The Use of Divisia Monetary Aggregate to target Nominal GDP

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1. Introduction

The recent financial crisis has made central banks undertake various kinds of actions, including some unconventional ones. In recent years, one of the hottest topics in monetary policy is the revival of the idea of "Nominal GDP targeting", advocated by some leading monetary economists including Michael Woodford, Christina Romer, Paul Krugman etc. It is claimed that nominal GDP targeting has merits such as better stabilizing macro-economy than inflation targeting. 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.

Taking no position on whether nominal GDP should be adopted as the new monetary target, this paper focuses on examining the feasibility of using a monetary aggregate to influence the growth path of nominal GDP, so as to fulfill the Fed's dual mandate. Feldstein and Stock (1994) has shown that the relation between M2 and nominal GDP is sufficiently strong to warrant a further investigation into using M2 to influence nominal GDP in a predictable way. Inspired by this, we want to examine the relation between Divisia M2 and nominal GDP since Divisia index has been shown to be of much superiority over simple sum M2.

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, and we can make predictions based on our estimated model, checking how growth rate of Divisia money supply is going to impact nominal GDP and vice versa.

2. Literature review

A nominal GDP target (used to be called a "nominal income target" for earlier supporters such as Bennett McCallum, during the 1980s to 1990s) is an alternative to an inflation target. The central bank would try to keep nominal GDP growing at a predetermined rate. A nominal GDP *level* target is the same thing except that the central bank would remember any previous deviations of nominal GDP growth compared to the target and try to make it up in later years. For example, assume central bankers would set or be given an annual growth rate of 4-5%, with around 2% inflation target and 2-3% long-term potential growth in real GDP. If nominal GDP fell below the target growth rate in one year, central banks would seek to make up for that in subsequent years. In fact, Apart from Bennett McCallum, who advocates nominal GDP growth rate targeting, most of the enthusiastic supporters of nominal GDP targeting are more in favor of nominal GDP level targeting, such as Michael Woodford, Michael Belongia and Peter Ireland, Scott Sumner, David Beckworth, Clive Crook, etc.

As early as in October 2011, Christina Romer, the chairwoman of President Obama's Council of Economic Advisers, has urged "bold measures" to Fed Chairman Ben Bernanke: adopting nominal GDP targeting as 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. Though temporary increase in inflation expectation is inevitable, the current interest rate lower-bound constraint makes such a change turn out helpful: it could lower real borrowing costs, and therefore encourage spending on big-ticket items for households and entrepreneurs. Because nominal GDP directly reflects the Fed's dual mandate: stable price level and maximum real output, it should have a better chance of meaningfully reducing unemployment than any other monetary policy under discussion.

As for the conventional inflation targeting regime, Michael Woodford (2013) argues that the previous wisdom does not need to be repudiated as a policy framework, but it needs to be completed. For example, central banks, by committing themselves not only to a medium-run inflation target but also to criteria for making nearer term policy decisions that will imply that the inflation rate should be near the target if one averages over a sufficient number of years. Such a criteria could be nominal GDP targeting: a central bank might commit itself to make short-run decisions so as to keep nominal GDP as close as possible to a particular target path, even in the nearer term. The target path for nominal GDP could be chosen so 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 is such a policy that completes inflation targeting rather than conflicting it. Nominal GDP targeting should reduce the tension between the goals of restraining risks to financial stability on the one hand and maintaining macroeconomic stability on the other.

Scott Sumner (2012), persistent advocator of nominal GDP targeting and relentless blogger of "The Money Illusion", argues that the recent financial crisis exposed serious flaws with inflation targeting monetary policy regimes. Nominal GDP targeting would have greatly reduced the severity of the recession, and also eliminated the need for fiscal stimulus. Nominal GDP targeting also makes it much easier for politicians to resist calls for bailouts of private sector firms. It assures low inflation on average, and reduces the severity of the business cycle. It also makes asset price bubbles slightly less likely to occur. In sum, nominal GDP targeting provides the best environment for free-market policies to flourish.

On September 12, 2012, the Fed undertook some policy initiatives influenced by Michael Woodford, an open-ended quantitative easing program, in which the amount of purchases will depend on progress toward the policy goals. The Fed also announced that it would maintain an easy money policy for some period after the economy has recovered, which represents an incremental move toward level targeting.

Considering the trade-off between quantitative target and a vague formulation, Michael Woodford commented on the Fed's move: "I personally would have gone further but I think what they did is definitely a step in the right direction and I could certainly understand the conditions that would have led them to not put numeric measures in it."

