating inventory, $y^\star$, and the cost of floating storage, R_0.

Intuitively, when $F > S_0 + R_0$, i.e., the deferred futures price is higher than the current spot (or nearby futures) price and the cost of off-shore storage; hence, it is optimal to set $y^\star > 0$ (and $\lambda_y < 0$) and profit from the carry trade. In contrast, when $F \leq S_0 + R_0$, it is optimal to set $y^\star = 0$ (and $\lambda_y \geq 0$). From this intuition, a change in λ_y is negatively related to a change in $y^\star$, where λ_y is a shadow price on speculative floating inventory (or carry traders' storage activities). However, this relationship is non linear due to the non negativity constraint on off-shore storage, $y \geq 0$, in Eq.(5.11).

5.3 Data

As noted by Kilian and Murphy (2014) and Kilian and Lee (2014), data on global crude oil inventories is not publicly available; the two studies construct proxies for global crude oil inventories using publicly available data from the U.S. Energy Information Administration (EIA) and the Energy Intelligence Group, respectively. Furthermore, the component of global crude oil inventories associated with speculative activity is also not publicly observable. Therefore, it is even more difficult to extract speculative floating inventory out of the publicly available data.

In this section, we use granular data on every tanker that delivered seaborne crude oil into the United States during 2008-2012 to derive a proxy for the off-shore inventory associated with cash-and-carry trading activity. First, we describe our source data then, we use two network representations to transform the data. Finally, we group data into categories and extract our category of interest: the proxy for speculative floating inventory.

5.3.1 Source Data - Bill of Lading

Our source data consists of 200,930 individual Bills of Lading (BOL) for all seaborne imports of crude oil and energy products into the United States during 2008–2012 made available to us by DataMyne, a data aggregator and analytics company.

A Bill of Lading (BOL) is "a document that establishes the written evidence of a contract for the carriage and delivery of goods sent by sea for a certain freight." [3] It serves as evidence of the right to entry into the U.S. [4] An example of Bill of Lading is provided in Appendix B.2 (Figure B1). Similarly to customs declarations that must be submitted by individuals entering the United States, BOL must be mandatorily submitted by all cargo carriers entering U.S. ports to the U.S. Customs and Border Protection (CBP) — the federal law enforcement agency of the United States Department of Homeland Security. The enforcement mandate of the CBP ensures that the BOL source data is accurate as counterparties are obligated to accurately report the name of the transportation company, the vessel, and the route. Because a BOL is typically linked to a Letter of Credit and associated payments, counterparties are motivated to report the date of arrival in a U.S. port as close to the verified date of arrival as possible so they get paid faster.

However, not all of the BOL information is fully standardized. As the responsibility for filing the BOL and assigning classification codes is delegated to transportation companies, product description codes and counterparty codes could vary. We utilize internal standardization protocols for company names, products and destinations implemented by DataMyne, which first collected source BOL data for each arriving vessel from the CBP under the U.S. Freedom of Information Act and then standardized them for subsequent analytics.

[3] Mason v. Lickbarrow, 1 H. Bl. 359.
[4] Trade Act of 2002, U.S. Customs and Border Protection.

Furthermore, some important information is not required to be reported in a BOL such as the date of a vessel's departure and whether some or all of the cargo is used as floating storage. The BOL fails to contain information on the price or value of the cargo.

To overcome the shortage of information contained in the BOL, we will employ statistical learning tools to classify whether some vessels fall into a speculative floating storage category.

To check the completeness of the granular BOL data, we calculated monthly statistics for the volume of seaborne oil imports and compared them to aggregate seaborne oil import statistics reported by the U.S. Energy Information Administration (EIA) — all imports minus imports from Canada and Mexico which have a land border with the U.S. We found that statistics calculated from the granular BOL source data nearly perfectly match statistics reported by the EIA. This is important as the EIA data is compiled from summary reports by importers and refineries, while the BOL data is compiled from reports by transportation companies for individual vessels entering U.S. ports. The difference between the two series is about 3 percent (BOL series is smaller than the EIA series) or approximately five to six days of seaborne import flow and could be associated with a time lag between dates in BOLs and custom declarations, as well as, differences in methodologies for identifying the country of origin and sea/land routes.

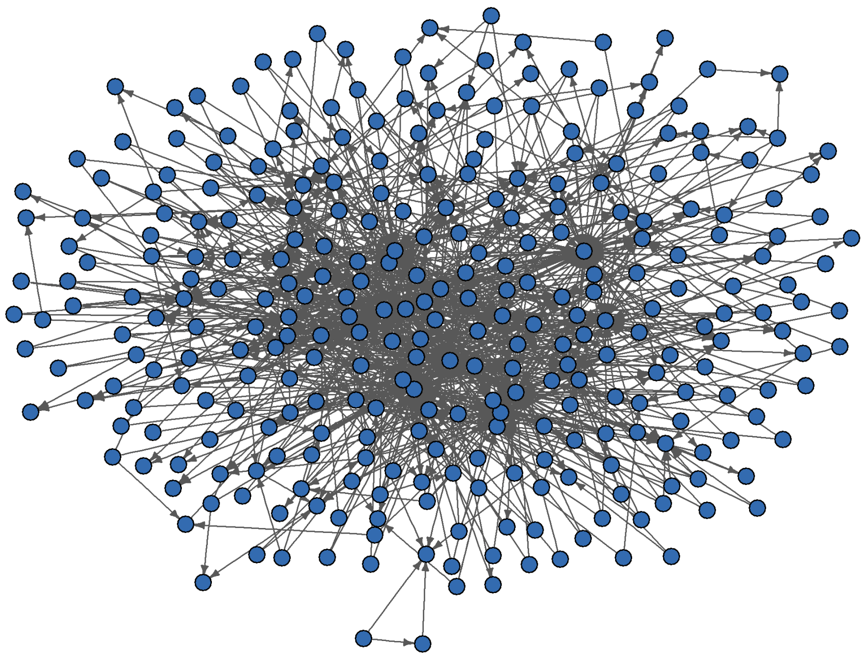
5.3.2 Data Transformation—Nodes

We represent information on U.S. seaborne import shipments imbedded in source BOL data as a directed dynamic acyclic graph $G_t = (V_t, E_t)$ consisting of a set of nodes, V_t, and edges, E_t, at time t, from 01/01/2008 to 12/31/2012, where t denotes one day.

Specifically, V_t consists of shippers and receivers at time t. The entire 2008–2012 data sample allows us to construct V — a finite set of size $n \in \mathbb{N}$ that represents all n companies shipping and receiving shipments during the sample period. We construct the reference set V with the unique numbered vertices as 1, 2,. . . , n such that $V_t \in V$ for each t. E_t set represents instances of Bills of Lading or transactions between shipping u_t^i and receiving v_t^j companies, where transactions, edges, are indicated by the ordered pair (u_t^i, v_t^j) with $u_t, v_t \in V$.

To help us better identify receiving nodes, we have further augmented information associated with each receiving node with the data about the U.S. port of arrival for each particular vessel. Thus, vertices for

Figure 5.2: Network Representation of All BOL Shipments During 2011
Vertices represent companies and directed edges represent individual shipments from overseas companies to receivers in the U.S. Calculations of the authors.

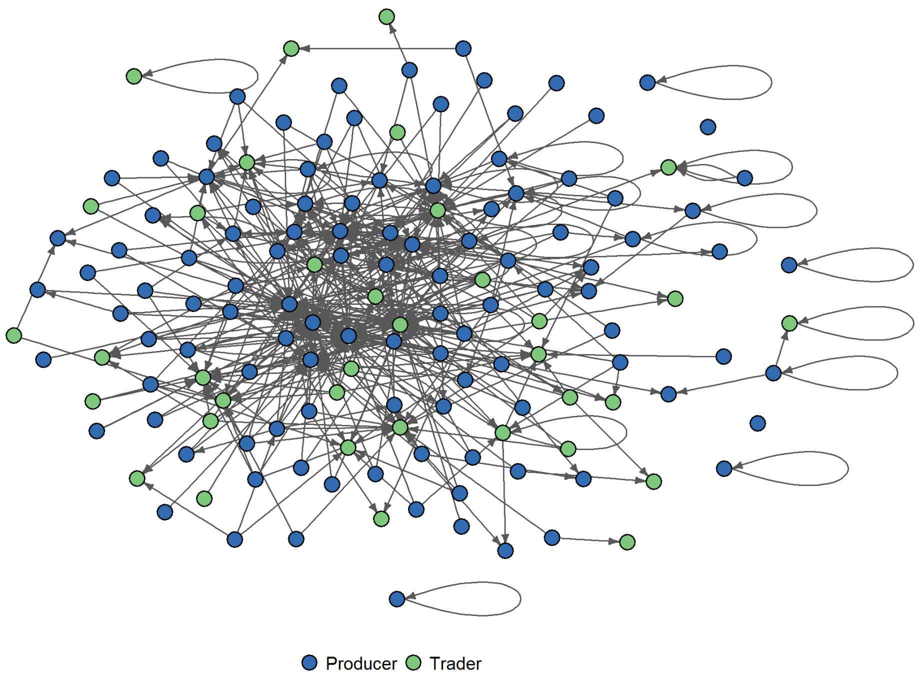


US buyers (consignees) v_t^j are defined by a pair of fields "Company ID" and "U.S. Port of Arrival", while vertices for seller (shipper) u_t^i are defined only by "Company ID." Figure 5.2 is a network representation of BOL shipments during 2011. The graph layout uses a force-based algorithm proposed by Fruchterman and Reingold (purely for aesthetics) "to position the nodes of a graph so that all the edges are of more or less equal length and there are as few crossing edges as possible." (Ding et al. (2011)).

Following the initial representation, we further transform the data by adding information on ownership structure and a coarse industry classification of the owner — P for producer and T for trader. Figure 5.3 presents a network representation of BOL shipments during 2011 with this additional information.

In the figure, all subsidiaries of a company are represented by one node — the parent. For example, the node "Exxon Mobil" represents all 35 subsidiaries and companies working under the Exxon Mobil umbrella in the market. This transformation leads to a decrease in the number of nodes from 348 to 174 and a reduction in the number of edges from 1318 to 623. It modifies the type of a graph from directed acyclic to directed and allows for self-loops. Self-loops are shipments from a foreign to a domestic division (child) of the same parent company. Note that we keep industry classification at the level of children companies,

Figure 5.3: Network Representation of All BOL Shipments Auring 2011 with Ownership Information and Industry Classification of Companies
Vertices represent parent companies and directed edges represent individual shipments from overseas companies to receivers in the U.S. Blue vertices denote producers and green vertices denote traders. Loops represent shipments from one company owned by a parent company to another company owned by the same parent company. Calculations of the authors.



while connections among companies at the level of parent companies. We do not use an industry attribute for parent companies due to high degree of vertical integration in the oil industry, where a parent is often a company managing upstream, downstream, logistic and/or trading children divisions (companies).

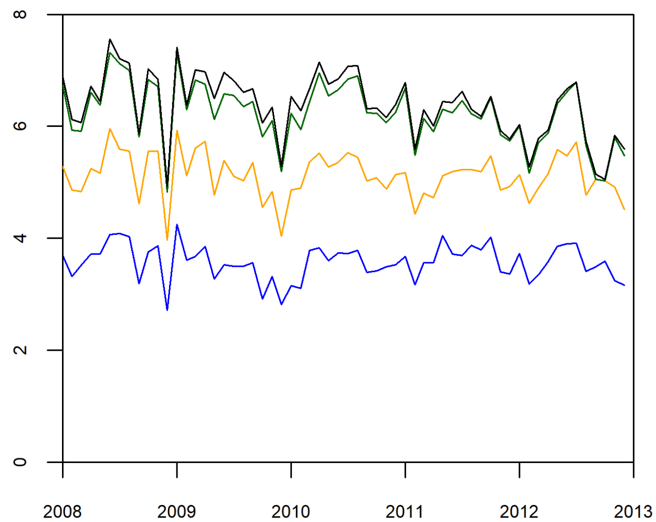
5.3.3 Data Transformation—Edges

Having transformed the nodes or companies, we now proceed to transform the edges that follow very similar patterns into a single edge using the intuitive concept of a "trading agreement." According to a "trading agreement", a buyer and a seller agree that within a calendar year, the seller will deliver a certain total quantity of a certain blend of crude oil to the buyer at a certain U.S. port with a certain periodicity. For example, over the year 2012, A agrees to deliver to B a total of 120 metric tons of light sweet crude oil to a specific port in the U.S. Gulf by delivering 10 metric tons of the specified crude oil every month.

We do not observe actual long-term and short-term trading agreements between importers and exporters,

Figure 5.4: Shipments using Transformed Data

Stacked plot of monthly shipments in millions of barrels per day. PPEdges are blue, PPTPPTLoops are orange, TPPTTTEgdes are green, and TTLoops are black.



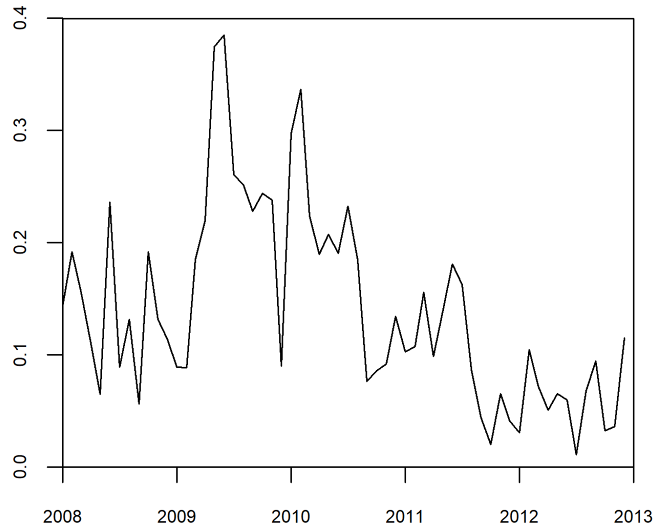
but we believe that the arrival of each shipment that we do observe (at time $t+T$) is associated with entering into such an agreement at some prior date t. The fields we use to learn about latent trading agreements are the unique ID for a US buyer (consignee) with US port of arrival, $u^{pi} \in V^p$, the unique ID for an international seller (shipper) $v^{pj} \in V^p$, the product (custom code group HS 2709 crude oil), the quantity (in metric tons) $\{X_1, ..., X_{n_t}\}$, and the date of arrival t.

Trading agreements that we construct do not contain prices, because BOL data does not include prices. However, each trading agreements can be further associated with over 240 different brands and blends of crude oil within the product code HS 2709. Thus, we can use available price data for each brand and blend of crude oil at each date in each location to put a price on each arrival. Then, we can calculate average price for each trading agreement and validate this information against customs data provided by the US Census.

5.3.4 Data Categories

Having transformed the data on both nodes and edges, we proceed to characterize patterns in the data for the following categories: PPEdges, PPTPPTLoops, TPPTTTEgdes, and TTLoops. PPEdges represent shipments from producers to other producers. PPTPPTLoops represent shipments from a producer to itself,

Figure 5.5: Speculative Floating Oil: 2008-2012
Monthly shipments in millions of barrels per day. Calculations of the authors.



from a trader owned by a parent company to a producer owned by the same parent company or from a producer owned by a parent company to a trader owned by the same parent company. TPPTTTEgdes represent shipments from a producer to a trader, from a trader to a producer or from a trader to another trader. TTLoops represent shipments from a trader to itself. Figure 5.4 presents monthly shipments in millions of barrels per day.

5.3.5 Speculative Floating Oil

We define Speculative Floating Oil (SFO), Y_t, as shipments from a trader to itself: TTLoops. Y_t is an empirical proxy for $y^{\star}$. SFO is a fraction of crude oil and oil products imported into the U.S. by sea during 2008-2012. Figure 5.5 presents monthly shipments of SFO during 2008-2012 in millions of barrels per day.

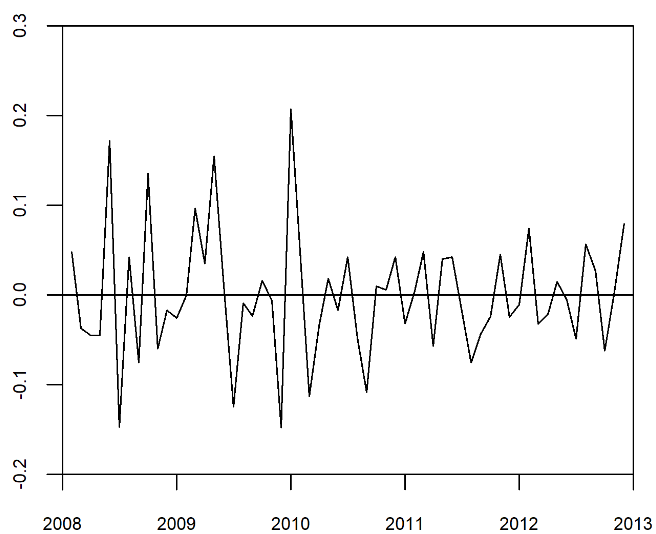
Table 5.1 presents summary statistics for monthly time series of SFO in levels, in differences, in logs, and in log-differences. Statistically, SFO monthly series in levels, Y_t is well approximated by a non-stationary ARIMA(1,1,1) process while the SFO series in differences, ΔY_t is well approximated by a stationary ARIMA(1,0,1) process. The process ΔY_t, is presented in Figure 5.6 below.

Visually, Figure 5.6 indicates that the volatility of ΔY_t is lower after about mid-2010. In order to

Table 5.1: . Speculative Floating Oil: January 2008 - December 2012
This table presents summary statistics for the monthly time series of Speculative Floating Oil, Y_t (in million barrels per day). ADF probability refers to the p-value of the ADF test for the null of unit root with two lags used for error term correction. ρ_τ is autocorrelation ρ at lag τ. Values in brackets below autocorrelation coefficients refer to p-values of the Portmanteau Q-test for no serial correlation at 1,3,6,9,12 lags, Ljung & Box (1978).

	Y_t	$ln(Y_t)$	ΔY_t	$\Delta ln(Y_t)$
Mean	0.14	-2.18	0.00	0.00
STD	0.09	0.73	0.07	0.65
Skewness	0.83	-0.75	0.51	0.43
Kurtosis	3.23	3.64	4.00	3.66
ADF probability	0.35	0.40	0.01	0.01
ρ_1	0.68 (0)	0.60 (0)	-0.27 (0.03)	-0.35 (0.01)
ρ_3	0.46 (0)	0.51 (0)	-0.08 (0.11)	0.09 (0.02)
ρ_6	0.30 (0)	0.35 (0)	-0.06 (0.34)	0.11 (0.02)
ρ_9	0.26 (0)	0.35 (0)	0.03 (0.6)	0.17 (0.02)
ρ_{12}	0.11 (0)	0.17 (0)	-0.06 (0.76)	-0.04 (0.06)

Figure 5.6: Speculative Floating Oil in differences, ΔY_t: January 2008 - December 2012
Calculations of the authors. Changes in monthly shipments, $\Delta Y_t = Y_t - Y_{t-1}$, in millions of barrels per day.



empirically test for a change in regime of the ΔY_t process, we assume that it follows an autoregressive process of order 1 and test for the instability in variance. Figure 5.8 shows the time series of Wald test statistic for an unknown regime change point. The Wald test statistic peaks at September 2010. These results are also presented in Table 5.4. Appendix B.3 presents an economic discussion about the presence of the structural break in mid-2010 period.

5.3.6 Price data

Source data for the slope of the Brent term structure, log twelve month deferred minus the log nearby, in dollars per barrel are from the Intercontinental Exchange. To create a time series of futures prices, the roll date was set for the first day of each month. No price adjustments were made to eliminate artificial jumps in the prices of consecutive futures contracts. Brent futures contract is specified for 1000 barrels; to get to the dollars per barrel specification, we divided the series by 1000. Monthly series are computed by averaging daily data over each month.

Source data for the daily cost of chartering a vessel for the route between the Arabian Gulf and the U.S. Gulf is from the Platts Oilgram Price Report. These are monthly flat spot dirty tanker rates for a route Arab Gulf to the U.S. Gulf Coast for a 270,000 metric tons tanker. By Platts methodology, contracted as "the average rate for routes Ras Tanura LOOP (via Quoin island, L&B via: Cape), Mina al-Ahmadi Houston via Cape (via Quoin island), Kharg Island Corpus Christi (via: Quoin Island, L&B via: Cape)." Monthly series are computed by averaging over weekly published source data.

Since we only observe when loaded vessels enter U.S. ports, we need to make an assumption to align the date when the oil arrives in the U.S., i.e., the time $t + T$, with the date t when the associated carry trade might have been put in. We assume that $T = 180$ days. This way, when we observe that on January 1, 2008, a vessel loaded with what we classify as speculative floating oil enters the U.S., we will statistically relate it to the data for the term structure of Brent crude oil futures prices and for the costs of chartering a vessel as of July 1, 2007, i.e., lagged six months, which is when we believe the carry trade was put in.

5.4 Empirical Analysis

Our model predicts that the slope of Brent futures prices should be strongly positively related to speculative floating inventory after accounting for charter (freight) costs.

5.4.1 From Equilibrium Representation to Empirical Setting

Suppose that at time t, we are able to observe a proxy for the aggregate speculative floating inventory Y_t. The equilibrium model specified in Eq.(5.19) implies the following empirical specification:

$$(F_t^{t+T} - F_t^t) + \Lambda(Y_t) - TR_t = \epsilon_t \tag{5.20}$$

where $F_t^{t+T} - F_t^t$ is the slope of the term structure of futures prices, and R_t is the daily cost of chartering a vessel. The variables $F_t^{t+T} - F_t^t$ and R_t, which are expressed in dollars per barrel, are market determined and observable. These three variables $F_t^{t+T} - F_t^t$, Y_t, and R_t are contemporaneous and co-move – we will later show that they are co-integrated. The residual is denoted by ϵ_t.

Note that Eq. (5.20) is another way of representing the equilibrium arbitrage condition. Indeed, since the denominator is a constant in Eq. (5.19), we can take both the shadow price λ_y – proxied by $\Lambda(Y_t)$ in Eq. (5.20) – and the cost of storage on the right hand side while leaving the slope of the term structure of futures prices on the left hand side. Such a specification, with prices on the left hand side and quantity and costs on the right hand side, reminds us an asset pricing framework.

We know that $\Lambda(Y_t)$ is a non linear function hence, we are taking a Taylor series expansion of $\Lambda(Y_t)$ at the level Y_{t-1}, which is the past and known level of Y_t. We also don't know if this function $\Lambda(Y_t)$ is continuously differentiable therefore we differentiate both from the left and from the right. The Taylor series expansion of $\Lambda(Y_t)$ at the level of Y_{t-1} is:

$$\begin{aligned}\Lambda(Y_t) &\approx \Lambda(Y_{t-1}) + \frac{\partial \Lambda}{\partial Y_t}\Big|_{Y_{t-1}}^{+}(Y_t - Y_{t-1}) + \frac{\partial \Lambda}{\partial Y_t}\Big|_{Y_{t-1}}^{-}(Y_{t-1} - Y_{t-2}),\\ &\approx \Lambda(Y_{t-1}) + \frac{\partial \Lambda}{\partial Y_t}\Big|_{Y_{t-1}}^{+}\Delta Y_t + \frac{\partial \Lambda}{\partial Y_t}\Big|_{Y_{t-1}}^{-}\Delta Y_{t-1},\end{aligned} \tag{5.21}$$

Intuitively, this translates into an empirical representation of the following form:

$$\Lambda(Y_t) \approx \alpha + \beta_0(Y_{t-1}) + \beta_1 \Delta Y_t + \beta_2 \Delta Y_{t-1}, \tag{5.22}$$

5.4.2 Baseline Representation

To check the theory prediction, we specify a baseline regression of the slope of the term structure of futures prices on the changes in speculative floating oil controlled for the costs of chartering a vessel.

$$L^6(F_t^{t+12} - F_t) = \alpha + \beta_0 Y_{t-1} + \beta_1 \Delta Y_t + \beta_2 \Delta Y_{t-1} + \beta_3 t L^6(R_t) + \epsilon_t \tag{5.23}$$

where ΔY_t denotes changes in monthly shipments of speculative floating oil, $(F_t^{t+12} - F_t)$ is the slope of Brent term structure (log twelve month deferred futures minus log nearby) in dollars per barrel, R_t is the daily cost of chartering a vessel for the route between the Arabian Gulf and the U.S. Gulf, the relative time trend t is as a fraction of T=180 days, and L^6 denotes a six-months lag operator.

The regression specification accounts for the autoregressive empirical properties of the ΔY_t process. The regression specification also accounts for the fact that ΔY_t are arithmetic rather logarithmic differences by including the previous period price Y_{t-1}.

The carry trader's decision is made 6 months before we observe the BOL from the actual tanker which enters into the U.S. therefore, we observe Y_t with a lag of 6 months. We lag only the variables relevant to the decision of the carry trader taken 6 months before, i.e., slope of the Brent term structure and the daily chartering cost.

The coefficients of the baseline regression and the goodness–of–fit statistics are represented in Table 5.2. The coefficient on the slope of the speculative floating oil is positive and statistically significant at the one percent level and the coefficient on the shipping cost is positive but statistically insignificant. F-statistic = 26.31 on 4 and 53 DF; p-value = 0.0000.

5.4.3 Regime Change Considerations

Model predictions reflect the assumption that producers operate a specialized production technology that exogenously generates g_0 barrels of crude oil in period zero and g_1 barrels in period one. While we maintain this exogenous supply assumption for commodity producers as in Deaton and Laroque (1992, 1996), the presence of cash-and-carry traders effectively introduces a mechanism to adjust oil supply between adjacent periods, albeit of limited capacity. It is, thus, straightforward to extend our empirical predictions by allowing for endogenous supply response of Dvir and Rogoff (2009, 2014) as long as we can pinpoint these regimes in the data. The authors derive equilibrium responses to higher current oil prices under two stylized regimes: constrained supply and unconstrained supply.

They show that if the supply of oil in the current period is technologically or otherwise unconstrained, then, in a rational expectations equilibrium, suppliers respond by selling oil in the current period until the temporarily elevated current price declines to the level where current price and the expected future price minus storage costs equalize. In this regime, inventories held in speculative storage decline; thus, carry traders activities possibly tend to zero.

Yet, if for technological, regulatory or other reasons, the supply of oil in the current period is constrained while the demand for oil is expected to remain elevated, the equilibrium dynamics of prices and inventories follows a different pattern. In the constrained supply regime, in equilibrium, both (already high) current price and expected future price will increase because as the authors put it "rising prices due to rising demand can be seen as a process which is likely to continue." All in all, the expected future price minus storage costs rises to the level of the elevated current price because the supply response is not expected to be forthcoming. Equilibrium inventories held in speculative storage also increase; thus, carry traders activities intensify.

The empirical specification should also account for a possibility of two separate regimes (constrained and unconstrained overall supply) as per Dvir and Rogoff (2009, 2014). If the supply is unconstrained, the amount of speculative floating inventory might be quite small even though the slope of the term structure may be positive and steep and the costs of shipping may be relatively low. If the supply is constrained, however, an increase in the amount of the speculative floating inventory should be positively associated with the slope of the term structure of crude oil futures prices for given costs of floating storage.

5.4.4 Representation with Regime Change

In order to account for the regime change in the SFO series due a change in the supply regime from constrained to unconstrained, we adjust the baseline representation as follows:

Table 5.2: Regression Specification
Regression specification is

$$L^6(F_t^{t+12} - F_t) = \alpha + \beta_0 Y_{t-1} + \beta_1 \Delta Y_t + \beta_2 \Delta Y_{t-1} + \beta_3 tL^6(R_t) + \epsilon_t \quad (5.24)$$

for full sample (Baseline), unconctrained (Unconstrained) and constraint (Constrained) regimes. P-values are calculated according to the approximation method proposed by Doornik (1998). Standard errors are given in parenthesis below the coefficients. The statistical significance is shown as *p<0.1, **p<0.05, and ***p<0.01.

Variable	Baseline	Unconstrained	Constrained
intercept	-0.008	0.003	-0.012***
	(0.002)	(0.004)	(0.002)
Y_{t-1}	0.063***	0.045**	0.064***
	(0.007)	(0.017)	(0.008)
ΔY_t	0.033***	0.026	0.030***
	(0.007)	(0.016)	(0.007)
ΔY_{t-1}	-0.015**	-0.023	-0.015**
	(0.007)	(0.014)	(0.007)
$tL^6(R_t)$	0.276	-1.014**	1.389***
	(0.227)	(0.402)	(0.392)
Observations	58	58	58
Multiple R-squared	0.67	0.79	0.79
Adj. R-squared	0.64	0.75	0.75

$$L^6(F_t^{t+12} - F_t) = D_t^C\left(\alpha^C + \beta_0^C Y_{t-1} + \beta_1^C \Delta Y_t + \beta_2^C \Delta Y_{t-1} - \beta_3^C tL^6(R_t)\right) \quad (5.25)$$

$$+ D_t^U\left(\alpha^U + \beta_0^U Y_{t-1} + \beta_1^U \Delta Y_t + \beta_2^U \Delta Y_{t-1} - \beta_3^U tL^6(R_t)\right) + \epsilon_t, \quad (5.26)$$

where $D_t^C = 1$ during Jan 2008 - July 2010 and zero, otherwise, and $D_t^U = 1$ during Aug 2010 - Dec 2012 and zero, otherwise. The subscripts C and U denote constrained and unconstrained supply regimes, respectively.

The coefficients of the regression with the regime change dummies and the goodness–of–fit statistics are represented in Table 5.2. As predicted by theory, the regression coefficient on speculative floating oil is positive and statistically significant at the one percent level during the constrained regime and remains positive, but is not statistically significant during the unconstrained regime. The coefficient on the cost of shipping is positive and statistically significant at the one percent level during the constrained regime, but

Table 5.3: . Johansen et al. (2000) Modified Trace Test for Cointegration in the Presence of a Single Known Structural Break: January 2008 - December 2012

This table presents test results for the existence of cointegration vectors using Johansen et al. (2000) modified trace test in the presence of a single known structural break. Adjusted trace statistics adjust for small sample size as suggested in Ahn and Reinsel (1990). P-values of adjusted statistics are calculated according to the approximation method proposed by Doornik (1998). Asymptotic critical values are from Giles and Godwin (1991) for one breakpoint and its relative location in the sample. Significance: '***' 0.001, '**' 0.01, '*' 0.05.

	Cointegrating Rank		
	0	1	2
Trace Statistics	72.41***	34.00***	13.18*
Trace Statistics, adjusted	63.17***	30.60***	11.86
10 % Critical Value	55.46	34.46	16.77
5 % Critical Value	59.09	37.42	18.90
1 % Critical Value	66.32	43.41	23.35

turns negative and nearly statistically insignificant during the unconstrained regime. F-statistic = 18.44 on 10 and 48 DF; p-value = 0.0000.

To check for nonstationarity in individual time series we conduct an efficient ADF, DF-GLS unit root tests (see Table 5.5). According to the tests, Y_t is mean-reverting along a trend, I(0) at 1% significance level, in the Restricted Supply regime. After the structural break, Y_t starts following a stochastic I(1) trend in the Unrestricted Supply regime. Slope, $L^6(F_t^{t+12} - F_t)$, is a I(1) process consistently. Freight cost, $L^6 R_t$, is trend stationary in the full sample, but I(1) in both subsamples.

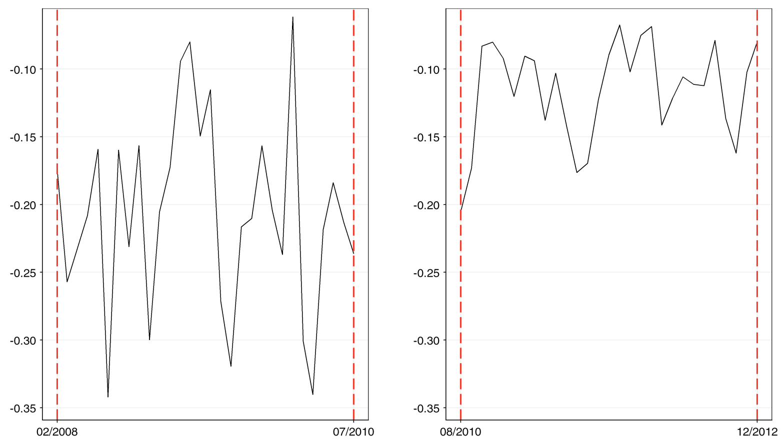
5.4.5 Cointegration

According to theory, arbitrage activities of commodity cash-and-carry traders in the physical and futures markets impact the risk premium because both commodity carry traders and commodity producers demand a short position in the futures markets against the limited capacity of capital-constrained commodity asset managers. This introduces additional limits to hedging for commodity producing firms and manifests itself in the risk premium. Thus, the time series for the risk premium, storage costs, and floating inventory are likely to exhibit a cointegrating relationship.

We test for the presence of a cointegrating relationship in the three times series both with and without a structural break. Johansen (1991) test results for the full times series without accounting for a possible

Figure 5.7: Cointegrating vector $\{\beta_0 Y_{t-1}$, $\gamma L^6(F_t^{t+12} - F_t)$, $\beta_3 L^6 R_t\}$ in Restricted and Unrestricted Supply Regimes

Calculation by the authors. Cointegrating vector in restricted supply regime is $-1.12Y_{t-1} + 13.53L^6(F_t^{t+12} - F_t) - 15.93L^6 R_t$; in unrestricted supply regime it is $-0.84Y_{t-1} + 4.06L^6(F_t^{t+12} - F_t) - 5.13L^6 R_t$.



structural break are in Table 5.6. As shown in the table, we fail to reject the null hypotheses that the number of cointegration vectors is less than one, but reject the hypothesis that the number of cointegration vector is less than two against the alternative that there is one cointegrating vector. However, after adjusting for the small sample size, the statistical significance of test results weakens.

