Treasury Bills, Bonds And Sector Inflation Indices: A Spectral Analysis

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Abstract

This paper uses spectral and correlation techniques to analyze the relationship between several inflation indicators and nominal interest rates. Empirical definitions of real interest rates reduce to stating real rates are equal to nominal interest rates minus expected inflation. To represent a number for inflation, economy-wide measures such as the GDP deflator or the Consumer Price Index are employed. This uncritical usage results more often than not in implausible values for real interest rates. In particular, volatile negative real rates are encountered for prolonged periods ranging from six months to up to three years. Such long time intervals for negative real rates amounts to accepting the unrealistic proposition that profit maximizing lenders, such as commercial bank officers, pay hefty fees to borrowers to have them use their institution's loanable funds. This paper questions the effectiveness of GDP or CPI inflation measures in surrogating for expected inflation. We find instead that narrower sector (industry) inflation indices such as fuels or raw materials prices appear to be improved measures. The issue matters since accurate real interest rate estimates are necessary for policy (Taylor rules), financial model evaluation, and discounting.

1. Introduction

This paper uses spectral and correlation techniques to analyze the relationship between several inflation indicators and nominal interest rates. Empirical definitions of real interest rates reduce to stating real rates are equal to nominal interest rates minus expected inflation. To represent a number for inflation, economy-wide measures such as the GDP deflator or the Consumer Price Index are employed. This uncritical usage results more often than not in implausible values for real interest rates. In particular, volatile negative real rates are encountered for prolonged periods ranging from six months to up to three years. Such long duration real rates amount to accepting the unrealistic proposition that profit maximizing lenders, such as commercial banks, pay hefty fees to borrowers to have them use their institution's loanable funds. This paper questions the effectiveness of GDP or CPI inflation measures in surrogating for expected inflation. We find instead that narrower sector (industry) inflation indices such as fuels or raw materials prices appear to be improved measures. The issue matters since accurate real interest rate estimates are necessary for policy (Taylor rules), financial model evaluation, and discounting.

The real interest rate is a fundamental concept in finance and economics because it is the rate upon which agents supposedly base their saving, investment and portfolio decisions. The real interest rate, expected inflation, and the nominal rate are also a fundamental input to central bank monetary policy. However, both the real interest rate, as well as expected inflation, are unobservable quantities, though theoretically both make up the observable nominal interest rate. Put more formally, the ex-ante nominal interest rate is the sum of the unobservable ex-ante real interest rate and expected inflation. One way favored by empirical analysts around the difficulty posed in trying to quantify the unobservable real interest rate is to use the ex-post real interest rate instead. The ex-post real interest rate is calculated as the difference between the observed nominal interest rate and the observed inflation rate. The

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substitution of ex-post for ex-ante values is possible under the assumption that agents use available information efficiently. With the exception of independent forecast errors, this would be equivalent to analyzing the ex-ante real interest rate.

Nevertheless such methods of estimating ex ante real rates have produced results that seem implausible. Ex-ante real interest rates have been estimated as low as a negative 7 percent and as high as a positive 10 percent in the two decades since 1980. Fluctuations of this magnitude (as well as the existence of negative interest rates over sustained periods of time), have the appearance of being inconsistent with most theories of real interest rates (Emmons 2000). At the very least, both the size of the fluctuations and the existence of negative interest rates appear to indicate something amiss in either the concept or in the conversion process that goes from the observed nominal to the calculated real interest rate. One area where estimation may go awry is if the inflation index is inappropriate to the task of measuring inflationary expectations. Since only broad inflation indices (ie: the GDP deflator or the consumer price index (CPI)), are used to go from nominal to real rates, a simple test can be constructed to measure their adequacy. Because of the unobservable nature of the data, such a test will be completely dependent on the assumptions made regarding the behavior of real rates.

One strong simplifying assumption that can be made is that real interest rates are constant over sustained periods of time. A less restrictive yet plausible assumption would be that changes in the nominal rate are due more to changes in inflationary expectations than to changes in real rates. That is, the primary cause of variability in nominal interest rates over time would be due to inflation, with changes in real rates playing a more attenuated role (Kennedy, 2000). That substantive changes in the nominal interest rate are usually due more to changes in expected inflation than to changes in interest rates is less polemical than assuming real rates are constant, since the consensus among economists is that they are not (Garcia and Perron, 1996). Nevertheless these two authors empirically support the constant real rate proposition by treating the constancy as a stationary process. Real rates therefore, are viewed not as a fixed numerical value (e.g.: 2 percent), but are instead defined as random processes around a constant mean and variance that has substantial, yet infrequent changes (e.g.: a 2 percent mean plus or minus random noise of fixed variance).

Under the strong assumption of fixed real rates (if for example, changes in the GDP deflator are the appropriate expected inflation factor), statistical analysis would find that changes in the nominal interest rate would differ from changes in the GDP deflator only by a constant term. Under the weaker second assumption, changes in the GDP deflator and changes in nominal interest rates would differ by more than a constant term, but would nevertheless be positively correlated. The degree of correlation would be a function of the degree to which changes in inflation overwhelm changes in real interest rates. Under either the strong or weak assumption, once again presuming the GDP deflator is indeed the appropriate inflation factor, using an inflation measure different from GDP, such as narrowly defined oil prices, should result primarily in lower, not higher correlations. In this paper we test these propositions with nine different price indices and report some counter-intuitive statistical results.

