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MONETARY SHOCKS AND REAL FARM PRICES: A RE-EXAMINATION

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ABSTRACT

The effect of monetary policy on the farm sector remains controversial. Studies attempting to quantify the effects of monetary disturbances on real farm prices report conflicting results: some find that positive monetary shocks increase real farm prices in the short run, while others detect no such effect.

We offer a resolution of these conflicting findings by re-estimating existing models on a common data set. When sample periods corresponding to the original studies are used, the conflicting results are confirmed. In contrast, when samples are updated through 1993, all models supply the same result: monetary shocks do not affect real farm prices. (*JEL* E50, C32, Q10)

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Introduction

Disparate sectoral responses are a common theme in monetary policy discussions. The responses of housing, consumer durables, and agriculture receive particular attention. We focus on agriculture. Specifically, we re-examine whether money affects the relative prices faced by the agricultural sector.

Events of the early 1980s--tight money coupled with falling real farm prices--suggested to many economists that monetary policy affects relative farm prices. Both theoretical and empirical responses followed. The theoretical work describes channels through which monetary shocks can generate short-run fluctuations in the relative price of agriculture commodities (real farm price, henceforth RFP). There are two primary stories: overshooting of flexible agricultural prices in the presence of sticky prices for non-agricultural goods, based on the Dornbusch (1976) overshooting model, and shifts in relative prices due to imperfect signal extraction, based on the Barro (1976) monetary misperceptions model.[1] The standard theoretical prediction is that positive monetary shocks increase RFP.[2] A corresponding body of empirical work attempts to verify this theoretical

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[1]For applications of the overshooting model, see Frankel (1986) and Stamoulis and Rausser (1988). For applications of the monetary misperceptions model, see Lapp (1990) and Belongia (1991).

[2]However, the effect can be ambiguous in a monetary misperceptions model (Lapp 1990, Belongia 1991).

prediction, but it is marked by conflicting results.[3]

The empirical controversy motivates our work. Our primary goal is to reconcile the conflicting empirical results. We want to emphasize this difference between our research and that of Belongia (1991), who shows that a variety of model specifications fail to support the importance of money for RFP over his sample period. In our view, a reconciliation must show how *existing* empirical models produce their conflicting results. We therefore estimate a set of models that are tied very closely to the prominent models in the literature. We focus on four well-known empirical studies that characterize the controversy: Chambers (1984), Devadoss and Meyers (1987), Lapp (1990), and Belongia (1991). The first two find that positive M1 shocks increase RFP; the last two find that M1 shocks leave RFP unaffected. The studies differ in specification, data definition, sample frequency, and sample period. This suggests a variety of possible approaches to attempting reconciliation, and it is far from our intent to explore these systematically. Instead, we wish to emphasize that sample period extension reduces the likelihood of misleading correlations. We therefore focus on demonstrating that sample period alone can account for the divergence in results.

In order to discount the role of data differences (e.g., differences in sample frequency and variable definition) in generating divergent results across existing studies, we begin by reproducing the controversy with a common data set. Using a quarterly data set and samples corresponding to the original studies, we replicate the conflicting results and in this sense

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[3]In this literature, monetary shocks are unpredictable innovations in the money supply (usually M1). See Belongia (1991, p. 32) for a list of empirical studies.

"verify" the controversy. We then update all samples through 1993. After updating, all specifications yield the same result: monetary shocks do not affect RFP. Since this finding is robust to specification once samples are updated, we have found a resolution of the controversy.

The paper is organized as follows. Section 1 summarizes four existing studies, Section 2 presents our empirical results, and Section 3 concludes.

1. Four Existing Empirical Studies

Chambers (1984), Devadoss and Meyers (1987), Lapp (1990), and Belongia (1991) estimate dynamic systems containing M1 and RFP. Each study tests the influence of monetary shocks on RFP. The first two studies find important monetary effects, while the last two find none. A brief overview follows.

Devadoss and Meyers estimate several vector autoregressions (VARs) with monthly data (1960:01-1985:12) in log-levels. We focus on their bivariate VAR in M1 and RFP. (We label the M1-RFP and RFP-M1 orderings DM I and DM II.) The authors find that the RFP impulse responses to an M1 shock are positive and significant for up to two years in both DM I and DM II. This constitutes evidence that money affects RFP.

Using monthly data (1976:05-1982:05) in log-levels, Chambers estimates a four-variable VAR(4) containing M1, the net value of nominal agricultural exports, RFP, and nominal farm income. He includes a time trend in his regressions, and the variables are ordered as listed.

Chambers uses a block exogeneity test to assess the influence of M1. He rejects the null hypothesis that the parameters on lagged M1 are jointly zero in the three agricultural-aggregate equations--M1 "causes" the agricultural variables. RFP impulse responses to an M1 shock are positive for all periods reported, and the variance decompositions show that M1 innovations account for approximately 2%-6% of the variability in RFP at various horizons. So, like Devadoss and Meyers, Chambers finds significant monetary effects.

Lapp estimates monetary misperceptions models using a standard two-step procedure. He considers a variety of data generating processes for M1, and his RFP equation regressors are lagged RFP, lagged relative farm output, and unexpected money. (The residuals from models of M1 growth proxy unexpected money.) Using first differences of log-levels of quarterly data, he estimates a number of RFP equations for the 1951-1972 and 1973-1985 periods. For the later period, the coefficients on unexpected money are jointly insignificant in all the RFP equations.

Belongia's approach to the monetary misperceptions model is similar to Lapp's. None of the coefficients on his unexpected M1 shocks (lags 0-3) are significant in his RFP equations.

