Social Sentiment and Stock Trading via Mobile Phones

Completed Research Paper

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Abstract

What happens when uninformed investors trade stocks via mobile phones? Do they react to social sentiment differently than more informed traders in traditional trading? Based on 16,817 data observations and econometric analysis for the trading of 251 equities in Korea over 39 days, we present evidence of herding behavior among uninformed traders in the mobile channel. The results indicate that mobile traders seem more easily swayed by changing social sentiment. In addition, stock trading in the traditional channel probably influences sentiment formation in the market overall. Mobile traders follow signals in social media suggesting that they engage in less beneficial herding behavior, based on evidence that we obtained for the occurrence of more negative feedback trading. This allows us to offer a new interpretation of how mobile channel stock trading works, and open a new portal for analytics with digital data related to the trading behavior of different investors.

Keywords

Econometric analysis, herding behavior, investor reactions, machine learning, mobile channel, social media, social sentiment, stock trading, uninformed traders, value traders.

Introduction

The impact of investor sentiment on stock markets has been widely studied in Finance. This is interesting for IS research, since the new capabilities for investment-related trading have been made possible with IT innovations. Prior studies, such as Baker and Wurgler (2007), investigated the impact of sentiment on asset pricing patterns. Also, Brown and Cliff (2004) assessed investor sentiment, identifying *direct sentiment measures* based on surveys and *indirect sentiment measures* relying on objective variables. Their study shows that individual investors are easily swayed by social sentiment. Other studies have supported this finding. Institutional investors perform better than individual investors because the latter are at an informational disadvantage and make irrational decisions (Barber et al. 2009). Investors can be *informed value traders*, rationally anticipating asset value, or *uninformed traders* (referred to as *noise traders* in Finance), reacting irrationally to changing sentiment, causing persistent mispricing (De Long et al. 1990).

Important news does not explain the large market returns that occur when macroeconomic events are absent (Cutler et al. 1989). Yet there are interesting relationships between communication activity and stock trading volumes (Coval and Shumway 2001; Antweiler and Murray 2004). The ability of social media to inform decision-makers depends on how sentiment is measured and analyzed. Past studies used data from Twitter (Toubia and Stephen 2013), message boards (Godes and Mayzlin 2004), and product reviews (Moe and Trusov 2011). Such research identified performance measures, such as sales (Moe and Trusov 2011), ROI (Hoffman and Fodor 2010), and stock prices (Tirunillai and Tellis 2012).

With social media, most news spreads through mobile devices. Twitter has been more appropriate for mobile users than other Internet platforms. Facebook announced in 2013 that 78% of U.S. users were in the mobile channel. So a question arises: Are mobile investors affected by social media news? Uninformed traders are known to lose money by trading on social signals. They are not as fast as *high-frequency* (HFT) *traders*, who trade in millisecond intervals. Investors who trade on uniformative market signals may lose out to faster arbitrageurs. Yet many investors still have become involved in trading via mobile phones.

We will study what happens with stock trading when mobile phones are involved. How do uninformed traders on mobile phones react to sentiment? Do they react differently compared to traders in the traditional market? We explore the relevant theory and conduct empirical research to see what is going on. Hereafter, we will cover research related to sentiment and mobile trading, and our research objectives. We then present our data and variables, and discuss our analysis approach, and what the results it can produce. We close with a discussion of our findings, and theoretical and practical implications.

Research Context

The impact of investor sentiment on stock markets and sentiment posted in social media are known to influence returns and asset valuation, and information disclosure and market reactions to announcements (Baker and Wurgler 2007). Social media marketing research further suggests that consumer posting, social networks and social influence must be considered (Schweidel and Moe 2014). There is also a link between social media and various performance measures, and changes in social sentiment based on tweets posted in Twitter.com are correlated with the changes in the values of the Dow-Jones Industrial Average (DJIA) that occurred 3 or 4 days later (Bollen et al. 2011). Social media is known to predict different kinds of outcomes in the world. And sentiment is significant in predicting returns for large companies, though the effect was not observed for small firms (Brown and Cliff 2005).

Mobile communications play an important role in trading stocks. The benefits are potentially large because mobile phones give clients more control over their day-to-day orders and bid-ask quotes in near real-time. Over time, investors have begun to buy and sell stocks through the mobile channel. The growth in such trading is natural due to IT advances that have made the speed and reliability between trading by phone or PC indistinguishable, though the channel is slow relative to HFT trading, and the much more direct connections of market brokers and institutions. Still, many non-professional traders have grown accustomed to the mobile channel and are eager to control their accounts this way. Mobile trading offers investors specific benefits, such as near real-time financial market information, account inquiries, and automated execution without human brokers regardless of the investor's location. Also, under the current rules of most markets across the world, investors are increasingly guaranteed that their trades will be sent to market on a *best-execution basis*, unaffected by *preferencing* and *front-running* for other customers.

