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The interactions between China and US stock markets: New perspectives

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ABSTRACT

This paper takes a new approach to investigate the interaction between the U.S. and China's stock markets. Since the U.S. and China's stock markets have no overlap in their trading hours, many empirical studies show that the daily returns on these two markets are not correlated. In this paper, we examine the ability of the daily returns on the S&P500 and the DJIA to forecast the direction of the openings of the SSEC and SZCI, two benchmark indexes in the China's stock market, and vice versa. We show that the daily returns on the U.S. stock market have had significant ability to forecast Chinese stock market openings since 2006, while the daily returns on the China's stock market have not shown the similar ability to forecast the U.S. stock market openings.

1. Introduction

With the dramatic growth of China's economy in the last few decades, the China stock market has emerged as one of the largest stock markets in the world. As China's economy and the U.S. economy have shown a definite interaction, there is considerable interest to study the interaction between the China and the U.S. stock markets. However, most studies, in particular those investigating the issue

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before the recent global financial crisis, found no or weak co-integration between these two stock markets (see Huang et al., 2000; Chen et al., 2003; Hsiao et al., 2003; Lin and Wu, 2003; Yang et al., 2003; Zhu et al., 2004; Tian, 2007; Wang and Di Iorio, 2007; Masson et al., 2008; Lin et al., 2009; Luo et al., 2011; Li, 2012, among others). It is commonly argued that China stock market is insulated from the rest of the world.

Some more recent studies, however, show that the level of integration between those two markets has been increasing. For example, by using copulas to investigate the relationships between stock market indexes in China (Shanghai Stock Exchange Composite Index) and those in the U.S. (S&P500 index), Japan (Nikkei index), Hong Kong (Hang Sheng Index) and the world (MSCI index), Johansson (2010) evidence suggests that China stock market has experienced an increasing level of integration with several major financial markets during the last decade, especially during the recent global financial crisis. Instead of investigating the relationship between those two stock markets, Goh et al. (2013) find that some US economic variables have significant forecasting ability for the China stock market. Though a close relationship exists between economic activity and stock prices in the US, as indicated by Schwert (1990) and Roll (1992), it is still not clear whether the US stock market would affect the China stock market, because those US economic variables may affect the stock markets in both countries simultaneously. Overall, no significant relationship has been observed between the US and the China stock markets in the literature.

The aim of this paper is to better understand the interactions between the China stock market and the U.S. stock market, which have changed year by year in the past decade and, more importantly, in which ways these two markets have interacted. In this paper we investigate the interaction of the stock price movements in these two markets by examining the forecasting abilities of the stock price movement in one country on the stock price movement in another country. Similar to Johansson (2010), major benchmark stock market indexes are used as proxies for the U.S. and China stock markets. In particular, we use the S&P500, the Dow Jones Industrial Average (DJIA) and the NASDAQ Composite Index (NASDAQ) to represent the U.S. stock market, and the Shanghai Stock Exchange Composite Index (SSEC) and the Shenzhen Stock Component Index (SZCI) to represent the China stock market.[1]

Our approach has two features different from those employed in the literature:

First, while previous studies almost exclusively conduct parametric test and follow correlation/regression type of approaches, a nonparametric test is conducted in this paper to test the ability of the daily returns on the US stock market for forecasting the opening prices in China stock markets and vice versa, by calculating the conditional probabilities of a correct forecast. The forecast model is adapted from Henriksson and Merton (1981) for testing the ability of market timing, or the ability of forecasting when stocks will outperform bonds and when bonds will outperform stocks. My forecast model differs from those of earlier studies in that we assume that the forecaster either forecast that the stock market will open high or low, conditional on the daily return in the other market. According to Henriksson and Merton, the nonparametric test has the advantage that conditional probabilities of a correct forecast are sufficient statistics to measure forecasting ability and yet they do not depend on the distribution of returns on the market or on any particular model for security price valuation.

