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Why U.S. Money does not Cause U.S. Output, but does Cause Hong Kong Output*

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Abstract

Standard econometric tests for whether money causes output will be meaningless if monetary policy is chosen optimally to smooth fluctuations in output. If U.S. monetary policy were chosen to smooth U.S. output, we show that U.S. money will not Granger cause U.S. output. Indeed, as shown by Rowe and Yetman (2000), if there is a (say) 6 quarter lag in the effect of money on output, then U.S. output will be unforecastable from any information set available to the Fed lagged 6 quarters. But if other countries, for example Hong Kong, have currencies that are fixed to the U.S. dollar, Hong Kong monetary policy will then be chosen in Washington D.C., with no concern for smoothing Hong Kong output. Econometric causality tests of U.S. money on Hong Kong output will then show evidence of causality. We test this empirically. Our empirical analysis also provides a measure of the degree to which macroeconomic stabilisation is sacrificed by adopting a fixed exchange rate rather than an independent monetary policy.

Keywords: Monetary Policy, Causality, VECM, U.S. Money, U.S. Federal Funds Rate.

JEL Classication: C3, C5, E4, E5.

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1 Introduction

Does money cause real output? If the Federal Reserve were suddenly, capriciously, without warning, to cut the money supply by 20%, what effect would this have? Nearly all macro-economists would agree that the cut in the money supply would cause a fall in aggregate demand, and that the fall in aggregate demand would cause, at least temporarily, real output to fall. As Christiano, Eichenbaum and Evans (1999) argue, even when the literature has not yet converged to a particular set of assumptions for identifying the effects of an exogenous shock to monetary policy, "there is considerable agreement about the qualitative effects of a monetary policy shock in the sense that inference is robust across a large subset of the identification schemes that have been considered in the literature."

The only disagreement would come from the two extreme ends of the macroeconomic spectrum. Some Post-Keynesian macroeconomists would argue that the money supply has no effect on aggregate demand, and so will not affect real output. And some Classical macro-economists would argue that the money supply might affect aggregate demand, but perfectly flexible prices and wages, and the resulting vertical aggregate supply curve, would mean that only the price level would fall, and real output would not.

Despite this very general agreement that money causes output, the supporting econometric evidence is weak or inconclusive. The basic reason for the weak econometric evidence is simple. The sort of experiment described above is very unlikely ever to happen. The Federal Reserve, believing that a capricious 20% cut in the money supply would have disastrous consequences for real output, would not willingly conduct such an experiment. It would not capriciously cut the money supply by 20% merely to see how big a recession this would cause. So the sort of experiment which could properly test whether money causes output is never in fact conducted. To say the same thing another way, an OLS regression of output on money will only give unbiased estimates if the money supply has a positive variance and if money is exogenous with respect to output. But exogeneity of money with respect to output would mean that the Federal Reserve chooses monetary policy without considering the effect its policy will have on output. No responsible Federal Reserve would ever choose monetary policy that way.

If money were found to cause output in an OLS regression, this would mean that the Fed had caused or permitted the money supply to vary in such a way that the variance of output was higher than it would have been if the Fed had acted differently. Such a finding would be evidence not just that money causes output, but that the Federal Reserve had behaved irresponsibly or foolishly. A responsible and sensible Fed would never carry out the sort of experiment which would let us directly test whether money causes output.

This problem with testing whether money causes output is at its starkest when the Fed adopts as its overriding objective the goal of smoothing output fluctuations. Many economists think that a significant fraction of the variation in central bank policy actions reflects policy makers' systematic responses to variations in the state of the economy (see Christiano, Eichenbaum and Evans (1999)). This systematic component is typically formalized with the concept of a feedback rule or reaction function[1].

Suppose there is some underlying structural equation, known to the Fed, linking level of real output y_{t+j} with the level of money supply m_t, and some other variables, with a j-period lag in the effect of money on output:

$$y_{t+j} = F(m_t, ...). \tag{1}$$

The Fed ideally wants real output to grow at some constant sustainable rate

[1] Other strategies to identify monetary policy shocks do not involve modelling the monetary reaction function. For example, one approach consists in looking at data to identify exogenous monetary policy actions. It is the way adopted by Romer and Romer (1989). The other way of identifying monetary policy shocks is by using the assumption that they do not affect economic activity in the long run. At this respect, see Faust and Leeper (1997) and Pagan and Robertson (1995).

