Indices of Chinese Financial Market Liquidity: 2007-2017*

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Abstract

I use order book and transactions data from the Chinese financial market to calculate daily measures of bid-ask spreads, depth, and price impact(Amihud) for a 11-year sample period(2007-2017). From these measures, daily indices of Chinese financial market liquidity are constructed, reflecting the fact that the varying measures capture different aspects of market liquidity. Taking advantages of the liquidity index, I use VAR model to investigate the relationship between the change of stock liquidity and the change of bond liquidity, and find that change of stock liquidity is significantly negatively related to the future change of bond liquidity but not vice verse.

1 Introduction

Liquidity describes the degree to which an asset or security can be quickly bought or sold in the market without affecting the asset's price. In recent years, market liquidity has taken on special interest because of the 2007-09 financial crisis, because of post-crisis regulatory changes, and because of the increasing role of high-frequency trading firms (HFTs) in the market.

Despite its importance, no studies have used order book and transactions data to assess market liquidity over an extended period.[1] In the aspect of American financial market liquidity, some studies have examined liquidity using order book data over relatively short time spans (e.g., Fleming (2003), Engle, Fleming, Ghysels, and Nguyen (2012), and Adrian, Fleming, Shachar, and Vogt (2017)). Other studies, such as Goyenko and Ukhov (2009) and Goyenko,

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[1] I summarize liquidity indices used in the literature and highlight the advantages of our liquidity indices based on the comments from the course of Time Series Analysis.

Subrahmanyam, and Ukhov (2011), have used bid-ask spread data from the Center for Research in Security Prices (CRSP) which have at times been based on a maturity-dependent spread curve that does not change from day to day. In the aspect of Chinese financial market, few paper use the information of high-frequency transaction and order-book data to construct indicators of liquidity. In comparison, I assess Chinese financial market liquidity over a 11-year sample period, from 2007 to 2017, using order-book and transactions data from the CSMAR high-frequency database of GTA company.

2 Liquidity Indices

2.1 Liquidity Measures

The liquidity measures used frequently in the literature are price impact(Amihud), the relative bid-ask spreads and depth.

Amihud(2002) proposed an indicators to assess the price impact of transaction, which is defined as:

$$Amihud = \frac{1}{n}\sum_{i=1}^{n}\frac{|r_i|}{Volume_i}$$

The relative bid-ask spread is defined as:

$$Rpd = \frac{S_1 - B_1}{(S_1 + B_1)/2} * 100$$

And the depth is defined as:

$$Depth = \frac{\sum_{i=1}^{5}(S_i * SV_i + B_i * BV_i)}{2}$$

To summarize the information of Amihud, Rpd and Depth, I calculated the liquidity index by the following procedure: (1) I calculated Amihud, Rpd and Depth of every asset on every trading day using high-frequency data during 9:45-11:30 to 13:00-14:45(Frequency: SHSE 5s and SSE 3s), excluding the time point when the price reached the 10 percent upper bound or lower bound[2]. (2) I standardized these 3 time series of each asset, took the average of 3 indicators and attained daily liquidity index of each asset. (3) I took the average of the liquidity index in a specific category, such as stock, bond, fund and so on, and attained the liquidity index of a category. Higher value of liquidity index indicates poorer liquidity in the category.

[2]In these cases, the meaning of these indicators are changed because of Chinese specific market micro-structure.

2.2 Time Plot

I plot the liquidity index of stock, bond, fund and currency. The stock liquidity was poorest during the financial crisis in 2008, and it was most adequate in June, 2015. The stock liquidity was more volatile than the bond liquidity. The liquidity indices contain a lot of stories in Chinese financial market.

