

Disagreement Spillovers on Social Platform

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Abstract

We construct a “investor-cognition stock network” in which each node represents a stock while each edge represents a distance of how investors perceive two stocks closely using data on the investment social platform, “StockTwits”. We verified the disagreement generated by investors in a stock is spilt over to the other stock that is located near in terms of cognitive distance. In addition, the disagreement is transferred through a channel of investors’ overconfidence and has an additional negative effect on the return and positive effect on the volatility of near stock.

Keywords: Disagreement, Spillovers, Overconfidence, Social Network

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1. Introduction

Finance literature has produced enormous papers about spillover or contagion across assets or market. However, only a few papers tried to discover an effect of investor behavior on the other stocks. Liu, Zhang, and Zhao (2015) addressed the possibility and impact of the contagious property of investors' behavior by demonstrating that speculative activities can spill over across markets. It implies that other types of investor behaviors could also be possible to be spread out and be incorporated into the dynamics of variables of other stocks.

In another paper, Han, Lu, and Zhou (2014) built a model to project the possibility that a positive relation between investor disagreements of one stock and the expected return and volatility of the other stock exist. By see this phenomenon through the lens of a contagious property of investors' behavior, we can rationally hypothesize that investors' behavioral component could be involved in transferring a disagreement generated in one stock into another stock.

As well pointed out in Liu et. al (2015), a spillover effect of speculation is more pronounced when assets (warrants) attract more investor attention since investors' behavior (speculative trading) cause other investors who are attracted those stocks to trade more in the underlying stocks. We hypothesize that this kind of spillover phenomenon of investor behavior would happen across the stocks that share common investors i.e. that attract the similar types of investors. Furthermore, limitation of cognitive resource as a human being, make people have interest in several stocks among whole universe of stocks. It increases the possibility that a contagious property of investors' behavior would be more pronounced among stocks that are likely to be viewed by investors at a time.

Thanks to new social platform for sharing investment ideas, StockTwits, we can capture investors' perspective about relations of stocks and project it into a form of network. Specifically, from the twits about every tickers they uploaded every day, it is possible to exploit

the relation between for every pair of two stocks by measuring how they are attracted by investors simultaneously. In other words, investors' participation in social platform could be mapped into a layer of stock relation in the form of network.

To reveal the role of limited resource of cognition on the contagious property of a disagreement, we constructed the “cognitive network” in which nodes are stocks and edges are cognitive distance perceived by investors using network theory and the comprehensive investors' social platform dataset. We attempt to shed more light on the dynamic nature of social platform by reconstructing cognitive network every month. In this network, a short distance represents a higher likelihood that two stocks are co-mentioned so that investors are interested in simultaneously.

Based on the ‘Investor-Cognition network’ we constructed using StockTwits data, we verified that investors' disagreement generated by investors in a stock has a contagious property that spills over to the other stock that is located in near position in terms of cognitive distance. That means, the result of investors behavior is more likely to be transferred to the stocks which attract the similar investors.

We discover more detail mechanisms for how disagreement spills over with the hypothesis that investors' disagreement and their overconfidence generate each other as verified in Daniel, Hirshleifer, and Subrahmanyam, (2001) and Schenkman and Xiong (2003). With an abnormal turnover ratio as an overconfidence measure for a stock, we verified that a disagreement increases an overconfidence of its own investors, other stocks that these overconfident investors follow, becomes to have higher disagreement. In other words, investors' overconfidence and limited attention serve as a channel for a disagreement to pass through.

Moreover, a spilt part of disagreement of each stock has an additional effect on its market variables such as return and volatility. Interestingly, spilt component of disagreement

has a larger effect on return and volatility than its own part of disagreement. These empirical results stress out the importance of investors' behavior for stocks' dynamics again.

Our paper mainly belongs to the literature of spillover of investors' behavior by providing empirical evidences. From the perspective of variables we dealt with, our research also contributes to a disagreement literature in that a series of empirical results support Merton's hypothesis that higher disagreement of opinions are incorporated as negative return. In addition, our research is related to network theories for stocks although a few papers exist, in that we construct the stock network by investigating investors' tweets.

