The Dynamic Responses of Crop and Livestock Prices to Money-Supply Shocks: A Bayesian Analysis Using Long-Run Identifying Restrictions

Jeffrey H. Dorfman and William D. Lastrapes

The impact of monetary policy on agriculture has been much debated. This study examines the dynamic responses of U.S. agricultural prices to money-supply shocks using three innovations. First, the variables' responses are identified by long-run money neutrality restrictions instead of the more common contemporaneous ordering. Second, a Bayesian approach to model uncertainty is used to add robustness to the estimation process. Third, agricultural prices are disaggregated into crop and livestock components. The empirical results find that both agricultural sectors benefit in the short run from positive money-supply shocks with agricultural prices increasing relative to the general price level.

Keywords. crop prices, livestock prices, monetary policy, money neutrality.

As U.S. agriculture has become more integrated into the rest of the economy and exports play an enhanced role in the demand for U.S. agricultural products, the impact of monetary policy on the farm sector has been pushed to the forefront. In particular, researchers have examined whether the responses of agricultural prices to money-supply shocks differ from those of prices in the rest of the economy. Economic theory provides little guidance; different production processes, market structure, inventory policy, and reliance on world markets are just some of the factors that can lead to either positive or negative, rapid or persistent effects of money on real agricultural prices. Empirically, Tweeten has found that expansionary monetary shocks hurt the agricultural sector by causing a shrinkage in agricultural prices relative to other prices, resulting in the so-called cost-price squeeze. However, Chambers, Chambers and Just, and Orden find that agriculture benefits from expansionary monetary shocks and is harmed by contractionary money policies. Rausser et al. build a highly complex and disaggregated structural simulation model of the U.S. economy which focuses on the agricultural sector. Their simulations show that feed grains and livestock both benefit from easy-money policies, with the livestock sector gaining in particular.

The goal of this paper is to reinvestigate the issue of how agricultural prices respond to monetary policy relative to the general price level, while improving on earlier work by adding depth and robustness. These improvements can be grouped into three main innovations. First, the variables' responses to shocks are identified with the aid of theoretically based, long-run economic restrictions as first presented by Blanchard and Quah. The particular restrictions employed here are those of long-run money neutrality. Second, due to recent criticism that such methods are highly sensitive to model specification (Faust and Leeper), Bayesian methods are used to add robustness to the estimated responses by treating the model specification as uncertain and deriving results based on a broad range of potentially valid specifications. Third, agricultural prices are

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The authors are associate professors in the Departments of Agricultural and Applied Economics and Economics, respectively, at the University of Georgia

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disaggregated into crop and livestock price series to examine the responses of these two subsectors, and to look for possible differences, even within the agricultural sector.

Statistical Model of Prices and Money

To estimate the dynamic responses of farm prices, we embed these prices in a standard macroeconomic model. We assume that the economy consists of a bond market; a money market; markets for crops, livestock, and energy; and markets for domestic and foreign aggregate output. We use this framework to model the dynamic interactions among the equilibrium values of nominal money, real money, the nominal interest rate, the real exchange rate, domestic aggregate output, and the real prices of the three disaggregated sectors, where real prices are nominal prices deflated by the price of domestic aggregate output. The behavioral equations describing general equilibrium constitute the structure of the model.

Let $\mathbf{y}_t$ denote a vector containing the $n = 8$ endogenous random variables listed above. We assume the structure is consistent with the class of dynamic, linear, stochastic models, which can be represented as

$$\text{(1a)} \quad \Delta\mathbf{y}_t = (\mathbf{D}_0 + \mathbf{D}_1 L + \mathbf{D}_2 L^2 + \mathbf{D}_3 L^3 + \ldots)u_t = \mathbf{D}(L)\mathbf{u}_t$$

$$\text{(1b)} \quad \mathrm{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{I}$$

where L is the backshift operator, $\Delta = (\mathbf{I} - L)$, the $\mathbf{D}_s$ ($s = 1, 2, \ldots, \infty$) are (8×8) matrices of finite coefficients that satisfy $\lim_{\sigma\to\infty} \mathbf{D}_s = 0$, and $\mathbf{u}_t$ is a conformable vector of white noise errors.[1] Each of the u_{jt} is to be interpreted as an exogenous structural shock to the jth equation in the model. For example, if $j = 8$ represents the nominal money-supply equation, then u_{8t} is a random variable depicting the innovation to the money-supply process as determined by the economic behavior of the Federal Reserve and the financial sector. The structural coefficient matrices measure the dynamic equilibrium responses of the endogenous variables to the structural shocks. Our aim is to estimate dynamic responses to money-supply shocks, i.e., the eighth column of $\mathbf{D}_s$, for all s.

[1] The form of the structural covariance matrix is a normalization that does not affect the generality of the model

Identification

As it stands, equation (1) is consistent with any linear theoretical model and contains little empirical content. Without further theoretical restrictions, the data record does not uniquely identify $\mathbf{D}(L)$. The sample second moments of the joint probability distribution generating the data are fully summarized by the following moving average representation:

$$\text{(2a)} \quad \Delta\mathbf{y}_t = (\mathbf{I} + \mathbf{C}_1 L + \mathbf{C}_2 L^2 + \ldots)\mathbf{v}_t = \mathbf{C}(L)\mathbf{v}_t$$

$$\text{(2b)} \quad \mathrm{E}(\mathbf{v}_t\mathbf{v}_t') = \mathbf{\Sigma}.$$

If the data-generating process for $\Delta\mathbf{y}_t$ is covariance stationary, $\lim_{s\to\infty} \mathbf{C}_s = 0$. Furthermore, if $\mathbf{C}(L)$ is invertible, the coefficients in $\mathbf{C}(L)$ and $\mathbf{\Sigma}$ are directly obtainable from the vector autoregressive (VAR) representation of $\Delta\mathbf{y}_t$:

$$\text{(3)} \quad \mathbf{A}(L)\Delta\mathbf{y}_t = \mathbf{C}(L)^{-1}\Delta\mathbf{y}_t = \mathbf{v}_t$$

where $\mathbf{A}(L) = \mathbf{I} + \mathbf{A}_1 L + \mathbf{A}_2 L^2 + \ldots + \mathbf{A}_p L^p$. The lag parameter p, in principle, may approach infinity, but in practice it is truncated to some finite value.

