A revisit on the role of macro imbalances in the US recession of 2007-2009

Aviral Kumar Tiwari[#]
ICFAI University Tripura, India

Abstract

The present study is an attempt to revisit the evidences of a very recent study of Paul (2010) on the role of macro imbalances in the US recession of 2007-09. Contrary to Paul (2010) who finds that great recession was due to, particularly, twin deficits, I found central cause of the problem was prolonged fiscal deficit.

Key words: macro imbalances, US recession, nonlinear Granger causality.

JEL Classification: E3, E56, E6.

Research scholar and Faculty of Applied Economics, Faculty of Management, ICFAI University Tripura, Kamalghat, Sadar, West Tripura, Pin-799210, India, Email-Id: aviral.eco@gmail.com

1. Introduction

The discussion of the US great recession of 2007-09 has brought considerable interest of both researchers and policy makers. Number of attempts has been made to identify reasons of this great depression. In a very recent study, Paul (2010) show that, using vector Autoregressive (VAR) model, trade deficits and fiscal deficits has contributed to the low interest rate and decreasing the output over the period of 1987-2009. He also shows that low interest rate is caused by low private saving which greatly contributed to the housing bubble. And hence, Paul (2010) concluded that low saving and twin deficits have been the main reason for the great recession experienced.[1]

However, I have made an attempt in this study to revisit the findings and conclusions drawn by Paul (2010). Since, Paul (2010) has used VAR model to analyze the problem and if there is evidence of nonlinearity in the data series conclusion drawn from the study will be biased. Therefore, in the present study I made and attempt to analyze the problem by using the nonlinear Granger causality analysis in the framework of Hiemstra and Jones (1994) which was improved upon Baek and Brock (1992) proposed test.

2. Nonlinear Granger causality

It is important to mention that the linear approach to causality testing can have the low power detecting certain kinds of nonlinear causal relation. In this regard Baek and Brock (1992) is the first study to the best of our knowledge which proposed a test based on a nonparametric statistical method for uncovering nonlinear causal relations that cannot be detected by traditional liner Granger causality test. Baek and Brock's (1992) proposed test was based on an approach that utilizes the correlation integrals, which is an estimator of spatial probabilities across time based upon the closeness of the points in hyperspace to detect the relation between two time series. The distribution of the test statistic is one tailed and hence, rejections of the hypothesis are restricted to one tail of the distribution. Hiemstra and Jones (1994) modified the statistic of Baek and Brock (1992) and show that their test statistics has better small-sample properties and it can be applied to the series that relaxes the assumption that the series are i.i.d. Hiemstra and Jones (1993) show in their Monte Carlo simulations that their modified test is robust to the presence of structural breaks in the series and contemporaneous correlations in the errors of the VAR model used to filter out linear cross- and auto-dependence. Baek and Brock (1992) developed a nonparametric statistical technique for detecting nonlinear causal relationships from the residuals of linear Granger causality models. Following Hiemstra and Jones (1994), we let $F(X_t \mid I_{t-1})$ denote the conditional probability distribution of X_t given the information set I_{t-1}, which consists of an L_X -length lagged vector of X_t, say $X_{t-Lx}^{Lx} \equiv (X_{t-Lx}, X_{t-Lx+1}, ..., X_{t-1})$, and an L_Y -

[1] More comprehensive review on this aspect can be referred in Paul (2010) as this study is just a revisit of the evidence of Paul (2010) therefore, review has been avoided.

length lagged vector of Y_t, say $Y_{t-Ly}^{Ly} \equiv (Y_{t-Ly}, Y_{t-Ly+1}, ..., Y_{t-1})$. Hiemstra and Jones (1994) consider testing, for a given pair of lags L_X and L_Y, the following relationship:

$$H_0: \quad F(X_t \mid I_{t-1}) = F(X_t \mid (I_{t-1} - Y_{t-Ly}^{Ly})) \tag{1}$$

