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Intra-industry information diffusion in China's stock market

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Abstract

This study concentrates its attention on the China stock market, and employs the panel data and the time-series data methodologies to explore the occurrence of intra-industry information diffusion. The results show the existence of a gradual occurrence of intra-industry information diffusion in China's stock market, by means of a significant lead-lag relationship between big firms and small firms. This paper further confirms that gradual information diffusion actually appears within an industry rather than across the different industries of a national entity. We also respectively analyze a number of individual industries with different suitable lag lengths. We discover a useful finding that fairly predicts according to different industries in China, a wisdom that investors ought to choose some high quality small firms in the appropriate investment timing from the same industry rather than seeking investment opportunities in the whole market, whenever any good common information comes to some big firms. We also use the data from trading volume portfolios to process findings from previous analyses. The results are highly consistent.

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1. Introduction

The Efficient Market Hypothesis (EMH) argues that information diffusion happen instantly in an efficient market. Thus, a trading strategy based solely on information and information acquisition is usually ineffective. However, plenty of empirical studies show that sometimes stock prices react slowly to new information and that in reality; information gradually diffuses among the financial market. In other words, information and even publicly available information does not readily saturate and be digested and reacted to within a given market. There exists a time lag for any information and knowledge to diffuse and spread throughout the market and illicit a response or reaction. There exist several factors that determine this diffusion rate and the acceptance of such information and hence any possible reaction to the said information.

As an influential work, Lo and MacKinlay (1990) discover that information gradually diffuses in the U.S. stock market. After examining the positive cross-autocorrelation between the returns of the big and the small firms, they document the source of the pattern of cross-autocorrelation in return is a gradual market-wide information diffusion. They suggest that big firms have a faster speed of information diffusion than that of smaller firms. Hereafter, studies on gradual information diffusion (e.g., Brennan et al., 1993; Badrinath et al., 1995; Chordia & Swaminathan, 2000; Hou, 2007; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Zhang et al., 2016), to name a few, are numerous.

Previous studies investigate the phenomena of gradual information diffusion not only focusing on its occurrence within the whole market but also paying attention to the impacts on the individual industry factor (e.g., Barberis and Shleifer, 2003; Chou et al., 2012). A few noteworthy studies increasingly consider the relations among industries to explore information diffusion, such as the relationship between the market and industries (e.g., Hong et al., 2007) as well as the relationship among related industries (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010). Focusing on the intra-industry circumstances, Hou (2007) analyzes the gradual information diffusion in the U.S. financial market. He discovers the lead-lag effect caused by slow diffusion of information between big firms and small firms is mainly due to the existence of an intra-industry phenomenon rather than an occurrence that happens across industries. He claims that common information gradually diffuses from big firms to small firms within an industry. Haque (2011) and Cen et al. (2013) support the hypothesis of Hou (2007) on other markets.

As the biggest emerging market, the China stock market is always under abundant attention from the rest of the world. Despite of its rapid progress and rising significance, the China stock market undergoes investor irrationality. Kim and Nofsinger (2008) preserve the view that individual investors in Asian suffer from cognitive biases more than people from Western cultures. Chang et al. (2014) argue that common Chinese investors show more irrational behavior and possess more restricted attention and perception to the emergence of genuine decision-worthy information. According to Kang et al. (2002), most of the typical Chinese individual investors seem to make use of information in a confused and panicky manner and operates in largely uninformed conditions due to a lack of their information processing capacity and an absence of trusted channels. These investors are easily gullible and tend to believe often unsubstantiated rumors and are more like noisy traders who entirely speculate and “gamble” in the financial market. As Kang et al. (2002) state, these “wild-cat” practices are termed as ‘‘stir-frying stocks’’ in China.

