Do monetary and financial variables cause real economic activity? Empirical Evidence from multiscale decomposed series from Romanian Economy

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Abstract
The paper adds evidence to the problem of whether money and other monetary and financial variables cause economic activity using monthly data from Romanian economy starting with 1991. We perform a multiscale decomposition of monthly monetary and financial variables as well as of industrial production from Romanian economy using the wavelet approach. Additional monthly time series from Euro Area are considered in our sample. We test whether the monetary and financial variables from Romania or Euro Area cause in a Granger sense the real economic activity using the details resulted from the multiscale decomposition of the time series.

Keywords: business cycles, wavelets, nonlinear techniques.
JEL Classification: C22, C32, E44.

1. Introduction

In analyzing the economic process, there is a very important causal relationship between economic variables and means by which causality can be measured. Causality is a phenomenon of a particular interest because it can extend the analysis to the evolution of the economic fluctuations, the causes of economic cycles and in order to formulate the most appropiate economic policies to minimize the volatility of key macroeconomic policies. Throughout the development of the economic theory there were many contradictions about the existence/absence of a correlation between real and monetary/financial variables, to what extend and direction one influences the other, and especially if this influence is long or/and short term.

In economics, Granger causality (Granger, 1969) is one of the most commonly applied research methods. Granger made a test to check if the oscillations of a variable precede systematic oscillations of another variable on the principle that a present or future event may be influenced by a past event, but not vice versa. The standard Granger test is based on standard asymptotic distribution hypothesis. Granger and Newbold (1974), using Monte Carlo simulations, showed that if the data series are non-stationary, the generated regressions may be spurious. The differentiation solution didn't prove to be very effective because it has the disadvantage of loss of long term information (Philips, 1986).

With the introduction of unit root in time series analysis, several changes were made to test the causal relationships. Toda-Yamamoto(1995) modified the Wald test in a new test (called Mwald) that is more attractive because it is easier to be applied and no pre-test biases and reliance on standard asymptotic distribution hypothesis regardless of the number of unit roots and cointegration properties of data are needed.

Scott Hacker and Abdulnasser Hatemi(2006) used the Toda-Yamamoto test to check Granger causality when variables are integrated of order 0,1 or 2, using Monte Carlo simulations for standard chi-square and bootstrap distributions. They estimated a VAR model with a number of lags (equal to the order of integration of variables) and concluded that bootstrap distribution is better than standard distribution in the presence of one ARCH process, but not necessarily a homoscedastic one, especially if the sample has reduced dimensions. The model was tested on the U.S. economy to test the efficiency of stock market information depending on the interest rate and the real exchange rate, using monthly data during 1987-2002. The results showed that agents take into account information provided by these variables, taking full advantage of it, and not being able to get further information. Inverse correlations were also tested and a significant coefficient was found. Further, interest rates affects the real exchange rate but opposite correlation is not preserved. In other words, monetary policy of the FED has a great impact on the exchange rate, but opposite to that, the real exchange rate acts independently of the money market.

A new stage of analysis of causality was made later by Engle and Granger(1987), and Johansen(1988); they used VECM (Vector Error Correction Model) to analyze causality for integrated data series. This method involves testing unit roots and cointegrating the series before testing causality. In the early literature on Granger causality in relation to issues of cointegration, the relationship between money and output has not been analyzed. Stock and Watson(1989) showed that under the hypothesis of lack of cointegration a specification error by differentiation of first order can be obtained.

Konishi and Ramey(1993) examined the relationship between financial variables and real activity using the concept of "separation cointegration", introduced by Granger and Konishi in 1992 (it means that two groups of variables can be uncorrelated in the long run, but the error correction term in a group can affect the error term from the other group). They concluded that US interest rates have a stochastic trend different from other financial variables and real aggregates. Many studies have concluded that if interest rates are included in the model, the financial variables lose predictive capacity (Sims, 1980, Littermann and Weiss, 1985, Friedman and Kuttner, 1992).

Caporale, G.M., Hassapis,C., Pittis, N.(1998) analyzed the correlation of the following quarterly data series for the period January 1979 and December 1993, using VAR models: the real GDP, the monetary aggregate M1, the short-run interest rate and the long-run interest rate for five industrialized states: US, UK, Germany, Canada and Japan. The interest rates used are 3-month interbank rates, for the short-term interest rate, and 10-year Government bonds yields for the long-term rate. Other monetary aggregate variables were used only if their inclusion changed the relevance of the model. After testing the presence and persistence of the unit root (integrated series of first order), bivariate models (incomplete models) or trivariate models (complete models) have been made, and the most statistically significant models were chosen.

