The Use of Divisia Monetary Aggregates in Nominal GDP Targeting

by

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Abstract: One of the hottest topics in monetary policy research has been the revival of the proposal for "nominal GDP targeting." Recent research has emphasized the potential importance of the Divisia monetary aggregates in implementing that policy. We investigate bivariate time series properties of Divisia money and nominal GDP to investigate the viability of recent proposals by authors who advocate a role for a Divisia monetary aggregate in nominal GDP targeting.

There are two particularly relevant proposals: (1) the proposal by Barnett, Chauvet, and Leiva-Leon (2015) to use a Divisia monetary aggregate as an indicator in the monthly Nowcasting of nominal GDP, as needed in implementation of any nominal GDP targeting policy; and (2) the proposal by Belongia and Ireland (2015) to use a Divisia monetary aggregate as an intermediate target, with nominal GDP being the final target of policy.

We run well known diagnostic tests of bivariate time series properties of the Divisia M2 and nominal GDP stochastic processes. Those tests are for properties that are necessary, but not sufficient, for the conclusions of Belongia and Ireland (2014) and Barnett, Chauvet, and Leiva-Leon (2015). We find no time series properties that would contradict those implied by either of those two approaches.

Keywords: money, aggregation theory, index number theory, Divisia index, Divisia monetary aggregates, nominal GDP targeting.

JEL Classification Codes: C43, E01, E3, E40, E41, E51, E52, E58.

1. Introduction

The recent financial crisis has induced central banks to explore and undertake unconventional approaches to monetary policy. One of the hottest topics in monetary policy research has been the revival of the proposal for "nominal GDP targeting", advocated by many leading monetary economists, including Michael Woodford, Christina Romer, and Paul Krugman. Proponents argue that nominal GDP targeting can stabilize the macroeconomy more effectively than inflation targeting. In particular, they argue that by committing to return nominal GDP to its pre-crisis trajectory, the Federal Reserve could improve confidence and expectations of future growth.

We take no position on whether nominal GDP should be adopted as the new monetary policy target, but we investigate the bivariate time series properties of Divisia money and nominal GDP that are relevant to recent results by authors who do advocate a role for a Divisia monetary aggregate in nominal GDP targeting. There are two such proposals. (1) The least controversial is the approach of Barnett, Chauvet, and Leiva-Leon (2015) to the use of Divisia money in Nowcasting of nominal GDP. Any approach to targeting nominal GDP requires availability of monthly measurements of nominal GDP. Monthly measurements of nominal GDP are needed regardless of the instrument of policy adopted to implement the targeting. But nominal GDP data are available only quarterly. Using an advanced dynamic factor analysis approach to Nowcasting, Barnett, Chauvet, and Leiva-Leon (2015) find that the most accurate available approach to Nowcasting nominal GDP would use a Divisia monetary aggregate as one of the relevant and highly significant associated variables, with the others being measures of real economic activity and inflation dynamics. While Nowcasting does not imply unidirectional causation, Nowcasting approaches do require existence of strong bivariate time series associations among the interpolated variable and the associated variables. (2) The more controversial approach, suggesting a monetarist perspective, advocates the use of a Divisia monetary aggregate as an intermediate target in the procedure for targeting nominal GDP. Such an approach has been advocated by Belongia and Ireland (2015), while a new Keynesian approach has been proposed by the same authors in Belongia and Ireland (2014).

Early suggestions of the possible use of monetary aggregates in nominal GDP targeting include Feldstein and Stock (1993), who showed that the relation between M2 and nominal GDP is sufficiently strong to warrant further investigation into using M2 to influence nominal GDP, as would be relevant to the second approach described above. Since recent research has found Divisia monetary aggregates to be substantially superior to simple sum aggregates, we concentrate in this paper on Divisia M2. See, e.g., Barnett (2012,2015) and Barnett and Chauvet (2011) regarding the superiority of Divisia monetary aggregates over the now largely discredited simple sum monetary aggregates. But since our results are relevant to Nowcasting nominal GDP as well as intermediate targeting, our results are relevant even to proposals in which money is not used to influence nominal GDP, but only to interpolate the quarterly GDP data. In that case, our results need not be interpreted as having implications for the choice of instrument or intermediate targets in the policy rule.

