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The Impact of Market Condition and Policy Change on the Sustainability of Intra-Industry Information Diffusion in China

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Abstract: Through an investigation into seven major industries in China's stock market from 2002 to 2013, this study focuses on two main external determinants: market condition and policy change on intra-industry information diffusion. We employ both time-series and panel Vector Auto-regression (VAR) methods on a sample data of 1175 firms for the analysis. The investigation reveals that market conditions and policy changes affect the process of intra-industry information diffusion in China. The speed of intra-industry information diffusion in a down-market state is slower than an upmarket, especially when the evidence is more significant in the longer horizon of the market condition. Policy changes, especially the split-share structure reform, impede the process of intra-industry information diffusion. The investigation outcome also reveals that there is an increasing delay in intra-industry information diffusion over time in China's stock market after 2005. However, because of the decreasing information volatility of intra-industry information diffusion, policy changes are useful to a certain extent.

Keywords: market condition; policy change; information diffusion; intra-industry; China

1. Introduction

Under the Efficient Market Hypothesis (EMH), information diffuses without any delay in a complete and frictionless market. However, ever since the seminal work of Lo and MacKinlay [1], researchers increasingly discover that information gradually diffuses in the realistic market. From research views to research methods, an abundance of researchers continually explore the study of gradual information diffusion [2–7]. Many past studies contribute internal determinants, such as the firm's characteristics in the process of information diffusion [8–10].

Additionally, external factors that could affect the process of information diffusion have also been explored. Two potential external determinants that can affect information diffusion are market condition and policy change. Certain literatures focus on market condition to explore information diffusion. For example, McQueen et al. [11] and Chang et al. [12] suggest that, by reason of small stocks' lagged response in up market, gradual information diffusion is more significant in up market rather than down market. In contrary to McQueen et al. [11], Hameed and Kusnadi [3] claim that the speed of information diffusion is supposed to be slower when the market falls. Chen & Rhee [13] suggest that both short sale and market conditions could affect the speed of information diffusion.

They argue that the speeds of information diffusion are similar in the both up and down markets. Therefore, the market condition that can delay the diffusion of information seems be controversial.

Another external determinant is policy change. As an important setting in a market environment, policy change has significant impact on the financial market from various aspects and the influence on information diffusion is just a sub-fraction. It is the process of gradual discovery. Any policy change is not always smooth and successful and the market environment and institutional arrangement can be responsible for the speed of information diffusion. Merton [14] recognizes the importance of institutional constraints in the information achievement and diffusion procedure. In recent years, the impact of policy changes on financial markets has become one of the more recent research hotspots. Theoretically and empirically, the importance of a variety of policies and environmental changes on the process of information diffusion is explored by several researchers. Lin & Swanson [15] argue that policy changes in China could influence the China segmented stock market more. They suggest that the policy changes alleviate barriers of information diffusion. In addition, Bae et al. [16] argue that the policy of liberalization of stock market produces more information on the efficiency of stock prices for emerging markets. They discover that foreign investors can facilitate the diffusion of global market information into stock prices. On the other hand, Mori [17] investigates how policy and environmental changes in the Real Estate Investment The trust market could affect the process of information diffusion in the United States (U.S.) market. He discovers that changes of the process of information diffusion depend on both different government policies and changes of firm size.

On the other hand, most of the previous studies investigate the process of information diffusion based on the whole market and, by narrowing the research scope, a few researches have also examined information diffusion that relates to industries such as customer-supplier and upstream-downstream industries [5,6,18]. However, researches rarely focus on firms within an industry to investigate the process of information diffusion. Cen et al. [19] report that industry-wide information is first incorporated into the stock prices of industry leaders who are more liquid and have high level of analyst coverage, and then the information gradually distributes to other industry followers. Importantly, Hou [4] particularly examines the intra-industry information diffusion. He argues that gradual information diffusion mainly exists in intra-industry rather than cross-industry or outside-industry. Haque [20] further support the hypotheses of Hou [4] with data in Australia. However, they only focus on the internal impact factors of intra-industry information diffusion. External determinants of intra-industry information diffusion have not been adequately touched on in their researches.

By including the market conditions and policy changes, this study stresses the roles of external determinants on intra-industry information diffusion in China's stock market. To the best of our knowledge, this study is the first of its kind, which focuses on the intra-industry to investigate the process of information diffusion with views of market conditions and policy changes. The research not only focuses on individual industries, but it also processes a major investigation of intra-industry. The findings of this research contribute to the pool of existing literature in several ways. First, as an external determinant, how market conditions affect information diffusion in the stock market is still controversial. Moreover, the research scope focuses on intra-industry. This study is the first attempt to explore the impact of market condition on information diffusion with focus on intra-industry.

Second, as the largest emerging market, China's stock market has unique microstructures and institutional arrangement, which are different with most developed markets. Due to the relatively shorter development period, China's stock market suffers from market immaturity and investors irrationality. With the specific conditions in China, the study focuses on whether and how policy changes influence the process of intra-industry information diffusion. Institutional frictions are accountable for producing the delay in the process of information diffusion. Thus, comprehending the process of information diffusion is very important for policy considerations. Institutional reforms in China's stock market have been implemented for many years since the establishment of the market. However, the effectiveness of the changes in policy is still in dispute. Whether policy reforms are effective in China stock market? Whether China government can professionally regular and controls the market? How to smooth the process of information diffusion and increase informativeness of stock price? How do investors make use of information? These problems always puzzle government authorities and investors. Therefore, revolving around intra-industry information diffusion, further systematic investigation and exploration are necessary. Policy considerations and market mechanisms in China should keep pace with the times, which could, in turn, ensure that stock prices develop more effectively and informatively. Based on the most important policy changes, i.e., the split-share structure reform in 2005 and lifting short-sale constraints in 2010, this study is the first to investigate the impact of policy change on intra-industry information diffusion. Consequently, this study provides several evidences to help the government authorities in smoothing the process of intra-industry information diffusion and augmenting the market efficiency.

Third, the study focuses on China's stock market. As the biggest emerging market, research on China's stock market is a significant reference for investigation into other emerging markets. Most researches about information diffusion in China concentrate on the whole market [7,21] or segmented markets, such as A-share and B-share [15,22]. As far as we know, no literature focuses on intra-industry to investigate information diffusion in China's stock market. Based on the main intra-industry analysis, the study fills the gap.

The organization of the paper is stated, as follows: Section 2 discusses policy changes in China's stock market; Section 3 shows the data and main methods, whereas the impact of market condition on intra-industry information diffusion is examined in Section 4; Section 5 presents the impact of policy changes on the process of intra-industry information diffusion; and, the conclusion and discussion are described in Section 6.

2. Policy Changes in China's Stock Market

Since the reform and opening in 1978, China has experienced a fast transformation from the planned economy to market economy at the national level. Over the past three decades, China has gone through impressive economic growth and turned into the world's second largest economy. It became a member of the World Trade Organization (WTO) that is recognized as one of the BRICs (Brazil Russia India China) by international investment banks (Goldman Sachs) in 2001. Due to its fast economic development and enormous growth opportunities in China, as an indispensable part of the Chinese economy, China's stock market increasingly attracts domestic and foreign investors' attention. As an emerging market, China's stock market has the second largest trading volume, as well as the second largest market capitalization of $6.4 trillion in 2014 [23], only after the U.S. China's stock market became one of the most active markets based on the number of listed companies, the total trading volume, the market capitalization, participation of foreign investors, and the unique categorization of stocks. Therefore, a considerable amount of investment interests and academic attention around the world concentrate on China's stock market.

Notwithstanding its fast development and emerging importance, China's stock market may suffer from market irrationality and excessive fluctuation. Therefore, China's government has to continuously regulate and control the market, as well as stabilize its stock prices. However, the regulation effects are always met with skepticism. For the last ten years, among all of the policies, two policies are the most significant and they show the greatest impact to China's stock market. First, the split-share structure reform that happened in 2005. Based on the tradability, the stocks of listed companies can be put into two major classes: tradable stocks and non-tradable stocks. More specifically, non-tradable stocks belong to all levels of government or government-controlled financial institutions. Wu [24] argues that the issuance of non-tradable stocks increases the inefficiency of China's stock market. For example, less tradable stocks can bring about a decrease in liquidity and they are convenient to the practice of insider information trading.

