# Agricultural Interest Rates and Inflationary Expectations: A Regional Analysis

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***Abstract.*** *The Fisherian hypothesis was tested for four regional agricultural interest rates in the 11th Federal Reserve District (Dallas). These interest rates represented agricultural loans of different terms to maturity. Shocks in expected inflation resulted in positive but less than equivalent responses in all four rates. The empirical evidence from the impulse response function suggested that Fisher's relationship holds imperfectly for agricultural interest rates in the Dallas Federal Reserve District.*

***Keywords.*** *Fisher's hypothesis, vector autoregression, cointegration, stationarity, impulse responses, agricultural interest rates.*

Fisher's theory stated that a one-for-one relationship exists between changes in nominal interest rates and changes in expected inflation (*8*).[1] We concentrate on the agricultural credit or interest rates of the 11th Federal Reserve District (the Dallas District) and employ cointegration tests and vector autoregression (VAR) econometrics to discern whether the Fisherian hypothesis holds, to reveal the degree or strength with which it holds, and to reveal evidence in the data concerning the dynamic patterns with which the relationship operates.

## Theoretical Background

The Fisherian hypothesis

$$r_n = E(r_r) + E(i) + [E(r_r)E(i)], \tag{1}$$

states that the nominal rate of interest $r_n$ depends upon the expected real rate of return on assets $E(r_r)$ plus the expected inflation rate over the period of the loan $E(i)$ plus their cross product. The expected real rate of return depends upon longrun factors such as productivity and thrift in the economy. In previous analyses, the cross product was considered insignificant, and $E(r_r)$ was considered constant over time. Thus, only changes in the inflationary forecast for the period of the loan would influence movements in the nominal rate of interest. Expectations of price inflation raise nominal rates by reducing lenders' willingness to lend and/or by increasing borrowers' willingness to borrow at given nominal yields (*9*). Fisher hypothesized this relationship between expected inflation (or the inflation rate) and nominal interest to be one-for-one. Equation 1 is not meant to represent a full and complete theory of interest rate determination, but seeks to quantify the effects of inflationary expectations on nominal interest rates (*11*).

At least three effects (the wealth, income, and depreciation tax effects) have since been advanced which suggest that real rates are inversely related to inflationary expectations. So, increases in nominal rates due to this inflation premium would be somewhat offset over time by the resulting decline in the expected real rate. An alternative view suggests that the income tax effect may create a greater than one-for-one response. It follows from these alternative theories that changes in inflationary expectations would have two separate temporal influences on nominal rates. The first would be an immediate, positive, and direct effect from the inflation shock on nominal rates. The second would come as a lagged, indirect, and uncertain effect upon the nominal rate through its influence on the expected real rate (*22, 27*).

## Review of the Literature

In Fisher's original test, long-term bond yields and 4- to 6-month prime commercial paper rates were tested against a weighted average of past rates of inflation (*8*). Fisher's results suggested that the response of nominal rates to a long history (up to 30 years) of inflationary expectations was less than one-for-one. However, price changes did affect interest rates in the direction indicated by Fisher's theory.

Sargent (*23*), using a dynamic linear macroeconomic model, said that an increase in expected inflation would eventually drive up nominal interest rates by an equivalent amount. These changes, however, would be distributed over long periods (up to 10 years or longer). He further stated that the higher the inflation rate, the shorter the period of adjustment.

Gibson (*11*) showed that adjustment of nominal rates to inflationary expectations had evolved toward unity from 1952 through 1965, especially for short-term rates. The post-1965 period gave evidence that rates had overadjusted. Treasury securities were used to eliminate the effects of changing default risk premiums. However, similar results were shown for a variety of risky market rates such as commercial paper and various corporate bonds.

Fama (*7*) tested how well information about future inflation was used in setting prices for 1- to 6-month U.S. Treasury bills (T-bills) during 1953-71. Based upon sample autocorrelations and regression estimates, Fama concluded that the markets were effi-

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[1] Italicized numbers in parentheses cite sources listed in the References section at the end of this article.

cient and that expected real returns were constant over time He inferred that all variation through time in nominal rates mirrored the variance in the expected inflation rate

Lahiri (*18*) combined information from observed price expectations (Livingstone data) with past rates of inflation in order to derive new estimated price expectation variables Four different estimates of inflationary expectations were used to test Fisher's theory These short-term expectations explained about 80 percent of the variation in nominal rates for 3-month T-bills