Setting up a VAR model to indicate such relationship, we focus on $d(lnNGDP)$ and $d(lnM2)$, which are the growth rates of nominal GDP and Divisia M2. The estimated model indicates that there is a bidirectional Granger Causality relation between the two. We can make predictions based on our estimated model and can investigate how growth rate of Divisia money supply is going to impact nominal GDP and vice versa. The primary objective of this research is to run well known diagnostic tests of bivariate time series properties of the Divisia M2 and nominal GDP stochastic processes. Those tests are for properties that are necessary, but not sufficient, for the conclusions of Belongia and Ireland (2014) and Barnett, Chauvet, and Leiva-Leon (2015).

2. Literature Review

A nominal GDP target was previously called a "nominal income target" by early supporters such as McCallum (2011,2013). This approach is often contrasted with inflation targeting. Under some proposals on nominal GDP targeting, the central bank would try to keep nominal GDP growing at a predetermined rate. A nominal GDP *level* target is similar, except that the central bank would recall any previous deviations of nominal GDP growth from target and seek to compensate in later years. Apart from Bennett McCallum, who advocates nominal GDP growth rate targeting, most of the current supporters of nominal GDP targeting favor nominal GDP level targeting, such as Woodford (2013), Belongia and Ireland (2015), and Sumner (2012).

Christina Romer (2011), then chair of the Council of Economic Advisers, has urged adopting nominal GDP targeting as the monetary policy rule. In Romer's view, such a policy would be a powerful communication tool. By pledging to do whatever it takes to return nominal GDP to its pre-crisis trajectory, the Fed could improve confidence and expectations of future growth. Because nominal GDP reflects the Fed's dual mandate, stable price level and maximum real output, Romer argues that nominal GDP targeting would have a better chance of reducing unemployment than any other monetary policy approach under discussion.

Woodford (2013) argues that long run inflation targeting does not need to be repudiated as a policy framework, but rather needs to be completed. He argues that the target path for nominal GDP could be chosen such that keeping nominal GDP on that path should ensure, over the medium run, an average inflation rate equal to the inflation target. In his view, nominal GDP targeting can complete inflation targeting without conflicting with it. He further maintains that nominal GDP targeting would reduce the tension between the goals of restraining risks to financial stability, on the one hand, and maintaining macroeconomic stability, on the other.[2]

Sumner (2012), a persistent advocator of nominal GDP targeting and relentless blogger of "The Money Illusion," argues that the recent financial crisis

[2] Regarding inflation targeting, see, e.g., Bernanke and Mishkin (1997) and Svensson (1998).

exposed serious flaws with inflation targeting monetary policy regimes. In his view, GDP targeting would have greatly reduced the severity of the recession and also eliminated the need for fiscal stimulus. He also argues that nominal GDP targeting would make it easier for politicians to resist calls for bailouts of private sector firms, while assuring low inflation and reducing the severity of the business cycle. He also argues that nominal GDP targeting would make asset price bubbles less likely to occur. In summary, advocates of nominal GDP targeting believe it would provide the best environment for free-market policies to flourish.

On September 12, 2012, the Federal Reserve undertook policy initiatives influenced by Woodford (2003,2005,2012): an open-ended quantitative easing program, in which the amount of purchases depends on progress toward the policy goals. The Federal Reserve also announced it would maintain an easy money policy for some period after the economy has recovered. That announcement can be interpreted as an incremental move toward nominal GDP level targeting.

