Googling Investor Sentiment around the World

Zhenyu Gao, Haohan Ren, and Bohui Zhang*

Current Version: April 2016

---

*Zhenyu Gao and Haohan Ren are from the Department of Finance, CUHK Business School, The Chinese University of Hong Kong, Shatin, Hong Kong, and Bohui Zhang is from the School of Banking and Finance, UNSW Business School, UNSW Australia, Sydney, NSW, Australia, 2052. Authors' contact information: Gao: gaozhenyu@baf.cuhk.edu.hk, (852) 39431824; Ren: haohan@baf.cuhk.edu.hk, (852) 39431824. Zhang: bohui.zhang@unsw.edu.au, (61) 2-93855834. We are grateful for valuable comments from Zhanhui Chen, Oleg Chuprinin, Lili Dai, Stephen Geoffrey Dimmock, David Feldman, Huasheng Gao, Jun-Koo Kang, Paul Karehnke, Chuan-Yang Hwang, Jiang Luo, Chenghu Ma, Phong Ngo, Jerry T. Parwada, Peter Pham, Hong Ru, Konark Saxena, Jianfeng Shen, Qian Sun, Shaun Shuxun Wang, Chishen Wei, Takeshi Yamada, Jason Zein, Xianming Zhou, Qi Zhu, Xiaoneng Zhu, and the seminar participants at Australian National University, Fudan University, Nanyang Technological University, Shanghai University of Finance and Economics, the Chinese University of Hong Kong, and UNSW Australia. Zhenyu Gao acknowledges research support from the Early Career Scheme (ECS) (2192091). Bohui Zhang acknowledges research grants from the ARC discovery grant (DP 120104755) and ARC linkage grant (LP130101050) from the Australian Research Council and CIFR research grants (E026 and E028) from the Centre for International Finance and Regulation.

Googling Investor Sentiment around the World

Abstract

We study how investor sentiment affects stock markets around the world. Relying on households' Google search behavior, we construct a weekly search-based measure of sentiment for 40 countries during the 2004–2014 period. We first validate the sentiment index in tests using sports outcomes, dual-listed firms, and earnings announcements and then show that the sentiment measure is a contrarian predictor of country-level market returns. Two experiments suggest a causal relationship between the return prediction of sentiment and theoretical channels. Finally, we document an important role of global sentiment in driving sentiment and predicting returns across countries. These findings support the view that sentiment prevails in stock markets.

Keywords: Sentiment; Google search; International markets; Limits to arbitrage; Co-movement
JEL Code: G12; G14; G15

1. Introduction

Investor sentiment has long been proposed to play an important role in explaining stock price variation (Keynes, 1936; Shiller, 1990; Baker and Wurgler, 2000). This sentiment conjecture is supported by both the DeLong et al. (1990) model in which stocks are held predominantly by noise traders and the Shleifer and Vishny (1997) theory that rational investors are limited by arbitrage constraints. Empirically, this conjecture has been tested in the influential works of Baker and Wurgler (2006) and Baker, Wurgler, and Yuan (2012), who construct a composite market-based sentiment index and document its return prediction in the U.S. and five non-U.S. developed markets.[1]

However, several challenges remain in the sentiment literature. First, investor sentiment is **difficult to measure** (Baker and Wurgler, 2007). For example, Sibley et al. (2016) argue that the return predictability of the Baker and Wurgler (2006) sentiment index is mainly driven by the business cycle and risk components.[2] Second, there is a **lack of causal evidence** that the return prediction of sentiment indices is tailored to sentiment theories. For example, considerable anecdotal evidence of sentiment can be explained by rational models (e.g., Pastor and Veronesi, 2003, 2005, and 2006). Third, previous evidence is **constrained by time frequency and market coverage**. For example, Huang et al. (2015) summarize that the return prediction of investor sentiment is mainly observed at one-year or longer horizons,[3] and Baker, Wurgler, and Yuan (2012) find few studies that investigate sentiment outside the U.S.

Given the exploding interests in investor sentiment among economists, it is imperative to resolve the above issues by using alternative sentiment measures and out-of-sample analyses. Thus, in this paper, we directly measure investor sentiment based on households' Google search behavior (via Google Trends) and explore the sentiment effect at a weekly frequency in a large sample of 40 countries for the period between 2004 and 2014. Google Trends provides an ideal platform for our cross-country study to measure investor sentiment and examine its price effect:

[1] Stambaugh, Yu, and Yuan (2012) study the effect of investor sentiment on a broad set of anomalies in cross-sectional stock returns. Their findings are further confirmed by Stambaugh, Yu, and Yuan (2014).
[2] Qiu and Welch (2004) raise a concise question: "How does one test a theory that is about inputs→outputs with an output measure?"
[3] However, theories make the common assumption that noise traders cannot survive in the long run (Kogan et al., 2006, 2009).

Google serves as the most popular search engine around the world,[4] Google searches not only reflect the attitudes of market participants but also reveal information in a timely manner,[5] and accumulated evidence shows that the volume of Google search queries predicts households' future actions. For example, scientists can detect influenza epidemics by using Google search queries (Ginsberg et al., 2009).

The idea for our sentiment index originates from the Da, Engelberg, and Gao (2015) measure, which is calculated by aggregating the volume of search queries related to negative sentiment. We advance their approach by measuring both positive and negative sentiment for two reasons. First, lower negative sentiment does not necessitate higher positive sentiment, given the dispersion of investor opinions (e.g., Diether, Malloy, and Scherbina, 2002). Second, positive sentiment may be more important than negative sentiment in substantiating the market impact of noise traders (Yu and Yuan, 2011). In addition, we construct our sentiment index based on the predominant language in each country (20 different languages in total), whereas the Da, Engelberg, and Gao (2015) measure is coded in English.[6]

This paper has four objectives: **(i)** to validate our search-based index as a proxy for investor sentiment; **(ii)** to examine whether the sentiment measure is a contrarian predictor of country-level market returns worldwide; **(iii)** to test whether a causal relationship exists between the return prediction of sentiment and the theoretical channels proposed by Baker and Wurgler (2006), namely, *the difficult-to-value channel* and *the limits-to-arbitrage channel*; and **(iv)** to investigate whether and how sentiment travels across countries and study the return prediction of global sentiment.

We begin by providing three validation tests for our search-based sentiment index. First, we connect our sentiment measure to international soccer results (i.e., the knockout stage match

[4] For example, according to NetMarketShare's statistics in 2014, Google holds a 67.5% global market share in household searches. Though censored or banned in some countries, such as China, Google dominates most developed and emerging markets, such as Australia (93.0%), Brazil (96.9%), India (97.0%), Japan (75.3%), and Poland (97.4%).

[5] According to Google statistics for 2014, the top search terms regarding China included "China largest economy," "China overtakes U.S. economy," "China passes U.S. economy," and so on. However, after the stock market rout in June 2015, the top search terms changed substantially: "China economy collapse," "China economy crash," and "China economy crisis." See http://www.bloomberg.com/news/articles/2015-12-20/googling-china-s-economy-shows-shifting-sentiment.

[6] According to Wikipedia, preceded by Chinese (14.1%) and Spanish (5.85%), English was the third most popular language in the world, with 5.52% of the world population speaking English in 2007. See https://en.wikipedia.org/wiki/List_of_ languages_by_number_of_native _ speakers.

outcomes of World Cup and regional tournaments). We find that a country's sentiment index is negatively and significantly correlated with its soccer losses, which is consistent with the findings of Edmans, Garcia, and Norli (2007). Second, we explore the relationship between our sentiment measure and price deviations for dual-listed companies.[7] The difference in sentiment between the parent countries of American Depositary Receipts (ADRs) and the U.S. is positively associated with the difference in price between ADRs' parent stocks and ADRs. The third validation test involves earnings announcements for small stocks. Future abnormal returns around earnings announcements are inversely related to our sentiment measure for small stocks. Overall, these findings strengthen our confidence in using our search-based index as a proxy for investor sentiment.

Further evidence that we obtain supports the prevalence of sentiment in stock markets around the world. For all 40 countries in our sample, we find a negative relationship between sentiment and the next week's market returns. Among them, 29 countries display a significant pattern at the 5% level. In terms of economic significance, a one-standard-deviation increase in investor sentiment predicts a decline in the weekly return of 28 basis points. In addition, in line with sentiment theory, there are sentiment reversals and contemporaneous co-movement between sentiment and market returns. Our results are robust to the use of subsamples of developed and emerging countries, the exclusion of the financial crisis period, the use of local currency returns, the use of longer time horizons, and the orthogonalization of a set of fundamental variables.

Next, two quasi-natural experiments offer supporting evidence for the sentiment channels proposed by Baker and Wurgler (2006): *the difficult-to-value channel* and *the limits-to-arbitrage channel*. First, we study the implementation of the Markets in Financial Instruments Directive (MiFID) as an exogenous shock to the information environment. With an improvement in market transparency, we indeed find that asset valuation would be less subjective and that investors would be less likely to react to sentiment. This finding supports the difficult-to-value channel. Our second experiment employs the short-selling ban following the global financial crisis as evidence of limits to arbitrage. In response to market crashes during the financial crisis of 2007-2009, several countries banned the short selling of stocks for a period of time. In line with the

[7] Gagnon and Karolyi (2010) find arbitrage opportunities by comparing the intraday prices and quotes of ADRs with synchronous prices of their home-market shares for a sample of 506 U.S. cross-listed stocks from 35 different countries.

limits-to-arbitrage channel, our sentiment measure has a larger impact on the markets affected by the short-selling ban because rational investors find it difficult to correct the mispricing caused by market sentiment.

Finally, by aggregating country-level sentiment indices into a global sentiment measure, we find that global sentiment prevails in international markets. Specifically, we start by documenting the commonality of sentiment across countries. In this regard, global sentiment, on average, explains 19.4% of the sentiment variation for all countries and 25.9%, for developed countries. The result supports the contagious characteristic of investor sentiment proposed by Baker, Wurgler, and Yuan (2012). Moreover, we use the adoption of International Financial Reporting Standards (IFRS) as a quasi-natural experiment to test the effect of capital market integration on sentiment co-movement. The results show that global sentiment has a larger positive impact on the sentiment of countries that adopted IFRS. Finally, we document that global sentiment significantly predicts future market returns in 33 countries, whereas local sentiment has significant power in predicting market returns in only 15 countries.

Our paper contributes to two streams of literature. Our primary contribution is to the literature that quantifies investor sentiment and investigates the effect of sentiment on asset prices (Hirshleifer and Shumway, 2003; Kamstra, Kramer, and Levi, 2003; Brown and Cliff, 2004; Qiu and Welch, 2004; Baker and Wurgler, 2006, 2007; Lemmon and Portniaguina, 2006; Das and Chen, 2007; Edmans, Garcia, and Norli, 2007; Tetlock, 2007; Barber, Odean and Zhu, 2009; Kaplanski and Levy, 2010; Hwang, 2011; Yu and Yuan, 2011; Baker, Wurgler, and Yuan, 2012; Stambaugh, Yu, and Yuan, 2012, 2014; Soo, 2014; Huang et al., 2015; Da, Engelberg, and Gao, 2015; Sibley et al., 2016). Our findings support the market prevalence of sentiment with **direct** measurement, **causal** evidence, **high** frequency, and **broad** market coverage.

Our paper also contributes to the literature that studies market participant behavior by using search engines. Specifically, search engine data can be used to predict flu outbreaks (Ginsberg et al., 2009); to forecast economic activities, such as automobile sales (Choi and Varian, 2012); to evaluate investor attention (Mondria, Wu, and Zhang, 2010; Da, Engelberg, and Gao, 2011); to measure investor information demand (Drake, Roulstone, and Thornock, 2012); and to identify economically related peer firms (Lee, Ma, and Wang, 2015). In contrast to these studies, we advance the Da, Engelberg, and Gao (2015) approach by constructing a **composite** search-based index of investor sentiment.

The remainder of the paper proceeds as follows. We construct our search-based sentiment measure in Section 2. We present the validation tests in Section 3. In Section 4, we study the relationship between investor sentiment and stock market returns. In Section 5, we test the theoretical channels proposed by Baker and Wurgler (2006). In Section 6, we study the commonality of sentiment across countries. Finally, we provide concluding remarks in Section 7.

2. Data and Methodology

2.1. Google Search

As the largest search engine in the world, Google search captures 67.5% of the global market share.[8] Panel A of Table 1 reports the Google search volume from 2004 to 2014 by year, month, day, and second. There were 2.095 trillion search queries made through Google in 2014; that is, 66,440 search queries on average were performed globally on Google every second. This figure has increased by almost 25 times since 2004. Panel B shows the popularity of Google search across both developed and emerging countries. For example, Google search has a market share of more than 90% in 27 of the 40 countries in the sample, and astonishingly Google search has a market share of up to 99% in countries such as Belgium, Thailand, and Turkey. Overall, the data show that Google search can serve as a powerful platform to track households' search behavior across countries.

[Insert Table 1 Here]

2.2. Sentiment Index

Our task is to track households' search activity and measure investor sentiment for each country in our sample. We follow and improve upon the approach in Da, Engelberg, and Gao (2015) to construct weekly sentiment indices for 40 countries. Below, we start with a description of construction procedures and then highlight the differences between our method and the Da, Engelberg, and Gao (2015) approach.

The main data source, Google Trends (https://www.google.com/trends/), provides a Search Volume Index (*SVI*) of search items across various countries in different languages since 2004. To determine the sentiment toward economic conditions, we download the weekly *SVI* of search

[8] See https://www.netmarketshare.com/search-engine-market-share.aspx?qprid=4&qpcustomd=0.

terms related to economics and finance and ensure that these exact terms are searched in each country based upon the country's main language.[9] The set of economics- and finance-related search terms is constructed by using words from the Harvard IV-4 Dictionary and the Lasswell Value Dictionary. These two dictionaries are widely used in the text analytics literature (e.g., Tetlock, 2007).

The construction is performed for each country as follows:

1) In the set of 743 words with markers "Econ@" or "ECON," we focus on words that are likely to be associated with positive or negative sentiment (those that are labeled with the "positive" or "negative" tag). This method provides us with 149 words, such as "bankruptcy," "cost," "gold," "jobless," and "profit."
2) Because we are interested in local households' search activities, we translate these 149 English words into each country's corresponding language by using Google Translate.[10] For example, when we input "gold," Google Translate returns "金" in Chinese, "or" in French, and "oro" in Spanish.
3) We input these 149 translated words into Google Trends and identify the top ten terms associated with each word. For example, in the U.S., the top queries related to "gold" include "gold price," "price of gold," and "buy gold."
4) We keep only search terms that have at least 100 weekly *SVI* observations and remove those that are not clearly related to economics or finance. For example, in the terms related to "gold" searched by Australian households, "Gold Coast" is a metropolitan region south of Brisbane on Australia's east coast, which is famous for its long sandy beaches and surfing; thus, we exclude this term from our list for Australia.
5) We download the weekly *SVI* (covering the search volume from Sunday to Saturday) of search terms from January 2004 to December 2014.
6) We calculate the weekly change in *SVI* (ΔSVI) for each search term, winsorize extreme observations, eliminate seasonality, and standardize time series to make them

[9] Panel B of Table 1 presents the languages that we employ to construct our sentiment indices and the corresponding population shares of these languages. We choose the predominant or official language for each country. If a country has multiple official or predominant languages, we use the one that provides us with the most weekly observations of search terms.
[10] See https://translate.google.com/. Google Translate returns only one word that is the most common translation of each input.

comparable.[11] We eventually obtain the adjusted weekly change in search volume (*ΔASVI*).

7) To label search terms with positive or negative sentiment and identify how these search terms are relevant to market returns, we let the market data speak for itself. Specifically, we employ the expanding backward rolling regressions of *ΔASVI* on the country's market returns from the beginning of the sample to the most recent June or December and identify the historical relationship between the weekly change in search volume and returns.[12] Based on a U.S. daily sample, Da, Engelberg, and Gao (2015) find no terms with significant positive *t*-statistics and thus focus on the top 30 negative terms in constructing their "*FEARS*" ("Financial and Economic Attitudes Revealed by Search") index. However, our weekly data provide a large number of search terms with significant positive (and negative) *t*-statistics in most countries. One explanation for this difference is that weekly frequency potentially reduces noise in daily observations. Positive sentiment plays a more important role than negative sentiment in the capital market when pessimistic investors stay on the sidelines because of short-selling constraints (e.g., Miller, 1977). We therefore account for both positive and negative terms in forming our sentiment indices.

8) We construct our sentiment indices by averaging *ΔASVI* of the top 30 positive and the top 30 negative search terms for every week and calculate the difference as the measure of sentiment:

$$Sentiment_t = \sum_{i=1}^{30} R_+^i(\Delta ASVI_i) - \sum_{i=1}^{30} R_-^i(\Delta ASVI_i), \quad (1)$$

where $\sum_{i=1}^{30} R_\pm^i(\Delta ASVI_i)$ is the *t*-statistic-weighted average of the top 30 positive (negative) search items. Given the dispersion of investors' belief (e.g., Diether, Malloy, and Scherbina, 2002), our index measures the net effect of sentiment on the market. We form the weekly sentiment proxy for 40 countries from July 2004 to December 2014, in

[11] Specifically, we winsorize *ΔSVI* of each query at the 5% level. We regress *ΔSVI* on monthly dummies to control for seasonality and keep the residuals. We then normalize these residuals by using their standard deviations.

[12] Specifically, during every June and December, we regress ΔASVI on the contemporaneous market returns by using historical data from January 2004. We keep the top 30 search terms with the largest positive (negative) *t*-statistics as our positive (negative) sentiment portfolio to construct our sentiment measure for the following six months.

which the first six-month period from January 2004 to June 2004 is used as the initial rolling regression window.

Figure 1A plots the cumulative U.S. and Portuguese sentiment from July 2004 to December 2014 as an example. Apparently, our sentiment indices vary substantially over time. As highlighted, the financial crisis and influential events during the European debt crisis caused investor sentiment to plunge immensely. Interestingly, the Portuguese sentiment seems to be more vulnerable to European shocks than the U.S. sentiment. Table IA1 in the Internet Appendix presents the summary statistics of our sentiment indices.[13] The mean and median of the sentiment indices are close to zero across countries. The quartiles of the indices show that our sentiment measures are largely symmetrically distributed around zero. Moreover, our sentiment indices are similarly distributed, with an average standard deviation of 0.540 for developed countries and 0.404 for emerging countries.

[Insert Figure 1 Here]

2.3. Other Data

Our market return data come from Datastream. We download the country-level daily and weekly total return index (RI) in U.S. dollars. We use daily returns to calculate the market volatility (*Volatility*) for each week and use weekly returns to test the return prediction of sentiment. We also download the market index in the country's local currency to test the robustness of our results.

Our validation tests on sentiment indices mainly incorporate three data sets. We first test the relationship between sports events and our sentiment indices. We obtain the results of knockout stage matches from the four most influential soccer cups during the period from 2004 to 2014, i.e., World Cup 2006, 2010 and 2014; European Championship 2008 and 2012; Copa América 2007 and 2011; and Asian Cup 2007 and 2011. Specifically, we collect information on the winner, the loser, and the event date for each match. The knockout stage matches of these tournaments usually begin in late June and end in early July. The only exception is Asian Cup 2011, which began in late January. We do not include European Championship 2004 because our sentiment data began in the first week of July 2004 while European Championship 2004 ended

[13] We define the tables in the Internet Appendix with the prefix "IA."

on July 1. Table IA2 in the Internet Appendix presents the summary statistics of match results. We report the total number of wins and losses for each country in each tournament. In total, we have 76 matches played by 20 of our 40 sample countries. For example, between these 20 countries, Italy, Spain, and Germany won the World Cup championship in 2006, 2010, and 2014, respectively.

