

NBER WORKING PAPERS SERIES

IS THE FISHER EFFECT FOR REAL?
A REEXAMINATION OF THE RELATIONSHIP BETWEEN
INFLATION AND INTEREST RATES

Frederic S. Mishkin

Working Paper No. 3632

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 1991

Research support has been provided by the Faculty Research Fund of the Graduate School of Business, Columbia University. I thank Ben Bernanke, Ron Gallant, Bruce Greenwald, Jordi Galli, Alastair Hall, Kevin Hassett, Ben McCallum, Pierre Perron, Mark Watson and participants in seminars at Columbia University, CUNY Graduate Center, North Carolina State University, Princeton University, Rice University, University of Maryland, and the University of Pennsylvania for helpful comments. The data in this paper will be made available free of charge to any researcher who sends me a standard formatted 5 1/4" 360KB diskette with a stamped, self-addressed mailer. This paper is part of NBER's research program in Financial Markets and Monetary Economics. Any opinions expressed are those of the author and not those of the National Bureau of Economic Research.

NBER Working Paper #3632
February 1991

IS THE FISHER EFFECT FOR REAL?
A REEXAMINATION OF THE RELATIONSHIP BETWEEN
INFLATION AND INTEREST RATES

ABSTRACT

The basic puzzle about the so-called Fisher effect, in which movements in short-term interest rates primarily reflect fluctuations in expected inflation, is why a strong Fisher effect occurs only for certain periods but not for others. This paper resolves this puzzle by reexamining the relationship between inflation and interest rates with modern time-series techniques. Recognition that the level of inflation and interest rates may contain stochastic trends suggests that the apparent ability of short-term interest rates to forecast inflation in the postwar United States is spurious. Additional evidence does not support the presence of a short-run Fisher effect but does support the existence of a long-run Fisher effect in which inflation and interest rates trend together in the long run when they exhibit trends.

The evidence here can explain why the Fisher effect appears to be strong only for particular sample periods, but not for others. The conclusion that there is a long-run Fisher effect implies that when inflation and interest rates exhibit trends, these two series will trend together and thus there will be a strong correlation between inflation and interest rates. On the other hand, the nonexistence of a short-run Fisher effect implies that when either inflation and interest rates do not display trends, there is no long-run Fisher effect to produce a strong correlation between interest rates and inflation. The analysis in this paper resolves an important puzzle about when the Fisher effect appears in the data.

Frederic S. Mishkin
Department of Economics
Fisher Hall
Princeton University
Princeton, New Jersey 08544

I. Introduction

The relationship between the level of interest rates and inflation is one of the most studied topics in economics. A standard view, which is commonly referred to as the Fisher effect, is that movements in short-term interest rates primarily reflect fluctuations in expected inflation, so that they have predictive ability for future inflation. Although the Fisher effect is widely accepted for the period after the Fed-Treasury Accord in 1951 until October 1979 in the United States,¹ this relationship between the level of short-term interest rates and future inflation is not at all robust. The level of short-term interest rates has no ability to predict future inflation in the United States prior to World War II² or in the October 1979 to October 1982 period.³ In addition, the Fisher effect is not found to be strong for many other countries even in the postwar period.⁴

The Fisher effect's lack of robustness raises two issues. First, it leaves us with the puzzle of why a strong Fisher effect occurs only for certain periods but not for others. Second, the Fisher effects lack of robustness should make us somewhat suspicious about its validity.

Recent developments in the time-series econometrics literature help resolve these two issues and explain why the Fisher effect is not robust. A large body of current work has focused on testing for stochastic trends in time-series and has studied the implications of stochastic trends on statistical

¹For example, Fama(1975), Nelson and Schwert (1977), Mishkin (1981,1988), Fama and Gibbons (1982).

²See, for example, Barsky (1987), Mishkin (1981) and Summers (1983).

³See Huizinga and Mishkin (1986a).

⁴Mishkin (1984).

inference.⁵ Research beginning with Nelson and Plosser (1982) indicates that many macroeconomic time series such as interest rates and inflation may be characterized as having stochastic trends. We are also by now familiar with the potential for misleading inference when variables have stochastic trends from the work on the spurious regression phenomenon by Granger and Newbold (1974) and Phillips (1986). Both these lines of research suggest that the evidence for the Fisher effect in the postwar United States needs to be reexamined.

This paper conducts such a reexamination and finds that the evidence does not support a short-run relationship between interest rates and future inflation. However, the nonexistence of a short-run Fisher effect does not rule out the possibility that there is a long-run Fisher effect in which inflation and interest rates share a common trend when they exhibit trends. This paper also conducts tests for cointegration along the lines of Engle and Granger (1987) to test for a common trend in interest rates and inflation, and it does find evidence for a long-run Fisher effect in the postwar U. S. data.

The above evidence resolves the puzzle of why the Fisher effect appears to be strong in some periods but not in others. The existence of a long-run Fisher effect implies that when inflation and interest rates exhibit trends, these two series will trend together and thus there will be a strong correlation between inflation and interest rates. Just as this analysis predicts, the Fisher effect appears to be strong in the periods when interest rates and inflation exhibit trends. On the other hand, when these variables do not exhibit trends, a strong correlation between interest rates and inflation will not appear if there is no short-run Fisher effect. Thus the presence of a long-run but not a short-run Fisher effect predicts that a Fisher effect will not be detectable

⁵See Stock and Watson (1988) for an excellent review of this topic.

during periods when interest rates and inflation do not have trends. It is exactly in these periods that we are unable to detect any evidence for a Fisher effect.

The next section describes the data used in the empirical analysis, which is followed by an empirical reexamination of the ability of interest rates to forecast future inflation. The section following then describes tests for long-run and short-run Fisher effects, and the paper ends with a set of conclusions.

II. The Data

The empirical analysis makes use of monthly data on inflation rates and one to twelve-month U.S. Treasury bills for the period February 1964 to December 1986.⁶ The sample starts with February 1964 because this is the first date that data on all the Treasury bills became available (twelve-month Treasury bills were not issued until late 1963). End of month T-bill data were obtained from the Center for Research in Security Prices (CRSP) at the University of Chicago. The one-month bill was defined to have a maturity of 30.4 days, the three-month bill 91.25 days, on up to the twelve month bill with a maturity of 365 days. For each defined maturity the interest rate was interpolated from the two bills that were closest to the defined maturity. In effect, this means that the slope of the term structure is assumed to be constant between these two bills.⁷ The interest rates are expressed on a con-

⁶Note that the need for up to twelve-month inflation rates in the empirical analysis requires CPI data through the end of 1987.

⁷Fama (1984) instead chooses a bill that has a maturity closest to six months and then keeps on taking the interest rate from this same bill every month as its maturity shortens in order to get interest rates on one to six-month bills. In effect, Fama is assuming that the slope of the term structure is flat around the chosen bill. The procedure for data construction in this paper, which

tinuously compounded basis at an annual rate in percent as are the inflation rates. The inflation data are calculated from a CPI series which appropriately treats housing costs on a rental-equivalence basis throughout the sample period. For more details on this series see Huizinga and Mishkin (1984, 1986).

The timing of the variables is as follows. A January interest rate observation uses the end of December bill rate data. A January observation for a one-month inflation rate is calculated from the December and January CPI data; a three-month inflation rate from the December and March CPI data; and so on.⁸

III. A Reexamination of the Methodology for Testing the Fisher Effect

In previous work, examination of the Fisher effect has involved testing for a significant correlation of the level of interest rates and the future inflation: i.e., testing for the significance of β_m in following regression equation (which can also be thought of as a forecasting equation).

$$(1) \quad \pi_t^m = \alpha_m + \beta_m i_t^m + \eta_t^m$$

assumes that the slope around the desired maturity is constant rather than zero, makes a less restrictive assumption than Fama's procedure. The differences between these two procedures, however, are very slight and make no appreciable difference to the results.

⁸The appropriate dating for the CPI is a particular month is not clear since price quotations on the component items of the index are collected at different times during the month. As a result, there is some misalignment of the inflation data and the interest rate data which is collected at the end of the month. In order to see if this misalignment could have an appreciable effect on the results, I also estimated the regressions in this paper lagging the interest rate data one period (i.e., for the January observation I used the end of November bill rate). The results with the lagged interest rate data are very similar to those found in the text and none of the conclusions of the paper changes.

where,

$$\begin{aligned}\pi_t^m &= \text{the } m\text{-period future inflation rate from time } t \text{ to } t+m. \\ i_t^m &= \text{the } m\text{-period interest rate known at time } t.\end{aligned}$$

One way of interpreting this regression is to assume that expectations are rational as in Fama (1975). Then it is easy to show that a test of the correlation of interest rates with future inflation is also a test for the correlation of interest rates and expected inflation.⁹ Alternatively, we can view the correlation of interest rates and future inflation as interesting in its own right.

In this section we will reexamine this methodology for testing the Fisher effect and show that it does not provide reliable evidence on the existence of the Fisher effect. The problem with this methodology is that it is subject to the spurious regression phenomenon described by Granger and Newbold (1974) and Phillips (1986) because both the right and left-hand-side variables in the regression equation above can be characterized as having unit roots.

⁹The correlation of the level of interest rates and expected inflation is examined by testing for the significance of β_m in the following regression:

$$(*) \quad E_t[\pi_t^m] = \alpha_m + \beta_m i_t^m + u_t^m$$

where,

$$E_t[\dots] = \text{the expectation conditional on all information available at time } t.$$

Under rational expectations, the realized future inflation rate can be written as,

$$\pi_t^m = E_t[\pi_t^m] + \epsilon_t^m$$

where the ϵ_t^m term, the forecast error of inflation, is orthogonal to any information known at time t which includes i_t^m . Combining these two equations results in equation (1) in which its error term η_t^m equals $\epsilon_t^m + u_t^m$. Since u_t^m is orthogonal to i_t^m by construction (this is what makes (*) a regression equation) and ϵ_t^m is also orthogonal to i_t^m under rational expectations, the η_t^m error term in (1) is also orthogonal to i_t^m and an ordinary least squares (OLS) estimate of β_m in the forecasting equation in (1) is a consistent estimate of β_m in equation (*).

Table 1 contains the estimates of the inflation forecasting equations for horizons of one, three, six, nine and twelve months.¹⁰ Panel A contains the results for the full sample period, February 1964 to December 1986, while Panels B, C and D contain the results for three sub-periods, February 1964 to October 1979, November 1979 to October 1982, and November 1982 to December 1986. The sample has been split into these three sub-periods because results in Clarida and Friedman (1984), Huizinga and Mishkin (1986a) and Roley (1986) suggest that the relationship of nominal interest rates and inflation shifted with the monetary regime changes of October 1979 and October 1982.

Note that because of serial correlation induced by the use of overlapping data, in which the horizon of the interest rate and the inflation rate is longer than the one month observation interval, standard errors of the OLS parameter estimates in equation (1) are generated in the analysis here using the method outlined by Hansen and Hodrick (1980), with a modification due to White (1980) and Hansen (1982) that allows for heteroscedasticity¹¹ and a modification by Newey and West (1987) that insures the variance-covariance matrix is positive definite by imposing linearly declining weights on autocor-

¹⁰All regression estimates and Monte Carlo results in this paper have been generated with the GAUSS programming language.

¹¹The Hansen (1982) modification is the same numerically as that proposed by White (1980). The Hansen modification applies when there is conditional heteroscedasticity while White's results are obtained with unconditional heteroscedasticity rather than conditional heteroscedasticity, but additional assumptions are required. The correction for heteroscedasticity is used here because Lagrange-multiplier tests outlined by Engle (1982) reject conditional homoscedasticity for the error term of the forecasting equation. The results were very similar to those reported in the text when a heteroscedasticity correction was not used in calculating the standard errors of the coefficient estimates.

