

# An Empirical Study on the Time-Varying Connectedness Between Shanghai and Hong Kong Markets — A Perspective from Liquidity and Trading Activities

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**Abstract** We conduct an empirical analysis of Shanghai-Hong Kong Stock Connect to reveal the dynamic impacts of stock connect trading activity on the stock pool's Amihud illiquidity proxy, index return, and CNY-HKD exchange rate. From pairwise conditional g causality analysis, we note a mutual significant causal connection between northbound net buying volume and Shanghai stock exchange return on all frequency levels. Meanwhile, we find a significant causal impact on the Shanghai portfolio's liquidity from northbound net buying volume. And there is a significant causal impact from the southbound net buying volume on Hang Seng Index return. Both are significant at the low-frequency level. In particular, northbound trading activity stimulates the Shanghai portfolio's liquidity in the low trading activity regime from the threshold VAR analysis. In robust analysis, we find similar significant dynamic causal connection and stimulation effects for the northbound trades when replacing Amihud illiquidity with the turnover rate. The result might relate to the investment behaviors looking for opportunity in the low trading activity regime. In contrast, the investors' beliefs may vary in the high trading activity regime, which weakens the connection between trading activities and other factors like liquidity.

**Keywords** stock connect; Amihud illiquidity ratio; MVGC; threshold VAR

## 1 Introduction

The “Stock Connect” link between China's mainland markets and the Hong Kong Stock Exchange is a milestone in financial liberalization in Chinese financial history. The “Stock Connect” allows qualified mainland China investors to access Hong Kong shares (southbound) as well as Hong Kong and overseas investors to trade eligible A shares (northbound) subject to a certain amount of daily quota<sup>1</sup>. The link was officially launched on November 17, 2014, between

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Received April 27, 2023, accepted July 14, 2023

Supported by the National Natural Science Foundation of China (71988101)

<sup>1</sup><http://english.sse.com.cn/access/stockconnect/introduction/>.

the Shanghai and Hong Kong exchanges and was extended in late 2016 to encompass the Shenzhen market<sup>2</sup>. The stock connect is direct and flexible, as the eligible investors can determine the stocks independently compared to the passive investment of QDII and QFII. The opening up of stock markets in China is expected to enhance the risk adaption capacity, elevate the pricing efficiency, and improve liquidity. Among all mentioned impacts, the direct influences of stock connect trading activities on liquidity are particularly essential. Previous studies find that the connection between trading volume and market liquidity has regime-dependent patterns<sup>[1]</sup>. Market liquidity is confirmed to relate to trading activities directly and further influence stocks' expected returns<sup>[2, 3]</sup>. Meanwhile, investors' attention impacts stock liquidity and volatility<sup>[4]</sup>. Traders' strategies also significantly impact stocks liquidity in a regime-switching way<sup>[5]</sup>. Individual investors are likely to benefit from providing liquidity during market stress<sup>[6]</sup>. Moreover, liquidity is critical in monitoring market status, for which high market liquidity might indicate potential herding behavior on the system level, particularly around the financial crisis period<sup>[7]</sup>. Understanding the connection between trading activities and stock liquidity is essential for investors' strategies management and for regulators monitoring market risk.

Recent discussions about the "Stock Connect" focus on premiums<sup>[8, 9]</sup> and price disparity<sup>[10, 11]</sup> of the A+H cross-listing stock, the impact of "Stock Connect" on liquidity and turnover state<sup>[12]</sup>, volatility spillover<sup>[13]</sup> market efficiency and co-movement<sup>[14]</sup>. Besides, a comprehensive analysis of the asymmetric impacts on market liquidity and systemic risk has been discussed<sup>[15]</sup>. However, little attention is paid to the time-varying impacts of trading activities on "Stock Connect."

The paper takes "Stock Connect" as an ideal experiment. It aims to compare the impacts of trading activities on the portfolio liquidity status for the respective markets and potential impacts on the index returns and CNY-HKD exchange rate. In particular, we examine the time-varying connection between northbound and southbound net buying volume and other factors. We apply time-varying causal techniques and conduct threshold VAR to compare potential regime-dependent influences between liquidity and trading activities in Shanghai and Hong Kong stock connects portfolios. There are five steps in the empirical analysis.

Step 1. Calculate the liquidity proxies for both portfolios.

Step 2. Conduct the multivariate causality test to check the connection for the northbound and southbound investments.

Step 3. Examine the linearity of trading activities in each portfolio.

Step 4. Illustrate accumulated impulse responses on different regimes.

Step 5. Compare and discuss the possible root cause of the time-varying connections.

We find dynamic causal impacts of trading activities on the portfolio's liquidity. The impacts are insignificant in the short term and switch to significant in the long term for the Shanghai market. The linearity ratio test confirms the threshold separating the trading activity into low and high regimes for both markets. In the accumulated impulse response of threshold VAR, the northbound trading significantly improves the Shanghai stock connect pool's liquidity in the low regime. Furthermore, southbound trading significantly elevates Hang Seng Index return in the low regime. We suggest that the stimulation impacts of stock connect trading activity relates to

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<sup>2</sup><https://www.goldmansachs.com/insights/pages/stock-connect/>.

the behaviors of experienced behaviors looking for an opportunity in the low trading regime on both markets. In contrast, investment beliefs may vary in high trading activity regime, making the connection between trading behaviors and other factors less clear.

The arrangement of the paper is as follows: Section 1 introduces the background of the Shanghai-Hong Kong Stock Connect and relevant research. Section 2 explains the material and methods. Section 3 illustrates the empirical results. Section 4 discusses the results. Finally, Section 5 concludes the paper.