Nominal GDP targeting defines the final target of policy, but not the instrument, intermediate target, or rule used to implement the final target commitment. Many proposed approaches exist, including those that implement the final target for a new-Keynesian approach, a post-Keynesian approach, a monetarist approach, a classical approach, a new-classical approach, or an Austrian School approach. McCallum (1987) proposes a monetarist rule that uses the monetary base as instrument to target nominal GDP. He advocates targeting the growth rate of nominal GDP, rather than the level. His view is that if growth rates are on average equal to the target value over time, the policy would be unlikely to permit much departure from the planned path and should therefore be preferred. His rule employs a four-year moving average of past growth in monetary base velocity to forecast that velocity's growth in the coming quarter. Based on that forecast, the rule specifies the percentage of the gap between the targeted and actual levels of nominal GDP that the central bank should plan to close in the coming quarter.

In simulations, Dueker (1993) confronts McCallum's nominal GDP targeting rule with a world in which coefficients in the velocity equation for the monetary instrument are subject to unpredictable stochastic change. His approach differs from McCallum's by using explanatory variables to help forecast velocity in a time-varying parameter model. By allowing for time-varying coefficients, Dueker's forecasting model is argued to be more stable over time than fixed-coefficient models. Dueker concludes that McCallum's approach to nominal GDP targeting is simple yet robust to velocity behavior. However, Dueker's forecast-based rule performed somewhat better in simulations in which velocity was generated from a time-varying parameter model.

Recent contributors to the literature on nominal GDP targeting also incorporate aggregation theoretic monetary aggregates. Belongia and Ireland (2015) derive an approach to targeting the level of nominal GDP using a framework first outlined by Working (1923) and used, with minor modifications, by Hallman, et al. (1991) in their P-Star model. Belongia and Ireland's framework is built on traditional quantity theoretic foundations and draws directly from Barnett's (1978,1980) economic approach to monetary aggregation. With any desired long-run trajectory for nominal GDP, the framework can find a consistent intermediate target path for Divisia money. The central bank can use the monetary base to control the intermediate target path for either a narrow or broad Divisia monetary aggregate and thereby keep nominal GDP growing along any desired long-run path.

Their innovation lies in employing Divisia monetary aggregates to establish a path for the intermediate target and uses a one-sided filtering algorithm to control for slow-moving trends in velocity. The merits of this approach are its transparency to outside observers, its forward-looking design, and its potentially straightforward implementation.

Barnett, Chauvet, and Leiva-Leon (2015) developed dynamic factor models to Nowcast nominal output growth, using information from the previous release of nominal GDP, Industrial Production, Consumer Price Index, and Divisia M3. Their model is useful in giving monthly assessment of the current nominal GDP quarterly growth. This ability plays an essential role in monitoring the effectiveness of nominal GDP targeting monetary policy, regardless of the approach to implementation. In fact any approach that uses monthly feedback in its nominal GDP targeting approach becomes undefined, and thereby not applicable, without access to monthly GDP Nowcasts.

3. The Bivariate Time Series Relationship between Divisia M2 and Nominal GDP

As explained above, the use of Divisia monetary aggregates has been proposed in two different potential roles in nominal GDP targeting. One role is as an indicator variable in Nowcasting of monthly nominal GDP, as needed in any implementation of nominal GDP targeting. The other roles is direct use as an intermediate target in the policy design. Both cases imply the existence of a bivariate time series relationship between a Divisia monetary aggregate and nominal GDP. In this paper, we explore the nature of that relationship.

The Divisia monetary aggregate we use is Divisia M2, as provided by the Federal Reserve Bank of St. Louis in its FRED database. We use those data since they are well known and have a long history in this literature. But in future research, we plan to use the broader Divisia monetary aggregates, M3 and M4, supplied by the Center for Financial Stability in New York City.[3] The GDP data we use are supplied by the U.S. Bureau of Economic Analysis (BEA). Both series are seasonally adjusted. We eliminate heteroskedasticity by taking logarithms of the variables. We use $lnNGDP$ and $lnM2$ to denote the transformed data.