Second, since no significant correlation between two stock markets has been found by investigating time series of daily returns in the literature, we examine the intraday data and investigate the market microstructure. Namely, first in the literature, we test the ability of daily return in one market to forecast the opening in the other market. In particular, we examine the closing-to-closing daily returns, opening-to-closing overnight returns and closing-to-opening trading-hour returns and test the ability of the daily return in one market as a lead indicator to forecast the opening of the other market. Our basic argument for choosing this approach is as follows: since stock price movement is mainly driven by trading activities, and there is no overlap of trading hours between the US and China stock markets,[2] the daily returns in those two markets are mainly driven by different information sets and hence may

[1] The S&P 500 and DJIA are benchmark indexes for the New York Stock Exchange (NYSE), NASDAQ for the Nasdaq Stock Exchange (NASDAQ), the SSEC and SZCI are the most popularly used benchmark indexes for the Shanghai Security Exchange (SSE) and Shenzhen Security Exchange (SZSE), respectively.

[2] There exists a five and a half hour gap between the major U.S. stock market closing and the China stock market opening, and a five and a half hour gap between the China stock market closing and the major U.S. stock market opening. These gaps

have insignificant correlation. However, it does not imply no-interaction between two markets. The daily return in one market is a piece of non-trading hour information that may affect the opening of the other market. That is, the daily return in one market may have ability to forecast the opening value of the other market. Further, if the market is efficient, this effect should not persist after market opens. In other word, the daily return in one market can only affect the opening value of the other market, but not be necessary to cause the correlation between two markets.

In more detail, our approach is that we consider a forecast that either a stock market index will be higher or lower at the opening of a trading session in relation to its value in the previous close, called open-high or open-low. In particular, we examine the forecasting abilities of the daily returns on the U.S. stock market to forecast whether the China stock markets will open-high or open-low in the following session. On the other hand, we examine the forecasting abilities of the daily returns on the China stock market to forecast whether the U.S. stock market will open-high or open-low in the following session.

A brief formal description of our forecast model is as follows:

Let A be an index in one country, B an index in the other country, and $M > 0$ a positive number.

- when A has a daily return greater than M, the forecast is that the following opening value of B will be higher than its value at the previous close;
- when A has a daily return not greater than $-M$, the forecast is that the following opening value of B will be not higher than its value at the previous close.

Note that, if $M = 0$, the forecast will be made every trading day. However, if $M > 0$, the forecasts will be made only if the daily return on A has a magnitude greater than M.

By employing the approach mentioned above, we made contributions to the literature by uncovering a number of new interesting empirical facts as follows:

First, we show that the ability of the daily return on the U.S. stock market for forecasting the China stock market has experienced three stages of development during the period from 2001 to 2010. During the first stage from 2001 to 2005, the forecasting ability was not significant. While Goh et al. (2013) show that after China joined the WTO in December 2001 the ability of the US economic variables for forecasting China stock market had increased significantly, we find no significant evidence that the event of joining WTO increased the ability of the US stock market to forecast China stock market. During the second period from 2006 to 2007, perhaps because the China currency exchange rate regime started to change from the peg system to the managed floating system in July 2005, the ability of the US stock market to forecast the China stock market increased, though still at a low level. The forecasting ability became significant and considerably stronger after 2007 when the recent global financial crisis started. It seems that the financial crisis had a great impact on the linkage between the China and U.S. economies, and consequently, they might also have a great impact on the linkage between the stock markets in these two countries.

Second, while earlier studies in the literature show that the US economic variables have significant ability for predicting China stock market, but there is *no significant* correlation between the US and China stock market, we, first in the literature, document evidence that the US and China stock markets interact in a special way, that is, the US stock market can forecast the China stock market after 2005, especially after the recent financial crisis occurred.

Third, it also shows that the China stock market became having significant ability to forecast the US market opening in 2010. However, it is not clear whether this implies that China stock market became more influential on the U.S. stock market starting in 2010. Another possible explanation is that there was the greatest ever number of Chinese firms newly listed in the U.S.[3] in 2010, which may draw the attention of American investors to China stock market and hence the performance of China stock market may affect the opening of the U.S. market. In Johansson (2010), it shows that cross-listing is

become a six and a half hour and a four and a half hour, respectively, during the daylight saving season, since China does not make this change.

[3] In 2010, 40 Chinese firms launched IPOs in the U.S., with $34.7 billion raised by NYSE alone.

one of the most probable explanations for why China's financial markets are becoming increasingly dependent on U.S. markets.

Though we show that it is possible to forecast the stock price movement several hours ahead, it is not necessarily a violation against the market efficiency hypothesis (MEH). Since the daily returns announced at the close of a market is a type of non-trading hour information to the other market, it should be incorporated into the market opening. If the markets are efficient, any non-trading hour information should have little impact on the price movement after the opening.