Research Objectives

Mobile technology provides an important communication channel in facilitating social connections, allowing people to create, develop, and strengthen social ties. Much like social network sites on the Internet, these services help users to build networks to share information. The lack of studies on social sentiment and mobile technology related to financial markets encouraged us to study if uninformed traders in the mobile channel react differently than those who use value-based, *buy-and-hold strategies*.

Uninformed traders participate more in financial markets due to easy access to financial information (Looney et al. 2004), driven by diminished transaction costs. They exhibit increased *herding*, when an investor sets aside private information and follows the pack, leading to the mispricing of securities (Bikhchandani and Sharma 2000, Chang et al. 2000), and *positive feedback trading*, which involves the illogical actions of *buying in up-markets* and *selling in down-markets* (Barber and Odean 2001). Such uninformed traders may respond to changes in market sentiment that are not fully justified by the available information, and for which the apparent trends may only be transitory and impermanent.[1]

Social media permits people to communicate their feelings and emotions, and characterize those of people close to them. *Collective social sentiment*, as a result, is based on the aggregate expression of people in a society over time. We examine if such sentiment is different each day from the cumulative sentiment, and how mobile channel users react to each. We ask: Do uninformed traders react to sentiment for a traded

[1] Uninformed traders tend to chase unconsolidated trends, contrasting with Warren Buffet-style value-focused investing. Individual investor behavior has been viewed as *biased decision-making under uncertainty* (Hirshleifer 2001).

stock more than informed traders do? What evidence suggests herding behavior among uninformed traders? Are there patterns of positive feedback trading due to changes in sentiment? Our research design permits us to examine the reaction patterns of uninformed traders to social sentiment.

Data and Variables

Based on the assumption that most financial markets have similarities for trading via the mobile channel, we collected stock trade volumes in the Korean market culled from traditional and mobile platforms. We used sentiment posted in social media, such as Twitter and blogs, for May through September 2012. We focused on 251 firms discussed in social media.[2] The firms are divided into two groups listed on the Korean Exchange (KRX): the 125 largest and another 126 in terms of business size. We divided them into IT and non-IT firms, and by index categories of the Korean Composite Stock Market Index (KOSPI) and Korean Dealers Association Automated Quote System (KOSDAQ). This classification may uncover nuanced results for the changing impact of social sentiment on the observed stock trading volumes over time.

We expect stratification-driven differences between the firm-size segments, since they are different kinds of investments. Moreover, IT companies are likely to be responsive to public opinion, and smaller firms more vulnerable to unanticipated changes in sentiment. The data include the number of negative and positive words, and posts that occur about a firm. To assess the content of the data, we used an opinion-mining procedure. This supports discerning the social sentiment about certain products by building systems to understand the public conversations happening around the products. Current social sentiment tracking techniques can extract sentiment indicators from Twitter and blog posts.[3]

- *Stock trading volume.* To examine the impact of technology on an individual firm's stock trading volumes for social sentiment, we measured trading volume and sentiment across the platforms.

- *Firm-related posting frequency. Unobserved common factors*, such as news that may influence stock markets and public sentiment, are a challenge in empirical research. Many investors rely on such factors when they make decisions, and major news is positively correlated with stock prices.[4,5]

- *Social media sentiment.* The independent variables are related to sentiment. We further examine whether sentiment affects stock trading volume. Positive sentiment represents a good or positive response towards company. So sentiment about profit, improvement, innovativeness, new concepts – with 200 different words in all – are related to business progress. Negative sentiment is classified as showing a negative response or opposition to something. Recession, faults, illegality, losses, deficit -- altogether about 184 words -- are associated with roadblocks for business development.

- *Controls.* We applied three dummy variables to control for confounding factors. They categorize companies for business scale, IT focus, and the markets where they trade (KOSPI and KOSDAQ).

Research Model Development

Generalized Least Squares and Granger Causality Test

We modeled the impact of social sentiment on stock trading volume not explained by overall market reac-

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[2] For the baseline analysis, we used 16,817 observations (17,068 for 68 days × 251 firms, log differences for non-stationarity). For machine learning, we used 39 days for the marginal effect of social sentiment for KRLS over time.
[3] We used a social matrix program to mine text messages, reflecting the opinions of online users in social media.
[4] A possible approach is to examine *StockTradingVolume* differences over time, to associate them as abnormal activity in the traditional versus the mobile channel. Another consideration is the sample. It might be possible to take advantage of *a full market-wide sample* in different ways. Although this would require the collection of much more data, which we have not done (e.g., more firms beyond those we have selected, over a longer period of time). We have work-in-progress on the approach with differences, and will report on its results at AMCIS.
[5] Financial news articles may affect stock trading and public sentiment at the same time. If common factors are not properly handled, then our estimation will be biased because of omitted variables. So if any information for a publicly-traded company is posted in social media, it implies that the firm is experiencing some kind of newsworthy event. We use the number of daily posts that occur for such firms to proxy for unobserved factors.

