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The Empirical Analysis of Relationship between Chinese Stock Market and Macroeconomic Indicators

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Abstract: In this paper, we analyze the potential long-term relationship between Chinese Stock market and Macroeconomic indicators through Johansen Method and Engle-Granger Two-Step Approach by taking the monthly data since the first month of 2011 to 2019. Also, we apply VAR model into investigating the granger-causality and impulse-response results between Chinese stock performance and Macroeconomies. Through comparing the pseudo-forecast results of cointegration method by Engle-Granger and VAR model, we find that the cointegration model of Engle-Granger yields the best forecasts. Lastly, we test the volatility of Chinese stock market through GARCH families and find that TGARCH is the most appropriate model by evaluating the minimum AIC among applicant GARCH models.

1. Introduction

China has experienced a rapid economic boost in the past thirty years, but its relatively young stock market starting at Dec. 1990 is still developing to be more efficient [1]. Although macroeconomic polies are generally aimed to stabilize economic growth [2], the performance of stock market is commonly accepted as a leading indicator of economy because it reflects individual's expectation and firm's preparations to future policy change [3]. Therefore, we hope this paper could provide a solid fundament for further research, and this paper could untwist a common puzzle on the relationship between China's stock market performance and macroeconomic propensity, even though stock market is particularly mysterious [4].

With the quick rally of Chinese stock market during the first quarter of 2019, many investors are curious about the relationship between Chinese stock market and its macroeconomic performance, since this round of bully stock market seems unsupported by the weakening Chinese economy [5]. Reviewing the bully Chinese stock market in 2007, many investors argue for the effectiveness of applying momentum analysis into Chinese stock market [6]; but few researchers comprehensively analyze the correlation between the performance of stock and macro-economy, which becomes one of the important motivations for us to research this topic. Considering the mismatch between quarterly updating economic indicators, such as GDP growth, and almost daily changing stock price, we select those monthly posted macroeconomic indicators for our analysis; for example, Macroeconomic Propensity Index (MPI) and Consumer Confidence Index (CCI). Also, we decide to use the monthly closed price of Shanghai Exchange Composite Index (SSEC 000001.SS) as shown in Figure 1.

Figure 1: SSEC Index closed price since Jan. 2011 to Jan. 2019

This paper has three objectives to detailed analyze and interpret the relationship between China's stock market and macroeconomic performance. The first objective is to find the potential cointegration and build VEC model between the performance of SSEC and macroeconomic indicators for pseudo-forecasting. The second objective is to build VAR model for finding granger-causality and forecast. Then, the third objective is to test the volatility of SSEC through GARCH families and find the most appropriate GARCH model by evaluating the minimum AIC for the future study of Chinese stock market. Also, we will compare the forecast results from cointegration model and VAR model to find out the best forecast.

2. Data

Before introducing methodologies and test results, we first observe the inconsistent frequency of daily changing stock market with quarterly posting economic indicators. Hence, we compromise to use monthly data for our analysis not only because we must match the frequency of variables, but also due to the unattainable daily economic data. Therefore, we select SSEC Index closed price as the measurement of overall Chinese stock market from Jan. 2011 to Jan. 2019, because this decade is viewed as a recovery period of global economy after 2008 crisis [7]. Moreover, we researched 16 macroeconomics indicators, such as M2 stock and consumer confidence index; however, after a quick test of stationarity for cointegration by Dicky Fuller Test [8], we delete 10 series from our data set. There are 6 macroeconomic indicators left servicing as variables: average exchange rate of RMBUSD (AVGRMBUSD), Chinese official reserve asset (REVAST), Chinese Macroeconomic Propensity Index (MPI), consumer price index (CPI), consumer confidence index (CCI), and producer price index (PPI).

Many Asian countries use the official asset reserve management as an important macroeconomic monetary toolkit [9]. The government usually treats the official asset reserve as a sovereign saving in order to stabilize the country's economy when the government introduces relatively aggressive policy. For example, Chinese government introduces "The Economic Reform on Supply Side" since 2015 [10]; essentially, the main purpose of this policy is to transform the major driven-force of Chinese

GDP growth from export-driven to consumption-driven through tightening the supply and boosting the corporate revenues by closing many upstream companies to improve the household income and enhance the human capital. However, it is a huge economic reform which needs funds to be implemented, so the government would use the official asset reserve. Therefore, the empirical observation is that official asset reserve is a leading indicator to the prosperity of a country's economy. The series of stock of Chinese official asset reserve plots as Figure 2.