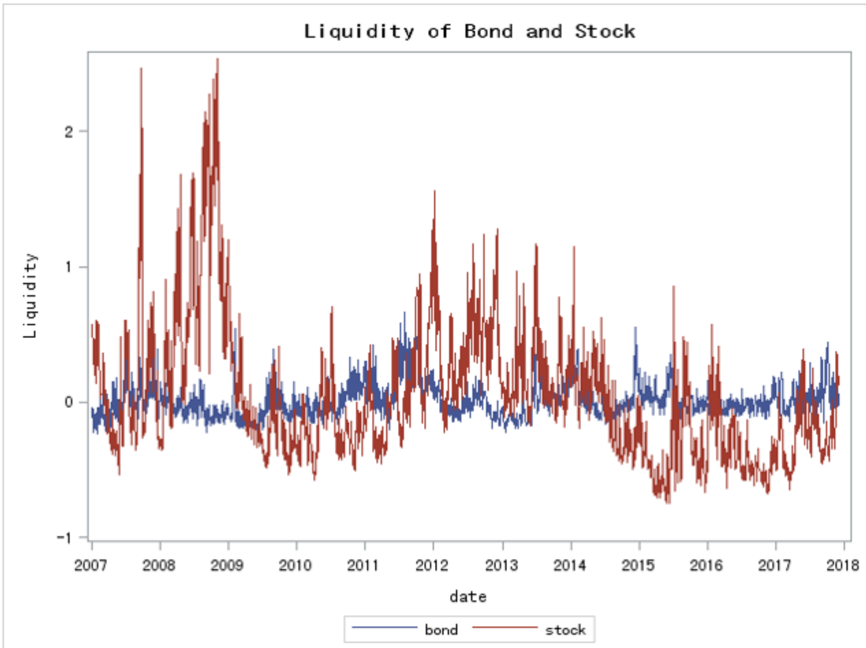

Figure1: Liquidity of Bond and Stock

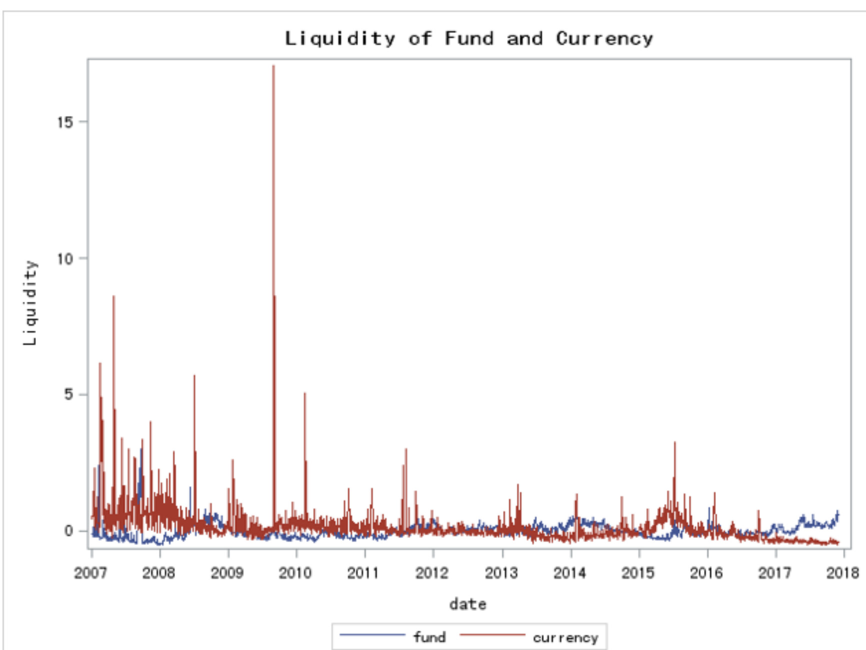

Figure2: Liquidity of Fund and Currency

In this project, I focus on the depth of stock and bond market and investigate the interdependence of them. At first, I sum up the depth of all stocks(or bonds) on every trading date. Then I take the average of the depth every month and attain a monthly depth index.