That is, the null hypothesis of interest states that taking the vector of past Y-values out of the information set does not affect the distribution of current X-values. Adopting the notation used by Hiemstra and Jones (1994), we denote the *m*-length lead vector of X_t by X_t^m, so that we can summarize the vectors defined so far, for $t \in Z$, as:

$$\begin{aligned} X_t^m &= (X_t, X_{t+1}, ..., X_{t+m-1}), && m = 1, 2, \dots \\ X_{t-Lx}^{Lx} &= (X_{t-Lx}, X_{t-Lx+1}, ..., X_{t-1}), && Lx = 1, 2, \dots \\ Y_{t-Ly}^{Ly} &= (Y_{t-Ly}, Y_{t-Ly+1}, ..., Y_{t-1}), && Lx = 1, 2, \dots \end{aligned} \tag{2}$$

A crucial claim made by Hiemstra and Jones (1994) without proof, states that the null hypothesis given in equation (1) implies, for all ε > 0:

$$P\left(\left\|X_t^m - X_s^m\right\| < \varepsilon \mid \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < \varepsilon\right)$$

$$= P\left(\left\|X_t^m - X_s^m\right\| < \varepsilon \mid \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon\right), \tag{3}$$

where P(A|B) denotes the conditional probability of A given B, and $\|\bullet\|$ the maximum norms-a distance measure (in this case supremum norm), which for a d-dimensional vector $x = (x_1, ..., x_d)^T$ is given by $\|x\| = \sup_{i=1}^{d} |x_i|$. The probability on the left-hand side of equation (3) is the conditional probability that two arbitrary m-length lead vectors $\{X_t\}$ (i.e., X_t^m and X_s^m) are within a distance ε for each other (or ε-close), given the corresponding L_X-length lag vector of $\{X_t\}$ (i.e., X_{t-Lx}^{Lx} and X_{s-Lx}^{Lx}) and L_Y-length lag vector $\{Y_t\}$ (i.e., X_{t-Ly}^{Ly} and X_{s-Ly}^{Ly}) are within ε of each other (or ε-close). The probability on the Right hand Side (RHS) of equation (3) is the conditional probability that two arbitrary *m*-length lead/lag vectors of $\{X_t\}$ (i.e., X_t^m and X_s^m) are within a distance ε for each other (or ε-close), given that the corresponding lagged Lx-length lag vectors of $\{X_t\}$ (i.e., X_{t-Lx}^{Lx} and X_{s-Lx}^{Lx}) are within a distance of ε of each other (or ε-close). Hence, non-Granger causality implies that the probability that two arbitrary lead vectors of length *m* are within a distance of ε of each other is the same conditional upon the two lag vectors of $\{X_t\}$ being within a distance ε of each other and two lag vectors of $\{Y_t\}$ being within a distance ε of each other; and conditional upon the lag vectors of $\{X_t\}$ only being within a distance ε of each other. In other words, no Granger causality means that the probability that lead vectors are within distance ε is the same whether we have information about the distance between $\{Y_t\}$ lag vectors or not.

We can write the conditional probability expressed in equation (3) as ratios of joint probabilities. Assuming that $C1(m+L_x, L_y, \varepsilon)/C2(L_x, L_y, \varepsilon)$ and $C3(m+L_x, \varepsilon)/C4(L_x, \varepsilon)$ denote the ratio of joint probabilities corresponding to the Left Hand Side (LHS) and RHS of equation (3), the joint probabilities can be written as:

$$C1(m+L_x, L_y, \varepsilon) = P\left(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < \varepsilon, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < \varepsilon\right),$$

$$C2(L_x, L_y, \varepsilon) = P\left(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon, \left\|Y_{t-Ly}^{Ly} - Y_{s-Ly}^{Ly}\right\| < \varepsilon\right),$$

$$C3(m+L_x, \varepsilon) = P\left(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < \varepsilon\right),$$

$$C4(L_x, \varepsilon) = P\left(\left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon\right) \qquad (4)$$

Further, we can write the strict Granger non-causality condition in equation (3) as follows

$$\frac{C1(m+L_x, L_y, \varepsilon)}{C2(L_x, L_y, \varepsilon)} = \frac{C3(m+L_x, \varepsilon)}{C4(L_x, \varepsilon)} \qquad (5)$$

For given values of m, $L_x, L_Y \geq 1$ and $\varepsilon > 0$.

