University of California at Berkeley
Independent Research

Does the Stock Connect Program Eliminate the Price Disparities of Cross-listed Companies?

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Abstract:

China launched the Shanghai – Hong Kong Stock Connect Program on November 17th, 2014. It announced the first time that China opened its capital market to foreign retail investors. This paper seeks to analyze the effect of this program on the companies cross-listed on the Shanghai Stock Exchange and Hong Kong Stock Exchange. With a more liquid market, the price disparities between these cross-listed companies should decrease. However, from the time series and econometric regression analysis conducted in this paper, the result shows the price disparities actually increases. In addition, different industries respond differently to this program.

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1. Introduction

1.1 Background Information of Chinese Stock Market

On November 17th 2014, the Shanghai-Hong Kong Stock Connect program was officially launched. It declared the first time in China's history opening its capital market to foreign retail investors. China remains conservative and protective to its capital market and has a solid control over the stock market, regardless of its Revolution and Opening Up since 1980s. China has four categories of shares – i.e. A-share, B-share, H-share, and ADRs. A-shares are traded in the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange. H-shares target only international investors and are traded in the Hong Kong Stock Exchange (HKSE). In this paper, I will focus mainly on A-share traded in SSE and H-share.

The Shanghai – Hong Kong Stock Connect program builds up the cross-boundary stock investment channel between the SSE and HKSE. Before the program, only Qualified Foreign Institutional Investors (QFII) can access A-shares, but now foreign retail investors can directly trade shares on the other market using their local brokers and clearing houses.

1.2 Objective

The empirical studies have shown there were price disparities for companies cross-listed on A-share and H-share (Cai, McGuinness, and Zhang (2011), Arquette, Brown Jr., and Burdekin (2008), Han, Jokhadar, and Taghinejad Namini (2006)), but there were no literature analyzing the price disparities after the launch of the Stock Connect Program. Hence, in this paper I will analyze how does the Shanghai – Hong Kong Stock Connect Program affect the price disparities of the Chinese cross-listed companies on A-share and H-share.

I will mainly use the financial data including stock prices of the cross-listed companies and exchange rates between Chinese Yuan (CNY) and Hong Kong Dollar (HKD), which are drawn from Yahoo Finance and Oanda.com. I will use the event study method and time series analysis to conduct the research.

The prices of cross-listed companies on different stock exchanges should be the same in a perfectly liquid market. The Shanghai-Hong Kong Stock Connect Program brought more liquidity to the Chinese stock market. Hence, I intuitively expect to see a decrease in price disparities. Surprisingly, the result of my research shows the price disparities actually increase.

In the next section, I will review the literatures discussing cross-listing companies and price disparity issues, and compare the stock connect program with the American Depositary Receipt (ADR). I will then talk about the data I used and the methodology in Section 3. After that, I will give a detailed analysis of my topic and show the research result in Section 4.

2. Literature Review

2.1 Cross-listed Companies

Before getting to the question of how does the Shanghai-Hong Kong Stock Connect Program affect the companies cross-listed on A and H-share, I first started the review of past studies by looking at researches about cross-listed companies.

Besides the obvious benefit of trading in different currencies and different time zones, many scholars have studied other purposes for companies to list on a foreign stock market. Based on the empirical data analyses of 481 multinationals, Saudagaran (1988) found that firms based in the smaller domestic capital market are more likely to list on a foreign market in order to lower their cost of capital. In addition, listing abroad is a way to gain exposure in that country and eventually raise capital there. Hargis (2000) showed that cross-listing alters the incentives for companies and individuals to take part in the market and hence increases the market liquidity and capitalization to reach a higher level of market integration.

Based on the advantages of cross-listing, many Chinese companies choose to issue their stocks in multiple markets. One of the common ways of cross-listing in China is to list on both SSE and HKSE. There are some unique reasons related to Chinese capital market for companies choosing this specific type of combination. In Section 1, I mentioned that before the Shanghai-Hong Kong Stock Connect program, only QFII could access A-shares. Meanwhile, these foreign institutional investors faced many regulations and quota that restricted the amount of trades. Based on the data from MCF Global Investment Management (2010), QFII share in the Chinese stock markets is less than 1%. Hence, in order to attract more foreign investment, Chinese companies will also list on H-share which is opened to international investors.

2.2 Price Disparities of Cross-listed Companies

One of the basic rules in theoretical economics is *The Law of One Price*, which states that "identical goods must have identical price" by Lamont and Thaler (2003). Otherwise, there will be arbitrage opportunities. In general, a certain company's shares listed in different market should share the same company information and therefore most of these shares should have similar prices (adjusted by exchange rate), and the correlation of movements between these shares should be high. The price synchronicity is supported theoretically and empirically by Morck, Yeung and Yu (2000) and Chan, Hameed and Kang (2013).

However, just as indicated in Lamont and Thaler (2003)'s article, the law of one price holds "in competitive market with no transaction costs and no barriers to trade", but in practice, the violation of the Law does occur. The price of cross-listed companies on A-share and H-share is one example of the violation. Han, Jokhadar, and Taghinejad Namini (2006) examined 21 companies that issued both A-share and H-share. Calculating their expected returns and correlations and compared to those of companies issuing A shares and B shares, they concluded that firms that cross-list A and H shares have significantly different expected monthly returns and have a considerably low coefficient of correlation because of speculative traders. In general, the Chinese stock markets are more highly valued than the Hong Kong companies traded in the HKSE (Berg 2012).