To examine this issue, we further investigate whether or not the daily return in one country can forecast the trading-hour return in the other country and find no significant evidence supporting this claim. Since the trading activities and stock price movements in these two markets are virtually driven by different information sets, the daily returns on these two markets should have little correlation. Thus, our study may help us to understand the processes of stock market opening price discoveries.

The rest of this paper is organized as follows. Section 2 describes the methodology of measuring and testing the forecasting ability. Our database and some primary processes of the database are introduced in Section 3. Section 4 reports the empirical results, and the discussion concludes in Section 5.

2. Theoretical framework

In this section, we introduce our methodology to measure and test the abilities of the performance in a stock market to forecast the performance in another stock market in a foreign country. Mathematically, our model is of the form similar to one that Merton (1981) and Henriksson and Merton (1981) proposed to evaluate the performance of investment fund managers and to test the market-timing abilities, although these two models are economically different in nature.

2.1. Measuring forecasting abilities

Let $R1(t)$ be a signal variable and $R2(t)$ be the forecast variable forecasted by $R1(t)$, i.e., the response to $R1(t)$. We consider a forecast as follows:

If $R1(t) \leq M$, we forecast that $R2(t) \leq 0$;
If $R1(t) > M$, we forecast that $R2(t) > 0$.

where $M \geq 0$, represents the strength of the signal. In the case of $M > 0$, if $-M < R1(t) \leq M$ at any date t, no forecast would be made at the date and the observations $R1(t)$ and $R2(t)$ will be neglected in the forecast.

Define:

$$P_1(t) = P\left[\frac{R2(t) \leq 0}{R1(t) \leq -M}\right] \quad (2.1)$$

$$P_2(t) = P[R2(t) > 0 | R1(t) > M] \quad (2.2)$$

$P_1(t)$ is the conditional probability of a correct forecast given that $R1(t) \leq -M$, and $P_2(t)$ is the conditional probability of correct forecast given $R1(t) > M$. Then, the forecasting ability is defined by:

$$P(t) = P_1(t) + P_2(t) - 1 \quad (2.3)$$

where $P(t) = 0$ means no forecasting ability and $P(t) = 1$ means perfect forecasting.

2.2. Testing forecasting abilities

Note that the above definition of the forecasting ability, P, is mathematically similar to the definition of the market timing ability in Henriksson and Merton (1981). Thus, we can apply the mathematics on market timing ability in Henriksson and Merton to our forecasting ability. Following their analysis, a sufficient and necessary condition for a forecaster to have no forecasting value is that $P(t) = 0$. Therefore, the null hypothesis of no forecasting ability is:

$$H_0 : P(t) = P_1(t) + P_2(t) - 1 = 0 \tag{2.4}$$

To implement the test, we define:

n_1 = number of successful forecasts, given that $R1(t) \leq -M$;
n_2 = number of unsuccessful forecasts, given that $R1(t) > \mathrm{M}$;
n'_1 = number of unsuccessful forecasts, given that $R1(t) \leq -M$;
n'_2 = number of successful forecasts, given that $R1(t) > M$.

Then

$n = n_1 + n_2$ is the number of times forecast that $R2(t) \leq 0$;
$n = n'_1 + n'_2$ is the number of times forecast that $R2(t) > 0$;
$N = n_1 + n'_1$ is the number of observations with $R1(t) \leq -M$;
$N_2 = n_2 + n'_2$ is the number of observations with $R1(t) > M$;
$N = N_1 + N_2$ is the total number of observations at which a forecast is made.

From these definitions, we have:

$$P_1 = E\left(\frac{n_1}{N_1}\right) \tag{2.5}$$

$$P_2 = E\left(\frac{n'_2}{N_2}\right) = 1 - E\left(\frac{n_2}{N_2}\right) \tag{2.6}$$

$$P = E\left(\frac{n_1}{N_1} + \frac{n'_2}{N_2}\right) - 1 \tag{2.7}$$

where $E(\cdot)$ is the expected value operator.