Now, assuming that $\{X_t\}$ and $\{Y_t\}$ denote the actual realization of the process and $I(A, B, \varepsilon)$ denoting an indicator function that takes the value one if the vector A and B are within a distance ε of each other and zero otherwise and considering that the properties of the supremum norm allow us to inscribe $P\left(\left\|X_t^m - X_s^m\right\| < \varepsilon, \left\|X_{t-Lx}^{Lx} - X_{s-Lx}^{Lx}\right\| < \varepsilon\right)$ as $P\left(\left\|X_{t-Lx}^{m+Lx} - X_{s-Lx}^{m+Lx}\right\| < \varepsilon\right)$, then the estimates of the correlations integrals in equation (5) can be expressed as:

$$C1(m+L_x, L_y, \varepsilon, n) \equiv \frac{2}{n(n-1)} \sum\sum I\left(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, \varepsilon\right) \cdot I\left(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, \varepsilon\right),$$

$$C2(L_x, L_y, \varepsilon, n) \equiv \frac{2}{n(n-1)} \sum\sum I\left(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, \varepsilon\right) \cdot I\left(Y_{t-Ly}^{Ly}, Y_{s-Ly}^{Ly}, \varepsilon\right)$$

$$C3(m+L_x, \varepsilon, n) \equiv \frac{2}{n(n-1)} \sum\sum I\left(X_{t-Lx}^{m+Lx}, X_{s-Lx}^{m+Lx}, \varepsilon\right)$$

$$C4(L_x, \varepsilon, n) \equiv \frac{2}{n(n-1)} \sum\sum I\left(X_{t-Lx}^{Lx}, X_{s-Lx}^{Lx}, \varepsilon\right)$$

For $t, s = \max(L_x, L_y) + 1, \ldots, T - m + 1; n = T + 1 - m - \max(L_x, L_y)$.

Assuming that X_t^m and Y_t^m are strictly stationary and meet the required mixing conditions as specified in Denker and Keller (1983), under the null hypothesis that Y_t^m does not strictly Granger cause X_t^m, the test statistic T is asymptotically normally distributed. That is,

$$T = \left(\frac{C1(m+L_x, L_y, \varepsilon, n)}{C2(L_x, L_y, \varepsilon, n)} - \frac{C3(m+L_x, \varepsilon, n)}{C4(L_x, \varepsilon, n)} \right) \sim N\left(0, \frac{1}{\sqrt{n}} \sigma^2(m, L_x, L_y, \varepsilon)\right), \quad (6)$$

where, $n = T + 1 - m - \max(L_x, L_y)$ and $\sigma^2(\cdot)$ is the asymptotic variance of the modified Baek and Brock (1992) test statistic.[2] One sided critical values are used, based upon this asymptotic results, rejecting when the observed value of test statistic in equation (6) is too large. To test for nonlinear Granger causality between $\{X_t\}$ and $\{Y_t\}$; test statistic in equation (6) is applied to the estimated residual series from the bivariate VAR model. In this case, the null hypothesis is that $\{Y_t\}$ does not nonlinearly strictly Granger cause $\{X_t\}$, and equation (6) holds for all *m*, $L_x, L_Y \geq 1$ and $\varepsilon > 0$. By removing a linear predictive power form a linear VAR model, any remaining incremental predictive power of one residual series for another can be considered nonlinear predictive power (see Baek and Brock, 1992). A significantly test statistics in equation (6) suggests that lagged values of Y help to predict X, whereas a significant negative value suggest knowledge of the lagged value of Y confounds the prediction of X. For this reason, the test statistic in equation (6) should be evaluated with right-tailed critical values when testing for the presence of Granger causality. Using Monte Carlo simulations Hiemstra and Jones (1993) find that the modified Baek and Brock (1992) test has remarkably good finite sample size and power properties against a variety of nonlinear Granger causal and non-causal relations.