In addition, Belongia estimates a VAR(2) composed of RFP, M1, the real exchange rate, and industrial production. He uses quarterly data (1976:1-1990:4), and all variables are transformed to first differences of log-levels. Belongia cannot reject the null hypothesis that the sum of the lagged M1 coefficients in the RFP equation is zero.[4] Furthermore, M1 shocks account for less than 1% of the variability in RFP at the four-, eight-, and twelve-quarter-ahead horizons. The results are qualitatively unchanged when he replaces the real exchange rate with real farm exports.

In sum, these studies capture the controversy in the literature. Some find that monetary shocks affect RFP, while others conclude the opposite. Unfortunately, direct comparisons

[4]Belongia uses this as a test of long-run neutrality.

between the studies are difficult given the variation in specification, data definition, sample frequency, and sample period (see Table 1). We therefore re-estimate versions of the models described above with a common data set. Section 2 describes our results and suggests a resolution of the controversy.

2. Re-Estimation of Existing Empirical Models

Our data are quarterly observations (1960:1-1993:4) for M1, RFP, real farm business GDP (FGDP), real farm exports (RFX), and real business GDP (BGDP). An appendix describes the data in detail.[5]

Since Devadoss and Meyers (1987) and Chambers (1984) use monthly data, we match the month to the corresponding quarter to specify a lag length. The Devadoss and Meyers VAR has a lag length of 14, so we report a quarterly VAR(5). Similarly, we report a quarterly VAR(2) to conform to Chambers's monthly VAR(4).

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[5]We present results using quarterly data for a number of reasons. First, the best measure of farm output, real farm GDP, is a quarterly series. Furthermore, a monthly price index such as the CPI or the PPI is needed to construct monthly RFP, and these series seem to be especially sensitive to certain items (e.g., food and energy). While items could be dropped, this detracts from the indices' generality. Finally, with quarterly data, NIPA GDP series can be used to construct consistent measures of RFP, farm output, and overall output. Nevertheless, to dismiss concern that our results depend on our sample frequency, at times we note the results obtained using monthly data.

2.1. Devadoss and Meyers DM I and DM II Models

We estimate a VAR(5) from 1960:1-1985:4. The variables are first transformed to log-levels, as in the original.[6] As above, the DM I and DM II models correspond to the M1-RFP and RFP-M1 orderings. Figure 1 gives the RFP impulse responses to an M1 shock in each of the models, and the results are very similar to those found by Devadoss and Meyers. RFP impulse responses are positive and a number are significant (or nearly significant) for up to two years in both models. We also report RFP variance decompositions in Table 2, although these were not reported in original study.[7] These provide an additional gauge of the importance of M1 shocks. The impulse responses and variance decompositions both indicate that M1 shocks play a significant role in determining RFP.

We next estimate the VAR with an updated sample, extending the end of the sample period to 1993:4. Figure 2 and Table 3 give the new RFP impulse responses to an M1 shock and RFP variance decompositions. Using the extended sample, none of the RFP responses are significant. The peak responses fall from 4.00 to 1.48 in the DM I model and from 3.13 to 1.22 in

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[6]We multiply the log-levels by 100 so that the impulse responses can be read as percentages.

[7]We obtain confidence intervals using the Runkle (1987) bootstrapping method with 500 replications. The 95% bands are determined from the bootstrapped pseudo-samples using the modified percentile method presented in Davidson and MacKinnon (1993, pp. 765-66).

the DM II model.[8] The proportion of RFP variance due to M1 shocks shrinks at all horizons considered. The largest M1 shares of RFP variance (for the horizons considered) drop from 21.59 to 4.35 and from 10.94 to 2.32. Simply extending the sample vitiates the result that M1 shocks affect RFP.[9]

2.2. Chambers VAR Model

To match Chambers's study, we estimate a M1-RFX-RFP-FGDP VAR(2) with a time trend for 1976:2-1982:2, where the variables are transformed to log-levels.[10] Following

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[8]We consider responses up to 15 quarters, so the peak response is chosen from this set.

[9]We also re-estimated the models using monthly data with the ratio of prices received by farmers to the all-item CPI-U measuring RFP. Using a 1960:01-1985:12 sample corresponding to the original, RFP responses to an M1 shock (not reported) are very close to those reported by Devadoss and Meyers (a number are significant). When the sample is updated through 1993:12, the responses shrink and none are significant.

[10]Again, we multiply the log-levels by 100. As noted above, Chambers uses nominal farm exports (actually, net exports) and nominal farm income (proprietors). We use real counterparts to stress similarities with the other empirical models (Belongia uses real farm exports and Lapp uses relative real farm GDP). Strictly speaking, Chambers's model could not be re-estimated using monthly data since some of the updated farm proprietors income observations are negative, and no other monthly measure of farm income is available. One would have to add a constant to the farm proprietors income series to eliminate the negative numbers and then treat the series as

Chambers, we test the null hypothesis of zero restrictions on the lagged values of M1 in the farm equations. Our data fail to support Chambers's result with this test: the null cannot be rejected at any usual significance level (a standard likelihood ratio test yields a p-value of 0.31). However, the RFP impulse responses and variance decompositions, given in Figure 3 and Table 4, reveal that monetary shocks have significant effects in this VAR. The initial responses are positive and the first period response is significant.[11] In Table 4, the percentage of RFP variance attributable to M1 shocks at various horizons is even larger than Chambers's.