g. Then,

$$y^*_{t+j} = g_{t+j}. \tag{2}$$

Assuming the Fed has a symmetric quadratic loss function, and that the structure of the economy is linear, the Fed will set the money supply in each period so that the rational expectation of real output in $t + j$, conditional on all information available at time t (I_t) equals the ideal level:

$$E(y_{i+j}|I_t) = E[F(m_t, ...)|I_t] = Y^*_{t+j}. \tag{3}$$

Because any variable can be decomposed into its rational expectation and a forecast error, where that forecast error must be uncorrelated with anything in the information set at time t, we have that

$$y_{t+j} = E(y_{t+j}|I_t) + e_{t+j}. \tag{4}$$

Substituting from (2) and (3) into (4) we get

$$y_{t+j} = g_{t+j} + e_{t+j}. \tag{5}$$

What equation (5) says is that output will be equal to a time trend plus a random error which is totally uncorrelated with any information available at time t. Presumably the money supply is part of that information set. This means that if the Federal Reserve is using monetary policy to smooth real output, output will necessarily be uncorrelated with the lagged money supply; see also Rowe and Yetman (2002). Even though by assumption money causes output, with a j-period lag, any econometric causality test will find no evidence for causality.

To understand this result better, let us ask under what circumstances the Federal Reserve would choose to cut the money supply by 20%. It would do this only if it learned some information (about one of the other variables in the structural equation $F(.)$, like a major tax cut for example) which would lead it to expect a big increase in output if it held the money supply constant. If the Fed forecasts correctly, the money supply will fall by 20%, but output will continue to grow at trend. The only fluctuations in output will be the result of the Fed's forecast errors, and these should be uncorrelated with anything the Fed knows at the time when its monetary policy can influence output.

In order to test whether money causes output we have to find a data set where the monetary authority varies the money supply with no concern for its effect on output. Hong Kong provides just such a data set[2]. For many years, Hong Kong has maintained approximately fixed exchange rates with the U.S. dollar. Since Hong Kong is small relative to the U.S., and since the Federal Reserve undertakes no responsibility to help Hong Kong maintain the fixed exchange rate, Hong Kong monetary policy is effectively set in Washington D.C. If the shocks to the U.S. and Hong Kong economies are imperfectly correlated, and if the Federal Reserve conducts monetary policy to smooth U.S. output, but does not care about Hong Kong output, this means that monetary policy is at least partly exogenous with respect to Hong Kong output.

Suppose the Fed sees a positive shock about to hit the U.S. economy. It lowers the money supply in order to lean against the wind and offset this shock. If its forecast is successful, U.S. output continues to grow at trend. But if no similar shock hits the Hong Kong economy, Hong Kong will be hit by the full impact of the cut in U.S. money supply, with no offsetting shock, and will suffer a recession. Similarly, if the Fed anticipates a negative shock to the U.S. economy, it will raise the money supply. No change in U.S. output is subsequently observed, but Hong Kong enjoys a boom[3].

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[2] Other countries such as Thailand and Argentina were also considered. Unfortunately, availability of data represented the principal limitation to extend our empirical analysis to these and other countries.

[3] Our story here assumes the shock to the U.S. economy is an IS shock. A positive IS shock to the U.S. economy means the Fed will reduce the money supply and raise interest rates to hold U.S. aggregate demand constant. But the higher U.S. interest rates will mean higher Hong Kong interest rates also, provided there is at least some capital mobility. And the higher Hong Kong interest rates will reduce aggregate demand in Hong Kong (unless

Thus, if the Federal Reserve is smoothing U.S. output, but is not concerned about Hong Kong output, and if other shocks to the U.S. and Hong Kong economies are imperfectly correlated, U.S. money will be seen to Granger-cause Hong Kong output, but not to Granger-cause U.S. output.

In practical terms, the situation observed for Hong Kong is equivalent to the situation observed during the Great Depression where many countries were working under the gold standard. In fact, some of the literature about the Great Depression, presents evidence concerning the role of monetary factor during this time; see Bernanke (1995). According to him, "the shocks were transmitted around the world primarily through the workings of the gold standard"; see also Chodhri and Kochin (1980), Eichengreen (1984), Hamilton (1988), among others. In fact, the new gold standard research allow the economists to assert with considerable confidence that monetary factors played an important causal role, both in the world decline in prices and output, and their eventual recovery. The evidence suggests that countries that left the gold standard recovered from the Depression more quickly that countries that remained on gold. No country exhibited significant recovery while remaining on the gold standard. The strong dependence of the rate of recovery on the choice of exchange-rate regime is further, powerful evidence of the importance of monetary factors.

2 Empirical Application

In this section we present the empirical evidence from the causality tests.

