Divergence of Sentiment and Stock Market Trading

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ABSTRACT

This paper introduces the concept of divergence of sentiment to the behavioral finance literature. We measure the distance between people with positive and negative sentiment on a daily basis for 20 countries by using data from status updates on Facebook. The prediction is that a higher divergence of sentiment leads to more diverging views on prospects and risks, and thus to more diverging views on the value of a stock. In line with this prediction, divergence of sentiment is positively related to trading volume. We further predict and find a positive relation between divergence of sentiment and stock price volatility. The observed relations are stronger when individual investors are more likely to trade. We compare the effect of our country-specific measures to a global measure of divergence of sentiment. We find that the separate effects of country-specific and global divergence measures depend on a country's level of market integration.

Keywords: Sentiment, Disagreement Models, Divergence of Opinion, Small Investors, Market Integration

1. Introduction

Sentiment is a relatively generic term that has been used extensively in the behavioral finance literature. As discussed in detail by Liu (2015), sentiment can affect choices in unconscious ways and covers both emotions and mood. Based on evidence from psychology (Johnson and Tversky, 1983; Loewenstein et al., 2001), sentiment influences judgment of a potential prospect and the assessment of risk. Investor sentiment, defined as a belief about future cash flows and investment risk that is not justified by the facts at hand, is important for stock markets (Baker and Wurgler, 2007). Kaplanski et al. (2015) show that happy investors are not only positive on expected stock returns, but they also believe that the risks involved are relatively low.

The relations between the level of sentiment and stock markets are well documented (Baker and Wurgler, 2007). However, the average sentiment level hides a significant variation on a given day. A day in which each person in a country has a neutral sentiment obtains the same average sentiment level score as a day in which half the country is happy and the other half is equally unhappy. Our paper contributes to the literature by investigating divergence of sentiment rather than the average level of sentiment.

We predict that divergence of sentiment affects trading volume. Imagine that particular information reaches investors, for example a firm's announcement about a particular project or merger. Investors with positive sentiment would be more optimistic about the potential benefits and risks of the newly arrived information than investors with negative sentiment. Consequently, on days with high divergence of sentiment, investors differ in how they interpret public information, which leads to a difference of opinion. When investors transact in line with their diverging beliefs on firms' value, days with high divergence in sentiment are expected to be related to high contemporaneous trading volume.

Our predictions are in line with theoretical models developed in the disagreement literature. Karpoff (1986), Harris and Raviv (1993), Banerjee and Kremer (2010), and Atmaz and Basak (2016) predict that higher disagreement is associated with more trading. For example, in Banerjee and Kremer (2010), investors disagree about the interpretation of public information. In their model, trading volume reflects revisions to the level of disagreement, and periods of high disagreement are related to higher volume. Hong and Stein (2007) stress that heterogeneous priors can generate disagreement of the "value" of new information even when that information is available to investors simultaneously.

This paper also examines the relation between divergence of sentiment and stock price volatility. Because higher disagreement can lead to higher absolute price changes (e.g., Banerjee and Kremer, 2010), one might expect a positive relation between divergence of sentiment and stock price volatility. We treat the relation between divergence of sentiment and stock price volatility mostly as an empirical question, because the expected strength of this relation depends on the extent to which investors affected by sentiment are able to move prices.

To capture divergence of sentiment, we use data from Facebook. Sentiment levels have previously been established by household survey data (Brown and Cliff, 2004; Lemmon and Portniaguina, 2006; Qiu and Welch, 2006; Schmeling, 2009; Kaplanski et al., 2015), economic and financial variables (Lee et al., 1991; Baker and Wurgler, 2007; Brown et al., 2008; Firth et al., 2015), social media (Das and Chen, 2007; Bollen et al., 2011; Karabulut, 2014; Siganos et al., 2014), the weather (Saunders, 1993; Hirshleifer and Shumway, 2003), and sport results

(Edmans et al., 2007; Kaplanski and Levy, 2010). We use data from Facebook and exploit the percentage of positive and negative terms used by Facebook users when updating their status. Facebook users write their status updates in a box that contains an open question such as “What’s on your mind?”. Siganos et al. (2014) and Karabulut (2014) validate the Facebook sentiment index by showing that the level of sentiment on Facebook is positively related to other sentiment indexes, including the US Gallup index and the Google sentiment index of Da et al. (2014).

Using Facebook data has both advantages and disadvantages. A first advantage is the availability of both positive and negative sentiment scores. The availability of both positive and negative sentiment estimates allows us to measure divergence of sentiment as the absolute distance between positive and negative sentiment levels. Second, Facebook’s data are available at a daily frequency, which allows us to explore the relation between divergence of sentiment and stock markets in a contemporaneous setting. Third, Facebook is the world’s largest social network site (Wilson et al., 2012), with approximately 55 million status updates per day; its sheer size makes it very likely that many investors are represented on Facebook. Fourth, Facebook’s status updates are likely to reflect external phenomena that could affect individuals to different degrees, creating a divergence of sentiment. Examples are a national sports event dividing the nation, the weather varying within the nation, or the nation experiencing high temperatures that are preferred by some but not by others. Fifth, divergence of sentiment could be driven by relatively random factors, such as an individual investor having had a good night’s sleep, and social media sentiment proxies are the only proxies that could potentially capture these types of factors. Finally, Facebook data are available for 20 international markets, which allow us to test some hypotheses that exploit differences between countries. We obtain one divergence of sentiment score per day per country.

The data from Facebook also come with limitations. One limitation is that the measurement of sentiment depends on the quality of the word analysis. Linguistic programs typically fail to cope with double negatives (e.g., Baker, 1970), and the sentiment of non-English-speaking communities might be relatively difficult to capture with word analysis (Mihalcea et al., 2007). A second limitation is the relatively short sample period available, from November 2007 to March 2012. Third, even though the average age of Facebook users is increasing over time, stock investors are likely to be underrepresented on Facebook. We believe that our approach is still valuable, because some of the factors that make Facebook users' sentiment more diverse are also likely to have differential effects on the sentiment of investors. Facebook sentiment reflects investor sentiment because some investors are active on Facebook, and because factors that make Facebook users' sentiment more diverse, such as the outcome of the Super Bowl, are also likely to have differential effects on investor sentiment. Fourth, there is a great deal of noise in Facebook posts. Our tests could have been sharper if one could filter posts based on relevance and/or obtain sentiment scores combined with demographic information. We do not have access to this demographic information. Consequently, we need to interpret our results with the appropriate caution.

Our empirical analysis shows that high divergence of sentiment is positively related to contemporaneous trading volume and stock price volatility. These findings are in line with groups of investors with diverging sentiment levels within a day disagreeing on the value of stocks, which could make them trade. The increase in stock price volatility is in line with higher disagreement leading to higher absolute price changes and with traders affected by sentiment being able to move prices.