## **2 Material and Methods**

### **2.1 Data and Proxies**

In stock connect trading, eligible investors of one of the markets can invest in the other pool and generally settle in two trading days. The settlement system automatically exchanges the CNY and HKD. And the relevant buy and sale volumes are recorded at the end of each day. To examine the potential impacts, we assume there are four primary components on the stock connect system, i.e., the net buy volume reflecting the trading activities (SH\_NB for the northbound portfolio and HK\_NB for the southbound portfolio), the stock index indicating the macro market status (SSER for Shanghai market and HSIR for Hong Kong market), and the CNY-HKD exchange rate which might be impacted by investment behaviors relating to currency hedge trade to retain original equities exposure. The last component is the liquidity proxy (SH\_AQ for the northbound portfolio and HK\_AQ for the southbound portfolio). The sample periods start on Nov 17, 2014, and end on Jun 29, 2018. We only keep the active settlement trading days on both markets for easy comparison. In total, there are 808 observations of the daily record. When the stock connect officially launched, 568 and 268 stocks were in the northbound and southbound pools, respectively. The northbound pool comprises stocks in SSE 180, SSE 380, cross-listing A+H, and excludes the stocks of special treatment. The latter comprises Hang Seng Composite Large Cap Index, Hang Seng Composite Medium Cap Index, and A+H cross-listing stocks. Both pools are adjusted according to the situation. The corresponding change is published timely. We filter the daily record and keep a valid list according to the official announcement. Furthermore, we download the closing price and trade volumes for all stocks in both portfolios and construct the liquidity proxy. The temporal data of the northbound/southbound net buying volume, the Hang Seng and Shanghai Stock Exchange Index, and the CNY-HKD exchange rate are prepared at the same time. All data is from Oriental Choice finance termination.

There are different measures of stock liquidity<sup>[16]</sup>: For example, the classic bid-ask spread; the Roll measure, which uses a model to estimate the effective spread based on the serial covariance of the price change<sup>[17]</sup>; the Zeros, which capture the transaction cost dimension based on the frequency of zero return<sup>[18]</sup>; Pastor-Stambaugh liquidity series, which is constructed base on the principle that order flow induces greater return reversals when liquidity is lower<sup>[19]</sup>; stock turnover rate<sup>[3]</sup>; and a measure generated from the connection between noise amount of arbitrage capital in the market and observed noise<sup>[20]</sup>.

Among all the existing liquidity proxies, the Amihud illiquidity ratio is the most common and effective measure that uses the absolute value of the daily return-to-volume ratio to capture

price impact<sup>[21–23]</sup>. The proxy is defined below.

$$\text{ILLIQ}_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{|R_{iyd}|}{\text{VOLD}_{iyd}}, \quad (1)$$

where  $D_{iy}$  is the number of days for which data are available for stock  $i$  in year  $y$ .  $R_{iyd}$  is the return of stock  $i$  on day  $d$  of year  $y$  and  $\text{VOLD}_{iyd}$  is the respective daily volume in millions of dollars (here we update to millions of CNY in the calculation). This illiquidity measure is strongly related to the liquidity ratio known as the Amivest measure, the ratio of the sum of the daily volume to the sum of the absolute return. A higher value of ILLIQ means a lower level of liquidity of the stock. Moreover, the average market illiquidity across stocks each year is calculated below.

$$\text{AILLIQ}_y = \frac{1}{N_y} \sum_{t=1}^{N_y} \text{ILLIQ}_{iy}, \quad (2)$$

where  $N_y$  is the number of days for which data are available in year  $y$ . This paper uses the above function to calculate each pool's daily Amihud illiquidity ratio. We use SH\_AQ and HK\_AQ to mark the Amihud illiquidity ratio for Shanghai and Hong Kong portfolios, respectively.

## 2.2 Methods

We use the multivariate  $g$  causality (MVGC) in studying the time-varying effects in multivariate systems<sup>[24]</sup>. MVGC is a mature technique for identifying dynamic causal correlations on both time and frequency domains in various fields and has been applied in financial studies<sup>[25]</sup>. The directions of time-varying effects are further explored with threshold VAR (TVAR)<sup>[26]</sup>. TVAR has been widely used in analyzing regime-dependent policy impacts, for example, fiscal developments and financial stress<sup>[27, 28]</sup>, financial and monetary stability<sup>[29]</sup>, macroeconomic activity<sup>[30]</sup>, impacts regarding international reserves holding<sup>[31]</sup>, exchange rate and macro economy<sup>[32]</sup>, and impacts from oil price on macroeconomic outputs<sup>[33]</sup>.

### 2.2.1 MVGC

We apply the conditional  $g$  causality to reveal the inner connections of multivariate systems. Consider an example with the universe  $U$  of unknown recorded variables splits into three inter-dependent multi-variate process

$$U_t = (X_t \quad Y_t \quad Z_t)'. \quad (3)$$

We may consider the full and reduced regressions as below to eliminate any joint effect of  $Z$  on the inference of the  $g$ -causality from  $Y$  to  $X$ .

$$X_t = \sum_{k=1}^p A_{xx,k} \cdot X_{t-k} + \sum_{k=1}^p A_{xy,k} \cdot Y_{t-k} + \sum_{k=1}^p A_{xz,k} \cdot Z_{t-k} + \varepsilon_{x,t}, \quad (4)$$

$$X_t = \sum_{k=1}^p A'_{xx,k} \cdot X_{t-k} + \sum_{k=1}^p A'_{xz,k} \cdot Z_{t-k} + \varepsilon'_{x,t}. \quad (5)$$

By testing the performance between the full and reduced regression, i.e.,  $\mathcal{F}_{Y \rightarrow X|Z} \equiv \ln \frac{|\sum'_{XX}|}{|\sum_{XX}|}$ , the degree to which the past of  $Y$  helps predict  $X$ , over and above the degree to which  $X$  is already predicted by its own past and the past of  $Z$  can be quantified and accepted or rejected. In particular, the pairwise conditional  $g$  causality (pwgc) tests the bivariate pairwise conditional situation with the rest variables eliminated. The causality analysis is conducted with the MVGC toolbox<sup>[24]</sup> on both the time and frequency domain.