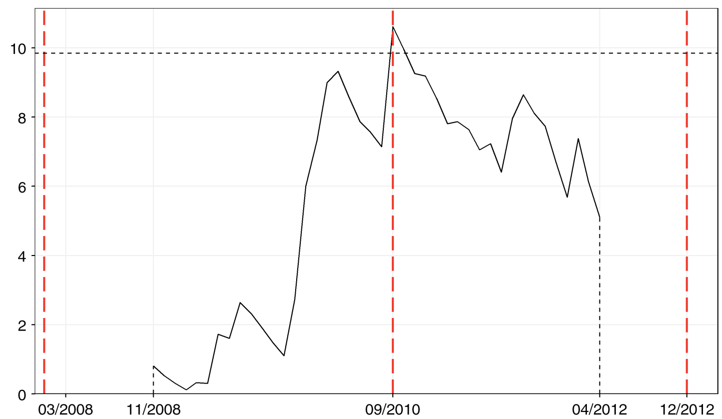
We repeat the test using a modified test by Johansen et al. (2000) that accounts for known structural breaks in the cointegrating relationship. Results of the Johansen et al. (2000) test are presented in Table 5.3. As shown in the table, the results strongly statistically confirm the presence of a single cointegration vector linking the three times series.

Fitting cointegrating vectors estimated under the two regimes gives rise to a two fitted series for speculative floating oil. The fitted speculative floating oil series under the two regimes as plotted in Figure 5.7.

Despite there is a clear difference both in the level and the variance of the two fitted series, the signs and the sizes of coefficients are as expected – positive signs on the slope of the term structure of futures prices and negative signs on the cost of shipping. We note that, for each of the two fitted series, these coefficients have roughly the same magnitude supporting evidence for Eq.(5.19).

Figure 5.8: Wald Sequence for Variance: November 2008 - April 2012

Calculations of the authors. The plot presents time series of Wald statistics, $W(\pi)$, as a function of a single break date, T_1. The specification is $\Delta Y_t = \alpha + \rho \Delta Y_{t-1} + e_t$. The break dates, T_1, are on the x-axis and $W(\pi)$ is on the y-axis. Dotted horizontal black line shows asymptotic critical value at 5%. Restricted time interval of candidate break dates, $\Pi = [.15n, .85n]$, is used as suggested in Andrews (1993). The $Sup_{\pi \in \Pi} W(\pi)$ value of the test is 10.61, where $\pi = \frac{T_1}{n}$, $k = 1$, 5% asymptotic critical value = 9.84, Asymptotic p-value=0.031.



5.5 Conclusion

Accounting for commodity cash-and-carry traders' activities, we provide a limits to arbitrage extension to speculative storage framework shown in the literature. Carry traders, who arbitrage between the physical and futures markets, are assumed to have access to a market for off-shore storage technology - shipping vessels can be chartered to store physical commodity bought in one period for delivery in the next period. By delivering a closed form equilibrium solution, our model links cash and futures market prices with speculative inventory decisions in order to shadow the level of carry traders' activities. We show that in equilibrium, arbitrage activities of carry traders are associated with additional limits to hedging for commodity producing firms and affect equilibrium commodity prices.

Our model overcomes recurrent issues found in the literature. First, we propose a closed form pricing equation for the term structure of commodity futures prices with a critical nonlinearity parameter that captures the nonnegativity of speculative storage. Second, we test empirical predictions of the model using a new data set collecting granular information on every tanker that delivered seaborne crude oil into the United States during 2008-2012.

As predicted by the model, we find that the slope of Brent futures prices is strongly positively related

Table 5.4: . Tests for Constancy of Autoregression Parameters and Error Variance

This table presents test results for a change in regime of the ΔY_t process assuming it follows an autoregressive process of order 1 and test for the instability in variance of the residuals. Variance of the residuals is calculated as a sum of squared residuals divided by a sample size, n, $\frac{1}{n}\sum e_t^2$. We used the Quandt Likelihood Ratio (QLR) (Quandt, 1960) a.k.a. maximum Wald statistic ($supW$) and the logarithm of Andrews and Ploberger exponential Wald statistic ($expW$). The tests check for structural breaks under the assumption of unknown break date. The $supW$ test statistic is the largest value of all the sequence of Wald F-statistic calculated for each candidate breakdate and the $expW$ test statistic is the exponential transformation of the F-statistic. We use restricted time interval for candidate breakdates, $\Pi = [.15n, .85n]$, where n denotes the length of the sample size as suggested in Andrews (1993). Significance: '***' 0.001, '**' 0.01, '*' 0.05.

$\Delta Y_t = \alpha + \rho \Delta Y_{t-1} + e_t$				
	AR(1) parameter, ρ	Intercept, α	Joint, ρ and α	Variance, σ^2
$supW$	5.8	1.31	8.49	10.61**
$expW$	1.08	0.11	2.07	3.72***

to speculative floating inventory, which we derive from the total seaborne crude imported into the U.S. after taking into account the costs of using vessels for use as speculative storage. Not only are our empirical results consistent with the predictions of the model but they also provide empirical support to the existing literature on arbitrage, its limits and their impact on equilibrium prices. Consistent with extensions to the canonical speculative storage framework by Dvir and Rogoff (2009, 2014), speculative floating inventory imported into the U.S. increased during January 2008–August 2010 when the global supply response was constrained; and then decreased to zero during the second half of 2010 and in 2011 when the U.S. was increasing its domestic production of crude oil, even though the term structure of Brent futures prices remained in contango.

Thus, carry traders, by investing in speculative floating commodity inventory, send a powerful signal about the state of the market and alert market participants as well as policy makers to potential supply disruptions.

Table 5.5: . DF-GLS Unit Root Tests

This table presents test results for nonstationarity in individual time series using efficient ADF, DF-GLS unit root tests. Y_t denotes monthly speculative floating oil. $L^6(F_t^{t+12} - F_t)$ denotes six month lag of the slope of the terms structure of Brent futures prices. L^6R_t denotes lagged freight costs. Significance: '***' 0.001, '**' 0.01, '*' 0.05.

	Full Sample, Jan 2008 - Dec 2012		Restricted Supply, Jan 2008 - Aug 2010		Unrestricted Supply, Sept 2010 - Dec 2012	
	Constant, trend	Constant	Constant, trend	Constant	Constant, trend	Constant
$L^6(F_t^{t+12} - F_t)$	-1.57***	-1.37***	-1.47**	-1.37**	-1.42***	-1.25***
L^6R_t	-2.52*	-2.17*	-2.18	-1.68	-2.3***	-2.03***
Y_t	-2.43***	-2.08***	-2.63**	-2.03**	-1.81***	-1.45***
ΔY_t		-5.29***		-4.82***		-5.14***

Table 5.6: . Johansen (1991) Tests for the Existence of Cointegrating Vectors: January 2008 - December 2012

This table presents test results for the existence of cointegration vectors using Johansen (1991) trace test. Adjusted trace statistics adjust for small sample size as suggested in Ahn and Reinsel (1990). P-values are calculated according to the approximation method proposed by Doornik (1998). Significance: '***' 0.001, '**' 0.01, '*' 0.05.

	Restricted Supply, Jan 2008 - Jul 2010			Unrestricted Supply, Aug 2010 - Dec 2012		
Cointegrating Rank, r	0	1	2	0	1	2
Trace Statistics	33.78***	16.51***	6.36	54.77***	16.42***	4.71
Trace Statistics, adjusted	27.24**	13.31	5.13	44.17***	13.24**	3.8
10 % Critical Value	39.06	22.76	10.49	39.06	22.76	10.49
5 % Critical Value	42.44	25.32	12.25	42.44	25.32	12.25
1 % Critical Value	48.45	30.45	16.26	48.45	30.45	16.26
Number of observations	31			29		
Lags	2			2		

Chapter 6

Transmission of Foreign Monetary Policy Shocks Under Structural Instability: Case of Russia

6.1 Introduction

This chapter studies inward transmission of foreign monetary policy shocks to an open economy using an unbalanced panel of bank-level data augmented with macroeconomic time series. Specifically, we study how monetary policy shocks in a systemic economy such as the U.S. affect lending of domestic banks to private non-financial borrowers in Russia. We adopt a standard definition of a monetary policy shocks, which is a change in the monetary policy stance that was unanticipated by economic agents (Gali (2015); Christiano et al. (1999)).

U.S. monetary policy shocks are estimated in a structural vector autoregression (SVAR) framework using a high-frequency identification (HFI) procedure with monetary surprises as external instruments (Gertler and Karadi (2015)). Monetary surprises are defined as changes in the price of a futures contract on an interest rate within 30-minute window surrounding a U.S. monetary policy announcement.

Literature on monetary policy transmission generally distinguish between two main channels through which banks respond to change in the monetary policy stance: bank lending (Bernanke and Blinder (1988);

Disyatat (2011)) and portfolio channels (Bernanke and Gertler (1995)). A special issue of the Journal of International Money and Finance (Buch et al. (2017)) provides an overview of literature on channels of monetary transmission and states that transmission channels are much richer as there is no single balance sheet item or bank characteristics that determines how banks respond to shocks. In reality adjustment to shocks depends on the frictions that banks are facing. We focus on two specific channels of transmission that reflect a friction in bank's ability to access alternative source of funding: one related to cross-border liabilities of domestic banks and the other to liquid asset holdings. We exploit heterogeneity across banks to identify and estimate the dynamic effect of foreign monetary policy shocks on domestic lending. The heterogeneity implies that the effect of a shock of certain size is likely to be different for different institutions depending on their exposure to cross-border funding and liquid asset holdings. Credit growth of banks with a greater share of foreign funding in liabilities should be be more sensitive to foreign monetary shocks compared with institutions that rely mainly on domestic sources of funds. Similarly, banks with a greater share of liquid assets in total assets should be better insulated from foreign monetary policy shocks causing the response of their credit growth to be more muted. The time period covered by our data, 2000Ql through 2018Ql, features the transition from one domestic monetary policy regime to another, namely, from exchange rate targeting (or exchange rate band) to inflation targeting, and this transition was finalized in November 2014.

Monetary policy trilemma hypothesis outlined by Mundell (1963) implies that, assuming free movement of capital across borders, the domestic economy should be more insulated from foreign monetary policy shocks when its currency free-floats than when it is fixed. Specifically, the intensity of transmission of external monetary shocks should be attenuated. Empirical studies have found support for insulation of foreign shocks under flexible exchange rate. Hausman and Wangswan (2011) find that equity indexes and interest rates in countries with a less flexible exchange rate regime respond more to U.S. monetary policy surprises. Obstfeld et al. (2018) provide evidence on a sample of 43 emerging countries that the spillovers of global financial shocks are amplified for economies with fixed exchange rates as compared to those who have relatively flexible exchange rates. In contrast, Rey (2015) suggests that "cross-border flows and leverage of global institutions transmit monetary conditions globally, even under floating exchange-rate regimes." In other words "Large gross cross-border flows are moving in tandem across countries regardless of the exchange rate regime..." (Passari and Rey (2015)). Thus global financial cycle transforms the trilemma into an "irreconcilable duo," making exchange rate regime superfluous. So when capital is freely mobile the role of exchange rate regime in insulating monetary autonomy is quite limited. As for empirical support, Rey (2015) emphasises that "U.S. monetary policy shocks transmit internationally and affect financial conditions even in inflation-targeting economies with large financial markets. Hence, flexible exchange rates are not enough to guarantee monetary autonomy in a world of large capital flows." The above-mentioned feature of our data allows us to track how (if any) the effect of U.S. shocks on domestic credit growth in Russia has changed as long as the domestic monetary policy regime has gradually switched from one to another.

Our empirical findings suggest that the inward transmission of foreign monetary policy shocks is seen in the data. The lending of Russian bank that rely on foreign funding is more responsive to U.S. monetary shocks with contractionary shocks having a negative effect on the growth of credit. This effect, which is both statistically and economically significant, is born entirely by dollar-denominated loans to domestic borrowers with lending in rubles remaining unaffected. Surprisingly, this effect is found to be remarkably stable over time. As our rolling regressions show, the effect of foreign monetary shocks on domestic lending do not become more muted as long as the domestic monetary policy transits from exchange rate targeting toward inflation targeting.

The chapter is related to the literature on the international bank lending channel of monetary policy transmission and international spillovers of monetary policy from systemic economies. Using aggregate data, Bruno and Shin (2015) document that a loosening of U.S. monetary policy gives rise to higher leverage of global financial institutions, flow of capital from center economies to the periphery, lower risk aversion and more risk taking. Morais et al. (2015) use credit registry data from Mexico matched with information banks and borrowers. They find that following a monetary policy in a foreign country affiliates of banks headquartered in that country expand the volume of credit to Mexican firms and tend to make riskier loans. This study also implies that, due to certain market frictions, domestic and foreign funding sources are only imperfectly substitutable in the short run. For this reason and following the literature (surveyed, e.g., in Buch et al. (2017) , we view the currency composition of funding as predetermined, at least, at a four-quarter horizon. Using bank-level data, Correa and Murry (2009) report that a monetary tightening in the U.S. by 100 p.p. leads to a reduction in cross-border claims of U.S. banks by 4 percent, which is consistent with the existence of the international bank lending channel. Cetorelli and Goldberg (2012) show that a monetary tightening in the U.S. triggers reallocations of funds from foreign affiliates of U.S. banks towards headquarters through internal capital markets, thus propagating the U.S. monetary shock internationally. Temesvary et al. (2015) find strong cross-border effects of changes in the U.S. monetary policy on lending by affiliates of U.S. banks, both before and after the most recent financial crisis. Correa et al. (2015) employ a BIS multi-country bilateral panel dataset and show that, in response a monetary tightening at home, U.S. banks re-allocate their cross-border claims towards safer destinations.

The chapter studies the international from a host country perspective. It was written as the Bank of Russia's research team contribution to the International Banking Research Network (IBRN) initiative on the international transmission of monetary policy (Buch et al. (2017)). It contributes in the existing literature on international monetary policy spillovers in two ways. First, most of empirical studies exploiting bank-level data we are aware of measure monetary policy shocks as first-differences of the U.S. short-term policy rate or a shadow policy rate. Unlike them, we use a novel high-frequency identification approach (Gertler and Karadi (2015)). Second, we are not aware of a study addressing how international monetary transmission transforms when domestic monetary policy in a given country changes from one regime (exchange rate targeting) to another (inflation targeting). All empirical papers that we are familiar with and that address international transmission typically emphasize a distinct reaction to external monetary shocks between two subsets of countries, peggers and floaters. In this chapter, instead, we look at how (if any) a specific channel of international transmission was reshaped with a change of the domestic monetary policy regime within borders of the same country.

The remainder of the chapter is organized as follows. Section 2 explains how we identify U.S. monetary shocks and set up our regressions. Section 3 describes the data we use. Section 4 reports empirical findings. Section 5 offers a discussion of our results, and Section 6 concludes.

6.2 Methodology

In order to estimate the dynamic effect of shocks in the U.S. monetary policy on credit growth in Russia, we employ a panel data regression with bank and time fixed effects, and bank controls. Regressors of interest are a distributed lag of the U.S. monetary policy shock interacted with a bank-level variable that is related to a specific channel of transmission of U.S. monetary shocks to Russian economy. We consider two such variables, the ratio of all foreign liabilities to total assets and the ratio of liquid assets to total assets. In what follows we refer to these variables as channel variables and label them, respectively, as nonres and liquid. The U.S. monetary shock is identified in a structural vector autoregression framework (SVAR) using a high-frequency identification (HFI) procedure of Gertler and Karadi (2015). Subsection 2.1 lays out details of this identification method. Subsection 2.2 describes our fixed-effect panel data regression specification.

6.2.1 Identification of U.S. monetary policy shocks

U.S. monetary shocks are identified in a SVAR framework, which is similar to Gertler and Karadi (2015). The VAR model contains four variables for the U.S.: consumer price index, industrial production, one-year interest rate on government bonds, and the excess bond premium (EBP) developed by Gilchrist and Zakrajsek (2012). The EBP is a credit spread, the difference in the yield of corporate bonds and government bonds with the same term to maturity net of the probability of default on the corporate bond. As Gilchrist and Zakrajsek (2012) document, this variable features a well-pronounced cyclical behavior and predicts well future economic activity. Together with one-year rate on government bonds, the EBP characterizes the cost of debt finance for private firms. The reduced-form four-variable VAR estimated on quarterly data. The order of the SVAR is set equal to 4, which is a conventional choice in the literature when data is quarterly.

The high-frequency identification (HFI) method of Gertler and Karadi (2015) employs data on so-called monetary surprises as external instruments for the identification of monetary policy shocks. This is a special case of a more general external instrument approach developed by Mertens and Ravn (2013) and Stock and Watson (2012). The idea behind the external instrument method is simple and appealing. Suppose that there is some imperfect proxy for a structural shock of interest. Gertler and Karadi (2015) use various series of monetary surprises as such a proxy. A monetary surprise is measured as a change in the price of a futures contract on an interest rate within a narrow (10-minuts before and 20-minutes after) window surrounding a time of interest rate decision announcement by the U.S. Federal Open Market Committee or any other watched-out monetary policy event. The identifying assumption is that during this narrow window a monetary policy announcement is the only development that occurs in the macroeconomic environment, with everything else remaining unchanged. It follows that a systematic component of the monetary surprise, i.e.

one that is related to the exogenous change in monetary policy and is free of any noise due to market over- or underreaction, can be interpreted as a monetary policy shock. For each variable, its VAR innovation, which is a residual from an OLS regression of this variable on its own lags and lags of all other variables, is a surprise change that cannot be forecast by past information. Macroeconomic theory considers all unforeseeable developments in the environment as driven by structural shocks of different nature, i.e. exogenous shifts in preferences, technology, or economic policy, one of them being a monetary policy shock. It follows that a reduced-form VAR innovation should be a mixture of structural structural shocks. If a VAR contains a sufficient number of variables, then the space of VAR innovations should span the space of structural shocks. To the extent that the monetary shocks is the only structural shock that gives rise to a monetary surprise, an OLS projection of the monetary surprise on the space of VAR innovations, which spans the space of structural shocks, should isolate the structural monetary shock from noise. In practice, the monetary policy shock is identified as the predicted value from an OLS regression of a VAR innovation for a monetary policy indicator (one- or two-year interest rate on government bonds in Gertler and Karadi (2015) on a monetary surprise.

Following Gertler and Karadi (2015), we use monetary surprises on five different interest rate derivatives: a current-month futures on the federal funds rate (labeled as MP1), a three month-ahead futures on the federal funds rate (FF4), and six month, nine month, and a year ahead futures on three month Eurodollar deposits (ED2, ED3, and ED4, respectively). For each derivative contract, all individual monetary surprises are aggregated to the quarterly frequency.

On the language of instrumental variable estimation, the OLS regression of the interest rate innovation on a monetary surprise is called a first-stage regression of an endogenous regressor, the interest rate, on an instrumental variable, a monetary surprise. It is well understood that standard methods of statistical inference cannot be applied when instruments are weakly correlated with the instrumented endogenous regressor. As a screening device, Stock et al. (2002) suggest using a threshold of 10 for the F-statistic that tests the null hypothesis that in population all instrumental variables in the first-stage regression are jointly insignificant. We applied this method to the five candidate instrumental variables and found that only two of them were strong instruments, MP1 and FF4, with first-stage F-statistics being 17.3 and 15.8, respectively. Our baseline regressions therefore employ U.S. monetary policy shocks identified with three different sets

Table 6.1: Description of variables

Name	Description
	Dependent Variables
all loans	Growth rate of all loans to nonfinancial borrowers, % per quarter
ruble loans	Growth rate of ruble loans to nonfinancial borrowers, % per quarter
dollar loans	Growth rate of dollar loans to nonfinancial borrowers, % per quarter
	Channel Variables
nonres	Ratio of liabilities to nonresidents to total assets, %
liquid	Ratio of liquid assets to total assets, %
	Foreign Monetary Policy Variables
us	US monetary policy (MP) shock, percentage points
	Bank control Variables
leverage	Ratio of capital to assets, %
core	Ratio of core deposits to total liabilities, %
ta	Log real total assets, constant

of external instruments: (i) MP1, (ii) FF4, and (iii) MPl and FF4.

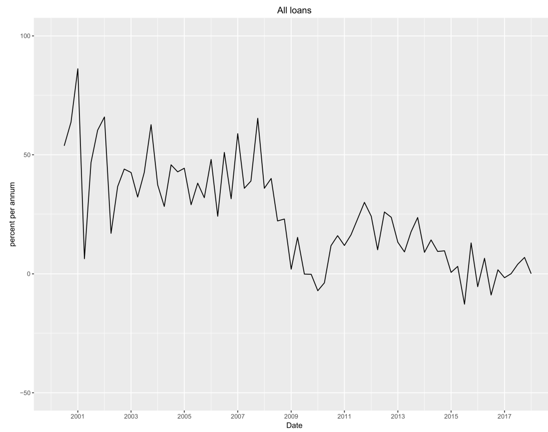
6.2.2 Econometric specification

Our econometric specification is a fixed effects panel data regression. The dependent variables is the quarterly growth rate of loans granted by a bank to private non-financial borrowers. We run separate regressions for (i) loans denominated in all currencies, (ii) ruble denominated loans, and (iii) dollar-denominated loans. The regressors of interest are a contemporaneous value of the identified U.S. monetary policy shock along with its three lags, all interacted with the fourth lag of a channel variable. We consider two alternative channel variables separately. These are (i) the ratio of foreign liabilities of a bank to its total assets and (ii) the ratio of liquid assets to total assets.

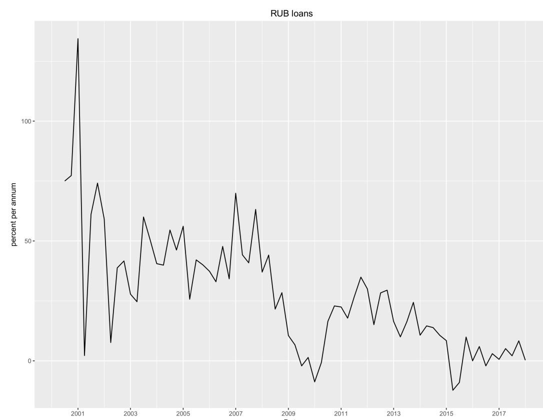
Some specifications also include bank-level control variables: log of total real assets, the ratio of core deposits to total assets, and (the reciprocal of) the leverage ratio defined as the ratio of banks tier 1 capital to total assets.

The effect of time-invariant factors at the bank level is captured by bank fixed effects u_i. The effect of time-varying factors that affect all banks uniformly is captured by time fixed effects Vt· These factors potentially include domestic and foreign levels of economic activity, risk appetite of international investors, etc. The interactions of contemporaneous and lagged foreign monetary policy shocks with lagged channel

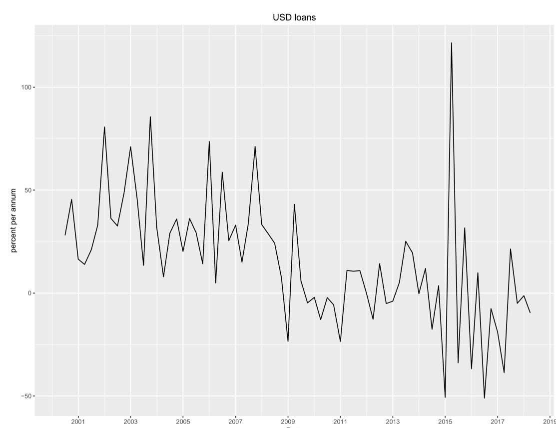
Figure 6.1: Quarterly Loan Growth in Russia



(a) All Loans



(b) Ruble-Denominated Loans



(c) Dollar-Denominated Loans

variables capture the idea that the dynamic effect of U.S. monetary policy can be heterogeneous across banks. For example, institutions that rely on external funding to a greater extent than their peers are likely to cut their lending more intensively in response to monetary tightening in the U.S.

The fixed-effects panel regression specification is thus given by

$$\text{loans}_{\,i,t} = \sum_{k=0}^{3} \alpha_k \,\text{channel}_{\,i,t-4}\,\text{us}_{\,t-k} + \beta\,\text{channel}_{\,i,t-4} + \gamma_1\,\text{ta}_{\,i,t-1} \tag{6.1}$$

$$+ \gamma_2\,\text{tier}_{\,i,t-1} + \gamma_3\,\text{cor}_{\,i,t-1} + u_i + v_t + e_{it} \tag{6.2}$$

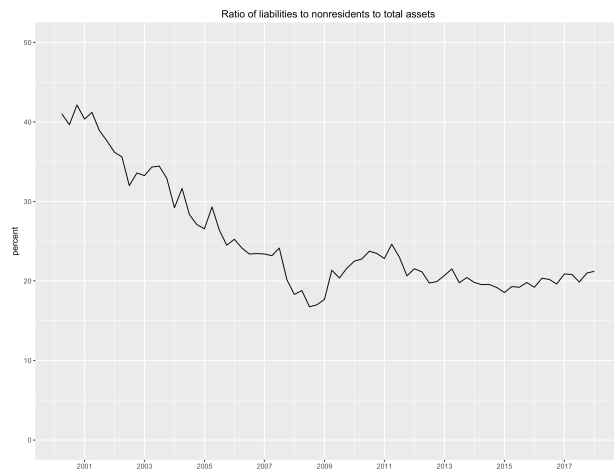
where $\text{loans}_{\,i,t}$ is either all, ruble, or dollar, and channel is either nonres or liquid. As specification (1) implies, channel variables enter the regression with lag 4. This is motivated by the intention to estimate the dynamic effect of foreign monetary policy shocks given the exposure of a bank to cross-border financial flows or its buffer of liquid assets just before the arrival of the shock. In general, both channel variables are endogenous and will therefore respond to a monetary shock in the U.S. Taking predetermined, namely, date $t-4$, values of this variables should make OLS estimates of the coefficients of interest - those on the distributed lag of the U.S. monetary policy shock interacted with a lagged channel variable - free of a simultaneity bias.

We estimated four versions of specification (1). Two of them included bank-level controls, two others did not. We also experimented with dropping bank-level fixed effects to see if the point estimates of the effects of interest change substantially. The specification with no bank-level fixed effects is motivated by a well-known fact that entity (group) fixed effects tend to exacerbate the bias caused by a measurement error in regressors (Wooldridge (2010), p. 365). The regressors of interest in our study are interactions of the distributed lag of the estimated U.S. monetary policy shock and predetermined channel variables, nonres and liquid. Potentially, both terms in the interactions are subject to a measurement error. When estimating regressions (1), the standard errors are clustered at the bank level in order to account for serial correlation in the idiosyncratic error term e_{it}.

In our study we also address three important structural changes in macroeconomic environment that occurred after 2014. First, in November 2014 the Bank of Russia announced that the transition from one monetary policy regime to another, namely, from exchange rate targeting to inflation targeting, which had

Figure 6.2: Transmission Channel Variables

(a) Aggregate Foreign-Liabilities-To-Assets Ratio

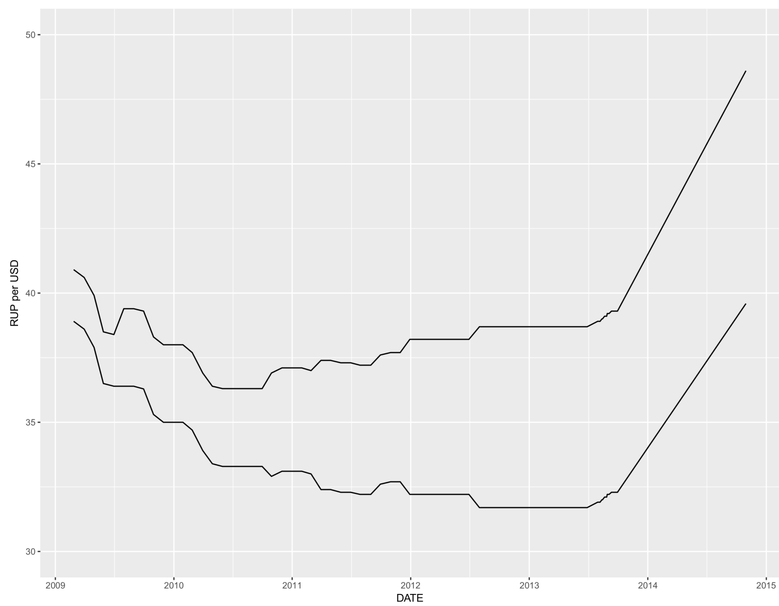


(b) Aggregate Liquid-To-Total-Assets Ratio

taken several years, was finally completed. As a result, the target band for the exchange rate was removed so that the ruble was allowed to free-float, with CB committed to intervene on the FX market only occasionally in times of extreme volatility. As a medium-term policy target, the Bank of Russia declared the rate of inflation 4% by the end of 2017. Figure 6.3 shows that there was a clear tendency for the target zone of the ruble exchange rate to widen over time. At the same time the upper and lower bounds of policy rates, which are, respectively, REPO (repurchase agreement) lending and borrowing (deposit) rates offered by the Bank of Russia to commercial banks, tended to converge, as Figure 6.4 illustrates.

Second, in the fall 2014, the price of oil, a major Russian exports commodity, on the world market

Figure 6.3: Target Zone For Ruble (Rubles Per US Dollar)
Source of data is Bank of Russia



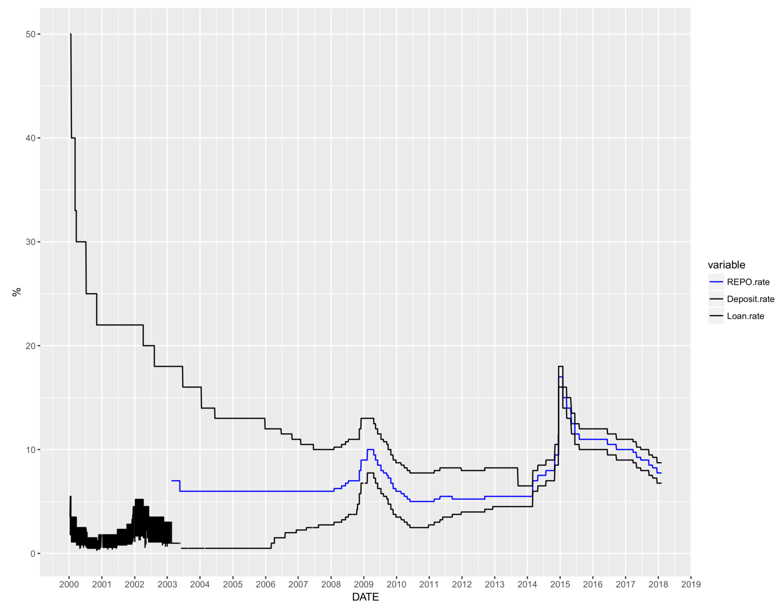
dropped dramatically from about USD 100 per barrel to below USD 40 per barrel. This abrupt decline was accompanied by growing uncertainty with regard to the future prospects for the price of oil.

Third, due to geopolitical factors, governments of the U.S. and European countries introduced financial sanctions against Russia. These sanctions were supposed to limit the access of Russian financial institutions to long-term funding from their U.S. and European counterparts.

In terms of potential effects on cross-border financial flows to Russia, all three events worked in the same direction. The financial sanctions directly affect availability of funding. To the extent that the price of oil is a main determinant of the ruble exchange rate, a rise in uncertainty surrounding the oil price increases foreign exchange risks and therefore makes external funding more costly, all other things being equal. Finally, letting the ruble to free float elevated implicit hedge against currency risks and passed on the entire responsibility for handling them on borrowers themselves.

Being specific to Russia, these three developments are likely to affect the international transmission mechanism of foreign monetary policy shocks to Russia. To capture potential changes in the mechanism, we estimated rolling-window versions of the baseline specification (1) setting the width of the rolling window equal to 43 quarters. The purpose was to see if the above-mentioned changes in the macro environment

Figure 6.4: Bank of Russia's Policy Rates
Source of data is Bank of Russia



affected the point estimates of the effects of interest. All three developments should presumably discourage domestic banks in Russia to borrow from abroad. Free-floating ruble raised foreign exchange risks associated with borrowing in foreign currency and lending in rubles domestically. If hedging opportunities are limited, then a likely consequence of that would be to reduce a currency mismatch between liabilities and loans by financial institutions, with dollar-denominated liabilities being mainly the source of funding for dollar-denominated loans to exporters whose sales revenues are denominated in dollars. The effect of changes in the U.S. monetary policy on lending by Russian banks with cross-border liabilities could become muted under the new policy regime, as a result.

The effect of uncertainty with regard to the future price of oil translates immediately into the uncertainty regarding the future exchange rate of the ruble. It should therefore reinforce the effect of the first development in the macro environment, namely, the finalized switch to inflation targeting resulting in potentially higher ruble exchange rate volatility. It is worth mentioning, though, that the empirical link between the price of oil and volatility of the ruble exchange rate became much weaker after adoption of a fiscal rule in 2017.

The effect of sanctions, in principle, works in the same direction as the effects of the two other factors.

The financial sanctions involved restrictions for U.S. and European financial institutions to do business with certain industries in Russia and also sat an upper limit of 90 days on the term to maturity for new loans.

6.2.3 Hypotheses of interest

In this study, we investigate if

(i) U.S. monetary policy shocks transmit to the economy of Russia;

(ii) if present, this transmission works through the foreign borrowing and/or liquid asset channels;

(iii) the transmission mechanism has changed or remains stable over time;

(iv) the structural change in the macroeconomic environment that occurred around 2014 attenuated the effect of U.S. monetary policy shocks on lending in Russia.

In the Section 4 we formally test statistical hypotheses related to research questions (i)-(iv).

To approach (i) and (ii), we look at the statistical significance of the four-quarter cumulative effect of the U.S. monetary shock interacted with the fourth lag of a transmission channel variable. This cumulative effect equals the sum of the coefficients of the distributed lag of the U.S. monetary policy shock interacted with a channel variable: $a_0 + a_1 + a_2 + a_3$ in the notation of equation (1).