tions. We first tested for *unit roots* (stationary variables) in our panel data. We conducted the *Harris–Tzavalis* (1999) *test* based on an augmented *Dickey-Fuller test* for whether there is a unit root at some level of significance. The former test indicated that some variables appeared to be non-stationary. So we created new variables involving percentage changes to estimate the non-spurious effects of social sentiment in parallel with normal market returns.[6]

$$\begin{aligned} StockTradingVolume_{it} = {} & \beta_0 + \beta_{Industry\text{-}Level}\,(Dummy\ factors\!: Size_t,\ Industry_t,\ Market_t) \\ & + \beta_{Industry\text{-}Level}\,(Normal\ returns\ factor\!: MarketTradingVolume_t) \\ & + \beta_{Firm\text{-}Level}\,(Common\ factors\!: Frequency_{it},\ Cumulative_{it}) \\ & + \beta_{Firm\text{-}Level}\,(Social\ sentiment\ factors\!: Positive_{it},\ Negative_{it},\ Cumulative_{it}) \\ & + u_i\,(Unobserved\ fixed\ effects\ for\ firm\ i) + \mu_t\,(Unobserved\ fixed\ effects\ for\ time\ t) \\ & + \varepsilon_{it}\,(Residuals)\ \text{with}\ \varepsilon_{it} = \rho\varepsilon_{it-1} + \varphi_{it}\ \text{and}\ \varphi_{it} \sim N(0, \sigma^2) \end{aligned}$$

Another concern is the possibly endogenous relationship between stock trading volumes and social sentiment, which may involve *reverse causality*.[7] This led us to apply a Granger causality test.

Kernel Regularized Least Squares

Generalized least squares (GLS) is easy to use and interpret even though the method imposes stringent assumptions that sometimes are not accurate for data in real-world settings. For example, one assumption is that the marginal effects of the explanatory variables are constant. *Kernel regularized least squares* (KRLS) imposes a different assumption though, and one that is better in our research design: observations with similar values of their variables ought to have similar outcomes on average. This reduces misspecification bias, and avoids the need for guessing the underlying functional form for the relationships.[8] For the bigger picture related to our empirical methods choices, the interest reader should see the Appendix.

Results

The Impact of Social Media Sentiment on *StockTradingVolume*

We next report on the results in Table 1. They depict the effects of social sentiment on *StockTradingVolume* for individual stocks, when they are not explained by the average market return in a given stock market. By analyzing confounding factors such as *FirmSize*, *Industry* and the *FinancialMarket* used, we examined whether a firm's structure affects the beliefs of investors about the reaction of *StockTradingVolume* to shifting sentiment. Our analysis did not suggest that these variables mattered though.

Our other results more closely match the theory we offered earlier. The first significant variable is *MarketTradingVolume* for KOSPI and KOSDAQ, which controls for differences between the market trading volume levels and captures the normal return beta. The remaining variables are common factor (*Frequency*) and social sentiment variables (*Positive, Negative*). Higher social media exposure *Frequency* appears to have increased traditional and mobile channel trading volumes ($\beta_{Frequency}$ = 0.140 in the traditional channel, 0.103 in the mobile channel, and 0.122; all with $p < 0.01$). The test results indicate that the impact of daily sentiment on *StockTradingVolume* was only marginally significant, so we will not discuss the coefficient estimates. All else equal, the higher the *Frequency* of a firm's exposure is in social media, the more its *StockTradingVolume* will increase, consistent with the results of Bollen et al. (2011). *Positive* sen-

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[6] We took the difference between ln(*StockTradingVolume*) on days t and t - 1. We estimated each analysis using *ordinary least squares* (OLS) to obtain multicollinearity statistics: *variance inflation factor* (VIF) and *condition index* (CI). The results showed multicollinearity was not a problem (VIFs < 2.0 and CIs < 3.8. We also considered unobserved firm and time effects to assess social sentiment impact. We used tests for autocorrelation and heteroskedasticity, and *feasible generalized least squares* (FGLS) for unobserved fixed effects.

[7] $|\rho|$ is less than 1 and φ_{it} is independent and identically-distributed with mean zero and variance σ^2. We used the *autocorrelation parameter*, $\rho = (\varepsilon' \varepsilon_{t-1} / \varepsilon' \varepsilon)$, where ε is the residuals and ε_{t-1} is the lagged residuals. Our estimations verified the cross-sectional covariance between the panels for different firms. So we specified a heteroskedastic error structure with cross-sectional correlation. We also assumed time-wise autocorrelation, which uses available information to produce a reasonable estimate of the regression coefficients. This works when a time-series is short.