Our application of spectral techniques and traditional correlation appears to show that the major economy-wide inflation measures do not have as strong a correlation to short and long term interest rates as sector price indices do. The statistical analysis seems to show different sector price indices are more strongly related to changes in the T-bill (sensitive and raw materials prices), and to changes in the T-bond (fuel prices and energy costs), than either the CPI or the GDP deflator. Both spectral and correlation results confirm each other and possibly shed some doubt on the appropriateness of using major inflation indices to act as surrogates for the expected inflation component of real short and long term interest rates.

2. Nominal and Real Interest Rates

Much as real interest rates are considered fundamental and are placed at the heart of decision making by economic agents, there are also empirically based counter arguments that downplay the importance of real rates in actual financial and economic choices. These arguments minimize the role of real rates in the cyclical behavior of the economy, and they additionally presume far less impact, if any, of real interest rates on individual and business choices. On the one hand, Mishkin (1981) finds there is little evidence that real interest rates have a stable relationship to the business cycle. On the other, there is strong evidence that nominal rates rise in recoveries and fall in downturns. This stronger association between nominal interest rates and business cycle variables may in part be due to the practice of individuals and firms to typically base their financial planning in nominal rather than in real terms (Romer, (1996)). Last but not least, in addition to theoretical issues, there are also nontrivial data problems in the empirical calculation of real interest rates. Boskin (1996), found serious overestimation in CPI inflation data over the 1974 to 1994 period. The result of this overestimation has been to further distort calculations of historical real interest rates.

Notwithstanding these counter arguments downplaying the role of real interest rates, there are at least four broad areas involving practical applications in which miscalculations of expected inflation and real rates can have detrimental financial consequences. These are the fixed income market; monetary policy analysis; financial modeling, and the use of inverted real rates as a predictive tool of future output. Each of these areas needs to distinguish nominal from real rates, or as is the case for some financial models, additionally requires the constancy of real interest rates.

In the first area, the fixed income market, real ex-post capital losses to either borrowers or lenders will be dependent on whether ex-ante inflation expectations, which determine the inflation premium added to real rates, turn out to be different from actual ex-post inflation. The wider this divergence, the more fixed income instruments will fluctuate in value, leading to investment decision uncertainty. This may in part explain why statistical analysis shows inflation and investment to be negatively correlated (Fischer, 1993). The second area is monetary policy. A central bank needs to know the outlook for inflation, and needs to decide on the appropriate policy steps necessary to regulate the extremes of the business cycle. To do this efficiently and not grope in the dark, policy makers need to clearly distinguish real from nominal rates. The "Taylor rule", for example, introduces expectations of a central bank reaction function (Kennedy 2000), which is itself based on the real versus nominal interest rate distinction.

In the third area, financial models such as the Black-Scholes option pricing formula as well as capital asset pricing models are dependent not only on the real versus nominal distinction, but they also have the additional requirement of a constant real interest rate. Rose (1988) shows that nonstationarity of real interest rates could lead to the rejection of some equilibrium asset models such as the consumption CAPM. Ahn and Thompson (1988) additionally find jump diffusion processes in underlying state variables tend to invalidate standard capital asset pricing models. The interpretation and the practical application of these financial models would of course benefit from empirical estimations that would more reliably distinguish between nominal, real and constant interest rates. Yet as Emmons (2000) argues, plausible estimates of real interest rates are not feasible with the current practice of using broad inflation indicators such as the CPI.

The fourth and last area is the use of interest rates in forecasting future economic growth. Business cycle analysts working on Leading Indicators have recognized since the 1970's that inverted interest rates are associated with future output (Zarnowitz, 1988). The supposition that real (and nominal) interest rates anticipate many real macroeconomic variables is also borne out by research done in the 1990's. Several recent studies concur in empirically supporting the proposition that inverted real rates are predictive of future output. These include Fiorito and Kollintzas (1994), who find inverted real interest rates for the G7 countries lead real GDP by 4 quarters, by King and Watson (1996), who also find real rates are predictive of output, and by Boldrin, Christiano and Fisher (2001), who show similar results for the real Federal Funds rate. Finding predictive power for interest rates can be a powerful and useful tool in business and financial applications. However, this usefulness is possibly in doubt, if as previously mentioned, the methodology used to empirically calculate real interest rates produces implausible results.

3. Data and Sectors

We look at the one year Treasury bill, the ten year Treasury note, and their relationship to three major inflation indices (the CPI, and the PCE and GDP deflators), and six sector price measures (Raw Materials, Sensitive Materials, PPI Fuels and Related Products, the CPI Energy Component, and the Manufacturing and Trade Sales deflator). Changes in all the variables are month-to-month 12-month differences of logarithms. ie: June 1990 to June 1991; July 1990 to July 1991; and so forth. The data range from January 1966, to December 2000.

4. Spectral Analysis of Interest rates and Inflation

The term "spectral" leads to the following analogy. Suppose you analyze an apparently uninteresting beam of white sunlight for the first time. If we then view the same beam of light through a prism, we would be surprised by the appearance of a wide array of colors, each with different wavelengths. In similar fashion spectral techniques are capable of finding underlying cycles that are either hidden in the data, or not readily apparent to visual inspection. In essence, performing spectral analysis on a time series is like putting the series through a prism in order to uncover cyclical patterns and identify component wavelengths and their relative importance.