Why is the companies cross-listed on A and H-shares have different prices on different exchanges? In the background review of the China's equity market, Han, Jokhadar, and Taghinejad Namini (2006) indicated "Regulations for stock segmentation make it impossible to have order flows across different stock categories, which exclude arbitrage possibilities." Indeed, China as an emerging market has strict rules about the capital flows and had not yet taken major steps to opening-up its capital market before the announcement of the Shanghai-Hong Kong Stock Connect program. In addition, the exchange rate expectation and investor sentiment also influence the discounts attached to Chinese securities (Arquette, Brown Jr., and Burdekin (2008)). Chan and Kwok (2014) pointed out that since the announcement date in April, "the price disparity between cross-listed shares in both markets to reduce by one-sixth" (Chan and Kwok 2014). However, the exact facts after the official launch of the program have not been studied yet. Hence in this paper, I will study how exactly does this program affect Chinese cross-listing companies across A-share and H-share after 10 months of performance.

2.3 Comparison With ADR

Since the Shanghai-Hong Kong Stock Connect program is the first scheme in China that lowers the barrier of cross-market investment and has just launched for less than a year, there are very little existing studies analyzing the effect of the subject in detail. Yet another similar product, American Depositary Receipt (ADR) was studied over decades. Through ADR, the U.S. investors can directly buy stocks of foreign companies and can convert the ADR and home market stock to each other conveniently. Yoon K Choi and Dong-soon Kim (2000) empirically examined the ADRs underlying stock returns and the influence of global market especially of emerging market using the ADR data from 1990 to 1996, and concluded the effectiveness of international diversification caused by ADR. Michael Hertzel, Paul Lowengrub and Michael Melvin (2000) studied and emphasized the macro “listing effects” of German ADR programs in 1990s, and the result showed the Germany companies listed as ADRs were exposed to the U.S. market and increased the liquidity and profit in general. Before the Shanghai-Hong Kong Stock Connect Program, Chinese investors often did not have the access to such diversification or faced extremely high transaction costs for the foreign stocks, but now they have a convenient way to form a more diverse portfolio on both A and H shares. Therefore, the stock connect program can be regarded as the generalization and extension of ADRs because it also increases the liquidity of capital flow.

Regardless of the increased liquidity, price disparities still exist in ADRs. Thaler and Lamont (2003) gave one example of the price discrepancy. The ADR of an Indian information technologies company named Infosys was trading at a 136% premium to its Bombay shares. The reason behind this discrepancy may be that Infosys offered diversification to American investor’s portfolio. In addition to the diversification explanation for the price disparities in ADRs, there are also other factors that are influential. The study of Axel Grossmann, Teofilo Ozuna, and Marc W. Simpson (2007) examined 74 ADRs from nine countries and covers the time period between 1996 and 2003. Using a fixed-effects panel data approach, they found that ADRs with higher transactions costs and lower dividend payments were more likely to exhibit higher price disparity. I can synthesis the methods and results in the study of ADRs to this paper, and apply to examine the Chinese companies that cross-listed on both SSE and HKSE after the introduction of Shanghai-Hong Kong Stock Connect Program.

To sum up, existing papers discussed about the historical price disparities of Chinese companies cross-listed on A and H-shares, but no studies have been conducted regarding the Shanghai-Hong Kong Stock Connect program's influence on the price disparities of those cross-listed companies. Therefore, in this paper, I will analyze the impact in details with references to the ADRs literatures.

3. Data and Methodology

3.1 Description of Data

Referring to the studies of ADR, the ADR stock price in the U.S. are mostly very close to the stock price in the home market after being adjusted by exchange rate if with the 1:1 conversion rate. Since the Shanghai-Hong Kong Stock Connect program is aimed to reduce the capital flow barriers and to enable people to make transaction of stocks listed in both markets more conveniently, I expect to see a reduction in price disparity of cross-listed stock on each side of the markets as they did in the case of ADR. My hypothesis is that after the launch of the Shanghai-Hong Kong Stock Connect program, companies cross-listed on A-shares and H-shares have decreased price disparity on both markets.

The subjects I will be investigating at in this paper are the 49 companies cross-listed on both A-share and H-share prior to January 1st 2009. Table 1 in Appendix A contains the list of these companies. The primary data is the daily historical prices and daily traded volumes of these companies from January 1st 2009 to September 30th 2015 (1754 days) and the annual dividend from 2009 to 2014 retrieved from Yahoo Finance. In addition, the daily exchange rates (mid-market rates) retrieved from Oanda.com are used to convert the stock prices in HKD to CNY. The longitudinal price data will be used to construct the time series model and to test event influence after the launch of the program on Nov 17th 2014.