3. Data analysis and results interpretation

Before testing for nonlinear Granger causality, it is important to first determine if the data are characterized by nonlinearities.[3] Therefore, I perform a formal nonlinear dependence test known as the Brock, Dechert, and Scheinkman (BDS) test. The BDS approach essentially tests for deviations from identically and independently distributed (i.i.d.) behavior in time series. Results of the BDS test reveal that the vast majority of the estimates of the BDS statistics are statistically significant, indicating significant nonlinearities in the univariate time series.[4] To conduct tests for nonlinear causality we use the residuals from the linear VAR model, from which any linear

[2] The asymptotic variance is estimated using the theory of U-statistic for weakly dependent processes (Denker and Keller, 1983). For a complete and detailed derivation of the variance see the appendix in Hiemstra and Jones (1994).

[3] I am thankful for Prof. Paul for sharing the data which he used in the analysis in his paper. Data source for related variables can be found in his paper. I am also thankful to Panchenko for providing me the codes for this analysis.

[4] Results of correlation and descriptive statistics are presented in the appendix of the paper and results of the BDS test are available upon request to the author. Results of correlation has been presented just to match with the results of Paul (2010) presented in Table 1.

predictive relationship has already been removed. Values for the lead length m, the lag lengths L_x and L_Y, and the distance measure ε must be selected in order to implement the Baek and Brock (1992) test. In contrast to linear causality testing, we do not have any well developed methods for choosing optimal values for lag lengths and distance measure. Therefore, I followed Hiemstra and Jones (1994) and set the lead length at m = 1 and set $L_x = L_Y$ for all cases. In the present study I use common lag lengths of one to five lags and a common distance measure of $\varepsilon = 1.5\sigma$, where σ denotes the standard deviation of the time series.[5] In the results of this paper I focus on p-values for the modified Baek and Brock (1992) test as this enables us to compare them with the empirical p-values obtained using the re-sampling procedure. The empirical p-values account for estimation uncertainty in the residuals of the VAR model used in the modified Baek and Brock (1992) test, thereby, making these results more reliable.[6] Diks and DeGoede (2001) have conducted a number of experiments in order to determine the best randomization procedure for obtaining empirical p-values. There, finding show that the best finite sample properties of the tests are obtained when only the causing series were bootstrapped in the analysis. Hence, I adopt this methodology in this analysis. I used the Stationary bootstrap of Politis and Romano (1994) to preserve potential serial dependence in the causing series. The re-sampling scheme which is robust with respect to parameter estimation uncertainty is implemented as follows:

1. First, estimate a parametric model and obtain the fitted values of the conditional mean and the estimated residuals.[7]
2. Next, resample the residuals in such a way that satisfies the null hypothesis.[8]

[5] In the estimation we also considered ε = 0.5σ and 1.0σ. There were no qualitative differences in our results.