Conversely, useful information is usually captured more effectively and efficiently by Chinese institutional investors; they are well informed and tend to react faster than the common variety individual investors. Meanwhile, without sufficient information and qualified security analyses, Chinese individual investors are mostly unsophisticated and display a herding mentality, tending to follow institutional investors. Hence, information generally diffuses from institutional investors to individual investors (e.g. Tan et al., 2008; Piotroski & Wong, 2012). Possessing superiority in information acquisition, institution investors are well-placed and can conveniently manipulate the stock market. Under asymmetric information, insider trading is also more likely to take place. Therefore, understanding the process of information diffusion has considerably empirical significance and advantages to both the Chinese authorities and the Chinese investors.

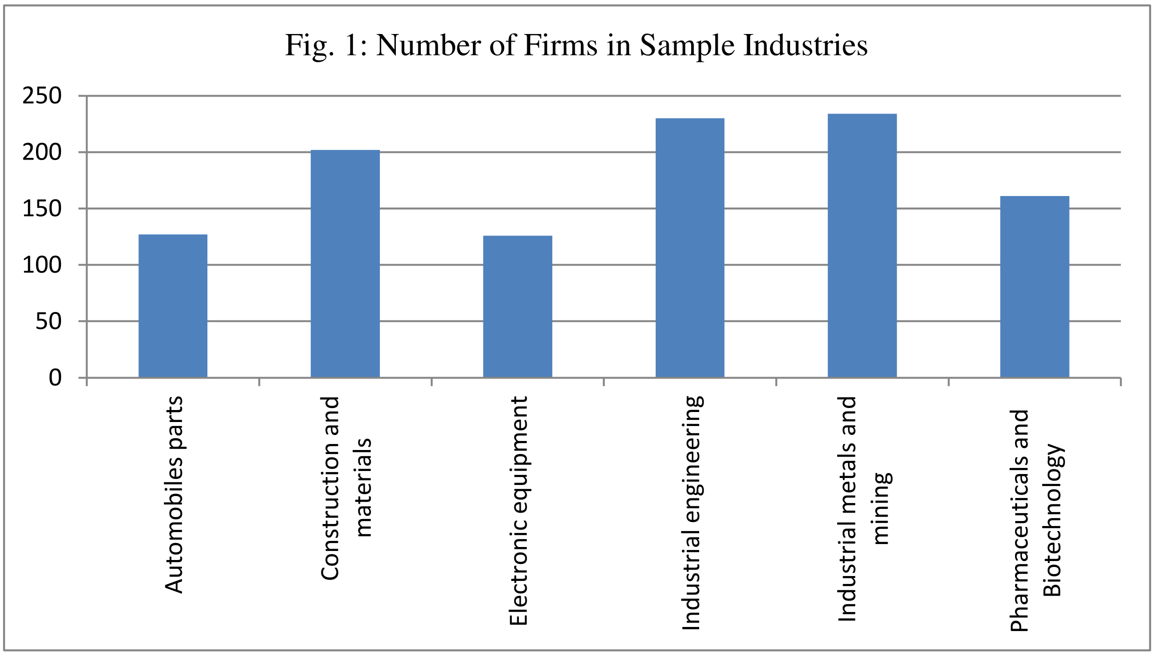
This paper aims to investigate whether intra-industry information diffusion really exists in China’s stock market and how wide-spread is its occurrence. Furthermore, according to different industries in China, this paper explores how information diffuses within different industries. We are able to contribute to the literatures in several ways. First, adding to Hou (2007), we use both the panel data and the time-series data to explore intra-industry information diffusion. We not only process a major investigation on general intra-industry occurrences, but also focus on its happenings within each individual industry. When new good and commonly available information comes to some big firms, we suggest to the investors to select some high quality small firms in appropriate investment timing from the same industry rather than try to seek investment opportunities within the whole market. Second, this paper processes a main investigation of China’s stock market. China’s stock market has much higher research value than many other emerging markets because of its sheer size and potential for profitability among other factors. Previous studies on information diffusion mainly focus on the whole market or segmented markets in China (e.g., Chui & Kwok, 1998; Sjoo & Zhang, 2000; Wu, 2013). This paper fills the research gap by exploring intra-industry information diffusion.

The organization of the paper is stated as follows: Section 2 discusses the data and methodology. The results will be displayed in Section 3. The Conclusion is presented in Section 4.