Our data consist of the vector z_t of dimension $n \times 1$ which contains the three time series used in the subsequent analysis. That is, $z_t = (y_{1t}, y_{2t}, y_{3t})'$, where y_{1t} denotes the logarithm of the output of Hong Kong (y_t^{hk}); y_{2t} denotes the logarithm of the output of US (y_t^{us}); and y_{3t} denotes either the

Hong Kong happens to face a similar positive IS shock). If the shock to the U.S. economy were an LM shock, such as a fall in U.S. money demand, the Fed would reduce the money supply proportionately, leaving interest rates unchanged, and there would be no effect in either country.

logarithm of the US money supply (m_t^{us}) or the level of the US Federal Fund Rate (R_t^{us}). The data is quarterly and it spans from 1986:1 until 1999:4.

The empirical application that follows consists of three steps. In the first step, we test for the order of integration of each time series, using the univariate augmented Dickey Fuller (ADF) unit root test (Dickey and Fuller, 1979, Said and Dickey, 1984). In second step, we test for the existence of cointegration relations using the Johansen procedure (Johansen, 1988). In the third and last step, we estimate the vector error correction model ($VECM$) and test for Granger causality using the recommendations of Phillips and Toda (1994).

In fact, the appropriate way to test for causality depends on whether or not there exist cointegrating relations. When there are cointegration relations, we can test for short run causality using an F- test of the significance of the lagged first differences of the relevant variables (in our case, Δm_{t-k}^{us} or ΔR_{t-k}^{us} for $k = 1, 2, ...k^{*}$). And we can test for long run causality by, in addition, using an F- test of the significance of the error correction term. Some empirical references are Hayo (1999), Khalid and Guan (1999), Wernerheim (2000).

In the application of the ADF test, the lag length was chosen using the sequential procedure suggested by Campbell and Perron (1991) which consists of initially assuming some maximal lag (say k_{max}) in the estimation of the ADF autoregression and testing for the significance (at 90%) of the last lag. If no significance is found, the statistic is again estimated using k_{max}-1 lags. The procedure is repeated until a significant lag is found. If no significant lag is found, $k = 0$ is selected.

Results[4] show evidence of nonstationarity for all series. In other words, all series can be considered as $I(1)$ processes. Given this fact, our second step is to verify the existence of cointegration relations between the set of variables.

[4] In order to save space, results are not presented but they are available upon request.

The vector z_t containing the n variables, can be represented by the following $VAR(k)$:

$$z_t = \sum_{i=1}^{k} \Pi_i z_{t-i} + \Phi D_t + \epsilon_t \tag{6}$$

where it is assumed that ϵ_t is a sequence of *i.i.d.* zero mean with covariance matrix . In most cases it is also assumed that the errors are Gaussian which is denoted by $\epsilon_t \sim N(0, \ )$. The variable D_t contains the possible deterministic components of the process, such as a constant, a time trend, seasonal dummies and intervention dummies. This is the model proposed by Johansen (1988, 1995) and is widely used in empirical applications[5].

The system (6) is reparameterized as a vector error correction model (VECM):

$$\Delta z_t = \Pi z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta z_{t-i} + \Phi D_t + \epsilon_t \tag{7}$$

with $\Pi = -I + \sum_{i=1}^{k} \Pi_i$, $\Gamma_i = \sum_{j=i+1}^{k} \Pi_j$. Notice that the matrix $\Gamma = I - \sum_{i=1}^{k-1} \Gamma_i$.

I(1) cointegration occurs when the matrix Π is of reduced rank, $r < n$ where Π may be factorized into $\Pi = \alpha\beta'$, α and β are both full rank matrices of dimension $n \times r$; the matrix α contains the adjustment coefficients and β the cointegration vectors. These vectors have the property that $\beta' z_t$ is stationary, even though z_t itself is non-stationary. Notice that there also exist full rank matrices $\alpha_\perp$ and $\beta_\perp$ of dimension $n \times (n-r)$ which are orthogonal to α and β, such that $\alpha'_\perp \alpha = 0$ and $\beta'_\perp \beta = 0$, and the $rank(\beta_\perp, \beta) = n$.

To test the rank of matrix Π, Johansen (1988, 1995) developed maximum likelihood cointegration testing methods using the reduced rank regression technique based on canonical correlations. The procedure consists of obtaining an $n \times 1$ vector of residuals r_{0t} and r_{1t} from auxiliary regressions

[5] There are large number of empirical applications using this statistical framework. Two very detailed and influencial applications are Johansen and Juselius (1992, 1994).