Figure 2: Chinese official asset reserve

We realize that those macroeconomic indicators accurately reflect Chinese macroeconomy in the past decade influenced by "Supply Side Reform" on 2015: Chinese official asset reserve drops significantly since 2015 for supporting the domestic economic reform, exchange rate of RMBUSD rises for weakening RMB to create a favorable condition of exporting, PPI starts rising and CPI plummets significantly since 2015 due to the economic reform, CCI improves as the policy aims to achieve, but MPI keeps below 100 in the past decade meaning that Chinese macroeconomy is undermined by this economical structural change but might recover in future.

3. Cointegration

In this paper, we analyze the long-term relationship between SSEC and Chinese macroeconomic indicators through building cointegrated equation by two applicant methodologies: 1) the Johansen cointegration test [11], and 2) the Engle-Granger Two-step approach [12]. However, before constructing a cointegration model to analyze the relationship between Chinese stock price and macroeconomic indicators, we need to confirm two conditions: 1) all series of variables themselves are nonstationary, because cointegration only exists among nonstationary series, and 2) all series of variables must have the same order of integration.

3.1. Stationarity Test

To check the stationarity, we apply unit-root tests of Dickey Fuller test [8] and the Phillips-Peron test [13] with trend to each series of variable. Also, Dickey Fuller test and Phillips-Peron test are both designed to have the same testing hypotheses:

Ho: Presence of unit root in the testing series, so the series is nonstationary

Ha: Unit root does not exist in the testing series, so the series is stationary

By applying the Stata command: dfuller, trend regress and pperron, trend regress, we can conduct Dicky Fuller test and Phillips-Peron test to each variable in Stata. Dickey Fuller test results are shown in Table 1, and Phillips-Peron test results are cited in Table 2.

Table 1: Dickey Fuller Test of stationarity for each series

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
SSEC	-2.168	-4.049	-3.454	-3.152
MPI	-1.525	-4.077	-3.467	-3.16
AVGRMBUSD	-1.941	-4.049	-3.454	-3.152
REVAST	-2.936	-4.214	-3.528	-3.197
CPI	-2.182	-4.051	-3.455	-3.153
CCI	-2.473	-4.049	-3.454	-3.152
PPI	-0.187	-4.051	-3.455	-3.153

Table 2: Philips-Peron Test of stationarity for each series

		Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
SSEC	Z(rho)	-10.918	-27.264	-20.628	-17.444
	Z(t)	-2.425	-4.049	-3.454	-3.152
MPI	Z(rho)	-6.561	-26.822	-20.394	-17.262
	Z(t)	-1.817	-4.077	-3.467	-3.16
AVGRMBUSD	Z(rho)	-7.476	-27.264	-20.628	-17.444
	Z(t)	-2.2	-4.049	-3.454	-3.152
REVAST	Z(rho)	-5.245	-24.804	-19.268	-16.464
	Z(t)	-2.729	-4.214	-3.528	-3.197
CPI	Z(rho)	-7.542	-27.23	-20.61	-17.43
	Z(t)	-2.145	-4.051	-3.455	-3.153
CCI	Z(rho)	-11.146	-27.264	-20.628	-17.444
	Z(t)	-2.318	-4.049	-3.454	-3.152
PPI	Z(rho)	-1.044	-27.23	-20.61	-17.43
	Z(t)	-0.524	-4.051	-3.455	-3.153

We can observe from both Dicky Fuller test results and Phillips-Peron test outputs that all series of variables are nonstationary if we believe in 10% critical value, because the test statistics are all smaller than 10% critical value. It means we fail to reject the null hypothesis that the unit root exists, and we can confirm that each series is nonstationary and good to test the order of integration.

