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Evidence on the Direction of Causation in the Money-Income Relationship: An Alternative Methodology[1]

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Abstract

In this paper, the evidence reported in the large literature on testing for money-output Granger causality is revisited by applying an alternative methodology based on the leveraged bootstrapped simulation techniques, using data from Denmark and Sweden. Based on the estimation results, the authors find unidirectional causality from money to output for the sample countries. The established unidirectional causality between money and output supports monetary business-cycle models and reveals two policy implications. First, active monetary policy has a role in reducing the severity of the business cycles and unobservable shocks. Second, in looking for the sources of output fluctuations, money is a major factor.

1. Introduction and Overview

A well-known area of debate in macroeconomics literature has been the precise relationship between money and output (Blanchard, 1990; Lucas, 1996; Sargent, 1996). The direction of causation between money and output is an important issue for many policymakers and economists since it reveals appropriate monetary policy. Why does money influence output or vice versa? The purpose of this study is to explore the direction of causation between money supply and output by applying an alternative methodology.

There are two very different theories, which explain the direction of causation.[2] The first, monetary-business-cycle theory, explains that changes in growth of the money supply cause changes in output growth, i.e., money causes output. Models in this category are known as new Keynesian models or sticky-wage models, which consider wage contracts as a central feature of the economy. Individuals sign long-term wage contracts that fix their money wage over the length of the contract. If money supply grows at a faster rate than it was predicted at the time of the contract negotiation, inflation will be higher than expected, so individuals' real wage will decrease. This, in turn, influences firms' behavior and they demand for more workers, which leads an increase in the economy's output. Thus, the sticky-wage theory with unanticipated changes in money describes a positive relationship between money growth and output growth (Gray, 1976; Fisher, 1977; Taylor, 1980).

Another explanation by monetary-business-cycle theorists for non-neutrality of money stems from a class of models known as imperfect-information models (Lucas, 1972, 1975; Barro, 1976). These models explain that monetary changes can have real effects because individuals

[2] For a survey of literature see Ahmed (1993) and Holmes and Hutton (1992).

have limited information and thus may misperceive aggregate and relative changes. In other words, in these models, if the money supply increases, prices will tend to rise throughout the economy but individuals attribute part of the price increase to a shift in demand toward their own product and away from the goods produced by other sectors. This implies that an increase in the relative demand as a result of the misperception leads to a rise in production.

The second, real-business-cycle theory, differs primarily in the direction of causation between money growth and output growth. Real-business-cycle-models assign a causal role to real economic activity in affecting money supply. That is, changes in output growth cause changes in growth of the money, not vice versa. Shocks can affect supplies of real resources and relative prices that individuals expect to face over time. These shocks include technological innovations, other sources of productivity changes, environmental conditions, the world price of energy, developments in the labor market, and government spending and taxes. Thus, in real-business-cycle-theory, output growth is determined by real shocks, not by money growth (Kydland and Prescott, 1982; Long and Plosser, 1983). In real-business-cycle-models, money is related to output because it reacts to the same real shocks that output responds to.

The advocates of real-business-cycle models offer two reasons why money reacts to real shocks. The first reason rests on the idea that developments in the real sectors of the economy influence individuals' financial decisions. This, in turn, affects the quantity of money demanded. So long as the financial system reacts to the changes in money demand, changes in output growth create changes in money growth. This implies that output causes money, not vice versa. The second reason stems from the assumption that individuals have information about economic activity that cannot be quantified. For example, higher expected output might create a rise in the demand for money and credit. Policymakers will permit the money supply increase to accommodate the rise in money demand so that interest rate does not change. This implies that there is a unidirectional causality between output growth and money growth, running from output to money supply.

Thus, this paper seeks to find out which of these two theories mentioned above is more in accord with the Danish and Swedish data for the period 1961-1999. The choice of Denmark and Sweden is justified by the fact that the economies are small, open, market-oriented economies with a relatively unregulated capital account, and non-reserve currency countries. Furthermore, the sample period does include boom period with improved government finances, external net borrowing, and full employment and a bust period with rapidly increasing unemployment and deteriorating government finances. Thus, the sample is not tranquil in a way that could favor any theory mentioned above. On the other hand, there is a large body of the literature documenting evidence on the direction of causation in the money-output relationship for the UK and the US, but few studies concentrate on small open economies.

