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碩士論文

美國股市與中國股市股價報酬之共移性

Co-movements between American and Chinese Stock Markets

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摘　要

本文目的在探討中國與美國股票市場的共移性。利用 2005 年至 2010 年的資料，建立中國股票在紐約證券交易所的美國存託憑證投資組合及美國股票相對應產業的投資組合，並計算它們二者間在日間以及夜間的報酬。這個分析結果顯示，中國股市和美國股市會因為不同的市場資訊和影響規模，而有一定程度的相關性。此外，透過建立二階段潛在變數模型，在文中進一步推論出競爭性衝擊是影響兩國間股票市場共移性的主因。然而，市場對人民幣與美元匯率、美國國庫券利率報酬變化的衝擊有落後效果。而此結果可以為國際投資組合的風險分散提供更細部的訊息。

JEL **分類代號**：C32, F36, F40, G1, G11, G15

關鍵詞：共移性，美國存託憑證，潛在變數模型，競爭性衝擊，全球性衝擊。

ABSTRACT

This paper investigates stock market co-movements betweenthe the U.S. and China. We construct daytime and overnight returns for a portfolio of Chinese stocks using their NYSE-traded ADRs and an industry-matched portfolio of American stocks between 2005 and 2010. The results show that Chinese stock market is linked to American stock market through different sources and magnitudes of shocks. The analysis, based on the two-stage latent variables regression, further indicates that the market correlations between China and the U.S. mostly come from competitive shocks. However, competitive shocks of the Yuan/Dollar foreign exchange rate and Treasury bill returns have lagged effects on the markets. The classifications of shocks into competitive and global ones suggest a finer information for international risk diversification.

JEL Classification: C32, F36, F40, G1, G11, G15

Key Words: Comovement; ADR; Latent variables model; Competitive shocks; Global shocks.

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1. INTRODUCTION

The degree of correlations among different international stock markets is an important issue for both theoretical and empirical research in international finance. By estimating the intensity of the interdependency between national stock markets, we can measure the benefits of international portfolio diversification. While the earlier analysis has mainly focused on major developed markets, recent research has been extended to the linkages between emerging and developed markets. One reason doing this is that benefits of international diversification rely increasingly on investment in emerging markets (Goetzmann, Li, and Rouwenhorst, 2001). In this paper we investigate the fundamental factors that affect American and Chinese stock return correlations.

Given China's increasing global importance, it is not only of academic interest but also of significance from the perspectives of policy makers and financial analysts to investigate if and how the Chinese stock market is correlated to global markets, and if China's liberalization policies on cross-country investment strengthen the international linkages. Figure 1 shows the impact of China's liberalization policies, captured by the net inflows of portfolio equity from 1997 to 2010. The net inflows are clearly on the upward trend, and the growth rate is around 454% within 13 years. However the net inflows of portfolio equity are volatile, in response to changing economic conditions. This has implication for asset diversifications. If China's stock market becomes more integrated with overseas markets, it could decrease the benefits of international diversification. Hence, it is interesting to investigate the benefits of international diversification by examining to what degrees Chinese stock market integrates with overseas markets.

[INSERT FIGURE 1 HERE]

There have been some analyses of interactions between the stock exchanges in China (Chui and Kwok, 1998 ; Kang, Liu, and Ni, 2002). Also, a few studies have investigated interdependence between the Chinese stock market and overseas markets. Huang, Yang, and Hu (2000), for example, using Granger causality and cointegration test, find that stock markets' variations of Hong Kong and Taiwan are affected by the previous trading day's American stock market variations. Shih, Hsiao, and Chen (2007) examine if there is a long-time relationship among China, the U.S., and Japan. They conclude that there is no co-integration relationship among these markers. However, Shanghai B Shares are found to be ahead of other three stock markets, and the U.S. stock market ahead of Shenzhen B Shares and Japan's. They all show that there is a lead-lag effect among China and overseas countries.

In this paper, instead, we focus on whether there are co-movements between American and Chinese stock markets, with particular attention to decomposing the underlying shocks into global and competitive ones. Global shocks are those that affect the value of all firms in the same direction. Competitive shocks increase the market value of firms in the same direction relative to firms in another country. On the basis of the hypothesis that stock linkages are related to trade links (Bekaert and Harvey, 2003), we select the U.S. stock market, China's most important trade partners, in this study. By sorting the nature of different shocks, we could analyze the covariances of underlying portfolio more precisely. Most of the past studies calculated covariance by looking at return surprises (deviations from expected return) in each scenario as the indicator to adjust portfolio combinations.

Karolyi and Stulz (1996) examine the U.S.-Japan stock return comovements by decomposing shocks into global and competitive ones. They find that the U.S. macroeconomic announcements, shocks to the Yen/Dollar foreign exchange rate and Treasury bill returns have little influence on the U.S. and Japanese return correlations. However, large shocks to aggregated market indices positively impact the magnitude and persistence of the return correlations from 1988 to 1992. Motivated by this study, we investigate if the correlations between Chinese and American stock markets would differ from market shocks. Our analysis is enabled by applying the two-stage latent variable regression provided by Pindyck and Rotemberg (1990) to distinguish global shocks from competitive ones.

We discuss the impact of each shock on the co-movements between two portfolios. The shocks we choose are composed of competive and global ones, such as returns of S&P 500, Shanghai A shares, and Hong Kong Hang Seng index, trading volumes of each markets, exchange rate (Yuan/Dollar), and treasury bill rate.

It is important to justify the choice of these shocks. Hong Kong Hang Seng index plays a key role in international stock markets. Chinese stock markets are closely related to its variations recently. On the other hand, trading volumes of each markets reflect the inflows and outflows of capitals, and they are key indicators to estimate stock markets' trend. Yuan/Dollar exchange rate impacts economic activities on both the countries.

We use daily transactions data from 2005 to 2010 to construct overnight and daytime returns for a portfolio of Chinese cross-listed stocks using their NYSE-traded American Depository Receipts (ADRs) and a matched-sample portfolio of the U.S. stocks. The portfolio of China's ADR is composed of 12 companies which are distributed over 11 different industries. The total market values of these stocks play crucial roles in Chinese stock market. For each ADR, we select three matching American firms of comparable size within the Chinese firm's industry. Industries are defined using four-digit Standard Industrial Classification (SIC) codes. The reason for adopting Chinese cross-listed stocks using their NYSE-traded ADRs is non-synchronous trading periods need to be reduced in order to reveal the impact of information on returns simultaneously. This is different from the past studies where the lead-lag effect is emphasized. This is because the studies look at different time intervals in different stock markets.

An alternative approach to analyzing market co-movements is using time-varying second-order methodologies such as ARCH or GARCH framework to estimate the variance-covariance transmission mechanisms between countries. Hamao, Masulis, and Ng (1990) employ ARCH model to examine the 1987 crisis in the U.S. stock market, and find that there are price volatility spillovers from New York to Tokyo, London to Tokyo, and New York to London. Becker, Finnerty, and Tucker (1992), adopting GARCH-M model, on the other hand, uncover that an hour before the opening of Japan's stock market, the variances of prices would reflect the latest trading conditions in the U.S. stock markets. Theodossiou and Lee (1993) reveal that statistically significant mean spillovers radiate from stock markets of the United States to those of the U.K., Canada, and Germany, and then from the stock market of Japan to that of Germany. To summarize, each of these tests reaches a similar indication: there are spillover mechanisms working among the countries under investigation. However, this approach is unable to answer the question of what the underlying shocks drive the co-movements.

Other series of papers examining international transmission mechanisms attempt to directly measure how different factors affect co-movements by looking at return correlation coefficients. Applying the factor analysis, Ripley (1973) investigates the systematic covariation between stock prices of developed countries. Results show that the major pattern of covariance between national indices can offer interesting economic interpretations, for instance, interdependence on international trade, geographic proximity, policies on monetary system, or cultural similarities. Johnson and Soenen (2002) examine to what degrees twelve equity markets in Asia are integrated with Japan's equity market. Evidence suggests that Asian markets become more integrated overtime, and factors triggering stock markets co-movements include import shares, inflation rates, real interest rates, and gross domestic product growth rates. However, these analyses have mainly focused on major developed markets and are unable to understand benefits of international diversification on investment in emerging markets.