To approach (iii) and (iv), we estimate rolling regressions (1) mentioned above with the time width equal to 32 quarters, or 8 years of observations. We then compare the estimated cumulative effect across all subintervals to see if this effect is stable over time or not and, if not, if there is a tendency for the effect to become less pronounced in subsamples that contain time observations for 2014 to 2017.

In all cases, when point estimates prove statistically significant, we pay attention to the sign of the estimated coefficient and check if it is consistent with theoretical predictions. We also make some simple calculations to figure out if the estimated effect is significant quantitatively.

6.3 Data

The dataset that we employ in this study consists of two parts: (a) a panel of supervisory bank-level data and (b) U.S. macroeconomic time series for SVAR that serves to estimate a time series of the U.S. monetary policy shock. The data are quarterly and cover the time period from the first quarter of 2000 through the first quarter of 2018.

The bank-level panel data come from obligatory reports that all commercial banks with operations in Russia are required to submit to the Bank of Russia every month. There are more than 700 banks in our dataset. During the period of our analysis a number of banks were reorganised via mergers and acquisitions. To deal with this issue we follow the traditional approach: if two banks merged at some point, we created a synthetic bank, as if both institutions had been a single entity for the entire sample period. More than that during the period under study the number of banks has decreased substantially not least because of enhancement of supervision policy in 2013. We dropped the last four quarters of observations that a bank had reported before its exit (due to a licence withdrawal) to clean the dataset from idiosyncratic business decisions that might distort our dataset.

The bank-level data include such variables as the growth rate of loans to resident private nonfinancial borrowers in rubles and in foreign currencies, the liabilities to nonresidents as a fraction of total assets (nonres), the ratio of liquid assets to total assets (liquid), total assets (ta), the inverse of the leverage ratio (leverage) defined as the ratio of tier-one capital to total assets and core deposits as a fraction of total assets (core). Balance sheet characteristics and channels of transmission are adjusted for outliers to ensure that large observations are not driving the results[1]. We eliminate valuation effects caused by exchange rate fluctuations from our bank-level variables. We do this in attempt to avoid substantial movements in our bank-level regressors that are uninformative from the perspective of our empirical exercise. For example, a sharp depreciation of the ruble such as one that occurred in December 2014 will reduce the dollar value of ruble-denominated balance sheet items producing a spurious spike in the ratio of cross-border liabilities to assets, a key bank-level variable in our study, even if the dollar value of cross-border liabilities remains unchanged. This spike obviously does not anything to do with a change in the composition of banks' funding sources. From the estimation perspective, noise in a regressor of interest (interacted with a distributed lag of foreign monetary policy shock) will be equivalent to measurement error in the regressor and, hence, bias estimated effect toward zero. In fixed-effect panel regressions, this bias is magnified (Wooldridge (2010), p. 365). To solve this issue, we convert all ruble denominated asset and liability items involved into

[1]We exclude observations where the value of the respective variable lies in the top 100 percentile or in the bottom 1 percentile of the sample distribution

construction of bank-level variables to U.S. dollars using the average exchange rate of the ruble against the U.S. dollar for the period under estimation. Foreign currency denominated items are expressed in rubles in banks' financial statements. We converted them to U.S. dollars using the contemporaneous exchange rate of the ruble against U.S. dollar.

Figure 6.1 shows the time paths of sample averages for the growth rates of all loans, ruble-denominates loans, and dollar-denominated loans. Figure 6.2 shows time paths of sample averages for the two transmission channel variables that we employ in our study, $nonres$ and $liquid$.

Four U.S. macroeconomic time senes employed in the SVAR are index of industrial production (seasonally adjusted), the rate of CPI inflation (seasonally adjusted), the interest rate on one-year government bonds, and Gilchrist - Zakrajsek's excess bond premium (EBP). The first three series are taken from the online Federal Reserve Database (FRED - www. fred. org). The EBP data up to August 2016 is available from Simon Gilchrist's webpage. We extend the EBP series beyond August 2016 by recursively forecasting it one quarter ahead using the reduced-form VAR estimated on a subsample ending the third quarter of 2016. Data on external instruments MPl, FF4, ED2, ED3, and ED4 up to 2012 are taken from Peter Karadi's webpage. We updated these time series through the first quarter of 2018 using data from Bloomberg and dates of FOMC meetings from the website of the Federal Reserve Board.

6.4 Findings

6.4.1 Dynamic Effect of U.S. Monetary Policy Shocks on Domestic Lending Estimated on Full Sample

In this section we report our estimation results obtained on the full sample of observations, 2000Ql through 2018Ql. Tables C.2, C.3, and C.4 show estimated regressions for the foreign borrowing transmission channel whereas Tables C.5,C.6, and C.7 estimated regressions for the liquid asset channel.

All specifications contain a set of regressors of interest - contemporaneous and first three lags of the identified U.S. monetary policy shock, each interacted with the fourth lag of the channel variable. The channel variable enters all specifications as a control variables. Specifications (1) and (2) do not include any bank-level control variables in addition to the lagged channel variable whereas specifications (3) and (4) do include them. These additional controls are (i) the logarithm of a bank's total real assets, (ii) the inverse of leverage ratio defined as the tier one capital divided by total assets, and (iii) core deposit ratio defined as the volume of core deposits divided by total assets. Regressions (1) and (3) contain both time and bank fixed effects whereas regressions (2) and (4) only time fixed effects. Time fixed effects absorb the effect of all factors that change over time and affect all banks uniformly. Examples are the state of economic activity in Russia and the stance of domestic monetary policy. Bank fixed effects absorb the effect of bank-specific factors that vary across banks but remain constant over time.

Technically, bank fixed effects can be interpreted as bank-specific intercepts in the regression. The dependent variable is the growth rate of loan portfolios. It is not obvious if there are any time-invariant bank-specific factors that force loan portfolios of some banks to grow systematically faster than those of the others over eighteen years covered by our sample. Being agnostic, though, we report regressions with and without bank fixed effects.

Numbers in parentheses are standard errors clustered by the bank level. Each table contains three sections. The upper section shows estimation results for the U.S. monetary shock identified using MPl monetary surprises as an external instrument, the middle section the same for FF4 monetary surprises, and the bottom section the same for both MPl and FF4 monetary surprises serving as external instruments in SVAR. Regressions shown in Tables C.2 and C.5 have the quarterly growth of credit denominated in all currencies as the dependent variable, Tables C.3 and C.6 the growth of ruble-denominated credit, and Tables C.4 and C.7 the growth of dollar-denominated credit.

Regressions in Table C.2 provide some evidence in support of the operativeness of the foreign borrowing channel of transmission. For quite a few specifications, the sign of estimated coefficients on the regressors of interest is consistent with theoretical predictions. The estimates suggest that the effect of monetary policy tightening in the U.S. is more negative for those banks that rely more heavily on cross-border financing as proxied by a higher fraction of liabilities to non-residents in total assets. In specifications (1) and (3) featuring bank fixed effects with U.S. monetary policy shocks identified using either FF4 only or MPl and FF4 monetary surprises, the three-quarter cumulative effect of the U.S. monetary shock has the expected negative sign and is statistically significant. For a bank with foreign liabilities equal to 6% of its total assets, which is the sample mean, a 0.5 p.p. contractionary monetary shock in the U.S. will decelerate the growth of its overall loan portfolio by about 0.5 x 0.35 x 6 1 p.p. per quarter, or by 4 p.p. per year. The effect is quite significant in economic terms.

Regressions reported in Tables C.3 and C.4 suggest that the effect on the reduction of overall lending is entirely driven by a decline in the growth of dollar-denominated loans. Neither specification in Table C.3 where the dependent variable is the quarterly growth in ruble-denominated loans produces a statistically significant effect. On the contrary, regressions in Table C.4 where the dependent variable is the growth rate of dollar-denominated loans yields highly statistically significant four-quarter cumulative effect of the U.S. monetary policy shock in specifications where the shock is identified using MP1 or MP1 cum FF4 monetary surprises. The effect is quantitatively large: the point estimate, depending on specification, lies in the range between -0.65 and -0.95, which is more than twice as large as the size of the cumulative effect on lending in all currencies. The midpoint of this interval suggests that a 0.5 p.p. contractionary monetary shock in the U.S. will cumulatively reduce the growth rate of dollar loans of a bank with the sample-mean value of foreign liabilities as percentage of total assets by 0.5 x 0.8 x 6 2.5 p.p. per quarter, or by 10 p.p. per year, which is huge compared with the sample-mean quarterly growth of dollar-denominated loans of merely 0.5% per quarter, or 2% per year.

Regressions in Tables C.5, C.6, and C.7 look into the working of the liquid asset channel. Neither specification in these tables features a statistically significant (at conventional significance levels) point estimate of the cumulative effect of the U.S. monetary policy shock interacted with predetermined liquid-to-total asset ratio. This implies that the strength of the effect of exogenous monetary disturbance in the U.S. on lending by a bank does not depend on its liquid asset holdings.

6.4.2 Alternative proxies for the U.S. monetary policy shock

Along with U.S. monetary policy shocks identified in a SVAR framework with monetary surprises as external instruments, we also consider a set of alternative proxies for the U.S. monetary policy shock. First, we employ monetary surprises themselves as direct measurements of monetary policy shocks. A similar approach was taken in Gurkaynak et al. (2005). Second, we try quarterly changes of the shadow policy rate derived in Wu and Xia (2013) as a proxy for the U.S. monetary policy shock. The shadow policy rate is backed out from the data on the term structure of interest rates using a conventional theoretical affine model of term structure. Third, we consider quarterly changes in one-, five-, and ten-year U.S. Treasury bonds as proxies for the U.S. monetary policy shock. Our choice of first-differenced interest rates is due to the observation that, from the practical point of view, Russia is a small open economy, which takes international prices, including interest rates in systemic economies, as given. We re-do the analysis for each alternative proxy separately using specification (3) in Table C.2 to C.7 that features bank controls and bank and time fixed effects. Tables C.8 and C.9 report four-quarter cumulative effects of U.S. monetary shocks interacted with a transmission channel variable for the foreign borrowing and liquid asset channels, respectively.

Regressions shown in Table C.8 reveal two patterns in the data. First, first-differenced interest rates do not yield any statistically significant effects. Second, monetary surprises as shock proxies produce statistically significant estimated cumulative effects of a negative sign, which is consistent with theoretical predictions. What is less clear is why the size of the estimated effect increases with the maturity term of a related futures contract. It is also remarkable that the futures contracts on the Eurodollar deposits that proved to be weak instruments in our SVAR framework produce statistically significant effects for the growth in loans denominated in all currencies and, especially, in dollar-denominated loans. Overall, we take the evidence reported in Table C.8 as an important robustness check for our main findings reported in the previous subsection.

Table C.9 shows similar regressions for the liquid asset transmission channel. Only Wu - Xia shadow policy rate is significant at the conventional level in the specification with all denomination loans as dependent variable. Its sign is counterinutitive, however: the more liquid assets has a bank on its balance sheet, the more it cuts on lending in all currencies in response to a contractionary monetary shock in the U.S. Furthermore, the cumulative effect looses its statistical significance and becomes less sizable if we turn the the specification with either ruble-denominated or dollar-denominated credit growth as dependent variable. We explain this pattern by peculiarity of data.

6.4.3 Change in Transmission Mechanism Over Time

We have established so far that the inward transmission of U.S. monetary shocks to bank lending in Russia works through the foreign liabilities channel: institutions with greater foreign-liabilities-to-assets ratios tend to cut more on their lending to private non-financial borrowers in response to a contractionary shock. This effect is produced exclusively by a reduction in dollar-denominated credit growth with no reaction from from the ruble-denominated credit growth. The liquid asset channel though is not operative: the effect of a monetary shock on lending does not depend on liquid asset holding of a bank on the eve of the arrival of the shock. We now investigate if the estimated cumulative through the foreign liabilities channel is stable over time.

To check time stability of the effect of interest, we estimate a series of rolling window regressions. We employ specification with dollar-denominated credit growth as dependent variable and foreign-liabilities-to-assets ratio as transmission channel variable featuring our set of bank controls as well as bank and time fixed effects, i.e. specification (3) in Table C.4. The rolling regressions are reported in Table C.10. The width of the rolling window is set to 41 quarter, with the earliest estimation subsample being 2000Ql:2010Ql and the latest estimation subsample 2008Ql-2018Ql. We repeat computations separately for different versions of the U.S. monetary policy shock identified with a different set of external instruments, namely, MP1, FF4, and MP1 cum FF4. The inspection of Table C.9 suggests that, up to 2017Ql, the cumulative effect of the U.S. shock interacted with the foreign-liabilities-to-assets ratio on dollar-denominated credit growth remains remarkably stable over time and across alternative identifications. It is always significant at 1% level in the case of MPl and MP1-cum-FF4 identifications whereas occasionally significant in the case of FF4 identification (recall that the this identification does not yield a statistically significant effect - see the middle section of Table C.4). Numerically, the point estimates of the cumulative effect lie, roughly speaking, between 1 and 1.5. To the extent that confidence intervals of substantially overlap across different estimation subsamples and identifications, the estimated effects are statistically indistinguishable among each other.

One reason why the estimated effect ceases to be stable once the estimation window is moved beyond 2007Ql-2017Ql is related to two specific deficiencies of our macro data. As mentioned in Section 3, the time series for the excess bond premium (EBP) is available only through 2016Q3. In order to be able to estimate our reduced-form VAR on the full sample, we had to extend this series through 2018Ql by forecasting EBP iteratively with the help of the same VAR. Given that our VAR contains only four variables, this exercise is likely to produce unwanted noise in the generated data and distort estimates of U.S. monetary policy shocks for dates that are close to the end of the sample. Another peculiarity of our data is due to data availability for monetary surprises. Up to 2015Ql, monetary surprises are computed based on a symmetric 30-minute window around a U.S. monetary policy announcement. For the rest of the sample, only daily data on the five interest rate futures contracts are available for us. We therefore had to extend the times series of quarterly aggregates of 30-minute surprises by quarterly aggregates of daily surprises for the period 2015Q4-2018Ql, which are presumably much noisier than daily surprises. To the extend that this subperiod has a substantial weight in estimation-window subsample close to the right end of the sample, the apparent loss of stability on subsamples ending in 2017Ql to 2018Ql might be a product of either or both of the two above-mentioned circumstances.

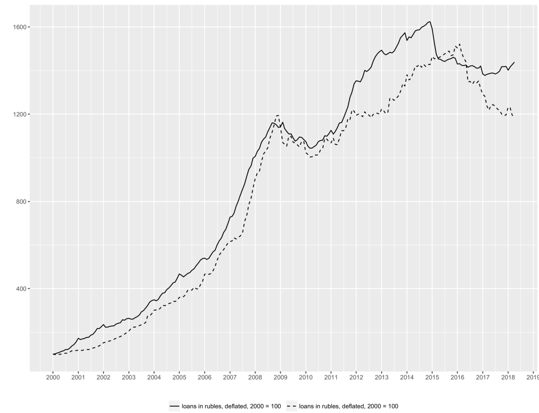
6.5 Discussion

We have documented several patterns in the data. First, monetary policy shocks in the U.S. transmit across borders to Russia affecting domestic lending by Russian banks to private non-financial borrowers. The effect is negative with contractionary shocks suppressing credit growth and quantitatively important. Second, it is dollar-denominated but not ruble-denominated loans that respond to U.S. monetary shocks. Third, the effect works through the foreign liability channel but not through the liquid asset channels. Loan portfolios of banks with a greater exposure to foreign borrowing are more sensitive to U.S. monetary shocks whereas the strength of the effect does not depend on the buffer of liquid assets held by a bank. Fourth, the effect proved to be remarkably stable over time despite the fact that the time period covered by our sample features a transition from one monetary policy regime, exchange rate targeting, to another, inflation targeting, turbulence on the world oil market, an important source of export revenue for the economy of Russia, and seismic geopolitical events. As we already mentioned, first two factors, in theory, should raise the degree of uncertainty and foreign exchange risk associated with borrowing in foreign currency and hence potentially attenuate the foreign liabilities transmission channel. This is not what we observe: the strength of this channel as measured by the four-quarter cumulative effect of the U.S. monetary shock interacted with lagged foreign-liabilities-to-assets ratio remains unchanged. The geopolitical factor brought about financial sanctions on Russian banks and therefore should have worked in the same direction, which is not something readily seen in the data. It is worth mentioning that, during 2015-2017, the Bank of Russia introduced a few macroprudential policies aiming to limit borrowing and lending in foreign currency. It raised substantially risk weights on foreign-currency-denominated loans to individuals and firms without sufficient exports revenues and also increased reserve requirements on foreign liabilities of Russian banks. These interventions should have reinforced the process of de-dollarization of bank assets and liabilities.

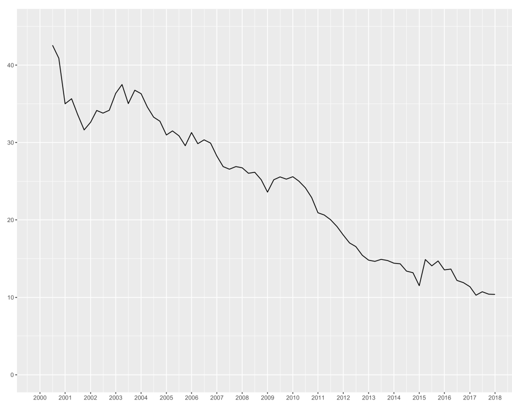
The documented empirical patterns have an important implication for economic policy: merely a more flexible exchange rate does not seem capable to insulate the economy from the Global Financial Cycle given the exposure of its financial sector to foreign capital market. One tendency that emerged in the data and accompanied the unfolding of the three above-mentioned factors along with macropru policy intervention has been a gradual decline in foreign borrowing as shown on the upper section of Figure 6.2. It is accompanied by a downward trend in dollar-denominated loans, both in absolute and relative terms, as shown on Figure 6.5. Unfortunately, our data do not allow us to answer the question which of the three factors contributed the most to this downward trend on the aggregate scale, the effect of the macropru policy also remaining unclear.

Another remarkable finding is unresponsiveness of ruble-denominated credit growth to monetary policy shocks in the U.S. A rise in the cost of funding in U.S. dollars as a consequence of a contractionary shock in the U.S. should encourage domestic borrowers in Russia switch from dollar-denominated loans, since they become more expensive, to ruble-denominated loans. We do not observe this to happen in the data as ruble-denominated credit growth remains unaffected, even for earlier estimation subsamples that correspond to a narrower target band for the exchange rate as Figure 6.4 illustrates. The lack of substitutability between dollar-denominated and ruble-denominated loans from the borrower's perspective seems puzzling. One possible interpretation is that borrowers are extremely averse with respect to foreign exchange risks whereas the opportunities for hedging them are limited. In this situation, exporters whose revenues are dollar-denominated would have a strong preference to borrow in U.S. dollars, while firms catering domestic market would prefer to borrow in rubles. It follows that a rise in the cost of U.S. dollar funding will make dollar-denominated loans more expensive discouraging exporters from borrowing in U.S. dollars, with or without financial sanctions being imposed. It is also conceivable that, being very risk averse, banks are willing to make dollar-denominated loans only to exporters while ruble-denominated loans only to non-exporters. It is not obvious though how appealing either interpretation is from the practical point of view.

Figure 6.5: Loans Denominated In Rubles And In U.S. Dollars



(a) Loans Denominated In Rubles (solid line) And In U.S. Dollars (dashed line)



(b) Share Of Loans Denominated In U.S. Dollars In Total Loans

(c) Loans Denominated In U.S. Dollars (solid line) and Foreign Liabilities (dashed line) As Fraction Of Total Assets

6.6 Conclusion

We study the inward transmission of foreign monetary policy shocks on lending by Russian banks to private non-financial borrowers. We find that, on the full sample, the transmission does occur through the cross-border liability channel: institutions with higher fraction of cross-border liabilities in total assets are more sensitive to U.S. monetary policy shocks than those that tap mainly domestic sources of funding. The effect is entirely due to the reaction of dollar-denominated loans with ruble-denominated loans being unresponsive. The cumulative dynamic effect tends to be remarkably stable over time as our rolling-window regressions demonstrate. This is surprising given the dramatic developments in macroeconomic environment that occurred after 2014, namely, finalized transition to from exchange rate to inflation targeting in Russia, turbulence in the oil market, and financial sanctions. One policy implication from our findings is that a free-floating currency regime might not be capable to insulate a small open economy from the influence of monetary policy shocks in systemic economies through the international lending channel. It follows that, to the extent that these shocks are a major driving force of the Global Financial Cycle, as documented, e.g., in Bruno and Shin (2015), domestic monetary policy has to bear a burden of curbing unwanted capital inflows, perhaps, in a combination with macroprudential policy. We leave for future research the question to what extent macroprudential policies are able to reshape the dynamic effect of foreign monetary shocks on domestic outcomes and thus insulate a small open market economy from the influence of the Global Financial Cycle.

Chapter 7

Conclusion

This thesis contributes to the understanding of how learning, derived from both primary and secondary sources, shapes financial and economic activities. The four essays presented offer a comprehensive exploration into how learning impacts investor behavior, market dynamics, and the transmission of foreign monetary policy shocks.

An essential revelation from this study is the way retail investors interact with and learn from the secondary information market, specifically through analyst reports and stock TV shows. It is discernible that more active information providers significantly influence retail investors, often leading to potential biases and distortions in their subjective expectations. Notably, it is these retail investors, often the most vulnerable, who heavily rely on secondary information markets.

The critical role of the secondary information market in influencing investor behavior and decision-making cannot be overstated. It not only frames the perception of retail investors but also potentially impacts their financial wellbeing. This finding accentuates the need for more in-depth studies into the operations and impacts of the secondary information market, which can, in turn, guide the development of protective measures, such as policy interventions or educational programs, for these vulnerable investors.

The three other essays in the thesis elaborate on how sophisticated investors and policy makers learn from primary data sources in diverse scenarios, be it through understanding pandemic-induced uncertainties, accumulating granular data from individual oil shipments, or scrutinizing micro-level cross-border activities. The intricate interplay of learning with investor behavior and market dynamics underpins the critical role of comprehensive and ongoing research in financial economics.

Future research could delve deeper into the evolving behaviors of retail investors and how modern technology might be shifting the balance between primary and secondary information usage. With my research highlighting the reliance of all investors on secondary information, especially among retail investors with lower income, the role of financial media comes into sharper focus. Understanding this landscape is essential for shaping regulatory policies, financial education initiatives, and market design to guide investors towards well-informed decision-making.

The focus of my upcoming research will be to study the effects of the artificial intelligence (AI) revolution on the information market. Specifically, I plan to explore how these changes influence the way retail investors learn and how it impacts their decision-making process regarding asset allocation. Recent studies have shown that AI-powered market information has the potential to improve the efficiency and performance of investment decision-making by providing investors with real-time market data and analytics. However, little research has been done on how this revolution in the market for information is affecting the learning and expectation formation of retail investors.

The urgency of the study is driven by the high weight of AI-powered information on markets for financial information. To explore the topic, I narrowed it to market of equity analytics and collected 14 days of analyst reports covering 3,787 US companies in December 2019 from the InvesText universe. Data shows that 80% of reports are written by 7 small information providers that employ AI information production technology, while remaining 20 % is composed of reports of traditional providers of financial expertise, such as banks and equity research firms. Given the high weight of AI technologies driving information production on financial markets, I ask the following questions. How does access to AI-powered market information affect the learning of retail investors? What is the impact of AI-powered market information on the asset allocation decisions of retail investors? How do individual characteristics, such as risk tolerance and financial literacy, moderate the relationship between AI-powered market information and the learning and asset allocation of retail investors? This study will provide valuable insights into how AI-powered market information is affecting the learning and decision-making processes of retail investors. The findings will inform the development of more effective investment education and guidance strategies for retail investors, especially those who are less familiar with AI technology. Furthermore, this research will contribute to the broader literature on the impact of technology on decision making and on investor behavior in the context of the market for information.

For my next research direction, I aim to explore how to balance bias and accuracy in financial markets. The introduction of large language models (LLMs) lowered the cost of producing biased information while increasing the cost of generating unbiased, factually accurate information. The cost of creating factually accurate and unbiased information goes up because investors have to sift through more and more biased information. This has the potential to lead to negative consequences for both investors and society as a whole, as truth might cease to exist in favor of opinion only. Given the magnitude of the LLM innovation, I ask the following questions. What are the mechanisms that can be used to align individual incentives within centralized and platform-based ecosystems to counterbalance the high costs of unbiased information? What are the value creation outcomes from AI-driven transformation on financial services markets, given the high costs of unbiased information? The findings from this research could be used to inform policy and decision-making in financial services markets, ultimately helping to promote truth and cooperation while minimizing misinformation.

In conclusion, this thesis collectively offers a broad and multifaceted understanding of how different types of information and learning methodologies inform and shape the dynamics of financial markets. It notably highlights the crucial role of secondary information markets, urging us to delve further into understanding its structure and implications, especially for the most vulnerable group of investors. The aim is to ensure that the processes and outcomes of learning in the financial markets are as equitable, efficient, and beneficial to all market participants as possible.

Bibliography

ACEMOGLU, D. AND A. SCOTT (1994): "Consumer confidence and rational expectations: Are agents' beliefs consistent with the theory?" *The Economic Journal*, 104, 1–19.

ACHARYA, V. V., L. A. LOCHSTOER, AND T. RAMADORAI (2013): "Limits to arbitrage and hedging: Evidence from commodity markets," *Journal of Financial Economics*, 109, 441–465.

ANDERSEN, T. G., T. BOLLERSLEV, F. X. DIEBOLD, AND C. VEGA (2003): "Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange," *American Economic Review*, 93, 38–62.

——— (2007): "Real-time price discovery in global stock, bond and foreign exchange markets," *Journal of International Economics*, 73, 251–277.

ANG, A. AND G. BEKAERT (2001): "Stock Return Predictability: Is It There?" *Review of Financial Studies*, 20, 651–707.

ANTWEILER, W. AND M. Z. FRANK (2004): "Is all that talk just noise? The information content of internet stock message boards," *The Journal of Finance*, 59, 1259–1294.

ARELLANO, C., Y. BAI, AND P. J. KEHOE (2019): "Financial Frictions and Fluctuations in Volatility," *Journal of Political Economy*, 127, 2049–2103.

BAE, K.-H. (1994): "Good news, bad news and international spillovers of stock return volatility between Japan and the US," *Pacific-Basin Finance Journal*, 2.

BAKER, M. AND J. WURGLER (2007): "Investor sentiment in the stock market," *Journal of Economic Perspectives*, 21, 129–152.

BAKER, S. R., N. BLOOM, AND S. J. DAVIS (2016): "Measuring Economic Policy Uncertainty*," *The Quarterly Journal of Economics*, 131, 1593–1636.

BAKER, S. R., N. BLOOM, S. J. DAVIS, AND S. J. TERRY (2020): "COVID-Induced Economic Uncertainty," Working Paper 26983, National Bureau of Economic Research.

BAKER, S. R. AND A. FRADKIN (2017): "The impact of unemployment insurance on job search: Evidence from Google search data," *The Review of Economics and Statistics*, 99, 756–768.

BALDUZZI, P., E. J. ELTON, AND T. C. GREEN (2001): "Economic News and Bond Prices: Evidence from the U.S. Treasury Market," *Journal of Financial and Quantitative Analysis*, 36, 523.

BANSAL, R., R. DITTMAR, AND D. KIKU (2007): "Cointegration and Consumption Risks in Asset Returns," Working paper, National Bureau of Economic Research.

BANSAL, R., R. F. DITTMAR, AND C. LUNDBLAD (2005): "Consumption, dividends, and the cross-section of equity returns," *Journal of Finance*, 60, 1639–1672.

BANSAL, R. AND A. YARON (2004): "Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles," *Journal of Finance*, 59, 1481–1509.

BARBER, B. M. AND T. ODEAN (2001): "Boys will be boys: Gender, overconfidence, and common stock investment," *The Quarterly Journal of Economics*, 116, 261–292.

BARBERIS, N. (2018): "Psychology-based models of asset prices and trading volume," *Handbook of Behavioral Economics*, 1, 79–128.

BARBERIS, N., A. SHLEIFER, AND R. VISHNY (1998): "A model of investor sentiment," *Journal of Financial Economics*, 49, 307–343.

BARSKY, R. B. AND E. R. SIMS (2012): "Information, animal spirits, and the meaning of innovations in consumer confidence," *American Economic Review*, 102, 1343–77.

BERK, J. B. AND R. C. GREEN (2004): "Mutual fund flows and performance in rational markets," *Journal of political economy*, 112, 1269–1295.

BERNANKE, B. AND A. BLINDER (1988): "Credit, Money, and Aggregate Demand," *American Economic Review Papers and Proceedings*, 78, 435–439.

BERNANKE, B. AND M. GERTLER (1995): "Inside the Black Box: The Credit Channel of Monetary Policy Transmission," *Journal of Economic Perspectives*, 9, 27–48.

BLOOM, N. (2014): "Fluctuations in uncertainty," *Journal of Economic Perspectives*, 28, 153–176.

BLOOM, N., M. FLOETOTTO, N. JAIMOVICH, I. SAPORTA-EKSTEN, AND S. J. TERRY (2018): "Really Uncertain Business Cycles," *Econometrica*, 86, 1031–1065.

BOGUTH, O., V. GRÉGOIRE, AND C. MARTINEAU (2019): "Shaping Expectations and Coordinating Attention: The Unintended Consequences of FOMC Press Conferences," *Journal of Financial and Quantitative Analysis*, 54, 2327–2353.

BOSSAERTS, P. AND P. HILLION (1999): "Implementing Statistical Criteria to Select Return Forecasting Models: What Do We Learn?" *Review of Financial Studies*, 12, 405–428.

BOUDOUKH, J., R. FELDMAN, S. KOGAN, AND M. RICHARDSON (2013): "Which news moves stock prices? A textual analysis," *NBER Working Paper No. w18725*.

BOX, G. E. AND G. M. JENKINS (1976): *Time Series Analysis: Forecasting and Control*, Holden-Day.

BOYD, J. H., J. HU, AND R. JAGANNATHAN (2005): "The Stock Market's Reaction to Unemployment News: Why Bad News Is Usually Good for Stocks," *Journal of Finance*, 60, 649–672.

BRAM, J. AND S. LUDVIGSON (1998): "Does consumer confidence forecast household expenditure? A sentiment index horse race," *Federal Reserve Bank of New York Economic Policy Review*, 4, 59–78.

BRENNAN, M. J., S.-W. HUH, AND A. SUBRAHMANYAM (2016): "Asymmetric effects of informed trading on the cost of equity capital," *Management Science*, 62, 2460–2480.

BRENNAN, M. J., N. JEGADEESH, AND B. SWAMINATHAN (1993): "Investment Analysis and the Adjustment of Stock Prices to Common Information," *The Review of Financial Studies*, 6, 799–824.

BRUNNERMEIER, M. K., A. SIMSEK, AND W. XIONG (2014): "A welfare criterion for models with distorted beliefs," *The Quarterly Journal of Economics*, 129, 1753–1797.

BRUNO, V. AND H. SHIN (2015): "Capital flows and the risk-taking channel of monetary policy," *Journal of Monetary Economics*, 71, 119–132.

BUCH, C., M. BUSSIERE, L. GOLDBERG, AND R. HILLS (2017): "The International Transmission of Monetary Policy," Working Paper, International Banking Research Network.

BUSHEE, B. J., J. E. CORE, W. GUAY, AND S. J. HAMM (2010): "The role of the business press as an information intermediary," *Journal of Accounting Research*, 48, 1–19.

CAMPBELL, J. Y. AND R. J. SHILLER (1988a): "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *The Review of Financial Studies*, 1, 195–228.

——— (1988b): "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies*, 1, 195–228.

——— (1988c): "Stock Prices, Earnings, and Expected Dividends," *The Journal of Finance*, 43, 661–676.

CARROLL, C. D., J. C. FUHRER, AND D. W. WILCOX (1994): "Does consumer sentiment forecast household spending? If so, why?" *American Economic Review*, 84, 1397–1408.

CETORELLI, N. AND L. GOLDBERG (2012): "Banking Globalization and Monetary Transmission," *Journal of Finance*, LXZII, 1811–1843.

CHEN, H., P. DE, Y. J. HU, AND B.-H. HWANG (2014): "Wisdom of crowds: The value of stock opinions transmitted through social media," *Review of Financial Studies*, 27, 1367–1403.

CHEN, N.-F., R. ROLL, AND S. ROSS (1986): "Economic Forces and the Stock Market," *Journal of Business*, 59, 383–403.

CHRISTIANO, L., M. EICHENBAUM, AND C. EVANS (1999): "Monetary Policy Shocks: What Have We Learned and to What End?" in *Handbook of Macroeconomics*, ed. by J. Taylor and M. Woodford, North-Holland: Elsevier.

CHRISTIANO, L. J., R. MOTTO, AND M. ROSTAGNO (2014): "Risk Shocks," *American Economic Review*, 104, 27–65.

CIESLAK, A., A. MORSE, AND A. VISSING-JORGENSEN (2019): "Stock Returns over the FOMC Cycle," *Journal of Finance*, 74, 2201–2248.

COCHRANE, J. H. (1991): "Production-Based Asset Pricing and the Link between Stock Returns and Economic Fluctuations," *Journal of Finance*, 46, 209–237.

——— (2006): "The Dog That Did Not Bark: A Defense of Return Predictability," *Review of Financial Studies*, 21, 1533–1575.

COHEN, L., C. J. MALLOY, AND L. POMORSKI (2012): "Decoding Inside Information," *The Journal of Finance*, 67, 1009–1043.

CORREA, R., T. PALIGOROVA, H. SAPRIZA, AND A. ZLATE (2015): "Cross-Border Bank Flows and Monetary Policy," Tech. rep., Federal Reserve Board of Governors.

CUTLER, D. M., J. M. POTERBA, AND L. H. SUMMERS (1989): "What moves stock prices?" *Journal of Portfolio Management*, 15, 4–12.