2. Data and methodology

2.1 **Data**

There are 38 industries in China’s stock market as at the present time. However, many industries only have less than 50 firms and some industries comprise of just a few firms. In order to assure sufficient data for processing the portfolio analyses and major industries are included to guarantee the comprehensiveness of the study, six major industries are selected as the sample industries and 1080 firms are chosen for the analysis depending on the data availability. Figure 1 shows the number of firms in each sample industry.



In order to avoid the impacts of nonsynchronous trading and the microstructure effects, weekly data is used (Foerster and Keim, 2000; Hou, 2007). We estimate the weekly returns from Wednesday close to the subsequent Wednesday close. If the following Wednesday is not a trading day, it will be extend to the next trading day. Closing stock prices cover the period from January 2002 to December 2013 is obtained from Thomson Financial DataStream.

We form size portfolios within an industry, ranking all firms based on their market capitalization in December of each year. Firms are divided into three portfolios: the bottom 30%, the middle 40%, and the top 30%. Portfolio S represents the smallest 30% of firms and portfolio B contains the largest 30% of firms. We compute the equal-weighted portfolio weekly returns for each size-ranked portfolio. R_B and R_S are the weekly returns of the biggest and smallest size portfolios, respectively.

Based on the study period, each industry has 626 weekly observations. The average weekly return of the smallest 30% of firms is greater than the average weekly return of the largest 30% of firms. This observation is consistent with previous studies on size premium (e.g. Banz, 1981; Fama and French, 2012). Moreover, the standard deviation of the smallest 30% portion of firms' return is always greater than the standard deviation of the largest 30% portion of firms' return. These results show that small firms are faced with higher risks and are able to achieve higher returns.

2.2 Methodology

The bivariate unconditional VAR model used in Brennan et al. (1993) is mainly employed to investigate the process of intra-industry information diffusion. This VAR model is utilized to examine lead-lag cross-autocorrelations in financial market. The lead-lag cross-autocorrelation is also recognized as the lead-lag effect. It describes a scenario where the big firms' lagged returns are associated with the small firms' current returns, but the small firms' lagged returns are not associated with the big firms' current returns. The sources of the lead-lag effect mainly come from nonsynchronous trading (Cohen et al., 1986), different degrees of time variation in expected returns (Conrad & Kaul, 1988) and the gradual information diffusion (Lo & MacKinlay, 1990). Nevertheless, most studies maintain the gradual information diffusion as the main source of the lead-lag effect (e.g. Lo & MacKinlay, 1990; Hou, 2007; Menzly & Ozbas, 2010; Mori, 2015). Chordia & Swaminathan (2000) state that the VAR model not only proves whether big firms' lagged returns lead small firms' current returns, but more importantly, it can provide a kind of measure about the speed of information diffusion.

Combing all sample firms regardless of the industry, we build a panel VAR model to process an entire investigation of intra-industry information diffusion.

$$R_{S,i}(t)=a_{i,0}+\sum_{k=1}^{K}a_k\ R_{S,i}(t\text{-}k)+\sum_{k=1}^{K}b_k\ R_{B,i}(t\text{-}k)+u_{i,t} \qquad (1)$$

$$R_{B,i}(t)=c_{i,0}+\sum_{k=1}^{K}c_k\ R_{S,i}(t\text{-}k)+\sum_{k=1}^{K}d_k\ R_{B,i}(t\text{-}k)+v_{i,t} \qquad (2)$$

In equation (1) and (2), $R_{S,i}(t)$ and $R_{S,i}(t\text{-}k)$ denote the equal-weighted weekly returns on the smallest 30% portfolio at period t and period t-k in industry i, while $R_{B,i}(t)$ and $R_{B,i}(t\text{-}k)$ are the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k in industry i. Moreover, a_k and b_k present the coefficients of lagged returns of R_S and R_B in equation (1), while c_k and d_k are the coefficients of lagged returns of R_S and R_B in equation (2). $a_{i,0}$ and $c_{i,0}$ correspondingly are the constant terms. Finally, $u_{i,t}$ and $v_{i,t}$ are the error terms respectively.