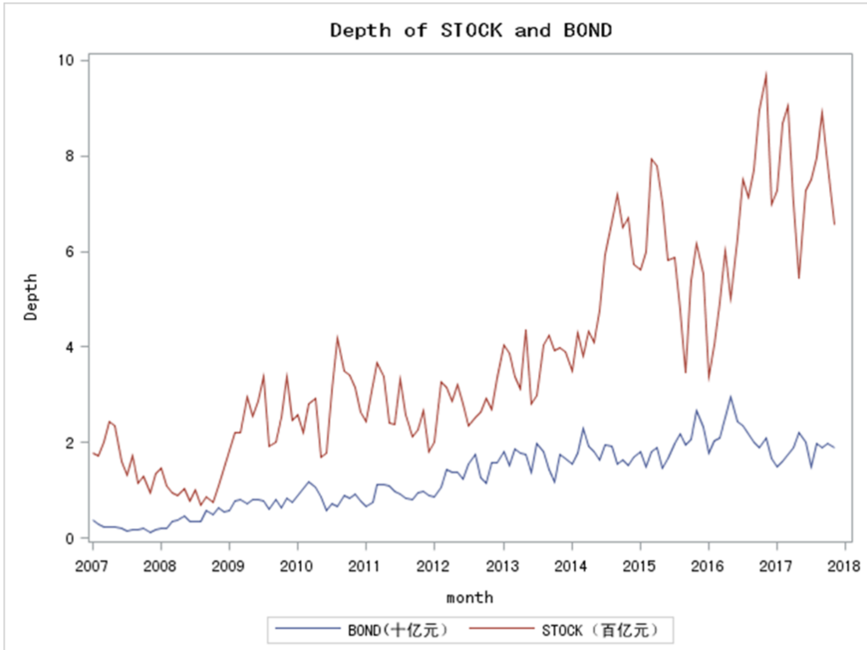

Figure3: Depth of Stock and Bond

From Figure 3, I see that the depth of stock and bond are exponentially growing, therefore I take log of them and plot the new series in Figure 4.

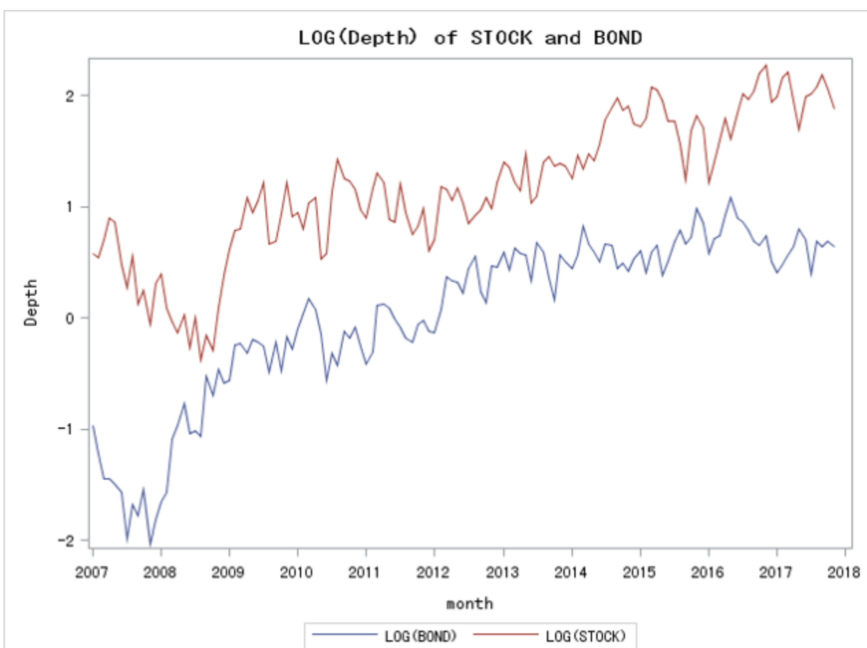

Figure4: Log(Depth) of Stock and Bond

There are evident trend in the series of log-depth of stock and bond, therefore, I take first order difference of them, the new series are plotted in Figure 5.

