Information Flows Within and Across Sectors in China's Emerging Stock Markets

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ABSTRACT

We examine the patterns of information flows within and across sectors of the two Chinese stock exchanges in Shanghai and Shenzhen, using daily data during 1994 - 2001. Using the generalized forecast error variance decomposition, we find a high degree of interdependence, indicating that the sectors are highly integrated and sector prices reflect information from other sectors. Industry is the most influential sector in both exchanges, while Finance in Shenzhen is the least integrated with other sectors. Implications of the findings for investors and policymakers are discussed.

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1. INTRODUCTION

Stock markets in China have expanded rapidly following the establishment of two stock exchanges in Shanghai and Shenzhen in the early 1990's. As of January 2001, there were 584 and 514 firms listed in the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE), respectively. The combined capitalization of the markets reached $500 billion in 2000, making up 50% of China's GDP. This figure suggests that the stock market activity may have real economic effects. Recognizing the significance of stock markets in China, researchers have studied many different aspects of the markets. In this paper, we study the pattern of information flows at the sector level in Chinese stock market.

The study contributes to the literature in two aspects. First, filling a gap in the literature, we examine the pattern of information flows both *across* and *within* the sectors of two Chinese stock exchanges. As reviewed below, most of previous studies (e.g., Chui and Kwok, 1998; Long, Payne, and Feng, 1999; Fung, Lee, and Leung, 2000; Xu and Fung, 2002; Yang, 2003) on the information linkages in Chinese stock markets have focused on the A- and B-shares in Shanghai and Shenzhen, as well as the China-backed securities markets (i.e., H-shares and red chips). A missing link in the literature is how the information transmits across sectors. Such an investigation of the pattern of information flows at the sector level should be important, as individual and institutional investors often use sector indexes as a benchmark to track the performance of actively managed portfolios (Ewing, 2002; Ewing, Forbes, and Payne, 2003). Examining the relative importance of the sectors in Chinese stock markets also allows a better

understanding of the dynamics of financial markets in an economy undergoing significant reforms and regulatory changes such as China.

Second, this study also employs a relatively new technique, the generalized forecast error variance decomposition of Pesaran and Shin (1998) to investigate the pattern of information flows. Different from the traditional orthogonalized forecast error variance decomposition (see Sims (1980)), this technique is able to circumvent the problem of sensitivity of forecast error variance decompositions to the ordering of variables in the system and result in a robust solution. This method has not been commonly applied in financial research, with the recent exceptions of Ewing (2002) and Yang, Min and Li (2003).

In the next section, we provide a review of the related literature. In section III, we outline our empirical methodology. In Section V, we describe the data used, while we report our empirical results in Section IV. We discuss the policy implications of our findings in the concluding section.

2. LITERATURE REVIEW

Researchers have studied many aspects of the Chinese stock markets from different angles, including asset pricing in segmented Chinese markets (e.g., Poon, Firth and Fung, 1998; Sun and Tong, 2000; Fernald and Rogers, 2002), the return and volatility link (e.g., Su and Fleisher, 1999), market efficiency, and the price-volume relation (Long, Payne and Feng, 1999). In particular, a number of recent works have examined the information transmission patterns in Chinese stock markets. These studies have focused on the information flows between: (1) the A and B-share markets in Shanghai and

Shenzhen; (2) China-backed securities in Hong Kong (H shares and red chips) and New York and the A and B-share markets in Shanghai and Shenzhen; and (3) global markets and the Shanghai and Shenzhen markets. However, it appears that no studies have been done to explore the information flow patterns at the sector level.

