Divergence of Sentiment and Stock Market Trading

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Acknowledgements
We would like to thank Howard Chan, Jo Danbolt, Bruce Grundy, Guy Kaplanski, Agnieszka Markiewicz, Dimitris Petmezas, Meir Statman, Vadym Volosovych, Jeffrey Wurgler, Remco Zwinkels and seminar participants at the University of Glasgow, the 2013 Scottish BAFA, the 2013 World Finance Conference and the 2014 International Symposium on Forecasting for valuable suggestions.

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Abstract

We examine the effects of divergence of sentiment on trading volume and stock price volatility. Sentiment varies substantially among people on any given day, and we use status updates on Facebook across 20 countries to capture daily divergence in sentiment within a country. In agreement with theoretical models predicting that differences of opinion cause trading, we find that divergence of sentiment positively affects trading volume and stock price volatility. Our results highlight an important effect of sentiment on financial markets that goes beyond an effect of the level of sentiment.

Keywords: Sentiment, Disagreement models, Divergence of opinion, Facebook's Gross National Happiness Index.

I. Introduction

Several studies in the field of behavioral finance have empirically examined the relation between the level of sentiment and stock markets.[1] This paper contributes to the behavioral finance literature by investigating divergence of sentiment rather than the average level of sentiment. The average sentiment level on a given day hides any variation in sentiment. That is, a day with each person in a country having a neutral sentiment obtains the same average sentiment level as a day in which half the country is happy and the remainder is equally unhappy.

If sentiment affects beliefs about the future, as argued by the behavioral finance literature, then divergence of sentiment among investors could have strong implications for financial markets. It seems intuitive that trading is more likely to occur on days when one half of the population experiences positive sentiment and a more positive view of the future, while the other half experiences negative sentiment and a more negative view of the future, compared to days on which people have an identical view of the future. Theoretical models of Karpoff (1986), Harris and Raviv (1993) and Banerjee and Kremer (2010) indeed predict that higher disagreement is associated with more trading. For example, in Banerjee and Kremer (2010), traders agree to disagree, which means that they do not fully update their beliefs based on other traders' decisions. In their model, trading volume reflects revisions to the level of disagreement, and periods of high disagreement are related to higher volume. Because higher disagreement also

[1] The level of sentiment is typically estimated by using household survey data (Brown and Cliff, 2004; Lemmon and Portniaguina, 2006; Qiu and Welch, 2006, Schmeling, 2009; Kaplanski et al., 2014), economic and financial variables (Lee et al., 1991; Baker and Wurgler, 2007; Brown et al., 2008), social media (Bollen et al., 2011; Karabulut, 2014; Siganos et al., 2014), the weather (Saunders, 1993; Hirshleifer and Shumway, 2003), or sport results (Edmans et al., 2007; Kaplanski and Levy, 2010).

leads to higher absolute price changes, their model further predicts a positive relation between disagreement and stock price volatility.[2]

Potential divergence of sentiment within a nation could result from various factors. For example, a national sports event might divide the nation, the weather might vary within the nation, or the nation might experience high temperatures, which are preferred by some but not by others. In addition, divergence of sentiment is likely as people's sentiment might be driven by relatively random factors like a good night's sleep, and different people might respond to different factors – some care more about sports, while others care more about the weather.

To capture the divergence of sentiment in a nation, we examine status updates on Facebook. Facebook is the world's largest social network site, with about 40 million status updates per day (Kramer, 2010). These status updates are informative about sentiment, which is defined by *investorwords.com* as "a measurement of the mood of a given investor or the overall investing public, either bullish or bearish." Because Facebook's Data Team records both the daily appearance of positive and negative words in status updates, we are able to construct a measure of divergence of sentiment. Importantly, sentiment on Facebook is likely to capture investor sentiment as participation rates on Facebook are very high (Siganos et al., 2014). Although many Facebook users are relatively young, the average age is about 31 years (Kramer