It's interesting to compare the results of the two models: the bivariate model may be considered erroneously and causality is more complex; at the bivariate stage output affects SR (short-run interest rate), and the trivariate model shows a causality in both directions. The bivariate analysis is most significant for Germany and Canada from M1 to Y (output). Only the trivariate analysis expresses causality from SR to M1. The same model was done for the variables: LR, M1 and Y. The article concluded that SR is a better predictor for Y than M1, with the exception of Germany where monetary aggregates supervision recommended.

Masanori Amano (2005) tested the Granger causality using annual data for SUA and UK(between 1874-1920 and 1953-1999), and for Japan (1894-1940 and 1954-2000) from historical and availability considerations. As a proxi for the financial indicators he used: the deposits of the commercial banks, commercial banks claims on the private sector, money multiplier (M2/monetary base) and the marshalian multiplier (M2/nominal GDP), where the first two variables were divided by the nominal GDP to be normalized. Before moving to the Granger causality test, the Engle-Granger cointegration test that showed cointegrated series was performed. The results confirms Patrick and GS's assumptions especially for the second period. The GS hypothesis stresses that the development financial institutions favor increasing the flow of savings and increase investment value, all of that developing the real economy; Patrick's hypothesis or supply leading pattern considers that financial variables affects the production, a pattern noticed especially in the case of the emerging countries. The reverse causality from output to financial variables seem to be very weak.

Transmission mechanisms of monetary policy have traditionally been explained by the exchange rate channel or the interest rate channel. Exceptions were Modigliani (1971) who described the important role of asset prices by property and wealth effect, and Bernanke and Gertler (1989) who argues that asset prices influence the credit channel of monetary policy. Meanwhile, Benmelech and Bergman (2009) analyzed how monetary policy can become inactive despite the infusion of money within the banking system because liquidity is still inside (credit trap).

Bayoumi and Darius (2011) showed that motivational oscillations of the banks to lend influences the welfare, but the welfare value doesn't impact lending decisions. The assumption that information on credit conditions can predict price changes contradicts the hypothesis of efficient financial market saying that these prices are unpredictable. By measuring changes in financial conditions on the production fluctuations, the financial instruments on the business cycles can be analyzed. The study shows that credit availability has a direct impact on the output though accelerator mechanism traditionally emphasize that output is influenced by market conditions through changes in general welfare.

Most studies have shown that financial development supported by an effective banking system increased influence on growth (Levine, 2005; Watchel, 2001). Levine (2005) argued that financial development affects economic growth through several channels: provides simplifying the exchange of goods and services by providing payment services, mobilize savings from a large number of investors, processes and registers information about firms and investment projects for possible better resource allocation, increases liquidity and decreases the inter-temporal risk. All these elements can affect saving or investment decisions with effects on the economic growth.

Reforming the banking system began in the '90s, when foreign banks began to invest in CEE countries and by 2004, most of them were foreign owned.

The credit to private sector grew rapidly during this period, but with different rates, a significant boom being achieved on mortgages. The credit heterogeneity may have different causes, such as the different degree of development of the financial intermediation or different institutional and regulatory frameworks. The main factors of credit process are: the income increase or decrease lending rate, bad or inflation debt and the implementation of reforms in the banking sector. Noteworthy is that a boom in lending to households may adversely affect the current account, a common problem for economies in transition.

A few studies were focused on the CEE countries (Bonin and Watchel, 2003; Fink, 2005, 2008). Fink(2005) showed (using a sample of 33 countries) that financial development affects the real economy rather than short term. Winkler(2009) demonstrated that targeting financial development by the appearance of the foreign banks does not necessarily ensure financial stability.

Caporale, Rault, Sova(2009) examined the correlation between the financial sector and real activity in 10 new Member States (Bulgaria, Estonia, Czech Republic, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia); they estimated an annual dynamic panel model for the period 1994-2007 and conclude that stock market and credit market are still underdeveloped and their contributions to the GDP growth are still insignificant. All these conclusions are due to the lack of the financial depth. The Granger causality test shows a weak trend of causality from financial development to economic growth (but the coefficients are not statistically significant), but the lack of correlation appears in the reverse direction. The long term causality between variables is rejected. Also, a causal relation was found between capitalization securities and economic growth on short term.

