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Does Uncertainty Impact Money Growth? A Multivariate GARCH Analysis

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Abstract

The impact of uncertainty on money growth has occupied a prominent place in monetary policy analysis in recent years. Some papers examining this issue use ad hoc estimates and measure variability rather than uncertainty. We employ a multivariate GARCH model, which measures uncertainty by the conditional variance of the data series, to investigate whether macroeconomic uncertainty and monetary uncertainty Granger-cause changes in real money. We find that macroeconomic uncertainty impacts positively on US real M2 growth over a one- to two-year horizon but that monetary uncertainty does not cause changes. Instead, our results indicate that real money growth causes monetary uncertainty.

Does Uncertainty Impact Money Growth? A Multivariate GARCH Analysis

1. Introduction

The impact of uncertainty on money growth has occupied a prominent place in monetary policy analysis in recent years. The European Central Bank (ECB), in particular, has identified “portfolio shifts” as a critical factor in the development of the euro area M3 aggregate between 2000 and 2003, attributing those shifts to global shocks which “have had a profound impact ... on the dynamics of monetary aggregates” (ECB, 2005, p.57). According to the ECB, heightened geopolitical, economic and financial uncertainties led to increased money holdings in the euro area during the early years of this decade.

Against this background, the challenge for econometricians is to quantify the influence of uncertainty on money growth. Some papers use ad hoc estimates and measure variability rather than uncertainty. In contrast, a generalized autoregressive conditional heteroskedasticity (GARCH) model measures uncertainty as the conditional variance of shocks to the data series. In this paper, a multivariate GARCH model is used to investigate whether macroeconomic uncertainty and monetary uncertainty Granger-cause changes in real money.

Our findings, in summary form, are that macroeconomic uncertainty impacts positively on US real M2 growth but that monetary uncertainty does not. Instead, our results indicate that it is real money growth that causes monetary uncertainty.¹

¹ Euro area M3 and related data were also examined. Features of the euro area data, however, did not allow us apply the GARCH method to that data. Nevertheless, we would hope that the paper’s findings can contribute to the discussion of this issue in the euro area and more generally.

2. The Influence of Uncertainty on Money Growth

- *Recent Contributions*

The interest of policymakers in recent years in the effect uncertainty has on money holdings has coincided with a number of contributions to the literature in this area. A key theoretical contribution is that of Choi and Oh (2003). They employ a general equilibrium framework where output and money growth are determined by independent stochastic processes and a monetary policy parameter, with the representative investor's preferences being captured by a money-in-the-utility function. They derive both output uncertainty and monetary uncertainty coefficients and incorporate them in a money demand function. They point out that those coefficients' influence on money holdings is *a priori* ambiguous as they depend on the curvature of the utility function and the policy rule parameter. An increase in either form of uncertainty generates both substitution and precautionary effects that have opposing consequences for money holdings.²

Monetary volatility is assumed in Choi and Oh's model to occur from the money supply side. Friedman (1983, 1984) argues that a pickup in monetary volatility from the same source generates, or adds to, a degree of perceived uncertainty within the economy and, accordingly, will increase the demand for, and lower the velocity of, money. In other words, he argues that more volatile money growth will induce agents to increase their real money holdings. Friedman writes that greater monetary volatility can lengthen the lag between changes in money and subsequent inflation as a rise in monetary volatility initially increases the demand for real balances for precautionary purposes.

² ECB (2005, p.65) also makes the point that the impact of another form of uncertainty - asset price uncertainty - on money demand is ambiguous on conceptual grounds and, therefore, can only be resolved empirically.

The implication of Choi and Oh's model is that with the influence of uncertainty on money holdings seemingly ambiguous on theoretical grounds, the relationship between the two can only be determined empirically. Choi and Oh follow up their theoretical contribution by constructing measures of both output uncertainty and monetary uncertainty. These measures are based on a bivariate VAR model comprising the first-differences of the logs of US real GNP and US M1. Rolling regressions of these VARs provide time-varying volatilities of output and monetary shocks. The inclusion of these variables improves the statistical performance of the money demand function. The output volatility variable has a negative impact on US M1 demand while the monetary volatility variable has a positive effect.