Table 1
Estimates of Inflation Forecasting Equations

$$\pi_t^e = \alpha_m + \beta_m i_t^e + \eta_t^e$$

m (months)	α_m	β_m	R ²	SE	t-statistic for $\beta_m=0$
Panel A: February 1964 - December 1986 Sample Period					
1	1.2232 (0.4482)	0.5966 (0.0714)	0.207	3.200	8.36
3	1.4486 (0.5659)	0.5296 (0.0845)	0.248	2.669	6.27
6	1.7363 (0.7573)	0.4730 (0.1129)	0.237	2.465	4.19
9	2.1852 (0.9062)	0.4075 (0.1322)	0.189	2.428	3.08
12	2.5011 (1.0302)	0.3647 (.1485)	0.156	2.407	2.46
Panel B: February 1964 - October 1979 Sample Period					
1	-2.2721 (0.6330)	1.3746 (0.1216)	0.439	2.590	11.30
3	-2.2135 (0.6887)	1.2941 (0.1187)	0.549	1.976	10.90
6	-2.6634 (0.6739)	1.3236 (0.1117)	0.649	1.654	11.85
9	-2.6410 (0.7421)	1.3070 (0.1266)	0.657	1.595	10.32
12	-2.6099 (0.7906)	1.3009 (0.1332)	0.648	1.589	9.76

Table 1 Continued

m (months)	α_*	β_*	R ²	SE	t-statistic for $\beta_*=0$
Panel C: November 1979 - October 1982 Sample Period					
1	7.1035 (1.8326)	0.0890 (0.1552)	0.005	3.498	0.57
3	5.0256 (3.4120)	0.2353 (0.2526)	0.036	2.937	0.93
6	7.0521 (4.1291)	0.0356 (0.2887)	0.001	2.674	0.12
9	10.7631 (3.3672)	-0.2785 (0.2129)	0.055	2.382	-1.31
12	10.6754 (2.7065)	-0.2918 (0.1567)	0.064	2.239	-1.86
Panel D: November 1982 - December 1986 Sample Period					
1	-1.7349 (1.9260)	0.6341 (0.2362)	0.112	2.474	2.68
3	-0.1532 (1.6798)	0.4054 (0.1910)	0.099	1.806	2.12
6	1.2817 (1.7622)	0.2351 (0.1867)	0.077	1.301	1.26
9	1.8158 (1.7917)	0.1706 (0.1803)	0.061	1.109	0.95
12	2.4821 (1.5415)	0.0927 (0.1518)	0.024	1.017	0.61

Notes for Table 1:

Standard errors of coefficients in parentheses.

SE = standard error of the regression.

variance matrices.¹²

The t-statistics for β_m in the last column of Table 1 appear to indicate that one to twelve month Treasury bill rates contain a highly significant amount of predictive power for inflation. This finding is especially strong for the pre-October 1979 sample period (Panel B) where the t-statistics on the β_m coefficient range from 9.76 to 11.85. However, after October 1979, the one to twelve month interest rates contain much less information about future inflation. In the October 1979 to October 1982 period of the Fed's nonborrowed reserves target operating procedure, none of the β_m t-statistics exceed 2.0 and in two cases are even negative. Although there is a positive relationship between inflation and nominal interest rates at all time horizons in the post-October 1982 period, the β_m t-statistics are greater than 2.0 only at time horizons of one and three months.

The results in Table 1 are consistent with earlier findings in the literature which have examined the relationship between future inflation and short-term interest rates for a more limited range of time horizons (one to six months). Using standard critical values of the test statistics, the ability of short-term interest rates to predict inflation is highly significant. However, the conclusion that the β_m coefficients are statistically significant rests on the appropriateness of using the t-distribution to conduct statistical inference with the test statistics found in Table 1. Yet, it is well known that if the

¹²Note that in constructing the corrected standard errors, η_t^m is assumed to have a MA process of order $m-1$. This is standard practice in the literature, as in Fama (1975), Fama and Bliss (1987), Huizinga and Mishkin (1984), and Mishkin (1989). However, examination of the residual autocorrelations in the regression estimates here suggest that η_t^m has significant correlation with its values lagged more than $m-1$ periods. To see if this additional serial correlation has any effect on the results, I have calculated the standard errors for all the forecasting equations allowing for non-zero autocorrelations going back three years (36 periods) and have conducted Monte Carlo experiments for all the resulting test statistics along the lines described in the text. Allowing η_t^m to have a MA process of order 36, does not alter any of the conclusions reached in the text.

variables in a regression contain stochastic trends because their time series processes have unit roots, then inference with t-distributions can be highly misleading, as has been forcefully demonstrated by Granger and Newbold (1974) and Phillips (1986).

To determine if the levels of inflation and interest rates contain stochastic trends, Table 2 presents several types of unit root tests for the four sample periods and time horizons studied in Table 1. The t-test statistic is the Dickey-Fuller (1979,1981) t-statistic, $(\hat{\rho} - 1)/s(\hat{\rho})$, from the following regression:

$$(2) \quad Y_t = k + \rho Y_{t-1} + u_t$$

where $s(\hat{\rho})$ is the OLS standard error of $\hat{\rho}$ and Y_t is the variable being tested for unit roots. The Z_t statistic is a modification of the Dickey-Fuller t-statistic suggested by Phillips (1987) which allows for autocorrelation and conditional heteroscedasticity in the error term of the Dickey-Fuller regression. The Z_{α} statistic, also suggested by Phillips (1987), is a similar modification of the test statistic $T(\hat{\rho} - 1)$, where T is the number of observations.¹³

As the Monte Carlo simulations in Schwert (1987) point out, the critical values calculated by Dickey and Fuller for the test statistics in Table 2 can be very misleading if the time-series models of the variables tested for unit roots are not pure autoregressive processes but rather include important moving average terms. This is exactly what is found for the inflation rates examined here, and therefore it is necessary to obtain the correct small sample distributions for these test statistics from Monte Carlo simulations which

¹³The Z_t and Z_{α} test statistics are calculated allowing for 12 non-zero autocovariances in the error term of regression (2).

Table 2
Unit Root Tests for π_t^m and i_t^m

m (months)	<u>Test Statistics for π_t^m</u>			<u>Test Statistics for i_t^m</u>		
	t	Z _t	Z _z	t	Z _t	Z _z
Panel A: February 1964 - December 1986 Sample Period						
1	-7.73 (0.405)	-9.14 (0.348)	-146.96 (0.336)	-2.67 (0.233)	-2.46 (0.351)	-11.22 (0.338)
3	-3.53 (0.384)	-3.21 (0.353)	-18.07 (0.389)	-2.18 (0.663)	-2.13 (0.738)	-8.31 (0.770)
6	-2.12 (0.374)	-2.28 (0.310)	-8.96 (0.369)	-2.17 (0.494)	-2.10 (0.544)	-8.00 (0.564)
9	-1.77 (0.295)	-2.18 (0.260)	-7.90 (0.303)	-2.13 (0.359)	-2.07 (0.379)	-7.74 (0.358)
12	-1.60 (0.230)	-2.10 (0.261)	-7.30 (0.292)	-2.13 (0.432)	-2.06 (0.423)	-7.65 (0.420)
Panel B: February 1964 - October 1979 Sample						
1	-6.92 (0.259)	-8.43 (0.273)	-124.25 (0.277)	-1.34 (0.637)	-1.41 (0.537)	-6.12 (0.307)
3	-2.82 (0.193)	-2.56 (0.216)	-11.43 (0.214)	-1.17 (0.594)	-1.36 (0.499)	-5.69 (0.269)
6	-0.99 (0.606)	-1.15 (0.597)	-3.56 (0.431)	-1.20 (0.624)	-1.30 (0.568)	-5.17 (0.359)
9	-0.66 (0.554)	-1.20 (0.486)	-3.38 (0.371)	-1.09 (0.652)	-1.24 (0.552)	-4.75 (0.330)
12	-0.42 (0.595)	-1.16 (0.501)	-3.11 (0.357)	-1.20 (0.639)	-1.25 (0.597)	-4.76 (0.392)

Table 2 Continued

m (months)	Test Statistics for π_1^m			Test Statistics for i_1^m		
	t	Z_t	Z_a	t	Z_t	Z_a
Panel C: November 1979 - October 1982 Sample Period						
1	-2.98 (0.062)	-3.02 (0.056)	-15.09* (0.021)	-2.01 (0.283)	-1.89 (0.338)	-7.51 (0.154)
3	-1.15 (0.405)	-0.85 (0.754)	-2.45 (0.648)	-1.71 (0.507)	-1.66 (0.512)	-6.49 (0.295)
6	0.11 (0.699)	0.78 (0.732)	0.82 (0.813)	-2.08 (0.287)	-1.94 (0.334)	-7.54 (0.167)
9	-0.35 (0.578)	0.04 (0.863)	0.03 (0.866)	-2.29 (0.198)	-2.14 (0.241)	-8.18 (0.140)
12	-0.58 (0.495)	-0.56 (0.755)	-0.33 (0.826)	-2.32 (0.172)	-2.16 (0.218)	-8.17 (0.122)
Panel D: November 1982 - December 1986 Sample Period						
1	-4.40 (0.339)	-4.25 (0.386)	-24.74 (0.372)	-0.96 (0.785)	-0.92 (0.766)	-2.64 (0.648)
3	-2.54 (0.236)	-2.24 (0.251)	-8.68 (0.161)	-0.20 (0.863)	-0.40 (0.841)	-0.94 (0.814)
6	-1.71 (0.358)	-2.00 (0.190)	-7.79 (0.075)	-0.23 (0.854)	-0.35 (0.795)	-0.77 (0.747)
9	-0.89 (0.585)	-1.50 (0.421)	-5.18 (0.187)	-0.35 (0.793)	-0.51 (0.710)	-1.16 (0.622)
12	-0.90 (0.544)	-1.50 (0.411)	-4.92 (0.213)	-0.32 (0.799)	-0.53 (0.704)	-1.21 (0.619)

Notes for Table 2:

t = the Dickey-Fuller t-statistic, $(\hat{\rho} - 1)/s(\hat{\rho})$.

Z_t = the Phillips modified t-statistic.

Z_a = the Phillips modified $T(\rho - 1)$ statistic.

The number in parentheses is the marginal significance level of the test statistic

calculated from Monte Carlo simulations under the null hypothesis of a unit root. The number directly under this describes the power of the test statistic: i.e., it is the probability of rejecting the null of a unit root given the alternative of no unit root using the size corrected 5% critical value for the test statistic.

* = significant at the 5% level.
** = significant at the 1% level.

allow for more general time-series processes of the tested variables.

The Monte Carlo simulation experiments were conducted as follows. The data generating process for the π_t^m and i_t^m variables were obtained from ARIMA models in first differenced form (i.e., assuming unit roots) whose parameters were estimated from the relevant sample periods.¹⁴ Because Lagrange-multiplier tests described by Engle (1982) revealed the presence of ARCH (autoregressive conditional heteroscedasticity) in the error terms, the error terms were drawn from a normal distribution in which the variance follows an ARCH process whose parameters were also estimated from the relevant sample periods. Start-up values for AR terms in the times series models were obtained from the actual realized data from six and seven years before the sample period (or at the start of the sample period if earlier data were unavailable), and then five years of draws from the random number generator produced start-up values for the error terms. Then a sample size corresponding to the relevant regression was produced using errors drawn from the distribution described above and the test statistics were calculated. To check out the robustness of the Monte Carlo results, I also conducted experiments where the error terms were assumed to be i.i.d. rather than ARCH and the results were very similar to those reported in the text.

¹⁴There is a potential problem that the estimated first differenced ARIMA models for inflation and interest rates could have unit roots in the moving average polynomial which would cancel out the autoregressive unit root and thus yield series which are stationary in levels rather than in first differences. To rule out this possibility, I did check the roots of the moving average polynomials to make sure that they were outside the unit circle and found this to be the case, thus guaranteeing that the moving average polynomials do not have unit roots. I also checked that the roots of the autoregressive polynomials are outside the unit circle. The estimated ARIMA models thus yield data generating processes that, as desired, produce series that are stationary in first differences, but not in levels. For the inflation series, the one-month series was generated as described in the text and the three, six, nine and twelve month series were then calculated from the one-month series. I also tried the alternative of generating each of the inflation series with its own estimated ARIMA model and there was no appreciable difference in the results.

In Table 2 the value in parentheses under the test statistic is the marginal significance level of the test statistic using the Monte Carlo simulation results described above. The marginal significance levels are the probability of getting that high a value of the test statistic or higher under the null hypothesis that the variable has a unit root: i.e., a marginal significance level less than 0.05 indicates a rejection at the 5% level. As we can see from the results in Table 2, there is some support for the view that both the levels of inflation and interest rates contain stochastic trends.¹⁵ In only 1 test statistic out of 120 in Table 2 do we find a rejection of the null hypothesis of a unit root. (Interestingly, this rejection occurs during the October 1979 to September 1982 sample period.)