Chui and Kwok (1998) found that movements in the B-shares traded by foreign investors lead A-share returns traded by domestic investors. Fung, Lee, and Leung (2000) reported one-way causality of stock returns, running from Shenzhen to Shanghai. However, Song, Liu, and Romilly (1998) found significant information feedback between the two markets. Yang (2003) documented that the Shanghai B-share market leads both A-share markets in Shanghai and Shenzhen, and the Shenzhen B-share market. Poon and Fung (2000) presented evidence that red chips, compared to H-shares, play a stronger leading role in spreading the return and volatility information to the A and B markets in both Shanghai and Shenzhen. Contradictory to Poon and Fung (2000), Yang (2003) found that the Hong Kong H-share market more significantly explains the price variations of A- and B- share markets than red chip stocks. Further exploring the pattern of information flows of China-backed stocks that are cross-listed on exchanges in Hong Kong and New York, Xu and Fung (2002) found strong two-way information flows between the two markets. Obviously, the pattern of informational flow among the A and B-share markets and China-backed securities is inconclusive.

Other studies examined the significance of global information in Chinese markets. Bailey (1994) provided evidence that B-share returns are not correlated with major world equity indexes and U.S. bond yields, suggesting significant diversification benefits. Hu, et al. (1997) reported that movements in Taiwan and Hong Kong stock markets have no

effect on both A and B-share returns, but the returns in the latter are related to the volatility of Japan and the U.S. indexes contemporaneously. By contrast, Huang, Yang, and Hu (2000) argued that there are no long- and short-run linkages between the A-share returns and stock market returns in Taiwan, Hong Kong, Japan and the U.S.. Obviously, the evidence for the importance of global information is also mixed.

The aforementioned studies do not examine the information linkages at the sector level. We fill this gap in the literature by providing evidence from both the Shanghai and Shenzhen Exchanges. We investigate the information flows not only across sectors within each market, but also between the pairs of sectors in both markets.

3. EMPIRICAL MODEL

The generalized forecast error variance decomposition is employed in this paper to study the information linkages. Pesaran and Shin (1998) developed this model. Ewing (2002) and Yang, Min and Li (2003) have recently employed this approach to study transmission of shocks in the US and European financial markets. In this section, we first describe the procedure and then explain its advantages over the traditional forecast error variance decomposition approach.

To begin with, let's define Y_t as a vector with m stationary processes, and model the dynamic relationship among these processes as a VAR of order k

$$Y_t = \sum_{i=1}^{k} \Phi_i Y_{t-i} + BX_t + e_t \qquad (t = 1,...,T)\ , \tag{1}$$

where $Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{mt})'$ is a (m $\times$ 1) vector of endogenous variables; X_t is an (n $\times$ 1) vector of deterministic and/or exogenous variables such as intercept, dummy variables,

A_i and ψ are (m $\times$ m) and (m $\times$ n) coefficient matrices; and e_t is a (m $\times$ 1) vector of innovations following multivariate normal distribution with variance Σ. In this study, the vector Y_t is defined as a (4 $\times$ 1) vector consisting of four sectors returns for SHSE (i.e., *DLNIN*, *DLNCM* , *DLNRE* , and *DLNUT* , as defined below) and a (5 $\times$ 1) vector consisting of five sectors returns for SZSE (i.e., *DLNIN*, *DLNCM* , *DLNRE* , *DLNFN* , and *DLNUT* , as defined below).

Researchers (e.g., Sims, 1980; Bessler and Yang, 2003) advocate that a good way to summarize dynamic interactions among individual series is to examine forecast error variance decompositions. More specifically, under the assumption of covariance stationarity, we can write Equation (1) as the infinite moving average representation,

$$Y_t = \sum_{i=0}^{\infty} \Psi_i e_{t-i}, \quad (t = 1,...,T). \tag{2}$$

We note that in Equation (2) we omit the part corresponding to BX_t in (1), since it is irrelevant in subsequent calculations. We can derive the moving average coefficient matrices Ψ_i from the autoregressive coefficient Φ_i's through the following iteration:

$$\Psi_s = \Phi_1\Psi_{s-1} + \Phi_2\Psi_{s-2} + \ldots + \Phi_k\Psi_{s-k}, \quad s = 1, 2, \ldots, \tag{3}$$

with $\Psi_0 = \mathbf{I}_m$, an (m $\times$ m) identity matrix, and $\Psi_s = \mathbf{0}$ for $s < 0$. It is easy to show that the error in forecasting Y_t s periods into the future conditional on information available at $t-1$ is