Spectral analysis decomposes a variable into underlying sine and cosine functions of particular wavelengths or cycles. For example, our data sample has 420 monthly observations, and spectral analysis identifies a 7 frequency or recurring 60-month cycle as the most important wavelike pattern for most of our variables. It then gives this 60-month "wave/frequency" an appropriate weight known statistically as a density measurement. The density values can be viewed as the percent contribution of each frequency in explaining a variable. Spectral analysis proceeds to identify other recurring cycles in the sales data as being of descending importance, assigning them densities of lower magnitude. This is shown in Table 1, which displays the densities of the first 15 frequencies for the 9 sector price indices as well as the T-bill and T-bond.

Table 1
Densities

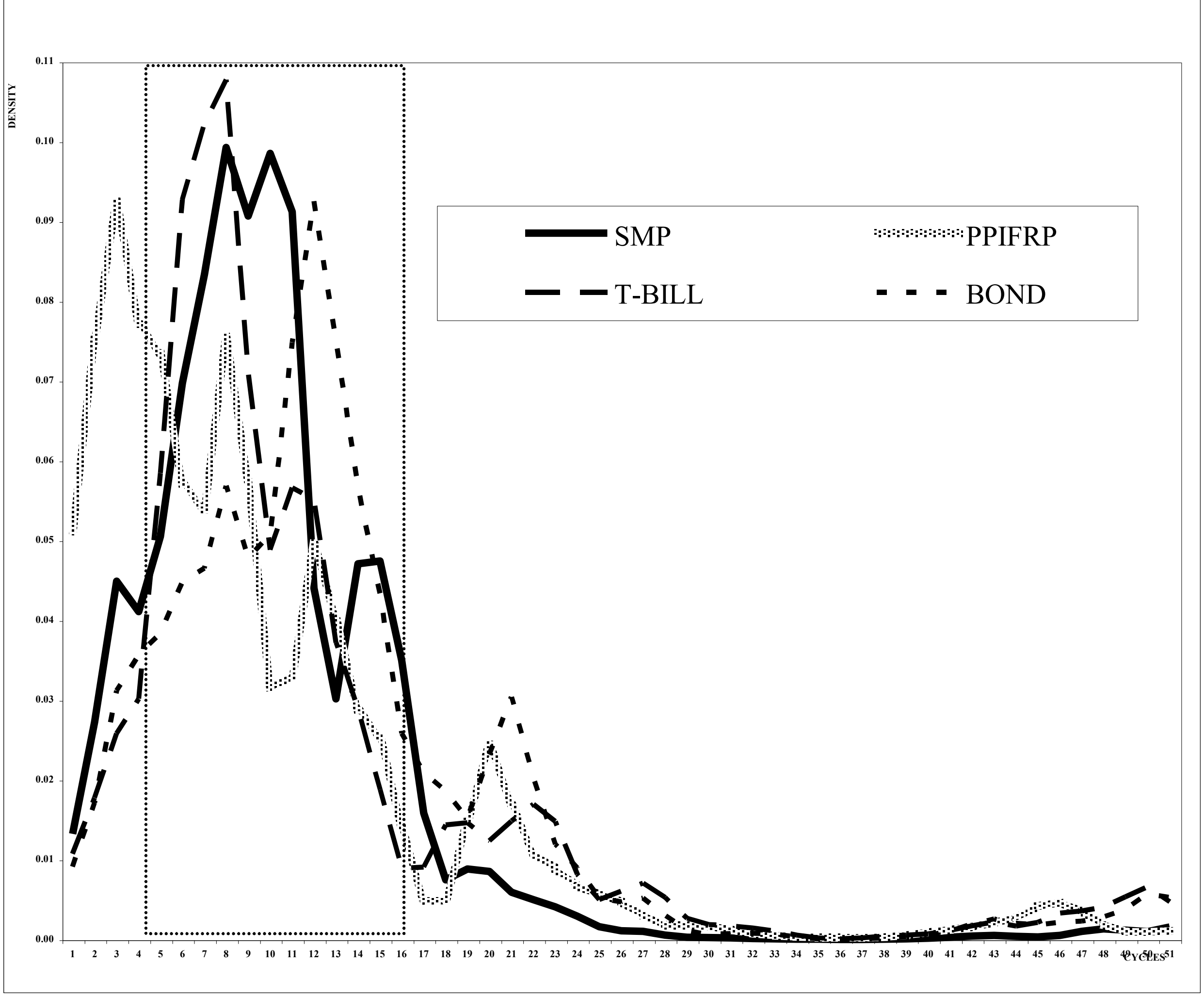
Cycles	Months	Tbsdef	Smp	Rim	Ppi	Ppifrp	Cpinrgy	Pce D2	Gdp D2	Cpi D2	Bill1	Bnd10
0	0	0.111	0.013	0.013	0.104	0.051	0.059	0.014	0.025	0.013	0.011	0.009
1	420	0.147	0.027	0.027	0.143	0.075	0.085	0.023	0.029	0.018	0.018	0.017
2	210	0.146	0.045	0.047	0.155	0.092	0.105	0.036	0.033	0.028	0.026	0.031
3	140	0.077	0.041	0.044	0.105	0.077	0.083	0.043	0.044	0.043	0.030	0.036
4	105	0.055	0.051	0.050	0.087	0.074	0.068	0.058	0.067	0.063	0.058	0.038
5	84	0.066	0.070	0.064	0.077	0.057	0.055	0.067	0.106	0.110	0.093	0.045
6	70	0.081	0.083	0.078	0.073	0.054	0.058	0.092	**0.122**	**0.159**	0.102	0.047
7	60	**0.097**	**0.099**	**0.098**	**0.083**	**0.076**	**0.080**	**0.120**	0.102	0.150	**0.108**	0.057
8	53	0.061	0.091	0.092	0.053	0.057	0.059	0.104	0.071	0.086	0.071	0.048
9	47	0.022	0.099	0.089	0.021	0.032	0.031	0.072	0.071	0.050	0.049	0.051
10	42	0.016	0.091	0.085	0.014	0.033	0.024	0.055	0.083	0.042	0.057	0.075
11	38	0.022	0.044	0.043	0.016	0.050	0.037	0.062	0.071	0.034	0.055	**0.093**
12	35	0.015	0.030	0.028	0.009	0.040	0.041	0.069	0.039	0.032	0.037	0.075
13	36	0.008	0.047	0.045	0.004	0.029	0.032	0.048	0.017	0.029	0.029	0.057
14	30	0.010	0.047	0.046	0.003	0.025	0.025	0.019	0.011	0.016	0.019	0.043
15	28	0.009	0.035	0.037	0.002	0.014	0.015	0.006	0.013	0.007	0.009	0.026
TOTAL		**0.943**	**0.913**	**0.886**	**0.950**	**0.836**	**0.856**	**0.887**	**0.903**	**0.880**	**0.771**	**0.746**