On the other hand, tradable stocks can be freely traded by individual, as well as institutional investors. All companies have non-tradable shares in varying proportions. Before 2005, non-tradable shares contain about two-thirds of the total number of outstanding shares. An excess of non-tradable shares in the stock market bring out several problems for further development of the market. In April 2005, the China Securities Regulatory Commission (CSRC) initiated the reform of non-tradable shares, i.e., the split-share structure reform, trying to transfer all non-tradable shares into tradable shares. The central focus of the split-share structure reform is that holders of non-tradable shares are obliged to compensate the holders of tradable shares in order to obtain the liquidity rights for the option to sell their shares in the future [25]. The potential impact of the split-share structure reform has been discussed by a few empirical literatures. Li et al. [26] suggest that the split-share structure reform might be the most powerful policy reform of China's stock market in recent years. Beltratti et al. [25] discuss that this reform lays down the conditions for essential future changes in ownership, liquidity, and corporate governance in China. However, Carpenter et al. [27] suggest that the split-share structure reform has only little direct immediate impact on the structure of China's stock market in the short term.

The second important policy is lifting short-sale constraints. Before 2010, there were strict short-sale constraints in China's stock market. Under short-sale constraints, due to the ban of law, investors are unable to freely short-sell stocks that they do not hold. Theoretically, short-sale constraints could affect the process of information diffusion. Diamond and Verrecchia [28] maintain that short-sale constraints could delay new information that is to be incorporated into stock prices. Negative information also has difficulties in incorporating stock price and diffusing slowly. In order to improve the process of China's financial market marketization, as well as acting on international convention, CSRC finally abolished the short-sale constraints of China's stock market in February 2010. Therefore, after 2010, after short-sale constraints disappeared, market transactions might have further development room. Chang et al. [29] report that Chinese investors seemed to be unfamiliar with the short-sale mechanism and it is deemed that many of them choose to keep away from short-sales. However, Zhao et al. [30] argue that permitting short-sales could decrease market volatility and provide more suitable stock return allocation in China's stock market. As a result, China's stock market provides appropriate areas to investigate the process of information diffusion with or without short-sale constraints.

3. Data and Methodology

3.1. Data

China's stock market was established in the early 1990s, and in the initial ten years, stock prices fluctuated excessively. CSRC is obliged to continuously introduce policies to stabilize the market. For the purpose of obtaining a relatively stable period of China's stock market, we exclude the initial years since its establishment. Hence, the study period will be from January 2002 to December 2013.

It also focuses on the investigation of intra-industry in China's stock market, because the number of industry is relatively larger. There are 38 industries in China's stock market in the present. However, the number of firms within the industry varies in different industries. Some have more than 100 firms, while some industries only have a few. Sufficient research data is necessary to support the research objectives of this study. The industry that had the number of firms greater than 80 is chosen. (Hou [4] chooses the industry in the U.S. market with the number of firms that are greater than 80. This is a better reference. Not only that, the number of firms in each portfolio should be enough for analysis. Examining information diffusion within an industry in the Australian market, Haque [20] chooses industries that have five to 26 firms. Thus, the number of firms in each portfolio is only two to seven. Due to a smaller firm number, it is difficult to not suspect the validity of the results. Consequently, we chose the industry where the number of firms is greater.) However, the number of firms constantly changes every year. Therefore, to be more specific, we chose the industry with more than 80 firms in 2013. In addition, major industries in China also required selection to guarantee the comprehensiveness of the study. Consequently, we chose the industry with a number of firms greater than 80 and consider this to be a major industry in China. As a result, we chose seven industries and 1175 firms to be the sample in this study. Table 1 shows the number of firms in the sample industries.

Table 1. Number of Firms in Sample Industries.

Industry	Number of Firms
Automobiles parts	127
Construction and materials	202
Food producers	95
Electronic equipment	126
Industrial engineering	230
Industrial metals and mining	234
Pharmaceuticals and biotechnology	161

In order to avoid the considerable bias that is connected with nonsynchronous trading and some microstructure effects at the daily level, weekly returns rather than daily returns are employed in our paper. In addition, seasonal patterns might affect weekly autocorrelations of stock returns [31]. Hou [4] argues that, based on five trading days, if Friday is close, then the autocorrelations of the corresponding weekly return should be higher. On the other hand, if Tuesday is closed, then the autocorrelations of the corresponding weekly return should be smaller. Thus, if Wednesday is closed, then the autocorrelations of the corresponding weekly return should be in between. Using this finding, 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 extended to the next trading day. This method of calculating weekly returns is commonly used in the literature, see, for example, Hameed and Kusnadi [3], and Hou [4]. Nevertheless, Chordia and Swaminathan [10] and Haque [20] employ both the weekly data and daily data to run the Vector Auto-regression (VAR) model. They find that the result of weekly data and the result of daily data are similar.

3.2. Descriptive Statistics

In order to avoid the impact of non-synchronous trading and microstructure effects, many studies use weekly and size-based portfolio data [3,4]. Following the same scenario, the empirical investigation is processed on a weekly and size-based portfolio return.

The size portfolios within the industry are formed, ranking all the firms based on their market capitalization i.e., total capital in the December of each year. The firms are divided into three portfolios: bottom 30%, middle 40%, and top 30%. Portfolio S denotes the smallest 30% firms and portfolio B includes the largest 30% firms. The equal-weighted portfolio weekly returns for each size-ranked portfolio are estimated. R_B and R_S are the weekly returns of the biggest and smallest size portfolios, respectively. Before the empirical analysis is presented, necessary descriptive statistics are essential. More specific descriptive statistics are stated in Table 2:

Table 2 displays the descriptive statistics for the largest and smallest 30% size portfolios of all sample industries from 2002 to 2013. There are 626 weekly returns in each industry-size portfolio. The average weekly returns of the smallest 30% firms are obviously greater than the average weekly returns of the largest 30% firms. Therefore, small firms usually obtain a higher average return, which is consistent with previous studies on size premium [32–35]. Moreover, the standard deviation of the smallest 30% firms' return is always greater than the standard deviation of the largest 30% firms' return. These results imply that the small firm poses higher risk with regards to higher returns. Kurtosis in each portfolio is greater than three, while the skewness in each portfolio is closed to zero. Furthermore, the unit root test is generally employed to examine the stationary of the time-series data. As shown in Table 2, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests reject the null hypothesis at 1% level in all industries, which exhibited that the data has no root unit. The results displayed in these returns are stationary.

Table 3 describes the results from the first through fourth order autocorrelations and cross-autocorrelations of the largest 30% firms and the smallest 30% firms in each industry. The first-order autocorrelation coefficient declines as we move from the smallest firms to the largest.

The longer it lags, from two to four weeks, the autocorrelation functions decline faster. Second, for most industries, the correlation coefficient between the returns on the lagged largest 30% firms and the current smallest 30% firms is greater than the correlation coefficient between returns on the lagged smallest 30% firms and the current largest 30% firms. Table 3 also shows that the cross-autocorrelations decay in most industries, as more lags come. Therefore, the cross-autocorrelations show that the big firms' lagged returns provide predictive ability for smaller firms' current returns. Consequently, the lead-lag effect between the big and small firms is evidently displayed within the industry. Furthermore, these asymmetric cross-autocorrelations are consistent with the hypothesis of gradual information diffusion: when new information comes, small firms react more slowly than big firms.

Table 2. Descriptive Statistics for the weekly return of Intra-industry Portfolios.

Industry Portfolio	Mean	Std	Median	Max	Min	Kurtosis	Skewness	ADF Test	PP Test
Auto-big	0.0005	0.048	−0.0005	0.1580	−0.1866	4.2936	−0.0812	−14.969 ***	−25.490 ***
Auto-small	0.00056	0.051	0.0026	0.1481	−0.2524	5.0236	−0.5042	−23.492 ***	−23.614 ***
Cons-big	0.0002	0.047	0.0006	0.1523	−0.2028	4.5305	−0.2174	−15.479 ***	−25.159 ***
Cons-small	0.0009	0.052	0.0048	0.1601	−0.3004	5.5341	−0.5967	−24.146 ***	−24.158 ***
Elec-big	0.0003	0.047	0.0015	0.1822	−0.1893	4.2391	−0.1793	−25.130 ***	−25.129 ***
Elec-small	0.0014	0.051	0.0056	0.1535	−0.2241	4.9526	−0.4652	−24.822 ***	−24.823 ***
Food-big	0.0006	0.046	0.0024	0.1414	−0.2388	4.5246	−0.1952	−24.630 ***	−24.630 ***
Food-small	0.0009	0.049	0.0036	0.1931	0.2543	5.4559	−0.4885	−24.121 ***	−24.172 ***
Engi-big	0.0001	0.049	6.82E-05	0.1608	−0.1982	4.2426	−0.0678	−24.940 ***	−24.947 ***
Engi-small	0.0012	0.051	0.0040	0.1498	−0.2764	5.4045	-0.5923	−24.221 ***	−24.279 ***
Meta-big	−0.0006	0.049	−0.0024	0.1793	−0.1796	4.4632	−0.0823	−15.329 ***	−24.292 ***
Meta-small	0.0010	0.051	0.0034	0.1380	−0.2672	4.8873	−0.4950	−14.906 ***	−23.702 ***
Phar-big	0.0014	0.042	0.0040	0.1656	−0.1710	4.7004	−0.0728	−15.413 ***	−25.626 ***
Phar-small	0.0017	0.049	0.0039	0.1497	−0.2486	5.2476	−0.5787	−15.234 ***	−24.081 ***

Notes: Auto-big and Auto-small refer to the largest 30% size portfolio and the smallest 30% size portfolio in Automobiles parts industry, respectively. Similarly, Cons-big and Cons-small, Elec-big and Elec-small, Food-big and Food-big, Engi-big and Engi-small, Meta-big and Meta-small, and Phar-big and Phar-small refer to the largest 30% size portfolio and the smallest 30% size portfolio in Construction and materials industry, Electronic equipment industry, Food producer industry, Industrial engineering industry, Industrial metals and mining industry, andPharmaceuticals and biotechnology industry, correspondingly. N denotes the average number of firms in each portfolio from 2002 to 2013. Finally, ***, **, and * denote the significance at the 1, 5, and 10 % levels, respectively.