[8] KRLS uses *regularization*, which gives a preference to smoother functions over somewhat more erratic ones. As a result, over-fitting is minimized, and KRLS tends to diminish the influence of outliers (Hainmueller and Hazlett 2014). It also is suitable for modeling problems when the functional form is unknown, and for our exploratory analysis.

timent was associated with increase in the traditional channel and mobile channel *StockTradingVolume* for buy and sell activity ($\beta_{Positive}$ = 0.020, 0.019, 0.039; $p < 0.01$). *Negative* sentiment also increased in the traditional and mobile channel *StockTradingVolumes* ($\beta_{Negative}$ = 0.011, 0.027, 0.019; $p < 0.01$).

Variable	*Traditional Channel StockTradingVolume*	*Mobile Channel StockTradingVolume for Buying Stock*	*Mobile Channel StockTradingVolume for Selling Stock*
FirmSize	-0.039 (0.089)	0.004 (0.109)	-0.018 (0.096)
Industry	0.0319 (0.089)	0.020 (0.113)	0.023 (0.099)
FinancialMarket	0.058 (0.163)	-0.013 (0.093)	0.010 (0.078)
MarketTradingVolume	**0.555***** (0.032)	**0.433***** (0.042)	**0.586***** (0.040)
Frequency	**0.140***** (0.005)	**0.103***** (0.009)	**0.122***** (0.008)
Positive	**0.020***** (0.004)	**0.019***** (0.007)	**0.039***** (0.006)
Negative	**0.010**** (0.004)	**0.027***** (0.007)	**0.019***** (0.007)
CumulativeFrequency	0.033 (0.037)	0.060 (0.063)	-0.055 (0.059)
CumulativePositive	**0.117****(0.025)	0.084 (0.054)	0.052 (0.051)
CumulativeNegative	**-0.071**** (0.032)	**-0.119**** (0.053)	0.002 (0.050)
Constant	-0.010 (0.071)	0.008 (0.081)	-0.006 (0.065)
Observations	16,817	16,817	16,817
Number of firms	251	251	251
χ^2	2,648.4***	523.7***	881.3***
VIF/CI	1.98/3.77	1.97/3.75	1.98/3.76

Note. Dep. var.: Traditional channel trade volume. Variables represent % changes. Wald test, full model: χ^2. Signif.: * = $p < 0.1$; ** = $p < 0.05$ =; *** = $p < 0.01$. No multicollinearity since VIF < 10 and CI < 30.

Table 1. *StockTradingVolume* Responses to Social Sentiment Estimation

We also report stock-related sentiment results (*Positive, Negative*). When mobile traders bought stock, the effect when the sentiment was *Negative* ($\beta_{Negative}$ =0.027) was greater than when it was *Positive* ($\beta_{Positive}$ = 0.019). Also the effect when the sentiment was *Positive* ($\beta_{Positve}$ = 0.039) was greater than when it was *Negative* (0.019) when mobile traders sold stock. When social sentiment was *Positive* there was more cumulative impact on traditional channel *StockTradeVolume* ($\beta_{Positive}$ = 0.117, $p < 0.05$). So the higher was historical *Positive* sentiment about a firm, the smaller was the increase of its *StockTradingVolume*.

Negative social sentiment had a cumulative impact on firm *StockTradingVolume* ($\beta_{Negative}$ = -0.071, $p < 0.05$), so the more negative the sentiment about a firm was over time, the more there was a decrease in its *StockTradingVolume*. The cumulative impact of *Negative* sentiment (β = -0.119, $p < 0.05$) was significant and negative when investors bought stock via mobile phones. This matches research that found people respond more to negative than to positive stimuli (Baumeister 2001).[9]

Panel vector auto regression (PVAR) estimates are seldom interpreted in isolation. Researchers are interested in the impact of exogenous changes in each endogenous variable on other variables in the PVAR system. The results of our Granger causality panel data tests are shown in Table 2.

They indicate that traditional channel *StockTradingVolume* Granger-caused social sentiment (*Frequency, Positive, Negative*), but the reverse appears to have been false. However, sentiment Granger-caused mobile channel *StockTradingVolume* when mobile investors bought stocks; the reverse was false though. Last,