The spectral pairwise conditional  $g$ -causality analysis is to decompose the time domain causality to the different frequency levels. Hence the time domain  $g$  causality can be considered an average of overall spectral  $g$  causality on all frequency levels, which provides a referable reflection of the dynamic impacts between variables. For our study, we conduct daily samples and decompose the time causality to spectral causality on 0 to 0.5 Hz, where the low-frequency level indicates the long-term period and the high-frequency level indicates the short-term period. Causal connection changes in continuous frequency levels imply the dynamic impacts on different regimes.

Furthermore, to ensure the robustness of the calculation, we perform the permutation test (1000 times) in calculating both the time and frequency domain causality.

### 2.2.2 Threshold VAR

To check the time-varying interactions, we conduct the linearity likelihood ratio (LR) test for the multivariate model<sup>[26]</sup>. The LR test is defined as comparing the covariance matrix of different models.

$$LR_{ij} = T(\ln(\det \hat{\Sigma}_I) - \ln(\det \hat{\Sigma}_J)), \quad (6)$$

where  $\hat{\Sigma}_I$  is the estimated covariance matrix of the model with  $i$  regimes. We focus on the inactive and active trading activities regimes, corresponding to a low net buying volume and a high net buying volume, respectively. The LR test compares the performance of linear VAR and one threshold VAR. When the threshold is significant, we estimate the following two regimes TVAR model:

$$y_t = a_1 + A_1 y_t + B_1(L)y_{t-1} + (a_2 + A_2 y_t + B_2(L)y_{t-1})I(c_{t-d} > \theta) + \varepsilon_t, \quad (7)$$

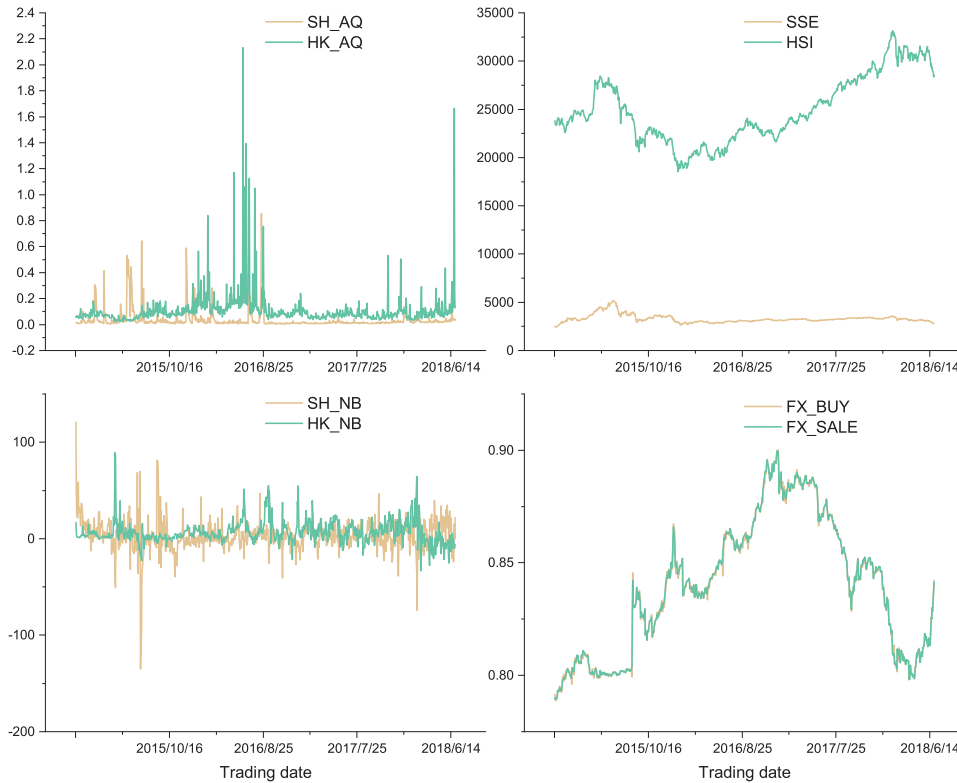
where the vector of variables  $y_t$  consists of the net buying volume of the market (SH\_NB and HK\_NB), the Amihud illiquidity ratio of each market (SH\_AQ and HK\_AQ), the index daily return (SSER and HSIR), and CNY-HKD buy rate change (FX).  $a_1$  and  $a_2$  are constants, and  $A_1$ ,  $A_2$ ,  $B_1$  and  $B_2$  are coefficients, constituting the parameter group of interest, where  $L$  is the lag operator.  $\theta$  is the threshold, and  $\varepsilon_t$  is the residuals. The threshold variable is the net buying volume of each portfolio.