2. Research Setting and Methodology

StockTwits (stocktwits.com) is a social media platform exclusively designed for sharing ideas on stock market which was ranked as the 1,028th most popular website in the US as of Aug, 2017. For each user in StockTwits, it owns the self-reported characteristics such as his/her investment approach (Fundamental, Global Macro, Growth, Momentum, Technical or Value), experience level (Novice, Intermediate or Professional) and holding strategy (Day Trader, Long Term Investor, Position Trader or Swing Trader). Also, when a user posts a tweet, he/she can choose to indicate whether the tweets is considered to be bullish or bearish. Therefore, the dataset provides millions of labeled tweet sentiments that is the ground-truth investor sentiment data. Compared with many other sentiment measures, it is a clear and comprehensive sentiment measure in that an opinion is directly published and collected from all types of market participants.

In this study, we collect dataset through self-developed crawlers and identify stocks by applying regular expressions on cashtags (e.g. \$IBM, \$GOOG) through Python. In results, we have 31,410,411 tweets from Sep, 2010 to Aug, 2015 by 152,476 unique users who mentions 13,440 stocks which is one of the largest ever twitter corpus in a very domain specific issue.

To reveal cognitive relationships between stocks and quantitatively identify the propagation of disagreement, we employ a two-mode network model (bipartite network) which is a particular type of networks with two classes of nodes which are only connectable when the nodes are belonging to different classes. We define the two-mode network as “stock-user network” where stocks and users are two classes of nodes. The weight of links between stock and user indicates the number of mentions during a specific timeframe which is one month of time periods in our study.

After constructing the stock-user network, we reduce it into a one-mode network, referred to as “cognitive stock network.” To find distance between stocks, we measure the stock correlation when there are at least two users who mention the focal stocks. More formally, for Stock A and Stock B, we calculate the stock correlation ρ_{AB-AB} as $\sum_{i=1}^n \frac{w_{iA}w_{iB}}{\sigma_A\sigma_B}$ where w_{iA} and w_{iB} is the number of mentions from user i to stock A and B, and σ_A and σ_B is standard deviations of number of mentioning across common users. If they have strong positive value, then these two stocks have high joint probability to be mentioned together by users in that month.

By applying this methodology to StockTwits datasets, it is possible to project investors’ perception about stocks into the network structure. Further, we can investigate how disagreement propagates through cognitive distances represented by edges in the network and through characteristics of stocks represented by nodes. Our approach is novel from previous methods that try to construct underlying structures or network of stock market based on correlation structures of stock returns in significant ways. (Chi et al. 2010; Heiberger and Raphael 2014; Mantegna et al. 1999; Naylor et al. 2007; Tumminello et al. 2007)

Previous approaches construct network using correlations between each pair of stocks for time series of returns (RH heilberger, 2014) or closing price. (Chi, Liu and Lau, 2010) This kind of network based on the stock market values can hardly capture investors’ perceptions to

which are the direct channel connecting the stock market. Therefore, the primary difference from previous stock networks is that we constructed stock networks from investors' social platform behavior to exploit the market participants' cognition on the stocks. Our network structure reflects how the stocks are cognitively related with true label. The second difference is more important, we include investor characteristics into cognitive stock network that enables us to empirically measure how the investors interact with each other.