Therefore, from Eq. (2.4), it follows that the null hypothesis is:

$$H_0 : P = E\left(\frac{n_1}{N_1} - \frac{n_2}{N_2}\right) = 0 \tag{2.8}$$

Assuming that n_1 and n_2 are sums of independently and identically distributed binary random variables, given N, N_1, n and n_1, the p-value for the test can be calculated by using the following approach[4]:

First, for small samples, n_1 follows a hypergeometric distribution, and we can calculate the p-value by:

$$P\text{-value} = \frac{\sum_{i=n_1}^{\bar{n}_1} \binom{N_1}{i} \binom{N_2}{n-1}}{\binom{N}{n}} \tag{2.9}$$

where $\bar{n}_1 = \min(N_1,\ n)$.

4 See Henriksson and Merton (1981) for more details.

Thus, one can reject the null hypothesis at a probability confidence level of α if $n_1 \geq n_1^*$ where $n_1^*(\alpha)$ is defined as the solution to the following equation:

$$\sum_{i=n_1^*(\alpha)}^{\bar{n}_1} \frac{\begin{pmatrix} N_1 \\ i \end{pmatrix} \begin{pmatrix} N_2 \\ n-1 \end{pmatrix}}{\begin{pmatrix} N \\ n \end{pmatrix}} = 1 - \alpha \tag{2.10}$$

Second, for large samples, since the computations with Eqs. (2.9) and (2.10) have become a problem, normal distribution is used as a good approximation of the hypergeometric distribution. The normal distribution has the following parameters:

$$E(n_1) = \frac{nN_1}{N} \tag{2.11}$$

and

$$\sigma^2(n_1) = \frac{n_1 N_1 (N - N_1)(N - n)}{[N^2(N - 1)]} \tag{2.12}$$

Let

$$z(n_1) = \frac{n_1 - E(n_1)}{\sigma(n_1)} \tag{2.13}$$

then $z(n_1)$ is of standard normal distribution.

Thus, the p-value is calculated by:

$$p\text{-value} = 1 - N[z(n_1)] \tag{2.14}$$

where $N(\cdot)$ is the cumulative probability function of the standard normal distribution. Therefore, we can determine the critical number, $n_1^*(\alpha)$, by solving the following equation:

$$N[n_1^*(\alpha)] = \alpha \tag{2.15}$$

If $n_1 \geq n_1^*(\alpha)$, one can reject the null hypothesis at a probability confidence level of α.

3. The data

Our database consists of the opening and closing values of the S&P500, DJIA, NASDAQ, SSEC and SZCI, all from Bloomberg.

The daily closing and opening values of those five indexes cover a period of 11 years from 2000 to 2010, except that only the opening values of the S&P500 from 2007 to 2010 are used. This is because the opening values of the S&P500 index are equal to the closing values of the previous days before 2007, as in Bloomberg.

Let:

$O(I, t)$ = the opening value of index I at date t;
$C(I, t)$ = the closing value of index I at date t.

We define the daily rate of return (RD), the overnight rate of return (RN), and the trading-hour rate of return (RT) as follows:

$$\mathrm{RD}(I, t) = \frac{C(I, t) - C(I, t-1)}{C(I, t-1)} \tag{3.1}$$

$$\mathrm{RN}(I, t) = \frac{O(I, t) - C(I, t-1)}{C(I, t-1)} \tag{3.2}$$

$$\mathrm{RT}(I, t) = \frac{C(I, t) - O(I, t)}{O(I, t)} \tag{3.3}$$

Table 1
Summary statistics of the data series.

Sample		Period	Sample size	Mean	Std. dev.	N^+/N^- ($M=0$)	N^+/N^- ($M=1\%$)	N^+/N^- ($M=2\%$)
S&P500	Daily returns	2000–10	2766	0.0000	0.0138	1458/1308	439/468	141/156
	Overnight returns	2007–10	1009	−0.0001	0.0022	411/598	–	–
DJIA	Daily returns	2000–10	2766	0.0001	0.0129	1442/1324	418/441	131/137
	Overnight returns	2000–10	2766	−0.0001	0.0012	1079/	–	–
NASDAQ	Overnight returns	2000–10	2766	0.0003	0.0089	1475/1291	–	–
SSEC	Daily returns	2000–10	2639	0.0004	0.0171	1402/1237	604/536	240/240
		2007–10	972	0.0003	0.0218	533/439	301/242	141/147
	Overnight returns	2000–10	2639	−0.0002	0.0075	1299/1340	–	–
	Trading-hour returns	2000–10	2639	0.0006	0.0158	1329/1310	–	–
SZCI	Overnight returns	2000–10	2656	−0.0002	0.0077	1353/1303	–	–

Notes. This table reports the basic characteristics of the data series used in this study. N^+ is the number of observations greater than M and N^- the number of observations that are equal to or lower than $-M$, where $M=0$, 1% and 2%, respectively.