Updating the sample through 1993:4 once again revises our conclusions.[12] Results are given in Figure 4 and Table 5. No impulse response is significant, and the M1 percentages of RFP variance decompositions generally fall below those reported by Chambers. This fall is noteworthy: whereas M1 shocks account for between approximately 17%-52% of RFP variability using the shorter sample, they account for less than 4% using the updated sample. As in the Devadoss and Meyers model, the finding that M1 is an important determinant of RFP is sample specific.[13]

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an index.

[11]Chambers does not report significance tests of his impulse responses and variance decompositions.

[12]There is no news in the likelihood ratio test, but there is a jump in the p-value (the new p-value is 0.77).

[13]Since we had to make a judgment call as to the best quarterly match to a monthly

Can the overturning of the original results be explained? Belongia (1991, p. 31) observes that in contrast with the early 1980s, "real farm income [and RFP] rose during the late 1980s, a period some analysts would characterize as one of substantial monetary contraction." Furthermore, monetary policy eased during the early 1990s, and RFP dropped. A close inspection of Figure 5, which plots the log-levels of M1 and RFP from 1988:1-1993:4, reveals these co-movements. In this sense, recent history works against the story about monetary policy and agricultural prices that emerged in the early 1980s. Our work with an updated sample confirms the impression left by Figure 5: early evidence that money influences RFP is an artifact of the sample period.[14]

2.3. Belongia VAR Model

The Belongia sample covers 1976:1-1990:4; we extend the sample through 1993:4 to see

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VAR(4), we note that the results of this section are qualitatively unchanged when we estimate a VAR(1) instead of a VAR(2).

[14]In the absence of a salient event, we see no reason to seek a "deeper" explanation (e.g., in terms of a mid-1980s structural change in the relationship between money and RFP).

if updating affects his main conclusions.[15] Belongia estimates a RFP-M1-real exchange rate-industrial production VAR(2). He obtains qualitatively similar results using RFX instead of the real exchange rate. We focus on RFX since that increases comparability with our other models. This emphasis on comparability also led us to replace industrial production with BGDP, which is our choice for a real output measure in our data set. We estimate a VAR(2) in annualized percentage growth rates (the first differences of log-levels multiplied by 400). As in Belongia, the sum of the coefficients on lagged M1 in the RFP equation is not significantly different from zero. Furthermore, the coefficients are not jointly different from zero, so M1 does not Granger-cause RFP.[16]

The RFP impulse responses to an M1 shock (not reported in Belongia) and variance decompositions are given in Figure 6 and Table 6. None of the RFP responses are significant. As in Belongia, M1 shocks account for less than 1% of the forecast-error variance in RFP at various horizons; RFP variability is dominated by RFP's own shocks.

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[15]We do not report the results for the 1976:1-1990:4 sample as they are qualitatively unchanged. This is not surprising, since the sample update adds few observations to this study. Re-estimation over our entire data set also verifies our qualitative conclusions (see note 21 below), as does re-estimation with monthly data.

[16]The F-statistics for the sum of coefficients and Granger-causality tests have p-values of 0.77 and 0.94.

2.4. Belongia Monetary Misperceptions Model

We also re-estimate the Belongia monetary misperceptions model. As noted above, Belongia first estimates an AR(6) M1 growth rate model as represented by (1).

$$(1)\qquad DM1_t = \alpha_c + \Sigma_{i=1}^{6}\alpha_i DM1_{t-i} + DM1R_t$$

Here $DM1_t$ is the growth rate of $M1_t$ and $DM1R_t$, the unanticipated component of M1 growth, is white noise. Following a standard two-step procedure, Belongia uses the OLS residuals from (1) in the RFP growth rate equation. As discussed earlier, the motivation is a standard monetary misperceptions model, which he represents by (2).

$$(2)\qquad DRFP_t = \beta_c + \Sigma_{i=0}^{3}\beta_i DM1R_{t-i} + u_t$$

Here $DRFP_t$ is RFP growth rate at time t and u_t is the associated white noise error. Following Belongia, we estimate (1) and (2) using the two-step procedure.

In Table 7, the Belongia+ column presents our estimation results over the 1976:1-1993:4 sample. For concision, we report only the sensitivity of RFP to monetary shocks. Since the shocks are generated regressors, we report corrected standard errors based on Pagan (1984). Considering the coefficients individually, not one is significant at the 5% level. Furthermore, using the Pagan (1984) correction to the parameter covariance matrix, we can construct an asymptotic Chi-Square(4) test (from the Wald form of the F-test) of the null hypothesis that

$\beta_0=\beta_1=\beta_2=\beta_3=0$; the null hypothesis is not rejected (p-value=0.74).[17]

2.5. Lapp Monetary Misperceptions Model

Here, we estimate a model based on Lapp's (1990) monetary misperceptions models. We simply retain (1), since we take the primary difference between the Belongia and Lapp models to be that Lapp adds lagged RFP and lagged relative farm output as regressors in (2). We compute relative farm output (RFGDP) as the difference between FGDP and BGDP. (Lapp uses the difference between FGDP and GDP.) Following Lapp, we include four lagged values of each variable, so (2) becomes (2").

(2") $$DRFP_t = \beta_c + \Sigma_{i=0}^{3}\beta_i DM1R_{t-i} + \Sigma_{i=1}^{4}\gamma_i DRFP_{t-i} + \Sigma_{i=1}^{4}\delta_i DRFGDP_{t-i} + u_t$$

Here DRFGDP is the growth rate of relative farm GDP. Following Lapp, we again use the two-step procedure to estimate (1) and (2"). The results for 1973:1-1985:4, which corresponds to Lapp's later period, are found in the Lapp-A column of Table 7. Corrected standard errors are

[17]As with Belongia's VAR model, these results are qualitatively unchanged if a sample corresponding to the original (ending in 1990:4) is used. The results are also unchanged if we include anticipated as well as unanticipated money in the regression.

