



**The Return of the Liquidity Effect: A Study of the Short-Run Relation between Money Growth and Interest Rates**

John H. Cochrane

*Journal of Business & Economic Statistics*, Vol. 7, No. 1. (Jan., 1989), pp. 75-83.

Stable URL:

<http://links.jstor.org/sici?sici=0735-0015%28198901%297%3A1%3C75%3ATROTLE%3E2.0.CO%3B2-M>

*Journal of Business & Economic Statistics* is currently published by American Statistical Association.

---

Your use of the JSTOR archive indicates your acceptance of JSTOR's Terms and Conditions of Use, available at <http://www.jstor.org/about/terms.html>. JSTOR's Terms and Conditions of Use provides, in part, that unless you have obtained prior permission, you may not download an entire issue of a journal or multiple copies of articles, and you may use content in the JSTOR archive only for your personal, non-commercial use.

Please contact the publisher regarding any further use of this work. Publisher contact information may be obtained at <http://www.jstor.org/journals/astata.html>.

Each copy of any part of a JSTOR transmission must contain the same copyright notice that appears on the screen or printed page of such transmission.

---

The JSTOR Archive is a trusted digital repository providing for long-term preservation and access to leading academic journals and scholarly literature from around the world. The Archive is supported by libraries, scholarly societies, publishers, and foundations. It is an initiative of JSTOR, a not-for-profit organization with a mission to help the scholarly community take advantage of advances in technology. For more information regarding JSTOR, please contact [support@jstor.org](mailto:support@jstor.org).

# The Return of the Liquidity Effect: A Study of the Short-Run Relation Between Money Growth and Interest Rates

John H. Cochrane

Department of Economics, University of Chicago, Chicago, IL 60637

In this article, I use band-pass filters to investigate the short-run relationship between money growth and interest rates. I find a negative correlation between short-run movements in money growth and interest rates, which I interpret as evidence that the liquidity effect dominates the anticipated inflation effect.

KEY WORDS: Filter; Frequency domain; Monetary policy; Spectrum.

## 1. INTRODUCTION

The liquidity effect was once unquestioned; rises in money growth were thought to cause temporary declines in both real and nominal interest rates. Recent empirical studies have found either small liquidity effects or none at all. Many economists now believe in the “anticipated inflation” effect—a rise in money growth has no effect on real interest rates, and it signals increased inflation, so nominal interest rates rise.

These two views are separated by a stylized fact. The liquidity effect explains a negative correlation between short-run movements in money growth and interest rates, whereas the anticipated inflation effect explains a positive correlation. In this article, I present evidence of a negative short-run correlation between money growth and interest rates, which I interpret as evidence that the liquidity effect dominates the anticipated inflation effect.

Theoretical explanations of the liquidity effect have a long history. Friedman (1968) presented a classic exposition of the traditional view: If money growth rises, agents bid up the price of bonds in an attempt to rid themselves of an excess quantity of money. Eventually their efforts result in greater inflation, but until that time, (real) interest rates decline.

Rational-expectations models refined the traditional view and provided a more rigorous explanation of the short-run nonneutrality of money that underlies a liquidity effect. In rational-expectations models, anticipated money-growth changes are neutral, so only unanticipated money-growth increases can lower real interest rates. More recent models that feature long-term nominal contracts, such as that of Taylor (1979), or general equilibrium monetary models, such as Lucas and Stokey's (1987) cash-in-advance model or that of Grossman and Weiss (1983), generate a liquidity effect from anticipated money-growth changes as well.

We can cast the results of this article as a test of the varied theoretical models that explain the liquidity effect, including the examples mentioned previously. This is an unfair revision of history, however, because these theories were developed precisely to explain the kind of stylized fact that I present.

Finding a liquidity effect on a scale of months also adds weight to the resolution of the *announcement-effect* puzzle in favor of expected correction by the Federal Reserve Board over expected inflation. The article by Cornell (1983) is one of many that discuss this puzzle. A weekly announcement of high money growth can be associated with an increase in interest rates either if agents think the announcement signals higher future inflation, or if they think that the rise today will force the Federal Reserve Board to lower money growth in the future. When it does lower money growth, interest rates must increase for the latter explanation to work; there must be a liquidity effect.

The existence of a liquidity effect is also at the heart of debate over desirable Federal Reserve Board policy. If it *cannot* lower real interest rates temporarily, it clearly should never try to do so. Of course, the finding that it can does not conversely imply that it should.

Finally, which effect dominates the other tells us something about the economy. The anticipated inflation effect should dominate if money growth is a good predictor of future money growth (if money growth is essentially a random walk), if the lag from money growth to inflation is short, and if changes in money growth are largely anticipated. The liquidity effect should dominate if short-term changes in money growth are typically not interpreted as signals that long-term policy has changed, if the lag from money to inflation is long, and if changes in money growth are largely unanticipated. Furthermore, the existence of a liquidity effect implies that (expected) real returns vary over time.

### 1.1 Current Opinion of the Liquidity Effect

Cagan and Gandolfi (1969) made some of the first, classic measurements of the response of interest rates to money growth. They ran unrestricted reduced-form regressions of interest rates on money growth and found that the liquidity effect reached a trough six months after a money-growth increase. Melvin (1983) reproduced their results and extended the sample through the 1970s. He found that the liquidity effect lasted two months or less in the late 1970s.

Mishkin (1981, 1982) estimated the magnitude of the liquidity effect from the structural restriction that only unanticipated money growth can cause a liquidity effect. He found either no correlation or a positive correlation between unanticipated money growth and interest rates, using quarterly data. He took care to avoid some of the sources of bias that commonly occur when a proxy for anticipated money growth is constructed by regression on other variables. Stokes and Newberger (1979) restricted their attention to autoregressive integrated moving average models and also found a small liquidity effect.

All of these studies were conducted on data prior to 1979, and so may suffer from simultaneous-equations bias, because the Federal Reserve Board smoothed interest-rate fluctuations. As a result, I concentrate on the nonborrowed reserve targeting period, from October 1979 to November 1982, when it is likely that there is less feedback from interest rates to money growth in the short-run spectral windows that I study.