Table 3. Autocorrelation Matrices.

Industry Portfolio	ρ_0(j,B)	ρ_0(j,S)	ρ_1(j,B)	ρ_1(j,S)	ρ_2(j,B)	ρ_2(j,S)	ρ_3(j,B)	ρ_3(j,S)	ρ_4(j,B)	ρ_4(j,S)
Auto-big	1	0.814	−0.029	−0.082	0.163	0.053	0.065	−0.049	−0.038	−0.013
Auto-small	0.913	1	0.083	0.034	−0.045	0.074	0.057	0.060	0.017	−0.049
Cons-big	1	0.831	−0.022	−0.062	0.134	0.045	0.071	−0.034	−0.083	0.010
Cons-small	0.974	1	0.086	0.016	−0.044	0.069	0.041	0.054	−0.011	−0.089
Elec-big	1	0.869	−0.023	−0.026	0.113	−0.001	−0.002	−0.032	−0.123	−0.043
Elec-small	0.988	1	0.032	−0.015	−0.002	0.093	0.040	0.034	0.045	−0.051
Food-big	1	0.876	−0.003	−0.037	0.095	0.009	0.061	−0.006	−0.103	0.010
Food-small	0.977	1	0.035	0.022	−0.002	0.075	0.021	0.067	−0.135	−0.096
Engi-big	1	0.854	−0.016	−0.069	0.116	0.034	0.091	−0.004	−0.113	−0.014
Engi-small	0.911	1	0.047	0.003	−0.025	0.090	0.008	0.050	0.023	−0.063
Meta-big	1	0.819	0.020	−0.049	0.122	0.042	0.058	−0.033	−0.091	−0.022
Meta-small	0.863	1	0.064	0.037	−0.014	0.129	0.027	0.055	0.022	−0.084
Phar-big	1	0.753	−0.039	−0.076	0.148	0.035	0.053	−0.003	−0.097	−0.016
Phar-small	0.991	1	0.083	0.018	−0.029	0.116	0.003	0.020	0.005	−0.058

Notes: ρ_m(j,k), m = 0 to 4, j = B or S, and k = B or S, is correlation coefficient. B and S refer to the largest 30% size portfolio and the smallest 30% size portfolio, respectively. ρ_m(j,k) refers to the m^{th} order correlation coefficient between returns on the largest 30% size portfolio and the smallest 30% size portfolio. For example, ρ1(S, B) denotes the correlation between week t return on the smallest 30% size portfolio and week t−1 return on the largest 30% size portfolio. ρ2 (B, S) represents the correlation between week t return on the largest 30% size portfolio and week t−2 return on the smallest 30% size portfolio. On the other hand, ρ_m(j,k) also displays autocorrelation of portfolios' return. For instance, ρ1 (B, B) refers to the first-order autocorrelation of the largest 30% size portfolio. ρ4 (S, S) means the fourth-order autocorrelation of the smallest 30% size portfolio.

3.3. Vector Auto-regression (VAR)

According to the hypothesis of time-varying expected returns, the cross-autocorrelations between the big firms' lagged returns and the small firms' current returns are caused by a combination of small firms' high autocorrelations and a high contemporaneous correlation between the big and small firms [31,36] Moreover, the contemporaneous correlation coefficients between the small and the big firms are always greater than 0.7 in all sample industries. These results imply that high contemporaneous correlation also appear between the small and big firms. Thus, vector-autoregressive regression (VAR) tests are employed to control the autocorrelations of small firms and the contemporaneous correlation between big and small firms. Brennan et al. [8] first employ the VAR model to investigate the process of intra-industry information diffusion. They conclude that, when there is only lagged impact rather than contemporaneous impact among variables, it is suitable to set up the VAR procedure. They further propose that error term actually implies contemporaneous impact. Chordia and Swaminathan [10] state that the VAR model not only prove whether big firms' lagged returns lead small firms' current returns, but more importantly, it could provide a kind of measure about the speed of information diffusion. The corresponding VAR model for each respective industry is described in the following equations:

$$\mathrm{R}_{\mathrm{S,t}} = a_0 + \sum_{k=1}^{K} a_k R_{S,t-k} + \sum_{k=1}^{K} b_k R_{B,t-k} + u_t \tag{1}$$

$$\mathrm{R}_{\mathrm{B,t}} = c_0 + \sum_{k=1}^{K} c_k R_{S,t-k} + \sum_{k=1}^{K} d_k R_{B,t-k} + v_t \tag{2}$$

Furthermore, by combining all the sample firms, regardless of the industry, a panel VAR model to process the entire investigation of intra-industry is also built:

$$\mathrm{R}_{\mathrm{S,i(t)}} = a_{i,0} + \sum_{k=1}^{K} a_k R_{S,i(t-k)} + \sum_{k=1}^{K} b_k R_{B,i(t-k)} + u_{i,t} \tag{3}$$

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

In Equations (1) and (2), $\mathrm{R}_{\mathrm{S,t}}$ and $\mathrm{R}_{\mathrm{S,t\text{-}k}}$ are the equal-weighted weekly returns on the smallest 30% portfolio at period t and period t-k, while $\mathrm{R}_{\mathrm{B,t}}$ and $\mathrm{R}_{\mathrm{B,t\text{-}k}}$ present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k. (We obtain similar results using value-weighted weekly returns, results are available upon request.) On the other hand, in Equations (3) and (4), $\mathrm{R}_{\mathrm{S,i}}$(t) and $\mathrm{R}_{\mathrm{S,i}}$(t-k) are the equal-weighted weekly returns on the smallest 30% portfolio at period t and period t-k in industry i, while $\mathrm{R}_{\mathrm{B,i}}$(t) and $\mathrm{R}_{\mathrm{B,i}}$(t-k) present the equal-weighted weekly return on the largest 30% portfolio at period t and period t-k in industry i. Moreover, in Equations (1) and (3), a_k and b_k are the coefficients of the lagged returns of R_{S} and R_{B}, respectively. In Equations (2) and (4), c_{k} and d_{k} are the coefficients of lagged returns of R_{S} and R_{B}, respectively. a_0 and c_0 ($a_{i,0}$ and $\mathrm{c}_{i,0}$) are the constant terms, correspondingly. Finally, u_t and v_t ($u_{i,t}$ and $\mathrm{v}_{i,t}$) are the error terms, respectively.

In the above time-series and panel VAR settings, $\sum_{k=1}^{K} a_K$ and $\sum_{k=1}^{K} d_K$ denote the degree of the autocorrelations of small and big firms, respectively. $\sum_{k=1}^{K} b_K$ and $\sum_{k=1}^{K} c_K$ refer to the impact of lagged big firms' returns on current small firms' returns, as well as the impact of lagged small firms' returns on current big firms' returns correspondingly. If there is lead-lag relation between the big and small firms, which is generated by gradual information diffusion, the sum of coefficients $\sum_{k=1}^{K} b_K \geq 0$ is expected. Furthermore, according to Brennan et al. [8], we could employ 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 predict 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 $\sum_{k=1}^{K} b_K > \sum_{k=1}^{K} c_K$. (We estimate the VAR for the full sample period and find the impact of lagged big firms' returns on current small firms' returns is significantly greater than the impact of lagged small firms' returns on current big firms' returns. The results suggest the existence of the significantly gradual intra-industry information diffusion in China's stock market, by means of a significant intra-industry lead-lag relationship between big stocks' lagged returns and small stocks' current returns. The empirical results are available upon request.) Additionally, we also exclude the effect of cross-industry information diffusion in this study. The gradual information diffusion between big and small firms only appears within the industry, rather than across the different industries. (We confirm the gradual information diffusion actually is intra-industry information diffusion.)