DANIEL, K., D. HIRSHLEIFER, AND A. SUBRAHMANYAM (1998): "Investor Psychology and Security Market Under- and Overreactions," *The Journal of Finance*, 53, 1839–1885.

DEATON, A. AND G. LAROQUE (1992): "On the behaviour of commodity prices," *The review of economic studies*, 59, 1–23.

——— (1996): "Competitive storage and commodity price dynamics," *Journal of Political Economy*, 104, 896–923.

——— (2003): "A model of commodity prices after Sir Arthur Lewis," *Journal of Development Economics*, 71, 289–310.

DEES, S. AND P. S. BRINCA (2011): "Consumer confidence as a predictor of consumption spending: Evidence for the United States and the Euro area," *International Economics*, 128, 1–14.

DING, W., H. JIANG, M. ALI, AND M. LI (2011): "Modern Advances in Intelligent Systems and Tools," .

DISYATAT, P. (2011): "The Bank Lending Channel Revisited," *Journal of Money, Credit, and Banking*, 43, 711–734.

DOR, A. B. AND C. ROSA (2019): "The Pre-FOMC Announcement Drift: An Empirical Analysis," *Journal of Fixed Income*, 28, 60–72.

DVIR, E. AND K. ROGOFF (2014): "Demand effects and speculation in oil markets: Theory and evidence," *Journal of International Money and Finance*, 42, 113–128.

DVIR, E. AND K. S. ROGOFF (2009): "Three epochs of oil," Tech. rep., National Bureau of Economic Research.

D'ACUNTO, F., M. WEBER, AND C. JIN (2019): "The Effect of Large Investors on Asset Quality: Evidence from Subprime Mortgage Securities," *The Journal of Finance*.

EATON, GREEN, R. AND WU (2021): "Social Media and the Stock Market: The Impact of Social Media on Retail Investors," .

ELLIOTT, G., C. GRAHAM, T. J. ROTHENBERG, AND J. H. STOCK (1996): "Efficient Tests For An Autoregressive Unit Root," *Econometrica*, 64, 813–836.

ENGLE, R. F. AND C. W. GRANGER (1987): "Co-Integration and Error Correction: Representation, Estimation, and Testing," *Econometrica*, 55, 251–276.

ERIC, A. (2016): "Why oil speculators are turning to ships as floating storage," *The Globe and Mail*.

ERNST, R., T. GILBERT, AND C. M. HRDLICKA (2021): "More Than 100% of the Equity Premium: How Much Is Really Earned on Macroeconomic Announcement Days?" *Working Paper*.

FAMA, E. F. AND K. R. FRENCH (1988): "Dividend Yields and Expected Stock Returns," *Journal of Financial Economics*, 22, 3–25.

FEDYK, A. (2015): "How to Exploit Noise Traders: A Framework for Institutional Investors," *Working Paper*.

FERSON, W. E., S. SARKISSIAN, AND T. T. SIMIN (2003): "Spurious Regressions in Financial Economics?" *Journal of Finance*, 58, 1393–1413.

FISHMAN, A. AND K. M. HAGERTY (2019): "The impact of news on stock prices," .

FRANKEL, J. A. (2014): "Effects of speculation and interest rates in a "carry trade" model of commodity prices," *Journal of International Money and Finance*, 42, 88–112.

GALI, J. (2015): *Monetary Policy, Inflation, and the Business Cycle*, Princeton and Oxford: Princeton University Press, 2nd ed.

GERTLER, M. AND P. KARADI (2015): "Monetary Policy Surprises, Credit Costs, and Economic Activity," *American Economic Journal: Macroeconomics*, 7, 44–76.

GILCHRIST, S., J. W. SIM, AND E. ZAKRAJŠEK (2014): "Uncertainty, Financial Frictions, and Investment Dynamics," *NBER Working Papers*.

GILCHRIST, S. AND E. ZAKRAJSEK (2012): "Credit Spreads and Business Cycle Fluctuations," *American Economic Review*, 102, 1692–1720.

GOETZMANN, W. N., B. HUANG, AND N. ZHANG (2015): "Individual Investors and Financial Disclosure," *Journal of Finance*, 70, 167–207.

GOETZMANN, W. N. AND P. JORION (1993): "Testing the Predictive Power of Dividend Yields," *Journal of Finance*, 48, 663–679.

GORODNICHENKO, Y. AND M. WEBER (2016): "Are Sticky Prices Costly? Evidence from the Stock Market," *American Economic Review*, 106, 165–99.

GOYAL, A. AND I. WELCH (2003): "Predicting the Equity Premium With Dividend Ratios," *Management Science*, 49, 639–654.

——— (2004): "A Comprehensive Look at the Empirical Performance of Equity Premium Prediction," *Review of Financial Studies*, 21, 1455–1508.

GREENWOOD, R. AND A. SHLEIFER (2014): "Expectations of Returns and Expected Returns," *The Review of Financial Studies*, 27, 714–746.

GU, C., A. KUROV, AND M. H. WOLFE (2018): "Relief Rallies after FOMC Announcements as a Resolution of Uncertainty," *Journal of Empirical Finance*, 49, 1–18.

GUISO, L. AND T. JAPPELLI (2006): "Information acquisition and portfolio performance," *CEPR Discussion Paper No. DP5901*.

GURKAYNAK, R. S., B. SACK, AND E. T. SWANSON (2005): "Do Actions Speak Louder than Words? The Response of Asset Prices to Monetary Policy Actions and Statements," *International Journal of Central Banking*, 1, 55–93.

GÂRLEANU, N. AND L. H. PEDERSEN (2018): "Efficiently Inefficient Markets for Assets and Asset Management," *The Journal of Finance*, 73, 1663–1712.

HALIASSOS, M., M. C. J. VAN ROOIJ, AND J. K. WINTER (2016): "Financial literacy and financial behavior: Evidence from the Netherlands," *Journal of Financial Intermediation*, 24, 434–466.

HANSEN, L., J. HEATON, AND N. LI (2005): "Consumption strikes back?" Working paper, University of Chicago.

HANSEN, L. P. AND R. J. HODRICK (1980): "Forward Exchange Rates as Optimal Predictors of Future Spot Rates: An Econometric Analysis," *Journal of Political Economy*, 96, 829–853.

HARDOUVELIS, G. A. (1987): "Macroeconomic information and stock prices," *Journal of Economics and Business*, 39, 131–140.

HASSAN, T. A., S. HOLLANDER, L. VAN LENT, AND A. TAHOUN (2019): "Firm-Level Political Risk: Measurement and Effects," *Quarterly Journal of Economics*, 134, 2135–2202.

HASTINGS, J. S. AND L. TEJEDA-ASHTON (2008): "Financial Literacy, Information, and Demand Elasticity: Survey and Experimental Evidence from Mexico," *The Journal of Consumer Affairs*.

HAUSMAN, J. AND J. WANGSWAN (2011): "Global Asset Prices and FOMC Announcements," *International Journal of Money and Finance*, 547–571.

HELLWIG, M. F. (1980): "On the aggregation of information in competitive markets," *Journal of economic theory*, 22, 477–498.

HERSKOVIC, B., T. KIND, AND H. KUNG (2018): "Micro Uncertainty and Asset Prices," *Working Paper*.

HODRICK, R. J. (1992): "Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement," *Review of Financial Studies*, 5, 357–386.

HONG, H. AND J. D. KUBIK (2003): "Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts," *The Journal of Finance*, 58, 313–351.

HU, G. X., J. PAN, J. WANG, AND H. ZHU (2018): "Premium for Heightened Uncertainty: Solving the FOMC Puzzle," *NBER Working Papers*.

JEGADEESH, N. AND S. TITMAN (1993): "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *The Journal of Finance*, 48, 65–91.

JOHANSEN, S. (1988): "Statistical Analysis of Cointegration Vectors," *Journal of Economic Dynamics and Control*, 12, 231–254.

——— (1991): "Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models," *Econometrica: journal of the Econometric Society*, 1551–1580.

JOHANSEN, S., R. MOSCONI, AND B. NIELSEN (2000): "Cointegration analysis in the presence of structural breaks in the deterministic trend," *The Econometrics Journal*, 3, 216–249.

KILIAN, L. AND T. K. LEE (2014): "Quantifying the speculative component in the real price of oil: The role of global oil inventories," *Journal of International Money and Finance*, 42, 71–87.

KILIAN, L. AND D. P. MURPHY (2014): "The role of inventories and speculative trading in the global market for crude oil," *Journal of Applied econometrics*, 29, 454–478.

KIM, O. AND R. E. VERRECCHIA (1991): "Trading Volume and Price Reactions to Public Announcements," *Journal of Accounting Research*, 29, 302.

KLEPPE, T. S. AND A. OGLEND (2017): "Estimating the competitive storage model: A simulated likelihood approach," *Econometrics and statistics*, 4, 39–56.

KNITTEL, C. R. AND R. S. PINDYCK (2016): "The simple economics of commodity price speculation," *American Economic Journal: Macroeconomics*, 8, 85–110.

KOTHARI, S. (2001): "Capital markets research in accounting," *Journal of Accounting and Economics*, 31, 105–231.

KOZENIAUSKAS, N., A. ORLIK, AND L. VELDKAMP (2018): "What are uncertainty shocks?" *Journal of Monetary Economics*, 100, 1–15.

KUROV, A. AND R. STAN (2018): "Monetary policy uncertainty and the market reaction to macroeconomic news," *Journal of Banking & Finance*, 86, 127–142.

KUROV, A., M. H. WOLFE, AND T. GILBERT (2021): "The disappearing pre-FOMC announcement drift," *Finance Research Letters*, 40, 101781.

LEMMON, M. AND E. PORTNIAGUINA (2006): "Consumer confidence and asset prices: Some empirical evidence," *The Review of Financial Studies*, 19, 1499–1529.

LETTAU, M. AND S. LUDVIGSON (2001): "Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying," *Journal of Political Economy*, 109, 1238–1287.

LEWELLEN, J. (2004): "Predicting Returns with Financial Ratios," *Journal of Financial Economics*, 74, 209–235.

LIU, L., H. R. MOON, AND F. SCHORFHEIDE (2021): "Panel forecasts of country-level Covid-19 infections," *Journal of Econometrics*, 220, 2.

LOUGHRAN, T. AND B. MCDONALD (2016): "Textual Analysis in Accounting and Finance: A Survey," Available at SSRN: https://ssrn.com/abstract=2504147 or http://dx.doi.org/10.2139/ssrn.2504147.

LUCCA, D. O. AND E. MOENCH (2015): "The Pre-FOMC Announcement Drift," *Journal of Finance*, 70, 329–371.

LUDVIGSON, S. C. (2004): "Consumer confidence and consumer spending," *Journal of Economic Perspectives*, 18, 29–50.

LUSARDI, A. AND O. S. MITCHELL (2014): "The Economic Importance of Financial Literacy: Theory and Evidence," *Journal of Economic Literature*, 52, 5–44.

LUSTIG, H. AND S. VAN NIEUWERBURGH (2005): "Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective," *Journal of Finance*, 60, 1167–1219.

MALMENDIER, U. AND S. NAGEL (2011): "Title of the Paper," *Journal Name*, Page numbers.

MALMENDIER, U. AND D. SHANTHIKUMAR (2007): "Are Small Investors Naive About Incentives?" *Journal of Financial Economics*, 85, 457–489.

MANNING, C., M. SURDEANU, J. BAUER, J. FINKEL, S. BETHARD, AND D. MCCLOSKY (2014): "The Stanford CoreNLP Natural Language Processing Toolkit," in *Proceedings of 52nd Annual Meeting of the Association for Computational Linguistics: System Demonstrations*, Baltimore, Maryland: Association for Computational Linguistics, 55–60.

MATSUSAKA, J. G. AND A. M. SBORDONE (1995): "Consumer confidence and economic fluctuations," *Economic Inquiry*, 33, 296–318.

MCQUEEN, G. AND V. V. ROLEY (1993): "Stock Prices, News, and Business Conditions," *Review of Financial Studies*, 6, 683–707.

MENZLY, L., T. SANTOS, AND P. VERONESI (2004): "Understanding Predictability," *Journal of Political Economy*, 112, 1–47.

MERTENS, K. AND M. O. RAVN (2013): "The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States," *American Economic Review*, 103, 1212–1247.

MORAIS, B., J. PEYDRO, AND C. RMZ (2015): “The International Bank Lending Channel of Monetary Policy Rates and QE: Credit Supply, Reach for Yield, and Real Effects,” International Finance Discussion Paper 1137, Federal Reserve.

MOSKOWITZ, T. J. AND M. GRINBLATT (1999): “Do Industries Explain Momentum?” *The Journal of Finance*, 54, 1249–1290.

MUNDELL, R. A. (1963): “Capital Mobility and Stabilization Policy under Fixed and Flexible Exchange Rates,” *Canadian Journal of Economics and Political Science*, 29, 475–485.

MUTH, J. F. (1961): “Rational Expectations and the Theory of Price Movements,” *Econometrica*, 29, 315–335.

NAGEL, S. AND Z. XU (2019): “Asset Pricing with Fading Memory,” *The Review of Financial Studies*, 32, 4273–4313.

NELSON, C. R. AND M. J. KIM (1993): “Predictable Stock Returns: The Role of Small Sample Bias,” *Journal of Finance*, 48, 641–661.

NEUHIERL, A. AND M. WEBER (2019): “Monetary policy communication, policy slope, and the stock market,” *Journal of Monetary Economics*, 108, 140–155.

OBSTFELD, M., D. OSTRY, S. MAVASH, AND M. READ (2018): “A Tie That Binds: Revisiting the Trilemma in Emerging Market Economies Metrics,” *Review of Economics and Statistics*.

O’HARA, M. (1995): *Market Microstructure Theory*, Blackwell.

OZDAGLI, A. K. AND M. WEBER (2017): “Monetary Policy through Production Networks: Evidence from the Stock Market,” *NBER Working Papers*.

PANKRATZ, A. (1983): *Forecasting with Univariate Box-Jenkins Models: Concepts and Cases*, Wiley Series in Probability and Statistics, Wiley.

PARK, S. N., H. H. KIM, AND K. B. LEE (2021): “Inherently high uncertainty in predicting the time evolution of epidemics,” *Epidemiology and health*, 43.

PASSARI, E. AND H. REY (2015): "Financial Flows and the International Monetary System," *Economic Journal*, 125, 675–698.

PAYE, B. S. AND A. TIMMERMANN (2003): "Instability of Return Prediction Models," *Unpublished Manuscript*.

PEARCE, D. K. AND V. V. ROLEY (1985): "Stock Prices and Economic News," *Journal of Business*, 58, 49.

REY, H. (2015): "Dilemma Not Trilemma: The Global Financial Cycle and Monetary Policy Independence," Working Paper 21162, National Bureau of Economic Research.

RINKER, T. W. (2021): "sentimentr: Calculate Text Polarity Sentiment," Version 2.9.0.

ROLL, R. (1988): "R2," *Journal of Finance*, 43, 541–566.

ROUTLEDGE, B. R., D. J. SEPPI, AND C. S. SPATT (2000): "Equilibrium forward curves for commodities," *The Journal of Finance*, 55, 1297–1338.

SAVOR, P. AND M. WILSON (2013): "How Much Do Investors Care About Macroeconomic Risk? Evidence from Scheduled Economic Announcements," *Journal of Financial and Quantitative Analysis*, 48, 343–375.

SCHAAL, E. (2011): "Uncertainty, Productivity and Unemployment in the Great Depression," *2011 Meeting Papers from Society for Economic Dynamics*.

SCHWERT, G. W. (1981): "The Adjustment of Stock Prices to Information About Inflation," *Journal of Finance*, 36, 15.

——— (1988): "Tests For Unit Roots: A Monte Carlo Investigation," Working Paper 73, National Bureau of Economic Research.

SHEFRIN, H. (2008): *A Behavioral Approach to Asset Pricing*, Academic Press.

SHLEIFER, A. AND L. H. SUMMERS (1990): "The Noise Trader Approach to Finance," *Journal of Economic Perspectives*, 4, 19–33.

SHLEIFER, A. AND R. W. VISHNY (1997): "The limits of arbitrage," *The Journal of finance*, 52, 35–55.

SIMS, C. A. (1980): "Macroeconomics and Reality," *Econometrica*, 48, 1–48.

SIRIGNANO, J. AND R. CONT (2019): "Deep Learning for Mortgage Risk," *International Journal of Theoretical and Applied Finance*, 22, 1950006.

SOULELES, N. S. (2001): "Consumer sentiment and household expenditure," *Journal of the American Statistical Association*, 96, 1359–1367.

——— (2004): "Expectations, heterogeneous forecast errors, and consumption: Micro evidence from the Michigan Consumer Sentiment Surveys," *Journal of Money, Credit, and Banking*, 36, 39–72.

STAMBAUGH, R. F. (1999): "Predictive Regressions," *Journal of Financial Economics*, 54, 375–421.

STOCK, J. H. AND M. W. WATSON (1993): "A Simple Estimator of Cointegrating Vectors in Higher Order Integrated System," *Econometrica*, 61, 783–820.

——— (2012): "Disentangling the Channels of the 2007-2009 Recession," *Brookings Papers on Economic Activity*, 42, 81–135.

STOCK, J. H., J. H. WRIGHT, AND M. YOCO (2002): "A Survey of Weak Instruments and Weak Identification in Generalized Method of Moments," *Journal of Business and Economic Statistics*, 20, 518–529.

TEMESVARY, J., S. ONGENA, AND A. OWEN (2015): "Global Lending Channel Unplugged? Does US Monetary Policy Affect Cross-Border and Affiliate Lending by Global US Banks?" Mimeo.

TETLOCK, P. C. (2007): "Giving Content to Investor Sentiment: The Role of Media in the Stock Market," *The Journal of Finance*, 62, 1139–1168.

——— (2011): "All the news that's fit to reprint: Do investors react to stale information?" .

THROOP, A. W. (2010): "Consumer sentiment: its rationality and usefulness in forecasting expenditure—evidence from the Michigan micro data," Tech. rep., Federal Reserve Bank of San Francisco.

TODA, H. Y. AND P. C. PHILLIPS (1991): "Vector Autoregression and Causality: A Theoretical Overview and Simulation Study," Tech. Rep. 1244, Cowles Foundation Discussion Papers.

VALKANOV, R. (2003): “Long-Horizon Regressions: Theoretical Results and Applications,” *Journal of Financial Economics*, 68, 201–232.

VELDKAMP, L. L. (2005): “Information markets and the comovement of asset prices,” *The Review of Economic Studies*, 72, 823–845.

——— (2011): *Information Choice in Macroeconomics and Finance*, Princeton University Press.

VERONESI, P. (1999): “Stock Market Overreactions to Bad News in Good Times: A Rational Expectations Equilibrium Model,” *Review of Financial Studies*, 12, 975–1007.

VICEIRA, L. M. (1996): “Testing for Structural Change in the Predictability of Asset Returns,” *Unpublished Manuscript*.

VUOLTEENAHO, T. (2002): “What Drives Firm-Level Stock Returns?” *The Journal of Finance*, 57, 233–264.

WANKHADE, M., A. C. S. RAO, AND C. KULKARNI (2022): “A survey on sentiment analysis methods, applications, and challenges,” *Artificial Intelligence Review*, 55, 5731–5780.

WOLD, H. (1954): *A Study in the Analysis of Stationary Time Series*, Uppsala: Almqvist and Wiksell Book Co., 2 ed., with an Appendix on "Recent Developments in Time Series Analysis" by Peter Whittle.

WOOLDRIDGE, J. M. (2010): *Econometric Analysis of Cross Section and Panel Data*, MIT Press, 2 ed.

WU, J. C. AND F. D. XIA (2013): “Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound,” Working Paper 13-77, Chicago Booth.

ZIVOT, E. AND D. W. ANDREWS (1992): “Further Evidence on the Great Crash, the Oil-Price Shock, and the Unit-Root Hypothesis,” *Journal of Business & Economic Statistics*, 10, 251–270.

Chapter A

Appendix A

A.1 Data on Subjective Expectations

A.1.1 Conference Board. Consumer Confidence Survey

The Conference Board[1] runs Consumer Confidence Survey (CCS).

Sampling frame. The monthly survey uses an address-based mail sample design. The sampling frame is derived from the files created by the U.S. Postal Service, which represent near-universal coverage of all residential households in the United States. The CCS frame is updated monthly to ensure up-to-date coverage of U.S. households.

Sampling. The CCS uses a probability sample design to select each month's random sample from the household universe frame. The frame is first stratified geographically within the census division to provide a proportionate geographic distribution, after which a systematic sample of household addresses is selected. The sample addresses are then used for the mailing.

Sample size. About 3,500 surveys are completed each month. About 2,500 for end-of-month release; 3,500 for later revision.

[1] https://conference-board.org/data/consumerconfidence.cfm

Field period. The CCS mailing is scheduled so that the questionnaires reach sample households on or about the first of each month. Returns flow in throughout the collection period, with the sample close-out for preliminary estimates occurring around the eighteenth of the month. Any returns received after then are used to produce the final estimates for the month, which are published with the release of the following month's data. Completed questionnaires are checked in as they are received and then scheduled for data entry. Data fields are edited for invalid entries and, if necessary, are flagged for review. As part of the ongoing quality control process, a random sample of questionnaires is selected for independent review/validation by a senior member of the data collection staff. The targeted responding sample size - approximately 3,000 completed questionnaires - has remained essentially unchanged throughout the history of the CCS.

Fieldwork. The Nielsen Company[2].

Weighting. To improve the accuracy of the estimates and ensure the proportionate representation of key categories in the estimates, the CCS uses a post-stratification weighting structure covering the following categories: Census Division (9 Census divisions), Age of Head of Household (<30, 30-39, 40-49, 50-59, 60+), Gender of Head of Household (Male/Female), Income of Household (<15,000; 15,000-24,999; 25,000-34,999; 35,000-49,999; 50,000-74,999; 75,000-99,999; 100,000-124,999; 125,000+).

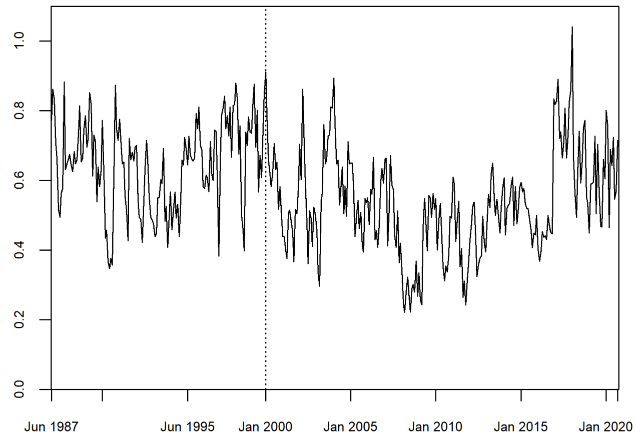
The post-stratification weighting uses an iterative proportional fitting technique for simultaneously balancing sample weights across several different population control groups. This technique ensures that sample-based estimates of the household population categories match the independent census population controls within +/- 1 percent.

Seasonal Adjustment. Data as of January 2011 use the Census X-12 seasonal adjustment software for the publication series where needed. Seasonal adjustment helps remove periodic seasonal fluctuations in the series due to events such as weather, holidays, and the beginning and end of the school year. While the

[2]As of February 2011, The Conference Board has changed survey providers from TNS to The Nielsen Company for ongoing CCS operational support. Nielsen uses a mail survey specifically designed for the Consumer Confidence Survey. The new design uses a probability-design random sample, poststratification weights (for gender, income, geography, and age), and the U.S. Census X-12 seasonal adjustment. The CCS concepts, questions and mail survey collection method remain unchanged.

From September 2010 to January 2011, a five-month pilot test of the new sample design was conducted in parallel with the existing design. Three months of previously published data (November 2010 to January 2011) have been restated to smooth the transition, which makes November 2010 the effective changeover month.

Figure A.1: Conference Board Index IND_t^{CB}, monthly: June 1987 - September 2020



CCS series are typically not highly seasonal, the X-12 software helps reduce any residual seasonality in the various data series.

Release. Preliminary figures are released on last Tuesday of month. Final figures are released with next month's release.

Questions about return expectation. The surveys elicit respondents simple categorical beliefs about whether the stock prices will likely increase, decrease, or stay the same (or whether they are undecided, which we include in the same category).

As per Nagel & Xu (2019), I construct the Index IND_t^{CB} as the ratio of those who respond with an increase to the sum of those who respond with a decrease or the same:

$$IND_t^{CB} = \frac{n_t^{increase}}{n_t^{decrease} + n_t^{same}} \tag{A.1}$$

A.1.2 Michigan Survey of Consumers

Sampling frame. The Michigan Survey of Consumers[3] is a monthly nationally representative survey based on approximately 500 telephone interviews with adult men and women living in households in the

[3] https://data.sca.isr.umich.edu/

coterminous United States (48 States plus the District of Columbia). The sample is designed as a rotating panel. For each monthly sample, an independent cross-section sample of households is drawn. The respondents chosen in this drawing are then reinterviewed six months later. A rotating panel design results, and the total sample for any one survey is normally made up of 60% new respondents, and 40% being interviewed for the second time. The MSC provides access to panel of individual monthly responses.

The MSC uses random digit dialing (RDD) telephone sampling to draw the monthly national probability sample. The specific RDD procedure used at the Survey Research Center (SRC) is a one-stage list-assisted design. The list-assisted sampling frame consists of all hundred series[4] which have at least one listed household number. The frame is produced by aggregating all directory-listed household telephone numbers to the hundred series level. These listed hundred series form a subset of approximately 40 percent of the total possible hundred series which can be formed from all Area Code/Exchanges in the Bellcore system. Each hundred series is associated with 100 possible phone numbers - which can be listed household, unlisted household, nonresidential, non-working or unassigned. Because of the way telephone numbers are assigned, a hundred series which has at least one listed household number is more likely to have other residential telephone numbers. Business numbers are often segregated in reserved hundred series and other hundred series are not used. While the incidence of working household numbers is about 22 percent in the set of all possible hundred series from the Bellcore Area Code/Exchanges, the incidence of working household numbers is about 50 percent in the set of listed hundred series.

Household telephone samples fail to include the approximately 6% of U.S. households that are not telephone subscribers, although the percentage of nonsubscribers is declining over time. Past analysis suggests that nonsubscribers are disproportionately poor, live in the rural areas, and are more likely to rent and live alone than the rest of the population. Current studies of the bias which results from the exclusion of non telephone subscribers indicate that it is not severe and probably is within the accuracy requirements for most, but not all, survey research projects.

Sampling. The monthly Survey of Consumers sample, which are selected from a list-assisted RDD frame using the GENESYS Sampling System, are stratified, one-stage, equal probability samples of telephone

[4]The term "hundred series" refers to the first eight digits of a phone number - the area code, exchange, and the first two digits of the remaining four numbers. One hundred possible phone numbers can be formed from each hundred series by adding the set of numbers "00" to "99" to create 10-digit phone numbers.

households in the contiguous United States (48 states and the District of Columbia). GENESYS uses the Donnelly Quality Index Database (100% Phone File) as the basis for its RDD sampling frame along with auxiliary files including the Bellcore file of valid area codes and exchanges.

The GENESYS list-assisted frame is stratified by geography and urbanicity. Explicit strata are formed by crossing Census Division by MSA/non-MSA status[5]. Within each MSA stratum, there is an ordering by size of MSA and within MSA by exchanges serving the county containing the central city, followed by those serving remaining non-central city counties; within non-MSA strata, exchanges are ordered geographically in a serpentine fashion within each Census Division. The GENESYS sampling frame is updated twice yearly. Area code changes are incorporated as needed between the semi-annual updates.

List-assisted RDD sample designs for telephone surveys differ from those for personal interview surveys in that selection probabilities are assigned on the basis of the number of possible phone numbers which can be formed from the set of listed hundred series in a defined group of area codes/ exchange codes rather than on population totals for geographic areas such as counties, cities, and blocks.

The list-assisted RDD design provides for an equal probability sample of all telephone households; within each household, probability methods are also used to select one adult as the designated respondent. At the time of the initial contact with the household, a listing is taken of all household members that are 18 or older. From this list of eligible respondents, a specific member of the household is selected by the interviewer using the "respondent selection table" assigned to that household's coversheet. These selection tables are assigned to households so that each adult has a known selection probability, across households of all sizes, as well as differences in age and sex composition. Giving each selected respondent a weight equal to the number of adults in the household would then transform the sample of households to a sample of the adult population.

Sample size. 250-300 for mid-month release. 500 for end-of-month revision.

Field period. Michigan conducts its survey by phone throughout most of the month. Final figures for the full sample are subsequently made available at the end of the month and are not subject to further revision.

[5]MSA is Metropolitan Statistical Areas. Definition can be found in https://www2.census.gov/geo/pdfs/reference/GARM/Ch13GARM.pdf

Fieldwork. Michigan Survey Research Center.

Weighting. Household head weight is used in the monthly expectation surveys. The household weights are designed to yield a representative sample of all U.S. households.

Data from the Current Population Surveys conducted by the Census are used to adjust for variations in the age and income distributions observed in the monthly samples. In practice, the post stratification weights do not yield "weighted" response distributions that differ significantly from the "unweighted" results - that is, the differences are within the margin of the expected sampling error.

The RDD and reinterview portions of the sample are post-stratified separately. This permits the construction of weights designed for analyses based solely on cases in either portion of the sample, and allows the pooling of cases when the analyses are based on the full sample. The separate post-stratification also explicitly recognizes the underlying differences between initial refusals and panel attrition. The potential non response bias in the RDD portion of the sample relate to several factors:

a) establishing contact with the selected households - for example, some phones may never be answered as the occupants are away for an extended period of time, or because answering machines are used to screen and avoid calls;

b) establishing contact with the selected respondent - interviews are conducted only with the designated respondent, no substitutions are allowed even if the designated respondent is unavailable for the entire study period due to work schedules, travel, and so forth;

c) the willingness of the selected respondent to be interviewed.

For the reinterview portion of the sample, there are additional sources of non response bias related to our ability to recontact respondents that have moved, changed phone numbers, or discontinued phone service. Willingness to be interviewed a second time may reflect different considerations on the part of the respondent, especially given their knowledge about the content of the interview. Before the weights for the RDD and the reinterview portions of the sample are integrated one further adjustment is made, based on the strengths of the rotating panel design of the monthly surveys.

The rotating panel design offers important statistical advantages for the measurement of change over time. The statistical advantage stems from the reduction in the standard errors of the observed differences in observed means between two overlapping samples as compared with two independent samples. The variances of the estimated differences over time are reduced to the extent that the repeated measures in the reinterview portion of the sample are positively correlated. Due to the correlation, each case in the reinterview portion of the sample contributes less to the variance (by one minus the correlation coefficient) than cases from the RDD sample. To take advantage of this variance reduction feature, the weights given to the RDD cases are decreased relative to the reinterview cases so as to achieve estimates of differences with minimum variance.

Seasonal Adjustment. No information on seasonal adjustment.

Release. Preliminary figures are released mid-month. Final figures are released at end of the month.

Questions about return expectation. The MSC reports the perceived probability that an investment in a well-diversified stock fund will increase in value over a one-year horizon.

The question is: "What do you think the percent chance that this one thousand dollar investment will increase in value in the year ahead, so that it is worth more than one thousand dollars one year from now?" The question is available from June 2002 to current date. The aggregated response data can be found in Table 20 “Probability of Increase in Stock Market in Next Year” in the Saving and Retirement section of the survey. Answers are reported as a mean probability of increase in stock market in next year $\bar{p}$ and a coarse answers' distribution in $\{0\%,\ 1-24\%,\ 25-49\%,\ 50\%,\ 51-74\%,\ 75-99\%,\ 100\%\}$ with "Do not Know" and "NA" options. The MSC also gives access to individual responses with post-stratification weights.

Using law of iterated expectations, mean probability of increase in stock market in next year, $\bar{p}$, %, can be calculated from aggregated data as

$$\bar{p}_t^{MSC} = \frac{1}{\sum_{i=1}^{N} w_{i,t}} \sum_{i=1}^{N} w_{i,t} p_{i,t} \tag{A.2}$$

where $N = 7$ is a number of probability partitions in $\{0\%,\ 1-24\%,\ 25-49\%,\ 50\%,\ 51-74\%,\ 75-99\%,\ 100\%\}$, p_i average probability in a partition i and w_i is a number of respondents estimated probability of increase in value in partition i. It is equivalent to weighted sum of individual responses.

Figure A.2: MSC: Expected Percent Chance of Increase of $1,000 Investment in Diversified Stock Mutual Fund in the Year Ahead, $\bar{p}_t^{MSC}$, monthly
Data is from June 2002 to October 2020

Figure A.3: MSC: Share of Interviewed People With More (black line) and Less $10,000 (blue line) Investment in Stock Market, Monthly
Data is from June 2002 to November 2020.

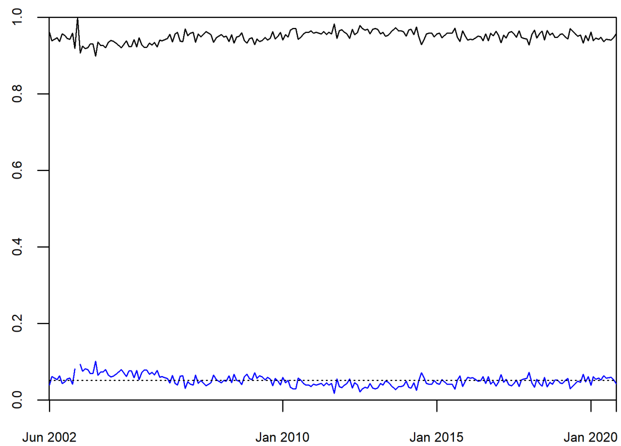


Table A.1: Monthly MSC Expectation Index (Equally-Weighted Average) for Investors Investing More and Less $ 10,000: June 2002 - November 2020

Statistic	Mean	St. Dev.	Min	Max
Invested less $10,000	49.70	9.13	24.42	72.14
Invested more $10,000	49.36	6.13	33.44	61.44

The MSC expectations index $\bar{p}_t^{MSC}$ is

As the UBS/Gallup's benchmark surveys contain responses of investors with minimum of $10,000 invested in stock market, I check MSC statistics for respondents reported to invest more and less $ 10,000. Based on MSC sampling methodology, 5 % of people interviewed have investment in stock market less than $10,000.