As for the specific application of nominal GDP targeting, McCallum (1987) proposes a monetary policy rule that uses the monetary base to target nominal GDP. He stands for targeting the growth rate of nominal GDP, rather than level targeting. His view is that if growth rates are on average equal to the correct value over time, such regime would be unlikely to permit much departure from the planned path and so should probably be preferred. The rule employs a four-year moving average of past growth in base velocity to forecast its growth in the coming quarter. Based on this forecast, the rule then specifies the percentage of the gap between target and actual levels of nominal GDP that policymakers should try to close in the coming quarter. On top of that, Dueker (1993) confronts McCallum's nominal GDP targeting rule in simulations with a world in which coefficients in the velocity equation for the monetary instrument are subject to unpredictable stochastic change. It differs in that it uses explanatory variables to help forecast velocity; it also uses a time-varying parameter model. By allowing for time-varying coefficients, the forecasting model will be less prone than fixed-coefficient models to breaking down as time passes. Dueker claims that even though McCallum's approach to nominal GDP targeting proves to be simple yet robust to velocity behavior, his forecast-based rule performed somewhat better in simulations in which velocity was generated in a time-varying parameter model.

Recent contributors of nominal GDP targeting also incorporate the consideration of the correctness of measurements of monetary aggregates. Michael Belongia and Peter Ireland (2013) derive a practical approach to targeting the level of nominal GDP based on a framework first outlined by Holbrook Working (1923) and used, with minor modifications, by Hallman, et al. (1991) in the P-Star model. The framework is built on traditional quantity theoretic foundations, and draws directly from Barnett's (1980) economic approach to monetary aggregation. They find a path for money that is consistent with any desired long-run trajectory for nominal GDP. It shows that the central bank can use the monetary base to control the path for either a narrow or broad Divisia monetary aggregate and, through this device, it can keep nominal GDP growing along any desired long-run path. Their innovation lies in that they employ Divisia monetary aggregates, in establishing a path for money that the central bank should try to maintain and use a one-sided filtering algorithm that can be implemented in real time to control for slow-moving trends in velocity. The merits of their approach are that it is transparent to outside observers, forward-looking, and can be implemented in a fairly straightforward manner. Barnett, Chauvet and Leiva-Leon (2012) also developed dynamic factor models to nowcast nominal output growth, using information of the previous release of nominal GDP, Industrial Production, Consumer Price Index and Divisia M3. Their model is useful in giving earlier assessment of the current nominal GDP quarterly growth, which enables it to play an essential role in monitoring the effectiveness of nominal GDP targeting monetary policy.

3. The relationship between Divisia M2 and nominal GDP of the United States

The data of Divisia M2 and nominal GDP are collected from the Federal Reserve Bank of St. Louis (FRED) and U.S. Bureau of Economic Analysis (BEA). Since both of the series are seasonally adjusted already, the data transformation process can skip that step and start from eliminating heteroskedasticity by taking logarithm of the variables. We will use $lnNGDP$ and $lnM2$ to denote the transformed data.

3.1 Unit Root Test

First we need to conduct the unit root test to examine the stationarity of the sieries. If the series are non-stationary, the regression model could turn out to be spurious regression. We adopt ADF method for unit root test and the test results are in the appendix (table 1).

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

In order to check the causality relationship between nominal GDP and Divisia M2 money supply, we need to make sure the series we are testing with are stationary. A conventional way to eliminate non-stationarity is simply differencing the series. So now we generate two first order differenced series $d(lnNGDP)$ and $d(lnM2)$. Then we do ADF test on each of those series again. The probability of not rejecting null hypothesis that $d(lnNGDP)$ has a unit root is 0.0000%, which makes us reject the null. That is, $d(lnNGDP)$ is a stationary process. Similarly, the ADF test on $d(lnM2)$ also indicates that it is a stationary process (detailed test results are in appendix table 2).

3.2 Cointegration Test

Next we need to test cointegration between $lnNGDP$ and $lnM2$, which indicates whether there exists long run association between the two variables. If the two variables are not cointegrated, we can set up an unrestricted VAR model; if they are indeed cointegrated, we should choose vector error correction model (VECM). Here we use Johansen's methodology. The p values for unrestricted cointegration rank tests (trace and maximum eigenvalue) are 0.0828 and 0.0646 respectively (as shown in appendix table 3), both higher than 5% significance level. So we fail to reject null hypothesis that there is no cointegration between $lnNGDP$ and $lnM2$. Therefore, we can just choose unrestricted VAR model in the following step.