Table 3: Dickey Fuller Test of stationarity for each $I(1)$ series

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
D.SSEC	-7.232	-4.051	-3.455	-3.153
D.MPI	-7.7	-4.08	-3.468	-3.161
D.AVGRMBUSD	-5.487	-4.051	-3.455	-3.153
D.REVAST	-3.882	-4.224	-3.532	-3.199
D.CPI	-10.815	-4.053	-3.456	-3.154
D.CCI	-11.531	-4.051	-3.455	-3.153
D.PPI	-7.257	-4.053	-3.456	-3.154

Similarly, we can generate the first-differencing series by using Stata command: D., and utilize the stationarity tests again to all first-differenced series. Dickey Fuller test results are referred in Table 3, and Phillips-Peron test results are presented in Table 4. From the results of both tests, we can state that all series are stationary in first-differencing. Therefore, all series are good to test the cointegration relationship.

Table 4: Philips-Peron Test of stationarity for each $I(1)$ series

		Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
D.SSEC	Z(rho)	-64.433	-27.23	-20.61	-17.43
	Z(t)	-7.085	-4.051	-3.455	-3.153
D.MPI	Z(rho)	-73.553	-26.788	-20.376	-17.248
	Z(t)	-7.76	-4.08	-3.468	-3.161
D.AVGRMBUSD	Z(rho)	-47.657	-27.23	-20.61	-17.43
	Z(t)	-5.425	-4.051	-3.455	-3.153
D.REVAST	Z(rho)	-21.908	-24.676	-19.192	-16.416
	Z(t)	-3.796	-4.224	-3.532	-3.199
D.CPI	Z(rho)	-106.67	-27.196	-20.592	-17.416
	Z(t)	-10.8	-4.053	-3.456	-3.154
D.CCI	Z(rho)	-107.426	-27.23	-20.61	-17.43
	Z(t)	-11.658	-4.051	-3.455	-3.153
D.PPI	Z(rho)	-71.716	-27.196	-20.592	-17.416
	Z(t)	-7.313	-4.053	-3.456	-3.154

3.2. Johansen Method and Vecm with Forecast

From previous section, we have confirmed that all series of variables themselves are nonstationary, but are all I(1) processes. Therefore, we can perform Johansen methodology by using Stata command: varsoc for identifying the number of lags, vecrank for determining the number of ranks, and vec for constructing vector error correction model (VECM).

Hence, we can state that the number of lags to be applied into VEC model is 2 and the number of ranks is 5. To interpret the results of our VEC model, we can write down the following equation:

$$\begin{aligned} D.SSEC_t = {} & 0.0002796 - 1.6767 * EC_{1,t-1} - 49.7209 * EC_{2,t-1} + 1505.273 * EC_{3,t-1} \\ & +0.2614 * EC_{4,t-1} + 44.8783 * EC_{5,t-1} + 0.6202 * D.SSEC_{t-1} - 86.884 * D.MPI_{t-1} \\ & -691.1781 * D.AVGRMBUSD_{t-1} + 0.1627 * D.REVAST_{t-1} + 33.45 * D.CPI_{t-1} \\ & -4.3383 * D.CCI_{t-1} + 154.7417 * D.PPI_{t-1} \end{aligned} \tag{1}$$

We highlight the significant coefficients and we can observe that error correction terms of 1,3,4,5 are all significant, D.SSECt-1 is significant, and D.PPIt-1 is significant. Then, based on the VEC model, we can state that other than the error correction terms, the differences of SSEC and PPI in the last period have significant and positive relationship to the first-difference of SSEC at this period. Since we only focus on the relationship between SSEC and macroeconomic indicators, we can state that a positive shock to PPI may contribute to a significantly positive push on SSEC based on our model.

Also, by using Stata command: fcast, we can plot the pseudo-forecast results nested on our VEC model. The pseudo-forecast results starting from Jan. 2017 do not accurately forecast SSEC, nor do other macroeconomic indicators. For figuring out the reasons of previous inaccurate forecast, we test the stability of our VEC model by Stata Command: vecstable. We find that our VEC model fails the stability test. Hence, we decide to move our attention to the Engle-Granger Two-Step Approach.