$$x_{t,s} = \sum_{h=0}^{s} \Psi_h e_{t+s-h}, \tag{4}$$

with a variance of

$$Var(x_{t,s}) = \sum_{i=0}^{s} \Psi_i \Sigma \Psi_i^{'}. \tag{5}$$

Traditionally, the *i*th diagonal element of this variance (corresponding to variable y_{it}) is decomposed into *m* terms as $\sum_{h=0}^{s} (e_i^{'} \Psi_h P e_j)^2,\ j = 1,2,...,m$, where P is Cholesky factor of Σ and e_i is the selection vector that has all elements equal to 0 except for the *i*th element being 1. We can normalize these terms by the total variance associated with variable y_{it} at step *s* to yield the following orthogonalized forecast error variance decomposition:

$$q_{ij,s} = \frac{\sum_{h=0}^{s} (e_i^{'} \Psi_h P e_j)^2}{\sum_{h=0}^{s} (e_i^{'} \Psi_h \Sigma \Psi_h^{'} e_i)}, \qquad i, j = 1,2,...,m, \tag{6}$$

where $q_{ij,s}$ is a measure of the contribution of *j*th-orthogonalized innovation to the total forecast error variance of variable y_{it}, *s*-steps-ahead. However, it is well known that this decomposition critically depends on the ordering of variables in the VAR. Different orderings could led to different inferences depending on the degree of correlations between different shocks. For example, a particular ordering implies that we *a priori* impose a particular structure on the multivariate process. However, we first need to identify and measure this process.

As an extension of Koop et al. (1996), Pesaran and Shin (1998) developed an alternative method that explains the proportion of the *s*-step forecast error in (4) by conditioning on the non-orthogonalized shocks, e_{it}, $e_{i,t+1}$, … , $e_{i,t+s}$ and explicitly allowing for contemporaneous correlations between the shocks. We recall that e_t follows

multivariate normal distribution. Conditioning on information e_{it}, $e_{i,t+1}$, … , $e_{i,t+s}$, we can write:

$$E(e_{t+s-h} \mid e_{i,t+s-h}) = (s_{ii}^{-1}\Sigma e_i)\, e_{i,t+s-h}, \quad h = 0,1,2,\ldots,s, i = 1,2,\ldots,m, \tag{7}$$

where s_{ii} is the ith diagonal element of Σ. Correspondingly, the forecast errors $x_{t,s}$ in (4) becomes

$$x_{t,s}^{(i)} = \sum_{h=0}^{s} \Psi_h (e_{t+s-h} - s_{ii}^{-1}\Sigma e_i e_{i,t+s-h}), \tag{8}$$

and therefore, the new conditional forecast error variance is given by

$$Var(x_{t,s}) = \sum_{i=0}^{s} \Psi_i \Sigma \Psi_i' - s_{jj}^{-1} (\sum_{h=0}^{s} \Psi_i \Sigma e_i e_i' \Sigma \Psi_h'). \tag{9}$$

By comparing (9) with (5), we can see that by conditioning on future shocks in ith variable, e_{it}, $e_{i,t+1}$, … , $e_{i,t+s}$, the s-step forecast error variance declines by an amount of

$$s_{ii}^{-1} (\sum_{h=0}^{s} \Psi_i \Sigma e_i e_i' \Sigma \Psi_h').$$

As in the case of the above orthogonalized decomposition, we normalize the jth diagonal element of this matrix by total forecast error variance of the variable y_{it}, which yields

$$\tilde{q}_{i,j,s} = \frac{s_{ii}^{-1} \sum_{h=0}^{s} (e_i' \Psi_h \Sigma e_j)^2}{\sum_{h=0}^{s} (e_i' \Psi_h \Sigma \Psi_h' e_i)}, \qquad i, j = 1,2,\ldots,m. \tag{10}$$

Pesaran and Shin (1998) called Equation (10) the generalized forecast error variance decomposition, which resembles the traditional orthogonalized decomposition, except for a key difference. Namely, the variance Σ in Equation (10) replaces its particular form of factor, P, in Equation (9). Therefore, the generalized decomposition is invariant to the ordering of variables in the VAR model. While the orthogonalized

decompositions sum (over *j*) to 100% by construction, this is not necessarily true for the generalized decompositions because of the non-zero covariance between original non-orthogonalized shocks.