Technically, the number of frequencies in spectral analysis is half the total number of observations in the data set. Our data therefore has waves ranging from a low frequency of 1 cycle, to a maximum high frequency of 210 cycles. The complete set of all 210 waves is known as a power spectrum.

It should be emphasized at this point, however, that spectral analysis is not deterministic, but is instead a statistical procedure. It is appropriate then that the density values we refer to above should be interpreted in terms of a probabilistic variance (sums of squares) of the data at the respective frequency. Furthermore, as with other statistical techniques, sampling errors can affect the parameters of the data spectrum, which are just estimates of true but unknown population data. What the statistical methods are doing is attaching weights to various frequencies reflecting their relative strengths in fitting the data. These weights, however, are not precise values. The randomness in the data tends to lead to a smearing effect across frequencies in the spectrum that is analogous to wide confidence bands on the coefficients of the regression.

Figure 1 depicts the shape of 4 power spectra: the T-bill, the T-bond, Sensitive Materials, and Fuel price indices. The latter two are the price indices with the highest spectral association for the T-bill and T-bond, respectively.

FIGURE 1 Spectra of Sensitive Materials Prices, PPI-Fuel Related Products, T-Bill and T-Bond



For graphical convenience, the chart shows the first 50 frequencies of each spectrum. The remaining 170 frequencies, which are not shown, are characterized by a continuation of very low density values. A conventional frequency domain definition of the business cycle is that these are cycles between 24 and 128 months, roughly equivalent to the interval between the 3rd and the 15th frequencies of Figure 1. The range of this domain definition derives from the duration of business cycles isolated by NBER researchers using the methods of Burns and Mitchell (1946). We can note in Figure 1 that this business cycle interval contains: (a) the peak of our interest rate and inflation spectra. (b) the bulk of the variance of the T-bill (77%), the T-bond (75%), Sensitive Materials (89%), and

Fuels (84%); and (c) substantial predictability of the cyclical component of these growth rates (which is not the same as predictability of the variables), indicated by the hump shape of the power spectrum.

The power spectrum of interest rates, and sector price indices shown in Figure 1, is similar to the growth rate spectrum of a wide range of macroeconomic variables. In particular our growth rate spectrum shares the following broad features with the growth rate spectrum of other macroeconomic variables: the power spectrum is relatively low at low frequencies (a small number of cycles per period), rises to a peak , then rapidly declines at higher frequencies. The height of the spectrum in Figure 1 indicates the extent of that frequency's contribution to the variance of the growth rate.

