Do Chinese Industries Predict the Stock Market Due to Slow Diffusion of Information ? Analysis of the Shanghai Stock Exchange

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Abstract

Returns predictability and cross autocorrelations is an important consideration in behavioral finance and is of considerable interest to investors and financial economists. This area gained much attention due to developments in behavioral finance during the last two decades. Previously, lead-lag patterns were supported by argument of rational expectations, however, it lacked much empirical evidence. According to behaviorists' views, it is human inability to process all sorts of information and thus, information moves diffuse slowly from one market to another. In this study, we tested this slow diffusion of information using an extensive set of data over a period from 2004-2013. We found that the market was led by industry returns up to a period of four weeks. This predictive power of industries decreased as the prediction horizon increased. These findings are robust, even if we control for industry size and trading volume. Thus, these findings add considerable support to the slow diffusion of information hypothesis.

Key words: lead-lag pattern, slow diffusion of information, Shanghai Stock Exchange, Chinese industries

JEL Classification : G10, G11, G12

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If returns of two groups of stocks possess a systematic lead-lag relationship between them, then it will be very easy for a portfolio manager to predict the returns of one group of stocks from the return pattern of other group of stocks. In this way, the managers can follow a buy-winner and sell-loser strategy and earn above normal profits. However, this whole lead-lag phenomenon is in contrast with the "random walk hypothesis" coined by Louis Bachelier (1900) in his thesis *"Theory of Speculation"*. This area has attracted enormous research studies with the support of random walk hypothesis (Cootner, 1964 ; Fama, 1965 ; Malkiel & Fama, 1970). The integral argument of random walk hypothesis is the unpredictability of stock returns. However, more recent studies regarding stock return predictability has surprised the advocates of the efficient market hypothesis. There exists evidence regarding the weak form of market efficiency in Asian countries. Ryaly, Kiran Kumar, and Urlankula (2014) studied the presence of market efficiency in five Asian countries, namely India, South Korea, Singapore,

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Hong Kong, and Japan. They applied parametric and non-parametric tests to a very extensive set of data and reported a very weak form of market efficiency in Asian stock markets. For these reasons, this area has attracted much research and is considered very important by financial economists.

The discussion on lead-lag patterns between stock returns can be traced back to a study conducted by Fisher (1966). According to Fisher (1966), the lead-lag relationship between stock returns exists due to the presence of nonsynchronous trading. He further argued that this relationship can be attributed to autocorrelation between stock returns. In preceding studies, this lead-lag relationship was further explored in portfolio returns sorted on a wide range of factors. According to Lo and MacKinlay (1990) and Cohen, Maier, Schwartz, and Whitcomb (1986), thin trading is responsible for the lead-lag pattern between stock returns. Small stocks normally exhibit thin trading, and trading in these stocks takes place when investors have enough evidence that new information is incorporated in the prices of large stocks. Thus, a lag is created in response to the market for the adjustment of prices of small stocks.

Thus, large stocks lead the small stocks. Lo and MacKinlay (1990) argued that lead-lag pattern among stocks can be attributed to size, which is due to the mechanism of information dissemination between stocks. Availability of information is another important attribute to explain the lead-lag relationship between stock returns (Chan, Chung, & Johnson, 1993). Chan et al. (1993) argued that institutional investors are more focused towards large stocks ; hence, they issue more information about large stocks. Thus, investors and portfolio managers focusing on small stocks have to look for large stocks and the institutional investors for availability of information. They assumed that this information of price movements in large stocks reveals the quality of information generated by the institutional investors. Thus, investors predict the movements in small stocks by following the trails of large stocks' price movements. However, Chan et al.'s (1993) view is in contrast with the view of Badrinath, Kale, and Noe (1995). They argued that institutional ownership is more responsible for lead lag pattern rather than size of the firm. Jegadeesh and Titman, (1995) ; Brennan, Jegadeesh, and Swaminathan (1993) ; and Badrinath et al. (1995) argued that autocorrelation in portfolio returns can be attributed to factors like liquidity. Some other factors like stock market overreaction hypothesis and slow diffusion of information are responsible for lead-lag effects between stock returns (De Bondt & Thaler, 1985, 1987 ; De Long, Shleifer, Summers, & Waldmann, 1989; Lehmann, 1990 ; Shefrin & Statman, 1985).

More recently, research in this area has shifted focus towards behavior explanations for lead-lag pattern in stock returns. For example, Hong, Torous, and Valkanov (2007), Merton (1987), and Hong and Stein (1999) argued that information is slowly diffused among different segments of the market due to weakness and limited ability of human race to process all the available information or equally treat or equally pay attention to information coming from different segments of the market. Thus, a lag of information is created from one segment to another segment of the market due to limited cognitive ability of the human race, which creates lead-lag patterns in asset returns. One of the important studies in this behavior explanation of the lead-lag effect was conducted by Hong et al. (2007). They put forward evidence in support of their hypothesis that if an industry has the ability to predict various economic indicators, then it can lead the stock market index even after controlling for other stock market predictors.

Evidence in support of the lead-lag relationship between stock returns is well documented in emerging economies (Hong et al., 2007; Hong & Stein, 1999 ; Merton, 1987). The main objective of this paper is to provide evidence in support that lead-lag relationship exists between industry returns and stock market returns in China. In this study, we tested this slow diffusion of information using an extensive set of data over a period from 2004-2013. We found that market is led by industry returns up to a period of four weeks. This predictive power of industries decreases as the prediction horizon is increased. These findings are robust, even if we control for industry size and trading volume. Thus, these findings add considerable support to slow diffusion of information hypothesis. These findings are robust, even if we control for industry size and trading volume. Thus, these findings add considerable support to slow diffusion of information hypothesis.