### 1.2 Long-Run Effects and Low-Pass Filters

In the long run, money growth is positively related to the nominal interest rate through the inflation or Fisher effect. The very short-run relation (one to four weeks) is dominated by noise in the money stock and other effects on interest rates—the announcement effect and the effects of lagged reserve accounting, for example. Rather than estimate the entire relation between money and interest rates—long run, short run, very short run, secular, seasonal, and so forth—and then examine the short run, I first isolate the short-run movements of money growth and interest rates with simple band-pass filters. In this way, all of the “effects” in which we are not interested and all of the errors in their measurement do not cloud up the short-run effects in which we are interested.

Several authors have used low-pass filters to isolate long-run movements in series and long-run relations between series. Lucas (1980) used a low-pass filter (an exponentially weighted, centered moving average) to demonstrate the long-run neutrality of money. He ran regressions between filtered money growth and inflation and showed that, as the filters excluded more and more high frequencies, the regression coefficient approached 1. Whiteman (1984) showed that Lucas’s filter is a better test than the sum of distributed lag coeffi-

cients. Summers (1983) used the same idea to study the long-run Fisher effect. Geweke (1982) generalized the notion of Granger–Sims causality to a measure of feedback decomposed by frequency. Therefore, he can measure the short- or long-run relation between two series by their feedback in a frequency interval. He also demonstrated long-run neutrality.

This article is a generalization of these ideas. I use spectral-window filters to isolate short-run movements in money growth and interest rates from long-run movements and high-frequency noise. Regressions using these filtered data tell us about the short-run relation between money growth and interest rates.

Regressions of interest rates on money growth using filtered data mean no more or less than distributed lag regression (to which they are equivalent, as I shall show). They can document a correlation, but to interpret them as evidence for a liquidity or anticipated inflation effect requires the usual assumptions for a regression—in particular, we must assume that money growth is exogenous and uncorrelated with other variables that may change interest rates (budget deficits) and that money growth and interest rates are both stationary stochastic processes.

### 1.3 A Look at Filtered Data

Consider first passing the series through a filter that eliminates high frequencies. Figure 1 presents the treasury-bill rate (weekly) and a filtered treasury-bill rate. The filter is a two-sided, centered weighted moving average. The moving-average weights are chosen so that the filter blocks sine waves with a period shorter than 12 weeks but passes sine waves with a period greater than 12 weeks unchanged in either amplitude or phase. The Appendix contains detailed descriptions of the data and the filters.

Figure 1 gives an intuitive understanding of how the filter works and shows how useful it can be as a device

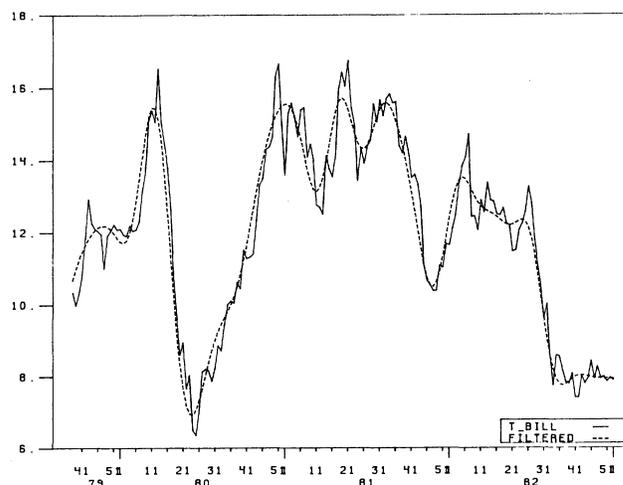


Figure 1. Three-Month Treasury-Bill Rate and Filtered Treasury-Bill Rate.

to purge data of high-frequency noise while doing little damage to components of the original series with periodicity higher than 12 weeks.

Figure 2 presents the M1-growth rate along with the treasury-bill rate, both filtered as in Figure 1. The money-growth rate is seasonally adjusted by eliminating seasonal frequencies, following Sims (1974). All of the results that follow are essentially identical whether produced by Sims's technique or using the Federal Reserve Board's seasonally adjusted M1 series.

Next, consider passing the series through a spectral-window filter, which eliminates both high-frequency noise and low-frequency (long-run) movements. Figures 3 and 4 present the M1 growth rate, the treasury-bill rate, and the 20-year government-bond rate in two such windows, 12–26 weeks and 26–52 weeks. To interpret the figures, remember that the period is the time required to complete a full cycle. The filtered series have a mean of 0, because removing the long periods (low frequencies) from the spectrum is a detrending device.

What precisely do these pictures mean? What precisely does the correlation between two filtered series mean? In Section 2, I interpret these filters based on their signal extraction properties and as a useful way to restrict the parameter space of a distributed lag regression.

**2. INTERPRETING FILTERED DATA**

**2.1 Signal Extraction**

Think of the observed money series and interest-rate series as composed of two components, short-run movements (the signal) and long-run movements combined with high-frequency noise. We want to isolate the signal based on a notion of its characteristic frequency.

For any given shape of the spectra of signal and noise, we can derive the two-sided moving-average filter that best separates the signal from the noise under the usual

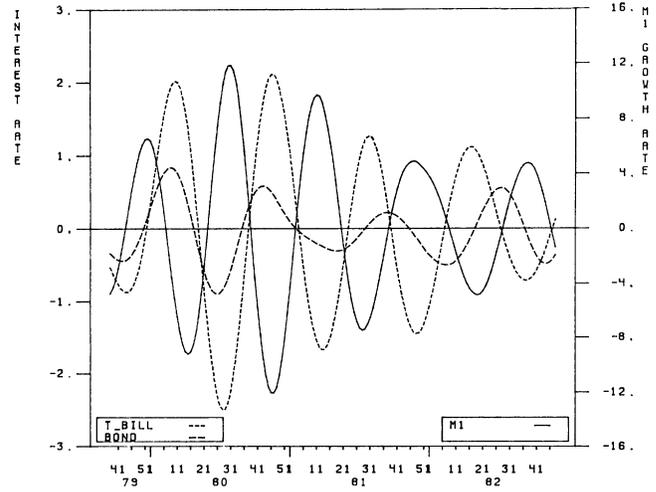


Figure 3. Filtered M1 Growth Rate and Interest Rates, 26–52-Week Window.