We examine the presence of unit root nonstationarity and noninvertibility of the equation (2) due to cointegration and find that a first difference specification without cointegration is consistent with the data set used in the application below.[2] Therefore, we estimate the VAR model in equation (3) as a step toward recovering an estimate of the data-generating process described by equation (2). Previous studies of the dynamics of farm prices that rely on VAR models are Bessler; Chambers; Choe and Koo; Devadoss and Meyers; and Orden and Fackler.

To see the identification problem, note that equations (1) and (2) imply

$$\text{(4a)} \quad \mathbf{v}_t = \mathbf{D}_0\mathbf{u}_t$$

$$\text{(4b)} \quad \mathbf{\Sigma} = \mathbf{D}_0\mathbf{D}_0'$$

and

[2] Bayesian and sampling theoretic unit root tests on the set of data showed that all the series can be reasonably characterized as being integrated of order one. The results of Bayesian and sampling theoretic cointegration tests support invertibility. Johansen's cointegration test could not reject the null of no cointegration at reasonable significance levels, while Bayesian cointegration tests either favored the hypothesis of no cointegration, or had posterior support that was almost equally divided between cointegration and its absence.

(4c) $\mathbf{D}(L) = \mathbf{C}(L)\mathbf{D}_0$.

The $n(n + 1)/2$ free elements in $\mathbf{\Sigma}$ are not sufficient to identify the n^2 unknown coefficients in $\mathbf{D}_0$, and, hence, the coefficients in $\mathbf{D}(L)$.

We impose a minimal set of economic restrictions on the structure to identify the desired dynamic multipliers. In particular, we assume that the levels of all real variables in the model are ultimately unaffected by a sudden, permanent change in the supply of nominal money. That is, once-and-for-all shocks to the level of the nominal money supply are neutral in the long run.

In the context of the above model these restrictions can be formalized as

$$(5) \qquad \lim_{s\to\infty} \frac{\partial y_{it}}{\partial u_{8,t-s}} = 0, \quad i = 1, 2, 3, 4, 5, 6, 7.$$

The nature of equation (1) is consistent with the empirical example below in which nominal money is the eighth, and last, series in a system where all other variables are in real terms.[3] From equation (1), the set of infinite horizon dynamic multipliers is

$$(6) \qquad \lim_{s\to\infty} \frac{\partial y_t}{\partial u_{t-s}} = D_0 + D_1 + D_2 + \ldots = D(1).$$

Thus, long-run monetary neutrality implies that the first seven elements in the eighth column of $\mathbf{D}(1)$ are zero.

These restrictions are not sufficient to fully identify the structural model, but they are sufficient to isolate the responses of the endogenous variables to money-supply shocks. From equation (4), $\mathbf{D}_0 = \mathbf{C}(1)^{-1}\mathbf{D}(1)$. Substituting this expression into the mapping in equation (4) yields the final column of the dynamic response coefficients, the responses to money-supply shocks, which are of interest here:

$$(7) \qquad \mathbf{D}_s\mathbf{e} = \mathbf{C}_s\mathbf{C}(1)^{-1}\mathbf{D}(1)\mathbf{e}$$

where $\mathbf{e}$ is an (8×1) vector containing all zeroes except for a one as the eighth element. The long-run neutrality restrictions in equations (5) and (6) imply that $\mathbf{D}(1)\mathbf{e} = [0\ 0\ 0\ 0\ 0\ 0\ 0\ \delta]'$, where δ is a scale factor that defines the magnitude of the nominal shock. Thus, given the estimated (inverted) VAR coefficients the dynamic multipliers $\partial y_{it}/\partial u_{8t}$ are identified up to a scale transformation.

Such long-run neutrality-identifying restrictions were pioneered by Blanchard and Quah, King et al., and Shapiro and Watson.[4] Long-run neutrality is compatible with a wider class of theoretical models than exclusionary restrictions on contemporaneous interactions previously used to identify farm price dynamics. For example, early studies imposed a recursive structure on $\mathbf{D}_0$ to just identify $\mathbf{D}(L)$. Although this approach is convenient, the dynamics from such an identification scheme in our framework are inconsistent with any plausible model of the macroeconomy. A more general approach than this is taken by Orden and Fackler, who, following Bernanke and Sims, use standard macroeconomic theory to exclude certain elements of $\mathbf{D}_0$ (or more precisely, its inverse). But these restrictions may potentially cause severe restrictions on short-run channels of interaction, which is the primary issue of interest here.

Faust and Leeper criticize the use of infinite-horizon restrictions on the grounds that finite samples contain no information about the long run. This implies that long-run restrictions can be consistent with any set of short-run dynamic multipliers without affecting the fit of the statistical model. We deal with this criticism by incorporating into our Bayesian analysis the possibility that a steady state, or long run, can be approximately attained in a finite period of time. In particular, we impose money neutrality on the multiplier $\partial y_t/\partial u_{t-k}$ for large, but finite, k. To account for the uncertainty regarding the timing of the long run, various values of k (including infinity) are given prior weight in the derivation of the posterior densities for the dynamic multipliers. In effect, we use the suggestion of Faust and Leeper to restrict finite-horizon dynamics to improve the robustness of the identification procedure, while approximately maintaining the use of infinite-horizon monetary neutrality. This strategy is appropriate as long as the responses beyond horizon k do not actually deviate significantly from the assumed steady-state values.