However, this study is a first attempt to use an alternative methodology based on the leveraged bootstrapped simulation techniques to test for the causal nexus of money and output. The procedure performs well when data generating process is characterized by non-stationarity, and when the sample size is relatively small.

This paper is organized as follows: Section 2 reviews previous empirical studies on money-output relationship. Section 3 describes data set and methodology, and also presents estimation results. Conclusions and policy implications are offered in Section 4.

2. Previous Studies

The money-output relationship has been documented by casual and rigorous empiricism in a number of studies employing a variety of data sets. Sophisticated empirical models have been devised to examine the implication of anticipated and unanticipated (Barro, 1977), positive and negative (Cover, 1992; Thoma, 1994), and large and small monetary shocks (Ravn and Sola, 1996) on output fluctuations. While some studies have supported unidirectional causality, running from money to income (e.g., Sims 1972; Hafer, 1982; Devan and Rangazar, 1987), other studies have provided evidence on unidirectional causality, running from income to money (e.g., Williams, et al., 1976; Putman and Wilford, 1978; Cuddington, 1981; King and Plosser, 1984). There is also empirical evidence of bi-directional causality between money and output for a number of countries (e.g., Hayo, 1999).

However, the existing empirical evidence based on testing of causality between money growth and output growth is, at best, mixed and contradictory (Ahmad, 1993; Hayo, 1999). The instability of results in Granger causality test simply stems from (i) whether the variables are modeled as (log-) level variables or growth rates (Christiano and Ljungquist, 1988) and (ii) whether they are modeled as trend- or difference stationary (Hafer and Kutan, 1997). Christiano and Ljungquist (1988) argue in favor of using level variables, since they find that power of the tests on growth variables is very low. Hafer and Kutan (1997) assert that the variables, which are assumed to be trend stationary, money Granger causes output and if the variables are assumed to be difference stationary, output Granger causes money.

3. Data, Methodology, and Estimation Results

The data used in this study is yearly for the period 1961-1999. The following variables are used in this study: narrow money (M1 and M0 for Denmark and Sweden, respectively), broad money (M2 and M3 for Denmark and Sweden, respectively), and gross domestic national product. All variables are expressed in logs and constant prices (see the Appendix for details).

In this paper our interest is focused on the causal nexus of the variables. By causality we mean causality in the Granger sense. A variable Granger causes another variable if including it in the information set will improve the forecast of the second variable. It is widely accepted now that in the vector autoregressive (VAR) framework, the Wald test for testing the Granger causality may have non-standard asymptotic properties if the variables considered in the VAR are integrated. Toda and Yamamoto (1995) proposed solutions based on lag augmentation of the VAR model that guarantees standard c^2 asymptotic distribution for the Wald tests performed on the coefficients of VAR processes with I(1) variables.

However, Hacker and Hatemi-J (2002) conducted Monte Carlo experiments to investigate the properties of lag augmented tests for causality between integrated variables. The authors found that these tests do not have correct size when usual standard distributions are used but the tests perform very well when bootstrap distributions are used, especially if multivariate ARCH effects exist in the VAR model. For this reason we will use the leveraged bootstrapped tests suggested by Hacker and Hatemi-J (2002) in order to increase the probability of drawing valid inference in testing for the causal nexus of money and output. The authors show that the bootstrap test performs well when the data generating process is characterized by non-stationarity and when multivariate ARCH effects are present. There are two other advantages using this procedure: first, it has more precision particularly when the sample size is relatively small as in our case, and second, the bootstrap procedure is not sensitive for the normal distribution because it is based on the empirical distribution of the underlying data.[3]

In this study, we use the bootstrap simulation techniques performed on the Toda-Yamamoto test. Consider the following vector autoregressive model of order p, VAR(p):

$$x_t = n + A_1 x_{t-1} + \ldots + A_p x_{t-p} + e_t \,, \tag{1}$$

where $e_t = (e_{1t}, ..., e_{nt})'$ is a zero mean independent white noise process with non-singular covariance matrix Σ_e. In order to rule out explosive cases, we assume j = 1, ... , n, $\mathrm{E}|e_{jt}|^{2+t} < \infty$ for some $\tau > 0$. An important issue in this regard is the choice of the optimal lag length (p) in the VAR model because all inference in the VAR is of course based on the chosen lag length. To bring about this, we make use of a new information criterion introduced by Hatemi-J (2003). This information criterion is shown to perform well for choosing the optimal lag order, especially if the variables in the VAR model are integrated. The lag length that minimizes the following equation is chosen as the optimal lag order:

$$HJC = \ln\left(det\, \widehat{W}_j\right) + j\left(\frac{n^2 \ln T + 2n^2 \ln(\ln T)}{2T}\right), \qquad j = 0, \cdots, p, \tag{2}$$

[3] See Hongyi and Maddala (1997).