## 3 Results

### 3.1 Descriptive Summary

Figure 1 depicts the data for the two systems. For the Amihud illiquidity ratio, the Hong Kong stock connect pool (HK\_AQ) reveals a generally higher level than the Shanghai pool

(SH\_AQ). Meanwhile, northbound trading net buying volume (SH\_NB) fluctuates more intensely than southbound trading (HK\_NB). Since there are noticeable trends in the stock index and CNY-HKD exchange rate, we calculate the log returns of SSE (SSER) and HSI (HSIR) for further processing. Meanwhile, as the FX\_BUY and FX\_SALE rates have a consistent pattern, we only use the FX-BUY rate in the analysis and conduct first-order differences on the rate (hereafter FX) to ensure stability.



Note: The HK\_NB and SH\_NB are measured by hundreds of millions of CNY.

**Figure 1** Temporal Pattern

After the preliminary processing, the descriptive summary is presented in Table 1. The descriptive summary agrees with the Figure 1 impression. All temporal data are stationary in ADF and PP tests. Moreover, the JB test rejects the hypothesis of data normality.

### 3.2 Time Varying Causal Connection

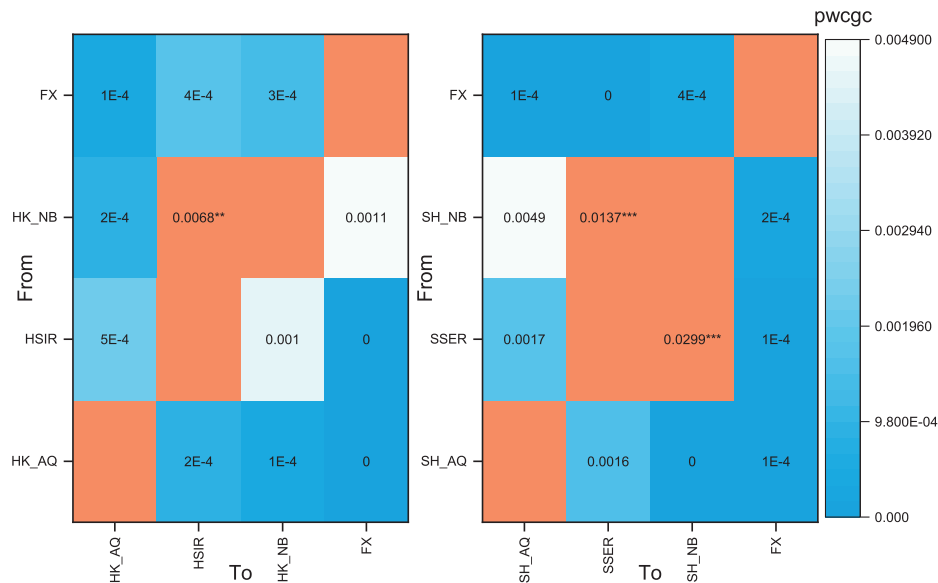
Firstly, we compare the causal connection of the two systems. Figure 2 illustrates the pairwise conditional  $g$ -causality on the time domain. For both Hong Kong and Shanghai portfolios, stock connects net buying volume is insignificantly in predicting the liquidity of the corresponding pool. While net buying volume can significantly predict the index daily returns for both markets. The daily index returns for the Shanghai stock connect can also significantly forecast the corresponding net buying volume.

**Table 1** Descriptive summary

Index	HK_NB	HSIR	HK_AQ	SH_NB	SSER	SH_AQ	FX difference
Min	-33.4657	-0.0602	0.0226	-135.2320	-0.0887	0.0050	-0.0148
Median	4.5779	0.0006	0.0813	2.0210	0.0010	0.0165	0.0000
Mean	6.5587	0.0002	0.1110	3.1850	0.0001	0.0377	0.0011
Max	89.1075	0.0580	2.1320	81.4880	0.0997	0.8556	0.8644
Std.Dev.	11.7173	0.0117	0.1438	15.6667	0.0173	0.0801	0.0305
Skewness	1.6967	-0.2432	8.0496	-0.8505	-0.9081	5.3895	28.0347
Kurtosis	11.0939	6.5947	86.5967	16.4210	10.3812	37.2413	793.2316
ADF	-10.3781 ***	-20.5879 ***	-13.9211 ***	-14.5285 ***	-20.0318 ***	-10.6250 ***	-20.0458 ***
PP	-12.5620 ***	-28.5640 ***	-24.3150 ***	-19.6310 ***	-27.1160 ***	-12.9520 ***	-28.3090 ***
Jarque-Bera	2593.2000 ***	442.9900 ***	244004 ***	6161.5000 ***	1945.3000 ***	43385 ***	21129527 ***
Observations	809	808	809	809	808	809	809

Data Source: Oriental choice finance termination.