3.3 VAR model

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

VAR Lag Order Selection Criteria
Endogenous variables: DLNM2 DLNNGDP
Exogenous variables: C
Sample: 1967Q1 2013Q4
Included observations: 183

Lag	LogL	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

* indicates lag order selected by the criterion
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 need to examine whether there exist autocorrelation issues. By Autocorrelation LM test with lag equal to 12, we get the following table with most of the p value greater than 5%, significance level:

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Date: 08/18/14 Time: 02:41
Sample: 1967Q1 2013Q4
Included observations: 184

Lags	LM-Stat	Prob
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

Probs from chi-square with 4 df.

So we fail to reject the null hypothesis that there is no serial correlation in the residuals of the VAR(3) model. Now, this VAR(3) model is well-specified.

3.4 Granger Causality Test

Finally, we conduct Granger Causality Test 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 is the Granger Causality Test results

VAR Granger Causality/Block Exogeneity Wald Tests
Sample: 1967Q1 2013Q4
Included observations: 184

Dependent variable: DLNM2

Excluded	Chi-sq	df	Prob.
DLNNGDP	11.28757	3	0.0103
All	11.28757	3	0.0103

Dependent variable: DLNNGDP

Excluded	Chi-sq	df	Prob.
DLNM2	11.67938	3	0.0086
All	11.67938	3	0.0086

The probability of not to reject H_0: $d(lnNGDP)$ does not Granger Cause $d(lnM2)$ is 0.0103, which is smaller than the confidence interval 0.05. So we reject H_0 and $d(lnNGDP)$ does Granger Cause $d(lnM2)$. The probability of not to reject H_0: $d(lnM2)$ does not Granger Cause $d(lnNGDP)$ is 0.0086, also smaller than the confidence interval 0.05. So again, we reject null hypothesis, and $d(lnM2)$ does Granger Cause $d(lnNGDP)$. Therefore, there exists a bidirectional Granger Causality relationship between $d(lnNGDP)$ and $d(lnM2)$.

3.5 OLS estimation

Then, we are going to quantify the bidirectional Granger Causality relationship between $d(lnNGDP)$ and $d(lnM2)$. We use OLS by EViews to estimate the equations . We are going to generate the model by selecting criteria $C(p)$, as shown in appendix table 6.

The p value for $C(1)$ is 0.0000, which means the coefficient for $d(lnM2)_{t-1}$ is significant. So the growth rate of Divisa M2 money supply in the previous period has a significant impact on predicting the current growth rate of Divisia M2. Then moving on to $C(2)$, we notice that the corresponding p value is 0.9735. So $C(2)$ is not significant, implying that the second lag of growth rate of M2 does not have a significant predicting power to the current growth rate of M2. By this criteria, we can eliminate those insignificant coefficients and get the estimation of our model:

$$\begin{cases} d(lnM2)_t = 0.483728d(lnM2)_{t-1} + 0.146457d(lnM2)_{t-3} - \\ \quad 0.223671d(lnNGDP)_{t-1} + 0.006672 \ldots\ldots (eq\ 1) \\ d(lnNGDP)_t = 0.223336d(lnM2)_{t-1} + 0.318158d(lnNGDP)_{t-1} \\ \quad +0.288470d(lnNGDP)_{t-2} \ldots\ldots (eq\ 2) \end{cases}$$

Since $d(lnM2)$ and $d(lnNGDP)$indicate the growth rate of Divisia money supply and nominal GDP, the estimated equations can be interpreted as the growth rate of Divisia M2 is affected by the growth rate of itself 1 and 3 quarters ago as well as influenced by the growth rate of nominal GDP of the previous quarter simultaneously. Furthermore, holding other variables constant, by the first equation, if the growth rate of Divisia M2 money supply of last quarter increase by 10%, the growth rate of M2 this quarter will increase by 4.83728%; if the nominal GDP growth rate of the previous quarter increase by 10%, however, the M2 growth rate this quarter will decrease by 2.23671%; When M2 growth rate of the former 3rd quarter 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 equation (1) and (2) in the previous subsection, we are able to predict the growth rate of Divisia M2 and nominal GDP in 2014 Q1 using our quarterly data up until 2013 Q4.