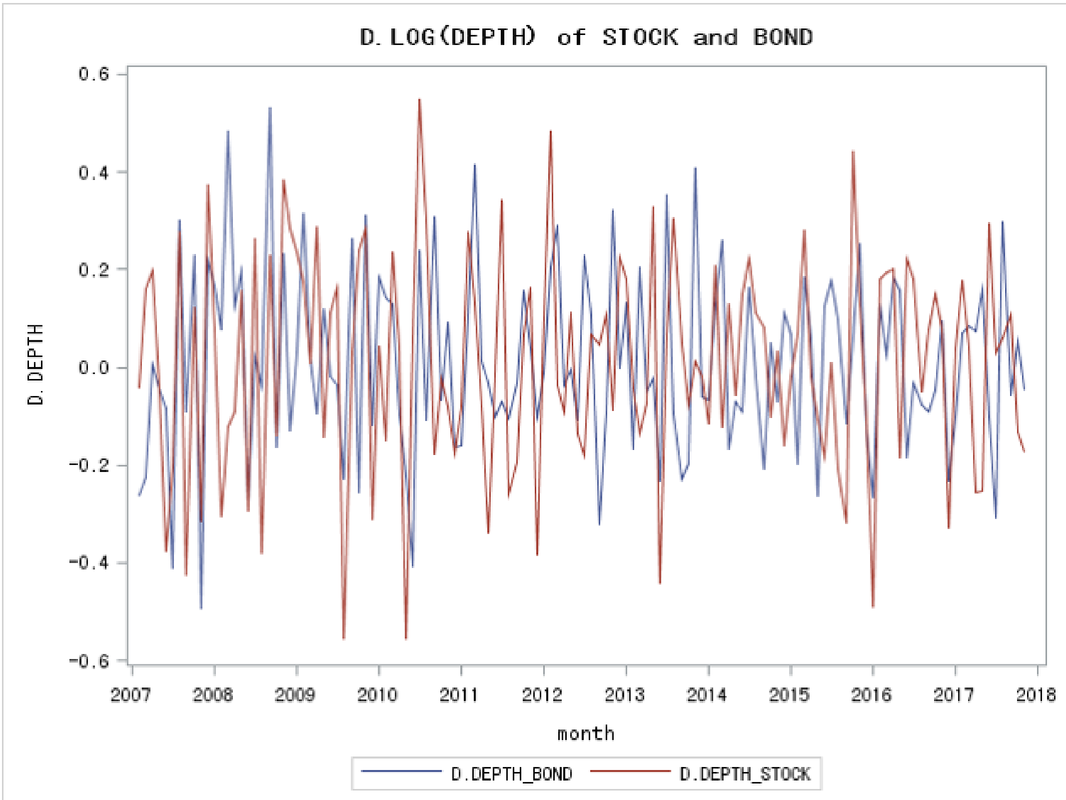

Figure5: Difference of Log(Depth) of Stock and Bond

The differenced series seem like common stationary time series. I will do stationary test to verify whether it is stationary.

2.3 Descriptive Statistics

Table 1 shows the descriptive statistics of the log depth of stock and bond as well as the first order difference of them. The mean of differenced log-depth of stock is 0.01, which indicates that the depth of stock grows 1 percent per month on average. Similarly, the depth of bond grows 1.2 percent per month on average. The skewness of differenced log-depth of stock is -0.27 and the kurtosis is 2.81, which are closed to the normal distribution. It is similar for differenced log-depth of bond.

depth_stock

	Percentiles	Smallest		
1%	-.292925	-.3832872		
5%	-.0384608	-.292925		
10%	.2763265	-.265176	Obs	131
25%	.7982254	-.1533395	Sum of Wgt.	131
50%	1.184466		Mean	1.165314
		Largest	Std. Dev.	.6294317
75%	1.707828	2.18636		
90%	1.984369	2.193272	Variance	.3961842
95%	2.071902	2.203808	Skewness	-.3639366
99%	2.203808	2.270593	Kurtosis	2.564376

depth_bond

	Percentiles	Smallest		
1%	-1.983233	-2.036422		
5%	-1.574224	-1.983233		
10%	-1.090521	-1.817338	Obs	131
25%	-.3069682	-1.772717	Sum of Wgt.	131
50%	.2330717		Mean	.0208714
		Largest	Std. Dev.	.741617
75%	.5913405	.8931582		
90%	.7127285	.9224525	Variance	.5499958
95%	.8284864	.9809601	Skewness	-1.049259
99%	.9809601	1.078483	Kurtosis	3.281611

D.depth_stock

	Percentiles	Smallest		
1%	-.5554998	-.5562626		
5%	-.380578	-.5554998		
10%	-.3079603	-.4882793	Obs	130
25%	-.1345881	-.4414109	Sum of Wgt.	130
50%	.0372038		Mean	.0100342
		Largest	Std. Dev.	.2201127
75%	.1744904	.3848768		
90%	.2829245	.4419091	Variance	.0484496
95%	.3275394	.4846561	Skewness	-.2678368
99%	.4846561	.5488455	Kurtosis	2.811506