The remainder of the study is organized as follows. Section 2 describes our simple framework of the two-stage latent regression procedure proposed by Karolyi and Stulz (1996). Section 3 presents the sample data and reports basic statistical results. In Section 4, we present the empirical results based on the latent variable regression for returns of Chinese and a matching American portfolios. Also we discuss the primary application in international portfolio diversification. Section 5 concludes.

2. METHODOLOGY

To analyze, we start introducing a simple framework of cross-country comovement, and a latent regression procedure. Both the framework and estimated method are proposed by Karolyi and Stulz (1996). A brief description of these is given below:

2.1 A simple framework of cross-country comovement

To understand cross-country co-movements, one may expect some shocks to affect stock returns in the same direction in all countries, and some shocks to be purely idiosyncratic. Supposed that, there are a portfolio of the Chinese firms in Petroleum industry and a portfolio of the U.S. firms in the same industry. An economic shock to the Petroleum industry could benefit all firms, hurt all firms, or have mixed effects across firms. For instance, it is intuitive that Yuan/Dollar foreign exchage rate, as a competitve shock, could benefit the returns of the Chinese Petroleum firms but hurt those in the U.S., and vice versa. A sub-prime crisis shock, decreasing the returns of worldwide Petroleum industry then, would be a global shock. On the other hand, a shock to the taxation policy in China may be a idiosyncratic one.

This distinction between global and competitive shocks can now be formalized. Denote the return from date $t-1$ to date t on security i by $r_{i,t}$. Also denote $E^{t-1}r_{i,t}$ as the expectation of the return formed at $t-1$ using information available at $t-1$. We assume that this return satisfies the following representation:

$$r_{i,t} = E^{t-1}(r_{i,t}) + \beta_{i,t}^{t-1} e_{G,t} + \gamma_{i,t}^{t-1} e_{C,t} + \varepsilon_{i,t} \tag{2.1}$$

where $\beta_{i,t}^{t-1}$ is the loading of security i on the global shock conditional on information available at $t-1$, $e_{G,t}$ denotes a global shock occurring from $t-1$ to t,$\gamma_{i,t}^{t-1}$ is the loading of security i on the competitive shock conditional on information available at $t-1$, $e_{C,t}$ is a competitive shock from $t-1$ to t, and $\varepsilon_{i,t}$ denotes a firm-specific, idiosyncratic shock. We define the competitive and global shocks to be uncorrelated, so that most observable economic shocks are mixtures of pure competitive and global shocks.

Using this representation of returns, we now consider the relation between the unexpected return of a portfolio of Chinese stocks, denoted by $e_{CN,t}$, and the unexpected return of a portfolio of the U.S. stocks, denoted by $e_{US,t}$, conditional on expectations based on the information available at $t-1$. The following expression for the cross-product of unexpected returns of the CN and US portfolios:

$$[r_{US,t}-E^{t-1}r_{US,t}][r_{CN,t}-E^{t-1}r_{CN,t}] = e_{US,t}e_{CN,t} =$$
$$\beta^{t-1}_{US,t}\ \beta^{t-1}_{CN,t}\ e^2_{G,t}+\ \gamma^{t-1}_{US,t}\ \gamma^{t-1}_{CN,t}\ e^2_{C,t}+\ \varepsilon_{US,t}\varepsilon_{CN,t}+$$
$$\beta^{t-1}_{US,t}\ \mathrm{e}_{G,t}[\gamma^{t-1}_{CN,t}\ \mathrm{e}_{C,t}+\varepsilon_{CN,t}]+\gamma^{t-1}_{US,t}\mathrm{e}_{C,t}[\beta^{t-1}_{CN,t}\mathrm{e}_{G,t}+$$
$$\varepsilon_{CN,t}]+\varepsilon_{US,t}[\beta^{t-1}_{CN,t}\ \mathrm{e}_{G,t}+\gamma^{t-1}_{CN,t}\ \mathrm{e}_{C,t}] \tag{2.2}$$

Turning to the conditional and unconditional covariances, define the expectation of the left-hand side of equation (2.2) conditioned on the information available as the conditional covariance at $t-1$. All terms, except for the first two, have an expectation of zero. It follows that the conditional covariance is:

$$E^{t-1}[e_{US,t}e_{CN,t}] = \beta^{t-1}_{US,t}\beta^{t-1}_{CN,t}E^{t-1}(e_{G,t})^2 + \gamma^{t-1}_{US,t}\gamma^{t-1}_{CN,t}E^{t-1}(e_{C,t})^2 \tag{2.3}$$

Equation (2.3) therefore implies that the conditional covariance would increase (decrease) when the conditional volatility of global and competitive shocks are high (low). However we could infer that if a shock is global shock, the response coefficient $\beta^{t-1}_{US,t}\beta^{t-1}_{CN,t}$ would be positive. Instead, if a shock is competitive shock, the response coefficient $\gamma^{t-1}_{US,t}\gamma^{t-1}_{CN,t}$ would be negative. It immediately follows that the conditional covariance between the Chinese and American portfolios would increase (decrease) when the conditional loadings of the returns on the competitive (global) shocks are small. With this framework, the conditional covariances of portfolio returns can increase when the conditional covariance of portfolio returns falls. To see this, note that the conditional variances of these portfolios are, respectively:

$$E^{t-1}[e^2_{US,t}] = (\beta^{t-1}_{US,t})^2 E^{t-1}(e_{G,t})^2 + (\gamma^{t-1}_{US,t})^2 E^{t-1}(e_{C,t})^2 + E^{t-1}(\varepsilon_{US,t})^2 \quad (2.4)$$

$$E^{t-1}[e^2_{CN,t}] = (\beta^{t-1}_{CN,t})^2 E^{t-1}(e_{G,t})^2 + +(\gamma^{t-1}_{CN,t})^2 E^{t-1}(e_{C,t})^2 + E^{t-1}(\varepsilon_{CN,t})^2 \quad (2.5)$$

To explore further the relationship between conditional covariances and conditional variances, consider a linear projection of the conditonal covariance on the conditional variance:

$$E^{t-1}[e_{US,t}e_{CN,t}] = a + bE^{t-1}[e^2_{US,t}] + \eta_t \quad (2.6)$$

Using a linear regression model to estimate the slope coefficient b, we have:

$$E[b] = \frac{E\{[E^{t-1}(e_{US,t}e_{CN,t}) - E(e_{US,t}e_{CN,t})][E^{t-1}(e^2_{US,t}) - E(e^2_{US,t})]\}}{E[E^{t-1}(e^2_{US,t}) - E(e^2_{US,t})]^2} \quad (2.7)$$

The sign of the slope coefficient b depends on types of shocks in conditional variances of Chinese and American portfolios, containing global ($e_{G,t}$), competitive ($e_{C,t}$), and idiosyncratic shocks (see (2.4) and (2.5)). If idiosyncratic shocks dominate the covariances between the returns of Chinese and American portfolios, the slope coefficient b would be near zero. If global shocks are the major factors in portfolios covariance, there will be positive slope coefficients on b. On the other hand, a negative relationship between conditional covariance and conditional variance would indicate that changes in the competitive shocks are dominant factors in the dynamics of the conditonal covariance.

2.2 Latent variable regression model

As the previous section states the covariances would differ in levels of shocks. In order to better understand why these correlations vary, we can apply a regression model that allows us to evaluate what the underlying shocks drive the co-movements, which explicitly allows for an effect of the information variables on the comovement between Chinese ADR and American portfolio returns, even after accounting for their direct effects on the return of the American portfolio and the Chinese portfolio.

