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CAN FUTURES MARKET DATA BE USED TO UNDERSTAND THE BEHAVIOR OF REAL INTEREST RATES?

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ABSTRACT

Understanding the behavior of real interest rates is a central issue in monetary/macro economics. Recently researchers have begun to use futures market data to examine real interest rate behavior. Futures market data can be used to directly construct own-commodity real interest rates -- i.e., the ex-ante real return on a bond in terms of specific commodities -- and then the own-commodity real rates can be used to make inferences about the real interest rate for the aggregate economy.

This paper examines whether futures market data can be used to understand the behavior of real interest rates. The conclusion is a negative one: Futures market data do not appear to be particularly informative about real interest rates. In coming to this conclusion, the paper examines the data in several ways. First, the ex-ante relative price movement embedded in the own-commodity real rates (the noise) is calculated to be on the order of over one hundred times more variable than the aggregate real interest rate (the signal). Own-commodity real rates are thus unlikely to contain much information about the aggregate real interest rate. Second, several widely accepted facts about the behavior of aggregate real interest rates in the 1980s are not at all evident in the own-commodity real rate data. Thus, analysis of own-commodity real rates provides a misleading impression of aggregate real rate movements for a period which displays the most striking movements of real interest rates in the postwar period. Finally, an econometric analysis of own-commodity real rate behavior fails to find evidence of a shift in the behavior of real interest rates when the monetary policy regime changes in October 1979, a finding that is at odds with previous strong findings in the literature.

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I. Introduction

Understanding the behavior of real interest rates is a central issue in monetary/macro economics.[1] In previous research on this topic, several approaches have been used to measure real interest rates. In one approach, real interest rates have been calculated by subtracting survey data on inflation expectations, such as the Livingston data, from nominal interest rates.[2] The problem with survey-based measures of real interest rates is that they are only as good as the survey measure of inflation expectations and there may be little incentive for the survey respondents to answer accurately. An even more telling criticism of survey-based measures, often ignored in the literature, is that the behavior of market expectations is driven by economic agents at the margin who are eliminating unexploited profit opportunities. Market expectations are unlikely, therefore, to be well measured by the average expectations of survey respondents.[3]

Because of doubts about survey-based measures of real interest rates, other researchers have used the assumption of rational expectations and ex-post real interest rate data calculated with aggregate

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[1] Here, the term "real interest rate" refers to the ex-ante real interest rate, that is the expected real return on a bond. When referring to the actual realized real return on a bond, the term "ex-post real interest rate" will be used.

[2] For example, see Gibson (1972), Cargill (1976), Lahiri (1976), Carlson (1977), Levi and Makin (1979), Tanzi (1980) and Wilcox (1983).

[3] See Mishkin (1981b).

price level data to make inferences about real interest rate behavior.[4] There are several difficulties with this approach as well. First is the need for the rational expectations assumption. Although rational expectations is a maintained hypothesis in much current research in monetary economics, there are questions about its validity particularly when there is a shift from one policy regime to another. An additional problem with this approach is that unanticipated inflation appears as a component of the error term in the statistical analysis. As a result, statistical tests may have low power.[5] Another consequence of the presence of unanticipated inflation in the error term is that the variability of real interest rates cannot be examined directly.

Because of the difficulties with the analysis of ex-post real interest rates derived with aggregate price level data, recent research has begun to use futures market data to examine real interest rate behavior.[6] Futures market data can be used to directly construct own-commodity real interest rates -- i.e., the ex-ante real return on a bond in terms of specific commodities -- and then the own-commodity real rates can be used to make inferences about the real interest rate for the aggregate economy. This approach avoids the use of the rational expectations assumption and eliminates unanticipated inflation from the error term, while allowing the researcher to directly examine the variability of real interest rates.

Despite the advantages of futures market data for examining real interest rates, it does suffer from one major potential disadvantage.

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[4] For example, Mishkin (1981a), Fama and Gibbons (1982), Hamilton (1985) and Huizinga and Mishkin (1986).

[5] See Nelson and Schwert (1977) and Mishkin (1981a) for a discussion of this point.

[6] See Cornell and French (1986) and Hamilton (1986), for example.

Own-commodity real rates constructed using futures market data contain not only information about the real interest rate for the aggregate economy, but also information about ex-ante relative price movements. If the ex-ante relative price movements (which can be thought of as noise) are greater in magnitude than movements in the aggregate real interest rate (the signal), then the noise to signal ratio in own-commodity real rates will be high. Own-commodity real rates constructed using futures market data might thus contain little information about the aggregate real interest rate, which is of primary concern to economists.

This paper examines whether futures market data can be used to understand the behavior of real interest rates. The conclusion is a negative one: Futures market data do not appear to be particularly informative about real interest rates.[7] In coming to this conclusion, the paper examines the data in several ways. First, the ex-ante relative price movement embedded in the own-commodity real rates (the noise) is calculated to be on the order of over one hundred times more variable than the aggregate real interest rate (the signal). Own-commodity real rates are thus unlikely to contain much information about the aggregate real interest rate. Second, several widely accepted facts about the behavior of aggregate real interest rates in the 1980s are not at all

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[7] More precisely stated, the conclusion is that own-commodity real rates constructed with futures market data for specific commodities cannot be used to understand the behavior of aggregate real interest rates. However, reliable data from a futures contract for an aggregate price level index, such as the CPI, would get around the problems described in this paper. There is currently a CPI futures contract which is traded on the Coffee, Sugar and Cocoa Exchange, but data from this contract cannot be used to understand the recent behavior of real interest rates. The CPI futures contract has not been very successful and so has very low trading volume. The thinness of the market thus makes the data suspect. In addition, the contract has only been traded since June of 1985, so that no data is available to examine the behavior of real interest rates around the critical date of October 1979.

evident in the own-commodity real rate data. Thus, analysis of own-commodity real rates provides a misleading impression of aggregate real rate movements for a period which displays the most striking movements of real interest rates in the postwar period. Finally, an econometric analysis of own-commodity real rate behavior fails to find evidence of a shift in the behavior of real interest rates when the monetary policy regime changes in October 1979, a finding that is at odds with previous strong findings in the literature.

The overall strategy of the paper has been to beat the data with a rubber hose -- i.e., to look at the own-commodity real rate data in as many ways as possible. All the evidence consistently casts doubt on the usefulness of futures market data for understanding real interest rate behavior. Not only does this cast serious doubt about some of the results in previous research such as Cornell and French (1986) and Hamilton (1986) that make use of futures market data to draw inferences about real interest rates, but it also indicates that future research on real interest rates must turn to a different line of attack.

II.
A Comparison of Methodologies

The own-commodity real rate for a particular commodity equals the ex-ante return on a one-period bond in terms of that specific commodity. With the existence of a futures market, an investor can lock in this ex-ante real return at time t by selling the commodity $\underline{j}$ at a price of S_t^j, use the proceeds to purchase a one-period bond with a nominal return (interest rate) of i_t, and then transform the proceeds received at time t+1 back into the commodity at the futures price set at time t, F_t^j. The own-commodity real rate for commodity *j* is thus defined as,[8]

$$(1) \qquad rr_t^j = i_t - \ln(F_t^j/S_t^j)$$

where,

rr_t^j = the own-commodity real rate at time t for commodity *j*,

$\ln(F_t^j/S_t^j)$ = the ex-ante rate of change of commodity *j* -- i.e., the logarithmic basis,

F_t^j = the futures price at time t for delivery of commodity *j* at time t+1,[9]

S_t^j = the spot price at time t for commodity *j*.

An attractive feature of the own-commodity real rate rr_t^j defined above is that it is directly observable at time t and does not require any assumption about expectations formation, such as rational expectations, in order to be measured. This enables the researcher to examine a more complete specification of the stochastic process of the own-commodity real rate which involves how the variability of real rates evolves over time.

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[8] Note that all returns, inflation, and interest rates in this paper are continuously compounded, so that no second-order terms are needed in equation (1).

[9] Strictly speaking, F_t^j in equation (1) should be the price of a forward contract rather than a futures contract. As Black (1976) has pointed out, futures contracts are priced differently from forward contracts. However, this difference should be minor relative to movements of real interest rates. To the extent that prices of forward contracts and futures contracts differ, this is just one more reason why futures market data may not provide reliable information about the behavior of real interest rates.

To see how own-commodity real rates are linked to the real interest rate, we can note, as in Cornell and French (1986), that if futures markets existed for all commodities in the commodity bundle of the aggregate price index, then the riskless real interest rate for the aggregate economy, rr_t, can be written as a weighted average of all the own-commodity real rates.

$$(2) \qquad rr_t = \sum_{j=1}^{n} \omega_j rr_t^j = i_t - \sum_{j=1}^{n} \omega_j \ln(F_t^j/S_t^j)$$

where,

rr_t = the (aggregate) real interest rate,

n = the number of commodities in the economy,

ω_j = the expenditure weight for commodity j -- i.e., the relative expenditure on commodity j in the futures commodity bundle -- where $\sum_{j=1}^{n} \omega_j = 1$.