3.1. Unit Root Test

First we conduct a unit root test to examine stationarity of the series. If the series are non-stationary, regression could be spurious. We adopt the ADF (Augmented Dickey-Fuller) method for unit root test. The test results are displayed in the appendix as Table 1a.

[3] See Barnett, Liu, Mattson, and van den Noort (2013).

The p values of both tests are greater than the 5% significance level, with 0.9951 for $lnNGDP$ and 0.4876 for $lnM2$ respectively. Hence, for each of the tests, we fail to reject the null hypothesis that the series has a unit root. Both $lnNGDP$ and $lnM2$ series are non-stationary.

To test for causality relationship between nominal GDP and Divisia M2 money supply, we need the series to be stationary. For that purpose, we first difference the series to produce two first order differenced series $d(lnNGDP)$ and $d(lnM2)$. We then again conduct the ADF test on each of those transformed series. The null hypotheses that $d(lnNGDP)$ and $d(lnM2)$ have unit roots are decisively rejected. The differenced time series are stationary processes. See Table 2a in the appendix.

3.2. Cointegration Test

Next we test cointegration between $lnNGDP$ and $lnM2$ to investigate whether there exists long run association between the two processes. If the two variables are not cointegrated, we could apply an unrestricted VAR model. If the variables are cointegrated, we should prefer a vector error correction model (VECM). We use Johansen's (1988,1991) methodology. The p values for unrestricted cointegration rank tests using trace and maximum eigenvalue are 0.0828 and 0.0646 respectively, both higher than 5% significance level. See Table 3a in the appendix. Hence we fail to reject the null hypothesis of no cointegration between $lnNGDP$ and $lnM2$. We use an unrestricted VAR model in the following step.

3.3. VAR Model

We begin with a preliminary unrestricted VAR(2) model, as shown in appendix table 4a. We use the Akaike Information Criterion (AIC) to determine the appropriate maximum lag length for the variables in the VAR. Since we are using quarterly data, we choose lag equal to 4, when conducting VAR lag order selection. As the following table 1 shows, lag equal to 3 gives us the lowest AIC value. Therefore, we revise our model to a VAR(3) and estimate its coefficients. Detailed results are in appendix table 5a.

Table 1: VAR Lag Order Selection Criteria

Endogenous variables: $d(lnM2)$, $d(lnNGDP)$

Sample: 1967Q1 - 2013Q4

Included observations: 183

Lag	Log L	LR	FPE	AIC	SC	HQ
0	1201.558	NA	6.94e-09	-13.10992	-13.07485	-13.09571
1	1259.317	113.6242	3.86e-09	-13.69745	-13.59222	-13.65480
2	1269.885	20.55929*	3.59e-09	-13.76924	-13.59386*	-13.69815*
3	1274.130	8.164230	3.58e-09*	-13.77191*	-13.52638	-13.67238
4	1277.989	7.338699	3.59e-09	-13.77037	-13.45468	-13.64241

* Identifies the lag order selected by the criterion in that column.

Log L: log likelihood

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Next we examine whether there exist autocorrelation problems among the disturbances. Using the Autocorrelation LM (Lagrange Multiplier) test with lag equal to 12, we acquire the following table 2 with most of the p values greater than the 5% significance level.

Table 2: VAR Residual Serial Correlation LM Tests

Null Hypothesis: no serial correlation at lag order

Sample: 1967Q1 - 2013Q4

Included observations: 184

Lags	LM-Statistic	P value*
1	8.170979	0.0855
2	10.45168	0.0335
3	6.668278	0.1545
4	6.192919	0.1852
5	10.20056	0.0372
6	7.367825	0.1177
7	2.768448	0.5973
8	4.482638	0.3446
9	9.023472	0.0605
10	1.994479	0.7368
11	12.65099	0.0131
12	5.147886	0.2725

*P value from chi-square with 4 degrees of freedom.

We fail to reject the null hypothesis of no serial correlation among the residuals of the VAR(3) model. The VAR(3) model is well-specified.