We estimate the latent variable regression model in two steps. The first model conditions the American and Chinese overnight and daytime portfolio returns, $R_{i,t}$ on a set of information variables, Z_{t-1}:

$$R_{it} = E(R_{it}|Z_{t-1}) + \varepsilon_{it} \tag{2.8a}$$

$$E(R_{it}|Z_{t-1}) = \delta_{i0} + \Sigma_k \delta_{ik} z_{k,t-1} \tag{2.8b}$$

The second pass regression model then extracts the residual series from equation (2.8). The difference is that we adapt the information at time $t-i$ (Z_{t-i}), where i=0 to 5, to catch the shocks left in the equation (2.8):

$$\varepsilon_{CN,t} = c + \sum_{i=1}^{5} \alpha(Z_{t-i}) + \beta_0 + \sum_{i=1}^{5} \beta(Z_{t-i})\varepsilon_{US,t} + \eta_t \tag{2.9}$$

where $\alpha(Z_{t-i})$ and $\beta(Z_{t-i})$ allow the coefficients to be linear functions of the instrumental variables. For example, we specify that:

$$\alpha(Z_{t-i}) = \alpha_0 + \Sigma_k \alpha_k \mathrm{Z}_{k,t-1} \tag{2.10a}$$

$$\beta(Z_{t-i}) = \beta_0 + \Sigma_k \beta_k \mathrm{Z}_{k,t-1} \tag{2.10b}$$

where the coefficient β_0 can be interpreted as the average "normalized" conditional correlation coefficient between the Chinese and American portfolios and β_k are response coefficients of the conditional correlation with respect to the information variables in Z_t. The $\alpha(Z_t)$ function can be similarly interpreted. For each information variable, $z_{k,t}$, however, we introduce two terms with associated coefficients: β_1 measures the impact on the Chinese portfolio return residual of the increase in comovement resulting from the level of the shock itself, and β_2 measures the impact from an increase in comovement from the absolute value of a shock.

3. SAMPLE DATA AND BASIC STATISTICS

In this paper, we use a sample of 12 Chinese firms traded on the New York Stock Exchanges as ADRs. The details of Chinese ADRs is given in Appendix A. The total numbers of China's ADRs traded on the NYSE till June, 2011 are 73. However, because the Chinese ADRs must be simultaneously traded on the Shanghai class A shares stock market and NYSE stock market, and also be cross-markets listed from 2005 to 2010. There are 12 companies qualified under our selection.

Moreover, there are at least two reasons for examining Shanghai class A share markets, instead of Shanghai class B share markets. First, the Shanghai class B shares market has been losing its appeal to foreign investors while the Shanghai class A share market dominates that of Shanghai class B shares in terms of the number of listed companies, trade volume and market capitalization.

Second, it allows us to address an interesting issue: how the co-movement of Chinese stock market, which is largely closed to foreign investors, is related to foreign stock markets.

The daily stock prices and ADR prices are drawn from the Datastream from January 1, 2005 to December 31, 2010. Daily percentage changes of the stock prices are calculated using first difference of logarithmic prices. This provides us with 1465 daytime returns and 1502 overnight returns.

$$\Delta y_{t,i} = (log y_{t,i} - log y_{t-1,i}) \tag{3.1}$$

where $\Delta y_{t,i}$ denotes the percentage change of stock price for the ith market on day t and $y_{t,i}$ denotes the corresponding stock price index. Daytime returns are computed as log changes between the opening and closing price within the day. Overnight returns are computed from the previous day's closing price to today's opening price. The sample contains 12 China's ADRs which distribute over 11 different industries, including coal & mining, crude petroleum & natural gas, plastic materials, synth resins & nonvulcan elastomers, petroleum refining, semiconductors & related devices, railroads, air transportation, radiotelephone communications, telephone communications, Electric services, and life insurance.

Because of differences in time zones, the U.S. overnight return overlaps with the Chinese trading day return. In calendar time, previous night's Chinese return is the Chinese day returns for today's calendar date. With our timing convention, for any calendar day the Chinese market opens first, and the U.S. market opens only after the Chinese market has closed. Appendix B gives a diagram of the overnight and daytime return definitions and trading periods for a 24-hour clock.

In preliminary statistical analysis, we found that the daytime returns for Chinese portfolio are higher than the overnight returns; however, the overnight returns for American portfolio are slightly higher than the daytime returns. Comparing the return volatility, the portfolio of American securities is higher than for the ADR portfolio, but this relation is reversed for the overnight returns. The results are similar to finding in MacKinlay and Ramaswamy (1988) and Karolyi and Stulz (1996). The distributions of these entire national and portfolios' stock returns are non-normal. Both the skewness and the excess kurtosis statistics for these return series are significantly higher than for comparable normal distributions at all meaningful significance levels.

[INSERT TABLE 1 HERE]

The last part of table 1 provides correlation of other variables with the returns of the two portfolios. These variables include daily open and close stock index returns for the Shanghai Stock A, Hong Kong Hang Seng index (HKHS hereafter), and S&P 500, trading volume for the HKHS and S&P 500. The close-to-close returns on the Yuan/Dollar and the U.S. Treasury bill rates are from the Datastream. The overnight correlation of the Shanghai A index series with the U.S. matching industries portfolio is very similar to that of the Chinese ADR portfolio with the same American matching portfolio. The Shanghai A's daytime or overnight returns exhibit little correlation with American daytime returns since the Shanghai's daytime and overnight returns for a calendar day have already occurred when the U.S. market opens. On the other hand, the next day's overnight return for the Shanghai index is correlated with the daytime American returns, since these two returns are computed from overlapping time periods.

The relationship between HKHS index to Chinese and American portfolios are interesting. For the daytime returns, HKHS open-to-close is positively correlated both portfolios. Nevertheless, its close-to-open is negatively correlated both portfolios. As shown, the shock has bigger influence over the overnight returns than over the daytime returns.

4. EMPIRICAL RESULTS

In this section, we build on the framework already presented and utilize the latent variable regression methodology to find the main determinants of Chinese and American stock markets comovements. First, we present the evidence that the correlations differ significantly by the information variables across various subsamples. The considered information variables include the returns on the Yuan/Dollar exchange rate, the U.S. Treasury bill rate, the index returns of Shanghai A shares, HKHS, and S&P 500. We also test whether these correlations vary using regression models that allow us to distinguish between global and competitive shocks.

4.1 Intraday and Overnight Return Correlations between the Chinese and American Industry-Matched Stock Portfolios

Table 2 illustrates the daytime and overnight return correlations. The second column of the Table shows the cross-country correlations by weekday. Monday daytime cross-country correlation is the highest and Friday's correlation is the highest for overnight cross-country correlation. Further, the lowest cross-country correlation is associated with Wednesday for both daytime and overnight returns. Daytime correlations are high on Monday and Thursday, and low on Wednesday and Friday. Overnight correlations are high on Monday and Friday, low on Wednesday.

Table 2 shows the patterns that daytime cross-country correlations are higher than overnight cross-country correlation every weekday except Friday. The finding is different from the cross-country correlations between Japan and the U.S., documented by Karolyi and Stulz (1996), that the overnight returns correlations are greater. The difference might be that information used to calculate overnight returns from our samples is noisier than that of daytime returns. Also the cross-country correlations are greater at the opening of the week, descend till Wednesday, and then turn high during Thursday and Friday.

In the remaining columns of Table 2, we sort each type of the shocks to asset prices and volumes by quartiles. All of the shocks here are computed as the absolute changes of log returns, consistent with the notion given by the framework in Section 2.1. Other than the real exchange rates and T-bill rates, shocks to returns are computed as close-to-open and open-to-close. Given the framework in Section 2.1, two results are expected. Firstly, the cross-country correlations will differ by types of shocks. Secondly, correlation coefficient at each quartile can be used to make distinction between global and competitive shocks.

[INSERT TABLE 2 HERE]

If a shock is a global one, we can expect that the greatest correlation will be in Q1 (the highest quartile), and then decrease from Q2 to Q4. However, if a shock is a competitive one, the correlation in Q4 (the lowest quartile) will be the greatest, and then increase from Q3 to Q1 in a reverse order. The Yuan/Dollar (REX) shock, expected to be a competitive one, in the third columns of Table 2 fits this intuition.

However, the variations of the change rate of Yuan/Dollar (REX) are not significantly different at each quartile. This might be due to that Yuan/Dollar exchange rates are not quite freely determined by markets. That limits the changes of variation or appreciations in Yuan. Therefore, it is not easy to find the effects of the change rate of Yuan/Dollar shocks. For Treasury bill rates, as expected to be global shocks, the associated results are even harder to fit the intuition. For example, the correlation in last quartile is the highest one, implying instead that Treasury bill rates be regarded as competitive shocks.