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[2] On the other hand, in many other asset-pricing models trading volume is caused by unanticipated liquidity and portfolio balancing needs of investors (Hong and Stein, 2007), and differences of opinion should then be less relevant. In fact, the no-trade theorem of Milgrom and Stokey (1982) states that disagreement does not induce trading but leads to a revision of market beliefs as each trader considers why other traders might be willing to trade at a particular price.

and Chung, 2011), with more than a quarter of Facebook users older than 45, and less than ten percent younger than 18. It is also important to note that although investors may be underrepresented on Facebook, factors that make Facebook users' sentiment more diverse, like the outcome of the Super Bowl, are also likely to have differential effects on the sentiment of investors.

We obtain the divergence of sentiment on Facebook for 20 countries during the period from September 2007 to March 2012, and find that high divergence of sentiment is positively related to contemporaneous trading volume and stock price volatility. In addition, as status updates also occur after the close of trading, we show that our divergence of sentiment measure is related to trading volume and volatility on the next trading day. These results hold for different regions and are robust to controlling for the level of sentiment.

Our results add to the behavioral finance literature by highlighting the importance of divergence of sentiment rather than the level of sentiment. Other studies have focused on sentiment levels. For example, Chang et al. (2008) find that cloudy weather is related to high transaction volumes, and Brown (1999) and Lee et al. (2002) find that unusual high levels of sentiment are associated with high volatility. We corroborate findings of earlier studies on the effects of the level of sentiment, but document that the effect of divergence goes beyond this initial effect.

The main strengths of using Facebook data are the availability of daily data and the extremely high number of participants. Alternative sources such as surveys typically have to rely on monthly data, which highly complicates testing contemporaneous relations between sentiment and stock markets. Surveys also have to rely on a much smaller set of respondents. For example, the Michigan Consumer Sentiment survey is distributed to 500 households and the Consumer Confidence Index to 5,000 households. Our measure is based on millions of participants and is available every day. When we were reading through Facebook status updates, it also quickly became clear that these updates indeed predominantly represent people's mood, rather than events with potentially important effects on the economy.[3] Moreover, Facebook data allows us to study the relations in an international setting as over 80% of Facebook users reside outside of the United States (Wilson et al., 2012).

We also 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.[4] We differ from these studies by specifically focusing on differences in sentiment, rather than on, for example, opinions on earnings announcements. 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.

[3] We checked all the status updates of our Facebook friends over January 2013 and observed that less than one percent of the updates relate to an event with potentially important effects on the economy. Much more popular are sporting events. For example, the 2014 World Cup led to more than one billion Facebook interactions, consisting of status updates and reactions to these updates (http://newsroom.fb.com/news/2014/06/world-cup-2014-facebook-tops-a-billion-interactions/).

[4] Differences of opinion have been measured in several ways. Ajinkya et al. (1991), Diether et al. (2002), and Berkman et al. (2009) measure divergence of opinion by using the dispersion of analyst forecasts, Bessembinder et al. (1996) use open interest on index futures, Goetzmann and Massa (2005) use data from investor accounts, Giannini et al. (2014) focus on Twitter posts on particular stocks around earnings announcements, Antweiler and Frank (2004) and Kim and Kim (2014) examine Internet postings on, for example, Yahoo! Finance, and Li and Li (2011) focus on disagreement on macroeconomic variables based on a household investor survey.

Finally, our results contribute to the literature on the determinants of trading volume and stock price volatility (see, for example, Karpoff, 1987). An understanding of the drivers of trading volume and stock price volatility is important for forecasting, derivatives pricing, risk management, and financial market regulation. We show that divergence of sentiment is a significant determinant of the probability of trade and the volatility of stock markets.

The remaining of the paper is structured as follows. Section II describes our data, and we discuss our results in Section III. Section IV concludes this study.