[6] Baek and Brock (1992) suggest that a weakness of their test is that it could spuriously reject the null hypothesis of Granger non-causality due to the presence of non-stationarity induced by structural breaks in the data and heteroskedasticity (recent finding by Diks and Panchenko (2005, 2006) also suggests that the rejection of the null in this case may also indicate the presence of conditional heteroskedasticity in the data). Further, Granger non-causality test does not identify the underlying source of causality which may be due to due to structural breaks in the data (Baek and Brock, 1992; Andersen, 1996) or to a differential reaction to information flow as proxied by volatility (Ross, 1989) or some combination of the two. To test whether results are period sensitive we can conduct an experiment for sub periods however, we have avoided this testing because if we conduct this kind of test are left with a very small sample in both periods which again may provide us misleading results. Further, since modified Baek and Brock (1992) test for Granger non-causality is applied to the residuals of the VAR model, rather than to original untreated observations. This may also lead to erroneous inferences because of an unaccounted estimation uncertainty. The reason for this is the potential difference of the null distribution when the test is applied to residuals rather than to original observations (Randles, 1984). This difference arises because the parameter estimation uncertainty is not reflected in the test statistics. To eliminate any erroneous inference we use a re-sampling scheme that incorporates parameter estimation uncertainty. We continue to use the test statistics of the modified Baek and Brock (1992) test and modify the re-sampling procedure of Diks and DeGoede (2001) to determine empirical p-values of the nonlinear Granger causality tests. The test statistics T_i is given in equation (6).

[7] The estimation uncertainty of the calendar effects is accounted by starting with the unadjusted returns and explicitly including the calendar dummies in the conditional mean equation.

[8] The re-sampling procedure imposes a more restrictive null hypothesis of conditional independence. However, the test detects the deviations from the null in the direction of interest, that is, Granger causality. Let N denote the length of the series and PS is the stationary bootstrap switching probability. We start a new bootstrapped sequence from a random position in the initial series selected from the uniform distribution between 1 and N. With probability 1−PS the next element in the bootstrapped sequence corresponds to the next element in the initial series. With probability PS we randomly select an element from the initial sequence and put it as the next element in the bootstrapped sequence. The procedure continues until we obtain a bootstrapped sequence of length N. To ensure stationarity of the bootstrapped sequence, we connect the beginning and the end of the initial sequence.

3. In the next step, create artificial data series using the fitted values and the re-sampled residuals.
4. Further, re-estimate the model using the artificial data and obtain new series of the residuals.
5. Finally, compute test statistics T_i for the artificial residuals.

By repeating the bootstrap N-times and calculating test statistic T_i for each bootstrap i=1…N, we obtain empirical distribution of the test statistics under the null. Further, to obtain the empirical p-values of the test we compare the test statistics computed from the initial data T_0 with the test statistics under the null T_i:

$$p = \frac{\sum_{i=0}^{N} \#(T_0 \leq T_i)}{N+1},$$

where, $\#(\cdot)$ denotes the number of events in the brackets. The test rejects the null hypothesis in the direction of nonlinear Granger causality whenever T_0 is large. For the bootstrapping I set the number of bootstraps N=99.[9] The bootstrap switching probability PS is set to 0.05. The results based on the bootstrapped empirical p-values of non-linear Granger causality analysis are reported in the following Table 1.

[9] B=99 is the smallest commonly suggested number of bootstrap replications (see Davidson and MacKinnon, 2000 for details). Because of computational limitations we were unable to increase N, which may possibly result in some loss of power for our tests.

Table 1: Results of nonlinear Granger causality

Null hypothesis	Lag1	Lag2	Lag3	Lag4	Lag5
1. Fiscal deficit does not Granger cause Fed rate	0.25	0.21	0.38	0.36	0.32
2. Trade deficit does not Granger cause Fed rate	0.91	0.54	0.70	0.28	0.44
3. Fed rate does not Granger cause saving rate	0.26	0.11	0.18	0.18	0.28
4. Fiscal deficit does not Granger cause GDP growth	0.81	0.73	0.27	0.18	0.61
5. Trade deficit does not Granger cause GDP growth	0.37	0.14	**0.09**	0.11	0.12
6. Trade deficit does not Granger cause fiscal deficit	0.10	**0.06**	0.25	0.22	0.28
7. Fiscal deficit does not Granger cause Trade deficit	0.62	0.25	0.22	0.23	0.32
8. Trade deficit does not Granger cause saving rate	0.18	0.62	0.60	0.42	0.16
9. Fed rate does not Granger cause Fiscal deficit	**0.01**	0.32	0.50	0.54	0.27
10. Saving rate does not Granger cause trade deficit	0.46	0.44	0.63	0.14	0.23
11. Fiscal deficit does not Granger cause saving rate	0.24	0.70	0.60	0.26	**0.03**
12. Saving rate does not Granger cause fiscal deficit	**0.06**	0.62	0.62	0.72	0.35
13. Fed rate does not Granger cause trade deficit	0.76	0.93	1.00	0.96	0.95
14. Saving rate does not Granger cause Fed rate	0.15	0.42	0.15	**0.07**	0.32
15. GDP growth does not Granger cause fiscal deficit	**0.01**	**0.08**	0.21	**0.09**	0.24
16. GDP growth does not Granger cause trade deficit	0.52	0.11	**0.07**	0.74	0.79