Where:

ln = the natural logarithm,

$det\ \widehat{\Omega}_j$ = the determinant of the estimated variance and covariance matrix of e_t for lag order j,

n = the number of variables in the model, and

T = the number of observations used to estimate the VAR model.

It is well known in the literature that standard asymptotical distributions cannot be used to test for Granger causality. To remedy this shortcoming Toda and Yamamoto (1995) suggest the following augmented VAR(p+d) model:

$$x_t = n + A_1 x_{t-1} + \ldots + A_p x_{t-p} + \ldots + A_p x_{t-p-d} + e_t. \tag{3}$$

Note that d is representing the integration order of the variables. The kth element of x_t does not Granger-cause the jth element of x_t if the following hypothesis is not rejected at a given significance level:

$$H_0\text{: the row } j\text{, column } k \text{ element in } A_r \text{ equals zero for } r = 1,\ldots, p. \tag{4}$$

It should be pointed out that the parameters for the extra lag(s), i.e. d, are unrestricted under the null hypothesis. According to Toda and Yamamoto (1995) these unrestricted parameters make sure that the asymptotical distribution theory can be utilized when test for Granger causality are conducted between integrated variables. We make use of the following denotations in order to describe the Toda-Yamamoto test statistic in a compact way:

$X := (x_1, \cdots, x_T)$ $\quad (n \times T)$ matrix,

$$D := \left(v, A_1, \cdots, A_p, \cdots, A_{p+d}\right) \quad (n \times (1 + n(p + d))) \text{ matrix,}$$

$$Z_t := \begin{bmatrix} 1 \\ x_t \\ x_{t-1} \\ \vdots \\ x_{t-p-d+1} \end{bmatrix} \quad ((1 + n(p + d)) \times 1) \text{ matrix, for } t = 1,$$

…,T,

$$Z := \left(Z_{\mathbf{0}}, \cdots, Z_{T-\mathbf{1}}\right) \quad ((1 + n(p + d)) \times T) \text{ matrix, and}$$

$$\boldsymbol{d} := \left(e_1, \cdots, e_T\right) \quad (n \times T) \text{ matrix.}$$

Via this notation, the estimated VAR(p+d) model is written compactly as:

$$X = DZ + \boldsymbol{d}\,. \tag{5}$$

Toda and Yamamoto (1995) introduce the following modified Wald (MWALD) test statistic for testing the null hypothesis of non-Granger causality:

$$MWALD = \left(C\boldsymbol{b}\right)' \left[C\left((Z'Z)^{-1} \otimes S_U\right)C'\right]^{-1} \left(C\boldsymbol{b}\right) \sim \boldsymbol{c}_p^2\,. \tag{6}$$

Where:

$\otimes$ = element by element multiplication operator (the Kronecker product).

C = a $p \times n(1+n(p+d))$ matrix. Each of the p rows of C is associated with the restriction to zero of one parameter in $\boldsymbol{b}$. The elements in each row of C acquire the value of one if the related parameter in $\boldsymbol{b}$ is zero under the null hypothesis, and they get the value of zero if there is no such restriction under the null.

S_U = the estimated variance covariance matrix of residuals in equation (5) when the the null hypothesis of non-Granger causality is imposed.

$b = vec(D)$, where *vec* represents the column-stacking operator.

The MWALD test statistic is asymptotically χ^2 distributed, conditional on the assumption that the error terms are normally distributed, with the number of degrees of freedom equal to the number of restrictions to be tested. The number of restrictions is equal to p in our case. Nevertheless, Hacker and Hatemi-J (2002) show via Monte Carlo simulations that the MWALD test statistic overrejects the null hypothesis, especially if the data generating process for the error terms is characterized by non-normality and autoregressive conditional heteroscedasticity (ARCH). To improve on the size properties of tests for causality under such circumstances, the authors propose using leveraged bootstrap simulations. The bootstrap method was originally introduced by Efron (1979) and it is based on resampling the underlying data to estimate the distribution of a test statistic. It has become a very useful tool to remedy cases when asymptotical distributions have low performance.