A number of other empirically-orientated papers have also appeared recently which investigate the impact of uncertainty on money holdings. Two of these have a euro-area focus. Carstensen (2006) presents a money demand function augmented by stock market variables, specifically equity returns and stock market volatility, and finds that adding those variables brings stability to the money demand function. The stock market volatility variable has a positive coefficient, a finding that tallies with Friedman (1988). Greiber and Lemke (2005) construct a single measure of uncertainty from several observable indicators for the euro area. In the main, those indicators are financial market-based (they include the covariation between bond and stock returns, as well as a measure of stock market returns) but sentiment indicators from surveys are also included. Greiber and Lemke find adding this uncertainty variable improves the explanatory power of the estimated money demand function for euro area M3 and that it has a positive coefficient therein.

Atta-Mensah (2004) also discusses the impact that general uncertainty in the economy has on money demand. He highlights five factors that contribute to an uncertain economic environment in Canada, namely the stock market, the bond market, monetary policy, external influences and economic activity/output. The individual volatilities of proxy variables for these five factors are estimated using standard GARCH (1,1) models with an economic uncertainty index (EUI) being constructed as an equally weighted average of those estimated volatilities. Atta-Mensah is then using a linear combination of volatility measures to produce a broad measure of uncertainty. Once constructed, the EUI is added to an otherwise standard money demand function for Canadian money aggregates.

- *Our Approach*

Serletis and Shahmoradi (2006) investigate the Friedman hypothesis that money supply volatility Granger-causes the velocity of money, focusing on US money aggregates.

They refer to earlier papers on this subject (e.g., Hall and Noble, 1987, and Thornton, 1995) and note that they use moving sample standard deviations of money growth rates in testing the Friedman hypothesis. Serletis and Shahmoradi are critical of the use of such variability measures, which they point out as being ad hoc estimates.

Furthermore, moving standard deviation or variance series only measure variability, not uncertainty.

We believe that these points also apply to many of the recent papers on the effect of uncertainty on money demand. Choi and Oh (2003), for instance, use a rolling regression VAR model to provide time-varying volatilities that are used as measures of uncertainty. Carstensen's (2006) stock market volatility variable is constructed as the two-year average of the conditional variance estimated from a leveraged GARCH

model applied to daily data. In Atta-Mensah (2004), individual uncertainties are estimated using GARCH models and are then added together to provide a broadly-based measure of uncertainty.

The issue of whether uncertainty, specifically macroeconomic uncertainty and monetary uncertainty, impacts money holdings can be investigated by using a bivariate GARCH model that utilises features of the data (namely, the presence of ARCH effects in growth rate series) to produce measures of macroeconomic uncertainty and monetary uncertainty.

Like Serletis and Shahmoradi (2006), we initially investigate the univariate properties of the series. The features of the data allow us to pursue a multivariate – in effect, a bivariate, GARCH modelling of the macroeconomic and real money growth series.

Whereas Serletis and Shahmoradi use an “in-mean” version of the multivariate GARCH model to examine Granger causality in the data, we use a two-step method, similar to that used by Fountas, Karanasos and Kim (2006). This method involves first estimating the conditional variances of both macroeconomic and real money growth within a bivariate GARCH model and then using those estimates to undertake Granger causality tests. This allows us to examine causality on a bidirectional basis between various pairings of macroeconomic growth, money growth and the conditional volatility of both series at various lag lengths. Our reading of the 1980s literature discussing and testing, in the main, the Friedman hypothesis (e.g., Belongia 1984, Hall and Noble 1987, Brocato and Smith 1989, and Mehra 1989) is that uncertainty can be expected to have a delayed impact on real money holdings. Those papers test for Granger causality at lags of up to 24 months. We need to be able, therefore, to examine causal influences over various lag lengths, which the two-step method easily allows. Furthermore, we

note that this approach also minimizes the number of parameters to be estimated (Fountas and Karanasos, 2007, p. 236).