4. Market Conditions and Intra-Industry Information Diffusion

To explore the impact of market conditions, they are categorized as up or down, depending on whether the previous market return is positive or negative. According to Hameed and Kusnadi [3], the period definition of market conditions might affect the impact of market condition on cross-autocorrelations. There is no theoretical guide on period definitions regarding up and down markets, as it depends on the research objectives and sample markets. Some studies employ longer period definitions of market conditions. For example, both Cooper et al. [33] and Wu [24] employ 36-month market returns as the definition of market conditions in order to examine momentum strategy in the U.S. and China markets. However, some of the studies use shorter period definitions of market conditions. For instance, in examining the lead lag effect in the Warsaw's stock market, Gębka [37] defines market conditions using daily market return. In the U.S. and six Asia markets, McQueen et al. [11] and Chang et al. [12] employ a month's market return as the proxy of up and down markets to examine the cross-autocorrelation of stock returns.

Therefore, we employ four weeks to be the shorter horizon of the market condition. On the other hand, to comprehensively investigate the impact of market conditions on the process of intra-industry information diffusion, longer period definitions of market conditions should also be considered. Meanwhile, due to excessive volatility in China's stock market, periods that are too long have difficulties reflecting the fluctuations in market returns. Therefore, we employ 26 weeks to be the longer horizon of market condition in this study. (Hameed and Kusnadi [3] examine information diffusion and market conditions in the Japan market using both shorter and longer period definitions. They define the previous four or 26 weeks to determine market conditions.) As a result, by employing shorter and longer standards of period definitions, we define the previous four and 26 weeks to respectively establish the market conditions. (We obtain similar results using other period definitions, such as the previous 12 weeks, to determine market conditions; the results are available upon request.)

Consequently, if the previous four-week or 26-week market return is positive, the market condition can be confirmed as the up market state, or otherwise the down market state. Our main objective is to investigate the impact of market conditions on intra-industry information diffusion. To test this objective, two dummy variables, i.e., $D_{up,t\text{-}k}$ and $D_{down,t\text{-}k}$, are added into the original VAR model. Particularly, the new conditional VAR model is stated in the following equations:

$$R_{S,t} = a_0 + \sum_{k=1}^{K} a_{k,up} R_{s,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} b_{k,up} R_{B,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} a_{k,down} R_{s,t-k} \cdot D_{down,t-k} + \sum_{k=1}^{K} b_{k,down} R_{B,t-k} \cdot D_{down,t-k} + u_t \quad (5)$$

$$R_{B,t} = a_0 + \sum_{k=1}^{K} c_{k,up} R_{s,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} d_{k,up} R_{B,t-k} \cdot D_{up,t-k} + \sum_{k=1}^{K} c_{k,down} R_{s,t-k} \cdot D_{down,t-k} + \sum_{k=1}^{K} d_{k,down} R_{B,t-k} \cdot D_{down,t-k} + v_t \quad (6)$$

In Equations (5) and (6), $D_{up,t-k}$ and $D_{down,t-k}$ are dummy variables, which correspondingly reflect the up and down markets conditions at period t-k. $D_{up,t-k}$ equals one if the market condition becomes up and zero otherwise. In a similar way, $D_{down,t-k}$ equals one if the market state is down and zero otherwise. The reason that two dummy variables are set is to achieve the VAR investigations independently of the up and down conditions. For example, we examine whether big firms react faster than smaller firms to acquire common information in the down market state by employing a cross-equation test of null hypothesis: $\sum_{k=1}^{K} b_{K,down} = \sum_{k=1}^{K} c_{K,down}$. On the other hand, in an up market condition, we examine whether big firms react faster than smaller firms to acquire common information by using a cross-equation test of null hypothesis: $\sum_{k=1}^{K} b_{K,up} = \sum_{k=1}^{K} c_{K,up}$.

In Equation (5), $a_{k,\,up}$ and $b_{k,\,up}$ are the coefficients of the lagged returns of R_S and R_B in a up market state, respectively. $a_{k,\,down}$ and $b_{k,\,down}$ are the coefficients of the lagged returns of R_S and R_B in down market state correspondingly. Similarly, in Equation (6), $c_{k,\,up}$ and $d_{k,\,up}$ are, respectively, the coefficients of the lagged returns of R_S and R_B in up market state, while $c_{k,\,down}$ and $d_{k,\,down}$ are the coefficients of the lagged returns of R_S and R_B in a down market state.

With regards to the smaller firms' current returns, $\sum_{k=1}^{K} b_{K,up}$ and $\sum_{k=1}^{K} b_{K,down}$ reflect the impact of the big firms' lagged returns in an up market state and the impact of the big firms' lagged returns in a down market state. Greater coefficients show more striking cross-autocorrelations between the big firms' lagged returns and the smaller firms' current returns, which suggest that the more significant lead-lag relation between big and small firms. As the lead-lag relation reflects slow diffusion of information from big to small firms, the more significant lead-lag effect suggests a slower diffusion of information. (Most studies argue that slow diffusion of common information is a primary cause of the lead-lag effect. Thus, the stronger lead-lag effect suggests slower diffusion of information [1,4,8–10].) Therefore, in order to estimate the speed of intra-industry information diffusion in different market conditions, we compare $\sum_{k=1}^{K} b_{K,down}$ and $\sum_{k=1}^{K} b_{K,up}$. If $\sum_{k=1}^{K} b_{K,down} > \sum_{k=1}^{K} c_{K,up}$, intra-industry information diffusion is slower in a down market state, and vice versa.

4.1. Shorter Horizon of Market Conditions

Based on the seven sample industries, we first employ the previous four-week market returns to be the shorter horizon of market conditions. The time-series empirical results of the seven industries are stated in Table 4:

In Panel A of Table 4, in regards to the small firms' current returns, "Big-up" is the sum of coefficients of the lagged big firms' returns in an up market state, reflecting the impact of the big firms' lagged returns in an up market state. On the contrary, "Big-down" denotes the sum of coefficients of lagged big firms' returns in a down market state, revealing the impact of the big firms' lagged returns. It is found that the "Big-down" is greater than the "Big-up" in all industries (except the electronic equipment industry and the industrial engineering industry that are not significant). It shows that the impact of the big firms' lagged returns in a down market state is greater than the impact of the big firms' lagged returns in the up market state. Furthermore, the cross-equation test is more significant in the down market in four of the industries. These results display the more significant lead-lag effect in down market state, which suggest that slower information diffusion appears in the down market state than the up market state. The results also suggest that there are more obstacles in the process of intra-industry information diffusion when market condition becomes a down market state. Furthermore, to process an entire investigation of intra-industry, a conditional panel VAR is employed by including all firms. Panel B of Table 4 displays the conditional panel VAR in a shorter horizon.

Table 4. Conditional Vector Auto-regression (VAR) in Shorter Horizon of Market condition.

Industry		Conditional Vector Auto-Regression				
		Small-up	**Big-up**	**Small-down**	**Big-down**	**Cross-Equation Tests**
Panel A: The time-series Conditional VAR						
Automobiles parts	R_S	−0.111	0.582 ***	−0.614 ***	0.654 ***	Up:
		(0.315)	(7.218)	(6.164)	(6.273)	0.652
	R_B	−0.410 **	0.735 ***	−0.666 ***	0.629 ***	Down:
		(5.473)	(13.527)	(8.850)	(7.048)	27.446 ***
Construction and materials	R_S	−0.376	0.748 ***	−0.728**	0.750 ***	Up:
		(2.254)	(6.986)	(6.175)	(7.013)	15.393 ***
	R_B	−0.364	0.628 **	−0.693 **	0.68 5**	Down:
		(2.474)	(5.710)	(6.548)	(5.822)	22.096 ***
Electronic equipment	R_S	0.065	0.189	−0.286	0.305	Up:
		(0.059)	(0.386)	(0.651)	(0.682)	1.126
	R_B	−0.134	0.240	−0.120	0.043	Down:
		(0.289)	(0.709)	(0.131)	(0.015)	1.324
Food producers	R_S	−0.413	0.616 **	−0.610 **	0.774 ***	Up:
		(2.455)	(4.233)	(5.165)	(6.821)	11.302 ***
	R_B	−0.391	0.498 *	−0.615 **	0.734 ***	Down:
		(2.570)	(3.226)	(6.144)	(7.168)	21.958 ***
Industrial engineering	R_S	0.052	0.236	−0.264	0.269	Up:
		(0.069)	(1.066)	(0.876)	(1.141)	2.415
	R_B	−0.119	0.379 *	−0.241	0.221	Down:
		(0.397)	(2.983)	(0.792)	(0.690)	3.766 *
Industrial metals and mining	R_S	0.148	0.214 *	−0.257	0.318 *	Up:
		(0.545)	(2.810)	(1.293)	(2.773)	1.668
	R_B	−0.061	0.309 *	−0.196 *	0.189 *	Down:
		(−0.061)	(2.842)	(3.487)	(2.922)	4.374 **
Pharmaceuticals and biotechnology	R_S	0.405 *	0.198 *	−0.404	0.521 *	Up:
		(3.574)	(2.746)	(2.380)	(3.006)	1.661
	R_B	0.147	0.072	−0.499 **	0.500 **	Down:
		(0.661)	(0.102)	(5.108)	(3.886)	11.532 ***
Panel B: The Panel Conditional VAR						
All sample industries	$R_{S,i}$	0.028	0.296 ***	−0.389 ***	0.420 ***	Up:
		(0.12)	(10.03)	(14.61)	(15.35)	23.70 ***
	$R_{B,i}$	−0.159 **	0.397 ***	−0.359 ***	0.328 ***	Down:
		(4.33)	(20.66)	(14.21)	(10.69)	52.74 ***