2. Methodology

2.1 Granger Causality Test

The Granger test(1969), with subsequent developments of Toda and Yamamoto version, is used to check the existence of a relationship between two variables. This test says that if a previous value of y variable contributes significantly to forecast future values of the variable x, then y is said to Granger cause the variable x. Conversely, if the past values of x help to improve (in the statistical sense) the prediction of y, then x is said to Granger cause the variable y.
The test is based on the following ecuations:

$$y_t = \beta_0 + \sum_{k=1}^{N} \beta_k y_{t-k} + \sum_{l=1}^{N} \alpha_l x_{t-l} + u_t$$

$$x_t = \gamma_0 + \sum_{k=1}^{N} \delta_k y_{t-k} + \sum_{l=1}^{N} \gamma_l x_{t-l} + v_t$$

where yt and xt are two variables, ut and vt are the uncorrelated disturbances, t is time, and k and l are lags

H0: $\alpha_l = 0$ for any l and $\delta_k = 0$ for any k

H1: $\alpha_l \neq 0$ şi $\delta_k \neq 0$ for at least some l and/or k.

If at least one α_l is statistically significant and δ_k is not statistically significant, then x Granger causes y. Conversely, y causes x. If both α_l and δ_k are statistically significant, then we have bilateral causality.

The steps involved in implementing the Granger causality test are as follows:

1. Regress current y on all lagged y terms and other variables, if any, but do not include the lagged x variables in this regression. This is the restricted regression. From this regression obtain the restricted residual sum of squares, RSS_r .
2. Now run the regression including the lagged x terms. This is the unrestricted regression. From this regression obtain the unrestricted residual sum of squares, RSS_{ur}.
3. The null hypothesis is H0: $\sum\alpha_l=0$, that is, lagged x terms do not belong in the regression.
4. To test this hypothesis, we apply the F test, which follows the F distribution with l and (T-l-1) df. l is the number of lagged x terms:

$$F = \frac{(RSS_r - RSS_u)/l}{RSS_u/(T-2l-1)}$$

5. If the computed F value exceeds the critical F value at the chosen level of significance, we reject the null hypothesis, in which case the lagged x terms belong in the regression. This is another way of saying that x causes y.
6. Steps 1 to 5 can be repeated to test whether y causes x.

Before the Granger causality test, there are several things that need to be noted:

- ✓ It is assumed that the two variables, y and x, are stationary. Sometimes taking the first differences of the variables makes them stationary, if they are not already stationary in the level form.

✓ The number of lagged terms to be introduced in the causality tests is an important practical question. As in the case of the distributed lag models, we may have to use the Akaike or Schwarz information criterion to make the choice. But it should be added that the direction of causality may depend critically on the number of lagged terms included.

✓ Since our interest is in testing for causality, one need not present the estimated coefficients of models and they are sufficient just the results of the F test.

2.2 Wavelets Decomposition

The wavelet analysis is very similar to the Fourier approach. Basically, the Fourier approach consists in describing a certain function by using sums of sine and cosine functions. However, as Crowley (2005) pointed, the main drawback of the Fourier approach is that it assumes that the frequency content of the function is stationary along the time axis.

The main advantage of the wavelet transform is that it allows for both time and scale representation and analysis. By the wavelet approach one can decompose a signal into different frequency components.

We describe in the following paragraphs of this section the main features of the wavelet analysis. There are two fundamental types of wavelets, father wavelets φ and mother wavelets ψ.
The father wavelet has the property that it integrates to one:

$$\int \phi(t)dt = 1$$

The mother wavelet integrates to zero:

$$\int \psi(t)dt = 0$$

As the literature explains, see Crowley (2005) for example, the father wavelet stands for the trend component. The mother wavelet stands for the high frequency components of the signal. Mallat's algorithm for *discrete wavelet transform* (DWT) is in the signal processing literature known as a two-channel subband coder using conjugate quadrature filters or quadrature mirror filters (QMFs). Interpreting the wavelets as filters, we can see that the father wavelet acts as a low pass filter, whereas the mother wavelets act as high pass filters.

Unlike Fourier analysis which breaks a signal into sine waves of different frequencies, the wavelet analysis breaks the signal into shifted and scaled versions of the mother wavelet. The goal of wavelet analysis is to reveal aspects of the signal such as trends, breakdown points, jump discontinuities which are missed by Fourier analysis.

The *continuous wavelet transform* (CWT) algorithm turns a signal *f(t)* in a function *c (a,b)* with two variables (scale and time):

$$c(a,b) = \int f(t)\psi(at+b)dt$$

For a faster algorithm, the *discrete wavelet transform* (DWT) transforms and dilates a wavelet only by discrete values, by a power of 2. Therefore, DWT uses only wavelets of the form

$\psi(2^k t + l)$, where k and l are whole numbers

Therefore, because the scaling parameter is 2^J, the multiresolution analysis is equivalent of putting signal components in successive frequencies.