Summary statistics of average monthly responses for the two groups of investors shows that expectations of respondents invested less $ 10,000 is mean-preserving spread of expectations of respondents invested more that $ 10,000.

Given the stability of the sampling and that time series of expectations of investors invested less $ 10,000 is a mean-preserving spread of the expectation index of investors who invested more than $ 10,000, I take full MSC sample for the analysis.

A.1.3 UBS/Gallup Survey

The Roper Center for Public Opinion Research [6] at the Cornell University provides access to UBS/Gallup US Investor Optimism Index surveys. The monthly data ranges from February 1999 to October 2007 and profiles individual investors. As metrics in 1999 are volatile, I use a sample from January 2000 through October 2007. It constitutes 93 monthly polls.

Sampling frame. The survey is conducted on a nationally representative sample of respondents holding stocks, bonds, or mutual funds worth at least $10,000.[7] Gallup screens for U.S. investors using a nationally representative sample of U.S. adults aged 18 and older living in all 50 states and the District of Columbia.

Sampling frame includes a listing of all possible household telephone numbers in the continental United States. It's created from all telephone exchanges in the U.S. and estimates of the number of residential households for each exchange.

Sampling. Gallup samples phone numbers using random-digit-dial (RDD) methods[8]. The RDD procedure utilizes random generation of phone numbers from the sample frame. Participants change from survey to survey.

Traditionally, the Gallup implements the following stratification scheme. The United States is divided into seven size of-community strata: cities of population 1,000,000 and over, 250,000 to 999,999, and 50,000 to 249,999, with the urbanized areas of all these cities forming a single stratum; cities of 2,500 to 49,999; rural villages; and farm or open country rural areas. Within each of these strata, the population is further divided into seven regions: New England, Middle Atlantic, East Central, West Central, South, Mountain, and Pacific Coast. Within each size-of-community and regional stratum the population is arrayed in geographic order and zoned into equal size groups of sampling units. Pairs of localities in each zone are

[6] https://ropercenter.cornell.edu/

[7] Information on Gallup survey sampling procedures was excerpted from George H. Gallup, The Gallup Poll, Public Opinion 1934-1971, Vol. 1, 1935-1948 (New York: Random House, 1972), pp. vi-viii; George H. Gallup, The Gallup Opinion Index, Report No. 162 (Princeton, NJ: The Gallup Poll, January 1979), pp. 29, 30; George Gallup, The Sophisticated Poll Watcher's Guide (Princeton, NJ: Princeton Opinion Press, 1976), p. 102; and from information provided by The Gallup Organization, Inc.

[8] https://www.albany.edu/sourcebook/pdf/app5.pdf

selected with probability of selection proportional to the size of each locality's population-producing two replicated samples of localities.

The stratification by regions is routinely supplemented by fitting each obtained sample to the latest available U.S. Census Bureau estimates of the regional distribution of the population. Also, minor adjustments of the sample are made by educational attainment (for males and females separately), based on the annual estimates of the U.S. Census Bureau derived from their Current Population Survey. The sample procedure described is designed to produce an approximation of the adult civilian population living in the United States, except for those persons in institutions such as prisons or hospitals.

Systematic procedures are in place to maintain the integrity of the sample. If there is no answer or the line is busy, the number is stored in the computer and redialed a few hours later or on subsequent nights of the survey period. Procedures are utilized to assure that the within-household selection process is random in households that include more than one adult. One method involves asking for the adult with the latest birthday; if that adult is not home the number is stored for a call back. These procedures are standard methods for reducing the sample bias that would otherwise result from under representation of persons who are difficult to find at home.

Sample size. There are about 1000 observations per month.

Field period. The UBS/Gallup conducts interviews of investors during the first two weeks of every month.

Fieldwork. The Gallup company[9]

Weighting. Individual responses are weighted by UBS/Gallup's Weighting Variable for Aggregation WT-FCTR, $w_{i,t}$. Gallup weights samples to correct for unequal selection probability, nonresponse in the sampling frame. Gallup also weights its final samples to match the U.S. population according to gender, age,

[9] https://www.gallup.com/178685/methodology-center.aspx

race, ethnicity[10], education, region[11], population density[12], and phone status (cellphone only, landline only, both, and cellphone mostly). Demographic weighting targets for the U.S. are based on the most recent Current Population Survey figures for the aged 18 and older U.S. population. Population density targets are based on the most recent U.S. Census.

Seasonal Adjustment. No information on seasonal adjustment.

Release. The UBS/Gallup reports the results on the last Monday of the month.

Questions about return expectation. Following Nagel and Xu (2018), I use data from two survey questions about expected returns. The first question[13] asks about the expected rate of return the respondent expects to receive from investing in the stock market over the next 12 months:

"What overall rate of return do you expect to get on your portfolio in the next twelve months?"

This question is available until April 2003.

The second question[14] asks participants about the return they expect on their own portfolio: "Thinking about the stock market more generally, what overall rate of return do you think the stock market will provide investors during the coming twelve months? (Open ended and code actual percent)"

This question was in the survey until October 2007.

For both questions, possible answers are

---

[10] Race, ethnicity - Nonwhite is comprised of individuals who report themselves as any combination of the following classifications: Hispanic, American Indian, other Indian, Asian, and black. Black and Hispanic are subcategories of nonwhite. However, due to variation in respondent reporting, the category white may also include some Hispanics.

[11] The four regions of the country as reported in Gallup public opinion survey results are

- East - Maine, New Hampshire, Vermont, Massachusetts, Rhode Island, Connecticut, New York, New Jersey, Pennsylvania, Maryland, Delaware, West Virginia, District of Columbia;
- Midwest - Ohio, Michigan, Indiana, Illinois, Wisconsin, Minnesota, Iowa, Missouri, North Dakota, South Dakota, Nebraska, Kansas;
- South - Virginia, North Carolina, South Carolina, Georgia, Florida, Kentucky, Tennessee, Alabama, Mississippi, Arkansas, Louisiana, Oklahoma, Texas; and
- West- Montana, Arizona, Colorado, Idaho, Wyoming, Utah, Nevada, New Mexico, California, Oregon, Washington, Hawaii, Alaska.

[12] Urbanization - Central cities have populations of 50,000 and above. Suburbs constitute the fringe and include populations of 2,500 to 49,999. Rural areas are those that have populations of under 2,500.

[13] It is Question # 15 from February 1999 to December 2001, and Question # 10 form January 2002 to April 2003

[14] It is Question # 16 from February 1999 to December 2001, and Question # 12 form January 2002 to October 2007

Score	Answer
0-99	Code actual percent, %
997	997+
998	(Do not know)
999	(Refused)

After every respondent's answer, an interviewer codes in a separate entry whether the expected rate of return number is positive or negative, $sgn_{i,t}$.[15] The UBS/Gallup interviewer's instructions states that "if you are unsure whether the number is positive or negative, then ask the respondent. As a general rule, you should assume it to be positive, unless the respondent explicitly says "Minus"; or in some other way indicates the number is negative."

I use micro data from 93 polls, to calculate aggregate expected market $\tilde{r}^{(12)}_{m,t}$ and portfolio $\tilde{r}^{(12)}_{p,t}$ returns for the next 12 months as

$$\tilde{r}^{(12)}_{m,t} = \sum_i w_{i,t} sgn_{m,i,t} \tilde{r}^{(12)}_{m,i,t} \tag{A.3}$$

$$\tilde{r}^{(12)}_{p,t} = \sum_i w_{i,t} sgn_{m,i,t} \tilde{r}^{(12)}_{m,i,t} \tag{A.4}$$

where $\sum_{i,t} w_{i,t} = 1$. I use UBS/Gallup aggregated means[16] to cross verify the expectations that I get form microdata. Weighted mean of expected stock return from microdata is 99.1% correlated with UBS/Gallup aggregated mean of expected stock market return. Equally weighted mean of expected stock return from mictodata is 98.2% correlated with UBS/Gallup aggregated mean of expected stock market return. Weighted mean of expected portfolio return from microdata is 90.4 % correlated with UBS/Gallup aggregated mean of expected portfolio return. Equally weighted - 89.0 %.

The time series of corresponding aggregated weighted expected return proxies are provided below.

[15] It is Question # 16A from February 1999 to December 2001, and Question # 13 from January 2002 to October 2007 .

[16] April 2003 report contains monthly expected stock market returns aggregated by UBS/Gallup and can be found in the Reports, Data Tables & Other Materials section of "Gallup/UBS Poll # 2003-INVEST04: April, 2003 US Investor Optimism Index [Roper # 31089585]" poll, https://doi.roper.center/?doi=10.25940/ROPER-31089585. October 2007 report contains history of monthly expected portfolio returns aggregated by UBS/Gallup and can be found in the Reports, Data Tables & Other Materials section of "Gallup/UBS Poll # 2007-INVEST10: October, 2007 US Investor Optimism Index [Roper # 31089639]" poll. https://doi.roper.center/?doi=10.25940/ROPER-31089639. December 2001 report contains monthly expected interest rates https://doi.roper.center/?doi=10.25940/ROPER-31089569

Figure A.4: Aggregated UBS Gallup Investors' Expectations from Microdata, 12 month Ahead
Stock Market Return Expectations (top plot), Percent, Portfolio Return Expectations (dottom plot), Annual Percent Monthly: January 2000 - October 2007.

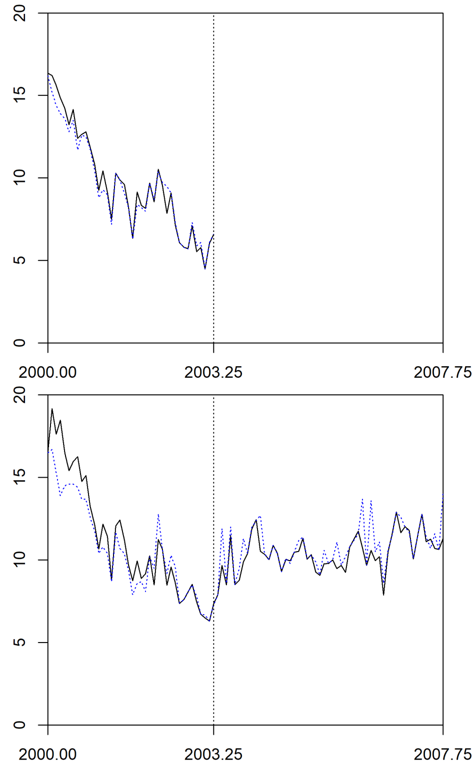


Table A.2: Summary Statistics
UBS/Gallup Expected Annual Stock Market $\tilde{r}_{m,t\to t+12}^{UBS/Gallup}$ and Portfolio Return $r_{port,t\to t+12}^{UBS/Gallup}$ A Year From Now, Annual Percent Monthly: January 2000 - October 2007

	N	Mean	St. Dev.	Min	Max
From microdata. $\tilde{r}_{m,t\to t+12}^{UBS/Gallup}$	40	9.68	3.21	4.49	16.34
Aggregate. $\tilde{r}_{m,t\to t+12}^{UBS/Gallup}$	40	9.50	2.95	4.50	16.20
From microdata. $r_{port,t\to t+12}^{UBS/Gallup}$	93	10.77	2.53	6.31	19.18
Aggregate. $r_{port,t\to t+12}^{UBS/Gallup}$	93	10.78	2.14	6.30	16.70

Sampling error. All sample surveys are subject to sampling error, that is, the extent to which the results may differ from those that would be obtained if the entire population surveyed had been interviewed. The size of sampling errors depends largely on the number of interviews.

The following table may be used in estimating sampling error in the Gallup surveys. The computed allowances have taken into account the effect of the sample design upon sampling error. They may be inter-

Table A.3:

Gallup. Recommended Allowance For Sampling Error (Plus or Minus) at 95% Confidence Level, Points

Percentages near	Sample size					
	1,000	750	600	400	200	100
10	2	3	3	4	5	7
20	3	4	4	5	7	9
30	4	4	4	6	8	10
40	4	4	5	6	8	11
50	4	4	5	6	8	11
60	4	4	5	6	8	11
70	4	4	4	6	8	10
80	3	4	4	5	7	9
90	2	3	3	4	5	7

preted as indicating the range (plus or minus figure shown) within which the results of repeated samplings in the same time period could be expected to vary, 95% of the time, assuming the same sampling procedure, the same interviewers, and the same questionnaire.

The table would be used in the following manner: Assume a reported percentage is 33 for a group that includes 1,000 respondents. Proceed to row "Percentages near 30" in the table and then to the column headed, "1,000." Figure in this cell is four, which means that at the 95% confidence level, the 33% result obtained in the sample is subject to a sampling error of plus or minus four points.

A.1.4 Survey of Professional Forecasters

The Survey of Professional Forecasters[17] is the oldest quarterly survey of macroeconomic forecasts in the United States. The survey began in 1968 and was conducted by the American Statistical Association and the National Bureau of Economic Research. The Federal Reserve Bank of Philadelphia took over the survey in 1990.

Sampling frame. The monthly survey uses an address-based mail sample design. The sampling frame is derived from the files created by the U.S. Postal Service, which represent near-universal coverage of

[17] https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/survey-of-professional-forecasters

all residential households in the United States. The CCS frame is updated monthly to ensure up-to-date coverage of U.S. households.

Sampling. The CCS uses a probability sample design to select each month's random sample from the household universe frame. The frame is first stratified geographically within the census division to provide a proportionate geographic distribution, after which a systematic sample of household addresses is selected. The sample addresses are then used for the mailing.

Sample size. About 3,500 surveys are completed each month. About 2,500 for end-of-month release; 3,500 for later revision.

Field period. The CCS mailing is scheduled so that the questionnaires reach sample households on or about the first of each month. Returns flow in throughout the collection period, with the sample close-out for preliminary estimates occurring around the eighteenth of the month. Any returns received after then are used to produce the final estimates for the month, which are published with the release of the following month's data. Completed questionnaires are checked in as they are received and then scheduled for data entry. Data fields are edited for invalid entries and, if necessary, are flagged for review. As part of the ongoing quality control process, a random sample of questionnaires is selected for independent review/validation by a senior member of the data collection staff. The targeted responding sample size - approximately 3,000 completed questionnaires - has remained essentially unchanged throughout the history of the CCS.

Fieldwork. The Nielsen Company[18].

Weighting. To improve the accuracy of the estimates and ensure the proportionate representation of key categories in the estimates, the CCS uses a post-stratification weighting structure covering the following

[18] As of February 2011, The Conference Board has changed survey providers from TNS to The Nielsen Company for ongoing CCS operational support. Nielsen uses a mail survey specifically designed for the Consumer Confidence Survey. The new design uses a probability-design random sample, poststratification weights (for gender, income, geography, and age), and the U.S. Census X-12 seasonal adjustment. The CCS concepts, questions and mail survey collection method remain unchanged.

From September 2010 to January 2011, a five-month pilot test of the new sample design was conducted in parallel with the existing design. Three months of previously published data (November 2010 to January 2011) have been restated to smooth the transition, which makes November 2010 the effective changeover month.

categories: Census Division (9 Census divisions), Age of Head of Household (<30, 30-39, 40-49, 50-59, 60+), Gender of Head of Household (Male/Female), Income of Household (<15,000; 15,000-24,999; 25,000-34,999; 35,000-49,999; 50,000-74,999; 75,000-99,999; 100,000-124,999; 125,000+).

The post-stratification weighting uses an iterative proportional fitting technique for simultaneously balancing sample weights across several different population control groups. This technique ensures that sample-based estimates of the household population categories match the independent census population controls within +/- 1 percent.

Seasonal Adjustment. Data as of January 2011 use the Census X-12 seasonal adjustment software for the publication series where needed. Seasonal adjustment helps remove periodic seasonal fluctuations in the series due to events such as weather, holidays, and the beginning and end of the school year. While the CCS series are typically not highly seasonal, the X-12 software helps reduce any residual seasonality in the various data series.

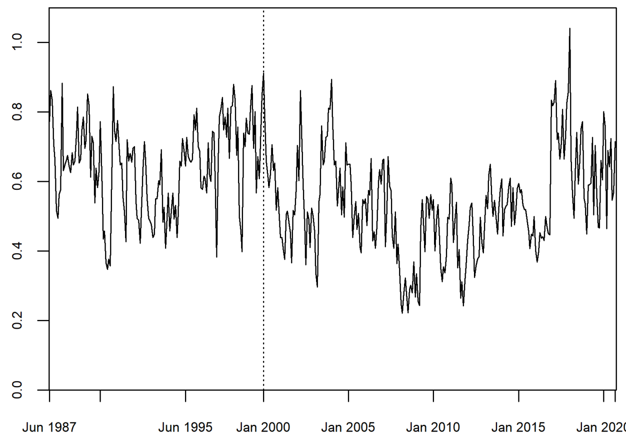
Release. Preliminary figures are released on last Tuesday of month. Final figures are released with next month's release.

Questions about return expectation. The surveys elicit respondents simple categorical beliefs about whether the stock prices will likely increase, decrease, or stay the same (or whether they are undecided, which we include in the same category).

As per Nagel & Xu (2019), I construct the Index IND_t^{CB} as the ratio of those who respond with an increase to the sum of those who respond with a decrease or the same:

$$IND_t^{CB} = \frac{n_t^{increase}}{n_t^{decrease} + n_t^{same}} \tag{A.5}$$

Figure A.5: Conference Board Index IND_t^{CB}, Monthly
Data is from June 1987 to September 2020



A.1.5 Panel on Household Finances (PHF) by Bundesbank since 2011

The German Panel on Household Finances (PHF)[19] is a panel survey on household finance and wealth in Germany, covering the balance sheet, pension, income, work life and other demographic characteristics of private households living in Germany. The panel survey is conducted by the Research Centre of the Deutsche Bundesbank.

The first two waves were carried out in 2010/2011 and 2014, respectively, in cooperation with infas Institut für angewandte Sozialwissenschaften, Bonn. Net samples of 3,565 (wave 1) and 4,461 (wave 2) randomly selected households were collected. The collection of the data of the third wave ended in November 2017. The data are currently in the preparation stage. First results and a scientific use file are expected to be published in early 2019. Around 5,000 households participated in the third wave.

Wealthy households are oversampled on the basis of microgeographic indicators in order to better match the distribution of wealth across households and to shed light on the composition of wealth. A strong attempt is being made to select households from all economic strata. Participation is strictly voluntary.

The survey is designed to be a full panel, i.e. all households are re-contacted. The intended survey frequency is three years. Almost half of the 4,461 households in wave two took part for the second time.

The results of the first waves of our study were published in several Bundesbank monthly bulletin arti-

[19] https://www.bundesbank.de/en/bundesbank/research/panel-on-household-finances

cles, reports and papers. The micro data from wave one and two are available for scientific research projects through the Bundesbank's Research Data and Service Centre.

Aside from being an encompassing survey on household finance in Germany, PHF is an integral part of the Household Finance and Consumption Survey (HFCS). This system of wealth surveys collects ex ante harmonised micro data in every country of the euro area.

A.1.6 European Community Household Panel by ECB and member national banks

The European Community Household Panel (ECHP) [20] is an eight-year, longitudinal household survey covering 14 EU member states from 1994 to 2001. For more recent, comparable, panel data, are in EU Statistics on Income and Living Conditions (EU-SILC) and described below.

Subject interviews in ECHP covered: overall financial situation, income data, working life, housing, social relations, health and biographical observations. EU Member States included in ECHP were Austria, Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and the United Kingdom.

These interviews cover a wide range of topics concerning living conditions. They include detailed income information, financial situation in a wider sense, working life, housing situation, social relations, health and biographical information of the interviewed.

The total duration of the ECHP was 8 years, running from 1994 to 2001 (8 waves). The then Member States involved were Belgium, Denmark, Germany, Ireland, Greece, Spain, France, Italy, Luxembourg, the Netherlands, Austria, Portugal, Sweden and the United Kingdom. As from 2003/2004, the EU-SILC survey covers most of the above-mentioned topics.

The ECHP consists of panel data, meaning that the same respondents within each country have answered the survey year after year. All EU households and citizens of 16 years of age or more are in the target population. Common sampling requirements and standards are employed in all countries – probability sampling procedures are used. In the first wave, 60,500 households and 130,000 individuals were interviewed.

The data is collected through face-to-face interviews

Plenty of the datasets under the Income and living conditions (ILC) domain under theme "Population

[20] https://ec.europa.eu/eurostat/web/microdata/european-community-household-panel

and social conditions" contain ECHP based data for the above mentioned periods. This includes several indicators on monetary poverty and distribution of income, which are analysed in different ways (eg. different cut-off thresholds, by age, gender, activity status, tenure status...).

There is also a selection of indicators on non-monetary deprivation derived from ECHP, notably on housing conditions.

Some indicators in the health care collections of the public health domain are derived from ECHP as well.

A.1.7 EU Statistics on Income and Living Conditions (EU-SILC)

EU-SILC is a cross-sectional and longitudinal sample survey, coordinated by Eurostat, based on data from the European Union member states. EU-SILC provides data on income, poverty, social exclusion and living conditions in the European Union. EU-SILC stands for 'European Union Statistics on Income and Living Conditions.' There are two data scopes:

- Cross-sectional data pertaining to fixed time periods, with variables on income, poverty, social exclusion and living conditions, and
- Longitudinal data pertaining to individual-level changes over time, usually observed over four years.

Details of the database are on the Eurostat EU-SILC resource page. The 2019 EU-SILC data coverage table is at this link.

Social exclusion and housing-condition observations are collected at household level. Income data is collected at personal level, with some components included in the 'Household' section. Labour, education and health observations only apply to persons aged 16 or older.

EU-SILC was established to provide data on structural indicators of social cohesion (at-risk-of-poverty rate, S80/S20 and gender pay gap) and to provide relevant data for the two 'open methods of coordination' in the field of social inclusion and pensions in Europe.

The EU-SILC 2019 release extended data coverage from Junem 2015 to Novemberm 2019. Eurostat periodically issues revisions of earlier waves. The data dossier is structured as follows:

- Data: Cross-sectional

- Data: Longitudinal
- Documentation
- Metadata (for all waves)

A.1.8 Survey of Consumer Expectations by New York Fed since 2013

The New York Fed's Survey of Consumer Expectations (SCE)[21] gathers information on consumer expectations regarding inflation, household finance, the labor and housing markets, and other economic issues. Its overall goal is to fill the gaps in existing data sources (such as the University of Michigan Survey of Consumers, the Federal Reserve Board's Survey of Consumer Finances, and the Bureau of Labor Statistics' Consumer Expenditure Survey) pertaining to household expectations and behavior by providing a more integrated data approach.

The SCE started in June 2013, after a six-month initial testing phase. It is a nationally representative, internet-based survey of a rotating panel of about 1,300 household heads, where household head is defined as the person in the household who owns, is buying, or rents the home. The survey is conducted monthly. New respondents are drawn each month to match various demographic targets from the American Community Survey (ACS), and they stay on the panel for up to twelve months before rotating out. The survey instrument is fielded on an internet platform designed by the Demand Institute, a nonprofit organization jointly operated by the Conference Board and Nielsen. The respondents for the SCE come from the sample of respondents to the Consumer Confidence Survey (CCS), a mail survey conducted by the Conference Board. In turn, the respondents for the CCS are selected from the universe of U.S. Postal Service addresses. From that universe, a new random sample is drawn each month, stratified only by Census division.

The SCE has several components. First, it includes a core monthly module on expectations about a number of macroeconomic and household-level variables. In this module, respondents are asked about their inflation expectations, as well as their expectations regarding changes in home prices and the prices of various specific spending items, such as gasoline, food, rent, medical care, and college education. The core survey also asks for expectations about unemployment, interest rates, the stock market, credit availability, taxes, and government debt. In addition, respondents are asked to report their expectations about several

[21] https://www.newyorkfed.org/microeconomics/sce

labor market outcomes that pertain to them, including changes in their earnings, the perceived probability of losing their current job (or leaving their job voluntarily), and the perceived probability of finding a job. Finally, the core survey asks about the expected change in respondent households' overall income and spending. As described in more detail below, these questions about expectations are fielded at various time horizons and with various formats, including both point and density forecasts. Second, each month, the SCE contains a supplementary "ad hoc" module on special topics. Three such modules are repeated every four months, leaving three "floating" supplements per year on topics that are determined as the need arises. The three repeating supplements are on credit access, labor market, and spending. Topics covered so far in the "floating" supplement include (but are not limited to) the Affordable Care Act, student loans, workplace benefits such as childcare and family leave, and the use of insurance products.

Together, the core monthly module and the monthly supplement take about fifteen minutes to complete. Finally, SCE respondents also fill out longer surveys (up to thirty minutes in length, and separate from the monthly survey) each quarter on various topics. Most of these surveys are repeated at a yearly frequency. Since each SCE panelist stays in the panel for up to twelve months, these annual surveys can be used as independent repeated cross sections, although they obviously can be linked to the monthly core survey panel responses. The SCE currently contains quarterly surveys on the housing market, the labor market, informal work participation, and consumption, saving, and assets. A subset of these surveys is designed in part or wholly by other Federal Reserve Banks.

A.1.9 Survey of Household Economics and Decision making by the Federal Reserve Board since 2013

The Federal Reserve Board has conducted the Survey of Household Economics and Decisionmaking (SHED)[22], which measures the economic well-being of U.S. households and identifies potential risks to their finances. The survey includes modules on a range of topics of current relevance to financial well-being including credit access and behaviors, savings, retirement, economic fragility, and education and student loans. [23]

[22] https://www.federalreserve.gov/consumerscommunities/shed.htm

[23] Also, the SHED asks about informal income-earning activities that happen outside of formal work. Many types of arrangements that are included in other studies—such as temp-agency work or subcontracted work—are unlikely to be included, whereas activities that are excluded by other studies—such as working under the table and selling goods—are included. Informal and independent work overlap, but are not synonymous.

The survey is designed with three primary motivations

1. Monitor trends in consumer behavior and sentiment particularly among low- and moderate-income populations
2. Cast light on current issues affecting financial well-being
3. Fill data gaps and provide insights into questions for which there may not be other reliable data sources.

It's conducted annually in the fourth quarter of each year since 2013.

Ipsos, a private consumer research firm, administers the survey using its KnowledgePanel, a nationally representative probability-based online panel. Ipsos selects respondents for the KnowledgePanel based on address-based sampling (ABS)[24] SHED sample is made up of three components:

- New respondents randomly selected (3,054 adults),
- Oversample of adults with household income under $40,000 (1,556 adults),
- Reinterviewed respondents from 2015 SHED survey (2,033 adults).

A.1.10 Canadian Survey of Consumer Expectations since 2015

The Canadian Survey of Consumer Expectations (CSCE) [25] is a quarterly survey aimed at measuring household views of inflation, the labour market and household finances, as well as topical issues of interest to the Bank of Canada. The CSCE also provides data by age, geography, income and education.

The Canadian Survey of Consumer Expectations is a nationally representative, internet-based quarterly survey of a rotating panel of approximately 2,000 heads of households.2 It is administered by a large polling firm on behalf of the Bank of Canada. Respondents participate in the panel for up to a year, with a roughly equal number joining and leaving the panel each quarter. This reduces variability caused by changes in composition, allowing for greater stability and precision in the estimates. The survey's target population is

[24] Prior to 2009, respondents were also recruited using random-digit dialing.

[25] https://www.bankofcanada.ca/publications/canadian-survey-of-consumer-expectations/ https://www.bankofcanada.ca/publications/canadian-survey-of-consumer-expectations/canadian-survey-of-consumer-expectations-references/

adult residents of Canada aged 18 or older. The survey is conducted in February, May, August and November and is offered in both English and French. Respondents answer questions about inflation, the labour market and household finances and demographic questions about themselves and their household.

A.1.11 Online Survey of Consumer Expectations by Bundesbank in 2019

The Bundesbank is currently undertaking a pilot study to investigate whether a regular consumers expectation survey can provide information that is useful for policy-making[26]. There are chiefly two questions that are of relevance in this context:

Would such a study be able to supply the Bundesbank and policymakers with a broad and up-to-date picture of consumers' economic expectations in Germany? To what extent can the obtained data assist the Bundesbank's and other institutions' researchers in analysing current economic developments? The survey and the questionnaire were designed and prepared by the Deutsche Bundesbank's Research Centre in cooperation with external experts. The public opinion research company forsa has been commissioned with conducting the survey. The pilot survey will initially comprise three waves containing both recurring and wave-specific questions. For each wave of the survey, around 2,000 representative members of the general public will be asked to respond. Some of the respondents will be asked multiple times. Participation in the study is voluntary and will take about 20 minutes.

The collected data will be used exclusively for the production of statistics, for monetary and financial stability purposes, as well as for study and research. There will be no commercial use. The collected data will always be stored separately from personal data and identification of individual persons will not be possible, even for the researchers at the Bundesbank.

A.1.12 Ifo Business Tendency Survey

The Ifo Business Climate Survey [27] is a leading indicator of German economic activity, compiled by the Munich-based Ifo Institute for Economic Research.

The Ifo Business Climate Survey is based on approximately 9,000 monthly survey responses from Ger-

[26] https://www.bundesbank.de/en/bundesbank/research/pilot-survey-on-consumer-expectations/bundesbank-online-pilot-survey-on-consumer-expectations-794568

[27] https://www.ifo.de/en

man firms in manufacturing, construction, the service sector, and trade. The companies surveyed are asked to provide feedback on whether their current business situation is good, satisfactory, or poor, as well as assess their expectations for the next six months as either more favorable, unchanged, or more unfavorable.

The responses of the firms are weighted according to the economic importance of each industry, and a net balance is calculated for each assessment: good/poor for the current situation, and more favorable/more unfavorable for the outlook—the "satisfactory" and "unchanged" responses are regarded as neutral and thus not included.

The business climate itself, the main subject of the survey, is then calculated as the mean of these two balances. The outcome is constructed to yield outcomes between ˘100, assuming every firm gives a negative response to both questions, and $+100$, meaning every firm gives a positive response to both questions.

The headline survey number that is released is, however, recalculated in the form of an index, which will be set to 100 in a base year. The base year currently in use is 2005.

A.1.13 Atlanta Fed Survey of Business Uncertainty since 2015

In partnership with Steven Davis of the University of Chicago Booth School of Business and Nicholas Bloom of Stanford University, the Federal Reserve Bank of Atlanta has created the Atlanta Fed/Chicago Booth/Stanford Survey of Business Uncertainty (SBU). This innovative panel survey measures the one-year-ahead expectations and uncertainties that firms have about their own employment, capital investment, and sales. The sample covers all regions of the U.S. economy, every industry sector except agriculture and government, and a broad range of firm sizes.

The SBU elicits a 5-point probability distribution over 12-month-ahead sales, employment, and capital expenditures for each firm. It also elicits current values of these quantities. The survey's innovative design allows the calculation of each firm's expected growth rate over the next year and its degree of uncertainty about its expectations. Policy makers and researchers can use SBU data to help forecast economic activity and better understand how business expectations and uncertainty affect employment, sales, investment, and other economic outcomes.

Each survey form below goes to about one-third of the panel members each month. A given panel member will receive each of the three forms over the course of three months. In addition to the core survey questions posed in the forms below, we typically ask at least one special question each month.

A.1.14 Vanguard Research Initiative

The Vanguard Research Initiative (VRI)[28] is a collaboration of the University of Michigan, New York University, and Vanguard.

VRI surveys are administered via the internet to a panel of Vanguard clients to gather complementary information to Vanguard's administrative data. The panel was chosen by inviting Vanguard account holders fulfilling the following criteria: over 55 years old, have a domestic address, no immediate record of a Vanguard annuity purchase, hold between $10,000 and $5 million in assets with Vanguard, have a valid email registered with Vanguard, have logged on in the past six months.

The sample was stratified such that each age group above 55 will be adequately represented, as well as singles. The sample is also divided between individual accounts and employer-sponsored accounts.

The initial cohort of 9,000 respondents joined the VRI in 2013 with Survey 1. A new cohort of 3,700 respondents joined the VRI in 2016 with Survey 5. The original cohort was also given Survey 5.

The project employs data on a panel of savers that includes detailed wealth, health, and demographic information. This panel data set comprises over 9,000 Vanguard clients. By the joint use of administrative account data and surveys, the project employs an innovative infrastructure for understanding the decision-making and well-being of older Americans. The project also innovates by combining this distinctive measurement infrastructure with survey questions, modeling, and estimation that can yield precise quantification of the considerations that affect decisionmaking and well-being leading up to retirement and during retirement. A key innovation is to pose strategic survey questions (SSQs), a form of contingent stated preference question.

[28] https://ebp-projects.isr.umich.edu/VRI/index.html

A.2 Imputation of Point Estimates

A.2.1 Imputation of Percent Return Expectations

As the Consumer Confidence Survey (CCS) from the Conference Board[29], and the Michigan Survey of Consumers[30] (MSC) surveys contain coarse probability estimations of stock market return, and UBS/Gallup surveys contain percent return expectations, I use UBS/Gallup[31] data to construct benchmark source of expectations.

Figure A.6 shows timing of the CCS, the MSC and the UBS/Gallup surveys. The top green line shows timing of the CCS survey that starts on June 1987 and ends on December 2019. The blue line shows timing of the MSC survey that starts on June 2002 and ends on December 2019. The UBS/Gallup surveys overlap the CSS and the MSC surveys. However, it is clear that regressing subjective market growth probabilities on UBS/Gallup subjective market returns directly would not work for the MSC data, as the UBS/Gallup subjective market return expectations overlaps with UBS/Gallup market returns only in ten points, from June 2002 to April 2003. The UBS/Gallup data allows to extend subjective expectations in percents by utilizing a UBS/Gallup survey on subjective portfolio return expectations. $E^s[r_{port}]$ that overlaps with the MSC survey over five and a half years, from June 2002 to October 2007.