conditions that projections are optimal estimates. Suppose that an observed series  $X_t$  is composed of unobserved independent components  $X_t = x_t + u_t$  and that the spectra of  $x_t$  and  $u_t$  are believed to be  $S_x(e^{-i\omega})$  and  $S_u(e^{-i\omega})$ , respectively. Write the projection of the signal  $x_t$  on the observed  $X_t$  as

$$x_t^* = \sum_{j=-\infty}^{\infty} b_j X_{t-j} = b(L)X_t. \tag{2.1}$$

We may find the  $b$ 's from the given beliefs about the spectra by

$$b(e^{-i\omega}) = S_x(e^{-i\omega})/S_x(e^{-i\omega}). \tag{2.2}$$

[Sargent (1979) is a good reference for this formula. In Cochrane (1986), I gave explicit optimal filtering formulas for finite data on  $X_t$ , or finite-length moving averages. In the special case of spectral-window filters, the truncated infinite-length moving average is also the optimal finite-length filter, but this is not generally true,

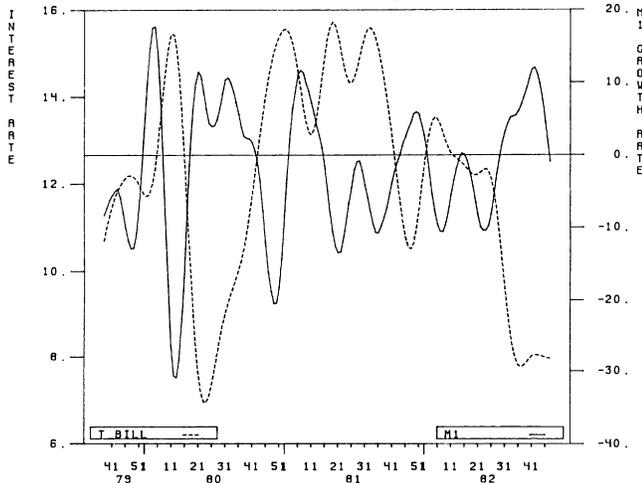


Figure 2. Filtered Treasury-Bill Rate and M1 Growth Rate, 12-Week-to-Infinity Window.

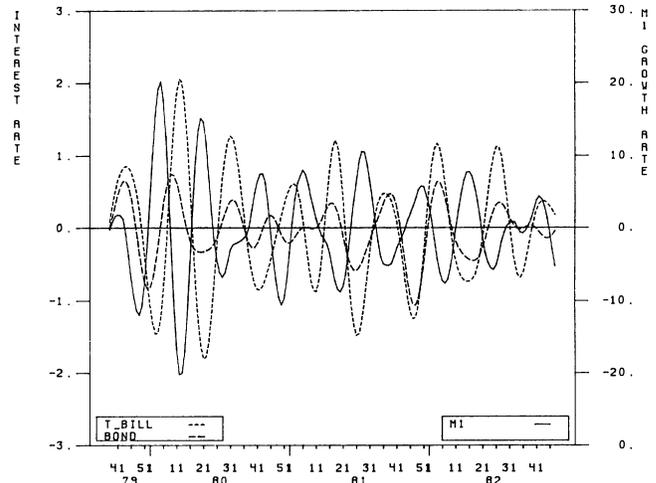


Figure 4. Filtered M1 Growth Rates and Interest Rates, 12–26-Week Window.

and filters derived from projection on a finite set of  $X_t$ , often perform better in practice.]

If one believes that the spectral density of  $x_t$  lies between frequencies  $a$  and  $b$  and that the spectral density of  $u_t$  lies outside this range, (2.2) yields

$$b_j = \frac{1}{\pi} \left( \frac{\sin(aj)}{j} - \frac{\sin(bj)}{j} \right). \quad (2.3)$$

This spectral-window filter best separates signal from noise when one believes that the signal is all concentrated in the given frequency window and the noise outside it. Generally, an investigator's knowledge of the spectra of signal and noise are more diffuse, so a filter with a more diffuse gain is appropriate. For example, the exponential filters used by Lucas (1980) and Summers (1983) correspond to less discrete assumptions about the spectra of signal and noise. For money growth and interest rates, the filtered data corresponding to Figures 1–4 using exponential or Gaussian filters produced essentially identical results as the spectral-window filters.

Filtering is a common device, by other names. Two examples of signal extraction are permanent income and seasonal adjustment. In seasonal adjustment, the uninteresting component is known to have a strong spectral spike at periods of a year, six months, and so forth. In permanent-income theory, one thinks that observed income contains a permanent and a transitory component and that transitory income changes more quickly than permanent income, so a low-pass filter produces a series that more closely reflects permanent income. The moving averages of observed income traditionally used to estimate permanent income are precisely low-pass filters.

Practically every empirical economic investigation includes the separation of series into components based on their characteristic frequencies. For example, all of the cited studies of money growth and interest rates use quarterly, or at best monthly, averages rather than the easily available weekly M1 and daily interest-rate data, because the latter are too "noisy." The Federal Reserve Board has, on occasion, advocated the use of moving averages to measure the money stock purged of weekly noise.

Infrequent observations, moving averages, centered moving averages, regressions on simple functions of time, peak clipping, changes from a year earlier, annual changes of quarterly observations, decade averages, and first differences are all commonly used to separate long-run, short-run, noise, trend, and cyclical components of series based on the characteristic frequencies of those components. An explicit filtering perspective can sometimes improve these common techniques. They often needlessly throw out data (quarterly or annual averages), throw out more signal and less noise than is easily possible (unweighted moving averages), introduce lags (change from a year earlier), or commit a combination of these sins.

## 2.2 Regressions on Filtered Data

Imagine that there is an underlying distributed lag relation between interest rates and money growth:

$$r_t = \sum_{j=0}^{\infty} a_j m_{t-j} + \varepsilon_t = a(L)m_t + \varepsilon_t, \quad (2.4)$$

where  $\varepsilon_t$  is a serially uncorrelated disturbance. We may represent this relationship equally well by the lag coefficients  $a(L)$  or by their frequency response  $a(e^{-i\omega})$ . With the lag coefficients, we represent actual money as a sum of impulses and actual interest rates as the sum of the responses to those impulses plus noise. With the frequency response, we represent actual money growth as a sum of sine waves and actual interest rates as a sum of the responses to pure sine waves plus noise.