Friedman (*9*) investigated the role of lenders' portfolio behavior in the relationship between price expectations and risky nominal interest rates Simulation over six major lender categories showed that nominal long-term fixed-interest yields on corporate bonds rose by 0 65 percent for each 1-percent rise in expected inflation This less than one-for-one adjustment occurred over a period of 4 years

Urich and Wachtel (*29*) examined the effect of the announcements of both the consumer price index (CPI) and the producer price index (PPI) on 3-month T-bill rates No effect of PPI during 1977-79 and CPI for 1977-82 was shown An unanticipated increase of one standard deviation in PPI during 1979-82, however, yielded an 11 4-basis-point increase in nominal rates for 6- to 12-month maturities Evidence of any lagged effects was very weak, suggesting new information was rapidly incorporated into market interest rates

## Data Series

We examine the probable relationship between inflationary expectations and four series of average nominal rates on new agricultural (farm) loans for the 11th District Federal Reserve Bank of Dallas The Dallas District includes Texas, Oklahoma, New Mexico, and Louisiana The four interest rates considered were feeder cattle loans (RFC), other operating loans (ROO), intermediate-term nonreal estate loans (RIT), and long-term real estate loans (RLT) The quarterly interest rate survey data (for the third quarter of 1975 through the third quarter of 1989) was obtained from the Federal Reserve Board's *Agricultural Finance Databook* The Federal Reserve Board surveys of interest rates were initiated in the third quarter of 1975

Because Fisher's hypothesis relates nominal interest rates to expected rather than actual inflation rates, we must create a series of quarterly expected (or forecast) inflation rates A naive forecast approach generates a time series of forecast CPI levels We aim to model the expected inflation rate as the percentage change in forecasted CPI levels (This article follows previously cited research (*9* and *29*) in using the Bureau of Labor Statistics' CPI series (all urban consumers, all items) )

Given a naive forecast approach, the "best" or "optimal" forecast for all future quarters' CPI levels is the present quarter's CPI However, the present quarter's (t) CPI would not be fully known to borrowers and lenders when interest rates for quarter (t) are discovered Hence, the previous quarter's (t–1) CPI is used as the present quarter's (t) forecast for all future levels of CPI For example, the actual CPI for 1975 2 would be used as the 1975 3 forecast The actual CPI for 1975 3 would be used as the 1975 4 forecast, and so on In this manner, a series of forecast levels of CPI is generated for the 1975 3-1989 3 period

Changes in a variable's natural logarithms approximate the proportional change in the (nonlogged) variable's levels The forecast CPI levels were therefore transformed into their natural logarithmic counterparts The logged forecast CPI series (CPIF) is then used in formulating the VAR model The impulse responses of the CPIF series act as the proxy for changes in the expected rate of inflation Because the impulse response function measures the responses of interest rates to a shock to the residual (or innovation) element of the CPIF series, the shock may be considered as equivalent to a change in the expected inflation rate So the VAR system models CPI forecasts in natural logarithms, so that shocks to, or impulse responses in, this variable are equivalent to proportional changes in the nonlogged CPI forecasts, that is, expected inflation (These proportional changes are converted to percent changes when multiplied by 100 )

Stationarity tests conducted on the CPIF levels (discussed below) support our decision to model the CPI forecasts (logged) as naive forecasts of the logged CPI levels Results fail to reject the null hypothesis that CPIF, and hence the logged CPI levels, constitute a random walk at a 5-percent significance level

## Cointegration and Fisher's Relationship

Until recently, much of the literature's econometric work assumed that underlying economic series were stationary and ergodic, despite economic time series often being nonstationary (*15*, p 201)

A stationary process is one in which the mean and variance do not change through time, and the covariance between values of the process at two points depends only on the distance between these time points and not on time itself A time series is stationary when its generating mechanism is time-invariant, so that neither the form nor the parameter values change through time (*13*, *26*) If the generating process is linear, then the major properties of the process are captured in the mean and variance (*13*)

Yet much econometric research assumes that the underlying processes are stationary (*15*, *26*) When a series is not stationary, the statistical consequences are onerous regression estimates do not converge in probability with increased sample size, r-square values have nondegenerate distributions, and a divergence in t-value distributions often exists such that asymptotically correct critical values do not exist (*15*) Econometric estimates and their distributions are not guaranteed to have the desirable statistical properties when this assumption is violated (*15*)