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

$$\begin{cases} d(lnM2)_{2014Q1} = 0.483728 * 0.017785 + 0.146457 * 0.010364 - \\ \quad 0.223671 * 0.012135 + 0.006672 \\ d(lnNGDP)_{2014Q1} = 0.223336 * 0.017785 + 0.318158 * 0.012135 \\ \quad +0.288470 * 0.007053 \end{cases}$$

So the predicted growth rates are:

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

The estimated growth rates can be used to further predict M2 and NGDP in 2014Q1:

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

$$\begin{cases} M2_{2014Q1} = 11595.5 * (1 + 0.014079) \\ NGDP_{2014Q1} = 17078.3 * (1 + 0.012193) \end{cases}$$

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

The 1.4% growth rate of Divisia M2 money supply in 2014Q1 is in consistence with the Fed's accommodative monetary policy. To fight unemployment and to boost the economy, the Fed has been applying loose monetary policy to stimulate an expansion in US economy. On the other hand, the almost-non-growing 1.2% nominal GDP prediction in 2014Q1 is in line with the actual sluggish economy. In fact, the growth rate of 2014Q1 was -0.2% according to calculation based on the data released by Bureau of Economic Analysis (BEA).

4. Conclusion

In this paper we discuss the relationship between Divisia M2 money supply and nominal GDP. The bidirectional Granger Causality relationship between the two reveals the endogeneity property of money in the US. Since the Fed can control the supply of money by increasing or decreasing the monetary base, Divisia M2 can be considered as an exogenous and controllable variable. Thus, theoretically, it is feasible and effective to use Divisia M2 as an intermediate monetary policy target. By following the relationship between money supply and nominal GDP, the Fed can keep nominal GDP growing at a steady and predictable rate. Thereby, with public confidence of such commitment to target total output growth, the effectiveness of such monetary policy will be further enhanced and the expectation of inflation rate will be better managed as well.

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Appendix

Table 1. Unit Root Test Result for lnNGDP and lnM2

Null Hypothesis: LNNGDP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
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.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNGDP)
Method: Least Squares
Date: 08/15/14 Time: 01:57
Sample (adjusted): 1967Q3 2013Q4
Included observations: 186 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNNGDP(-1)	-0.000254	0.003906	-0.065053	0.9482
D(LNNGDP(-1))	0.276331	0.070616	3.913154	0.0001
C	0.020055	0.027096	0.740141	0.4602
@TREND("1967Q1")	-6.58E-05	6.60E-05	-0.996801	0.3202

R-squared	0.342127	Mean dependent var	0.016124
Adjusted R-squared	0.331283	S.D. dependent var	0.009628
S.E. of regression	0.007873	Akaike info criterion	-6.829450
Sum squared resid	0.011281	Schwarz criterion	-6.760079
Log likelihood	639.1389	Hannan-Quinn criter.	-6.801339
F-statistic	31.54966	Durbin-Watson stat	2.082470
Prob(F-statistic)	0.000000		

Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
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.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNM2)
Method: Least Squares
Date: 08/15/14 Time: 01:53
Sample (adjusted): 1967Q3 2013Q4
Included observations: 186 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNM2(-1)	-0.020199	0.009190	-2.197872	0.0292
D(LNM2(-1))	0.508881	0.063055	8.070429	0.0000
C	0.144072	0.062095	2.320169	0.0214
@TREND("1967Q1")	0.000269	0.000125	2.147537	0.0331

R-squared	0.281505	Mean dependent var	0.014479
Adjusted R-squared	0.269662	S.D. dependent var	0.008556
S.E. of regression	0.007312	Akaike info criterion	-6.977286
Sum squared resid	0.009731	Schwarz criterion	-6.907915
Log likelihood	652.8876	Hannan-Quinn criter.	-6.949175
F-statistic	23.76911	Durbin-Watson stat	2.027846
Prob(F-statistic)	0.000000		

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

Null Hypothesis: D(LNNGDP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
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.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNNGDP,2)
Method: Least Squares
Date: 08/15/14 Time: 01:57
Sample (adjusted): 1967Q3 2013Q4
Included observations: 186 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNNGDP(-1))	-0.724156	0.070027	-10.34110	0.0000
C	0.018297	0.002097	8.723571	0.0000
@TREND("1967Q1")	-7.00E-05	1.26E-05	-5.573252	0.0000

R-squared	0.368944	Mean dependent var	3.29E-05
Adjusted R-squared	0.362047	S.D. dependent var	0.009830
S.E. of regression	0.007852	Akaike info criterion	-6.840180
Sum squared resid	0.011282	Schwarz criterion	-6.788152
Log likelihood	639.1367	Hannan-Quinn criter.	-6.819096
F-statistic	53.49506	Durbin-Watson stat	2.081818
Prob(F-statistic)	0.000000		

Null Hypothesis: D(LNM2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
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.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNM2,2)
Method: Least Squares
Date: 08/15/14 Time: 01:54
Sample (adjusted): 1967Q3 2013Q4
Included observations: 186 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNM2(-1))	-0.491737	0.063711	-7.718251	0.0000
C	0.007632	0.001486	5.135386	0.0000
@TREND("1967Q1")	-5.43E-06	1.01E-05	-0.535968	0.5926