In line with other behavioral studies (e.g., Kumar and Lee, 2006), it is important to control for macroeconomic news to ensure that the established relations are not simply due to macroeconomic information driving sentiment. We exploit data on economic uncertainty and macroeconomic surprises in the US and find that our results are robust. Limitations are that we cannot control for the arrival of all news and that our macroeconomic variables are only available for the US.

We examine additional predictions regarding the extent to which divergence of sentiment on Facebook may matter for international stock markets. Given that Facebook users also update their status after the close of trading, an interesting prediction is that divergence of sentiment on day *t* relates to trading volume and stock price volatility on day *t+1*. We find evidence in line with this prediction, which reduces concerns about reverse causality. We further hypothesize that our relations are stronger when trading is more frequent by individual investors and find some evidence in line with this prediction. Further, our results in this paper depend on how accurately we can capture sentiment in status updates. This approach is expected to be more accurate for English than for other languages (Mihalcea et al., 2007). In line with this expectation, we find stronger results for English-speaking countries.

We exploit the international dimension of our study by contrasting the effects of country-specific and global divergence of sentiment. In a truly globally integrated world, stocks are priced in a global rather than a local equilibrium (e.g., Bekaert and Harvey, 2003). We use the standard deviation of individual countries' sentiment levels on a given day as a measure of global divergence of sentiment and find that this measure also matters for international stock markets. We predict that while local sentiment may matter more for relatively poorly integrated countries, globally integrated markets are likely to be affected by global sentiment. By using interaction terms between local and global divergence of sentiment and a de facto measure of market integration, we find evidence in line with this prediction.

We contribute to the finance literature in various ways. We first contribute to empirical studies on sentiment levels. We introduce the concept of divergence of sentiment and show that its effect on financial markets goes beyond the effect of the level of sentiment. Second, we contribute to empirical studies on divergence of opinion. Most of these studies confirm the positive relation between differences of opinion and the probability of trade, using measures based on, for example, the dispersion of analyst forecasts (Ajinkya et al., 1991; Diether et al., 2002; Berkman et al., 2009), open interest on index futures (Bessembinder et al., 1996), and macroeconomic variables based on a household investor survey (Li and Li, 2011). We differ from these studies by specifically focusing on differences in sentiment. Because we find evidence in line with theories of trade based on differences of opinion, our results suggest that previously developed propositions in the disagreement literature apply to the behavioral field.

The remainder of the paper is structured as follows. Section 2 describes our data, and we discuss our main results and robustness tests in Section 3. We examine further predictions in Section 4. Section 5 concludes this study.

2. Data

We obtain daily data on positive and negative sentiment from Facebook for 20 international markets between November 2007 and March 2012.[1] Facebook constructs sentiment indexes by

[1] Facebook's Data Team stopped reporting information for Argentina, Australia, Austria, Canada, Ireland, New Zealand, Singapore, and South Africa beginning in October 2011. Facebook also has data available for September

analyzing the percentage of positive and negative status update terms as defined in the Linguistic Inquiry and Word Count Dictionary (LIWC). One defining feature of status updates is that they are self-descriptive messages and are not responses to any question from a researcher. Facebook's use of LIWC to determine positive and negative sentiment is supported by the academic literature (Pennebaker et al., 2001). For example, Gill et al. (2008) find that LIWC is a good indicator for identifying negative words (used by angry users), as opposed to positive words (used by happy users).

The specific formulas used by Facebook are $\frac{x_{p,i,j} - x_{p,all,j}}{\sigma_{p,all,j}}$ for positive sentiment and $\frac{x_{n,i,j} - x_{n,all,j}}{\sigma_{n,all,j}}$ for negative sentiment, where $x_{p,i,j}$ and $x_{n,i,j}$ show the average percentage of positive (p) and negative (n) words used on day i for country *j*, and $x_{p,all,j}$, $x_{n,all,j}$, $\sigma_{p,all,j}$, and $\sigma_{n,all,j}$ are the average (x) percentage of positive and negative words used for country *j* over the duration of the index and the standard deviation (σ) of those variables. As explained by Kramer (2010), a status update of "I am happy today" would receive a positivity rating (p) of 0.25 (only the word "happy" is positive) and a negativity rating (n) of 0. Facebook excludes the highest and lowest 10% of the days when estimating $x_{p,all,j}$, $x_{n,all,j}$, $\sigma_{p,all,j}$, and $\sigma_{n,all,j}$, to minimize the impact of extreme values on the estimation of daily sentiment levels. Sentiment scores are standardized because the potential for positive and negative word use is not equivalent, due to the construction of languages and dictionaries. We exclude the top 5% of daily sentiment levels, which is defined as positive sentiment minus negative sentiment. The reason for this exclusion is

and October 2007, but because of the unusually low variability in those first two months, we start in November 2007. We have confirmed that this choice does not affect our conclusions.

that these values are commonly related to days with many status updates, such as “Happy New Year,” “Happy Mother’s Day,” or “Happy Valentine’s Day”.[2]

We calculate divergence of sentiment (*DoS*) as the daily absolute distance between positive and negative sentiment as follows:

$$DoS_{i,j} = \left| \frac{x_{p,i,j} - x_{p,all,j}}{\sigma_{p,all,j}} + \frac{x_{n,i,j} - x_{n,all,j}}{\sigma_{n,all,j}} \right| \tag{1}$$

where $DoS_{i,j}$ is the daily divergence of sentiment of country j on day i. Our divergence of sentiment score reflects the distance between positive and negative sentiment for the people in a country on a given day. If positive and negative standardized sentiment indexes in a country are both high on a given day, which indicates the presence of many happy and unhappy people that day, then our divergence measure will also be high. If a given day in a particular country is associated with a high number of positive status updates and a low number of negative status updates, then our divergence measure will be relatively low.

[please insert Fig. 1 here]

Figure 1 reports the average daily divergence of sentiment in our sample over time, and the increase in the number of Facebook users over time. We find that the relatively high scores for DoS in the early part of our sample are largely attributable to days in which both positive and negative sentiment are below average. This mostly happens at a time when the huge growth in the number of Facebook users still has to materialize. Because these days might simply represent days with low emotional expression on Facebook, we exclude trading days in which both

[2] We also find that a substantial number of excluded days are related to country-specific celebrations, like those in India.

standardized positive sentiment and standardized negative sentiment are low. More specifically, we delete observations in the bottom quartile of a variable that is the sum of standardized positive sentiment and standardized negative sentiment (i.e., without taking the absolute value).

The increased divergence of sentiment during the 2008-2009 period concurs with the global financial crisis, which affected people to varying degrees. For example, employees in cyclical industries are affected differently by a recession than are employees in defensive industries, with discount retailers, for example, performing relatively well during a financial crisis. People can also show substantial differences in the extent to which their mood depends on financial setbacks and other stressful events (e.g., Billings and Moos, 1981). In Section 3.2, we examine how the effect of divergence of sentiment on trading volume and stock price volatility differs between periods with positive versus negative stock market returns.