(regressions of Δz_t and z_{t-1} on a constant and the lagged Δz_{t-1} ... Δz_{t-k+1}). These residuals are used to obtain the $(n \times n)$ residual product matrices:

$$S_{ij} = (1/T) \sum_{t=1}^{T} r_{it} r'_{jt}, \tag{8}$$

for $i, j = 0, 1$. The next step is to solve the following eigenvalue problem

$$|\lambda S_{11} - S_{10} S_{00}^{-1} S_{01}| = 0 \tag{9}$$

which gives the eigenvalues $\widehat{\lambda}_1 \geqslant ... \geqslant \widehat{\lambda}_n$ and the corresponding eigenvectors $\widehat{\beta}_1$ through $\widehat{\beta}_n$, which are also the cointegrating vectors. A test for the rank of matrix Π can now be performed by testing how many eigenvalues λ equals to unity. One test statistic for the resulting number of cointegration relations is the Trace statistic which is a likelihood ratio test defined by

$$Trace = -T \sum_{i=r+1}^{n} log(1 - \widehat{\lambda}_i). \tag{10}$$

Another useful statistic is given by testing the significance of the estimated eigenvalues themselves

$$\lambda_{\max} = -T log(1 - \widehat{\lambda}_i). \tag{11}$$

In the trace test, the null hypothesis is $r = 0$ (no cointegration) against the alternative hypothesis that $r > 0$ (cointegration). The $\lambda_{\max}$ statistic tests the null hypothesis that $r = r_0$ versus the alternative hypothesis that $r = r_0 + 1$, where $r_0 = 0, 1, ..., n - 1$. For further details regarding the construction of these statistics, see Johansen (1995).

Critical values for these tests have been tabulated by Osterwald-Lenum (1992). However, limiting distributions depend on the set of deterministic components considered in equation (6) and depend also on the set of deterministic components allowed in the cointegrating relations. Given the nature of our series, we always consider an intercept in the estimation of the equation (6)[6]. For the cointegration relations, we consider two cases. The first case includes only an intercept in the long run relationship. In the second case, we include an intercept and also a time trend in the long run equation. In the tables, we refer to the former as the "first specification" and the latter as the "second specification".

Another important issue, in the application of the Johansen test, is the specification of the lag length. Many suggestions appear in the literature. One suggestion is to use informational criteria such as AIC or SIC.[7] Given that our goal is to identify causality, we are particularly interested in some longer lag specification. Hence, the SIC procedure is not considered, because it is known that this criteria will choose a more parsimonious model. Using AIC, we have selected $k = 8$ for the specification in levels, which implies using $k = 7$ in the $VECM$ specification.

The results from the application of the Johansen test are shown in Tables 1a and 1b. There is clear evidence of cointegration in all systems. Using the U.S. Federal Funds rate as the monetary instrument reveals one cointegration relationship using the first specification, and two cointegration relations in the second specification. Using the U.S. money supply as the monetary instrument reveals two cointegration relations in the second specification. Notice however, that in the first specification we found $r = 3$, which implies that all variables are stationary. This result might be a consequence of the small sample size used in the application. In fact, there is evidence (see Maddala and Kim (1999) for a survey) that small samples can cause spurious rejection of the null hypothesis of no cointegration. One recommended solution for this problem to adjust the values of the statistics to take into account for small sample size. We do this only in the case where $r = 3$. Following Reimers (1992), we adjusted the $\lambda_{\max}$ test by $(T - kn)/T$, where

[6] It is equivalent to assume that there is a linear trend in the time series.

[7] Another suggestion is to use the likelihood ratio test, based either on the log value of the likelihood or based on the determinant of the covariance matrix. We obtain essentially the same results as the AIC.

T is the total number of observations, k is the lag number and n is the number of variables used in the system. With this adjustment, the values for the $\lambda_{\max}$ test are 21.70, 11.13 and 6.21. Only the first of these vectors is significant at 95.0%. Hence, we will work with $r = 1$.

Our third and final step is to estimate the equation (6) in order to test for causality from the monetary instruments to output. The equations to be estimated are:

$$\begin{aligned} \Delta y_t^i &= \sum_{h=1}^{k} a_h \Delta y_{t-h}^i + \sum_{h=1}^{k} b_h \Delta y_{t-h}^j + \sum_{h=1}^{k} c_h \Delta R_{t-h}^{us} + \\ & \sum_{s=1}^{r} d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t \qquad (12) \\ \Delta y_t^i &= \sum_{h=1}^{k} a_h \Delta y_{t-h}^i + \sum_{h=1}^{k} b_h \Delta y_{t-h}^j + \sum_{h=1}^{k} c_h \Delta m_{t-h}^{us} + \\ & \sum_{s=1}^{r} d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t \qquad (13) \end{aligned}$$

where $i =$Hong Kong and $j =$US; ect_{t-1} corresponds to the error correction term; D_i is a seasonal dummy variable defined as $D_i = 1$ for $i = 1, 2, 3$ quarters. Equations (12) and (13) consider the US Federal Funds Rate (R_t^{us}) and US money supply (m_t^{us}) as the monetary instruments, respectively.