From (1) and (2), we can immediately see that the own-commodity real rate for commodity j is equal to the aggregate real interest rate plus the ex-ante relative price movement for commodity j: i.e,

$$(3) \qquad \begin{aligned} rr_t^j &= rr_t - [\ln(F_t^j/S_t^j) - \sum_{j=1}^{n} \omega_j \ln(F_t^j/S_t^j)] \\ &= rr_t - \phi_t^j \end{aligned}$$

where,

ϕ_t^j = the ex-ante relative price movement for commodity j at time t.

We can thus think of each own-commodity real rate as a measure of the aggregate real interest rate which is subject to a measurement error of ϕ_t^j, the ex-ante relative price movement.

It is important to point out that there is a possibility that an own-commodity real rate may contain no information about the real interest rate. Suppose that a commodity is storable at zero cost and there are no restrictions on selling this commodity short in the spot market. Then this commodity will be subject to a cash-and-carry arbitrage condition in which the percentage difference between the forward rate and the spot rate must equal the nominal interest rate. In this case, the own-commodity real rate will necessarily be constant and equal to zero. For commodities that are likely to be subject to cash-and-carry, own-commodity real rates should not be very helpful for learning about the behavior of real interest rates.

The real interest rate usually studied in the literature is the ex-ante real return on a nominally riskless bond, which is defined as,

$$(4) \qquad rr_t^* = i_t - \pi_t^e$$

where,

rr_t^* = the expected real return at time t of a one-period bond maturing at time t+1,

π_t^e = the expected rate of change (at time t) in the aggregate price level from time t to t+1.

Note that this real interest rate is not riskless in real terms because there is uncertainty about the inflation rate. It will thus differ from the riskless real interest rate, rr_t, by a risk premium. If this risk premium is small relative to the movements in real interest rates as seems likely, then it is reasonable to assume that $rr_t = rr_t^*$, and to simplify the discussion, we will treat them as identical below.

The real interest rate in (4) is not observable because π_t^e is unobservable, but, as discussed in Mishkin (1981a), we can examine the ex-post real rate which is defined as,

$$eprr_t = i_t - \pi_t \tag{5}$$

where,

$eprr_t$ = the realized real return on the one-period bond held from time t to t+1,

π_t = the change in the aggregate price level from time t to t+1.

The ex-post real rate can be written in terms of the real interest rate as,

$$eprr_t = i_t - \pi_t^e - (\pi_t - \pi_t^e) = rr_t - \epsilon_t \tag{6}$$

where,

$\epsilon_t = \pi_t - \pi_t^e$ = the forecast error of inflation.

The equation above thus tells us that the ex-post real rate is just equal to the real interest rate plus an error term which is the forecast error of inflation.

Two disadvantages of using ex-post real interest rate data to examine the behavior of real interest rates are readily understandable from the equation above. The presence of the ϵ_t forecast error of inflation term in ex-post real rates means that the researcher cannot directly examine how the variability of the real interest rate changes over time. Specifically, without knowledge about the variability of inflation forecast errors, information about the variability of the real interest rate cannot be directly extracted from information about the variability of the ex-post real interest rate. The second disadvantage stems from the fact noted in Mishkin (1981a) that the presence of the ϵ_t inflation forecast error term implies that statistical tests using ex-post real rates will have low statistical power. Equation (3) and our discussion of own-commodity real rates indicates, however, that they are also subject to a similar disadvantage. Specifically, for both ex-post real rates and own-commodity real rates there is a signal to noise problem. For own-commodity real rates, the noise is the ex-ante relative price movement, ϕ_t^j, while for ex-post real rates, the noise is the inflation forecast error, ϵ_t. If the ex-ante relative price movements, ϕ_t^j, are far greater in magnitude than movements in the real interest rate, then examining own-commodity real rates is unlikely to help us understand the behavior of real interest rates. Furthermore, if the variance of ϕ_t^j greatly exceeds the variance of ϵ_t, then we are likely to obtain better information about the behavior of real interest rates from using ex-post real rate data than from own-commodity real rate data constructed using futures market data.

Now that we understand the issues relating to the advantages and disadvantages of using futures market data, we can go on to examine what the data on own-commodity actually looks like.

III.
An Examination of the Own-Commodity Real Rate Data

The futures market data were obtained from the Center for the Study of Futures Markets, Columbia Business School. The empirical analysis requires a choice of non-financial commodities with equal spacing between contracts that also were traded for a substantial period both before and after October 1979. Precious metals are not included in the study because they are most likely to be subject to cash-and-carry arbitrage which implies that they will contain little information about real interest rates. These criterion lead to the selection of five commodities: live cattle (id #2), live hogs (id #4), soybeans (id # 17), frozen orange juice (id # 12), and lumber (id # 27). The sample period for cattle, hogs and soybeans extends from January or February, 1967 until January or February 1986. Because earlier data was not available, the sample period for orange juice extends from January 1968 until January 1986, while that for lumber is from January 1971 until January 1986.

These commodities have contracts maturing every two months, so that the observation interval and holding period for the own-commodity real rates is two months long. In calculating the logarithmic basis (i.e., the ex-ante rate of change in the commodity price), it is important to make sure that the future and spot prices pertain to the exact same commodity. Thus the futures price for the maturing contract is used as the spot price for the commodity. For example, the logarithmic basis for cattle (at an annual percentage rate) in February, 1967 is calculated as 600 times the log of the April futures price at the closing on January 31, 1967 minus the log of the February futures price at the closing on

January 31, 1967. The nominal interest rate is computed as a continuously compounded percentage rate at an annual rate from beginning of month prices of U.S. Treasury bills with two months to maturity (obtained from the Center for Research in Security Prices at the University of Chicago). For the February, 1967 own-commodity real rate, the nominal interest rate is 600 times the log of 100 minus the two-month bill price at the closing on January 31, 1967.

Figures 1 to 5 plot the own-commodity real rates for the five commodities. The most prominent feature of the own-commodity real rates is their tremendous variability.[10] The own-commodity rates often are outside the range ± 50% (annual rate) and the standard deviations for the five commodities are:

Cattle	Hogs	Soybeans	Orange Juice	Lumber
25.9%	41.7%	16.1%	28.5%	39.2%

As a comparison, Figure 6 contains the ex-post real rate calculated using aggregate price level data (the CPI), as well as a measure of the ex-ante aggregate real rate calculated using the procedure found in

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[10] Because the high variability of own commodity real rates is so striking, I did check outliers in the data for accuracy by comparing the Center for Futures Markets data with published quotes in the Wall Street Journal. In no case did I find a discrepancy between the two data sources. Furthermore, although at first glance it might appear as though the tremendous variability of an own-commodity real rate implies an unexploited profit opportunity, closer inspection of the market suggests that this is unlikely. For example, Bruce Hamilton has pointed out to me that the variability of the own-commodity real rate for hogs (which is the highest of the five commodities) is exactly what might be expected because hogs must be slaughtered at a specific point in their lives in order to get a good price for their meat.

