Money, Income, and Causality: Some Additional Evidence on the U.K. Experience

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I. Introduction

Recently, the importance of the seminal pieces by Granger (1969) and Sims (1972) on "causal" relations and statistical exogeneity in economic relationships has been recognized and their theories and methodologies have been applied in various contexts.[1/] Using the methodology of Sims (1972), Williams, Goodhart, and Gowland (1976) have investigated the causal relations between money and income, and between money and prices in the United Kingdom between 1958 and the third quarter of 1971. Their primary objective was to determine whether Sims' results for the United States could also characterize the data for a smaller, open economy like that of the United Kingdom.

The results of Williams, Goodhart, and Gowland (hereafter referred to as WGG) suggest that the causal relations characterizing the U.K. data are different from those found by Sims with U.S. data. WGG found some evidence of a unidirectional causal ordering from nominal income to money and from money to prices. Thus, the WGG results may be considered consistent with the theories of the U.K. economy in which money responds passively to economic activity.[2/]

The purpose of this study is to extend the sample period of WGG and to present some further statistical evidence about the nature of the relationships among the U.K. variables. The extension of the data period is viewed as interesting for at least three reasons. First, it is desired to capture movements in money, income, and prices in the U.K. during the recent period of high rates of price inflation.[3/] In addition, a significant reform of the U.K. financial system went into effect at the end of the third quarter of 1971, thus possibly altering the historically prevailing relationships between money and economic activity.[4/] Finally, at the end of 1972II, a switch was made from a fixed to a floating exchange rate system; for an open economy like that of the U.K. such a change could have significant effects on the monetary mechanism.

The remainder of the paper is organized as follows: The next section presents a brief discussion of Granger-causality and Sims' theorems on exogeneity. The specific methodology of this paper is described, and some comments on the methodology of WGG are made. The next section presents the empirical results and discussions. A summary section is included.

II. Testing for Granger-Causality

The foundation for the tests reported in this paper lies in the work of Granger (1969). A variable X is said to Granger-cause another variable Y if current Y can better be predicted by taking into account the history of X in addition to the history of Y than it can be by predicting conditional on the history of Y alone. In addition, X Granger-causes Y without feedback if the above condition is met along with the failure of the history of Y to improve the prediction of X over that obtained from the history of X alone.

Based upon the assumption that Y and X form a jointly covariance stationary stochastic process, Sims (1972) established the conditions under which Granger-causality from X to Y is equivalent to the econometricians definition of the statistical strict exogeneity of X in a regression of Y on X. In Sims' framework, a necessary condition that Y fail to Granger-cause X or, alternatively, that X be strictly exogenous in a regression of Y on X, is that in a regression of current Y on current, past, and future values of X, the coefficients on future values of X be zero.

In this study, no particular model of the U.K. economy is advanced at the outset to explain the relations between money, income, and prices or wages. Competing theories are generally cast in one of two general veins however; movements in money are primary determining factors of movements in income or money responds passively to changes in economic activity.[5/] In view of these competing views, then, it is reasonable to confront ourselves with the alternative relationships:

$$(0a) \qquad Y_t = \sum_{i=0}^{\infty} \alpha_i M_{t-i} + e_t,$$

and

$$(0b) \qquad M_t = \sum_{i=0}^{\infty} \beta_i Y_{t-i} + u_t,$$

where Y_t is income (or another measure of aggregate economic activity) at time t, M_t is the money stock at time t, and e_t and u_t are white noise residuals. The question with which we are concerned is: does either (0a) or (0b) represent a regression with the right-hand side variable strictly exogenous? If so, then the data would be consistent with interpreting that relation as a reduced form equation and the estimates of the coefficients in the relationship would be consistent. While there are ample reasons to question the use of even this sort of result for policy making, the determination of one-way Granger-causality would be important for not only the statistical reason alluded to above but also because the "reduced form" relation would be suggestive of the types of structural models consistent with the data.[6/]

The tests for Granger-causality are implemented in two ways in this study. First, the methodology outlined in Sims (1972) is employed. Equation (0a) is estimated including future values of the money stock; tests of the null hypothesis that the coefficients on these leading values of M are zero as a group are made. Then, in the face of (0b), the same sorts of tests with futures values of Y included.

Second, under appropriate conditions, an equivalent test is conducted based directly of Granger's definition of causality. Relationships of the form (1a) and (1b),

$$Y_t = \sum_{i=1}^{\infty} \gamma_i Y_{t-i} + \sum_{i=1}^{\infty} \delta_i M_{t-i} + v_t \tag{1a}$$

$$M_t = \sum_{i=1}^{\infty} \theta_i M_{t-i} + \sum_{i=1}^{\infty} \phi_i Y_{t-i} + w_t, \tag{1b}$$

are estimated and tests are made of the hypotheses that $\{\delta_i;\ i=1, \ldots\}$ are all zero and that $\{\phi_i;\ i=1, \ldots\}$ are all zero.[7/]

The tests in this study are made for relationships between the nominal money stock and both nominal and real measures of aggregate economic activity. Only Granger causality as discussed above is investigated; no attempt is made to assess the relationships for contemporaneous causality.[8/]

III. Empirical Study

A. Comments on Data

The data used in this study are quarterly, seasonally unadjusted data on the money stock of the U.K. and on various measures of aggregate economic activity. The money data are the series from the Bank of England for M1 and for M3, adjusted for changes in definition and other breaks in earlier published series. Measures of nominal aggregate economic activity used in the study include nominal gross national product (NGNP), nominal gross domestic product at factor cost (FGDP), and nominal final expenditures on goods and services (NG&S). From FGDP and from data on nominal taxes and subsidies, a series on nominal gross domestic product at market prices (MGDP) was constructed. The data period is defined by that over which a consistent series for M3 is available, 1963I-1977II.[9/]