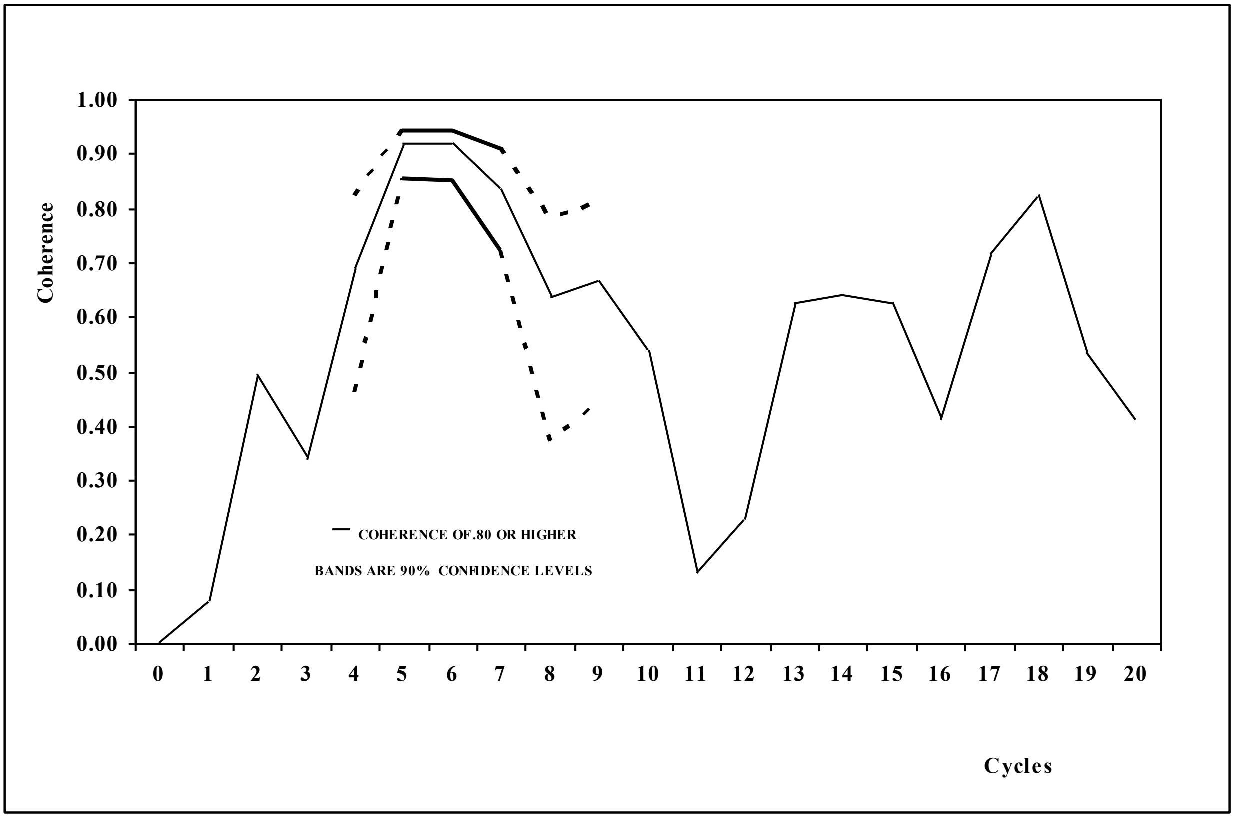
5. Cross-Spectral Analysis

Cross-spectral analysis is the bivariate extension of spectral analysis and relates to pairs of equal frequencies. It measures the strength of the statistical association of waves of equal cycles corresponding to any two economic variables, and also measures their respective leads or lags. This is possible because the spectral density matrix has real and imaginary mathematical components, which can be transformed into two cross-spectral statistics of direct relevance to cycle analysis. The first is coherence, which defines the association between variables. The coherence statistic (which applies to any two waves of equal cycles) can take a value between 0 and 1 and is analogous to the R-squared of regression. Coherence measures the proportion of variance in one frequency as explained by the other. The second statistic is the phase value. Phase estimates lead/lag relationships by wavelength pairs, and measures the time difference for comparable frequencies.

It is important though, to note a distinct feature of the phase statistic. The interpretation of the phase spectrum is highly dependant on the values of the coherence spectrum (Warner, 1998). The phase statistic can only be estimated reliably if the coherence is reasonably high. This is because the statistical sampling error of the phase is inversely related to the squared coherence. As coherence falls, the error in estimating the phase gets larger. This implies we need relatively high coherence values between pairs of frequencies in order to obtain reliable estimates of lead/lag relationships.

There is, however, no uniform approach to identifying lead-lag relationships in economic data with spectral methods, and some researchers do not think this is feasible at all. With these caveats in mind, our approach to lag estimation follows. Our choice as to the criteria used in selecting cut-off points is to ascertain confidence bands around coherence values. This can be combined with a selection process that relies on selecting frequencies that have relatively high densities. This will help rule out some of the phase estimates on statistical grounds, and the most likely phase leads will then be those with highest coherence. The charts for the T-Bill and Sensitive Materials prices, and for the T-bond and Fuel prices (Figures 2 and 3) give a visual flavor of this selection process.

Figure 2 T-Bill And Sensitive Materials Prices



They first report waves with coherence above .70, and individual frequency densities for each variable higher than 2 percent. More stringent criteria are then used to narrow down this first set. Using the confidence bands around the coherence to help rule out some of these frequencies, we end up with coherence values above .80 and individual density requirements of 5% and higher. This narrower selection in turn leaves us with the most likely phase leads as determined by the highest coherence values. All coherence values show 90% confidence bands derived from tables developed by Amos and Koopmans (1963). We now detail below this selection process for the two price indices of highest coherence with the T-bill and T-bond.

6. Cross Spectral Analysis: The T-bill and Sensitive Materials

The cross spectral relationship of the T-bill and Sensitive Materials prices has the highest coherence. The statistics for the T-bill and Materials are shown in Table 2 and Figure 2.