Under the imposition of long-run monetary neutrality, agriculture can neither benefit nor suffer from the effects of monetary policy in

[3] In the long run, given permanent changes in the level (not growth rate) of nominal money, the nominal interest rate behaves identically to the real interest rate.

[4] The general Blanchard and Quah approach entails imposing a lower triangular structure on $\mathbf{D}(1)$, which just identifies the $\mathbf{D}(L)$ but requires additional theoretical restrictions.

the long run, since farm prices are constrained not to be influenced by money-supply shocks for an infinite horizon. However, in the short run, farm prices can respond to monetary policy at a different rate than the price index. This allows for a monetary expansion to yield a short-term cost/price expansion which benefits the agricultural sector, or a cost/price squeeze which harms agriculture.[5]

A Bayesian Approach to Add Robustness

The above discussion has proceeded on the assumption that the VAR representation of the system in equation (3) is fixed and known. Indeed, conventional VAR studies condition inference on a particular model specification (such as the choice of lag length p), and, at best, informally examine robustness to alternative specifications. In this paper, Bayesian methods are used to formalize the treatment of specification uncertainty and to remove the conditioning on a single model formulation, as well as to examine the sensitivity to alternate assumptions about the timing of the long-run identifying restrictions.

A Bayesian approach allows prior support for a variety of model specifications and for the subsequent integration across model uncertainty to derive the marginal posterior distribution of the impulse responses. When posterior means are computed, the Bayesian methodology provides a weighted average impulse-response function using the individual impulse-response functions from all the models with prior support and weights which are optimal combinations of prior beliefs and support from the data for that model specification. This integration across model specifications can be with respect to lag length, the presence of trends or seasonality, the set of variables to be included, or any other facet of model specification.[6] For example, Poirier examines the effect of nominal money shocks on real output in a Bayesian framework which incorporates 147 possible model specifications, each representing different combinations of economic restrictions or hypotheses previously discussed in the literature. The benefit from recognizing model uncertainty within the Bayesian framework is that the resulting posterior estimates of the impulse responses gain robustness in the face of an unknown model specification. To increase robustness further, the results presented below will focus on the posterior medians of statistics of interest.

Denote the set of models with nonzero prior support by $M = \{m_j, j = 1, \ldots, J\}$. Represent the prior support for each of these models by ω_j, and the likelihood function value of the data set for each model when estimated conditional on that specification by $\mathcal{L}_j$.[7] The ω_j embody the researcher's relative belief in each model as a satisfactory approximation to the true data-generating process before investigating the data's characteristics and must sum to one across all models in the set M. The likelihood function values $\mathcal{L}_j$ measure each model's ability to approximate the particular data being employed. The posterior probability of each of the J models is derived by application of Bayes Theorem:

$$(8)\qquad \Omega_j = (\omega_j \mathcal{L}_j) \Big/ \left(\sum_{i=1}^{J} \omega_i \mathcal{L}_i \right), \quad j = 1, 2, \ldots, J.$$

These posterior probabilities represent the *ex post* relative support of each model in the set M as a data-generating approximation by combining the prior support with the information contained in the data (summarized by the likelihood function). For example, the posterior mean dynamic responses to money-supply shocks are

$$(9)\qquad De = \sum_{j=1}^{J} \Omega_j C_{sj} \left(\sum_{i=0}^{k_j} C_{ij} \right)^{-1} \left(\sum_{i=0}^{k_j} D_{ij} \right) e, \qquad s = 1, 2, \ldots, \infty.$$

where the j subscript denotes a parameter from the jth model with prior support and k_j is the

[5] In a study which actually imposed long-run money neutrality through an error-correction model for New Zealand, Robertson and Orden found that the farm sector captured short-run benefits from monetary expansions.

[6] While changes in the set of exogenous variables in a regression model are straightforward, changes in the set of endogenous variables raises a complication in the application of Bayes Theorem because the scale of the likelihood function is affected. When uncertainty exists with respect to the endogenous variables belonging in a model, caution must be used (and corrective action taken) to ensure that such scale effects are not allowed to make the posterior results arbitrary.

[7] Implicit here is that while informative prior information is possessed by the researcher with respect to more or less likely model specifications, no informative prior information is possessed with respect to the VAR model coefficients. If the standard diffuse prior on the VAR coefficient matrices A_i and an inverted Wishart prior on the covariance matrix of the v_t are assumed, then the maximum likelihood estimates (which are also OLS for this model) are equal to the Bayesian posterior mean, making them optimal Bayesian point estimates in a quadratic-loss sense. Note that this approach differs from Litterman's Bayesian VAR method.

horizon at which neutrality is imposed for model j. Such posterior means are weighted averages of individual impulse-response point estimates from each model with the posterior probabilities of each model serving as the weights. Thus, $\{\bar{\mathbf{D}}_s, s = 1, 2, \ldots\}$ is not the posterior mean of the entire distribution but a posterior mean with respect to the set of point estimates from the J models considered.

Further robustness can be added to protect against outliers through the use of posterior medians as the summary measure. To compute the posterior median of a particular scalar estimator, first order all the individual point estimates from the J models from smallest to largest. Then, using the posterior probabilities associated with the models corresponding to these individual estimators, sum the probabilities as you move from smallest to largest. The individual estimator which is closest to causing this sum to equal 0.50 is the posterior median. The individual models' impulse responses and their associated posterior probabilities can also be used to derive an interquartile range of the point estimates, highest posterior support regions for the impulses, or any other summary measure of interest. For example, to get the lower quartile boundary, perform a procedure identical to that used to calculate the posterior median except stop when the cumulative probability reaches 0.25 instead of 0.50.