Given a nonstationary series, univariate procedure, often extended to multivariate analysis, would require mathematically transforming (usually through first-order differencing) the data to a stationary series [2] Yet, this approach of differencing nonstationary economic series into stationary series has been criticized by Hendry 'By analyzing only the differences in economic series, all information about potential (long-run) relationships between the levels of economic variables is lost, this seems a drastic 'solution' " (*15*, p 204) Nerlove, Grether, and Carvalho (*20*) also reject stationarity-inducing transformations to let the nonstationarity in one series explain the nonstationarity in the other On the one hand, statistical procedure requires stationary series, while economic time series with which one builds econometric and statistical models are often nonstationary (*15*) Otherwise, the mathematical data transformations that would induce stationarity, such as differencing, are criticized for throwing out and ignoring valuable longrun equilibrium information (*6*, *15*) Engle and Granger (*6*) said that modeling with differenced data can raise serious misspecification problems through the ignoring of theoretically relevant longrun components in the levels data

The researcher can avoid the serious misspecification problems encountered by differencing data Granger writes

> "At the least sophisticated level of economic theory lies the belief that certain economic variables should not diverge from each other by too great an extent, at least in the long-run Such variables may drift apart in the short-run [but] then economic forces begin to bring them back together " (*12*, p 213)

Fisher's equation relating the Dallas District credit rates and changes in the logged CPI forecasts (expected inflation) could be considered one of the forces which imposes longrun equilibrium relationships on the variables, shortrun divergences notwithstanding

A set of variables is cointegrated when each variable is individually nonstationary in levels, and when the individually nonstationary variables form stationary linear combinations with the contemporaneous values of the other variables, that is, the resulting linear equation generates stationary residuals (*6*, *15*) The cointegrating restriction would be "Fisher's hypothesis," and is hereafter referred to as the "cointegrating restriction" or relationship (*8*) So, testing for the cointegrating relationship between forecast CPI and the four Dallas District interest rates requires two sets of stationarity tests (1) on the data levels of each series, and (2) on the residuals of each cointegrating regression (CR), where each CR is one of the variables regressed against the contemporaneous values of the other four variables (*6*, *14*, *15*)

We followed the procedure of testing a time series for a unit root (for nonstationarity) developed by Dickey and Fuller (*2*, *4*), and augmented by Engle and Granger (*6*) (hereafter the augmented Dickey-Fuller or ADF test) One tests for nonstationarity by regressing the first differences of a variable (data levels or CR residuals) against a constant, a one-period lag of the nondifferenced variable, and a selected number of lagged dependent variables We employed Hsiao's (*16*) lag selection procedure based on the criterion of minimized final prediction error to determine the number of lagged dependent variables to include in the ADF regressions These ADF regressions provide what are called pseudo t-values on the nondifferenced lagged regressor, since they are calculated as, but not distributed as, a Student t-statistic (*6*, *14*) Critical values are published in Fuller (*10*), Dickey and Fuller (*3*), and Hall (*14*) One rejects the null hypothesis that a unit root exists (that the variable is nonstationary) when the calculated pseudo t-value is negative and of an absolute value in excess of that of the critical value

The ADF test was performed on each variable's levels and on the residuals on each variable's CR or linear combination of the other variables We also performed a second test, the "cointegrating regression Durbin-Watson" or CRDW test on the five sets of CR residuals (see *6*, *14*) For the CRDW test, one rejects the null hypothesis that the residual series is nonstationary when the CR equation's Durbin-Watson value exceeds the critical value Hall (*14*) has published critical CRDW values

Table 1 shows the ADF pseudo t-values for the data levels, the ADF pseudo t-values for the CR residuals, and the Durbin-Watson values for the residuals of the cointegrating regressions While each of section I's pseudo t-values are negative, all have an absolute value of less than that of the ADF critical value of -2 89 at the 5-percent significance level (*10*, p 373) So, evidence at the 5-percent significance level is insufficient to reject the null hypothesis of nonstationary levels of all five modeled variables Evidence suggests that the five modeled variables are individually nonstationary

[2]Differencing removes one order of integratedness from the data, and the order of integratedness is the number of times the data must be differenced for the series to be stationary For example, a series that is integrated of order one, I(1), must be differenced once to transform the series into a stationary one, denoted an I(0) series