Figure 3 T-Bond And CPI-Energy

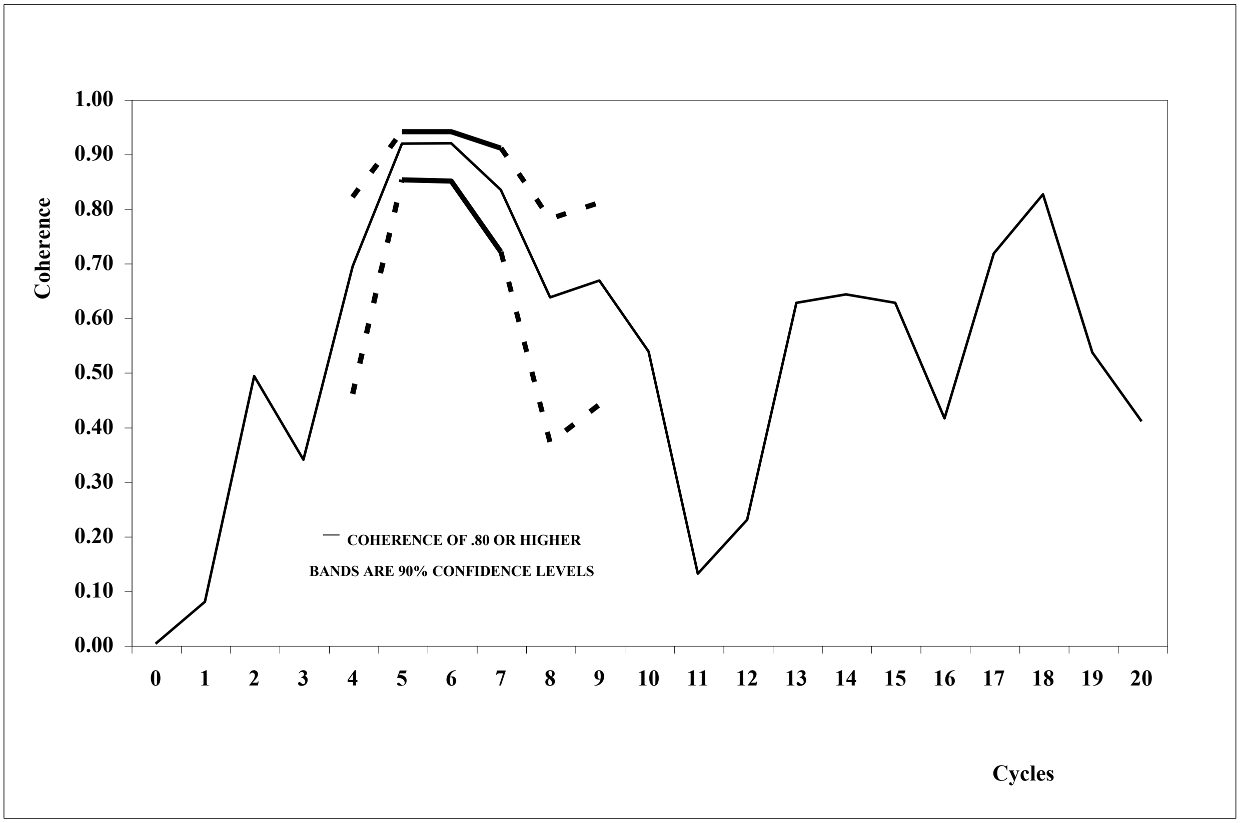


Table 2
T-Bill and Sensitive Materials Prices

	Length	Phase		Confidence Bands (90%)	
Cycles	**(Months)**	**(Months)**	**Coherence**	**Lower**	**Upper**
4	105	-5.4	0.69	0.46	0.82
5	84	-3.8	0.92	0.85	0.94
6	70	-3	0.92	0.85	0.94
7	60	-2.7	0.83	0.72	0.91
8	53	-2.2	0.64	0.37	0.78
9	47	-3.4	0.67	0.44	0.81

Once again, for graphical convenience we only show a few data points, in this case it is the first 20 of 210 frequencies. There are two sets of data shown in this chart. One set has coherence values above .60 but below .80, and density values higher than 2% (dotted lines). This set ranges from frequency 4 to frequency 9, and its phase values range from 2 to 5 months. The second set has more rigorous requirements, with coherence values of .80 and higher, and frequencies for the T-bill and Materials prices with density values explaining 5% or more of their respective variation. These correspond to frequencies 5 through 7 (thick lines). The lead of Sensitive Materials on the corresponding T-bill frequencies is now narrower, and ranges from 3 to 4 months, with the highest coherence value indicating a 4-month lead.

We have applied this last cross-spectral result to the actual time domain data on the T- bill and prices which is shown in Figure 4. This chart plots the 12 month change in the logarithm of the T-bill against the 12 month change in the logarithm of Sensitive Materials prices, with the T-bill "shifted back" in time by 3 months to reflect its stronger correlation as well as its lead by Materials. Figure 5 is similarly structured, with the T-bill "shifted forward" in time by 7 months to reflect its lower correlation and its lead on the GDP deflator.