I have also conducted unit root tests using Augmented Dickey-Fuller (ADF) tests described by Said and Dickey (1984) in which lags of ΔY are included in equation (2) and performed the same Monte Carlo simulation experiments to obtain the marginal significance levels of these test statistics. Four different lag lengths were chosen for these ADF tests: two tests used a procedure similar to that in Perron (1990) in which the lag length was chosen to be that which produced a t-statistic on the last lagged value of ΔY that was significant either at the 10% or the 5% level; one ADF statistic had a fixed lag length of twelve and the other chose the lag the length with the criterion used in Schwert (1987) in which the lag length grows with sample size. The results using these ADF statistics support the findings of Table 2. Just as in Table 2, only in the October 1979 to September 1982 sample period when $\underline{m} = 1$ is

¹⁵This conclusion contrasts with that found in Rose (1988). His rejection of a unit root in inflation arises because he uses the Dickey-Fuller critical values to make his inferences. However, as the Monte Carlo results in Schwert (1987) and in Table 2 indicate, using the correct small sample distribution to conduct inference does not lead to rejection of a unit root in inflation.

there a rejection of a unit root for inflation, and in no other cases could the null hypothesis of a unit root in inflation or interest rates be rejected.

The conclusion from Table 2 and the additional Augmented Dickey-Fuller tests is that we cannot reject the null hypothesis that the levels of inflation and interest rates contain stochastic trends.¹⁶ Thus it is entirely possible that the inference using the t-distribution which tells us that interest rates have significant forecasting ability for inflation could be highly misleading.

To explore this possibility, we again run Monte Carlo simulation experiments using the procedures described above in which the data generating process for the π_t^m and i_t^m variables was obtained from ARIMA models in first differenced form (i.e., assuming unit roots) using the procedure described earlier. In addition, the error terms from the π_t^m and i_t^m ARIMA models are allowed to be contemporaneously correlated as in Mankiw and Shapiro [1986] and Stambaugh [1986] because this correlation is often found

¹⁶The view that interest rates and inflation have stochastic trends in particular sample periods does not imply that there is no tendency to mean reversion in the policy process that generates money growth and inflation rates. In accommodating monetary regimes -- the pre-October 1979 period might be characterized as a good example -- the conduct of monetary policy could certainly lead to non-stationary behavior of money growth and inflation. However, the high inflation that such a regime creates is likely to lead to a change in regime that would bring inflation back down again, thus producing a tendency for mean reversion in the long run. Note, however, that this tendency to mean reversion in the long run is consistent with nonstationary behavior within a regime period. Another way to see this point is to recognize that a hyperinflation involves a monetary regime in which money growth and inflation are clearly nonstationary. Yet, at some point the problems created by such a high inflation regime will result in a change in monetary regime which brings the inflation rate back to low levels and leads to mean reversion of inflation in the long run.

to be statistically significant.¹⁷ The correlation of the error terms is also estimated using the relevant sample periods. Then a sample size corresponding to the relevant regression was produced using errors drawn from the distribution described above and the test statistics using the Hansen-Hodrick-Newey-West-White method allowing for heteroscedasticity described earlier were calculated. Table 3 reports the results of Monte Carlo simulations of one thousand replications of the t-tests for all the horizons and sample periods in Table 1.¹⁸

The difference between the small sample distribution of these statistics and that under the t-distribution is striking. As we can see from the results in columns 7 and 8, the probability of rejecting the null when it is true using either the t-distribution's 5% or 1% critical value is typically greater than 50%.¹⁹ Furthermore, as we see from a comparison of Panel A and B with the shorter sample period results in Panel C and D, the bias does not diminish

¹⁷The dating convention for interest rates in this paper is off by one period from the conventional dating used in Mankiw and Shapiro (1986) and Stambaugh (1986). Hence my allowing for contemporaneous correlation of the error terms from the π_t^m and i_t^m ARIMA models means that I allow for a correlation between the i_t^m -equation error term and one lag of the π_t^m -equation error term.

¹⁸I also conducted Monte Carlo experiments which 1) added lags of past π_t^m to the i_t^m ARIMA models, 2) assume no correlation of the error terms from the π_t^m and i_t^m ARIMA models, 3) do not correct the test statistics for heteroscedasticity, or 4) assume that the error terms are i.i.d. These experiments yield identical conclusions to the Monte Carlo results reported in the text.

¹⁹Note that in Table 3 the probability of rejecting the null using the standard critical values often declines as \underline{m} increases. This reflects the fact that η_t^m has significant autocorrelations for lags greater than $\underline{m} - 1$ although the Hansen-Hodrick-Newey-West-White standard error correction used here, which is standard in the literature, does not allow for non-zero autocorrelations for lags greater than $\underline{m} - 1$. When the standard error correction allows for non-zero autocorrelations for up to 36 lags, the Monte Carlo experiments no longer show that the probability of rejecting the null using the standard critical values declines as \underline{m} increases.

Table 3

Monte Carlo Simulation Results
for t-test of $\beta_m = 0$
Assuming Unit Roots for π_t^m and i_t^m

m (months)	Critical Values of t from Monte Carlos					% Reject Using Standard 5% Critical Value	% Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table 1
	<u>Significance Levels</u>							
	50%	25%	10%	5%	1%			
Panel A: February 1964 - December 1986 Sample (275 observations)								
1	5.16	9.25	13.66	17.26	24.36	79.2%	72.6%	0.298
3	3.34	6.03	9.11	11.36	15.76	67.5%	57.8%	0.239
6	3.04	5.44	8.31	9.65	13.55	64.4%	55.6%	0.361
9	2.76	5.09	7.90	10.24	15.01	64.5%	53.3%	0.443
12	2.76	4.95	7.50	9.55	12.18	61.2%	52.5%	0.542
Panel B: February 1964 - October 1979 Sample (189 observations)								
1	8.94	15.48	21.97	25.95	34.84	87.7%	84.3%	0.398
3	6.15	11.58	16.33	19.32	26.08	81.6%	76.0%	0.285
6	5.11	9.23	13.70	16.72	21.99	79.0%	72.4%	0.148
9	5.42	8.96	13.19	15.98	23.50	82.3%	76.0%	0.191
12	4.52	7.76	11.20	13.14	17.24	75.4%	68.6%	0.147

Table 3 Continued

m (months)	Critical Values of \hat{I} from Monte Carlo Significance Levels					α Reject Using Standard 5% Critical Value	α Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table 1
	50%	25%	10%	5%	1%			
Panel C: November 1979 - October 1982 Sample (36 observations)								
1	3.28	5.97	8.61	10.71	13.89	68.4%	59.8%	0.906
3	2.30	4.26	6.56	7.97	12.01	56.3%	46.2%	0.753
6	2.04	3.72	6.43	8.41	13.11	51.8%	39.7%	0.963
9	2.07	3.74	6.45	8.45	16.63	52.9%	40.9%	0.657
12	2.31	4.33	7.40	9.82	14.16	56.0%	45.4%	0.577
Panel D: November 1982 - December 1986 Sample (50 observations)								
1	2.04	3.72	5.49	6.69	8.97	51.6%	41.4%	0.395
3	1.76	3.32	5.31	6.45	8.71	45.2%	34.8%	0.422
6	2.06	4.14	6.69	7.93	12.11	52.3%	42.4%	0.664
9	2.68	5.00	8.02	10.42	15.77	61.5%	51.2%	0.807
12	2.62	5.14	8.37	11.19	19.15	60.6%	50.9%	0.858

appreciably with an increased sample size.²⁰ We also see from the Monte Carlo 5% critical values of the t-statistics in column 5, that t-statistics need to be greater than 9.5 to indicate a statistically significant β_m coefficient for the full sample, while they need to exceed 13.0 for the pre-October 1979 sample. The potential for a spurious regression result between the level of interest rates and future inflation is thus very high.

The last column of Table 3 indicates that the test results in Table 1 do not provide evidence for the forecasting ability of short-term interest rates for future inflation. This column contains the marginal significance levels for the t-tests of $\beta_m = 0$ in Table 1 calculated from the Monte Carlo simulations assuming that the levels of inflation and interest rates have unit roots. These marginal significance levels are indeed quite high, and for no horizon or sample period do they indicate that a β_m coefficient is statistically significant.²¹ The results in Table 3, along with the finding that unit roots in inflation and interest rates cannot be rejected, thus indicates that the usual methodology of regressing the level of inflation on the level of an interest rate is not able to provide evidence that the level of short-term interest rates has

²⁰Indeed, as Phillips (1986) points out, the bias is likely to increase as the sample size grows. We do see this tendency in the table; the longer Panel A and B samples have greater bias than the shorter Panel C and D samples.

²¹Using data for one and three month Treasury bills (which are available before 1959) along with the inflation data, I also conducted all the tests and Monte Carlo simulations reported in Tables 1 to 4 for the January 1953 to July 1971 sample period used in Fama (1975), as well as for the January 1953 to October 1979 sample period and the January 1953 to December 1986 sample period. The results were very similar to those for the sample periods used in the text. In no case was the null of a unit root rejected for the interest rate or inflation rate in any of these sample periods. Under the assumption of unit root, none of the β_m coefficients was found to be statistically significant in any of these sample periods when η_t^m is assumed to have a MA process of order $\underline{m} - 1$. When η_t^m is allowed to have a MA process of order 36, however, a β_m coefficient is found to be statistically significant in only one case in these sample periods: in the January 1953 to July 1971 period when $\underline{m} = 1$, the marginal significance level of the t-statistic on β_m calculated from the Monte Carlo simulations assuming unit root is 0.028.

any ability to forecast future inflation.²² Thus we need to look at other methodologies to examine the relationship between interest rates and inflation.

IV. Testing For Long-Run and Short-Run Fisher Effects

The forecasting regression equation in (1) does not make a distinction between short-run and long-run forecasting ability and hence between short-run and long-run Fisher effects. An absence of short-run forecasting ability for interest rates might lead to an inability to reject $\beta_m = 0$ in equation (1) even though higher levels of interest rates are associated with higher levels of inflation in the long-run. Thus the finding that the regression relationship between short-term interest rates and future inflation may be spurious if they have unit roots does not rule out the existence of a long-run Fisher effect in which inflation and interest rates have a common trend when they exhibit trends.

Engle and Granger (1987) have demonstrated the linkage between the presence of common stochastic trends and the concept of cointegration. If π_t^m and i_t^m are both integrated of order 1 [denoted by saying that they are $I(1)$] then

²²Note that as Dejong, Nankervis, Savin and Whiteman (1988) point out, the failure to reject unit roots may be the result of low power for unit root tests. This conjecture is confirmed for the unit root tests of Table 2 by conducting Monte Carlo simulations. The resulting power calculations found in the first appendix indeed indicate that the power of the unit root tests is extremely low, rarely getting above one-half. Thus the possibility that the levels of inflation and interest rates are stationary time series cannot be ruled out. Monte Carlo simulations for the t-tests of Table 1 which assume stationarity rather than unit roots in these series do yield significant rejections of $\beta_m = 0$ in the full sample and the pre-October 1979 sample periods, but not in the post October 1979 sample periods. Priors that interest rates and inflation rates are stationary stochastic variables would then lead to a view that the results in Table 1 do provide evidence for the ability of the level of interest rates to forecast the future level of inflation. However, this view would be based on a prior rather than evidence in the data.

they are said to be cointegrated of order 1,1 [denoted by CI(1,1)] if a linear combination of them is integrated of order zero. In other words π_t^m and i_t^m are CI(1,1), if they are both I(1) and if η_t^m is I(0) in the following so-called cointegrating regression:

$$(3) \quad \pi_t^m = \alpha_m + \beta_m i_t^m + \eta_t^m$$

Note that this cointegrating regression is identical to the forecasting regressions in (1). Engle and Granger then show that a test for cointegration involves estimating the cointegrating regression above using ordinary least squares (unless β is assumed to be known) and then conducting unit root tests for the regression residual η_t^m . In other words, the cointegration of π_t^m and i_t^m , which is what we mean by a long-run Fisher effect, implies that a linear combination of these variables is stationary.

Table 4 presents the results of two sets of cointegration tests using the Dickey-Fuller t-statistic and the Phillips Z_t and Z_α statistics. The first set which are found in columns two through four in Table 4 test for a unit root in $\pi_t^m - \hat{\beta}_m i_t^m$, i.e., the cointegration tests using the estimated cointegrating regressions already presented in Table 1. The second set, in columns five through seven, conduct unit root tests for $\pi_t^m - i_t^m$ and assume that $\beta = 1$ in the cointegrating regression. These latter tests can be characterized [Galli (1988)] as testing for a full Fisher effect in which inflation and interest rates move one-for-one in the long run.