Note that if we were willing to impose normality, we could use FIML estimation. We report the FIML results in the working paper antecedent to the present paper (Isaac and Rapach 1995), and they yield the same conclusions.

reported due to the generated regressors problem. The results are consistent with those of Lapp. None of the coefficients on unexpected money are individually significant, and our asymptotic Chi-Square(4) test again fails to reject the null hypothesis that $\beta_0=\beta_1=\beta_2=\beta_3=0$ (p-value=0.48).

As evinced by the Lapp-B column of Table 7, when the sample is updated to 1993:4, all of the coefficients on expected money shrink in absolute size and remain individually insignificant. Again, the null hypothesis that $\beta_0=\beta_1=\beta_2=\beta_3=0$ is not rejected by our asymptotic Chi-Square(4) test (p-value=0.20).[18]

2.6. Alternative VAR Data Transformations

Finally, since all the VARs considered here use different data transformations, we re-estimate each of the VARs using alternative transformations. Table 8 summarizes our findings on the updated samples.[19]

Devadoss and Meyers use log-levels; hence, we now re-estimate using detrended log-levels and first differences. The results are qualitatively unchanged from Section 2.1. Chambers

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[18]In the Lapp-A and Lapp-B models, including anticipated as well as unanticipated money in the RFP regression leaves the qualitative results unchanged. And again, if we impose normality and proceed with FIML estimation, the results are largely unchanged. There is one exception: FIML estimation on an updated sample (Lapp-B) finds the coefficient on the contemporary monetary shock to be significant at the 5% level. The shocks are still jointly insignificant, however.

[19]The impulse responses and variance decompositions are not reported; they are available upon request from the authors.

employs detrended log-levels, so we re-estimate using log-levels and first differences. With first differences, the results are qualitatively unchanged from Section 2.2. Using log-levels, impulse responses from period six and later are significant and *negative* (one of the percentages of RFP variance due to M1 shocks is insignificant). For the Belongia VAR, we now re-estimate using log-levels and detrended log-levels, since he uses first differences. The pattern is similar to the Chambers case: impulse responses are insignificant for detrended log-levels but significant and negative for log-levels (some of the percentages of RFP variance due to M1 shocks are significant for log-levels).

The significance of money when data are in log-levels and are not detrended is readily explained. M1 trends up and RFP generally trends down over the updated Chambers and Belongia samples. When this trend is not accounted for in the data transformation, a negative relationship is detected. Thus, the results of Sections 2.1-2.3 are robust to alternative data transformations when allowances are made for the apparent trends in M1 and RFP.[20]

3. Conclusion

An empirical controversy has developed around the question of whether money affects the relative prices faced by the agricultural sector. We illustrate this controversy by estimating a set of models based on four prominent studies. We then offer a reconciliation of conflicting empirical results. When our versions of the Devadoss and Meyers (1987) and Chambers (1984)

[20]Over the 1976:1-1993:4 period, the t-statistics for the time-trend coefficients in regressions of the log-levels of M1 and RFP on a constant and a linear time trend are 3.31 and -1.91.

models are estimated using samples ending in the mid-1980s, M1 shocks have significant effects, as reported in the original studies. However, when the samples are extended through 1993:4, these shocks cease to be important. Updating samples does not alter the conclusion that monetary shocks have no significant effects in our versions of the Belongia (1991) and Lapp (1990) models. These results suggest that the controversy over the effects of monetary shocks is an artifact of the sample periods used in existing studies.

Belongia (1991) is the first to eclectically seek a consensus on the effects of monetary shocks on RFP. He proceeds by estimating alternative RFP models using a common sample period and common data transformations. In this setting, Belongia finds monetary shocks are not important for RFP. However, Belongia's paper merely contributes to one side of the controversy and does not investigate the reasons for the divergent results in the literature. Since we wish to shed light on the source of the controversy, our exploration is tied much more closely to existing studies. In contrast with Belongia, we retain the data transformations used in existing studies, and we even maintain the beginning-of-sample date. We then demonstrate that updating samples alone can explain the divergent findings in the literature.[21] While we corroborate Belongia's and Lapp's findings, our results go much further: we resolve the conflict and explain its basis.

To our core exploration, we add a supplementary discussion of the role of the various

[21]We do not report the results in this paper, but when we extend the Chambers, Belongia, and Lapp samples back to the 1960s (the Devadoss and Meyers sample starting point), as well as forward to 1993, it remains true that there are no significant monetary effects in any of these models.

data transformations used in the literature. (In the process, we explore the role of sample-specific trends in the data.) Re-estimating our VARs with updated samples under alternative data transformations, we provide further evidence that monetary shocks are unimportant for RFP.

Since updating the samples proves crucial for resolving the empirical controversy, recent M1-RFP events clearly warrant attention. Belongia observes that the late 1980s witnessed tight money and rising RFP. We add that the early 1990s saw easy money and falling RFP. These recent outcomes contrast with the conventional view that positive monetary shocks boost RFP.

The attention paid to the effect of money on the agricultural sector is a fairly recent phenomenon. Given the size and number of real agricultural shocks, real shocks obviously account for much of RFP volatility. The view that has emerged in the last decade, however, is that monetary shocks have also contributed significantly to the variability in RFP. We believe that the available data indicate otherwise: monetary shocks are not an important determinant of RFP.

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DATA APPENDIX

The data set is constructed from the National Economic, Social, and Environmental (NESE) database. Each of the five time series comprising the data set is described below. Each series, except for real farm exports, covers 1960:1-1993:4. The original time series used to construct the data set are prepared by the Bureau of Economic Analysis. Each original series, except for nominal agricultural exports, is measured in billions of dollars.[22] The date given for each series is May 13, 1994.