The next two columns demonstrate the effects of correlations between Chinese and American portfolios by shocks to Shanghai A shares Index. Although the open-to-close Shanghai A shares (SHAOC) are traded earlier than the US stock markets, shocks to SHAOC still have influences over daytime returns correaLtions. Shocks to Shanghai A shares are deemed as global in nature. However, there is no clear evidence that shocks to close-to-open Shanghai A shares (SHACO) are global ones. To summarize, global shocks consist of shocks to aggregated market indices, such as S&P 500, Shanghai A shares, and Hong Kong Hang Seng index. Besides, shocks to the change of S&P 500 has the greatest influence over portfolio correlations.

We also present the results on volume shocks. It is not clear to tell whether shocks to HKHS volume are global or competitive ones for daytime returns. However, shocks to the HKHS volume seems to be global for overnight returns. Shocks to the volumes of S&P 500 has global influence over cross-country correlations. Overall, as Table 2 shows, the daytime return correlations are slightly greater than the overnight ones across all information shocks. This is different from that found between Japanese and American stock markets in Karolyi and Stulz (1996).

The results presented in Table 2 further show that: (a) there is variation in correlations across days; (b) Except shocks to aggregated market indices, it is hard to define whether other shocks are global or competitive ones. Therefore, we shall apply latent variable regressions in the next section to distinguish between global and competitive shocks, and to better understand how the underlying shocks drive the co-comvements.

4.2 Estimating the Impact of Shocks on the Comovement of Returns

The considered conditioning information shocks include the lagged return on the Yuan/Dollar exchange rates, Treasury bill rates, and the preceding returns on the S&P 500, Shanghai A shares, and HKHS. Table 3 and Table 4 reveal the estimates of conditional mean returns, based on equation (2.8), for the Chinese ADRs and American industry-matched portfolios. Results are presented separately for daytime and overnight returns.

First, we find that the R^2 of the conditional mean equation for overnight returns is greater than that of for daytime returns. They are on average 23% and 5% respectively. In other words, the conditioning information explains more for the Chinese and American overnight portfolio returns.

Second, the preceding returns on HKHS stock index is the only one variable that has significant impact on Chinese and American portfolios in daytime. With the positive coefficient correlation on portflio returns, we infer that when there is a profit gain on the preceding HKHS stock return, the Chinese and American portfolios returns would increase. Moreover, the HKHS stock index has greater effect on the Chinese portfolio than over the American portfolio. This observation supports the notion that markets within the same geographical region are more correlated. For the overnight returns, shocks to aggregated market index are more important. Shocks to both Shanghai A shares and to S&P 500 have significant impacts on the portfolios returns. However, the S&P 500 information shock exerts negative influence over portfolio returns.

[INSERT TABLE 3 HERE]

[INSERT TABLE 4 HERE]

In order to distinguish the global shocks from competitive ones, we apply the two-stage latent variables regression model, by adopting the same instrumental variables shocks for the z_{t-i}, where $i = 0$ to 5, as shown in Table 1. Table 5 and Table 6 display the results from the second stage latent variable regressions (equation (2.9) and (2.10)) that focus on the covariations of the variables. Indeed the absolute values of shocks matter when we control for the returns of the matching portfolio and for the level of the information variables. In other words, by applying the absolute values of shocks facilitate a better understand their impacts of the instrumental variables variations on portfolio comovements.

We summarize a few findings from Table 5 and Table 6. Firstly, as for the daytime return co-movements, there are some shocks that show statistically significant impacts at different times. It is interesting to find that Yuan/Dollar exchange rates shock still shows its impact on Chinese and American portfolios co-movements even four days after it appears the first time. Shocks to Yuan/Dollar exchange rates is competitive, suggesting that the industries in China compete against with those in the U.S.. When one country benefits from the exchange rate variations, the other one would get hurt.

We also show that shocks to close-to-open returns of Shanghai A shares are competitive ones. As for the overnight returns co-movements between Chinese and American portfolios, there is no significant effect of all the shocks from the preceding day. This might be due to that information on the overnight returns is noiser than that on the daytime return. However, shocks to Treasury bills and to exchange rate returns shocks show their impacts on portfolio co-movements after two days.

[INSERT TABLE 5 HERE]

[INSERT TABLE 6 HERE]

Table 5 and Table 6 show that most of the shocks appearing in time t are global ones, except shocks to Treasury bill rate for overnight return comovements.

4.2.1 Implications for International Diversification

Given portfolio managers' objective is to decrease the risk of the underlying assets, they would strive to have their portfolio allocation diversified. Diversification reduces the variability of the portfolio, because the prices of different assets vary differently. In many cases, decrease in return on one asset is compensated by increase on another. Therefore, they need to invest on the efficient frontier whenever thay can, yielding the minimum risk (i.e. standard deviation). This can be achieved at each level of expected return for a given set of risky securities. To achieve the goal, portfolio managers would do the following. First of all, they need to have an estimate of the expected returns and the covariance matrix for the set of risky securities which will be used to build the optimal portfolio. Then, they would calculate the portfolio weights for each of the various risky assets for any point on the efficient frontier.

By repeating the abovementioned procedure in given point of time, portfolio managers would adjust the optimal weight on each of the various risky assets. So how could they find our analysis useful for their portfolio allocation decisions? First we have to look the portfolio covariance matrix as below. The $(a; b)$ element in the matrix is the (X$_a$, X_b,σ_{ab}), where X_a is the weights on assets A, and X_b is the weights on B in the portfolio. Also, σ_a^2 and σ_b^2 are portfolio variance on Asset A and Asset B respectively. The covarianve in the matrix is denoted as (σ_{ab}).

	Asset A	Asset B
Asset A	$x_a^2\sigma_a^2$	$x_a x_b \sigma_{ab} = x_a x_b \rho_{ab} \sigma_a \sigma_b$
Asset B	$x_a x_b \sigma_{ab} = x_a x_b \rho_{ab} \sigma_a \sigma_b$	$x_b^2\sigma_b^2$

Next, they calculate the portfolio variance as follows:

$$\sigma^2 = {X_a}^2{\sigma_a}^2 + {X_b}^2{\sigma_b}^2 + 2(X_a X_b \rho_{ab} \sigma_a \sigma_b) \tag{4.1}$$

Note that the calculated covariance may include all the information, regardless of whether they are global and competitive shocks, affecting the portfolio allocation. However, portfolio managers should only care about the covariance due to competitive shocks. In other words, if the covariance is able to be seperated into three parts, they are covariance caused by global, competitive, and idiosyncratic shocks:

$$\sigma_{ab} = \sigma_{ab,global} + \sigma_{ab,competitive} + \sigma_{ab,idiosyncratic} \tag{4.2}$$

It is the part of the covariance due to competitive shocks that should be taken seriously for portfolio managers in their allocation decisions.

Take our results for example, suppose now a manager holds a portfolio consisting of Chinese and American securities at time t, and then at time $t + 6$ he would like to adjust the weight of each of the various risky assets. Instead of directly calculating the covariance of the underlying assets at $t+6$, he would exclude information on the covariance caused by shocks to the open-to-close returns of Shanghai A shares at time $t + 4$ impacting both the Chinese and American securities.

5. CONCLUSION

In this paper we investigate the comovements between Chinese and American stock markets, using data from January 2005 to December 2010. Our empirical analysis was conducted within the framework of a two-stage latent regression model proposed by Karolyi and Stulz (1996). The method thus enables us to examine not only whether there are co-movements between American and Chinese stocks, but also what the underlying shocks drive the co-movements.

This article investigates the properties of cross-country stock return comovements. Using dollar-denominated returns of American and Chinese shares trading in the United States, we show that foreign exchange rates do not immediately affect comovement between American and Chinese share returns. Furthermore, stock returns comovements exhibit day-of-the-week effects, with Monday's daytime and Friday's overnight comovements being higher than other weekday's. We also show that comovements are highly correlated when contemporaneous absolute returns of national market indices. Also, there is time delay in macroeconomic information over the comovement between China and the U.S..