↳ **Overview of Chinese Sectors :** Traditionally, sectors have been categorized into three major categories, that is, agriculture, manufacturing, and services sectors. Agriculture and related industries are categorized as the primary sector ; manufacturing of goods and energy production is called as industrial sector ; and services constitute the rest of the economic sector and are often called as intangibles.

According to National Bureau of Statistics of China, the portion of the agriculture sector is on a constant decrease over the past 30 years. The services sector is increasing at a double rate. Its portion in national economy has increased from 20% in 1979 to 43.14% in 2009. Over the past three decades, the manufacturing sector has maintained a level of 40% to 50% (see Figure 1). This is due to the export orientation of the Chinese economy, and the manufacturing sector has become resource intensive over the past three decades. Energy production is also a major sector, and China is the largest energy producer in the world through coal. For the services sector, the Chinese government has eased some of the policies like tax reductions, and the services sector is becoming more sustainable (Liping & Evenett , 2010). The Figure 1 is adapted from the National Bureau of Statistics of China Annual Report of 2010. The figure indicates the sectorial composition of China's gross domestic product.

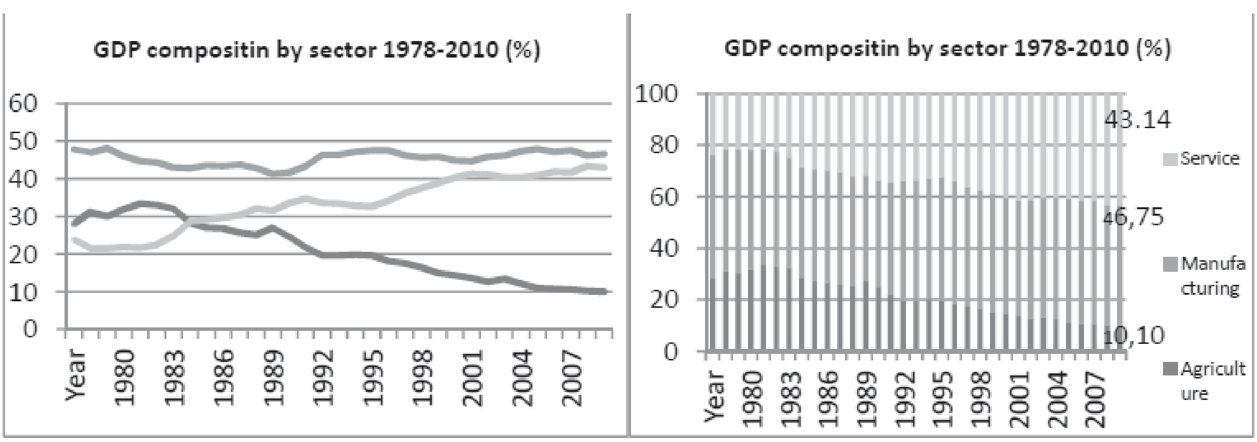
According to the World Finance Report (2010), some of the top Chinese industries that have proven to be the integral drivers of Chinese economic growth include automobiles, steel, construction, IT, textiles, energy, and cement industries. The processing and manufacturing of chemicals such as petroleum goods, fertilizers, and pharmaceuticals is another sizable and growing segment.

Literature Review

In the following section, we provide a summary of evidence from prior literature on lead-lag pattern between stock returns. The literature in this regard can be categorized into stock market overreaction hypothesis, nonsynchronous and thin trading, institutional ownership effects, and slow diffusion of information hypothesis.

(1) Stock Market Overreaction Hypothesis : Advocates of this hypothesis argue that investors' extreme optimism and pessimism drive the movement in the stock market. Such overreaction creates waves that move stock prices away from their fair values. More optimistic investors buy stocks at once, while pessimistic investors join the rally slowly and gradually. Thus, the rally converts into momentum until pessimistic investors become large in number and reverse the momentum. These waves create patterns and hence make stock movements

Figure 1. China's Sectorial Composition of GDP



Source: National Bureau of Statistics of China predictable. Researchers in support of this stock market overreaction hypothesis include DeBondt and Thaler (1985, 1987), Shefrin and Statman (1985), DeLong et al. (1990), and Lehmann (1990). However, Lo and MacKinlay (1990) argued that this hypothesis is still far from to be converted into a well-established theory. In the contemporary era, evidence on the existence of the overreaction hypothesis has been provided by Parikh and Baruah (2013). They analyzed monthly returns of Nifty 50 stocks listed on the Indian stock exchange and found that the stock market overreacts to certain global and macroeconomic indicators of a country. The study found that behavioral justification of overreaction occurred due to traders' activity in the short run, and in the long run, that momentum is reversed for the large-cap stocks (De Bondt & Thaler, 1985, 1987; Jegadeesh & Titman, 1993). Another important study in this regard is the study of Hossan and Park (2013). They reported that investors overreacted to firm specific information, and it acted as the source of investors' contrarian profits. They further found that lead and lag pattern did not contribute to profits that were expected from momentum profits.

