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Edited by Cheng-Few Lee
and Min-Teh Yu

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DIVERGENT OPINION, TRADING INFORMATION, AND STOCK PRICE CO-MOVEMENTS

Lin Chen, Junbo Wang, Chunchi Wu
and Hongquan Zhu

ABSTRACT

Although stock price co-movement has been examined extensively, its causes are not well understood. Using a decomposition method, we extract three information components from the turnover rate: market information, firm-specific information, and investors' opinion divergence. We find that market information strengthens stock price co-movement, whereas firm-specific information weakens it. Moreover, our analysis shows that divergence of investors' opinion increases stock price variations but weakens price co-movement.

Keywords: Stock price co-movement; trading activity; information content; investors' opinion divergence; heterogeneous belief; market information; firm-specific information

JEL classification: G12; G13

1. INTRODUCTION

In traditional asset pricing models, stock price movements are attributed to information flows. It is assumed that the market is efficient and prices impound all relevant information in the market (e.g., Chiang, 2019; Fama, 1991; Malkiel & Fama, 1970). Market microstructure theory further considers the mechanism of assimilating information into prices through trading activity. Trades reflect private information and differences in opinions. Investors adjust to new information

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by buying or selling securities. Trading leads to price changes, and in equilibrium the price fully reflects all available information.

Traditional asset pricing theory assumes that investors are homogeneous. This implies that all market participants have the same trading horizon, information set, and expectations. Such strong assumption ignores differences among investors. Investors often have different knowledge (prior belief), analytical skills, and risk tolerance. These differences can result in heterogeneous expectations and valuations of assets. The arrival of information in the market can thus generate heterogeneous belief, which affects investment decisions of market participants and asset prices (Hong & Stein, 2007).

Trading activity may reflect both rationality of market participants and behavioral biases of investors. As suggested by Bessembinder, Chan, and Seguin (1996) and Garfinkel and Sokobin (2006), trading activity is mainly driven by three factors: (1) investors' exogenous liquidity needs; (2) information impacts, including public, private, macro and firm-specific information; and (3) divergence in investor opinion (heterogeneous belief). Among these factors, the role of different types of information has been the focus of recent research. However, given the difficulty to measure information directly, researchers have typically used returns as an indirect measure of information to explain stock price movement (Cavaglia, Brightman, & Aked, 2000; Pirinsky & Wang, 2006). Recent research finds that stock price co-movement offers a new avenue to understand the role of different types of information in the asset pricing process.

Stock price co-movement (or synchronicity) refers to the phenomenon that prices of different assets or portfolios move synchronously, i.e., rise or fall simultaneously. Stock price co-movement has three forms: (1) synchronous changes in prices of individual stocks (Froot & Dabora, 1999); (2) price co-movement between an individual stock and the market portfolio within the same economic entity (Barberis, Shleifer, & Wurgler, 2005; Gul, Kim, & Qiu, 2010; Morck, Yeung, & Yu, 2000); and (3) co-movement between different economic entities (indices) (Karolyi & Stulz, 1996). In this study, we focus on the second case. Although the issue of stock price co-movement has received substantial attention, its forming mechanism is still not well understood (Brockman, Liebenberg, & Schutte, 2010). Studies have shown that for different economies or at different developing stages of the same economy, the stock price co-movement behavior can be quite different (Campbell, Lettau, & Malkiel, 2001; Jin & Myers, 2006; Morck et al., 2000).

There are two major explanations for stock price co-movement. One is based on information efficiency and the other on behavioral factors. Morck et al. (2000) argue that price co-movement reflects the assimilation of firm-specific or private information into stock prices. If the stock price co-movement is measured by R^2 of individual stock return regression (i.e., based on the Capital Asset Pricing Model (CAPM) model), the larger the R^2 is, the less firm-specific information the stock price contains. To a certain extent, this means that when price co-movement is high, the market is relatively inefficient. Subsequent studies, such as Durnev, Morck, and Yeung (2004), Gul et al. (2010), Crawford, Roulstone, and So (2012), elaborate this point from a different angle.