Another way of looking at the second set of tests is to recognize that they are tests for unit roots in the ex-ante real interest rate under the assumption of rational expectations. This can be demonstrated as follows. The ex-ante real interest rate for an m -period bond (rr_t^m) is defined to be:

Table 4
Cointegration Tests

m (months)	Test Statistics for Unit Root in $\pi_t^* - \hat{\beta}_m i_t^*$			Test Statistics for Unit Root in $\pi_t^* - i_t^*$		
	t	Z _t	Z _a	t	Z _t	Z _a
Panel A: February 1964 - December 1986 Sample Period						
1	-9.16 (0.270)	-11.05 (0.167)	-208.62 (0.136)	-8.75 (0.068)	-10.59* (0.038)	-194.06* (0.031)
3	-4.08 (0.338)	-3.75 (0.309)	-25.79 (0.319)	-3.98 (0.222)	-3.66 (0.251)	-24.96 (0.257)
6	-2.47 (0.452)	-2.42 (0.494)	-11.00 (0.518)	-2.70 (0.286)	-2.51 (0.352)	-12.26 (0.332)
9	-1.97 (0.433)	-2.21 (0.485)	-9.01 (0.518)	-2.36 (0.239)	-2.29 (0.309)	-10.36 (0.269)
12	-1.64 (0.456)	-2.10 (0.490)	-7.93 (0.555)	-2.06 (0.386)	-2.11 (0.428)	-8.81 (0.382)
Panel B: February 1964 - October 1979 Sample						
1	-10.60* (0.049)	-11.43 (0.124)	-187.94 (0.227)	-9.96* (0.036)	-11.35 (0.056)	-199.71 (0.094)
3	-4.68* (0.033)	-4.25 (0.068)	-32.18 (0.070)	-4.44* (0.019)	-4.09* (0.028)	-28.65* (0.030)
6	-3.79* (0.012)	-3.43* (0.036)	-21.23* (0.037)	-3.15* (0.033)	-2.79 (0.102)	-14.25 (0.089)
9	-3.19* (0.042)	-3.02 (0.092)	-16.92 (0.086)	-2.65 (0.062)	-2.49 (0.125)	-11.15 (0.098)
12	-2.90 (0.083)	-2.82 (0.139)	-14.85 (0.121)	-2.35 (0.108)	-2.31 (0.186)	-9.67 (0.162)

Table 4 Continued

m (months)	Test Statistics for Unit Root in $\pi_t - \hat{\beta}_m i_t$			Test Statistics for Unit Root in $\pi_t - i_t$		
	t	Z _t	Z _m	t	Z _t	Z _m
Panel C: November 1979 - October 1982 Sample Period						
1	-2.98 (0.162)	-3.22 (0.097)	-17.42* (0.037)	-3.14 (0.055)	-3.36* (0.041)	-18.47* (0.014)
3	-1.43 (0.548)	-1.05 (0.855)	-2.67 (0.861)	-2.01 (0.150)	-1.92 (0.190)	-6.25 (0.106)
6	-0.04 (0.872)	0.57 (0.918)	0.60 (0.948)	-2.02 (0.157)	-1.94 (0.201)	-4.39 (0.338)
9	0.15 (0.805)	1.10 (0.772)	0.78 (0.909)	-1.96 (0.191)	-1.87 (0.247)	-4.47 (0.322)
12	-0.27 (0.783)	0.20 (0.934)	0.17 (0.945)	-1.91 (0.203)	-1.85 (0.235)	-4.03 (0.366)
Panel D: November 1982 - December 1986 Sample Period						
1	-4.63 (0.405)	-4.36 (0.455)	-15.10 (0.860)	-4.75 (0.180)	-4.52 (0.253)	-16.81 (0.742)
3	-2.65 (0.312)	-2.16 (0.429)	-7.98 (0.352)	-2.23 (0.348)	-1.76 (0.536)	-6.99 (0.317)
6	-1.56 (0.725)	-1.78 (0.536)	-7.06 (0.292)	-0.98 (0.703)	-1.32 (0.583)	-5.18 (0.298)
9	-0.66 (0.875)	-1.39 (0.774)	-5.13 (0.589)	0.00 (0.858)	-0.54 (0.755)	-1.76 (0.611)
12	-0.74 (0.847)	-1.42 (0.768)	-4.83 (0.676)	-0.05 (0.843)	-0.50 (0.757)	-1.47 (0.646)

Notes for Table 4:

t = the Dickey-Fuller t-statistic, $(\hat{\rho} - 1)/s(\hat{\rho})$.

Z_t = the Phillips modified t-statistic.

Z_α = the Phillips modified $T(\hat{\rho} - 1)$ statistic.

The number in parentheses is the marginal significance level of the test statistic calculated from Monte Carlo simulations under the null hypothesis of a unit root. The number directly under this describes the power of the test statistic: i.e., it is the probability of rejecting the null of a unit root given the alternative of no unit root using the size corrected 5% critical value for the test statistic.

* = significant at the 5% level.

** = significant at the 1% level.

$$(4) \quad rr_t^m = i_t^m - E_t \pi_t^m$$

where E_t denotes the expectation taken at time t . By subtracting the forecast error of m -period inflation, $\epsilon_t^m = \pi_t^m - E_t \pi_t^m$, from both sides and multiplying both sides by -1 , we then see that $\pi_t^m - i_t^m$ can be written as:

$$(5) \quad \pi_t^m - i_t^m = \epsilon_t^m - rr_t^m$$

Since under rational expectations the forecast error of inflation ϵ_t^m must be unforecastable given any information known at time t , ϵ_t^m will be $I(0)$. Hence, $\pi_t^m - i_t^m$ can only be $I(1)$ if rr_t^m is also $I(1)$. Testing for a unit root in $\pi_t^m - i_t^m$ is thus equivalent to testing for a unit root in the ex-ante real rate, rr_t^m . Looking at the second set of cointegration tests in this light indicates that the full long-run Fisher effect can be interpreted as the hypothesis that the ex-ante real rate is stationary.

The format of Table 4 is identical to that of Table 2. The first number in the column is the test statistic, the number in parentheses directly under this is the marginal significance level of that test statistic generated by Monte Carlo simulations. In the Monte Carlo experiments used to construct the marginal significance levels of the cointegration tests, the data generating process for the π_t^m and i_t^m variables was obtained from ARIMA models in first differenced form (i.e., assuming unit roots). The Monte Carlo experiments again used the procedures outlined earlier, allowing for contemporaneous correlation of the error terms along the lines of Mankiw and Shapiro (1986) and Stambaugh (1986).

The cointegration tests in Table 4 tell the following story. For the pre-October 1979 period, there is strong evidence for a common stochastic trend

in inflation and interest rates. The null of no cointegration is rejected at the five percent level using the unit root tests for $\pi_t^m - \hat{\beta}_m i_t^m$ in all the horizons except twelve months. Similarly unit root tests of $\pi_t^m - i_t^m$ also find support for cointegration for horizons of one to six months.

There is also evidence for cointegration in the other sample periods of Table 4, but it is not as strong as for the pre-October 1979 sample period. In Panel A, C and D we find rejections of unit roots when the horizon is one month, but not for longer horizons. However, as Dejong, Nankervis, Savin and Whiteman (1988) point out the power of these unit root tests may be quite low and power calculations provided in the first appendix confirms the low power of the tests in Table 4. Hence the inability to reject unit roots in these periods should not be viewed as evidence against the existence of a long-run Fisher effect. Furthermore, using data on one and three month Treasury bills for the January 1953 to October 1979 and January 1953 to December 1986 sample periods provides strong support for the cointegration of inflation and interest rates: the null hypothesis of a unit root in $\pi_t^m - i_t^m$ is always rejected at the 1% level. Overall, then, the evidence is quite supportive of the existence of a long-run Fisher effect.²³ Indeed, any reasonable model would almost surely suggest that real interest rates have mean-reverting tendencies, and this is consistent with the evidence here which supports the existence of a long-run Fisher effect.

The long-run Fisher effect we have found evidence for above tells us that when the interest rate is higher for a long period of time, then the expected inflation rate will also tend to be high. A short-run Fisher effect, on the other hand, indicates that a change in the interest rate is associated with an immediate change in the expected inflation rate. In other words, we should

²³Galli (1988) also comes to this conclusion.

expect to find a significant positive β_m coefficient in the following regression equation.

$$(6) \quad E_t[\pi_t^m] - E_{t-1}[\pi_{t-1}^m] = \alpha_m + \beta_m[i_t^m - i_{t-1}^m] + u_t^m$$

Because this equation is not estimable, we need to substitute in for expected inflation by recognizing that $\pi_t^m = E_t[\pi_t^m] + \epsilon_t^m$, where ϵ_t^m is orthogonal to any information available at time t under rational expectations. This substitution results in,

$$(7) \quad \Delta\pi_t^m = \alpha_m + \beta_m\Delta i_t^m + \eta_t^m$$

where,

$$\eta_t^m = u_t^m + \epsilon_t^m - \epsilon_{t-1}^m.$$

The presence of ϵ_{t-1}^m in the error term, means that the error term can be correlated with the explanatory variable Δi_t^m in (7) since rational expectations does not rule out the correlation with ϵ_{t-1}^m and information known at time t , such as Δi_t^m . Consistent estimates are obtained here by using the two-step two-stage least squares procedure outlined in Cumby, Huizinga and Obstfeld (1983),²⁴ where the instruments contain information only known at time $t-1$.²⁵

²⁴Note that the Newey-West (1987) technique is used to ensure positive-definiteness of the variance-covariance matrix rather than a spectral method as in Cumby, Huizinga and Obstfeld (1983).

²⁵In the estimation η_t^m is assumed to have a MA process of order \underline{m} rather than $\underline{m} - 1$. The order of the MA process is one greater than that used in estimating Table 1 because the presence of ϵ_{t-1}^m , as well as ϵ_t^m in the error term of equation (7) means that an additional lagged autocorrelation can be non-zero.

Because of the evidence for cointegration, one natural way to choose these instruments is by estimating error correction models of the type described by Engle and Granger (1987) in which the variables do not contain information known after time $t-1$, and then choose the significant variables from these models as instruments.

The results from estimating the regression equation above for the different m -horizons and sample periods (starting with the January 1965 date because the need for lagged instruments rules out starting earlier) are found in Table 5.²⁶ In assessing the statistical significance of the t -statistics on β_m , we again conduct Monte Carlo simulations to provide the marginal significance level of the t -statistic reported in the last column of Table 5. Given the evidence for cointegration, the data generating process is specified to be one in which the $\Delta\pi_t^m$ and Δi_t^m variables are generated from error correction models in which the current and past values of Δi_t^m do not appear in the $\Delta\pi_t^m$ equation, since under the null Δi_t^m has no forecasting ability for $\Delta\pi_t^m$.²⁷

²⁶Note that the R^2 's from an instrumental variables procedure are not as meaningful as in an OLS regression and are not guaranteed to be positive. This is why we sometimes see negative R^2 's in Table 5.

²⁷Note that these error-correction models differ from the ones used to choose the instruments because there is no longer the restriction that the explanatory variables in these models must only contain information available at time $t-1$. Also, since the power of the cointegration and unit root tests is low, we often cannot rule out that π_t^m and i_t^m are stationary in levels or have unit roots but with no cointegration. Since these are also reasonable choices for specification of the data generating process of π_t^m and i_t^m , Monte Carlo simulations have been conducted for these two cases as well using the same procedures described earlier which allow for the contemporaneous correlation of error terms. Because $\Delta\pi_t^m$ and Δi_t^m do not display much serial correlation in the regression equation (7) above, these Monte Carlo simulations produce similar results. They both indicate that the t -statistic when $\underline{m} = 1$ in the Panel C sample period is significant at the 5% level but not at the 1% level, as is found in Table 5. The experiments in which π_t^m and i_t^m have unit roots but are not cointegrated indicate that no other t -statistics are statistically significant, just as in Table 5, while the experiments in which π_t^m and i_t^m are stationary in levels indicate that only one other t -statistic is significant at the 5% but not the 1% level (when $\underline{m} = 6$ in the Panel C sample period).