TABLE 4 SQUARED COHERENCE AND LEADS/LAGS

	INFLATION BY SECTOR	HIGHEST SQ. COHERENCE (0-1.0)	*LEAD(-) LAG(+) MONTHS	SQ.CHRN RANGE (0-1.O)	LD-/LG+ RANGE MONTHS
BILL AND:					
SN-MTRL	SENSITIVE MATERIALS**	0.92	-3	(.64/.92)	(-2/-5)
RW-MTRL	RAW INDUSTRIAL MATERIALS***	0.91	-2	(.63/.91)	(-1/-5)
P-FUELS	PPI FUELS & RELATED PROD.	0.83	11	(.69/.83)	(10/11)
PPI	PPI	0.8	9	(.61/.80)	(8/10)
C-ENRGY	CPI ENERGY	0.79	9	(.68/.79)	(9/10)
PCEDEF	PCE DEFLATOR	0.75	5	(.69/.75)	(3/5)
GDPDEF	GDP DEFLATOR	0.74	7	(.67/.70)	(0/8)
CPI	CONSUMER PRICE INDEX	0.71	4	(.61/.70)	(3/4)
SALES	TOTAL BUSINESS SALES	0.69	8	(.68/.69)	(7/8)
BOND AND:					
P-FUELS	PPI FUELS & RELATED PROD.	0.94	6	(.63/.94)	(2/6)
C-ENRGY	CPI ENERGY	0.91	5	(.61/.91)	(2/5)
SALES	TOTAL BUSINESS SALES	0.87	2	(.61/.86)	(0/-2)
PPI	PPI	0.86	4	(.67/.86)	(2/4)
SN-MTRL	SENSITIVE MATERIALS	0.85	-4	(.73/.84)	(-2/-10)
GDPDEF	GDP DEFLATOR	0.85	-11	(.70/.85)	(0/-20)
RW-MTRL	RAW INDUSTRIAL MATERIALS	0.81	-4	(.73/.81)	(-3/-9)
PCEDEF	PCE DEFLATOR	0.79	-2	(.64/.75)	(0/-2)
CPI	CONSUMER PRICE INDEX	0.77	-2	(.61/.72)	(0/-2)

*LEAD (-) MONTHS BY WHICH THE PRICE INDEX LEADS THE BILL OR BOND
LAG (+) MONTHS BY WHICH THE PRICE INDEX LAGS THE BILL OR BOND

**SENSITIVE MATERIALS	***RAW INDUSTRIAL MATERIALS
CATTLE HIDES	LEAD SCRAP
LUMBER & WOOD PRODUCTS	TIN
IRON AND STEEL SCRAP	ZINC
COPPER BASE SCRAP	BURLAP
ALUMINUM BASE SCRAP	PRINT CLOTH
NONFERROUS SCRAP	WOOL TOPS
RAW COTTON	ROSIN
DOMESTIC APPAREL WOOL	RUBBER
	TALLOW

Table 4 shows an additional seven price indices and their spectral statistics. Columns 1 and 2 display the cycles with the highest coherence and their phase values, for the bill and bond and the nine inflation indices.

TABLE 5 COMPARISON OF SPECTRAL AND CORRELATION STATISTICS

	SPECTRAL STATISTICS			CORRELATION STATISTICS			
INFLATION BY SECTOR	HIGHEST SQUARED COHERENCY	POINT LEAD(-) LAG(+)	%S.E.*	r	CROSS-CORRELATIONS POINT LEAD(-) LAG(+)	RANGE ONE S.E.	RANGE LD-/LG+
SENSITIVE MATERIALS	*0.92*	*-3*	*0.80*	**0.61**	**-1**	**.61/.57**	**(-1/-3)**
RAW INDUSTRIAL MATERIALS	*0.91*	*-2*	*0.37*	**0.60**	**-1**	**.60/.55**	**(-1/-3)**
PPI FUELS & RELATED PROD.	*0.83*	*11*	*0.60*	**0.37**	**14**	**.37/.32**	**(14/2)**
PPI	*0.8*	*9*	*0.54*	**0.41**	**14**	**.41/.36**	**(14/3)**
CPI ENERGY	*0.79*	*9*	*0.52*	**0.36**	**14**	**.36/.31**	**(14/0)**
PCE DEFLATOR	*0.75*	*5*	*0.42*	**0.39**	**2**	**.39/.34**	**(2/7)**
GDP DEFLATOR	*0.74*	*7*	*0.88*	**0.46**	**3**	**.46/.41**	**(3/8)**
CONSUMER PRICE INDEX	*0.71*	*4*	*0.68*	**0.55**	**2**	**.55/.50**	**(2/5)**
TOTAL BUSINESS SALES	*0.69*	*8*	*0.08*	**0.39**	**5**	**.39/.34**	**(5/15)**
PPI FUELS & RELATED PROD.	*0.94*	*6*	*1.74*	**0.49**	**1**	**.49/.44**	**(1/5)**
CPI ENERGY	*0.91*	*5*	*0.92*	**0.50**	**1**	**.50/.45**	**(1/6)**
TOTAL BUSINESS SALES	*0.87*	*2*	*0.00*	**0.46**	**0**	**.46/.41**	**(1/6)**
PPI	*0.86*	*4*	*0.39*	**0.46**	**1**	**.46/.41**	**(1/6)**
SENSITIVE MATERIALS	*0.85*	*-4*	*0.74*	**0.44**	**-1**	**.44/.39**	**(-1/-5)**
GDP DEFLATOR	*0.85*	*-11*	*2.70*	**0.40**	**0**	**.40/.35**	**(0/-8)**
RAW INDUSTRIAL MATERIALS	*0.81*	*-4*	*0.90*	**0.44**	**-1**	**.44/.39**	**(-1/-5)**
PCE DEFLATOR	*0.79*	*-2*	*0.28*	**0.30**	**0**	**.30/.24**	**(0/-7)**
CONSUMER PRICE INDEX	*0.77*	*-2*	*0.72*	**0.45**	**0**	**.45/.40**	**(0/-3)**

ITALICS: SPECTRAL STATISTICS
BOLD : CORRELATION STATISTICS

S.E. STANDARD ERROR OF CORRELATION POINT ESTIMATE

*% S.E. : Spectral lead/lag as proproportion of the correlation standard error,
ie: Sensitive Materials 3 month lead is within .80 S.E. of the 1 month correlation lead.