An alternative explanation attributes price co-movement to behavioral factors. According to this explanation, price co-movement mainly results from the category-based thinking (Mullainathan, 2002) of different investors when processing the information (Barberis & Shleifer, 2003; Hameed, Morck, Shen, & Yeung, 2015), and the sentiment of investors with certain characteristics (Green & Hwang, 2009).

Recent research on stock price co-movement focuses more on behavioral factors and emphasizes the role of convergence rather than diversity of investors. This literature suggests that investor opinion divergence is an important factor driving stock trading and liquidity and ultimately stock price changes. Building on this literature, we study stock price co-movement by decomposing the information of turnover into marketwide information, firm-specific information, and information related to investors' opinion divergence. Our empirical results show that besides market information and firm-specific information, investor opinion divergence has a significant negative effect on stock price co-movement.

This chapter contributes to the current literature in several ways. First, we explain stock price co-movement from the perspective of behavioral biases and heterogeneous belief. Although past studies have looked into price co-movement from different sources of information, research from the perspective of investor behavioral biases is burgeoning. Existing studies have focused on the behavioral convergence due to investor behavioral biases or sentiment. However, different channels of information, speed of information dissemination, and interpretations of the same information can also cause investor opinion divergence. These issues are relatively underexplored in price co-movement research.

Investor opinion divergence can affect asset pricing and stock trading activity. The impact of investors' opinion divergence on stock price variations has been studied by Harrison and Kreps (1978), Diether, Malloy, and Scherbina (2002) and Scheinkman and Xiong (2003). This chapter extends this literature by investigating the impact of investors' opinion divergence on stock price co-movement. We find strong evidence that investor opinion divergence has significant (both economically and statistically) explanatory power for price co-movement even after controlling for the effect of other information.

Second, this chapter uses a more precise measure of investor opinion divergence. Bid–ask spreads, stock return volatility, and analysts' forecast dispersion are proxies commonly used in the literature. Bid–ask spreads may reflect both liquidity and information asymmetry, and stock return volatility is affected by information and risk. Both are noisy measures of divergence in investor opinions. Although analyst forecast dispersion is viewed as a reasonable proxy for opinion divergence (Basak, 2005; Diether et al., 2002; Moeller, Schlingemann, & Stulz, 2007; Verardo, 2009; Yu, 2011), there are two potential problems in this measure. First, not all investors make a decision based on analyst forecasts. Analyst forecast dispersion largely represents belief differences among professional investors. Second, analyst forecast dispersion is subject to the impact of uncertainty. For example, analysts may issue biased forecasts due to their personal interests. This leads to a distortion in the estimation of opinion divergence measured by forecast divergence. In this chapter, we extract investor opinion

divergence from unexpected trading volume. This approach generates a better measure of opinion divergence as unexpected volume reflects diversion in investor opinions.

Third, this chapter interprets stock price co-movement from the perspective of information efficiency. By comparing the co-movement effect of a mature market with that of an emerging market, Morck et al. (2000) find that the latter has stronger co-movement than the former. The main reason is that the emerging markets do not provide sufficient protection for private property. The better legal system that protects private property in the mature market enables investors to incorporate firm-specific information into stock price through arbitrage, which weakens the co-movement between stock price and the market. Using Chinese stock market data, Gul et al. (2010) study the difference in stock price co-movement among different companies from the perspective of corporate governance. They use several proxies, such as equity concentration, nature of major shareholders (state-owned or non-state-owned), foreign ownership, and quality of audit reports to measure the information efficiency indirectly. Crawford et al. (2012) find that the initial forecast of an analyst is based more on macroeconomic and industrial information, resulting in stronger co-movement, whereas the subsequent forecasts are based more on firm-specific information, thus reducing price co-movement. Our chapter differs from these papers by extracting the information from trading activity. In this chapter, the information-based transaction is represented as expected trading volume and the unexpected trading volume proxies for investor opinion divergence.