4. DATA, SAMPLE PERIOD, AND DESCRIPTIVE STATISTICS

We employ daily sector indexes of Shanghai and Shenzhen stock exchanges that are obtained from the Taiwan Economic Journal Financial Database. The dataset for SHSE consists of four sectors: Industry (*LNIN*), Commerce (*LNCM*), Realty (*LNRE*) and Utility (*LNUT*) where LN represents the logarithmic of sector price indexes. The sample period is from May 3, 1993 through November 16, 2001, totaling 1860 daily observations. In its earlier years, the Chinese stock market was subject to irregular closing other than weekends or holidays. The data set for SZSE consists of five sectors: Industry, Commerce, Realty, Finance (*LNFN*) and Utility. We note that there is no separate sector data published for the Finance sector in the SHSE market. The sample period for this market runs from July 20, 1994 through November 16, 2001, with a total of 1544 daily observations.

The plot of the data (not shown here) shows that all SHSE sector indexes share an upward trend and tend to move together. The initial index values for Industry, Commerce, Realty and Utility, which were 1348, 1384, 1356 and 1346 at the beginning of the sample period, increased to 1611, 1999, 2384 and 3092, respectively, by the end of the sample. We find a similar pattern for the Shenzhen market with one exception: the Realty index is less volatile, especially in the second half of the sample. Also noteworthy, after a peak in early May 1997, all sector indexes in both markets show a continuous downward trend until mid May 1999. This might reflect the impact of the recent Asian

financial crisis. By the end of sample period, we see that the three indexes in SHSE are higher than the pre-crisis levels, while no SZSE index is fully recovered.[1]

In Table 1, we report the descriptive statistics for daily returns. The results for the Shanghai market (Panel A) show that the Realty sector has the lowest returns (0.08%), and the Utility sector has the highest (0.13%), followed by Commerce (0.11%) and Industry (0.10%). The higher returns in the Utility sector correspond to relatively higher standard deviation as well, and the relationship between stock returns and standard deviation follows similar patterns. In Panel B, we display the results for the Shenzhen market. We find that the Finance and Commerce sectors have the highest returns, while Realty has the smallest. The returns of the Realty sector in SHZE are much lower than those in SHSE. This could reflect the thin trading in SHZE. We see that the Commerce sector has the largest standard deviation, followed by Realty.

5. EMPIRICAL RESULTS

A. Information Flows *Across* Sectors but *Within* the Same Market

As we noted above, the sector price indexes appear to be moving together. In establishing the time series properties (stationarity) of each index, we implemented a battery of unit root tests and found that we could not reject a unit root in both markets at the 5% significance level when we use level data. However, we rejected the unit root hypothesis when we use the first differences of the series. Therefore, we model all the series as nonstationary and integrated of order one and also enter all variables into analysis in the form of logarithm. Because we found that the level of the series is

[1] To test the significance of the effect of the Asian crisis on China's markets, we include a dummy variable in the vector autoregressions. We find this effect significant in all sectors in the Shanghai market, but only

nonstationary, we also need to consider possible cointegration relation. Using Johansen's (1991) trace test, we found no evidence of cointegration in either SHSE or SZSE, at the 5% or 10% significance level, regardless of whether we allow a linear trend in estimations.[2]

Consistent with our finding, Yang (2003) documented that during 1995-2000, A-share markets for domestic investors in Shanghai and Shenzhen did not share long run comovements, and neither did B-share markets for foreign investors on the two exchanges. As pointed out by Yang (2003), both A-share and B-share markets on Shanghai and Shenzhen exchanges may represent two different stock portfolios. For example, Chakravarty, Sarkar, and Wu (1998, p. 327) observed that B-share stocks listed on the Shanghai Securities Exchange are dominated by former state-owned enterprises and B-share stocks listed on the Shenzhen Securities Exchange are dominated by joint-venture companies with foreign investors. The finding of this study confirms Yang (2003) at the sector level.