Clearly, from (3.2), RN > 0 (<0) is equivalent to a higher (lower) opening. Using Eqs. (3.1)–(3.3), we form eight time series from our database with our special interest as follows:

(1) RD(SSEC): the daily rates of returns on SSEC, 2000 – 2010;
(2) RN(SSEC): the overnight rates of returns on SSEC, 2000–2010;
(3) RT(SSEC): the trading-hour rates of returns on SSEC, 2000–2010;
(4) RN(SZCI): the overnight rates of returns on SZCI, 2000–2010;
(5) RD(S&P500): the daily rates of returns on S&P500, 2000–2010;
(6) RN(S&P500): the overnight rates of returns on S&P500, 2007–2010;
(7) RN(DJIA): the overnight rates of returns on DJIA, 2000–2010;
(8) RN(NASDAQ): the overnight rates of returns on NASDAQ, 2000–2010.

When RD(SSEC) is used to forecast RN(S&P500), we only take a sample period that is the same as the one of RN(S&P500). The descriptive statistics of these series are shown in Table 1.

4. Empirical results

We test two groups of forecasts: Groups A and B.

Group A consists of those forecasts which forecast performances in China markets using the daily returns from the U.S. markets. In this group, we test five forecasts as follows:

A-1: Forecasting the overnight returns on the SSEC using the daily returns on the S&P500;
A-2: Forecasting the overnight returns on the SZCI using the daily returns on the S&P500;
A-3: Forecasting the overnight returns on the SSEC using the daily returns on the DJIA;
A-4: Forecasting the overnight returns on the SZCI using the daily returns on the DJIA;
A-5: Forecasting the trading-hour-returns on the SSEC using the daily returns on the S&P500.

Therefore, in these forecasts, the time series RD(S&P500), RD(DJIA) are used as the signals, while RN(SSEC), RN(SZCI) and RT(SSEC) are used as the responses.

Group B consists of those forecasts that predict performances in the U.S. markets using the daily returns in the China markets. In this group, we test three forecasts as follows:

B-1: Forecasting the overnight returns on the S&P500 using the daily returns on the SSEC;
B-2: Forecasting the overnight returns on the DJIA using the daily returns on the SSEC;
B-3: Forecasting the overnight returns on the NASDAQ using the daily returns on the SSEC.

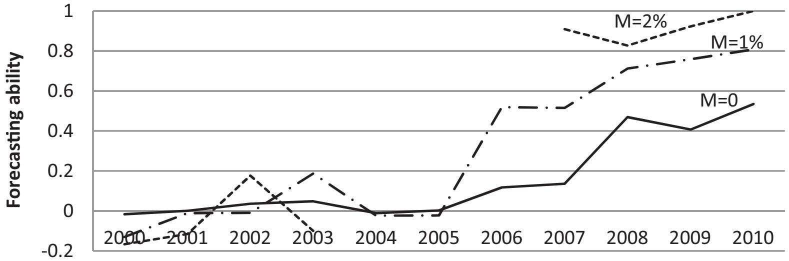

Fig. 1. Forecasting ability of the daily returns on S&P500 to the SSEC opening (2000–2010). *Notes*: the forecasts in year 2004, 2005 and 2006 are not available for $M = 2\%$ because the S&P500 had no daily return with a magnitude over 2% during those years.

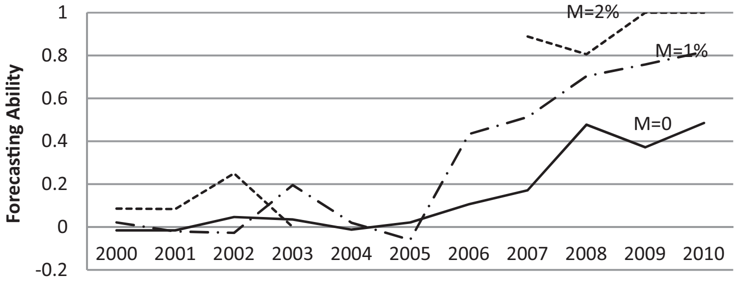

Fig. 2. Forecasting ability of the daily returns on DJIA to the SSEC opening (2000–2010). *Notes*: the forecasts in year 2004, 2005 and 2006 are not available for $M = 2\%$ because the DJIA had no daily return with a magnitude over 2% during those years.