Table 1—Stationarity test results on the series levels and on the cointegrating regression (CR) residuals

| Test | CPIF | RFC | ROO | RIT | RLT |
|---|---|---|---|---|---|
| I. Levels, ADF [1] | −2.19 | −2.11 | −2.09 | −2.04 | −2.16 |
| II. CR residuals | | | | | |
| a. ADF [2] | −1.72 (−5.50)[4] | −5.96 | −4.70 | −4.90 | −5.12 |
| b. CRDW [3] | 1.42 | 2.60 | 2.45 | 1.68 | 1.61 |

[1]The ADF critical value at the 5-percent significance level is −2.89 (*9*, p. 373). One rejects the null hypothesis of a unit root (random walk or nonstationarity) when the calculated pseudo t-value is negative and has an absolute value in excess of that of the critical value.

[2]The ADF critical value for a three-variable case at the 5-percent significance level is −3.13 (*13*). At this writing, the critical values for a five-variable case were not located in published form. We followed Hall and applied this critical value for the three-variable case to a five variable case with caution. One rejects the null hypothesis when the pseudo t-value is negative and has an absolute value in excess of the critical value.

[3]Hall reports the CR Durbin-Watson test critical value to be 0.367 for a 3-variable case at the 5-percent significance level (*13*). One rejects the null hypothesis of nonstationary residuals when a cointegrating regression's Durbin-Watson value exceeds the critical value. Following Hall, we applied this critical value for the 3-variable case to a 5-variable case with caution (see *13*).

[4]Evidence of nonstationarity of CR residuals is more ambiguous for CPIF than with the other four variables, although, on balance, the results generally point to stationarity. The CR pseudo t-value of −1.72 for the ADF test fails to reject the null hypothesis of nonstationarity, and because this value contradicted the CRDW result which suggests stationarity at the 5-percent significance level, we provided the Dickey-Fuller or DF test (as opposed to the ADF test) for additional evidence. This −5.50 value suggests that evidence is sufficient to reject the null of nonstationarity at the 5-percent significance level when Fuller's (*9*) critical value of −2.89 is used, and is adequate to reject the null when Hall's DF critical value of −3.37 is used. (Hall reported DF critical values only for the 2-variable case.) So, despite the ADF pseudo t-value being insufficient to reject the null hypothesis of nonstationary CR residuals for CPIF, we feel that on balance, evidence suggests stationarity because both the CRDW and DF tests suggest stationarity at the 5-percent significance level.

In section II, ADF results suggest that evidence is adequate to reject the null hypothesis of nonstationary CR residuals, and to accept the alternative hypothesis of stationarity in all but one case (CPIF) at the 5-percent level. Note, however, that the additional evidence and footnotes in table 1 reveal considerable evidence that CR residuals for CPIF are also stationary. CRDW results suggest that evidence is sufficient to reject the null hypothesis of nonstationary CR residuals for all five cases at the 5-percent significance level. So, on balance, the combined results suggest that the residuals of all five cointegrating regressions are stationary. Evidence suggests that the logged forecast CPI values and the four agricultural interest rates for the Dallas District are cointegrated with Fisher's relationship (equation 1).

## Model Selection Criteria and Model Choice

Sims (*24*, p. 489) has recently noted that economists are confronted with the situation experienced by natural scientists of having an expanding array of analytical tools at our disposal. Meaningful modeling efforts constitute a wide spectrum, from purely theoretical models with no connection to observed data to purely data-oriented statistical models with little connection to theory (*24*, p. 489). The latter category includes data-oriented vector autoregression (VAR) models with few *a priori* theoretical restrictions. Midway between such efforts would be "structural time series" efforts such as the "cointegration" (vector error corrections or VEC) models of Robertson and Orden (*21*) who combine time-series or VAR methods with a more intensive use of theory. Sims notes that all of these models have valid uses, that no one model type is "right" or "wrong" in an absolute sense, and that economists should not waste energy in fruitless debate over which modeling style is universally correct. Rather, the researcher decides on an appropriate modeling style after careful consideration of the following criteria: (a) the desired degree of connection to the data, (b) the desired intensity with which theory is used, (c) the desired confidence levels with which one invokes and tests hypotheses with inference, (d) the degree to which the chosen model facilitates the analytical purpose, and (e) how well the model predicts beyond the information set (*24*). Sims sees that no existing model can be expected to perfectly meet all of these criteria, and that all existing models are compromises concerning the fulfillment of these criteria.