(2) Nonsynchronous and Thin Trading : Returns on large stocks tend to lead returns on small stocks. This pattern is supported by various research studies. This theoretical behavior between returns of large and small stock has several theoretical explanations. For example, Fisher, (1966) and Cohen et al. (1986) argued that nonsynchronous trading or thin trading can be attributed to small stocks. Their findings do not possess enough empirical support. Lo and MacKinlay (1990), Mech (1993), McQueen, Pinegar, and Thorley (1996), and Chordia and Swaminathan (2000) argued that lead-lag effects cannot be fully explained by nonsynchronous and thin trading.

(3) The Institutional Investors' Effect : Chan et al. (1993) argued that institutional investors are more attracted towards large stocks. Empirical evidence indicates that trades by institutional investors have sizable effects on asset prices, generating phenomena such as index effects, asset-class effects, and others. They produce more information and in-depth analysis regarding large stocks ; thus, these stocks have better ability to lead other stocks for which there is less information in the market, especially small stocks. Chan et al.'s (1993) findings were objected to by Badrinath et al. (1995). They argued that institutional ownership is more related to lead-lag patterns rather than size of the firm. Analysts and institutional investors follow these stocks, and thus, they are more liquid.

(4) Slow Diffusion of Information Hypothesis : Advocates of this hypothesis put forward more convincing explanations in support of lead-lag patterns between different stocks. Their main argument is that lead-lag effect can be attributed to incomplete market framework and behavioral aspects of the human race. For example, Shiller (2000) and Sims (2005) argued that it is human inability to process all the available information, and thus, people have bounded rationality. Furthermore, human attention is an important cognitive resource which is not universal and abundant in human nature. This implies that stocks which issue delayed information or generate less information about economic activity will react slowly and will lack a large investor base (Hong et al., 2007).

The hypothesis of slow diffusion of information was applied to industry and market returns by Hong et al. (2007). They formulated and tested various hypotheses regarding large industries with more macroeconomic information and found that these industries lead the market returns. They found that information of such industries will reach investors and analysts specializing in broader market segment index with a delay. They found that if the industry does not possess enough information, it will have less ability to lead the market whether or not this information moves slowly. Another important consideration with regard to slow diffusion of information is investors' expertise in a specific sector and market segmentation. These two factors can be the causes of slow diffusion of information as argued by Menzly and Ozbas (2010).

The main objective of the present paper is built upon the work of Hong et al. (2007) and Shah, Munir, Khan, and Abbas (2011) to test lead-lag patterns between stock returns. More recently, Chen and Lu (2015) provided evidence in conformance with Hong and Stein (1999). They found that those stocks for which information diffuses slowly are in a better position to reap up contrarian profits. They empirically proved that a phenomenon of slow diffusion of information even exists in the options market. More informed traders wait for the realization of such slowly diffused information, and thus rely on slow diffusion of information hypothesis. Their approach is based on the co-movements of option markets with stock markets (An, Ang, Bali, & Caciki, 2014).

Data and Methodology

(1) Sample Construction : Sample includes weekly data of all the industries listed on the Shanghai Stock Exchange over a period from 2004-2013. Industries are classified on the basis of China Securities Regulatory Commission (CSRC) first-level code for analysis. Data were collected from RESET, WIND, and CSMAR (China Stock Market and Accounting Research) databases. According to first level CRSC code, a total of 18 industries are listed on the Chinese stock market. We took data from all the 18 industries for our regression analysis. After winsorizing our data at the 1% level, we were left with 9340 industry level observations. The decade - long time span for the study captures numerous short and long term trends in the Shanghai Stock exchange. We followed Hong et al. (2007) and Shah et al. (2011). Market returns are regressed on industry returns. A total of 360 regressions were run for a total of 18 industries.

(2) Dependent Variable : Holding period market return is the dependent variable to investigate the lead lag relationship between different industries and market returns. Data for market return is taken from RESET, WIND, and CSMAR databases. The Chinese stock market is divided into 18 industries according to the first level industry codes of the China Securities Regulatory Commission (See Table 1). In our analysis, we included all the industries to capture an overall behavior of industry returns towards the market returns.

Table 1. China Securities Regulatory Commission - Industry Classification and Codes

S.NO	CSRC Code	Industry Name
1	A	Forestry
2	B	Exploitation of Petroleum and Natural Gas
3	C	Railway, Marine, Aerospace, and Other Transportation Equipment Manufacturing
4	D	Production & Supply of Power and Heat
5	E	Civil Engineering Construction
6	F	Wholesale Trade
7	G	Marine Traffic Industry
8	H	Accommodation
9	I	Internet and related Services
10	J	Financial Service Industry
11	K	Realty Business
12	L	Business Services
13	M	Professional Technical Services
14	N	Ecological Protection and Environmental Management Industry
15	O	Other Service Industries
16	Q	Health
17	R	Broadcast Television, Film, and Video Production Industry Recordings
18	S	Complex

(3) Independent Variables

(i) Industry Returns : Weekly industry returns for both CSRC first and second level industry codes were taken from RESET database. These returns were then used for calculation of lagged market returns.

(ii) Lagged Market Returns : In order to account for autocorrelation of in market own returns, lagged market returns are included as independent variable. This is in agreement with Boudoukh, Richardson, and Whitelaw (1994), who argued that lead-lag phenomena between portfolio returns can be rejected on the basis of autocorrelation in portfolio own returns.