DWT applies the shifted and translated versions of the mother wavelet to the function for breaking its structure in simpler components. In order to decompose the signal using wavelets, we used some filters operating as averaging filters, named *approximations* and others that produce *details.*

While the *approximations* are high scale, low frequency components of the signal, slowly changing characteristics of the signal, the *details* are exactly the opposite. The DWT's algorithm splits the signal in an approximation and a detail at the first level, and because the process is iterative, the approximation is then split in a second approximation and detail and so on until we reach a significant level of detail. For example, if we take the signal as being the volatility of BET index, we may say that the approximation of the volatility correspond to the main trend, while the details may correspond to secondary trends or may be used to identify seasonal or specific patterns in the data for different time scales. Using wavelet analysis may help us identify the main trend and other patterns camouflaged in the data, if there are.

Given the fact the approximation are the low frequency, slowly changing characteristic of the signal, we may interpret approximations to be largely related to the aggregated trading investment strategies with a higher investment horizon, associated mostly with institutional investors, while the details, which are highly irregular, characterize high frequency trading may be associated with fast changing investment sentiment while linked with shorter investment horizons.

A multiresolution analysis of the signal may allow us to understand the dynamic behaviour of investors operating on several time scales simultaneously and, while perceiving both the low and high frequency components of the signal, to identify specific trading patterns.

3. Data and results

We use as an indicator for the economic activity in Romania using data on industrial production between 1991 and 2010 at a monthly frequency. This approach ensures the maximum available data. As monetary and financial variables we selected three series for Romania and two further series from Europe. We first selected monthly M2, non-governmental debt and the exchange rate against the dollar. From Euro Area we used the DAX stock market index as a proxy for world stock market activity and Euro Area M2 as an indicator of money dynamics in Euro Area. We seasonally adjusted the series and computed the log difference in order to obtain stationary series.

We selected the Daubechy type of wavelet and performed a multiscale decomposition up to level five. We decomposed thus the series starting from 2^1=2 month frequency up to 2^6=64 months frequency (or five years and a half), representing roughly the business cycles frequency.

We applied afterwards tests for Granger causality between the obtained frequencies and for original (not decomposed) time series. The results are presented in the table below.

Table 1. Test for Granger causality for multiscale decomposed time series

Variable	Frequency 2^1 months	Frequency 2^2 months	Frequency 2^3 months	Frequency 2^4 months	Frequency 2^5 months	Frequency 2^6 months
Debt	7.34*	2.65	27.19*	0.16	0.70	1.81
M2 Romanian	10.27*	20.70*	34.59*	2.66	0.38	0.30
Exchange rate	7.58*	10.81*	32.88*	0.39	1.32	1.79
M2 Euro Area	14.27*	1.23	24.27*	0.36	1.17	0.72
DAX index	9.10*	1.27	22.63*	0.14	0.13	0.85

Source: Own computations.

Notes: We present F statistics for null hypothesis that a series does not cause in a Granger sense the industrial production; The critical value is considered of a 0.1 confidence interval; An asterisk indicates the rejection of the null hypothesis.

We detect a few interesting patters for all series: causality appears from monetary and financial variables at both a horizon of two months and at 8 months, representing the short term. For horizons larger than one year, there is no Granger causality for any series. We also detect causality at four months for Romanian M2 and the exchange rate.

Table 2. Test for Granger causality in the case of two lags for undecomposed time series

Variable	F-stat(2 lags)	F-stat(4 lags)	F-stat(8 lags)
Debt	1.32	2.45	1.02
M2 Romanian	11.77*	10.73*	5.44*
Exchange rate	0.55	5.58*	3.61*
M2 Euro Area	4.48*	2.52	1.86
DAX index	1.41	2.59	1.58

Source: Own computations.

Notes: We present F statistics for null hypothesis that a series does not cause in a Granger sense the industrial production; The critical value is considered of a 0.1 confidence interval; An asterisk indicates the rejection of the null hypothesis.

For the un-decomposed series, we did not get Granger causality for debt and the DAX index. However, for the other series, for some specifications of the test, we got Granger causality. The causality from money M2 to industrial production seems robust to any specification of the test.

4. Conclusions

The causality on the short term from money supply M2 to the output dynamics indicates the existence of monetary policy effects on the real economy. Wavelet decomposition also confirms the money neutrality theory, which states that a monetary expansion will affect only long term prices while real activity will not increase except in the short run. The renouncement of monetary aggregates targeting and the transition to inflation targeting may be one of the causes for that the correlation between M2 and output become weaker over time (this fact is indicated by the lack of causality for horizons larger than one years).