M1: This series is item EA BUSTAT S06116. The observations are monthly and seasonally adjusted. The series is made quarterly by averaging over the monthly observations comprising each quarter.

Real Farm Price: Real farm price is measured as the ratio of the implicit farm business GDP price deflator and the implicit GDP price deflator (item EA NIPA 701-008). The implicit farm business GDP price deflator is obtained by dividing farm business GDP (item EA NIPA 107-006) by farm business GDP in constant 1987 dollars (item EA NIPA 108-006) and multiplying this quotient by 100. Each of the original series is quarterly and seasonally adjusted.

Real Farm Exports: Nominal agricultural exports (item EA CYCIND A0M604) are first converted from millions to billions of dollars. Real farm exports are obtained by dividing

[22]The original series, apart from nominal agricultural exports, begin prior to 1960.

nominal agricultural exports by the implicit farm business GDP price deflator. (The implicit farm business GDP price deflator is first divided by 100.) The original nominal agricultural series is monthly and seasonally adjusted, and begins in January 1965. The quarterly series is obtained by summing over the monthly observations comprising each quarter.

Real Farm Business GDP: This is the farm business GDP in constant 1987 dollars series cited above.

Real Business GDP: This series, item EA NIPA 108-002, is measured in constant 1987 dollars, and observations are quarterly and seasonally adjusted.

TABLE 1

SUMMARY OF EXISTING M1-RFP EMPIRICAL MODELS

Study; Data transformation	Sample	Does money matter for RFP?; Important findings
Devadoss and Meyers (1987); Log-levels	1960:01-1985:12	Yes; VAR model: Positive and significant RFP impulse responses to an M1 shock
Chambers (1984); Detrended log-levels	1976:05-1982:05	Yes; VAR model: Coefficients on lagged M1 jointly significant in agricultural aggregate equations and positive RFP impulse responses to an M1 shock
Belongia (1991); First differences, log-levels	1976:1-1990:4	No; VAR model: M1 shocks explain small percentage of RFP variance; Monetary misperceptions model: Coefficients on unexpected M1 shock individually insignificant in RFP equation
Lapp (1990); First differences, log-levels	1973:1-1985:4	No; Monetary misperceptions models: Coefficients on unexpected M1 shock jointly insignificant in RFP equations

TABLE 2

RFP VARIANCE DECOMPOSITIONS AND 95% CONFIDENCE INTERVALS
IN THE DM VAR MODELS, 1960:1-1985:4 SAMPLE:
(A) DM I MODEL; (B) DM II MODEL[a]

A.

Quarters-ahead	M1	RFP
1	3.96 (0,16)	96.04 (84,100)
2	5.96 (0,20)	94.04 (80,100)
4	8.63 (0,29)	91.37 (71,100)
8	21.59 (2,50)	78.41 (50,98)
12	21.57 (2,49)	78.43 (51,98)

B.

Quarters-ahead	M1	RFP
1	0 (0,0)[b]	100 (100,100)[c]
2	0.42 (0,4)	99.58 (96,100)
4	1.38 (0,10)	98.62 (90,100)
8	10.94 (1,30)	89.06 (70,100)
12	10.84 (1,30)	89.16 (70,100)

Notes: [a]The DM I and DM II models correspond to the M1-RFP and RFP-M1 orderings.

[b]The RFP-M1 ordering restricts this value to 0.

[c]The RFP-M1 ordering restricts this value to 100.

TABLE 3

RFP VARIANCE DECOMPOSITIONS AND 95% CONFIDENCE INTERVALS IN THE DM VAR MODELS, 1960:1-1993:4 SAMPLE: (A) DM I MODEL; (B) DM II MODEL[a]

A.

Quarters-ahead	M1	RFP
1	0.90 (0,6)	99.10 (94,100)
2	1.41 (0,9)	98.59 (91,100)
4	0.86 (0,10)	99.14 (90,100)
8	3.13 (0,16)	96.87 (84,100)
12	4.35 (0,19)	95.65 (81,100)

B.

Quarters-ahead	M1	RFP
1	0 (0,0)[b]	100 (100,100)[c]
2	0.11 (0,3)	99.89 (97,100)
4	0.15 (0,5)	99.85 (95,100)
8	1.47 (0,13)	98.54 (87,100)
12	2.32 (0,17)	97.68 (83,100)

Notes: [a]The DM I and DM II models correspond to the M1-RFP and RFP-M1 orderings.

[b]The RFP-M1 ordering restricts this value to 0.

[c]The RFP-M1 ordering restricts this value to 100.

TABLE 4

RFP VARIANCE DECOMPOSITIONS AND 95% CONFIDENCE INTERVALS
IN THE CHAMBERS VAR MODEL, 1976:2-1982:2 SAMPLE

Quarters-ahead	M1	RFX	RFP	FGDP
1	52.25 (10,88)	15.89 (0,40)	31.86 (4,72)	0 (0,0)[a]
2	32.57 (3,69)	32.94 (2,58)	19.14 (2,48)	15.35 (1,38)
4	17.43 (2,57)	40.96 (5,68)	10.21 (2,41)	31.40 (1,50)
8	16.82 (3,55)	40.20 (6,66)	9.78 (2,39)	33.20 (1,51)
12	16.56 (3,55)	39.99 (5,66)	9.61 (2,39)	33.84 (1,51)

Note: [a]The M1-RFX-RFP-FGDP ordering restricts this value to 0.