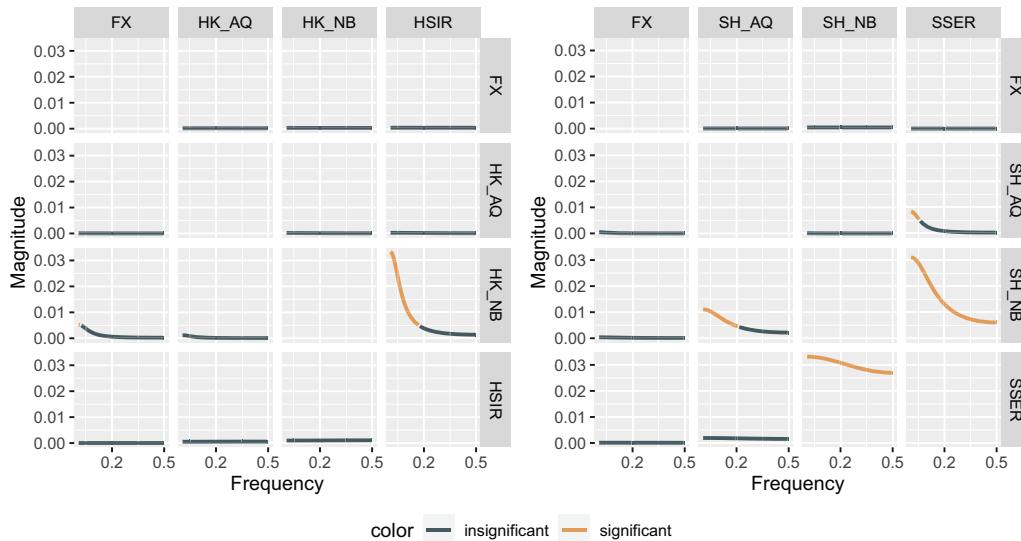
Note: \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed). HK\_NB and SH\_NB are measured by hundreds of millions of CNY, and the FX (difference) is based on the CNY-HKD buy rate on the trading day.



Note: Permutation test: 1000 times. \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed).

**Figure 2** Pairwise conditional causal connection on the time domain

Regarding the frequency domain causality decomposition, the dynamic causal connections are identified in both systems. As Figure 3 illustrates, the significant causal impact of HK\_NB on HSIR is on the low-frequency level (middle and long term). For the Shanghai portfolio, the significant connection and feedback between SH\_NB and SSER across all frequency levels. Both agree with the causal connection in the time domain. At the same time, the long-term impacts from SH\_NB to SH\_AQ and SH\_AQ to SSER are not captured in the time-domain causal analysis. The dynamic significant causal connections only on the low-frequency level might imply a potential threshold in the stock connects trade activities. We further test the threshold and process TVAR to examine the impacts in different regimes.



Note: Permutation test: 1000 times. The rows indicate the origin of the causal connection, and the columns stand for the destination. The spectral pairwise conditional g causality is depicted at the 5% significance level.

**Figure 3** Dynamic pairwise conditional causal connection on the frequency domain

### 3.3 Impulse Response from the Threshold VAR

Table 2 shows the result of threshold VAR on the two systems with illiquidity proxy. The dependent variable is north or southbound trading net buying volume. LR test confirms a significant threshold in stock connect trading volume for both markets, marking a low regime for inactive and a high regime for active trading. The northbound and southbound trading threshold values are 10.1148 and 17.7982, respectively. Meanwhile, about 74.2% northbound and 88.2% southbound are within the low regime. According to BIC, we build thresholds VAR with one lag.

Figure 4 depicts the accumulated impulse response of threshold VAR regarding one positive unit shock from the net buying volume on the two regimes. For the northbound trading, a positive unit shock from the net trading volume results in a negative response to the Shanghai pool's illiquidity in both regimes. However, only the response in the low regime is significant. It indicates a stimulation effect from the northbound trade on the Shanghai stock connect pool's



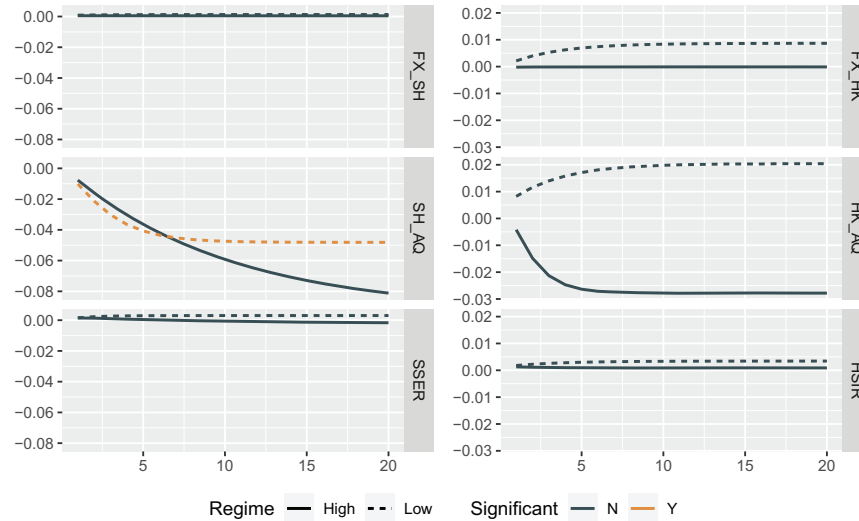
Table 2 LR test and threshold VAR estimation

Threshold:	Regime L:	Regime H:	Threshold:	Regime L:	Regime H:
SH_NB	SH_NB ≤ 10.1148	SH_NB > 10.1148	HK_NB	HK_NB ≤ 17.7982	HK_NB > 17.7982
Constant	2.1229 (0.6345)***	8.3621 (2.0323)***	Constant	1.9742 (0.4544)***	4.8114 (2.1294)*
SH_NB(−1)	0.5021 (0.0478)***	0.0549 (0.0835)	HK_NB(−1)	0.7225 (0.0444)***	0.5318 (0.0654)***
SH_AQ(−1)	−7.5666 (7.1036)	17.3091 (12.2087)	HK_AQ(−1)	−0.2767 (2.5895)	4.0557 (3.6425)
SSER(−1)	−263.8973 (36.3725)***	−37.6623 (48.9083)	HSIR(−1)	−16.7124 (27.9414)	323.9422 (75.3097)***
FX(−1)	−8.3878 (16.0025)	−247.1256 (435.5164)	FX(−1)	−4.4500 (9.8976)	−650.6417 (373.4865)
AIC	−12518.0700		AIC	−12485.0100	
BIC	−12325.6400	Lag: −1	BIC	−12292.5800	Lag: −1
SSR	152657.2000		SSR	58561.0900	
Observations	74.2%	25.8%	Observations	88.2%	11.8%
Threshold LR value	107.9706		Threshold LR value	34.5854	
P value of LR test	0.0000		P value of LR test	0.0000	

Note: Values in the brackets are the standard errors. \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed).

liquidity status, mainly in the inactive trading activity status. The responses of Shanghai Stock Index returns and CNY-HKD exchange rate are minimal and insignificant.