3. Empirical Modelling and Testing

- Data

Two monthly US data series are used in our study. They are the real M2 stock (denoted $m2cpi$) (calculated as the natural log of nominal M2 less the natural log of the CPI), and the natural log of the Composite Index of Lagging Indicators (lai), a series published by the Conference Board.

We choose this index because it represents a broadly-based monthly indicator of macroeconomic activity, in comparison with more narrowly-defined indicators such as Industrial Production. It is a composite index of several economic variables: the average duration of unemployment, the inventories-to-sales ratio, the change in the labour cost per unit of output, the average bank prime rate, the amount of commercial and industrial loans outstanding, the ratio of consumer instalment credit to personal income, and the CPI. A benefit of this composite indicator is that it captures many features of macroeconomic activity in a single variable whose volatility can then be examined.

First-differences of these series, $\Delta m2cpi$ and Δlai (i.e., their month-to-month changes), are the variables used in the model. The sample period is 1959m2-2007m4.

- Analysis of the Individual Series

It is necessary initially to see whether $\Delta m2cpi$ and Δlai are stationary variables. This is confirmed to be the case in Table 1 where the null hypothesis of a unit root is rejected at conventional significance levels by the augmented Dickey-Fuller statistic [with optimal

lag lengths selected by, in turn, the Akaike (AIC) and Schwartz-Bayesian (SBC) criteria] and the non-parametric Phillips-Perron test. Descriptive statistics for both series are shown in Table 2. Excess kurtosis seems to be a feature of the series and the Jarque-Bera test does not support the hypothesis that the series each have a normal distribution. This is prima facie evidence that ARCH is present in both series.

- Testing for the Presence of ARCH Effects

Given these univariate properties, we can estimate VAR regressions using $\Delta m2cpi$ and Δlai . The general form of the bivariate VAR to be estimated is:

$$z_t = A_0 + A_1 z_{t-i} + e_t \quad (1)$$

where z_t is a vector containing both variables, $\Delta m2cpi$ and Δlai , A_0 is a vector containing two intercept terms, A_1 is a matrix of coefficient estimates, and z_{t-i} is a matrix containing lagged values of both variables. Finally, e_t is a vector containing the two residual terms from the VAR equations.

The chosen VAR order is twelve.³ For space considerations, we do not show the coefficient values from these regressions but can report that for each equation the sum of the lagged own variable parameters is less than one and the equation coefficients seem well-behaved in general. We are more interested in the residual diagnostic tests associated with these regressions, which are reported in Table 3. These reject the null hypothesis of serial correlation in the residuals, if only at the one percent significance level for Δlai . Non-normality and ARCH, however, appear to be present in the regression residuals.

³ While a lag length of 10 was suggested by the Akaike information criterion, a VAR lag length of 12 is used because shorter lag length estimations had serially correlated error terms.

- A Bivariate GARCH Model

Given these properties of the VAR error terms, we can proceed to a bivariate VAR (12) – constant conditional correlation (CCC) GARCH (1,1) model of the respective series.⁴

The CCC GARCH (1,1) model takes the form:

$$h_{\Delta lai_t} = \mathbf{a}_{10} + \mathbf{a}_{11} \mathbf{e}_{\Delta lai_{t-1}}^2 + \mathbf{b}_{11} h_{\Delta lai_{t-1}} \quad (2)$$

$$h_{\Delta m2cpi_t} = \mathbf{a}_{20} + \mathbf{a}_{22} \mathbf{e}_{\Delta m2cpi_{t-1}}^2 + \mathbf{b}_{22} h_{\Delta m2cpi_{t-1}} \quad (3)$$

$$h_{\Delta m2cpi, \Delta lai_t} = \mathbf{r} \sqrt{h_{\Delta m2cpi_t}} \sqrt{h_{\Delta lai_t}} \quad (4)$$

where $h_{\Delta m2cpi_t}$ denotes the conditional volatility of $\Delta m2cpi$, $h_{\Delta lai_t}$ the conditional volatility of Δlai , and $h_{\Delta m2cpi, \Delta lai_t}$ the conditional covariance between the two residuals terms generated from Equation (1).