Our results suggest that competitive shocks are a more important source of return variation than global ones in Chinese and American stock markets. Therefore, although Chinese stock market becomes more integrated with overseas markets, portfolio managers can still increase the benefits of international diversification by investing in Chinese stock market.

Further, it is useful for managers in their allocation decisions because only the covariance due to competitive shocks that should be taken into serious consideration. The portfolio weights for each of the various risky assets would be different from those calculated by the past method. In the past, portfolio managers calculated covariance instead by looking at return surprises (deviations from expected return) in each scenario. Therefore, the classifications of shocks into competitive and global ones render a finer information for international risk diversification possible.

Appendices

Appendix A:
Portfolio of Chinese ADRs

Tab. .1: Portfolio of Chinese ADRs

SIC Codes	Industry	Company name
1221	Coal & Mining	Yanzhou Coal Mining Co. Ltd.
1311	Crude Petroleum & Natural Gas	CNOOC Limited
2821	Plastic Materials, Synth Resins Nonvulcan Elastomers	Sinopec Shanghai Petrochemical Company Limited
2911	Petroleum Refining	China Petroleum & Chemical Corporation
3674	Semiconductors & Related Devices	Semiconductor Manufacturing International Corporation
4011	Railroads	Guangshen Railway Company Limited
4512	Air Transportation	China Eastern Airlines Corporation Limited
4812	Radiotelephone Communications	China Unicom (Hong Kong) Limited
4813	Telephone Communications (No Radiotelephone)	China Telecom Corporation Limited
4813	Telephone Communications (No Radiotelephone)	China Mobile Limited
4911	Electric Services	Huaneng Power International, Inc.
6311	Life Insurance	China Life Insurance Company Limited

[a] The total numbers of China's ADRs traded on the NYSE till June, 2011 are 73. However, owing to the time span (2005 – 2010) and cross-markets listed constrained, there are 12 companies simultaneously traded on the Shanghai and NYSE markets.

Appendix B: Timing Conventions for Daily and Overnight Returns for Chinese and American Portfolios

Daily returns are measured as log changes in open-close prices from January 1, 2005 to December 31, 2010. Overnight returns are computed from the previous day's closing price to today's opening price. The overnight and daytime returns on these portfolios align with New York trading hours. Daily open and close stock index for Shanghai A shares and Hong Kong Hang Seng index and for S&P 500 stock index are from Datastream. Overnight timing conventions for a 24-hour period (Day t) set the trading day in China to precede that of New York: China's open-close return ($SHAOC_t$) is contemporaneous with New York's overnight return ($SPCO_t$), and both precede China's overnight return ($SHACO_{t+1}$), contemporaneous with New York's open-close return ($SPOC_t$).

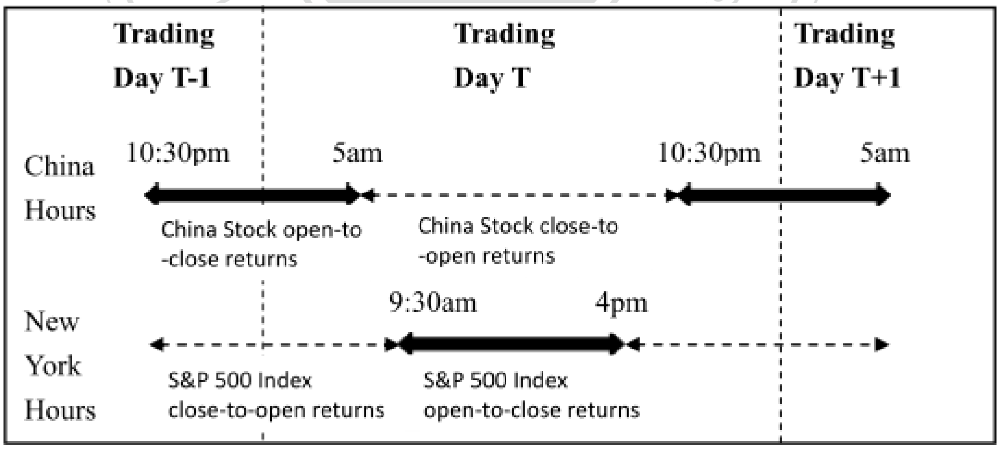

Fig. .1: Timing Conventions for Daily and Overnight Returns for Chinese and American Portfolios

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Table 1

Summary Statistics for Intraday and Overnight Returns of the China ADR and U.S. Stock Portfolios, 2005–2010

REX is absolute returns of the daily Yuan/Dollar foreign exchange return. TB is Treasury Bill Futures return. SHAOC (HKOC) is Shanghai A shares (Hong Kong Hang Seng) daytime return. SHACO (HKCO) is Shanghai A shares (Hong Kong Hang Seng) overnight return. SHAVOL (HKVOL) is Shanghai A shares (Hong Kong Hang Seng) trading volume. SPCO is S&P 500 overnight return. SPOC is S&P 500 daytime return. SPVOL Quartile is S&P 500 trading volume.

	Daytime Returns		Overnight Returns	
	China ADRs	U.S. Industry	China ADRs	U.S. Industry
Mean returns(%)	−2.62E−05	−1.57E−04	−7.25E−06	1.5E−0.4
Standard deviation	0.0067	0.0071	0.0072	0.0039
t-value (mean=0)	−0.14	−0.84	−0.04	1.46
Skewness	−0.107	−0.951	−0.487	−0.468
Excess kurtosis	9.854	11.094	9.400	19.315
Cross-correlations:				
China ADR (OC)	1.000	0.825	0.226	0.112
US industry (OC)	0.825	1.000	0.158	0.107
China ADR (CO)	0.226	0.158	1.000	0.688
US industry (CO)	0.112	0.107	0.688	1.000
With Instruments:				
SHAOC	0.093	0.038	0.412	0.185
SHACO	−0.126	−0.048	0.014	0.077
SHACO (t+1)	0.476	0.438	0.372	0.326
HKOC	0.257	0.176	0.740	0.459
HKCO	−0.148	−0.04	0.175	0.240
HKCO (t+1)	0.735	0.696	0.108	0.177
HKVOL	0.042	0.004	−0.04	−0.022
SPOC	0.035	0.060	0.486	0.632
SPCO	0.811	0.851	0.387	0.459
SPVOL	0.012	−0.047	−0.05	0.002
REX	0.010	−0.003	0.019	−0.001
TB	0.032	0.037	0.048	−0.014

Table 2
Daily and Overnight Returns Correlations of the China ADR and U.S. Stock Portfolio

Daily returns are measured as log changes in open-close prices from January 1, 2005 to December 31, 2010. Overnight returns are computed from the previous day's closing price to today's opening price. The China's portfolio consists of 12 New York Stock Exchange (NYSE)-listed American Depository Receipts. The U.S. portfolios comprise 36 U.S. stocks matched on SIC. Q_k is the Box-Ljung Pormanteau test for the k_th autocorrelations for raw returns. REX is absolute returns of the daily Yuan/Dollar foreign exchange return. TB is Treasury Bill Futures return. SHAOC (HKOC) is Shanghai A shares (Hong Kong Hang Seng) daytime return. SHACO (HKCO) is Shanghai A shares (Hong Kong Hang Seng) overnight return. SHAVOL (HKVOL) is Shanghai A shares (Hong Kong Hang Seng) trading volume. SPCO is S&P 500 overnight return. SPOC is S&P 500 daytime return. SPVOL Quartile is S&P 500 trading volume. Significance at the 5% level is denoted by ** and at the 10% level by *.