The five modeled variables are cointegrated. And Engle and Granger (*6*) and Campbell and Shiller (*2*) show how one should use "cointegration" models—vector error correction (VEC) models—to effect certain goals of analysis. A VEC framework accounts for the longrun cointegrating relationships through the use of levels-based error correction terms reflecting how far the cointegrated system has been from the longrun equilibrium in the shortrun (*6*, *21*). A VEC model would be appropriate when the researcher (1) is required to work with differenced data and needs to mitigate misspecification problems through the inclusion of levels-based error correction terms, (2) wants to make longrun forecasts beyond the sample, and (3) wants maximal estimate efficiency to conduct reliable inference about the theoretically based parameter estimates. Our analytical purpose does not include these three analytical purposes. Engle and Granger (*6*) acknowledge that other modeling efforts along the Sims spectrum, say a VAR model in nondifferenced levels with large samples, successfully capture the cointegrating relationships such as Fisher's equation 1 in our Dallas District data. Sims suggests that analytical purpose and other selection criteria should determine whether a VEC or a VAR model in levels would be appropriate. The researcher is not mandated to build a VEC model simply because there is cointegration. Our analytical purpose favors a VAR in levels with maximal observation numbers.

Our analytical purpose is twofold We first test the CPIF, RFC, ROO, RIT, and RLT data levels for the existence of Fisher's longrun cointegrating relationship Second, we test the data levels (with Fisher's cointegrating relationship embodied) for evidence concerning how perfectly and with what dynamic patterns the cointegrating relationship has held in the Dallas District We have chosen a VAR model in levels, rather than a VEC model restricted for Fisher's relationship We chose the VAR model in levels over the VEC model because one should not restrict a model for the very theoretical restriction that the model is being used to test the data for (see *1*) A VEC model is inappropriate for our analytical purpose because it uses error correction terms to restrict the model for the very restriction we are testing the data for We follow Sims' model selection procedure because our criterion (d) or analytical purpose requires an emphasis of criterion (a) or data connections at the expense of criterion (b) or intensity of theory usage Testing data for a theory—here, for Fisher's relationship in the Dallas District's agricultural credit markets—often "requires fitting models to view the dynamic system with as few *a priori* restrictions as possible, allowing what regularities that are present in the data to reveal themselves " (*1*, p 111)

## Estimated VAR Model

VAR econometrics involves a multivariate system in which each of the system's variables is allowed to influence every other variable in the system with lags VAR methods allow characterizing a dynamic system without forcing particular *a priori* (theoretical) interactions within the variable set The method may be considered as the first step in describing the average behavior concerning Fisher's hypothesis for Dallas District agricultural credit rates over the observation period (*1*) We do not develop the VAR econometric method here Interested readers should consult Sims (*25*) and Bessler (*1*) We proceed directly to the estimated VAR model

The following VAR model was estimated during 1977 1-1989 3

$$
\begin{aligned}
X_t = {} & a_{X0} + a_{X,T}{*}TRD + a_{X,1}{*}CPIF_{t-1} + \\
& + a_{X,3}{*}CPIF_{t-3} + a_{X,4}{*}RFC_{t-1} + \\
& + a_{X6}{*}RFC_{t-3} + a_{X,7}{*}ROO_{t-1} + \\
& + a_{X9}{*}ROO_{t-3} + a_{X,10}{*}RIT_{t-1} + \\
& + a_{X12}{*}RIT_{t-3} + a_{X,13}{*}RLT_{t-1} + \\
& + a_{X15}{*}RLT_{t-3} + e_{X,t}, \qquad (2)
\end{aligned}
$$

where X = CPIF, RFC, ROO, RIT, RLT, the first right-side regressor represents an intercept, and all a-coefficients are regression coefficients TRD is a time trend variable and $e_{Xt}$ represents X's stochastic error or innovation in period (quarter) t The five equations, of equation 2's form, represent the five modeled variables

Tiao and Box's (*28*) method of lag selection was chosen to obtain a lag structure large enough to approximate white noise but small enough to be operational The Tiao-Box likelihood ratio tests, conducted at Lutkepohl's (*19*) suggested 1-percent significance level, implied a 3-order lag for the VAR Observations during 1975 3-76 4 were saved for the lag search, leaving the 1977 1-89 3 observations for the estimation period Coefficients were estimated for the VAR using ordinary least squares Doan and Litterman's (*5*) package, Regression Analysis of Time Series (RATS), generated all results