3.2 Description of Model

The first step is to set the price disparity measurements. Under the perfect liquidity, the stocks in different markets can be converted to each other freely or at a very low transaction cost as in ADRs. The prices should be consistent to avoid arbitrage opportunity. I will use the percentage price difference compared to the theoretical parity to measure the price disparity quantitatively. As discussed earlier, I will convert the stock price on Hong Kong Stock Exchange to RMB by multiplying the exchange rate E_t (HKD per RMB). For company i at time t, the price disparity PD_{it} is calculated as:

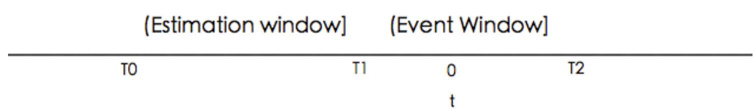
Price Disparity = [(A-share Price) – (H-share Price * Exchange Rate)]÷(A-share Price)

Or simply, $PD_{it} = (P_{Ait} - P_{Hit} * E_t) \div P_{Ait}$

When PD_{it} is equal to 0, it indicates that $P_{Ait} = P_{Hit} * E_t$. The prices on both markets are consistent, and therefore there is no disparity for stock i at time t. When PDit is greater than 0, $P_{Ait} > P_{Hit} * E_t$, which means the actual price for stock i at time t on A-share is higher than that on H-share. I define this situation as there is a positive price disparity, which also indicates the imperfect liquidity. Similarly, when PDit is less than 0, $P_{Ait} < P_{Hi}t * E_t$, which means that there is a negative price disparity and it also shows the imperfect liquidity.

Since I want to examine the effect of the Shanghai-Hong Kong Stock Connect program on the valuation of cross-listed companies on A-share and H-share, I will mainly use the event study method on security's valuation introduced in Mackinlay's article (Mackinlay 1997) together with the time series analysis to do the detailed research. The event of interest is the launch of Stock Connect Program. The launch date of the program, November 17th 2014, is the event date, denoted as t=0. According to Mackinlay, a short period of time around the event date -- i.e. t=T1+1 to t=T2 -- is the event window. The time between T0+1 and T1 is the estimation window, in which I use the data to predict the expected price parity and correlation. Therefore, November 2014 to September 2015 would be my event window, and the time before November 2014 is the estimation window. Figure 1 illustrates the time line.

Figure 1. Event Study Time Line Illustration



The article discussed the abnormal return as the "actual ex post return of the security over the event window minus the normal return of the firm over the event window" (Mackinlay 1997). In my paper, I can exchange the abnormal return to the abnormal price disparity. The idea here is to construct the time series model -- ARIMA model using the data in the estimation window to make prediction about the price disparity along with confidence interval during the event window. I will compare the actual data after the event with the predicted values. If the actual price disparities do not fall into the predicted interval I can claim with certain confidence level that the launch of the program changed the price disparities for cross-listed companies.

As the basic and important model in time series analysis, ARIMA model can catch different inter-correlations and seasonality. The general ARIMA (p, d, q) model is formulated as:

$$(1 - \sum_{k=1}^{p} \alpha_k L^k)\,(1 - L)^d\, PD_{it} \;=\; (1 + \sum_{k=1}^{q} \beta_k L^k)\varepsilon_t$$

where L is the time lag operators that LXi=Xi – 1.

I will use Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine the optimal value of p and q. Also I will expect some seasonality on the price disparity (every month or every year) thus I will try the seasonality parameter d as 22 and 260 (trading days per month and per year). The best-fitted ARIMA model will leave the residue as white noise.

I will then make the prediction along with the 95% confidence interval using the ARIMA package in R, and plot the actual values and predicted interval. If the actual value of price disparity is out of the interval, I can say that the price disparity changed after the event at 5% significant level. In other words, as I hypothesized, the launch of Shanghai Hong Kong Connect program have the significant influence to lower the capital flow barrier and decrease the price disparity for cross-listed companies.

The next thing that I am interested in is to see if different industries result in different price disparity changes. According to the China Security Index, the 49 cross-lisitng companies are broken down to eight industries. The industry classification is also showed in Table 1. I will now conduct a regression with 8 dummy variables D to represent each industry. Take the industrials sector for example, the dummy variable D_I equals 1 if the company i is in the industrials sector, and D_I equals 0 other wise. To avoid the perfect multicollinearity, I will set the financial sector as the reference point. I can then run the regression:

$$PD_i=\beta_0 + \beta_1*D_{CS} + \beta_2*D_I + \beta_3*D_e + \beta_4*D_m + \beta_5*D_t + \beta_6*D_h + \beta_7*D_u + \beta_7*DV_{Hi} +\beta_8*\rho_{Hi}+ \beta_9*AV_{Hi+}\, u_i$$

where DV_{Hi} is the average annual dividend from 2009 to 2014 on H-share, ρ_{Hi} is the correlation between stock price on H-share and exchange rate (HKD/CNY), and AV_{Hi} is average volume traded on H-share divided by 1,000,000.

More specifically, I will look at the slopes of those dummy variables. A positive slope indicates the price disparities in this industry increase (decrease) more (less) than the financial sector. Similarly a negative slope shows the price disparities for this industry increase (decrease) less (more) than the financial sector. I can then look at the P-Values for the coefficients to test the significance of the difference.