B. Comments on Methodology

The data used are all assumed to be contaminated in some unspecified way by the presence of time trends of uncertain source. In the remainder of the text we shall adopt the convention that M represents the money stock (either M1 or M3) and Y represents one of the measures of aggregate activity. At time t the trend-uncontaminated values M(t) and Y(t) are assumed to be related to the observed $\hat{M}(t)$ and $\hat{Y}(t)$ via the following specifications:

$$\hat{M}(t) = M(t)e^{\rho_1 t}$$

and

$$\hat{Y}(t) = Y(t)e^{\rho_2 t}.$$

Therefore, prior to estimation, money and income (or output) are detrended in accordance with this assumed relationship. Additionally, the variables are used as deviations from mean values, and each variable has a deterministic seasonal pattern removed via least squares regression. Both M and Y are used as natural logarithms of levels both to ensure consistency with the above assumptions and to attempt to force the error structure in the reported regressions to be homoskedastic.

The results reported are based upon two estimation procedures: ordinary least squares regression (OLS) and the Hannan efficient (HE) procedure.[10/] The Granger-causality tests, in either the form given by (0a) and (0b) or by (1a) and (1b) are predicated on the whiteness of the residual vector. Furthermore, for the asymptotic justification for the

HE procedure to be even approximately valid, the first-stage residual vector must be as nearly white as possible. Accordingly, for the Sims test for Granger-causality an appropriate prefilter for <u>both</u> M and Y is chosen by examining the properties of the first-stage (OLS) residual vector in the time and frequency domains. A search is made over first-order prefilters from (1-.0L) to (1-.9L) in steps of 0.1L and over second-order prefilters from $(1-.0L)^2$ to $(1-.9L)^2$ in steps of 0.1L.[11/] Based on the null hypothesis that all future coefficients are zero, equations (0a) and (0b) are estimated. The prefilter selected is based on two criteria for assessing the absence of serial correlation in the residual vector: (i) the usual Durbin-Watson (DW) statistic for first-order serial correlation, and (ii) the Kolmogorov-Smirnov (KS) statistic based on the cumulative periodogram of the residuals for higher than first-order serial correlation.[12/] Though the KS test is less powerful than a test based on the DW statistic for first-order correlation, it is generally preferred for these procedures where more general orders of correlation must be considered.

The HE procedure is implemented according to the following scheme. A first-stage regression (OLS) is run, the residual vector is obtained, and its periodogram is estimated using the Fast Fourier Transform algorithm. The spectrum of the residuals is then estimated by smoothing the estimated periodogram. The width of the smoothing window is determined roughly from examination of the covariogram of the residuals obtained by inverse-Fourier transforming the periodogram. In all cases reported, the spectrum is computed over the interval $[-\pi,\pi]$ at 128 evenly spaced ordinates. For the regressions reported, the window is a triangular shaped one of width $3\pi/32$. The square root of the estimated spectrum of the residuals is then divided into the Fourier transforms of Y and M at each frequency point. The resultant series are inverse-Fourier transformed, and the new series are then used to test the relevant hypotheses.

Whether the Sims or Granger test for Granger-causality is implemented, the choice of the appropriate truncation point for the estimated lag distribution is nontrivial. The criteria for determining the truncation points in this study are that coefficients on additional lags (positive or negative) are not, as a group, statistically significantly different from zero and that coefficients on additional lags become small in absolute value relative to the other estimated coefficients. Additionally, when implementing the Granger test, the lag distribution for the history of the dependent variable must be long enough to exhaust the serial correlation in the residual vector.

A few comments are in order on the methodology of WGG. Their study is a good one, but one aspect of their method deserves some additional attention. As WGG, note (p. 419), Sims (1972) recommends symmetrical deseasonalization of both M and Y in an attempt to prevent the appearance of spurious seasonality in the estimated relationship. WGG, therefore, use the same deseasonalization procedure for both M and Y (the procedure is not made known to us) and then test the regression residuals for fourth-order serial correlation. However, as Sims (1974) makes clear, if M and Y are contaminated in a certain way by seasonal noise, this contamination results in an asymptotic bias in the estimated lag distribution. Furthermore, in the absence of constraints on the two-sided lag distribution, symmetric deseasonalization does nothing to this asymptotic bias. The rationale for a symmetric adjustment procedure rests on another argument entirely.[13/]

Of course, there are constraints on the estimated lag distribution of WGG, i.e., the lag profile is truncated at lags of -4 and +8. But as Sims (1974) demonstrates, deseasonalization which removes power in the Fourier transforms of M and Y in some band centered at the seasonal frequencies can be expected to induce serial correlation of a seasonal nature in the regression residuals. WGG rely on the failure of the regression residuals to show significant fourth-order correlation as evidence that their adjustment procedure did not induce that seasonal type of serial correlation in the residuals. But in the absence of some test for higher-order serial correlation, it is not clear that the regression residuals are white over the nonseasonal bands--a condition upon which Sims' test, in the face of symmetric adjustment procedures, is predicated.