Thus, in the forecasts, the time series RD(SSEC) is used as the signal, while RN(S&P500), RN(DJIA) and RN(NASDAQ) are used as the responses.

Since the NYSE and the SSE are located in two different time zones and local dates and times are used in the database and the two exchanges have different holidays, it is critical to match each pair of signals and responses appropriately. An algorithm was developed to reorganize the data set into appropriate pairs of signals and responses.[5]

4.1. Forecasting China markets by the U.S. markets

In this section, we test the forecasting abilities of the S&P500 and DJIA to forecast the signs of overnight returns on the SSEC and SZCI.

First, we test the forecasting abilities of the daily returns on the S&P500 and DJIA to forecast the signs of the SSEC in the next trading session opening for each year during the period from 2000 to 2010. The results are reported in Fig. 1 for the S&P500 and Fig. 2 for the DJIA, with three different magnitudes of the rate of the return on the S&P500 and DJIA, or the strengths of the signal, $M = 0$, 1% and 2%, respectively. When $M = 0$, we use a normal distribution as an approximation to the hyper-geometric distribution of n_1 due to a large N. When $M = 1\%$ and 2%, the values of N are much smaller and the hyper-geometric distribution is used. n_1^* is the minimum value of n_1 required to reject the null hypothesis with 99% confidence. That is, if $n_1 \geq n_1^*$, the null can be rejected and the signal has no significant forecasting ability.

From Fig. 1, it can be seen that with $M = 0$, there are no significant forecasting abilities during 2000–2005. However, the forecasting abilities increased significantly and the null hypothesis can be rejected with a 99% confidence level from 2006 to 2010. This indicates that the daily rates of returns

[5] The algorithm is available upon request.

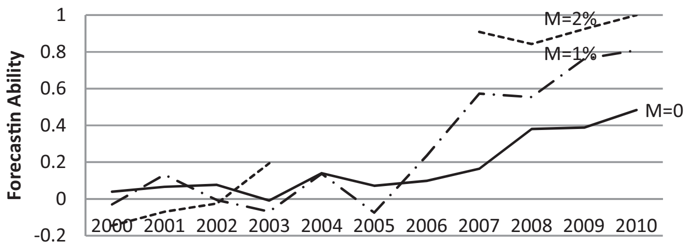

Fig. 3. Forecasting SZCI opening by the daily returns on S&P500 (2000–2010). *Notes*: the forecasts in year 2004, 2005 and 2006 are not available for $M = 2\%$ because the S&P500 had no daily return with a magnitude over 2% during those years.

on the S&P500 have significant forecasting abilities in forecasting the directions of the SSEC opening values during these years. In addition, while the forecasting abilities in 2006 and 2007 were not high, they increased considerably after 2007, with $P = 0.53$ in 2010.

When the strength of the signal increases to $M = 1\%$ and 2%, as shown in Fig. 1, the forecasting abilities increased significantly for the period from 2006 to 2010.[6] For instance, in 2010, the forecasting ability increased from $P = 0.53$ with $M = 0$, to $P = 0.81$ with $M = 1\%$ and $P = 1$ with $M = 2\%$. However, while the null hypothesis can be rejected at 99% for each year during 2006–2010, the forecasting abilities are still considered insignificant during 2000–2005.

Similar results are reported in Fig. 2 in which the daily return on DJIA is used to make the forecast.

We conduct similar tests for the forecasts on the SZCI openings. The forecasting abilities of the daily returns on the S&P500 on the SZCI openings are reported in Fig. 3. The results show significant forecasting abilities at a 99% confidence level on the SZCI openings from 2006 to 2010. However, in case of $M = 0$, the forecasting abilities of the S&P500 are significant at 95% confidence in 2005 and 99% confidence in 2004.