4. Analysis and Results

4.1 Basic Set Up

After converting the HKD of H-share price to CNY and calculating the daily price disparities using the method discussed in previous section, i.e.

$$PD_{it} = (P_{Ait} - P_{Hit} * E_t) \div P_{Ait},$$

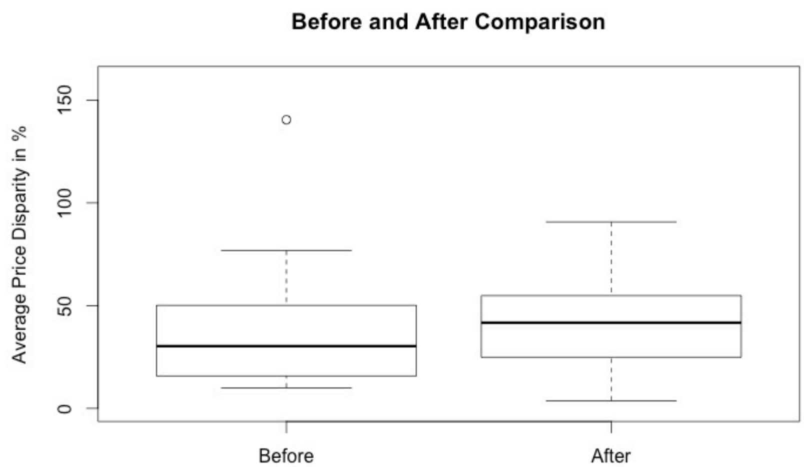
I then divided the price disparity data into two time periods – the first 1526 days' data are before the launch of the Shanghai-Hong Kong Stock Connect Program, which is labeled as *Before*, and the remaining 228 days' data are after the launch, which is labeled as *After*. The next step is to calculate the average price disparity for each individual company for both *Before* and *After* periods. Here I use the absolute values since the disparities for these companies contain both positive and negative values thus simply averaging them may get the disparities less volatile than the actual disparities. Comparing the two time periods' average price disparities, I got the summary results in Table 2. It shows that after the event, the largest price disparity and smallest price disparity both decrease, but the mean increases. The standard deviation of price disparities after the event is smaller than before, indicating that the average price disparity distribution is now more concentrated. The results can be more directly perceived from Figure 2.

Table 2. Descriptive Data of Average Price Disparity in %

Statistic	N	Mean	St. Dev.	Min	Max
Before	49	36.426	25.074	9.989	140.446
After	49	38.658	20.895	3.706	90.729

Note: China Construction Bank has largest price disparities before and after the event, whereas Shenji Group Kunming Machine Tool has the minimum price disparity before the event and China Coal Energy has the minimum after the event.

Figure 2. Average Price Disparity – Before vs. After



From Figure 2, it seems that the average price disparity after the event is even larger than before, which contradicts with the initial hypothesis that with greater capital flow Shanghai-Hong Kong Stock Connect Program brought, the price disparities of cross-listed companies on A-share and H-share should decrease. I will now use the time series model ARIMA to further examine the problem.

4.2 Time Series Analysis

First of all I calculated the overall disparity index by averaging each company for each t from 1 to 1623:

$$PD_t=\sum_{i=1}^{49}|PDti|/49$$

Here I used the absolute values again. I will fit the proper ARIMA time series model to the overall disparity PD_t before the program (t=1 to t=1526) and make prediction along with the confidence interval (t=1527 to t=1754) based on the model. Then I can compare the predicted interval and actual overall disparity after the launch of the program.

Figure 3. Disparity Before Event

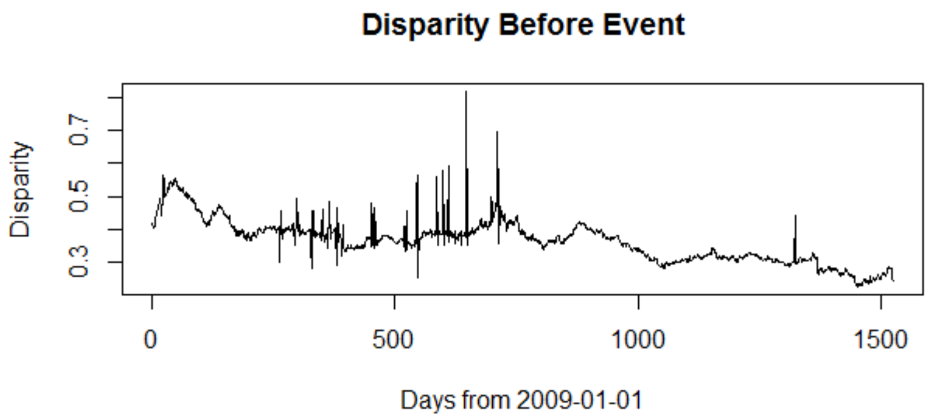


Figure 3 above shows the overall price disparity for the time period *Before* and I will choose the best ARIMA (p,d,q) to fit the time series data. The model selection process can be seen in details from Appendix B. The optimal ARIMA model is ARIMA(0,1,2) with θ_1=-0.7179 and θ_2=-0.0814

$$d_t=PD_t-PD_{t-1}$$

$$d_t=\varepsilon_t-0.7179\ \varepsilon_{t-1}-0.0814\ \varepsilon_{t-2}$$

where ε 's are assumed to be independent, identically distributed variable sampled from a normal distribution with zero mean.