(4) Statistical Model : In order to test the predictive power of industry returns to forecast the market returns, we follow Hong et al. (2007).

$$R_{mt} = \alpha + \beta_i R_{it\text{-}k} + \beta_2 Z_{t\text{-}m} + e_{it}$$

R_{mt} is the market return at time t. $R_{it\text{-}k}$ is the industry returns that lagged upto k terms. β_i is the coefficient for industry returns and it measures the degree up to which an industry can predict market returns. The value of this coefficient must be significantly different from zero to confirm that phenomenon of slow diffusion of information exists. These returns are lagged up to a range of 5 weeks. The term $Z_{t\text{-}m}$ includes the control variables such as lagged market returns and lagged trading volume of a particular industry and market. The lagged market returns are used to account for the argument put forward by Boudoukh et al. (1994). According to them, lead-lag pattern in portfolio returns may also occur due to autocorrelation in the dependent variable's own returns. They argued that once the autocorrelation in portfolio returns is accounted for, the lead-lag effects due to autocorrelation in portfolio's own returns will disappear. Moreover, Chui and Kwok (1998) argued that lagged trading volume can also account for slow diffusion of information. Following them, we included lagged trading volume of industry and market as control variables. Chui and Kwok (1998) argued that trading activity is a sign of vigorous transmission of information, and thus, trading volume is a proxy of information, which is yet to be embedded in stock prices. Separate regression will be run for each industry. We can also estimate a single regression equation for all industries. However, Hong et al. (2007) argued that in such a case, the estimates will be less precise and will result in high slandered errors for the coefficients.

Analysis and Results

As shown in the Table 2, Ind code is CSRC first level industry code ranging from *A* to *S*. Where *A* = forestry, *B*= Exploration of petroleum and natural gas, *C* = Railway, marine, aerospace, and other transportation equipment manufacturing, *D* = production & supply of power and heat, *E* = civil engineering construction, *F* = wholesale trade, *G* = marine traffic industry, *H* = accommodation, *I* = Internet and related services, *J* = financial service industry, *K* = reality business, *L* = business service, *M* = professional technical services, *N* = ecological protection and environmental management industry, *O* = other service industry, *Q* = health industry, *R* = broadcast television, film, and video production industry recordings, *S* = complex industry.

Average industry returns are in the ranges of 0.003 to 0.003, with majority having the value of 0.003 (see Table 2). Maximum returns are reported by the industry *O* (other service industry) and minimum returns are reported by industry *D* (production & supply of power and heat). Furthermore, as shown in Table 2, the greatest variations in returns belong to other service industry, which reports a standard deviation of 0.286.

The Table 3 and Table 4 represent regression results after regressing market returns on industry lagged returns from week 1 to week 10. First column of the tables represent the industry codes. For each industry, separate

Table 2. Descriptive Statistics : Weekly Industry Returns

Industry Code	Mean	Std. Dev.	Min	Max
A	0.003	0.050	-0.171	0.243
B	0.003	0.044	-0.175	0.175
C	0.003	0.043	-0.150	0.191
D	0.001	0.039	-0.183	0.148
E	0.003	0.045	-0.167	0.265
F	0.004	0.044	-0.153	0.214
G	0.002	0.041	-0.162	0.165
H	0.003	0.047	-0.157	0.167
I	0.003	0.042	-0.157	0.176
J	0.003	0.045	-0.170	0.217
K	0.004	0.052	-0.217	0.213
L	0.004	0.048	-0.181	0.210
M	0.005	0.058	-0.211	0.260
N	0.004	0.049	-0.200	0.179
O	0.006	0.067	-0.286	0.275
Q	0.005	0.053	-0.137	0.190
R	0.004	0.058	-0.172	0.219
S	0.003	0.048	-0.200	0.173

regression was estimated. From column R_i , t-1 to R_i , t -10, coefficients of each industry is reported. R_i , t-1 shows that market returns were regressed on one week lagged industry returns. R_i, t-2 shows that market returns were regressed on two weeks lagged industry returns (see Table 3). There are 18 industries and 10 regressions are run for each industry. Due to the issue of parsimony, coefficient of each lagged industry returns are reported and coefficients for other control variables are avoided. *, **, and *** represent statistical significance at 90%, 95%, and 99 % significant levels.

It is essential that coefficients of lagged industry returns are statistically significant to confirm the slow diffusion of information hypothesis. Most of the industries lead the Shanghai stock market returns (see Table 3 and Table 4). Most of the coefficients are not only statistically significant, but also have a positive sign. As shown in the Table 3, 14 out of 18 industries lead stock market returns up to one week lag. The predictive power decreases to 12 industries for a lag of two weeks when we include the control variables (see Table 4) . For industries *A, B, C,* and *D* (*A* = forestry, *B* = exploration of petroleum and natural gas, *C* = railway, marine, aerospace, and other transportation equipment manufacturing, *D* = production & supply of power and heat), the predictive power is stronger and has great statistical significance up to 3 weeks (see Table 3). Beyond the third week, their significance is lowered, however, again from the seventh to sixth week, they regain their predictive power of the market returns (see Table 5).