For example, an impulse response function of the traditional shape—interest rates decline and then rise in response to a change in money growth—corresponds to a frequency response that is near 0 for very high-frequency movements, negative for periods corresponding to the decline in the distributed lag, and positive for long periods.

Suppose that the frequency response of the distributed lag (2.4),  $a(e^{-i\omega})$ , is constant in a spectral window, and write it as

$$a(e^{-i\omega}) = \alpha + i\beta, \quad |\omega| \in (\omega_L, \omega_H). \quad (2.5)$$

Let  $b(L)$  stand for the moving-average representation of the band-pass filter as in Equation (2.1). By construction

$$\begin{aligned} b(e^{-i\omega}) &= 1 \quad \text{if } |\omega| \in (\omega_L, \omega_H) \\ &= 0 \quad \text{otherwise.} \end{aligned} \quad (2.6)$$

From (2.4), the filtered series satisfy

$$b(L)r_t = a(L)b(L)m_t + b(L)\varepsilon_t. \quad (2.7)$$

Suppose we run a simple ordinary least squares (OLS) regression on the filtered series

$$b(L)r_t = a'b(L)m_t + u_t. \quad (2.8)$$

By Sims's approximation formula (Sargent 1979), OLS picks  $a'$  in population to minimize

$$\int_{|\omega| \in (\omega_L, \omega_H)} |a' - (\alpha + i\beta)|^2 S_m(e^{-i\omega}) d\omega, \quad (2.9)$$

so, in population, OLS picks  $a' = \alpha$ . The OLS coefficient of a regression on filtered data is a consistent estimate of the real part of the frequency response of the underlying distributed lag.

If  $a' = \alpha$ , from (2.8) and (2.9),

$$\sigma_\mu^2 = \frac{1}{2\pi} \int_{|\omega| \in (\omega_L, \omega_H)} (\beta^2 S_m(e^{-i\omega}) + \sigma_\varepsilon^2) d\omega, \quad (2.10)$$

which I write as

$$\sigma_\mu^2 = \beta^2 \sigma_m^2(\omega_L, \omega_H) + \sigma_\varepsilon^2(\omega_L, \omega_H). \quad (2.11)$$

Therefore,

$$\beta^2 \leq \sigma_\mu^2 / \sigma_m^2(\omega_L, \omega_H). \quad (2.12)$$

The standard error of the regression provides a consistent upper bound of the imaginary part of the frequency response of the underlying projection. If there is no imaginary part (if the phase is 0), then the OLS coefficient is a consistent estimate of the amplitude of the frequency response.

The intuition here is straightforward. Imagine running one sine wave on another of the same frequency, which may be shifted. If the sine waves are perfectly in phase, there will be no standard error; as the phase shift increases, the standard error of this regression increases.

If the imaginary part of the frequency response is substantial, if the investigator is interested in a phase shift, and if the spectral window is narrow, the real and imaginary parts (and hence amplitude and phase) may be separately and consistently estimated by estimating an additional lag. If a lag of  $k$  is included on the right side of (2.8) least squares minimize

$$\int_{|\omega| \in (\omega_L, \omega_H)} |(a'_0 + a'_k e^{-i\omega k}) - (\alpha + i\beta)|^2 S_m(e^{-i\omega}) d\omega. \quad (2.13)$$

If the window is small,  $\alpha$  and  $\beta$  are approximately

$$a'_0 + a'_k \cos(\omega k) = \alpha \quad (2.14)$$

and

$$a'_k \sin(\omega k) = \beta \quad (2.15)$$

for an  $\omega$  in the small window.

Moreover, regressions on filtered data are an implementation of bandspectrum regression, Engle's (1974, 1978) elegant formulation of a regression whose coefficients vary with frequency (see also Harvey 1978).

Why run regressions on filtered data? With finite data, we cannot estimate the entire distributed lag (2.4), so we must limit the range of the estimated lag coefficients. This is commonly done by truncating the coefficients, imposing a smooth functional form, or using quarterly or annual averages. There is always a trade-off between the number of degrees of freedom chewed up in estimating coefficients and the inaccuracies of the restriction.

As I showed previously, regressions between band-pass filtered series amount to a restriction that the frequency response of the lag coefficients is constant in that band. When we can characterize an interesting economic hypothesis by the frequency response of the lag coefficients in a certain range, the regression on filtered series amounts to a credible restriction on the lag coefficients.

Second, regressions on filtered data can let us estimate the effects in which we are interested without estimating the effects in which we are not interested.

If we restrict the coefficients  $a_j$  of (2.4) by a functional form, truncation, and so forth, least squares picks the coefficients  $a'(L)$  in population that minimize

$$\int_{-\pi}^{\pi} |a'(e^{-i\omega}) - a(e^{-i\omega})| S_m(e^{-i\omega}) d\omega, \quad (2.16)$$

the magnitude of the difference between  $a(e^{-i\omega})$  and  $a'(e^{-i\omega})$  over the entire frequency range, weighted by the spectral density of  $m$ ,  $S_m(e^{-i\omega})$ . When we are only interested in a limited range of frequencies, we should make  $a(e^{-i\omega})$  and  $a'(e^{-i\omega})$  close only in the interesting range. If we run the regression on filtered data, the integral (2.16) only runs over the included frequencies. Ordinary least squares then make no effort to match  $a(e^{-i\omega})$  and  $a'(e^{-i\omega})$  at uninteresting frequencies.

Most authors implicitly use this idea; they use monthly or quarterly data rather than the easily available weekly data. They do not care about the weekly coefficients, but they do care about degrees of freedom lost in estimating them. Quarterly averages are inefficient compared with a low pass filter of weekly data, however. Proceeding from a regression on weekly data with many lags to regression on monthly data with a few lags to a regression of filtered data with one lag is a simple extension of a good idea.

### 2.3 Results

Table 1 presents regressions on the filtered data of Figures 3 and 4 and some more windows. In each spectral window, I ran a regression of the filtered interest rate on filtered money growth and a second regression that included a lagged money-growth term, where the lag was the closest integer to one quarter of the mean period in the spectral window. The regression with a lag picks up any phase shift between money growth and interest rates, as explained in Section 2.2. The column headed "Lags" gives the value of this lag in weeks.