All Days	By Day of Week	REX Quartile	TB Quartile	SHAOC Quartile	SHACO Quartile	HKOC Quartile	HKCO Quartile	HKVOL	SPCO Quartile	SPOC Quartile	SPVOL Quartile
Panel A: Daytime Return correlation											
0.825	Mon 0.861	Q1 0.747	0.877	0.851	0.853	0.843	0.874	0.831	0.857	0.894	0.882
	Tue 0.840	Q2 0.815	0.769	0.794	0.811	0.798	0.724	0.837	0.798	0.724	0.730
	Wed 0.796	Q3 0.814	0.766	0.839	0.792	0.807	0.725	0.781	0.816	0.517	0.735
	Thu 0.850	Q4 0.854	0.784	0.805	0.637	0.816	0.554	0.807	0.773	0.411	0.747
	Fri 0.782										
Panel B: Overnight Return correlation											
0.688	Mon 0.702	Q1 0.578	0.751	0.727	0.745	0.744	0.752	0.750	0.815	0.757	0.784
	Tue 0.684	Q2 0.474	0.681	0.727	0.729	0.571	0.666	0.614	0.427	0.612	0.599
	Wed 0.616	Q3 0.659	0.515	0.586	0.547	0.580	0.505	0.483	0.421	0.578	0.496
	Thu 0.636	Q4 0.776	0.663	0.645	0.426	0.573	0.589	0.310	0.542	0.611	0.355
	Fri 0.793										

Table 3

Daytime Returns Regression of the China ADRs and U.S. Matched-Sample Portfolios on Information Variables

Each returns series is regressed on a set of information variables, including a lagged closing return on the Yuan/Dollar exchange rate, EX_{t-1}, on the Treasury bill, TB_{t-1}, on the returns on the Shanghai A shares, HK Hang Seng, and S&P 500 stock indices immediately preceding the trading period ($SHAOC_t$, $HKOC_t$, and $S\&P500_t$ for daytime returns; $SHACO_t$, $HKCO_t$, and $SPOC_{t-1}$ for overnight returns).The t-statistics are computed using robust standard errors with Newey and West (1987) serial-correlation (7 lags) and heteroscedasticity correction. Statistical significance is denoted by ** at the 5 percent level and * at the 10 percent level.

Statistic	China ADRs Portfolio	US Industry Portfolio
Constant	0.0000	−0.0001
EX_{t-1}	0.0000	−0.0000
TB_{t-1}	0.0029	0.0033
$SHAOC_t$	−0.0024	−0.0318
$HKOC_t$	0.3253**	0.2477**
$SPCO_t$	−0.2503	0.0056
R^2	0.069	0.036
DW	2.230	2.002
Obs.	1238	1238

Table 4
Overnight Returns Regression of the China ADRs and U.S. Matched-Sample Portfolios on Information Variables

Each returns series is regressed on a set of information variables, including a lagged closing return on the Yuan/Dollar exchange rate, EX_{t-1}, on the Treasury bill, TB_{t-1}, on the returns on the Shanghai A shares, HK Hang Seng, and S&P 500 stock indices immediately preceding the trading period ($SHAOC_t$, $HKOC_t$, and $S\&P500_t$ for daytime returns; $SHACO_t$, $HKCO_t$, and $SPOC_{t-1}$ for overnight returns).The t-statistics are computed using robust standard errors with Newey and West (1987) serial-correlation (7 lags) and heteroscedasticity correction. Statistical significance is denoted by ** at the 5 percent level and * at the 10 percent level.

Statistic	China ADRs Portfolio	US Industry Portfolio
Constant	−0.0001	0.0079**
EX_{t-1}	−0.0000	−0.0000
TB_{t-1}	0.0050	0.0071**
$SHACO_t$	0.5922**	0.2540**
$HKCO_t$	0.6004**	0.2678**
$SPOC_{t-1}$	−0.5469**	−0.1854**
R^2	0.262	0.191
DW	1.951	2.25
Obs.	1187	1187

Table 5
Second-stage Instrumental Variables Regression of Daytime Returns of the China and U.S. Stock Portfolios

The first stage regression estimates the conditional mean returns for daily and overnight returns series for the Chinese ADR and U.S. matched-sample portfolios on information variables. In the second stage regression, daily and overnight returns residuals series for the Chinese ADR portfolios are regressed on the returns residuals of the U.S. industry-matched portfolios:

$$\varepsilon_{CN,t} = c + \alpha_0 + \sum_{i=1}^{5} \alpha(Z_{t-i}) + \beta_0 + \sum_{i=1}^{5} \beta(Z_{t-i})\varepsilon_{US,t} + \eta_t$$

where $\alpha(Z_{t-i})$, $\beta(Z_{t-i})$ are linear functions of an instrumental variable in level, $Z_{k,t-i}$, and in absolute terms $|Z_{k,t-i}|$. Table 2 lists the instrumental variables and descriptions. The t-statistics are computed using robust standard errors with Newey and West (1987) serial-correlation (7 lags) and heteroscedasticity correction. Statistical significance is denoted by ** at the 5 percent level and * at the 10 percent level.

Variables	*lag*	c	$\alpha_0(z_{t-i})$	$\alpha_1(\lvert z_{t-i}\rvert)$	β_0	$\beta_1(z_{t-i})$	$\beta_2(\lvert z_{t-i}\rvert)$	R^2
when $i=1$:								
EX	−1	0.000	0.005**	−0.000	0.773**	−0.014	−0.138	0.67
TB	−1	−0.000*	−0.001	0.001	0.749**	0.195	−0.288	0.62
$SHAOC_t$	−1	−0.000	−0.005	0.040*	0.820**	−4.150	−7.020*	0.68
$HKOC_t$	−1	−0.000*	−0.022	0.086*	0.758**	−1.197	1.248	0.68
$SPCO_t$	−1	−0.000*	−0.130	0.453**	0.807**	−2.766	−31.975	0.68
HKVOL	−1	−0.000	−0.000	−0.000	0.711**	0.288*	−0.373**	0.63
SPVOL	−1	−0.000	−0.000	0.000	0.703**	0.645**	−0.921**	0.64
when $i=2$:								
EX	−1	0.000	0.006**	0.002	0.778*	0.024	0.068	0.67
	−2		0.004	−0.001		0.009	−0.311	
TB	−1	−0.000*	−0.001	0.000	0.762**	0.158	−0.111	0.63
	−2		−0.003	−0.000		−0.202*	−0.263	
$SHAOC_t$	−1	−0.000**	−0.009	0.040*	0.812**	−5.792*	−7.509*	0.68
	−2		0.014	0.041*		−4.870*	1.406	
$HKOC_t$	−1	−0.000*	−0.021	0.113**	0.799**	0.410	4.487	0.68
	−2		0.032	−0.035		−2.078	−11.391**	

Table 5
Second-stage Instrumental Variables Regression of Daytime Returns of the China and U.S. Stock Portfolios (cont.)

HKVOL	−1	−0.000	−0.000	−0.000	0.693**	0.296*	−0.353*	0.62
	−2		−0.000	0.001		−0.074	0.173	
SPVOL	−1	0.000	−0.000	0.001	0.706**	0.633**	−0.902**	0.64
	−2		0.000	−0.002		−0.168	−0.037	
when $i=3$								
EX	−1	0.000	0.006**	0.004	0.795**	0.173	0.283	0.67
	−2		0.005*	0.000		0.340	−0.157	
	−3		0.001	−0.002		−0.035	−0.603	
TB	−1	0.000	−0.001	0.000	0.760**	0.171	−0.114	0.63
	−2		−0.003**	−0.001		−0.205*	−0.269	
	−3		0.000	0.003		0.073	0.069	
$SHAOC_t$	−1	0.000	−0.013	0.037	0.817**	−4.916*	−5.819	0.69
	−2		0.013	0.044*		−4.368	−0.473	
	−3		−0.003	−0.038		2.564	0.295	
$HKOC_t$	−1	0.000*	−0.022	0.112**	0.811**	0.897	6.517	0.68
	−2		0.035	−0.042		−2.063	−11.216	
	−3		−0.024	0.018		1.073	−3.710	
$SPCO_t$	−1	0.000*	−0.194	0.432**	0.855**	0.497	−21.693	0.68
	−2		0.046	0.005		3.707	−46.127*	
	−3		−0.052	−0.126		−2.954	−16.626	
HKVOL	−1	0.000	0.000	−0.001	0.660**	0.195	−0.270	0.62
	−2		0.000	0.001		−0.076	0.067	
	−3		0.000	0.003**		0.177	0.396	
SPVOL	−1	0.000	0.000	0.001	0.731**	0.670**	−0.881**	0.64
	−2		0.000	−0.003		−0.046	0.304	
	−3		0.000	0.003		0.343	−0.742*	
when $i=4$								
EX	−1	0.000	−0.001	0.000	0.759**	0.016	−0.029	0.64
	−2		−0.004**	−0.001		−0.287**	−0.312*	
	−3		0.000	0.004**		0.052	0.068	
	−4		−0.001	−0.002		−0.338**	−0.089	
TB	−1	0.000	−0.020	0.041*	0.760**	−3.360	−3.054	0.70
	−2		0.012	0.043*		−3.395	−1.921	
	−3		0.002	−0.048*		0.600	−2.002	
	−4		−0.005	0.014		−9.429**	6.978**	
$SHAOC_t$	−1	0.000	−0.024	0.114**	0.818**	0.918	7.301**	0.68
	−2		0.039	−0.042		−1.947	−10.990**	
	−3		−0.018	0.027		1.544	−2.783	
	−4		−0.007	−0.026		−0.264	−2.947	
$HKOC_t$	−1	0.000	−0.214	0.451**	0.870**	−1.744	4.630	0.69
	−2		0.015	0.100		−1.034	−32.747	
	−3		−0.040	−0.108		11.834	−13.702	