Figure 1

Own Commodity Real Rate: Cattle 67–85

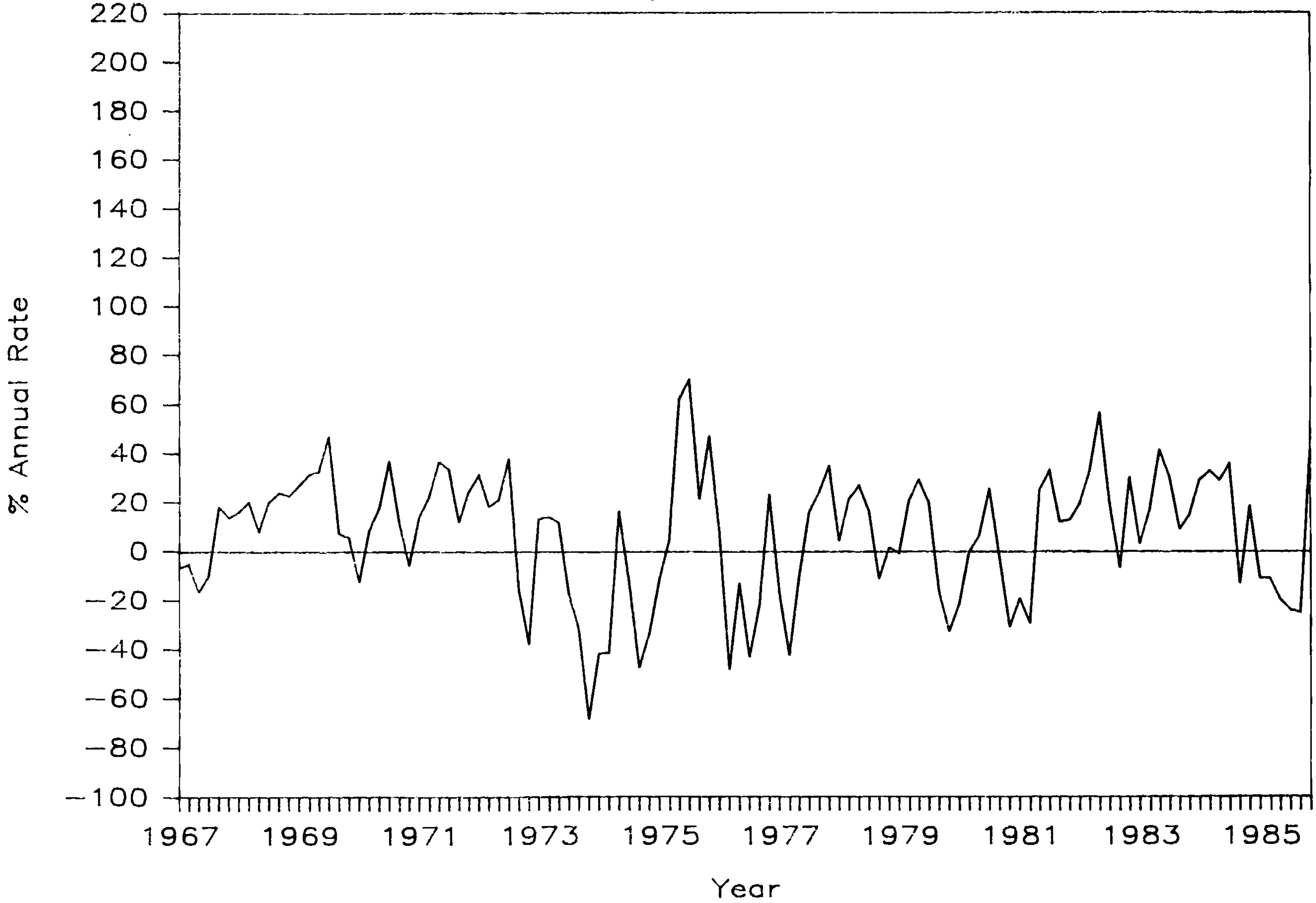


Figure 2

Own Commodity Real Rate: Hogs 67–85

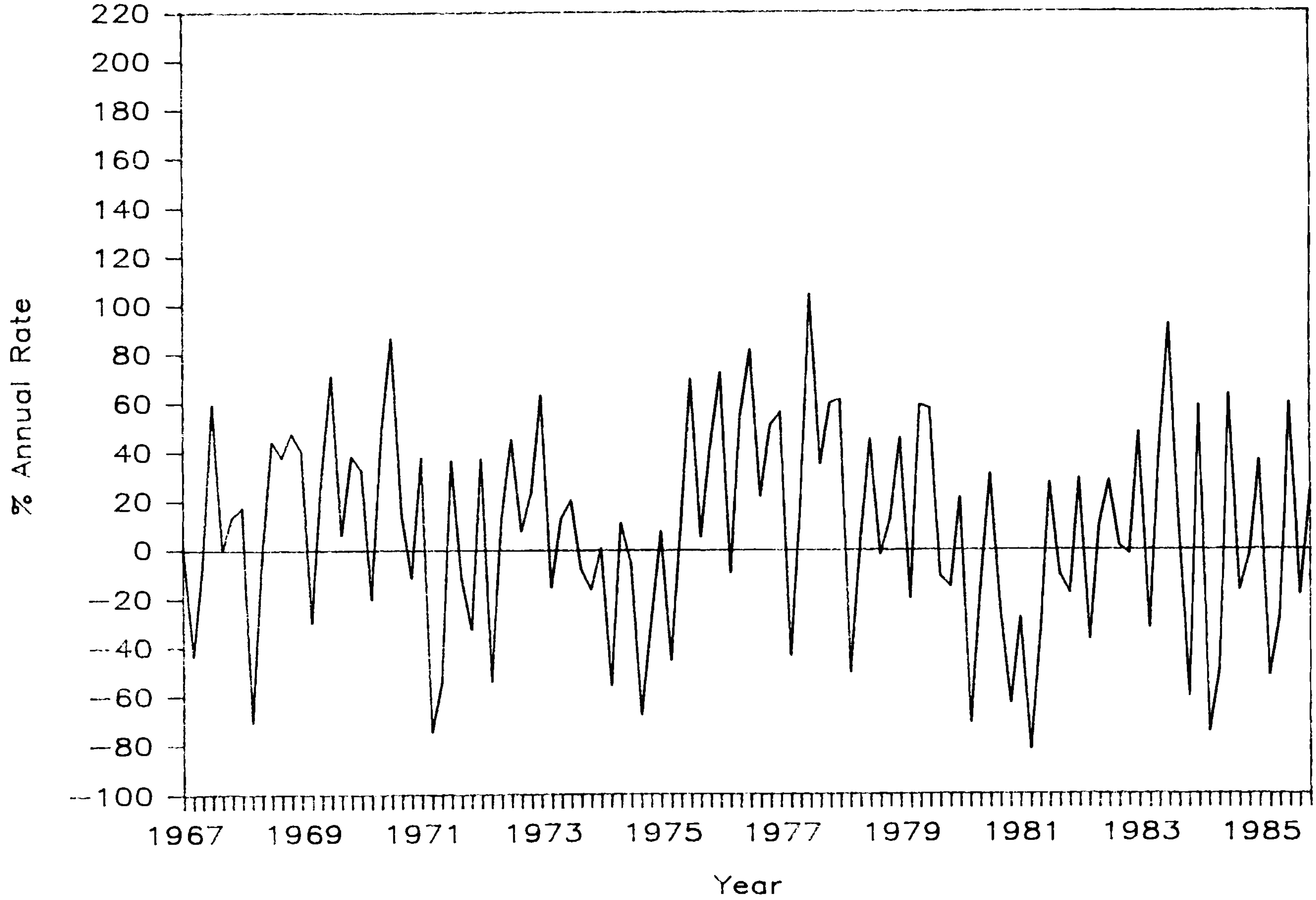


Figure 3

Own Commodity Real Rate:Soybeans 67–85

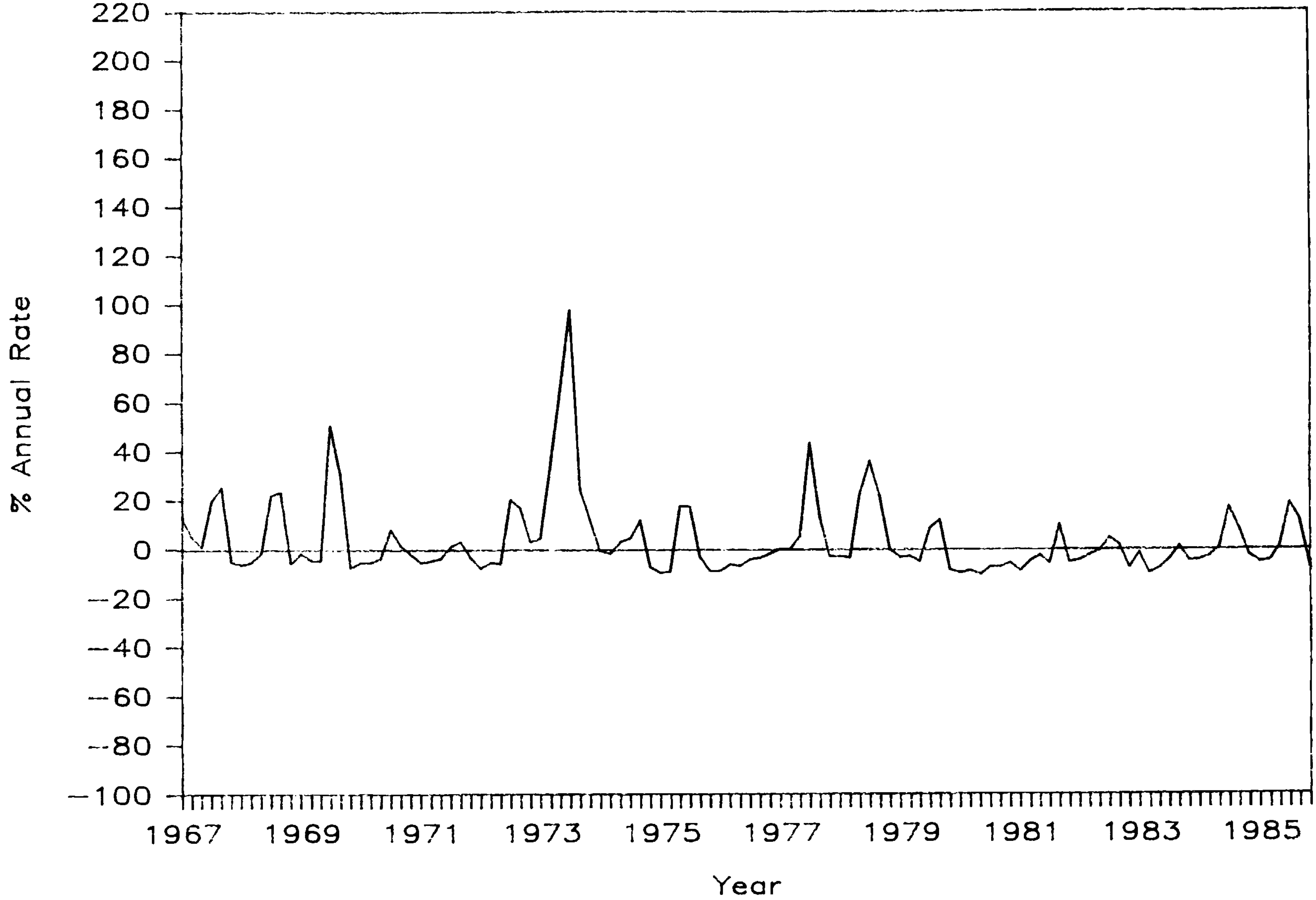


Figure 4

Own Commodity Real Rate:Orange Juice

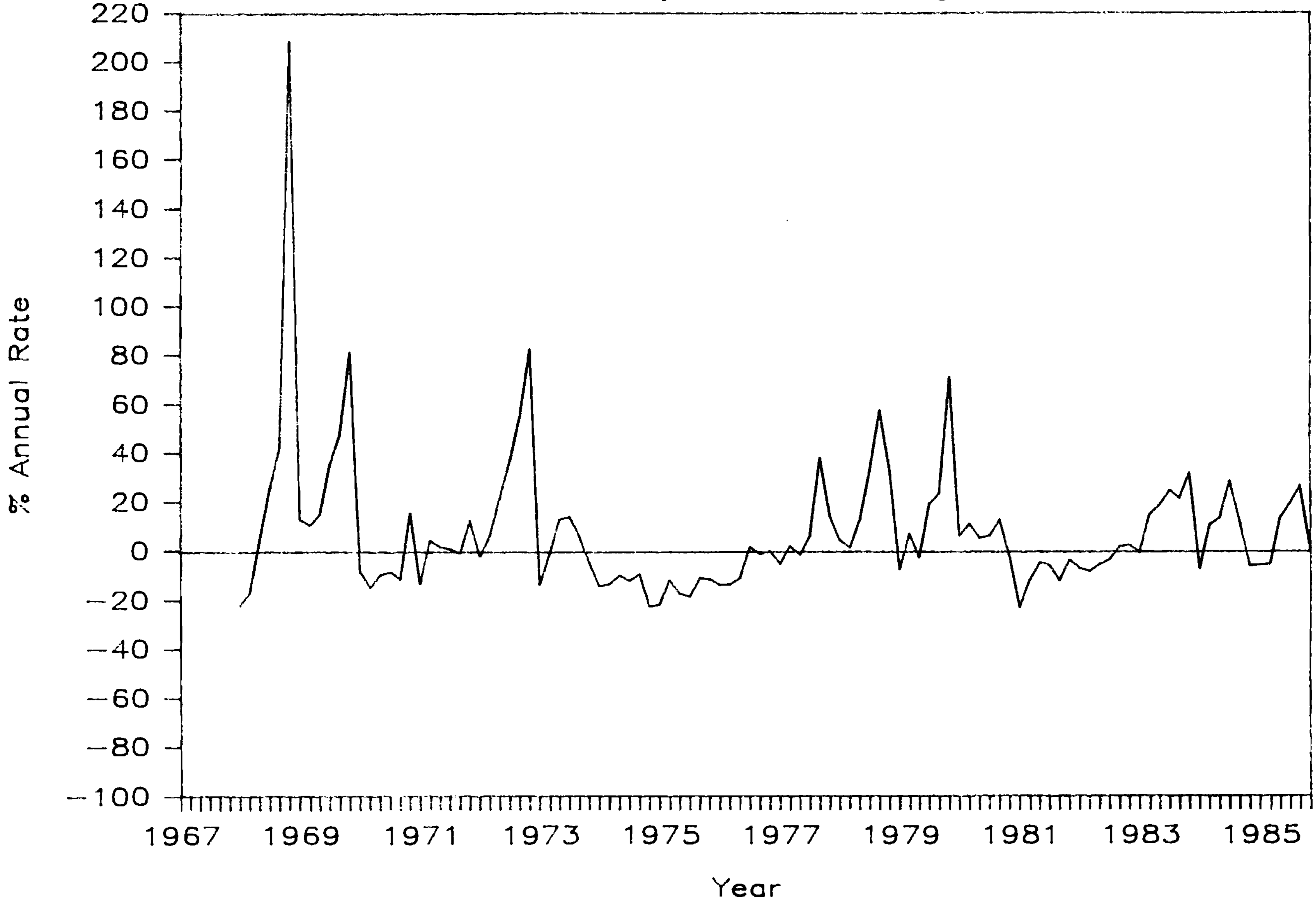


Figure 5

Own Commodity Real Rate: Lumber 71–85

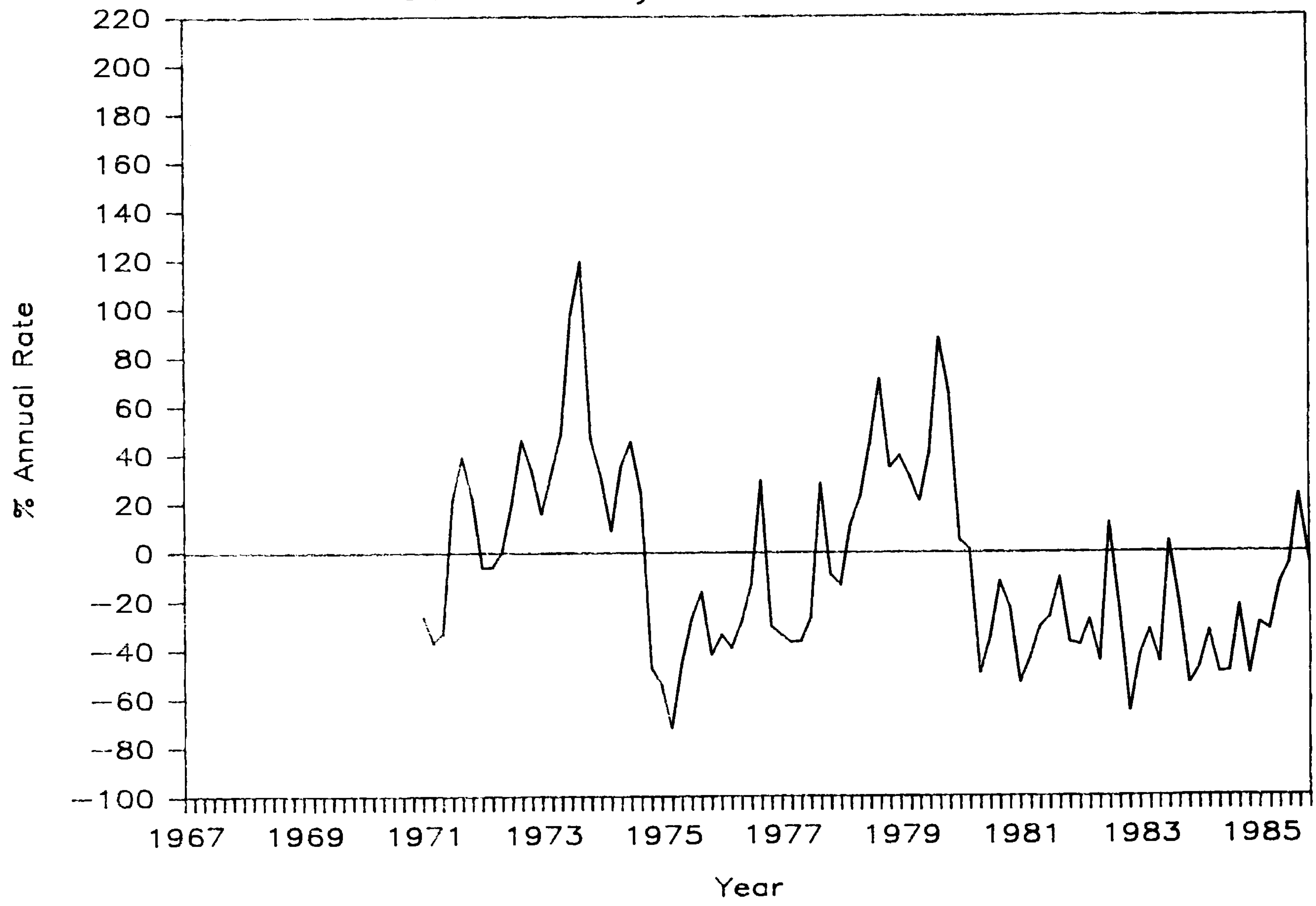
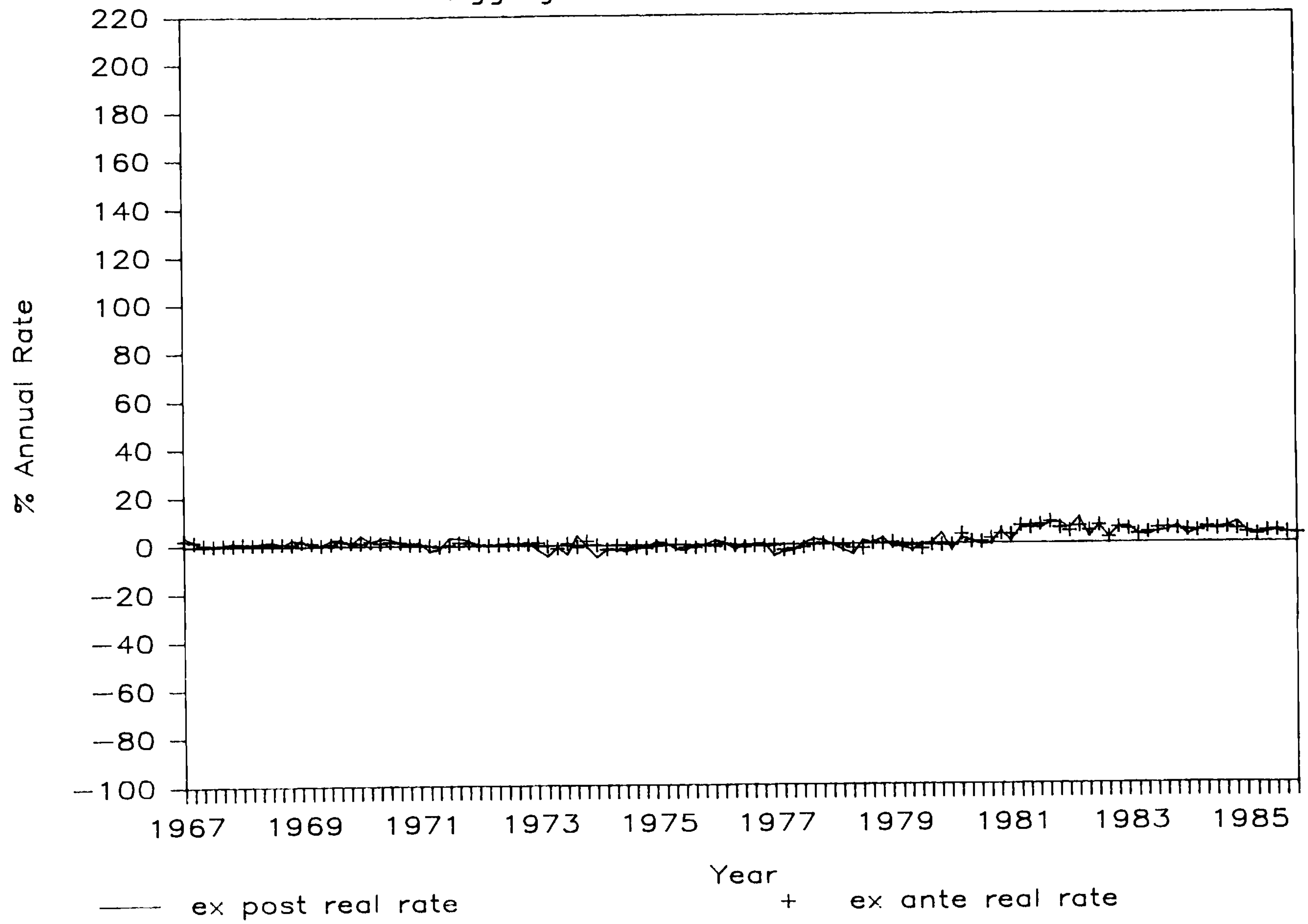


Figure 6

Aggregate Real Interest Rate:67–85



Huizinga and Mishkin (1986) with similar data.[11] Not only is the variability of the ex-ante aggregate real rate orders of magnitude smaller than those of the own-commodity rates, but this is also the case for the ex-post aggregate real rate: the standard deviation of the ex-ante aggregate real rate is 2.6%, while it is 3.2% for the ex-post aggregate real rate.

As discussed in the methodology section, the ex-post aggregate real interest rate differs from the ex-ante aggregate real interest rate by the forecast error of inflation. On the other hand, the own-commodity real rate differs from the ex-ante aggregate real rate by the amount of the ex-ante relative price movements for the specific commodity. Thus which method gives more accurate inference about the behavior of real interest rates depends on whether the noise represented by the ex-ante relative price movements is greater than the noise attributable to the forecast error of inflation. The standard deviations of the own-commodity real rates and the ex-post aggregate real rate does provide us with information about the relative size of the noises. The upper bound on the standard deviations of the forecast error of inflation equals the