The use of summary measures taken with respect to the J individual point estimates (which are all optimal Bayesian estimators conditional on that model specification and squared error loss) has two advantages over the computation of summary measures with respect to the full posterior distribution, which would account for the entire distribution of the estimators for each possible model. The first advantage is that it focuses on the estimation uncertainty related to model specification which is of particular interest here. The second advantage is that it avoids the need for a numerical approximation; the use of the full posterior distribution would require Monte Carlo integration to compute posterior measures. Such numerical integration would be extremely computer-intensive if the number of models considered, J, is large (as in the application below).

Data

The data used in this study are a set of monthly observations from 1959(02) to 1993(11), for a total sample of 418. The interest rate used is the three-month Treasury bill rate. Output is measured by the total index of industrial production. Real livestock and crop price series are prices received by farmers, total livestock and products, and total crops, respectively, both deflated by the CPI for urban consumers. The real energy price index is the producer price index for fuel-related products and power, deflated by the same CPI. The real exchange rate (the reciprocal of the real exchange value of the dollar) is the $/SDR rate times an index of world prices, deflated by the CPI. The money supply is measured by M1. The real money measure is the money supply deflated by the same CPI. Data are collected from the Survey of Current Business, St. Louis Federal Reserves Economic Data Bulletin Board, and the IMF International Financial Statistics. The eight-series model employed here is very large by comparison to most applications in the VAR literature. Including so many series helps to avoid the dangers of aggregating too many shocks into a few "composite" shocks (Faust and Leeper), ensuring that the money-supply shock is precisely identified.

This study is the first to examine general agricultural price responses to monetary policy by utilizing two sector-specific agricultural price series in a time-series framework. While still measuring agricultural price response relative to the price level of the general economy (because both are deflated by the CPI), using disaggregated price series for crops and livestock allows investigation of differences in the two agricultural sectors' responses, as well as the dynamics between the two sectors. Chambers and Just examined the impacts of monetary policies on agriculture using a structural model which concentrated on three agricultural markets: corn, soybeans, and wheat. Thus, while they had a more disaggregated model than is estimated here, the rest of the agricultural sector was not modeled in depth. Since crops are an important input for the livestock sector, such intra-agriculture relationships may well be important in revealing the underlying dynamics of agriculture's response to monetary shocks. Rausser et al. had both disaggregated crop prices and disaggregated livestock prices in a structural simulation model which they used to investigate the impact on U.S. agriculture of various macroeconomic policies. They had more in-depth detail than is provided here, at the cost of having to specify precise functional forms for many price and quantity linkages of goods and financial markets.

Estimation and Results

For estimation with the data set described above, the statistical model is augmented by a vector of constants and eleven monthly dummy variables to allow for seasonality. By varying three features of the model in all possible combinations, we construct a set of 130 models with positive prior support.

First, the model is estimated with two possible formulations for structural shifts. One formulation is a structural shift in 1973(01) (to represent the change to floating exchange rates), modeled as a dummy variable equal to one for all periods after 1973(01), and zero before. This dummy allows for shifts in unconditional means due to the change in international monetary arrangements. The alternative formulation is a series of dummy variables to represent exogenous shocks to energy prices. These five dummy variables are set equal to one in 1973(8), 1973(12)-1974(2), 1986(2)–1986(7), 1990(8)–1990(10), and 1990(11)–1991(3), respectively, and zero otherwise. These dummies allow energy-prices shocks to cause exogenous changes in drift that cannot be captured by zero-mean stationary shocks such as the u_t.

The second dimension of model specification uncertainty deals with the Faust and Leeper critique and is taken to be the horizon at which long-run restrictions take hold. Horizons of 100, 200, 300, and 400 months and the infinite horizon are considered. By including five possible horizons for long-run money neutrality identification restrictions, the sensitivity of the results with respect to imposing an infinite horizon restriction on a finite length data set can be evaluated. Traditionally studies that have used the money neutrality restrictions have only imposed them at the infinite horizon. Four of the five horizons used here are not only finite, but also bounded by the sample size so that the data contains information about responses at such horizons. In employing finite horizons for the restrictions it is important to empirically verify that the impulse responses do not veer away from neutrality after the restriction point (thereby invalidating the concept of long-run neutrality). In the discussion of the results below, the responses are checked to ensure that neutrality is satisfied within reasonable approximations for horizons past when the restriction is imposed.

The third dimension of model uncertainty is the lag length in the VAR model; the maximum lag included in the VAR model, p, is varied from 6 to 18. This reduces the period for estimation to 1960(08)–1993(11), with the earlier observations used in the creation of lagged terms. Forming all possible combinations of these three model uncertainty specifications yields 130 models.

The prior distribution for these 130 models is constructed as the product of independent priors on the three separate dimensions of model uncertainty. The prior on the structural break specification is 0.30 on the single 1973 break and 0.70 on the multiple oil shock breaks. The prior on the length of time to reach the long run is 0.20 on each of the five horizons. The prior on the lag parameter is a simple triangular distribution centered on $p = 12$, rising from 6 until it peaks at 12, then declining in a reverse pattern for lag lengths 13 through 18. The full distribution of prior support is shown in table 1.[8]

In the first step to estimation, the 130 models with prior support are estimated. Next, for each model specification, we derive the Bayesian maximum *a posteriori* impulse-response functions for the eight series with respect to a nominal money-supply shock and the posterior probabilities for that model. The posterior probabilities for each model are shown in table 1. Finally, the posterior probabilities for the models and impulse responses are used to calculate the mean, median, and interquartile range of the posterior distribution of impulse-response function, thereby integrating out model specification uncertainty.

The scale of the responses was chosen by setting $\delta = 1$, making the long-run response of nominal money to the initial money-supply shock equal to unity. Thus, the eight impulse-response functions for the variables in logs (everything except the interest rate) are a type of elasticity function, representing period s elasticity with respect to the final long-run change in nominal money.

Empirical Results

The posterior probabilities of the models reported in table 1 show little change from the prior probabilities placed on the individual models. There is some shifting of support to-

[8] Note that the imposition of the "long-run" restrictions does not overidentify the model, thus, the likelihood function is unaffected as the horizon varies. This results in the marginal posterior distribution of the horizon length being identical to the marginal prior distribution of this parameter.