Notes: R_S is the equal-weighted weekly return on the smallest 30% portfolio, while R_B presents the equal-weighted weekly return on the largest 30% portfolio. $R_{S,i}(t)$ and $R_{B,i}(t)$ are the equal-weighted weekly return on the portfolio of the smallest and the largest 30% firms at period t in industry i, correspondingly. Small-up indicates the sum of coefficients of lagged small firms' returns in up market. Small-down show the sum of coefficients of lagged small firms' returns in down market. Small-up indicates the sum of coefficients of lagged small firms' returns in up market. Small-down show the sum of coefficients of lagged small firms' returns in down market. On the other hand, Big-up indicates the sum of coefficients of lagged big firms' returns in up market, while Big-down denotes the sum of coefficients of lagged big firms' returns in down market. F-statistics are reported in parentheses. Furthermore, in cross-equation tests, Up is the F-statistic for the null hypothesis in up market i.e., $\sum_{k=1}^{4} b_{K,up} = \sum_{k=1}^{4} c_{K,up}$. Down is F-statistic for the null hypothesis in down market i.e., $\sum_{k=1}^{4} b_{K,down} = \sum_{k=1}^{4} c_{K,down}$. Finally, ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive order criteria. Thus, four-lag is used in the VAR model. (The result is similar with the view of Hou [4]. He claims that the lag order should be one or four because it is reasonable to assume that small firms will react to information within a month's time.)

Regarding the small firms' current returns, "Big-up" is 0.296 and "Big-down" equals 0.420. Both are significant at the 1% level. It shows that the impact of the big firms' lagged returns in the down market state is greater than the impact of the big firms' lagged returns in the up market state. These results display the more significant lead-lag effect in the down market state, which suggest that slower information diffusion appears in down market state. Therefore, the results of the conditional panel VAR also support that the intra-industry information diffusion from big firms to small firms becomes slower in down market state than the up market state. (The results of value weighted portfolios are consistent. The results are available upon request.)

The results are consistent with Hameed and Kusnadi's study [3], which claims that the speed of information diffusion becomes faster in the up market condition rather than the down market condition. On the other hand, Hong et al. [38], Doukas and McKnight [39], and Yalçın [40] argue that bad news diffuses slower in the market. When the market is turning downward, increasingly bad information is full of the market. However, firms react slower to bad news, especially the smaller ones. Negative information diffuses more slowly from big firms to small firms in a down market. Therefore, the gradual intra-industry information diffusion is more significant when the market goes down. Additionally, from another aspect, as the market continually declines, pessimistic sentiment is full of the market. Thus, investors ultimately lose investment confidence and they take less notice of the stocks. Da et al. [41,42] discuss that less investors' attention generates slower information diffusion. Consequently, slower information diffusion appears more easily in the down market.

4.2. Longer Horizon of Market Conditions

As a robustness check, a longer horizon of market condition (previous 26-week market return) is also employed to explore the impact of market conditions on intra-industry information diffusion. The empirical results of seven industries are shown in Table 5:

Table 5. Conditional VAR in Longer Horizon of Market condition.

Industry		**Conditional Vector Auto-Regression**				
		Small-up	**Big-up**	**Small-down**	**Big-down**	**Cross-Equation Tests**
Panel A: The time-series Conditional VAR						
Automobiles parts	R_S	−0.043 (0.050)	0.386 * (3.400)	−0.637 *** (7.482)	0.815 *** (11.269)	Up: 11.996 ***
	R_B	−0.339 * (3.526)	0.539 *** (7.498)	−0.698 *** (10.152)	0.803 *** (12.342)	Down: 38.835 ***
Construction and materials	R_S	−0.246 (0.943)	0.521 * (3.667)	−0.770 *** (7.426)	0.919 *** (8.935)	Up: 7.906 ***
	R_B	−0.244 (1.080)	0.430 * (2.902)	−0.753 *** (8.281)	0.846 *** (8.826)	Down: 29.572 ***
Electronic equipment	R_S	0.068 (0.067)	0.069 (0.056)	−0.276 (0.577)	0.398 (1.071)	Up: 0.320
	R_B	−0.096 (0.156)	0.109 (0.159)	−0.138 (0.165)	0.140 (0.150)	Down: 1.943
Food producers	R_S	−0.246 (0.943)	0.521 * (3.667)	−0.767 *** (7.426)	0.919 *** (8.935)	Up: 7.907 ***
	R_B	−0.244 (1.079)	0.430 * (2.902)	−0.753 *** (8.281)	0.846 *** (8.826)	Down: 29.901 ***
Industrial engineering	R_S	0.225 (1.368)	0.018 (0.008)	−0.581** (4.203)	0.701** (5.839)	Up: 0.110
	R_B	0.049 (0.069)	0.093 (0.229)	−0.529 * (3.739)	0.613 ** (4.798)	Down: 12.902 ***
Industrial metals and mining	R_S	0.264 (1.643)	0.029 * (3.020)	−0.341 * (2.515)	0.490 ** (4.300)	Up: 0.272
	R_B	−0.078 (0.152)	0.120 (0.360)	−0.299 (2.003)	0.358 * (2.798)	Down: 11.146 ***
Pharmaceuticals and biotechnology	R_S	0.400 * (3.565)	0.217** (4.689)	−0.318 * (1.978)	0.486 ** (4.393)	Up: 1.074
	R_B	0.054 (0.090)	0.136 (0.380)	−0.297 (1.928)	0.362 * (2.868)	Down: 7.246 ***
Panel B: The Panel Conditional VAR						
All sample industries	$R_{S,i}(t)$	0.143 (0.145)	0.097 (1.20)	−0.493 *** (24.63)	0.626 *** (34.62)	Up: 2.52
	$R_{B,i}(t)$	−0.044 ** (4.33)	0.201 *** (20.66)	−0.465 *** (25.00)	0.528 *** (28.07)	Down: 105.11 ***

Notes: The settings of coefficients are same to Table 4.

Consistent with the analysis of the four-week horizon of market condition, the time-series empirical results show that market conditions affect intra-industry information diffusion under the investigation of a longer horizon of market condition. The results also suggest that the gradual intra-industry information diffusion is more significant in the down market state than the up market state.

As stated in Panel B, in regards to the small firms' current returns, "Big-down" is much bigger and significant than the "Big-up". It shows that the impact of the big firms' lagged returns in a down market state is greater than the impact of the big firms' lagged returns in an up market state. Moreover, we find that the cross-equation test (F = 105.11) is significant only in a down market state. These results display the more significant lead-lag effect in down market state as compared to the up market state, which suggest that slower information diffusion appears in down market state. Therefore, the results of the conditional panel VAR also suggest that information diffusion from big firms to small firms becomes slower in the down market condition than the up market condition under the analysis of a longer horizon of market condition.

When compared to Table 4, the results of a longer horizon of market condition are more significant than the results of a shorter horizon of market condition. These results also suggest that when the market turned downwards for a longer period, the speed of intra-industry information diffusion develops more slowly. As the longer bearish market exists, investors become gloomier and their investment sentiment becomes lower. Hence, many investors might lose investment interest on stocks. Consequently, when the market falls off for a longer period, less investors' attention is brought into the market. Thus, when compared to a shorter horizon down market condition, information diffuses more slowly in a longer horizon down market condition.