For the southbound trading, Hong Kong pool's illiquidity reacts positively in the low regime and negatively in the high regime to one positive unit shock from the net buying volume, which implies a crowding-out effect on the stock's liquidity in the low regime and a stimulation effect on the stock's liquidity in the high regime. However, neither effect is significant. The one positive unit shock from the net buying volume also has opposite impacts on the CNY-HKD exchange rate and an identical positive impact on Hang Seng Index daily return in the two regimes, while none is significant.



Note: The Left is for northbound trading, and the right is for southbound trading. The accumulated impulse response is depicted at the 5% significance level.

**Figure 4** Accumulated impulse response of threshold VAR to the one positive unit shock from stock connect net buying volume

### 3.4 Robust Analysis

In robust analysis, we replace the Amihud illiquidity ratio with the turnover rate for both markets. Similar to calculating the Amihud illiquidity ratio for each pool's average state, the turnover rate is also averaged within the pool and marked as SH\_TO and HK\_TO, respectively. The descriptive summary of the turnover rate is presented in the supplementary. ADF and PP tests suggest SH\_TO and HK\_TO are stationary at the 1% significance level. The Pearson correlation indicates that the relationship between SH\_AQ and SH\_TO is insignificant. HK\_AQ significantly and negatively connects to HK\_TO.

Time domain pairwise conditional  $g$  causality suggests the southbound trading (HK\_NB) can predict the HSIR. The northbound trading (SH\_NB) can predict both SH\_TO and SSER. Moreover, there is feedback on SSER, i.e., Shanghai Index returns can predict SH\_NB and SH\_TO.

The spectral pairwise conditional  $g$ -causality analysis further captures the time-varying causal impacts from HK\_NB and HK\_TO to the FX rate, respectively. Meanwhile, the frequency

domain causal analysis also captures the dynamic causal connection from SH\_TO to FX rate and SH\_NB. All the time-varying causal connections are significant on the low-frequency level, i.e., middle or long-term.

The LR test supports a threshold in both north and southbound trading activities. The threshold value for the northbound trading is 10.4539, close to the threshold value of 10.1148 based on the Amihud illiquidity ratio. The threshold value for the southbound trading is the same based on the Amihud illiquidity ratio. Moreover, the observation ratios are very close to the results in Subsection 3.3.

The accumulated impulse response for the southbound trading indicates HSIR positively reacts to the one positive unit shock from HK\_NB in the low regime, which means a stimulation impact of the southbound trading on Hang Seng Index returns during the inactive southbound trading activities. And the impact is significant. Furthermore, the positive response of HK\_TO to a positive unit shock from the southbound trading in both low and high regimes means the stock connect trade improves the Hong Kong pool's liquidity, but only the responses in the first two periods are significant. For northbound trading, the response of SH\_TO to a positive unit shock of northbound trading is positive in both regimes but only becomes significant from the fourth period in the low regime. Therefore, the northbound trading improves the Shanghai pool's liquidity situation when the stock connect trade is in the low regime.

Considering the Amihud illiquidity ratio is in a reversed direction to the turnover rate in reflecting the stock's liquidity, the MVGC and threshold VAR results on both liquidity proxies are robust. The turnover rate might be more sensitive than the Amihud illiquidity ratio in time-varying causal analysis.

## 4 Discussion

In this paper, we discuss the time-varying connection of the stock-connect trading activity in the Shanghai and Hong Kong markets and compare the two systems. We collect daily data on net buying volume, index return, and FX rate. We calculate the Amihud illiquidity ratio of each stock connect portfolio. Later, we use the turnover rate replacing the Amihud illiquidity ratio for robust analysis.

In the time domain pairwise conditional g causal analysis, we find a significant unidirectional causal impact of Hong Kong stock connect net buying volume on Hang Seng Index return in the middle and long term at the low-frequency level. We also find significant bidirectional causal connections between Shanghai stock net buying volume and Shanghai Securities Exchange index return on all frequency levels. While the classic time domain approach does not reflect the causal impact of the Shanghai stock trading net buying volume to the Shanghai stock connects portfolio's illiquidity or the causal impact of the Shanghai stock connects portfolio's illiquidity to the Shanghai stock trading net buying volume. Both are significant at the low-frequency level. The time-varying causal connection implies the dynamic impacts of the stock connect trading activity.

In further examination of the time-varying connection, the LR test supports a significant threshold in separating the stock connect trading activity to active and inactive regimes for the two markets, respectively. The accumulated impulse response confirms that the northbound

trading net volume significantly stimulates the Shanghai portfolio's liquidity in the low regime for both liquidity proxies. Moreover, the turnover rate analysis indicates that southbound trading in the low regime significantly impacts the Hang Seng Index's daily returns.