For the second validation test, we obtain identifiers and firm names of ADRs from the four primary depository institutions: Citibank, The Bank of New York, J.P. Morgan, and Deutsche Bank. We then collect the daily price information of these ADRs and their parent stocks from Datastream. Table IA3 in the Internet Appendix reports the descriptive statistics of ADRs and their parent stocks used in the regression analysis. Our sample includes 1,778 pairs of ADRs and their parent stocks from 40 countries. Japan and the U.K. have the largest number of ADRs (277 and 213, respectively), whereas Hungary and Peru have the fewest number of ADRs (3 and 6, respectively).

Data in the third validation test are obtained from IBES and Datastream. We collect annual earnings announcements and daily stock returns in major stock exchanges, and we then calculate three-day and five-day cumulative abnormal returns (*CARs*) around annual earnings announcements for each stock in our sample. Because small firms are more sensitive to the effect of investor sentiment than large stocks, we conduct the third validation test by using a sample of small firms. In doing so, we exclude firms with market value above the sample median each year.

Moreover, we include a set of U.S. and local stock market and macroeconomic variables as controls. The market volatility index (VIX_{US}) is the implied volatility of the U.S. Standard & Poor's (S&P) 500 index options, and this measure reflects investors' expectation about the volatility of the U.S. stock market over the subsequent 30 days. We obtain VIX_{US} from the Chicago Board Options Exchange (CBOE). We also add market volatility (*Volatility*), which is calculated as the standard deviation of daily returns in a week, to control for the local stock market risk. We further include a variable to measure U.S. macroeconomic activities ($Economy_{US}$), which is constructed by Aruoba, Diebold, and Scotti (2009). $Economy_{US}$ consists of several seasonally adjusted macroeconomic factors, such as weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real gross domestic product (GDP).[14] In addition, we control for the index of U.S. economic policy uncertainty (EPU_{US}), which is constructed by Baker, Bloom, and Davis (2015). EPU_{US} counts the number of U.S. newspaper articles with at least one term from the following three categories: (a) "economic" or "economy;" (b) "uncertain" or "uncertainty;" and (c) "congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House." Furthermore, we include lagged stock market returns as controls, especially in the return prediction analysis.

Finally, to further address the concern about the correlation between the sentiment index and business cycle and risk factors, we follow Sibley et al. (2016) and construct business cycle and risk variables. Because of the lack of high-frequency macroeconomic information in non-U.S. countries, we can construct only U.S. variables as a proxy for global fundamental and risk factors. Specifically, we obtain the U.S. monthly unemployment rate ($Unemp_{US}$) and the consumer price index (CPI_{US}) from the U.S. Department of Labor website. Monthly data on consumption ($Consumption_{US}$) and disposable income ($Income_{US}$) are taken from the U.S. Department of Commerce website. We obtain the monthly level of industrial production ($IndProd_{US}$), the weekly three-month Treasury Bill rate ($TBill_{US}$), the weekly term spread ($Term_{US}$) and the weekly default spread ($Default_{US}$) from the Board of Governors of the Federal Reserve System website. $Term_{US}$ is the difference in yields between ten-year Treasury bonds and three-month T-bills, and $Default_{US}$ is the difference in yields between BAA corporate bonds and AAA corporate bonds. We follow Lesmond, Ogden, and Trzcinka (1999) in constructing the weekly liquidity risk measure ($Illiq_{US}$), which is the percentage of stocks with zero returns in a week.

3. Validation of the Search-based Sentiment Index

Given the intrinsic nature of sentiment and the complexity of measurement, it is important to validate our sentiment indices externally before we conduct any investigation into the return prediction of sentiment indices. In this section, we employ three validation tests for our sentiment measures: international sports events, ADRs and their parent stocks, and returns around earnings announcements.

[14] The authors have updated the data at https://www.philadelphiafed.org/research-and-data/real-time-center/business-conditions-index.

3.1. Sports

Edmans, Garcia, and Norli (2007) use international soccer results as an indicator of investor sentiment and argue that international soccer results drive investor sentiment in a substantial and unambiguous way and that such impact is correlated across the majority of individuals within a country. To test this conjecture, they examine the impact of international soccer results on stock prices and find that losses in soccer matches have a significant negative effect on the losing country's stock market. For example, a loss in the World Cup knockout stage leads to a next-day abnormal stock return of -49 basis points. Their finding is consistent with previous psychological evidence that sports results have a significant effect on sentiment (e.g., Hirt et al., 1992).

Because sports sentiment is independent of a country's economic performance and fundamentals, it is straightforward and easy to examine the impact of influential soccer matches on our sentiment measure. Specifically, we connect our indices to the knockout stage match outcomes of tournaments including World Cup 2006, 2010 and 2014; European Championship 2008 and 2012; Copa América 2007 and 2011; and Asian Cup 2007 and 2011. Our test includes 20 countries that played knockout stage matches in our soccer cups sample during the period from 2006 to 2014.

We then run the following panel regression:

$$Sentiment_{i,t}=a+bLoss_{i,t}+cWin_{i,t}+Controls_{i,t}+\varepsilon_{i,t}, \quad (2)$$

where $Sentiment_{i,t}$ is country i's sentiment in week t. $Loss_{i,t}$ equals one if country i loses a match in week t and zero otherwise. $Win_{i,t}$ equals one if country i wins a match in week t and zero otherwise. $Controls_{i,t}$ constitute a set of control variables that include stock market volatility ($Volatility_{i,t}$) and lagged market returns in the prior four weeks ($Return_{i,t-1}$, $Return_{i,t-2}$, $Return_{i,t-3}$, and $Return_{i,t-4}$). We include country fixed effects and year-week fixed effects in the regression and cluster standard errors at both the country and the year-week levels.

Table 2 presents the results. Interestingly, our sentiment index is negatively correlated with the loss dummy at the 5% level of significance. In terms of economic significance, a loss in these soccer matches reduces the sentiment index by 0.101 (or 0.105 without controls) in absolute magnitude and by 17.8% (or 18.5% without controls) relative to the standard deviation of the sentiment index. Although the sentiment index is positively associated with the win dummy, the results are not statistically significant. This asymmetric finding between wins and losses is highly consistent with the findings of Edmans, Garcia, and Norli (2007), who provide two reasons for this result: first, while an increase in heart attacks, crimes, and suicides is shown to accompany soccer losses, there is no evidence of improvements in mood of a similar magnitude after wins; second, a win at the knockout stage advances a country only to the next stage, but a loss immediately removes the country from the competition. For robustness, we also limit our sample to a 14-month event window that includes the six months before and the six months after a two-month soccer tournament period in Models (3)-(4) and to an eight-month event window that includes the three months before and the three months after a two-month soccer tournament period in Models (5)-(6). All of these specifications yield similar evidence.

[Insert Table 2 Here]

3.2. ADRs

Our second validation test follows Baker, Wurgler, and Yuan (2012) and focuses on dual-listed companies. Dual-listed companies have the same cash flows but trade in different stock markets. In principal, the prices of the pair of stocks should be identical. However, deviations between the prices of paired stocks do exist because of explicit and implicit market frictions, such as transactions costs, taxes, holding costs, and short-sale restrictions (Karolyi, 2006; Gagnon and Karolyi, 2010). For example, Gagnon and Karolyi (2010) document significant price-parity deviations by comparing the intraday prices and quotes of ADRs with synchronous prices of their home-market shares in a sample of 506 cross-listed U.S. stocks from 35 different countries. Most important, the price-parity deviations cannot be explained in rational markets, which leaves room for behavioral factors.

We conjecture that the price-parity deviations are driven by the difference in sentiment between the two stock markets in which the stock pair is listed. If our sentiment index captures the mispricing, we expect to find a positive relationship between the sentiment index and the price difference that firms' fundamentals fail to explain. Specifically, we test how the difference in sentiment between ADRs' parent countries and the U.S. would affect the difference in price between ADRs' parent stocks and ADRs by using 1,778 pairs of ADRs and their parent stocks. We specify our regressions as follows:

$$\Delta Ln(P_{i,t}/P_{US,t})=a+b(Sentiment_{i,t}-Sentiment_{US,t})+c\Delta Ln(P_{i,t-1}/P_{US,t-1})+Controls_{i,t}+\varepsilon_{i,t} \quad (3)$$

$$Ln(P_{i,t}/P_{US,t})=a+b(Sentiment_{i,t}-Sentiment_{US,t})+cLn(P_{i,t-1}/P_{US,t-1})+Controls_{i,t}+\varepsilon_{i,t}, \quad (4)$$

where $P_{i,t}/P_{US,t}$ is the weekly average of the ratio of a stock's daily price in its parent country i multiplied by its ADR ratio to the ADR's daily price in week t. All prices are converted to U.S. dollars. $Sentiment_{i,t}$ is the sentiment of the stock's parent country i in week t, and $Sentiment_{US,t}$ is the sentiment of the U.S. in week t. $Controls_{i,t}$ includes the lagged change ($\Delta ln(P_{i,t-1}/P_{US,t-1})$) in or level ($ln(P_{i,t-1}/P_{US,t-1})$) of the price-deviation ratio, the difference in stock market volatility between the stock's parent country i and the U.S. in week t ($Volatility_{i,t}$-$Volatility_{US,t}$), and the difference in lagged market returns in the prior four weeks between stock i and its corresponding ADR ($Return_{i,t-1}$-$Return_{US,t-1}$, $Return_{i,t-2}$-$Return_{US,t-2}$, $Return_{i,t-3}$-$Return_{US,t-3}$, and $Return_{i,t-4}$-$Return_{US,t-4}$). Again, we control for both country and year-week fixed effects, and standard errors are two-way clustered at the country and year-week levels.

Panel A in Table 3 provides evidence showing that our sentiment measure captures the mispricing implied in the price-parity deviations. That is, the sentiment differences are positively associated with the stock price differences in other countries away from the benchmark in the U.S. The results are both statistically and economically significant. For example, a one-standard-deviation increase in the sentiment difference is associated with a 16.7% increase in the change of price deviation in Model (2). In Models (3) and (4), we also use the level of the natural logarithm of the price-deviation ratio ($Ln(P_{i,t}/P_{US,t})$) as the dependent variable. All specifications show that sentiment is a force that drives stock prices away from parity, thereby validating our sentiment indices across countries.

3.3. Earnings Announcements

Our last validation test involves earnings announcements. La Porta et al. (1997) employ earnings announcements to examine whether value premiums are related to mispricing. They hypothesize that investors rigidly extrapolate the past good performance of growth stocks into the future and realize their mistakes when earnings are released. Their empirical prediction is that growth stocks have large negative abnormal returns around earnings announcements, which would reflect investors' correction of the overestimation of stocks' earnings.

In the context of sentiment, Baker and Wurgler (2006) investigate the impact of sentiment on earnings announcement returns and show that earnings announcement returns are lower after high sentiment periods. Given that investors are more likely to suffer errors in earnings expectations for small-sized firms, earnings announcement returns would be significantly lower for small-sized stocks after periods of high sentiment.[15] Therefore, we focus on the small stock sample (whose market value is lower than the median for each country) and run the following regression to examine the relationship between our sentiment measure and earnings announcement returns:

$$CAR_{i,\,t} = a + bSentiment_{i,\,t\text{-}1} + Controls_{i,\,t} + \varepsilon_{i,\,t}, \tag{5}$$

where $CAR_{i,\,t}$ is the average of CARs around annual earnings announcements of small stocks in country *i* at week *t*.

To eliminate the noise from individual stocks, we require that the number of CARs used to calculate $CAR_{i,\,t}$ in week *t* is larger than a critical value of 15. For robustness, we also report the results of regressions using 20 as the critical value. $Sentiment_{i,\,t\text{-}1}$ is the average sentiment over the four weeks prior to week *t*. $Controls_{i,\,t}$ constitutes a set of control variables that include stock market volatility ($Volatility_t$) and lagged market returns in the prior four weeks ($Return_{t-1}$, $Return_{t-2}$, $Return_{t-3}$, and $Return_{t-4}$). We use both three-day CARs ($CAR(-1,1)_t$) and five-day CARs ($CAR(-2,2)_t$) as the dependent variables to run regressions with two-way fixed effects and standard errors clustered at the country and year-week levels.

As shown in Panel B of Table 3, the coefficients of sentiment are significantly negative for all specifications, and the abnormal returns around earnings announcements are inversely related to sentiment at the 5% level of significance. The estimate of -2.249 in Model (2) suggests that the effect of sentiment on earnings announcement returns is economically meaningful. For example, the estimate of -2.249 in Model (2) suggests that a one-standard-deviation increase in sentiment over the past four weeks is associated with a 28.6% decrease in the abnormal returns around earnings announcements.

In sum, these international tests validate our measure as a proxy for sentiment. Note our attempt to control for both country and year-week fixed effects and to cluster standard errors in these two dimensions. These exercises are important for addressing the heterogeneity across countries and over time and providing a powerful support for our sentiment indices' ability to capture sentiment around the world.

[Insert Table 3 Here]

[15] Baker and Wurgler (2006) argue that sentiment would lead investors to make errors in earnings expectations for stocks that are sensitive to sentiment, such as small stocks.

4. Return Predictability

In this section, we study the relationship between our sentiment indices and market returns across countries. We further attempt to address the doubt concerning sentiment as a behavioral factor by examining whether our indices are correlated with contemporaneous business cycle and risk variables, which might potentially attenuate the predictive ability of our indices.

4.1. Baseline Analysis

According to theory on sentiment, sentiment drives market prices away from economic fundamentals in the presence of limits to arbitrage. If high or low sentiment is not persistent, market prices will revert to the fundamentals after sentiment retreats. We form three basic empirical predictions based on this theory: first, sentiment should revert rather than persist in the following week; second, there is a positive contemporaneous relationship between sentiment and market returns because high (low) sentiment pushes market prices up (down); third, market returns should present a reversal pattern following sentiment—that is, high (low) sentiment should predict low (high) returns in the following week.

We construct a panel for the 40-country sample for the period from July 2004 to December 2014. In this panel, we pool our weekly sentiment indices ($Sentiment_{t+1}$ and $Sentiment_t$) and weekly market returns ($Return_{t+1}$ and $Return_t$) together and run the following regressions:

$$Sentiment_{i,\,t+1}=a+bSentiment_{i,\,t}+Controls_{i,\,t}+\varepsilon_{i,\,t}, \tag{6}$$

$$Return_{i,\,t}=a+bSentiment_{i,\,t}+Controls_{i,\,t}+\varepsilon_{i,\,t}, \tag{7}$$

$$Return_{i,\,t+1}=a+bSentiment_{i,\,t}+Controls_{i,\,t}+\varepsilon_{i,\,t}, \tag{8}$$

where $Controls_{i,\,t}$ constitute an array of control variables that includes the weekly average of economic policy uncertainty in the U.S. ($EPU_{US,t}$), the weekly average of the CBOE daily market volatility index ($VIX_{US,t}$), the weekly average of daily macroeconomic activities ($Economy_{US,t}$), stock market volatility ($Volatility_{i,\,t}$), and lagged market returns in the prior four weeks ($Return_{t-1}$, $Return_{t-2}$, $Return_{t-3}$, and $Return_{t-4}$). In addition, all of these regressions include country fixed effects, and standard errors are clustered at the country and year-week levels.[16]

[16] Note that we do not control for year-week fixed effects in subsequent tests because we find that global sentiment (as defined in Section 5) is crucial to sentiment across countries and prediction tests. The time fixed effects would absorb this important factor.

First, we examine the autocorrelations of our sentiment indices. Models (1) and (2) of Table 4 report the coefficient estimates obtained from regressing the sentiment indices in week *t*+1 on sentiment in week *t*. The autocorrelation is significantly negative with and without the control variables. The coefficient of -0.442 (-0.423 without controls) suggests that almost half of the sentiment movement would revert in the following week. The strong reversal pattern of the sentiment indices is consistent with our first prediction that sentiment is temporary and frequently fluctuates over time. Interestingly, none of the controls have significant coefficients at the 5% level, indicating that lagged economic fundamentals and market returns fail to predict future sentiment movement.

[Insert Table 4 Here]

In the Internet Appendix, we also examine this autocorrelation by country. The first part of Panel A in Table IA4 reports the results for each country, and the first part of Panel B summarizes the results for developed countries, emerging countries, and all of the countries. All of the countries in our sample consistently evince strong reversal patterns.

Second, we examine the contemporaneous relationship between sentiment and market returns. Models (3) and (4) of Table 4 report a significantly positive relationship between $Return_t$ and $Sentiment_t$. On average, a one-standard-deviation increase in our sentiment index is associated with an increase in weekly market returns of 93 basis points.

Again, we examine this contemporaneous relationship for each individual country and report the results in Table IA4. All 40 countries in our sample exhibit a positive relationship—market prices increase (decrease) with a high (low) level of sentiment. These findings support our hypothesis regarding the co-movement between sentiment and market returns.

Third, the most important prediction concerns return reversals following market sentiment. Models (5) and (6) of Table 4 show the return predictability of sentiment. As shown, a one-standard-deviation increase in market sentiment predicts a decline in weekly returns of 28 basis points (29 basis points without controls). We can make further use of the return predictability of our sentiment measure to create a profitable trading strategy. Specifically, for every week, we group countries into two equally weighted portfolios: a high sentiment portfolio, which contains countries with positive sentiment indices, and a low sentiment portfolio, which contains countries with negative sentiment indices. We then long the low sentiment portfolio and short the high sentiment portfolio for one week. This trading strategy generates, on average, a weekly return of 32 basis points with a *t* statistic of 6.28. Applying to this trading strategy solely to the U.S. stock market index, we are able to obtain a weekly return of 43 basis points with a *t* statistic of 2.04.

Table IA4 also presents the regression for each country. All 40 countries in our sample present a negative relationship between $Sentiment_t$ and $Return_{t+1}$. Moreover, 29 of the 40 countries display a significant pattern at the 5% level. Among all the countries, South Africa has the strongest reversal pattern, where a one-standard-deviation increase in sentiment predicts a decrease in weekly market returns of 90 basis points.

In sum, our sentiment measure can predict future market returns across countries. Consistent with sentiment theory, we find that sentiment is transitory, that market returns and sentiment exhibit co-movement, and that future returns show a reversal pattern in the week following sentiment.

4.2. Robustness Tests

To ensure the robustness of the aforementioned three predictions, we conduct several additional tests and summarize the main findings in Table IA5 of the Internet Appendix.

First, we run the panel regressions separately for subsamples of emerging and developed countries. Panels A and B of Table IA5 report the results. Comparing the coefficients of the three specifications between the two panels, we obtain the following findings:

1) Developed markets have an autocorrelation of -0.482 (with controls), which is lower than the value of -0.324 (with controls) for emerging markets; that is, almost half the sentiment change would revert in developed markets, whereas less than one-third would revert in emerging markets. This result suggests that the reversal pattern is stronger in developed markets than in emerging markets. In other words, relative to developed markets, emerging markets may exhibit more persistent sentiment.
2) Emerging markets display a stronger co-movement pattern than developed markets. The coefficient of the sentiment indices for emerging markets is 1.397, which is more than two times as large as the value of 0.645 for developed markets. Specifically, a one-standard-deviation increase in sentiment is associated with a contemporaneous change in market returns of 153 basis points in emerging markets, which is larger than the 70-basis-point change in developed markets.

3) Sentiment indices provide a stronger prediction for future returns in emerging markets than in developed markets; as shown in Model (6), the coefficient of the sentiment indices is -0.379 for emerging markets, compared with -0.209 for developed markets. The economic difference is also notable; a one-standard-deviation increase in sentiment leads to a decrease in the market return in the following week of 41 basis points in emerging markets, which is larger than the 23-basis-point decrease in developed markets.

In summary, sentiment in emerging markets is more persistent, tends to co-move with market returns, and leads to a powerful prediction of future returns. Emerging markets are susceptible to behavioral factors such as sentiment because these markets tend to have less transparent information environments (e.g., Morck, Yeung, and Yu, 2000 and Jin and Myers, 2006) and stricter arbitrage restrictions (e.g., Bris, Goetzmann, and Zhu, 2007). In the following section, we will formally test these two channels by using quasi-natural experiments in international markets.