Table 5

Tests for Short-Run Fisher Effects

$$\Delta \pi_t^* = \alpha_m + \beta_m \Delta i_t^* + \eta_t^*$$

m (months)	α_m	β_m	R ²	SE	t-statistic for $\beta_m=0$	Marginal Significance Level for t-statistic
Panel A: January 1965 - December 1986 Sample Period						
1	-0.0623 (0.1448)	-0.3354 (0.5151)	0.001	3.058	-0.65	0.605
3	0.0075 (0.0786)	0.6347 (0.3000)	0.016	1.217	2.12	0.066
6	0.0172 (0.0433)	0.3265 (0.1574)	0.022	0.611	2.07	0.489
9	0.0111 (0.0321)	0.0909 (0.1383)	0.003	0.407	0.66	0.578
12	0.0263 (0.0301)	0.0085 (0.1005)	-0.002	0.309	0.09	0.951
Panel B: January 1965 - October 1979 Sample Period						
1	0.0996 (0.1971)	-1.4691 (1.9069)	0.003	3.143	-0.77	0.609
3	0.0594 (0.0949)	-0.5256 (0.8334)	0.002	1.129	-0.63	0.577
6	0.0339 (0.0478)	0.1300 (0.2835)	0.000	0.591	0.46	0.853
9	0.0484 (0.0370)	-0.1792 (0.1670)	0.005	0.387	-1.07	0.410
12	0.0498 (0.0380)	0.0671 (0.1467)	0.001	0.297	0.46	0.688

Table 5 Continued

m (months)	α_m	β_m	R ²	SE	t-statistic for $\beta_m=0$	Marginal Significance Level for t-statistic
Panel C: November 1979 - October 1982 Sample Period						
1	-0.1849 (0.5524)	-0.8378 (0.2459)	0.100	2.993	-3.41*	0.025
3	-0.1058 (0.2304)	0.1763 (0.1465)	0.022	1.578	1.20	0.503
6	-0.2211 (0.1066)	0.2063 (0.0735)	0.063	0.646	2.81	0.074
9	-0.1960 (0.0453)	-0.0099 (0.1185)	0.000	0.478	-0.08	0.974
12	-0.1835 (0.0447)	0.0968 (0.1255)	0.014	0.285	0.77	0.368
Panel D: November 1982 - December 1986 Sample Period						
1	-0.1096 (0.3415)	0.7023 (1.1819)	-0.006	2.779	0.59	0.641
3	0.0179 (0.2104)	0.7432 (1.0140)	0.007	1.298	0.73	0.545
6	0.0444 (0.1432)	-0.1159 (0.7822)	0.001	0.648	-0.15	0.820
9	0.0273 (0.0852)	0.0216 (0.4803)	0.000	0.393	0.05	0.956
12	-0.1158 (0.6588)	-1.4405 (7.8807)	0.004	0.320	-0.18	0.780

Notes for Table 5:

Standard errors of coefficients in parentheses.

SE = standard error of the regression.

* = significant at the 5% level.

** = significant at the 1% level.

The most striking feature of the Table 5 results is that the β_m coefficients are as likely to be negative, and thus have the wrong sign for a short-run Fisher effect, as they are to be positive. Furthermore, only one β_m coefficient is found to be significantly different from zero (when $\underline{m} = 1$ in Panel C) and in this case the coefficient is negative.²⁸ Therefore, there is absolutely no evidence for the presence of a short-run Fisher effect in the regression results of Table 5. In addition, regression results using data on one and three month Treasury bills for the January 1953 to October 1979 and January 1953 to December 1986 sample periods also do not reveal any significant β_m coefficients, and so suggest that there is no short-run Fisher effect.

V. Interpreting Inflation Forecasting Equations

The conclusion from the preceding empirical analysis is that there is evidence for a long-run Fisher effect but not for a short-run Fisher effect. This characterization of the inflation and interest rate data along with the assumption of rational expectations can be used to provide a straightforward interpretation of when we will be likely to see estimated β_m coefficients substantially above zero in the inflation forecasting equations. As in Mishkin (1990), we can derive an expression for the coefficient β_m in the inflation forecasting equation (1) by writing down the standard formula for the projection coefficient β_m , while recognizing that the covariance of the inflation

²⁸Similar results are found when equation (7) is estimated by OLS rather than by two-step, two-stage least squares. With OLS there are two significant β_m coefficients, but again they are negative. The fact that OLS yields similar conclusions to those in Table 5 suggests that the inability to find a short-run Fisher effect does not stem from the procedure used here for choosing instruments.

forecast error with the real interest rate, rr_t^m , equals zero given rational expectations. The resulting formula for β_m is:

$$(8) \quad \beta_m = \frac{\tilde{\sigma}^2 + \rho\tilde{\sigma}}{1 + \tilde{\sigma}^2 + 2\rho\tilde{\sigma}}$$

where,

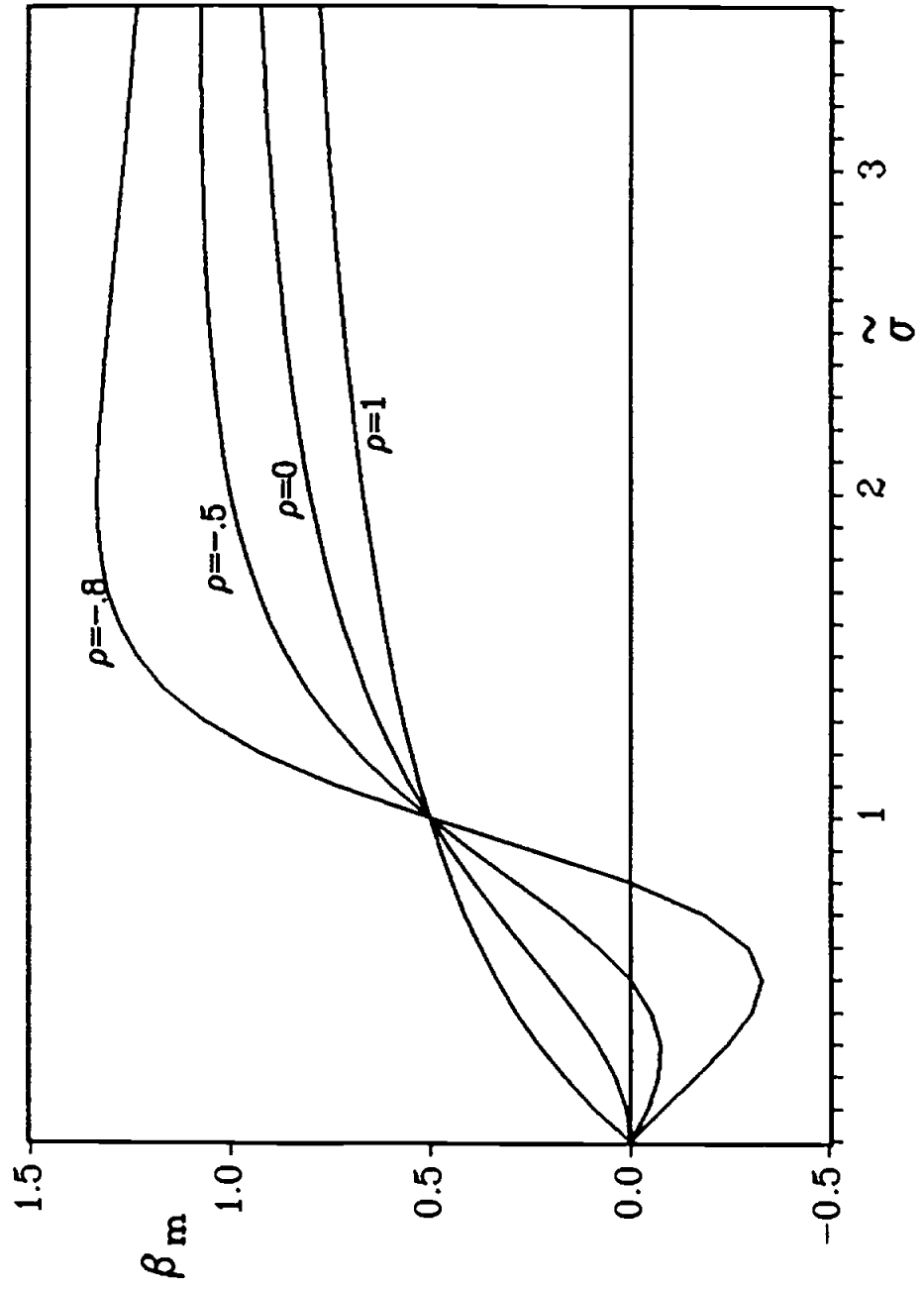
$\tilde{\sigma}$ = $\sigma[E_t(\pi_t^m)]/\sigma[rr_t^m]$ = the ratio of the unconditional standard deviation of the expected m-period inflation rate to the unconditional standard deviation of the m-period real interest rate.

ρ = the unconditional correlation coefficient between the expected m-period inflation rate, $E_t(\pi_t^m)$, and the m-period real interest rate, rr_t^m .

The equation above indicates that β_m is determined by how variable the level of expected inflation is relative to the variability of the real interest rate [represented by $\tilde{\sigma}$, the ratio of the standard deviations of $E_t(\pi_t^m)$ and rr_t^m], as well as by the correlation of the expected inflation rate with the real interest rate (ρ). Figure 1 shows how β_m varies with $\tilde{\sigma}$ and ρ .

As we can see in Figure 1, when the variability of the level of inflation is greater than the variability of the real interest rate, so that $\tilde{\sigma}$ is above 1.0, the β_m coefficient will exceed 0.5 and will increase as $\tilde{\sigma}$ increases. If inflation has a unit root and thus does not have a stationary stochastic process, as is consistent with the empirical evidence in this paper, then its second moment is not well defined and the standard deviation of the inflation level will grow with the sample size. On the other hand, the existence of a long-run Fisher effect implies that even if inflation and interest rates have unit roots, the real interest rate has a stationary stochastic process and will have a well defined

FIGURE 1



standard deviation that does not grow with the sample size. Hence when we are in sample period in which inflation and interest rates have unit roots, the existence of a long-run Fisher effect means that $\tilde{\sigma}$ must necessarily exceed one and produce a value of β_m substantially above zero, as long as the sample size is large enough.

It is important to note that the reasoning above applies equally well if inflation and interest rates have a deterministic trend rather than a stochastic trend. A deterministic trend also implies that the standard deviation of the inflation level will grow with the sample size. On the other hand, the long-run Fisher effect of a common deterministic trend for inflation and interest rates leads to stationary behavior for the real rate so that it has a well defined standard deviation that does not grow with the sample size. Then the reasoning follows as above.

We now see that a long-run Fisher effect in which inflation and interest rates have a common trend will produce β_m substantially above zero in long samples even when there is substantial variation in the real interest rate. However, if there is substantial variation in the real rate when we are in a sample in which inflation is a stationary stochastic variable, the standard deviation of the real rate might well exceed the standard deviation in expected inflation, which is now well defined and does not grow with the sample size. The result would be a $\tilde{\sigma}$ less than one. Thus in a period when inflation and interest rates do not have trends, we might expect to find estimated values of β_m that are close to zero.

The above interpretation does help explain the results we have found in Table 1. We can calculate estimated values of $\tilde{\sigma}$ and ρ using the procedure outlined in Mishkin (1981), in which estimates of the real rate, rr_t^m , are obtained from fitted values of regressions of the ex-post real rate on past

inflation changes and past interest rates.²⁹ Then the estimated expected inflation is calculated from the following definitional relationship,

$$(9) \quad E_t(\pi_t^m) = i_t^m - rr_t^m$$

Finally estimates of $\sigma[E_t(\pi_t^m)]$, $\sigma[rr_t^m]$, and ρ are calculated from the estimated $E_t(\pi_t^m)$ and rr_t^m .³⁰

Consistent with the view that inflation has a unit root, which we were unable to reject except in one instance in the November 1979 - October 1982 sample period, we find that the estimated standard deviation of expected inflation is much larger for the longer full sample and pre-October 1979 sample periods than it is for either of the shorter post-October 1979 sample periods. On the other hand, our rejection of a unit root in the real rate, implies that the standard deviation of the real rate should not necessarily be larger in the longer sample periods. Again this is exactly what we find: the post-October 1982 and pre-October 1979 sample periods have standard deviations of the real rate that are similar in magnitude. However, as is documented in Huizinga and Mishkin (1986), the standard deviation of the real rate is extremely high during the November 1979 - October 1982 sample period, which also raises the standard deviation of the real rate in the full sample period. The outcome is that the $\tilde{\sigma}$'s for the longer sample periods

²⁹The estimates described in the text were generated from OLS regressions in which the ex-post real rate, epr_t^m , was regressed on i_t^m and on π_{t-m}^m and π_{t-2m}^m . I also experimented with other choices of lags and the estimated values of σ and ρ were robust to different specifications of the regression equations.