3.3. Engle-Granger Two-Step Method with Forecast

Two-step methodology is a classical approach for testing cointegration [12]. The Engle-Granger Two-Step Approach is essentially an OLS regression but needs to fulfill three conditions for constructing a cointegration model: 1) series themselves are nonstationary, 2) all series have the same order of integration, and more importantly, 3) the residual sequence does not contain a stochastic trend; in other words, the OLS residual is stationary. We have confirmed condition 1) and 2) in the previous section, so we just need to confirm the OLS residual's stationarity now. And we find OLS coefficients are the cointegration coefficients. In fact, we can use Stata command: egranger to complete the Engle-Granger Two-Step Approach.

We believe in 10% critical value, and the test statistic falls into the rejection region; so, we can reject the null hypothesis of nonstationary and state that the residual is stationary meaning that it does not have stochastic trend. Then, based on the OLS results, we can write down our cointegrated equation as following:

$$SSEC = -11083 - 23.3115 * MPI + 666.2121 * AVGRMBUSD + 0.1551 * REVAST + 16.2073 * CPI + 5.3753 * CCI + 46.2930 * PPI \tag{2}$$

We highlight the significant coefficients and find that PPI becomes significant variable to SSEC again and official asset reserve becomes significant. Therefore, both PPI and official asset reserve positively relate to the Chinese stock price as suggested by our VEC model; and this result is along with empirical observations.

Next, we do the pseudo-forecast based on our OLS cointegrated model, and the results are presented on Figure 3. Notice that due to missing values in MPI and REVAST, we can only forecast from June 2015 to Dec. 2017. However, the forecast results based on the cointegrated equation by Engle-Granger Approach are close to the true observation.

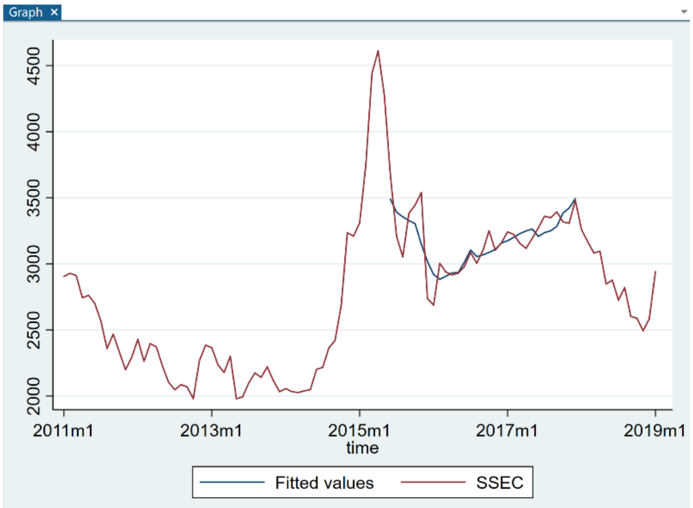

Figure 3: Forecast results of Engle-Granger Two-Step Approach

4. VAR Application

Although the cointegrated model suggested by Engle-Granger Two-Step Approach works, we still want to construct VAR model for comparing forecast results. The main difference of applying VAR and VEC model is that VAR model needs to apply all stationary series; otherwise, VAR model would yield spurious results [14]. We have determined the number of lags is 2 from varsoc command in Section 3.2; so, let's construct our VAR model by using Stata command: var.

Again, we aim to analyze the relationship between Chinese stock price and macroeconomic indicators, so we only cite the equation that the first-differenced SSEC closed price is on the left-hand side and other macroeconomic indicators are on the right-hand side. From the result, we can define our VAR equation with 2 lags as following:

$$\begin{gathered} DSSEC_t = 32.1905 - 0.3891 * D.SSEC_{t-1} - 0.6278 * D.SSEC_{t-2} - 59.8562 * D.MPI_{t-1} \\ -11.6558 * D.MPI_{t-2} + 717.1116 * D.AVGRMBUSD_{t-1} + 536.4268 * D.AVGRMBUSD_{t-2} \\ +0.4692 * D.REVAST_{t-1} - 0.1840 * D.REVAST_{t-2} + 41.2183 * D.CPI_{t-1} \\ -9.8998 * D.CPI_{t-2} - 9.6676 * D.CCI_{t-1} + 99.8514 * D.PPI_{t-1} - 70.5685 * D.PPI_{t-2} \quad (3) \end{gathered}$$