The two figures allow for a visual time series comparison of T-bill relationships with these two indices.

7. Cross Spectral Analysis: The T-bond and Fuel Prices

We now turn our attention to the price index with the highest coherence for the T-bond. This is the bond's cross spectral relationship with Fuel prices. The statistics for the T-bond and Fuel prices are shown in Table 3 and Figure 3.

Once again, for graphical convenience we only show the first 20 of 210 data points. There are two sets of data shown in this chart. One set has coherence values above .60 and density values higher than 2% (dotted lines). This set ranges from frequency 5 to frequency 8, and its phase values range from 3 to 6 months. The second set has more rigorous requirements, with coherence values above .80, and frequencies for the T-bond and Fuel prices with density values explaining 5% or more of their respective variation. These are frequencies 7 and 8 (thick lines). The lead of the Bond on the corresponding Fuel prices frequencies is narrower, with the highest coherence value indicating a 6-month lead.

Table 3
T-Bond and CPI-Energy

Cycles	Length (Months)	Phase (Months)	Coherence	Confidence Bands (90%) Lower	Upper
4	**84**	**2.1**	**0.61**	**0.34**	**0.76**
5	**70**	**0.4**	**0.65**	**0.38**	**0.79**
6	**60**	**3.4**	**0.73**	**0.53**	**0.84**
7	**53**	**5.2**	**0.91**	**0.84**	**0.93**
8	**47**	**4.5**	**0.84**	**0.72**	**0.91**

Ranges for both statistics are also shown. Table 4 compares the results of correlation and spectral analysis.

Both spectral and correlation statistics show Sensitive Materials and Raw Materials as the top two associations of the T-bill. As to the major inflation indices, the results are straightforward. Spectral and correlation rank the GDP and PCE deflator associations with both interest rates as lowest. The CPI comes out relatively better in the correlation statistics, and ranks third. This compares with the CPI's very low overall spectral ranking for both interest rates. The T-bond shows similar results, with Fuels and Energy sector prices ranked as first in both spectral and correlation statistics, while the GDP and PCE deflators rank low.

Some of our results have some indirect support. Among other topics Christiano (1996), studies the effects of monetary shocks on two price indices. These are commodity prices and the GDP deflator. After a monetary change the results show a sharp immediate decline in commodity prices, and a delayed response in the GDP deflator, which remains flat for 12 months before falling. Though we did not study monetary shocks, our Raw Materials price data shows an immediate, if not anticipatory response to T-bill changes, while the GDP deflator behaved sluggishly, adjusting after a 7-month delay. Cecchetti (2000) states analysts seeking evidence of rising inflation often focus on the movements of a single indicator such as the price of oil or gold. In discussing the poverty of the predictive power of such indicators when used in isolation, Cecchetti nevertheless highlights two empirical results of interest to us. This is that out of nineteen indicators of future inflation the price of oil outperformed CPI autoregressions 9 out of 13 times, while Industrial Materials prices had the single highest score, outperforming CPI autoregressions 10 out of 13 times.

We do not pretend that Sensitive Materials prices or the PPI of Fuels and Related Products are a "better" source of inflationary expectations formation, or that they should replace broader inflation measures in calculating real interest rates. Yet our results appear to be counter-intuitive. They show the puzzling fact that these sector price indices have a far better statistical fit and a more realistic lag structure than the GDP deflator or CPI. This in turn raises some uncertainty regarding the current practice of real interest rate calculations. We do not offer a suggestion regarding an appropriate deflator for interest rates. Our paper only points out a further empirical inconsistency to add to Emmons' (2000) criticisms. Together they appear to show a need to improve current practices of estimating ex ante real interest rates.

Caution, however, has to be exercised in the interpretation of these results for two reasons. One reason is that spectral analysis selects, ranks and associates important component cycles, while correlation and regression analysis covers the total (instead of selective), association of two variables. In selecting cycles with highest coherence the strongest relationships will stand out. This spectral parsimony can be viewed as showing both a positive and a negative side. On the positive side it can be said that spectral analysis filters out the noise in the data and concentrates on the remaining significant cycles. On the negative side this statistical fact can be turned around to say that spectral analysis does not explain the total variation while correlation certainly does, and is therefore more complete. A second reason to be cautious regarding our statistical analysis is that this paper shows our first set of spectral and correlation results in studying interest rates and sector inflation. Accordingly, the nature of the empiricism is exploratory, and is therefore statistically simple. We hope nevertheless that our preliminary results will achieve their purpose. This is to raise questions among applied finance and economics practitioners regarding the empirical definitions and calculations pertaining to the use of real interest rates.

8. Suggestions for Future Research

Three possible avenues lend themselves to further investigation. One is to do a comparative study between major economies such as the U.S., Germany, the U.K., France and Italy, though standardizing the data will present some difficulties. Another is to analyze a different time period for the U.S. and compare the results with those obtained here. The third avenue is an indirect route. Tests of the Monetary Model (Purchasing-Power) of exchange rates have been notoriously unsuccessful. The reason could well be that the nominal exchange rate is defined as the real exchange rate plus relative inflation expectations; the latter being measured by either relative CPI or GDP deflators. This may present problems similar to those we encountered in this paper for nominal interest rates.

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