Note: This table reports parametric bootstrap p-values for the standard Baek and Brock (1992) nonlinear Granger causality test given in equation (6). The number of lags on the residuals series used in the test is one. In all cases, the tests are applied to the unconditional unstandardized residuals. The lead length, m, is set to unity, and the distance measure, ε, is set to 1.5. Bold are significant.

It is evident from Table 1 that fiscal deficit and trade deficit do not Granger cause Fed rate; fiscal deficit does not Granger cause GDP growth and trade deficit; Fed rate does not Granger cause saving rate and trade deficit. However, trade deficit Granger case GDP growth and fiscal deficit; fiscal deficit Granger cause saving rate and saving rate Granger fiscal deficit and fed rate and GDP growth Granger cause both trade deficit and fiscal deficit.

Therefore, we have contrary findings to Paul (2010). He found that fiscal and trade deficit Granger cause Fed rate and argued that high fiscal and trade deficit lowered the fed rate that implies that macroeconomic imbalances indirectly contributed to the cheap monetary policy and hence the housing bubble before the financial crises. However, I argue there might be any other reason for chap monetary policy of US but at least these two imbalances were not. Further, Paul (2010) found that fed rate Granger cause saving rate and hence he concluded that fed rate called falling saving rates which lower down the payments for home buying, lower equity, higher leverage, higher risk and a bigger bubble in the housing market. However, again, my findings do not provide any support to his argument. Further, Paul (2010) finds that twin deficit Granger cause GDP growth and hence, twin deficit supported in output decline however, I find that it the trade deficit which is the causing phenomenon for output decline not the fiscal deficit. In addition to that I also find that GDP growth is also causing twin deficit that implies that GDP growth has increased the burden of trade deficit and fiscal deficit. Further, contrary to Paul (2010) who found that twin deficit are augmenting (reinforcing each other) i.e., Granger causality runs in both directions my study finds that trade deficit Granger cause fiscal deficit while fiscal deficit does not. Further, study shows that fiscal deficit and saving rate Granger cause each other i.e., fiscal deficit and savings rate appeared to have reinforcing each other. I also find that fed rate Granger cause fiscal deficit i.e., cheap monetary policy has been the cause of high fiscal deficit. Contrary to Paul (2010), I did not find evidence that trade deficit appeared to have lowered the saving rates or savings appeared to have increased the trade deficit.

4. Conclusions

This study is an attempt to revisit the evidences of a very recent study by Paul (2010) on the finding out the causing factors of recent witnessed the great recession of 2007-09 in the US, the worst one, since the Great Depression. Paul (2010) in his study finds that, without checking the stationarity property of the data series and applying the Granger causality, both the trade deficit and fiscal deficit have contributed in lowering the interest rate and output decline over the period of 1987-2009. However, this study reveals a different story. I do not find any evidence to support for his evidence that this is the twin deficit, which is contributed to cheap monetary policy. Further, it is the trade deficit which has lowered the GDP growth not the twin deficit (fiscal deficit and trade deficit). Further, it is not the low interest rate which caused low savings but it is low rate of savings which caused the low rate of interest rate and that contributed to the housing bubble. The central cause of housing bubble is related to fiscal deficit. Low rate of fed rate (interest rate), GDP growth rate and high saving rate and trade deficit have contributed to high fiscal deficit and high fiscal deficit have increased the saving rate and increased savings have lowered the interest rate (i.e., cheap monetary policy) and that has been the cause of housing bubble.