D.depth_bond

	Percentiles	Smallest		
1%	-.4106325	-.4927444		
5%	-.2645386	-.4106325		
10%	-.2283534	-.4086858	Obs	130
25%	-.1021009	-.3211457	Sum of Wgt.	130
50%	-.0145745		Mean	.012363
		Largest	Std. Dev.	.1906308
75%	.141767	.4081448		
90%	.2599746	.4144877	Variance	.0363401
95%	.3128963	.4837029	Skewness	.1370155
99%	.4837029	.5313284	Kurtosis	2.895268

Table1: Descriptive Statistics

2.4 Stationarity Test

Table 2 shows the results of the KPSS test for the differenced series. I cannot reject the null hypothesis "the serie is stationary" at the significance level of 10%. I also do ADF, PP and DFGLS test, and "there exists unit root" is rejected at 1% level. Therefore, I accept that the differenced series are stationary. Figure 6 shows the ACF and PACF of them.

Critical values for H0: D.depth_stock is level stationary

10%: 0.347   5% : 0.463   2.5%: 0.574   1% : 0.739

Lag order	Test statistic
0	.0196
1	.0223
2	.0289
3	.0371
4	.0369
5	.0379
6	.0435
7	.0446
8	.0457
9	.0452
10	.0502
11	.0511
12	.0507

Critical values for H0: D.depth_bond is level stationary

10%: 0.347   5% : 0.463   2.5%: 0.574   1% : 0.739

Lag order	Test statistic
0	.04
1	.0507
2	.0566
3	.0715
4	.0727
5	.0768
6	.0796
7	.0832
8	.0799
9	.0807
10	.0853
11	.0906
12	.0895