Second, we calculate market returns again in the country's own currency to avoid the concern that sentiment affects the movement of the local currency's value and that the sentiment effect on exchange rates contaminates market returns.[17] Panel C shows that the three tests remain robust with a similar magnitude of coefficients and testing power.

Third, we perform the analysis while excluding the global financial crisis period from September 2008 to September 2009, as one may be concerned that this unusual period drives our results.[18] All our tests remain significant in the non-crisis period, as shown in Panel D. This result confirms that our sentiment indices still predict market returns in the following week after the crisis period is excluded.

Finally, we look into the longer horizon of sentiment by extending the time frequency from one week to two weeks. Panel E shows that all the patterns of sentiment and market returns remain with the two-week window. In terms of economic significance, a one-standard-deviation increase in sentiment is associated with a decrease in bi-weekly market returns of 76 basis points.

4.3. Fundamental Factors

[17] To a large extent, sentiment could influence foreign exchange markets; however, this topic is beyond the scope of this paper, and we leave it for future research.
[18] We indeed find a sharp decline in sentiment during the recent financial crisis (see Figure 1 for the cumulative sentiment over the sample period).

Sibley et al. (2016) cast doubt on the Baker and Wurgler (2006) sentiment index and argue that business cycle and risk factors could simply explain its predictive power regarding cross-sectional stock returns. In this subsection, we confirm that the return prediction of sentiment is not driven by economic fundamentals. In practice, we aim to show that our sentiment indices have little correlation with these fundamental factors and that the residuals from regressing sentiment indices on fundamental factors have similarly strong predictability with respect to market returns, as shown in the last subsection.

We first regress our weekly sentiment measure on changes in all eight business cycle and risk variables from Sibley et al. (2016). For variables only available on a monthly frequency, we use the monthly change as weekly controls. We report the results in Panel A of Table 5. Model (1) includes all 40 countries, whereas Model (2) includes only the U.S. Both the international sample and the U.S. sample indicate that business cycle and risk factors have little explanatory power with respect to our sentiment indices; R^2 is only 0.3% in Model (1) or 3.2% in Model (2). By contrast, Sibley et al. (2016) find that approximately 63% of the variations in the Baker and Wurgler (2006) index can be explained by these business cycle and risk factors.

After controlling for these factors, we perform our return prediction tests again with sentiment residuals. Panel B reports the results. Interestingly, the estimates turn out to be even stronger with sentiment residuals. Again, we find compelling evidence that sentiment measured by our proxy is indeed sentimental, which leads to mispricing and portends future returns.

[Insert Table 5 Here]

5. Theoretical Channels of the Sentiment Effect

Theoretically, the return prediction of sentiment documented in the section above depends on two channels: *the difficult-to-value channel* and *the limits-to-arbitrage channel*. The first channel suggests that investors are subject to sentiment when assets are difficult to value (DeLong et al., 1990), whereas the second channel suggests that rational investors are limited by arbitrage constraints (Shleifer and Vishny, 1997). The two channels are proposed and tested in the Baker and Wurgler (2006) framework of the cross-sectional variation of stocks. However, they acknowledge the difficulty of disentangling these channels empirically: "In practice, *the same stocks that are the hardest to arbitrage also tend to be the most difficult to value*. While for expositional purposes we have outlined the two channels separately, they are likely to have overlapping effects. This may make them difficult to distinguish empirically.”

Taking advantage of the heterogeneity of institutional environments and regulatory implementations across countries, in this section, we implement two quasi-natural experiments to test the two theoretical channels. Importantly, this empirical design avoids potentially endogenous issues. First, we study the implementation of the MiFID as an exogenous shock to the information environment. With the improvement in market transparency and efficiency, we expect asset valuation to be less subjective and investors to be less likely to react to market sentiment. Our second experiment uses the short-selling ban as evidence of limits to arbitrage. In response to market crashes during the financial crisis from 2007 to 2009, several countries banned the short selling of financial stocks or all stocks for a period of time. Sentiment is expected to have a larger impact on markets with more limits to arbitrage, as investors find it difficult to correct the mispricing caused by market sentiment.

5.1. The Difficult-to-value Channel and MiFID

MiFID is an influential European Union financial markets directive that became effective for all European Union members on November 1, 2007. It aims to establish an integrated, transparent, competitive, and efficient European financial market. MiFID contains a series of harmonized rules that enhance market transparency and investor protection. Following the implementation of MiFID, trading rules for European exchanges became more comprehensive, and the information environment of the European financial market improved (Cumming, Johan, and Li, 2011). We thus use the implementation of MiFID to test whether changes in the market information environment affect the relationship between future returns and current sentiment.

Specifically, we collect information on the implementation of MiFID and exchange trading rules from Cumming, Johan, and Li (2011). We focus on two measures of exchange trading rules: the False Disclosure Rules Index (FDI), which is used to assess regulation of false disclosure or a failure to disclose information, and the Market Manipulation Rules Index (MMI), which is a more composite index pertaining to several information sensitive rules against price manipulations, volume manipulation, spoofing, and false disclosure. The two indices are most relevant to the information environment of markets.[19] Table IA6 in the Internet Appendix presents the changes in these indices around the implementation date of MiFID (November 1, 2007) for each country. Some of the indices in European countries such as Austria and Germany changed significantly after November 2007, while other countries that are not subject to MiFID experienced no changes in these indices.[20]

To test the impact of information environments on the relationship between market returns and sentiment, we run the following panel regressions with country fixed effects and standard errors clustered at the country and year-week levels over the period from January 2007 to August 2008:

$$Return_{i,\,t+1}=\alpha+\beta_1 Sentiment_{i,\,t}+\ \beta_2 Sentiment_{i,\,t}\times InfEnv_{i,\,t}\ +\beta_3 InfEnv_{i,\,t}\ +Controls_{i,\,t}+\varepsilon_{i,\,t}, \quad (9)$$

where $Return_{i,\,t+1}$ is country i's market returns in week t+1 and $Sentiment_{i,\,t}$ is country i's market sentiment in week t. In Model (2) of Table 6, $InfEnv_{i,\,t}$ equals one if country i is exposed to MiFID at time t and zero otherwise. In Model (3) and Model (4), $InfEnv_{i,\,t}$ equals the change in the corresponding index of exchange trading rules (MMI or FDI) if the date is after November 1, 2007, and zero otherwise.

If the information environment of stock markets improves, the stock price would respond less to the change in market sentiment. We thus expect β_2 to be significantly positive. Table 6 confirms our prediction with the evidence that β_2 is significantly positive in Models (2)-(4). The magnitude of β_2 is also economically significant. For example, in Model (2), a one-standard-deviation increase in sentiment in countries that are not affected by MiFID is associated with a decrease in market returns of 67 basis points, whereas for countries that are subject to MiFID, the corresponding decrease in market returns is 23 basis points. Similarly, in Model (3), a one-standard-deviation increase in FDI reduces the return predictability of sentiment by 30.4%. These findings indicate that the implementation of MiFID and the increase in the two indices of exchange rules substantially weakened the sentiment effect on market returns.

[Insert Table 6 Here]

[19] A more detailed definition of these indices is provided in Table 1 of Cumming, Johan, and Li (2011).

[20] Cumming, Johan, and Li (2011) do not have information on the changes in these two indices for some European countries, including Belgium, Hungary, the Netherlands, Poland, and Portugal.

Furthermore, we conduct several robustness tests. In Table IA7 of the Internet Appendix, Panels A and B report the regression results based on a different sample period and a different sample of countries, respectively. Specifically, Panel A reports the results of regressions based on a longer sample period: February 2006 to September 2008. In Panel B, we match 16 European countries that are subject to MiFID (the treatment group) with 16 countries that are not affected by MiFID (the control group) by using the average of the ratio of stock market capitalization to GDP (hereafter MktCap) for the period from 2004 to 2014. We then repeat the same regressions in Table 6 with the matched sample. The results are quite similar to those in Table 6: β_2 is positive and statistically significant in all of the specifications, and the magnitude of the effect is also economically significant.

Finally, to rule out the endogeneity concern that the effect of MiFID on the return prediction of sentiment is not driven by a time trend, we conduct a placebo test and report the results in Panel C. Specifically, we bootstrap 16 event dates between May 2005 (the ten months after the beginning of our sample period) and February 2014 (the ten months before the end of our sample period) and assign them to the 16 European countries that are subject to MiFID. The sample period ranges from the ten months before the earliest bootstrapped event date to the ten months after the latest bootstrapped event date. We then run the regression and obtain β_2. We repeat the procedure 1,000 times, which provides us with 1,000 β_2s. We sort these 1,000 β_2s from smallest to largest and report the 90th percentile, 95th percentile, and 99th percentile. In all of the specifications, our β_2 based on the true MiFID effective date is larger than the 99th percentile of β_2s generated from the bootstrapped pseudo effective dates for MiFID.

5.2. The Limits-to-arbitrage Channel and Short-selling Bans

Short-selling constraints are considered one of the most important limits to arbitrage (e.g., Jones and Lamont, 2002; Nagel, 2005; Gromb and Vayanos, 2010; Chu, Hirshleifer, and Ma, 2016). In practice, there are significant cross-country variations in scope and types of short-selling constraints, which are called short-selling bans (Jain et al., 2013). Even within a country, short-selling bans may vary over time. For example, during the financial crisis period from 2007 to 2009, many countries that did not previously forbid short sales imposed short-selling bans on either financial stocks or all stocks. An interesting characteristic of these short-selling bans is that different countries imposed and then lifted these bans on different dates over the financial crisis period.[21]

To test the limits-to-arbitrage channel, we collect information on short-selling bans for our 40 countries from Beber and Pagano (2013) and Jain et al. (2013). As shown in Table IA8 of the Internet Appendix, the inception dates of short-selling bans range from September 19, 2008 (Canada, the U.K., and the U.S.) to October 30, 2008 (Japan). The durations of these bans also vary across countries, with the longest being over two years (e.g., Japan) and the shortest being less than one month (e.g., the U.S.). We choose the six months before the inception date of the first ban and the six months after the inception date of the last ban as the sample period for our main analysis. There are also countries that never imposed bans during our sample period and other countries that have always forbidden the short sale of stocks.

To test the impact of short-selling bans on the relationship between stock market returns and investor sentiment, we run the following panel regressions with country fixed effects and standard errors clustered at the country and year-week levels:

$$Return_{i,\,t+1}=\alpha+\beta_1 Sentiment_{i,\,t}+\beta_2 Sentiment_{i,\,t}\times Ban_{i,\,t}+\beta_3 Ban_{i,\,t}+Controls_{i,\,t}+\varepsilon_{i,\,t}, \quad (10)$$

where $Return_{i,\,t+1}$ is country i's market returns in week t+1 and $Sentiment_{i,\,t}$ is country i's market sentiment in week t. $Ban_{i,\,t}$ equals one if country i has imposed a short-selling ban on either financial stocks or all stocks at week t and zero otherwise. Our main interest is the coefficient of the interaction term β_2. We conjecture that short-selling bans would make it more difficult for investors to correct the stock mispricing caused by market sentiment, which would lead to a larger impact of the current week's sentiment on the next week's market returns. Given the negative relationship between future returns and current sentiment documented in the previous section, we expect β_2 to be significantly negative.

The results in Table 7 are consistent with our prediction. A negative β_2 at the 5% level of significance indicates that the return prediction of market sentiment is greater for countries with short-selling bans than for countries that did not impose short-selling bans on stocks. In addition, compared with a β_1 of -0.119, a β_2 of -0.215 suggests that the effect of short-selling bans is also

[21] Two types of bans were imposed on short sales during the financial crisis period: bans on naked short sales, where the seller does not first borrow the security, and bans on covered short sales, where the seller manages to borrow the security. Some countries imposed only a ban on naked short sales, whereas other countries may have used a combination of these two types of bans. According to Beber and Pagano (2013), covered short-selling bans were more frequently used than naked short-selling bans at the beginning of financial crisis period, while only naked short-selling bans were in effect at the end of the financial crisis.

economically significant. Specifically, a one-standard-deviation increase in sentiment for countries with no bans on short sales is associated with a decrease in market returns of 13 basis points, whereas for countries with bans on short sales, the corresponding decrease is 36 basis points.

[Insert Table 7 Here]

To ensure the robustness of our results, we conduct several additional tests in Table IA9 of the Internet Appendix. In Panel A, we use the same sample countries in Beber and Pagano (2013) with a sample period from January 2008 to June 2009. In Panel B, we match 16 countries that imposed short-selling bans (the treatment group) with 16 countries that never imposed short-selling bans (the control group) by using the average of MktCap for the period from 2004 to 2014. All the results are robust to the use of different countries and different sample periods.

Finally, we conduct a placebo test in Panel C. We first bootstrap 24 event dates between January 2005 and July 2014. Then, we treat the 24 bootstrapped event dates as the pseudo starting dates of short-selling bans and allocate them to the 24 countries that have imposed short-selling bans. The durations of each short-selling ban remain the same as those in Table IA8. We then run the regressions in Table 7 by using the newly bootstrapped event dates. The sample period ranges from the six months before the earliest bootstrapped event date to the six months after the latest bootstrapped event date. We repeat the procedure 1,000 times to obtain 1,000 β_2s and report the 10^{th}, 5^{th} and 1^{st} percentiles of β_2s. The result shows that β_2 in Panel A is beyond the 5^{th} percentile of the 1,000 β_2s generated from bootstrapping the event dates. We take this result as corroborating evidence that short-selling bans amplify the negative relationship between future market returns and current investor sentiment.

6. Global Sentiment and Sentiment Co-movement

Does sentiment co-move across countries? Is there global sentiment that affects sentiment in specific countries? In this section, we study the commonality of sentiment across countries. Moreover, we examine whether capital market integration affects sentiment co-movement. We use a quasi-natural experiment to test this hypothesis: the implementations of IFRS across countries and over time. Finally, we investigate whether global sentiment predicts future market returns.

6.1. Sentiment Co-movement

The conjecture of sentiment co-movement is proposed and tested by Baker, Wurgler, and Yuan (2012). They construct annual investor sentiment indices for six developed markets (i.e., Canada, France, Germany, Japan, the U.K., and the U.S.), and they further decompose the six total sentiment indices into a global sentiment index and six local sentiment indices. Their results reveal the crucial role of the global sentiment index as a contrarian predictor of country-level market returns. Given that this finding is the only evidence of sentiment co-movement, it is important to further elucidate the commonality of sentiment by using a different sentiment measure with a larger sample of countries at a higher frequency.

Specifically, we construct a global sentiment index and examine to the extent to which global sentiment affects local sentiment. We simply average the sentiment indices of the 40 countries in our sample to form the global sentiment index. We also consider different weighted averages, including weighted population, weighted GDP per capita, weighted Internet usage, and weighted sentiment averages of Google's search market share; all of these measures yield similar results. To make our construction more transparent, we choose to use the simple average method to construct the global sentiment index when reporting the following analysis. We plot the weekly time series of the cumulative global sentiment from July 2004 to December 2014 in Figure 1B. The cumulative global sentiment index is immensely volatile. Not surprisingly, we observe that global sentiment climbed to a peak during the economic boom period, declined sharply over the global financial crisis from 2008 to 2009, bounced back in 2010, and then waned in 2011-2012 when the Eurozone crisis intensified. Given the vibrancy of sentiment, the high frequency of data for the sentiment measure is valuable for capturing the short-lived sentiment phenomena.

We next examine how a country's sentiment is explained by global sentiment in the following regression:

$$Sentiment_{i,t}=a+bSentiment_{G,t}+Controls_{i,t}+\varepsilon_{i,t}, \tag{11}$$

where $Sentiment_{i,t}$ is country i's sentiment in week t and $Sentiment_{G,t}$ is the simple average of $Sentiment_{i,t}$ for our 40 sample countries in week t.

Table 8 reports the results of regressing a country's sentiment on global sentiment. First, Models (1) and (2) show that, on average, 13% of the variation in a country's sentiment is driven by global sentiment. Second, we document a significant difference between developed and emerging countries in Models (3) and (4): investor sentiment has a higher correlation with global sentiment in developed countries than in emerging countries. In terms of economic significance, a one-standard-deviation change in global sentiment is associated with a 0.38-standard-deviation change in sentiment in developed markets compared with a 0.29-standard-deviation change in sentiment in emerging markets. The difference in the estimates between developed and emerging countries is also statistically significant, with a *p*-value of 0.034.

[Insert Table 8 Here]

In addition, we perform the regression for each country and report the results on the left-hand side of Panel A of Table IA12 in the Internet Appendix. Apparently, sentiment in all countries except China has a significant positive relationship with global sentiment. As developed countries are more integrated into global market, sentiment in developed countries has a higher correlation with global sentiment than that in emerging countries. Specifically, global sentiment can, on average, explain 19.4% of the variation in sentiment for all countries and 25.9% (13.0%) of the variation in sentiment for developed countries (emerging countries).

Overall, these results suggest that global sentiment plays a significant role in driving sentiment across countries.

6.2. Market Integration and Sentiment Co-movement

There are two mechanisms through which global sentiment travels around the world. First, the trading activities of foreign sentiment investors could influence the sentiment of domestic investors, which is similar to the correlated trading behavior of international and institutional investors (e.g., Kamara, Lou, and Sadka, 2008; Karolyi, Lee, and Dijk, 2012).[22] Second, investor sentiment can be spread across countries through information sharing in channels such as word-of-mouth, the Internet, and the media (e.g., Hong, Kubik, and Stein, 2004; Tetlock, 2007; Baker, Wurgler, and Yuan, 2012). Both of these mechanisms can be characterized as the effect of market integration (e.g., Bekaert et al., 2013; Carrieri, Chaieb, and Errunza, 2013; Ng et al., 2014). In this subsection, we use IFRS as the basis of an experiment to examine the impact of market integration on sentiment co-movement.

IFRS have been widely adopted around the world. According to the website of the IFRS – Foundation and International Accounting Standards Board (IASB), at least 116 jurisdictions

[22] If foreign investors represent a group of marginal investors in the domestic market, the sentiment of foreign investors would drive asset prices to deviate from economic fundamentals in the domestic market.

worldwide have required IFRS up to 2015 for all or most publicly accountable entities. Regulators advocate IFRS to enhance the comparability of financial statements (Daske et al., 2008), and the increased comparability of financial statements across countries consequently benefits investors. For example, prior literature shows that IFRS would improve information sharing and capital flows across countries, which contributes to a higher degree of capital market integration (DeFond et al., 2011; De George, Li, and Shivakumar, 2015). We thus use the adoption of IFRS to test how market integration affects co-movement between a country's market sentiment and global sentiment.

Table IA10 in the Internet Appendix presents the years of mandatory IFRS adoption for each country. European countries, Hong Kong, and South Africa adopted IFRS in 2005. Several countries, such as Israel and New Zealand, adopted IFRS between 2007 and 2013, whereas the remaining countries, such as Japan and India, never adopted IFRS during our sample period. Given the relatively wide distribution of the IFRS adoption years, we use the full sample period from 2004 to 2014 for our main analysis. In robustness tests, we also follow the prior literature in using event windows around approximately 2005. Specifically, we run the following regression:

$$Sentiment_{i,t}=\alpha+\beta_1 Sentiment_{G,t}+\beta_2 Sentiment_{G,t}\times IFRS_{i,t}+\beta_3 IFRS_{i,t}+\varepsilon_{i,t}, \qquad (12)$$

where $Sentiment_{i,t}$ is country i's market sentiment in week t and $Sentiment_{G,t}$ is global sentiment in week t. $IFRS_{i,t}$ equals one when country i adopted IFRS at year t-1 and zero otherwise. Table 9 presents our main results, where Model (1) is the baseline model without the IFRS dummy and Model (2) is our main regression with the IFRS dummy. The coefficients of $Sentiment_{G,t}$ are positive and significant at the 1% level in both Models (1) and (2), indicating that a country's sentiment is positively correlated with global sentiment. Our focus is β_2, the interaction between global sentiment and the IFRS adoption dummy. As shown in the table, β_2 is significantly positive, suggesting that global sentiment has a greater positive impact on sentiment in countries that adopted IFRS than on sentiment in countries that did not. The effect is also economically significant. Specifically, for countries that did not adopt IFRS, a one-standard-deviation increase in global sentiment is related to an 11.6% increase in countries' market sentiment, while for countries that adopted IFRS, the corresponding increase is 26.2%. This result is consistent with our prediction that market integration increases co-movement between countries' market sentiment and global sentiment.