³⁰The estimates of ρ are around -0.8 in the pre-October 1979 and November 1979 - October 1982 sample periods, are around -0.25 in the full sample period and range from -0.5 to +0.8 in the post-October 1982 sample period. These values are not crucial to the interpretation outlined in the text, but they do indicate that the curves drawn in Figure 1 are the relevant ones to use in interpretation of the estimated β_m 's.

generally exceed 1.0, especially in the pre-October 1979 sample period when they are above 2.0, and they thus generate β_m 's which are greater than 0.5. On the other hand, for the two shorter post-October 1979 sample periods, the $\tilde{\sigma}$'s are always below 1.0, except for $\underline{m} = 1$ in the post-October 1982 period and this explains why the β_m 's are so low. The fact that the estimated β_m 's are substantially above zero in the longer postwar sample periods is then well explained by inflation and interest rates having a common trend.³¹

VI. Conclusions

This paper has reexamined the widely accepted view that there is a strong Fisher effect in postwar U. S. data. Recognition that the level of inflation and interest rates may contain stochastic trends suggests that the apparent ability of short-term interest rates to forecast inflation in the postwar United States is spurious. This finding explains why a finding of inflation forecasting ability for short-term interest rates has so little robustness. The evidence presented here thus calls for a major rethinking about the strength of the Fisher effect.

The finding that the forecasting relationship between inflation and short-term interest rates might be spurious suggests that there might be no short-run Fisher effect. Direct tests confirm that this is the case. However,

³¹So far we have been interpreting when we are likely to see a strong correlation between the level of interest rates and inflation using the assumption of rational expectations. An alternative interpretation would be that expectations are not rational and that expectations of inflation adjust slowly. Then when there are no trends in inflation and interest rates, their correlation would be low even if the correlation of expected inflation and interest rates are high. On the other hand, if inflation and interest rates have strong trends, then a strong correlation of expected inflation and interest rates would necessarily yield a strong correlation of realized inflation and interest rates.

the absence of a short-run Fisher effect does not rule out the possible existence of a long-run Fisher effect in which inflation and interest rates trend together in the long run when they exhibit trends. Cointegration tests for a common trend in interest rates and inflation provides support for the existence of a long-run Fisher effect. Indeed, the findings here are more consistent with the views expressed in Fisher (1930) than with the standard characterization of the so called Fisher effect in the last fifteen years. Fisher did not state that there should be a strong short-run relationship between expected inflation and interest rates. Rather he viewed the positive relationship between inflation and interest rates as a long-run phenomenon. The evidence in this paper thus supports a return to Irving Fisher's original characterization of the inflation-interest rate relationship.

In addition, the evidence here can explain why the Fisher effect appears to be strong only for particular sample periods, but not for others. The conclusion that there is a long-run Fisher effect implies that when inflation and interest rates exhibit trends, these two series will trend together and thus there will be a strong correlation between inflation and interest rates. The postwar period before October 1979 is exactly when we find the strongest evidence for stochastic trends in the inflation and interest rates. Not surprisingly, then, this should be the period where the Fisher effect is most apparent in the data, and this is exactly what we find. On the other hand, the nonexistence of a short-run Fisher effect implies that when either inflation and interest rates do not display trends, there is no long-run Fisher effect to produce a strong correlation between interest rates and inflation. Thus, it is again not surprising during periods when there is some evidence that inflation does not exhibit a stochastic trend, as in the October 1979 to September 1982 period or pre World War II, that we can not detect a Fisher effect in U.S. data.

The analysis in this paper resolves an important puzzle about the presence of the Fisher effect.

Appendix I Power Calculations for Tables 2 and 4

The power calculations found in Tables A1 and A2 are obtained from Monte Carlo simulations using the same procedure that was used for Tables 2 and 4, but where the data generating process is estimated from ARIMA models estimated in levels rather than first differences.³² The power calculation for each test statistic in the tables are the probability obtained from this Monte Carlo simulation of rejecting the null of a unit root given the alternative of no unit root using the size-corrected 5% critical value for the test statistic.

³²I have checked the roots of the autoregressive polynomial from the estimated ARMA models to make sure that the roots were outside the unit circle, thus guaranteeing that the data generating process for the inflation and interest rate variables are stationary.

Table A1

Power Calculations for Unit Root Tests in Table 2

m (months)	Test Statistics for π_1^*			Test Statistics for i_1^*		
	t	Z_t	Z_a	t	Z_t	Z_a
Panel A: February 1964 - December 1986 Sample Period						
1	0.150	0.125	0.091	0.171	0.171	0.225
3	0.078	0.096	0.113	0.054	0.054	0.060
6	0.097	0.268	0.420	0.118	0.122	0.134
9	0.070	0.302	0.471	0.158	0.192	0.258
12	0.017	0.176	0.365	0.081	0.119	0.129
Panel B: February 1964 - October 1979 Sample						
1	0.059	0.061	0.059	0.080	0.106	0.120
3	0.045	0.064	0.072	0.163	0.158	0.236
6	0.034	0.229	0.503	0.100	0.116	0.172
9	0.018	0.248	0.707	0.098	0.107	0.148
12	0.011	0.202	0.553	0.145	0.136	0.183
Panel C: November 1979 - October 1982 Sample Period						
1	0.263	0.206	0.309	0.190	0.097	0.277
3	0.024	0.037	0.097	0.158	0.130	0.155
6	0.009	0.017	0.050	0.255	0.178	0.338
9	0.009	0.023	0.051	0.284	0.228	0.318
12	0.009	0.024	0.073	0.385	0.267	0.348
Panel D: November 1982 - December 1986 Sample Period						
1	0.253	0.267	0.187	0.025	0.023	0.024
3	0.112	0.087	0.139	0.061	0.057	0.127
6	0.033	0.028	0.094	0.078	0.071	0.085
9	0.028	0.023	0.178	0.091	0.085	0.120
12	0.013	0.022	0.140	0.082	0.076	0.132

Notes for Tables A1 and A2

The power calculation for each test statistic is the probability of rejecting the null of a unit root given the alternative of no unit root using the size corrected 5% critical value for the test statistic.

Table A2
Power Calculation for Cointegration Tests in Table 4

m (months)	Test Statistics for Unit Root in $\pi_1^* - \hat{\beta}_m i_1^*$			Test Statistics for Unit Root in $\pi_1^* - i_1^*$		
	t	Z _t	Z _a	t	Z _t	Z _a
Panel A: February 1964 - December 1986 Sample Period						
1	0.394	0.199	0.115	0.757	0.596	0.505
3	0.515	0.652	0.669	0.386	0.491	0.509
6	0.375	0.423	0.461	0.352	0.394	0.411
9	0.212	0.287	0.384	0.252	0.341	0.416
12	0.092	0.157	0.223	0.101	0.185	0.311
Panel B: February 1964 - October 1979 Sample						
1	0.654	0.220	0.027	0.655	0.213	0.031
3	0.897	0.834	0.794	0.951	0.920	0.936
6	0.984	0.958	0.973	0.876	0.776	0.814
9	0.816	0.777	0.840	0.746	0.671	0.811
12	0.674	0.643	0.767	0.457	0.395	0.496
Panel C: November 1979 - October 1982 Sample Period						
1	0.375	0.335	0.249	0.315	0.276	0.369
3	0.257	0.182	0.211	0.485	0.468	0.716
6	0.066	0.066	0.094	0.249	0.201	0.384
9	0.056	0.078	0.079	0.194	0.130	0.417
12	0.082	0.115	0.114	0.192	0.121	0.399
Panel D: November 1982 - December 1986 Sample Period						
1	0.087	0.096	0.013	0.220	0.199	0.007
3	0.154	0.089	0.050	0.290	0.161	0.357
6	0.069	0.057	0.080	0.083	0.056	0.151
9	0.050	0.038	0.061	0.051	0.038	0.098
12	0.024	0.034	0.032	0.045	0.045	0.066

Appendix II

The Implications of Nonstationarity of Regressors and Cointegration for Tests on Real Rate Behavior

The evidence in this paper is consistent with the view that interest rates and inflation are nonstationary, but are cointegrated of order $CI[1,1]$. However, the standard regression tests on real interest rate behavior appearing in the literature which uses interest rates and inflation as regressors are based on asymptotic distribution theory which assumes the stationarity of the regressors. Thus the inferences in the literature about real rate behavior are somewhat suspect. This appendix reexamines the regression evidence on real interest rates using Monte Carlo experiments which follow along lines similar to those in the text.

Table A3 reports regression results in which the ex-post real rate ($epr_t^m = i_t^m - \pi_t^m$) is regressed on the nominal interest rate, i_t^m . The standard errors are calculated with the Hansen-Hodrick-Newey-West-White procedure allowing for heteroscedasticity which is described in the text. As is pointed out in Mishkin (1981, 1989), regressions with the ex-post real rate as the dependent variable allow us to make inferences about the relationship of the ex ante real rate with the regressors under the assumption of rational expectations. In addition, the tests of $\beta_m = 0$ in Table A3 are identical to Fama's (1975) test for constancy of the real rate in which he tests for a unit coefficient on the nominal interest rate in a regression of inflation on the interest rate.

The quite large t-statistics for β_m in Table A3 appear to strongly reject the constancy of the real interest rate. The β_m are positive for the full sample period and the post-October 1979 sample periods, indicating a positive correlation of real and nominal interest rates in those periods, while the pre-October 1979 sample period displays negative β_m and hence a negative

Table A3

Regressions of Real Rates on Nominal Interest Rates

$$cpr_{t,m} = \alpha_m + \beta_m i_t + \eta_t$$

m (months)	α_m	β_m	R ²	SE	t-statistic for $\beta_m=0$
Panel A: February 1964 - December 1986 Sample Period					
1	-1.2232 (0.4482)	0.4034 (0.0714)	0.107	3.200	5.65
3	-1.4486 (0.5659)	0.4704 (0.0845)	0.207	2.669	5.57
6	-1.7363 (0.7573)	0.5270 (0.1129)	0.278	2.465	4.67
9	-2.1852 (0.9062)	0.5925 (0.1322)	0.329	2.428	4.48
12	-2.5011 (1.0302)	0.6353 (.1485)	0.360	2.407	4.28
Panel B: February 1964 - October 1979 Sample Period					
1	2.2721 (0.6330)	-0.3746 (0.1216)	0.055	2.590	-3.08
3	2.2135 (0.6887)	-0.2941 (0.1187)	0.059	1.976	-2.48
6	2.6634 (0.6739)	-0.3236 (0.1117)	0.099	1.654	-2.90
9	2.6410 (0.7421)	-0.3070 (0.1266)	0.095	1.595	-2.42
12	2.6099 (0.7906)	-0.3009 (0.1332)	0.090	1.589	-2.26

Table A3 Continued

m (months)	α_n	β_n	R ²	SE	t-statistic for $\beta_n=0$
Panel C: November 1979 - October 1982 Sample Period					
1	-7.1035 (1.8326)	0.9110 (0.1552)	0.337	3.498	5.87
3	-5.0256 (3.4120)	0.7647 (0.2526)	0.282	2.937	3.03
6	-7.0521 (4.1291)	0.9644 (0.2887)	0.384	2.674	3.34
9	-10.7631 (3.3672)	1.2785 (0.2129)	0.552	2.382	6.00
12	-10.6754 (2.7065)	1.2918 (0.1567)	0.573	2.239	8.25
Panel D: November 1982 - December 1986 Sample Period					
1	1.7349 (1.9260)	0.3659 (0.2362)	0.040	2.474	1.55
3	0.1532 (1.6798)	0.5946 (0.1910)	0.191	1.806	3.11
6	-1.2817 (1.7622)	0.7649 (0.1867)	0.470	1.301	4.10
9	-1.8158 (1.7917)	0.8294 (0.1803)	0.605	1.109	4.60
12	-2.4821 (1.5415)	0.9073 (0.1518)	0.701	1.017	5.98

Notes for Table A1:

Standard errors of coefficients in parentheses.
SE = standard error of the regression.

correlation of real and nominal interest rates. These results are consistent with those found earlier in the literature.³³

Table A4 reports similar ex-post real rate regressions, but with expected inflation, $E_t[\pi_t^m]$, as the explanatory variable. Here the regressions are estimated with the two-step two-stage least squares procedure outlined in Cumby, Huizinga and Obstfeld (1983), generating expected inflation using as instruments the nominal interest rate and two lags of inflation following along the lines of Huizinga and Mishkin (1986a).³⁴ These results also appear to strongly reject the constancy of the real rate with large t-statistics on β_m , with the exception of the post-October 1982 sample period. Furthermore, the β_m coefficients are almost always negative suggesting a negative correlation between real rates and expected inflation. This negative association of real rates and expected inflation has also been repeatedly found in the literature for many sample periods.³⁵

Table A5 and A6 examine whether the high t-statistics in Tables A3 and A4 really do produce statistically significant rejections of the constancy of the real rate. The Monte Carlo simulation experiments were conducted as follows. The data generating process is specified to be one in which the $\Delta\pi_t^m$ and Δi_t^m variables are generated from error correction models in which the parameters were estimated from the relevant sample periods. The ex-post real rates were generated assuming that the ex-post real rates were serially uncorrelated, which must be the case under the null hypothesis of constant

³³For example, in Mishkin (1981) and Huizinga and Mishkin (1984, 1986).