Statistical results obtained from applying the F-test shows that the financial variable „governmental debt" has an impact on short and medium term as the decomposed data shows. The presence of this type of causality can be explained by the preference for short and medium term loans (as long term loans include uncertainties and risk premiums much higher), by the fact that lending process was aimed mainly for consumption and not for investment or by the bad credits.

The exchange rate impacts output only in the short and medium term, the impact distribution is revealed for the first three levels of wavelet decomposition. On the other hand, Granger test using un-decomposed series shows an insignificant influence of exchange rate on the output in the very short term.

Regarding the influence of the external factors, it can be observed that the wavelet decomposition shows how the money supply M2 from the euro area and the DAX index have a significantly impact on the output from Romania at 2 and 8 months, but not at 4 months. On the other hand, the Granger test for the un-decomposed series does not detect any significant influence of the mentioned variables in the current period and in the short term. Regarding the impact of the DAX index, taken as a proxy for world markets, an explanation is the importance world markets on the expectations of economic agents regarding the evolution of euro area businesses.

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Annexes

Appendix 1

Pairwise Granger Causality Tests
Date: 09/27/11 Time: 08:28
Sample: 1991M01 2011M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_DEBT does not Granger Cause DLOG_IP	237	1.32105	0.2689
DLOG_IP does not Granger Cause DLOG_DEBT		0.04752	0.9536

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:39
Sample: 1991M01 2011M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_DEBT	235	0.62588	0.6445
DLOG_DEBT does not Granger Cause DLOG_IP		2.45073	0.0470

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:40

Sample: 1991M01 2011M12
Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_DEBT	231	0.72163	0.6723
DLOG_DEBT does not Granger Cause DLOG_IP		1.02685	0.4167

Appendix 2

Pairwise Granger Causality Tests
Date: 09/27/11 Time: 08:30
Sample: 1991M01 2011M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2	237	0.45353	0.6359
DLOG_M2 does not Granger Cause DLOG_IP		11.7734	1.E-05

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:42
Sample: 1991M01 2011M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2	235	1.22505	0.3010
DLOG_M2 does not Granger Cause DLOG_IP		10.7347	6.E-08

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:42
Sample: 1991M01 2011M12
Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2	231	2.97984	0.0035
DLOG_M2 does not Granger Cause DLOG_IP		5.44048	3.E-06

Appendix 3

Pairwise Granger Causality Tests
Date: 09/27/11 Time: 08:31
Sample: 1991M01 2011M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2EUR	237	0.25877	0.7722
DLOG_M2EUR does not Granger Cause DLOG_IP		4.48113	0.0123

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:43
Sample: 1991M01 2011M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2EUR	235	0.28558	0.8872
DLOG_M2EUR does not Granger Cause DLOG_IP		2.52812	0.0415

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:43
Sample: 1991M01 2011M12
Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_M2EUR	231	0.42381	0.9060
DLOG_M2EUR does not Granger Cause DLOG_IP		1.86097	0.0676

Appendix 4

Pairwise Granger Causality Tests
Date: 09/27/11 Time: 08:32
Sample: 1991M01 2011M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.

DLOG_IP does not Granger Cause DLOG_DAX	237	0.12886	0.8792
DLOG_DAX does not Granger Cause DLOG_IP		1.41009	0.2462

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:44
Sample: 1991M01 2011M12
Lags: 4

Null Hypothesis:	Obs
DLOG_IP does not Granger Cause DLOG_DAX	235
DLOG_DAX does not Granger Cause DLOG_IP	

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:45
Sample: 1991M01 2011M12
Lags: 8

Null Hypothesis:	Obs
DLOG_IP does not Granger Cause DLOG_DAX	231
DLOG_DAX does not Granger Cause DLOG_IP	

Appendix 5

Pairwise Granger Causality Tests
Date: 09/27/11 Time: 08:33
Sample: 1991M01 2011M12
Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_EXR	237	3.67685	0.0268
DLOG_EXR does not Granger Cause DLOG_IP		0.55513	0.5748

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:45
Sample: 1991M01 2011M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_EXR	235	3.90480	0.0044

DLOG_EXR does not Granger Cause DLOG_IP		5.58174	0.0003

Pairwise Granger Causality Tests
Date: 10/06/11 Time: 23:46
Sample: 1991M01 2011M12
Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
DLOG_IP does not Granger Cause DLOG_EXR	231	3.29702	0.0014
DLOG_EXR does not Granger Cause DLOG_IP		3.61925	0.0006