Table 5

Second-stage Instrumental Variables Regression of Daytime Returns of the China and U.S. Stock Portfolios (cont.)

	−4		0.242*	−0.010		56.541**	−55.209**	
SPCO$_t$	−1	0.000	0.000	−0.001	0.623**	0.191	−0.282	0.62
	−2		0.000	0.001		−0.068	0.110	
	−3		0.000	0.003**		0.178	0.310	
	−4		0.001*	−0.001		0.022	0.358	
HKVOL	−1	0.000	−0.001	0.001	0.775**	0.699**	−0.910**	0.65
	−2		0.000	−0.003		−0.103	0.231	
	−3		0.000	0.003		0.367	−0.837*	
	−4		−0.001	−0.002		−0.179	−0.498	
SPVOL	−1	0.000	−0.001	0.000	0.759**	0.016	−0.029	0.64
	−2		−0.004**	−0.001		−0.287**	−0.312*	
	−3		0.000	0.004**		0.052	0.068	
	−4		−0.001	−0.002		−0.338**	−0.089	
when $i=5$								
EX	−1	0.000	0.003	−0.002	0.821**	−0.264	−0.300	0.69
	−2		0.007*	0.001		0.282	0.927**	
	−3		0.005*	−0.001		0.480	0.320	
	−4		−0.001	−0.001		0.797**	−0.732**	
	−5		0.004	0.001		0.107	−0.802**	
TB	−1	0.000	−0.002	0.000	0.758**	−0.019	−0.053	0.64
	−2		−0.004**	−0.001		−0.350**	−0.283	
	−3		0.000	0.003*		0.049	0.041	
	−4		−0.001	−0.003		−0.302*	−0.091	
	−5		−0.001	0.003**		−0.197	−0.030	
SHAOC$_t$	−1	0.000	−0.024	0.043*	0.766**	−2.552	−3.662	0.70
	−2		0.013	0.040		−3.104	−0.408	
	−3		0.007	−0.049*		−0.435	−2.986	
	−4		−0.006	0.029		−8.894**	6.054*	
	−5		−0.001	−0.021		−1.280	0.449	
HKOC$_t$	−1	0.000	−0.019	0.113**	0.811**	3.540	8.179**	0.69
	−2		0.040	−0.047		−2.295	−11.339**	
	−3		−0.017	0.037		0.848	−8.949**	
	−4		−0.007	−0.017		−0.701	0.355	
	−5		0.015	0.005		4.317	3.591	
SPCO$_t$	−1	0.000	−0.152	0.353**	0.855**	5.584	−6.778	0.70
	−2		0.008	0.052		−1.954	−27.435	
	−3		−0.021	−0.180		15.944	−12.938	
	−4		0.118	−0.054**		56.957**	−57.522**	
	−5		−0.076	0.336		39.580**	25.064	
HKVOL	−1	0.000	−0.001	−0.001	0.605**	0.195	−0.264	0.62
	−2		0.000	0.000		−0.094	0.155	
	−3		0.000	0.003**		0.153	0.283	

Table 5
Second-stage Instrumental Variables Regression of Daytime Returns of the China and U.S. Stock Portfolios (cont.)

	−4		0.001	−0.001		−0.045	0.373	
	−5		0.000	0.000		−0.127	0.109	
SPVOL	−1	0.000	−0.001	0.002	0.792**	0.666**	−0.914**	0.65
	−2		0.000	−0.003		−0.036	0.157	
	−3		0.000	0.003		0.388	−0.820*	
	−4		−0.001	−0.002		−0.036	−0.241	
	−5		−0.001	−0.003		0.291	−0.511	

Table 6
Second-stage Instrumental Variables Regression of Overnight Returns of the China and U.S. Stock Portfolios

The first stage regression estimates the conditional mean returns for daily and overnight returns series for the Chinese ADR and U.S. matched-sample portfolios on information variables. In the second stage regression, daily and overnight returns residuals series for the Chinese ADR portfolios are regressed on the returns residuals of the U.S. industry-matched portfolios:

$$\varepsilon_{CN,t} = c + \alpha_0 + \sum_{i=1}^{5} \alpha(Z_{t-i}) + \beta_0 + \sum_{i=1}^{5} \beta(Z_{t-i}) \varepsilon_{US,t} + \eta_t$$

where $\alpha(Z_{t-i})$, $\beta(Z_{t-i})$ are linear functions of an instrumental variable in level, $Z_{k,t-i}$, and in absolute terms $\left|Z_{k,t-i}\right|$. Table 2 lists the instrumental variables and descriptions. The t-statistics are computed using robust standard errors with Newey and West (1987) serial-correlation (7 lags) and heteroscedasticity correction. Statistical significance is denoted by ** at the 5 percent level and * at the 10 percent level.

Variables	*lag*	c	$\alpha_0(z_{t-i})$	$\alpha_1(\lvert z_{t-i}\rvert)$	β_0	$\beta_1(z_{t-i})$	$\beta_2(\lvert z_{t-i}\rvert)$	R^2
when $i=1$:								
EX	−1	0.000	−0.001	−0.001	1.703**	−0.002	−0.757	0.33
TB	−1	0.000	−0.001	−0.005**	1.026**	−0.106	−0.540	0.33
$SHACO_t$	−1	0.000**	0.005	−0.144**	0.963**	−5.898	0.716	0.33
$HKCO_t$	−1	0.000	−0.004	−0.017	0.878**	−4.986	11.353	0.33
$SPOC_{t-1}$	−1	0.000	0.010	−0.017	1.012**	−8.100**	−3.475	0.33
HKVOL	−1	0.000	−0.001	0.001	0.996**	0.700	−0.419	0.33
SPVOL	−1	0.000	0.002	−0.003	0.960**	0.064	0.191	0.33
when $i=2$:								
EX	−1	0.000	−0.001	0.000	1.180**	0.125	−0.488	0.34
	−2		0.002*	−0.002		0.413	−0.821**	
TB	−1	0.000	0.000	−0.003	1.014**	−0.208	−0.659	0.33
	−2		−0.002	−0.003		0.052	0.354	
$SHACO_t$	−1	0.000**	0.004	−0.121**	0.937**	−5.505	0.843	0.34

Table 6
Second-stage Instrumental Variables Regression of Overnight Returns of the China and U.S. Stock Portfolios (cont.)