We employ Datastream to obtain daily country-level trading volume and corresponding daily country-level return indexes (variable TOTMK). We standardize trading volume by subtracting the mean trading volume over our sample period in a country and dividing the result by the standard deviation of a country's trading volume over our sample period. We measure daily volatility using daily squared stock market returns (see, e.g., Schwert, 1989).

Table 1 shows the list of countries used in our study and the descriptive statistics for *DoS* per country. We also report average positive and negative sentiment scores per country and average trading volume (in millions of shares, before our standardization) and volatility per country. The number of observations varies across countries because of variations in the number of trading days, sample periods, and the availability of Datastream data. We find that the average *DoS* is 0.014. We find some variation across countries and we examine differences based on country characteristics in Section 4.3. The standardized positive and negative sentiment scores do not equal zero, because of the exclusion of outliers. We examine the treatment of outliers in Section 3.2.

[please insert Table 1 here]

3. Empirical results: The relation between divergence of sentiment, trading volume, and stock price volatility

3.1 Main results

We first test the prediction that divergence of sentiment is positively related to trading volume. We pool countries and focus on contemporaneous relations. Our regression analysis includes country and day-of-the-week fixed effects. In addition, to address time trends in trading volume within a year, such as seasonality effects, we include week and month fixed effects. We further use three lags of volume and returns, i.e., the volume and returns in the days prior to observing sentiment, to control for the possibility that past volumes and returns drive the relation between today's divergence of sentiment and volumes. We further add MV/GDP, a country's stock market capitalization divided by its Gross Domestic Product, to control for the relative size of stock markets and macroeconomic developments. A full list of variables used in this study and their definitions is available in Appendix A. We cluster standard errors by date to control for correlation in our variables across countries.

[please insert Table 2 here]

Table 2 shows that there is a strong positive relation between *DoS* and trading volume. The effect is statistically significant at the 1% level, indicating that an increase in divergence of sentiment is related to a contemporaneous daily increase in trading volume. These findings appear in line with a story in which investors with a diverging level of sentiment interpret publicly available information differently, with optimistic investors interpreting the information more positively and pessimistic investors interpreting the information more negatively. These investors then trade to reflect their expectations.

To examine the representativeness of our results, we also pool countries in only America or Europe. Table 2 shows that the relations are statistically significant in both regions. In short, diverging sentiment corresponds to a relatively high transaction volume in stock markets. The parameter coefficient is highest in America, with a value of 5.025. This value implies that if our divergence measure increases by 0.010 (the standard deviation in the American region), then country-level trading volume in America increases by 0.010 x 5.025 = 0.05 standard deviations, which corresponds to an increase of approximately 100 million shares per day. A one standard deviation increase in our divergence of sentiment variable for our overall sample increases average country-level daily trading volume by approximately 27 million shares.

An increase in trading volume does not necessarily imply an increase in return volatility. Imagine, for example, that only retail investors are affected by divergence of sentiment. This could lead to an increase in trading, but it is not immediately obvious that this trading affects prices. In Table 3, we empirically examine the relation between divergence of sentiment and stock price volatility. We measure stock market volatility with squared stock market returns. Our regression analysis includes country fixed effects, day-of-the-week fixed effects, week and month fixed effects, three lags on returns and volatility, MV/GDP, and standard errors clustered by date.

In Column 1, we find that our divergence of sentiment measure is positively related to stock price volatility. This finding is in line with, for example, Banerjee and Kremer (2010), who model investors that disagree about the interpretation of public information and show that higher disagreement leads to higher absolute price changes, and thus to higher stock price volatility. The finding suggests that traders affected by sentiment can influence stock prices. The relation is statistically significant at the 1% level. We also report the results for America and Europe, in Columns 2 and 3. We find that the effects are positive in both regions, with relations that are also statistically significant at the 1% level.

[please insert Table 3 here]

In Columns 4-6, we include as additional control variables contemporaneous trading volume and trading volume in each of the preceding three trading days. The reason for this inclusion is that trading volume and stock price volatility are strongly positively related (e.g., Karpoff, 1987). Fully isolating the effect of divergence of sentiment on volatility is not straightforward, but Columns 4-6 provide some insights into the relation between divergence of sentiment and stock price volatility when trying to keep trading volume fixed. We find only minor reductions in the magnitude of the parameter coefficient of *DoS* as compared to the results in Columns 1-3. In each specification, the relation between divergence of sentiment and stock price volatility remains statistically significant at the 1% level, which suggests that the relation between *DoS* and stock price volatility is not mechanically caused by changes in trading volume.

3.2 Robustness tests

We perform a range of additional tests to examine the robustness of our main results. First, we examine whether the effect of divergence of sentiment surpasses the effect of the level of sentiment. Siganos et al. (2014) report that pessimism on Facebook is related to increases in both trading volume and stock price volatility. They argue that this evidence is in line with predictions that temporary pessimism causes investors to trade in an attempt to overcome their negative sentiment with a positive outcome from an alternative activity. Relatedly, Chang et al. (2008) find that cloudy weather is related to high transaction volumes, Brown (1999) and Lee et al. (2002) find that unusually high levels of sentiment are associated with high volatility, and Coval and Shumway (2005) report that traders with losses in the morning tend to take higher risks in the afternoon. Our robustness test is therefore essential to establish whether the effect of divergence of sentiment holds after controlling for the relation of the level of sentiment with trading volume and stock price volatility.

Table 4 includes both divergence of sentiment and the level of sentiment in one regression specification, along with the control variables that we used earlier. We find that the effect of divergence of sentiment on trading volume remains positive when controlling for the level of sentiment. The relation is statistically significant at the 1% level for both our overall and our American sample, and at the 10% level for our European sample. Interestingly, divergence of sentiment seems to be a more important explanatory variable for trading volume than the level of sentiment, as the inclusion of divergence of sentiment causes the effect of the level of sentiment to become nonsignificant in some circumstances. Our focus is on divergence, but the results for trading volume indicate that it would be important for studies that focus on the relation between sentiment levels and trading volume to control for the effects of divergence of sentiment.

For stock price volatility, we find that the coefficients for divergence of sentiment remain significantly positive at the 1% level after including sentiment levels. Sentiment levels are negatively related to stock price volatility, in line with the results in Siganos et al. (2014). Overall, our results highlight the importance of examining divergence of sentiment beyond examining sentiment levels.