Results using the Federal Funds Rate as the instrument monetary are shown in Table 2a, and the results using the money supply as the monetary instrument are shown in Table 2b. We present the value of the F-statistic (and its associated p-value in parenthesis), under both the first and second specifications used in the cointegration analysis. Overall, our principal conclusion is clear, and is also robust to whether the Federal Funds Rate or the money supply is treated as the monetary instrument. There is clear evidence in favor of our hypothesis that U.S. monetary policy causes Hong Kong output, but does not cause U.S. output. When the F-test includes testing for the error correction terms, the results give even stronger evidence in favor of long run causality from U.S. monetary policy to Hong Kong output.

Notice, however, that our results from Granger causality tests need to be considered with caution because of the small sample size used in the applications. Phillips and Toda (1994) show, based in Monte Carlo simulations, that it is difficult to support validity of the F-statistic when sample sizes are small and when three or more variables are used in the system. In order to take into account for this possibility, Tables 3a and 3b present the results obtained from a bivariate system[8]. It means that when estimating equations (12) and (13) for Hong Kong, the variables Δy_{t-h}^{US} $(h = 1, 2, ..., k)$ are excluded. In similar way, when estimating equations (12) and (13) for US, the variables Δy_{t-h}^{hk} $(h = 1, 2, ..., k)$ are excluded.

Overall, the results suggest similar conclusions as obtained from previous results. Using the first specification, non Granger causality is rejected for Hong Kong real output (see Table 3a). When the error correction terms are taken into account in the F-statistic, the evidence is stronger and therefore, long-run causality is observed. When using second specification, the evidence is weak. Observing results for the US output (Table 3a, bottom panel), evidence suggest some weak rejection of the null hypothesis of non-Granger causality.

Results presented in Table 3b, using monetary supply as monetary instrument, confirm the results that US monetary instrument causes Hong Kong output. It is needed to say that this result is obtained when the error correction term is included in the F-statistic and the results are independent of the number of deterministic components include in the cointegrating relationship (first or second specification).

In summary, results obtained from the bivariate system confirm that US monetary instrument causes Hong Kong output but does not cause US output. In particular, the results are clearly observed when the error correction

[8] Notice, however, that we continue to use the same cointegrating vectors identified using the trivariate system. The issue discussed in the Introduction is supported by the fact that the 3 variables are related in the long term (cointegration exists) even if the short-run dynamics excludes some of these variables.

terms are included in the F non-causality statistic.

If all values of the Johansen statistics are adjusted using the rule suggested for Reimers (1992), we have evidence in favor of $r = 1$ only for the case where U.S. money is used as monetary instrument and using the first specification. In all other cases, cointegration is no longer found.

Decomposition of variance can be used to measure the importance of one shock in the explanation of the variance error. We present these results only for the case where U.S. money is used as monetary instrument using our first specification. Remember that in this case $r = 1$ was found. Results are presented in Table 4 and they are not sensitive to the order of the variables used to estimate the equation (6)[9]. Table 4 shows that the variance error of the Hong Kong output is explained at the end of the third year (an horizon equal to 12 quarters) around 35.5% for U.S. output and 26.4% for U.S. money. Using a horizon of 24 quarters these values are 43.6 and 17.6%, respectively. When the variance error of U.S. output or U.S. money are analyzed, we see a different picture: Hong Kong output has no short or long run effects on U.S. output. But more importantly, U.S. money is not able to explain the variance error of the U.S. output. This is in concordance with our causality analysis.

3 Conclusion

This paper analyzes two issues concerning the use of Granger-causality statistics in examining influence of money on economic activity. First, if monetary policy reacts to the state of the economy, money may not be found to Granger cause output. This issue is obviously not very new. It is well recognized by now that monetary authority reacts to the economy using a reaction function; see Christiano, Eichenbaum and Evans (1999). Sec-

[9] Orthogonalisation of the disturbances is performed using Choleski decomposition. We verified all possible orders of variables in the $VECM$ estimation and no substantial changes were observed. Results are available upon request.

ond, for: an economy maintaining fixed exchange rate with the US, Granger causality statistics from US money to small output economy reveal real effects of money. This second issue may be observed as closely related to the role played by monetary factors during the Great Depression. In fact, as Bernanke (1995) argues, the way as countries maintained the exchange rate to the gold standard determined the way and speed of recovery from the Great Depression. The point that an economy has exchange rate regime fixed to another country implies a strong support of the monetary factors role in the economic activity of the fixed exchange rate economy.

This paper shows that U.S. monetary policy does not cause U.S. output, but does cause Hong Kong output. To show this, we used the Granger causality test in the context of cointegration, as was suggested by Phillips and Toda (1994). Because the sample size used is very small, our results have to be interpreted with caution. However, all results confirm the finding that the U.S. monetary instrument (U.S. Federal Funds Rate or U.S. money supply) affects real output in Hong Kong but has no effect on U.S. output.