To perform the bootstrap simulations we first estimate regression (5) with the null hypothesis of no Granger causality imposed. For each bootstrap simulation we generate the simulated data, X^*, in the following way:

$$X^* = \hat{D}Z + d^*, \qquad (7)$$

here $\hat{D}$ is the estimated value of the parameters in equation (5). That is:

$$\hat{D} = XZ'\left(ZZ'\right)^{-1}. \qquad (8)$$

Note that the bootstrap residuals (d^*) are based on T random draws with replacement from the regression's modified residuals, each with equal probability of $1/T$. The mean of the resulting set of drawn modified residuals is subtracted from each of the modified residuals in that set. This modification is done to ensure that the mean value of the bootstrapped residuals is zero. The modified residuals are the regression's raw residuals modified to have constant variance, through the use of *leverages*.[4]

In order to calculate the bootstrap critical values, we run the bootstrap simulation 1000 times and calculate the MWALD test statistic each time. In this way, we are able to produce the empirical distribution for the MWALD test statistic. Subsequent to these 1000 estimations we locate the (α)*th* upper quantile of the distribution of bootstrapped MWALD statistics and attain the α-level "bootstrap critical values" (c_a^*). We create the bootstrap critical values for 1%, 5% and 10% significance levels. The next step is to calculate the MWALD statistic using the original data (not the bootstrapped simulated data). Then, the null hypothesis of no causality in the Granger's sense is rejected based on bootstrapping if the actual MWALD is greater than c_a^* (the simulations are conducted in GAUSS).[5]

[4] For more details on leverage adjustment the interested reader is referred to Davison and Hinkley (1999) and Hacker and Hatemi-J (2002). The latter authors suggest this adjustment for multivariate equation cases.

[5] The program procedure written in Gauss to conduct leveraged bootstrap simulations is available on request from the authors.

Before testing for causality, we conducted tests for integration order for each variable using the KPSS test (Kwiatkowski, et al., 1992) and Perron's (1989) test. The results are presented in Tables 1 and 2. Based on the estimation results, we can conclude that the data-generating process for each variable is generally characterized by one unit root. As mentioned previously, the asymptotic critical values are not valid for causality tests when the variables are integrated. To remedy this problem, we have applied bootstrap simulation techniques to calculate our own critical values based on the empirical distribution of the data set, which does not require necessarily to be normally distributed. According to the results reported in Table 3, there exists uni-directional causality running from money (narrow and broad measures in the case of Denmark and only broad money measure in the case of Sweden) to output.

4. Conclusions and Policy Implications

Previous studies of the direction of causation between money and income, based on the Granger causality tests, have demonstrated mixed and contradictory results. We discuss that such tests are problematic and suggest an alternative methodology based on the leveraged bootstrapped simulation technique. The evidence is provided for Denmark and Sweden. Based on the estimated results, the authors find that Granger causality is uni-directional running from money to output.

However, our results are, more or less, in line with those of Serletis and King (1994) with respect to Canada (unidirectional causality from narrow money growth to output growth) and the US (unidirectional causality from broad money growth to real output growth), Sephton (1995) with respect to Canada (unidirectional causality from monetary base to nominal income and from nominal income to narrow money), Artis (1992) with respect to

Canada (narrow money Granger-causes output), the US (broad money Granger-causes output), Britain (unidirectional causality from narrow money to real output), and Germany and France (unidirectional causality from both narrow and broad money to real output), and finally, Hayo (1999) with respect to Denmark and Sweden (unidirectional causality from narrow money to output when the money growth rate is positive).

Generally speaking, the established uni-directional causality from money to output reveals two policy implications. First, active monetary policy has a role in reducing the severity of the business cycles and unobservable shocks. Second, in looking for the sources of output fluctuations, money is a major factor.