The point of all of this discussion is that the asymptotic bias induced in the lag distribution by seasonal contamination can manifest itself as a significantly <u>two-sided</u> lag distribution. Thus, one should test not only for whiteness in the regression residuals but also for seasonality in the estimated lag distribution. A cursory look at the lag profiles reported by WGG (p. 422, Table 4) shows, for GDP on M_N, the pattern of alternating coefficients one would expect if there was seasonality in the lag distribution. A calculation of the periodogram of those coefficients, as reported, at sixty equally spaced ordinates does in fact show sharp peaks at the seasonal frequencies.[14/] This finding is significant in view of the fact that, for the regressions on nominal quantities, this is the one regression in which a significant causal relation was reported.

These comments should not be construed as unfavorable criticisms of the WGG effort, but rather as a possible explanation for some of their results. The question of whether or not such seasonality ought, in general, to appear in the estimated lag distribution is a deeper and as yet unresolved issue.[15/] The tests presented here employ raw, unadjusted data with only a deterministic seasonal removed. Because of the small sample size and the loss of degrees of freedom when deseasonalization is appropriately accounted for, it is impossible in this effort to symmetrically deseasonalize and still retain a sufficient number of degrees of freedom for the test statistics to be considered very useful. Thus, the reported results may be expected, in some cases, to show seasonality in the estimated lag distributions. The procedure used should guarantee, however, whiteness of the residuals under the null hypothesis.

C. Empirical Results

All of the results presented below employ M3 as the monetary variable. In addition to the coefficients shown in the tables, each regression includes a constant and a trend. A plethora of problems were encountered in implementing the causality tests for these data. Early efforts indicated that the trend contamination of the data is significant. Regressions were used to remove a linear trend, a linear trend and a trend-squared, and a trend-squared alone. In each case, all trend terms were highly significant, and yet subsequent results showed that the causality tests were relatively insensitive to the detrending scheme. Accordingly, the data were detrended linearly as indicated above in order to conserve degrees of freedom.

Determination of the optimal prefilter for various sample periods and lag lengths also turned out to be a thorny problem. In no cases studied did a first-order prefiltering scheme work for both M and Y as dependent variables. In a few cases, a first-order prefilter was found which whitened the residuals for a regression of M on Y, but in no case did a first-order prefilter work for the reverse regression. In order to facilitate comparisons between regressions in both directions, it was decided to use second-order prefilters. Even for these cases, the best prefilter did not always render a residual vector as white as one would prefer.

A third and most troublesome problem was that of determining optimal truncation points for the estimated lag distributions. Most of the sample periods and lag lengths investigated generally were characterized by smaller coefficients in the early portion of the lag profile and larger (though not necessarily more statistically significant) coefficients as the length of the lag increased. Whether or not these observations reflect significant correlations between Y and M as the lag length increases or merely spurious results due to small sample size and very few degrees of freedom is unclear. The initial assumption behind the sample period and lag lengths studied was that the effects of Y on M or of M on Y should die out within four years. It was logical to expect that a period of sixteen quarters was actually too large for a reasonable lag distribution and that it would be possible to shorten the estimated lag. Instead, it was generally found that the lag length, based on both criteria mentioned earlier, could be expanded even more, at least for the Sims tests. As the lag length was increased, however, not only did the number of degrees of freedom approach zero but also the collinearity among the right-hand variables became too high to yield reliable estimates.

Based on the considerations just noted, the following strategy was adopted. Regressions were run and Sims tests for causality were made for sixteen lags and six leads. Then, for the same sample period on the dependent variable, regressions were run and Sims tests made for nine lags and six leads. Since the number of degrees of freedom in these cases is very small, the F-statistics may be of questionable value even when the residual vector is white by our criteria (and certainly where it is not). Furthermore, the small sample size certainly implies that care must be exercised in using the HE procedure. With appropriate detrending and centering (removing of sample mean values) of data, the problems with the procedure can be reduced. The justification, however, is still asymptotic. Accordingly, Sims tests are reported both for the HE procedure and for simple OLS regressions.

The Granger tests are run over the same sample period as the Sims tests. Again, it was difficult to choose optimal truncation points for the estimated lag distributions, so the results of alternative configurations are reported. Only the OLS results are shown, the lags on the dependent variable being used to whiten the residual vector as much as possible.

Tables 1A and 1B show the results of OLS regressions and tests for feedback between M3 and NGNP with sixteen lags and nine lags, respectively, over the period 1967III-1975IV. For each regression the adjusted coefficient of determination, standard error of estimate, adjusted, Durbin-Watson and Kolmogórov-Smirnov statistics are shown. Two F-statistics and their marginal significance levels are shown for each regression: one testing the hypothesis that coefficients on the current and all lags of the right-hand-side variable are zero, and a second testing the coefficients on only lagged values. T-statistics and significance levels are shown for coefficients with a marginal significance level of less than 0.30. The maximum and minimum standard errors on regression coefficients are shown in parentheses beside the relevant coefficients for each regression.

The regression under the null hypothesis (no feedback from M3 to NGNP) with sixteen lags shows large and relatively significant coefficients throughout the lag distribution. Whiteness of the residuals cannot be rejected at even the 0.20 level. The addition of six leads changes the shape of the lag distribution somewhat, and coefficients on leads four and six quarters ahead are large and significant. Whiteness of the residuals can be rejected now at a level only slightly above 0.20.

Because the inclusion of six future terms reduces the number of degrees of freedom to only six, the second pair of regressions with nine lags was run (despite large and significant coefficients at the end of the lag profile). In Table 1B we see that the coefficients are somewhat larger in absolute value in the early part of the estimated lag distribution and somewhat smaller in the latter part, but the shape of the lag distribution is roughly the same as before. The goodness of fit decreases, and residual whiteness can be rejected at almost the 0.20 level. The addition of six future coefficients only slightly alters the lag profile, and the future coefficients, while individually fairly large, are also not significant.