Table 1. Prior and Posterior Probabilities of the Models

	Priors		
Lag	D1	D2	Marginals
6	0.008	0.00343	0.0571
7	0.009	0.00386	0.0643
8	0.010	0.00428	0.0714
9	0.011	0.00472	0.0786
10	0.012	0.00514	0.0857
11	0.013	0.00557	0.0929
12	0.014	0.00600	0.1000
13	0.013	0.00557	0.0929
14	0.012	0.00514	0.0857
15	0.011	0.00472	0.0786
16	0.010	0.00428	0.0714
17	0.009	0.00386	0.0643
18	0.008	0.00343	0.0571
Marginal	0.140	0.060	1.0000
	Posteriors		
Lag	D1	D2	Marginals
6	0.00564	0.00209	0.03865
7	0.00672	0.00249	0.04605
8	0.00801	0.00296	0.05485
9	0.00922	0.00341	0.06315
10	0.01051	0.00390	0.07205
11	0.01203	0.00447	0.08250
12	0.01432	0.00532	0.09820
13	0.01436	0.00530	0.09830
14	0.01414	0.00517	0.09655
15	0.01370	0.00501	0.09355
16	0.01313	0.00479	0.08960
17	0.01255	0.00456	0.08555
18	0.01189	0.00431	0.08100
Marginal	0.14622	0.05378	1.00000

Notes D1 is the model with multiple oil-price shock dummies, D2 is the model with a single dummy for a structural break in 1973 The horizon length for the restrictions does not affect the likelihood, and with equal priors this causes the prior and posterior probabilities to be equal for all horizons The probabilities shown are for a representative horizon (i e , they sum to 0 2)

ward models with a larger number of lags and a very small shift toward the specification with a set of dummy variables for each oil-price shock.

The discussion of the results will concentrate on the posterior medians of the distribution of impulse responses with respect to a shock in the nominal money supply. Figure 1 plots the median response functions of the six macroeconomic series, while figures 2 and 3 plot the median response functions of livestock and crop prices, respectively, along with the upper and lower quartiles of the posterior densities for these two series.[9] All the response functions are normalized so that the long-run response of nominal money equals one.

The results for the nonagricultural series generally conform with a priori expectations and standard dynamic macroeconomic theory (compare Lastrapes and Selgin), lending validity to the identification scheme employed and suggesting reliability in the results for the two agricultural price series. Given a positive money-supply shock that causes a gradual but permanent 1% increase in nominal money stock, the interest rate falls steeply for two months (the liquidity effect), then rises over the next nine months to approach the zero long-run response forced by monetary neutrality. The initial rate decline is estimated to be about 45 basis points, for a 1% permanent change in money. Output rises fairly monotonically for fifteen months following the initial shock and then begins a gentle descent back to its original value. The peak elasticity is approximately 0.78, meaning that a money-supply shock which results in a long-run 1% increase in the money stock increases real output by 0.78% at a nine-month horizon. Real energy prices respond positively to the money-supply shock, reaching a peak impact of 0.43 at the five-month horizon. Real money responds by a very steep increase until month seven, and then begins a fairly monotonic, slow asymptote toward its long-run zero response. Finally, the real exchange value of the dollar depreciates in the short run by about 0.30% as the interest rate falls.

The results for real and nominal money allow deductions about the behavior of the price index. Because the response of real money lies everywhere below the response for nominal money, the CPI rises, albeit gradually, in response to a money-supply increase. Thus, our results do not suffer from the "price puzzle" of earlier studies (e.g., Eichenbaum) where the price level responds negatively to money-supply shocks. The nominal and real money-supply responses are quite similar for the first eight

[9] A reviewer correctly warned about possible misrepresentation of summary measures based on the distribution of point estimates from the 130 models if the posterior distributions of response functions conditional on individual models had very large variances Using standard Monte Carlo integration techniques, checks on the coefficients of variation (mean divided by standard deviation) for the response functions of individual models showed this fear to be unfounded in this application While some coefficients of variation were small (with a minimum of about 0 2) the average values were in the range of 1 5 to 2 0 for most horizons and most model specifications