Doan and Litterman (*5*) have programmed the Ljung-Box Q-statistic into RATS Distributed as a chi-squared distribution, the Q-value tests the null hypothesis of white noise innovations, that is, the hypothesis of an adequate model The five equations' Q-values fell within the 19 5-27 3 range, less than the critical value of 38 9 (1-percent significance level) For all five equations, evidence was insufficient to reject the null hypothesis that innovations constitute a white noise process, leading to the conclusion that evidence fails to reject the hypothesized adequacy of the estimated VAR model equations (*13*, pp 99-100) [3]

The equations of the VAR may have contemporaneously correlated innovations Failure to correct for contemporaneous correlation between the equations' errors will produce responses not representative of historical patterns (*25*) A Choleski decomposition was imposed on each VAR to orthogonalize the current innovation matrix, such that the covariance matrix of the modeled innovations is identity The Choleski decomposition resolves the problem of contemporaneous feedback

The Choleski decomposition requires a sometimes arbitrary imposition of a Wold causal ordering among the current values of the dependent variables (*1*) A VAR ordering usually begins with the shock variable, and then proceeds on the *a priori* belief of the

[3] Evidence suggests that the estimated VAR model is stationary We performed the augmented Dickey-Fuller (ADF) test on the residuals of each of the VAR model's five estimated regressions Hsiao's (*16*) criterion of minimized final prediction error was chosen to determine the number of lagged regressors All five pseudo t-values fell within the –5 5 to –4 7 range At the 5-percent significance level, Fuller (*10*, p 373) reports a –2 89 critical value A VAR regression resembles a cointegrating regression in certain ways, and if the researcher deems the VAR equations to be enough like CR equations, then the researchers might decide to use Hall's (*14*) critical value for the 3-variable case of –3 13 (5-percent significance level) Little practical consequence arises from choosing among these two critical values, insofar as they are both of similar magnitudes With either the Fuller or Hall critical values evidence is sufficient at the 5-percent level to reject the null hypothesis of nonstationarity Evidence suggests that the residuals are stationary in all five cases The estimated VAR model appears stationary

sequence in time over which the different variables will respond to the initial shock. No *a priori* belief held that any of the four interest rates should precede the others in responding to changes in inflationary expectations. The VAR model was therefore ordered (following CPIF) on the basis of term-to-maturity of the loan series. Thus, the series were ordered as CPIF, RFC, ROO, RIT, and then RLT. Other orderings were possible, but were not considered.

The impulse response function is a technical operation performed on an estimated VAR. The impulse response function simulates over time the effect of a typically sized shock in one series on itself and on other series in the system. Calculating impulse responses provides the dynamics of how variables in the modeled system respond to the imposed one-time shock. The estimated VAR model (equation 2) was shocked with a one-time increase in CPIF, and this shock represents a rise in expected inflation. Following standard procedure, the typically sized shock was a one-standard-error increase in the variable's historical innovation. This shock amounted to a 0.25-percent, or 25-basis-point, rise in forecast CPI.

Kloek and van Dijk's Monte Carlo method (*17*) provided a t-value for each impulse response. The t-value tests the null hypothesis of a nonzero impulse value at the chosen (here, 5-percent) significance level. Significantly nonzero responses were the ones that were emphasized.

We examined the impulse responses in the four agricultural interest rate variables (RFC, ROO, RIT, and RLT). The dynamic patterns of the impulse responses included the "reaction" times required for each variable to respond to the shock in expected inflation, the directions and patterns of each variable's impulse responses, and the durations of the variable's impulse responses. How the interest rate responses contrast in magnitude to the size of the impulses of the proxy for expected inflation is particularly important to the Fisherian hypothesis. These dynamic results from the impulse response function provide the very information needed to discern the strength and dynamic patterns with which Fisher's relationship has historically operated in the Dallas District's agricultural credit markets.

## Responses to a Shock in Expected Inflation

Table 2 provides the responses over time for the five series that were subjected to a one-time shock (of 0.25 percent, 25 basis points) in CPIF. The four interest rate responses were statistically significant at the 5-percent significance level in the first period and statistically insignificant thereafter.