3.4. Granger Causality Test

We conducted Granger causality tests between $d(lnNGDP)$ and $d(lnM2)$. The results indicate that $d(lnNGDP)$ Granger causes $d(lnM2)$, and $d(lnM2)$ also Granger Causes $d(lnNGDP)$. Listed below in table 3 are the Granger causality test results.

Table 3: VAR Granger Causality, Block Exogeneity Wald Tests

Sample: 1967Q1 2013Q4

Included observations: 184

Dependent variable: $d(lnM2)$

Excluded	Chi-sq	df	P value
$d(lnNGDP)$	11.28757	3	0.0103
All	11.28757	3	0.0103

Dependent variable: $d(lnNGDP)$

Excluded	Chi-sq	df	P value
$d(lnM2)$	11.67938	3	0.0086
All	11.67938	3	0.0086

The P value of the null hypothesis that $d(lnNGDP)$ does not Granger cause $d(lnM2)$ is 0.0103, which is smaller than the conventional critical value 0.05. We reject the null and therefore conclude that $d(lnNGDP)$ does Granger cause $d(lnM2)$. The P value of the null hypothesis that $d(lnM2)$ does not Granger cause $d(lnNGDP)$ is 0.0086, also smaller than the critical value 0.05. We reject the null hypothesis and therefore conclude that $d(lnM2)$ does Granger cause $d(lnNGDP)$. There exists a bidirectional Granger causality relationship between $d(lnNGDP)$ and $d(lnM2)$.

3.5. Estimation of the Final Bivariate VAR

We implemented the bidirectional Granger Causality relationship between $d(lnNGDP)$ and $d(lnM2)$ by estimating a bivariate VAR in those two stochastic processes with optimized lag lengths selected from the EViews program. The coefficients of the two equations are stacked into one vector having elements, $C(i)$, i

= 1, … , 14, as defined in table 6a in the appendix. The two equations we estimated in this VAR are defined in Table 6a. The coefficients of the first equation are $C(i)$, i = 1, … , 7 , while the coefficients of the second equation are $C(i)$, i = 8, … , 14. See the table for the specification of those two equations and the estimates of their coefficients.

The p value for $C(1)$ is 0.0000, demonstrating that the coefficient of $d(lnM2)_{t-1}$ is significant in the first equation. The growth rate of Divisa M2 money supply in the previous period has a significant impact on prediction of the current growth rate of Divisia M2. The corresponding p value of $C(2)$ is 0.9735, demonstrating that the second lag of the growth rate of M2 does not have significant predicting power for the current growth rate of M2. By eliminating the statistically insignificant coefficients, we acquire the following two estimated equations:

$$d(lnM2)_t = 0.483728d(lnM2)_{t-1} + 0.146457d(lnM2)_{t-3} - \\ - 0.223671d(lnNGDP)_{t-1} + 0.006672 \quad (1)$$

$$d(lnNGDP)_t = 0.223336d(lnM2)_{t-1} + 0.318158d(lnNGDP)_{t-1} \\ +0.288470d(lnNGDP)_{t-2} \,. \quad (2)$$

Since $d(lnM2)$ and $d(lnNGDP)$ indicate the growth rates, the estimated equations can be interpreted as follows. The growth rate of Divisia M2 is affected by the growth rate of itself, lagged by 1 and 3 quarters, as well as by the growth rate of the previous quarter's nominal GDP. Furthermore, holding other variables constant, we can reach the following conclusions. From the first equation, if the growth rate of Divisia M2 during the last quarter increases by 10%, then the growth rate of M2 this quarter will increase by 4.83728%. But if the nominal GDP growth rate of the previous quarter increases by 10%, the M2 growth rate this quarter will decrease by 2.23671%. If the M2 growth rate, lagged three quarters, reaches 10%, the current growth rate will increase by 1.46457%. Similar analysis applies to the second equation, where $d(lnNGDP)_t$ is the dependent variable.