The remainder of the chapter is organized as follows. Section 2 presents the theoretical analysis and test hypothesis. Section 3 discusses the data sample and variables used in empirical analysis, and Section 4 presents empirical results. Finally, Section 5 summarizes major findings and concludes the paper.

2. OPINION DIVERGENCE AND PRICE CO-MOVEMENT

Information efficiency of the financial market can affect co-movement in stock prices. In a market with more informed traders and less noise traders, stock price will reflect more firm-specific information. Since firm-specific information is of idiosyncratic nature, correlation among firms is likely low. Consequently, price co-movement among stocks would tend to be weak. By contrast, in a market with lower information efficiency or fewer informed traders, stock price will reflect less firm-specific information and more market information. As market information affects all stocks, price co-movement among stocks would tend to be strong. Thus, the co-movement between individual stock and market index prices may hinge on the information efficiency of the stock market.

This reasoning allows us to link price co-movement to the information content of stock price. In this chapter, we construct a measure of investor opinion divergence to explore the effect of opinion divergence on the stock price co-movement in the China stock market. Previous studies have documented that investor opinion divergence affects stock prices, but none of them has

directly examined the relationship between opinion divergence and stock price co-movement.

Miller (1977) investigates the impact of investors' opinion divergence on asset pricing. He shows that in a market with short-sale constraints, the bullish opinion is easy to be revealed through trading, but the bearish opinion is restricted. Ultimately, this leads to a higher stock price than the firm's intrinsic value. The more divergent the investors' opinions are, the higher the price premium is. Miller's proposition was supported by subsequent studies.[1] Thus, in the presence of short-sale constraints, investors' opinion divergence can be an important factor affecting stock price movement. Because short sales were prohibited in the China stock market before March 2010, this provides us a unique opportunity to test the hypothesis of investors' opinion divergence on stock price co-movement. After March 2010, some of the stocks were allowed to have short sales. This enables us to uncover the differences in investor opinion divergence on stock price co-movement for stocks with and without short-sale constraints.

Microstructure theory suggests that trading is mainly driven by information. At the same time, trading conveys information. Because of heterogeneity in investors' background, knowledge, analytical skills, investors can have different interpretations on the same information, resulting in opinion divergence (Hong & Stein, 2007).

Market environments can also produce opinion divergence. Veldkamp (2005) argues that in a bull market, investors not only are optimistic and trade more but also are more willing to unearth information (especially firm-specific information) and conduct analysis because of lower cost in information search and processing. As such, in a bull market, both the quantity and quality of information increase (Van Nieuwerburgh & Veldkamp, 2006). Thus, it tends to have more information in the bull market than in the bear market. However, because of limited attentiveness, investors cannot pay attention to all information, but only a subset of it. As a consequence, it widens investor opinion divergence. Greater investor opinion divergence, accompanied by abundant firm-specific information, can attenuate stock price co-movement in the bull market. In contrast, trading is inactive (lower turnover rate, higher transaction cost, and lower liquidity) in the bear market. As the cost of information acquisition is relatively high, investors are less willing to engage in private information production. This leads to information convergence and lowers investors' opinion divergence, thereby contributing to stock price co-movement.

This effect of market environment can play an important role in the Chinese equity market. The Chinese equity market was established in the early 1990s and has robust growth since then. Though institutional investors (close-end funds and mutual funds) entered the market in 1998, they have not been the dominant players in the stock market. The main market participants in China are still individual investors. For example, in 2013, the market value of A-shares is 19.03

[1]See, for example, Harrison and Kreps (1978), Diether et al. (2002), and Scheinkman and Xiong (2003).

trillion in Renminbi (*RMB*) and the net asset value of stock funds is 3 trillion, which only accounts for 15.8% of A-share market value (www.chinafund.cn). Given the short history of the stock market and the lack of professional skills of individual investors, the level of opinion divergence is expected to be higher in the bull market than in bear market. As shown later, our empirical evidence supports this hypothesis.