Eliminating frequencies has the same effect as eliminating observations. The  $t$  statistics and standard errors reported in Table 1 account for this bias by multiplying the raw standard error by the ratio of the window width to  $2\pi$ . The wider windows have larger  $t$  statistics, because they have more degrees of freedom. The coefficients in the wider windows may be more biased, however, because the approximation that the spectra are constant in the window becomes worse as the window is enlarged. This trade-off between bandwidth and bias is common in spectral applications.

Window width is proportional to the inverse of the periods, so the 4–12-week window is much wider than the 26–52-week window. Table 1 includes for each window the effective number of data points in the window. For example, the 26–52-week window contains  $166 \times (2/26 - 2/52) = 6.4$  "effective" data points.

The liquidity effect is most pronounced in the 26–52-week window for the three-month rate and in the 12–26-week window for the 20-year bond rate. It is

Table 1. Regressions of Filtered Interest Rates on Filtered Money Growth

Window (data)	Lags	3-month treasury bills				20-year bonds			
		Coefficient	SE	t	Feedback	Coefficient	SE	t	Feedback
4-12 (53.3)	0	-1.0	1.4	-.7	1.6	-.2	.7	-.2	1.4
					(2.9)				(2.9)
	0	-2.3	1.4	-1.6		-.3	.7	-.4	
	2	-2.9	1.4	-2.1		-.3	.7	-.3	
12-26 (14.9)	0	-12.5	6.2	-2.0	1.4	-4.6	1.1	-4.1	1.4
					(9.6)				(9.6)
	0	-12.6	6.2	-2.0		-5.0	3.6	-1.4	
	4	1.0	6.2	.2		2.5	3.6	.7	
26-52 (6.4)	0	-17.4	19.5	-.9		-3.3	5.3	-.6	
	0	-17.3	19.5	-.9		-3.2	12.3	-.3	
	9	1.6	19.8	.1		1.0	12.3	.1	
12-52 (21.3)	0	-11.1	6.4	-1.7	1.5	-2.3	3.6	-.6	1.6
					(7.5)				(7.5)
	0	-11.7	8.0	-1.5		-3.6	4.3	-.8	
	3	.9	8.0	.1		2.1	4.3	.5	
4-52 (76.6)	0	-8.9	1.7	-5.1	1.5	-2.4	10.4	-.2	1.9
					(2.7)				(2.7)
	0	-7.3	1.6	-4.5		-2.3	.9	-2.5	
	2	-5.0	1.6	-3.2		-.4	.9	-0.5	

NOTE: Window gives the spectral window in weeks. Data (in parentheses below the window) gives the equivalent number of data points in the window. Coefficient gives the regression coefficient; the units are basis points per annualized percent growth. SE and *t* are the standard error and *t* statistic, corrected for the size of the window. Feedback gives the *F* statistic for no feedback with the 5% critical value in parentheses. The sample is 166 observations, 79:38-82:48. Feedback was not calculated for 26-52 because there are only six effective data points.

surprising that the coefficient for the 20-year bond rate is negative. This suggests that market participants expect the negative impact on short rates to last a long time.

These reduced-form coefficients are biased if there is feedback (reverse causality) from interest rates to money growth. I used data from the nonborrowed-reserve targeting experiment precisely because the Federal Reserve Board was smoothing interest rates outside this sample. There are several potential sources of feedback in the sample, however. Poole (1982) and others have argued that the Federal Reserve Board was, in fact, pegging interest rates during at least part of the nonborrowed-reserve targeting period. Nonborrowed-reserve targeting and lagged-reserve requirements imply feedback in the very high-frequency windows that may continue to the windows I have studied. If money-growth changes are well anticipated, then real-interest-rate innovations caused by the money innovations occur before the measured-money innovation. Finally, it is possible that the negative correlation between money growth and interest rates reflects the Federal Reserve Board's responses to exogenously caused fears of inflation.

Following Geweke (1982) we need to test for feedback in the included frequencies. Since nonintersecting spectral windows are independent, the presence of feedback outside a spectral window does not affect a regression inside that window. I implemented Geweke's test by the conventional regression test as advocated by Feige and Pearce (1979) on the filtered data. The fil-

tered data were sampled infrequently so that only the effective number of data points given in Table 1 were used for each window. [In Cochrane (1986), I gave a proof that a conventional test on filtered data is equivalent to Geweke's test.] The column headed "Feedback" in Table 1 presents the test statistics and the critical values at the 5% level. None of the tests rejected the absence of feedback.

I made similar graphs and ran similar regressions using 76-79 and 82-86 sample periods. The negative correlation is almost absent in these samples, reflecting the acknowledged short-run interest rate targeting by the Federal Reserve Board.

Figure 5 presents the coefficients from an unconstrained OLS-distributed lag regression of interest rates on 12 lags of money growth as a check that the results are not an artifact of the new technique. I also ran regressions with 26 lags instead of 12, which results in about the same coefficients and fairly steady behavior past 12 lags. These regressions are consistent with the filtered-data regressions of Table 1.

*Limitations of Filtered Data.* A band-pass filter is not the most efficient method of separating signal from noise if the economist has other identifying information. For example, permanent income declined overnight on the imposition of the 1973 oil embargo, although a moving average of income responded quite slowly. We are usually not so fortunate. In fact, we often have no choice but to *define* conceptually interesting components of the data by their frequency ranges.

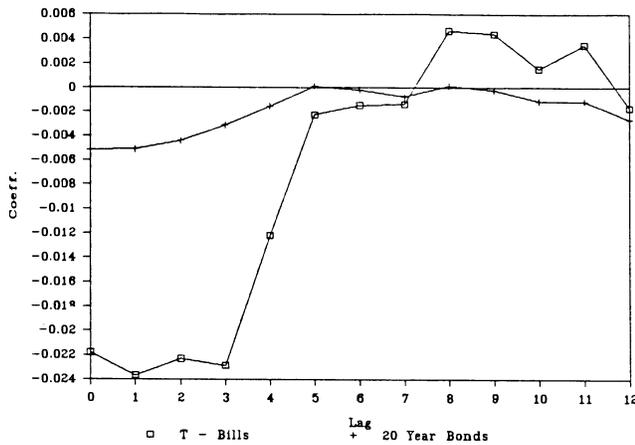


Figure 5. Coefficients of OLS-Distributed Lag Regression of Interest Rates on Money Growth.