Table2: KPSS Test

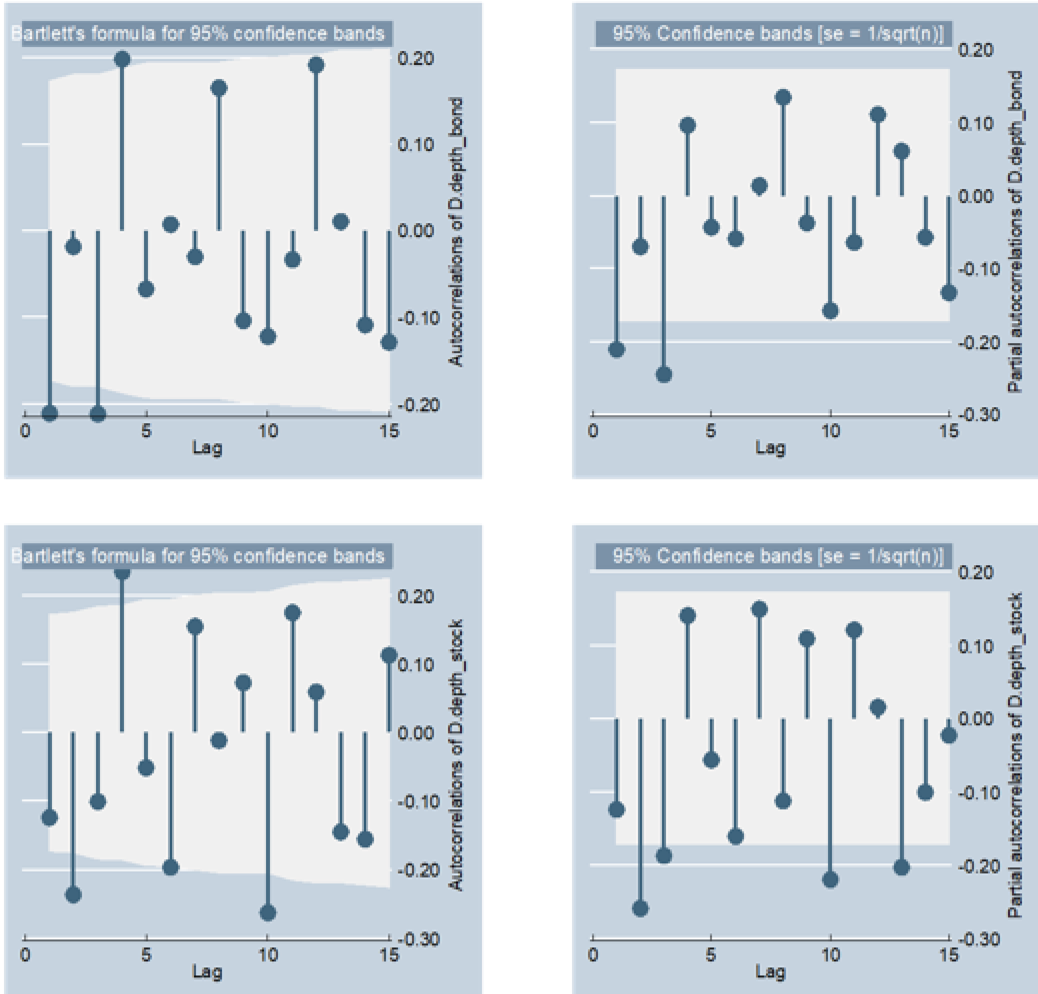

Figure6: ACF and PACF

3 Model Specification

In order to investigate the relationship of the change of stock liquidity and the change of bond liquidity, I use the VAR model and put them in a system to estimate and predict. Based on the minimum of FPE and AIC, I choose 3 as the number of lags in the VAR model. The estimation period is 2007.02-2017.06 and I use the last 5 observations to do out of sample forecast.

```
Selection-order criteria
Sample:  12 - 126                          Number of obs      =       115
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	48.6584				.001523	-.81145	-.792074*	-.763712*
1	52.0334	6.75	4	0.150	.001539	-.800581	-.742451	-.657367
2	58.7919	13.517	4	0.009	.001467	-.848555	-.751672	-.609865
3	65.3487	13.114	4	0.011	.001404*	-.893021*	-.757385	-.558856
4	66.9743	3.2511	4	0.517	.001464	-.851726	-.677337	-.422085
5	68.1173	2.2861	4	0.683	.001539	-.80204	-.588897	-.276923
6	72.5298	8.825	4	0.066	.001529	-.809214	-.557319	-.188621
7	76.5497	8.0398	4	0.090	.00153	-.80956	-.518911	-.093491
8	80.2559	7.4124	4	0.116	.00154	-.804451	-.475048	.007095
9	84.5777	8.6436	4	0.071	.001534	-.810047	-.441892	.096974
10	92.5244	15.893*	4	0.003	.001436	-.878684	-.471776	.123813