R-squared	0.245624	Mean dependent var	-4.72E-07
Adjusted R-squared	0.237380	S.D. dependent var	0.008460
S.E. of regression	0.007388	Akaike info criterion	-6.961843
Sum squared resid	0.009989	Schwarz criterion	-6.909815
Log likelihood	650.4514	Hannan-Quinn criter.	-6.940759
F-statistic	29.79233	Durbin-Watson stat	2.014098
Prob(F-statistic)	0.000000		

Table 3. Johansen cointegration test between lnNGDP and lnM2

Date: 08/17/14 Time: 21:55
Sample (adjusted): 1968Q2 2013Q4
Included observations: 183 after adjustments
Trend assumption: Linear deterministic trend
Series: LNM2 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	Prob.**
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	Prob.**
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 (normalized by b'*S11*b=I):

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

1 Cointegrating Equation(s): 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 4. VAR(2) estimation

Vector Autoregression Estimates
Date: 08/18/14 Time: 02:13
Sample (adjusted): 1967Q4 2013Q4
Included observations: 185 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DLNNGDP	DLNM2
DLNNGDP(-1)	0.343726	-0.203535
	(0.07111)	(0.06393)
	[4.83377]	[-3.18391]
DLNNGDP(-2)	0.296876	0.110804
	(0.07117)	(0.06398)
	[4.17157]	[1.73192]
DLNM2(-1)	0.230714	0.502884
	(0.08198)	(0.07370)
	[2.81432]	[6.82361]
DLNM2(-2)	-0.018083	0.051093
	(0.08169)	(0.07344)
	[-0.22137]	[0.69573]
C	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. resids	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 resid covariance (dof adj.)		3.38E-09
Determinant resid covariance		3.20E-09
Log likelihood		1284.335
Akaike information criterion		-13.77659
Schwarz criterion		-13.60252

Table 5. VAR(3) estimation

Date: 08/18/14 Time: 02:14
Sample (adjusted): 1968Q1 2013Q4
Included observations: 184 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DLNNGDP	DLNM2
DLNNGDP(-1)	0.318158	-0.223671
	(0.07460)	(0.06667)
	[4.26460]	[-3.35472]
DLNNGDP(-2)	0.288470	0.062865
	(0.07726)	(0.06904)
	[3.73398]	[0.91053]
DLNNGDP(-3)	0.076208	0.074424
	(0.07535)	(0.06734)
	[1.01134]	[1.10515]
DLNM2(-1)	0.223336	0.483728
	(0.08300)	(0.07418)
	[2.69084]	[6.52140]
DLNM2(-2)	0.061580	0.002791
	(0.09397)	(0.08398)
	[0.65531]	[0.03323]
DLNM2(-3)	-0.113475	0.146457
	(0.08194)	(0.07323)
	[-1.38480]	[1.99990]
C	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. resids	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 resid covariance (dof adj.)		3.34E-09
Determinant resid covariance		3.09E-09
Log likelihood		1280.607
Akaike information criterion		-13.76747
Schwarz criterion		-13.52286

Table 6. VAR coefficient selecting criteria $C(p)$

System: UNTITLED
Estimation Method: Least Squares
Date: 08/20/14 Time: 00:31
Sample: 1968Q1 2013Q4
Included observations: 184
Total system (balanced) observations 368

	Coefficient	Std. Error	t-Statistic	Prob.
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
Determinant residual covariance		3.09E-09		

Equation: DLNM2 = C(1)*DLNM2(-1) + C(2)*DLNM2(-2) + C(3)*DLNM2(-3) + C(4)*DLNNGDP(-1) + C(5)*DLNNGDP(-2) + C(6)*DLNNGDP(-3) + C(7)
Observations: 184

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

Equation: DLNNGDP = C(8)*DLNM2(-1) + C(9)*DLNM2(-2) + C(10)*DLNM2(-3) + C(11)*DLNNGDP(-1) + C(12)*DLNNGDP(-2) + C(13)*DLNNGDP(-3) + C(14)
Observations: 184

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		

Fall 2014 Office Hours

Please Return By August 27th

Please print your name, office number, and hours in the space provided below. TAs and GTAs are required to hold at least 3 hours per week, preferably not all in the same day.

If you have a web page for your classes, provide that information in the space below.

If you change any aspect of your office hours after they have been posted please let me know. This is vital for providing accurate information to people looking for you.

Thank you.

NAME Erhan ORUC

Name you go by ______

OFFICE HOURS W ⇒ 12:00pm – 1:30pm

F ⇒ 9:15 am – 10:45 am

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