The empirical results suggest that the stock connect trading activities benefit both markets, and the impacts are mainly in the inactive trading regime. The reason might relate to the investment behaviors looking for opportunities in low trading activity regime in both markets. Unlike speculators who may incline to short-term trading activities, experienced investors pursuing stable profits prefer concentrating on market index returns and liquidity in the long term. In an inactive regime, experienced investors pursuing long-term profits can lead the market direction. Hence the causality and impulse response are significant. In contrast, speculators and herding behaviors are likely active in the high regime, which might drive the market to an unclear prospect. Therefore, the high trading regime's causal connection and impulse response are insignificant. It requires structural information to examine the deep connectedness mechanism.

## 5 Conclusions

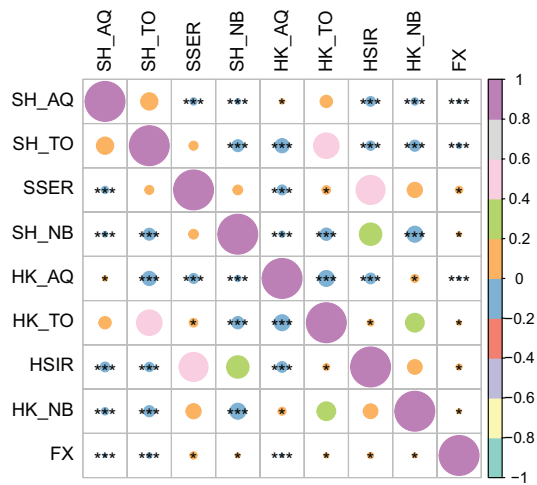
In this paper, we conduct an empirical analysis of the time-varying connection of the Shanghai-Hong Kong Stock Connect. We apply dynamic causal analysis and threshold VAR in studying the Shanghai and Hong Kong stock connect pools. The empirical results can help investors and regulators in their daily activities. Investors need to note the switching impacts of northbound and southbound trading activities on the two markets and take advantage of the positive connection on the market level for profits. Local regulators are suggested continuously monitor the dynamic changes in Shanghai stock's liquidity in different stock connect trading regimes since the liquidity status might be close to market risk. We propose that MVGC and TVAR are effective techniques in identifying time-varying interactions. As trading activities reflect investors' behaviors and beliefs, our study can extend to various areas of future research in liquidity risk, pricing, and volatility.

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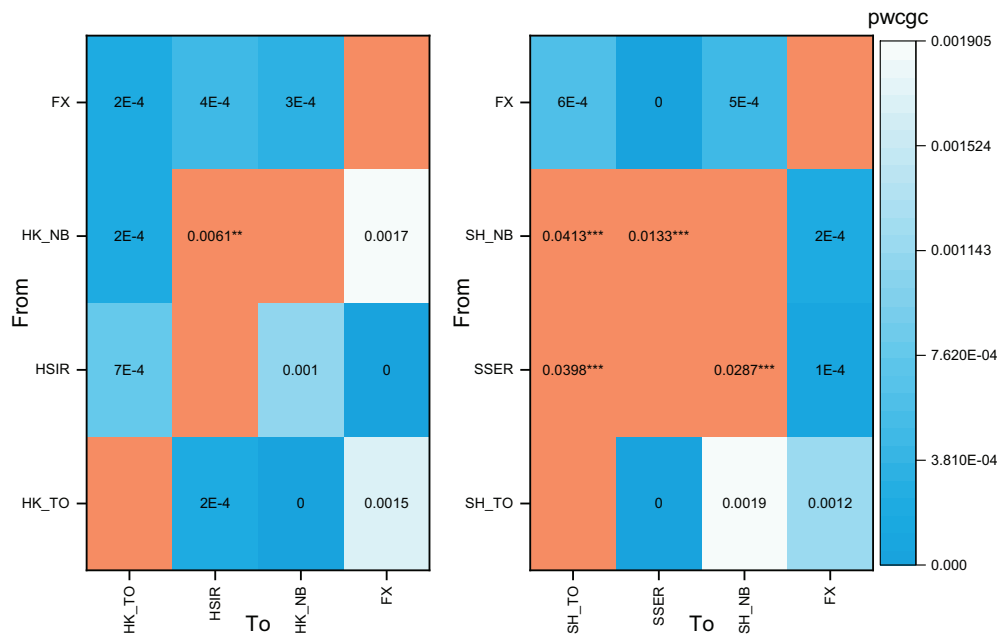
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Appendix  
Robust Analysis Details



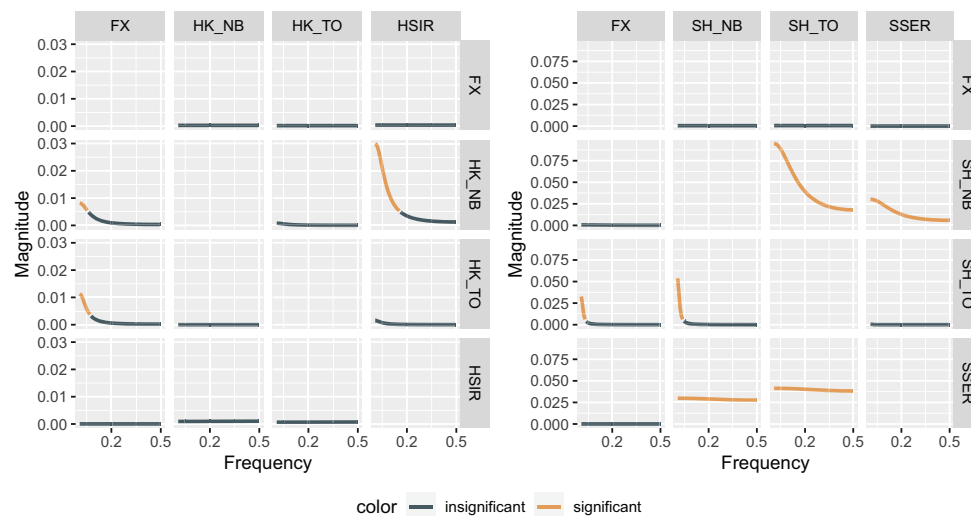
Note: \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed).