TABLE 5

RFP VARIANCE DECOMPOSITIONS AND 95% CONFIDENCE INTERVALS
IN THE CHAMBERS VAR MODEL, 1976:2-1993:4 SAMPLE

Quarters-ahead	M1	RFX	RFP	FGDP
1	3.63 (0,20)	12.83 (0,29)	83.55 (62,97)	0 (0,0)[a]
2	1.98 (0,17)	12.53 (0,30)	77.40 (49,89)	8.08 (0,19)
4	1.28 (0,17)	8.50 (2,28)	69.84 (38,86)	20.38 (3,43)
8	2.06 (0,24)	10.21 (1,30)	66.58 (29,77)	21.15 (3,45)
12	3.42 (1,27)	10.72 (2,31)	65.17 (29,78)	20.70 (2,43)

Note: [a]The M1-RFX-RFP-FGDP ordering restricts this value to 0.

TABLE 6

RFP VARIANCE DECOMPOSITIONS AND 95% CONFIDENCE INTERVALS
IN THE BELONGIA VAR MODEL, 1976:1-1993:4 SAMPLE

Quarters-ahead	RFP	M1	RFX	BGDP
1	100 (100,100)[a]	0 (0,0)[b]	0 (0,0)[b]	0 (0,0)[b]
2	98.62 (92,100)	0.09 (0,3)	0.11 (0,3)	1.18 (0,6)
4	99.10 (86,100)	0.06 (0,6)	0.16 (0,5)	0.67 (0,9)
8	99.31 (81,100)	0.18 (0,11)	0.18 (0,6)	0.33 (0,11)
12	99.29 (79,100)	0.31 (0,15)	0.16 (0,7)	0.24 (0,12)

Notes: [a]The RFP-M1-RFX-BGDP ordering restricts this value to 100.

[b]The RFP-M1 ordering restricts this value to 0.

TABLE 7

ESTIMATION RESULTS FOR THE MONETARY MISPERCEPTIONS MODEL:
BELONGIA+, 1976:1-1993:4 SAMPLE; LAPP-A, 1973:1-1985:4
SAMPLE; LAPP-B, 1973:1-1993:4 SAMPLE

Coefficient on	Belongia+ estimates	Lapp-A estimates	Lapp-B estimates
$DM1R_t$	1.18 (1.00)	2.09 (1.64)	1.79 (0.93)
$DM1R_{t-1}$	-0.16 (1.01)	-1.49 (1.68)	-0.74 (0.97)
$DM1R_{t-2}$	-0.64 (1.01)	0.52 (1.77)	-0.38 (0.98)
$DM1R_{t-3}$	-0.44 (1.01)	-1.13 (1.71)	-0.98 (0.94)

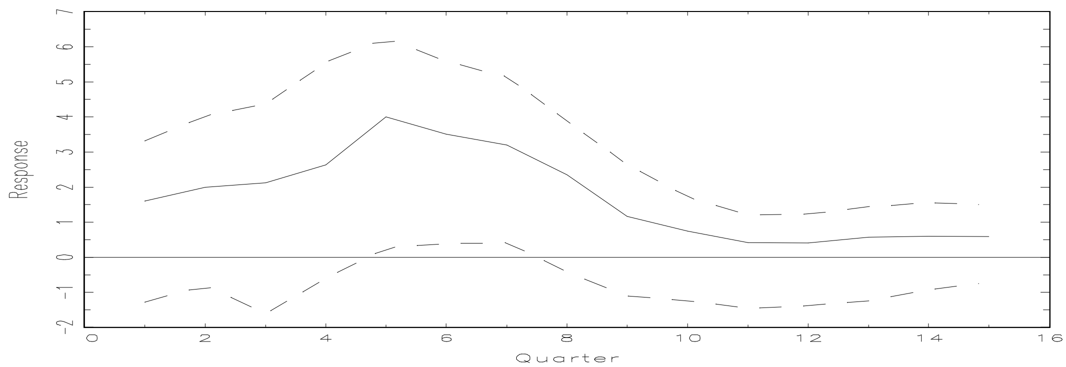
Note: Corrected standard errors given in parentheses.

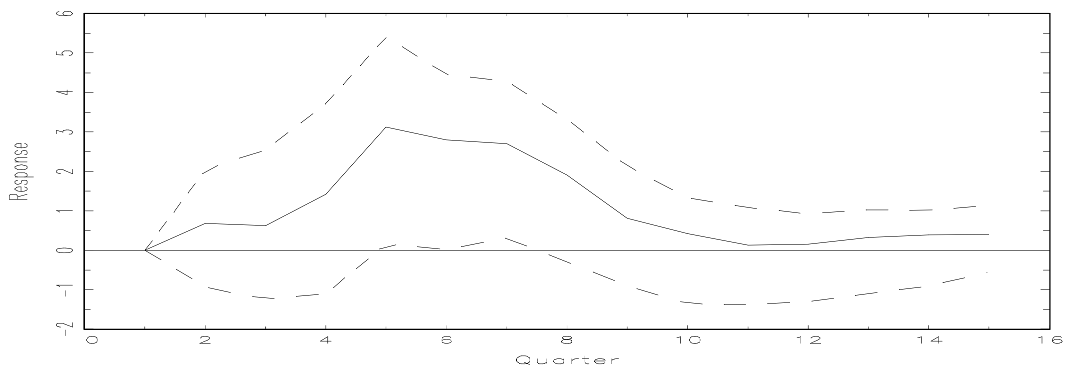
TABLE 8

SUMMARY OF EFFECTS OF M1 SHOCKS ON RFP IN VAR MODELS UNDER ALTERNATIVE DATA TRANSFORMATIONS

Model	Updated sample	Effects of M1 shocks
Alternative data transformation		
Devadoss and Meyers	1960:1-1993:4	
Detrended log-levels		Insignificant RFP impulse responses; insignificant variance decompositions
First differences, log-levels		Insignificant RFP impulse responses; insignificant variance decompositions
Chambers	1976:2-1993:4	
Log-levels		Some significant and negative impulse responses; one significant variance decomposition
First differences, log-levels		Insignificant RFP impulse responses; insignificant variance decompositions
Belongia	1976:1-1993:4	
Log-levels		Some significant and negative impulse responses; some significant variance decompositions
Detrended log-levels		Insignificant RFP impulse responses; insignificant variance decompositions