[Insert Table 9 Here]

Table IA11 in the Internet Appendix reports the results of three robustness tests. In Panel A, instead of using the full sample period from 2004 to 2014, we choose the period from 2004 to 2007 as the testing window, where 2004 to 2005 serves as the pre-IFRS adoption period and 2006 to 2007 serves as the post-IFRS adoption period. In Panel B, we match the seven countries that did not adopt IFRS before 2014 indicated in Table 9 with seven countries that did by using the average of MktCap for the period from 2004 to 2014. Both of the panels show consistent evidence that β_2 is significantly positive.

Panel C presents the results of a placebo test. We bootstrap 33 IFRS adoption years from 2003 (the earliest adoption year) to 2013 (the latest adoption year) and allocate them to the 33 countries that adopted IFRS. Using the newly bootstrapped IFRS adoption years, we then run the regressions. We repeat the procedure 1000 times and report the 90th, 95th, and 99th percentiles of β_2s generated from bootstrapping. We find that our β_2 from the main regression is larger than the 95th percentile of the β_2s created from bootstrapping IFRS adoption years.

6.3. Global Sentiment and Return Predictability

Having documented the strong international commonality of sentiment, we investigate the return predictability of global sentiment across countries. We decompose the sentiment of a country into the global sentiment component and the local sentiment component, where local sentiment is defined as the residual of regressing the country's sentiment on global sentiment. We then regress future market returns on both current global sentiment and current local sentiment in the following specification:

$$Return_{i,\,t+1} = a + bSentiment_{G,\,t} + cSentiment_{iL,\,t} + Controls + \varepsilon_{i,\,t}, \tag{13}$$

where $Return_{i,\,t+1}$ is country i's market returns in week t+1, $Sentiment_{G,\,t}$ is global sentiment in week t, and $Sentiment_{iL,\,t}$ is country i's local sentiment in week t.

Table 10 reports the results. Models (1) and (2) show that both global and local sentiment can predict the reversal of future returns. In our sample, global sentiment has stronger predictive power than local sentiment. Models (3) and (4) present the coefficient estimates for both developed and emerging countries as well as the difference in the coefficients of global and local sentiment. Evidently, although global sentiment rather than local sentiment plays a major role in predicting future returns for both developed and emerging countries, relatively speaking, the return prediction of global sentiment is more pronounced in developed countries, while local sentiment has stronger predictive power in emerging countries. Specifically, a one-standard-deviation increase in global sentiment predicts a decrease in the weekly return of 130 (versus 67) basis points in developed (emerging) countries. By contrast, a one-standard-deviation increase in local sentiment predicts a decrease in the weekly return of 14 (versus 27) basis points in developed (emerging) markets.

[Insert Table 10 Here]

Again, we examine this relationship for each country in Table IA12 in the Internet Appendix. The right-hand side of Panel A presents the coefficients and *t*-statistics of global and local sentiment for each country, and Panel B summarizes our findings for developed countries, emerging countries, and all of the countries. For 33 of the 40 countries in our sample, global sentiment can significantly predict the next week's market returns. By contrast, local sentiment can significantly predict the next week's market returns for only 15 countries.

Moreover, global sentiment has predictive power in all developed countries except Japan, while it has predictive power in only 14 of the 20 emerging markets. On the other hand, local sentiment rarely has an impact in predicting future returns in developed markets, whereas it may be more important in emerging markets, as the coefficient is significant at the 5% level of significance for 11 markets. As is evident, developed markets are more subject to global sentiment, and emerging markets are more subject to local sentiment. These findings again imply that developed countries are well integrated into the global market and that their markets are thus more likely to be influenced by global sentiment.

7. Conclusion

In this paper, we use households' Google search behavior to construct weekly sentiment indices for 40 markets for the period between 2004 and 2014. We take advantage of international settings to validate our sentiment indices based on three tests, including sports outcomes, dual-listed stocks, and earnings announcement returns. We show that our sentiment measure is a contrarian predictor of country-level market returns. We further test the two theoretical channels of the sentiment effect separately by using two quasi-natural experiments. Finally, we document an important role of global sentiment in driving sentiment and predicting market returns across countries.

There is still much to be done for future research. With international sentiment indices, researchers could improve our understanding of international markets from a behavioral perspective. Moreover, heterogeneity across countries, capital market integration, and the implementation of specific policies and regulations provide rich opportunities to explore the sentiment effect in a broader context.

References

Aruoba, S Borağan, Francis X Diebold, and Chiara Scotti, 2009. Real-time measurement of business conditions, *Journal of Business and Economic Statistics* 27, 417-427.

Baker, Malcolm, and Jeffrey Wurgler, 2000. The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219-2257.

Baker, Malcolm, and Jeffrey Wurgler, 2006. Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61, 1645-1680.

Baker, Malcolm, and Jeffrey Wurgler, 2007. Investor sentiment in the stock market, *Journal of Economic Perspectives* 21, 129-151.

Baker, Malcolm, Jeffrey Wurgler, and Yu Yuan, 2012. Global, local, and contagious investor sentiment, *Journal of Financial Economics* 104, 272-287.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2015. Measuring economic policy uncertainty, *Chicago Booth research paper*.

Barber, Brad M., Terrance Odean, and Ning Zhu. 2009. Do retail trades move markets? *Review of Financial Studies* 22, 151-186.

Beber, Alessandro, and Marco Pagano, 2013. Short-selling bans around the world: Evidence from the 2007–09 crisis, *Journal of Finance* 68, 343-381.

Bekaert, G., Harvey, C.R., Lundblad, C.T. and Siegel, S., 2013. The European Union, the Euro, and equity market integration, *Journal of Financial Economics*, 109, 583-603.

Bris, Arturo, William N. Goetzmann, and Ning Zhu, 2007. Efficiency and the bear: Short sales and markets around the world, *Journal of Finance* 62: 1029-1079.

Brown, Gregory W, and Michael T Cliff, 2004. Investor sentiment and the near-term stock market, *Journal of Empirical Finance* 11, 1-27.

Carrieri, F., Chaieb, I. and Errunza, V., 2013. Do implicit barriers matter for globalization? *Review of Financial Studies*, 26, 1694-1739.

Choi, Hyunyoung, and Hal Varian, 2012. Predicting the present with google trends, *Economic Record* 88, 2-9.

Chu, Yongqiang and Hirshleifer, David A. and Ma, Liang, 2016. The causal effect of limits to arbitrage on asset pricing anomalies, working paper.

Cumming, Douglas, Sofia Johan, and Dan Li, 2011. Exchange trading rules and stock market liquidity, *Journal of Financial Economics* 99, 651-671.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2011. In search of attention. *Journal of Finance* 66, 1461-1499.

Da, Zhi, Joseph Engelberg, and Pengjie Gao, 2015. The sum of all fears investor sentiment and asset prices, *Review of Financial Studies* 28, 1-32.

Das, Sanjiv R, and Mike Y Chen, 2007. Yahoo! For amazon: Sentiment extraction from small talk on the web, *Management Science* 53, 1375-1388.

Daske, H., Hail, L., Leuz, C. and Verdi, R., 2008. Mandatory IFRS reporting around the world: Early evidence on the economic consequences, *Journal of Accounting Research*, 46, 1085-1142.

DeFond, M., Hu, X., Hung, M. and Li, S., 2011. The impact of mandatory IFRS adoption on foreign mutual fund ownership: The role of comparability, *Journal of Accounting and Economics*, 51, 240-258.

De George, Emmanuel T, Xi Li, and Lakshmanan Shivakumar, 2015. A review of the IFRS-adoption literature, working paper.

De Long, J Bradford, Andrei Shleifer, Lawrence H Summers, and Robert J Waldmann, 1990. Noise trader risk in financial markets, *Journal of political Economy* 98, 703-738.

Diether, Karl B, Christopher J Malloy, and Anna Scherbina, 2002. Differences of opinion and the cross section of stock returns, *Journal of Finance* 57, 2113-2141.

Drake, Michael, Darren Roulstone, and Jake Thornock, 2012. Investor information demand: evidence from google searches around earnings announcements, *Journal of Accounting Research* 50,1001-1040.

Edmans, Alex, Diego Garcia, and Øyvind Norli, 2007. Sports sentiment and stock returns, *Journal of Finance* 62, 1967-1998.

Gagnon, Louis, and Andrew Karolyi, 2010. Multimarket trading and arbitrage, *Journal of Financial Economics* 97, 53-80.

Ginsberg, Jeremy, Matthew H Mohebbi, Rajan S Patel, Lynnette Brammer, Mark S Smolinski, and Larry Brilliant, 2009. Detecting influenza epidemics using search engine query data, *Nature* 457, 1012-1014.

Gromb, D. and Vayanos, D., 2010. Limits of arbitrage: the state of the theory, *Annual Review of Financial Economics*, 2, 251-275.

Hirshleifer, David, and Tyler Shumway, 2003. Good day sunshine: Stock returns and the weather, *Journal of Finance* 58, 1009-1032.

Hong, H., Kubik, J.D. and Stein, J.C., 2004. Social interaction and stock-market participation, *Journal of Finance*, 59, 137-163.

Huang, Dashan, Fuwei Jiang, Jun Tu, and Guofu Zhou, 2015. Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28, 791-837.

Hwang, B.H., 2011. Country-specific sentiment and security prices. *Journal of Financial Economics*, 100, 382-401.

Jain, Archana, Pankaj Jain, Thomas McInish, and Michael McKenzie, 2013. Worldwide reach of short selling regulations, *Journal of Financial Economics* 109, 177-197.

Jin, Li, and Stewart C. Myers, 2006. R2 around the world: New theory and new tests, *Journal of Financial Economics* 79, 257-292.

Jones, C.M. and Lamont, O.A., 2002. Short-sale constraints and stock returns, *Journal of Financial Economics*, 66, 207-239.

Kamara, A., Lou, X. and Sadka, R., 2008. The divergence of liquidity commonality in the cross-section of stocks, *Journal of Financial Economics* 89, 444-466.

Kamstra, Mark J, Lisa A Kramer, and Maurice D Levi, 2003. Winter blues: A sad stock market cycle, *American Economic Review* 93, 324-343.

Kaplanski, Guy, and Haim Levy, 2010. Sentiment and stock prices: The case of aviation disasters, *Journal of Financial Economics* 95, 174-201.

Keynes, John Maynard, 1936. The general theory of interest, employment and money, (London: Macmillan).

Kogan, Leonid, Stephen A Ross, Jiang Wang, and Mark M Westerfield, 2006. The price impact and survival of irrational traders, *Journal of Finance* 61, 195-229.

Kogan, Leonid, Stephen Ross, Jiang Wang, and Mark M Westerfield, 2009. Market selection, working paper.

Karolyi, G.A., 2006. The world of cross-listings and cross-listings of the world: Challenging conventional wisdom. *Review of Finance*, 10, 99-152.

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

Lee, C.M., Ma, P. and Wang, C.C., 2015. Search-based peer firms: Aggregating investor perceptions through internet co-searches, *Journal of Financial Economics* 116, 410-431.

Lemmon, Michael, and Evgenia Portniaguina, 2006. Consumer confidence and asset prices: Some empirical evidence, *Review of Financial Studies* 19, 1499-1529.

Lesmond, David A, Joseph P Ogden, and Charles A Trzcinka, 1999. A new estimate of transaction costs, *Review of Financial Studies* 12, 1113-1141.

Miller, Edward M., 1977. Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

Mondria, Jordi, Thomas Wu, and Yi Zhang, 2010. The determinants of international investment and attention allocation: Using internet search query data, *Journal of International Economics* 82, 85-95

Morck, Randall, Bernard Yeung, and Wayne Yu, 2000. The information content of stock markets: why do emerging markets have synchronous stock price movements? *Journal of Financial Economics* 58, 215-260.

Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics*, 78, 277-309.

Ng, Lilian, Solnik, Bruno, Wu, Eliza, and Bohui Zhang, 2014. Characterizing global financial and economic integration using cash flow expectations, working paper.

Pástor, Ľuboš, and Veronesi Pietro, 2003. Stock valuation and learning about profitability, *Journal of Finance* 58, 1749-1790.

Pástor, Ľuboš, and Pietro Veronesi, 2005. Rational IPO waves, *Journal of Finance* 60, 1713-1757.

Pástor, Ľuboš, and Pietro Veronesi, 2006. Was there a nasdaq bubble in the late 1990s?, *Journal of Financial Economics* 81, 61-100.

Porta, R.L., Lakonishok, J., Shleifer, A. and Vishny, R., 1997. Good news for value stocks: Further evidence on market efficiency, *Journal of Finance*, 52, 859-874.

Qiu, Lily, and Ivo Welch, 2004. Investor sentiment measures, working paper.

Shiller, Robert J, 1990. Speculative prices and popular models, *Journal of Economic Perspectives* 4, 55-65.

Shleifer, Andrei, and Robert W Vishny, 1997. The limits of arbitrage, *Journal of Finance* 52, 35-55.

Sibley, Steven E, Yanchu Wang, Yuhang Xing, and Xiaoyan Zhang, 2016. The information content of the sentiment index, *Journal of Banking and Finance* 62, 164-179.

Soo, Cindy, 2014. Quantifying animal spirits: News media and sentiment in the housing market, working paper.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2012. The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2014. The long of it: Odds that investor sentiment spuriously predicts anomaly returns, *Journal of Financial Economics* 114, 613-619.

Tetlock, Paul C, 2007. Giving content to investor sentiment: The role of media in the stock market, *Journal of Finance* 62, 1139-1168.

Yu, Jianfeng, and Yu Yuan, 2011. Investor sentiment and the mean–variance relation, *Journal of Financial Economics* 100, 367-381.

Figure 1: Cumulative sentiment over time

Figure 1A and 1B present the cumulative U.S., Portuguese, and global sentiment from July 2004 to December 2014, respectively. Global sentiment is the average of sentiment of 40 countries each week. The 2008 financial crisis period and periods with influential events during the European debt crisis are highlighted.

Figure 1A: Cumulative U.S. and Portuguese sentiment over time

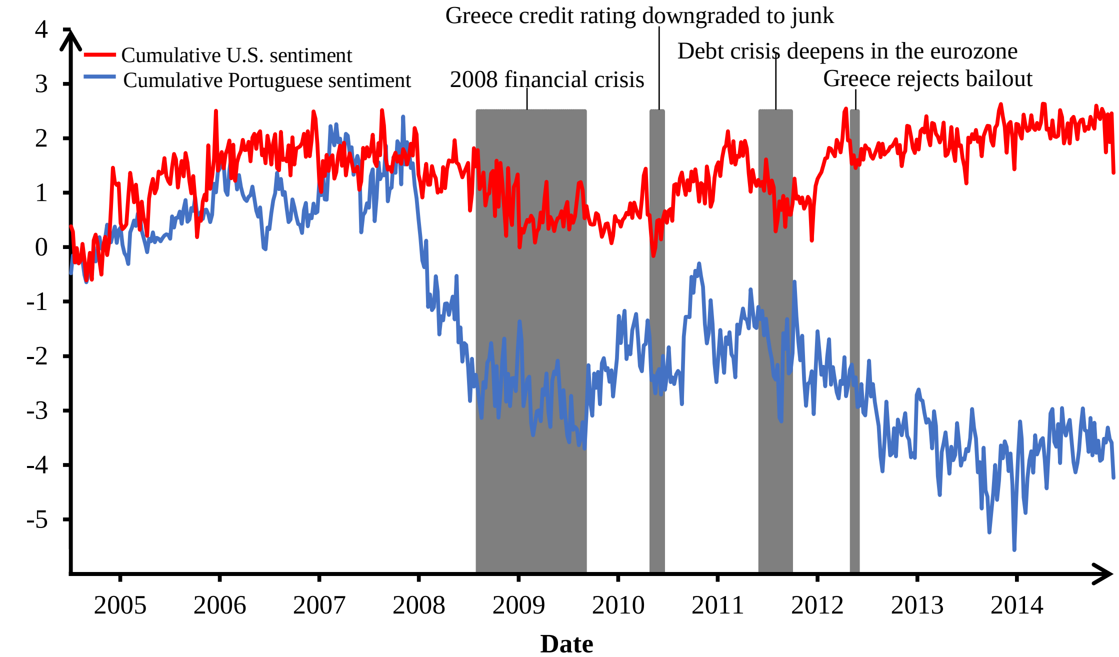

Figure 1B: Cumulative global sentiment over time

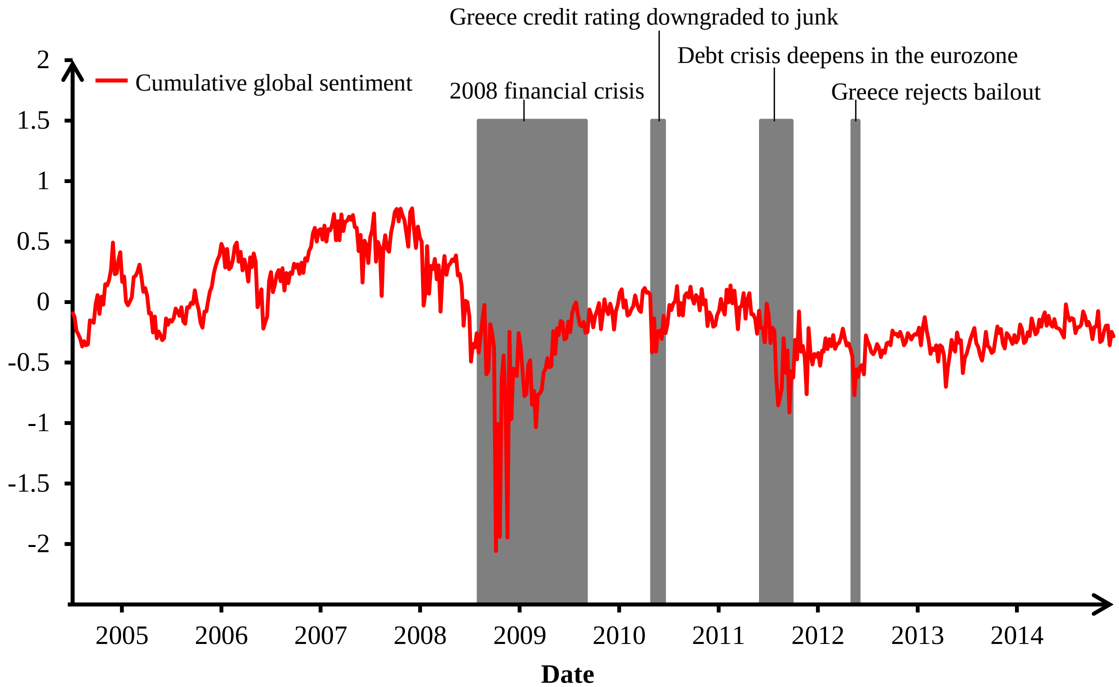

Table 1: Summary statistics of Google search

This table reports the summary statistics of Google search for 40 countries from 2004 to 2014. Panel A presents the total Google search volume around the world during the sample period.[1] Panel B shows the details of Google usage for each country. Internet user (*ITUsers*) from World Bank is measured as the 11-year average of internet users per hundred people and Google market share (*GoogleShare*) is Google's search market share[2] in each country at the end of 2013. *Language* denotes the languages used to construct the sentiment measure for each country. *LangShare* denotes their corresponding population shares obtained from the World Factbook of CIA[3] and the home page of each country on Wikipedia, respectively.