Given no cointegration between nonstationary sector price indexes, we should use the first-differences of (logged) sector price indexes, that is, returns in the following estimation and inference. Our VAR model for SHSE consists of four variables: *DLNIN*, *DLNCM*, *DLNRE* and *DLNUT*, where *D* represents the first-difference operator. To determine the optimal lag order k in equation (1), we implemented sequential likelihood ratio tests and calculate three information criteria (AIC, SC and HQ). Both the likelihood ratio test and AIC conclude with $k = 2$. Therefore, we use $k = 2$ in the VAR for SHSE (empirical results based on $k = 1$, as suggested by SC and HQ, are very similar).

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in three sectors in the Shenzhen market.

[2] The results are not reported for space considerations, but are available from the authors upon request.

Similarly, our VAR model for SZSE includes five endogenous variables: *DLNIN*, *DLNCM*, *DLNRE*, *DLNFN* and *DLNUT*, with an optimal lag order of 1 (the likelihood ratio test and three information criteria all conclude with $k = 1$). In both models, we include a constant term to allow for possible time trend in returns.

In Tables 2 and 3, we present Granger causality test results, which are based on the maximum likelihood estimates of the two VAR models. The tests provide evidence as to the significance of each sector in predicting the stock returns of other sectors. The small *p*-values at the bottom line of both tables indicate the significance level for the null that each sector index is not Granger-caused by the remaining ones jointly.

The results for SHSE in Table 2 show that the Industry sector Granger causes only Realty, while Commerce leads returns in all other sectors. We find no evidence that Realty and Utility Granger cause returns in other sectors. However, the joint tests, reported at the bottom of Table 2, show that the hypothesis that each sector is not Granger caused by the remaining sectors in the Shanghai market can be rejected at any conventional significance levels. On the other hand, we see no evidence in Table 3 that an individual sector in SHZE leads another. However, the joint tests again indicate that each sector is Granger caused by some other sectors in the Shenzhen market.

We note that the Granger causality tests consider only the *statistical* significance of variables. However, it might be misleading to consider only statistical evidence in making judgments, because the variables might be economically significant, even though they are not statistically significant for various reasons, Therefore, researchers strongly advocate using the forecast error variance decomposition as well to provide further insights about the *economic* significance of variables (Sims, 1972, p.545; Sims, 1980,

p.20; Abdullah and Rangazas, 1988, p.682). Therefore, in this study we also employ the forecast error variance decompositions.

As discussed previously, the generalized forecast error variance decompositions is preferred over the traditional forecast error variance decompositions of Sims (1980) if Σ or its corresponding correlation matrix is nondiagonal. We compute the empirical estimates of residual correlations for SHSE and SZSE, respectively, as follows:

$$\begin{pmatrix} 1 & & & \\ .945 & 1 & & \\ .856 & .845 & 1 & \\ .921 & .892 & .832 & 1 \end{pmatrix}$$

and

$$\begin{pmatrix} 1 & & & & \\ .850 & 1 & & & \\ .887 & .792 & 1 & & \\ .749 & .657 & .692 & 1 & \\ .909 & .807 & .866 & .697 & 1 \end{pmatrix}$$

We see that the off-diagonal elements of both matrixes are not zero, and therefore we conduct a likelihood ratio (LR) test. For SHSE, we calculate the log likelihood value of system (1) as 21132 when Σ is unrestricted, and as 15973 when Σ is restricted to have zero in off-diagonal elements under the null. We find that the LR test statistic is 2*(21132 – 15973) = 10317, which, under the null hypothesis, has a chi-squared distribution with 6 degrees of freedom. This allows us to reject the null that that Σ is diagonal at any conventional significance levels. Similarly, we calculate the LR test statistic for SZSE as 8559 with 10 degrees of freedom. Again, we reject the null hypothesis. Based on the tests results, we conclude that shocks in different sectors are contemporaneously

correlated, which requires that we use the generalized forecast error variance decompositions in estimations to make correct inferences.