Then I can see the predicted values of PD_t for time period *After* along with 95% confidence interval and compare them with the actual disparities. The red line in Figure 4 is the predicted PD_t from t=1527 to t=1754 and the orange lines give the lower and upper bounds of 95% confidence interval for the prediction. The blue line shows the actual disparity after the launch of

Shanghai-Hong Kong Stock Connect Program, which goes beyond the confidence interval. Thus the increase of overall price disparity between Shanghai and Hong Kong Exchanges is statistically significant. The zoom-in plot of predicted value vs. actual values is shown in Figure 5 which can show a better impression about the disparity.

Figure 4.Predicted vs. Actual Disparity

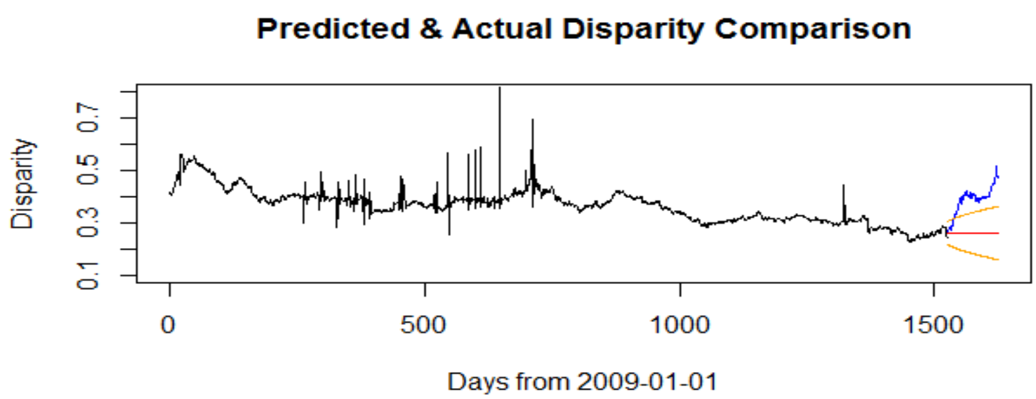
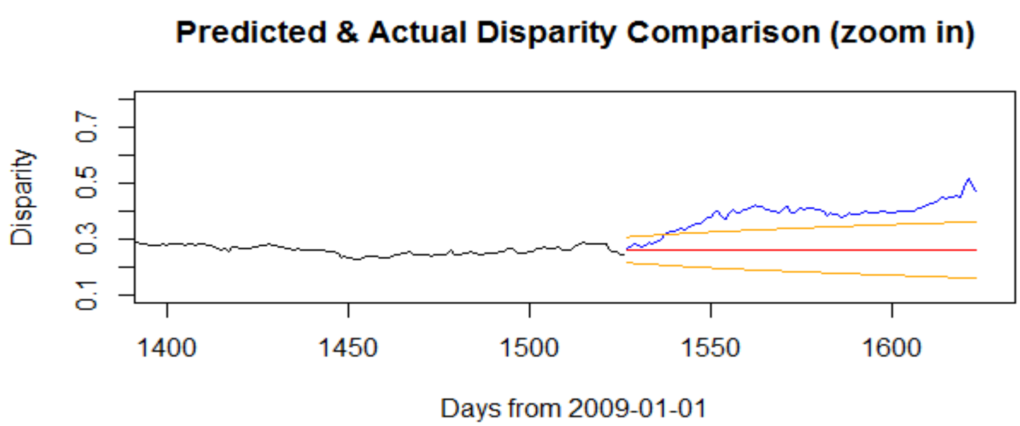


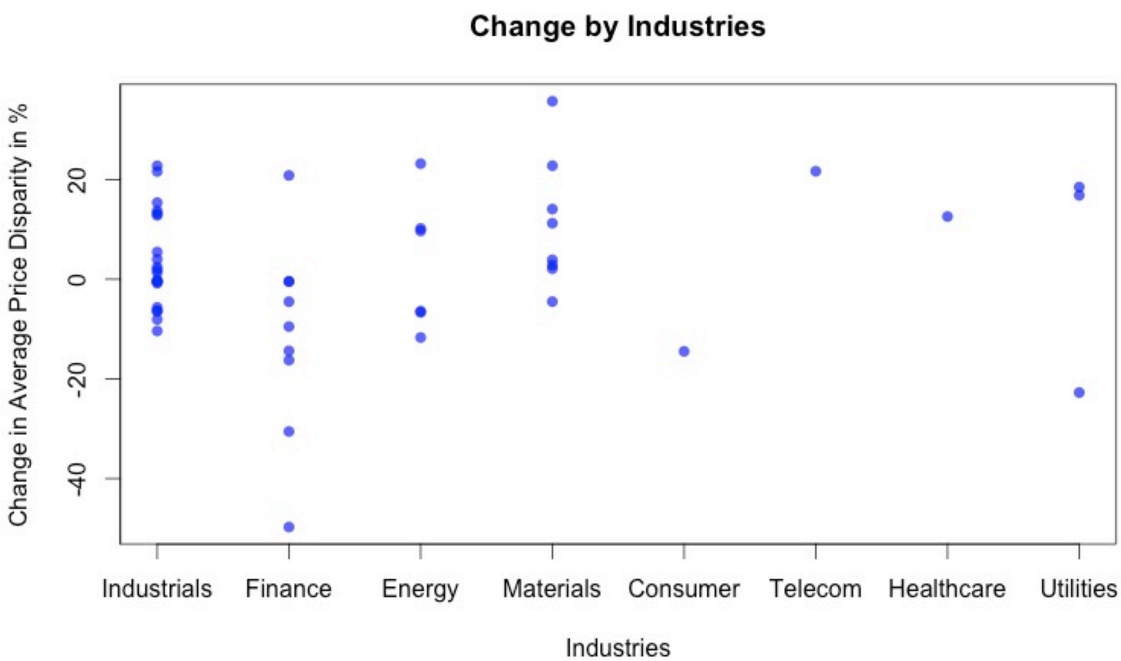
Figure 5. Predicted vs. Actual Disparity Zoom-in