The estimated parameters of the conditional variance equations are shown in Table 4. These are well-behaved according to the usual conditions required of GARCH models. The residual diagnostic tests in Table 5 indicate that the time-series models of the conditional means and conditional variances satisfactorily describe the joint distribution of the disturbances.⁵

Finally, we plot the conditional volatility series in Figures 1a and 1b. The conditional volatility of the Δlai series (Figure 1a) picked up considerably at times during the 1970s

⁴ The CCC approach offers an easy interpretation and testing of hypotheses and complements the series of subsequent Granger causality tests. In a recent, comprehensive survey of multivariate GARCH models, Bauwens, Laurent and Rombouts (2006, p. 104) conclude that “the crucial point in MGARCH modelling is to provide a realistic but parsimonious specification of the variance matrix ensuring its positivity.” We are happy that our GARCH results satisfy this criterion.

⁵ We also examined whether there are “leverage” effects in the conditional volatility series, i.e., whether negative shocks have a more or less pronounced effect on conditional volatility than positive shocks. The test used is described in Enders (2004, pp. 142-143) and it indicates an absence of asymmetric effects in both conditional volatility series.

and early 1980s and there have also been some short-lived rises in early-2001 and early-2005. The conditional volatility of $\Delta m2cpi$ (Figure 1b) was high in the mid-1970s and early-1980s and has also been relatively high in the current decade.

- *Does Uncertainty Impact Money Growth? Test Results*

With a satisfactory bivariate GARCH model, we can proceed to testing whether $h_{\Delta lai}$ and $h_{\Delta m2cpi}$ - measures of macroeconomic and monetary uncertainty, respectively – each Granger-cause changes in real M2, $\Delta m2cpi$, and whether their influence is positive or negative. Four variables ($\Delta m2cpi$, Δlai , $h_{\Delta lai}$ and $h_{\Delta m2cpi}$), along with a constant term, are included in the equations on which the Granger-causality tests are undertaken. The equations are estimated with a number of different lag structures separated at four-month intervals and the lag structures range from including only the first four lags of the four variables up to including the first 24 lags of each. The F -statistics arising from the variable deletion tests required to test for the presence of Granger causality are reported in Table 6. The statistical significance of the F -statistics is indicated and the signs of the sum of the lagged coefficients of the “causal” variable under consideration are shown in brackets.

The variable deletion tests in Table 6 indicate that the null hypothesis that the measure of macroeconomic uncertainty, $h_{\Delta lai}$, does not Granger-cause changes in real M2, $\Delta m2cpi$, can be rejected over longer lag lengths. This conditional volatility variable has a significant, positive cumulative effect on $\Delta m2cpi$ at lag lengths one to 12, one to 16, one to 20, and one to 24. In contrast, $\Delta m2cpi$ has no effect on $h_{\Delta lai}$ across the various lag lengths examined.

We find no significant causality from the measure of monetary uncertainty, $h_{\Delta m2cpi}$, to $\Delta m2cpi$ at all lag lengths examined. Instead, Table 6 indicates causation running in the opposite direction and in a positive manner, with the effect being particularly strong over a one to four month lag.⁶

4. Conclusion

A multivariate GARCH model was utilized in this paper to examine the interrelationship between real money growth and measures of macroeconomic and monetary uncertainty. We find macroeconomic uncertainty to have a positive and significant impact on US real M2 growth at longer lag lengths so that a rise in macroeconomic uncertainty will cause an increase in real money growth over a one to two year horizon. In contrast, monetary uncertainty has no discernable causal effect on real money growth at all lag lengths examined. Finally, our results indicate that changes in real money have a significant, positive effect on monetary uncertainty, particularly over a short horizon. This is noteworthy and topical given that the pickup in monetary uncertainty in this decade (as shown in Figure 1b) has occurred against a background of strong monetary growth, suggesting another feature of the data to be considered in monetary analysis.