In this panel VAR settings, $\sum_{k=1}^{K} a_k$ and $\sum_{k=1}^{K} d_k$ respectively denote the degree about own autocorrelations of small firms and big firms. $\sum_{k=1}^{K} b_k$ and $\sum_{k=1}^{K} c_k$ denote the impact of lagged big firms' returns on current small firms' returns and the impact of lagged small firms' returns on current big firms' returns, correspondingly. Under the null hypothesis that there is no lead-lag relation between big and small firms, which is produced by gradual information diffusion, we expect the sum of coefficients $\sum_{k=1}^{K} b_k = 0$. This is the standard Granger causality test for a lead-lag relation between big and small firms. The absence of any reverse lead-lag relation between big and small firms implies that $\sum_{k=1}^{K} c_k = 0$. Furthermore, according to Brennan et al. (1993), we use the cross-equation test for null hypothesis: $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} c_k$ to check whether one portfolio's lagged return can predicts another portfolio's current return. If the lead-lag relation is driven by a gradual diffusion of information from big firms to small firms, we expect $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} c_k$.

3. Results

3.1 Intra-industry Information Diffusion

Table 1 describes the results of panel VAR which have taken in all firms within the six sample industries. $\sum_{k=1}^{K} b_k$ is greater than $\sum_{k=1}^{K} c_k$ and both are significant at the 1% level. Furthermore, the F-statistic for the cross-equation test is significant at the 1% level (F=61.07). Therefore, the impacts of big firm on small firms are greater than the impacts of small firm on big firms. These results show the existence of the significantly gradual intra-industry information diffusion in China's stock market, by means of a significant lead-lag relationship between big stocks' lagged returns and small stocks' current returns. The results also support the view that big firms have a faster speed of information diffusion than small firms do within an industry.

Table 1: Intra-industry Panel VAR for Size Portfolios

	Four-Lag Panel VAR		Cross-equation test
	$\sum_{K=1}^{4} R_{S,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,i}(t\text{-}k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
$R_{S,i}(t)$	-0.094** (5.12)	0.342*** (18.98)	61.07***
$R_{B,i}(t)$	-0.235*** (15.96)	0.319*** (24.99)	

Notes: $R_{S,i}(t)$ and $R_{S,i}(t\text{-}k)$ are the equal-weighted weekly return on the smallest 30% portfolio at period t and period t-k in industry i. $R_{B,i}(t)$ and $R_{B,i}(t\text{-}k)$ present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k in industry i. Cross-equation test denotes F-statistic for the cross-equation null hypothesis: $\sum_{k=1}^{4}$ bk = $\sum_{k=1}^{4}$ ck. ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive lag order. Thus, four-lag is used in this VAR model.

3.2 Test of Intra- and Inter-industry Information Diffusion

Hou (2007) argues that common information usually gathers within industry rather than outside. Thus, once this intra-industry effect is controlled for, there is little evidence of the gradual information diffusion.

Hence, we presume that lagged returns on big firms from industry i are more important than those from other industries in explaining current returns on small firms of industry i. Consequently, with regard to the original panel VAR, for each industry, we employ an additional variable for small firms' current returns, which denotes the impact of big firms' lagged returns from other industries on small firms' current returns in industry i. The following new panel VAR is stated:

$$R_{S,i}(t) = a_{i,0} + \sum_{k=1}^{K} a_k\, R_{S,i}(t\text{-}k) + \sum_{k=1}^{K} b_k\, R_{B,i}(t\text{-}k) + \sum_{k=1}^{K} e_k\, R_{B,j}(t\text{-}k) + u_{i,t} \qquad (3)$$

$$R_{B,i}(t) = c_{i,0} + \sum_{k=1}^{K} c_k \, R_{S,i}(t\text{-}k) + \sum_{k=1}^{K} d_k \, R_{B,i}(t\text{-}k) + v_{i,t} \qquad (4)^{1}$$

$R_{B,j}(t\text{-}k)$ is the additional variable, which is the equal-weighted week return on the largest 30% portfolio from the other five industries at period t-k. e_k is the coefficients of lagged returns of R_B from the other five industries. $\sum_{k=1}^{K} e_k$ indicates the impact of big firms' lagged returns from other industries on small firms' current returns in industry i.