4.3 Industry Analysis

The overall price disparities between Shanghai and Hong Kong Exchanges indeed increased after the Connect Program. Yet different industries may response differently. In order to analyze if the stock connect program affect the price disparities of those cross-listed companies differently by industries, I subtracted the average price disparity before the event from the average price disparity after the event. The results are listed in the column "Change of Average Price Disparity in %" in Table 1. There are 8 industries in total, with Industrials, Finance, and Materials to be the top 3 industries. The changes of average price disparity of different industries after the event are shown in Figure 6.

Figure 6. Changes in average price disparity in different industries



From Figure 6, it is easy to tell that different industries do have different change in average price disparity. For a more precise statistical result, I ran the regression described in Section 3.2 with dummy variables indicating whether company i is in a particular industry:

$$PD_i=\beta_0 + \beta_1*D_{CS} + \beta_2*D_I + \beta_3*D_e + \beta_4*D_m + \beta_5*D_t + \beta_6*D_h + \beta_7*D_u + \beta_7*DV_{Hi} +\beta_8*\rho_{Hi}+ \beta_9*AV_{Hi+}\ u_i$$

The regression result is shown in Table 3 in Appendix A. The coefficients for Industrials Sector, Energy Sector, Materials Sector, and Telecommunication Sector are statistically significant, proving that industries do respond differently to the Shanghai-Hong Kong Stock Connect Program. The first model only includes 7 dummy variables to estimate the industries difference.

For instance, the coefficients for material industry dummy variable is 15.453, which indicates compared to financial sectors, the disparity change for industrial sectors is 15.453 higher in general. The second model adds the average annual dividend in HKSE from 2009 to 2014. The coefficients for *Dividend* is 0.153 but the standard deviation is as large as 15.117. As discussed in the literature review, Axel Grossmann, Teofilo Ozuna, and Marc W. Simpson (2007) showed the dividend has a negative relation with the price disparity on ADR. Yet it turns out that actually the dividend has very little influence on the disparity change on the Shanghai Hong Kong Exchange program. Our model 3 includes the company sensitivity to the exchange rate, which is measured as the correlation between the stock price in Hong Kong Exchange and exchange rates (HKD/CNY) from last five years. The estimation shows the coefficient has a negative sign, which is consistent with Han, Jokhadar, and Taghinejad Namini's finding (2008). The interpretation is that the more sensitive to the exchange rate, the less price disparity change for a company. The model 4 adds the average daily trade volume in the Hong Kong Exchange, which can reflect the popularity and liquidity of a stock. The regression indicates a negative sign of the coefficients. In other words, for the stock with more trade volumes, it was less influence by the Shanghai Hong Kong Exchange program in terms of price disparity. From model 1 to model 4, including additional explanatory variables does not change the coefficients of industries dummy variables significantly.

5. Conclusion

The research results show that after the launch of Shanghai-Hong Kong Stock Connect Program, the price disparities of cross-listed companies on A and H-share increased in general. This conclusion contradicts with the initial hypothesis that the price disparity should decrease since now the Chinese capital market is more liquid than before. The result also shows that different industries respond differently to this program. Six out of eight industries experienced an increase on average in the price disparities between A-share and H-share after the program compared to the financial sector, the most sensitive industry to stock market policy change. The overall disparity increases as well as shown in the time series analysis.

There could be several potential reasons behind such phenomena. Firstly, the Shanghai-Hong Kong Connect Program is aimed to lower the capital barrier between two markets, but as Chinese central government's very first attempt to open the capital market, the program may not be as smoothly accepted as expected. Many Chinese investors may choose not to put the money into the Hong Kong Exchange Market and similarly the foreign investors may also have doubts on the program. Hence, the investors' sentiment can be considered for future study. Secondly, The data for longer period could be more meaningful and significant. Finally, the stock market boom in China in 2015 coincides with the launch of the Stock Connect Program, which could also influence stock price disparities between two markets. The future study could check the disparity of daily return to find more insight into the price disparities.

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Appendix A.