Note: Impulse responses are RFP responses to an M1 shock and variance decompositions are the percentages of RFP variance accounted for by M1 shocks.



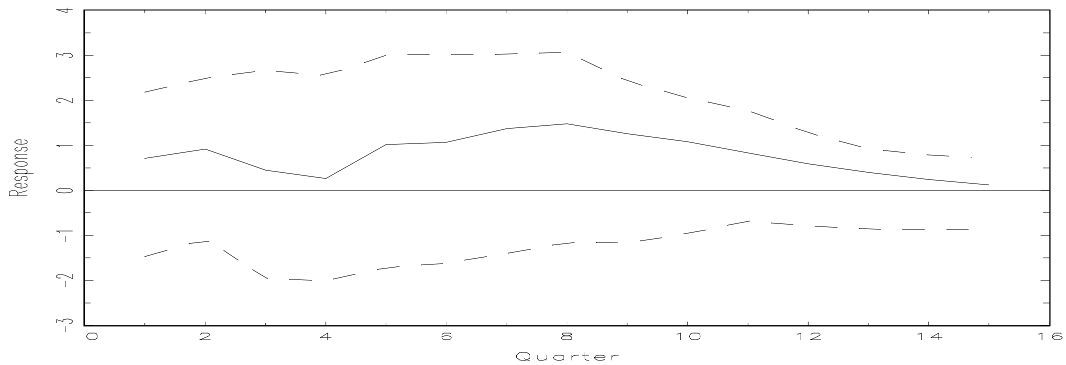


A.

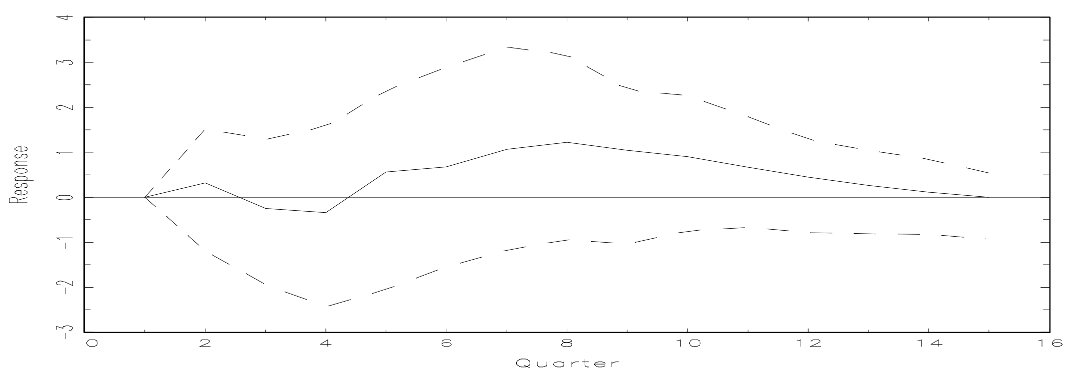
B.

Figure 1. RFP impulse responses to a one-standard-deviation M1 shock in the Devadoss and Meyers VAR models, 1960:1-1985:4 sample: (A) DM I model; (B) DM II model.

Note: The DM I and DM II models correspond to the M1-RFP and RFP-M1 orderings; dashed lines delineate 95% confidence intervals.


Response
Quarter
4
3
2
1
0
-1
-2
-3
0
2
4
6
8
10
12
14
16

A.


Response
Quarter
4
3
2
1
0
-1
-2
-3
0
2
4
6
8
10
12
14
16

B.

Figure 2. RFP impulse responses to a one-standard-deviation M1 shock in the Devadoss and Meyers VAR models, 1960:1-1993:4 sample: (A) DM I model; (B) DM II model.

Note: The DM I and DM II models correspond to the M1-RFP and RFP-M1 orderings; dashed lines delineate 95% confidence intervals.

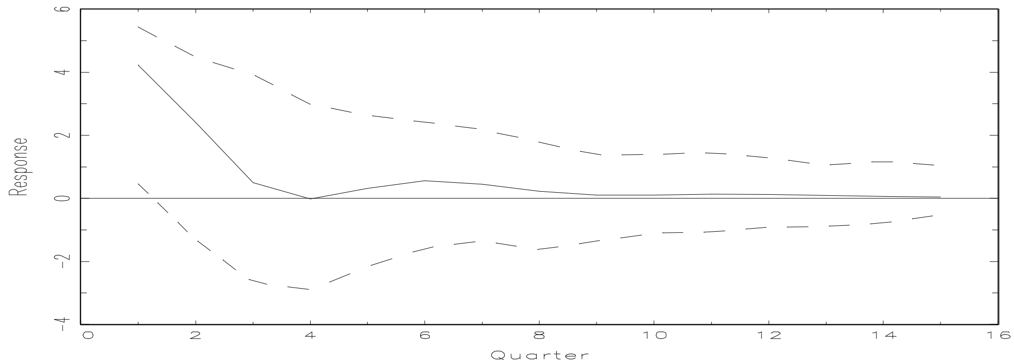


Figure 3. RFP impulse responses to a one-standard-deviation M1 shock: Chambers VAR model, 1976:2-1982:2 sample.