The characteristic frequencies of components must be constant through the data set. If short-run effects last for three weeks in part of the sample but for nine weeks later on, no time-invariant filter can separate the economically meaningful components. This just means that the components must be stationary time series.

McCallum (1984) criticized the whole idea of testing long-run hypotheses with low-pass filters for failure to distinguish between anticipated and unanticipated movements in variables. In a criticism of Lucas (1980), Whiteman (1984) also made the point that “measurement without theory” with filters is no more (or less) revealing of structural coefficients than it is with other reduced-form techniques. This criticism has nothing specifically to do with expectations and filters; any technique for measuring a reduced-form coefficient might not say much about an underlying structural coefficient.

### 3. AN INTERPRETATION

The debate between the liquidity and anticipated-inflation effects has included evidence on the persistence of money growth, the lag from money growth to inflation, and the extent to which money-growth changes are anticipated. For example, Mascaro and Meltzer (1983) argued for the anticipated inflation effect based on evidence that money growth is a random walk. This section presents these elements of the debate between advocates of the two “effects” in a very simple model. This section is *not* a general model of money and interest and ignores many other “effects.”

Let money growth follow an exogenous stochastic process (which may have a unit root)

$$m_t = A(L)\varepsilon_t. \tag{3.1}$$

Let real rates depend on current and past unanticipated money growth:

$$\rho_t^1 = R + B(L)(m_t - {}_{t-1}m_t) = R + B(L)\varepsilon_t. \tag{3.2}$$

(A subscript before a variable indicates conditional ex-

pectation.) Write the projection of inflation on money growth as

$$\pi_t = C(L)m_t. \tag{3.3}$$

Let the Fisher effect determine the one-period nominal rate

$$r_t^1 = \rho_t^1 + {}_{t-1}\pi_1, \tag{3.4}$$

and let a risk-neutral term structure relation define the interest rate at longer maturities:

$$1 + r_t^n = E_t \left( \sum_{j=0}^{n-1} (1 + r_{t+j}^1) \right)^{1/n} \approx 1 + \frac{1}{n} \sum_{j=0}^{n-1} r_{t+j}^1. \tag{3.5}$$

Equations (3.1)–(3.5) imply a reduced-form distributed-lag relation between money growth and interest rates of varying maturity:

$$r_t^1 = D(L)m_t, \quad r_t^n = F(L)m_t. \tag{3.6}$$

Different lag polynomials  $A$ ,  $B$ , and  $C$  produce different  $D$  and  $F$ , which are the objects we have studied.

Equations (3.2) and (3.3) are reduced forms that may capture a range of views about the ultimate cause of the short-run nonneutrality of money that causes a liquidity effect. Equation (3.3) includes the different effects of anticipated and unanticipated money growth. Just because the filters used to estimate the reduced forms  $D(L)$  and  $F(L)$  in (3.6) are two-sided does not mean that we ignore the possibly different effects of anticipated and unanticipated money growth.

#### 3.1 The Persistence of Money-Growth Changes

If changes in money growth are persistent, then short-term changes in money growth are good predictors of future inflation. In the extreme case, advocated by Mascaro and Meltzer (1983), money growth follows a random walk. On the other hand, if changes in money growth do not typically last long, then the anticipated inflation channel is weak. To illustrate, let money growth follow an autoregressive process, and suppress the liquidity effect:

$$m_t = \lambda m_{t-1} + \varepsilon_t, \quad \pi_t = m_t, \quad \rho_t^1 = R. \tag{3.7}$$

Expected inflation is

$${}_{t-1}\pi_{t+k} = \lambda^{k+1}m_{t-1}, \tag{3.8}$$

so the interest rate on bonds of maturity  $n$  is

$$r_t^n = R + \frac{1}{n} \frac{\lambda(1 - \lambda^n)}{(1 - \lambda)} m_{t-1}. \tag{3.9}$$

As  $\lambda \rightarrow 1$ , money growth becomes more persistent, and the positive correlation between  $m_{t-1}$  and  $r_t^n$  increases. As maturity  $n$  increases, the correlation declines as  $1/n$ : the anticipated-inflation effect is greatest for short maturities.

### 3.2 The Lag From Money Growth to Inflation

Suppose now that the projection of inflation on money growth (3.3) includes a lag of, for example, three periods:

$$m_t = m_{t-1} + \varepsilon_t, \quad \pi_t = m_{t-3}, \quad \rho_t^1 = R. \quad (3.10)$$

(Remember, this is the reduced-form projection of inflation on money growth. The lag could arise because of a three-period price stickiness, informational lags, etc.) Again, we can find expected inflation and interest rates  $r_t^1 = R + m_{t-3}$ ,  $r_t^2 = R + \frac{1}{2}(m_{t-3} + m_{t-2})$ ,  $r_t^3 = R + \frac{1}{3}(m_{t-3} + m_{t-2} + m_{t-1})$ , and  $r_t^n = R + (1/n)(m_{t-3} + m_{t-2} + \max(n-2, 0)m_{t-1})$  ( $n > 3$ ), where  $m_{t-1}$  has no contemporaneous effect on interest rates with maturity less than 3. If the lag in the projection of inflation on money growth is more than three months, money growth and the three-month bill rate *cannot* display an anticipated inflation effect.

### 3.3 Anticipated Money and Real Interest Rates

The projection of inflation on money growth, (3.3), will have shorter lags as money-growth changes are more anticipated. In the limit of a preannounced currency reform, there should be no lag between money growth and inflation. In this case, the anticipated inflation effect should dominate as explained in Section 3.2. Conversely, if changes in money growth are typically unanticipated, then the lag from money growth to inflation is likely to be longer, and the liquidity effect should dominate.

Finally, if changes in money growth are largely anticipated then innovations in (3.2) are small, so real interest rates vary little. If changes in money growth are largely unanticipated, then the liquidity effect in the real rate of interest has more room to operate.

## 4. CONCLUSION

In this article, I have presented evidence of a negative short-run correlation between money and interest rates during the period of nonborrowed reserve targeting. Higher monetary growth was associated with lower interest rates for periods up to a year. I interpreted this evidence to suggest that the liquidity effect dominated the anticipated inflation effect. In turn, the liquidity effect adds weight to the views that money-growth changes were largely unanticipated, that money growth was a poor predictor of future money growth, that inflation followed money growth with a long lag, and that real interest rates did vary in response to money-growth changes.