3. VARIABLE DEFINITION AND DATA

3.1. Measuring Stock Price Co-movement

Our measure of price co-movement is based on the R^2 of the market model of daily returns. Following Morck et al. (2000), we estimate the following regression:

$$R_{i,t} = \alpha_i + \beta_i R_{M,t} + \varepsilon_{i,t} \tag{1}$$

where $R_{i,t}$ and $R_{M,t}$ are daily returns of stock i and the market at day t, respectively. Previous studies, such as Morck et al. (2000) and Gul et al. (2010), use yearly intervals to gauge stock price co-movement. Since the bull and bear market conversion can occur during a year, it is not suitable to use yearly intervals for the hypothesis testing. To address this concern, we use data at quarterly intervals instead.[2] For each quarter, we estimate a firm-level measure of price co-movement $R^2_{i,Q}$. A high $R^2_{i,Q}$ suggests a high degree of co-movement between individual stocks and the market. This interpretation is akin to the Roll's (1988) study on individual stocks in the United States.

In their analysis of US stocks, Roll (1988) and Piotroski and Roulstone (2004) include industry returns to explain stock returns in the regression model. However, in the Chinese stock market, including industry returns as an additional factor is problematic because this market is dominated by manufacturing industry and there are strong collinearity between industry return and market return. As it is difficult to disentangle the industry effect from the market effect, we have not included industry returns in our study.

3.2. Measuring Investor's Opinion Divergence

Trading is mainly induced by information (including market information and firm-specific information) and investors' opinion divergence (Bessembinder et al., 1996; Garfinkel & Sokobin, 2006). The literature suggests that market information enhances co-movement, but firm-specific information and investors' opinion divergence weaken it. A challenge to test this hypothesis is that none of these variables is observable. To overcome this problem, we follow the approach

[2]Our results are qualitatively the same if we use monthly intervals. For brevity, we do not present these results, and they are available upon request.

suggested by Garfinkel and Sokobin (2006) and Garfinkel (2009) to decompose trading volume into expected and unexpected trading volume. The basic idea in this approach is that the expected trading volume is associated with the information, whereas the unexpected trading volume (measured by residuals from regression) is attributed to investors' opinion divergence. Our method differs from theirs by using the Fama-French three-factor model to fit stock returns, instead of the single-factor market model. The Fama-French model allows us to further divide the information into market information and firm-specific information, which can have opposite effects on price co-movement. Because the size and value factors in the Fama-French model capture not only the covariations in returns but also the effects of leverage and earning-price ratio on expected returns, which are not included in market portfolio returns (Fama & French, 1992, 2004; Liu & Wang, 2019), we can use this model to separate the information contents in stock returns.

To obtain the measures of market information and firm-specific information and investors' opinion divergence, we estimate Fama-French three-factor model for each stock based on daily stock returns for each quarter.

$$\left(R_{i,t} - R_{f,t}\right) = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{2}$$

where $R_{i,t}$ and $R_{M,t}$ are daily returns of stock i and the market at time t, respectively, $R_{f,t}$ is the risk-free rate, and SMB_t (small minus big) and HML_t (high minus low) are the size and value factors. After estimating (2), we set $R^M_{i,t} = \hat{\beta}_i(R_{M,t} - R_{f,t})$, and $R^F_{i,t} = \hat{\alpha}_i + \hat{s}_i SMB_t + \hat{h}_i HML_t$ where $R^M_{i,t}$ and $R^F_{i,t}$ represent the returns related to market information and firm-specific information, respectively.