In Table 4, we present the results of the generalized forecast error variance decompositions.[3] Since the values of decompositions do not change significantly over the horizons considered, we only report the decompositions at 10-day horizons. In panel A, which reports the results for the Shanghai market, we see that the most important variable in accounting for fluctuations in the Industry sector returns (*DLNIN*) is its own shocks. At the 10-day horizon, the proportion of Industry returns explained by its own shocks is 28.79%. Shock to the Commerce, Realty and Utility sectors explain 26.26%, 23.37%, and 25.40% of the variance of the Industry sector returns, respectively. We see that the variance of the Commerce (*DLNCM*) sector returns is explained mostly by its own shocks (29.34%), followed by Industry (25.67%), Utility (23.85%), and Realty (22.73%). We find that the own shocks also explain a large part of the variance of Realty sector returns (31.83%). The contribution of other shocks to changes in Realty returns is roughly equal: Industry (21.11%), Commerce (20.98%), and Utility (20.76%). The decomposition results of the Utility sector indicate that shocks to all four indexes are closely correlated. At the 10-day horizon, Industry explains 24.42% of fluctuations in Utility, followed by Commerce (23.41%) and Realty (22.07%).

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[3] As noted earlier, the generalized forecast error variance decomposition of variable *i* at horizon *s*, $\hat{q}_{i,j,s}$, does not sum to 100% over *j* (*j* = 1, 2, …, m). For example, according to (10), at *s* = 1, the forecast error variance of variable *DLNIN* are decomposed into 99.839% (all relative to total variance), 89.195%, 73.175% and 84.616% from innovations in variables *DLNIN*, *DLNCM*, *DLNRE*, and *DLNUT*. To simplify illustration, in Table 4 and 5, we further normalized these decompositions by their sum, so that the relative importance in total variance sum up to 100%.

In summary, the results indicate that the Industry index appears to be the most important sector in Shanghai in that it does the most to explain changes in other sector returns in SHSE. We can explain this finding by the relatively sheer size of the other sectors in SHSE. The industry sector has the highest number of firms listed in the market with relatively higher market capitalization. As of 2000, there were 584 firms in the SHSE with the following shares for each sector: Industry (61%), Commerce (9%), Realty (2%), Utility (9%), and others (20%) (Source: www.sse.com.cn/).

In Panel B of Table 4, we report the decomposition results for the Shenzhen market. We observe that each sector's own shocks dominate in explaining the total variance of individual sector returns. About 25.66% of the variability in Industry index (*DLNIN*) is still attributable to its own shocks, followed by Utility (22.25%), Realty (21.60%), Commerce (21.05%), and Finance (18.95%). Similar to what we observed in the SHSE, shocks to the Industry sector represent the most important factor (other than the own shock in each sector) to explain the variation of returns in the Commerce, Realty, Finance, and Utility sectors by 18.54%, 20.20%, 14.41%, and 21.19%, respectively. We find that the second most important factor in SZSE is the Utility sector, which contributes to 22.25%, 17.54%, 20.19%, and 13.07% of variations in Industry, Commerce, Realty, and Finance, respectively. We note that own shocks have the highest explanatory power for the Finance sector (33.91%). At the same time, the Finance sector has the least spillover effects to others, which range from 14.59% to 18.95%. This suggests that this sector is the least integrated with other sectors. This might be related to the structure of the industry. The Chinese government typically views the Finance sector as the more sensitive one, thus imposing more regulation and supervision. Such extensive

governmental intervention may prohibit the information flows between the Finance sector and other sectors[4].