Table 1: Test for unit roots using the KPSS test.[a]

TRUNCATION LAGS →	0	1	2	3	4	5	6	7	8
H_0: I(0), H_1: I(d)									
M1 Denmark	3.67	1.92	1.33	1.04	0.86	0.74	0.66	0.60	0.55
M2 Denmark	3.78	1.97	1.36	1.05	0.87	0.75	0.67	0.60	0.55
M0 Sweden	1.19	0.64	0.46	0.37	0.31	0.28	0.26	0.24	0.23
M3 Sweden	2.72	1.48	1.06	0.84	0.71	0.63	0.57	0.53	0.50
Income Denmark	3.54	1.86	1.29	1.01	0.84	0.73	0.65	0.60	0.55
Income Sweden	3.64	1.92	1.33	1.04	0.87	0.75	0.67	0.60	0.56
H_0: I(1), H_1: I(d)									
M1 Denmark	0.07	0.09	0.10	0.08	0.08	0.08	0.08	0.08	0.09
M2 Denmark	0.08	0.09	0.09	0.09	0.09	0.10	0.12	0.14	0.15
M0 Sweden	0.28	0.22	0.20	0.18	0.17	0.15	0.15	0.15	0.15
M3 Sweden	0.32	0.27	0.28	0.28	0.26	0.24	0.22	0.21	0.20
Income Denmark	0.49	0.49	0.46	0.41	0.37	0.35	0.33	0.31	0.30
Income Sweden	0.42	0.32	0.29	0.29	0.28	0.28	0.28	0.28	0.29

[a] The KPSS test is based on the following data generating process:

$y_t = r_t + e_t$, where ε_t is a stationary random error, and r_t is a random walk: $r_t = r_{t-1} + u_t$. The initial value (r_0) is treated as fixed and serves as an intercept. The null hypothesis of stationarity is that the variance of u_t is equal to zero. To carry out the test we first regress y_t on a constant. Then we estimate the residual ($\hat{e}_t$). The KPSS test is then given by: $KPSS = T^{-2} \sum S_t^2 / s^2(l)$, where T is the number of observations and S_t is defined as: $S_t = \sum_{i=1}^{t} \hat{e}_i$, t = 1, 2, …, T. $s^2(l)$ is the serial correlation and heteroscedasticity consistent variance estimator given by:

$s^2(l) = T^{-1} \sum_{t=1}^{T} \hat{e}_t^2 + 2T^{-1} \sum_{s=1}^{l} w(s,l) \sum_{t=s+1}^{T} \hat{e}_t \hat{e}_{t-s}$, where $w(s, l)$ is an optional weighting function corresponding to the choice of a spectral window. We have used the Bartlett window, which is defined as: $w(s, l) = 1 - s / (l + 1)$ in estimation (see Newey and West, 1987; and Kwiatkowski et al., 1992, for more details). The number of truncation (l) is chosen to be eight, which allows s = 0, 1 ,2 , 3, 4, 5, 6, 7, 8 The critical values are 0.12, 0.15, 0.18 and 0.22 at the 10%, 5%, 2.5% and 1% significance level, respectively.

Table 2: Test for unit roots using the Perron test.[a]

H_0: I(1), H_1: I(0)		H_0: I(2), H_1: I(1)	
M1 Denmark	-2.49 (0)	M1 Denmark	-6.36 (0)
M2 Denmark	-2.27 (1)	M2 Denmark	-6.03 (0)
M0 Sweden	-0.37 (0)	M0 Sweden	-4.15 (0)
M3 Sweden	-1.57 (1)	M3 Sweden	-5.25 (0)
Income Denmark	-1.79 (1)	Income Denmark	-5.12 (0)
Income Sweden	-2.01 (0)	Income Sweden	-4.73 (0)

The Perron (1989) regression for testing the variable *W* for unit root is of the following form:

$$W_t = c_1 + c_2 D_t + d_1 t + d_2 D_t t + g J_t + r W_{t-1} + \sum_{i=1}^{m} b_i D W_{t-i} + j_t ,$$

Where t = the time period (the linear trend term), D_t is equal to zero if t ≤ 1974 and it takes value one if t > 1974, J_t is equal to one if the time period t is the first period after that of the structural break, and is zero otherwise, the delta (*D*) is the first difference operator, j_t is a error term that is assumed to be white noise. This test allows for a structural break in both the mean value and the deterministic trend of the variable under investigation. The null hypothesis of a unit root is $r = 1$. The optimal number of lagged differences (*m*) is determined by including more lags until the null hypothesis of no serial autocorrelation for j_t is not rejected by LM test at the 5% significance level. This test has better size properties compared to alternative tests according to Hatemi-J (2003).

These lag values are presented in the parentheses. The critical value is -4.39, -4.03 and -3.46 at the 1%, 5% and 10% significance level, respectively.

Table 3: Test results for causality in the Granger sense, applying leveraged bootstrap technique.