Furthermore, for the small firms' current returns in industry i, we test the null hypothesis: $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} e_k$ to check the impact of big firms' lagged returns from other industries is greater/smaller than the impact of big firms' lagged returns in industry i. If there is intra-industry information diffusion rather than inter-industry information diffusion, we expect $\sum_{k=1}^{K} b_k > \sum_{k=1}^{K} e_k$.

Table 2 shows $\sum_{k=1}^{K} b_k$ is significant at the 1% level but $\sum_{k=1}^{K} e_k$ is insignificant. Moreover, $\sum_{k=1}^{K} b_k$ is greater than $\sum_{k=1}^{K} e_k$ and F-statistic rejects the null hypothesis: $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} e_k$ at the 1% significance level. These results infer that the lead-lag effect that is driven by a gradual diffusion of common information from big firms to small firms is mainly an intra-industry phenomenon. Therefore, the gradual information diffusion in China appears within industry rather than across the different industries.

Table 2: Intra- and Inter-industry Panel VAR

	Intra- and inter-industry panel VAR			Intra-industry effect test
	$\sum_{K=1}^{4} R_{S,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,j}(t\text{-}k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} e_k$
$R_{S,i}(t)$	-0.155 (0.81)	0.752*** (10.90)	-0.294 (1.76)	25.30***
$R_{B,i}(t)$	-0.235*** (15.96)	0.319*** (24.99)		

Notes: $R_{S,i}(t)$ and $R_{S,i}(t\text{-}k)$ are the equal-weighted weekly return on the smallest 30% firms at period t and period t-k in industry i. $R_{B,i}(t)$ and $R_{B,i}(t\text{-}k)$ present the equal-weighted weekly return on the largest 30% firms at period t and period t-k in industry i. $R_{B,j}(t\text{-}k)$ is the equal-weighted week return on the largest 30% firms from the other six industries at period t-k. Intra-industry effect test denotes the F-statistic for the null hypothesis: $\sum_{k=1}^{4} bk = \sum_{k=1}^{4} ek$. ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive lag order. Thus, four-lag is used in this VAR model.

[1] This equation is same as (2).

3.3 Intra-industry information diffusion in individual industries

Hou (2007) examines intra-industry information diffusion in the U.S. stock market. He only focuses on the panel data. Adding from Hou (2007), we use panel data as well as time-series data to explore intra-industry information diffusion. Besides investigating the intra-industry information diffusion as a whole market, we also focus on the individual industries.

Table 3 displays the time-series results of equal-weighted weekly returns on size portfolios for six industries. We respectively analyze these industries with different optimum lag lengths. First, it is found that the optimum lag length is four in the automobiles parts industry, the construction and materials industry as well as the industrial metals and mining industry. Moreover, $\sum_{k=1}^{4} b_k$ is greater than $\sum_{k=1}^{4} c_k$ in these three industries and the F-statistic of cross-equation test is significant at the 1% level. Big firms have faster speed of information diffusion than small firms within the industry. When good common information comes to some big firms, previous studies usually suggested that investor might choose some small firms from the whole market. However, this study discovers common information only diffuses within industry rather than the whole market. Therefore, investors ought to choose some high quality small firms from the same industry rather than the whole market. Investors should take long positions of these stocks in suitable timing. They may then wait for the increase of these small firms' prices and get the abnormal profits. For the above three industries, the timing of investing in small firms most likely to occur within four weeks of the common information comes to the industry.

Similarly, in the electronic equipment industry as well as the pharmaceuticals and biotechnology industry, we also discover information diffuses from big firms to small firms within industry. The timing of investing in small firms should happen within two weeks of the common information to the industry. Furthermore, information diffuses from big firms to small firms within industry is also found in the industrial engineering industry. For this industry, the timing of investing in small firms should be chosen within eight weeks of the common information to the industry.