How is it that U.S. monetary policy could appear to have no real effects at home, but to have big real effects on the opposite side of the world? Our answer to this apparent paradox is simple. U.S. monetary policy is chosen to smooth U.S. output, and so fluctuations of U.S. output from trend represent the Fed's forecast errors, which must under rational expectations be orthogonal to the Fed's information set at the control lag, and this information set includes the monetary instrument. No Granger test could ever show that an exogenous change in U.S. monetary policy would cause a change in U.S. output, because U.S. monetary policy is chosen specifically to avoid making exogenous changes which would cause U.S. output to fluctuate. But this does not mean that U.S. monetary policy is irrelevant for real variables. The fact that Hong Kong output is strongly influenced by an exogenous (to Hong Kong) U.S. monetary policy surely implies that U.S. output would also be strongly influenced if U.S. monetary policy were, counterfactually, exogenous to the U.S.

Our answer is simple and, we believe, plausible. No other resolution appears reasonable. It would not be reasonable to argue, for example, that the U.S. has perfectly flexible prices and therefore money is neutral in the U.S., while Hong Kong has sticky prices and therefore money is not neutral in Hong Kong. If our answer is accepted, this means that all previous empirical tests for the real effects of monetary policy are deeply flawed, and massively underestimated the importance of monetary policy for real variables. The fact that it is so hard to show empirically that U.S. monetary policy has real effects in the U.S. does not indicate the irrelevance of monetary policy. Instead it shows that the Federal Reserve has not managed monetary policy to make the money supply fluctuate like the weather. Indeed, a strong finding that money did Granger cause output would be good grounds for demanding the resignation of the Chairman of the Federal Reserve.

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Table 1a. Cointegration $\lambda_{\max}$ Test

Series	H_0	H_A	First specification	Second specification
			Intercept only	Intercept and time trend
$y_t^{hk}, y_t^{us}, m_t^{us}$	$r = 0$	$r = 1$	38.58^a	38.58^a
	$r = 1$	$r = 2$	14.58^b	19.79^b
	$r = 2$	$r = 3$	7.00^a	11.03
$y_t^{hk}, y_t^{us}, R_t^{us}$	$r = 0$	$r = 1$	29.46^a	32.74^a
	$r = 1$	$r = 2$	13.53	28.47^a
	$r = 2$	$r = 3$	1.02	8.95

a, b denote significance level at 99.0% and 95.0%, respectively.

Table 1b. Cointegration *Trace* Test

Series	H_0	H_A	First specification	Second specification
			Intercept only	Intercept and time trend
$y_t^{hk}, y_t^{us}, m_t^{us}$	$r = 0$	$r > 0$	59.87^a	69.40^a
	$r \leqslant 1$	$r > 1$	21.29^a	30.82^b
	$r \leqslant 2$	$r > 2$	6.71^a	11.03
$y_t^{hk}, y_t^{us}, R_t^{us}$	$r = 0$	$r > 0$	44.27^a	70.18^a
	$r \leqslant 1$	$r > 1$	14.81	37.47^a
	$r \leqslant 2$	$r > 2$	1.02	8.95

a, b denote significance level at 99.0% and 95.0%, respectively.

Table 2a. Causality Tests using R_t^{us} as the Monetary Instrument; Trivariate System

$$\Delta y_t^i = \sum_{h=1}^k a_h \Delta y_{t-h}^i + \sum_{h=1}^k b_h \Delta y_{t-h}^j + \sum_{h=1}^k c_h \Delta R_{t-h}^{us} + \sum_{s=1}^r d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t$$