[please insert Table 4 here]

As a second important robustness test, we control for macroeconomic conditions. News arrival is a clear omitted variable, and controlling for macroeconomic news is likely to be important (e.g., Kumar and Lee, 2006). Because of data restrictions, we focus on the US market and control for macroeconomic conditions in two ways. First, we control for the Economic Uncertainty Policy Index developed by Baker et al. (2016). This index is available at a daily frequency for the US market and measures policy uncertainty by counting terms such as "uncertain" and "deficit" in newspapers. Second, we control for macroeconomic surprises obtained from Reuters' Economic Polls, which report the actual numbers minus the median forecasts for a range of variables. In particular, we control for surprises related to the change in inflation, the growth rate of industrial production, the change in non-farm payrolls, the growth rate of retail sales, the change in unemployment, and the change in house prices. These variables are available monthly and follow from Bernanke and Kuttner (2005) and Kontonikas et al. (2015). We let these variables enter our regression in absolute form.[3]

[please insert Table 5 here]

[3] We obtain similar conclusions when the news variables are squared.

Table 5 shows that our results hold when we control for these macroeconomic conditions. The parameter coefficient of *US_DoS* remains significantly positive for both trading volume (7.914) and stock price volatility (0.005) after controlling for the Economic Uncertainty Policy Index, and both parameter coefficients are statistically significant at the 1% level. The parameter coefficients decrease to 5.896 and 0.003, respectively, when controlling for macroeconomic surprises, but both relations remain statistically significant, now at the 5% level.

As a third robustness test, we adjust the outlier treatment of sentiment values. Previously, we reported relations when excluding the top 5% of daily sentiment values and when excluding the bottom quartile with low emotional expression. In Table 6, we report the results when no outliers are excluded, when excluding the top 1% of daily sentiment values, and when excluding the bottom 5% of days with low emotional expression. We find that divergence of sentiment is positively related to both trading volume and stock price volatility for these alternate outlier treatments. The relations are statistically significant at the 1% level.

[please insert Table 6 here]

Fourth, we use alternate stock price volatility measures to explore the robustness of the relation between divergence of sentiment and volatility. Instead of using squared stock market returns, we measure volatility (1) using GARCH (1,1) that contains a constant element and one lag in stock returns (Bollerslev, 1986); (2) using the standard deviation of the daily high, low, open, and close stock market prices; and (3) using the daily squared unexpected stock returns, in which the unexpected stock return is calculated as the actual stock return minus the average return over the prior 60 days. Table 7 shows the results. We find that alternate proxies of stock price volatility show a significantly positive relation between divergence of sentiment and stock price volatility. In untabulated results, we obtain similar conclusions when we calculate unexpected stock returns by using the average return over, for example, the prior 20 or 30 days.

[please insert Table 7 here]

Fifth, we distinguish between positive and negative stock market returns to test whether results differ for alternate market conditions. This test is especially useful due to the observation that *DoS* is relatively high in the early stage of our sample period, when relatively low stock market returns were experienced. We estimate our regressions separately for days with positive stock market returns and days with negative stock market returns. In addition, we distinguish months that follow a month with negative returns and months that follow a month with positive returns. Table 8 shows that divergence of sentiment is positively related to both trading volume and stock price volatility, regardless of the stock market's direction. The relations are statistically significant at the 5% level or better in all sub-samples.

[please insert Table 8 here]

Finally, instead of clustering standard errors by day, we examine the results when we cluster standard errors by country. In untabulated results, we show that our findings are robust to these changes, i.e., divergence of sentiment remains positively related to both trading volume and stock price volatility.

4. Further predictions and results

In this section, we test further predictions. First, given that Facebook users also update their status after the close of trading, we test the prediction that divergence of sentiment on day *t* relates to trading volume and stock price volatility on day *t+1*. Second, we test whether the relations established in Section 3 are stronger when individual investors are more likely to trade. Third, we test the effect of the English language. Fourth, we consider market integration and contrast our local divergence of sentiment measure with a global divergence of sentiment measure.

4.1 Divergence of sentiment and next-day trading volume and volatility

We examine the relation between divergence of sentiment on day *t* and trading volume and stock price volatility on day *t+1*. In doing so, we exploit status updates in the evening. Vitrue (2012) reports that Facebook activity is still high after the close of the stock market. Therefore, divergence of sentiment resulting from, for example, an evening's sporting event may be reflected in the next day's trading activity. We believe that this is an interesting feature of Facebook's sentiment data, which may also limit concerns about potential reverse causality. We report the relation between our divergence of sentiment measure and the next day's trading volume and stock price volatility in Table 9.

[please insert Table 9 here]

We find that the parameter coefficient of *DoS* for both trading volume and volatility is again significantly positive at the 1% level. The coefficient for divergence of sentiment in the trading volume regression is 2.628, and the coefficient in the stock volatility regression equals 0.003.

We also explore the relation between divergence of sentiment during the weekend and trading on Monday. More specifically, Table 9 also reports the relation between average divergence of sentiment between Friday and Sunday and between Friday and Monday on

Monday's trading volume and volatility. We find that divergence of sentiment during the weekend is positively related to Monday's trading volume and stock price volatility. The parameter coefficient of *DoS* is significantly positive across all four estimations.

4.2 Trading by individuals

Evidence from most of the behavioral finance literature suggests that individual investors are more susceptible to sentiment than institutional investors (e.g., Baker and Wurgler, 2007). In this section, we build on prior evidence that individuals trade relatively more during the beginning of the week (e.g., Lakonishok and Maberly, 1990; Venezia and Shapira, 2007). Lakonishok and Maberly (1990) show that in each of their sub-periods, the most active trading day for individuals is Monday, and Tuesday is consistently the next most active trading day for individuals. Trading by individuals during the remainder of the week is relatively low. One explanation for this pattern is that individual investors use their weekends to contemplate their trading decisions. We thus predict that the relations between divergence of sentiment on Facebook and stock market activity are strongest during the beginning of the week.

[please insert Table 10 here]

Table 10 shows our results when estimating our regression specifications separately for Monday-Tuesday and Wednesday-Friday. The coefficient for divergence of sentiment in the trading volume regression is 6.393 for the Monday-Tuesday sample and 1.001 for the Wednesday-Friday sample. The coefficient for divergence of sentiment in the stock volatility regression is 0.005 for the Monday-Tuesday sample and 0.002 for the Wednesday-Friday sample. Both differences between the coefficients are statistically significant. These findings suggest that when individual investors are more likely to trade in stock markets, the observed relations between divergence of sentiment and stock market activity are stronger. We acknowledge that these findings are only an indirect test of the importance of trading by individuals and stress that our results must be interpreted with appropriate caution.

4.3 Language, global divergence of sentiment, and market integration

Our results in this paper depend on how accurately we can capture sentiment by examining positive and negative words in status updates. The difficulty of capturing sentiment with the use of a dictionary varies among languages, and the method is expected to be more accurate for English than for other languages (Mihalcea et al., 2007). We test this prediction in Table 11.

[please insert Table 11 here]

The parameter coefficient of *DoS* in our trading volume regression is 5.737 for English-speaking countries versus 1.567 for non-English-speaking countries. In line with our prediction, the coefficient for English-speaking countries is significantly higher than the coefficient for the remaining countries. In our stock price volatility regression, the coefficient is slightly higher for English-speaking countries, 0.0039 versus 0.0036, but in this case, the difference is not statistically significant.