We further discover size and number of firms might affect the speed of intra-industry information diffusion. In the industries with smaller size and industries which contain less number of firms such as the electronic equipment industry and the pharmaceuticals and the biotechnology industry, firms have a faster response speed to information (two weeks). On the contrary, firms have more delay time on reaction to new information (eight weeks) in industries with a bigger size and industries which have more numerous firm's in terms of numbers such as the industrial engineering industry.

Table 3: Intra-industry VAR in individual industries

INDUSTRY		Lag length	$\sum_{K=1}^{K} R_{S,(t-k)}$	$\sum_{K=1}^{K} R_{B,(t-k)}$	$\sum_{k=1}^{k} b_k = \sum_{k=1}^{k} c_k$
Automobiles parts	$R_{S,t}$	4	-0.312**	0.547***	41.796***
			(4.478)	(11.809)	
	$R_{B,t}$		-0.482***	0.614***	
			(12.126)	(16.968)	
Construction &	$R_{S,t}$	4	-0.504***	0.683***	32.210***

materials			（6.970）	（10.981）	
	$R_{B,t}$		-0.487***	0.601***	
			（7.632）	（9.935）	
Electronic	$R_{S,t}$	2	-0.207	0.344**	14.415***
equipment			（1.845）	（4.448）	
	$R_{B,t}$		-0.275*	0.364**	
			（3.687）	（5.648）	
Industrial	$R_{S,t}$	8	-0.417*	0.616**	19.589***
engineering			（3.107）	（6.309）	
	$R_{B,t}$		-0.470**	0.700***	
			（4.376）	（9.027）	
Industrial metals &	$R_{S,t}$	4	-0.056	0.248**	6.482***
mining			（0.151）	（4.659）	
	$R_{B,t}$		-0.136**	0.241*	
			（4.938）	（2.659）	
Pharmaceuticals &	$R_{S,t}$	2	-0.053	0.134**	7.939***
biotechnology			（0.197）	（4.520）	
	$R_{B,t}$		-0.114*	0.246**	
			（1.253）	（4.012）	

Notes: $R_{S,t}$ and $R_{S,t-k}$ are the equal-weighted weekly return on the smallest 30% portfolio at period t and period t-k, while $R_{B,t}$ and $R_{B,t-k}$ present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k. The F-statistics (t-statistics) for the null hypothesis that the sum of the coefficients equals 0 in the 4-lag (1-lag) VAR is displayed under the corresponding coefficient. Cross-equation test denotes F-statistic for null hypothesis that $\sum_{k=1}^{4} R_{B,(t-k)}$ from Equations (4.3) equals $\sum_{k=1}^{4} R_{S,(t-k)}$ from Equation (4.4), i.e. $\sum_{k=1}^{4} bk = \sum_{k=1}^{4} ck$. Finally, ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. We choose different order criteria of lag length based on the information criterions.

3.4 Robustness Check Using Trading Volume Portfolios as a Variable Indicator

Chordia and Swaminathan (2000) document that trading volume also plays a significant role in the process of information diffusion. They suggest high trading volume firms react faster to common information than the low trading volume firms. We examine intra-industry information diffusion based on trading volume portfolios. Since trading volume is greatly associated with firm size, we isolate size factor from trading volume in the underlying analyses. First, three size-ranked portfolios: top 30%, middle 40% and bottom 30% are formed based on firm size. Next, each size portfolio is further divided into three sub-portfolios: top 30%, middle 40% and bottom 30% based on trading volume. Furthermore, we choose the lowest trading volume portfolio from each of the three size portfolios and put them together to form a new portfolio. This new portfolio is only related to the lowest trading volume regardless the size. Similarly, we obtain the middle trading volume portfolio and the highest trading volume portfolio respectively. Thus, we have three new trading volume-ranked portfolios regardless the firm size. R_H and R_L represent the equal-weighted highest and lowest trading volume-ranked portfolio returns, correspondingly.