The reverse regressions show similar patterns, but the changes noted when leads are added are more pronounced. Reduction of lags from sixteen to nine reduces goodness of fit somewhat. In each case, the addition of leads alters the structure of the early part of the lag profile but not the latter part. For both cases, the coefficients on leads alternate between large and small, and in each case the coefficient on lead six is the largest and tightest estimate, thus being the most significant. In each case, addition of future terms results in our being able to reject whiteness about the 0.01 level.

Tables 2A and 2B present the HE estimated lag distributions based on the estimated residual spectra from the regressions in Tables 1A and 1B, respectively. As expected, under the null hypothesis, the standard errors on the coefficients fell and the goodness of fit improved. For the regressions of M3 on NGNP, with or without leads, whiteness of the residual vector deviated less from whiteness than under the OLS estimates. Truncations of the lag at nine past values dramatically changed the lag profile and reduced the significance of the current and past values. Addition of leads again altered the lag profiles and their significance, though in neither case did the KS statistic change appreciably. With sixteen lags the coefficients on leads varied from large to small, while for nine lags all but one coefficient on leads was large. With sixteen lags, the coefficient on lead six was the tightest estimate, and in both cases it was a moderately large coefficient.

The reverse regressions (NGNP on M3) are fruzzling in some ways. The standard errors generally fell, as expected, but whiteness of the residual vector could be rejected at levels of 0.10 to 0.01 in three of the four cases.[16/] The failure of whiteness to obtain, plus the small number of degrees of freedom, must make the F-statistics suspect in these cases. For both nine and sixteen lags, the addition of leads alters the lag structure. In both cases the coefficient on lead six is statistically significant (though only at the 0.21 level with sixteen lags), but in each case the sizes of coefficients on leads suggests that this result may be spurious.

Tables 3A and 3B present the estimated lag profiles over the same sample period for the OLS Granger tests with twelve lags on each variable and with six lags on each variable, respectively. In all cases whiteness of the residuals could not be rejected at even the 0.20 level. In Table 3A for M3 as dependent variable, the coefficients on past M3 after that on lag 1 become large again only at lag six and beyond. The coefficients on past NGNP are large between lags four and nine. None are individually statistically significant at less than the 0.30 level. For the reverse regression, the majority of coefficients are large and several are significant.

In Table 3B we see that truncation of the lag distribution leaves the residual vector white and, in three of four cases, clearly alters the size of the coefficient on the first lag. The significance of the lagged dependent variables, as evidenced by the first F-statistic under each regression, increases dramatically in every case. (The second and third F-statistics on Table 3A test for significance of the last four coefficients on past dependent and past other variables, respectively.)

The F-statistics summarizing tests for feedback in the regressions reported in Tables 1A through 2B are presented in Table 4A. For the OLS regressions, the only statistic suggesting significant feedback (at a significance level of 0.30 or better) is the NGNP on future, current, and past M3 with sixteen lags. As Table 1A shows, however, whiteness of the residuals can be rejected at the 0.01 level for this regression. This observation, along with the small number of degrees of freedom, implies that this statistic must be interpreted cautiously.

For the HE regressions, three of four regressions show feedback at the 0.30 level or better. Only M3 vs. NGNP (sixteen lags) fails to show this result. For M3 vs. NGNP (nine lags), the future coefficients are significant at the 0.29 level. The coefficients on leads for this regression (Table 2B) are relatively large, but they are noisy, and only the coefficient on lead four is statistically significant (at the 0.03 level). In addition, the entire regression fits poorly, so the significance of the futures may be due simply to the noisy estimates on coefficients for past as well as future coefficients.

Both HE estimates for NGNP vs. M3 show evidence of feedback. However, for the regression with sixteen lags, whiteness of the residual vector can be rejected not only for the regression with leads but also for the efficient regression under the null hypothesis at the 0.05 level or better. Also, as noted above, only the coefficients on leads one and six are large, the one on lead six being the only one with a marginal significance level of better than 0.30. These observations suggest caution in relying too heavily on this statistic as an indication of feedback. Similar comments apply to the final F-statistic, at least as far as the regression coefficients themselves are concerned. In this case, however, the residual vector for the regression with leads and lags is white, although the regression is derived from a first stage result where whiteness was rejected at the 0.10 level.

The F-statistics for Granger-causality from the regressions in Tables 3A and 3B are the final entries under each regression. For the estimates, based on twelve lags of each variable, the F-statistics imply that NGNP fails to Granger-cause M3 but that M3 Granger-causes NGNP (F significant at the 0.22 level). The results for six lags on each variable are consistent with these results; the F-statistic for significance of M3 in explaining NGNP is 2.06, significant at the 0.11 level.

One interesting caveat to the above results is not shown in the tables. Based on F-tests (on groups of coefficients from regressions with twelve lags of each variable), one set of regressions of the form given in Tables 3A and 3B were run with eight lags of M3, nine lags of NGNP with M3 as dependent variable, and with ten lags of NGNP, eight lags of M3 with NGNP as dependent variable. These two regressions showed each variable Granger-causing the other, NGNP being significant in M3 equation at the 0.22 level. The reverse regression showed lagged M3 as significant, but it was also characterized by a distinctly non-white residual vector (KS significant at the 0.10 level).