[9] *Neutral social sentiments* can be classified as neither showing support or appreciation nor opposition or denigration of something. We did not directly consider neutral sentiment in our research design, since such posts typically are not directly related to stock trading, though they are informational and provide useful background. We roughly estimated the effects based on (*OverallSentimentFrequency - PositiveSentimentFrequency – NegativeSentimentFrequency*) = *Effect*. We applied this to trading overall in the traditional channel, which yielded (0.14 – 0.02 – 0.01) = 0.11. For buying stock in the mobile channel, the effect was (0.103 – 0.019 – 0.027) = 0.057. For selling stock in this channel, the effect was was (0.122 – 0.039 – 0.019) = 0.064. We are reluctant to draw any strong conclusions from these numbers, other than to note the traditional market effect strength. These estimates are model-free in some sense: we did not design an empirical model that deals with neutral sentiment, since we have no theory on which to base its effects. For example, it may be the case that any neutral sentiment is suggestive of market interest related to the stock, and so there ought to be greater liquidity for it. Another theoretical possibility is that greater neutral interest in the market may precede social media mood swings, such that mobile traders may be more likely to jump into the market and trade when there is either positive or negative sentiment expressed. Our primary observation is that a different research design is probably needed to get to the bottom of this. We thank an anonymous reviewer for part of this insight.

sentiment Granger-caused mobile channel *StockTradingVolume* when investors sold stocks, while the reverse also was true in statistical terms. Thus, we conclude that sentiment had an impact on the *Stock-TradingVolume* in the mobile channel – without reverse causality. We see that uninformed traders were more easily swayed by social sentiment, while more informed traditional channel stock traders were likely to be more influential in sentiment formation in the stock market overall.

Variables		*Traditional Channel TradeVolume*	*Mobile Channel Buy Volume*	*Mobile Channel Sell Volume*
Volume	*Frequency*	2.698	9.702**	3.451
	Positive	5.790	7.464*	14.586**
	Negative	2.254	3.831	2.930
	All	**15.180***	**36.057*****	**34.176*****
Frequency	*Volume*	**28.014*****	5.691	27.129***
	Positive	2.716	2.631	2.577
	Negative	**6.986***	**7.268***	**7.030***
	All	**37.424*****	**15.059***	**36.655*****
Positive	*Volume*	27.789***	4.756	21.124***
	Frequency	**91.298*****	**95.987*****	**94.079*****
	Negative	1.931	2.043	1.810
	All	**130.721*****	**108.533*****	**125.346*****
Negative	*Volume*	9.261**	0.740	**15.504*****
	Frequency	**61.219*****	**66.192*****	**64.437*****
	Positive	4.008	3.555	3.851
	All	**92.335*****	**82.919*****	**98.706*****

Note. 251 firms. Variables represent % changes. Signif.: * = p < 0.1; ** = p < 0.05; *** = p < 0.01.

Table 2. Granger Causality Results for Panel Data

Herding behavior occurs during periods of extreme market fluctuation. If individual traders copy each other, the returns for stock prices do not deviate much from market returns. So if individual traders follow the market consensus, dispersion will be below the mean. Our results show that the standard deviation of *MarketTradeVolume* (KOSPI and KOSDAQ) was higher than that of the sentiment variables when mobile traders bought and sold stocks (0.042 > 0.009, 0.007, 0.007; and 0.040 > 0.008, 0.006, 0.007). (See mobile channel *StockTradingVolume* in Table 1.) Mobile traders chased sentiment trends that were expressed in social media, and carried out trades based on much the same social signals.

Pattern of mobile channel investor reactions to social media sentiment

Based on our GLS estimation, Figure 1 shows several graphs that provide estimates over time of the marginal effect of cumulative and daily sentiment-related posts in social media.

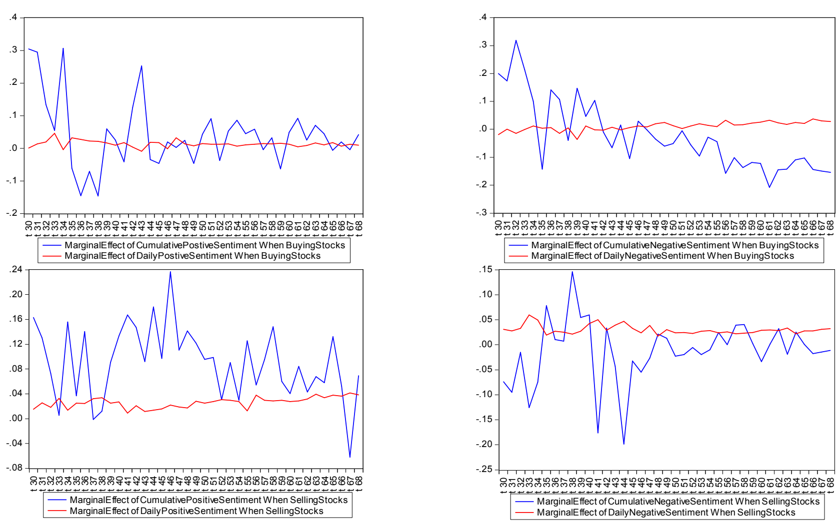

Figure 1. Marginal Effects of Each Covariate over Time

The upper-left of Figure 1 shows that the marginal effect of the cumulative social sentiment converged with the marginal effect of the social sentiment each day. This implies that when mobile traders bought stock, a cumulative *Positive* sentiment had a positive impact on the formation of the *Positive* sentiment each day. In contrast, the upper-right graph shows that the marginal effect of cumulative *Negative* sentiment decreased, while the marginal effect of a daily *Negative* social sentiment slightly increased. This pattern indicates that, with cumulative *Negative* sentiment about a stock, mobile traders were more sensitive to daily *Negative* sentiment than cumulative *Negative* sentiment when they bought stock.