The forecasting abilities in Figs. 1–3 show great changes from 2005 to 2006 and from 2007 to 2008, respectively. These jumps may have been caused by two important events which played a vital role in bringing the China and U.S. economies much closer. One event is that the China currency exchange rate regime started to change from the peg system to the managed floating system on July 21, 2005, and the other is the recent global financial crisis. To examine the impacts of these two events on the forecasting abilities, we divided the full sample into three subsets of the samples: (1) 01/01/2000–07/20/2005: the period before the China currency regime changed; (2) 07/21/2005–02/27/2007: the period after the China currency regime changed but before the financial crisis occurred[7]; (3) 02/28/2007–12/31/2010: the period after the financial crisis occurred. The results are reported in Table 2.

In the first period, the null hypothesis cannot be rejected no matter how strong the signal. However, the forecasting abilities became significant in the second period after the Chinese currency exchange rate regime changed. The null hypothesis can be rejected at a 95% confidence level for all of three signal strengths $M = 0$, 1% and 2%. Furthermore, in the third period after the financial crisis occurred, the null hypothesis can be rejected at a 99% confidence level for all of three signal strengths $M = 0$, 1% and 2% and the forecasting ability index P became much higher than that in the second period, given a certain level of signal strength. This indicates that the U.S. stock market exerted a greater influence on the China stock market after the financial crisis.

The daily returns on the S&P500 and DJIA are non-trading information to the SSE. If the SSE is efficient, this information should impact the opening stock prices in the SSE, but should have no impact on the stock price movements during trading hours. We examined the forecasting ability of the S&P500 on the stock price movement during the trading hours in the SSE. The results are reported in Fig. 4, which shows no convincing forecasting abilities. Actually our calculations show that we cannot reject the null hypothesis at 95% confidence level for all years as well as for the whole sample

[6] The forecasting abilities are not available in the years 2004, 2005 and 2006 for $M = 2\%$ because the samples are too small.

[7] On February 27, 2007, Freddie Mac announced that it would no longer buy the most risky subprime mortgages and mortgage-related securities, which marked the beginning of the financial crisis.

Table 2
Forecasting SSEC opening by S&P500 daily returns in different periods.

M	N	n_1	n_1^*	P	P-value
(a) 01/01/2000–07/20/2005					
$M=0$	1392	380	393	0.0086	0.3235
$M=1\%$	474	130	140	−0.0024	0.5283
$M=2\%$	128	34	42	−0.0166	0.6425
(b) 07/21/2005–02/27/2007					
$M=0$	536	126	127	0.0672**	0.0124
$M=1\%$	78	26	23	0.3846***	0.0000
$M=2\%$	11	5	6	0.8333**	0.0130
(c) 02/27/2007–12/31/2010					
$M=0$	794	290	212	0.4542***	0.0000
$M=1\%$	335	157	102	0.7594***	0.0000
$M=2\%$	148	77	52	0.9022***	0.0000

Notes. This table reports the forecasting abilities of the daily returns on the S&P500 to forecast the sign of the overnight returns on SSEC. The statistical results with $M=0$, 1% and 2% are reported, respectively, for three different periods. N is the total number of forecasts, n_1 is the number of correct forecasts on RN(SSEC) < 0, P is the forecasting ability. The null hypothesis is H_0: $P=0$. n_1^* is the minimum value of n_1 required to reject the null at 99% confidence.

** 95% significant level.
*** 99% significant level.

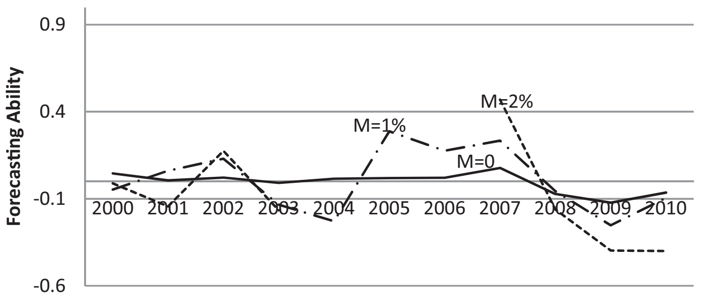

Fig. 4. Forecasting SSEC trading-hour return by the daily returns on S&P500 (2000–2010). *Notes*: the forecasts in year 2004, 2005 and 2006 are not available for $M=2\%$ because the S&P500 had no daily return with a magnitude over 2% during those years.

period with various signal strengths.[8] This indicates that the performances of the S&P500 do not have any significant forecasting ability on the SSEC movement during trading hours. This is consistent with the market efficiency hypothesis.