Table 4B presents some additional evidence about the possibility of feedback. The statistics presented are not based on a rigorously derived test for feedback, but they should contain useful information bearing on the question. Essentially, the notion is this: Let $\hat{Y}$ represent the projection of Y on some set of variables θ, i.e.,

$$\hat{Y} = E(Y|\theta)$$

so that

$$Y = E(Y|\theta) + e$$

where e is the residual orthogonal to all elements of θ. If an additional set of variables, say Z, is then included in the information along with θ so that we have $E(Y|\theta,Z)$, then the properties of the residual e should change only if this information Z is truly a conditioning set of information on which the projection of Y is defined.

Based on this notion, Table 4B presents the results of a Kolmogorov-Smirnov test for the cumulative periodogram of residuals from the OLS and HE regressions without and with leads. If this test suggests that the distribution functions of the residuals from regressions with leads differs from that of the regressions without leads, this result will be taken as an indication of the failure to reject feedback. The tabulated results suggest that only for the OLS and HE regressions of NGNP on M3 with sixteen lags did the residual structure change (i.e., we can reject identical distribution functions at the 0.05 level or better). These findings are broadly consistent with those outlined above.

The final set of statistics bearing directly on the possibility of Granger-causality between NGNP and M3 are given in Table 5. These statistics are constructed as a test of the joint hypotheses that one variable, say M3, fails to show feedback to NGNP in a two-sided test and that M3 fails to help explain NGNP in a Granger test. The test is due to John Geweke and Warren Dent.[17/] Essentially, the test is based on the notion that, under the null hypotheses, the residuals from the two regressions are realizations drawn from independent distributions. Based on this, a test statistic is derived from the two test statistics as follows:

(i) From the Sims test we have $F_S(n_s, m_s)$, and

(ii) from the Granger test we have $F_G(n_g, m_g)$.

(iii) Using (i) and (ii), the test statistic is

$$F(n_g + n_s, m_g + m_s) = \frac{n_g F_G + n_s F_S}{n_g + n_s}.$$

The statistics reported in Table 5 are derived from the F-statistics reported for the regressions in Tables 2B and 3B. As the results show, we can reject <u>no feedback</u> or absence of Granger-causality at significance levels better than 0.20 in either direction. The statistics thus incorporate the indicated Granger-causality running from NGNP to M3 as indicated by the Sims test and the reverse causality indicated by the Granger test.

To summarize, we note that the results of the causality tests between M3 and NGNP are mixed. There is source evidence, based on the Sims tests, that the data are consistent with one-way Granger-causality running from NGNP to M3. This result is consistent with the WGG results. On the other hand, our results based on the Granger tests suggest the data are consistent with unidirectional causality running from M3 to

NGNP, in contrast to the WGG results. The joint tests employed are consistent with bidirectional Granger-causality.

Some Observations on the Possibility of Structural Change

It was stated at the outset that a primary goal of this study was to investigate the causal relations between money and income in the U.K. during the post-WGG sample period. It is a distinct possibility that because of monetary reforms and/or the change from a fixed to a floating exchange rate system, the pattern of Granger-causality exhibited by the data could change over the sample period.

Tables 6A through 9B present the results of rather weak tests for structural change. The two-sided distributed lag regressions reported in Tables 1B and 2B are rerun twice: once with a 0-1 dummy (DUM1) to account for the monetary reforms and once with a 0-1 dummy (DUM2) to account for the change from a fixed to a floating exchange rate. The usual statistics are shown along with a ΔKS statistic, again testing the hypothesis that the residual structure changed after adding leads and dummy.

Comparing Table 6A with 1B, we see that the inclusion of DUM1, which is highly significant, dramatically alters the lag structure and goodness of fit. In Table 6B we see that DUM2 is also significant, though less so than DUM1, and that the changes in the estimated lag structure are less than with DUM1. In neither case did the results bearing on feedback change.

Comparison of Tables 7A and 7B with 1B shows that inclusion of either dummy variable does little to change the estimated two-sided lag profile. The coefficient on DUM1 is significant at the 0.18 level, while that on DUM2 is not statistically significant. The evidence for feedback remains unchanged when DUM2 is included, but the marginal significance level of the F-statistic for feedback changes from 0.39 to 0.24 when DUM1 is included.

Tables 8A and 8B are the HE estimates for M3 on NGNP. Inclusion of neither dummy markedly alters the lag distribution. Each dummary variable is significant, DUM1 being very significant. The inclusion of DUM1 does not change the F-statistic for feedback, but the presence of DUM2 changes the marginal significance level of the F-statistic on leads of NGNP from 0.29 to 0.16.

Tables 9A and 9B show the results for NGNP vs. M3 with the HE procedure. Again, the lag distributions changed little. DUM1 is significant at the 0.11 level, but, as before for the OLS version of this regression, DUM2 is not significant. The marginal significance level of the F-statistic for feedback changes in the presence of DUM1 from 0.13 to 0.06.

To summarize, dummy variables included to test for the effects of structural changes showed statistically significant coefficients in all cases except for those regressions of NGNP on M3 with DUM2, the dummy for the change from fixed to floating exchange rates. The coefficient on DUM1, the dummy variable for monetary reforms, always was more significant in regressions of M3 on NGNP than in the reverse regressions. To the extent that inclusion of either dummy variable altered the feedback pattern, we note that with DUM1 there was stronger evidence in support of feedback from NGNP to M3, while with DUM2 there was increased evidence of feedback in the reverse direction.