The lower-left shows that the marginal effect of cumulative *Positive* sentiment fluctuated, while the marginal effect of a daily *Positive* sentiment mostly was below the trace for selling stock. This implies that cumulative *Positive* sentiment was more influential than daily *Positive* sentiment when mobile traders sold stock. The lower-right shows that the marginal effect of cumulative *Negative* sentiment varies, but the same effect of daily *Negative* sentiment was observed: it lies mostly above the cumulative sentiment trace. So *Negative* sentiment each day may have had more influence than cumulative *Negative* sentiment over time when mobile traders sold stock. Thus, when mobile traders bought stock, cumulative and daily *Positive* sentiment tended to converge, but daily *Negative* sentiment drove *StockTradingVolume* more. When mobile traders sold stock, cumulative *Positive* and daily *Negative* sentiment seemed were influential.[10]

Figure 2 shows time-series plots over 68 working days for the marginal effects of the sentiment variables, which can be positive or negative when mobile traders buy or sell stocks.

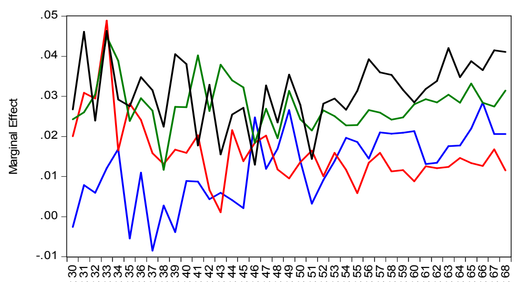

Figure 2. Marginal Effect of Daily Sentiment

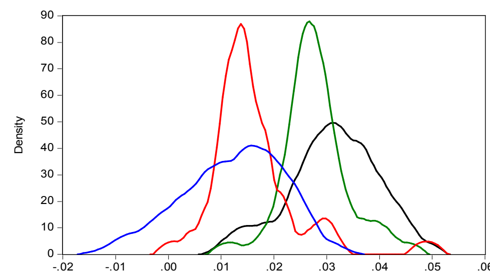

Figure 3. Kernel Distribution

From t = 30 to t = 51, the marginal effects of the four variables were unstable. When traders in the mobile channel sold stocks, the marginal effect of *Positive* sentiment (**black line**) was highest, followed by *Negative* sentiment (**green line**). After t = 51, the marginal effects of *Negative* and *Positive* sentiment seemed to tie in with investors in the *mobile channel* who bought stock. But Figure 2 reveals that when mobile traders were involved in buying stocks, the marginal effect of *Negative* social sentiment (**blue line**) was greater than for *Positive* social sentiment (**red line**). The opposite was true when they sold stocks though.

A *kernel distribution* is a non-parametric representation of the probability density function of a variable. It allows us to visualize the marginal effects between the variables and avoids making assumptions about the underlying distribution of the data. See Figure 3. Overlaying the density plots for *Positive* sentiment (**red line**) and *Negative* sentiment (**blue line**) when mobile traders bought stock, make the difference between the two distributions clear. The marginal effect of *Negative* social sentiment appears more influential because the **blue** density plot appears right-shifted compared to the **red** density plot for *Positive* social sentiment. Two other density plots for *Positive* and *Negative* sentiment relate to the patterns that occurred when mobile traders sold stock. The difference between distributions is clear. Moreover, we can see that the marginal effect of *Positive* sentiment was more influential because the density plot (**black line**) shifted to the right in comparison to that for *Negative* sentiment (**green line**). Overall, the plots show that social sentiment was more influential when mobile traders sold stock than when they bought it each day.

Table 3 presents the estimation results based on the marginal effects of the sentiment variables from GLS.

Marginal Effect of MarketTradingVolume on KOSPI and KOSDAQ =
+ Buy_1 (*Marginal Effect of Positive Sentiment When Buying Stock*)
+ Buy_2 (*Marginal Effect of Negative Sentiment When Buying Stock*)
+ $Sell_1$ (*Marginal Effect of Positive Sentiment When Selling Stock*)

[10] Negative sentiment tied in closely with mobile traders's reactions. Our graphs show that uninformed traders did *negative feedback trading* with respect to sentiment. They bought when *Negative* sentiment rose and sold when *Positive* sentiment fell. Such behavior among uninformed traders is at odds with the positive feedback trading strategy.