II. Data

We download daily positive and negative sentiment data from Facebook, which are available for 20 international markets. Facebook constructs these sentiment indexes by analyzing the percentage of positive and negative status update terms as defined in the Linguistic Inquiry and Word Count Dictionary.[5] A defining feature of status updates is that they are self-descriptive messages, and are not directed by any question from a researcher.[6] Karabulut (2014) and Siganos et al. (2014) find that the level of sentiment on Facebook is positively related to other sentiment indexes, including the Google sentiment index of Da et al. (2014).

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

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[5] For further details on Facebook's sentiment index, see Kramer (2010), Karabulut (2014) and Siganos et al. (2014).

[6] Facebook users write their status updates in a box that contains an open question, which is typically: "How are you feeling?", "How are you doing?", "What's on your mind?", or "How is it going?"

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

where $DoS_{i,j}$ is the daily divergence of sentiment of a country j on day i, $x_{p,i}$ and $x_{n,i}$ show the average positive (p) and negative (n) words used respectively on day i for the country, and $x_{p,all}$, $x_{n,all}$ $\sigma_{p,all}$, $\sigma_{n,all}$ are the average (x) positive and negative words used over the duration of the index and the standard deviation (σ) of those variables.[7] We exclude the top 1% of daily sentiment values, commonly related to days with many status updates such as "Happy Mother's day", before estimating *DoS*.

Facebook's Data Team provides us with the standardized positive and negative sentiment scores per day per country. The reason for estimating divergence of sentiment as the absolute difference between these scores is straightforward, as we want our score to reflect the distance between the positive sentiment 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 be relatively high. On the other hand, if a given day in a particular country is associated with an above average number of positive status updates and a below average number of negative status updates, our divergence measure will be relatively low.

Table 1 shows the list of countries used in our study and the descriptive statistics for *DoS*. We have one observation for *DoS* per country per day. We find that *DoS* varies from zero to

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[7] Facebook's Data Team excludes the high and low 10% of the days when estimating $x_{p,all}$, $x_{n,all}$ $\sigma_{p,all}$, $\sigma_{n,all}$, to minimize the impact of extreme values on the estimation of daily sentiment levels.

about 0.2. India has the highest average divergence of sentiment in our sample. As most countries are from either America or Europe, we also report statistics for these continents separately.

[please insert Table 1 here]

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 GARCH(1,1), which contains a constant element and one lag in stock returns (Bollerslev, 1986).

III. Empirical Results

A. The relation between divergence of sentiment and trading volume

We first examine whether divergence of sentiment is related to trading volume. In a world in which sentiment matters, it seems intuitive that people are more willing to trade with one another when sentiment is diverse. We pool countries and focus first on contemporaneous relations. Our regression analyses include country and day-of-the-week 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 cluster standard errors by date to control for correlation in our variables across countries.

[please insert Table 2 here]

Table 2 shows the results when pooling all countries. We find that there is a strong positive relation between *DoS* and trading volume. The parameter coefficient is 0.825 and the effect is statistically significant at the 1% level. Hence, a one standard deviation increase in divergence of sentiment is, on average, related to a contemporaneous daily increase in trading volume of 0.825 standard deviations. These results are in line with theoretical propositions by disagreement models (e.g., Karpoff, 1986; Harris and Raviv, 1993; Banerjee and Kremer, 2010), which suggests that propositions in the disagreement literature can be applied in the sentiment literature.

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 continents. In short, diverging sentiment corresponds to a relatively high transaction volume in stock markets.

To obtain more insights into causality, we further examine the relation between the divergence of sentiment on day *t* and trading volume on day *t+1*. In doing so, we exploit status updates in the evening. Vitrue (2010) reports that Facebook activity is still high at 8 pm, i.e., after the close of the stock market. Therefore, divergence of sentiment resulting from, for example, an evening's sport event may be reflected in the next day's trading activity. We report the relation between our divergence of sentiment measure and next day's trading volume in Table 3. We find that the parameter coefficient of *DoS* is again significantly positive. This finding is representative of our overall sample, our American sample, and our European sample.