Dependent Variable	Lags	First specification		Second specification	
		Intercept only		Intercept and time trend	
		$c_h = 0$	$c_h = 0$, $d_s = 0$	$c_h = 0$	$c_h = 0$, $d_s = 0$
Δy_t^{hk}	$h = 1, ..., 7$	1.79 (0.14)	2.04 (0.09)	1.74 (0.15)	3.21 (0.01)
	$h = 2, ..., 7$	2.09 (0.09)	2.32 (0.06)	2.03 (0.10)	3.60 (0.01)
	$h = 3, ..., 7$	2.51 (0.16)	2.68 (0.04)	2.42 (0.07)	4.09 (0.00)
	$h = 4, ..., 7$	3.05 (0.04)	3.22 (0.02)	3.00 (0.04)	4.77 (0.00)
	$h = 5, ..., 7$	3.22 (0.04)	3.84 (0.02)	3.27 (0.04)	5.53 (0.00)
	$h = 6, 7$	1.96 (0.16)	4.37 (0.01)	2.00 (0.16)	6.19 (0.00)
	$h = 7$	3.82 (0.06)	5.35 (0.01)	3.86 (0.06)	7.19 (0.00)
Δy_t^{us}	$h = 1, ..., 7$	0.33 (0.91)	0.35 (0.94)	0.49 (0.83)	0.74 (0.66)
	$h = 2, ..., 7$	0.36 (0.88)	0.35 (0.92)	0.48 (0.81)	0.79 (0.61)
	$h = 3, ..., 7$	0.39 (0.88)	0.34 (0.90)	0.55 (0.74)	0.84 (0.56)
	$h = 4, ..., 7$	0.48 (0.78)	0.40 (0.84)	0.64 (0.64)	0.98 (0.46)
	$h = 5, ..., 7$	0.56 (0.67)	0.50 (0.74)	0.85 (0.48)	1.16 (0.36)
	$h = 6, 7$	0.81 (0.48)	0.66 (0.58)	1.26 (0.30)	1.45 (0.25)
	$h = 7$	1.62 (0.25)	0.98 (0.39)	2.52 (0.13)	1.93 (0.15)

Table 2b. Causality Tests using m_t^{us} as the Monetary Instrument; Trivariate System

$$\Delta y_t^i = \sum_{h=1}^k a_h \Delta y_{t-h}^i + \sum_{h=1}^k b_h \Delta y_{t-h}^j + \sum_{h=1}^k c_h \Delta m_{t-h}^{us} + \sum_{s=1}^r d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t$$

Dependent Variable	Lags	First specification		Second specification	
		Intercept only		Intercept and time trend	
		$c_h = 0$	$c_h = 0$, $d_s = 0$	$c_h = 0$	$c_h = 0$, $d_s = 0$
Δy_t^{hk}	$h = 1, ..., 7$	2.19 (0.07)	2.86 (0.02)	2.40 (0.06)	4.24 (0.00)
	$h = 2, ..., 7$	2.13 (0.09)	3.23 (0.02)	2.03 (0.10)	4.73 (0.00)
	$h = 3, ..., 7$	2.49 (0.06)	3.72 (0.01)	2.42 (0.07)	5.34 (0.00)
	$h = 4, ..., 7$	3.10 (0.04)	4.21 (0.01)	2.96 (0.04)	5.95 (0.00)
	$h = 5, ..., 7$	0.74 (0.54)	3.85 (0.02)	1.00 (0.41)	5.66 (0.00)
	$h = 6, 7$	1.09 (0.35)	4.06 (0.02)	1.40 (0.27)	6.01 (0.00)
	$h = 7$	1.52 (0.23)	5.40 (0.01)	2.11 (0.16)	7.41 (0.00)
Δy_t^{us}	$h = 1, ..., 7$	0.67 (0.69)	0.59 (0.77)	0.72 (0.65)	0.83 (0.60)
	$h = 2, ..., 7$	0.75 (0.62)	0.64 (0.72)	0.78 (0.59)	0.90 (0.53)
	$h = 3, ..., 7$	0.89 (0.50)	0.75 (0.62)	0.93 (0.48)	1.03 (0.44)
	$h = 4, ..., 7$	0.96 (0.45)	0.79 (0.57)	0.93 (0.46)	1.10 (0.39)
	$h = 5, ..., 7$	1.28 (0.30)	0.97 (0.44)	1.18 (0.34)	1.32 (0.29)
	$h = 6, 7$	0.34 (0.72)	0.42 (0.74)	0.31 (0.74)	0.94 (0.46)
	$h = 7$	0.12 (0.73)	0.07 (0.93)	0.11 (0.74)	0.86 (0.47)

Table 3a. Causality Tests using R_t^{us} as the Monetary Instrument; Bivariate System

$$\Delta y_t^i = \sum_{h=1}^{k} a_h \Delta y_{t-h}^i + \sum_{h=1}^{k} c_h \Delta R_{t-h}^{us} + \sum_{s=1}^{r} d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t$$