Panel A: Google Search Volume Over the World

Year	Annual (10^{12})	Monthly (10^{11})	Daily (10^{9})	Second (10^{4})
2004	0.086	0.072	0.236	0.273
2005	0.141	0.118	0.386	0.447
2006	0.231	0.192	0.633	0.732
2007	0.438	0.365	1.200	1.389
2008	0.637	0.531	1.745	2.021
2009	0.954	0.795	2.610	3.024
2010	1.325	1.104	3.627	4.201
2011	1.722	1.435	4.717	5.461
2012	1.874	1.562	5.134	5.942
2013	2.162	1.801	5.922	6.854
2014	2.095	1.746	5.740	6.644

[1] Data available at http://www.internetlivestats.com/google-search-statistics/#trend & http://www.statisticbrain.com/google-searches/

[2] Data available at http://returnonnow.com/internet-marketing-resources/2013-search-engine-market-share-by-country/ & http://www.mvfglobal.com

[3] Data available at https://www.cia.gov/library/publications/the-world-factbook/fields/2098.html

Table 1: Summary statistics of Google search - Continued

Panel B: IT Users per 100 People & Google Market Share					
Country	EMG/DEV	*ITUsers*	*GoogleShare*	*Language*	*LangShare*
Argentina	EMG	39.83%	95.63%	Spanish	Official
Chile	EMG	47.20%	97.80%	Spanish	Official(99.5%)
China	EMG	29.30%	23.80%	Chinese	Official
Colombia	EMG	33.30%	96.30%	Spanish	Official(99.2%)
Hungary	EMG	61.10%	97.40%	Hungarian	Official(99.6%)
India	EMG	7.90%	97.00%	English	Subsidiary official
Indonesia	EMG	9.70%	96.00%	Indonesian	Official
Israel	EMG	57.20%	97.70%	Hebrew	Official
Malaysia	EMG	58.50%	82.10%	Malay	Official
Mexico	EMG	30.00%	92.60%	Spanish	Official(92.7%)
Peru	EMG	31.20%	98.00%	Spanish	Official(84.1%)
Philippines	EMG	19.70%	81.70%	English	Official
Poland	EMG	55.60%	97.40%	Polish	Official(98.2%)
Portugal	EMG	50.10%	97.10%	Portuguese	Official
Russia	EMG	39.20%	23.30%	Russian	Official(96.3%)
South Africa	EMG	23.80%	94.80%	English	Official
South Korea	EMG	81.40%	36.90%	Korean	Official
Taiwan	EMG	65.50%	47.60%	Chinese	Official
Thailand	EMG	22.10%	99.00%	Thai	Official(90.7%)
Turkey	EMG	35.40%	98.80%	Turkish	Official(85.0%)
Australia	DEV	74.50%	93.00%	English	Official(76.8%)
Austria	DEV	73.20%	92.80%	German	Official(88.6%)
Belgium	DEV	71.80%	98.50%	Dutch	Official(60.0%)
Canada	DEV	79.20%	92.70%	English	Official(58.7%)
Denmark	DEV	88.60%	95.00%	Danish	Official
France	DEV	69.80%	95.00%	French	Official(100%)
Germany	DEV	78.70%	91.70%	German	Official
Hong Kong	DEV	68.40%	68.00%	English	Official
Ireland	DEV	66.85%	94.82%	English	Official
Italy	DEV	48.80%	86.00%	Italian	Official(99%)
Japan	DEV	77.90%	75.30%	Japanese	Official(99%)
Netherlands	DEV	89.00%	94.70%	Dutch	Official
New Zealand	DEV	76.20%	92.00%	English	English(89.8%)
Norway	DEV	90.60%	96.10%	Norwegian	Official(95%)
Singapore	DEV	68.80%	84.40%	English	Official(29.8%)
Spain	DEV	62.20%	92.90%	Spanish	Official(74%)
Sweden	DEV	90.10%	96.80%	Swedish	Official
Switzerland	DEV	81.10%	92.00%	German	Official(64.9%)
United Kingdom	DEV	81.30%	89.90%	English	Official(95.0%)
United States	DEV	74.60%	80.60%	English	Official(79.2%)
Total	WRD	57.74%	86.33%	N.A.	N.A.

Table 2: Sentiment and soccer match results

We report the relationship between our sentiment measure and results of important soccer matches. We collect the results of the knockout stage games played by our sample countries in World Cup 2006, 2010 and 2014; European Championship 2008 and 2012; Copa América 2007 and 2011; and Asian Cup 2007 and 2011. We run the following regression:

$$Sentiment_{i,t}=a+bLoss_{i,t}+cWin_{i,t}+Controls_{i,t}+\varepsilon_{i,t},$$

where $Sentiment_{i,t}$ is country i's sentiment in week t. $Loss_{i,t}$ equals one if country i loses a match in week t and zero otherwise. $Win_{i,t}$ equals one if country i wins a match in week t and zero otherwise. $Controls_{i,t}$ include $Volatility_{i,t}$ that is country i's stock market volatility based on total market index in week t, and $Return_{i,t-1}$ to $Return_{i,t-4}$, which are weekly returns lagged one to four weeks for country i. Models (1) and (2) use all data from 2006 to 2014; Models (3) and (4) use the event window periods of the six months before and the six months after each soccer tournament period (usually June to July); Models (5) and (6) use the event window periods of the six months before and the six months after each soccer tournament period. We include country and year-week fixed effects in the regressions. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Sentiment_t$					
	Full sample		[-6 Month, 6 Month]		[-3 Month, 3 Month]	
Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Loss_t$	**-0.105**	**-0.101**	**-0.106**	**-0.101**	**-0.106**	**-0.103**
	(-2.21)	**(-2.17)**	**(-2.21)**	**(-2.18)**	**(-2.21)**	**(-2.20)**
Win_t	0.011	0.018	0.011	0.019	0.013	0.019
	(0.41)	(0.62)	(0.40)	(0.63)	(0.49)	(0.67)
$Volatility_t$		-0.083		-0.096		-0.119
		(-1.41)		(-1.24)		(-1.26)
$Return_{t-1}$		-0.021		-0.022		-0.012
		(-3.59)		(-3.02)		(-1.76)
$Return_{t-2}$		-0.000		-0.005		0.002
		(-0.23)		(-1.90)		(0.46)
$Return_{t-3}$		-0.013		-0.013		-0.009
		(-5.24)		(-4.06)		(-1.42)
$Return_{t-4}$		0.005		0.003		-0.004
		(0.96)		(0.45)		(-0.77)
Fixed Effects	CT	CT	CT	CT	CT	CT
Clustering	CT	CT	CT	CT	CT	CT
Obs	9,380	9,380	7,560	7,560	5,000	5,000
R^2	23.5%	23.9%	25.6%	26.0%	18.4%	18.6%

Table 3: Price deviation, earnings announcement returns, and sentiment

This table presents the impact of sentiment on stock price deviations and earnings announcement returns. In Panel A, we first collect data on the prices of ADRs in the U.S. and the prices of their parent stocks in local stock markets. The summary statistics of these ADRs and their parent stocks are in Table IA3. We next run the following regressions:

$$\Delta Ln(P_{i,t}/P_{US,t})=a+b(Sentiment_{i,t}-Sentiment_{US,t})+c\Delta Ln(P_{i,t-1}/P_{US,t-1})+Controls_{i,t}+\varepsilon_{i,t},\text{ and}$$

$$Ln(P_{i,t}/P_{US,t})=a+b(Sentiment_{i,t}-Sentiment_{US,t})+cLn(P_{i,t-1}/P_{US,t-1})+Controls_{i,t}+\varepsilon_{i,t},$$

where $P_{i,t}/P_{US,t}$ is the weekly average of the ratio of a stock's daily price in its parent country *i* to its ADR's daily price in week *t*. $Sentiment_{i,t}$ is the sentiment of the stock's country *i* in week *t* and $Sentiment_{US,t}$ is the sentiment of the U.S. market in week *t*. $Controls_{i,t}$ include the difference in stock market volatilities between the stock's parent country *i* and the U.S. in week *t* and the difference in weekly returns between its parent country *i* and the U.S. for the prior four weeks. We use the change in (Models (1) and (2)) or the level (Model (3) and (4)) of the natural logarithm of the price deviation ratio. In Panel B, we first calculate CARs for annual earnings announcements of stocks in our sample countries. We exclude firms whose market value is above the median of the sample. We then run the following regression: $CAR_{i,t}=a+bSentiment_{i,t-1}+Controls_{i,t}+\varepsilon_{i,t}$,

where $CAR_{i,t}$ is the average of CARs for country *i* in week *t*. We require that the number of stocks' CARs in week *t* is larger than a certain critical value. The critical value is set at 15 in Models (1), (2), (5) and (6), and at 20 in Models (3) and (4). $Sentiment_{i,t-1}$ is the average of the sentiment of country *i* over the four weeks prior to week *t*. We use three-day CARs in Models (1) to (4) and five-day CARs in Models (5) and (6). We use country and year-week fixed effects in all the regressions. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Panel A: Price deviation and sentiment

Dep. Variable=	$\Delta Ln(P_t/P_{US,t})$		$Ln(P_t/P_{US,t})$	
	Model (1)	Model (2)	Model (3)	Model (4)
$Sentiment_t$-$Sentiment_{US,t}$	**0.305**	**0.360**	**0.263**	**0.302**
	(2.36)	**(2.74)**	**(2.08)**	**(2.20)**
$\Delta Ln(P_{t-1}/P_{US,t-1})$	-0.437	-0.437		
	(-40.31)	(-40.13)		
$Ln(P_{t-1}/P_{US,t-1})$			0.502	0.502
			(7.93)	(7.93)
$Volatility_t$ -$Volatility_{US,t}$		1.505		2.647
		(1.30)		(2.83)
$Return_{t-1}$ -$Return_{US,t-1}$		-0.216		-0.135
		(-2.26)		(-1.39)
$Return_{t-2}$-$Return_{US,t-2}$		-0.130		-0.072
		(-1.06)		(-0.65)
$Return_{t-3}$-$Return_{US,t-3}$		-0.068		-0.036
		(-0.81)		(-0.43)
$Return_{t-4}$-$Return_{US,t-4}$		-0.055		0.039
		(-0.72)		(0.53)
Fixed Effects	CT	CT	CT	CT
Clustering	CT	CT	CT	CT
Obs	282,289	282,289	300,439	300,439
R^2	22.1%	22.1%	32.0%	32.0%

Table 3: Price deviation, earnings announcement returns, and sentiment - Continued

Panel B: Earnings announcement return and sentiment						
Dep. Variable=	$CAR(-1,1)_t$		$CAR(-1,1)_t$		$CAR(-2,2)_t$	
	No. of Firms≥15		No. of Firms≥20		No. of Firms≥15	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_{Month,t-1}$	**-1.762**	**-2.249**	**-1.422**	**-2.044**	**-1.166**	**-1.746**
	(-2.70)	**(-3.72)**	**(-2.20)**	**(-3.11)**	**(-1.77)**	**(-2.67)**
$Volatility_{t-1}$		2.386		2.058		3.031
		(2.19)		(1.09)		(2.24)
$Return_{t-1}$		0.166		0.270		0.193
		(2.24)		(2.71)		(2.20)
$Return_{t-2}$		0.120		0.074		0.156
		(1.49)		(0.66)		(1.66)
$Return_{t-3}$		-0.048		-0.042		0.014
		(-0.66)		(-0.44)		(0.13)
$Return_{t-4}$		0.147		0.006		0.148
		(2.13)		(0.06)		(2.55)
Fixed Effects	CT	CT	CT	CT	CT	CT
Clustering	CT	CT	CT	CT	CT	CT
Obs	1,247	1,247	911	911	1,248	1,248
R^2	40.1%	41.8%	49.7%	51.7%	42.7%	44.3%

Table 4: Sentiment and stock returns

This table presents the relation between weekly stock returns and our sentiment measure. We run the following regressions: 1) $Sentiment_{i,t+1}=a+bSentiment_{i,t}+Controls_{i,t}+\varepsilon_{i,t}$; 2) $Return_{i,t}=a+bSentiment_{i,t}+Controls_{i,t}+\varepsilon_{i,t}$; 3) $Return_{i,t+1}=a+bSentiment_{i,t}+Controls_{i,t}+\varepsilon_{i,t}$. In Models (1) and (2), the dependent variable is the sentiment of country *i* in week *t*+1 ($Sentiment_{i,t+1}$). In Models (3) and (4), the dependent variable is the weekly market return of country *i* in week *t* ($Return_t$). In Models (5) and (6), the dependent variable is the weekly market return of country *i* in week *t*+1 ($Return_{t+1}$). $Controls_{i,t}$ constitute a set of control variables: $EPU_{US,t}$ is the average of daily economic policy uncertainty measure from Baker, Bloom, and Davis (2013) in week *t*. $VIX_{US,t}$ is the average of the Chicago Board Options Exchange daily market volatility index in week *t*. $Economy_{US,t}$ is the average of a daily macroeconomic activities measure obtained from Aruoba, Diebold, and Scotti (2009) in week *t*. $Volatility_{i,t}$ is country *i*'s stock market volatility based on total market index in week *t*. $Return_{i,t-1}$ to $Return_{i,t-4}$ represents the lagged one to lagged four weekly returns for country *i*, respectively. We use country and year-week fixed effects in all the regressions. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.423**	**-0.442**	**0.864**	**0.848**	**-0.269**	**-0.256**
	(-8.16)	**(-8.86)**	**(3.35)**	**(3.25)**	**(-3.97)**	**(-4.37)**
$EPU_{US,t}$		-0.376		0.701		-2.544
		(-1.40)		(0.78)		(-1.66)
$VIX_{US,t}$		0.467		-2.904		2.489
		(1.66)		(-2.44)		(1.89)
$Economy_{US,t}$		0.028		-0.114		0.250
		(1.64)		(-1.30)		(2.45)
$Volatility_t$		-0.148		-0.341		-0.563
		(-1.11)		(-0.99)		(-1.44)
$Return_t$		0.018				0.007
		(1.80)				(0.21)
$Return_{t-1}$		-0.016		-0.023		0.028
		(-1.72)		(-0.83)		(0.88)
$Return_{t-2}$		-0.013		0.016		-0.010
		(-1.70)		(0.64)		(-0.28)
$Return_{t-3}$		0.000		-0.020		0.007
		(0.03)		(-0.61)		(0.21)
$Return_{t-4}$		0.004		-0.017		0.027
		(0.62)		(-0.59)		(0.83)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	21,840	20,880	21,880	20,880	21,840	20,880
R^2	17.8%	18.8%	11.0%	13.9%	1.2%	3.1%

Table 5: Sentiment and fundamentals

The table presents the relation between our sentiment measure and business cycle and risk variables. In Panel A, we regress sentiment on a set of business cycle and risk variables used in Sibley et al. (2016). $\Delta Illiq_{US,t}$ is the change in the weekly illiquidity measure that is the percentage of stocks with zero returns in week *t*. $\Delta TBill_{US,t}$ is the change in the weekly three-month T-Bill rate. $\Delta Unemp_{US,t}$ is the change in the monthly unemployment rate. $\Delta CPI_{US,t}$ is the change in the monthly consumer price index. $\Delta Default_{US,t}$ is the change in the weekly default spread which is the difference in yields between BAA corporate bonds and AAA corporate bonds. $\Delta Term_{US,t}$ is the change in the weekly term spread which is the difference in yields between ten-year Treasury bonds and three-month Treasury bills. $\Delta Income_{US,t}$ is the change in the monthly disposable income. $\Delta Consumption_{US,t}$ is the change in the monthly consumption. $\Delta IndProd_{US,t}$ is the change in the monthly industrial production. Model (1) includes all the 40 countries while Model (2) only includes the U.S. In Panel B, we regress market returns in week *t+1* on sentiment residuals ($Sentiment_{Residual,t}$) obtained from the above regressions in week *t* and a set of control variables. We use country and year-week fixed effects in all the regressions. Standard errors are clustered by the country and year-week levels in Model (1). *t*-statistics are reported in parentheses.

Panel A: Sentiment and Fundamentals

Dep. Variable=	$Sentiment_t$	
	WRD	U.S.
	Model (1)	Model (2)
$\Delta Illiq_{US,t}$	0.236	0.304
	(2.40)	(2.17)
$\Delta TBill_{US,t}$	0.054	0.111
	(0.97)	(1.97)
$\Delta Unemp_{US,t}$	-0.001	-0.004
	(-0.28)	(-0.61)
$\Delta CPI_{US,t}$	-0.001	0.025
	(-0.02)	(0.41)
$\Delta Default_{US,t}$	0.000	0.000
	(2.18)	(1.73)
$\Delta Term_{US,t}$	0.000	0.000
	(1.59)	(3.67)
$\Delta Income_{US,t}$	0.003	0.004
	(0.54)	(0.29)
$\Delta Consumption_{US,t}$	-0.001	-0.030
	(-0.03)	(-0.53)
$\Delta IndProd_{US,t}$	-0.011	-0.002
	(-0.51)	(-0.08)
Fixed Effects	C	N.A.
Clustering	CT	N.A.
Obs	21,880	547
R^2	0.3%	3.2%

Table 5: Sentiment and fundamentals - Continued

Panel B: The Sentiment Residual and Return Predictability		
Dep. Variable=	$Return_{t+1}$	
	WRD	U.S.
	Model	Model
	(1)	(2)
$Sentiment_{Residual,t}$	**-0.335**	**-0.384**
	(-3.81)	**(-2.12)**
$EPU_{US,t}$	-3.291	-2.714
	(-1.71)	(-1.53)
$VIX_{US,t}$	3.575	5.816
	(2.07)	(2.60)
$Economy_{US,t}$	0.334	0.339
	(2.44)	(2.51)
$Volatility_t$	-0.898	-3.255
	(-1.73)	(-2.12)
$Return_t$	0.020	-0.038
	(0.47)	(-0.50)
$Return_{t-1}$	0.038	0.010
	(0.86)	(0.17)
$Return_{t-2}$	-0.009	-0.116
	(-0.18)	(-1.49)
$Return_{t-3}$	0.011	-0.036
	(0.25)	(-0.51)
$Return_{t-4}$	0.030	0.032
	(0.74)	(0.49)
Fixed Effects	C	N.A.
Clustering	CT	N.A.
Obs	20,880	522
R^2	3.4%	8.7%

Table 6: Sentiment and information environments

This table reports the results of the following panel regression:

$$Return_{i,t+1}=\alpha+\beta_1 Sentiment_{i,t}+\beta_2 Sentiment_{i,t}\times InfEnv_{i,t}+\beta_3 InfEnv_{i,t}+Controls_{i,t}+\varepsilon_{i,t},$$

where $Return_{i,t+1}$ is country i's market returns in week t+1 and $Sentiment_{i,t}$ is country i's market sentiment in week t. In Model (2), $InfEnv_{i,t}$ equals one if country i is exposed to MiFID at time t and zero otherwise. In Models (3) and (4), $InfEnv_{i,t}$ equals the change in two indices of exchange trading rules if the date is after November 1, 2007 and zero otherwise, respectively. The two indices are the False Disclosure Rules Index and the Market Manipulation Rules Index. $Controls_{i,t}$ are the control variables used in Table 4. The sample period is from January 2007 to August 2008. We include country fixed effects in all the regressions. Standard errors are clustered at the country and year-week levels. t-statistics are reported in parentheses.