Industries returns for industries such as *H, L, M, Q* (*H* = accommodation, *L*= business service, *M* = professional technical services, *Q* = health industry) show that the returns of these industries do not predict market returns while applying a one week lag (see Table 3).The predictive power of industries decreases as we increase the lag. During the first week, 14 out of 18 industries are able to predict the market returns (see Table 5 and Table 6). Their return predictability decreases to 12 industries as we enter into the second week. The predictive power of industry returns to predict market returns decreases to 11 in the third week, one in the fourth, and 0 in the fifth week. Thus, it

Table 3. Regression Results for Industry Returns Using a Lag from First to Fifth Week

Ind Code	R_i ,*t*-1	*t* Value	R_i. *t* - 2	*t* value	R_i, *t*-3	*t* value	R_i, *t*-4	*t* value	R_i, *t*-5	*t* value
A	0.837***	4.75	0.06754*	1.89	0.077*	1.7	0.001	0.54	-0.016	-0.21
B	0.7274***	6.23	0.0875**	2.2	0.116**	2.17	0.079**	2.33	-0.001	-0.53
C	0.088***	3.21	0.107**	2.15	0.0989**	2.53	0.014	0.86	-0.038	-0.18
D	0.096**	5.12	0.1093**	2.34	0.094**	2.24	0.000	0.11	-0.034	-0.39
E	0.0945**	2.13	0.0991	0.678	0.0968**	2.31	0.011	1.23	-0.022	-0.47
F	0.091**	2.37	0.105**	1.97	0.087	0.13	0.032	0.24	-0.030	-0.24
G	0.101**	1.98	0.118**	2.15	0.092**	2.17	0.012	0.67	-0.042	-0.73
H	0.06	0.347	0.107**	2.43	0.08*	1.89	0.021	0.78	-0.030	-0.41
I	0.096**	2.27	0.086**	2.15	0.056	0.57	0.000	0.22	-0.038	-0.88
J	0.075*	1.85	0.103**	2.51	0.117**	2.15	-0.007	-0.89	-0.007	-0.15
K	0.075*	1.68	0.096**	2.49	0.08**	2.37	0.036	0.57	0.014	0.42
L	0.051	0.86	0.104**	2.23	0.102**	2.51	0.034	0.79	-0.024	-0.29
M	-0.089	-0.62	-0.004	-0.52	-0.04	-0.47	0.012	0.43	0.026	0.15
N	0.07*	1.78	0.091	0.97	0.10	0.254	0.034	0.81	-0.031	-0.71
O	0.065**	2.11	0.081	0.743	0.1**	2.32	-0.004	-0.92	0.022	0.27
Q	-0.041	-0.25	0.007	0.43	-0.048	-0.14	-0.037	-0.37	-0.044	-0.21
R	0.1**	3.21	0.073**	2.1	0.059	0.124	-0.021	-0.41	-0.025	-0.83
S	0.074*	1.72	0.121	0.43	0.089**	2.39	0.027	0.67	-0.027	-0.58
Ind Significant	**14**		**12**		**11**		**1**		**0**	

Notes : *, **, *** represent significance at 90%, 95%, and 99% significance levels, respectively. *t* value shows the corresponding significance. Ind code is CSRC first level industry code and it denotes industry returns. It ranges from A to S. Where A = Forestry, B = Exploration of Petroleum and Natural gas, C= Railway, marine, aerospace, and other transportation equipment manufacturing, D = Production & Supply of Power and Heat, E= Civil Engineering Construction, F = Wholesale Trade, G = Marine traffic industry H= Accommodation, I= Internet and Related Services, J= Financial Service Industry, K= Reality Business, L= Business Service, M= Professional Technical Services, N= Ecological protection and environmental management industry, O= Other Service Industry, Q= Health Industry, R= Broadcast television, film, and video production industry recordings, S = Complex Industry. R_i ,*t*-1 represent industry returns for 1 week, R_i ,*t*-2 is industry returns lagged for 2 weeks, R_i ,*t*-3 corresponds to industry returns lagged for 3 weeks, R_i ,*t*-4 represents industry returns lagged for 4 weeks, and R_i ,*t*-5 represents returns for industry lagged over a period of 5 weeks. Ind Significant shows number of industries that lead the stock market returns.

reveals that predictive power of each industry decreases with the prediction horizon of each industry. These findings are according to the slow diffusion of information hypothesis, which argues that industry reveals information which is slowly incorporated in broader market segments.

Similar results were reported by Hong et al. (2007) for a sample of U.S. firms for a period over 1946-2002. They found that 14 out of 18 industries reported statistically significant coefficients when market returns were regressed on one month lagged industry returns while controlling for industry size and other variables. In their findings, they reported that predictive power of each industry decreased as the prediction horizon increased. They found nine industries to be statically significant for 2 months lagged returns, which decreased to four industries when a lag of 3 months was applied. Our findings are in line with the findings of studies conducted in more developed economies. Hong et al. (2007) empirically found that for the U.S. market, out of 34 industries, 14 industries were able to predict stock market returns up to 2 months.

The Table 4 also reveals that in case of Chinese industries, there is a unique finding. The predictive power on industries increases from 1 to 10 for 8 weeks lagged industry returns.

Table 4. Regression Results for Industry Returns Using a Lag from Sixth to Tenth Week