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[11] The ex-ante real rate measure is a fitted value from ex-post real rate regressions using the same breakpoints as Huizinga and Mishkin (1986) with the two-month Treasury bill rate, two lags of the inflation rate and one lag of a supply shock variable as explanatory variables. The observation interval and holding period is two months long and the sources of the data are the same as in Huizinga and Mishkin (1986).

[12] This result follows from the fact that under rational expectations the forecast error of inflation is uncorrelated with the ex-ante aggregate real interest rate so that the variance of the ex-post real rate equals the variance of the ex-ante real rate plus the variance of the forecast error of inflation. Therefore, the maximum possible standard deviation of the forecast error of inflation occurs when the standard deviation of the ex-ante aggregate real rate is zero and it is equal to the standard deviation of the ex-post real interest rate.

standard deviation of the ex-post real interest rate, 3.2%.[12] The lower bound on the standard deviations of the ex-ante relative price movements can be computed using the fact that the minimum possible variance of the ex-ante relative price movements occurs when the variance of the ex-ante aggregate real rate is at its upper bound and there is perfect correlation between the ex-ante relative price movements and the ex-ante aggregate real rate.[13] The lower bounds for the standard deviations of the ex-ante relative price movements for the five commodities are:

Cattle	Hogs	Soybeans	Orange Juice	Lumber
22.7%	38.6%	13.0%	25.4%	36.0%

All of these standard deviation are many times greater than the upper bound for the standard deviation of the forecast error of inflation of 3.2%. Hence, the data indicates that the noise in the own-commodity real rates is many times greater than the noise in the ex-post aggregate real rate. Indeed, on average, the variation in the ex-ante relative price movements seems to be on the order of at least 100 times greater than the variation in the forecast errors of inflation. Therefore, futures