In summary, we find that the performance of the S&P500 has forecasting ability on the opening of the SSEC in the past five years, especially after the financial crisis. However, we find no evidence to support that there are significant forecasting abilities on the SSEC movement after the SSE opens.

4.2. Forecasting the U.S. market opening by the daily returns on the SSEC

In this section, we test the forecasting abilities of the daily returns on the SSEC to forecast the openings of the DJIA and NASDAQ, respectively. The results are reported in Figs. 5 and 6.

From these figures, it shows that in general, the forecasting abilities of the daily returns on the SSEC are insignificant from 2000 to 2009. According to our calculation, the null hypothesis cannot be rejected with all three levels of the signal strength during this period. Though in the case of NASDAQ, the null can be rejected at 95% confidence level in 2005 and 2006 with $M=0$, the forecasting abilities were not significant given that the values of P were lower than 0.1. This is in sharp contrast to the case

[8] The only exception is that the null is rejected at 95% level of confidence in 2007 with $M=1\%$.

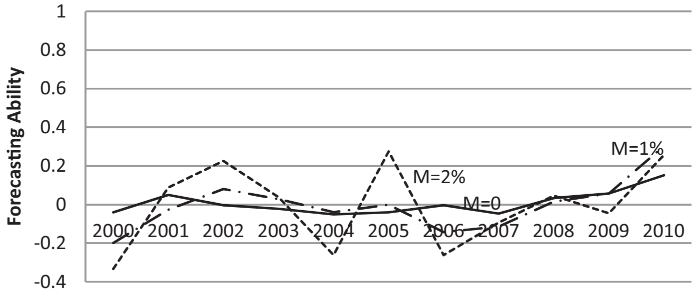

Fig. 5. Forecasting DJIA opening by the daily returns on the SSEC (2000–2010).

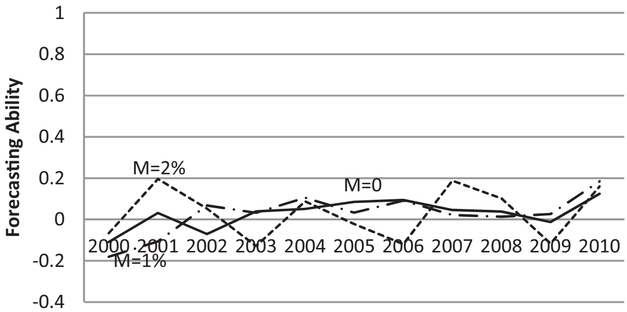

Fig. 6. Forecasting NASDAQ opening by the daily returns on the SSEC (2000–2010).

of forecasting the SSEC opening using the daily returns on the S&P500, in which the forecasting ability is significant at 99% confidence in each year after the global financial crisis.

5. Conclusions

In this paper, by employing a nonparametric test, we present new evidence of the increasing interactions between the China and the U.S. stock markets, two of the largest and most important stock markets in the world, after the global financial crisis occurred.

Because there is no overlap of trading hours between China's stock market and the U.S. stock market, the stock price movements during trading sessions in these two markets are driven by different information sets. As a result, the daily returns, which are mainly dependent on trading activities, on those two stock markets may not show significant correlations.

We show that since 2008 the daily returns on the main U.S. stock market indexes contain important overnight information which determines the direction of the China stock market movement at the next opening. In particular, we present evidence that the close-to-close daily returns on the S&P500 and other benchmark U.S. stock market indexes have significant forecasting abilities to forecast either open-high or open-low in China's stock market in the next trading session. Further, the forecasting ability can be stronger when the daily returns on the U.S. stock market are of higher magnitude. For instance, if the S&P500 falls by more than 2% in a day, it is almost certain to forecast that the SSEC would have a low-open in the next trading session.

While the U.S. stock market has recently shown a great degree of influence on the China stock market, the influence of the China stock market on the U.S. stock market has been weak. In fact, the ability of the daily returns on the SSEC for forecasting the openings of the U.S. stock market was found to be significant starting in 2010. However, further research will be needed to find out why it occurred.

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