Ind Code	R_i, t-6	t-value	R_i . t-7	t-value	R_i, t-8	t-value	R_i, t-9	t-value	R_i, t-10	t-value
A	-0.04	-0.14	0.01	0.21	0.0785*	1.85	0.8377***	7.54	0.8377***	6.27
B	-0.04	-0.63	0.01	0.68	0.0376	0.39	0.073*	1.66	0.06	0.23
C	-0.01	-0.27	0.03	0.33	0.099**	2.12	0.091**	2.35	0.02	0.18
D	-0.01	-0.25	0.03	0.82	0.1116**	1.98	0.122**	2.18	0.03	0.63
E	-0.02	-0.36	0.02	0.46	0.09342**	2.11	0.105**	2.36	0.05	0.19
F	0.01	0.49	0.05	0.41	0.108**	2.31	0.098	0.12	0.02	0.25
G	0.03	0.73	0.01	0.91	0.095**	2.22	0.086	0.48	0.01	0.48
H	0.04	0.67	0.03	0.83	0.015	0.38	0.018	0.64	0.02	0.33
I	0.00	-0.19	0.074**	2.23	0.108**	2.19	0.076*	1.91	0.02	0.68
J	0.075*	1.63	-0.01	-0.13	0.048	0.91	0.068**	2.11	0.02	0.41
K	0.01	0.21	0.04	0.47	0.086**	2.19	0.086**	2.17	0.03	0.18
L	-0.03	-0.31	0.05	0.29	0.131	0.22	0.0685	0.22	0.07	0.55
M	0.05	0.49	-0.01	-0.54	0.03	0.67	0.033	0.44	0.02	0.39
N	0.00	0.51	0.03	0.31	0.082*	1.82	0.071*	1.76	0.01	0.43
O	-0.01	-0.76	0.01	0.84	0.053	0.35	0.052	0.25	0.056*	1.65
Q	-0.05	-0.61	0.03	0.63	-0.027	-0.18	-0.015	-0.12	-0.08	-0.14
R	-0.03	-0.11	0.00	0.42	0.061*	1.68	0.056	0.68	0.02	0.14
S	0.00	0.79	0.01	0.28	0.09	0.37	0.06	0.68	0.01	0.11
Ind Significant	**1**		**1**		**10**		**9**		**2**	

Notes : *, **, *** represent significance at 90%, 95%, and 99% significance levels, respectively. *t* value shows the corresponding significance. Ind code is CSRC first level industry code and it denotes industry returns. It ranges from A to S. Where A = Forestry, B = Exploration of Petroleum and Natural gas, C= Railway, marine, aerospace, and other transportation equipment manufacturing, D = Production & Supply of Power and Heat, E= Civil Engineering Construction, F = Wholesale Trade, G = Marine traffic industry H= Accommodation, I= Internet and Related Services, J= Financial Service Industry, K= Reality Business, L= Business Service, M= Professional Technical Services, N= Ecological protection and environmental management industry, O= Other Service Industry, Q= Health Industry, R= Broadcast television, film, and video production industry recordings, S = Complex Industry. R_i,t-6 represent industry returns lagged for 6 weeks, R_i,t-7 is industry returns lagged for 7 weeks, R_i,t-8 corresponds to industry returns lagged for 8 weeks, R_i,t-9 represents industry returns lagged for 9 weeks, and R_i,t-10 represents returns for industry lagged over a period of 10 weeks. Ind Significant shows number of industries that lead the stock market returns.

The Tables 5 and 6 represent regression results while controlling for industry size and trading volume. For size of the industry, log of market capitalization of each industry is taken. Log of trading volume of the industry and market is taken as the second control variable, which accounts for the liquidity factor. Lagged value of these control variables were taken accordingly. These additional variables are as to confirm that market returns are led by industry returns, even in the presence of these variables, to add more support and reliability to our findings regarding slow diffusion of information hypothesis. Chui and Kwok (1998) used similar control variables in their study.

The findings reveal that industry returns lead stock market returns even after additional control variables (see Table 5 and Table 6). These results have close similarity with the results of Table 3 and Table 4. The predictive power of each industry decreases as the prediction horizon (lag) of each industry increases. Most of the industries maintain their sign and statistical significance. This gives additional support to the fact that ability of an industry to lead the stock market is not fully explained by size and trading volume of the industry, and slow diffusion of information plays an important role in this regard.

Table 5. Regression Results for Lagged Industry Returns After Controlling for Industry Size and Trading Volume

Ind Code	R_i,t-1	t Value	$R_{i,}$. t - 2	t value	R_i, t-3	t value	R_i, t-4	t value	R_i, t-5	t value
A	0.819***	6.34	0.067*	1.73	0.079**	2.41	0.084**	2.16	-0.03	-0.23
B	0.12***	5.9	0.135**	2.11	0.105**	2.12	-0.03	-0.14	-0.03	-0.13
C	0.102**	2.11	0.119**	2.19	0.12**	2.37	0.01	0.37	-0.04	-0.23
D	0.106**	2.17	0.12**	2.05	0.11**	2.11	-0.02	-0.19	-0.04	-0.24
E	0.13***	5.37	0.094**	2.12	0.112**	2.29	0.00	0.43	0.01	0.31
F	0.11***	6.33	0.112**	2.34	0.108**	2.14	0.02	0.83	-0.03	-0.29
G	0.112**	2.11	0.109	0.34	0.11**	2.13	0.00	-0.61	-0.04	-0.26
H	0.051	0.63	0.087**	2.38	0.051	0.29	0.03	0.76	-0.05	-0.31
I	0.12**	2.37	0.131	0.41	0.068	0.43	0.00	0.53	-0.05	-0.63
J	0.101**	1.97	0.11**	2.17	0.105***	4.25	0.07	0.91	0.01	0.89
K	0.051	0.129	0.053	0.11	0.07*	1.69	0.03	0.68	0.06	0.67
L	0.038**	2.33	0.089	0.37	0.06	0.38	0.04	0.63	-0.01	-0.38
M	-0.079	-0.21	-0.008	-0.29	-0.055	-0.11	0.01	0.53	0.01	0.25
N	0.054	0.17	0.083**	2.33	0.095**	2.18	0.02	0.25	-0.03	-0.39
O	0.066**	2	0.089**	2.25	0.101	0.13	0.02	0.15	0.04	0.13
Q	-0.04	-0.16	0.023	0.22	-0.04	-0.37	-0.06	-0.43	-0.02	-0.37
R	0.091**	2.19	0.06*	1.76	0.031	0.61	-0.02	-0.54	-0.04	-0.16
S	0.069*	1.68	0.124**	2.33	0.088**	2.39	0.03	0.84	-0.03	-0.46
Ind Significant	**13**		**12**		**11**		**1**		**0.00**	