³⁴More specifically, the instruments are the constant term i_t^m , π_{t-1}^m and π_{t-2}^m . The Newey-West (1987) technique is used to ensure positive-definiteness of the variance-covariance matrix rather than a spectral method as in Cumby, Huizinga and Obstfeld (1983).

³⁵See for example, Fama and Gibbons (1982), Summers (1983) and Huizinga and Mishkin (1986a).

Table A4

Regressions of Real Rates on Expected Inflation

$$cpr r_t^m = \alpha_m + \beta_m E_t[\pi_t^e] + \eta_t^m$$

m (months)	α_m	β_m	R ²	SE	t-statistic for $\beta_m=0$
Panel A: February 1964 - December 1986 Sample Period					
1	2.7188 (0.3742)	-0.3475 (0.0759)	0.008	3.372	-4.58
3	3.0886 (0.5260)	-0.3609 (0.1061)	-0.061	3.087	-3.40
6	3.4533 (0.6746)	-0.4120 (0.1291)	-0.073	3.004	-3.19
9	3.5984 (0.8256)	-0.4375 (0.1483)	-0.049	3.037	-2.95
12	3.4696 (1.0225)	-0.4086 (0.1788)	-0.052	3.086	-2.29
Panel B: February 1964 - October 1979 Sample Period					
1	2.4463 (0.2226)	-0.4301 (0.0441)	0.131	2.483	-9.76
3	2.4303 (0.2781)	-0.3644 (0.0503)	0.131	1.899	-7.24
6	2.3530 (0.2827)	-0.3094 (0.0481)	0.185	1.573	-6.44
9	2.3576 (0.3122)	-0.3252 (0.0512)	0.177	1.521	-6.35
12	2.2295 (0.3577)	-0.3131 (0.0562)	0.127	1.556	-5.57

Table A4 Continued

m (months)	α_*	β_*	R ²	SE	t-statistic for $\beta_*=0$
Panel C: November 1979 - October 1982 Sample Period					
1	11.5490 (1.6122)	-0.9466 (0.1878)	0.188	3.873	-5.04
3	7.7477 (1.9238)	-0.3556 (0.2600)	0.055	3.370	-1.37
6	11.4869 (1.7371)	-0.8022 (0.2324)	0.382	2.679	-3.45
9	14.4616 (1.2887)	-1.2095 (0.1429)	0.576	2.318	-8.47
12	14.0540 (1.3762)	-1.1829 (0.1502)	0.656	2.009	-7.88
Panel D: November 1982 - December 1986 Sample Period					
1	5.8701 (0.6834)	-0.4038 (0.1964)	0.068	2.439	-2.06
3	4.8182 (2.1181)	0.0755 (0.6249)	0.005	2.003	0.12
6	-1.4169 (9.6605)	1.9549 (2.7823)	0.289	1.506	0.70
9	6.6598 (2.6150)	-0.3669 (0.7203)	-0.056	1.813	-0.51
12	6.4606 (0.5918)	-0.3361 (0.1760)	0.016	1.844	-1.91

Notes for Table A2:

Standard errors of coefficients in parentheses.
SE = standard error of the regression.

Table A5

Monte Carlo Simulation Results
for Tests of Constancy of Real Rate
With Nominal Interest Rate as the Regressor

m (months)	Critical Values of t from Monte Carlos					χ Reject Using Standard 5%	χ Reject Using Standard 1%	Marginal Significance Level for t-tests in Table A1
	<u>Significance Levels</u>					Critical Value	Critical Value	
	50%	25%	10%	5%	1%			

Panel A: February 1964 - December 1986 Sample
(275 observations)

1	0.65	1.14	1.65	1.91	2.76	4.6%	1.2%	0.000
3	0.72	1.20	1.64	2.09	2.65	5.7%	1.3%	0.000
6	0.73	1.18	1.64	1.97	2.59	5.1%	1.0%	0.000
9	0.78	1.26	1.84	2.20	2.81	8.2%	2.0%	0.000
12	0.82	1.32	1.81	2.17	2.95	6.7%	1.8%	0.000

Panel B: February 1964 - October 1979 Sample
(189 observations)

1	0.69	1.13	1.68	2.01	2.81	5.7%	1.5%	0.003
3	0.70	1.19	1.69	1.92	2.61	3.8%	1.1%	0.014
6	0.71	1.23	1.80	2.10	2.74	6.9%	1.6%	0.006
9	0.79	1.26	1.73	2.03	2.64	6.0%	1.2%	0.021
12	0.75	1.32	1.82	2.18	2.86	7.1%	2.3%	0.041

Table A5 Continued

m (months)	Critical Values of \hat{t} from Monte Carlo					α Reject Using Standard 5% Critical Value	α Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table A1
	<u>Significance Levels</u>							
	50%	25%	10%	5%	1%			
Panel C: November 1979 - October 1982 Sample (36 observations)								
1	0.70	1.23	1.86	2.21	3.01	7.9%	2.8%	0.000
3	0.81	1.35	1.88	2.27	3.05	8.6%	3.1%	0.012
6	0.93	1.59	2.23	2.73	3.60	14.2%	6.4%	0.014
9	0.99	1.60	2.27	2.76	4.17	15.0%	6.0%	0.002
12	1.10	1.93	2.87	3.61	5.07	24.6%	13.9%	0.000
Panel D: November 1982 - December 1986 Sample (50 observations)								
1	0.66	1.19	1.78	2.10	2.97	6.8%	1.9%	0.145
3	0.81	1.25	1.82	2.20	3.19	8.0%	2.3%	0.011
6	0.80	1.36	1.96	2.24	3.50	10.1%	3.3%	0.003
9	0.93	1.45	2.09	2.60	3.87	12.0%	5.1%	0.006
12	1.08	1.69	2.46	3.03	4.10	18.7%	8.8%	0.002

Table A6

Monte Carlo Simulation Results
for Tests of Constancy of Real Rate
With Expected Inflation as the Regressor

m (months)	Critical Values of t from Monte Carlos					χ Reject Using Standard 5% Critical Value	χ Reject Using Standard 1% Critical Value	Marginal Significance Level for t -tests in Table A2
	Significance Levels							
	50%	25%	10%	5%	1%			

Panel A: February 1964 - December 1986 Sample
(275 observations)

1	0.70	1.18	1.65	1.96	2.68	5.0%	1.1%	0.000
3	0.72	1.21	1.72	2.03	2.55	5.8%	0.9%	0.000
6	0.69	1.17	1.70	2.00	2.80	5.2%	1.4%	0.005
9	0.75	1.24	1.79	2.12	2.73	6.6%	1.6%	0.003
12	0.78	1.33	1.88	2.21	3.07	8.7%	2.1%	0.041

Panel B: February 1964 - October 1979 Sample
(189 observations)

1	0.70	1.18	1.67	2.03	2.69	5.7%	1.2%	0.000
3	0.66	1.14	1.64	1.94	2.60	4.7%	1.0%	0.000
6	0.72	1.27	1.80	2.18	2.68	7.2%	1.5%	0.000
9	0.80	1.28	1.79	2.13	2.95	7.3%	2.3%	0.000
12	0.81	1.39	1.91	2.30	2.92	9.2%	2.5%	0.000

Table A6 Continued

m (months)	Critical Values of t from Monte Carlo Significance Levels					χ Reject Using Standard 5% Critical Value	χ Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table A2
	50%	25%	10%	5%	1%			
Panel C: November 1979 - October 1982 Sample (36 observations)								
1	0.78	1.28	1.81	2.24	3.13	7.8%	3.1%	0.000
3	0.78	1.27	1.77	2.09	2.88	6.4%	1.6%	0.215
6	0.93	1.61	2.38	2.92	4.17	16.2%	7.4%	0.025
9	1.04	1.75	2.60	3.25	4.44	20.8%	10.5%	0.000
12	1.21	2.14	3.20	3.98	5.75	29.2%	16.8%	0.000
Panel D: November 1982 - December 1986 Sample (50 observations)								
1	0.71	1.24	1.71	2.06	2.72	5.9%	1.3%	0.050
3	0.75	1.23	1.69	2.04	2.96	5.6%	1.8%	0.920
6	0.85	1.42	2.08	2.54	3.72	11.3%	4.4%	0.577
9	0.83	1.37	1.94	2.36	3.26	9.6%	3.1%	0.693
12	1.02	1.68	2.49	3.01	4.18	18.5%	8.9%	0.194

real rates and rational expectations. The error terms were drawn from a normal distribution in which the variance follows an ARCH process whose parameters were also estimated from the relevant sample periods. Start up values were generated with the procedure described earlier in the paper.

The results in Table A5 indicate that the nonstationarity of the regressors has little impact on inference. For the longer sample periods in Panels A and B, the critical values and the percentage rejections using the usual critical values are very close to those from the standard asymptotic distributions. With the shortening of the sample period in Panels C and D, the percentage rejections are higher than that indicated by the asymptotic distribution and grow with the degree of overlap in the data (i.e., a higher \underline{m}). However, this phenomenon does not appear to be the result of nonstationarity of the regressors, but is rather a small sample problem which appears in other contexts.³⁶ The last column in Table A5 gives the marginal significance levels for the tests of real rate constancy from the Monte Carlo experiments, and not surprisingly given the large t-statistics in Table A3, in all but one case the constancy of real rates is rejected, and usually the rejection is at the 1% level.

Table A6 tells a fairly similar story to Table A5. The constancy of the real rates is strongly rejected in all but the post-October 1982 sample period - but even in this period there is one rejection at the 5% significance level (for $\underline{m} = 1$ in Panel D).

The final two tables report on tests of correlation of the real rate with both nominal rates and expected inflation. Here the constancy of the real rate is no longer assumed. The interest rate and ex post real rate variables are generated with the same procedures as used in Tables A5 and A6, except that ex-post real rates are now allowed to have serial correlation, so that they are

³⁶For example, see the Monte Carlo simulation results in Mishkin (1990).

generated from ARIMA models. In other words, the null now assumes that inflation and interest rates are cointegrated, but that the real rate is not constant.