[please insert Table 3 here]

B. The relation between divergence of sentiment and volatility

This section examines the relation between divergence of sentiment and stock price volatility. The reason to examine stock price volatility originates from Harris and Raviv (1993) and Banerjee and Kremer (2010), who argue that higher disagreement leads to higher absolute price changes, which implies a positive relation between disagreement and stock price volatility. In addition, volatility is likely to increase as divergence of sentiment could increase the number of noise traders. We measure stock market volatility with the GARCH(1,1) model, and again our regression analyses include country fixed effects, day-of-the-week fixed effects, three lags on returns and volatility, and standard errors clustered by date.

Table 4 shows the parameter coefficients. We find that our divergence of sentiment measure is positively related to stock price volatility. The coefficient is 0.034 and statistically significant at the 1% level. This relation is economically significant, indicating that a one standard deviation increase in sentiment divergence is, on average, related to a contemporaneous daily increase in volatility of 3.4 basis points. We also report the results for America and Europe. We find a coefficient of 0.018 for countries in America, and a coefficient of 0.041 for countries in Europe, and both effects are statistically significant.

[please insert Table 4 here]

Table 5 reports our results when we use a one-day lag, and thus examines whether divergence of sentiment today affects stock market volatility tomorrow. Results are statistically significant at the 1% level for our sample and sub-samples. These results offer further credence to the relation between divergence and stock price volatility and limit concerns of potential reversed causality.

[please insert Table 5 here]

C. *Results after controlling for sentiment levels*

In this section, we add the level of sentiment to our analysis. Status updates on Facebook can be used to create a sentiment level index by subtracting the standardized negative sentiment levels on a day from the standardized positive sentiment levels that day. Karabulut (2014) and Siganos et al. (2014) argue that Facebook's sentiment level could affect financial markets. In fact, 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 from psychology that temporary pessimism could cause investors to trade more 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, and Brown (1999) and Lee et al. (2002) find that unusual high levels of sentiment are associated with high volatility. The goal of including the sentiment level in our analysis is to examine whether the effect of the divergence of sentiment is an effect beyond the effect of the level of sentiment.

[please insert Table 6 here]

Table 6 includes both the divergence of sentiment measure and a sentiment level measure in one regression specification, along with the control variables that we used earlier. We examine both trading volume and stock price volatility and estimate parameter coefficients for contemporaneous and for one-day lag regressions. Panel A of Table 6 reports the results for trading volume. Most importantly, we find that the effect of the divergence of sentiment remains positive and economically and statistically significant after controlling for the level of sentiment.

This is the case for both contemporaneous trading volume and trading volume on the next day. Sentiment levels are negatively related to trading volume, corroborating results of Chang et al. (2008) and Siganos et al. (2014).

The results in Panel B show that controlling for the level of sentiment does not change our main conclusion that divergence of sentiment is positively related to stock price volatility. For our overall sample, the relation is even statistically significant at the 1% level. Overall, our results suggest that divergence of sentiment and the level of sentiment capture different phenomena, which highlights the importance of examining the divergence of sentiment beyond examining sentiment levels.

IV. Conclusion

This study contributes to the behavioral finance field by highlighting the divergence of sentiment. We exploit Facebook data offering daily optimistic and pessimistic sentiment levels across 20 international markets and measure divergence as the distance between the optimistic and pessimistic levels of sentiment.

We base our predictions for the effects of the divergence of sentiment on the difference of opinion literature. Theoretical models of Karpoff (1986), Harris and Raviv (1993), and Banerjee and Kremer (2010) predict that higher disagreement is associated with more trading. 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, which also follows from the difference of opinion literature. We observe a positive relation between divergence of sentiment and stock price volatility.