References

Andersen, T.G., 1996. Return volatility and trading volume: an information flow interpretation of stochastic volatility. Journal of Finance. 51, 169–204.

Baek, E., Brock, W., 1992. A general test for nonlinear granger causality: bivariate model. Working Paper. Iowa State University.

Davidson, R., MacKinnon, J., 2000. Bootstrap tests: how many bootstrap? Econometric Reviews. 19, 55–68.

Denker, M., Keller, G., 1983. On u-statistics and von-mises statistics for weakly dependent processes. Zeitschrift fur Wahrscheinlichkeitstheorie und Verwandte Gebiete. 64, 505–522.

Diks, C., DeGoede, J., 2001. A general nonparametric bootstrap test for Granger causality, in: Broer, H.W., Krauskopf, W., Vegter, G. (Eds.), Global analysis of dynamical systems. Institute of Physics Publishing, Bristol, UK.

Diks, C., Panchenko, V., 2005. A note on the hiemstra-jones test for granger non-causality. Studies in Nonlinear Dynamics and Econometrics. 9(2), art. 4.

Diks, C., Panchenko, V., 2006. A new statistics and practical guidelines for nonparametric Granger causality testing. Journal of Economic Dynamics and Control. 30, 1647–1669.

Hiemstra, C., Jones, J.D., 1993. Some information relating to the finite sample properties of modified baek, and brock nonlinear granger causality test. Working paper, University of Strathclyde and Securites and Exchange Commission.

Hiemstra, C., Jones, J.D., 1994. Testing for linear and nonlinear granger causality in the stock price-volume relation. Journal of Finance. 49, 1639–1664.

Paul, B. P., 2010. The role of macro imbalances in the US recession of 2007-2009. International Journal of Business and Economics. 9(3), 253-258.

Politis, D.N., Romano, J.P., 1994. The stationary bootstrap. Journal of the American Statistical Association. 89, 1303–1313.

Ross, S., 1989. Information and volatility: the no-arbitrage martingale approach to timing and resolution irrelevancy. Journal of Finance. 44, 1–18.

Appendix 1: Table of correlation and descriptive statistics

Correlation

	FEDRATE	FISCALDEFICIT	GDPGROWTH	SAVINGRATE	TRADEDEFICIT
FEDRATE	1				
FISCALDEFICIT	-0.60902	1			
GDPGROWTH	0.16693287	-0.305938	1		
SAVINGRATE	0.42260866	0.1084869	0.12243425	1	
TRADEDEFICIT	-0.49485590	0.04961205	-0.13000290	-0.87084829	1

Descriptive statistics

	FEDRATE	FISCALDEFICIT	GDPGROWTH	SAVINGRATE	TRADEDEFICIT
Mean	4.499000	241.5109	0.663169	4.464819	324.6456
Median	4.990000	230.5815	0.732782	4.566700	274.8000
Maximum	9.730000	1226.422	1.951462	7.600000	756.4000
Minimum	0.120000	-291.6140	-1.647403	1.200000	24.90000
Std. Dev.	2.340018	284.6861	0.633128	1.842776	245.9741
Skewness	-0.010464	1.132413	-0.933979	-0.046723	0.362941
Kurtosis	2.433173	6.013619	5.057897	1.865499	1.608393
Jarque-Bera	1.206489	53.29251	28.96577	4.859343	9.238026
Probability	0.547034	0.000000	0.000001	0.088066	0.009863
Sum	404.9100	21735.98	59.68522	401.8337	29218.10
Sum Sq. Dev.	487.3358	7213108.	35.67576	302.2282	5384788.
Observations	90	90	90	90	90