+ $Sell_2$ (*Marginal Effect of Negative Sentiment When Selling Stocks*)
+ ε_{it} (Residuals)

The KRLS results show that when traders in the mobile channel bought stock, Buy_1 was negative (-2.49, $p < 0.05$). However, Buy_2 was positive (2.465, $p < 0.01$). Yet when a mobile investor sold stock, $Sell_1$ is positive (0.284), while $Sell_2$ is negative (-2.156), with both not significant. The results indicate that when mobile traders bought stocks, the impact of *Negative* sentiment was greater than *Positive* sentiment. Yet the opposite emerged when the traders sold stock. In addition, the results show that social media sentiment was most influential when mobile traders bought stock. This differs from the Figure 3 density plots.

Variable	Avg.	SE	*T*	$P > \|t\|$
Buy_1	**-2.488**	1.075	-2.314	0.027
Buy_2	2.465	0.769	3.205	0.003
$Sell_1$	0.284	0.951	0.298	0.767
$Sell_2$	**-2.156**	1.349	-1.599	0.119
Number of days	39 (Day 30 to Day 68)			
R^2	0.707			

Note. Dep. var.: *Marginal Effect of Market Trade Volume*

Table 3. Kernel Regularized Least Squares

Now, let's look again at the time-series plots of cumulative sentiment to examine the trading pattern in the mobile channel over time. We see that when mobile traders sold stock, the marginal effect of cumulative *Positive* sentiment (**black line**) was the highest, followed by the marginal effect of *Positive* social sentiment (**red line**) when they bought stock. The marginal effect of cumulative *Negative* sentiment (**green line**) was more likely to obtain when they sold stock and the marginal effect of cumulative *Negative* sentiment (**blue line**) when mobile investors bought stock. But a closer look at the plots reveals that the cumulative *Positive* sentiment (**black line, red line**) was always greater than the cumulative *Negative* sentiment (**green line, blue line**) when traders bought and sold stocks. See Figure 4 again.

In the kernel distribution, the first two density plots (**blue line**, **red line**) show that when mobile investors bought stock, the marginal effect of a cumulative *Positive* sentiment was at work because the **red** density plot shifted right compared to the **blue** density plot for a cumulative *Negative* sentiment even though they overlap to some extent. When mobile traders sold stocks, the marginal effect of the variable cumulative *Positive* sentiment appeared more influential because the **black** density plot shifted right relative to the **green** one for *Negative* sentiment. Overall, the plots show that the cumulative the *Positive* social sentiment variables were more influential than the cumulative *Negative* ones when mobile traders bought and sold stocks. See Figure 5 for these results.

In Table 4, we specify the model below based on the marginal effects of the sentiment variables from GLS.

Marginal Effect of MarketTradingVolume on KOSPI and KOSDAQ =
+ Buy_1 (*Marginal Effect of Cumulative Positive Sentiment When Buying Stocks*)
+ Buy_2 (*Marginal Effect of Cumulative Negative Sentiment When Buying Stocks*)
+ $Sell_1$ (*Marginal Effect of Cumulative Positive Sentiment When Selling Stocks*)
+ $Sell_2$ (*Marginal Effect of Cumulative Negative Sentiment When Selling Stocks*)
+ ε_{it} (*Residuals*)

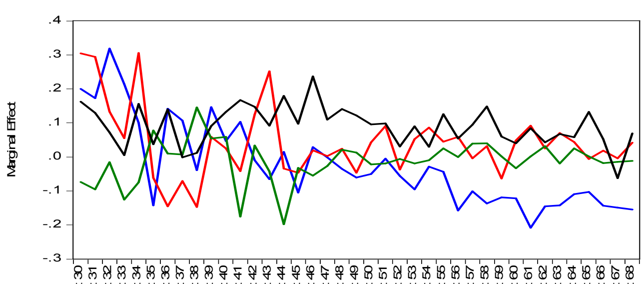

Figure 4. Marginal Effect of Cumulative Sentiment

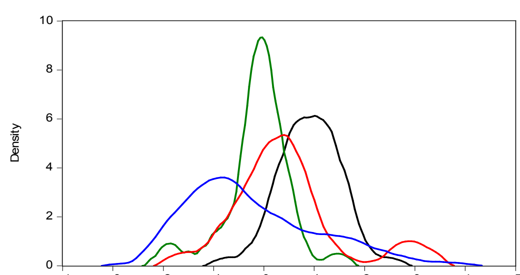

Figure 5. Kernel Distribution

The KRLS results show that when investors in the mobile channel bought stock, Buy_1 is positive (0.016), while Buy_2 is negative (-0.277). On the other hand, when traders sold stock via the mobile channel, $Sell_1$ was negative (-0.014), while $Sell_2$ was positive (0.199). These results do not exactly match the kernel distribution shown in Figure 5 for the cumulative *Positive* and *Negative* social sentiment. Overall, the results indicate that when mobile traders bought stock, the cumulative *Negative* sentiment related to a stock was always less influential than the cumulative *Positive* social sentiment, while the opposite was true for when they sold stock. Again, see Table 4 to understand this assertion more fully.