Dep. Variable=	$Return_{t+1}$			
$InfEnv_t$=		$MiFID_t$	ΔFDI_t	ΔMMI_t
	Model (1)	Model (2)	Model (3)	Model (4)
$Sentiment_t$	**-0.399**	**-0.609**	**-0.573**	**-0.581**
	(-2.21)	**(-4.69)**	**(-5.03)**	**(-4.64)**
$Sentiment_t \times InfEnv_t$		**0.401**	**0.490**	**0.051**
		(2.12)	**(3.72)**	**(2.40)**
$InfEnv_t$		-0.172	-0.152	-0.013
		(-0.83)	(-1.04)	(-0.67)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	C	C	C	C
Clustering	CT	CT	CT	CT
Obs	3,240	3,240	2,835	2,835
R^2	5.2%	5.6%	5.0%	4.9%

Table 7: Sentiment and short-selling bans

This table reports the results of the following panel regressions:

$$Return_{i,t+1}=\alpha+\beta_1 Sentiment_{i,t}+\beta_2 Sentiment_{i,t}\times Ban_{i,t}+\beta_3 Ban_{i,t}+Controls_{i,t}+\varepsilon_{i,t},$$

where $Return_{i,t+1}$ is country i's market returns in week t+1 and $Sentiment_{i,t}$ is country i's market sentiment in week t. $Ban_{i,t}$ equals one if country i has imposed a short-selling ban at week t and zero otherwise. The sample period is from March 2008 (the six months before the first initiation date of bans) to April 2009 (the six months after the last initiation date of bans). $Controls_{i,t}$ are the control variables used in Table 4. We include country fixed effects in all the regressions. Standard errors are clustered at the country level and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Return_{t+1}$	
	Model (1)	Model (2)
$Sentiment_t$	**-0.240**	**-0.119**
	(-2.63)	**(-0.83)**
$Sentiment_t \times Ban_t$		**-0.215**
		(-3.11)
Ban_t		0.409
		(1.03)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	2,280	2,280
R^2	18.4%	18.7%

Table 8: Co-movement of sentiment

This table reports the relation between market sentiment and global sentiment. We run the following regression:

$$Sentiment_{i,t}=a+bSentiment_{G,t}+Controls_{i,t}+\varepsilon_{i,t},$$

where $Sentiment_{i,t}$ is country *i*'s market sentiment in week *t* and $Sentiment_{G,t}$ is the simple average of $Sentiment_{i,t}$ of our 40 sample countries in week *t*. The sample period is from July 2004 to December 2014. Models (1) and (2) use all 40 countries (WRD). Models (3) and (4) focus on developed countries (DEV) and emerging countries (EMG), respectively. We also report the difference in coefficients on $Sentiment_{G,t}$ between developed countries and emerging countries. We include country fixed effects in all the regressions. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Sentiment_t$			
	WRD		DEV	EMG
	Model	Model	Model	Model
VARIABLES	(1)	(2)	(3)	(4)
$Sentiment_{G,t}$	**1.000**	**0.971**	**1.335**	**0.606**
	(5.85)	**(5.56)**	**(3.97)**	**(8.67)**
Diff in $Sentiment_{G,t}$			**0.729**	
[p-value]			**[0.034]**	
$EPU_{US,t}$		0.007	0.039	-0.051
		(0.08)	(0.21)	(-0.62)
$VIX_{US,t}$		-0.108	-0.269	-0.018
		(-0.83)	(-0.88)	(-0.17)
$Economy_{US,t}$		-0.005	-0.004	-0.006
		(-0.67)	(-0.34)	(-1.07)
$Volatility_t$		0.021	0.178	-0.088
		(0.20)	(0.72)	(-1.43)
$Return_{t-1}$		-0.012	-0.015	-0.010
		(-5.12)	(-2.18)	(-3.68)
$Return_{t-2}$		-0.003	-0.012	0.003
		(-1.29)	(-2.04)	(1.35)
$Return_{t-3}$		-0.003	0.005	-0.009
		(-0.84)	(0.52)	(-5.02)
$Return_{t-4}$		0.001	0.005	-0.001
		(0.14)	(0.50)	(-0.37)
Fixed Effects	C	C	C	C
Clustering	CT	CT	CT	CT
Obs	21,880	20,880	10,440	10,440
R^2	12.6%	13.0%	16.5%	10.3%

Table 9: Sentiment co-movement and IFRS

This table reports the panel regressions of market sentiment on global sentiment, the IFRS adoption dummy and the interaction between global sentiment and the IFRS dummy. The regression is specified as follows:

$$Sentiment_{i,t}=\alpha+\beta_1 Sentiment_{G,t}+\beta_2 Sentiment_{G,t}\times IFRS_{i,t}+\beta_3 IFRS_{i,t}+Controls_{i,t}+\varepsilon_{i,t},$$

where $Sentiment_{i,t}$ is country i's market sentiment in week t and $Sentiment_{G,t}$ is the simple average of $Sentiment_{i,t}$ of the 40 countries in week t. $IFRS_{i,t}$ equals one if country i adopted IFRS at year t-1 (t denotes year for IFRS and week for other variables) and zero otherwise. The sample period is from July 2004 to December 2014. $Controls_{i,t}$ are the control variables used in Table 4. We include country fixed effects in all the regressions. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Sentiment_t$	
	Model (1)	Model (2)
$Sentiment_{G,t}$	**0.971**	**0.574**
	(5.56)	**(9.00)**
$Sentiment_{G,t}\times IFRS_t$		**0.725**
		(2.37)
$IFRS_t$		-0.007
		(-1.05)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	21,880	20,880
R^2	13.0%	14.6%

Table 10: Global sentiment and stock returns

This table reports the regressions of the next week's market returns on global sentiment and local sentiment. We run the following regression:

$$Return_{i,t+1} = a + bSentiment_{G,t} + cSentiment_{iL,t} + Controls + \varepsilon_{i,t},$$

where global sentiment ($Sentiment_{G,t}$) is the simple average of market sentiment ($Sentiment_{i,t}$) of the 40 countries in week *t*. Local sentiment ($Sentiment_{iL,t}$) of country *i* is the regression residual of country *i*'s market sentiment ($Sentiment_{i,t}$) on global sentiment ($Sentiment_{G,t}$). The sample period is from July 2004 to December 2014. Models (1) and (2) use all the 40 countries. Models (3) and (4) focus on developed (DEV) and emerging countries (EMG), respectively. We also report the difference in coefficients on global and local sentiment between developed and emerging countries. Standard errors are clustered at the country and year-week levels. *t*-statistics are reported in parentheses.

Dep. Variable=	$Return_{t+1}$			
	WRD		DEV	EMG
	Model	Model	Model	Model
VARIABLES	(1)	(2)	(3)	(4)
$Sentiment_{G,t}$	**-1.640**	**-2.379**	**-3.343**	**-1.738**
	(-3.17)	**(-4.04)**	**(-5.73)**	**(-2.61)**
$Sentiment_{L,t}$	**-0.155**	**-0.270**	**-0.195**	**-0.364**
	(-3.36)	**(-4.91)**	**(-2.52)**	**(-5.20)**
Diff in $Sentiment_{G,t}$			**-1.605**	
[p-value]			**[0.001]**	
Diff in $Sentiment_{L,t}$			**0.169**	
[p-value]			**[0.089]**	
$EPU_{US,t}$		-3.002	-3.086	-2.888
		(-1.62)	(-1.58)	(-1.65)
$VIX_{US,t}$		2.963	3.302	2.693
		(1.89)	(1.83)	(1.84)
$Economy_{US,t}$		0.297	0.313	0.278
		(2.21)	(2.18)	(2.21)
$Volatility_{t}$		-0.651	-0.739	-0.601
		(-1.52)	(-1.15)	(-1.45)
$Return_{t}$		0.149	0.237	0.108
		(3.20)	(3.96)	(2.47)
$Return_{t-1}$		-0.001	-0.033	0.020
		(-0.03)	(-0.74)	(0.57)
$Return_{t-2}$		-0.012	-0.001	-0.018
		(-0.25)	(-0.01)	(-0.42)
$Return_{t-3}$		-0.004	-0.025	0.008
		(-0.11)	(-0.54)	(0.21)
$Return_{t-4}$		0.034	0.038	0.029
		(0.91)	(0.79)	(0.93)
Fixed Effects	C	C	C	C
Clustering	CT	CT	CT	CT
Obs	21,840	20,880	10,440	10,440
R^2	3.4%	6.5%	10.4%	4.4%

Internet Appendix

"Googling Investor Sentiment around the World"

This online appendix provides additional tables for "Googling Investor Sentiment around the World". We summarize the content as follows:

Table IA1: Summary statistics of sentiment indices

This table shows the summary statistics of our weekly sentiment measure for 40 countries over the sample period from July 2004 to December 2014. DEV, EMG and WRD denote developed, emerging and global markets, respectively. The summary statistics include the number of observations (Obs) and the mean, median, standard deviation (STD), quartiles (Q1 and Q3), minimum (Min), and maximum (Max) distributions of sentiment indices. Panel A present the summary statistics for emerging countries and Panle B present the summary statistics for developed countries.

Panel A: Emerging Countries

Country	EMG/DEV	Obs	Mean	STD	Min	Q1	Median	Q3	Max
Argentina	EMG	547	0.000	0.370	-1.603	-0.212	-0.001	0.225	1.187
Chile	EMG	547	0.004	0.356	-1.609	-0.205	0.004	0.211	1.897
China	EMG	547	-0.003	0.439	-1.546	-0.280	0.002	0.266	1.729
Colombia	EMG	547	-0.004	0.361	-1.315	-0.221	-0.013	0.223	1.135
Hungary	EMG	547	-0.003	0.678	-2.785	-0.421	-0.025	0.422	2.921
India	EMG	547	0.006	0.338	-1.270	-0.171	0.010	0.197	1.519
Indonesia	EMG	547	-0.006	0.322	-1.398	-0.156	-0.001	0.157	1.514
Israel	EMG	547	-0.001	0.484	-1.996	-0.316	0.001	0.310	1.946
Malaysia	EMG	547	0.003	0.367	-1.303	-0.213	-0.006	0.205	1.821
Mexico	EMG	547	0.002	0.341	-1.088	-0.223	-0.005	0.198	1.364
Peru	EMG	547	-0.003	0.371	-1.582	-0.215	0.002	0.214	1.176
Philippines	EMG	547	0.010	0.379	-1.258	-0.226	0.001	0.240	1.538
Poland	EMG	547	0.001	0.364	-1.233	-0.227	0.000	0.231	1.529
Portugal	EMG	547	-0.008	0.435	-1.273	-0.297	-0.016	0.257	1.620
Russia	EMG	547	-0.008	0.469	-3.260	-0.201	-0.006	0.178	3.302
South Africa	EMG	547	0.006	0.363	-1.420	-0.229	-0.003	0.265	1.900
South Korea	EMG	547	-0.013	0.539	-2.132	-0.320	-0.011	0.277	2.520
Taiwan	EMG	547	-0.003	0.404	-1.847	-0.250	-0.006	0.236	1.309
Thailand	EMG	547	0.005	0.303	-1.064	-0.190	-0.008	0.201	0.900
Turkey	EMG	547	0.005	0.387	-1.535	-0.236	-0.001	0.241	1.120

Table IA1: Summary statistics of sentiment indices - Continued

Panel B: Developed Countries									
Country	EMG/DEV	Obs	Mean	STD	Min	Q1	Median	Q3	Max
Australia	DEV	547	0.000	0.357	-1.342	-0.220	-0.005	0.227	1.141
Austria	DEV	547	0.005	0.544	-5.182	-0.272	0.019	0.301	3.032
Belgium	DEV	547	-0.006	0.466	-1.866	-0.302	0.002	0.274	1.809
Canada	DEV	547	0.002	0.359	-1.371	-0.185	0.016	0.206	1.457
Denmark	DEV	547	-0.005	0.529	-2.085	-0.297	-0.014	0.317	2.508
France	DEV	547	-0.001	0.409	-1.209	-0.282	0.006	0.259	1.586
Germany	DEV	547	0.003	0.486	-2.633	-0.263	0.003	0.238	3.881
Hong Kong	DEV	547	0.000	0.523	-2.342	-0.274	0.000	0.261	2.605
Ireland	DEV	547	0.005	0.420	-1.527	-0.240	0.011	0.255	1.687
Italy	DEV	547	0.001	0.481	-3.926	-0.249	0.035	0.254	3.045
Japan	DEV	547	0.002	0.375	-1.893	-0.219	0.010	0.224	1.311
Netherlands	DEV	547	0.005	0.406	-1.958	-0.234	0.017	0.230	1.737
New Zealand	DEV	547	0.006	0.453	-1.946	-0.261	-0.027	0.286	1.943
Norway	DEV	547	-0.030	2.395	-18.631	-0.313	-0.037	0.308	29.453
Singapore	DEV	547	0.003	0.535	-3.683	-0.282	-0.008	0.304	4.645
Spain	DEV	547	0.004	0.450	-1.935	-0.261	0.002	0.265	2.529
Sweden	DEV	547	-0.001	0.402	-1.547	-0.218	-0.010	0.255	1.340
Switzerland	DEV	547	-0.004	0.490	-2.756	-0.291	0.010	0.274	2.216
United Kingdom	DEV	547	0.000	0.378	-2.142	-0.215	0.003	0.241	1.820
United States	DEV	547	0.002	0.341	-1.342	-0.205	0.018	0.225	1.248
Total	WRD	21,880	-0.001	0.568	-18.631	-0.243	0.000	0.245	29.453

Table IA2: Summary statistics of soccer matches

This table presents the summary statistics of match results in knockout stages of influential soccer tournaments from 2006 to 2014. We include World Cup 2006, 2010 and 2014; European Championship 2008 and 2012; Asian Cup 2007 and 2011; and Copa América 2007 and 2011. We report the total number of wins and losses for each country in each tournament. Panel A reports the summary statistics of World Cups and Panel B reports the summary statistics of continental championships.

Panel A: World Cup

Country	Tournaments	Year	No.of Wins	No.of Losses
Argentina	World Cup	2006	1	1
Australia	World Cup	2006	0	1
France	World Cup	2006	3	1
Germany	World Cup	2006	2	1
Italy	World Cup	2006	4	0
Mexico	World Cup	2006	0	1
Netherlands	World Cup	2006	0	1
Portugal	World Cup	2006	2	1
Spain	World Cup	2006	0	1
Sweden	World Cup	2006	0	1
Switzerland	World Cup	2006	0	1
United Kingdom	World Cup	2006	1	1
Argentina	World Cup	2010	1	1
Chile	World Cup	2010	0	1
Germany	World Cup	2010	2	1
Japan	World Cup	2010	0	1
Mexico	World Cup	2010	0	1
Netherlands	World Cup	2010	3	1
Portugal	World Cup	2010	0	1
South Korea	World Cup	2010	0	1
Spain	World Cup	2010	4	0
United Kingdom	World Cup	2010	0	1
United States	World Cup	2010	0	1
Argentina	World Cup	2014	3	1
Belgium	World Cup	2014	1	1
Chile	World Cup	2014	0	1
Colombia	World Cup	2014	1	1
France	World Cup	2014	1	1
Germany	World Cup	2014	4	0
Mexico	World Cup	2014	0	1
Netherlands	World Cup	2014	2	1
Switzerland	World Cup	2014	0	1
United States	World Cup	2014	0	1

Table IA2: Summary statistics of soccer matches - Continued

Panel B: Continental Championships

Country	Tournaments	Year	No.of Wins	No.of Losses
Germany	European Championship	2008	2	1
Italy	European Championship	2008	0	1
Netherlands	European Championship	2008	0	1
Portugal	European Championship	2008	0	1
Russia	European Championship	2008	1	1
Spain	European Championship	2008	3	0
Turkey	European Championship	2008	1	1
France	European Championship	2012	0	1
Germany	European Championship	2012	1	1
Italy	European Championship	2012	2	1
Portugal	European Championship	2012	1	1
Spain	European Championship	2012	3	0
United Kingdom	European Championship	2012	0	1
Australia	Asian Cup	2007	0	1
Japan	Asian Cup	2007	1	1
South Korea	Asian Cup	2007	1	1
Australia	Asian Cup	2011	2	1
Japan	Asian Cup	2011	3	0
South Korea	Asian Cup	2011	1	1
Argentina	Copa América	2007	2	1
Chile	Copa América	2007	0	1
Mexico	Copa América	2007	1	1
Argentina	Copa América	2011	0	1
Chile	Copa América	2011	0	1
Colombia	Copa América	2011	0	1

Table IA3: Summary statistics of ADRs

This table reports the summary statistics of ADRs used in Table 3. We report the total number of ADRs used in regressions and the average number of days that each ADR lasts in our sample for each country. BeginDate/EndDate (Average) is the average first/last date when ADRs appear in the sample. BeginDate (First) is the first date when ADRs appear in the sample and EndDate (Last) is the last date when ADRs appear in the sample for each country.

Country	No. of ADRs	Days	BeginDate (Average)	EndDate (Average)	BeginDate (First)	EndDate (Last)
Argentina	17	2,594	21-Feb-06	29-Mar-13	6-Jul-04	23-Dec-14
Australia	154	1,637	22-Jan-09	16-Jul-13	6-Jul-04	26-Dec-14
Austria	19	2,535	5-Mar-07	10-Feb-14	6-Jul-04	23-Dec-14
Belgium	21	1,450	8-Feb-10	26-Jan-14	6-Jul-04	24-Dec-14
Chile	19	2,246	28-Mar-07	19-May-13	6-Jul-04	26-Dec-14
China	109	1,692	13-Sep-09	1-May-14	6-Jul-04	24-Dec-14
Colombia	6	1,376	14-Oct-10	19-Jul-14	13-Oct-04	26-Dec-14
Denmark	21	1,567	6-Feb-10	22-May-14	6-Jul-04	23-Dec-14
France	86	2,059	8-Oct-08	28-May-14	6-Jul-04	24-Dec-14
Germany	87	1,834	24-Sep-08	30-Sep-13	6-Jul-04	23-Dec-14
Hong Kong	144	2,066	18-Jul-08	14-Mar-14	6-Jul-04	26-Dec-14
Hungary	3	2,135	14-Sep-08	19-Jul-14	6-Jul-04	23-Dec-14
India	12	2,837	21-Jun-06	26-Mar-14	6-Jul-04	26-Dec-14
Indonesia	36	1,019	22-Sep-11	6-Jul-14	6-Jul-04	24-Dec-14
Ireland	20	1,849	28-Jul-08	20-Aug-13	6-Jul-04	24-Dec-14
Israel	21	2,015	10-Apr-09	15-Oct-14	6-Jul-04	26-Dec-14
Italy	44	1,737	10-May-09	9-Feb-14	6-Jul-04	24-Dec-14
Japan	277	1,878	18-Mar-09	8-May-14	6-Jul-04	26-Dec-14
Malaysia	7	2,141	15-Oct-08	25-Aug-14	7-Sep-04	26-Dec-14
Mexico	43	2,392	17-Nov-06	5-Jun-13	6-Jul-04	26-Dec-14
Netherlands	25	1,919	23-Oct-07	23-Jan-13	6-Jul-04	24-Dec-14
New Zealand	8	822	19-Aug-11	18-Nov-13	9-Jul-08	24-Dec-14
Norway	22	1,951	8-Dec-08	10-Apr-14	6-Jul-04	23-Dec-14
Peru	6	1,103	16-Dec-08	24-Dec-11	6-Jul-04	26-Dec-14
Philippines	22	862	22-Feb-12	2-Jul-14	6-Jul-04	23-Dec-14
Poland	9	1,057	5-Apr-11	24-Feb-14	28-Sep-04	23-Dec-14
Portugal	7	1,806	31-Jul-09	10-Jul-14	6-Jul-04	24-Dec-14
Russia	32	1,795	7-Mar-07	3-Feb-12	6-Jul-04	26-Dec-14
Singapore	49	1,820	10-Jul-09	3-Jul-14	6-Jul-04	26-Dec-14
South Africa	70	2,036	10-Mar-08	5-Oct-13	6-Jul-04	24-Dec-14
South Korea	11	2,949	10-Jan-06	5-Feb-14	6-Jul-04	26-Dec-14
Spain	38	1,714	10-Sep-09	20-May-14	6-Jul-04	24-Dec-14
Sweden	36	1,788	6-Nov-09	28-Sep-14	6-Jul-04	23-Dec-14
Switzerland	42	1,716	8-May-09	18-Jan-14	6-Jul-04	24-Dec-14
Taiwan	7	3,452	6-Jul-04	17-Dec-13	6-Jul-04	26-Dec-14
Thailand	16	790	23-Mar-11	21-May-13	9-Jul-04	26-Dec-14
Turkey	19	1,720	27-Nov-09	13-Aug-14	6-Jul-04	26-Dec-14
United Kingdom	213	1,799	2-Nov-08	4-Oct-13	6-Jul-04	24-Dec-14
Total	1,778	1,846	11-Dec-08	30-Dec-13	6-Jul-04	26-Dec-14

Table IA4: Sentiment and stock returns by country

This table reports the results of the following three regressions for each of our 40 countries from July 2004 to December 2014: a)$Sentiment_{t+1}=a+bSentiment_t+Controls$; b)$Return_t=a+bSentiment_t+Controls$; c)$Return_{t+1}=a+bSentiment_t+Controls$. $Return_t$ is the weekly market returns. *Controls* are the control variables used in Table 4. Panel A presents the regression results of each country and Panel B shows the summary statistics of the regression results in Panel A. We report the average of coefficients on $Sentiment_t$, the average of corresponding *t*-statistics and the average of R^2s over the 40 countries in Panel B. *Positive (Negative) Sig.* is the number of coefficients on $Sentiment_t$ that are positive (negative) and significant at 5% level. DEV, EMG and WRD denote developed, emerging, and global markets, respectively. *t*-statistics are reported in parentheses.