```
Endogenous:  D.depth_stock D.depth_bond
 Exogenous:  _cons
```

Table3: Selection-order Criteria

3.1 Model Estimation

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_depth_stock						
depth_stock						
LD.	-.1466117	.0928393	-1.58	0.114	-.3285735	.03535
L2D.	-.3216356	.0899196	-3.58	0.000	-.4978747	-.1453964
L3D.	-.1232432	.092674	-1.33	0.184	-.3048809	.0583945
depth_bond						
LD.	-.2194122	.1060714	-2.07	0.039	-.4273084	-.0115161
L2D.	-.0183994	.108026	-0.17	0.865	-.2301265	.1933278
L3D.	-.1839774	.1060125	-1.74	0.083	-.391758	.0238033
_cons	.022147	.0188464	1.18	0.240	-.0147914	.0590853
D_depth_bond						
depth_stock						
LD.	-.0343418	.0805674	-0.43	0.670	-.192251	.1235674
L2D.	.002872	.0780336	0.04	0.971	-.1500711	.155815
L3D.	-.0254277	.0804239	-0.32	0.752	-.1830557	.1322003
depth_bond						
LD.	-.2408943	.0920504	-2.62	0.009	-.4213097	-.0604788
L2D.	-.1257548	.0937466	-1.34	0.180	-.3094948	.0579853
L3D.	-.2410183	.0919992	-2.62	0.009	-.4213335	-.0607031
_cons	.0275385	.0163552	1.68	0.092	-.0045172	.0595942

Table4: VAR Model Estimation Result

Most coefficents of the lag-term is negative, and the change of stock liquidity is significantly negatively related to the future change of bond liquidity but not vice verse. In addition, I do Granger causality test and find that "bond" is the Granger cause of "stock" at significance level of 10% but not vice verse.

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
D_depth_stock	D.depth_bond	6.9169	3	0.075
D_depth_stock	ALL	6.9169	3	0.075
D_depth_bond	D.depth_stock	.23112	3	0.972
D_depth_bond	ALL	.23112	3	0.972

Table5: Granger Causality Wald Tests

4 Model Diagnostic

4.1 VAR Model Stationarity Test

The roots of the equation $|\lambda^3 I_2 - \lambda^2\Phi_1 - \lambda\Phi_2 - \Phi_3| = 0$ are all inside the unit root, therefore the VAR system is stationary.

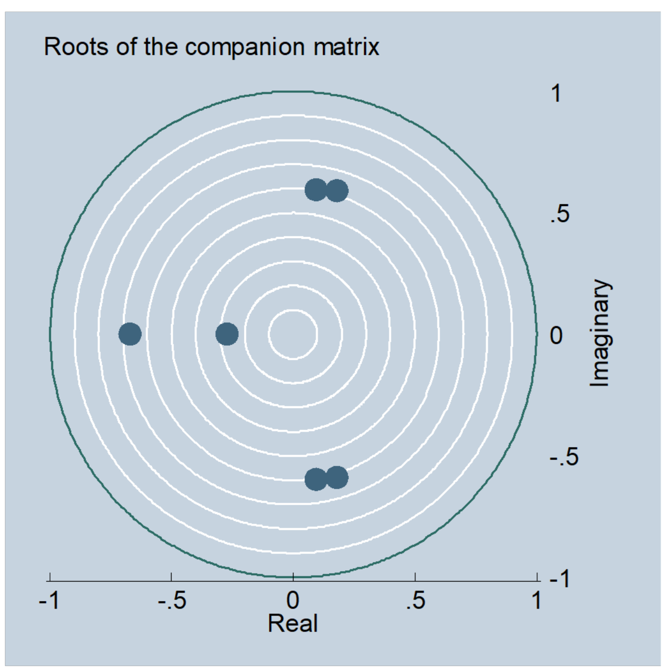

Figure7: VAR System Stationarity

4.2 LM Test and Normality Test of the Residuals