Although the above findings are in line with our prediction, our test is not precise enough to draw definite conclusions on the effect of language. An alternate explanation might be, for example, that national culture plays an important role. These types of explanations are difficult to test. Another potential explanation for our results in Table 11 is that English-speaking countries are more “news” integrated with one another and that their sentiment measures are more correlated with global sentiment. So far, we have ignored an impact of global sentiment. However, in a globally integrated world, global sentiment can obviously be important. This importance is likely to depend on the level of market integration, as countries have different levels of market integration (e.g., Bekaert and Harvey, 2003; Lane and Milesi-Ferretti, 2007). Consequently, while country-specific sentiment may matter more for relatively poorly integrated countries, globally integrated markets are likely to be more affected by global sentiment.

In Table 12, we contrast the effects of local and global divergence of sentiment. We calculate global divergence of sentiment as the standard deviation of the individual countries' sentiment levels on a given day. Our global divergence of sentiment measure thus obtains a high score when sentiment levels are highly diverse among countries on that day. To obtain insights into the relevance of market integration, we include interaction terms between divergence of sentiment and a measure of de facto market integration. We use the measure of market integration developed by Lane and Milesi-Ferretti (2007), which Quinn et al. (2011) describe as "perhaps the most widely used [quantity-based] de facto measure of a country's exposure to international financial markets." The measure is available for all countries in our sample on a yearly basis and can be downloaded from http://www.philiplane.org/EWN.html for the years up to 2011. For the observations that we have in 2012, we use the country's 2011 value of market integration. A high value of the measure denotes a high level of market integration.

[please insert Table 12 here]

The results in Table 12 indicate that local divergence of sentiment is still significantly positively related to trading volume when controlling for global sentiment. However, the effect of the interaction term between local divergence of sentiment and market integration is significantly negative, indicating that local divergence of sentiment matters less for trading volume when a market is more integrated. The global divergence of sentiment variable is insignificantly related to local trading volume, but it is important to note that the interaction term between global divergence of sentiment and market integration is significantly positive. This positive interaction term highlights that global sentiment matters more for local trading volume when a country is more integrated with the rest of the world.

For sentiment to affect stock price volatility, investors affected by sentiment have to be able to move prices. It is an interesting empirical question whether local divergence of sentiment or global divergence of sentiment has a larger impact on local stock price volatility. The results in Table 12 indicate that both measures of divergence of sentiment have a positive effect on stock price volatility, with a coefficient equal to 0.003 for both local and global divergence of sentiment. The effects of the interaction terms indicate that the local effect becomes significantly weaker when markets are more integrated, while this is not the case for the effect of global divergence of sentiment.

Overall, our results in Table 12 indicate that both local and global divergence of sentiment can play a role in our examination of trading volume and stock price volatility. In line with expectations, the relative importance of the local and global versions of our divergence of sentiment measure depends on the level of a country's market integration.

5. Conclusion

This study introduces divergence of sentiment to the finance literature. We measure divergence as the distance between the optimistic and pessimistic levels of sentiment. Based on evidence from the behavioral finance literature, we predict that investors with positive sentiment are more optimistic about the potential benefits and risks of a particular investment than investors with negative sentiment. Consequently, on days with high divergence of sentiment, investors differ in how they interpret public information, making it more likely that investors transact in line with their beliefs on firms' value. Days with high divergence in sentiment are thus expected to be related to contemporaneous high trading volume. We indeed find that high divergence of sentiment is related to an increase in trading activity.

In addition, we examine the prediction that divergence of sentiment affects stock price volatility. This prediction follows from the difference of opinion literature when we assume that investors affected by sentiment can move prices. We observe a positive relation between divergence of sentiment and stock price volatility. We find this relation both for local and global divergence of sentiment. The local effect becomes significantly weaker when markets are more integrated.

Importantly, our finding that divergence of sentiment affects stock market trading is robust to controlling for the level of sentiment. As such, we conclude that the average level of sentiment hides an important dispersion in people's sentiment. Indeed, when controlling for divergence, the effect of the level of sentiment on trading volume weakens.

As mentioned in the introduction, our approach is not without limitations. Divergence of sentiment is relatively hard to quantify, it is difficult to control for the arrival of news, and our data only allow for relatively general tests. Nonetheless, the results in this paper suggest that the introduction of the concept of divergence of sentiment to the finance literature is an important one.

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Table 1
Descriptive Statistics.

	N	Divergence of sentiment Mean	Median	Stdev	Min	Max	Positive sentiment Mean	Negative sentiment Mean	Volume Mean	Volatility Mean
All	14712	0.014	0.010	0.012	0.000	0.104	-0.009	0.001	555	0.00019
America	5205	0.011	0.008	0.010	0.000	0.072	-0.008	0.001	867	0.00015
Europe	6390	0.015	0.012	0.012	0.000	0.104	-0.009	0.001	407	0.00025
Argentina	616	0.010	0.008	0.009	0.000	0.045	-0.007	0.001	8	0.00021
Australia	656	0.013	0.010	0.011	0.000	0.067	-0.008	0.003	844	0.00013
Austria	818	0.015	0.014	0.011	0.000	0.045	-0.010	0.000	11	0.00033
Belgium	736	0.021	0.020	0.014	0.000	0.068	-0.003	0.006	25	0.00014
Canada	706	0.012	0.010	0.011	0.000	0.057	-0.009	0.002	214	0.00018
Chile	819	0.010	0.008	0.009	0.000	0.060	-0.009	0.001	383	0.00011
Colombia	797	0.010	0.007	0.009	0.000	0.045	-0.008	0.001	638	0.00012
Germany	941	0.013	0.010	0.012	0.000	0.045	-0.009	-0.003	4270	0.00025
India	373	0.021	0.019	0.015	0.000	0.045	-0.026	0.008	130	0.00011
Ireland	621	0.017	0.015	0.013	0.000	0.093	-0.012	0.002	34	0.00027
Italy	883	0.005	0.004	0.006	0.000	0.043	-0.002	0.000	950	0.00034
Mexico	806	0.012	0.008	0.011	0.000	0.044	-0.009	-0.002	206	0.00019
Netherlands	729	0.017	0.016	0.011	0.000	0.044	-0.012	0.003	113	0.00018
New Zealand	631	0.015	0.013	0.011	0.000	0.069	-0.009	0.003	30	0.00003
Singapore	642	0.012	0.010	0.009	0.000	0.045	-0.007	0.001	516	0.00011
South Africa	815	0.014	0.010	0.013	0.000	0.045	-0.011	0.001	118	0.00021
Spain	725	0.018	0.019	0.011	0.000	0.060	-0.012	-0.001	272	0.00023
UK	937	0.016	0.012	0.014	0.000	0.104	-0.012	0.000	1523	0.00024
US	721	0.012	0.009	0.011	0.000	0.072	-0.008	0.002	4669	0.00018
Venezuela	740	0.010	0.006	0.010	0.000	0.044	-0.007	0.001	0.3	0.00008

This table shows descriptive statistics for our divergence of sentiment measure (*DoS*), standardized positive and negative sentiment, trading volume, and volatility. *DoS* is defined as the absolute distance between positive and negative standardized sentiment on Facebook based on terms used by users when updating their statuses. We use squared stock market returns to estimate daily volatility, and trading volume is reported in millions of shares. Values arrive from trading days only.