Our measure of disagreement borrows Cookson and Niessner (2016). We defined the disagreement for each stock by calculating average sentiment and transformed it into the desired disagreement measure at the firm-month-group level, where "group" means the whole users or users who restricted by investment approach, experience, or investment horizon. Recall that users can report whether the tweet is considered to be bullish or bearish. Based on this binary sentiment variables, average sentiment can be defined as Antweiler and Frank (2004) and Cookson and Niessner (2016):

$$AvgSentiment_{itg} = \frac{N_{itg}^{bullish} - N_{itg}^{bearish}}{N_{itg}^{bullish} + N_{itg}^{bearish}}$$

AvgSentiment varies from -1 (all users tag bearish) to 1 (all users tag bullish). After then, we compute disagreement which captures the variance of the sentiment measure during a time period t as Antweiler and Frank (2004) and Cookson and Niessner (2016):

$$Disagreement = \sqrt{1 - AvgSentiment^2}$$

Disagreement varies from 0 (every user tag only bullish or bearish) to 1 (half of users tag bullish and others tag bearish) which can help us to capture the changes in disagreement by investigating disagreement during certain time horizons.

We hired two types of analysis to dissect the effect of both "distance" and "experience", portfolio sorting and regression analysis. Portfolio sorting method is free from overfitting issues, therefore robust, but can hardly prevent other characteristics from interrupting, while

regression analysis can include other independent variables that are known to affect the dependent variable, but has overfitting issues. These two methods complement each other. Time series regression for the returns series generated from difference between average returns of portfolios constructed in the portfolio sorting method can test whether return is come from the risk factors.

3. Empirical Results

In this section, we will verify a contagious property of investors' disagreement based on the network framework, investor-cognitive network we constructed in the previous section. First, we empirically show that investor's disagreement spills over, secondly, disagreement can be contagious to the other stock through the channel of investors' overconfidence, and lastly, an increased disagreement spilt from the other stock have an additional effect on stock return and volatility.

3.1 Disagreement Spillover

The disagreement generated by investors who participate in social network platform by sharing their ideas about stock trading, is verified as contagious to the stock that lies "near" in terms of cognitive distance.

For the first method to check the spillover effect of the disagreement, we adopt a univariate sort to see a trend of stocks' disagreement according to the distance to another stock that has high disagreement. To do that, we select stocks that have upper a third disagreement and sort the rest of stocks based on their distance to the high disagreement stocks using cognitive network we produced.

[Table 1]

As above table shows, an average disagreement of stocks are decreasing as its distance to ‘high-disagreement’ stocks is increasing and its difference is statistically significant. It implies that stocks that are located near high-disagreement stocks tend to have higher disagreement than those that are not.

As more details can be seen in the table of regression, the disagreement has an increasing tendency for its distance to high-disagreement stocks. Moreover, its disagreement also increases as its high-disagreement stock’s disagreement is high, which support the hypothesis the spillover effect of disagreement in the cognitive way.

Although we project investors perspective into the cognitive network, there is a possibility that a layer of this network overlap the industrial effect. In other words, the disagreement spillover effect could happens just because they are similar firms belonging to the same industry. Therefore, we include industrial classification dummy, which is equal to 1 if a stock and the high-disagreement stock has the same industrial classification code or 0 otherwise, to control industrial effect.

As the table of result of above regression verify, coefficients of stock’s distance to the high-disagreement stock remains significant. Notably, industrial dummy variable has also a significant coefficient implying that cognitive network is partly incorporating standard industrial classification value.

We have checked if investors’ disagreements are contagious or not in the framework of cognitive network constructed from investors’ social network. The disagreement seems to spillover more toward near stocks in terms of cognitive distance than far stock.

3.2. Disagreement Spillover Channel

In this section, we would like to dissect spillover phenomenon of investors’ disagreement verified in the previous section. Specifically, we will disclose the detail

mechanism of disagreement spillover by exploring which serves as a channel through disagreement passes.

As Da, Engerberg and Gao (2011) well point out, investors as human beings, have limited cognitive resource thus spend limited attention on some of interesting stocks, not a whole stock universe. The concept of an attention is closely related to our investors cognitive network in that a cognitive distance between two stocks represents how closely investors perceive and how simultaneously investors have an attention at the same time. From our previous empirical results that the contagious property of investors disagreement is pronounced to cognitively-near stocks, we hypothesize that the channel through which investors' disagreement passes would be investors' behavioral characteristics.