Notes : *, **, *** represent significance at 90%, 95%, and 99% significance levels, respectively. *t* value shows the corresponding significance. Ind code is CSRC first level industry code and it denotes industry returns. It ranges from A to S. Where A = Forestry, B = Exploration of Petroleum and Natural gas, C= Railway, marine, aerospace, and other transportation equipment manufacturing, D = Production & Supply of Power and Heat, E= Civil Engineering Construction, F = Wholesale Trade, G = Marine traffic industry H= Accommodation, I= Internet and Related Services, J= Financial Service Industry, K= Reality Business, L= Business Service, M= Professional Technical Services, N= Ecological protection and environmental management industry, O= Other Service Industry, Q= Health Industry, R= Broadcast television, film, and video production industry recordings, S = Complex Industry. R_i,*t*-1 represent industry returns for 1 week, R_i,*t*-2 is industry returns lagged for 2 weeks, R_i,*t*-3 corresponds to industry returns lagged for 3 weeks, R_i,*t*-4 represents industry returns lagged for 4 weeks, and R_i,*t*-5 represents returns for industry lagged over a period of 5 weeks. Ind Significant shows number of industries that lead the stock market returns.

One important study regarding slow diffusion of information in less developed markets was conducted by Shah et al. (2011). A sample of three large industries was taken, and they found no evidence that their industries predicted the stock market. Discrepancy in their study might be due to the discrepancy in their data. They used a sample for monthly data, while we used weekly data. However, our results are in line with the results obtained by their second study in which they used data of all industries of the Karachi Stock Exchange and found evidence in support of slow diffusion of information hypothesis. The findings of this study are also in conformance with the results obtained by Huang (2012). Huang (2012) empirically found that information is gradually diffused across the stock market, and an investment strategy based on the slow diffusion of information earned abnormal profits for investors.

The presence of slow diffusion of information in 14 out of 18 industries provides a considerable support for the presence of slow diffusion of information in Chinese industries. This is in line with the empirical findings of Chen and Lu (2015). They provided evidence in conformance with Hong and Stein (1999). They found that those stocks

Table 6. Regression Results for Industry Returns After Controlling for Industry Size and Trading Volume (5th to 10th Week Lags)

Ind Code	R_i, *t*-6	*t*-value	R_i. *t*-7	*t*-value	R_i, *t*-8	*t*-value	R_i, *t*-9	*t*-value	R_i, *t*-10	*t*-value
A	-0.037	-0.31	0.015	0.17	0.071*	1.86	0.05	0.11	0.033	0.37
B	0.0421	0.86	0.036	0.2	0.088*	1.66	0.113*	1.83	0.007	0.32
C	0.002	0.73	0.032	0.43	0.103**	2.12	0.11**	2.38	0.025	0.27
D	0.008	0.38	0.021	0.29	0.118**	2.28	0.172***	3.18	0.047	0.19
E	-0.026	-0.13	-0.01	-0.11	0.098**	2.39	0.111**	2.26	0.043	0.43
F	0.018	0.31	0.05	0.13	0.111**	2.3	0.0932**	2.31	0.024	0.29
G	0.039	0.21	0.008	0.55	0.089*	1.7	0.092*	1.67	0.014	0.17
H	-0.017	-0.19	0.063	0.67	0.097**	2.45	0.059	0.12	0.023	0.16
I	0.045	0.61	0.0641	0.42	0.093*	1.66	0.11**	2.41	0.056	0.24
J	0.104**	2.22	-0.012	-0.32	0.032	0.2	0.123*	1.68	0.035	0.38
K	0.034	0.73	0.056	0.19	0.089**	2.16	0.1*	1.73	0.046	0.67
L	-0.016	-0.37	0.077*	1.63	0.117**	2.44	0.062	0.19	0.029	0.29
M	0.05	0.28	-0.013	-0.21	0.037	0.31	0.046	0.21	0.011	0.14
N	0.001*	1.83	0.026	0.33	0.083**	2.36	0.069**	2.14	-0.002	-0.18
O	-0.009	-0.19	0.004	0.62	0.06	0.19	0.06	0.18	0.041	0.11
Q	-0.025	-0.23	0.021	0.34	-0.039	-0.36	-0.027	-0.18	-0.092	-0.17
R	-0.033	-0.17	0.007	0.63	0.053	0.25	0.053	0.22	0.033	0.37
S	-0.007	-0.18	0.026	0.42	0.083*	1.79	0.07*	1.95	0.016	0.53
Ind Significant	**2**		**1**		**13**		**10**		**0**	

Notes : *, **, *** represent significance at 90%, 95%, and 99% significance levels, respectively. *t* value shows the corresponding significance. Ind code is CSRC first level industry code and it denotes industry returns. It ranges from A to S. Where A = Forestry, B = Exploration of Petroleum and Natural gas, C= Railway, marine, aerospace, and other transportation equipment manufacturing, D = Production & Supply of Power and Heat, E= Civil Engineering Construction, F = Wholesale Trade, G = Marine traffic industry H= Accommodation, I= Internet and Related Services, J= Financial Service Industry, K= Reality Business, L= Business Service, M= Professional Technical Services, N= Ecological protection and environmental management industry, O= Other Service Industry, Q= Health Industry, R= Broadcast television, film, and video production industry recordings, S = Complex Industry. R_i,*t*-6 represent industry returns lagged for 6 weeks, R_i,*t*-7 is industry returns lagged for 7 weeks, R_i,*t*-8 corresponds to industry returns lagged for 8 weeks, R_i,*t*-9 represents industry returns lagged for 9 weeks, and R_i,*t*-10 represents returns for industry lagged over a period of 10 weeks. Ind Significant shows number of industries that lead the stock market returns.

for which information diffused slowly were in a better position to reap up contrarian profits. They empirically proved that a phenomenon of slow diffusion of information even exists in the options market. More informed traders wait for the realization of such slowly diffused information, and thus, rely on slow diffusion of the information hypothesis. The predictive power reduced as we increase the industry lag.