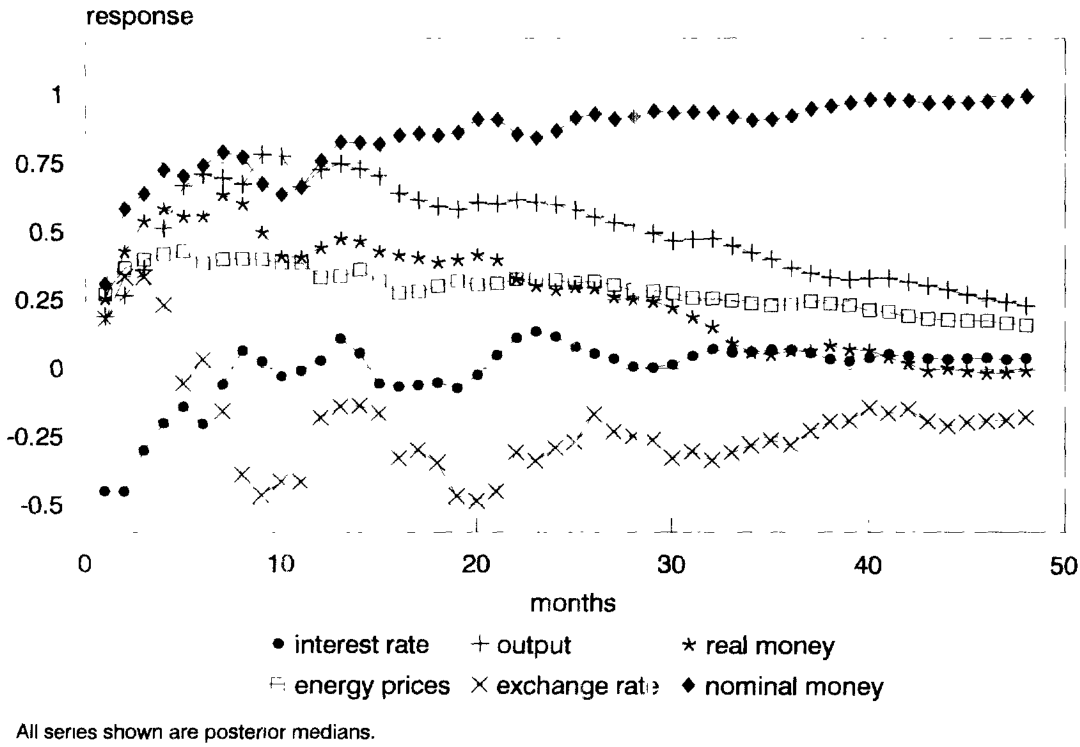

Figure 1. Responses of macro series

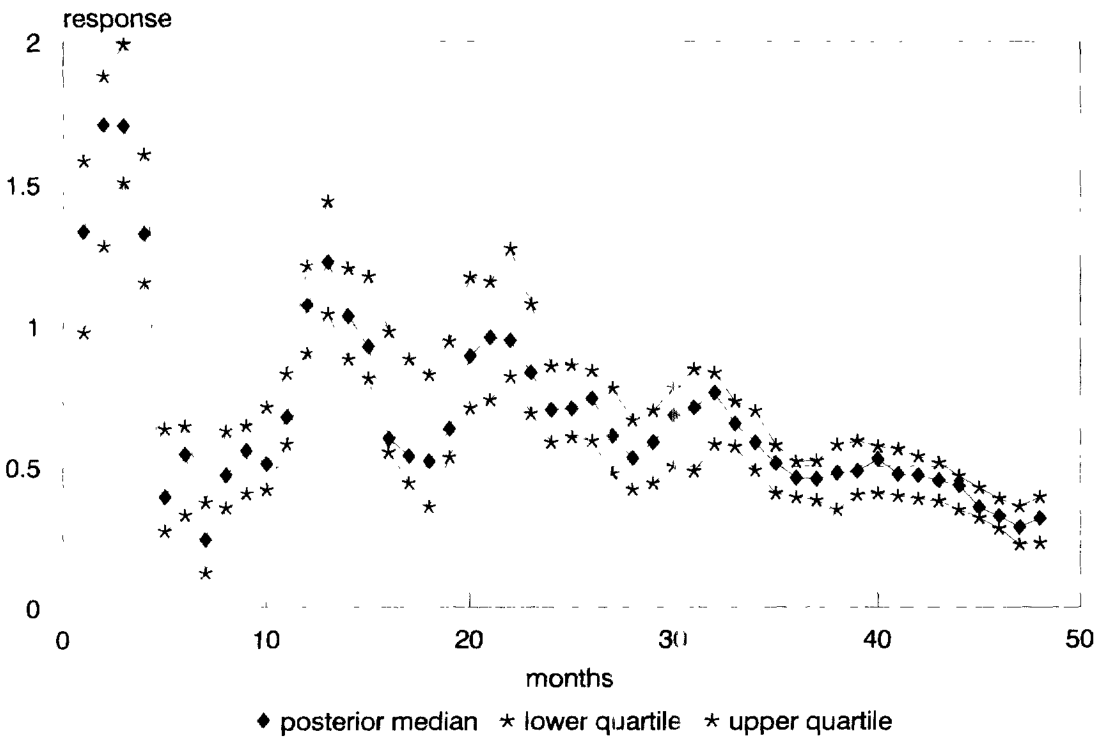

Figure 2. Responses of livestock prices

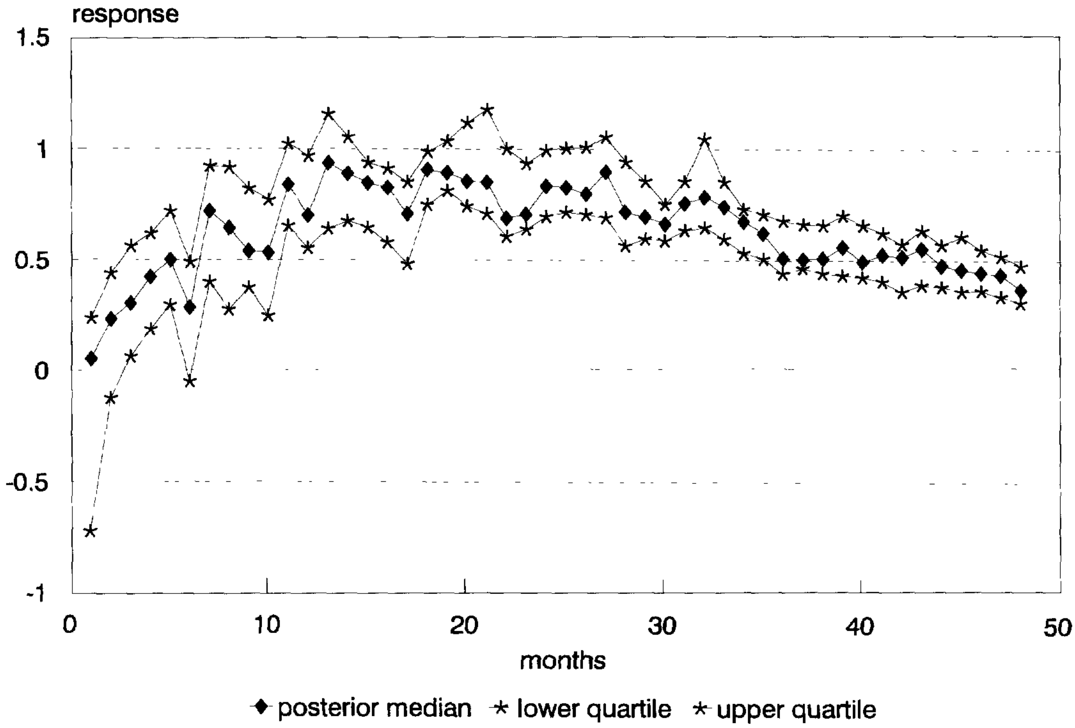

Figure 3. Responses of crop prices

months, implying a very slow response by the general price level. The price level then rises fairly monotonically and by forty-two months after the initial shock has risen by its full long-run proportional response.