It is well documented that investors' disagreement is closely related to their overconfidence. (Daniel, Hirshleifer, and Subrahmanyam, (2001) and Schenkman and Xiong (2003)) Therefore, we develop the hypothesis that investor overconfidence serve as a channel of disagreement spillover. Specifically, a disagreement of a stock increases the degree of overconfidence of its investors and its increased overconfidence has an effect on other stocks that the same investors have an attention to, i.e. increase the disagreement of other stocks.

Testing procedure consists of three steps as follows: 1) A disagreement of a stock generally increase a degree of overconfidence of its investors 2) A degree of overconfidence of investors of near stock also increases as short cognitive distance implies more likely the same common investors. 3) An increased overconfidence from other stocks increases own disagreement. We adopt two empirical test methods: univariate sort and regression method.

[Table 2]

As can be seen in both results of univariate sort and regression method, Overconfidence proxied by abnormal turnover tends to increase as of which investors' disagreement increases.

[Table 3]

Importantly, the degree of overconfidence of investors of stocks that are cognitively-close to high-disagreement (thus high-overconfidence) stocks tends to increase. This result becomes natural consequence if investor cognitive network captures investors' attention well because the network is constructed to map investors' common interesting stocks.

[Table 4]

Lastly, we should check whether an increased overconfidence (call it a spilt-overconfidence) have an increasing effect on own disagreement or not. Univariate sort doesn't show significant difference of disagreement.

We split the level of investors' overconfidence into two parts consisting of own overconfidence and spilt-overconfidence by regressing a current overconfidence level on lagged overconfidence and current near-stock's overconfidence level. With split overconfidence as independent variables, the regression results verify that split-overconfidence has an additional effect on own disagreement and its magnitude is about three times larger than own overconfidence level.

The level of investors' overconfidence is verified to serve as a channel for transferring investors' disagreement with three steps of empirical testing procedures.

3.3 Effect of Spilt Disagreement on return and volatility

So far, we have verified that the contagious property of investors' disagreement and the channel of disagreement spillover in previous two sections. Going back to our original motivation that disagreement of A stock is related to return and volatility of B stock although these two stocks are fundamentally uncorrelated, we will empirically show this relation can possibly exist between not fundamentally-related but cognitively-related stocks and testify this phenomenon happens by disagreement itself spillovers.

The method employed here is very similar with the method used in the previous section for overconfidence spillover. We split stock's disagreement into two components, own disagreement and spilt-over disagreement by regressing a current disagreement on own lagged disagreement and the disagreement of cognitively-close high-disagreement stock.

[Table 5]

First, we test the expectation projected from Han, Lu, and Zhou (2014) for stocks that are likely to attract attentions from the same investors. The disagreement of each upper a third high-disagreement stocks has a positive effect on the return volatility and a negative effect on the return of stock that is 'close' in the investors' cognitive network as can be seen in table. This spillover effect of disagreement still remains significant even after controlling industrial effect by including industrial dummy which is equal to 1 if the standard industrial classification is the same for two stocks or 0 otherwise. Even though the direction of the effect of disagreement on other stocks' return, which is negative, is opposite to the previous research that describes the relation between A stock's disagreement and B stock's return as positive, our result does not contradict () because we are focusing on the relation of stocks that are not just fundamentally uncorrelated but also cognitively close in terms of investors' perspective.

[Table 6]

In order to disentangle disagreement spillover, we generally show that disagreement has a positive effect on return volatility and a negative effect on return within a stock, and then show increased disagreement by cognitively-close high-disagreement has an additional effect on the return and volatility. From the table, disagreement seems to make return decrease and volatility increases within a stock. This result confirms that investors' disagreement strengthens investors overconfidence (Daniel et. al, 2001). More interestingly, it supports Merton(1987)'s hypothesis that higher dispersion of investors' opinions are reflected as negative contemporaneous return. By considering the structure of StockTwits where massive trading

ideas are shared and spread out every day, thus information diffuse fast, even negative opinion can be incorporated into a stock price soon.