Table 4: Intra- and Inter-industry Panel VAR based on trading volume portfolio

	Intra- and inter-industry panel VAR			Intra-industry effect test
	$\sum_{K=1}^{4} R_{L,i}(t-k)$	$\sum_{K=1}^{4} R_{H,i}(t-k)$	$\sum_{K=1}^{4} R_{H,j}(t-k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} e_k$
$R_{L,i}(t)$	-0.069 (0.74)	0.715*** (12.19)	-0.207 (1.51)	33.78***
$R_{H,i}(t)$	-0.114*** (18.75)	0.297*** (20.63)		

Notes: $R_{L,i}(t)$ and $R_{L,i}(t-k)$ are the equal-weighted weekly return on the lowest trading volume 30% firms at period t and period t-k in industry i. $R_{H,i}(t)$ and $R_{H,i}(t-k)$ present the equal-weighted weekly return on the highest trading volume 30% firms at period t and period t-k in industry i. $R_{H,j}(t-k)$ is the equal-weighted week return on the highest trading volume 30% firms from the other six industries at period t-k. Intra-industry effect test denotes the F-statistic for the null hypothesis: $\sum_{k=1}^{4}$ bk = $\sum_{k=1}^{4}$ ek. ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive lag order in this VAR model.

Table 4 reports the results of panel VAR based on the trading volume portfolios. Specifically, both $\sum_{k=1}^{K} b_k$ and $\sum_{k=1}^{K} c_k$ are significant at the 1% level and $\sum_{k=1}^{K} b_k$ is greater than $\sum_{k=1}^{K} c_k$. These results infer the existence of gradual intra-industry information diffusion in China's stock market, by means of a significant lead-lag relationship between the high trading volume firms' lagged returns and low trading volume firms' current returns. The results suggest high trading volume firms have faster speed of information diffusion than the low trading volume firms within industry.

On the other hand, $\sum_{k=1}^{K} e_k$ is insignificant and $\sum_{k=1}^{K} b_k$ is greater than $\sum_{k=1}^{K} e_k$ with F-statistic rejects the null hypothesis: $\sum_{k=1}^{K} b_k = \sum_{k=1}^{K} e_k$ at 1% significance level. These results suggest the impacts of lagged returns of high trading volume firms in industry i are greater than the impacts of lagged returns of high trading volume firms from other industries for the low trading volume firms' current returns in industry i. Again, we confirm the lead-lag effect that is driven by a gradual diffusion of common information from high trading volume firms to low trading volume firms is mainly an intra-industry phenomenon.

5. Conclusion

After investigating intra-industry information diffusion in China's stock market, this paper discovers that the occurrence of gradual information diffusion appears within an industry rather than across different industries. Besides investigating the intra-industry information diffusion as a whole market, we also examine information diffusion in individual industries. We discover different industries have dissimilar optimum information lag lengths. Therefore, some strategies based on the information obtained could be produced after this study. For example, when new good common information comes to some big firms, investors ought to choose some high quality small firms within appropriate investment timing from the same industry rather than from the whole market. Furthermore, industry size and number of firms might affect the speed of intra-industry information diffusion. Firms have a much faster response speed to information in the industries with smaller size and containing less numerous firms, while firms have more delay time on reaction to new information in industries with bigger size and containing more number of member firms.

From the view of policy implications and the empirical data which has been analyzed, we are able to offer useful suggestions. Understanding the nature and process of information diffusion has considerably empirical advantages and control significance to the Chinese authorities and investors. Policy makers could smoothen the process of information diffusion and ensure that stock prices develop more effectively and informatively. For small individual investors who have difficulty to grasp insider information, they could utilize the investment strategies based on general and publicly available information. In general, internal determinants of gradual information diffusion such as the firm's characteristics have been sufficiently explored in this study as well as in many previous studies. Future research should pay more attention to some external determinants of intra-industry information diffusion and macro-factors such as market conditions and government policy changes.

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