To study the sensitivity of our results to time aggregation, we also report the results with monthly data, using the end-of-month values. In Panels A and B of Tables 5, we report the decompositions for SHSE and SZSE, respectively. We find that the dynamic relations found among the sector indexes in Table 4 still hold when monthly data are used, and the relative magnitude of shocks largely remains the same. However, there are also some notable changes. Although the Industry sector still plays an important role, it is no longer the most significant one, especially in SZSE. In addition, we see an increase in the relative importance of the Commerce and Realty sectors. The Finance sector in SZSE becomes more exogenous in that a larger part (36.92%) of its variation is now explained by own shocks. The Finance sector also has a smaller influence on Industry, Realty and Utility. This suggests that potential gains from sector allocation, based on the Finance sector, are superior to those from other sectors.

B. Information Flows *Within* the Same Sector but *across* the Markets

To examine the dynamic relationship of a given sector in both Shanghai and Shenzhen exchanges, we also fit a bivariate VAR of order 1. In Table 6, which reports the results for both daily (Panel A) and monthly observations (Panel B), we find significant inter-market effects. These effects are almost symmetric for each pair. For example, the Industry sector in SZSE accounts for 42.48% of the variation of the same sector in SHSE, while Industry in SHSE explains 42.50% of the variation in Industry in SZSE. The inter-market effects of other pairs of sectors range from 35.60% to 37.97%.

[4] We thank the referee for pointing this out.

In Panel B, which reports the results for monthly data, we still find important feedback between sectors. However, it is relatively smaller than those reported in Panel A for daily data. The cross effects between the two Industry indexes remain the highest (about 41%), while it is the smallest for Utility (about 32%). Overall, there is significant feedback between the same sectors in Shanghai and Shenzhen. Our finding extends the finding of unidirectional causality from Shenzhen to Shanghai, as reported in Fung, Lee, and Leung (2000).

6. CONCLUSIONS

This study explores the dynamic relationship among major sector indexes in China's two stock exchanges. Using daily and monthly returns, we find a high degree of interdependence. A shock to any sector has a significant impact on other sectors, and this result holds for both markets. About 70% of forecast error variance in a sector typically can be attributed to shocks in other sectors at a 10-day horizon. Similar findings hold across the markets. Shocks to a sector in SHSE can explain more than one third of the variation of the same sector in SZSE, and vice versa. These findings suggest that sector returns reflect information from other sectors, and there are strong information flows, not only within each exchange, but also across both markets.

Our findings have implications for policymakers and investors. The results suggest that financial trouble in one sector could easily spread to others. The transmission of shocks in one sector to others might create financial market instability in a crisis, which could further spread to the production side of the economy. Similar to Ewing (2002), our findings also shed light on the direction of the transmission of shocks between sectors and how to determine the most influential sector. Policymakers could

design regulatory reforms to minimize its negative effects on the economy. If particular, policymakers could regulate the influential sector to prevent the transmission of shock from this sector to others.

Given the significant linkage across returns, our results also suggest that investors could (partly) predict index movements in a sector using information flows from other sectors. On the other hand, potential diversification benefits from sector-level investment may also be relatively limited, given the significant linkages and high correlations we found among sector returns. In this context, the Finance sector in the SZSE offers the best diversification tool within the Chinese stock market since this sector is the least integrated with other sectors. Given the limited investment alternatives in China, this finding for the Finance sector has significant implications regarding the construction of optimal equity portfolios that explicitly take into account sector as a relevant risk factor.

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Table 1. Descriptive Statistics of Returns

Panel A – Shanghai Market

Return	Mean	Std. Dev.	Minimum	Maximum
Industry	0.105	2.714	-13.661	27.451
Commerce	0.110	2.802	-18.941	28.488
Realty	0.083	2.776	-14.745	27.968
Utility	0.133	2.871	-13.075	33.714

Panel B – Shenzhen Market

Return	Mean	Std. Dev.	Minimum	Maximum
Industry	0.107	2.735	-20.031	30.204
Commerce	0.122	3.428	-22.599	32.737
Finance	0.134	2.863	-18.993	23.206
Realty	0.039	3.103	-20.825	29.797
Utility	0.098	3.000	-20.009	29.953

Note: For comparison purposes, we used a common sample period (July 20, 1994 – November 16, 2001) to compute the descriptive statistics.