⁶ As a robustness test, we undertook the Granger causality tests for the shorter sample period of 1960m2 to 2002m4 and found the qualitative results concur with those for the full sample.

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Table 1: Augmented Dickey-Fuller and Phillips-Perron Statistics

	Δlai	$\Delta m2cpi$
ADF (AIC)	-6.44	-4.33
ADF (SBC)	-10.21	-9.12
Phillips-Perron	-9.41	-9.32
Critical 95 per cent value	-2.89	-2.89

Note: An intercept but no time trend is included in the tests.

Table 2: Descriptive Statistics

	Δlai	$\Delta m2cpi$
Skewness	-0.74 [0.00]	0.17 [0.09]
Kurtosis (excess)	2.80 [0.00]	1.26 [0.00]
Jarque-Bera	242.03 [0.00]	41.21 [0.00]

Note: P-values in brackets.

Table 3: Residual Diagnostics from VAR Equations

	Δlai	$\Delta m2cpi$
LM test for serial correlation (χ^2 , 12 DF)	25.47 [0.01]	7.05 [0.74]
ARCH test (χ^2 , 1 DF)	17.85 [0.00]	9.72 [0.00]
ARCH test (χ^2 , 12 DF)	40.88 [0.00]	21.81 [0.04]
Bera-Jarque normality test (χ^2 , 2 DF)	153.89 [0.00]	97.99 [0.00]

Note: P-values in brackets.

Table 4: Bivariate CCC GARCH (1, 1) Model

$$h_{\Delta lai_t} = 0.0000077 + 0.431 e_{\Delta lai_{t-1}}^2 + 0.040 h_{\Delta lai_{t-1}}$$

(7.99) (5.99) (0.59)

$$h_{\Delta m2cpi_t} = 0.0000007 + 0.076 e_{\Delta m2cpi_{t-1}}^2 + 0.853 h_{\Delta m2cpi_{t-1}}$$

(1.75) (2.98) (14.69)

$$h_{\Delta lai, \Delta m2cpi_t} = -0.1496 \sqrt{h_{\Delta lai_t}} \sqrt{h_{\Delta m2cpi_t}}$$

(3.73)

Table 5: Residual Diagnostic Tests

	Δlai	$\Delta m2cpi$
Q_{12}	8.36	1.70
Q_{12}^2	19.37	11.16
Cross-equation		
Q_{12}	12.10	

Note: Q_{12} is the 12th order Ljung-box test for the standardized residuals. Q_{12}^2 is the Ljung-box test for the squared standardised residuals. The critical value at the 5% significance level is 21.02.

Table 6: Granger Causality Tests

M	$H_0 : \sum_{j=1}^M h_{\Delta lai_{t-j}} \rightarrow \Delta m2cpi_t$	$H_o : \sum_{j=1}^M \Delta m2cpi_{t-j} \rightarrow h_{\Delta lai_t}$
4	0.97 (-)	1.71 (-)
8	1.31 (+)	0.86 (-)
12	1.87** (+)	0.97 (-)
16	2.00*** (+)	0.65 (-)
20	1.61** (+)	1.03 (-)
24	1.40* (+)	1.14 (-)
M	$H_0 : \sum_{j=1}^M h_{\Delta m2cpi_{t-j}} \rightarrow \Delta m2cpi_t$	$H_0 : \sum_{j=1}^M \Delta m2cpi_{t-j} \rightarrow h_{\Delta m2cpi_t}$
4	0.15 (-)	3.69***(+)
8	0.72 (-)	1.76* (+)
12	1.19 (+)	1.31 (+)
16	1.23 (-)	1.33 (+)
20	0.97 (+)	1.50* (+)
24	1.04 (+)	1.42* (+)

Note: Entries in Tables 6 (a)-(d) are F-statistics. A + (-) indicates that the sum of the causing variable is positive (negative). ***, ** and * denote significance at the 1%, 5% and 10% significance levels, respectively. The first column gives the number of lags used in the causality tests.