IV. Concluding Remarks

Evidence has been presented bearing on the patterns of Granger-causality between money (M3) and nominal income (GNP) in the U.K. over a period characterized by high inflation rates, monetary reforms, and changes in the exchange rate structure. Many problems were encountered with the study. The data are heavily trended and when lagged are highly collinear. The sample size, determined by periods over which consistent series could be formed, was too small to allow the lag lengths to be extended as far as desired while retaining a reasonable number of degrees of freedom.

Based on two types of tests, the Sims and Granger tests, and on what were deemed reasonable marginal significance levels for the available sample size, the results were mixed. Tests for feedback suggest one-way feedback from NGNP to M3, while Granger-type tests suggest the opposite result. A joint test, proposed by Geweke and Dent, suggests that Granger-causality may run both ways. Finally, the inclusion of dichotomous dummy variables to represent structural changes indicated that such changes may be significant in explaining the money-income relationships, and that if they affected the feedback structure, it was likely in ways promoting bidirectional feedback.

Footnotes

[1]/See, e.g., Sargent and Wallace (1973), Sargent (1976), Geweke (1975), and Mehra (1977).

[2]/For some thoughts seeking to rationalize Sims' results for the U.S. and the WGG results for the U.K. in the context of a single, open-economy model, see Putnam and Wilford (1977).

[3]/Between 1971 and 1976, the GDP deflator rose at an average yearly rate in excess of 15 percent.

[4]/See Competition and Credit Control for a discussion of the financial reform.

[5]/See, e.g., Sheppard (1971) or Laidler and Parkin (1975).

[6]/For a critique of the usefulness of these relationships for policy decisions, see Lucas (1976).

[7]/The justification for the first procedure is, of course, defined in Sims (1972). The justification for the second procedure may be found in Sargent (1976). The conditions for both empirical procedures are succinctly stated in Mehra (1977).

[8]/Gordon (1977) almost applies the latter technique in his recent study of money, wages, and prices in eight countries. Gordon's method differs by inclusion of contemporaneous terms on the right-hand side of variables other than the dependent variable. It is not clear from his discussion that he realizes that these tests are tests of a slightly different notion of Granger-causality than we are considering.

[9]/These data were supplied by David Howard, Board of Governors of the Federal Reserve System. The money stock series are taken directly from the Quarterly Bulletin of the Bank of England. The series on NGNP, FGDP, NG&S, taxes, and subsidies are all taken directly from the Central Statistical Office, Economic Trends and Economic Trends Annual Supplement.

[10]/See Hannan (1963).

[11]/Here L is the lag operator, i.e., $L^n X_t \equiv X_{t-n}$.

[12]/See Lindgren (1968).

[13]/See Sims (1974), pp. 620-621.

[14]/These results are available on request.

[15]/See Sargent (1976) and Sims (1977) response.

[16]/It is possible that a too narrow smoothing window may have been chosen for these regressions.

[17]/I am indebted to John Geweke for describing this test to me in a private conversation.

Table 1A

OLS Estimates and Tests for Feedback Between M3 and NGNP, Sixteen Lags
Period: 1967III-1975IV

	M vs. Y Prefilter: $(1-.5L)^2$						Y vs. M Prefilter: $(1-.1L)^2$					
Lag	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.
-6				.3298 (.2311)	1.43	.2034				.4952 (.3131)	1.58	.1649
-5				-.0129						-.1923		
-4				.6330	2.22	.0686				-.0220		
-3				.2345						.2864		
-2				.1280						-.0333		
-1				-.2305						.2051		
0	-.2970 (.2265)	-1.31	.2142	-.0554			.4754 (.3210)	1.48	.1644	-.3059		
1	-.2182			.1044			-.3583			-.4005		
2	-.0238			.1447			.3568			.2486		
3	.0373			-.1340			-.2122			.2932		
4	.2194			.4076	1.41	.2083	.4959	1.14	.2770	.5045	1.16	.2890
5	-.0129			-.0855			-.4579			-.5151	-1.22	.2694
6	.6009	2.00	.0686	.7123	2.05	.0859	.0655			.1636		
7	.9187	3.40	.0053	.5010	1.35	.2261	-.0474			-.0675		
8	.7700	2.40	.0335	.5052	1.43	.2038	-.5657	-1.31	.2133	-.1048		
9	.7182	2.10	.0578	.4389	1.21	.2713	.5451	1.24	.2371	.2419		
10	.3013			.3200			.2703			.2824		
11	.1549 (.4141)			.0471			.7732	1.74	.1077	.7231	1.73	.1344
12	-.3478			-.3494			-.5877	-1.31	.2156	-.4900	-1.18	.2825
13	-.5045	-1.24	.2387	-1.1580 (.5153)	-2.25	.0657	.3583			.4472		
14	-.4712	-1.17	.2645	-.9246	-1.84	.1154	-.1271			-.2578		
15	-.8515	-2.15	.0522	-1.0228	-2.22	.0684	-.0991 (.5262)			-.5818 (.4775)	-1.22	.2688
16	-.6101	-1.73	.1090	-.1692			.9291	1.96	.0733	.6389	1.37	.2184
$\bar{R}^2$	.5915			.6329			.8830			.9197		
s.e.	.0192			.0182			.0219			.0181		
D.W.	2.0054			2.2475			1.8987			2.9462		
K.S.	.0421			.0925			.0373			.1593		
F(17,12)	1.9310 (.1251)						8.7480 (.0002)					
F(16,12)	2.0120 (.1124)						6.0470 (.0016)					
F(17,6)				1.5050 (.3206)						7.4350 (.0102)		
F(16,6)				1.5330 (.3119)						7.7280 (.0093)		

Table 1B

OLS Estimates and Tests for Feedback Between M3 and NGNP, Nine Lags
Period: 1967III-1975IV