Figure A1 Pearson correlation



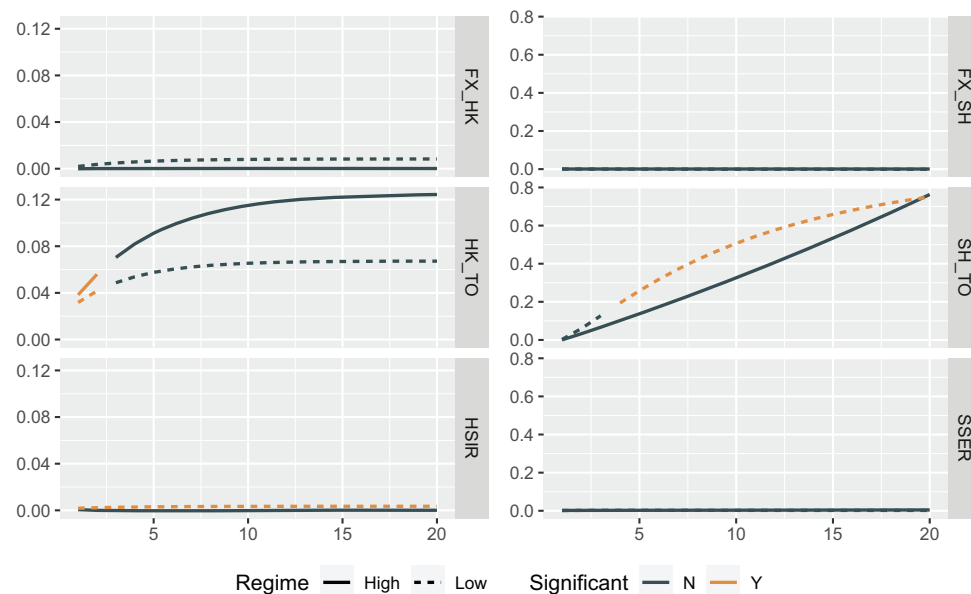
Note: Permutation test: 1000 times. \* Represents the 10% level of significance. \*\* Represents 5% level of significance. \*\*\* Represents 1% level of significance.

Figure A2 Time domain MVGC



Note: Permutation test: 1000 times. The rows indicate the origin of the causal connection, and the columns stand for the destination. The spectral pairwise conditional g causality is depicted at the 5% significance level.

**Figure A3** Frequency domain MVGC



Note: The Left is for northbound trading, and the right is for southbound trading. The accumulated impulse response is depicted at the 5% significance level.

**Figure A4** Accumulated impulse response of threshold VAR to the one positive unit shock from stock connect net buying volume

**Table A1** Descriptive summary of turnover data

Index	Min	Median	Mean	Max	Std Dev.	Skewness	Kurtosis	ADF	PP	JB	Observations
HK_TO	0.0909	0.3018	0.3297	1.6519	0.1353	3.8152	27.5261	-8.3287***	-10.4080***	22212***	809
SH_TO	0.5982	1.5372	1.9380	5.6819	1.0081	1.3053	3.8218	-6.5469***	-7.5926***	252.2000***	809

Data source: Oriental Choice finance termination.

Note: \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed). HK\_NB and SH\_NB are measured by hundreds of millions of CNY, and the FX (difference) is based on the CNY-HKD buy rate on the trading day.

**Table A2** LR test and threshold VAR estimation

	Threshold:	Regime L:		Regime H:		Threshold:	Regime L:		Regime H:	
	SH_NB	SH_NB $\leq$ 10.4539		SH_NB $>$ 10.4539		HK_NB	HK_NB $\leq$ 17.7982		HK_NB $>$ 17.7982	
Constant		1.9028 (1.2235)		9.6776 (2.5638)***		Contant	0.2226 (0.9675)		6.3896 (2.1253)**	
SH_NB(-1)		0.5124 (0.0489)***		0.1249 (0.0917)		HK_NB(-1)	0.7253 (0.0442)***		0.6594 (0.0797)***	
SH_TO(-1)		0.0264 (0.5783)		-1.2615 (1.0497)		HK_TO(-1)	5.3089 (2.7740)		-12.7302 (4.7573)	
SSEB(-1)		-259.0995 (35.6217)***		7.1719 (52.8326)		HSIR(-1)	-14.8257 (27.7273)		343.9653 (75.1084)***	
FX(-1)		-8.5642 (16.0191)		-264.4686 (442.1774)		FX(-1)	-4.8861 (9.8412)		-664.9363 (371.2763)	
AIC		-9628.3330				AIC	-13288.6100			
BIC		-9435.9070		Lag: -1		BIC	-13096.1800		Lag: -1	
SSR		153080.4000				SSR	57857.8200			
Observations		75.7%		24.3%		Observations	88.2%		11.8%	
Threshold LR value		81.0884				Threshold LR value	48.2789			
P value of LR test		0.0000				P value of LR test	0.0000			

Note: Values in the brackets are the standard errors. \*\*\*, \*\* and \* present the significance level of 1%, 5% and 10%, respectively (2-tailed).