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[13] As is shown in the subsequent footnote, the upper bound on the variance of the ex-ante aggregate real rate equals the standard deviation of the ex-post aggregate real rate, 3.2%. Denoting the ex-ante relative price movement for commodity j as ϕ^j, the relationship between the minimum possible standard deviation of the ex-ante relative price movements as $\sigma[\phi^j]_{min}$, the standard deviation of the own-commodity rate as $\sigma[rr^j]$ and the upper bound on the standard deviation of the ex-ante aggregate real rate as $\sigma[rr]_{max}$, we can describe the relationship between these variables as follows:

$$\sigma^2[rr^j] = \sigma^2[rr]_{max} + 2\sigma[\phi^j]_{min}\sigma[rr]_{max} + \sigma^2[\phi^j]_{min}$$

Solving this equation, the lower bound for the standard deviation of the ex-ante relative price movements simplifies to:

$$\sigma[\phi^j]_{min} = \sigma[rr^j] - \sigma[rr]_{max}$$

market data is unlikely to provide as reliable information about the behavior of the ex-ante aggregate real interest rate as ex-post aggregate real interest rate data does.

Since the upper bound for the standard deviation of the ex-ante aggregate real rate equals the standard deviation of the ex-post aggregate real interest rate,[14] 3.2%, the calculations above can be interpreted in a slightly different way. Ex-ante relative price movements (the noise) are on the order of over 100 times more variable than the aggregate real interest rate (the signal). Since the signal to noise ratio is apparently less than 1%, own-commodity real rates constructed with futures market data are unlikely to be useful in examining the behavior of aggregate real interest rates.