	M vs. Y Prefilter: $(1-.6L)^2$						Y vs. M Prefilter: $(1-.3L)^2$					
Lag	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.
-6				.2069						.4941 (.3487)	1.42	.1800
-5				-.1589						-.2502		
-4				.2252						.0504		
-3				.0248						-.0268		
-2				-.1307						.3683		
-1				-.2787	-1.23	.2398				.2382		
0	-.3156	-1.60	.1262	-.4378	-1.76	.1026	.3586 (.3227)	1.11	.2804	-.2809		
1	-.2145	-1.11	.2800	-.1834			-.3251			-.5478	-1.34	.2028
2	-.0152			-.0923			.0191			-.0062		
3	-.1780			-.1260 (.1998)			.1057			.4680	1.10	.2920
4	.0916 (.1599)			.3190	1.49	.1592	.4303 (.3966)	1.08	.2916	.3188 (.4390)		
5	-.0305			-.0443			-.4535	-1.15	.2644	-.3088		
6	.4163	1.78	.0912	.5699	1.77	.0993	-.0025			.1197		
7	.4818	1.94	.0678	.6038 (.3913)	1.54	.1468	-.1325			-.1073		
8	.3857	1.45	.1642	.4799	1.28	.2214	.1739			.4061		
9	.4632 (.2681)	1.73	.1003	.3206			.6399	1.76	.0940	.3478		
$\bar{R}^2$	.2519			.2034			.7094			.7221		
s.e.	.0191			.0197			.0234			.0229		
D.W.	1.8947			1.8647			2.1107			2.5131		
K.S.	.0929			.0947			.0645			.1410		
F(10,19)	.9321 (.5266)						4.6930 (.0019)					
F(9,19)	1.0330 (.4503)						3.9620 (.0055)					
F(10,13)				.7653 (.6593)						2.9630 (.0350)		
F(9,13)				.7790 (.6394)						3.2920 (.0256)		

Table 2A

HE Estimates and Tests for Feedback Between M3 and NGNP, Sixteen Lags
Period: 1967III-1975IV

	M vs. Y Prefilter: $(1-.5L)^2$						Y vs. M Prefilter: $(1-.1L)^2$					
Lag	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.
-6				.1643 (.2275)						.4132 (.2940)	1.41	.2096
-5				-.1120						-.0823		
-4				.4006	1.57	.1683				.0325		
-3				.0111						.1203		
-2				.0903						.0145		
-1				-.2155						.2947		
0	-.3402	-1.78	.0998	-.2267			.7514 (.3968)	1.89	.0826	-.1956		
1	-.1934			-.0468			-.2038			-.3985		
2	.0638			.1063			.1682			.0722		
3	.2227	1.15	.2729	.0034			-.4878			.2272		
4	.2424	1.25	.2338	.3484	1.22	.2686	.4277			.5233		
5	.0190 (.1890)			-.1307			-.2132			-.4214 (.5005)		
6	.5401	2.53	.0264	.6209	1.81	.1210	.2265			.1050		
7	.7372	3.77	.0027	.4762	1.29	.2453	-.0356			-.0794		
8	.4762	2.19	.0491	.4270	1.37	.2206	-.3933			.1138		
9	.3771	1.55	.1474	.2504			.5211			.2432		
10	.0857			.1166			-.0265			.1797		
11	-.0666			-.0478			.6263			.6547	1.51	.1807
12	-.4202	-1.62	.1309	-.2317			-.4868			-.3267		
13	-.2906	-1.11	.2874	-.5826	-1.52	.1792	.0084			.0724		
14	-.3250 (.2688)	-1.21	.2500	-.3680			-.0229			-.3480		
15	-.7421	-2.79	.0163	-.7084	-1.82	.1182	.0920 (.6036)			-.1363		
16	-.5938	-2.18	.0499	-.2145 (.4398)			.2865			.2169		
$\bar{R}^2$	.8883			.8490			.9592			.9805		
s.e.	2.9576			3.4385			4.5552			3.1513		
D.W.	2.0201			2.0440			1.1964			2.7459		
K.S.	.0404			.0590			.1357			.1789		
F(17,12)	6.0230 (.0015)						23.4100 (.0000)					
F(16,12)	5.6370 (.0022)						5.1810 (.0032)					
F(17,6)				1.2660 (.4101)						7.7520 (.0091)		
F(16,6)				1.1800 (.4478)						7.5920 (.0097)		

Table 2B

HE Estimates and Tests for Feedback Between M3 and NGNP, Nine Lags
Period: 1967III-1975IV

	M vs. Y Prefilter: $(1-.6L)^2$						Y vs. M Prefilter: $(1-.3L)^2$					
Lag	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.	Coefficient	t	Sig.
-6				.1469						.5071	1.96	.0715
-5				-.0545						-.0709		
-4				.4364	2.41	.0312				-.0820		
-3				.2007						.0111		
-2				.2045						.1439		
-1				.1015						.1488		
0	-.2009	-1.45	.1624	-.0310			.3148	1.47	.1584	.0076		
1	.0018			.1229			.0091 (.2090)			-.4333	-1.83	.0895
2	.2236	1.72	.1014	.1056 (.1424)			.0114			-.0748 (.2328)		
3	-.0597			-.0645			.0383			.5712	2.16	.0499
4	.0873 (.1007)			.0857			.4078	1.82	.0853	.3665 (.2989)	1.23	.2418
5	-.0315			-.3066	-1.62	.1298	-.4077	-1.81	.0869	-.4974	-1.76	.1026
6	.2174	1.37	.1863	.0964			.1301			.0852		
7	.1987	1.22	.2369	-.0099 (.2670)			-.0235			-.0419		
8	.0789			-.0605			.1235			.3555	1.20	.2503
9	.1856 (.1888)			-.0661			.3093 (.2398)	1.29	.2125	.3563	1.36	.1968
$\bar{R}^2$	.3505			.4234			.9649			.9735		
s.e.	2.5165			2.3711			2.5914			2.2524		
D.W.	1.8280			1.7654			1.5409			2.1071		
K.S.	.0527			.0837			.1108			.0803		
F(10,19)	1.4930 (.2169)						43.8400 (.0000)					
F(9,19)	1.3870 (.2613)						11.9900 (.0000)					
F(10,13)				.9440 (.5273)						6.2670 (.0015)		
F(9,13)				.9250 (.5344)						6.6060 (.0013)		