Table 2
Divergence of Sentiment and Contemporaneous Trading Volume.

	All	America	Europe
		Dependent: Volume{t}	
DoS{t}	2.829***	5.025***	1.783**
	(0.608)	(0.959)	(0.828)
Volume{t-1}	0.424***	0.358***	0.468***
	(0.012)	(0.017)	(0.020)
Volume{t-2}	0.163***	0.163***	0.132***
	(0.011)	(0.017)	(0.019)
Volume{t-3}	0.130***	0.121***	0.138***
	(0.011)	(0.016)	(0.018)
Return{t-1}	-2.272***	-0.975	-2.740***
	(0.606)	(0.794)	(0.761)
Return{t-2}	-0.732	-0.283	-0.870
	(0.573)	(0.813)	(0.744)
Return{t-3}	-0.472	-0.021	-0.629
	(0.644)	(0.922)	(0.804)
MV/GDP	-0.110***	-0.080**	-0.197***
	(0.021)	(0.031)	(0.035)
Country fixed effects	Yes	Yes	Yes
Day-of-the-week fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
N	14652	5184	6366
adj. R-sq	0.465	0.363	0.521

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume. The parameter estimate represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 3
Divergence of Sentiment and Contemporaneous Stock Price Volatility.

	Dependent: Volatility{t}					
	All	America	Europe	All	America	Europe
	(1)	(2)	(3)	(4)	(5)	(6)
DoS{t}	0.004***	0.006***	0.003***	0.003***	0.005***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Volume{t}				0.0001***	0.0001***	0.0002***
				(0.000)	(0.000)	(0.000)
Volatility{t-1}	0.095***	0.080**	0.089***	0.089***	0.077**	0.082***
	(0.023)	(0.036)	(0.031)	(0.023)	(0.035)	(0.030)
Volatility{t-2}	0.068***	0.083***	0.041	0.066***	0.083***	0.042
	(0.025)	(0.028)	(0.033)	(0.026)	(0.027)	(0.034)
Volatility{t-3}	0.103***	0.069**	0.107**	0.103***	0.071**	0.107**
	(0.037)	(0.028)	(0.051)	(0.037)	(0.029)	(0.052)
Return{t-1}	-0.003**	-0.003***	-0.003*	-0.002**	-0.003***	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Return{t-2}	-0.002**	-0.001	-0.003**	-0.002**	-0.001	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Return{t-3}	-0.004***	-0.003**	-0.005***	-0.004***	-0.003**	-0.005***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
MV/GDP	Yes	Yes	Yes	Yes	Yes	Yes
3-day lagged volume	No	No	No	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	14652	5184	6366	14652	5184	6366
adj. R-sq	0.126	0.098	0.134	0.151	0.116	0.169

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous stock price volatility. The parameter estimate represents the coefficient of regressing a daily measure of volatility, as estimated by squared stock market returns, on our daily *DoS* measure. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 4

The Relation between Divergence of Sentiment, Trading Volume, and Stock Price Volatility after Controlling for Sentiment Levels.

	All	America	Europe		All	America	Europe
	Dependent: Volume{t}				Dependent: Volatility{t}		
DoS{t}	2.928***	6.379***	1.668*	*DoS*{t}	0.003***	0.005***	0.002***
	(0.640)	(1.045)	(0.859)		(0.001)	(0.001)	(0.001)
Sentiment{t}	0.376	4.268***	-0.599	Sentiment{t}	-0.002***	-0.002**	-0.003***
	(0.601)	(1.139)	(0.817)		(0.001)	(0.001)	(0.001)
3-day lagged volume and returns	Yes	Yes	Yes	3-day lagged volatility and returns	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes	MV/GDP	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Country and time fixed effects	Yes	Yes	Yes
N	14652	5184	6366	N	14652	5184	6366
adj. R-sq	0.465	0.365	0.521	adj. R-sq	0.128	0.099	0.136

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility after controlling for the level of sentiment. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by using squared stock market returns, on our daily *DoS* measure. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 5 US Results when Controlling for Macroeconomic Conditions.

	Dependent: US_Volume{t}			Dependent: US_Volatility{t}	
US_DoS{t}	7.914***	5.896**	*US_DoS*{t}	0.005***	0.003**
	(2.778)	(2.872)		(0.002)	(0.002)
US_Daily Policy Index{t}	0.213		US_Daily Policy Index{t}	0.001*	
	(0.309)			(0.000)	
Inflation		0.400	Inflation		-0.037*
		(0.379)			(0.022)
Industrial Production		0.139	Industrial Production		-0.015
		(0.177)			(0.010)
Non-Farm Payrolls		0.343	Non-Farm Payrolls		-0.020
		(0.438)			(0.027)
Retail Sales		0.316***	Retail Sales		0.011
		(0.111)			(0.010)
Unemployment		0.360	Unemployment		-0.029*
		(0.246)			(0.017)
House Prices		-0.661	House Prices		0.250*
		(1.165)			(0.105)
3-day lagged volume and returns	Yes	Yes	3-day lagged volatility and returns	Yes	Yes
Time fixed effects	Yes	Yes	Time fixed effects	Yes	Yes
N	718	718	N	718	718
adj. R-sq	0.577	0.582	adj. R-sq	0.114	0.120

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility after controlling for macroeconomic conditions. Because of issues related to data availability, the test is only performed within the US market. US_Daily Policy Index is developed by Baker et al. (2016) and measures policy uncertainty based on counting words such as "uncertain" and "deficit" in newspapers. The remaining macroeconomic variables originate from Reuters Economic Polls and relate to surprises (actual values minus median forecasts) for the following variables: change in inflation, growth rate of industrial production, change in non-farm payrolls, growth rate of retail sales (excluding autos), change in unemployment, and change in house prices. We use the absolute values of these surprises. The coefficients for these macroeconomic variables in the stock volatility regression are multiplied by 100. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by squared stock market returns, on our daily *DoS* measure. All regressions include day-of-the-week, week, and month fixed effects. We report standard errors clustered by date, as shown in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

Table 6

The Relation between Divergence of Sentiment, Trading Volume, and Stock Price Volatility after Alternate Outlier Treatments.