The estimated response functions for the two agricultural price series are the main focus of this research, and their behavior matches the results found in several earlier studies using a single aggregated agricultural price. The real livestock price has a highly cyclical short-run response with very high peaks at three and thirteen months and smaller peaks at six- and twenty-one-month horizons. The real livestock price series is quite variable for the first three years before settling down to an asymptotic decline toward the zero long-run response. The real livestock price has a peak posterior median response of approximately 1.70. The real crop price displays a much smaller amount of variability around a fairly smooth, hump-shaped response function. The real crop price rises steadily to a peak of 0.936 in month thirteen and stays stable in a range of around 0.7 to 0.9 from month eleven until month thirty-three. Due to the faster and larger early response, it might appear the livestock sector gains more than crops; however, the real crop price falls back to its original value much more slowly, which allows the crop sector to capture significant benefits over a longer horizon. In fact, while the real livestock price has dropped to approximately the same range as the energy and output series by the forty-eight-month horizon (0.25), the real crop price still has a positive response in the range of 0.40 at the forty-eight-month horizon.

The real crop and livestock price responses suggest short- and medium-run benefits to both sectors of agriculture from expansive monetary policy; this result matches those of Chambers; Devadoss and Meyers; Orden and Fackler; and Rausser et al. The cyclic behavior exhibited early in the agricultural price response functions, particularly the real livestock price, can be explained by the pattern of responses in the other agricultural sector, as crops are an important input for livestock production. With low initial crop prices, it becomes profitable to feed some animals longer, reducing marketed livestock supplies and reenforcing the price increase in the livestock sector. As the crop price response becomes positive, real livestock prices plunge as the recently increased inventories are eliminated, and then rise again as the rate of increase in crop prices slows down. The two sectors reach a type of temporary equilibrium by about month twenty-four, with only very small cycles after that as the effects of the nominal money shock dissipate.

The empirical results show that model uncertainty concerning the horizon for neutrality to be achieved is not important. The results were essentially invariant across the horizon at which the restrictions were imposed. This implies that the results are not sensitive to the imposition of an infinite horizon restriction and that the long run occurs rather rapidly with respect to money-supply shocks. Further, all the impulse-response functions for the finite horizon models maintained the neutrality of money (within any reasonable definition of economic significance) at horizons longer than the point of the restriction.[10]

In light of the arbitrary scale of the money-supply shocks, it is difficult to assess the relative importance of such shocks on agricultural prices. If additional restrictions are imposed on the model, the contribution of money shocks to the forecast error variance of each series can be estimated. Using a triangularization of the long-run impact matrix to ensure consistent scaling across series, with the ordering of the interest rate, output, real livestock price, real crop price, real money, real energy price, real exchange rate, and nominal money, we derived the posterior medians of the variance decompositions for the same set of 130 possible model specifications.[11] The results are shown in table 2 for a sampling of horizons following a money-supply shock. These values describe the relative contribution of money-supply shocks to the conditional forecast error variance of each series at the relative horizon. For example, 7.92% of the one-month variation in real livestock prices is attributable to money-supply shocks; the same value for the real crop price is 1.53. The results demonstrate that money-supply shocks are not enormously important, on average, to the variance of the agricultural prices, although the early impact on the real livestock price series is still relatively larger than on the output series and the impact of money shocks on both agricultural price series is larger than on the real exchange rate. Still, these results suggest that the emphasis placed on monetary policy's impact on the agricultural sector's profitability may be somewhat exaggerated.

However, one should be careful not to confuse small (relative) statistical importance with small economic importance. These variances are for prices, which would translate most closely to shifts in gross farm income if production is treated as quasi-fixed at the time of price determination. With the recent ratio of net farm income to gross farm income running around 20%, a 1% price difference would translate into a 5% swing in profits. Net farm income is on the order of $40 billion per year, implying that monetary effects on net farm income could easily be in the neighborhood of $2 billion per year. Thus, while the forecast error variance decomposition results in table 2 suggest that monetary policy is not the whole story in terms of statistical modeling, it is still a very large story in terms of economic impact on farm incomes.

Conclusions

In this paper we make three contributions to the literature on agricultural price responses to monetary shocks. First, the impulse responses are identified using theory-based restrictions on long-run behavior that probably have more support among economists than the restrictions on contemporaneous behavior that have been used previously to identify such models. Second, a Bayesian approach is taken to model specification, allowing for derivation of a posterior distribution of impulse responses which integrates over model uncertainty and adding robustness to the results. Third, agriculture is disaggregated into two subsectors: crops and livestock. This allows the discovery of differences in the responses of the prices in these two sectors and

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[10] As a further sensitivity check, the model was identified using a standard set of recursivity restrictions by employing a Choleski decomposition of the error covariance matrix (Bessler; Sims) for a single model specification with twelve lags and the set of energy price dummy variables. The results of this model stand in stark contrast to those presented above. The price level overshoots the nominal money expansion, causing real money to drop along with all three of the real prices (crops, livestock, and energy) and output. The livestock price falls in nominal terms over the entire horizon. The effect on the interest rate is very small. Both agricultural sectors are hurt by the monetary expansion, livestock more than crops. The results demonstrate strange dynamics: the price level increase almost doubles the nominal money expansion; real money falls by an amount almost identical to the nominal money increase. Such results are very difficult to explain with any macroeconomic theory, casting suspicion on all of the model's results.