$HKCO_t$	−1	0.000**	0.010	0.005	0.978**	−3.236	13.290**	0.35
	−2		0.072**	−0.043		−21.088**	−20.340**	
$SPOC_{t-1}$	−1	0.000	0.017	−0.019	0.970**	−8.521**	−3.063	0.33
	−2		0.064**	0.025		−5.045	0.942	
HKVOL	−1	0.000	0.001	−0.001	0.850**	0.031	0.558	0.33
	−2		0.000	−0.001		−0.192	1.326	
SPVOL	−1	0.000	0.002	−0.003	1.117**	−0.511	0.417	0.33
	−2		0.001	0.003		0.617	−2.321**	
when $i=3$								
EX	−1	0.000	0.002	−0.004	1.022**	−0.412	0.181	0.33
	−2		−0.003	−0.002		0.269	0.546	
	−3		0.001	0.002		−0.103	−1.017**	
TB	−1	0.000*	−0.004	−0.147**	0.892	−6.514	−2.634	0.35
	−2		0.019	−0.013		−12.154	4.789	
	−3		0.082**	0.040		−20.894**	−0.402	
$SHACO_t$	−1	0.000	0.012	0.026	1.054**	−1.220	15.400	0.35
	−2		0.076**	−0.031		−19.404**	−20.920**	
	−3		0.045*	−0.040		−7.699	−12.892**	
$HKCO_t$	−1	0.000	0.014	0.022	1.053**	−9.181**	−1.155	0.34
	−2		0.064**	0.017		−1.215	2.754	
	−3		0.026	−0.025		−15.069**	−16.780	
$SPOC_{t-1}$	−1	0.000	0.000	−0.002	0.796**	0.050	0.553	0.33
	−2		−0.001	−0.001		−0.337	1.231	
	−3		−0.002*	−0.002		−0.086	0.576	
HKVOL	−1	0.000	0.001	−0.002	1.116**	−0.044	−0.228	0.33
	−2		0.000	0.002		1.046	−1.819	
	−3		0.000	0.002		0.510	−0.753	
SPVOL	−1	0.000	0.002	−0.004	1.022**	−0.412	0.181	0.33
	−2		−0.003	−0.002		0.269	0.546	
	−3		0.001	0.002		−0.103	−1.017**	
when $i=4$								
EX	−1	0.000	−0.001	0.001	1.146**	0.248	−1.036**	0.34
	−2		0.003*	−0.002		0.614**	−0.953	

Table 6

Second-stage Instrumental Variables Regression of Overnight Returns of the China and U.S. Stock Portfolios (cont.)

	−3		−0.001	0.000		−0.315	0.284**	
	−4		0.001	0.000		−0.179	0.665**	
TB	−1	0.000	0.004	−0.002	1.087**	−0.472	0.655	0.34
	−2		−0.002	0.000	–	0.569*	0.913**	
	−3		0.003	0.002		0.258	−0.787**	
	−4		0.000	−0.004		0.275	−1.792**	
$SHACO_t$	−1	0.000	−0.006	−0.141**	0.884**	−8.120	2.759	0.35
	−2		0.019	−0.012		−13.037	0.407	
	−3		0.089**	0.047		−17.637*	6.456	
	−4		−0.008	0.011		−16.700*	−15.298	
$HKCO_t$	−1	0.000	0.019	0.050	1.060**	−1.346	15.491*	0.36
	−2		0.081**	−0.005		−21.866**	−24.627**	
	−3		0.049*	−0.030		−9.025	−13.936	
	−4		0.023	−0.088		−1.739	2.256	
$SPOC_{t-1}$	−1	0.000	0.013	0.023	1.072**	−10.430**	0.015	0.35
	−2		0.078**	0.002		−1.990	13.001	
	−3		0.033	−0.023		−14.921**	−16.366	
	−4		0.037	−0.045		−1.868	−14.614**	
HKVOL	−1	0.000	0.000	−0.002	0.759**	0.050	0.555	0.33
	−2		−0.001	−0.001		−0.577	1.114	
	−3		−0.001	−0.002		−0.323	0.792	
	−4		0.000	0.000		−0.821	0.466	
SPVOL	−1	0.000	0.001	−0.002	1.207**	−0.093	−0.219	0.33
	−2		0.000	0.001		1.175	−1.818*	
	−3		0.000	0.002		0.053	−1.153	
	−4		0.002	0.001		−0.811	−0.993	
when $i=5$								
EX	−1	0.000	−0.001	0.001	1.115**	0.144	−1.062**	0.34
	−2		0.001	−0.002		0.645*	−0.813*	
	−3		−0.002	0.000		−0.320	0.427	
	−4		0.001	0.001		−0.239	0.733**	
	−5		−0.005**	−0.004*		−0.069	0.069	
TB	−1	0.000	0.004	−0.001	1.101**	−0.472	0.179	0.34
	−2		−0.002	−0.001		0.507	1.061**	
	−3		0.005	−0.001		0.305	−0.098	

Table 6
Second-stage Instrumental Variables Regression of Overnight Returns of the China and U.S. Stock Portfolios (cont.)

	−4		−0.001	−0.005*		0.611	−1.160	
	−5		0.000	0.003		0.382	−1.046	
$SHACO_t$	−1	0.000	0.020	−0.148**	0.942**	−3.102	−0.505	0.36
	−2		0.011	−0.013		−14.889	7.752	
	−3		0.087**	0.031		−13.188	13.208	
	−4		−0.005	0.018		−19.910**	−9.532	
	−5		−0.026	0.015		−9.691	−34.808**	
$HKCO_t$	−1	0.000	0.020	0.050	1.052**	−1.252	16.355**	0.36
	−2		0.079**	−0.005		−20.566**	−23.818*	
	−3		0.049*	−0.029		−9.879	−13.382	
	−4		0.023	−0.087**		−1.907	2.030	
	−5		−0.007	0.001		4.376	−1.174	
$SPOC_{t-1}$	−1	0.000	0.002	0.028	1.014**	−10.703**	−3.169	0.35
	−2		0.077**	0.009		−1.207	15.469	
	−3		0.038	−0.028		−15.813	−10.411	
	−4		0.035	−0.046		−1.389	−16.559*	
	−5		−0.045	−0.055		3.349	3.649	
HKVOL	−1	0.000	0.000	−0.001	0.823**	−0.012	0.671	0.34
	−2		0.000	−0.001		−0.435	0.987	
	−3		−0.001	−0.001		−0.261	0.789	
	−4		0.001	0.000		−0.319	0.977	
	−5		0.001	0.001		0.197	−0.703	
SPVOL	−1	0.000	0.001	−0.003	1.145**	0.018	−0.091	0.33
	−2		0.001	0.002		0.982	−1.634*	
	−3		−0.001	0.002		0.180	−0.425	
	−4		0.001	0.000		−1.366*	−1.427	
	−5		−0.001	0.001		−0.900	0.562	

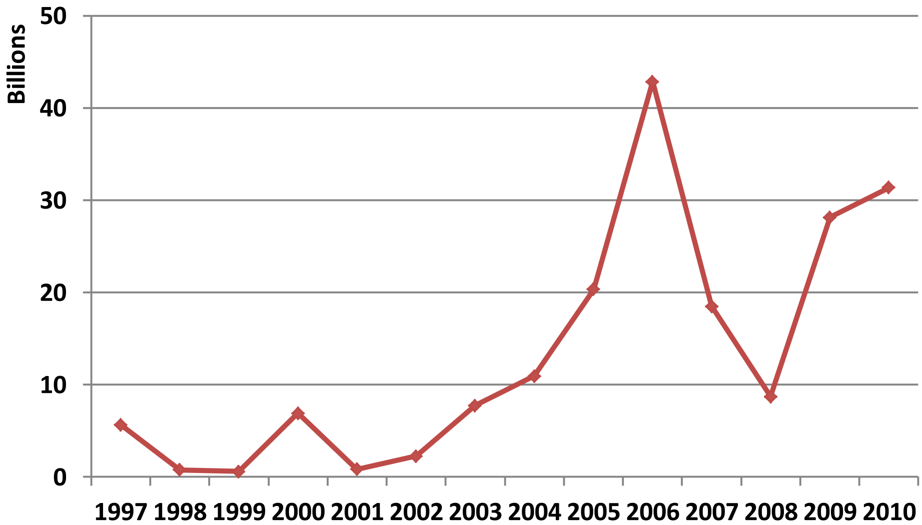

Figure 1: Portfolio equity, net inflows (Balance of Payment, current US$). Portfolio equity includes net inflows from equity securities other than those recorded as direct investment and including shares, stocks, depository receipts (American or global), and direct purchases of shares in local stock markets by foreign investors. Data are in current U.S. dollars.