	No outliers	1% outliers	5% emotional expression cutoff		No outliers	1% outliers	5% emotional expression cutoff
	Dependent: Volume{t}				Dependent: Volatility{t}		
DoS{t}	1.465***	2.609***	1.035***	*DoS*{t}	0.002***	0.003***	0.003***
	(0.558)	(0.585)	(0.345)		(0.000)	(0.001)	(0.000)
3-day lagged volume and returns	Yes	Yes	Yes	3-day lagged volatility and returns	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes	MV/GDP	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Country and time fixed effects	Yes	Yes	Yes
N	15184	15130	18612	N	15184	15130	18612
adj. R-sq	0.473	0.471	0.474	adj. R-sq	0.124	0.125	0.146

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility after alternate outlier treatments. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by squared stock market returns, on our daily *DoS* measure. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. *** indicates statistical significance at the one percent level.

Table 7 Divergence of Sentiment and Alternate Stock Price Volatility Measures.

	All	America	Europe	All	America	Europe	All	America	Europe
	Dependent: Volatility{t} GARCH(1,1)			Dependent: Volatility{t} Stdev of High, Low, Open, Close			Dependent: Volatility{t} Squared Unexpected Returns		
DoS{t}	0.075***	0.114***	0.039*	0.043***	0.081***	0.028***	0.004***	0.006***	0.003***
	(0.020)	(0.030)	(0.023)	(0.006)	(0.013)	(0.007)	(0.001)	(0.001)	(0.001)
3-day lagged volatility and returns	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13915	4447	6366	14576	5124	6366	14652	5184	6366
adj. R-sq	0.510	0.490	0.480	0.430	0.307	0.448	0.118	0.101	0.123

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous stock price volatility as measured using GARCH(1,1), the standard deviation of high, low, open, and close stock market prices, and the squared term of unexpected stock returns. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. * and *** indicate statistical significance at the ten and one percent levels, respectively.

Table 8

The Relation between Divergence of Sentiment, Trading Volume, and Stock Price Volatility for Different Stock Market Returns.

	Contemporaneous daily: Positive market returns	Contemporaneous daily: Negative market returns	Following monthly: Positive market returns	Following monthly: Negative market returns
	Dependent: Volume{t}			
DoS{t}	3.714***	1.743**	1.918**	3.457***
	(0.785)	(0.821)	(0.853)	(0.811)
3-day lagged volume and returns	Yes	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Yes
N	7732	6903	8031	6621
adj. R-sq	0.471	0.479	0.454	0.490

	Contemporaneous daily: Positive market returns	Contemporaneous daily: Negative market returns	Following monthly: Positive market returns	Following monthly: Negative market returns
	Dependent: Volatility{t}			
DoS{t}	0.004***	0.003***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
3-day lagged volatility and returns	Yes	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes	Yes
Country and time fixed effects	Yes	Yes	Yes	Yes
N	7732	6903	8031	6621
adj. R-sq	0.129	0.156	0.077	0.160

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility during days with contemporaneous positive and negative stock market returns, along with the subsequent months of positive and negative stock market returns. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by squared stock market returns, on our daily *DoS* measure. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. ** and *** indicate statistical significance at the five and one percent levels, respectively.

Table 9

Divergence of Sentiment and Next Day's Trading Volume and Stock Volatility.

	Dependent: Volume{t}	Dependent: *Monday*Volume{t}	Dependent: *Monday*Volume{t}
DoS{t-1}	2.628***		
	(0.648)		
Friday-SundayDoS{t}		4.511***	
		(1.296)	
Friday-MondayDoS{t}			6.226***
			(1.476)
3-day lagged volume and returns	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Day-of-the-week fix. effects	Yes	No	No
Week and month fixed effects	Yes	Yes	Yes
N	14632	2760	2760
adj. R-sq	0.384	0.455	0.457

	Dependent: Volatility{t}	Dependent: *Monday*Volatility{t}	Dependent: *Monday*Volatility{t}
DoS{t-1}	0.003***		
	(0.001)		
Friday-SundayDoS{t}		0.003**	
		(0.001)	
Friday-MondayDoS{t}			0.005***
			(0.002)
3-day lagged volatility and returns	Yes	Yes	Yes
MV/GDP	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Day-of-the-week fix. effects	Yes	No	No
Week and month fixed effects	Yes	Yes	Yes
N	14632	2760	2760
adj. R-sq	0.120	0.217	0.219

This table shows whether one-day lagged divergence of sentiment (*DoS*) is related to trading volume and stock price volatility. In addition, the table reports whether average Friday to Sunday and Friday to Monday divergence of sentiment (*DoS*) is related to Monday's trading volume and stock price volatility. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by squared stock market returns, on our daily *DoS* measure. All regressions include week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. ** and *** indicate statistical significance at the five and one percent levels, respectively.

Table 10

The Relation between Divergence of Sentiment, Trading Volume, and Stock Price Volatility during Days of the Week.

	Dependent: Volume{t}				Dependent: Volatility{t}		
	Mon-Tue	Wed-Fri			Mon-Tue	Wed-Fri	
DoS{t}	6.393***	1.001	14.68***	*DoS*{t}	0.005***	0.002***	5.26**
	(1.212)	(0.736)			(0.001)	(0.001)	
3-day lagged volume and returns	Yes	Yes		3-day lagged volatility and returns	Yes	Yes	
MV/GDP	Yes	Yes		MV/GDP	Yes	Yes	
Country and time fixed effects	Yes	Yes		Country and time fixed effects	Yes	Yes	
N	5812	8840		N	5812	8840	
adj. R-sq	0.401	0.473		adj. R-sq	0.147	0.148	

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility on Monday-Tuesday in relation to Wednesday-Friday. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by using squared stock market returns, on our daily *DoS* measure. We report chi-squared statistics indicating whether the estimated *DoS* coefficient differs between the sub-samples. All regressions include day-of-the-week, week, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. ** and *** indicate statistical significance at the five and one percent levels, respectively.

Table 11

The Relation between Divergence of Sentiment, Trading Volume, and Stock Price Volatility for English and Non-English-Speaking Countries.

	English-speaking countries (1)	Non-English-speaking countries (2)	(1) vs (2)		English-speaking countries (3)	Non-English-speaking countries (4)	(3) vs (4)
	Dependent: Volume{t}				Dependent: Volatility{t}		
DoS{t}	5.737***	1.567**	17.13***	*DoS*{t}	0.0039***	0.0036***	0.16
	(0.916)	(0.712)			(0.001)	(0.001)	
3-day lagged volume and returns	Yes	Yes		3-day lagged volatility and returns	Yes	Yes	
MV/GDP	Yes	Yes		MV/GDP	Yes	Yes	
Country and time fixed effects	Yes	Yes		Country and time fixed effects	Yes	Yes	
N	5705	8947		N	5705	8947	
adj. R-sq	0.452	0.476		adj. R-sq	0.167	0.116	

This table shows whether divergence of sentiment (*DoS*) is related to contemporaneous trading volume and stock price volatility for English- and non-English-speaking countries. The parameter estimate for trading volume represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. The parameter estimate for stock price volatility represents the coefficient of regressing a daily measure of volatility, as estimated by using squared stock market returns, on our daily *DoS* measure. We report chi-squared statistics indicating whether the estimated *DoS* coefficient differs between the sub-samples. All regressions include week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. ** and *** indicate statistical significance at the five and one percent levels, respectively.