[11] Note that this implies twenty-one additional restrictions above the long-run money neutrality used to identify the shape of the money-shock response functions. Real exchange rate shocks are long-run neutral for all series except the real exchange rate and nominal money; real energy prices are neutral for the five series preceding it in the order, etc.

Table 2. Variance Decomposition with Respect to Money-Supply Shocks

Horizon	Series r	o	l	c	m	e	s	M
1	27.57	1.87	7.92	1.53	6.36	15.51	0.72	11.56
2	17.87	1.97	7.85	1.19	10.69	17 91	1.20	19.20
3	13.23	2.28	8.12	1.03	13.77	18.80	1.35	23.98
4	10.36	3.01	7.40	0.97	15.30	19.62	1.23	26.46
5	8.65	3.92	6.11	0.99	15.35	20.04	1.04	26.74
6	7.63	4.54	5.24	0.95	15.28	19.73	0.91	27.23
12	4.23	6.29	3.17	1.20	10.53	18.59	1.21	23.59
24	2.31	6.36	2.96	1.60	4.94	12.05	1.30	19.34
36	1.68	5.64	2.67	1.66	2.78	9.09	1.12	17.53
48	1.35	4.51	2.30	1.46	1.86	6.86	0.93	16.90

Note: Series abbreviations are r = interest rate, o = output, l = real livestock price, c = real crop price, m = real money, e = real energy price, s = real exchange rate, and M = nominal money

for the study of the dynamics caused by the interactions between these two highly linked production activities.

In general, the empirical results show that in the short run agriculture benefits from expansionary monetary policies. Livestock prices exhibit a strong positive response to money-supply shocks on impact, while crop prices have a very small initial positive response. However, crop prices gradually rise and take longer to fully adjust than livestock prices. The relative dynamics of the two agricultural prices are consistent with crops being an important input to livestock production.

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References

Bernanke, B.S. "Alternative Explanations of the Money-Income Correlation." *Carnegie-Rochester Conference Series on Public Policy.* 25(1986):49–100.

Bessler, D.A. "Relative Prices and Money: A Vector Autoregression on Brazilian Data." *Amer. J. Agr. Econ.* 66(February 1984):25–30.

Blanchard, O.J. "A Traditional Interpretation of Macroeconomic Fluctuations." *Amer. Econ. Rev.* 79(December 1989):1146–64.

Blanchard, O.J., and D. Quah. "The Dynamic Effects of Aggregate Demand and Supply Disturbances." *Amer. Econ. Rev.* 79(September 1989):655–73.

Chambers, R.G. "Agricultural and Financial Market Interdependence in the Short Run." *Amer. J. Agr. Econ.* 66(February 1984):12–24.

Chambers, R.G., and R.E. Just. "An Investigation of the Effect of Monetary Factors on Agriculture." *J. Monetary Econ.* 9(March 1982):235–47.

Choe, Y.C., and W.W. Koo. "Monetary Impacts on Prices in the Short and Long Run: Further Results for the United States." *J. Agr. Res. Econ.* 18(December 1993):211–24.

Devadoss, S., and W.H. Meyers. "Relative Prices and Money: Further Results for the United States." *Amer. J. Agr. Econ.* 69(November 1987):838–42.

Eichenbaum, M. "Comments on 'Interpreting the Macroeconomic Time Series Facts: The Effects of Monetary Policy,' by Christopher Sims." *Eur. Econ. Rev.* 36(June 1992):1001–11.

Faust, J., and E.M. Leeper. "When Do Long-run Identifying Restrictions Give Reliable Results?" International Finance Discussion Paper No. 462, Board of Governors of the Federal Reserve System, 1994.

Johansen, S. "Statistical Analysis of Cointegration Vectors." *J. Econ. Dynamics and Control* 12(June/September 1988):231–54.

King, R.G., C.I. Plosser, J.H. Stock, and M.W. Watson. "Stochastic Trends and Economic Fluctuations." *Amer. Econ. Rev.* 81(September 1991):819–40.

Lastrapes, W.D., and G. Selgin. "The Liquidity Effect: Identifying Short-Run Interest Rate Dynamics Using Long-Run Restrictions." *J. Macroeconomics* 17(1994):387–404.

Litterman, R.B. "Forecasting with Bayesian Vector Autoregressions: Five Years of Experience." *J. Bus. Econ. Statist.* 4(January 1986):25–38.

Orden, D. "Money and Agriculture: The Dynamics of Money Financial Market-Agricultural Trade Linkages." *Agr. Econ. Res.* 38(1986):14–28.

Orden, D., and P.L. Fackler. "Identifying Monetary Impacts on Agricultural Prices in VAR Models." *Amer. J. Agr. Econ.* 71(May 1989):495–502.

Poirier, D.J. "A Bayesian View of Nominal Money and Real Output Through a New Classical Macroeconomic Window." *J. Bus. and Econ. Statist.* 9(April 1991):125–48.

Rausser, G.C., J.A. Chalfant, H.A. Love, and K.G. Stamoulis. "Macroeconomic Linkages, Taxes, and Subsidies in the U.S. Agricultural Sector." *Amer. J. Agr. Econ.* 68(May 1986):399–412.

Robertson, J.C., and D. Orden. "Monetary Impacts on Prices in the Short and Long Run: Some Evidence from New Zealand." *Amer. J. Agr. Econ.* 72(February 1990):160–171.

Sims, C.A. "Are Forecasting Models Usable for Policy Analysis?" *Federal Reserve Bank of Minnesota Quart. Rev.* (Winter 1986):2–16.

Tweeten, L.G. "An Econometric Investigation of Inflation Passthrough to the Farm Sector." *W. J. Agr. Econ.* 5(July 1980):89–106.