Variable	Avg.	SE	*T*	$p > \lvert t \rvert$
Buy_1	0.016	0.075	0.212	0.833
Buy_2	-0.277	0.062	-4.447	0.000
$Sell_1$	-0.014	0.108	-0.133	0.895
$Sell_2$	0.199	0.137	1.457	0.154
Number of days	39 (Day 30 to Day 68)			
R^2	0.909			
Note. Dep. var.: *Marginal Effect of Normal MarketTradingVolume*				

Table 4. Kernel Regularized Least Squares Results

The estimations support the behavior of uninformed traders in the mobile channel, who exhibited a pattern of *negative feedback trading* in response to sentiment expressed in social media. Such mobile traders tended to buy stocks that experienced negative sentiment daily, but which attracted cumulative positive sentiment. They tended to sell stocks with daily positive sentiment, but which attracted cumulative negative sentiment in social media. This pattern tended to negate the *positive feedback trading* pattern.

Conclusion

We studied the impact of social media sentiment for stock trading via mobile phones. We first showed that uninformed traders seem to be easily swayed by social sentiment, while stock trading in the traditional channel probably influenced the formation of sentiment in the market somewhat more. Second, uninformed traders in the mobile channel tended to chase social signals of trends from social media, and traded stocks based on the same social signals. This was evidence for herding behavior among uninformed traders. The standard deviation of social sentiment was smaller than that of market trade volume involving KOSDAQ and KOSPI. Last, our analysis showed that uninformed traders acted more on negative feedback trading with respect to social sentiment. They seem to have bought stocks when negative sentiment increased and sold stocks when positive sentiment diminished. This behavior for mobile channel traders goes against positive feedback trading strategy, which was surprising for the data that we analyzed.

The novelty of our work for the IS research context is that it examines the impact of social media sentiment when mobile phones were used for stock trading. This is a relatively new research direction, especially in terms of our effort to distinguish between the patterns of relatively uninformed mobile traders versus value-focused traditional market traders. Our results show that uninformed traders in the mobile channel seem to have been too easily swayed by social sentiment, specifically negative sentiment. They responded by herding to chase trends with respect to social signals. We were able to confirm in a new research design what the regulators of financial markets already know: that news obtained via social media can be dangerous, and can damage the quality of markets and diminish trader informedness. Transparency is important so the financial information that traders attend to is of high quality, rather than misleading and inaccurate. Thus, it will be helpful if bogus stories about firms in the market are kept to a minimum, so that bad news doesn't drive out other useful information. Beyond the results we have presented – especially our interpretation of what has been happening with *negative feedback trading*, our study opens a new portal for the application of analytics with digital data for mobile channel stock trading and trader informedness.

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Appendix. The modeling and estimation process

1. Baseline and Econometric Model Analyses

Baseline Data Analysis
- Unit root test for data stationary
- Create new variable with log differences
- Assess multicollinearity (VIF and CI)

→

Baseline Residual Analysis
- Conduct assessments for:
  - Linearity
  - Autocorrelation
  - Heterscedasticity
  - Data normality
- Data outliers

→

Feasible Generalized Least Squares (FGLS) Results
- Two-way unobserved fixed effects
- Aassessment for social sentiment impact on stock trade volume

→

Panel Vector Autoregression) (PVAR) Results
- Panel Granger causality Test
- Assessment of endogenous relationship between trading volumes and sentiment in mobile channel
- Whether reverse causality exists

2. Machine Learning Model Analyses

Generalized Least Squares (GLS) Results
- Preprocssed data set for mrgnl. effects of social sentiment

→

Graphical Technique Results
- Mrgnl. effects of daily / cumulative sentiment over time
- Kernel distribution analyses for covariates

→

Kernel Regularized Least Squares (KRLS) Results
- Herding behavior
- Negative feedback trading

3. Results Evaluation and Comparisons

Goals for the different kinds of analyses:

- **Baseline Analyses:** Established data appropriateness via test for empirical regularities
- **Econometric Model Analyses:** Establish sentiment variables' effects on stock trading
- **Machine Learning Model Analyses:** Establish variables' impact on herding behavior and negative feedback trading

Overall Evaluation Process
1. Baseline Analyses and Econometric Model Analyses
2. Machine Learning Model Analyses
3. Results Evaluation & Comparisons