Our findings indicate that sentiment can affect stock market trading, and show that some of these effects are not only due to an average level of sentiment. In fact, the average level of sentiment seems to hide an important dispersion in people's sentiment. Furthermore, our results suggest that previously developed propositions in the disagreement literature apply to the behavioral field, and we provide an additional determinant of trading volume and stock price volatility.

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Table 1. Descriptive statistics of divergence of sentiment

	N	Mean	Median	Stdev	Min	Max
All	21179	0.030	0.017	0.033	0.000	0.214
America	7357	0.030	0.012	0.037	0.000	0.214
Europe	8695	0.025	0.017	0.024	0.000	0.148
Argentina	991	0.039	0.016	0.042	0.000	0.165
Australia	1018	0.031	0.019	0.028	0.000	0.097
Austria	1006	0.022	0.016	0.020	0.000	0.108
Belgium	1117	0.038	0.030	0.030	0.000	0.148
Canada	1002	0.023	0.014	0.021	0.000	0.089
Chile	1085	0.029	0.011	0.039	0.000	0.168
Colombia	1068	0.028	0.010	0.039	0.000	0.192
Germany	1120	0.017	0.011	0.016	0.000	0.088
India	1091	0.072	0.056	0.054	0.000	0.213
Ireland	1019	0.034	0.029	0.026	0.000	0.123
Italy	1102	0.009	0.004	0.012	0.000	0.105
Mexico	1081	0.027	0.014	0.030	0.000	0.156
Netherlands	1119	0.033	0.025	0.025	0.000	0.112
New Zealand	1008	0.034	0.024	0.028	0.000	0.102
Singapore	1011	0.037	0.017	0.037	0.000	0.162
South Africa	999	0.020	0.013	0.019	0.000	0.093
Spain	1109	0.031	0.024	0.023	0.000	0.107
UK	1103	0.020	0.014	0.017	0.000	0.104
US	1087	0.026	0.014	0.023	0.000	0.085
Venezuela	1043	0.036	0.010	0.051	0.000	0.214

This table shows descriptive statistics for our divergence of sentiment measure (*DoS*). *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. Our sample period is between September 2007 and March 2012.

Table 2. Divergence of sentiment and contemporaneous trading volume

	All	America	Europe
	Dependent: Volume{t}		
DoS{t}	0.754***	1.571***	1.230**
	(0.215)	(0.266)	(0.485)
Volume{t-1}	0.450***	0.390***	0.486***
	(0.011)	(0.014)	(0.018)
Volume{t-2}	0.167***	0.160***	0.154***
	(0.010)	(0.015)	(0.018)
Volume{t-3}	0.131***	0.136***	0.126***
	(0.010)	(0.014)	(0.016)
Return{t-1}	-2.402***	-1.990***	-2.770***
	(0.474)	(0.677)	(0.650)
Return{t-2}	-0.976**	-0.683	-1.071*
	(0.464)	(0.627)	(0.634)
Return{t-3}	-0.602	-0.387	-0.506
	(0.470)	(0.666)	(0.662)
Intercept	0.072	-0.140	0.318***
	(0.077)	(0.086)	(0.116)
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	21119	7336	8671
adj. R-sq	0.481	0.394	0.547

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. Our sample period is September 2007 to March 2012. 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 next day's trading volume

	All	America	Europe
	Dependent: Volume{t}		
DoS{t-1}	1.042***	2.046***	1.514***
	(0.241)	(0.278)	(0.527)
Volume{t-1}	0.342***	0.291***	0.360***
	(0.011)	(0.015)	(0.018)
Volume{t-2}	0.151***	0.148***	0.139***
	(0.011)	(0.015)	(0.019)
Volume{t-3}	0.179***	0.168***	0.188***
	(0.011)	(0.014)	(0.017)
Return{t-1}	-2.074***	-1.295*	-2.541***
	(0.537)	(0.714)	(0.726)
Return{t-2}	-1.225**	-0.831	-1.232*
	(0.523)	(0.751)	(0.721)
Return{t-3}	-1.347**	-0.855	-1.746**
	(0.523)	(0.721)	(0.714)
Intercept	-0.148**	-0.314***	0.097
	(0.075)	(0.084)	(0.092)
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	21099	7329	8663
adj. R-sq	0.390	0.319	0.449