Panel A: Regression results by country

		$Sentiment_{t+1}=a+bSentiment_t$			$Return_t=a+bSentiment_t$			$Return_{t+1}=a+bSentiment_t$		
Country	EMG/DEV	*b*	*T Stat*	R^2	*b*	*T Stat*	R^2	*b*	*T Stat*	R^2
Argentina	EMG	-0.254	-5.89	18.5%	1.638	7.65	20.5%	-0.742	-2.97	3.8%
Chile	EMG	-0.329	-7.84	35.4%	2.110	11.74	24.8%	-0.375	-1.66	6.9%
China	EMG	-0.308	-7.31	27.0%	1.776	10.74	20.2%	-0.542	-2.68	2.8%
Colombia	EMG	-0.202	-4.64	20.3%	1.922	9.59	20.2%	-0.217	-0.92	6.7%
Hungary	EMG	-0.236	-5.46	24.5%	1.555	10.41	23.4%	-0.269	-1.47	5.0%
India	EMG	-0.186	-4.25	16.8%	2.126	8.68	17.6%	-0.209	-0.74	5.3%
Indonesia	EMG	-0.218	-4.91	10.6%	1.506	5.34	10.0%	-0.330	-1.10	3.6%
Israel	EMG	-0.351	-8.32	33.1%	1.485	11.87	25.9%	-0.598	-3.75	5.3%
Malaysia	EMG	-0.325	-7.68	29.5%	1.233	9.72	19.1%	-0.501	-3.35	5.0%
Mexico	EMG	-0.252	-5.86	19.4%	1.832	7.68	15.5%	-0.361	-1.37	7.6%
Peru	EMG	-0.210	-4.80	20.7%	1.416	9.83	21.7%	-0.486	-2.82	6.0%
Philippines	EMG	-0.280	-6.48	23.7%	1.661	9.59	19.6%	-0.675	-3.26	3.3%
Poland	EMG	-0.345	-8.22	27.3%	2.383	9.47	18.8%	-1.075	-3.65	5.6%
Portugal	EMG	-0.215	-4.93	24.2%	1.629	10.74	21.7%	-0.579	-3.09	4.2%
Russia	EMG	-0.336	-8.20	33.1%	2.240	9.71	18.8%	-0.157	-0.58	5.3%
South Africa	EMG	-0.349	-8.23	30.1%	2.445	10.32	20.6%	-1.228	-4.44	10.7%
South Korea	EMG	-0.307	-7.24	29.6%	1.760	11.25	23.5%	-0.528	-2.71	5.1%
Taiwan	EMG	-0.390	-9.41	35.9%	1.788	11.75	23.4%	-0.727	-3.82	5.9%
Thailand	EMG	-0.264	-6.16	18.0%	1.804	7.35	15.9%	-0.621	-2.26	5.0%
Turkey	EMG	-0.253	-5.93	25.8%	2.848	10.05	21.2%	-0.388	-1.13	4.6%
Australia	DEV	-0.298	-6.99	26.6%	2.034	9.32	21.7%	-0.807	-3.11	5.7%
Austria	DEV	-0.286	-6.63	30.4%	1.618	11.57	25.5%	-0.611	-3.51	8.3%
Belgium	DEV	-0.384	-9.30	34.6%	1.669	11.63	24.8%	-0.488	-2.69	5.5%
Canada	DEV	-0.317	-7.55	24.6%	1.600	8.03	17.8%	-0.167	-0.73	3.7%
Denmark	DEV	-0.310	-7.33	38.6%	1.723	13.81	32.5%	-0.473	-2.75	6.6%
France	DEV	-0.350	-8.38	28.5%	1.670	9.75	20.6%	-0.588	-2.87	4.6%
Germany	DEV	-0.414	-10.08	37.4%	1.565	11.07	24.8%	-0.719	-4.11	7.6%
Hong Kong	DEV	-0.380	-9.21	33.5%	1.293	11.46	23.2%	-0.392	-2.77	4.4%
Ireland	DEV	-0.322	-7.56	30.8%	1.934	10.62	23.0%	-0.957	-4.37	9.2%
Italy	DEV	-0.266	-6.12	33.3%	1.935	12.39	26.5%	-0.729	-3.60	5.4%
Japan	DEV	-0.267	-6.31	22.7%	1.214	8.84	17.0%	-0.085	-0.53	2.2%
Netherlands	DEV	-0.438	-10.91	36.4%	1.724	9.67	20.1%	-0.526	-2.50	6.1%
New Zealand	DEV	-0.367	-8.82	33.7%	1.384	11.23	26.0%	-0.450	-2.86	3.7%
Norway	DEV	-0.518	-14.20	47.0%	0.388	10.16	21.2%	-0.151	-3.37	9.8%

Table IA4: Sentiment and stock returns by country - Continued

Panel A: Regression results by country - Continued

		$Sentiment_{t+1}=a+bSentiment_t$			$Return_t=a+bSentiment_t$			$Return_{t+1}=a+bSentiment_t$		
Country	EMG/DEV	*b*	*T Stat*	R^2	*b*	*T Stat*	R^2	*b*	*T Stat*	R^2
Singapore	DEV	-0.328	-7.80	35.6%	1.327	12.78	28.2%	-0.222	-1.63	6.6%
Spain	DEV	-0.326	-7.65	27.2%	1.783	10.23	19.8%	-0.922	-4.44	5.9%
Sweden	DEV	-0.239	-5.48	29.6%	2.381	11.59	26.3%	-0.792	-3.02	5.4%
Switzerland	DEV	-0.304	-7.14	32.7%	1.290	11.74	28.6%	-0.449	-3.17	6.7%
United Kingdom	DEV	-0.268	-6.20	26.3%	1.726	9.86	22.1%	-0.711	-3.39	6.6%
United States	DEV	-0.275	-6.44	23.7%	1.441	9.22	20.5%	-0.408	-2.26	8.8%

Panel B: Summary statistics of the coefficients on $sentiment_t$ in Panel A

	$Sentiment_{t+1}=a+bSentiment_t$				$Return_t=a+bSentiment_t$				$Return_{t+1}=a+bSentiment_t$			
	b	*T Stat*	Negative Sig.	R^2	*b*	*T Stat*	Positive Sig.	R^2	*b*	*T Stat*	Negative Sig.	R^2
EMG	-0.281	-6.59	20 out of 20	25.2%	1.858	9.67	20 out of 20	20.1%	-0.530	-2.39	12 out of 20	5.4%
DEV	-0.333	-8.01	20 out of 20	31.7%	1.585	10.75	20 out of 20	23.5%	-0.532	-2.88	17 out of 20	6.1%
WRD	-0.307	-7.30	40 out of 40	28.4%	1.721	10.21	40 out of 40	21.8%	-0.531	-2.64	29 out of 40	5.8%

Table IA5: Robustness tests of sentiment and stock returns (Table 4)

We use different specifications to run the regressions in Table 4. We focus only on developed countries and emerging countries in Panel A and Panel B, respectively. In Panel C, we use market returns based on local currencies. In Panel D, we exclude the financial crisis period from September 2008 to September 2009. In Panel E, we use the bi-week frequency instead of the weekly frequency to construct our sentiment measure. *t*-statistics are reported in parentheses.

Panel A: Developed Countries

Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.462**	**-0.482**	**0.679**	**0.645**	**-0.240**	**-0.209**
	(-9.93)	**(-11.63)**	**(2.78)**	**(2.70)**	**(-3.57)**	**(-4.08)**
$EPU_{US,t}$		-0.462		0.925		-2.796
		(-1.23)		(0.89)		(-1.63)
$VIX_{US,t}$		0.670		-4.221		3.044
		(1.43)		(-2.99)		(1.85)
$Economy_{US,t}$		0.038		-0.133		0.297
		(1.62)		(-1.29)		(2.53)
$Volatility_t$		-0.233		0.395		-0.814
		(-0.75)		(0.79)		(-1.36)
$Return_t$		0.021				-0.018
		(1.18)				(-0.43)
$Return_{t-1}$		-0.030		-0.045		0.020
		(-1.91)		(-1.24)		(0.52)
$Return_{t-2}$		-0.014		0.007		-0.012
		(-1.23)		(0.22)		(-0.26)
$Return_{t-3}$		0.003		-0.034		0.000
		(0.26)		(-0.88)		(0.01)
$Return_{t-4}$		0.009		-0.033		0.035
		(0.82)		(-0.96)		(0.83)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	10,920	10,440	10,940	10,440	10,920	10,440
R^2	21.3%	22.5%	10.8%	15.1%	1.4%	4.3%

Table IA5: Robustness tests of sentiment and stock returns (Table 4) - Continued

Panel B: Emerging Countries						
Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.313**	**-0.324**	**1.384**	**1.397**	**-0.349**	**-0.379**
	(-17.39)	**(-19.08)**	**(11.09)**	**(11.43)**	**(-4.94)**	**(-7.31)**
$EPU_{US,t}$		-0.263		0.407		-2.230
		(-1.41)		(0.53)		(-1.64)
$VIX_{US,t}$		0.286		-2.113		2.012
		(1.70)		(-2.02)		(1.73)
$Economy_{US,t}$		0.017		-0.102		0.205
		(1.36)		(-1.37)		(2.22)
$Volatility_t$		-0.090		-0.679		-0.395
		(-1.75)		(-2.25)		(-1.08)
$Return_t$		0.009				0.036
		(2.18)				(1.10)
$Return_{t-1}$		-0.003		-0.002		0.032
		(-0.86)		(-0.10)		(1.07)
$Return_{t-2}$		-0.012		0.019		-0.009
		(-2.58)		(0.74)		(-0.28)
$Return_{t-3}$		-0.001		-0.005		0.011
		(-0.19)		(-0.19)		(0.36)
$Return_{t-4}$		-0.000		-0.005		0.019
		(-0.04)		(-0.19)		(0.74)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	10,920	10,440	10,940	10,440	10,920	10,440
R^2	9.8%	10.4%	13.6%	16.2%	1.0%	2.5%

Table IA5: Robustness tests of sentiment and stock returns (Table 4) - Continued

Panel C: Local Currency						
Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.423**	**-0.441**	**0.864**	**0.846**	**-0.269**	**-0.254**
	(-8.16)	**(-8.75)**	**(3.35)**	**(3.26)**	**(-3.97)**	**(-4.46)**
$EPU_{US,t}$		-0.387		0.594		-2.596
		(-1.42)		(0.67)		(-1.69)
$VIX_{US,t}$		0.457		-2.640		2.488
		(1.60)		(-2.22)		(1.88)
$Economy_{US,t}$		0.028		-0.117		0.248
		(1.61)		(-1.33)		(2.43)
$Volatility_t$		-0.157		-0.863		-0.707
		(-1.01)		(-2.51)		(-1.59)
$Return_t$		0.018				0.007
		(1.84)				(0.20)
$Return_{t-1}$		-0.016		-0.037		0.048
		(-1.43)		(-1.15)		(1.26)
$Return_{t-2}$		-0.016		0.027		-0.022
		(-1.58)		(0.89)		(-0.48)
$Return_{t-3}$		-0.000		-0.035		0.004
		(-0.05)		(-0.86)		(0.12)
$Return_{t-4}$		0.005		-0.025		0.036
		(0.78)		(-0.76)		(1.03)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	21,840	20,880	21,880	20,880	21,840	20,880
R^2	17.8%	18.7%	11.0%	14.3%	1.2%	3.3%

Table IA5: Robustness tests of sentiment and stock returns (Table 4) - Continued

Panel D: Excluding the Global Financial Crisis

Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.347**	**-0.360**	**1.254**	**1.234**	**-0.351**	**-0.361**
	(-21.42)	**(-20.71)**	**(10.54)**	**(10.11)**	**(-5.63)**	**(-6.20)**
$EPU_{US,t}$		-0.065		1.370		-0.475
		(-0.48)		(1.29)		(-0.35)
$VIX_{US,t}$		0.044		-3.705		0.097
		(0.29)		(-2.97)		(0.07)
$Economy_{US,t}$		0.021		0.036		0.257
		(1.33)		(0.30)		(1.88)
$Volatility_t$		0.043		-1.355		-0.032
		(0.73)		(-3.27)		(-0.08)
$Return_t$		0.009				0.002
		(2.22)				(0.08)
$Return_{t-1}$		-0.008		-0.049		0.007
		(-2.40)		(-1.78)		(0.22)
$Return_{t-2}$		-0.004		-0.015		0.002
		(-1.03)		(-0.52)		(0.04)
$Return_{t-3}$		-0.005		-0.018		-0.000
		(-1.28)		(-0.59)		(-0.00)
$Return_{t-4}$		-0.000		-0.015		-0.014
		(-0.11)		(-0.58)		(-0.43)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	19,560	18,600	19,600	18,600	19,560	18,600
R^2	11.9%	12.2%	11.4%	15.1%	1.0%	1.5%

Table IA5: Robustness tests of sentiment and stock returns (Table 4) - Continued

Panel E: Bi-weekly Frequency						
Dep. Variable=	$Sentiment_{t+1}$		$Return_t$		$Return_{t+1}$	
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
$Sentiment_t$	**-0.348**	**-0.383**	**0.959**	**0.934**	**-0.249**	**-0.345**
	(-16.96)	**(-17.33)**	**(8.64)**	**(9.20)**	**(-4.05)**	**(-6.36)**
$EPU_{US,t}$		-0.601		-0.757		-2.235
		(-1.52)		(-0.65)		(-1.40)
$VIX_{US,t}$		0.565		0.103		3.908
		(2.07)		(0.11)		(3.23)
$Economy_{US,t}$		0.051		-0.008		0.349
		(1.26)		(-0.07)		(2.41)
$Volatility_t$		-0.116		-2.110		-1.308
		(-1.28)		(-4.40)		(-2.57)
$Return_t$		0.031				0.107
		(2.12)				(1.90)
$Return_{t-1}$		-0.027		0.026		0.012
		(-2.70)		(0.59)		(0.25)
$Return_{t-2}$		-0.024		-0.000		0.028
		(-2.28)		(-0.01)		(0.59)
$Return_{t-3}$		0.004		0.014		0.054
		(0.47)		(0.34)		(1.13)
$Return_{t-4}$		-0.006		0.016		-0.041
		(-0.69)		(0.35)		(-0.91)
Fixed Effects	C	C	C	C	C	C
Clustering	CT	CT	CT	CT	CT	CT
Obs	10,880	10,440	10,920	10,440	10,880	10,440
R^2	12.2%	13.5%	19.1%	25.5%	1.4%	7.0%

Table IA6: Changes in indices of exchange trading rules

This table presents changes in two indices of exchange trading rules (ΔFDI and ΔMMI) across 40 countries after MiFID became effective for European countries on November 1, 2007. The definitions of the two indices are in Table IA6. The sample period is from January 2007 to August 2008 and the event date is November 1, 2007.

Country	Sample Period	Event Date	ΔFDI	ΔMMI
Austria	Jan.07-Aug.08	1Nov.07	1	11
Belgium	Jan.07-Aug.08	1Nov.07	N.A.	N.A.
Denmark	Jan.07-Aug.08	1Nov.07	0	6
France	Jan.07-Aug.08	1Nov.07	1	8
Germany	Jan.07-Aug.08	1Nov.07	1	11
Hungary	Jan.07-Aug.08	1Nov.07	N.A.	N.A.
Ireland	Jan.07-Aug.08	1Nov.07	1	10
Italy	Jan.07-Aug.08	1Nov.07	0	10
Netherlands	Jan.07-Aug.08	1Nov.07	N.A.	N.A.
Norway	Jan.07-Aug.08	1Nov.07	1	8
Poland	Jan.07-Aug.08	1Nov.07	N.A.	N.A.
Portugal	Jan.07-Aug.08	1Nov.07	N.A.	N.A.
Spain	Jan.07-Aug.08	1Nov.07	0	10
Sweden	Jan.07-Aug.08	1Nov.07	0	6
Switzerland	Jan.07-Aug.08	1Nov.07	0	7
United Kingdom	Jan.07-Aug.08	1Nov.07	0	1
Argentina	Jan.07-Aug.08	N.A.	0	0
Australia	Jan.07-Aug.08	N.A.	0	0
Canada	Jan.07-Aug.08	N.A.	0	0
Chile	Jan.07-Aug.08	N.A.	0	0
China	Jan.07-Aug.08	N.A.	0	0
Colombia	Jan.07-Aug.08	N.A.	0	0
Hong Kong	Jan.07-Aug.08	N.A.	0	0
India	Jan.07-Aug.08	N.A.	0	0
Indonesia	Jan.07-Aug.08	N.A.	0	0
Israel	Jan.07-Aug.08	N.A.	0	0
Japan	Jan.07-Aug.08	N.A.	0	0
Malaysia	Jan.07-Aug.08	N.A.	0	0
Mexico	Jan.07-Aug.08	N.A.	0	0
New Zealand	Jan.07-Aug.08	N.A.	0	0
Peru	Jan.07-Aug.08	N.A.	0	0
Philippines	Jan.07-Aug.08	N.A.	0	0
Russia	Jan.07-Aug.08	N.A.	0	0
Singapore	Jan.07-Aug.08	N.A.	0	0
South Africa	Jan.07-Aug.08	N.A.	0	0
South Korea	Jan.07-Aug.08	N.A.	0	0
Taiwan	Jan.07-Aug.08	N.A.	0	0
Thailand	Jan.07-Aug.08	N.A.	0	0
Turkey	Jan.07-Aug.08	N.A.	0	0
United States	Jan.07-Aug.08	N.A.	0	0

Table IA7: Robustness tests of sentiment and information environments (Table 6)
This table reports the results of robustness tests of Table 6. In Panel A, we use a longer sample period (February 2006 to August 2008) to run the regressions in Table 6. In Panel B, we match 16 European countries that are subject to MiFID with 16 countries that are not affected by MiFID using the 11-year (2004 to 2014) average of MktCap scaled by GDP and repeat the regressions in Table 6 with the matched 32 countries. In Panel C, we conduct placebo tests. Specifically, we bootstrap 16 event dates between May 2005 (the ten months after the beginning of our sample period) and February 2014 (the ten months before the end of our sample period), randomly assign them to the 16 European countries, and run the regressions in Table 6. The sample period of the regressions is the ten months before the earliest bootstrapped event date to the ten months after the latest bootstrapped event dates. We repeat the procedures 1000 times to obtain 1000 coefficients on the interaction term, $\beta_2 s$. Panel C shows the 90th percentile, 95th percentile and 99th percentile of the 1000 $\beta_2 s$. *t*-statistics are reported in parentheses.