5. Policy Change and Intra-Industry Information Diffusion

5.1. Examining the Impact of Policy Changes

There are two most important policy changes in China: the split-share structure reform in 2005 and lifting the short-sale constraints in 2010. These significant times in policy changes have generated two break points. The full study period is divided into three sub-periods: January 2002–February 2005, March 2005–January 2010, and February 2010–December 2013. The first sub-period mainly shows the situation of China's stock market before the split-share structure reform and the lifting of the short-sale constraints. What happens in China's stock market after the split-share structure reform is displayed in the second sub-period. Meanwhile, the second sub-period also shows the situation of China's stock market with the short-sale constraints. After lifting the short-sale constraints and the split-share structure reform, the situation is presented in the last sub-period.

Therefore, in order to examine the impact of policy changes from 2002 to 2013 on intra-industry information diffusion over time, the VAR procedure is continuously employed to estimate the lead-lag effect between the big and small firms. Three dummy variables, i.e., $\mathrm{D_{p1}}$, $\mathrm{D_{p2}}$, and $\mathrm{D_{p3}}$, are added into the original VAR model. Hence, the new conditional VAR model is stated in the underlying equations:

$$\mathrm{R_{S,t}} = a_0 + \sum_{k=1}^{K} a_{k,p1} R_{s,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} b_{k,p1} R_{B,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} a_{k,p2} R_{s,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} b_{k,p2} R_{B,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} a_{k,p3} R_{s,t-k} \cdot D_{p3,t-k} + \sum_{k=1}^{K} b_{k,p3} R_{B,t-k} \cdot D_{p3,t-k} + u_t \quad (7)$$

$$\mathrm{R_{B,t}} = a_0 + \sum_{k=1}^{K} c_{k,p1} R_{s,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} d_{k,p1} R_{B,t-k} \cdot D_{p1,t-k} + \sum_{k=1}^{K} c_{k,p2} R_{s,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} d_{k,p2} R_{B,t-k} \cdot D_{p2,t-k} + \sum_{k=1}^{K} c_{k,p3} R_{s,t-k} \cdot D_{p3,t-k} + \sum_{k=1}^{K} d_{k,p3} R_{B,t-k} \cdot D_{p3,t-k} + v_t \quad (8)$$

In Equations (7) and (8), $\mathrm{D_{p1,\,t\text{-}k}}$, $\mathrm{D_{p2,\,t\text{-}k}}$, and $\mathrm{D_{p3,\,t\text{-}k}}$ are dummy variables, which respectively reflect the three sub-periods at period t-k. $\mathrm{D_{p1,\,t\text{-}k}}$ equals one if the market is in the first sub-period (January 2002–February 2005) and zero otherwise. In a similar way, $\mathrm{D_{p2,\,t\text{-}k}}$ equals one if the market is in the second sub-period (March 2005–January 2010) and is zero otherwise. $\mathrm{D_{p3,\,t\text{-}k}}$ equals one if the market is in the third sub-period (February 2010–December 2013) and zero, or else. The purpose for setting the three dummy variables is to identify the VAR analysis separately for the different sub-periods. For example, the study examines whether big firms react faster than the smaller firms to common information in the first sub-period by employing a cross-equation test for null hypothesis: $\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}1} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}1}$. Similarly, a cross-equation test for the null hypothesis is used in the second (third) sub-period: $\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}2} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}2}$. ($\sum_{k=1}^{k} \mathrm{b}_{K,\mathrm{p}3} = \sum_{k=1}^{k} \mathrm{c}_{K,\mathrm{p}3}$.).

In Equation (7), $a_{\mathrm{k},p1}$ and $\mathrm{b}_{\mathrm{k},p1}$ ($a_{\mathrm{k},p2}$ and $\mathrm{b}_{\mathrm{k},p2}$; $a_{\mathrm{k},p3}$ and $\mathrm{b}_{\mathrm{k},p3}$) are the coefficients of the lagged returns of R_S and R_B, in the first (second; third) sub-period, correspondingly. Similarly, in Equation (8), $\mathrm{c}_{\mathrm{k},p1}$ and $\mathrm{d}_{\mathrm{k},p1}$ ($\mathrm{c}_{\mathrm{k},p2}$ and $\mathrm{d}_{\mathrm{k},p2}$; $\mathrm{c}_{\mathrm{k},p3}$ and $\mathrm{d}_{\mathrm{k},p3}$) are, respectively, the coefficients of the lagged returns of R_S and R_B in the first (second; third) sub-period.

In this conditional VAR setting, significances of coefficients are similar with the original VAR model. With regards to the smaller firms' current returns, $\sum_{k=1}^{K} b_{K,p1}$, $\sum_{k=1}^{K} b_{K,p2}$, and $\sum_{k=1}^{K} b_{K,p3}$ correspondingly reflect the impact of the big firms' lagged returns in the first, second, and third sub-periods. A greater coefficient shows more impact of the big firms' lagged returns on the small firms' current returns, which suggest a more prominent lead-lag relation between the bigger and smaller firms. Thus, a greater coefficient reflects slower diffusion of information from big firms to the smaller ones in this sub-period. By comparing $\sum_{k=1}^{K} b_{K,p1}$, $\sum_{k=1}^{K} b_{K,p2}$, and $\sum_{k=1}^{K} b_{K,p3}$, an estimation of the impact of policy changes on intra-industry information diffusion in different sub-periods is made.

Based on Panel A of Table 6, there is no strong statistical evidence to discover the relatively consistent intra-industry information diffusion in the second and third sub-periods. Most coefficients are insignificant or marginal significant in either one sub-period only (except the automobile parts industry and the construction and materials industry). Additionally, the cross-equation tests are also unable to show consistent results among the industries (except the automobile parts industry and the construction and materials industry). Due to these inconsistent results among the industries, we further employ panel data analysis by including all firms. Panel B of Table 6 displays the results of the panel data.

Based on Panel B, among the three coefficients in the small firms' current returns, "Big-P_3" is the biggest and "Big-P_2" is in the middle, whereas "Big-P_1" is the smallest. These results suggest that the intra-industry lead-lag effect becomes stronger over time. Therefore, intra-industry information diffusion from big firms to smaller firms becomes slower from the first sub-period to the third sub-period. The policy changes impede intra-industry information diffusion. More delay is brought into intra-industry information diffusion along with the policy changes.

Next, as for the robustness test, we separately employ the conditional panel VAR to analyze intra-industry information diffusion in each sub-period. The empirical results are described in Table 7.

With regards to the smaller firms' current returns, the sum of coefficients of big firms' lagged returns is correspondingly 0.069, 0.277, and 0.438 in the three sub-periods, respectively. They increase over time and are only statistically significant in the latter two sub-periods. Therefore, the impact of the big firms' lagged returns on the smaller firms' current returns becomes bigger over time. The results suggest that the lead-lag effect between the big firms and smaller firms becomes stronger over time. Thus, intra-industry information diffusion from big firms to small firms becomes slower over time. As a result, the policy changes influence the intra-industry information diffusion, which suggests that more delay is brought into the process of intra-industry information diffusion over time.

Table 6. Conditional VAR for Policy Changes.