From VAR results, we spot that official asset reserve and PPI are both positive and significant on lag 1, which is consistent with our findings from cointegration model. Furthermore, CPI and past 2 lags' differencing of SSEC seems to be significant in VAR model. Hamilton states a derivation of conditions for VAR processes in his book "The Mystic Economist" [15], and we can use Stata command: varstable, graph for plotting the VAR stability test as displayed on Figure 4.

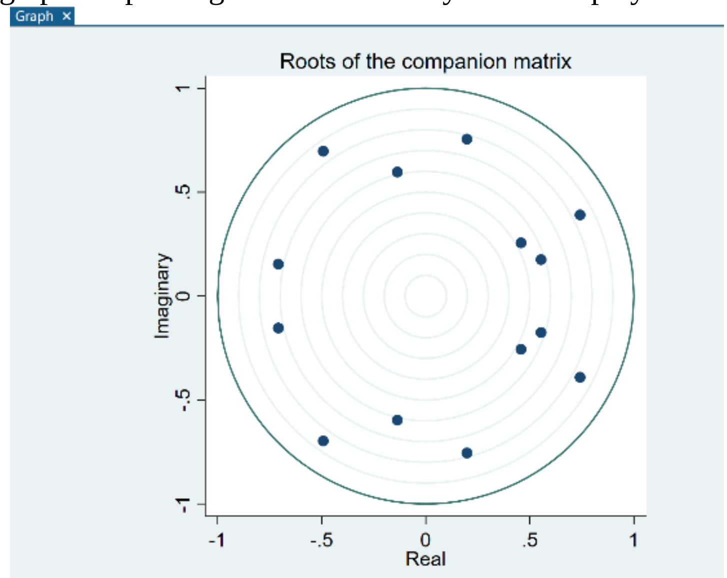

Figure 4: Passed VAR stability test

Since our VAR model passes stability test, so we can have certain level of confidence in applying this model; but we should not ignore that the design of our VAR model includes 7 equations since we introduce 7 variables. Therefore, instead of writing down each equation, we use Stata command: varwle for telling us whether any variables are helpful in explaining the current-period value of SSEC at specified lag in our VAR equation. We can observe that if we believe in 10% critical value, except CPI at lag 1, all variables' coefficients, at least some of them, are significant at lag 1 and 2.

Before leaving VAR model, we still need to complete 3 goals: 1) find the "granger causality" by using Stata command: vargranger, which implies some actual economic process happening between variables; 2) plot the IRF based on VAR model by Stata command: irf; and 3) output forecast results based on our VAR model through Stata command: fcast.

We can notice that if we impulse a positive shock to the first-differenced exchange rate of RMBUSD, the first-differenced SSEC will response accordingly; but imposing shocks on first-differenced MPI, CPI, and PPI does not receive noticeable response of stock price. It might be due to the presence of contemporaneous effects between variables. From Figure 5, we can compare the pseudo-forecast results nested on our VAR model with true observations to forecast results of VEC models: the forecast results from our VAR model performs better than VEC model of Johansen method but weaker than VEC model based on Engle-granger Approach.