THE NULL HYPOTHESIS	THE ESTIMATED TEST VALUE (MWALD)	1% BOOTSTRAP CRITICAL VALUE	5% BOOTSTRAP CRITICAL VALUE	10% BOOTSTRAP CRITICAL VALUE
$GDP_{DEN} \neq> M1_{DEN}$	0.144	7.424	4.326	2.875
$M1_{DEN} \neq> GDP_{DEN}$	4.290*	8.244	4.634	3.226
$GDP_{DEN} \neq> M2_{DEN}$	0.014	7.109	4.076	2.677
$M2_{DEN} \neq> GDP_{DEN}$	5.423**	6.835	4.294	3.102
$GDP_{SWE} \neq> M0_{SWE}$	1.642	8.003	4.459	3.152
$M0_{SWE} \neq> GDP_{SWE}$	2.218	7.011	3.835	2.751
$GDP_{SWE} \neq> M3_{SWE}$	1.225	7.126	4.257	2.982
$M3_{SWE} \neq> GDP_{SWE}$	2.882*	6.969	3.810	2.604

Notes:

(a) The notation $\neq>$ implies non-Granger causality.

(b) The notations ** and * imply significance at the 1% and 5% significance levels, respectively.

(c) MWALD represents the modified Wald test statistic as described in equation (6).

(d) The lag order of the VAR model, p, was set to one in each case. Also the augmentation lag, d, was set to one since each variable contains one unit root.

Appendix

Data Definitions and Sources

Data Sources: All data are yearly for the 1961-1999 period. The data are taken from the following two sources:

(a) The Swedish Central Bank, Stockholm,

(b) International Financial Statistics (various issues).

Real M0: This variable is defined as the ratio of *(M0/P*), where *M0*, in billions of domestic currency is collected from source (a) and *P* is consumer price index from source (b).

Real M1: This variable is defined as the ratio of *(M1/P*), where *M1*, in billions of domestic currency is collected from source (b) and *P* is consumer price index from source (b).

Real M2: This variable is defined as *M1* plus quasi money. Quasi money that is again deflated by *P* is from source (b).

Real M3: This variable is defined as *M0* plus quasi money. Quasi money that is again deflated by *P* is from source (a).

Real national income (GDP): This variable is defined as real *GDP*. The nominal *GDP* is deflated by consumer price index. This variable is expressed in billions of domestic currency and the data is available from source (b).

References

Ahmed, S. (1993) “Does Money Affect Output?”, *Business Review*: 13-28, Philadelphia: Federal Reserve Bank of Philadelphia.

Artis, M. J. (1992) “The Transmission Mechanism of Monetary Policy in a Causal Framework”, Paper Presented to the International Conference on the Transmission of Monetary Policy in Open Economies, Bern, Switzerland.

Barro, R. (1976) “Rational Expectations and the Role of Monetary Policy”, *Journal of Monetary Economics* 2: 1-32.

Barro, R. (1977) “Unanticipated Money Growth and Unemployment in the United States”, *American Economic Review* 67: 101-115.

Blanchard, O. J. (1990) “Why Does Money Affect Output? A Survey”, in Friedman, M. and Hahn, F. H. (eds.), *Handbook of Monetary Economics* 2, North-Holland, Amsterdam.

Christiano, L. J.; Ljungquist, L. (1988) “Money Does Granger-Cause Output in the Bivariate Money-Output Relation”, *Journal of Monetary Economics* 22: 271-284.

Cover, J. P. (1992) Asymmetric Effects of Positive and Negative Money-Supply Shocks”, *Quarterly Journal of Economics* 4: 1261-1282.

Cuddington, J. T. (1981) “Money, Income, and Causality in the United Kingdom: An Empirical Reexamination”, *Journal of Money, Credit and Banking* 13 (3): 342-351.

Davison, A. C., and Hinkley, D.V. (1999) *Bootstrap Methods and Their Application*. Cambridge University Press. Cambridge, UK.

Devan, A.; Rangazar, P. C. (1987) “Money and Business Cycle: Another Look”, *Review of Economics and Statistics* 69: 1-18.

Efron, B. (1979) “Bootstrap Methods: Another Look at the Jackknife”, *Annals of Statistics* 7: 1-26.

Fisher, S. (1977) “Long-Term Contracts, Rational Expectations and the Optimal Money Supply Rule”, *Journal of Political Economy* 85: 191-205.