Panel A: Different Sample Period				
Dep. Variable=	$Return_{t+1}$			
$InfEnv_t$=		$MiFID_t$	ΔFDI_t	ΔMMI_t
	Model (1)	Model (2)	Model (3)	Model (4)
$Sentiment_t$	**-0.396**	**-0.531**	**-0.508**	**-0.507**
	(-2.55)	**(-5.50)**	**(-5.85)**	**(-5.38)**
$Sentiment_t \times InfEnv_t$		**0.318**	**0.422**	**0.042**
		(1.84)	**(3.97)**	**(2.27)**
$InfEnv_t$		-0.202	-0.174	-0.020
		(-1.07)	(-1.36)	(-1.08)
Controls	Yes	Yes	Yes	Yes
Fixed Effects	C	C	C	C
Clustering	CT	CT	CT	CT
Obs	5,160	5,160	4,515	4,515
R^2	3.5%	3.7%	3.6%	3.5%

Table IA7: Robustness tests of sentiment and information environments (Table 6) – Continued

Panel B: Market Capitalization-matched Sample

Dep. Variable=	$Return_{t+1}$			
$InfEnv_t$=		$MiFID_t$	ΔFDI_t	ΔMMI_t
	Model (1)	Model (2)	Model (3)	Model (4)
$Sentiment_t$	**-0.340**	**-0.554**	**-0.478**	**-0.477**
	(-1.84)	**(-3.67)**	**(-4.07)**	**(-3.39)**
$Sentiment_t \times InfEnv_t$		**0.361**	**0.405**	**0.041**
		(1.94)	**(3.57)**	**(1.99)**
$InfEnv_t$		-0.197	-0.173	-0.016
		(-0.88)	(-1.06)	(-0.71)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	C	C	C	C
Country clustering	CT	CT	CT	CT
Obs	2,592	2,592	2,111	2,111
R^2	5.8%	6.2%	5.6%	5.4%

Panel C: Placebo Tests based on Bootstrapping

	$MiFID_t$	ΔFDI_t	ΔMMI_t
Ours	**0.401**	**0.490**	**0.051**
P90	0.275	0.327	0.032
P95	0.295	0.339	0.035
P99	0.325	0.359	0.041

Table IA8: Summary of short-selling bans

This table summarizes the details of short-selling bans for 40 countries during the financial crisis period. The information is from Beber and Pagano (2013) and Jain et al. (2010).

Country	Sample Period	Ban Begin Date	Ban End Date	Scope of Short-selling Ban
Australia	Mar.08-Apr.09	22-Sep-08	25-May-09	All Stocks
Austria	Mar.08-Apr.09	26-Oct-08	30-Nov-10	Financial Stocks
Belgium	Mar.08-Apr.09	22-Sep-08	21-Sep-09	Financial Stocks
Canada	Mar.08-Apr.09	19-Sep-08	8-Oct-08	Financial Stocks
Denmark	Mar.08-Apr.09	13-Oct-08	31-Dec-10	Financial Stocks
France	Mar.08-Apr.09	22-Sep-08	After 31Dec.10	Financial Stocks
Germany	Mar.08-Apr.09	20-Sep-08	After 31Dec.10	Financial Stocks
Indonesia	Mar.08-Apr.09	1-Oct-08	1-May-09	All Stocks
Ireland	Mar.08-Apr.09	19-Sep-08	After 31Dec.10	Financial Stocks
Italy	Mar.08-Apr.09	22-Sep-08	1-Jun-09	Financial, then All
Japan	Mar.08-Apr.09	30-Oct-08	After 31Dec.10	All Stocks
Netherlands	Mar.08-Apr.09	22-Sep-08	1-Jun-09	Financial Stocks
Norway	Mar.08-Apr.09	8-Oct-08	After 31Dec.10	Financial Stocks
Portugal	Mar.08-Apr.09	22-Sep-08	After 31Dec.10	Financial Stocks
Russia	Mar.08-Apr.09	18-Sep-08	15-Jun-09	All Stocks
South Korea	Mar.08-Apr.09	1-Oct-08	After 31Dec.10	All Stocks
Spain	Mar.08-Apr.09	24-Sep-08	After 31Dec.10	All Stocks
Switzerland	Mar.08-Apr.09	19-Sep-08	16-Jan-09	Financials
Taiwan	Mar.08-Apr.09	1-Oct-08	28-Nov-08	All Stocks
United Kingdom	Mar.08-Apr.09	19-Sep-08	16-Jan-09	Financial Stocks
United States	Mar.08-Apr.09	19-Sep-08	8-Oct-08	Financial Stocks
Argentina	Mar.08-Apr.09	N.A.	N.A.	No Ban
Chile	Mar.08-Apr.09	N.A.	N.A.	No Ban
China	Mar.08-Apr.09	N.A.	N.A.	Always Ban
Colombia	Mar.08-Apr.09	N.A.	N.A.	Always Ban
Hong Kong	Mar.08-Apr.09	N.A.	N.A.	No Ban
Hungary	Mar.08-Apr.09	N.A.	N.A.	No Ban
India	Mar.08-Apr.09	N.A.	N.A.	No Ban
Israel	Mar.08-Apr.09	N.A.	N.A.	No Ban
Malaysia	Mar.08-Apr.09	N.A.	N.A.	No Ban
Mexico	Mar.08-Apr.09	N.A.	N.A.	No Ban
New Zealand	Mar.08-Apr.09	N.A.	N.A.	No Ban
Peru	Mar.08-Apr.09	N.A.	N.A.	Always Ban
Philippines	Mar.08-Apr.09	N.A.	N.A.	No Ban
Poland	Mar.08-Apr.09	N.A.	N.A.	No Ban
Singapore	Mar.08-Apr.09	N.A.	N.A.	No Ban
South Africa	Mar.08-Apr.09	N.A.	N.A.	No Ban
Sweden	Mar.08-Apr.09	N.A.	N.A.	No Ban
Thailand	Mar.08-Apr.09	N.A.	N.A.	No Ban
Turkey	Mar.08-Apr.09	N.A.	N.A.	No Ban

Table IA9: Robustness tests of sentiment and short-selling bans (Table 7)

This table presents the results of robustness tests of Table 7. In Panel A, we use the sample countries in Beber and Pagano (2013) with a sample period from January 2008 to June 2009. In Panel B, using the 11-year (2004 to 2014) average of the ratio of MktCap to GDP, we match 16 countries that have never imposed bans during the sample period with 16 treated countries. We then use the matched 32 countries to run the regressions of Table 7. In Panel C, we first bootstrap 24 event dates between January 2005 and July 2014. Then we treat the 24 bootstrapped event dates as the pseudo starting dates of short-selling bans and allocate them to the 24 countries that have imposed short-selling bans. The durations of each short-selling ban remain the same as those in Table IA8. We run the regressions in Table 7 using the newly bootstrapped event dates and keep the coefficient on the interaction term, β_2. The sample period of the regressions is the six months before the earliest bootstrapped event date to the six months after the latest bootstrapped event dates. We repeat the procedure 1000 times to obtain 1000 $\beta_2 s$ and report the 10th, 5th and 1st percentile of $\beta_2 s$ in Panel C. *t*-statistics are reported in parentheses.

Panel A: Different Sample		
Dep. Variable=	$Return_{t+1}$	
	Model (1)	Model (2)
$Sentiment_t$	**-0.245**	**-0.110**
	(-2.74)	**(-0.81)**
$Sentiment_t \times ShortSellingBan_t$		**-0.244**
		(-4.03)
$ShortSellingBan_t$		0.205
		(0.48)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	1,900	1,900
R^2	17.3%	17.6%

Table IA9: Robustness tests of sentiment and short-selling bans (Table 7) - Continued

Panel B: Market Capitalization-matched Sample

Dep. Variable=	$Return_{t+1}$	
	Model (1)	Model (2)
$Sentiment_t$	**-0.920**	**-0.697**
	(-4.30)	**(-3.68)**
$Sentiment_t \times ShortSellingBan_t$		**-0.674**
		(-2.63)
$ShortSellingBan_t$		0.053
		(0.15)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	1,824	1,824
R^2	19.4%	19.8%

Panel C: Placebo Tests based on Bootstrapping

	$Sentiment_t \times ShortSellingBan_t$
Ours	**-0.215**
P10	-0.176
P5	-0.200
P1	-0.244

Table IA10: Summary of the IFRS adoption
This table presents the IFRS adoption years for 40 countries over our sample period from 2004 to 2014.

Country	Sample Period	IFRS Adoption Year
Argentina	Jun.04-Dec.14	2012
Australia	Jun.04-Dec.14	2005
Austria	Jun.04-Dec.14	2005
Belgium	Jun.04-Dec.14	2005
Canada	Jun.04-Dec.14	2011
Chile	Jun.04-Dec.14	2009
China	Jun.04-Dec.14	N.A.
Colombia	Jun.04-Dec.14	N.A.
Denmark	Jun.04-Dec.14	2005
France	Jun.04-Dec.14	2005
Germany	Jun.04-Dec.14	2005
Hong Kong	Jun.04-Dec.14	2005
Hungary	Jun.04-Dec.14	2005
India	Jun.04-Dec.14	N.A.
Indonesia	Jun.04-Dec.14	N.A.
Ireland	Jun.04-Dec.14	2005
Israel	Jun.04-Dec.14	2008
Italy	Jun.04-Dec.14	2005
Japan	Jun.04-Dec.14	N.A.
Malaysia	Jun.04-Dec.14	2012
Mexico	Jun.04-Dec.14	2012
Netherlands	Jun.04-Dec.14	2005
New Zealand	Jun.04-Dec.14	2007
Norway	Jun.04-Dec.14	2005
Peru	Jun.04-Dec.14	2012
Philippines	Jun.04-Dec.14	2005
Poland	Jun.04-Dec.14	2005
Portugal	Jun.04-Dec.14	2005
Russia	Jun.04-Dec.14	2012
Singapore	Jun.04-Dec.14	2003
South Africa	Jun.04-Dec.14	2005
South Korea	Jun.04-Dec.14	2011
Spain	Jun.04-Dec.14	2005
Sweden	Jun.04-Dec.14	2005
Switzerland	Jun.04-Dec.14	2005
Taiwan	Jun.04-Dec.14	2013
Thailand	Jun.04-Dec.14	N.A.
Turkey	Jun.04-Dec.14	2008
United Kingdom	Jun.04-Dec.14	2005
United States	Jun.04-Dec.14	N.A.

Table IA11: Robustness tests of sentiment co-movement and IFRS (Table 9)

This table reports the results of robustness tests of Table 9. In Panel A and Panel B, we run the regressions of Table 9 with different samples. Panel A uses the sample period of 2004-2007 where 2004-2005 is the pre-IFRS adoption period and 2006-2007 is the post-IFRS adoption period. In Panel B, we use the 11-year (2004 to 2014) average of the ratio of MktCap to GDP to match seven countries that have never adopted IFRS during the sample period with seven countries that have. Panel C reports the results of placebo tests. Specifically, we bootstrap 33 IFRS adoption years from 2003 (the earliest adoption year) to 2013 (the latest adoption year) and allocate them to the 33 countries that have adopted IFRS during the sample period of 2005-2014. We then run the regressions of Table 9 and report the coefficient on the interaction term, β_2. We repeat the procedure 1000 times to obtain 1000 $\beta_2 s$ and report the 90th, 95th and 99th percentiles of $\beta_2 s$ in Panel C. *t*-statistics are reported in parentheses.

Panel A: Different Sample Period		
Dep. Variable=	$Sentiment_t$	
	Model (1)	Model (2)
$Sentiment_{G,t}$	**0.979**	**0.812**
	(15.17)	**(11.07)**
$Sentiment_{G,t} \times IFRS_t$		**0.424**
		(4.75)
$IFRS_t$		-0.007
		(-1.37)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	7,320	7,320
R^2	13.3%	13.9%

Table IA11: Robustness tests of sentiment co-movement and IFRS (Table 9) - Continued

Panel B: Market Capitalization-matched Sample		
Dep. Variable=	$Sentiment_t$	
	Model (1)	Model (2)
$Sentiment_{G,t}$	**0.519**	**0.439**
	(6.91)	**(7.39)**
$Sentiment_{G,t} \times IFRS_t$		**0.350**
		(2.58)
$IFRS_t$		-0.002
		(-0.56)
Controls	Yes	Yes
Fixed Effects	C	C
Clustering	CT	CT
Obs	7,658	7,308
R^2	8.9%	9.5%

Panel C: Placebo Tests based on Bootstrapping	
	$Sentiment_{G,t} \times IFRS_t$
ours	**0.725**
P90	0.674
P95	0.725
P99	0.821

Table IA12: Local, global sentiment, and stock returns by country

This table reports the results of the regressions in Table 8 and Table 10 for each of the 40 countries. In Panel A, we run the following two regressions for each of 40 countries:
1) $Sentiment_t=a+bSentiment_{G,t}+Controls+\varepsilon_t$; 2) $Return_{t+1}=a+ bSentiment_{G,t}+ cSentiment_{L,t}+Controls+\varepsilon_{t.}$, where $Sentiment_t$ is market sentiment. $Sentiment_{L,t}$ is local sentiment that is the regression residual of $Sentiment_t$ on global sentiment ($Sentiment_{G,t}$). *Controls* is a set of control variables defined in Table 4. We report the corresponding coefficients, *t*-statistics, and R^2s of the two regressions for each country in Panel A. Panel B reports the summary statistics of the coefficients, *t*-statistics, and $R^2s$of the first and the second regressions, respectively. In Panel B, *b* is the average of coefficients on $Sentiment_{G,t}$ over the 40 countries and T_b is the corresponding average of *t*-statistics. N_{PSigG} is the number of countries in which the coefficients on $Sentiment_{G,t}$ are positive and significant at the 5% level. N_{NSigG} is the number of countries in which the coefficients on $Sentiment_{G,t}$ are negative and significant at the 5% level. N_{NSigL} is the number of countries in which the coefficients on $Sentiment_{L,t}$ are negative and significant at the 5% level. DEV, EMG, and WRD denote developed, emerging and global markets, respectively.

Panel A: Return and Local and Global sentiment									
		$Sentiment_t=a+ bSentiment_{G,t}$			$Return_{t+1}=a+bSentiment_{G,t}+cSentiment_{L,t}$				
Country	EMG/DEV	*b*	*T Stat*	R^2	*b*	T_b *Stat*	*c*	T_c *Stat*	R^2
Argentina	EMG	0.479	4.01	9.9%	-0.436	-0.58	-0.730	-2.48	3.7%
Chile	EMG	0.686	6.18	21.7%	-2.204	-2.87	-0.243	-0.99	10.3%
China	EMG	0.058	0.49	1.3%	1.501	4.03	-0.563	-2.58	5.7%
Colombia	EMG	0.538	7.35	10.8%	-1.623	-2.78	-0.129	-0.58	8.7%
Hungary	EMG	1.115	4.65	12.6%	-3.996	-3.71	-0.204	-0.87	9.7%
India	EMG	0.366	4.20	5.8%	-1.213	-1.47	-0.208	-0.80	6.3%
Indonesia	EMG	0.279	3.57	4.3%	-0.091	-0.11	-0.346	-1.09	3.6%
Israel	EMG	0.775	6.35	13.2%	-1.085	-2.08	-0.598	-3.38	5.7%
Malaysia	EMG	0.380	4.03	11.2%	-0.550	-1.44	-0.494	-3.21	5.2%
Mexico	EMG	0.469	6.31	11.5%	-4.174	-4.84	-0.244	-0.82	15.4%
Peru	EMG	0.467	5.70	7.8%	-1.469	-2.97	-0.465	-2.45	8.6%
Philippines	EMG	0.393	4.51	6.9%	-1.085	-2.17	-0.677	-3.49	4.0%
Poland	EMG	0.619	4.96	14.2%	-4.360	-3.52	-0.868	-2.39	11.7%
Portugal	EMG	0.764	6.74	14.4%	-3.469	-5.22	-0.468	-2.59	11.5%
Russia	EMG	0.994	4.34	27.8%	-4.448	-2.76	0.227	0.52	12.7%
South Africa	EMG	0.744	6.20	20.6%	-3.899	-2.77	-0.952	-2.98	15.0%
South Korea	EMG	1.217	11.50	22.1%	-3.561	-2.62	-0.366	-1.74	10.1%
Taiwan	EMG	0.643	6.09	14.7%	-1.782	-3.00	-0.655	-3.22	7.9%
Thailand	EMG	0.332	4.74	7.3%	-0.086	-0.14	-0.629	-2.32	5.0%
Turkey	EMG	0.785	8.97	21.4%	-3.268	-2.43	-0.032	-0.09	8.1%
Australia	DEV	0.641	8.07	17.8%	-4.071	-4.36	-0.625	-1.93	11.7%
Austria	DEV	1.379	4.47	27.9%	-3.579	-3.92	-0.453	-2.02	12.6%
Belgium	DEV	1.235	11.16	30.5%	-2.818	-3.35	-0.186	-0.88	9.6%
Canada	DEV	0.599	5.47	16.0%	-4.987	-5.54	0.086	0.35	17.5%
Denmark	DEV	1.477	14.45	35.0%	-4.260	-5.42	-0.129	-0.67	14.4%
France	DEV	0.962	9.36	23.8%	-4.903	-6.97	-0.137	-0.60	15.9%
Germany	DEV	1.450	10.69	38.6%	-5.039	-5.52	-0.060	-0.24	17.6%
Hong Kong	DEV	0.874	4.71	13.1%	-1.904	-3.12	-0.323	-1.82	6.7%
Ireland	DEV	0.797	7.71	19.5%	-2.834	-3.86	-0.833	-3.65	11.9%

Panel A: Return and Local and Global sentiment - Continued

Country	EMG/DEV	$Sentiment_t$=a+ $bSentiment_{G,t}$			$Return_{t+1}$=a+$bSentiment_{G,t}$+$cSentiment_{L,t}$				
		b	*T Stat*	R^2	*b*	T_b *Stat*	*c*	T_c *Stat*	R^2
Italy	DEV	1.344	6.48	36.1%	-4.438	-5.96	-0.202	-0.76	13.3%
Japan	DEV	0.494	3.53	10.6%	-0.559	-1.89	-0.086	-0.42	2.7%
Netherlands	DEV	0.903	7.61	25.2%	-4.304	-6.05	-0.171	-0.78	14.8%
New Zealand	DEV	0.787	7.25	15.9%	-2.069	-4.15	-0.416	-2.71	6.9%
Norway	DEV	7.724	5.73	49.5%	-3.930	-3.17	0.149	0.71	14.8%
Singapore	DEV	1.446	6.81	33.0%	-2.880	-4.21	-0.003	-0.02	14.1%
Spain	DEV	1.135	10.77	26.5%	-3.819	-5.30	-0.515	-2.03	11.1%
Sweden	DEV	0.940	9.27	27.0%	-4.324	-4.18	-0.409	-1.61	11.8%
Switzerland	DEV	1.201	7.75	27.1%	-3.303	-5.95	-0.283	-1.93	13.4%
United Kingdom	DEV	0.881	8.96	25.9%	-5.566	-7.28	-0.209	-0.78	20.8%
United States	DEV	0.655	12.57	18.2%	-2.644	-4.86	-0.188	-1.14	16.1%

Panel B: Summary statistics of results of regressions

	$Sentiment_t$=a+ $bSentiment_{G,t}$				$Return_{t+1}$=a+$bSentiment_{G,t}$+$cSentiment_{L,t}$						
	b	T_b	N_{PSigG}	R^2	*b*	T_b	N_{NSigG}	*c*	T_c	N_{NSigL}	R^2
EMG	0.605	5.54	19 out of 20	13.0%	-2.065	-2.17	14 out of 20	-0.432	-1.88	11 out of 20	8.4%
DEV	1.346	8.14	20 out of 20	25.9%	-3.612	-4.75	19 out of 20	-0.250	-1.15	4 out of 20	12.9%
WRD	0.976	6.84	39 out of 40	19.4%	-3.463	-3.46	33 out of 40	-0.341	-1.51	15 out of 40	10.7%