Another way of examining the value of own-commodity real rate data is to see whether this data confirms two widely accepted facts about the behavior of aggregate real interest rates since October 1979. The first fact is that aggregate real interest rose after October 1979 to levels well above those in the mid to late 1970s. We see evidence of this in Figure 6 where the measure of the ex-ante aggregate real rate averaged -0.8% from the beginning of 1975 until October 1979, while after October 1979 it averaged 4.5%. The conclusion that ex-ante aggregate real interest rates rose sharply after October 1979 is also supported by other methods for measuring the ex-ante aggregate real interest rate, such as those using survey measures of expected inflation. The second fact is the increase in variability of ex-ante aggregate real rates after Oc-

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[14] As we have seen in footnote 12, the the variance of the ex-ante real rate equals the variance of the ex-post real rate minus the variance of the forecast error of inflation. The upper bound on the variance of the ex-ante real rate is then reached when the variance of the forecast error of inflation is assumed to be zero; i.e., when the upper bound equals the variance of the ex-post real rate.

tober 1979: From the beginning of 1975 to October 1979, the standard deviation of the ex-ante real rate measure in Figure 6 is .8%, and after October 1979 it is 2.2%. These two facts about the behavior of ex-ante real interest rates seem to be accepted by almost all economists,[15] and yet they are not at all evident in the own-commodity real rate data.

In Figures 1 to 5, we see that, rather than rising after October 1979, there was some tendency for the own-commodity real rates to fall, with three of the own-commodity real rates (hogs, soybeans and lumber) falling into the negative range on average. The average values of the own-commodity real rates for the five commodities in the 1975 to October 1979 period and the post-October 1979 period are as follows:

Average Levels of Own-Commodity Real Rates

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
1975 to October 1979	1.8%	18.5%	3.7%	.9%	.0%
post-October 1979	9.0%	-4.2%	-2.1%	6.7%	-25.3%

Furthermore, the variability of the own-commodity real rates fall after October 1979 rather than rise, as can be seen below.[16]

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[15] To my knowledge, there has not been any serious disagreement with them.

[16] The finding here is however consistent with the evidence in Parks (1978) who suggests that there is a positive correlation between the level of inflation and relative price variability. Since the inflation level fell after October 1979, relative price variability would be expected to fall and this would be reflected in lower standard deviations of own-commodity real rates.

Standard Deviations of the Own-Commodity Real Rates

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
1975 to October 1979	30.7%	43.0%	12.8%	18.5%	39.3%
post-October 1979	24.1%	42.7%	7.2%	6.9%	25.8%

Since the behavior of the own-commodity real rates before and after October 1979 seems to be at odds with what most analysis suggests occurred for ex-ante aggregate real rates, we have further evidence that using futures markets to examine real interest rate behavior may not be particularly illuminating.

IV.
An Econometric Analysis of Own-Commodity Real Rate Behavior

One of the most striking economic phenomena in recent years is a major shift in the stochastic process of real interest rates in October 1979 which resulted in their sharp rise in the 1980s to levels unprecedented in the postwar period. Huizinga and Mishkin (1986) document a highly, statistically significant shift in the stochastic process in October 1979,[17] but they cannot examine all the features of the stochastic process because their use of ex-post real rate data does not allow them to examine the variability of ex-ante real rates. Own-commodity

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[17] Additional evidence in Clarida and Friedman (1984) and Roley (1986) is consistent with the Huizinga-Mishkin findings; these papers document a shift in the stochastic process of nominal interest rates when the monetary regime changes in October 1979.

real rate data does have the advantage that it allows direct statistical tests on the variability of own-commodity real rates. Thus, even though our results so far on the value of own-commodity real rate data for examining aggregate real interest rates are negative, we should see if econometric techniques that take advantage of the special features of own-commodity real rate data provide useful results.

Here the behavior of own commodity real rates are examined with a variant of the Huizinga-Mishkin methodology which is expanded to allow for direct tests on the variability of own-commodity real rates. A linear stochastic process of the own commodity real rate is described by,

$$rr_t^j = X_t\beta^j + u_t^j \tag{7}$$

where,

X_t = a vector of variables whose values are known at time t,

u_t^j = an error term which by construction is defined to be orthogonal to X_t.

A key feature of the own-commodity real rate is that it is observable and does not involve an additional ε error term representing the forecast error of inflation, as is the case for ex-post aggregate real rate data.

The absence of the ε error term allows the researcher to examine a more general specification of the stochastic process in which the variance of u_t^j changes over time. One convenient characterization of the time-series process describing the variance of u_t^j is with the Autoregressive Conditional Heteroscedasticity (ARCH) model outlined by Engle (1982), where

$$\text{(8)} \qquad var(u_t^j) = \alpha_0 + \sum_{i=1}^{p} \alpha_i (u_{t-i}^j)^2$$

The stochastic process of the own-commodity real rate described by equations (7) and (8) can be estimated by maximizing the log-likelihood[18]

$$\text{(9)} \qquad \ln(L) = -(N/2)\ln(2\pi) - \sum_{i=1}^{N} 1/2\ (\ln[var(u_t^j)] - (u_t^j)^2/var(u_t^j))$$

where,

N = number of observations.

Tests for a shift in the stochastic process of the own-commodity real rates at October 1979 involve a likelihood ratio test not only for a change in the β-parameters from before and after October 1979 (as in Huizinga-Mishkin (1986)), but also for a change in the α-parameters which describe the ARCH process. The tests for a shift in the stochastic process thus examine not only whether the relationship of own-commodity real rates to past economic variables changes, but also whether the

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[18] In order for the ARCH process to have a finite variance and be covariance stationary, $\alpha_i \geq 0$ and the roots of the associated characteristic equation must be outside the unit circle. Therefore, these regularity conditions are imposed when maximizing the likelihood function.

underlying variability of own-commodity real rates changes. A second test for the most likely date of the shift in the stochastic process of real rates involves a procedure outlined by Quandt (1958,1960), in which the most likely date of the shift in the α and β parameters is estimated by finding the breakpoint that produces the highest value of the likelihood function. For each breakpoint, the following Quandt statistic is calculated:

$$(10) \qquad -2\,[\ln(L_n) - \ln(L_b)]$$

where,

$\ln(L_n)$ = the maximized log-likelihood for the ARCH model assuming no breakpoint,

$\ln(L_b)$ = the maximized log-likelihood for the ARCH model assuming that particular breakpoint.

The most likely date of the break then occurs when the Quandt statistic reaches its highest value.

The first step in the empirical analysis is specifying the stochastic process of the own-commodity real rates: specifically, the choice of the X-variables and the order of the ARCH process. One desirable feature of the ARCH model is that consistent estimates of the β-coefficients can be obtained from a least squares regression under the assumption that $\alpha_i = 0$ for all i. After using least squares to specify the X-variables, then the order of the ARCH process can be chosen using Lagrange-Multiplier tests described in Engle (1982) in which the squared residuals from the least squares regression are regressed on past lags of the squared residuals.

Least squares estimates of the stochastic processes of the own-commodity real rate revealed that a first-order autoregressive model with seasonal dummies adequately fit the data for both the pre and post-October 1979 sample periods.[19] The correlogram of the residuals indicated that the null hypothesis that the residuals are white noise could not be rejected, and in addition other economic variables such as the supply shock variable used in Huizinga and Mishkin (1986) were not found to have statistically significant additional explanatory power. These findings are consistent with those of Litterman and Weiss's (1985) study of real interest rates who also found that other economic variables and additional lags of real interest rates did not have significant additional explanatory power over a first-order autoregressive model.

The Lagrange-Multiplier (LM) tests for the order of the ARCH process could not reject the hypothesis of no conditional heteroscedasticity (i.e., $\alpha_i = 0$ for $i \geq 1$) in the case of hogs, orange juice, and lumber in both the pre and post-October 1979 sample periods. However, the LM tests did reveal significant conditional heteroscedasticity in the pre-October 1979 sample period for soybeans at lag 1 and for cattle at lags 2 and 5.[20]

Maximum likelihood estimates of the own-commodity real rate models

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[19] It should be noted that the additive seasonal model with seasonal dummies outperforms the Box-Jenkins (1970) multiplicative model. When seasonal autoregressive parameters were included with the seasonal dummies, the seasonal dummies remained statistically significant, while the seasonal autoregressive parameters were not significant.

[20] I also conducted Lagrange-Multiplier tests to see whether there was any conditional heteroscedasticity related to seasonality as represented by seasonal dummies. Only in the case of soybeans did I find any evidence of seasonal conditional heteroscedasticity. However, allowing for seasonal conditional heterosedasticity in tests for shifts in the stochastic process of the own-commodity soybean rate led to similar conclusions to those found in the text.

using the specifications suggested by the results above can be found in Tables 1 and 2.[21] For both the pre-October 1979 sample periods, the models show statistically significant serial correlation in the own-commodity real rates, with the coefficient of the lagged own-rate as high as .90. Furthermore, except in the case of lumber, the coefficient of the lagged own-rate does not appear to change appreciably from pre-October 1979 to post October 1979. As expected from the Lagrange-Multiplier tests, the variance of the error term in the models for cattle and soybeans displays statistically significant autoregressive coefficients for the pre-October 1979 period, but these coefficients decline appreciably in the post-October 1979 period.