3.6. Prediction

Based on the estimation of equations (1) and (2), we can predict the growth rate of Divisia M2 and nominal GDP in 2014 Q1 using the quarterly data in our sample ending in 2013 Q4.[4]

$$\begin{cases} d(lnM2)_{2014Q1} = 0.483728d(lnM2)_{2013Q4} + 0.146457d(lnM2)_{2013Q2} - \\ \qquad 0.223671d(lnNGDP)_{2013Q4} + 0.006672 \\ d(lnNGDP)_{2014Q1} = 0.223336d(lnM2)_{2013Q4} + 0.318158d(lnNGDP)_{2013Q4} \\ \qquad +0.288470d(lnNGDP)_{2013Q2} \end{cases}$$

Substituting the measured values of the variables into the right hand sides, the predicted growth rates are:

$$\begin{cases} d(lnM2)_{2014Q1} = 0.014079 \\ d(lnNGDP)_{2014Q1} = 0.012193 \end{cases}$$

The predicted growth rates can be used to predict the levels of M2 and NGDP in 2014Q1 by the following equations:

$$\begin{cases} M2_{2014Q1} = M2_{2013Q4} * (1 + d(lnM2)_{2014Q1}) \\ NGDP_{2014Q1} = NGDP_{2013Q4} * (1 + d(lnNGDP)_{2014Q1}) \end{cases}$$

Substituting into the right hand sides, we acquire:

$$\begin{cases} M2_{2014Q1} = 11758.8 \\ NGDP_{2014Q1} = 17286.5 \end{cases}$$

The 1.4% predicted growth rate of Divisia M2 money supply in 2014Q1 was inconsistence with the Federal Reserve's accommodative monetary policy. A consequence is reflected in the almost-non-growing 1.2% nominal GDP prediction in 2014Q1. In fact, the out of sample growth rate of 2014Q1 was -0.2%, according to the data released by Bureau of Economic Analysis (BEA).

[4] We could have used a longer sample period including more recent quarters by using data from the Center for Financial Stability (CFS) in New York City. But we limited this study to data made available by the Federal Reserve Bank of St. Louis, which has not updated its data as regularly as the CFS, which does update monthly.

4. Conclusion

In this paper we discuss the relationship between Divisia M2 money supply and nominal GDP. The primary objective of this research is to run well known diagnostic tests of bivariate time series properties of the Divisia M2 and nominal GDP stochastic processes that are necessary but not sufficient for the conclusions of Belongia and Ireland (2014) and Barnett, Chauvet, and Leiva-Leon (2015). We find no evidence to contradict the conclusions of those two papers about the potential relevancy of Divisia monetary aggregates in targeting nominal GDP, either as an intermediate target or as an indicator. Our results are not specific to either of those approaches and hence cannot provide conclusions about which of those two approaches should be preferred. Since neither of those two approaches contradicts the other, one possibility would be to use both of those approaches simultaneously. In that case, Barnett, Chauvet, and Leiva-Leon (2015) could be used to interpolate the quarterly data to provide the needed Nowcast monthly nominal GDP data, while Belongia and Ireland (2014) would then be used to implement a policy design using a Divisia monetary aggregate as an intermediate target.

But if a different policy design were adopted without an intermediate target, Barnett, Chauvet, and Leiva-Leon (2015) would remain relevant to producing the monthly data necessary for any approach to nominal GDP targeting.

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Appendix

Table 1a. Unit Root Test Result for $lnNGDP$ and $lnM2$

Null Hypothesis: $lnNGDP$ has a unit root

		t-Statistic	P value*
Augmented Dickey-Fuller test statistic		-0.065053	0.9951
Test critical values:	1% level	-4.008154	
	5% level	-3.434167	
	10% level	-3.141001	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: $lnM2$ has a unit root

		t-Statistic	P value*
Augmented Dickey-Fuller test statistic		-2.197872	0.4876
Test critical values:	1% level	-4.008154	
	5% level	-3.434167	
	10% level	-3.141001	

*MacKinnon (1996) one-sided p-values.