The results in Tables A7 and A8 indicate that allowing real rates to be serially correlated does have a major impact on the Monte Carlo results. Now the percentage rejections are much greater than that indicated by the standard asymptotic distribution. Using a 5% critical value, we sometimes see that the test statistics reject over fifty percent of the time in Table A7 if the null is true. The last column in Tables A7 and A8 tell us the statistical significance of the correlation of real rates with nominal rates and expected inflation, not assuming constancy of the real rates. The Table A7 marginal significance levels from the Monte Carlo experiments indicate that there is some evidence for a positive correlation between nominal and real interest rates in the full Panel A sample period: we can reject the null of no correlation at the 5% level in two cases, when $\underline{m} = 9$ and 12 and at the 10% level for $\underline{m} = 1$ and 3. On the other hand, the Panel B results cast doubt on the view that real and nominal rates were significantly negatively correlated in the pre-October 1979 period because, except for $\underline{m} = 1$ when the marginal significance level is 0.069, the marginal significance levels are quite high despite the apparently large t-statistics in Table A3. The Panel C results, however, do suggest a significant positive correlation between real and nominal interest rates in the October 1979 to September 1982 period when the Fed altered its operating procedures. The null of no correlation can be rejected at the five percent level for $\underline{m} = 1$ and 12 and the marginal significance levels are fairly low for the other horizons. The post-October 1982 sample period provides some weak evidence for a positive correlation of real and nominal rates, because all the marginal significance levels are near the 10% level although there are no rejections at

Table A7
Monte Carlo Simulation Results
for Tests of Correlation of Real Rate
With Nominal Interest Rate

m (months)	Critical Values of t from Monte Carlo					Z Reject Using Standard 5% Critical Value	Z Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table A1
	Significance Levels							
	50%	25%	10%	5%	1%			

Panel A: February 1964 - December 1986 Sample
(275 observations)

1	2.08	3.43	5.03	6.16	9.12	53.1%	39.2%	0.068
3	2.28	3.87	5.40	6.67	9.62	55.3%	45.7%	0.090
6	1.83	3.22	5.05	6.12	8.00	46.7%	34.9%	0.119
9	1.45	2.53	3.65	4.47	6.51	36.2%	23.9%	0.049
12	1.26	2.28	3.36	4.05	5.69	31.4%	19.8%	0.042

Panel B: February 1964 - October 1979 Sample
(189 observations)

1	1.18	2.00	2.78	3.38	4.81	25.5%	13.4%	0.069
3	2.06	3.68	5.26	6.16	8.84	51.5%	41.0%	0.424
6	1.83	3.33	4.74	5.45	7.17	47.2%	35.6%	0.301
9	1.56	2.64	3.93	4.82	7.03	40.6%	26.4%	0.298
12	1.52	2.67	4.09	5.05	7.87	39.0%	26.5%	0.329

Table A7 Continued

m (months)	Critical Values of t from Monte Carlo Significance Levels					χ Reject Using Standard 5% Critical Value	χ Reject Using Standard 1% Critical Value	Marginal Significance Level for t -tests in Table A1
	50%	25%	10%	5%	1%			
Panel C: November 1979 - October 1982 Sample (36 observations)								
1	1.68	2.94	4.32	5.10	6.71	43.6%	31.1%	0.028
3	1.12	2.15	3.40	4.17	6.49	28.4%	18.0%	0.133
6	1.44	2.52	4.01	5.04	8.04	36.6%	23.8%	0.156
9	1.55	2.95	4.59	6.08	9.24	40.4%	29.1%	0.054
12	1.75	3.14	5.31	6.45	9.94	44.4%	32.5%	0.025
Panel D: November 1982 - December 1986 Sample (50 observations)								
1	0.65	1.14	1.67	2.12	2.80	6.7%	2.0%	0.134
3	1.09	2.02	2.96	3.56	5.48	26.4%	14.1%	0.085
6	1.46	2.67	4.30	5.37	7.79	39.6%	27.0%	0.115
9	1.64	3.00	4.49	5.89	9.34	43.1%	30.8%	0.093
12	1.67	3.30	5.18	6.62	10.67	44.4%	34.5%	0.067

Table A8

Monte Carlo Simulation Results
for Tests of Correlation of Real Rate
With Expected Inflation

m (months)	Critical Values of t from Monte Carlos					X Reject Using Standard 5% Critical Value	X Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table A2
	Significance Levels							
	50%	25%	10%	5%	1%			

Panel A: February 1964 - December 1986 Sample
(275 observations)

1	1.93	3.30	4.84	5.77	7.29	49.3%	37.1%	0.112
3	2.37	3.87	5.45	6.74	8.82	57.3%	46.2%	0.323
6	1.91	3.44	4.94	6.15	7.86	48.9%	37.8%	0.288
9	1.34	2.48	3.78	4.52	6.42	35.9%	22.7%	0.162
12	1.14	2.12	3.08	3.66	4.97	28.3%	16.6%	0.222

Panel B: February 1964 - October 1979 Sample
(189 observations)

1	1.18	1.96	2.75	3.27	4.59	24.9%	12.0%	0.000
3	2.14	3.70	5.08	6.07	8.16	54.3%	41.8%	0.021
6	1.93	3.38	4.71	5.62	7.76	48.9%	36.4%	0.025
9	1.61	2.80	4.19	4.97	7.25	41.8%	30.1%	0.016
12	1.56	2.76	4.39	5.28	7.84	40.7%	28.6%	0.038

Table A8 Continued

m (months)	Critical Values of t from Monte Carlo					χ Reject Using Standard 5% Critical Value	χ Reject Using Standard 1% Critical Value	Marginal Significance Level for t-tests in Table A2
	Significance Levels							
	50%	25%	10%	5%	1%			
Panel C: November 1979 - October 1982 Sample (36 observations)								
1	1.50	2.60	3.61	4.21	5.36	36.4%	25.3%	0.018
3	1.46	2.55	3.82	4.86	7.79	36.4%	24.8%	0.531
6	1.91	3.38	5.21	6.51	10.73	48.7%	36.4%	0.243
9	2.00	3.79	6.36	8.49	13.28	50.7%	39.7%	0.050
12	2.31	4.02	7.17	9.11	14.13	55.6%	46.7%	0.078
Panel D: November 1982 - December 1986 Sample (50 observations)								
1	0.80	1.32	1.82	2.23	2.97	8.4%	2.4%	0.065
3	1.03	1.72	2.43	2.97	4.19	18.7%	8.7%	0.947
6	1.73	3.08	4.83	6.10	9.29	43.8%	32.3%	0.769
9	1.43	2.61	4.11	4.98	8.47	38.2%	25.7%	0.816
12	1.85	3.19	4.90	5.88	9.35	47.8%	34.6%	0.486

the 5% level.

The Table A8 marginal significance levels suggest that the evidence for a negative association of real interest rates with expected inflation is weaker than we would expect from the large t-statistics found in the regressions. Only in the Panel B, pre-October 1979 sample period do we always find rejection of the null of no correlation between real rates and expected inflation at the five percent level. We also find two significant rejections of the null of no correlation between real rates and expected inflation in the Panel C, November 1979 to October 1982 sample period. However, we do not find that the rejections of the null in either the Panel A, full sample period, or in the Panel D, November 1982 to December 1986 sample period. Overall, Table 2 and 6 indicate that there is evidence for a negative association of real rates and expected inflation, but that it is not always strong in all the sample periods.

Analyzing the importance of nonstationarity of the regressors to inference about real interest rate behavior indicates that our views on the strong rejections of constancy of real interest rates does hold up to the scrutiny here. However, we may have to weaken somewhat our views of how strong the support is for the correlation of real rates with nominal rates and expected inflation.³⁷

³⁷Monte Carlo simulations which examine the strength of conclusions about whether there was a shift in the stochastic process of real interest rates in October 1979 and October 1982 have not been studied here because this has already been done in Huizinga and Mishkin (1986b). The set up of the experiments there is consistent with the conclusions reached in this paper, because nominal rates and inflation are assumed to be non-stationary but cointegrated of order $CI[1,1]$. The results there provide strong support for the position that shifts in the stochastic process of real interest rates did take place with the change of Federal Reserve operating procedures in October 1979 and October 1982.

References

- Barsky, Robert B., "The Fisher Hypothesis and the Forecastability and Persistence of Inflation," Journal of Monetary Economics, (1987).
- Campbell, John Y., and Mankiw, N. Gregory, "Permanent Income, Current Income, and Consumption," Princeton University and Harvard University, mimeo. (January 1989).
- Clarida, Richard H., and Friedman, Benjamin M., "The Behavior of U.S. Short-Term Interest Rates Since October 1979," Journal of Finance 39 (1984): 671-682.
- Cumby, Robert J., Huizinga, John and Obstfeld, Maurice, "Two-Step, Two-Stage Least Squares Estimation in Model with Rational Expectations," Journal of Econometrics, 21: 333-55.
- Dickey, David A. and Wayne A. Fuller, "Distribution of the Estimators for Autoregressive Time Series with a Unit Root," Journal of the American Statistical Association 74 (June 1979): 427-31
- , "Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root," Econometrica 49 (July 1981): 1057-72
- DeJong, David N., John C. Nankervis, N.E. Savin, and Charles H. Whiteman, "Integration Versus Trend-Stationarity in Macroeconomic Time Series," Department of Economics, University of Iowa, Working Paper # 88-27a (December 1988)
- Engle, Robert F., "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of the United Kingdom Inflation," Econometrica 50 (July 1982): 987-1007.
- , and Clive W. Granger, "Co-Integration and Error Correction: Representation, Estimation and Testing," Econometrica 55 (1987): 251-76.
- Fama, Eugene F., "Short Term Interest Rates as Predictors of Inflation," American Economic Review 65 (1975): 269-82.
- , "The Information in the Term Structure," Journal of Financial Economics 13 (1984): 509-528.
- , and Gibbons, Michael R., "Inflation, Real Returns and Capital Investment," Journal of Monetary Economics 9 (1982): 297-324.
- Fisher, Irving, The Theory of Interest (New York: Macmillan 1930).
- Galli, Jordi, "Cointegration and the Fisher Effect: A Note," mimeo., M.I.T. (November 1988)
- Granger, Clive W., and Paul Newbold, "Spurious Regression in Econometrics," Journal of Econometrics 2 (1974): 111-120.
- Hansen, Lars P., "Large Sample Properties of Generalized Method of Moments Estimators,"

Econometrica 50: 1029-54

- , Lars, and Hodrick, Robert, "Forward Exchange Rates as Optimal Predictors of Future Spot Rates," Journal of Political Economy 88 (1980): 829-53.
- Huizinga, John and Mishkin, Frederic S., "Inflation and Real Interest Rates on Assets with Different Risk Characteristics," Journal of Finance 39 (1984): 699-712.
- , "Monetary Policy Regime Shifts and the Unusual Behavior of Real Interest Rates," Carnegie-Rochester Conference Series on Public Policy, 24 (Spring 1986a): 231-74.
- , "How Robust Are the Results? A Reply," Carnegie-Rochester Conference Series on Public Policy, 24 (Spring 1986b): 289-302.
- Mankiw, N. Gregory and Matthew D. Shapiro, "Do We Reject Too Often? Small Sample Properties of Tests of Rational Expectations Models," Economics Letters 20 (1986): 139-45.
- Mishkin, Frederic S., "The Real Rate of Interest: An Empirical Investigation," The Cost and Consequences of Inflation, Carnegie-Rochester Conference Series on Public Policy, 15 (1981): 151-200.
- , "The Real Interest Rate: A Multi-Country Empirical Study," Canadian Journal of Economics 17 (May 1984): 283-311
- , "Understanding Real Interest Rates" American Journal of Agricultural Economics 70 (December 1988): 1064-72.
- , "What Does the Term Structure of Interest Rates Tell Us About Future Inflation?" Journal of Monetary Economics (January 1990) forthcoming.
- Nelson, Charles R., and Schwert, G. William, "Short-Term Interest Rates as Predictors of Inflation: On Testing the Hypothesis that the Real Rate of Interest is Constant," American Economic Review, 67 (1977): 478-86.
- , and Charles I. Plosser, "Trends and Random Walks in Macroeconomic Time Series," Journal of Monetary Economics (1982): 129-62.
- , and Richard Startz, "The Distribution of the Instrumental Variables Estimator and its t-Ratio When the Instrument is a Poor One," Discussion Paper # 88-07, University of Washington, (May 1988).
- Newey, W. and West Kenneth, "A Simple, Positive Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," Econometrica 53 (1987): 703-708.
- Perron, Pierre, "Testing for a Unit Root in a Time Series with a Changing Mean," Journal of Business and Economic Statistics, 8 (April 1990): 153-162.

- Phillips, Peter C. B., "Understanding Spurious Regressions in Econometrics," Journal of Econometrics, 33 (December 1986): 311-40.
- , "Time Series Regression with a Unit Root," Econometrica 55 (March 1987): 277-301.
- Roley, V. Vance, "The Response of Interest Rates to Money Announcements Under Alternative Operating Procedures and Reserve Retirement Systems," NBER Working Paper # 1812, 1986.
- Rose, Andrew K., "Is the Real Interest Rate Stable?" Journal of Finance 43 (December 1988): 1095-1112.
- Schwert, G. William, "Effects of Model Specification on Tests for Unit Roots in Macroeconomic Data," Journal of Monetary Economics 20 (1987): 73 -1-3.
- Said, S.E. and Dickey, D.A., "Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order," Biometrika, 71 (1984): 599-608.
- Stambaugh, Robert F., "Bias in Regressions with Lagged Stochastic Regressors," Graduate School of Business, University of Chicago, January 1986.
- Stock, James H. and Mark W. Watson, "Variable Trends in Economic Time Series," Journal of Economic Perspectives 3 (Summer 1988): 147-174
- Summers, Lawrence H., "The Non-Adjustment of Nominal Interest Rates: A Study of the Fisher Effect," in James Tobin (ed.) A Symposium in Honor of Arthur Okun (Washington, D.C.: Brookings Institution)
- White, Halbert, "A Heteroskedasticity-Consistent Covariance Matrix Estimator and Direct tests for Heteroskedasticity," Econometrica 48 (1980): 817-38.