[Table 7]

From our previous empirical results, that describe a contagious property of investors' disagreement and an impact of disagreement on returns and volatilities, we are able to divide the disagreement of each stock into two parts to isolate the spilt-over disagreement from its own component of disagreement. As verified in the table, split-over component of disagreement has an additional effect on the return and volatility while the effect of original component of own disagreement remains significant and industrial classification has no power.

Interestingly again here, the magnitude of the effect of split-disagreement is larger than own disagreement that implies the contagious property of human behavior is deeply involved in return and volatility dynamics.

By proceeding a series of tests, we analyzed 1) disagreement spillover effect, 2) disagreement spillover mechanism, and 3) the effect of spilt disagreement on the return and volatility. A bundle of empirical tests tells us that contagious property of investors' behavior, especially disagreement, is profoundly involved in the return and volatility dynamics.

4. Conclusion

We find empirical results that support the hypothesis that investors' disagreement spills over, this process happens through investors' overconfidence as a channel, and spilt disagreement has an additional and even larger effect on stock's return and volatility.

Although, we focused on specific phenomenon of investors' behaviors, overconfidence and disagreement, investor-cognition network could serve as a good framework for analyzing

diffusion of sentiment or contagious property of investors' behavior from a stock to another stock.

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| Table1. Panel A | | | | |
|------------------------|----------|----------|----------|--------------------|
| Distance group | | | | |
| Variable | 1 | 2 | 3 | Diff(1-3) |
| Disagreement | 0.858 | 0.828 | 0.790 | 0.066*** (4.09) |

| Table1. Panel B | | |
|-------------------------------|-----------------------|-----------------------|
| Dependent Variable | | |
| Independent Variables | Disagreement | |
| Intercept | 0.078 (0.86) | -0.408*** (-3.10) |
| Lagged Disagreemtn | 0.382*** (22.54) | 0.371*** (21.08) |
| Distance | -0.103*** (-5.93) | -0.099*** (-5.46) |
| Disagreement of near stock | 0.365*** (5.50) | 0.290*** (4.05) |
| Log(ME) | 0.005* (2.02) | 0.005 (1.71) |
| Vol | 0.428** (2.59) | 0.301 (1.79) |
| Return | -0.261*** (-12.24) | -0.251*** (-11.33) |
| Turnover | 0.024*** (3.35) | 0.024** (3.30) |
| Industry dummy | | 0.026** (3.15) |
| Average industry disagreement | | 0.612*** (4.91) |

| Table2. Panel A | | | | |
|----------------------------|----------|----------|----------|---------------------|
| Disagreement groups | | | | |
| Variables | 1 | 2 | 3 | Diff(1-3) |
| Abnormal Turnover | 0.021 | 0.060 | 0.137 | -0.12748 (-1.88) |

| Table2. Panel B | |
|---------------------------------|-------------------------------|
| | Dependent Variable |
| Independent Variable | Abnormal Turnover |
| Intercept | -0.044** (-2.54) |
| Disagreement | 0.142*** (5.95) |

| Table3. Panel A | | | | |
|---------------------------------|----------|----------|----------|----------------------|
| Abnormal Turnover groups | | | | |
| Variables | 1 | 2 | 3 | Diff(1-3) |
| Abnormal Turnover | 0.049 | 0.083 | 0.141 | -0.087*** (-4.66) |

| Table3. Panel B | | |
|---------------------------------------|------------------------------|---------------------|
| | Dependent Variable | |
| Independent Variable | Abnormal Turnover | |
| Intercept | 0.086*** (10.29) | 0.086*** (9.12) |
| Abnormal Turnover Of near stock | 0.033*** (4.80) | 0.033*** (4.79) |
| Lagged Abnormal Turnover | 0.284*** (11.92) | 0.284*** (11.92) |
| Industry Dummy | | -0.000 (-0.00) |