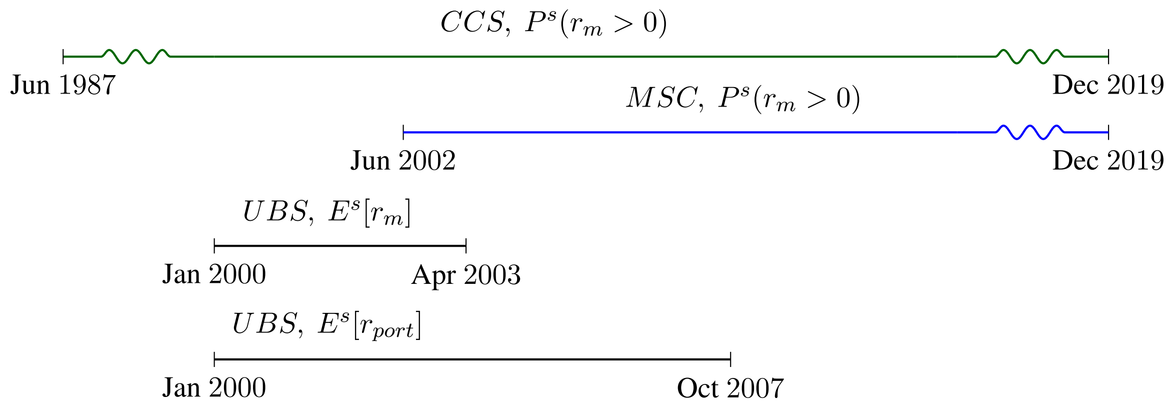
As a result, following Nagel & Xu (2019) methodology, I fit the UBS/Gallup return expectations to MSC and Conference Board probability estimates and impute the MSC and CCS percent return expectations in three steps.

First, I expand UBS/Gallup stock market expectations. Form January 2000 to April 2003 UBS/Gallup reports both expectations of stock market return and portfolio return. From May 2003 to October 2007, the UBS/Gallup survey respondents report only the return that they expect on their own portfolio. Following Nagel & Xu (2019) I impute market return expectations by regressing subjective expected market returns $\tilde{r}_{m,t\to t+12}^{UBS,\,01-2000\ to\ 04-2003}$ on individual subjective expected portfolio returns $\tilde{r}_{port,t\to t+12}^{UBS,\,01-2000\ to\ 04-2003}$ using the sample segment where both variables are provided and employing the fitted value from that regression

[29] https://conference-board.org/data/consumerdata.cfm
[30] https://data.sca.isr.umich.edu/
[31] https://ropercenter.cornell.edu/

Figure A.6: Timing and Output of Surveys on Expected Subjective Market Return Over the Next 12 Months

Two top lines, green and blue, show timing of the CCS Conference Board survey and the Michigan Surveys of Consumers. The surveys provide subjective probability that market return over the next 12 months will be positive, $P^s(r_m > 0)$. Bottom two lines show timing of UBS/Gallup surveys on expected market return. The upper of the two lines shows timing of UBS survey question asking about subjective expected stock market return in percent, $E^s[r_m]$. The lower of the two lines shows timing of UBS survey question about expected portfolio return.



$\hat{r}^{USB}_{m,t\to t+12}$ when market return expectations are not provided.

$$\tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{m,t\to t+12} = a_p + b_p \tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{port,t\to t+12} + \epsilon_t \tag{A.6}$$

$$\hat{r}^{USB}_{m,t\to t+12} = a_p + b_p \tilde{r}^{UBS}_{port,t\to t+12} \tag{A.7}$$

Because during this overlap period the movements in the expectations of returns are highly correlated, the overlap allows me to map the expected portfolio returns into expected market return over the entire period upto October 2007.

A blue line represents the fitted expected stock market return $\hat{r}^{USB}_{m,t\to t+12}$ in the plot below.

Second, to impute percentage expectations from MSC and Conference Board estimates, I regress the fitted percentage expectations $\hat{r}^{UBS}_{m,t\to t+12}$ from the UBS/Gallup on the MSC probability $\bar{p}^{MSC}_t$ and on IND^{CB}_t ratio. Since the Conference Board surveys ask about stock price increases, I subtract the current dividend yield[32] of the CRSP value weighted index from the dependent variable in this regression and add it back to

[32] CRSP: "Dividend Yield is another name for Income Return. It is the ratio of the ordinary dividends of a security or index to the previous price."

Table A.4: OLS Regression Specification

The regression is used for imputation of Market Return Expectations, $\tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{m,t\to t+12} = a_p + b_p \tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{port,t\to t+12} + \epsilon_t$

	Dependent variable:
	$\tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{m,t\to t+12}$, %
$\tilde{r}^{UBS,\ 01-2000\ to\ 04-2003}_{port,t\to t+12}$, %	0.867***
	(0.033)
Constant	−0.073
	(0.394)
Observations	40
R^2	0.947
Adjusted R^2	0.945

the fitted value.

Particularly, for the interval from January 2000 to October 2007 I run the following regressions to get coefficients for predictive regression $\{a_{MSC}, b_{MSC}; a_{BC}, b_{CB}\}$:

$$\hat{r}^{UBS}_{m,t\to t+12} - y^{div}_t = a_{MSC} + b_{MSC}\bar{p}^{MSC}_t + \epsilon_t \tag{A.8}$$

$$\hat{r}^{UBS}_{m,t\to t+12} - y^{div}_t = a_{BC} + b_{CB}IND^{CB}_t + \epsilon_t \tag{A.9}$$

where $\hat{r}^{UBS}_{m,t\to t+12}$ is expanded UBS/Gallup subjective expected market return and y^{div}_t is dividend yield calculated calculated from the CRSP as

$$y^{div}_t = \frac{vwretd_t + 1}{vwretx_t + 1} - 1 \tag{A.10}$$

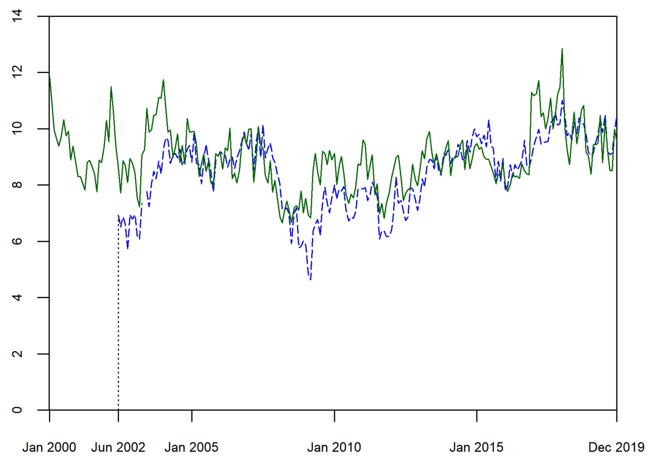
where $vwretd_t$ is value-weighted return including distributions and $vwretx_t$ is value-weighted return. Next, I use the coefficients $\{a_{MSC}, b_{MSC}; a_{BC}, b_{CB}\}$ and $\{\bar{p}^{MSC}_t, IND^{CB}_t\}$ coarse subjective probability estimates from the MSC and CB to impute subjective expected market returns in percents for the period from January 2000 to December 2020:

$$\tilde{r}^{MSC,no\ div}_{m,t\to t+12} = a_{MSC} + b_{MSC}\bar{p}^{MSC}_t \tag{A.11}$$

$$\tilde{r}^{CB,no\ div}_{m,t\to t+12} = a_{CB} + b_{CB}IND^{CB}_t \tag{A.12}$$

Figure A.7: Subjective Expected Market Return A Year Ahead, %

The green solid line corresponds to subjective market return imputed from the Conference Board, $\tilde{r}^{CB}_{m,t\to t+12} - \tilde{r}^{CB}_{f,t\to t+12}$. The blue dashed line is subjective market return imputed from the MSC $\tilde{r}^{MSC}_{m,t\to t+12} - \tilde{r}^{MSC}_{f,t\to t+12}$. The monthly time series are in percent and span from January 2000 to December 2019. Gray areas are NBER recessions.



and add back dividend yield to come up to subjective expected market return with dividends.

$$\tilde{r}^{MSC}_{m,t\to t+12} = \tilde{r}^{MSC,no_div}_{m,t\to t+12} + y^{div}_t \tag{A.13}$$

$$\tilde{r}^{CB}_{m,t\to t+12} = \tilde{r}^{CB,no_div}_{m,t\to t+12} + y^{div}_t \tag{A.14}$$

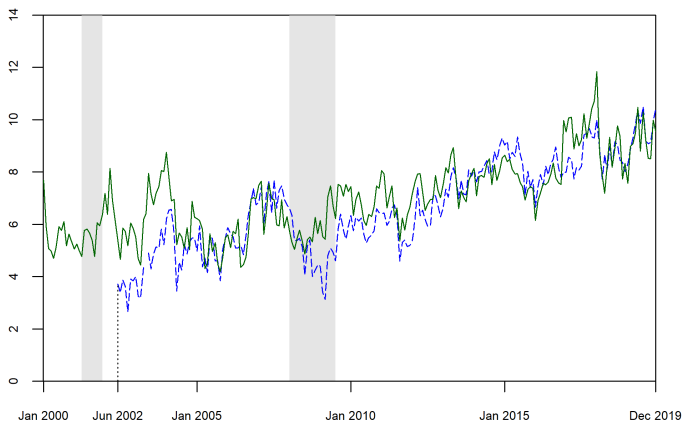
As a results, I have long time series of monthly subjective expected market returns in percent $r^{MSC}_{m,t\to t+12}$ and $r^{CB}_{m,t\to t+12}$ that I will use in my analysis.

Figure A.7 shows the imputed subjective expected stock market returns in the next twelve months from the MSC (dashed blue line), $\tilde{r}^{MSC}_{m,t\to t+12}$, and from the CCS (solid green line), $\tilde{r}^{CB}_{m,t\to t+12}$. Gray areas are recessions. We see that subjective expected market returns for a year ahead are positive and highly correlated. The correlation is 82.6 %. Both $\tilde{r}^{MSC}_{m,t\to t+12}$ and $\tilde{r}^{CB}_{m,t\to t+12}$ are time-varying and respond to recession of 2008-2009. They decrease beforehand and start moderate growth during the recession.

Table A.5: Moments of Imputed Subjective Expected Market Return

Variables	N	Mean	St. Dev.	Min	Max
Expected Subjective Stock Market Return					
$\tilde{r}^M_t$	210	8.24	1.30	4.26	11.01
$\tilde{r}^C_t$	240	8.98	1.09	6.66	12.84

Figure A.8: Subjective Expected Excess Market Return A Year Ahead, %
The green line corresponds to subjective excess market return imputed from the Conference Board, $\tilde{r}^{CB}_{m,t\to t+12} - \tilde{r}^{CB}_{f,t\to t+12}$. The blue line is subjective excess market return imputed from the MSC $\tilde{r}^{MSC}_{m,t\to t+12} - \tilde{r}^{MSC}_{f,t\to t+12}$. The monthly time series are in percent and span from January 2000 to December 2019. Gray areas are NBER recessions.



A.2.2 Imputation of Percent Interest Rate Expectations

I use the quarterly average of the daily levels of 3-month treasury bill rate expected over next four quarters from the Survey of Professional Forecasters[33], SPF, as a benchmark.

$$\bar{r}^{SPF}_{f,q\to q+4} = \frac{1}{4}\sum_{j=0}^{4} \tilde{r}^{SPR}_{q+j\to q+j+1|q} \tag{A.15}$$

where q is a quarter.

As the SPF forecasters include non-random, self-selected representatives from academia, government, labor, consulting and banking, I cannot use the SPF forecast as is. I use the SPF forecasts as a benchmark to impute investors expectations from the MSC and Conference Board surveys.

The MSC and Conference Board surveys contains investors' coarse probability estimation of an interest rate change. As the MSC and the Conference Board interest rate questions do not mention Treasury rate, the expected interest rate might include risk premium. Given extensive empirical evidence, I assume that interest rate expectations are associated with Treasury yield expectations and impute expected one-year Treasury yield using Nagel & Xu methodology.

[33] Survey of Professional Forecasters

Table A.6: Moments of Imputed Subjective Expected Risk-Free Rate

Variables	N	Mean	St. Dev.	Min	Max
Expected Subjective Risk-Free Rate					
$\tilde{r}^{M}_{f,t}$	240	2.02	1.27	0.00	5.61
$\tilde{r}^{C}_{f,t}$	240	2.00	1.17	0.00	5.00

To account for trend stationary, I add trend component t to the imputation regression:

$$\bar{r}^{SPF}_{f,q\to q+4} = a_{MSC} + b_{MSC}t + c_{MSC}\bar{p}^{MSC}_t + d_{MSC}t\bar{p}^{MSC}_t + \epsilon_t \quad (A.16)$$

$$\bar{r}^{SPF}_{f,q\to q+4} = a_{CB} + b_{CB}t + c_{CB}IND^{CB}_t + d_{CB}t\bar{p}^{MSC}_t + \epsilon_t \quad (A.17)$$

As the quarterly rates are daily averages within a quarter, I treat quarterly rates r_q as monthly rates within a quarter. So quarterly rates within a year $\{q_1, q_2, q_3, q_4\}$ are mapped to monthly rates as

$\{q_1, q_1, q_1, q_2, q_2, q_2, q_3, q_3, q_3, q_4, q_4, q_4\}$.

I use fitted values from the imputation regressions as expected subjective risk-free rates:

$$\tilde{r}^{MSC}_{f,t\to t+12} = a_{MSC} + b_{MSC}t + c_{MSC}\bar{p}^{MSC}_t + d_{MSC}t\bar{p}^{MSC}_t \quad (A.18)$$

$$\tilde{r}^{CB}_{f,t\to t+12} = a_{CB} + b_{CB}t + c_{CB}IND^{CB}_t + d_{CB}t\bar{p}^{MSC}_t \quad (A.19)$$

I use long monthly series $\tilde{r}^{MSC}_{f,t\to t+12}$ and $\tilde{r}^{CB}_{f,t\to t+12}$ as subjective expected risk-free rates.

The black solid line on the plot below shows the SPF forecast of three-month treasury bill rate four quarters ahead. It is highly correlated with actual one-year Treasury yield (black dotted line). Plot also shows imputed subjective expectations of interest rate form MSC (blue line) and Conference Board (green line) surveys.

A.3 Information Providers

A.3.1 Ton 10 information providers

A.3.2 Ton 10 Information Providers in Each Group

Table A.7: Top 10 InvesText's Information Providers by Number of Published Equity Reports About the Dow Companies

Tables show top 10 information providers by number of reports published, percent of number of reports published, number of covered companies, period when a information provider is in the InvesText and tickers of covered companies. There are 46 tickers in InvesTest out of 47 the Dow companies that were in the Dow in the sample period. Sample is from January 1, 2000 to December 31, 2019.

information provider	Percent of Reports, %	# Companies Covered	In InvesText From	In InvesText To	Tickers Covered
Credit Suisse	14.9	46	2000-01	2019-12	All
Oppenheimer & Co., Inc.	6.2	45	2000-01	2019-12	All except DOW
Deutsche Bank	6.0	46	2000-01	2019-12	All
JPMorgan	4.3	46	2000-01	2019-12	All
Cowen and Company	4.3	43	2000-01	2019-12	All except AIG, GM, TRV
RBC Capital Markets	4.1	46	2000-01	2019-12	All
Wells Fargo Securities, LLC	3.8	43	2000-01	2019-12	All except DOW, KODK, MMM
Bear Stearns & Co. Inc.	3.4	41	2000-01	2008-05	All except CRM, DOW, GM, PM, V
Refinitiv StreetEvents	3.1	46	2002-01	2019-12	All
Piper Sandler Companies	2.8	44	2000-01	2019-12	All except DOW, RTX

Table A.8: Top 10 InvesText's Information Providers by Number of Published Equity Reports About the Dow Companies

Tables show top 10 information providers in 5th and 1-4 quantiles, percent of number of reports published, number of covered companies, period when a information provider is in the InvesText and tickers of covered companies. There are 46 tickers in InvesTest out of 47 the Dow companies that were in the Dow in the sample period. Sample is from January 1, 2000 to December 31, 2019.

information provider	Percent of Reports In Group, %	# Companies Covered	In InvesText From	In InvesText To	Tickers Covered
Top 10 in 5th Quantile					
Credit Suisse	14.9	46	2000-01	2019-12	All
Oppenheimer & Co., Inc.	6.2	45	2000-01	2019-12	All except DOW
Deutsche Bank	6.0	46	2000-01	2019-12	All
JPMorgan	4.3	46	2000-01	2019-12	All
Cowen and Company	4.3	43	2000-01	2019-12	All except AIG, GM, TRV
RBC Capital Markets	4.1	46	2000-01	2019-12	All
Wells Fargo Securities, LLC	3.8	43	2000-01	2019-12	All except DOW, KODK, MMM
Bear Stearns & Co. Inc.	3.4	41	2000-01	2008-05	All except CRM, DOW, GM, PM, V
Refinitiv StreetEvents	3.1	46	2002-01	2019-12	All
Piper Sandler Companies	2.8	44	2000-01	2019-12	All except DOW, RTX
Top 10 in 1-4th Quantile					
Miller Tabak & Co.	1.7	31	2010-06	2015-06	AA, AAPL, AIG, AMGN, AXP, BA, BAC, C, CAT, CRM, CSCO, CVX, DD, DIS, GE, GS, INTC, JNJ, JPM, KO, MCD, MRK, MSFT, PFE, RTX, T, UNH, VZ, WBA, WMT, XOM
Summit Insights Group	1.7	12	2012-10	2019-10	AAPL, CRM, CSCO, DD, HPQ, IBM, INTC, MRK, MSFT, NKE, T, VZ
SEENSCO	1.7	34	2014-09	2019-10	AAPL, AMGN, AXP, BA, BAC, CAT, CSCO, CVX, DD, DIS, GE, GS, HD, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MO, MRK, MSFT, NKE, PFE, PG, RTX, T, TRV, UNH, V, VZ, WMT, XOM
Crispidea	1.7	31	2014-04	2019-12	AAPL, AMGN, BA, BAC, C, CAT, CRM, CSCO, CVX, DD, DIS, GE, GS, HON, HPQ, IBM, INTC, JNJ, JPM, KO, MCD, MMM, MRK, MSFT, PFE, RTX, T, UNH, VZ, WMT, XOM
Rosenblatt Securities, Inc.	1.6	8	2014-10	2019-12	AA, AAPL, CRM, CSCO, DIS, INTC, MSFT, T
Desjardins Securities	1.5	10	2004-02	2016-08	AA, CAT, CSCO, GM, HPQ, INTC, IP, PM, T, WMT
Yuanta Research	1.5	9	2007-07	2019-10	AAPL, BA, C, CSCO, HPQ, IBM, INTC, MSFT, NKE
Tucker Anthony Sutro Capital Markets	1.5	27	2000-01	2001-10	AXP, BA, BAC, C, CSCO, CVX, DD, DIS, GE, HD, HON, HPQ, IBM, INTC, JPM, MMM, MRK, MSFT, NKE, PFE, PG, RTX, T, VZ, WBA, WMT, XOM
Berenberg	1.5	23	2003-01	2019-12	AA, AAPL, BA, BAC, C, CAT, CRM, CSCO, CVX, GE, GM, GS, HON, IBM, JPM, MO, MRK, MSFT, NKE, PFE, PG, PM, XOM
Acquisdata	1.5	25	2014-05	2019-12	AA, AAPL, AMGN, BA, BAC, C, CAT, CRM, CSCO, CVX, DIS, GM, GS, HPQ, IBM, INTC, JNJ, JPM, MRK, MSFT, PFE, RTX, T, VZ, XOM

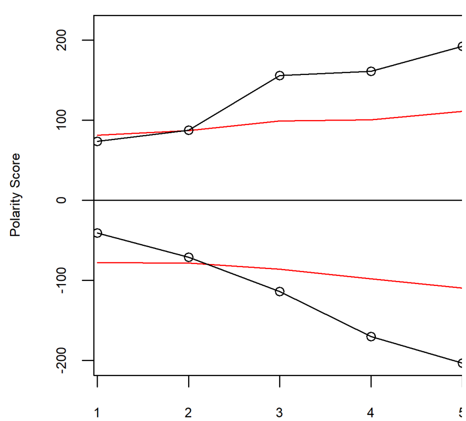
A.4 Types of Providers

Figure A.9: Measures of Cross-News and Time-Series Dispersion of Sentiment About Earnings Growth Per information provider Cluster

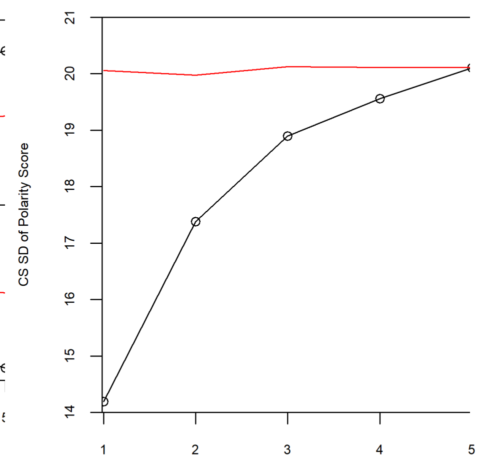
The left plot shows minimum, $\min(s^{cl}) == \min s_{e,d,f,c}|cl$, and maximum, $\max(s^{cl}) = \max s_{e,d,f,c}|cl$, of sentiments about earnings growth of individual reports per cluster cl per editorial e, day d, information provider f and company c, for $cl \in \{1, \ldots, 5\}$. Red lines are random minimum and maximum of a simulated sample of the size n^{cl} from Normal distribution with mean and standard deviation of a cross-news cluster number five $N(1.99, 20.10)$.

Right plot shows cross-news sample standard deviation of sentiment about earnings growth per information provider cluster. It is calculated as $\bar{\sigma}^{cl} = \sqrt{\frac{1}{n^{cl}-1} \sum (s^{cl}_{e,d,f,c} - \bar{s}^{cl})^2}$, for $cl \in \{1, \ldots, 5\}$, e is an event type, d is a day , f is an information provider and c is a company, $\bar{s}^{cl} = E[p(s_{e,d,f,c})|cl]$ is mean of sentiment about earnings growth per information provider cluster. Red line is a mean of a simulated sample of the size n^{cl} from Normal distribution with cross-sectional mean and standard deviation of a cluster number five $N(1.99, 20.10)$.

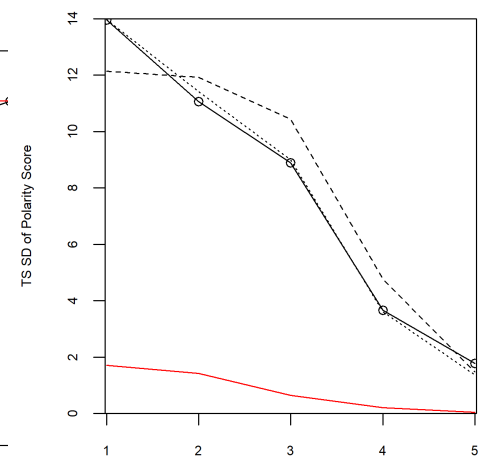
Bottom plot shows a sample standard deviation of monthly average sentiment about earnings growth per information provider's cluster. For every cluster, the sample standard deviation of monthly average sentiment is calculated as $\bar{\sigma} = \sqrt{\frac{1}{n-1} \sum (s_t - \bar{s})^2}$, where $s_t = \{s^m_t, s_t, s^w_t\}$ and $\bar{s} = \{\bar{s}^m, \bar{s}, \bar{s}^w\}$. Solid black line is a standard deviation of s^f_t per cluster. Dashed line is a standard deviation of s^m_t per cluster. Dotted line is a standard deviation of s^w_t per cluster. Red line a standard deviation of a simulated sample of the size a cluster from Normal distribution with mean and standard deviation of a cross-news cluster number five $N(1.99, 20.10)$. The sample is from July 1, 2002 to December 31, 2019.



(a) Cross-news: Range of Individual Sentiment Per Cluster



(b) Cross-news: SD of Individual Sentiment Per Cluster



(c) Time-series: SD of Monthly Sentiment Per Cluster

A.5 Rinker (2018) Sentiment Algorithm

Each sentence s is broken into an ordered words

$$s = \{w_1, w_2, \ldots, w_k, \ldots, w_n\} \tag{A.20}$$

where w_k are the words within sentences. Punctuation is removed with the exception of pause punctuation (commas, colons, semicolons) which are considered a word within the sentence. Denote pause words as cw.

First, the words in each sentence w_k are compared to a dictionary of polarized words[34] and weighted based on the sentiment dictionary. Denote polarized words as pw_k.

Second, each polarized word forms a polarized context cluster c_l which is a subset of the a sentence $c_l \subseteq s$. The polarized context cluster c_l of words is pulled from around the polarized word pw_k and defaults to two words before and five words after pw_k. The cluster can be represented as

$$c_l = \{w_{l,k-2}, \ldots, pw_{l,k}, \ldots, w_{l,k+5}\} \tag{A.21}$$

The words in this polarized context cluster l are tagged as neutral $w^0_{l,k}$ or as valence-shifters, such as negators $w^n_{l,k}$, amplifiers (intensifiers) $w^a_{l,k}$, or de-amplifiers (downtoners) $w^d_{l,k}$. Neutral words hold no value in the equation but affect word count n.

The polarized word $pw_{l,k}$ is then weighted based on words sentiment dictionary and then further weighted by the number of the valence shifters surrounding the positive or negative word $pw_{l,k}$ in cluster l.

Amplifiers (intensifiers) increase the polarity of the polarized word $pw_{l,k}$. Amplifiers $w^a_{l,k}$ become de-amplifiers if the context cluster contains an odd number of negators $w^n_{l,k}$. De-amplifiers (downtoners) work to decrease the polarity (deamplifier weight is constrained to -1 lower bound). Negation $w^n_{l,k}$ acts on amplifiers/de-amplifiers as discussed but also flip the sign of the polarized word. Negation is determined by raising -1 to the power of the number of negators $w^n_{l,k} + 2$. Simply, this is a result of a belief that two negatives equal a positive, 3 negatives a negative and so on.

The adversative conjunctions (i.e., 'but', 'however', and 'although') also weight the context cluster.

[34] I used Loughran & McDonald's (2016) positive/negative financial word list as sentiment lookup values that assigns $+1$ to positive polarity word and -1 to negative polarity word.

Denote a number of adversative conjunctions within the cluster before the polarized word as $n^b_{l,ad}$ and after polarized word as $n^a_{l,ad}$. Adversative conjunctions before polarized word up-weight the cluster by

$$1 + 0.85 * n^b_{l,ad} \tag{A.22}$$

while adversative conjunctions after the polarized word down-weight the cluster by

$$1 - 0.85 * n^a_{l,ad} \tag{A.23}$$

This corresponds to the belief that an adversative conjunction makes the next clause of greater values while lowering the value placed on the prior clause.

Last, these weighted context clusters c_l are summed c and divided by the square root of the word count $\sqrt{n}$ yielding an unbounded polarity score δ for each sentence.

$$\delta = \frac{c}{\sqrt{n}} \tag{A.24}$$

where

$$c = \sum_l ((1 + w_{l,amp} + w_{l,deamp}) * pw_{l,k}(-1)^{2+w_{l,neg}}) \tag{A.25}$$

$$w_{l,amp} = w_{l,b}\mathbb{1}_{w_{l,b}>1} + \sum(w_{l,neg} * (0.85 * w^a_{l,k}) \tag{A.26}$$

$$w_{l,b} = 1 + 0.85(n^b_{l,ad} - n^a_{l,ad}) \tag{A.27}$$

$$w_{l,neg} = \left(\sum w^n_{l,k}\right)(mod2) \tag{A.28}$$

$$w_{l,deamp} = \max\{w_{l,deamp'}, 1\} \tag{A.29}$$

$$w_{l,deamp'} = w_b\mathbb{1}_{w_{l,b}<1} + \sum(0.85 * (-w_{l,neg} * w^a_{l,k} + w^d_{l,k})) \tag{A.30}$$

Pause $cw_{l,k}$ locations are indexed and considered in calculating the upper and lower bounds in the polarized context cluster, as these marks indicate a change in thought and words prior are not necessarily connected with words after these punctuation marks.

The lower bound of the polarized context cluster is constrained to $\max\{pw_{l,k-4}, 1, \max\{cw_{l,k} < pw_{l,k}\}\}$

and the upper bound is constrained to $\min\{pw_{l,k+4}, n, \min\{cw_{l,k} > pw_{l,k}\}\}$ where n is the number of words in the sentence.

Figure A.9 shows two measures of dispersion, the range and the standard deviation of sentiment scores per information providers' quantile. The plot on the left shows minimum and maximum cross-news sentiment scores per quantile. The range, as a difference between maximum and minimum cross-news sentiment score is monotonically increasing. The right graph shows the standard deviation of cross-news sentiment scores. It increases monotonically from 12 to 20.

To show that the increase in dispersion is far from being mechanical consequence of increase in the sample size, I include a realization of Monte Carlo simulation of a range and a standard deviation of sentiment scores generated by a similar information structure with $\{132, 103, 111, 112, 113\}$ information providers that draw correspondingly one, two, ten, seventy-five and 2,039 random normal numbers from $N(1.99, 20.10)$ with a mean and standard deviation of the largest, fifth quantile 240 times (number of months in the sample). The red lines show the results of a simulation. Although the simulated range widens slightly for the fifth quantile, the magnitude of the change is significantly smaller than the change in the range in the data. The standard deviation of the simulated sentiment scores remains roughly the same, in contrast with the 1.4 times increase in cross-news standard deviation in the data.

A.6 Johansen (1988, 1991) Maximum Likelihood Estimation

An $(n \times 1)$ vector $\mathbf{y}$, was said to exhibit h cointegrating relations if there exist h linearly independent vectors $\mathbf{a_1}$,$\mathbf{a_2}$, ..., $\mathbf{a_h}$ such that $\mathbf{a_i^{'}y_t}$, is stationary. To uniquely identify the vectors, the normalization condition such as $a_{11} = 1$ is imposed. For this normalization we would put y_{1t}, on the left side of a regression and the other elements of y, on the right side.

Let $\mathbf{y}$ denote An $(n \times 1)$ vector. The maintained hypothesis is that $\mathbf{y}$ follows a $VAR(p)$ in levels. As any pth-order VAR can be written i the form

$$\mathbf{\Delta y_t} = \xi_1 \mathbf{\Delta y_{t-1}} + \xi_2 \mathbf{\Delta y_{t-3}} + \ldots + \xi_{\mathbf{p-1}} \mathbf{\Delta y_{t-p+1}} + \alpha + \xi_0 \mathbf{y_{t-1}} + \varepsilon_\mathbf{t} \quad \text{(A.31)}$$

with

$$E(\varepsilon_{\mathbf{t}}) = 0 \tag{A.32}$$

$$E(\varepsilon_{\mathbf{t}}\varepsilon_{\tau}^{'}) = \begin{cases} \mathbf{\Omega}, & \text{for} \quad t = \tau \\ \\ \mathbf{0}, & \text{otherwise} \end{cases} \tag{A.33}$$

Johansen (1991) describes his procedure using $\xi_{\mathbf{0}}\mathbf{y_{t-p}}$ instead of $\xi_{\mathbf{0}}\mathbf{y_{t-1}}$. Since $\mathbf{y_{t-p}} = \mathbf{y_{t-1}} - \mathbf{\Delta y_{t-1}} - \mathbf{\Delta y_{t-2}}, \ldots - \mathbf{\Delta y_{t-p+1}}$, the residuals are numerically identical to ones described in the text (of Hamilton (1994)).

Suppose that each individual variable $\mathbf{y_{i,t}}$ is $I(1)$, although h linear combinations of $\mathbf{y_t}$ are stationary. This implies that $\xi_{\mathbf{0}}$ can be written in the form

$$\xi_{\mathbf{0}} = -\mathbf{B}\mathbf{A}^{'} \tag{A.34}$$

for $\mathbf{B}$ an $(n \times k)$ matrix and $A^{'}$ an $(h \times n)$ matrix/ That is, under the hypothesis of h cointegrating relations, only h separate linear combinations of the level of $\mathbf{y_{t-1}}$ (the h elements of $\mathbf{z_{t-1}} = \mathbf{A}^{'}\mathbf{y_{t-1}}$ appears in the equation above.

Consider a sample of $T+p$ observations on $\mathbf{y}$ denoted $(\mathbf{y_{-p+1}}, \mathbf{y_{-p+2}}, \ldots, \mathbf{y_T})$. If the disturbances $\varepsilon_{\mathbf{t}}$ are Gaussian, then the log likelihood of $(\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_T})$ conditional on $(\mathbf{y_{-p+1}}, \mathbf{y_{-p+2}}, \ldots, \mathbf{y_T})$ is given by

$$L(\mathbf{\Omega}, \xi_{\mathbf{1}}, \xi_{\mathbf{2}}, \ldots, \xi_{\mathbf{p-1}}, \alpha, \xi_{\mathbf{0}}) = (-Tn/2)\log(2\pi) - (T/2)\log|\mathbf{\Omega}| \tag{A.35}$$

$$-\frac{1}{2}\sum_{t=1}^{T}\Big[(\mathbf{\Delta y_t} - \xi_{\mathbf{1}}\mathbf{\Delta y_{t-1}} \ldots - \xi_{\mathbf{p-1}}\mathbf{\Delta y_{t-p+1}} - \alpha - \xi_{\mathbf{0}}\mathbf{y_{t-1}})^{'} \tag{A.36}$$

$$\times\mathbf{\Omega}^{-1}(\mathbf{\Delta y_t} - \xi_{\mathbf{1}}\mathbf{\Delta y_{t-1}} \ldots - \xi_{\mathbf{p-1}}\mathbf{\Delta y_{t-p+1}} - \alpha - \xi_{\mathbf{0}}\mathbf{y_{t-1}})\Big] \tag{A.37}$$

The goal is to chose $\mathbf{\Omega}, \xi_{\mathbf{1}}, \xi_{\mathbf{2}}, \ldots, \xi_{\mathbf{p-1}}, \alpha, \xi_{\mathbf{0}}$ to maximize the likelihood function above subject to the constraint that $\xi_{\mathbf{0}}$ can be written in the form $\xi_{\mathbf{0}} = -\mathbf{B}\mathbf{A}^{'}$.