The reduced-form correlation between money growth and interest rates documented in this article suggests that there is a liquidity effect, but it does not quantitatively answer the structural question How much and for how long do interest rates decline if you raise money growth today? There may be some residual feedback from interest rates to money growth in the spectral

windows; the anticipated inflation effect may be present but masked by the liquidity effect; the reduced-form correlation does not pick out the possibly distinct effects of anticipated and unanticipated money growth.

Finally, I have argued by example for the use of simple filters in the analysis of series that contain noise, components, trends, and so forth, with different characteristic periodicities and in the analysis of relations between series that may be different in different runs.

### ACKNOWLEDGMENTS

This article is a revised version of one chapter of my Ph.D. dissertation at the University of California, Berkeley. I thank Roger Craine, Bill Poole, Lincoln Anderson, and many seminar participants for helpful comments and criticisms. I thank Eric Fisher for help in obtaining the data.

### APPENDIX: DATA SOURCE AND TRANSFORMATIONS

Data are all weekly, obtained from the Federal Reserve Board. They include all revisions to June 3, 1986. I used the Monday auction average three-month treasury-bill rate, the calendar-week average 20-year U.S. government average maturity yield, and nonseasonally adjusted M1. I eliminated 53rd weeks not common to all series. For use in filtering, the 2–3 day mismatch of these series does not matter. The sample is 592 data points from 75:1 to 86:20. I seasonally adjusted M1 using Sims's (1974) technique. The program is given in the RATS manual (Doan and Litterman 1985, pp. 11–17) with  $nords = 1,248$ ,  $nseasons = 52$ , and  $width = 5$ . The filters are two-sided weighted moving averages, which use 52 positive and negative lags. For a filter between frequencies  $a$  and  $b$ , the weights are given by (3.3). I adjusted the weights to sum to 1 for low-pass filters and 0 for band-pass filters.

[Received March 1987. Revised October 1987.]

### REFERENCES

- Cagan, P. D., and Gandolfi, A. (1969), "The Lag in Monetary Policy as Implied by the Time Pattern of Monetary Effects on Interest Rates," *American Economic Review*, 59, 277–284.
- Cochrane, John H. (1986), "Three Essays in Macroeconomics," unpublished Ph.D. dissertation, University of California, Berkeley, Dept. of Economics.
- Cornell, Bradford (1983), "The Money Supply Announcements Puzzle: A Review and Interpretation," *American Economic Review*, 73, 644–657.
- Doan, Thomas A., and Litterman, Robert B. (1985), *Rats User's Manual*, Minneapolis, MN: VAR Econometrics.
- Engle, Robert F. (1974), "Band Spectrum Regression," *International Economic Review*, 15, 1–11.
- (1978), "Testing Price Equations for Stability Across Spectral Frequency Bands," *Econometrica*, 46, 869–880.
- Feige, Edgar L., and Pearce, Douglas K. (1979), "The Casual Causal Relationship Between Money and Income: Some Caveats for Time Series Analysis," *Review of Economic Statistics*, 61, 521–533.
- Friedman, Milton (1968), "The Role of Monetary Policy," *American Economic Review*, 53, 3–17.

- Geweke, John (1982), "Measurement of Linear Dependence and Feedback Between Multiple Time Series," *Journal of the American Statistical Association*, 77, 304–324.
- Grossman, Sanford, and Weiss, Laurence (1983), "A Transactions-Based Model of the Monetary Transmission Mechanism," *American Economic Review*, 73, 871–880.
- Harvey, A. C. (1978), "Linear Regression in the Frequency Domain," *International Economic Review*, 19, 507–512.
- Lucas, Robert E. (1980), "Two Illustrations of the Quantity Theory of Money," *American Economic Review*, 70, 1005–1014.
- Lucas, Robert E., and Stokey, Nancy L. (1987), "Money and Interest in a Cash-in-Advance Economy," *Econometrica*, 55, 491–514.
- Mascaro, Angelo, and Meltzer, Allan (1983), "Long- and Short-Term Interest Rates in a Risky World," *Journal of Monetary Economics*, 12, 485–518.
- McCallum, Bennet T. (1984), "On Low Frequency Estimates of 'Long Run' Relationships in Macroeconomics," *Journal of Monetary Economics*, 14, 3–14.
- Melvin, Michael (1983), "The Vanishing Liquidity Effect of Money on Interest: Analysis and Implications for Policy," *Economic Inquiry*, 21, 188–202.
- Mishkin, Frederic S. (1981), "Monetary Policy and Long Term Interest Rates: An Efficient Markets Approach," *Journal of Monetary Economics*, 7, 29–55.
- (1982), "Monetary Policy and Short Term Interest Rates: An Efficient Markets Approach," *Journal of Finance*, 37, 63–72.
- Poole, William (1982), "Federal Reserve Operating Procedures: A Survey and Evaluation of the Historical Record Since October 1979," *Journal of Money, Credit, and Banking*, 14, 575–596.
- Sargent, Thomas J. (1979), *Macroeconomic Theory*, New York: Academic Press.
- Sims, Christopher A. (1974), "Seasonality in Regression," *Journal of the American Statistical Association*, 69, 618–626.
- Stokes, H. H., and Newberger, H. (1979), "The Effects of Monetary Changes on Interest Rates: A Box–Jenkins Approach," *Review of Economics and Statistics*, 61, 534–548.
- Summers, Lawrence H. (1983), "The Non-Adjustment of Interest Rates: A Study of the Fisher Effect," in *Macroeconomics, Prices and Quantities: Essays in Memory of Arthur M. Okun*, ed. J. Tobin, Washington, DC: Brookings Institution.
- Taylor, John B. (1979), "Staggered Wage Setting in a Macro Model," *American Economic Review*, 69, 108–113.
- Whiteman, Charles H. (1984), "Lucas on the Quantity Theory: Hypothesis Testing Without Theory," *American Economic Review*, 74, 742–749.

## LINKED CITATIONS

- Page 1 of 4 -



You have printed the following article:

### **The Return of the Liquidity Effect: A Study of the Short-Run Relation between Money Growth and Interest Rates**

John H. Cochrane

*Journal of Business & Economic Statistics*, Vol. 7, No. 1. (Jan., 1989), pp. 75-83.