Table 3A

OLS Estimates and Tests for Granger-Causality
Period: 1967III-1975IV

$$\text{Regression:} \quad Y_t = \sum_{i=1}^{12} \gamma_i Y_{t-i} + \sum_{j=1}^{12} \delta_j X_{t-j} + e_t$$

Y Variable	Lag	M3 Coefficient	M3 t	M3 Sig.	NGNP Coefficient	NGNP t	NGNP Sig.
Y	1	.5332 (.4881)		.3245	.1243		
	2	.0164			.3269		
	3	.0553			.1427		
	4	-.0014			.1576 (.2742)		
	5	.0324			.0183		
	6	-.2532			.6143	1.61	.1688
	7	-.2745 (.7551)			.0436		
	8	.1830			-.0175		
	9	-.2180			-.0044		
	10	.0102			-1.0230	-2.10	.0902
	11	-.3475			-.5121 (.5980)		
	12	-.1052			-.1269		
X	1	.0719			-.0728 (.3605)		
	2	.0807			.0624		
	3	.0107			.1955		
	4	.2053 (.3713)			.7855	1.87	.1203
	5	-.1190			-.6807	-1.36	.2314
	6	.1449			-.6104	-1.17	.2953
	7	.3105			.1822		
	8	.4500			.4346		
	9	.4882			.1138		
	10	.0190			-.0132	1.86	.1221
	11	.0887 (1.0270)			.8630		
	12	.0313			-.2404 (.6091)		
$\bar{R}^2$		.9604			.9577		
s.e.		.0226			.0167		
D.W.		1.8823			1.9549		
K.S.		.0413			.0652		
F(12,5)		4.8210 (.0470)			3.6460 (.0815)		
F(4,5)		.1809 (.9387)			1.6740 (.2905)		
F(4,5)		.2269 (.9121)			1.0900 (.4515)		
F(12,5)		.6343 (.7603)			2.0260 (.2248)		

Table 3B

OLS Estimates and Tests for Granger-Causality
Period: 1967III-1975IV

$$\text{Regression:}\quad Y_t = \sum_{i=1}^{6} \gamma_i Y_{t-i} + \sum_{j=1}^{6} \delta_j X_{t-j} + e_t$$

Y		M3			NGNP		
Variable	Lag	Coefficient	t	Sig.	Coefficient	t	Sig.
Y	1	1.0118 (.2489)	4.07	.0008	.5732 (.2206)	2.60	.0188
	2	-.0217			.0734		
	3	.0689			.1039		
	4	-.1197			.1081		
	5	.0907 (.3916)			.1623		
	6	-.3575	-1.19	.2520	.5438 (.2942)	1.85	.0820
X	1	.1045 (.1805)			-.4443 (.3042)	-1.46	.1624
	2	.0779			-.2097		
	3	-.0618			.5830	1.29	.2149
	4	.2590	1.32	.2044	.5010	1.08	.2966
	5	-.2215	-1.17	.2601	-.9551 (.4787)	-2.00	.0623
	6	.2450 (.2407)			.2349		
$\bar{R}^2$		.9744			.9251		
s.e.		.0182			.0222		
D.W.		2.1093			2.2500		
K.S.		.0515			.0714		
F(6,17)		26.4600 (.0000)			6.4790 (.0011)		
F(6,17)		.9342 (.4960)			2.0570 (.1132)		

Table 4A

F-Statistics in Tests for Feedback

Regression	F(6,6)	Sig.	F(6,13)	Sig.
OLS M3 vs. NGNP	1.2260	.4055	.8072	.5821
OLS NGNP vs. M3	1.9120	.2250	1.1440	.3912
HE M3 vs. NGNP	.4796	.8035	1.4000	.2861
HE NGNP vs. M3	3.1790	.0925	2.0250	.1348

Table 4B

Kolmogorov-Smirnov Statistics for Comparison of Residual Periodograms in Tests for Feedback*

Regression	ΔKS 16 Lags	9 Lags
OLS M3 vs. NGNP	.1073	.0279
OLS NGNP vs. M3	.1886	.0984
HE M3 vs. NGNP	.0536	.0477
HE NGNP vs. M3	.3016	.1244

*Critical values: $\Delta KS = 0.170$ for $\alpha = 0.05$.
$\Delta KS = 0.204$ for $\alpha = 0.01$.

Table 5

Joint F-Tests for Granger-Causality

Joint Hypothesis	F(12,30)	Sig.
No feedback from M3 to NGNP, M3 does not help predict NGNP	1.7285	.1100
No feedback from NGNP to M3, NGNP does not help predict M3	1.4796	.1865