Industry		Three Sub-Pperiods						Cross-Equation Tests		
		Small-P_1	**Big-P_1**	**Small-P_2**	**Big-P_2**	**Small-P_3**	**Big-P_3**	**Test-P_1**	**Test-P_2**	**Test-P_3**
Panel A: The time-series Conditional VAR										
Automobiles parts	R_S	−0.468	0.373	−0.241	0.523 **	−0.377	0.636 *			
		(1.664)	(0.767)	(1.598)	(6.565)	(1.345)	(3.582)	1.710	29.071 ***	10.754 ***
	R_B	−0.184	0.250	−0.578 ***	0.755 ***	−0.466	0.519 *			
		(0.293)	(0.390)	(10.473)	(15.450)	(2.344)	(2.712)			
Construction and materials	R_S	−0.693	0.575	−0.345	0.563 **	−0.644 *	0.830 **			
		(1.653)	(0.663)	(1.771)	(4.126)	(2.953)	(5.142)	2.035	12.580 ***	16.689 ***
	R_B	−0.433	0.295	−0.420 *	0.592**	−0.665 *	0.673 **			
		(0.753)	(0.204)	(3.078)	(5.335)	(3.673)	(3.951)			
Electronic equipment	R_S	0.425	0.717	−0.153	0.371	−0.368	0.477			
		(0.817)	(2.190)	(0.344)	(1.723)	(0.373)	(0.544)	4.191 **	4.920 **	0.907
	R_B	0.275	−0.662	−0.256	0.336	−0.139	0.152			
		(0.392)	(2.131)	(1.111)	(1.616)	(0.060)	(0.063)			
Food roducers	R_S	−0.480	0.215	0.030	0.148	−0.004	0.027			
		(0.797)	(0.180)	(0.011)	(0.237)	(0.068)	(0.003)	2.535	0.051	0.007
	R_B	−0.592	0.383	0.079	0.030	0.066	−0.017			
		(1.364)	(0.642)	(0.090)	(0.011)	(0.026)	(0.001)			
Industrial engineering	R_S	−0.489	0.261	0.110	0.062	−0.502	0.690 *			
		(0.820)	(0.187)	(0.355)	(0.108)	(1.594)	(2.897)	2.028	0.193	8.073 *
	R_B	−0.597	0.366	−0.021	0.175	−0.462	0.507			
		(1.334)	(0.403)	(0.014)	(0.927)	(1.467)	(1.699)			
Industrial metals and mining	R_S	−0.397	0.146	0.144	0.082	−0.358	0.580 *			
		(1.682)	(0.203)	(0.541)	(0.159)	(1.171)	(2.880)	2.199	0.066	8.731 ***
	R_B	−0.335	0.161	0.029	0.120	−0.430	0.481			
		(1.258)	(0.258)	(0.023)	(0.354)	(1.172)	(2.077)			
Pharmaceuticals and biotechnology	R_S	−0.500	0.262	−0.023	0.307	0.404	0.406			
		(0.708)	(0.141)	(0.014)	(1.605)	(1.526)	(1.188)	0.911	5.175**	2.577
	R_B	−0.404	0.252	−0.244	0.455 **	0.192	0.245			
		(0.640)	(0.181)	(2.158)	(4.905)	(0.478)	(0.600)			
Panel B: The Panel Conditional VAR										
All sample industries	$R_{S,i}(t)$	−0.353**	0.112	−0.048	0.267 ***	−0.262*	0.421 ***			
		(5.07)	(0.41)	(0.38)	(9.64)	(3.62)	(8.47)	4.84**	30.25 ***	35.05 ***
	$R_{B,i}(t)$	−0.272*	0.077	−0.206 ***	0.352 ***	−0.303**	0.343**			
		(3.43)	(0.23)	(7.72)	(19.12)	(5.52)	(6.45)			

Notes: R_S and R_B are the equal-weighted weekly return on the smallest and the largest 30% firms, correspondingly. $R_{S,i}(t)$ and $R_{B,i}(t)$ are the equal-weighted weekly return on the portfolio of the smallest and the largest 30% firms at period t in industry i, correspondingly. Small-P_1 and Big-P_1 respectively indicate the sum of coefficients of lagged small firms' returns and the sum of coefficients of lagged big firms' returns in the first sub-period. Similarly, Small-P_2 and Big-P_2, respectively, refer to the sum of coefficients of lagged small firms' returns and lagged big firms' returns in the second sub-period. Small-P_3 and Big-P_3 respectively refer to the sum of coefficients of lagged small firms' returns and lagged big firms' returns in the third sub-period. F-statistics are reported in parentheses. Test-P_1 is F-statistics for cross-equation tests for the null hypothesis in the first sub-period i.e., $\sum_{k=1}^{4} bk,_{P1} = \sum_{k=1}^{4} ck,_{P1}$., Test-$P_2$ and Test-P_3 are also corresponding F-statistics in the second sub-period and the third sub-period. Finally, ***, **, and * denote significance at the 1, 5, and 10 % levels, respectively. Both AIC and HQIC information criterions support the four-lag to be adaptive order criteria. Thus, four-lag is used in the VAR model.

Additionally, by observing the "Big-P_1", "Big-P_2", and "Big-P_3" in Table 6 and the sum of coefficients of big firms' lagged returns in Table 7, it is discovered that the sum of coefficients of big firms' lagged return decreasingly increase over time, i.e., the growth rate of the sum of coefficients decreases from sub-period 1 to sub-period 2 and from sub-period 2 to sub-period 3. It is found that the first policy change, i.e., the split-share structure reform, has more impact on intra-industry information diffusion than the lifting of short-sale constraints. The empirical results show that the split-share structure reform actually impedes the process of intra-industry information diffusion. However, most people think that the reforms help to improve market efficiency. Do the reforms improve market efficiency? As the most powerful policy reform of China stock market in recent years, the potential impacts of the split share structure reform have been discussed by a few empirical researches. However, effectiveness of the split share structure reform is still in dispute. For example, Chen et al. [13] argue that the split share structure reform improves the liquidity of the market and increases the market efficiency. Yet, Beltratti et al. [25] discover this reform had no impact on the ownership structure of firms in their research. They argue that only some small stocks and historically neglected stocks are partially beneficial from this reform. Additionally, Carpenter et al. [27] suggest that the split share structure reform has little direct immediate impact on the structure of the China stock market in the short term.

Table 7. Separate Panel VAR in Three Sub-periods.

Sub-period1: Jan 2002–Feb 2005			**Cross-equation tests**
	$\sum_{K=1}^{4} R_{S,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,i}(t\text{-}k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
$R_{S,i}(t)$	−0.454 *** (16.99)	0.069 (0.33)	11.86 ***
$R_{B,i}(t)$	−0.347 *** (12.46)	0.058 (0.29)	
Sub-period2: Mar 2005–Jan 2010			**Cross-equation tests**
	$\sum_{K=1}^{4} R_{S,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,i}(t\text{-}k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
$R_{S,i}(t)$	−0.070 (0.47)	0.277 ** (6.27)	20.75 ***
$R_{B,i}(t)$	−0.227 ** (5.71)	0.359 *** (12.16)	
Sub-period3: Feb 2010–Dec 2013			**Cross-equation tests**
	$\sum_{K=1}^{4} R_{S,i}(t\text{-}k)$	$\sum_{K=1}^{4} R_{B,i}(t\text{-}k)$	$\sum_{k=1}^{4} b_k = \sum_{k=1}^{4} c_k$
$R_{S,i}(t)$	−0.282 *** (6.84)	0.438 *** (15.01)	43.02 ***
$R_{B,i}(t)$	−0.304 *** (8.38)	0.340 *** (9.55)	

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

5.2. Additional Tests on the Impact of Policy Changes

5.2.1. The Time-series Change of Lead-lag Effects among Three Sub-periods

In the previous analysis, the impact of policy changes on intra-industry information diffusion is examined by considering the impact of lagged big firms' returns on the current smaller firms' returns and vice versa. Contrary to the previous section and following Mori [17], the effect of small firms leading to big firms is subsequently excluded. Only the lead-lag effect from big firms to small firms is exhibited. The lead-lag effect is estimated in a one-lag panel VAR that is based on the weekly returns of the same equal-weighted size portfolios with a quarterly window. More specifically, the one-lag panel VAR is stated in the following equations:

$$R_{S,i(t)} = a_{i,0} + a_1 R_{S,i(t-1)} + b_1 R_{B,i(t-1)} + u_{i,t} \quad (9)$$

$$R_{B,i(t)} = c_{i,0} + c_1 R_{S,i(t-1)} + d_1 R_{B,i(t-1)} + v_{i,t} \quad (10)$$

In Equations (9) and (10), $R_{S,i}(t)$ and $R_{S,i}(t\text{-}1)$ are the weekly returns of the smallest 30% portfolio at period t and period t-1, respectively, in industry i, while $R_{B,i}(t)$ and $R_{B,i}(t\text{-}1)$ present the weekly returns of the largest 30% portfolio at period t and period t-1 in industry i.

According to Mori [17], the time-series lead-lag effect could be evaluated by acquiring the difference between b_1 in Equation (9) and c_1 in Equation (10), which examines the size of the lead-lag effect from big firms to smaller firms. Although Mori [17] only investigates the Real Estate Investment Trust market in the U.S., this method is a better reference for our underlying analysis. Furthermore, b_1 actually implies the effect that big firms lead small firms, while c_1 suggests the effect that small firms lead big firms. Therefore, (b_1–c_1) evaluates the lead-lag effect from big firms to small firms, while control for the reverse lead-lag effect from small firms to big firms. If big firms actually could lead small firms, then b_1 should be greater than c_1 and (b_1–c_1) should be greater than zero. It presents a distinct lead-lag effect between big and small firms, which reflects that the delayed degree of information diffusion is stronger from big firms to smaller firms. Additionally, if (b_1–c_1) is less than zero, it implies that, instead of the lead-lag effect from big firms to small firms, the reverse lead-lag effect from small firms to big firms appears.