Table 12 Global Divergence of Sentiment and Stock Market Integration.

	(1) Dependent: Volume{t}	(2) Dependent: Volatility{t}
DoS{t}	2.486***	0.003***
	(0.701)	(0.001)
Global DoS{t}	1.303	0.003*
	(2.103)	(0.001)
*DoS{t}*Integration*	-1.850**	-0.002**
	(0.900)	(0.001)
*Global DoS{t}*Integration*	2.984**	-0.001
	(1.393)	(0.001)
Integration	Yes	Yes
3-day lagged returns	Yes	Yes
3-day lagged volume	Yes	No
3-day lagged volatility	No	Yes
MV/GDP	Yes	Yes
Country and time fixed effects	Yes	Yes
N	14652	14652
adj. R-sq	0.466	0.128

This table shows whether divergence of sentiment (*DoS*) and global divergence of sentiment (*Global DoS*) are related to contemporaneous trading volume and stock price volatility by taking into account stock market integration. *Global DoS* is measured as the standard deviation of GNH across the countries in our sample. Integration is measured as stock market integration per country per year, based on a country's aggregate assets plus liabilities relative to its gross domestic product as in Lane and Milesi-Ferretti (2007). Trading volume is daily standardized trading volume and stock price volatility is squared stock market returns. All regressions include day-of-the-week, week, month, and country fixed effects. We report standard errors clustered by date, as shown in parentheses. *, **, and *** indicate statistical significance at the ten, five, and one percent levels, respectively.

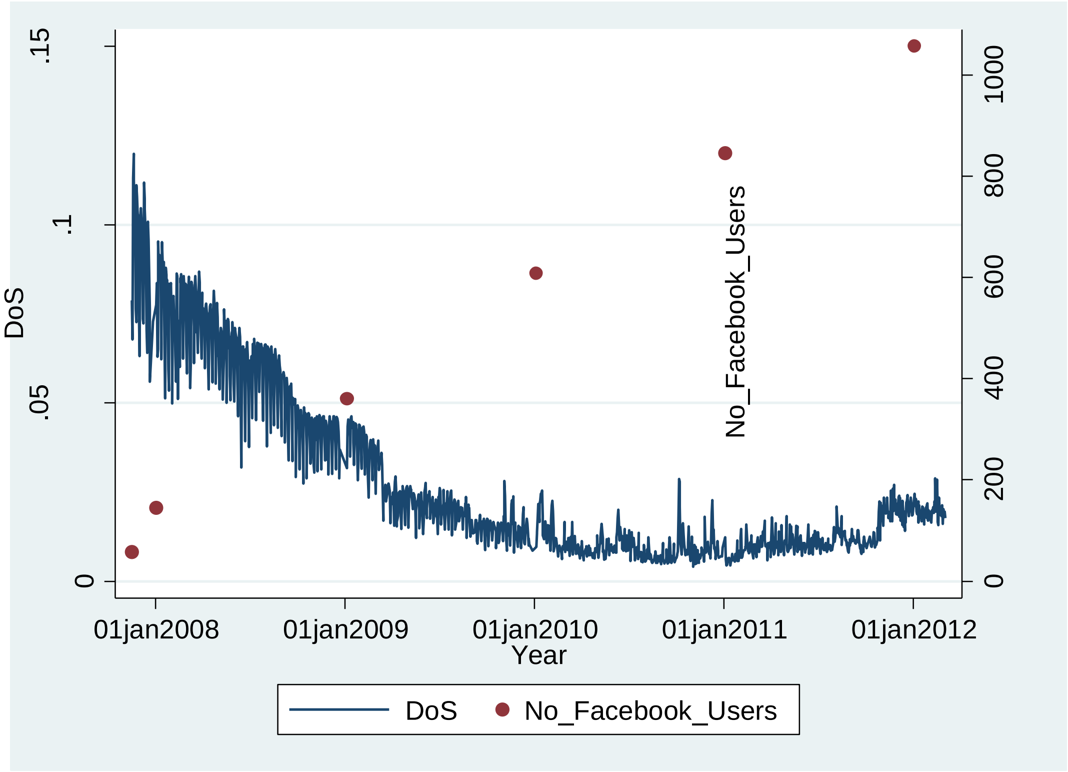

Fig. 1. Divergence of sentiment during the sample period. This figure shows the average daily divergence of sentiment (*DoS*) across countries during the sample period, and the number of Facebook users in millions (source: Facebook). *DoS* is defined as the absolute distance between positive and negative standardized sentiment on Facebook based on terms emplyed by users when updating their statuses.

Appendix A. Variable definitions (in alphabetical order).

Terms	Source	Definition
DoS	Facebook	Daily absolute distance between positive and negative sentiment in a country
Friday-Monday DoS	Facebook	Average divergence of sentiment (DoS) between Friday and Monday in a country
Friday-Sunday DoS	Facebook	Average divergence of sentiment (DoS) between Friday and Sunday in a country
Global DoS	Facebook	Daily standard deviation of sentiment (GNH) across the countries in our sample
House prices	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for changes in US house prices
Industrial production	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for changes in US industrial production
Inflation	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for changes in US inflation
Integration	Lane and Milesi-Ferretti (2007)	A country's aggregate assets plus liabilities relative to its Gross Domestic Product
MV/GDP	Datastream	Country's daily market capitalization divided by the Gross Domestic Product
Non-farm payrolls	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for changes in US non-farm payrolls
Retail sales	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for growth in US retail sales
Return	Datastream	Daily country-level return (TOTMK)
Sentiment	Facebook	The GNH index, which represents positive minus negative sentiment
Volatility	Datastream	Daily squared stock market returns in a country
Volatility: GARCH	Datastream	Daily GARCH(1,1) that contains a constant element and one lag in stock returns in a country
Volatility: Stdev	Datastream	Standard deviation of daily high, low, open, and close stock market prices in a country
Volatility: Squared unexpected returns	Datastream	Stock return on day t minus the average return over the prior 60 days, squared
Volume	Datastream	Daily standardized trading volume
Unemployment	Kontonikas et al. (2015)	The absolute value of the surprise based on Reuters' Economics Polls for changes in US unemployment
US_daily policy index	Baker et al. (2016)	US policy uncertainty index based on counting words such as "uncertain" and "deficit" in newspapers