Stable URL:

<http://links.jstor.org/sici?sici=0735-0015%28198901%297%3A1%3C75%3ATROTLE%3E2.0.CO%3B2-M>

---

*This article references the following linked citations. If you are trying to access articles from an off-campus location, you may be required to first logon via your library web site to access JSTOR. Please visit your library's website or contact a librarian to learn about options for remote access to JSTOR.*

## References

### **The Lag in Monetary Policy as Implied by the Time Pattern of Monetary Effects on Interest Rates**

Phillip Cagan; Arthur Gandolfi

*The American Economic Review*, Vol. 59, No. 2, Papers and Proceedings of the Eighty-first Annual Meeting of the American Economic Association. (May, 1969), pp. 277-284.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28196905%2959%3A2%3C277%3ATLIMPA%3E2.0.CO%3B2-F>

### **The Money Supply Announcements Puzzle: Review and Interpretation**

Bradford Cornell

*The American Economic Review*, Vol. 73, No. 4. (Sep., 1983), pp. 644-657.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28198309%2973%3A4%3C644%3ATMSAPR%3E2.0.CO%3B2-Y>

### **Band Spectrum Regression**

Robert F. Engle

*International Economic Review*, Vol. 15, No. 1. (Feb., 1974), pp. 1-11.

Stable URL:

<http://links.jstor.org/sici?sici=0020-6598%28197402%2915%3A1%3C1%3ABSR%3E2.0.CO%3B2-L>

## LINKED CITATIONS

- Page 2 of 4 -



### **Testing Price Equations for Stability Across Spectral Frequency Bands**

Robert F. Engle

*Econometrica*, Vol. 46, No. 4. (Jul., 1978), pp. 869-881.

Stable URL:

<http://links.jstor.org/sici?sici=0012-9682%28197807%2946%3A4%3C869%3ATPEFSA%3E2.0.CO%3B2-C>

### **The Role of Monetary Policy**

Milton Friedman

*The American Economic Review*, Vol. 58, No. 1. (Mar., 1968), pp. 1-17.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28196803%2958%3A1%3C1%3ATROMP%3E2.0.CO%3B2-6>

### **Measurement of Linear Dependence and Feedback Between Multiple Time Series**

John Geweke

*Journal of the American Statistical Association*, Vol. 77, No. 378. (Jun., 1982), pp. 304-313.

Stable URL:

<http://links.jstor.org/sici?sici=0162-1459%28198206%2977%3A378%3C304%3AMOLDAF%3E2.0.CO%3B2-H>

### **A Transactions-Based Model of the Monetary Transmission Mechanism**

Sanford Grossman; Laurence Weiss

*The American Economic Review*, Vol. 73, No. 5. (Dec., 1983), pp. 871-880.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28198312%2973%3A5%3C871%3AATMOTM%3E2.0.CO%3B2-I>

### **Linear Regression in the Frequency Domain**

A. C. Harvey

*International Economic Review*, Vol. 19, No. 2. (Jun., 1978), pp. 507-512.

Stable URL:

<http://links.jstor.org/sici?sici=0020-6598%28197806%2919%3A2%3C507%3ALRITFD%3E2.0.CO%3B2-C>

### **Two Illustrations of the Quantity Theory of Money**

Robert E. Lucas, Jr.

*The American Economic Review*, Vol. 70, No. 5. (Dec., 1980), pp. 1005-1014.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28198012%2970%3A5%3C1005%3ATIOTQT%3E2.0.CO%3B2-Q>

## LINKED CITATIONS

- Page 3 of 4 -



### **Money and Interest in a Cash-in-Advance Economy**

Robert E. Lucas, Jr.; Nancy L. Stokey

*Econometrica*, Vol. 55, No. 3. (May, 1987), pp. 491-513.

Stable URL:

<http://links.jstor.org/sici?sici=0012-9682%28198705%2955%3A3%3C491%3AMAIAC%3E2.0.CO%3B2-%23>

### **Monetary Policy and Short-Term Interest Rates: An Efficient Markets- Rational Expectations Approach**

Frederic S. Mishkin

*The Journal of Finance*, Vol. 37, No. 1. (Mar., 1982), pp. 63-72.

Stable URL:

<http://links.jstor.org/sici?sici=0022-1082%28198203%2937%3A1%3C63%3AMPASIR%3E2.0.CO%3B2-W>

### **Federal Reserve Operating Procedures: A Survey and Evaluation of the Historical Record Since October 1979**

William Poole

*Journal of Money, Credit and Banking*, Vol. 14, No. 4, Part 2: The Conduct of U.S. Monetary Policy. (Nov., 1982), pp. 575-596.

Stable URL:

<http://links.jstor.org/sici?sici=0022-2879%28198211%2914%3A4%3C575%3AFROPAS%3E2.0.CO%3B2-7>

### **Seasonality in Regression**

Christopher A. Sims

*Journal of the American Statistical Association*, Vol. 69, No. 347. (Sep., 1974), pp. 618-626.

Stable URL:

<http://links.jstor.org/sici?sici=0162-1459%28197409%2969%3A347%3C618%3ASIR%3E2.0.CO%3B2-R>

### **The Effect of Monetary Changes on Interest Rates: Box-Jenkins Approach**

Houston H. Stokes; Hugh Neuberger

*The Review of Economics and Statistics*, Vol. 61, No. 4. (Nov., 1979), pp. 534-548.

Stable URL:

<http://links.jstor.org/sici?sici=0034-6535%28197911%2961%3A4%3C534%3ATEOMCO%3E2.0.CO%3B2-W>

## LINKED CITATIONS

- Page 4 of 4 -



### **Staggered Wage Setting in a Macro Model**

John B. Taylor

*The American Economic Review*, Vol. 69, No. 2, Papers and Proceedings of the Ninety-First Annual Meeting of the American Economic Association. (May, 1979), pp. 108-113.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28197905%2969%3A2%3C108%3ASWSIAM%3E2.0.CO%3B2-I>

### **Lucas on the Quantity Theory: Hypothesis Testing without Theory**

Charles H. Whiteman

*The American Economic Review*, Vol. 74, No. 4. (Sep., 1984), pp. 742-749.

Stable URL:

<http://links.jstor.org/sici?sici=0002-8282%28198409%2974%3A4%3C742%3ALOTQTH%3E2.0.CO%3B2-A>