This table shows whether one-day lagged divergence of sentiment (*DoS*) is related to trading volume. The parameter estimate represents the coefficient of regressing daily standardized trading volume on our daily *DoS* measure. Our sample period is September 2007 to March 2012. 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. Divergence of sentiment and contemporaneous stock price volatility

	All	America	Europe
	Dependent: Volatility{t}		
DoS{t}	0.033***	0.018**	0.041***
	(0.009)	(0.007)	(0.015)
Volatility{t-1}	0.689***	0.655***	0.690***
	(0.074)	(0.078)	(0.093)
Volatility{t-2}	-0.045	0.001	-0.071
	(0.050)	(0.060)	(0.068)
Volatility{t-3}	-0.002	0.026	0.009
	(0.041)	(0.046)	(0.055)
Return{t-1}	-0.013	-0.043	0.016
	(0.064)	(0.090)	(0.082)
Return{t-2}	-0.056	-0.118**	-0.047
	(0.040)	(0.050)	(0.053)
Return{t-3}	0.009	0.034	0.014
	(0.044)	(0.053)	(0.053)
Intercept	0.007***	0.003*	0.007**
	(0.002)	(0.002)	(0.003)
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	20079	6296	8671
adj. R-sq	0.530	0.533	0.495

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 using GARCH(1,1), on our daily *DoS* measure. Our sample period is September 2007 to March 2012. All regressions include day-of-the-week, week, month and country fixed effects. We report standard errors clustered by date, as shown in parenthesis. ** and *** indicate statistical significance at the five and one percent levels, respectively.

Table 5. Divergence of sentiment and next day's stock price volatility

	All	America	Europe
	Dependent: Volatility{t}		
DoS{t-1}	0.055***	0.032***	0.063***
	(0.010)	(0.008)	(0.016)
Volatility{t-1}	0.428***	0.410***	0.409***
	(0.081)	(0.091)	(0.101)
Volatility{t-2}	-0.123*	-0.045	-0.177**
	(0.070)	(0.080)	(0.089)
Volatility{t-3}	0.135**	0.135**	0.207***
	(0.055)	(0.068)	(0.067)
Return{t-1}	-0.073	-0.150*	-0.045
	(0.066)	(0.086)	(0.083)
Return{t-2}	-0.032	-0.040	-0.025
	(0.049)	(0.063)	(0.061)
Return{t-3}	-0.152***	-0.187***	-0.156***
	(0.049)	(0.066)	(0.054)
Intercept	0.014***	0.007***	0.014***
	(0.002)	(0.002)	(0.003)
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	20060	6290	8663
adj. R-sq	0.318	0.343	0.275

This table shows whether one-day lagged divergence of sentiment (*DoS*) is related to stock price volatility. The parameter estimate represents the coefficient of regressing a daily measure of volatility, as estimated by using GARCH(1,1), on our daily *DoS* measure. Our sample period is September 2007 to March 2012. 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 6. Results after controlling for sentiment