The LM test cannot reject the null hypothesis "there is no autocorrelation in the residuals" at significance level of 10%, both for lag order of 1 and 2, therefore, I accept that the residual serie is white noise. In addition, the Jarque-Bera test cannot reject the null hypothesis "the residuals follow Normal distribution" at significance level of 10%, therefore I accept that the residuals follow Normal distribution. These 2 results indicate that the model specification is plausible.

Lagrange-multiplier test

lag	chi2	df	Prob > chi2
1	5.3773	4	0.25073
2	3.4446	4	0.48636

H0: no autocorrelation at lag order

Table6: LM test of the Residuals

Jarque-Bera test

Equation	chi2	df	Prob > chi2
D_depth_stock	3.757	2	0.15281
D_depth_bond	1.093	2	0.57905
ALL	4.850	4	0.30306

Skewness test

Equation	Skewness	chi2	df	Prob > chi2
D_depth_stock	-.42024	3.591	1	0.05810
D_depth_bond	.17047	0.591	1	0.44208
ALL		4.182	2	0.12358

Kurtosis test

Equation	Kurtosis	chi2	df	Prob > chi2
D_depth_stock	2.8192	0.166	1	0.68351
D_depth_bond	3.3142	0.502	1	0.47869
ALL		0.668	2	0.71604

Table7: JB test of the Residuals

5 Forecast

I forecast 5 values of the differenced log-depth of stock(or bond) and compare with true values. From Figure 8, the forecast of stock is more accurate than bond. Moveover, all of the true values fall in the 95% confidence interval.

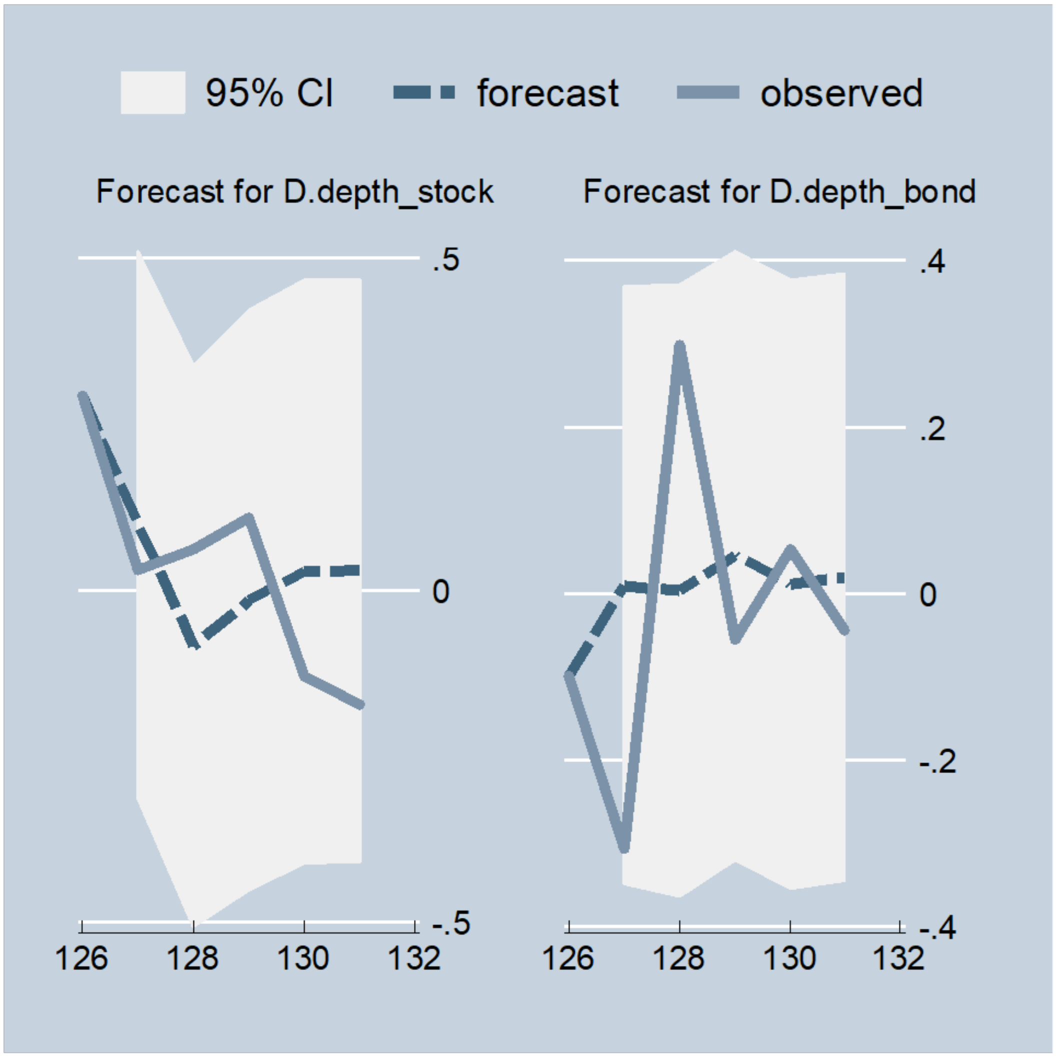

Figure8: Forecast

6 Conclusion

Using high-frequency order book and transactions data from the Chinese financial market in 2007-2017, I construct liquidity indices capturing the information of price impact, bid-ask spread and depth. Moreover, I use VAR model to investigate the relationship between the change of stock liquidity and the change of bond liquidity, and find that change of stock liquidity is significantly negatively related to the future change of bond liquidity but not vice verse. The future work includes studying the pattern of liquidity index higher frequency and investigating the interdependence of other financial markets liquidity, such as the Futures and options market.

7 References

Tobias Adrian, Michael Fleming, Erik Vogt, *An Index of Treasury Market Liquidity: 1991-2017*, Federal Reserve Bank of New York Staff Reports, 2017