Dependent Variable	Lags	First specification		Second specification	
		Intercept only		Intercept and time trend	
		$c_h = 0$	$c_h = 0$, $d_s = 0$	$c_h = 0$	$c_h = 0$, $d_s = 0$
Δy_t^{hk}	$h = 1, ..., 7$	2.20 (0.06)	2.81 (0.02)	0.68 (0.68)	1.05 (0.43)
	$h = 2, ..., 7$	5.55 (0.04)	3.12 (0.01)	0.67 (0.67)	1.12 (0.38)
	$h = 3, ..., 7$	2.96 (0.03)	3.27 (0.01)	0.69 (0.63)	1.05 (0.42)
	$h = 4, ..., 7$	3.38 (0.02)	3.87 (0.00)	0.66 (0.62)	1.19 (0.34)
	$h = 5, ..., 7$	3.56 (0.03)	4.74 (0.00)	0.69 (0.56)	1.37 (0.26)
	$h = 6, 7$	4.34 (0.02)	6.21 (0.00)	0.45 (0.64)	1.65 (0.19)
	$h = 7$	8.46 (0.00)	8.65 (0.00)	0.61 (0.44)	1.88 (0.16)
Δy_t^{us}	$h = 1, ..., 7$	0.64 (0.72)	0.66 (0.72)	1.27 (0.30)	1.13 (0.37)
	$h = 2, ..., 7$	0.69 (0.66)	0.65 (0.71)	1.44 (0.23)	1.17 (0.35)
	$h = 3, ..., 7$	0.72 (0.61)	0.74 (0.62)	1.66 (0.17)	1.31 (0.28)
	$h = 4, ..., 7$	0.85 (0.50)	0.77 (0.57)	1.97 (0.13)	1.43 (0.24)
	$h = 5, ..., 7$	0.98 (0.42)	0.92 (0.46)	2.55 (0.08)	1.67 (0.17)
	$h = 6, 7$	1.26 (0.30)	1.18 (0.33)	3.74 (0.04)	2.05 (0.11)
	$h = 7$	2.49 (0.13)	1.59 (0.22)	6.95 (0.01)	2.66 (0.07)

Table 3b. Causality Tests using m_t^{us} as the Monetary Instrument; Bivariate System

$$\Delta y_t^i = \sum_{h=1}^{k} a_h \Delta y_{t-h}^i + \sum_{h=1}^{k} c_h \Delta m_{t-h}^{us} + \sum_{s=1}^{r} d_s ect_{t-1}^s + \alpha + \gamma_1 D_{1t} + \gamma_2 D_{2t} + \gamma_3 D_{3t} + e_t$$

Dependent Variable	Lags	First specification		Second specification	
		Intercept only		Intercept and time trend	
		$c_h = 0$	$c_h = 0$, $d_s = 0$	$c_h = 0$	$c_h = 0$, $d_s = 0$
Δy_t^{hk}	$h = 1, ..., 7$	1.11 (0.38)	1.92 (0.09)	1.66 (0.16)	2.54 (0.03)
	$h = 2, ..., 7$	1.185 (0.34)	2.20 (0.06)	1.53 (0.20)	2.86 (0.02)
	$h = 3, ..., 7$	1.42 (0.24)	2.45 (0.05)	1.76 (0.15)	3.16 (0.01)
	$h = 4, ..., 7$	1.77 (0.16)	2.72 (0.04)	2.18 (0.09)	3.48 (0.01)
	$h = 5, ..., 7$	1.62 (0.20)	3.27 (0.02)	2.18 (0.11)	4.05 (0.00)
	$h = 6, 7$	1.36 (0.27)	4.33 (0.01)	1.69 (0.20)	5.04 (0.00)
	$h = 7$	2.26 (0.14)	5.48 (0.01)	2.76 (0.10)	5.95 (0.00)
Δy_t^{us}	$h = 1, ..., 7$	0.59 (0.76)	0.54 (0.82)	0.61 (0.74)	0.73 (0.68)
	$h = 2, ..., 7$	0.62 (0.72)	0.53 (0.80)	0.62 (0.71)	0.74 (0.65)
	$h = 3, ..., 7$	0.69 (0.63)	0.59 (0.73)	0.70 (0.62)	0.83 (0.57)
	$h = 4, ..., 7$	0.71 (0.59)	0.57 (0.72)	0.62 (0.65)	0.84 (0.55)
	$h = 5, ..., 7$	0.93 (0.44)	0.70 (0.59)	0.83 (0.49)	1.00 (0.44)
	$h = 6, 7$	0.07 (0.94)	0.11 (0.95)	0.25 (0.78)	0.61 (0.66)
	$h = 7$	0.01 (0.91)	0.05 (0.95)	0.22 (0.64)	0.74 (0.54)

Table 4. Variance Decomposition

Error Variance of	Contribution from	Horizon (in quarters)			
		$h = 1$	$h = 6$	$h = 12$	$h = 24$
y^{hk}	y^{hk}	100.0	62.7	38.1	38.7
	y^{us}	0.0	12.4	35.5	43.6
	m^{us}	0.0	24.8	26.4	17.6
y^{us}	y^{hk}	2.8	1.5	3.8	3.5
	y^{us}	97.2	94.2	91.9	94.2
	m^{us}	0.0	4.5	4.3	2.3
m^{us}	y^{hk}	9.7	14.8	14.6	21.0
	y^{us}	1.8	8.7	17.4	58.1
	m^{us}	88.5	76.5	67.9	20.8