Table 2a. Unit Root Test Result for $d(lnNGDP)$ and $d(lnM2)$

Null Hypothesis: $d(lnNGDP)$ has a unit root

		t-Statistic	P value*
Augmented Dickey-Fuller test statistic		-10.34110	0.0000
Test critical values:	1% level	-4.008154	
	5% level	-3.434167	
	10% level	-3.141001	

*MacKinnon (1996) one-sided p-values.

Null Hypothesis: $d(lnM2)$ has a unit root

		t-Statistic	P value*
Augmented Dickey-Fuller test statistic		-7.718251	0.0000
Test critical values:	1% level	-4.008154	
	5% level	-3.434167	
	10% level	-3.141001	

*MacKinnon (1996) one-sided p-values.

Table 3a. Johansen Cointegration Test Between $lnNGDP$ and $lnM2$

Sample (adjusted): 1968Q2 - 2013Q4
Included observations: 183
Series: $d(lnM2)$, $d(lnNGDP)$
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	P value**
None	0.071362	14.00454	15.49471	0.0828
At most 1	0.002488	0.455880	3.841466	0.4996

Trace test indicates no cointegration at the 0.05 level
*Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	P value**
None	0.071362	13.54866	14.26460	0.0646
At most 1	0.002488	0.455880	3.841466	0.4996

Max-eigenvalue test indicates no cointegration at the 0.05 level
*Denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients:

$lnM2$	$lnNGDP$
1.852061	-3.068247
9.671655	-7.514269

Unrestricted Adjustment Coefficients (alpha):

$d(lnM2)$	0.000987	0.000297
$d(lnNGDP)$	0.001715	-0.000217

One Cointegrating Equation: Log likelihood 1284.763

Normalized cointegrating coefficients (standard error in parentheses)

$lnM2$	$lnNGDP$
1.000000	-1.656666
	(0.23697)

Adjustment coefficients (standard error in parentheses)

$d(lnM2)$	0.001828
	(0.00098)
$d(lnNGDP)$	0.003177
	(0.00106)

Table 4a. VAR(2) Estimation

Vector Autoregression Estimates
Sample (adjusted): 1967Q4 - 2013Q4
Included observations: 185
Standard errors in ( ) & t-statistics in [ ]

	$d(lnNGDP)$	$d(lnM2)$
$d(lnNGDP)_{t-1}$	0.343726	-0.203535
	(0.07111)	(0.06393)
	[4.83377]	[-3.18391]
$d(lnNGDP)_{t-2}$	0.296876	0.110804
	(0.07117)	(0.06398)
	[4.17157]	[1.73192]
$d(lnM2)_{t-1}$	0.230714	0.502884
	(0.08198)	(0.07370)
	[2.81432]	[6.82361]
$d(lnM2)_{t-2}$	-0.018083	0.051093
	(0.08169)	(0.07344)
	[-0.22137]	[0.69573]
Constant intercept	0.002710	0.007922
	(0.00177)	(0.00159)
	[1.53297]	[4.98427]
R-squared	0.320419	0.300597
Adj. R-squared	0.305317	0.285055
Sum sq. residuals	0.011651	0.009416
S.E. equation	0.008045	0.007233
F-statistic	21.21725	19.34060
Log likelihood	632.2211	651.9214
Akaike AIC	-6.780769	-6.993745
Schwarz SC	-6.693732	-6.906708
Mean dependent	0.016113	0.014431
S.D. dependent	0.009653	0.008554
Determinant residual covariance (df adj)		3.38E-09
Determinant residual covariance		3.20E-09
Log likelihood		1284.335
Akaike information criterion		-13.77659
Schwarz criterion		-13.60252

Table 5a. VAR(3) Estimation

Sample (adjusted): 1968Q1 - 2013Q4
Included observations: 184
Standard errors in ( ) and t-statistics in [ ]