Panel A. Trading volume

	All	America	Europe	All	America	Europe
	Dependent: Volume{t}			Dependent: Volume{t}		
DoS{t}	0.628***	1.738***	1.103**			
	(0.235)	(0.320)	(0.493)			
DoS{t-1}				0.994***	2.183***	1.505***
				(0.260)	(0.328)	(0.532)
Sentiment{t}	-0.472	0.565	-0.784*			
	(0.317)	(0.612)	(0.453)			
Sentiment{t-1}				-0.179	0.464	-0.053
				(0.368)	(0.625)	(0.472)
Volume{t-1}	0.450***	0.390***	0.486***	0.342***	0.290***	0.360***
	(0.011)	(0.014)	(0.018)	(0.011)	(0.015)	(0.018)
Volume{t-2}	0.167***	0.160***	0.154***	0.151***	0.147***	0.139***
	(0.010)	(0.015)	(0.018)	(0.011)	(0.015)	(0.019)
Volume{t-3}	0.131***	0.135***	0.126***	0.179***	0.167***	0.188***
	(0.010)	(0.014)	(0.016)	(0.011)	(0.014)	(0.017)
Return{t-1}	-2.393***	-2.003***	-2.746***	-2.070***	-1.305*	-2.540***
	(0.473)	(0.678)	(0.649)	(0.537)	(0.714)	(0.726)
Return{t-2}	-0.970**	-0.691	-1.058*	-1.223**	-0.838	-1.231*
	(0.464)	(0.628)	(0.635)	(0.523)	(0.752)	(0.721)
Return{t-3}	-0.593	-0.396	-0.479	-1.344**	-0.862	-1.744**
	(0.471)	(0.667)	(0.664)	(0.523)	(0.722)	(0.714)
Intercept	0.077	-0.145*	0.320***	-0.146*	-0.318***	0.097
	(0.076)	(0.085)	(0.114)	(0.075)	(0.083)	(0.092)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-the-week fix. effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	21119	7336	8671	21099	7329	8663
adj. R-sq	0.481	0.394	0.547	0.390	0.319	0.449

Panel B. Stock price volatility

	All	America	Europe	All	America	Europe
	Dependent: Volatility{t}			Dependent: Volatility{t}		
DoS{t}	0.023***	0.009	0.033**			
	(0.008)	(0.007)	(0.014)			
DoS{t-1}				0.040***	0.022***	0.052***
				(0.010)	(0.008)	(0.016)
Sentiment{t}	-0.040***	-0.031***	-0.048***			
	(0.008)	(0.010)	(0.011)			
Sentiment{t-1}				-0.056***	-0.037***	-0.072***
				(0.009)	(0.011)	(0.014)
Volatility{t-1}	0.688***	0.654***	0.689***	0.427***	0.409***	0.407***
	(0.074)	(0.078)	(0.093)	(0.081)	(0.091)	(0.101)
Volatility{t-2}	-0.045	0.001	-0.071	-0.123*	-0.045	-0.178**
	(0.050)	(0.060)	(0.068)	(0.070)	(0.080)	(0.089)
Volatility{t-3}	-0.003	0.025	0.008	0.133**	0.134**	0.206***
	(0.041)	(0.046)	(0.055)	(0.055)	(0.068)	(0.067)
Return{t-1}	-0.012	-0.041	0.017	-0.072	-0.149*	-0.042
	(0.064)	(0.090)	(0.082)	(0.066)	(0.086)	(0.082)
Return{t-2}	-0.055	-0.117**	-0.046	-0.031	-0.039	-0.023
	(0.040)	(0.050)	(0.053)	(0.049)	(0.063)	(0.061)
Return{t-3}	0.010	0.035	0.016	-0.151***	-0.186***	-0.153***
	(0.044)	(0.053)	(0.052)	(0.049)	(0.066)	(0.054)
Intercept	0.007***	0.003*	0.007**	0.014***	0.007***	0.015***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-the-week fix. effects	Yes	Yes	Yes	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
N	20079	6296	8671	20060	6290	8663
adj. R-sq	0.531	0.533	0.496	0.319	0.344	0.277

This table shows whether divergence of sentiment (*DoS*) is related to trading volume and stock price volatility after controlling for the level of sentiment. The parameter estimate represents the coefficient of regressing a daily measure of standardized trading volume or volatility estimated by using GARCH(1,1) on our daily *DoS* measure. We estimate regressions when analyzing variables in contemporaneous frequency and with a one-day lag. Our sample period is September 2007 to March 2012. 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.