| Table4. Panel A | | | | |
|-----------------------------------|-----------|-----------|-----------|-------------------|
| Spilt overconfidence group | | | | |
| Variable | _1 | _2 | _3 | diff |
| Disagreement | 0.769 | 0.783 | 0.789 | -0.014 (-1.26) |

| Table4. Panel B | | |
|-----------------------------|---------------------|---------------------|
| Dependent variable | | |
| Independent Variable | Disagreement | |
| Intercept | 0.470*** (30.58) | 0.465*** (30.36) |
| Lagged Disagreement | 0.387*** (19.85) | 0.381*** (19.56) |
| Own Abnormal Turnover | 0.038*** (3.78) | 0.039*** (3.90) |
| Spilt Abnormal Turnover | 0.126* (2.35) | 0.117* (2.19) |
| Industry Dummy | 0.040*** (4.29) | |

| Table5. | | | | |
|------------------------------|--------------------------|--------------------------|---------------------|---------------------|
| Dependent Variable | | | | |
| Independent variables | Return | | Volatility | |
| Intercept | 0.136* (2.39) | 0.137* (2.41) | -0.014 (-1.82) | -0.013 (-1.76) |
| Lagged Variable | 0.034 (1.70) | 0.034 (1.70) | 0.681*** (31.90) | 0.681*** (31.90) |
| Volatility Or Return | 3.290*** (40.93) | 3.290*** (40.91) | 0.061*** (39.64) | 0.061*** (39.61) |
| Disagreement of near stock | - 0.222*** (-3.72) | - 0.221*** (-3.72) | 0.021** (2.67) | 0.021** (2.67) |
| Distance to near stock | 0.007 (0.48) | 0.007 (0.45) | 0.007*** (3.63) | 0.007*** (3.55) |
| Industry Dummy | -0.003 (-0.40) | | -0.002 (-1.58) | |

| Table6. Panel A | | | | | | |
|----------------------------|-----------|-----------|-----------|-----------|-----------|--------------------|
| Disagreement groups | | | | | | |
| Variable | _1 | _2 | _3 | _4 | _5 | diff |
| ret0m | 0.055 | 0.027 | 0.022 | 0.006 | -0.030 | 0.080*** (7.11) |
| std0m | 0.026 | 0.026 | 0.025 | 0.029 | 0.028 | -0.002 (-1.31) |

| Table6. Panel B. | | |
|-----------------------------|-----------------------|---------------------|
| Dependent Variable | | |
| Independent Variable | Return | Volatility |
| Intercept | 0.037*** (4.81) | 0.004*** (3.57) |
| Volatility /Return | 1.641*** (21.36) | 0.040*** (25.94) |
| Lagged Variable | -0.021 (-1.61) | 0.638*** (49.77) |
| Disagreement | -0.104*** (-10.27) | 0.011*** (8.10) |

| Table7. | | | | |
|-----------------------------|-----------------------|-------------------------|----------------------|----------------------|
| Dependent Variable | | | | |
| Independent Variable | Return | | Volatility | |
| Intercept | 0.132*** (6.31) | 0.132*** (6.29) | -0.009*** (-3.92) | -0.009*** (-3.81) |
| Lagged Variable | -0.059* (-2.02) | -0.059* (-2.02) | 0.952*** (35.63) | 0.954*** (35.68) |
| Volatility /Return | 1.293*** (9.29) | 1.293*** (9.29) | 0.022*** (9.96) | 0.022*** (9.97) |
| Own Disagreement | -0.175*** (-10.67) | -0.17523*** (-10.63) | 0.011*** (6.01) | 0.012*** (6.17) |
| Spilt Disagreement | -0.212*** (-7.87) | -0.212*** (-7.88) | 0.021*** (6.61) | 0.021*** (6.67) |
| Distance to near stock | -0.004 (-0.25) | -0.004 (-0.24) | 0.003 (1.59) | 0.003 (1.50) |
| Industry Dummy | | 0.00160 (0.21) | | -0.002 (-1.78) |