	$d(lnNGDP)$	$d(lnM2)$
$d(lnNGDP)_{t-1}$	0.318158	-0.223671
	(0.07460)	(0.06667)
	[4.26460]	[-3.35472]
$d(lnNGDP)_{t-2}$	0.288470	0.062865
	(0.07726)	(0.06904)
	[3.73398]	[0.91053]
$d(lnNGDP)_{t-3}$	0.076208	0.074424
	(0.07535)	(0.06734)
	[1.01134]	[1.10515]
$d(lnM2)_{t-1}$	0.223336	0.483728
	(0.08300)	(0.07418)
	[2.69084]	[6.52140]
$d(lnM2)_{t-2}$	0.061580	0.002791
	(0.09397)	(0.08398)
	[0.65531]	[0.03323]
$d(lnM2)_{t-3}$	-0.113475	0.146457
	(0.08194)	(0.07323)
	[-1.38480]	[1.99990]
Constant intercept	0.002610	0.006672
	(0.00190)	(0.00170)
	[1.37251]	[3.92561]
R-squared	0.331774	0.320114
Adj. R-squared	0.309123	0.297067
Sum sq. residuals	0.011451	0.009146
S.E. equation	0.008043	0.007188
F-statistic	14.64676	13.88960
Log likelihood	629.8995	650.5791
Akaike AIC	-6.770647	-6.995425
Schwarz SC	-6.648340	-6.873118
Mean dependent	0.016098	0.014412
S.D. dependent	0.009677	0.008574
Determinant residual covariance (df adj.)		3.34E-09
Determinant residual covariance		3.09E-09
Log likelihood		1280.607
Akaike information criterion		-13.76747
Schwarz criterion		-13.52286

Table 6a. Final VAR Coefficient Estimation

Estimation Software: EViews computer program
Sample: 1968Q1 - 2013Q4
Included observations: 184
Total system observations 368

	Coefficient	Std. Error	t Statistic	P Value
C(1)	0.483728	0.074176	6.521397	0.0000
C(2)	0.002791	0.083982	0.033235	0.9735
C(3)	0.146457	0.073232	1.999902	0.0463
C(4)	-0.223671	0.066674	-3.354718	0.0009
C(5)	0.062865	0.069043	0.910526	0.3632
C(6)	0.074424	0.067343	1.105148	0.2698
C(7)	0.006672	0.001700	3.925608	0.0001
C(8)	0.223336	0.082999	2.690835	0.0075
C(9)	0.061580	0.093971	0.655308	0.5127
C(10)	-0.113475	0.081943	-1.384797	0.1670
C(11)	0.318158	0.074604	4.264599	0.0000
C(12)	0.288470	0.077255	3.733981	0.0002
C(13)	0.076208	0.075353	1.011342	0.3125
C(14)	0.002610	0.001902	1.372509	0.1708

Equation: $d(lnM2)_t$ = C(1)$d(lnM2)_{t-1}$ + C(2)$d(lnM2)_{t-2}$ + C(3)$d(lnM2)_{t-3}$ + C(4)$d(lnNGDP)_{t-1}$+ C(5)$d(lnNGDP)_{t-2}$ + C(6)$d(lnNGDP)_{t-3}$ + C(7)

R squared	0.320114	Mean dependent var	0.014412
Adjusted R squared	0.297067	dependent var	0.008574
S.E. of regression	0.007188	Sum squared resid	0.009146
Durbin-Watson stat	1.977980		

Equation: $d(lnNGDP)_t$= C(8)$d(lnM2)_{t-1}$ + C(9)$d(lnM2)_{t-2}$ + C(10)$d(lnM2)_{t-3}$+ C(11)$d(lnNGDP)_{t-1}$ + C(12)$d(lnNGDP)_{t-2}$ + C(13)$d(lnNGDP)_{t-3}$ + C(14)

R squared	0.331774	Mean dependent var	0.016098
Adjusted R-squared	0.309123	S.D. dependent var	0.009677
S.E. of regression	0.008043	Sum squared resid	0.011451
Durbin Watson stat	1.998140		