Figure 1a: Conditional Volatility of the Change in the Lagged Indicator

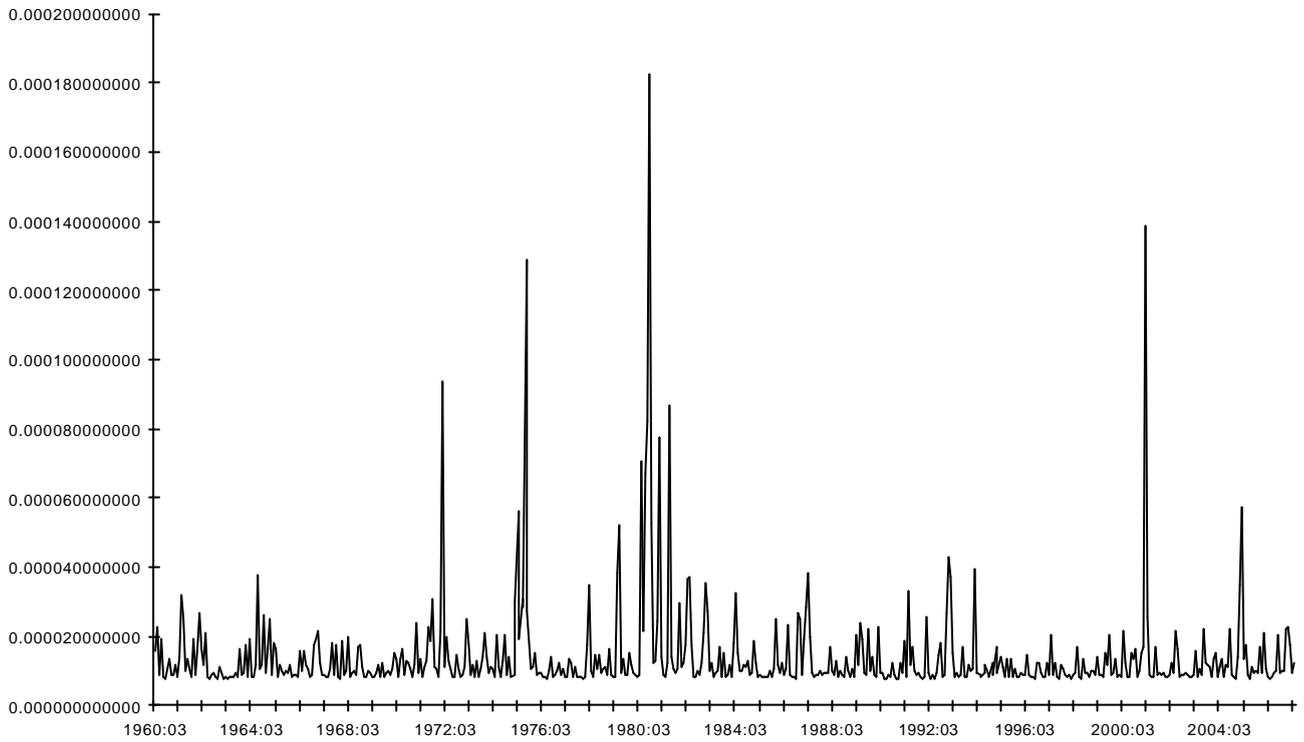


Figure 1b: Conditional Volatility of the Change in Real M2