Table 1. A&H-share Cross-listed Companies List

Company	**Industry**	**Change of Average Price Disparity in %**
Aluminum Corporation of China	Materials	35.70
China Petroleum & Chemical Corp	Energy	23.18
Luoyang Glass	Materials	22.77
Shenzhen Expressway	Industrials	22.75
Nanjing Panda Electronics	Telecommunication Services	21.65
China Railway Construction	Industrials	21.61
China Merchants Bank	Finance	20.82
Huadian Power Internatinoal	Utilities	18.48
Huaneng Power International Inc	Utilities	16.83
China Cosco Holdings	Industrials	15.36
Anhui Conch Cement	Materials	14.07
Shanghai Electric Group	Industrials	13.73
Jiangsu Expressway	Industrials	13.15
China Shipping Development	Industrials	12.81
Guangzhou Baiyunshan Pharmaceutical Holdings	Healthcare	12.57
Zijin Mining Group	Materials	11.23
China Oilfield Services	Energy	10.18
Sinopec Shanghai Petrochemical	Energy	9.67
Air China	Industrials	5.45
Shenji Group Kunming Machine Tool	Industrials	3.98
Sinopec Yizheng Chemical Fibre	Materials	3.88
Maanshan Iron and Steal	Materials	2.82
Dongfang Electric	Industrials	2.42
Jiangxi Copper	Materials	2.10
Guangzhou Shipyard International	Industrials	1.87
Tianjin Capital Environmental Protection Group	Industrials	1.35
Beijing Jingcheng Machinery Electric	Industrials	-0.19
China Eastern Airlines	Industrials	-0.40
China Life Insurance	Finance	-0.41
Anhui Expressway	Industrials	-0.42
Bank Of China	Finance	-0.50
China South locomotive & Rolling Stock	Industrials	-0.81
Chongqing Iron And Steel	Materials	-4.50
China Citic Bank	Finance	-4.51
China Shipping Container Lines	Industrials	-5.66
Guangshen Railway	Industrials	-6.39
China Southern Airlines	Industrials	-6.41
PetroChina	Energy	-6.41
China Coal Energy	Energy	-6.66
Yanzhou Coal Mining	Industrials	-8.08
Ping An Insurance Group	Finance	-9.51
China Railway Group	Industrials	-10.38
China Shenhua Energy	Energy	-11.70
Bank of Communications	Finance	-14.37
Tsingtao Brewery	Consumer Staples	-14.48
Beijing North Star	Finance	-16.25
Datang International Power Generation	Utilities	-22.73

Industrial and Commercial Bank of China	Finance	-30.55
China Construction Bank	Finance	-49.72

Note: Companies are ranked by their change in price disparity after the Shanghai-Hong Kong Stock Connect Program. Industry classifications are retrieved from China Securities Index.

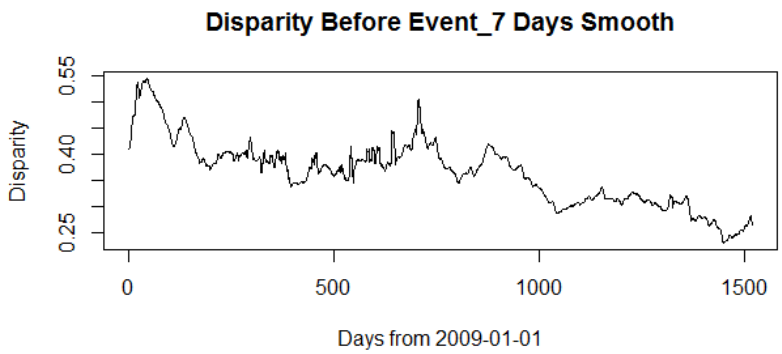
Table 3. Regression Result

	Dependent variable:			
	Change in Price Disparities			
	(1)	(2)	(3)	(4)
Industrial	15.453***	15.473**	15.191**	15.972**
	(5.671)	(6.051)	(6.081)	(6.133)
Consumer Staples	-2.814	-2.826	-3.128	-3.020
	(14.893)	(15.118)	(15.174)	(15.178)
Energy	14.710*	14.700*	13.225*	13.913*
	(7.446)	(7.605)	(7.824)	(7.857)
Materials	22.675***	22.695***	22.315***	24.984***
	(6.865)	(7.208)	(7.246)	(7.734)
Telecommunications	33.318**	33.349**	31.977**	32.455**
	(14.893)	(15.398)	(15.534)	(15.546)
Healthcare	24.238	24.261	22.303	22.417
	(14.893)	(15.240)	(15.463)	(15.468)
Utilities	15.858*	15.877	13.651	14.211
	(9.419)	(9.720)	(10.096)	(10.115)
Dividend		0.153	-1.142	-1.002
		(15.117)	(15.244)	(15.249)
Correlation with EX			-82.697	-81.019
			(96.902)	(96.944)
Avg Volume				-0.029
				(0.030)
Constant	-11.667**	-11.704*	-13.854**	-13.583**
	(4.709)	(5.999)	(6.526)	(6.534)
Observations	49	49	49	49
R2	0.280	0.280	0.293	0.311
Adjusted R2	0.157	0.136	0.130	0.130
Residual Std. Error	14.128 (df = 41)	14.304 (df = 40)	14.353 (df = 39)	14.357 (df = 38)
F Statistic	2.277** (df = 7; 41)	1.944* (df = 8; 40)	1.797* (df = 9; 39)	1.714 (df = 10; 38)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix B. ARIMA Model Selection