Table 8 shows the mean and standard deviation of (b_1–c_1) in each three sub-periods. First, the mean becomes bigger over time. It suggests that the lead-lag effects develop stronger from the first sub-period to the last sub-period. Second, the F-statistic for mean difference among three sub-periods is significant at the 1% level. Thus, intra-industry information diffusion is also dissimilar in different sub-periods. Based on the above two viewpoints, the delay of intra-industry information diffusion from big stocks to small stocks becomes greater over time, which imply that policy changes impede intra-industry information diffusion. These results support our results in the previous section.

Table 8. Mean compare and variance compare among Three Sub-periods.

Sub-Period	Mean	Std	Comparison Sub-Period	Mean Difference
Sub-period 1	−0.313	1.669	Sub-period 2	−0.711**
			Sub-period 3	−1.009**
Sub-period 2	0.398	1.562	Sub-period 1	0.711**
			Sub-period 3	−0.298
Sub-period 3	0.696	1.517	Sub-period 1	1.009**
			Sub-period 2	0.298
F-test	12.459 ***	2.658*		

Notes: Mean denotes mean of (b_1–c_1) in the sub-period. Std refers to standard deviation of (b_1–c_1) in the sub-period. F-test refers to F-statistics for mean compare and variance compare among three sub-periods. ***, **, and * denote significance at the 1, 5, and 10% levels, respectively. Mean Difference denotes the difference of mean between sub-periods.

On the other hand, the standard deviations of (b_1–c_1) show a downtrend over time. Moreover, the F-statistic for standard deviation difference among the three sub-periods is significant at the 10% level, which suggests that the difference of standard deviation exists among the three sub-periods. The results show that the volatility of lead-lag effects decrease over time, which suggests that the fluctuation amplitude of information diffusion reduces over time. Consequently, these results support the information volatility of China's stock market declines, along with its policy changes. With the policy changes, the information environment and transparency of market improve over time. Informational efficiency and transparency are brought into the Chinese stock market.

Table 8 also exhibits multiple comparisons of the mean among the three sub-periods. However, the difference of mean between sub-period 1 and sub-period 2, as well as the difference of mean between sub-period 1 and sub-period 3 are significant. The demarcation of the sub-period 1 depends on the first policy change, i.e., the split-share structure reform. Consequently, the impact of the split-share structure reform on the information diffusion has been relatively substantial. On the other hand, the difference of mean between sub-period 3 and sub-period 2 is insignificant. The demarcation of sub-period 3 depends on the second policy change, i.e., lifting of the short-sale constraints. Therefore, lifting short-sale constraints has less impact on information diffusion. As a result, the impact of the split-share structure reform in 2005 is more significant to intra-industry information diffusion in China, which generates more friction of intra-industry information diffusion.

5.2.2. Potential Reasons on the Lead-lag Changes

With the intention of investigating the potential reasons of increasing delay of intra-industry information diffusion over time, further analysis is stated in Table 9:

Table 9. Comparison of Market Situations among Three Sub-periods.

Variables	Mean	Std	Max	Min	F-Test	
Sub-period 1: Jan 2002–Feb 2005					Mean	Variance
Market-return	−0.029	0.106	0.152	−0.218	1.529	12.206 ***
Market-capitalization	41032	4867	50417	31590	41.792 ***	72.619 ***
Market-trading volume	414	179	682	137	31.087 ***	34.727 ***
Proportion-institutional	0.0056	8.64E-05	0.0057	0.0055	48.305 ***	62.510 ***
Proportion-individual	0.9943	8.64E-05	0.9945	0.9943	48.305 ***	62.510 ***
Sub-period 2: Mar 2005–Jan 2010						
Market-return	0.056	0.221	0.425	-0.416		
Market-capitalization	151824	87563	327140	32430		
Market-trading volume	2552	1334	4454	506		
Proportion-institutional	0.0052	0.0059	0.0059	0.0046		
Proportion-individual	0.9947	0.00042	0.9954	0.9941		
Sub-period 3: Feb 2010–Dec 2013						
Market-return	−0.026	0.101	0.101	−0.260		
Market-capitalization	233433	22013	277662	195138		
Market- trading volume	3226	956	5015	1961		
Proportion- institutional	0.0046	4.58E-05	0.0047	0.0045		
Proportion-individual	0.9953	4.58E-05	0.9954	0.9953		

Notes: Degree-lead lag is (b_1–c_1). F-test refers to F-statistics for mean compare and variance compare among three sub-periods. Finally, ***, **, and * refer to significance at the 1, 5, and 10% levels, respectively.

Table 9 describes the comparison of the different market situations among three sub-periods in China's stock market. As shown, market capitalization and market trading volume grow over time, which suggest the booming development of China's stock market. However, as opposed to the general uptrend of the proportions of individual investors, the proportion of institutional investors remarkably declines, especially after the split-share structure reform in 2005. This result is not consistent with many developed markets. An advanced market eventually needs more institutional investors. However, with the expansion of China's stock market, the proportion of institutional investors is not rising, while the proportion of individual investors is on the rise.

Due to the lack of information processing capacity and channel, most Chinese individual investors tend to follow institutional investors who possess superiority in information acquisition [43,44]. Hence, information generally diffuses from institutional investors to individual investors in China's stock market [45,46]. Reduced institutional investors might make the information diffusion more gradual between institutional investors and individual investors. As a result, the increasing proportion of individual investors and the decreasing proportion of institutional investors could potentially cause the delay of intra-industry information diffusion over time in China.

6. Conclusions

This paper investigates the impact of market conditions and policy changes on intra-industry information diffusion in China. Different with previous studies [4–6,18], the study focuses on intra-industry to investigate the process of information diffusion with view of both market conditions and policy changes. Moreover, according to specific conditions in China, different from previous studies [7,21], as far as we know, this paper is the first paper studying the impact of market conditions and policy changes on intra-industry information diffusion in China.

The main findings are: first, the market conditions significantly affect the process of intra-industry information diffusion. The speed of intra-industry information diffusion in the down market condition is slower than in the up market condition. Conversely, when the market is turning upward, the speed of intra-industry information diffusion develops faster. Second, the impact of a longer horizon of market condition is more significant than the shorter horizon. In other words, when the market turns downward for a longer period, the speed of intra-industry information diffusion develops more slowly. These findings are consistent with the gradual-information diffusion theory of Hong et al. [38]. They suggest that, when the market falls off, the market is full of negative information and negative information diffuses more slowly across the market. Market frictions are responsible for the gradual diffusion of information. Moreover, the impact of market frictions is usually more prominent when bad news arrives (for example, the short sale constraint will delay the incorporation of negative information into stock prices [28]).

This finding provides some trading strategies for investors. When good common information comes to some big firms, based on the principle of gradual information diffusion, investors usually choose small firms from the whole market. However, it is suggested that investors should choose high quality small firms from the same industry, rather than the whole market. Investors should take long positions in these stocks as early as possible and then wait for potential abnormal profit. When the market falls off, investors should slow these investments. Alternatively, investors might accelerate investment behaviors as the market turns upward.

Third, the policy change also has an effect on intra-industry information diffusion. Especially, we find that the split-share structure reform actually impedes the process of intra-industry information diffusion. These findings are consistent with previous theories, such as Merton [14], Lin and Swanson [15], and Mori [17], which mean some external institutional restrictions, such as policy changes, could significantly affect the process of information intra-industry information diffusion. The intra-industry information diffusion from big firms to small firms becomes slower along with policy changes. These results show that due to the policy changes in China, more delay is brought into the process of intra-industry information diffusion over time. Therefore, policy changes impede intra-industry information diffusion.

Fourth, there is a continuously decreasing information volatility of intra-industry information diffusion in China's stock market. Along with the policy changes in China's stock market, the information environment and transparency of market are improved over time. Fifth, the impact of the split-share structure reform in 2005 is more significant to the intra-industry information diffusion of China's stock market, which generates more friction regarding intra-industry information diffusion.

Finally, this paper provides policy implications to policy considerations and market mechanisms. The impact of policy changes on information diffusion is one of the impacts of policy changes on financial market. Based on the split share structure reform and lifting short sale constraints, this paper suggests that these policy changes in China stock market impede the process of intra-industry information diffusion and they seem ineffective in some degree. Institutional frictions are accountable for producing the delay in the process of information diffusion. Thus, comprehending the process of information diffusion is very significant for policy considerations. Institutional reforms in China's stock market have been implemented for many years since the establishment of the market. However, the effectiveness of the policy changes is still in dispute. Policy considerations and market mechanisms in China should keep pace with the times, which could, in turn, facilitate that stock prices to develop more effectively and informatively. Nevertheless, policy considerations, especially in China, seldom consider the effectiveness and informativeness of stock prices, as well as the principle of gradual information diffusion when policies are formulated. Therefore, smoothing the process of intra-industry information diffusion and augmenting the market efficiency should be included into policy-making in the future.

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