Next, following Garfinkel and Sokobin (2006) and Garfinkel (2009), we use the daily turnover rate as the proxy of trading volume and then associate the turnover rate with the two information components. Since positive and negative returns have different impacts on trading volume (Karpoff, 1987), we run the following regression:

$$TO_{i,t} = \kappa_i + \gamma_1^+ \left|R^M_{i,t}\right|^+ + \gamma_1^- \left|R^M_{i,t}\right|^- + \gamma_2^+ \left|R^F_{i,t}\right|^+ + \gamma_2^- \left|R^F_{i,t}\right|^- + \varepsilon_{i,t} \tag{3}$$

where $TO_{i,t}$ is the turnover rate of stock i at time t. If $R^M_{i,t}$ is positive, $\left|R^M_{i,t}\right|^+ = R^M_{i,t}$, and at the same time, $\left|R^M_{i,t}\right|^- = 0$; if $R^M_{i,t}$ is negative, $\left|R^M_{i,t}\right|^- = \left|R^M_{i,t}\right|$, and at the same time $\left|R^M_{i,t}\right|^+ = 0$. The values for $\left|R^F_{i,t}\right|^+$ and $\left|R^F_{i,t}\right|^-$ are obtained by the same method. We run the regression in (3) using the data in the preceding 1 year for each quarter with a quarterly rolling. $\hat{\kappa}_i$ denotes trading activity due to investors' exogenous liquidity reason.

Finally, we define the trading activities associated with market information ($TO^{MI}_{i,t}$), firm-specific information ($TO^{FI}_{i,t}$), and investors' opinion divergence ($TO^{OD}_{i,t}$) as follows:

$$TO_{i,t}^{MI} = \hat{\kappa}_i + \hat{\gamma}_1^{+} \left| R_{i,t}^{M} \right|^{+} + \hat{\gamma}_1^{-} \left| R_{i,t}^{M} \right|^{-} \tag{4}$$

$$TO_{i,t}^{FI} = \hat{\gamma}_2^{+} \left| R_{i,t}^{F} \right|^{+} + \hat{\gamma}_2^{-} \left| R_{i,t}^{F} \right|^{-} \tag{5}$$

$$TO_{i,t}^{OD} = TO_{i,t} - TO_{i,t}^{MI} - TO_{i,t}^{FI} \tag{6}$$

These measures for the components of market information and firm-specific information and divergence in opinion are used to test the hypotheses in our empirical study.

3.3. Data

We obtain daily returns and turnover rates of A-share stocks (excluded special treatment stocks) listed in the Shanghai and Shenzhen stock markets. Since there was price change limits imposed on the Chinese stock market before 1997, to avoid the potential policy bias, we select our sample period starting from 1997. Short sale is allowed after March 2010, so our sample period ends in 2009. To obtain reliable estimates, we exclude stocks within the first month of Initial Public Offerings (IPOs) and delete the firm/quarter in which there are less than 20 daily observations. Since accounting ratios of financial firms are different from other firms, financial firms are excluded to avoid the confounding effect of different accounting rules. Because we use the quarterly intervals to obtain the co-movement measures, to ensure enough observations, a firm must have data at least 12 quarters in the whole sample period to be included in the test. The final sample consists of 2,521,244 daily data of 1,057 listed companies. All data are retrieved from the China stock market and Accounting Research (CSMAR) database.

Table 1 provides summary statistics of data. Over the sample period, the Chinese stock market grows rapidly and the number of listed companies increases each year. The size of the firms in total asset value (billion) also increases over time. When both market and individual stocks' average daily returns are positive (negative), the turnover rates are relatively large (small). Standard deviations of daily returns and turnover rates of individual stocks are high which is typical for an emerging market.

Table 2 reports descriptive statistics of the measures for stock price co-movement and market information, firm-specific information, and investors' opinion divergence. $R_{i,Q}^2$ is the co-movement index for individual stock in each quarter. The mean (median) of $R_{i,Q}^2$ during the period of 1997–2009 is 0.436 (0.437), or about 44% of the variation of individual stock returns is explained by market. For the market information and firm-specific information, their standard deviations are smaller than their mean values. For investors' opinion divergence, however, the mean value is small and the standard deviation is large, suggesting that the opinion among investors is diverse. This pattern is also revealed in turnover rates.