Another astonishing aspect is that predictive power of industries vanishes as we increase the lag beyond 3 weeks. However, the predictive ability reemerges as the lag reaches beyond the 7th week. This peculiar characteristic of the Chinese market is of unique importance and can be a valuable question for future investigation. The important consideration in this regard is the persistence of slow diffusion of information, even after controlling for other control variables. Even after incorporating the industry size and trading (Table 5 and Table 6) volume in the main statistical model, a total of 13 industries showed a slow diffusion of information. This reduction of predictive power just by one industry as compared to Table 3 is an indication that our findings are statistically and economically robust, and that there exists strong evidence in support of slow diffusion of information in the Chinese stock market across different industries.

Our findings indicate that the market contains information that is incorporated in industries' returns. This information is incorporated about their fundamentals with a lag. Thus, the information diffuses differently across different industries. Explanation of lead- lag and behavioral aspect of investor's inability to process all the information of a market broad index left us with a possibility that market information is incorporated across different industries or sectors of the stock market with a lag.

Concluding Remarks

Returns predictability and cross autocorrelations are an important consideration in behavioral finance and are of considerable interest to investors and financial economists. This area gained much attention due to developments in behavioral finance during the last two decades. Previously, lead-lag patterns were supported by the argument of rational expectations, however, it lacks much empirical evidence.

According to behaviorists' views, it is human inability to process all sorts of information, and thus, information moves slowly from one market to another. In this study, we tested this slow diffusion of information using an extensive set of data over a period from 2004-2013. We found that the market is led by industries' industry returns up to a period of 4 weeks. This predictive power of industries decreases as the prediction horizon is increased. The presence of slow diffusion of information validates our hypothesis that information is slowly diffused across various sectors or industries of the stock market. These results in the context of findings of Huang (2012) and Chen and Lu (2015) have importance implications for investors who usually lack the information about the broader spectrum of the stock market. Moreover, managers can greatly benefit from studies on slow diffusion of information by including stocks of industries through which the stock market information is rapidly diffused. These findings are robust, even if we control for industry size and trading volume. Thus, these findings add considerable support to slow diffusion of information hypothesis.

Research Implications, Limitations of the Study, and Scope for Future Research

The notions of slow diffusion of information, lead-lag patterns, and industries' prediction of stock market returns have very important implications for investors. Investors who are better informed about certain sectors, and those investors having their investments in a specific industry will greatly benefit from the body of knowledge created by such type of studies. They will in a better position to ascertain future market trends as to those investors who have limited information or the information is slowly received by them. Especially equity managers specializing in a certain industry, they can greatly benefit from slow diffusion and lead-lag patterns across different industries. The findings will help managers to strongly correlate an industry to market prediction and the relative propensity of certain industries to predict market returns or lead in predicting market returns will greatly help portfolio managers to time their portfolios with the stocks of highly predictive industries. This information of industries' predictive power of market coupled with some firm fundamentals will equip managers with profitable investment decisions.

The conclusion derived for the study is subject to some limitations, and owing to these limitations, the study can be extrapolated across various dimensions. One important consideration in this regard will be to ascertain whether Chinese industries lead the stock markets across sub periods. The samples can be divided into pre and post crisis era (financial crisis of 2008). For example, during the financial crisis, liquidity of many companies evaporated, and thus, this will have an important implication for industries as a whole during crises. Thus, this lead and lag relationship can further be explored by incorporating pre and post crisis samples. Furthermore, the analysis is done according to the first-level code of CSRC (Chinese Securities Regulatory Commission) classification. By dividing the codes into CSRC second level code, the findings can further be streamlined to more specific industries, and this will also increase the number of industries to more than 50 industries as compared to the current level of 18 industries according to CSRC first-level code.

Furthermore, China specific indicators like banks' loan expansion rate can be included as an interactive term because of the peculiar characteristics of the Chinese stock market. Liquidity position of Chinese stocks was affected up to a larger degree as compared to developed countries. Another peculiar and unique question that needs future research consideration is the ability of Chinese industries to predict the market returns after a lag of 7 weeks. From the point of view of investors, it is much desirable to construct a variable that can capture investors' recognition ; so, there is a need to devise a direct and more viable test for industry lead-lag pattern. Apart from investor recognition, industry business cycles can also be incorporated (Wu & Shamsuddin, 2012). Apart from industry, another important consideration would be the firm size. It will add more pragmatism to incorporate size effects by constructing small and large cap portfolios of industries (Hou & Moskowitz, 2005; Hou, 2007). Another important addition would be to study the prediction patterns in bull and bearish markets to make the picture more clear in ascertaining that what are the implications and predictive power of industries across market conditions, especially when the market is bearish (Nyberg, 2013).

End Note

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