Gray, J. A. (1976) “Wage-Indexation: A Macroeconomic Approach”, *Journal of Monetary Economics* 2: 221-236.

Hacker, R. S.; Hatemi-J. A. (2002) “The Size Properties of Toda-Yamamoto Test Statistics for Causality Using Asymptotic and Bootstrap Distributions”, Unpublished Manuscript, University of Jönköping and University of Skövde, Sweden.

Hafer, R. W. (1982) “The Role of Fiscal Policy in the St. Louis Equation”, *Business Review*: 17-22, Federal Reserve Bank of St. Louis.

Hafer, R. W.; Kutan, A. M. (1997) “More Evidence on the Money-Output Relationship”, *Economic Inquiry* 35: 48-58.

Hatemi-J, A. (2003) “A New Method to Choose the Optimal Lag Order in Stable and Unstable VAR Models”, *Applied Economics Letters* 10(7): 135-137.

Hayo, B. (1999) “Money-Output Granger Causality Revisited: An Empirical Analysis of EU Countries”, *Applied Economics* 31: 1489-1501.

Holmes, J.; Hutton, P. (1992) ”A New Test of Money/Income Causality”, *Journal of Money, Credit, and Banking* 24: 338-355.

Hongyi, L.; Maddala, G. S. (1997) “Bootstrapping Cointegrating Regressions” *Journal of Econometrics* 80(2): 297-318.

King, R. G.; Plosser, C. I. (1984) “Money, Credit, and Prices in a Real Business Cycle”, *American Economic Review* 74: 363-380.

Kwiatkowski, D.; Phillips, P. C. B.; Schmidt, P.; Shin, Y. (1992) “Testing the Null Hypothesis of Stationarity against the Alternative of a

Unit Root: How Sure Are We that Economic Time Series Have a Unit Root?", *Journal of Econometrics* 54: 159-178.

Kydland, F.; Prescott, E. (1982) "Time to Build and Aggregate Fluctuations", *Econometrica* 50: 1345-1370.

Long, J.; Plosser, C. (1983) "Real Business Cycles", *Journal of Political Economy* 91: 39-69.

Lucas, R. (1972) "Expectations and the Neutrality of Money", *Journal of Economic Theory* 4: 103-124.

Lucas, R. (1975) "An Equilibrium Model of the Business Cycle", *Journal of Political Economy* 83: 1113-1144.

Lucas, R. (1996) "Nobel Lecture: Monetary Neutrality", *Journal of Political Economy* 104: 661-682.

Newey, W.; West, K. (1987) "A Simple Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix", *Econometrica* 55: 703-708.

Perron, P. (1989) "The Great Crash, the Oil Price Shock and the Unit Root Hypothesis", *Econometrica* 57: 1361-1401.

Putman, B. H.; Wilford, D. S. (1978) "Money, Income, and Causality in the United States and U.K.: A Theoretical Evaluation of Different Findings", *American Economic Review* 68 (3): 423-427.

Ravn, M. O.; Sola, M. (1996) "A Reconsideration of the Empirical Evidence on the Asymmetric Effects of Money-Supply Shocks: Positive vs. Negative or Big vs. Small?", Center for Non-Linear Modeling in Economics; Working Paper No. 1996-4, University of Aarhus.

Sargent, T. (1996) "Expectations and the Non-Neutrality of Lucas", *Journal of Monetary Economics* 37: 535-548.

Seletis, A. ; King, M. (1994) "Deterministic Trends and Money-Output Causality", *Applied Financial Economics* 4: 143-147.

Sephton, P. S. (1995) “A Non-Parametric View of Money/Income Causality”, *Applied Financial Economics* 5: 79-84.

Sims, C. A. (1972) “Money, Income, and Causality”, *American Economic Revie*w 62: 540-552.

Taylor, J. (1980) “Aggregate Dynamics and Staggered Contracts”, *Journal of Political Economy* 88: 1-23.

Thoma, M. A. (1994) “Subsample Instability and Asymmetrics in Money-income Causality”, *Journal of Econometrics* 64: 279-306.

Toda, Y. H.; Yamamoto, T. (1995) “Statistical Inference in Vector Autoregressions with Possibly Integrated Processes”, *Journal of Econometrics* 66: 225-250.

Williams, D.; Goodhart, C. A. E.; Growland, D. H. (1976) “Money, Income, and Causality: The U.K. Experience”, *American Economic Review* 66: 417-423.