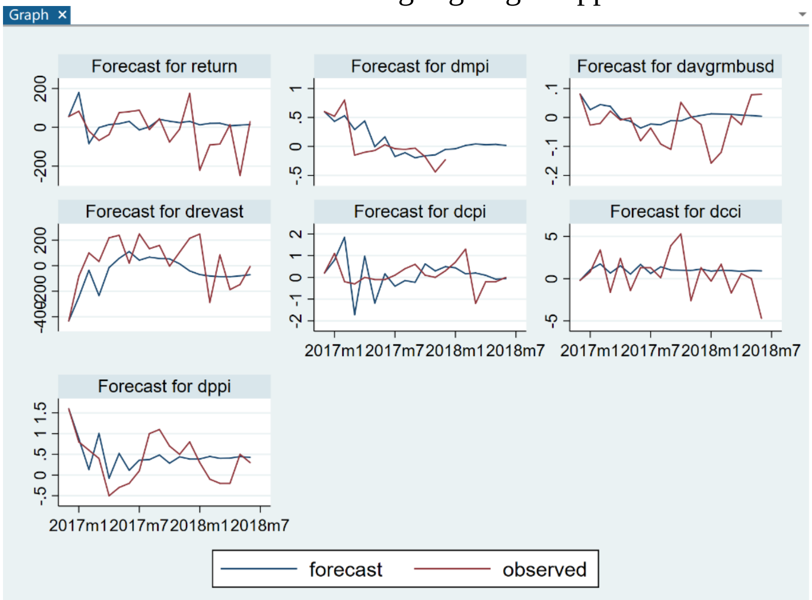

Figure 5: Forecast results of VAR model

5. Volatility

Many researchers are interested in analyzing the volatility of Chinese stock market [16, 17], because from the empirical observations, volatility in Chinese stock market may bring arbitrage opportunities. Although looking for arbitrage opportunities in Chinese stock market sounds interesting, this paper does not aim to research on that topic. Rather, we are considering which GARCH model would be the most appropriate to apply into Chinese stock market. Therefore, we select GARCH [18], ARCH-M [19], GARCH-M [20], TARGH [21], TGARCH [22], and EGARCH [23] models to find which model would be the most appropriate one by evaluating the minimum AIC.

Since TGARCH yields the minimum AIC, it suggests that we can use TGARCH model for analyzing volatility of Chinese stock price. We can interpret the results as following equations:

$$D.SSEC_t = 11.23709 + 0.0943 * D.SSEC_{t-1} + \varepsilon_t \tag{4}$$

$$\sigma^{\wedge}_{2t} = 2766.309 - 0.0270 * \varepsilon^{\wedge}_{2t-1} + 0.5549 * d_{t-1}\varepsilon^{\wedge}_{2t-1} + 0.7325 * \sigma^{\wedge}_{2t-1} \tag{5}$$

When considering leverage effect [24], we need to remember that TGARCH cannot differentiate between positive or negative shocks [22], since it treats all shocks as positive shocks. But we can observe that the coefficient before dt-1ε^2t-1 is greater than 0; and it means negative shocks would have greater effects on the volatility of Chinese stock market than positive shocks would, which is along with empirical observations.

6. Conclusion

In this paper, we have analyzed the long-term relationship between Chinese stock market and macroeconomic indicators in the past decade through time series models. We have applied VEC and VAR model for comprehensively interpreting the potential correlations. After testing the stationarity of series and their first-differencing processes, we apply Johansen method and Engle-Granger Two-Step Approach to construct our VEC model. However, the VEC model suggested by Johansen methodology fails the stability test; so, we focus on building VEC model by Engle-Granger methodology, and the model works. Our VEC model suggests that PPI and official asset reserve have positive and significant relationships to Chinese stock market.

Then, we construct VAR equations for comparing the pseudo-forecast results of VEC and VAR model. Our VAR model passes stability test, and we find that when comparing the forecast results, the VEC model by Engle-Granger methodology provides better forecasts. Also, we plot impulse-response function based on our VAR model to see the response of stock price if imposing shocks on Chinese macroeconomic indicators; but only average exchange rate of RMBUSD, CPI, MPI, and PPI seem to be significant.

Furthermore, we use GARCH families to identify the most appropriate model for measuring volatility of Chinese stock market from 2011 to 2019 by evaluating the minimum AIC. We find that TGARCH model has the minimum AIC, and it suggests that the negative shocks to Chinese stock market do contribute to generating more volatility than good shocks would.

This paper aims to untwist the puzzles in relating Chinese stock price to macroeconomic performance, but we believe future studies and research could further analyze this topic based on our findings and results. For example, we can replace macroeconomic variables by other macroeconomic instruments, such as floating ratio proxies. Also, the ultimate goal of macroeconomic polies is to stabilize the country's economic growth rather than motivating the prosperity of stock market; therefore, when investing in stock market, we might not overread and overreact to macroeconomic updates.

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