Table 3 examines whether there was a major shift in the own-commodity real rate processes after the change in the monetary policy regime in October 1979. Because the linkage between monetary regime shifts and changes in the seasonality of commodities is not a major concern of monetary economics, Table 3 focuses only on likelihood ratio test for shifts in the non-seasonal parameters of the own-commodity real rate stochastic processes -- i.e., the constant, the lagged own rate and the α-parameters. (The results for tests of shifts in both the seasonal dummies and the non-seasonal parameters can be found in Appendix I.) The likelihood ratio tests in column 1 indicate that there is a statistically significant shift in the real rate process in October 1979 only for soybeans and orange juice; there is no such shift for cattle, hogs or lumber. In order to see whether shifts in the own-rate processes in October 1979 are unusual, we need to examine whether similar shifts

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[21] Note that equation (7) and (8) are estimated jointly in the maximum likelihood estimation here so that the reported standard errors do allow for conditional heteroscedasticity.

Table 1

Maximum Likelihood Estimates of Own-Commodity Real Rate Models:
Pre-October 1979 Sample Period

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
COEFFICIENTS					
Constant	-.33	14.73	-7.89	29.19	-37.49
	(4.03)	(5.84)	(2.94)	(8.21)	(6.29)
Dum2	1.99	11.94	3.54	-52.00	29.24
	(5.70)	(8.17)	(3.74)	(11.09)	(8.28)
Dum4	10.74	-78.85	8.04	-28.70	33.68
	(5.78)	(8.61)	(4.06)	(11.39)	(8.47)
Dum6	13.73	26.15	14.50	-26.18	46.53
	(5.82)	(8.98)	(4.01)	(11.25)	(8.54)
Dum8	12.43	31.13	27.63	-18.48	61.69
	(5.22)	(8.16)	(4.19)	(11.15)	(8.29)
Dum10	-8.50	-47.69	14.16	-14.05	64.94
	(6.57)	(9.31)	(4.41)	(11.03)	(7.89)
Lagged Own Rate	.59	.63	.39	.42	.90
	(.08)	(.09)	(.11)	(.11)	(.06)
α_0	90.79	408.72	65.02	693.67	256.95
	(42.87)	(65.88)	(19.80)	(116.43)	(49.92)
α_1			.61		
			(.35)		
α_2	.36				
	(.16)				
α_5	.42				
	(.19)				
LOG LIKELIHOOD	-331.11	-340.76	-290.26	-332.99	-222.25

Dum2 = 1 for January or February observation, 0 otherwise; Dum4 = 1 for March or April observation, 0 otherwise; Dum6 = 1 for May or June observation, 0 otherwise; Dum8 = 1 for July or August observation, 0 otherwise; Dum10 = 1 for September or October observation, 0 otherwise.
Standard errors of coefficients in parentheses.

Table 2

Maximum Likelihood Estimates of Own-Commodity Real Rate Models:
Post-October 1979 Sample Period

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
COEFFICIENTS					
Constant	5.71 (6.25)	-15.61 (8.75)	-8.36 (2.69)	7.09 (5.25)	-25.88 (6.58)
Dum2	-4.01 (9.14)	53.69 (12.92)	5.16 (4.96)	-4.37 (7.30)	7.40 (10.17)
Dum4	6.68 (9.81)	-53.14 (14.04)	5.32 (4.34)	-1.82 (7.74)	17.90 (10.41)
Dum6	18.21 (10.52)	25.20 (14.79)	7.56 (4.48)	-1.06 (7.43)	2.90 (10.18)
Dum8	5.74 (9.22)	71.00 (12.65)	13.70 (3.17)	1.12 (7.32)	31.77 (10.59)
Dum10	-21.93 (10.19)	-14.05 (15.97)	10.91 (3.98)	-2.76 (7.28)	24.37 (9.88)
Lagged Own Rate	.53 (.11)	.39 (.16)	.43 (.20)	.52 (.14)	.57 (.10)
α_0	181.81 (102.36)	516.47 (120.09)	25.49 (8.02)	171.42 (39.86)	302.00 (70.22)
α_1			.00 (.19)		
α_2	.67 (.62)				
α_5	.00 (.00)				
LOG LIKELIHOOD	-159.23	-168.07	-112.41[a]	-147.67	-158.14

[a]This particular model was not well-behaved because the α_1 coeffcient exceeds one if the regularity condition $0 \leqq \alpha_1 < 1$ was not imposed during estimation. The model estimates reported here are for a local maximum in which α_1 is near zero. [illegible] estimates are reported because the model without seasonal dummies produces a global maximum at an α_1 near zero and [illegible]ause the OLS consistent estimate of α_1 was also near zero.

Table 3

Likelihood Ratio Tests for Shifts in the Non-Seasonal Parameters of the Own-Commodity Real Rate Processes

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
Shift in October 1979	$\chi^2(5)=4.68$ (.4564)	$\chi^2(3)=2.59$ (.4599)	$\chi^2(4)=15.77$** (.0034)	$\chi^2(3)=14.12$** (.0028)	$\chi^2(3)=2.32$ (.5091)
Shift in middle of Pre-October 1979 Sample Period	$\chi^2(5)=4.51$ (.4782)	$\chi^2(3)=.14$ (.9864)	$\chi^2(4)=4.15$ (.3857)	$\chi^2(3)=13.04$** (.0045)	$\chi^2(3)=3.96$ (.2653)
Shift in middle of Post-October 1979 Sample Period	$\chi^2(5)=9.44$ (.0929)	$\chi^2(3)=7.43$ (.0594)	$\chi^2(4)=1.96$ (.7435)	$\chi^2(3)=2.19$ (.5336)	$\chi^2(3)=.6635$ (.8818)

Marginal significance levels in parentheses.

* = significant at the 5% level

** = signficant at the 1% level

occur in both the pre and post-October 1979 sample periods. Likelihood ratio tests for shifts in the middle of the pre-October 1979 and the middle of the post-October 1979 sample periods are found in the second and third rows of Table 3. Although, there are no significant shifts in the own-rate processes in the post-October 1979 sample period, there is strong evidence of instability in the real rate process for orange juice in the pre-October 1979 period. The evidence in Table 3 is thus much less clear-cut on the linkage between the monetary regime shift in October 1979 and shifts in the stochastic process of own-commodity real rates than is the Huizinga-Mishkin (1986) evidence using aggregate price level data.

The evidence on dating the breakpoint in Table 4 also does not provide clear-cut support for the proposition that own-commodity real rates are linked to the monetary regime shift in October 1979. The rows of the table show for each commodity the value of the Quandt statistic at different breakpoints surrounding the October 1979 date.[22] (Recall that the most likely breakpoint occurs when the Quandt statistic reaches a peak.) Not only is October 1979 not chosen as the most likely date for the breakpoint for any of the commodities, but the dating of the most likely breakpoint (marked by the box around the highest Quandt statistic) differs substantially from one commodity to the other.

The results with own-commodity real rate data thus do not reveal the shift in the stochastic process of real interest rates which has been documented elsewhere. This failure of own-commodity real rate data to reveal this shift in the real rate process indicates that any advan-

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[22] Note that search for a second breakpoint is not conducted here as in Huizinga and Mishkin (1986) because the likelihood ratio tests in the third row of Table 3 did not reveal significant instability in the own-rate processes in the post-October 1979 sample period.

Table 4

Quandt Statistics for Dating Breakpoints in the
Non-Seasonal Parameters of the Own-Commodity Real Rate Processes

		Cattle	Hogs	Soybeans	Orange Juice	Lumber
1978	1/2	5.13	2.51	11.53	$\boxed{20.54}$	.93
	3/4	5.51	2.03	10.67	19.27	.72
	5/6	5.46	2.33	23.14	18.22	.83
	7/8	4.84	2.60	$\boxed{23.88}$	17.90	1.11
	9/10	4.62	3.01	22.40	20.22	1.25
	11/12	4.36	3.31	20.98	19.37	1.62
1979	1/2	4.80	3.72	19.61	18.04	1.74
	3/4	4.75	4.27	18.37	17.02	2.12
	5/6	5.18	3.18	17.05	16.11	2.45
	7/8	5.28	2.50	15.72	15.26	2.91
	9/10	4.68	2.59	15.77	14.12	2.32
	11/12	4.71	2.92	14.99	19.21	$\boxed{3.75}$
1980	1/2	5.39	3.36	13.44	17.54	1.06
	3/4	6.30	3.47	11.89	16.44	1.25
	5/6	7.20	4.14	17.22	15.16	.73
	7/8	6.95	4.62	13.08	14.02	1.23
	9/10	7.05	4.99	17.40	12.84	1.25
	11/12	11.05	3.40	16.99	14.39	1.06
1981	1/2	13.49	4.10	15.95	13.15	1.51
	3/4	$\boxed{14.58}$	4.54	14.58	12.05	1.36
	5/6	12.54	$\boxed{6.02}$	17.80	10.96	1.19

Boxed statistic indicates most likely date of breakpoint.

tages of this data because it allows direct examination of variability is overcome by the disadvantages stemming from the fact that the noise in the data (ex-ante relative price movements) is orders of magnitude larger than the signal (aggregate real interest rate movements).[23]

V. Conclusions

Rarely in monetary/macro economics does empirical work pay sufficient attention to the quality of the data it is analyzing. This paper is an attempt to be an exception since it asks whether a particular data set is appropriate for answering an important set of questions. The analysis here explores several pieces of evidence which provide information on the usefulness of own-commodity real rates constructed from futures market data for understanding the behavior of real interest rates. The evidence can be summarized as follows:

1. The noise in own-commodity real rates (the ex-ante relative price movements) is so large relative to the signal (the aggregate real interest rate) that own-commodity real rates are unlikely to contain much information about aggregate real interest rates.