Note: Dashed lines delineate 95% confidence intervals.

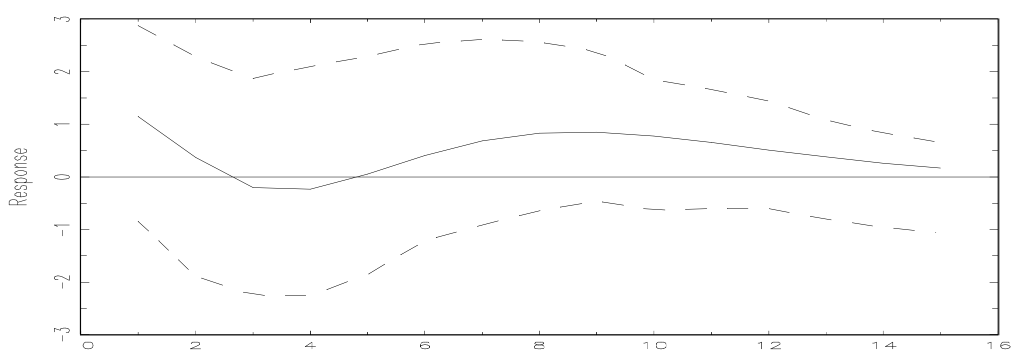
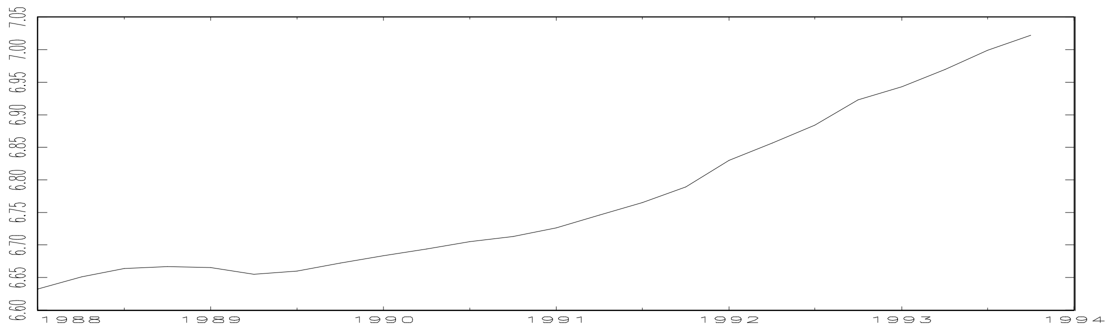
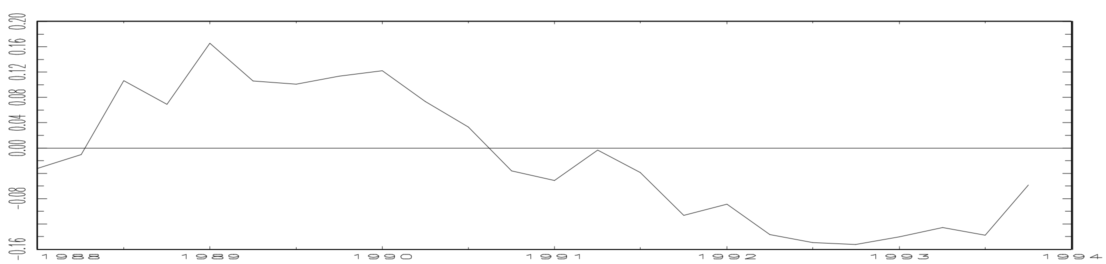


Figure 4. RFP impulse responses to a one-standard-deviation M1 shock: Chambers VAR model, 1976:2-1993:4 sample.

Note: Dashed lines delineate the 95% confidence intervals.



A.



B.

Figure 5. Time series (log-levels), 1988:1-1993:4: A. M1; B. RFP

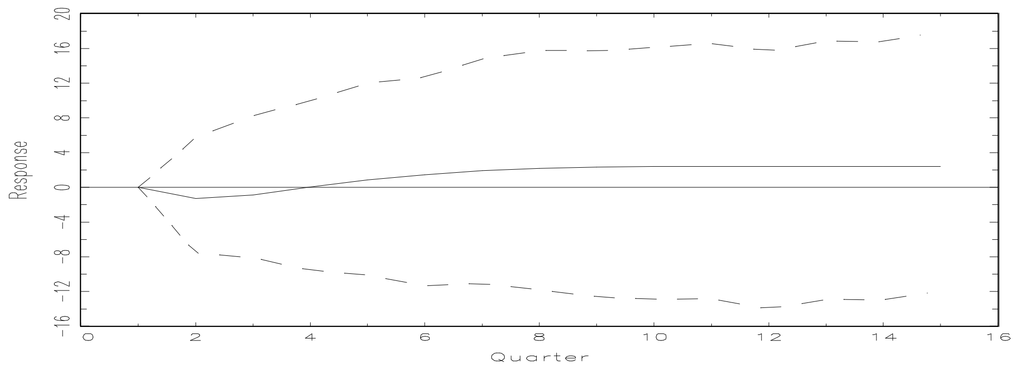


Figure 6. RFP impulse responses to a one-standard-deviation M1 shock: Belongia VAR model, 1976:1-1993:4 sample.

Note: Dashed lines delineate 95% confidence intervals.