In the first period following the shock, feeder cattle loans (RFC) and intermediate-term, nonreal estate loan rates (RIT) increased 15 basis points (0.15 percent), or 60 percent of the initial increase in CPIF. Other operating loan rates (ROO) increased almost 16 basis points, 64 percent of the shock to CPIF. Long-term real estate loan rates (RLT) increased 20 basis points, 80 percent of the initial shock in CPIF.

**Table 2—Impulse responses in CPIF and agricultural interest rates resulting from a shock in CPIF**

| Period | CPIF[1] | RFC[2] | ROO[3] | RIT[4] | RLT[5] |
|---|---|---|---|---|---|
| 1 | 0.25* | 0.15* | 0.16* | 0.15* | 0.20* |
| 2 | .31* | -.16 | -.14 | -.14 | -.08 |
| 3 | .29* | -.01 | -.02 | 0 | -.02 |
| 4 | .43* | .17 | .15 | .14 | .08 |
| 5 | .55* | .04 | .04 | .04 | .01 |
| 6 | .60* | .18 | .17 | .16 | .14 |
| 7 | .68* | .34 | .33 | .30 | .27 |
| 8 | .75* | .34 | .34 | .32 | .29 |
| 9 | .76* | .39 | .39 | .37 | .36 |

*Statistically significant at the 5-percent level of significance.
[1]Forecasted logged values of the quarterly Consumer Price Index whose impulse responses act as a proxy for changes in expected inflation. The impulses were multiplied by 100 for conversion into basis points in this table.
[2]Quarterly, nominal interest rates for feeder cattle loans for the Dallas District.
[3]Quarterly nominal interest rates for other operating loans for the Dallas District.
[4]Quarterly, nominal interest rates for intermediate-term, nonreal estate loans for the Dallas District.
[5]Quarterly, nominal interest rates on long-term real estate loans for the Dallas District.

All four rate series showed a significant positive association with CPIF. The change in the four rates was less than the initial shock in CPIF, which suggests the degree to which (that is, how perfectly) Fisher's relationship holds in the Dallas District for agricultural interest rates. The interest rate responses were immediate, occurring in the same quarter as the initial shock, and had no significant effects thereafter.

A possible reason for the less-than-equivalent responses in nominal interest rates may be that the income, wealth, and depreciation tax effects dominate any income tax effects. Given an increase in inflationary expectations, expected real rates respond inversely to the initial inflationary shock, offsetting the initial response of the nominal rates.

The magnitude of the results for the agricultural loans is similar to that found by previous research for government and corporate bond markets. This suggests that the presence of any additional risk (whether in corporate or farm loan rates), while increasing the magnitude of the levels of nominal rates with respect to the levels of risk-free loan rates, does not appear to affect the relationship between changes in inflationary expectations and changes in nominal interest rates.

## Conclusions

The empirical evidence suggests that Fisher's hypothesis holds, albeit imperfectly, for agricultural interest rates in the Dallas District. A rise in inflationary expectations resulted in less than a one-for-one change in all four series of farm loan rates. The effect was positive, as Fisher's theory and most previous research had indicated. Nominal rates rose, on average, by 66 percent of the increase in expected inflation, very close to Friedman's estimate (65 percent) for corporate bond yields. The changes in short-term rates of 15 and 16 basis points given a standard error change in CPIF, closely approximates Urich and Wachtel's estimate from a standard error change in PPI. We concur with Urich and Wachtel, unlike Friedman and Sargent, in that inflationary effects were incorporated immediately, and without lag, into nominal rates.

That agricultural interest rates rise by only about two-thirds of the perceived increase in inflation in the Dallas District, and that individual interest rate responses vary according to the farm loan's term-to-maturity, are policy-relevant results. Such results can be of interest to policymakers involved in the formulation of certain kinds of agricultural credit policy. Suppose, for example, that policymakers were to consider compensating certain financially stressed farmers for increased inflation through interest rate subsidies (write-downs) on farm loans, and that the write-down's cost (size) was a concern. Our results suggest that write-downs granted to farmers in and around the Dallas District need not meet recent CPI increases on a percent-by-percent basis, because the area's credit rate responses to inflationary expectations have been historically less. Our results further suggest that the size of any such write-down may vary with the terms-to-maturity of the farm loan types. Note that our results are relevant to the Dallas District, and should not be generalized to the agricultural credit markets of other (or broader) areas. Similar analyses are needed for the agricultural credit rates of other Federal Reserve districts.

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