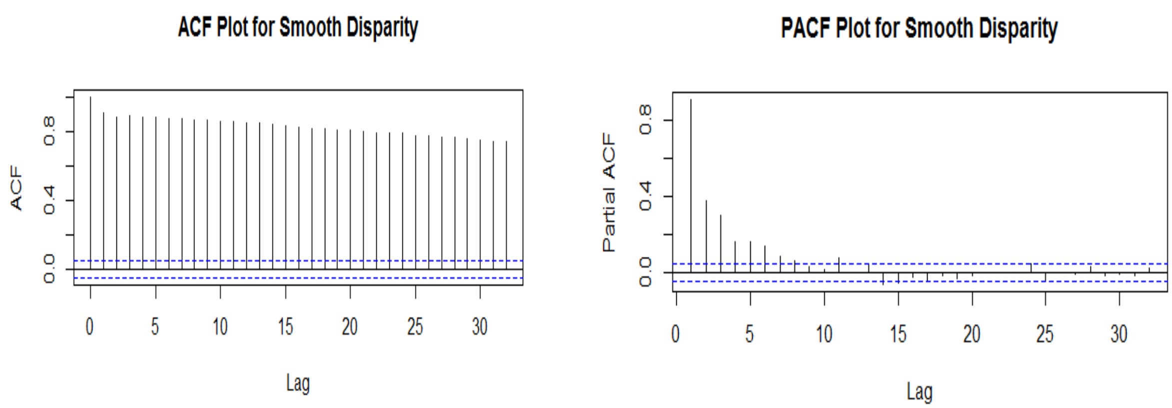
To catch the disparity trend I first eliminate the extra noise. Here I use the 7-days smooth by previous and past three days, totally 7-days average.

Figure 7. Smooth



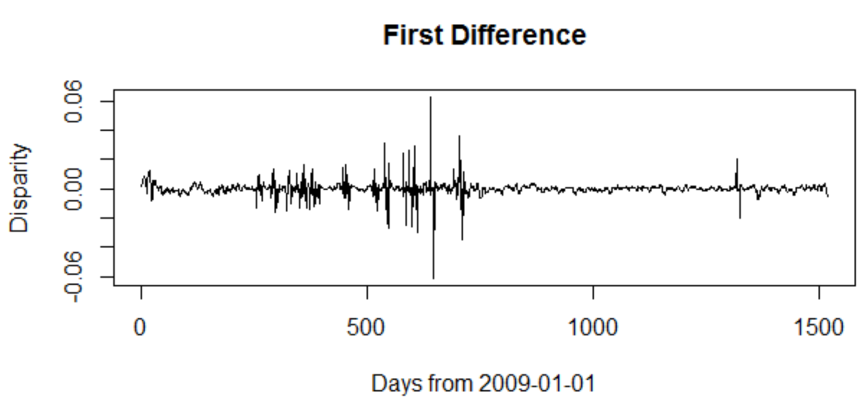
Then I use the ACF (autocorrelation function) and PACF (partial autocorrelation function) plot to choose the proper indices in the ARIMA(p,d,q) model.

Figure 8. ACF & PACF Plots



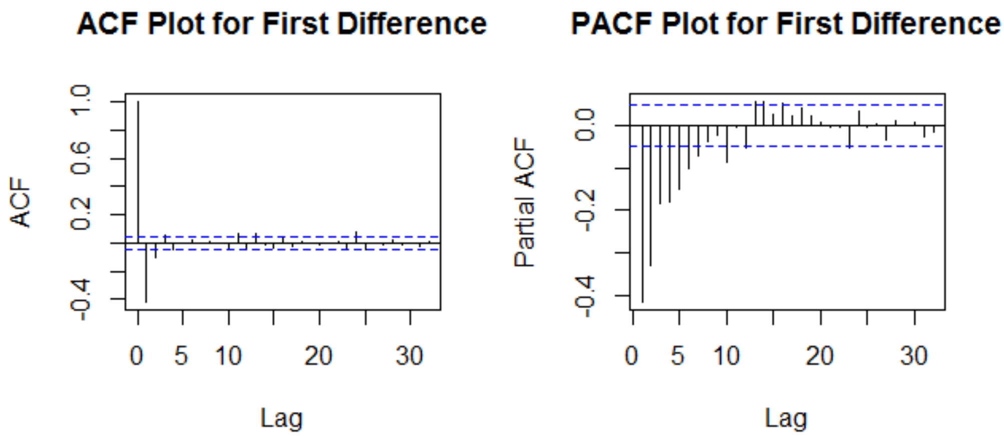
The acf and pacf plot for the original data is relatively insignificant. Though the ARMA(7,0) or ARIMA(7,0,0) could be a choice for the time series model, it's too complicated to compute and predict. I'll try the first difference, in other words, I'll set d=1.

Figure 9. First Difference



By taking the first difference the trend becomes clearer except a few noise and it's easier to find the simpler model and predict.

Figure 10. ACF & PACF First Difference



The acf and pacf is more significant and indicate ARIMA(0,1,1) or ARIMA(0,1,2) from the plot. The AIC criteria will help choose the better model.

Table 4. ARIMA Model

Models	ma1 (se)	ma2 (se)	Sigma^2 estimated	AIC
ARIMA(0,1,1)	-0.7880 (0.0157)	NA	0.0005458	-7124.85
ARIMA(0,1,2)	-0.7179 (0.0267)	-0.0814 (0.0262)	0.0005424	-7132.49

The absolute value of AIC is larger for ARIMA(0,1,2) and our final model is ARIMA(0,1,2) with ma1=-0.7179 and ma2=-0.0814