The next sections summarize Johansen's algorithm.

Step 1. Calculate Auxiliary Regressions

The first step is to estimate a $(p-1)$th-order VAR for $\mathbf{\Delta y_t}$; that is, regress the scalar $\Delta y_{i,t}$ on a constant and all the elements of the vectors $\mathbf{y_1}, \mathbf{y_2}, \ldots, \mathbf{y_{t-p+1}}$ by OLS. Collect the $i = 1, 2, \ldots, n$ OLS regressions in vector form as

$$\mathbf{\Delta y_t} = \hat{\pi_0} + \mathbf{\Pi_1} \hat{\Delta} y_{t-1} + \mathbf{\Pi_2} \hat{\Delta} y_{t-2} + \ldots + \mathbf{\Pi_{p-1}} \hat{\Delta} y_{t-p+1} + \mathbf{\hat{u}_t} \tag{A.38}$$

where $\mathbf{\Pi_i}$ denotes an $(n \times n)$ matrix of OLS coefficients estimates and $\mathbf{\hat{u}_t}$ denotes $(n \times 1)$ vector of OLS residuals.

We also estimate a second battery of regressions, regressing the scalar $\Delta y_{i,t-1}$ on a constant and $\mathbf{y_{t-1}}$, $\mathbf{y_{t-2}}, \ldots, \mathbf{y_{t-p+1}}$ for $i = 1, 2, \ldots, n$. Write this second set of OLS regressions as

$$\mathbf{\Delta y_{t-1}} = \hat{\theta} + \mathbf{\Psi_1} \hat{\Delta} y_{t-1} + \mathbf{\Psi_2} \hat{\Delta} y_{t-2} + \ldots + \mathbf{\Psi_{p-1}} \hat{\Delta} y_{t-p+1} + \mathbf{\hat{v}_t} \tag{A.39}$$

with $\mathbf{\hat{v}_t}$ the $(n \times 1)$ vector of residuals from this second battery of regressions.

Johansen (1991) paper's procedure calculates $\mathbf{v_t}$ instead of $\mathbf{\hat{v}_t}$, where $\mathbf{v_t}$ is OLS residual from regression of $\mathbf{y_{t-p}}$ on a constant and $\mathbf{y_{t-1}}, \mathbf{y_{t-2}}, \ldots, \mathbf{y_{t-p+1}}$.

Step 2. Calculate Canonical Correlations

Next calculate the sample variance-covariance matrices of the OLS residuals $\mathbf{\hat{u}_t}$ and $\mathbf{\hat{v}_t}$:

$$\hat{\Sigma_{VV}} \equiv \frac{1}{T} \sum_{t=1}^{T} \mathbf{\hat{v}_t} \hat{\mathbf{v_t}}' \tag{A.40}$$

$$\hat{\Sigma_{UU}} \equiv \frac{1}{T} \sum_{t=1}^{T} \mathbf{\hat{u}_t} \hat{\mathbf{u_t}}' \tag{A.41}$$

$$\hat{\Sigma_{UV}} \equiv \frac{1}{T} \sum_{t=1}^{T} \mathbf{\hat{u}_t} \hat{\mathbf{v_t}}' \tag{A.42}$$

$$\hat{\Sigma_{VU}} \equiv \hat{\Sigma'_{UV}} \tag{A.43}$$

From these, find the eigenvalues of the matrix

$$\hat{\Sigma_{VV}}^{-1}\hat{\Sigma_{VU}}\hat{\Sigma_{UU}}^{-1}\hat{\Sigma_{UV}} \tag{A.44}$$

with eigenvalues ordered $\hat{\lambda}_1 > \hat{\lambda}_2 > \ldots > \hat{\lambda}_n$. The maximum value attained by the log likelihood function subject to the constraint that there are h cointegrating relations is given by

$$L^* = -\frac{Tn}{2}\log(2\pi) - \frac{Tn}{2} - \frac{T}{2}\log|\hat{\Sigma_{UU}}| - \frac{Tn}{2}\sum_{i=1}^{h}\log(1-\hat{\lambda}_i) \tag{A.45}$$

Step 3. Calculate Maximum Likelihood Estimates of Parameters

If we are interested only in a likelihood ratio test of the number of cointegrating relations, step 2 provides all the information needed. If maximum likelihood estimates of parameters are also desired, these can be calculated as follows.

Let $\hat{\mathbf{a_1}}$, $\hat{\mathbf{a_2}}$, ..., $\hat{\mathbf{a_h}}$ denote the $(n \times 1)$ eigenvectors of $\hat{\Sigma_{VV}}^{-1}\hat{\Sigma_{VU}}\hat{\Sigma_{UU}}^{-1}\hat{\Sigma_{UV}}$ associated with the h largest eigenvalues. These provide a basis for the space of cointegrating relations; that is, the maximum likelihood estimate is that any cointegrating vector can be written in the form

$$\mathbf{a_1} = b_1\hat{\mathbf{a_1}} + b_2\hat{\mathbf{a_2}} + \ldots + b_h\hat{\mathbf{a_h}} \tag{A.46}$$

for some choice of scalars $(b_1, b_2, \ldots, b_n)$. Johansen suggested normalizing these vectors $\hat{\mathbf{a_i}}$ so that $\hat{\mathbf{a_i}}'\hat{\Sigma_{VV}}\hat{\mathbf{a_i}} = 1$. For example, if the eigenvectors $\hat{\mathbf{a_i}}$ of $\hat{\Sigma_{VV}}^{-1}\hat{\Sigma_{VU}}\hat{\Sigma_{UU}}^{-1}\hat{\Sigma_{UV}}$ are calculated from a standard computer program that normalizes $\tilde{\mathbf{a_i}}'\tilde{\mathbf{a_i}} = 1$, Johansen's estimate is $\hat{\mathbf{a_i}} = \tilde{\mathbf{a_i}} + \sqrt{\tilde{\mathbf{a_i}}'\hat{\Sigma_{VV}}\tilde{\mathbf{a_i}}}$. Collect the first h normalized vectors in an $(n \times h)$ matrix $\hat{\mathbf{A}}$:

$$\hat{\mathbf{A}} = [\hat{\mathbf{a_1}}, \hat{\mathbf{a_2}}, \ldots, \hat{\mathbf{a_h}}] \tag{A.47}$$

Then the MLE of $\hat{\xi_0}$ is given by

$$\hat{\xi_{\mathbf{0}}} = \hat{\Sigma_{UV}}\hat{\mathbf{A}}\hat{\mathbf{A}}^{'} \tag{A.48}$$

The MLE of $\hat{\xi_{\mathbf{i}}}$ for $i = 1, 2, \ldots, p-1$ is

$$\hat{\xi_{\mathbf{i}}} = \hat{\mathbf{\Pi}}_{\mathbf{i}} - \hat{\xi_{\mathbf{0}}}\hat{\mathbf{\Psi}}_{\mathbf{p-1}} \tag{A.49}$$

and the MLE of α is

$$\hat{\alpha} = \hat{\pi_{\mathbf{0}}} - \hat{\xi_{\mathbf{0}}}\hat{\theta} \tag{A.50}$$

The MLE of $\mathbf{\Omega}$ is

$$\hat{\mathbf{\Omega}} = \frac{1}{T}\sum_{t=1}^{T}[(\hat{\mathbf{u}}_{\mathbf{t}} - \hat{\xi_{\mathbf{0}}}\hat{\mathbf{v}}_{\mathbf{t}})(\hat{\mathbf{u}}_{\mathbf{t}} - \hat{\xi_{\mathbf{0}}}\hat{\mathbf{v}}_{\mathbf{t}})^{'}] \tag{A.51}$$

A.7 Loading Matrices

Table A.9: Matrix α

Matrix α of loading weights of potential cointegration vectors in the test procedure.

	$\tilde{r}_t^C$	$\tilde{r}_t^M$
s_t^w	$\begin{bmatrix} -0.369 & 0.027 \\ 0.096 & -0.044 \end{bmatrix}$	$\begin{bmatrix} -0.365 & 0.013 \\ 0.126 & -0.014 \end{bmatrix}$
s_t	$\begin{bmatrix} -0.687 & 0.001 \\ -0.008 & -0.007 \end{bmatrix}$	$\begin{bmatrix} -0.707 & 0.001 \\ 0.007 & 0.002 \end{bmatrix}$
s_t^m	$\begin{bmatrix} -0.652 & 0.001 \\ -0.011 & -0.006 \end{bmatrix}$	$\begin{bmatrix} -0.623 & 0.001 \\ 0.014 & 0.002 \end{bmatrix}$

A.8 VECM. Hypothesis 1

Table A.10: Hypothesis 1. VECM With Subjective Expectaions From MSC Survey

	Dependent variable:					
	VECM With Provider-weighted Sentiment		VECM With Equally-weighted Sentiment		VECM With Company-weighted Sentiment	
	$\Delta\tilde{r}_t^M$	Δs_t^w	$\Delta\tilde{r}_t^M$	Δs_t	$\Delta\tilde{r}_t^M$	Δs_t^m
	(1)	(2)	(3)	(4)	(5)	(6)
v_{t-1}	0.126^{**}	-0.365^{***}	0.007	-0.707^{***}	0.014	-0.623^{***}
	(0.050)	(0.074)	(0.040)	(0.092)	(0.034)	(0.094)
$\Delta\tilde{r}_{t-1}^M$	-0.317^{***}	0.174^{*}	-0.277^{***}	0.349^{**}	-0.277^{***}	0.332^{*}
	(0.070)	(0.105)	(0.070)	(0.160)	(0.069)	(0.191)
Δs_{t-1}^w	0.066	-0.684^{***}	0.020	-0.830^{***}	0.007	-0.920^{***}
	(0.047)	(0.070)	(0.031)	(0.072)	(0.026)	(0.071)
Constant	0.234^{**}	-0.585^{***}	0.028	-0.033	0.031	-0.145
	(0.093)	(0.139)	(0.045)	(0.104)	(0.046)	(0.127)
Observations	196	196	196	196	196	196
R^2	0.106	0.333	0.078	0.412	0.077	0.480
Adj. R^2	0.092	0.323	0.064	0.403	0.062	0.472

Table A.11: Hypothesis 1. VECM With Subjective Expectaions From CSS Survey

	Dependent variable:					
	VECM With Provider-weighted Sentiment		VECM With Equally-weighted Sentiment		VECM With Company-weighted Sentiment	
	$\Delta\tilde{r}_t^C$	Δs_t^w	$\Delta\tilde{r}_t^C$	Δs_t	$\Delta\tilde{r}_t^C$	Δs_t^m
	(1)	(2)	(3)	(4)	(5)	(6)
v_{t-1}	0.096^{*}	-0.369^{***}	-0.008	-0.687^{***}	-0.011	-0.652^{***}
	(0.056)	(0.070)	(0.045)	(0.089)	(0.040)	(0.094)
$\Delta\tilde{r}_{t-1}^C$	-0.228^{***}	0.155^{*}	-0.194^{***}	0.224	-0.192^{***}	0.294^{*}
	(0.073)	(0.092)	(0.070)	(0.138)	(0.070)	(0.164)
Δs_{t-1}^w	0.062	-0.695^{***}	0.001	-0.823^{***}	-0.028	-0.941^{***}
	(0.055)	(0.070)	(0.037)	(0.072)	(0.030)	(0.071)
Constant	0.327^{*}	-1.180^{***}	0.011	-0.376^{***}	0.002	-0.863^{***}
	(0.188)	(0.236)	(0.059)	(0.115)	(0.074)	(0.173)
Observations	196	196	196	196	196	196
R^2	0.053	0.343	0.039	0.413	0.044	0.491
Adj. R^2	0.039	0.333	0.024	0.404	0.029	0.483

A.9 VECM. Hypothesis 1.1

Table A.12: Hypothesis 1.1. VECM With Subjective Expectaions From MSC Survey

	Dependent variable:			
	VECM With Sentiment of More Active Providers		VECM With Sentiment of Less Active Providers	
	$\Delta\tilde{r}_t^M$ (1)	Δs_t^w (2)	$\Delta\tilde{r}_t^M$ (3)	Δs_t^w (4)
v_{t-1}	0.131***	−0.358***	−0.020	−0.668***
	(0.048)	(0.073)	(0.022)	(0.095)
$\Delta\tilde{r}_{t-1}^M$	−0.322***	0.157	−0.276***	0.354
	(0.070)	(0.107)	(0.069)	(0.305)
Δs_{t-1}^w	0.066	−0.662***	−0.004	−0.876***
	(0.046)	(0.070)	(0.017)	(0.073)
Constant	0.263***	−0.622***	0.018	−0.405**
	(0.096)	(0.147)	(0.047)	(0.205)
Observations	196	196	196	196
R^2	0.111	0.320	0.081	0.430
Adj. R^2	0.097	0.310	0.067	0.421

Table A.13: Hypothesis 1.1. VECM With Subjective Expectaions From CSS Survey

	Dependent variable:			
	VECM With Sentiment of More Active Providers		VECM With Sentiment of Less Active Providers	
	$\Delta\tilde{r}_t^C$ (1)	Δs_t^w (2)	$\Delta\tilde{r}_t^C$ (3)	Δs_t^w (4)
v_{t-1}	0.106**	−0.357***	−0.028	−0.678***
	(0.054)	(0.069)	(0.025)	(0.094)
$\Delta\tilde{r}_{t-1}^C$	−0.236***	0.137	−0.195***	0.140
	(0.073)	(0.094)	(0.070)	(0.264)
Δs_{t-1}^w	0.068	−0.668***	−0.022	−0.880***
	(0.054)	(0.069)	(0.019)	(0.073)
Constant	0.384**	−1.220***	−0.022	−0.972***
	(0.194)	(0.250)	(0.063)	(0.236)
Observations	196	196	196	196
R^2	0.058	0.328	0.046	0.433
Adj. R^2	0.043	0.317	0.031	0.424

A.10 VECM. Hypothesis 1.1. With r_{t-1}

Table A.14: Hypothesis 1.1. VECM With Subjective Expectaions From MSC Survey and Past Market Return

	Dependent variable:					
	VECM With Sentiment of More Active Providers			VECM With Sentiment of Less Active Providers		
	$\Delta\tilde{r}^C_t$	Δs^w_t	Δr_{t-1}	$\Delta\tilde{r}^C_t$	Δs^w_t	Δr_{t-1}
	(1)	(2)	(3)	(4)	(5)	(6)
v_{t-1}	-0.030^{*}	0.074^{***}	-1.113^{***}	-0.009	0.196^{***}	-0.992^{***}
	(0.016)	(0.026)	(0.097)	(0.016)	(0.075)	(0.094)
$\Delta\tilde{r}^M_{t-1}$	-0.292^{***}	-0.018	1.359^{***}	-0.298^{***}	0.261	1.674^{***}
	(0.071)	(0.113)	(0.421)	(0.073)	(0.353)	(0.442)
Δs^w_{t-1}	0.024	-0.548^{***}	1.172^{***}	0.008	-0.566^{***}	0.190^{**}
	(0.042)	(0.066)	(0.245)	(0.013)	(0.062)	(0.077)
Δr_{t-2}	-0.003	0.049^{**}	-1.018^{***}	0.008	0.049	-0.960^{***}
	(0.012)	(0.019)	(0.072)	(0.012)	(0.058)	(0.073)
Constant	0.044	-0.019	0.574^{**}	0.022	0.093	-0.735^{**}
	(0.046)	(0.072)	(0.269)	(0.047)	(0.227)	(0.284)
Observations	196	196	196	196	196	196
R^2	0.101	0.269	0.520	0.088	0.311	0.483
Adj. R^2	0.082	0.254	0.510	0.068	0.297	0.472

Table A.15: Hypothesis 1.1. VECM With Subjective Expectaions From CSS Survey and Past Market Return

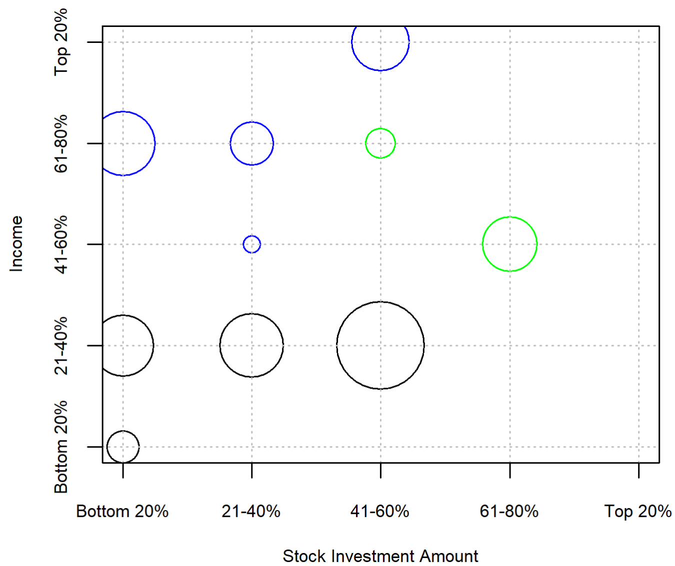
	Dependent variable:					
	VECM With Sentiment of More Active Providers			VECM With Sentiment of Less Active Providers		
	$\Delta\tilde{r}^C_t$	Δs^w_t	Δr_{t-1}	$\Delta\tilde{r}^C_t$	Δs^w_t	Δr_{t-1}
	(1)	(2)	(3)	(4)	(5)	(6)
v_{t-1}	-0.058^{***}	0.074^{***}	-1.053^{***}	-0.039^{**}	0.234^{***}	-0.974^{***}
	(0.019)	(0.025)	(0.098)	(0.018)	(0.076)	(0.098)
$\Delta\tilde{r}^C_{t-1}$	-0.217^{***}	-0.043	0.736^{*}	-0.201^{***}	0.185	1.145^{***}
	(0.074)	(0.102)	(0.395)	(0.076)	(0.316)	(0.408)
Δs^w_{t-1}	0.061	-0.545^{***}	1.065^{***}	0.0001	-0.582^{***}	0.252^{***}
	(0.048)	(0.065)	(0.254)	(0.015)	(0.062)	(0.080)
Δr_{t-2}	-0.017	0.050^{**}	-0.981^{***}	-0.007	0.065	-0.949^{***}
	(0.014)	(0.020)	(0.076)	(0.014)	(0.060)	(0.077)
Constant	0.038	-0.011	0.444	-0.060	0.397	-1.829^{***}
	(0.052)	(0.071)	(0.277)	(0.063)	(0.262)	(0.338)
Observations	196	196	196	196	196	196
R^2	0.094	0.271	0.485	0.070	0.321	0.457
Adj. R^2	0.075	0.255	0.474	0.051	0.306	0.446

A.11 VAR with Change in Sentiment

Figure A.10: "Best" VAR Specifications (Color) and Adjuster R^2 of VAR's Subjective Expectations Equations (Size of Circle)

The bubble plot shows adjusted R^2 of the "best" VAR with subjective expectations $\Delta\tilde{r}_t$ of investors with different level of investment in stocks and income from MSC survey. X-axis shows Stock Investment Amount quintile. Y-axis shows Income quintiles. The size of a circle is proportional to adjusted R^2 of VECM's subjective expectations equation. The biggest circle is equivalent adjusted $R^2 = 39\%$, the smallest to the $R^2 = 8\%$.

Gray color corresponds to VAR($\Delta^2 jc_t, \Delta^2 s_t, \Delta\tilde{r}_t$) with the following ordering of variables $\Delta^2 jc \rightarrow \Delta^2 s \rightarrow \Delta\tilde{r}$, where $\Delta^2 jc$ is second difference of polarity of the Mad Money episodes and $\Delta^2 s$ is a second difference of sentiment of equity reports. Blue color corresponds to VAR($\Delta r_{t-1}, \Delta^2 s_t, \Delta\tilde{r}_t$) or VAR($\Delta r_{t-1}, \Delta q_t, \Delta\tilde{r}_t$) with ordering $\Delta r \rightarrow \Delta^2 q \rightarrow \Delta\tilde{r}$, where $\Delta^2 q$ is polarity of the Squawk on the Street episodes. Green color corresponds to VAR($\Delta^2 s_t, \Delta\tilde{r}_t$) with ordering $\Delta^2 s \rightarrow \Delta\tilde{r}$ The calculations are based on monthly data from January 2012 to December 2018.



A.12 "Best" VECM or VAR Models With Subjective Expectations of Investors Within Income and Stock Invested Amount Quintiles

Table A.16: "Best" VECM or VAR Models With Subjective Expectations of Investors Within Income and Stock Invested Amount Quintiles

First three columns of table show VECM(v_1, v_2, v_3) variables v_1, v_2 and v_3. The first "Wald Statistics" column shows Wald test statistics with null hypothesis that lags of v_1 and $\alpha\beta^{'}$ are zero in v_2 equation of VECM. The second "Wald Statistics" column shows Wald test statistics with null hypothesis that lags of v_2 and $\alpha\beta^{'}$ are zero in v_3 equation of VECM. The first "Measures of Fit" column shows AIC, while the second - adjusted R^2 of subjective expectations equation. Monthly data is from January 2012 to December 2018.

VECM or VAR			Wald Statistics		Measure of Fit	
v_1	v_2	v_3	$H_0 : v_1 \nrightarrow v_2$	$H_0 : v_2 \nrightarrow v_3$	AIC	R_a^2
jc	s^w	$\tilde{r}(I2, S1)$	0.01	0.04	-15.91	0.27
r	q	$\tilde{r}(I2, S2)$	0.07	0.05	-13.80	0.43
jc	s^w	$\tilde{r}(I2, S3)$	0.01	0.13	-15.58	0.39
	$s_t^{w,5}$	$\tilde{r}(I3, S1)$		0.06	-9.88	0.12
	$s_t^{w,1:4}$	$\tilde{r}(I3, S3)$		0.10	-7.87	0.30
jc	s^w	$\tilde{r}(I3, S4)$	0.02	0.12	-14.83	0.16
	$s_t^{w,1:4}$	$\tilde{r}(I3, S5)$		0.07	-8.42	0.15
jc	s^c	$\tilde{r}(I4, S2)$	0.00	0.11	-14.66	0.20
	$s_t^{w,5}$	$\tilde{r}(I4, S3)$		0.06	-10.04	0.20
	$s_t^{w,1:4}$	$\tilde{r}(I4, S4)$		0.10	-7.84	0.19
	s^w	$\tilde{r}(I4, S5)$		0.04	-10.08	0.18
r	q	$\tilde{r}(I5, S2)$	0.13	0.06	-12.77	0.16
jc	s^c	$\tilde{r}(I5, S3)$	0.00	0.01	-13.86	0.32
	s^w	$\tilde{r}(I5, S4)$		0.13	-9.82	0.11
	s^w	$\tilde{r}(I5, S5)$		0.07	-9.56	0.16

A.13 Robustness Check

Figure A.11: AIC of VECM (s_t, $\tilde{r}_t$) Without One Year

Plot shows AIC of VECM regression explaining subjective equity premium without year on X-axis. Monthly data is from July 2002 to December 2019. The higher dashed line is the average AIC of the VECM with MSC expectations. The lower dashed line is AIC of VECM with the CCS expectations regression. Blue dots corresponds to AIC of VECM with subjective expectations from the CCS survey; white dots -AIC of VECM with subjective expectations from the MSC survey.

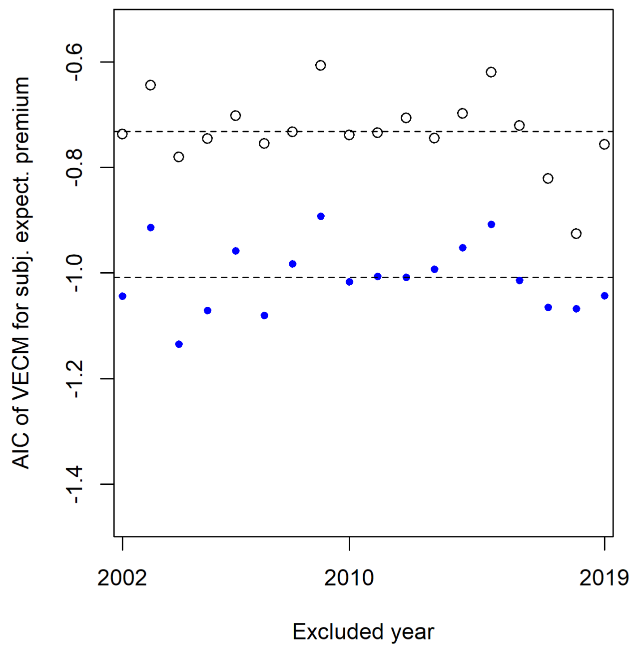
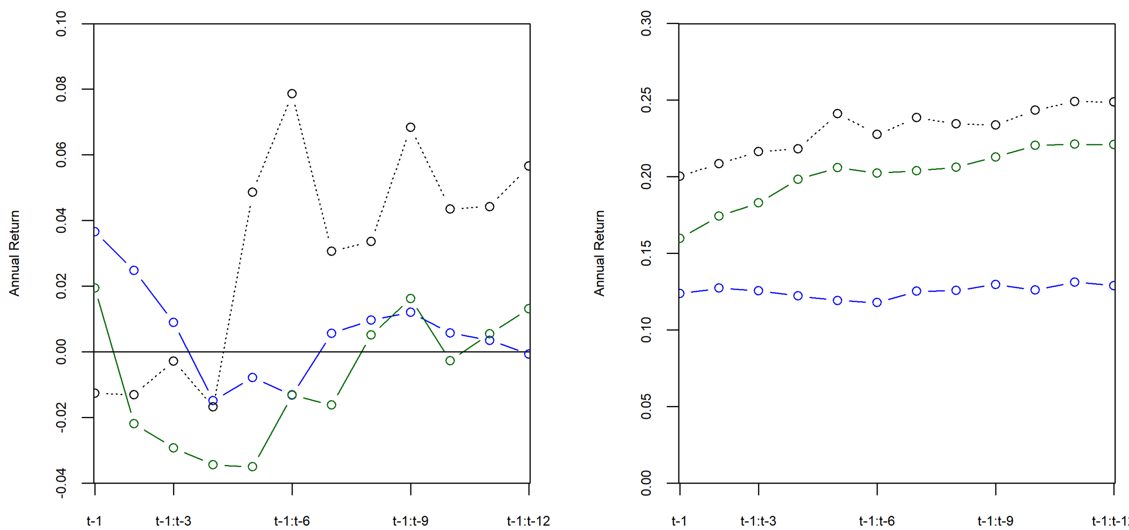


Figure A.12: Annualized Mean Return And Standard Deviation of Return Of Standard Momentum Strategy (Dashed Line) And Sentiment-Based Momentum Strategy Based on Information From Less Active (Blue Line) and More Active (Green Line) Information Providers Vs. Strategy Formation Period From $t-1$ to $t-1 \rightarrow t-12$

The calculations are based on the sample that consists of 45 US blue-chip companies and spans from July 2002 to December 2018.



(a) Annualized Mean Return Vs. Strategy Formation Period

(b) Annualized St.Dev. Of Return Vs. Strategy Formation Period

Chapter B

Appendix B

B.1 The cash-and-carry trade setting

In practice, a speculative cash-and-carry trade that links physical and futures markets for crude oil is set up in a way similar to the one described in the theoretical model. [1]

Consider the following simplified cash-and-carry trade between the Arabian Gulf and the U.S. Gulf. At time t, a carry trader buys Y_t barrels of crude oil in the Arabian Gulf at the price S_t dollars per barrel. The trader also charters a vessel at the daily cost R_t dollars per barrel in order to ship Y_t barrels to the U.S. Gulf. The vessel is expected to be at sea, both en route and as floating storage, for T days. Knowing that, the trader sells $Y_t \frac{S_t+R_tT}{F_t^{t+T}}$ barrels worth of crude oil futures contracts, where F_t^{t+T} is the time t price of the futures contract that matures in $t+T$. After T days, Y_t barrels of crude oil arrive in the U.S. Gulf. Of this amount, $Y_t \frac{S_t+R_tT}{F_t^{t+T}}$ barrels are delivered at the expiration of the futures contract to settle the short futures position. If $F_t^{t+T} > S_t + R_tT$, then there is $Y_t(1 - \frac{S_t+R_tT}{F_t^{t+T}})$ additional barrels to sell at F_t^{t+T} per barrel, earning $F_t^{t+T} Y_t(1 - \frac{S_t+R_tT}{F_t^{t+T}})$ dollars in profits or $Y_t(F_t^{t+T} - S_t - R_tT)$. The carry trader will continue buying, storing and shipping multiples of Y_t if $F_t^{t+T} - S_t - R_tT > 0$ subject to leverage or financing constraints, as well as additional frictions. Additional frictions include, for example, costs per vessel over and above the costs of shipping.

For illustrations purpose, we use the following numerical example closely based on actual data. Y_t is 2

[1] For cash-and-carry trades, see also Frankel (2014) and Knittel and Pindyck (2016).

million barrels, the capacity of a Very Large Cargo Carrier (VLCC). F_t^t, the price of the nearby Brent futures contract, which we assume to be approximately equal to S_t, is 57 dollars per barrel. T is 180 days. This includes the estimated time at sea for the route from Ras Tanura, Saudi Arabia to Houston, TX at an average speed of 13.5 knots. This time also includes loading time and unloading times (using Aframax vessels), adverse weather conditions adjustments, laytime, and possible use of the VLCC as floating storage. F_t^{t+180}, the price of the Brent futures contract expiring in 180 days is 66 dollars.

Daily time charter of the VLCC, R_t, is 47,000 dollars per day. Futures contracts with delivery in 180 days sold short, $Y_t \frac{F_t^t + R_t T}{F_t^{t+T}}$ is 1,855,455 barrels or 1,856 contracts of Brent futures contracts (per contract specifications, the size each contact is 1,000 barrels). Therefore, VLCC charter costs add up to 4.23 dollars per barrel (where $4.23 = \frac{47{,}000 * 180}{2{,}000{,}000}$).

Additional costs include monthly VLCC hull cleaning, two days steaming to remove growth and idle bunkering costs, as well as cargo insurance, lease of Aframax vessels for unloading, possible demurrage charges, margin and financing costs and trading fees. Based on the industry estimates, these additional costs add up to about 4.4 million dollars or 2.19 dollars per barrel (where $2.19 \approx \frac{4{,}400{,}000}{2{,}000{,}000}$).

Under these assumptions, total profits per VLCC amount to about 5.16 million dollars or 2.58 dollars per barrel (where $2.58 = \frac{5{,}160{,}000}{2{,}000{,}000} = 66 - 57 - 4.23 - 2.19$). If the price of the six months out futures contracts drops from 66 to 63.42 dollars per barrel, a cash-and-carry speculator becomes indifferent between engaging in the trade or not; his break-even point is then 63.42 dollars per barrel (where $63.42 - 57 - 4.23 - 2.19 = 0$).

B.2 An example of BOL

Figure B1: Bill of Lading

VICS Standard BOL: WWW.VICS.ORG For Complete VICS BOL Guideline Information

Date: 02/01/1999 **BILL OF LADING** Page 1

SHIP FROM	
Name: *ABC Company* Address: *1000 ABC Drive* City/State/Zip: *Any City, AB, 10000* SID#: FOB: ☐	Bill of Lading Number: _*06141411234567890*_
SHIP TO	
Name: *XYZ Company* Location #: _*0669*_ Address: *9000 XYZ Drive* City/State/Zip: *Some City, ZY 90000* CID#: FOB: ☐	CARRIER NAME: _*LTL Transportation*_ Trailer number: Seal number(s): SCAC: *ABCD* Pro number: *12345678901234567890*
THIRD PARTY FREIGHT CHARGES BILL TO:	
Name: Address: City/State/Zip:	Freight Charge Terms: *(freight charges are prepaid unless marked otherwise)* Prepaid ____ Collect _*X*_ 3rd Party ____
SPECIAL INSTRUCTIONS:	☐ (check box) Master Bill of Lading: with attached underlying Bills of Lading

CUSTOMER ORDER INFORMATION

CUSTOMER ORDER NUMBER	# PKGS	WEIGHT	PALLET	ADDITIONAL SHIPPER INFO
45012345698	*350 ctns*	*1750 lbs*	Y	
6805673	*50 ctns*	*250 lbs*	Y	
GRAND TOTAL	*400 ctns*	*2000 lbs*		

CARRIER INFORMATION

HANDLING UNIT QTY	HANDLING UNIT TYPE	PACKAGE QTY	PACKAGE TYPE	WEIGHT	H.M. (X)	COMMODITY DESCRIPTION	LTL ONLY NMFC #	LTL ONLY CLASS
5	*plts*	*100*	*ctns*	*500 lbs*		*Sport Accessories*	*154865 00*	*70*
		250	*ctns*	*1250 lbs*		*Video, Tape Recording*	*168955 03*	*92.5*
		50	*ctns*	*250 lbs*		*Recordings, Sound, Disc, Tape*	*168945 01*	*100*
5		400		2000 lbs		GRAND TOTAL		

Where the rate is dependent on value, shippers are required to state specifically in writing the agreed or declared value of the property as follows: "The agreed or declared value of the property is specifically stated by the shipper to be not exceeding ________ per ________."