Table 2. Granger Causality Tests for SHSE (P-values)

	Eq. *DLNIN*	Eq. *DLNCM*	Eq. *DLNRE*	Eq. *DLNUT*
Exclude:				
Industry	0.026	0.189	0.005	0.125
Commerce	0.003	0.046	0.001	0.053
Realty	0.681	0.251	0.155	0.424
Utility	0.404	0.526	0.536	0.861
All other three	0.000	0.002	0.000	0.008

Note: *DLNIN*, *DLNCM*, *DLNRE*, *DLNFN* and *DLNUT* are the first-differences of log prices of Industry, Commerce, Realty, Finance and Utility. The first five rows are *p*-values associated with the null hypothesis that the coefficients of all lags of the variable in the left column are zero in the regression with dependent variable in the top row. The last row contains *p*-values associated with the null hypothesis that the coefficients of all lags of all right-hand-side variables except those of dependent variables are zero.

Table 3. Granger Causality Tests for SZSE (P-values)

	Eq. *DLNIN*	Eq. *DLNCM*	Eq. *DLNRE*	Eq. *DLNFN*	Eq. *DLNUT*
Exclude:					
Industry	0.257	0.321	0.951	0.434	0.990
Commerce	0.320	0.432	0.612	0.725	0.349
Realty	0.593	0.322	0.365	0.123	0.703
Finance	0.236	0.673	0.152	0.000	0.262
Utility	0.469	0.658	0.563	0.714	0.738
All other four	0.055	0.079	0.069	0.002	0.137

Note: See Table 2.

Table 4. Generalized Forecast Error Variance Decompositions (Within Markets, Daily Observations)

Sector Explained:	Industry	Commerce	Realty	Finance	Utility
			Panel A. SHSE		
By innovations in:					
Industry	28.79	25.67	21.11	-	24.42
Commerce	26.26	29.34	20.98	-	23.41
Realty	23.37	22.73	31.83	-	22.07
Utility	25.40	23.85	20.76	-	29.97
			Panel B. SZSE		
Industry	25.66	18.54	20.20	14.41	21.19
Commerce	21.05	29.11	18.28	12.59	18.96
Realty	21.60	17.23	27.43	13.17	20.57
Finance	18.95	14.59	16.17	33.91	16.38
Utility	22.25	17.54	20.19	13.07	26.94

Note: The decompositions are calculated for 10-day horizons.

Table 5. Generalized Forecast Error Variance Decompositions (Within Markets, Monthly Observations)

Sector Explained:	Industry	Commerce	Realty	Finance	Utility
			Panel A. SHSE		
By innovations in:					
Industry	28.55	25.80	22.10		23.55
Commerce	26.20	28.74	22.59		22.47
Realty	22.95	23.30	30.32		23.44
Utility	24.25	23.05	23.29		29.42
			Panel B. SZSE		
Industry	26.06	19.41	20.45	13.45	20.63
Commerce	21.78	29.01	18.45	12.46	18.30
Realty	20.82	16.96	26.83	13.53	21.86
Finance	17.24	14.25	17.51	36.92	14.07
Utility	21.57	17.44	22.60	11.19	27.20

Note: See Table 4.

Table 6. Generalized Forecast Error Variance Decompositions (Across Markets)

	Industry		Commerce		Realty		Utility	
	SHSE	SZSE	SHSE	SZSE	SHSE	SZSE	SHSE	SZSE
Panel A. Daily Observations								
SHSE	57.52	42.48	62.26	37.74	64.42	35.58	62.05	37.95
SZSE	42.50	57.50	37.73	62.27	35.60	64.40	37.97	62.03
Panel B. Monthly Observations								
	Industry		Commerce		Realty		Utility	
SHSE	59.11	40.89	63.66	36.34	65.21	34.79	67.83	32.17
SZSE	40.45	59.55	35.32	64.68	34.50	65.50	32.87	67.13

Note: See Table 4.