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[23] Even though individual own-commodity real rates do not help us understand the behavior of real interest rates, it is possible that combining the information from the own-commodity real rates will prove more successful. However, as can be seen from the evidence in Appendix II, an optimal weighted average of the own-commodity real rates also provides little information about the behavior of real interest rates.

2. Data on own-commodity real rates is not consistent with several widely accepted facts about the behavior of aggregate real interest rates, indicating that own-commodity real rates can provide misleading information about aggregate real interest rates.
3. Econometric analysis of own-commodity real rate behavior fails to find a shift in the stochastic process which has been documented for aggregate real interest rates. The failure of own-commodity real rate data to reveal a shift in the real rate process indicates that any advantages of own-commodity real rate data for econometric analysis is overcome by the disadvantages stemming from the fact that the noise in the data is orders of magnitude larger than the signal.

The evidence in this paper thus casts serious doubt about some conclusions in recent papers that make use of futures market data to provide information about real interest rate behavior. Hamilton (1986) finds that during the contraction phase of the Great Depression the futures market in several commodities did not reveal expected price deflation -- in other words, the own-commodity real rate was not unusually high. He thus concludes that aggregate real interest rates were not high in the early years of the Depression and were therefore not a major transmission mechanism of contractionary monetary policy. The evidence in this paper suggests that this conclusion is unwarranted because own-commodity real rates do not reveal much information about aggregate real interest rates.[24]

Cornell and French (1986) study the response of own-commodity real rates to money supply announcements and conclude that six- and twelve-month aggregate real interest rates are positively correlated with unexpected components of money supply announcements. The key assumption in their analysis is that ex-ante relative price movements for the commodities they study are independent of the money supply announcement figure. Cornell and French provide no evidence that this key assumption is true. While nothing in this paper rules out their assumption, the evidence here does suggest that less than 1% of the variation in the own-commodity real rate data reflects aggregate real interest rates movements, while over 99% is due to ex-ante relative price movements. Hence, their results probably reflect information about ex-ante relative price movements rather than about aggregate real interest rates as they assume. This should make us very cautious about their findings.[25]

This paper would have a happier ending if it concluded that futures market data is useful for understanding real interest rate behavior. Instead, it indicates that a promising research line exploiting futures market data for analysing real interest rates is not so promising. In order to learn more about real interest rates, we

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[24] It should be pointed out that much of Hamilton's discussion of the Great Depression period does not depend on this conclusion and so the criticism here does not invalidate the basic points of Hamilton's very interesting paper.

[25] Cornell and French (1986) find only weak evidence that the response of real rate interest rates to money supply announcements shifts in October 1979. This finding is consistent with the inability of the econometric analysis of this paper to reveal a clear cut shift in the stochastic processes of own-commodity real rates in October 1979. As argued here, both of these findings may be a reflection of the problems with the own-commodity real rate data.

must pursue a different research route.

Appendix I

Table 3A

Likelihood Ratio Tests for Shifts in All Parameters of the Own-Commodity Real Rate Processes

	Cattle	Hogs	Soybeans	Orange Juice	Lumber
Shift in October 1979	$\chi^2(10)=7.34$ (.69)	$\chi^2(8)=17.96$** (.0216)	$\chi^2(9)=29.79$** (.0005)	$\chi^2(8)=24.89$** (.0016)	$\chi^2(8)=23.60$** (.0027)
Shift in Middle of Pre-October 1979 Sample Period	$\chi^2(10)=27.55$** (.0021)	$\chi^2(8)=9.00$ (.3425)	$\chi^2(9)=10.83$ (.2876)	$\chi^2(8)=60.00$** (4.7×10^{-10})	$\chi^2(8)=17.75$ (.0232)
Shift in Middle of Post-October 1979 Sample Period	$\chi^2(10)=16.95$ (.0754)	$\chi^2(8)=22.67$ (.0038)	$\chi^2(9)=10.88$ (.2840)	$\chi^2(8)=16.49$* (.0359)	$\chi^2(8)=8.88$ (.3526)

Marginal significance levels in parentheses.

* = significant at the 5% level

** = signficant at the 1% level

Table 4A

Quandt Statistics for Dating Breakpoints
in All Parameters of the Own-Commodity Real Rate Processes

		Cattle	Hogs	Soybeans	Orange Juice	Lumber
1978	1/2	19.94	13.44	18.72	31.34	10.70
	3/4	16.95	12.35	17.99	30.13	9.03
	5/6	18.81	12.59	33.63	28.89	11.19
	7/8	18.82	12.91	$\boxed{35.65}$	28.27	11.74
	9/10	15.55	13.38	35.49	31.99	13.53
	11/12	15.48	14.99	34.68	29.86	13.66
1979	1/2	11.01	14.98	33.14	28.86	14.52
	3/4	10.17	16.13	31.90	27.42	14.93
	5/6	10.13	19.33	29.06	26.63	14.89
	7/8	9.88	18.27	27.74	25.86	15.87
	9/10	7.34	17.96	29.79	24.89	23.60
	11/12	10.45	17.08	27.48	47.41	$\boxed{31.87}$
1980	1/2	14.56	17.58	29.74	$\boxed{48.72}$	25.25
	3/4	18.01	17.18	28.26	46.56	26.59
	5/6	20.14	17.27	23.68	45.23	17.93
	7/8	29.53	18.29	22.27	43.37	18.07
	9/10	29.47	18.50	22.22	41.79	17.60
	11/12	$\boxed{30.16}$	13.77	20.86	38.37	17.40
1981	1/2	25.52	18.98	20.32	37.81	17.93
	3/4	27.79	19.61	19.37	35.96	17.57
	5/6	13.68	$\boxed{19.68}$	17.79	34.34	17.76

Boxed statistic indicates date of most likely breakpoint

Appendix II

Does an Optimal Weighted Average of Own-Commodity Real Rates Provide Information About the Behavior of Real Interest Rates?

Nelson's (1972) discussion of jointly optimal linear composite predictions provides a methodology for examining this issue. Following Nelson, an optimal linear forecast of the aggregate real interest rate using _m_ own-commodity real rates can be obtained from the following regression equation

$$\text{(A1)} \qquad rr_t = c + \sum_{j=1}^{m} \gamma_j rr_t^j + \eta_t$$

(Note that the constant term is included if the own-commodity real rates are not unbiased predictors of the aggregate real interest rate, as is likely to be the case here.) Because the aggregate real interest rate is unobservable, this equation cannot be estimated to yield the optimal weights, γ_j. However, the ex-post real interest rate, $eprr_t$, is observable, and by equation (6) we know that it equals the aggregate real interest rate minus the forecast error of inflation, $rr_t - \epsilon_t$. Using the rational expectations assumption that the forecast error of inflation, ϵ_t, is uncorrelated with any information at time _t_ (which includes rr_t^j), the optimal weights γ can be estimated with ordinary least squares from the regression equation,

$$\text{(A2)} \qquad eprr_t = c + \sum_{j=1}^{m} \gamma_j rr_t^j + \eta_t - \epsilon_t$$

Fitted values from this regression equation can then be used as estimates of an optimal weighted average of the own-commodity real rates for the January 1971 to January 1986 sample period. Estimation of an ARCH model for the weighted average data then proceed as in the text and can be tested for shifts in non-seasonal parameters as in Table 3. The results for whether there is a shift in the real rate process in October 1979 is as follows: the likelihood ratio statistic is $\chi^2(4) = 7.76$ with a marginal significance level of .1008. The evidence using the weighted average data is no more successful in finding a linkage between the own-commodity real rate behavior and the monetary regime shift in October 1979 than are the individual commodity data.[26] Thus, the answer to the question asked in this appendix is no: An optimal weighted average of own-commodity real rates does not appear to provide substantial information about the behavior of real interest rates.

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[26] Likelihood ratio tests for shifts in the non-seasonal parameters of the ARCH model in the pre-October 1979 period and the post-October 1979 period also did not provide evidence that the parameters shift.

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