COD Amount: $ ________
Fee Terms: Collect: ☐ Prepaid: ☐
Customer check acceptable: ☐

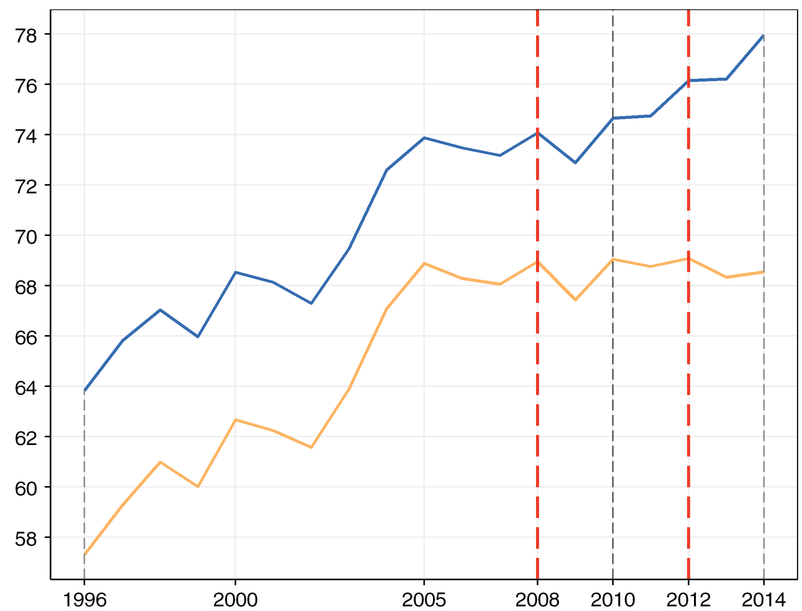
NOTE Liability Limitation for loss or damage in this shipment may be applicable. See 49 U.S.C. § 14706(c)(1)(A) and (B).

The carrier shall not make delivery of this shipment without payment of freight and all other lawful charges.
________ Shipper Signature

SHIPPER SIGNATURE / DATE	Trailer Loaded:	Freight Counted:	CARRIER SIGNATURE / PICKUP DATE
	☒ By Shipper ☐ By Driver	☒ By Shipper ☐ By Driver/pallets said to contain ☐ By Driver/Pieces	Property described above is received in good order, except as noted.

B.3 Supplementary information about crude oil market

Figure C1: Global Crude Oil Production With and Without the U.S.: 1996–2014
U.S. Energy Information Administration. The top line plots the total global production of crude oil in million of barrels per day averaged over a year. The bottom line plots global production minus production of crude oil in the United States. The difference between the two lines is crude oil production in the U.S. in million barrels per day averaged over a year.

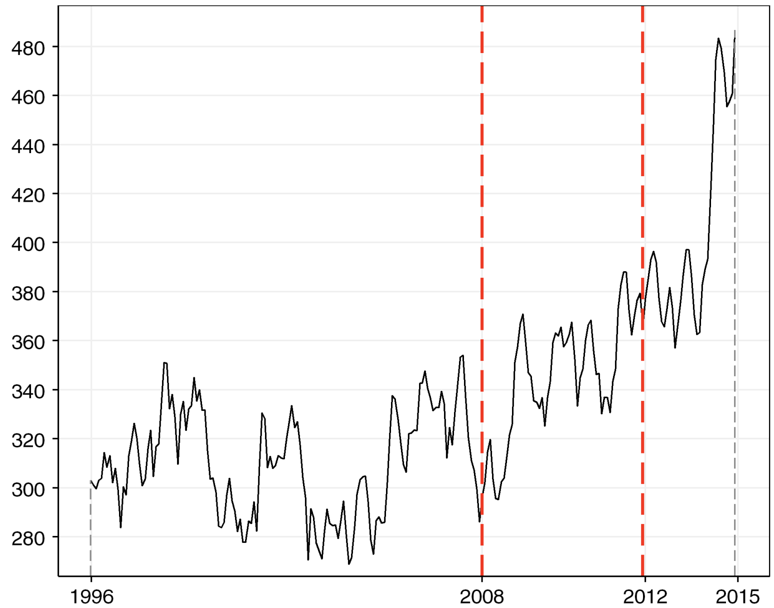


We provide an economic interpretation for the change in regime that we observe in the speculative floating oil series from mid-2010. Thus, we present background information about supply, demand, inventories, legal environment and prices.

Supply and inventories First, the increase in global oil supply from mid-2010 is primarily associated with the surge in oil production in the United States due to the use of new on-shore technologies such as slant drilling and hydraulic fracturing. Figure C1 illustrates that after a prolonged period of decline, U.S. oil production has been on the steady rise starting in mid-2010, while the supply response from the rest of the world remained flat. If the entire increase in the global oil supply can be associated with the increase in on-shore oil production in the U.S., then the change in the supply regime from constrained to unconstrained can be traced to the U.S.

Second, U.S. producers could not export any of its produced crude oil prior to 2015 due to the export ban in effect between 1975 and 2015. As a result, additionally produced oil needed to be first stored in the available U.S. on-shore storage facilities and then transported to and processed by U.S. refineries for both

Figure C2: U.S. Commercial Crude Oil Inventories: 1996–2015
U.S. Energy Information Administration. The solid line plots U.S. end of the month commercial crude oil inventories in millions of barrels.



domestic consumption and export (as there was no ban on exports of refined oil products from the U.S.). As Figure C2 illustrates, available inland storage facilities experienced a steady increase in U.S. inventories toward total available storage capacity from 2008.

However, the lack of pipelines to deliver inland crude oil in the East prevented inland crude oil to be transported to a large number of refineries in the U.S., especially along the Eastern seaboard.[2] This contributed to increase inland crude oil inventories even more.

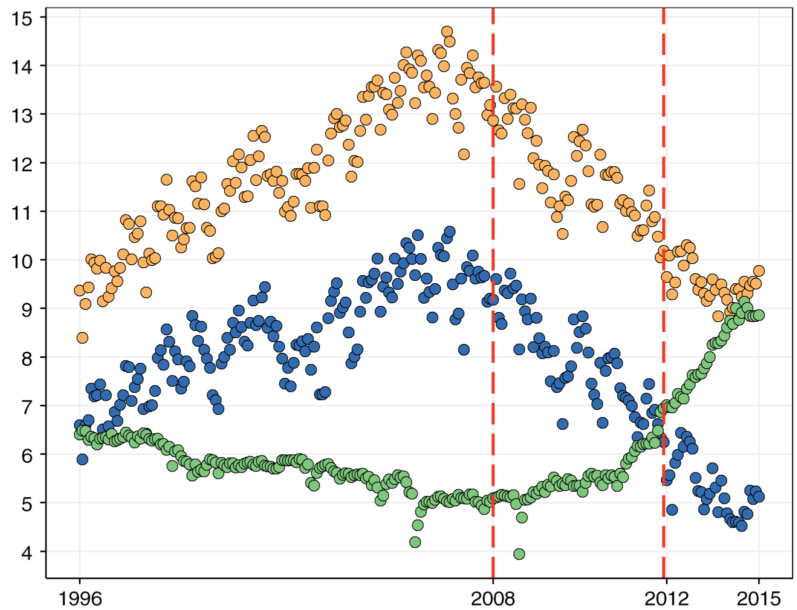
Demand and imports Third, these technological reasons increased the demand for crude oil on the East Coast. Indeed, the refineries on the East Coast were designed to refine seaborne oil (Brent); this created a need to import additional crude oil primarily by sea while the term structure of futures prices stayed in contango. It is possible then that seaborne oil imports into the U.S., while on a declining trend, can contain a component that can identified as speculative floating inventory. Trends in U.S. domestic production and seaborne imports into the U.S. are illustrated in Figure C3.

According to speculative storage theory, restricted supply should be associated with a build-up of speculative inventories and unrestricted supply should be associated with a decline in speculative inventories.

[2]We thank Vikas Raman for bringing the Brent–WTI spread as an indicator of a possible structural break in the crude oil market.

Figure C3: U.S. Crude Oil Imports and Production: 1996–2014

U.S. Energy Information Administration. The top series is the average monthly crude oil imports (in million barrels per day), including Strategic Petroleum Reserve. The middle series is the average monthly crude oil imports (in million barrels per day), including Strategic Petroleum Reserve, but excluding Canada and Mexico. The bottom series is the average monthly crude oil production (in million barrels per day).

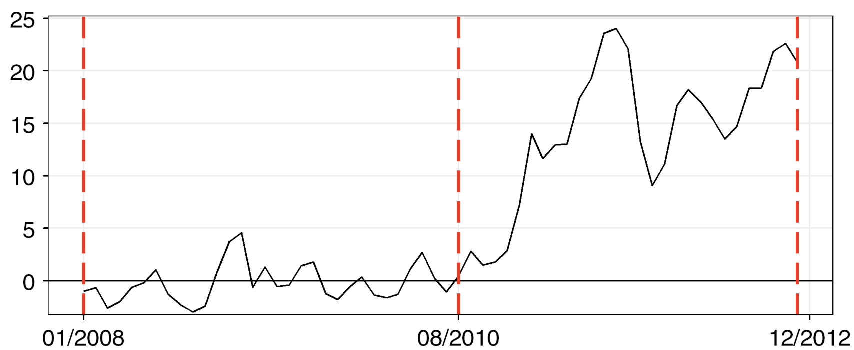


Supply of crude oil in the U.S. became unrestricted starting in about August 2010, while it remained restricted globally because of the ban on the export of crude oil from the U.S. Theory predicts that we should see speculative U.S. inventories increase from 2008 until about August 2010 and then decline. This suggests that the speculative floating inventory series is not only a constant proportion of the downward trend of crude oil imports but follows its own dynamics, which we show in Section 5.3.5.

Prices Finally, as inland crude oil in the U.S. became less demanded while global seaborne demand increased, a persistent positive spread developed between the price of the global seaborne benchmark Brent and the U.S. domestic benchmark, West Texas Intermediate (WTI). According to Figure C4, the Brent–WTI spread became persistently positive after August 2010, a barrel of global Brent crude trading for more than 20 dollars more than a barrel of U.S. domestic WTI crude.

Figure C4: Brent - WTI Spread: 2008 - 2012

Intercontinental Exchange and New York Merchantile Exchange. The line plots the difference between the average monthly price of the Brent nearby futures contract and the average monthly price of the WTI nearby futures contract.



Chapter C

Appendix C

C.1 Descriptive statistics

Table C.1: Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
Number of observations: 25,059				
all loans	6.2	15.7	-129.9	139.5
ruble loans	6.4	17.0	-140.5	142.6
dollar loans	0.5	23.1	-163.6	152.8
nonres	6.0	12.0	0.0	92.6
liquid	28.7	14.7	0.0	96.9
leverage	15.5	16.2	-484.3	260.2
core	38.0	19.1	0.0	88.9
ta	15.1	2.3	6.1	23.9

C.2 Cumulative Dynamic Effect of Foreign Monetary Policy Shocks On Domestic Lending Through Foreign Liabilities Channel

Table C.2: Cumulative Dynamic Effect of Foreign Monetary Policy Shocks On Domestic Lending In All Currencies Through Foreign Liabilities Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, M Pl, F F4, or M Pl and F F4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Regressor	(1)	(2)	(3)	(4)
		External Instrument: MP1		
$us_t * nonres_{t-4}$	$-0.055(0.097)$	$-0.039(0.100)$	$-0.052(0.097)$	$-0.020(0.100)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.108(0.121)$	$-0.068(0.125)$	$-0.105(0.121)$	$-0.030(0.124)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.238(0.156)$	$-0.161(0.160)$	$-0.238(0.155)$	$-0.110(0.158)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.219(0.165)$	$-0.118(0.172)$	$-0.220(0.163)$	$-0.054(0.171)$
$nonres_{t-4}$	$-0.056(0.020)^{***}$	$-0.009(0.012)$	$-0.041(0.020)^{**}$	$-0.021(0.013)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
		External Instrument: FF4		
$us_t * nonres_{t-4}$	$-0.156(0.120)$	$-0.124(0.122)$	$-0.153(0.120)$	$-0.107(0.121)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.246(0.185)$	$-0.164(0.183)$	$-0.248(0.184)$	$-0.129(0.181)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.391(0.218)^{*}$	$-0.248(0.214)$	$-0.402(0.216)^{*}$	$-0.202(0.214)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.344(0.232)$	$-0.164(0.233)$	$-0.356(0.228)$	$-0.111(0.234)$
$nonres_{t-4}$	$-0.054(0.020)^{***}$	$-0.007(0.013)$	$-0.039(0.021)^{*}$	$-0.019(0.014)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
		External Instruments: MP1 and FF4		
$us_t * nonres_{t-4}$	$-0.092(0.101)$	$-0.070(0.104)$	$-0.089(0.101)$	- 0.051(0.103)
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.156(0.139)$	$-0.100(0.141)$	$-0.155(0.138)$	$-0.064(0.139)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.296(0.1732)^{*}$	$-0.194(0.174)$	$-0.300(0.172)^{*}$	$-0.146(0.173)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.266(0.184)$	$-0.135(0.189)$	$-0.271(0.181)$	$-0.076(0.188)$
$nonres_{t-4}$	$-0.055(0.020)^{***}$	$-0.008(0.012)$	$-0.040(0.020)^{**}$	$-0.020(0.014)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes

Table C.3: Cumulative Dynamic Effect of Foreign Monetary Policy Shocks On Domestic Lending In Rubles Through Foreign Liabilities Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, MP1, FF4, or MP1 and FF4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

regressor	(1)	(2)	(3)	(4)
External Instrument: MP1				
$us_t * nonres_{t-4}$	$-0.084(0.136)$	$-0.067(0.138)$	$-0.080(0.136)$	$-0.051(0.137)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.015(0.188)$	$0.018(0.189)$	$-0.012(0.189)$	$0.051(0.188)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.132(0.217)$	$-0.059(0.221)$	$-0.132(0.218)$	$-0.015(0.221)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$0.011(0.225)$	$0.107(0.229)$	$0.011(0.224)$	
$nonres_{t-4}$	$-0.021(0.025)$	$0.027(0.014)^{*}$	$-0.004(0.025)$	$0.018(0.016)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instrument: FF4				
$us_t * nonres_{t-4}$	$-0.110(0.219)$	$-0.093(0.216)$	$-0.106(0.220)$	$-0.079(0.216)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.074(0.297)$	$-0.019(0.290)$	$-0.076(0.299)$	$0.010(0.289)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.207(0.286)$	$-0.087(0.2821)$	$-0.219(0.286)$	$-0.048(0.282)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.041(0.315)$	$0.108(0.310)$	$-0.053(0.312)$	
$nonres_{t-4}$	$-0.021(0.025)$	$0.027(0.015)^{*}$	$-0.004(0.026)$	$0.017(0.017)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instruments: MP1 and FF4				
$us_t * nonres_{t-4}$	$-0.093(0.160)$	$-0.076(0.159)$	$-0.089(0.160)$	$-0.060(0.159)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.035(0.220)$	$0.006(0.218)$	$-0.033(0.222)$	$0.037(0.217)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.160(0.237)$	$-0.069(0.237)$	$-0.163(0.237)$	$-0.028(0.238)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.008(0.252)$	$0.107(0.252)$	$-0.013(0.250)$	
$nonres_{t-4}$	$-0.021(0.024)$	$0.027(0.014)^{*}$	$-0.004(0.025)$	$0.017(0.016)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	ves

Table C.4: Cumulative Dynamic Effect Of Foreign Monetary Policy Shocks On Domestic Lending In Dollars Through Foreign Liabilities Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, M Pl, F F4, or M Pl and F F4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

regressor	(1)	(2)	(3)	(4)
External Instrument: MP1				
$us_t * nonres_{t-4}$	$-0.434(0.225)^{*}$	$-0.403(0.225)^{*}$	$-0.430(0.225)^{*}$	$-0.356(0.221)$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.573(0.272)^{**}$	$-0.506(0.268)^{*}$	$-0.556(0.273)^{**}$	$-0.413(0.265)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.614(0.300)^{**}$	$-0.494(0.284)^{*}$	$-0.587(0.301)^{*}$	$-0.374(0.280)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.978(0.322)^{***}$	$-0.780(0.304)^{***}$	$-0.945(0.323)^{***}$	$-0.633(0.299)^{**}$
$nonres_{t-4}$	$-0.110(0.039)^{***}$	$0.085(0.021)^{***}$	$-0.115(0.041)^{***}$	$0.028(0.023)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instrument: FF4				
$us_t * nonres_{t-4}$	$-0.529(0.233)^{**}$	$-0.453(0.233)^{*}$	$-0.518(0.233)^{**}$	$-0.413(0.230)^{*}$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.468(0.333)$	$-0.326(0.329)$	$-0.438(0.334)$	$-0.244(0.324)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.497(0.356)$	$-0.264(0.327)$	$-0.450(0.359)$	$-0.163(0.325)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.649(0.401)$	$-0.303(0.376)$	$-0.594(0.403)$	$-0.191(0.371)$
$nonres_{t-4}$	$-0.104(0.039)^{***}$	$0.085(0.021)^{***}$	$-0.108(0.040)^{***}$	$0.027(0.023)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instruments: MP1 and FF4				
$us_t * nonres_{t-4}$	$-0.484(0.218)^{**}$	$-0.434(0.218)^{**}$	$-0.478(0.219)^{**}$	$-0.390(0.215)^{*}$
$(us_t + us_{t-1}) * nonres_{t-4}$	$-0.531(0.286)^{*}$	$-0.433(0.283)$	$-0.509(0.287)^{*}$	$-0.345(0.279)$
$(us_t + us_{t-1} + us_{t-2}) * nonres_{t-4}$	$-0.570(0.309)^{*}$	$-0.403(0.288)$	$-0.535(0.311)^{*}$	$-0.292(0.285)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * nonres_{t-4}$	$-0.850(0.342)^{***}$	$-0.590(0.320)^{*}$	$-0.809(0.344)^{**}$	$-0.457(0.316)$
$nonres_{t-4}$	$-0.107(0.039)^{***}$	$0.087(0.021)^{***}$	$-0.111(0.040)^{***}$	$0.029(0.023)$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes

C.3 Cumulative Dynamic Effect of Foreign Monetary Policy Shocks On Domestic Lending Through Liquid Assets Channel

Table C.5: Cumulative Dynamic Effect Of Foreign Monetary Policy Shocks On Domestic Lending In All Currecncies Through Liquid Assets Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, MP1, FF4, or MP1 and FF4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

regressor	(1)	(2)	(3)	(4)
External Instrument: MP1				
$us_t * liquid_{t-4}$	$-0.037(0.082)$	$-0.030(0.083)$	$-0.046(0.083)$	$-0.038(0.083)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.005(0.105)$	$0.009(0.102)$	$-0.031(0.105)$	$-0.004(0.102)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.095(0.121)$	$-0.046(0.122)$	$-0.135(0.121)$	$-0.062(0.121)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.122(0.129)$	$-0.071(0.127)$	$-0.164(0.129)$	$-0.092(0.126)$
$liquid_{t-4}$	$0.111(0.014)^{***}$	$0.046(0.010)^{***}$	$0.121(0.014)^{***}$	$0.067(0.010)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instrument: FF4				
$us_t * liquid_{t-4}$	$-0.117(0.101)$	$-0.135(0.101)$	$-0.130(0.101)$	$-0.136(0.101)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.121(0.143)$	$-0.144(0.140)$	$-0.158(0.142)$	$-0.144(0.139)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.173(0.153)$	$-0.182(0.155)$	$-0.223(0.152)$	$-0.176(0.154)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.194(0.156)$	$-0.229(0.157)$	$-0.242(0.156)^{*}$	$-0.218(0.156)$
$liquid_{t-4}$	$0.112(0.014)^{***}$	$0.048(0.010)^{***}$	$0.122(0.015)^{***}$	$0.069(0.011)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instruments: MP1 and FF4				
$us_t * liquid_{t-4}$	$-0.067(0.086)$	$-0.072(0.086)$	$-0.077(0.086)$	$-0.077(0.086)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.047(0.116)$	$-0.050(0.113)$	$-0.077(0.115)$	$-0.057(0.112)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.124(0.129)$	$-0.101(0.131)$	$-0.166(0.129)$	$-0.107(0.130)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.150(0.135)$	$-0.136(0.135)$	$-0.194(0.135)$	$-0.143(0.134)$
$liquid_{t-4}$	$0.112(0.014)^{***}$	$0.047(0.010)^{***}$	$0.122(0.014)^{***}$	$0.068(0.010)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes

Table C.6: Cumulative Dynamic Effect Of Foreign Monetary Policy Shocks On Domestic Lending In Rubles Through Liquid Assets Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, MP1, FF4, or MP1 and FF4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Regressor	(1)	(2)	(3)	(4)
	External Instrument: MP1			
$us_t * liquid_{t-4}$	$-0.051(0.103)$	$-0.038(0.102)$	$-0.061(0.104)$	$-0.046(0.102)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.023(0.131)$	$-0.011(0.127)$	$-0.050(0.132)$	$-0.022(0.127)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.072(0.150)$	$-0.028(0.147)$	$-0.114(0.149)$	$-0.041(0.147)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.069(0.157)$	$-0.011(0.150)$	$-0.113(0.158)$	$-0.029(0.149)$
$liquid_{t-4}$	$0.096(0.016)$	$0.043(0.011)^{***}$	$0.106(0.016)^{***}$	$0.061(0.011)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
	External Instrument: FF4			
$us_t * liquid_{t-4}$	$-0.105(0.130)$	$-0.115(0.129)$	$-0.119(0.130)$	$-0.116(0.129)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.088(0.182)$	$-0.113(0.178)$	$-0.127(0.182)$	$-0.113(0.178)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.064(0.186)$	$-0.072(0.183)$	$-0.117(0.186)$	$-0.066(0.183)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.039(0.189)$	$-0.050(0.184)$	$-0.090(0.189)$	$-0.042(0.184)$
$liquid_{t-4}$	$0.096(0.016)^{***}$	$0.043(0.011)^{***}$	$0.106(0.016)^{***}$	$0.062(0.012)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
	External Instruments: MP1 and FF4			
$us_t * liquid_{t-4}$	$-0.070(0.109)$	$-0.068(0.108)$	$-0.081(0.110)$	$-0.072(0.108)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$-0.045(0.146)$	$-0.049(0.142)$	$-0.076(0.146)$	$-0.055(0.142)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.066(0.159)$	$-0.045(0.156)$	$-0.111(0.159)$	$-0.050(0.156)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.056(0.165)$	$-0.028(0.158)$	$-0.101(0.165)$	$-0.034(0.158)$
$liquid_{t-4}$	$0.096(0.016)^{***}$	$0.043(0.011)^{***}$	$0.106(0.016)^{***}$	$0.061(0.011)^{***}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes

Table C.7: Cumulative Dynamic Effect Of Foreign Monetary Policy Shocks On Domestic Lending In Dollars Through Liquid Assets Channel

Reported HAC standard errors are clustered at the bank level. US monetary policy shocks us was identified in a structural VAR similar to Gertler and Karadi (2015) with monetary surprises on, alternatively, MP1, FF4, or MP1 and FF4, as external instruments. Bank controls are leverage, core, and ta. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Regressor	(1)	(2)	(3)	(4)
External Instrument: MP1				
$us_t * liquid_{t-4}$	$0.169(0.208)$	$0.212(0.213)$	$0.161(0.209)$	$0.209(0.213)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$0.181(0.232)$	$0.316(0.229)$	$0.164(0.232)$	$0.320(0.229)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$0.103(0.268)$	$0.287(0.260)$	$0.078(0.269)$	$0.299(0.258)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.004(0.294)$	$0.195(0.283)$	$-0.031(0.295)$	$0.197(0.281)$
$liquid_{t-4}$	$0.099(0.029)^{***}$	$0.015(0.020)$	$0.106(0.029)^{***}$	$0.037(0.020)^{*}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instrument: FF4				
$us_t * liquid_{t-4}$	$-0.043(0.208)$	$-0.019(0.211)$	$-0.049(0.209)$	$-0.006(0.212)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$0.030(0.266)$	$0.069(0.260)$	$-0.047(0.267)$	$0.108(0.260)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.179(0.303)$	$-0.065(0.293)$	$-0.197(0.304)$	$-0.003(0.291)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.273(0.320)$		$-0.286(0.319)$	$-0.115(0.305)$
$liquid_{t-4}$	$0.102(0.029)^{***}$	$0.019(0.020)$	$0.109(0.029)^{***}$	$0.041(0.021)^{**}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes
External Instruments: MP1 and FF4				
$us_t * liquid_{t-4}$	$0.080(0.202)$	$0.112(0.206)$	$0.073(0.202)$	$0.115(0.206)$
$(us_t + us_{t-1}) * liquid_{t-4}$	$0.098(0.238)$	$0.215(0.234)$	$0.082(0.238)$	$0.233(0.234)$
$(us_t + us_{t-1} + us_{t-2}) * liquid_{t-4}$	$-0.019(0.272)$	$0.132(0.263)$	$-0.040(0.273)$	$0.165(0.262)$
$(us_t + us_{t-1} + us_{t-2} + us_{t-3}) * liquid_{t-4}$	$-0.116(0.293)$	$0.034(0.281)$	$-0.137(0.293)$	$0.062(0.280)$
$liquid_{t-4}$	$0.100(0.029)^{***}$	$0.016(0.020)$	$0.107(0.029)^{***}$	$0.038(0.020)^{*}$
bank controls	no	no	yes	yes
bank fixed effects	yes	no	yes	no
time fixed effects	yes	yes	yes	yes

C.4 Four-Quarter Cumulative Dynamic Effect of U.S. Monetary Policy Shock On Credit Growth In Russia Through Foreign Liabilities Transmission Channel

Table C.8: Four-Quarter Cumulative Dynamic Effect of U.S. Monetary Policy Shock On Credit Growth In Russia Through Foreign Liabilities Transmission Channel

The entries are estimated four-quarter cumulative effects of a U.S. monetary policy shock by 1 p.p. interacted with lagged foreign liabilities transmission channel variable. HAC standard errors clustered at the bank level are shown in the parentheses. ***, **,and* denote statistical significance at 1%, 5%, and 10%, respectively. The dependent variable is quarterly credit growth in respective currency. The regressors are the four-quarter distributed lag of a respective proxy of the U.S. monetary policy shock interacted with the fourth lag of nonres and first lags of core, tierl, and ta. Bank and state fixed effects are added.

Proxy For Shock	All loans	Ruble loans	Dollar loans
SVAR + MP1	$-0.220(0.163)$	$0.011(0.224)$	$-0.945(0.323)^{***}$
SVAR + FF4	$-0.356(0.228)$	$-0.053(0.312)$	$-0.594(0.403)$
SVAR + MP1 + FF4	$-0.271(0.181)$	$-0.013(0.250)$	$-0.809(0.343)^{**}$
MP1	$0.013(0.395)$	$0.079(0.667)$	$-1.431(0.788)^{*}$
FF4	$-0.228(0.545)$	$0.373(1.072)$	$-1.935(0.889)^{**}$
ED2	$-0.750(0.543)$	$0.371(1.001)$	$-3.848(0.928)^{***}$
ED3	$-0.832(0.445)^{*}$	$-0.122(0.807)$	$-3.551(0.785)^{***}$
ED4	$-0.869(0.403)^{**}$	$-0.098(0.724)$	$-3.760(0.756)^{***}$
Wu - Xia	$-0.019(0.029)$	$0.010(0.039)$	$0.016(0.056)$
GS1	$-0.036(0.039)$	$0.021(0.050)$	$-0.079(0.074)$
GS5	$-0.023(0.052)$	$0.045(0.068)$	$-0.091(0.105)$
GS10	$-0.002(0.058)$	$0.033(0.078)$	$-0.115(0.128)$

C.5 Four-Quarter Cumulative Dynamic Effect of U.S. Monetary Policy Shock On Credit Growth In Russia Through Liquid Assets Transmission Channel

Table C.9: Four-Quarter Cumulative Dynamic Effect of U.S. Monetary Policy Shock On Credit Growth In Russia Through Liquid Assets Transmission Channel

The entries are estimated four-quarter cumulative effects of a U.S. monetary policy shock by 1 p.p. interacted with lagged liquid assets transmission channel variable. HAC standard errors clustered at the bank level are shown in the parentheses. ***, **, and* denote statistical significance at 1%, 5%, and 10%, respectively. The dependent variable is quarterly credit growth in respective currency. The regressors are the four-quarter distributed lag of a respective proxy of the U.S. monetary policy shock interacted with the fourth lag of liquid and first lags of core, tierl, and ta. Bank and state fixed effects are added.

Proxy For Shock	All loans	Ruble loans	Dollar loans
SVAR + MP1	$-0.164(0.129)$	$-0.113(0.158)$	$-0.031(0.295)$
SVAR + FF4	$-0.242(0.156)$	$-0.090(0.189)$	$-0.286(0.319)$
SVAR + MP1 + FF4	$-0.194(0.135)$	$-0.101(0.165)$	$-0.137(0.293)$
MP1	$-0.121(0.348)$	$-0.179(0.428)$	$-0.338(0.737)$
FF4	$-0.145(0.446)$	$-0.162(0.571)$	$-0.889(0.877)$
ED2	$0.030(0.459)$	$-0.084(0.587)$	$-0.182(0.921)$
ED3	$0.022(0.385)$	$-0.097(0.494)$	$-0.114(0.794)$
ED4	$0.076(0.375)$	$-0.096(0.480)$	$-0.041(0.793)$
Wu - Xia	$-0.053(0.025)^{**}$	$-0.034(0.029)$	$-0.035(0.057)$
GS1	$-0.052(0.031)^{*}$	$-0.024(0.037)$	$-0.039(0.068)$
GS5	$-0.072(0.046)$	$-0.036(0.056)$	$-0.127(0.103)$
GS10	$-0.073(0.059)$	$-0.032(0.074)$	$-0.150(0.125)$

C.6 Rolling-Sample Cumulative Four-Quarter Effect of U.S. Monetary Policy Shock On Dollar-Denominated Credit Growth In Russia Through Foreign Liabilities Channel

Table C.10: Rolling-Sample Cumulative Four-Quarter Effect of U.S. Monetary Policy Shock On Dollar-Denominated Credit Growth In Russia Through Foreign Liabilities Channel
Reported HAC standard errors are clustered at the bank level. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Sample	MP1	FF4	MP1+FF4
2000Q1-2018Q1	$-0.945(0.323)^{***}$	$-0.594(0.233)$	$-0.809(0.344)^{**}$
2000Q1-2010Q1	$-0.999(0.360)^{***}$	$-0.589(0.453)$	$-0.843(0.385)^{**}$
2001Q1-2011Q1	$-1.130(0.397)^{***}$	$-0.634(0.637)$	$-0.999(0.468)^{**}$
2002Q1-2012Q1	$-1.306(0.382)^{***}$	$-1.034(0.682)$	$-1.292(0.456)^{***}$
2003Q1-2013Q1	$-1.482(0.396)^{***}$	$-1.482(0.666)^{**}$	$-1.521(0.459)^{***}$
2004Q1-2014Q1	$-1.406(0.408)^{***}$	$-1.395(0.681)^{**}$	$-1.437(0.473)^{***}$
2005Q1-2015Q1	$-1.109(0.417)^{***}$	$-0.866(0.714)$	$-1.081(0.488)^{**}$
2006Q1-2016Q1	$-1.243(0.444)^{***}$	$-1.595(0.796)^{**}$	$-1.371(0.527)^{***}$
2007Q1-2017Q1	$-1.280(0.446)^{***}$	$-1.227(0.779)$	$-1.318(0.528)^{**}$
2007Q2-2017Q2	$-1.645(1.172)$	$-0.949(0.894)$	$-1.302(0.946)$
2007Q3-2017Q3	$-1.006(1.195)$	$1.914(1.200)$	$0.387(1.126)$
2007Q4-2017Q4	$1.706(1.463)$	$3.856(1.263)^{***}$	$2.771(1.282)^{**}$
2008Q1-2018Q1	$6.453(1.889)^{***}$	$5.655(1.362)^{***}$	$5.238(1.431)^{***}$

Table C.11: Rolling-Sample Cumulative Four-Quarter Effect of U.S. Monetary Policy Shock On Ruble-Denominated Credit Growth In Russia Through Foreign Liabilities Channel
Reported HAC standard errors are clustered at the bank level. See Table 6.1 for detailed description of variables. *, **, and *** denote significance at 10%, 5%, and 1% level, respectively.

Sample	MP1	FF4	MP1+FF4
2000Q1-2018Q1	$0.011(0.224)$	$-0.053(0.312)$	$-0.013(0.250)$
2000Q1-2010Q1	$0.169(0.259)$	$0.152(0.352)$	$0.164(0.287)$
2001Q1-2011Q1	$0.172(0.256)$	$0.079(0.458)$	$0.166(0.311)$
2002Q1-2012Q1	$0.092(0.228)$	$0.390(0.403)$	$0.167(0.272)$
2003Q1-2013Q1	$0.002(0.215)$	$0.066(0.376)$	$0.015(0.254)$
2004Q1-2014Q1	$-0.196(0.212)$	$-0.280(0.369)$	$-0.222(0.250)$
2005Q1-2015Q1	$-0.259(0.221)$	$-0.449(0.391)$	$0.312(0.263)$
2006Q1-2016Q1	$-0.223(0.211)$	$-0.471(0.390)$	$0.286(0.253)$
2007Q1-2017Q1	$-0.168(0.215)$	$-0.273(0.398)$	$-0.199(0.258)$
2007Q2-2017Q2	$-0.355(0.667)$	$-0.027(0.453)$	$-0.040(0.526)$
2007Q3-2017Q3	$-0.407(0.678)$	$-0.216(0.700)$	$-0.227(0.618)$
2007Q4-2017Q4	$0.042(0.652)$	$0.211(0.769)$	$0.283(0.627)$
2008Q1-2018Q1	$1.440(1.258)$	$0.633(0.881)$	$0.970(0.878)$

C.7 Cross-Border Private Capital Flows

Figure C1: Cross-Border Private Capital Flows
Source of data is Bank of Russia