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Research Article

In Search of Leading Indicator Property of Yield Spread for India: An Approach Based on Quantile and Wavelet Regression

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The leading indicator ability of yield spread for future output growth and inflation is tested for India. Using the yields on securities with maturities ten years and three months to construct yield spread, we study the predictive power of yield spread for output growth and inflation. Our results based on regression of future inflation and output on yield spreads indicate that there is no information in the yield spread about future economic activity and inflation in India. Further, the predictive power of yield spread is analyzed over different quantiles of inflation and output growth using quantile regression; we find that there is again no evidence of predictive information in the yield spreads. Using multiscale wavelet based regression, predictive power is however unveiled at higher time scales for output growth only.

1. Introduction

A large body of literature on the role of asset prices—including interest rates, stock returns, dividend yields, and exchange rates—as predictors of inflation and growth is large and clearly of interest to consumers, investors, and policy makers. In particular, one financial variable that has been becoming popular in forecasting real economic activity is the difference between long-term and short-term risk free interest rates, usually known as the *yield spread*. The theoretical justification of this line of work is that since short-term interest rates are instruments of monetary policy and long-term interest rates reflect market's expectations on future economic conditions, the difference between short- and longer-term interest rates may contain useful information about future inflation and economic activity. In fact, the yield spread has been found very useful for forecasting financial variables such as output growth, inflation, industrial production, consumption, and recessions, and the ability of the spread to predict economic activity has become something of a stylized fact among macroeconomists.

In recent times, the relationship between output growth, inflation, and term spread (the difference between long and short yield of the term structure of the interest rate) has been widely studied. A plethora of research activity says that yield spread should have information for predicting future output and inflation. A large number of these empirical studies verify the predictive power of the spread in forecasting future GDP growth (see [1–8]). Another strand of literature focuses on the use of probit models to verify whether the term spread generates reliable probabilities concerning future recessions (see [3, 4, 9–12]).

A number of studies, including some of those mentioned above, also consider the ability of yield spread to predict inflation. According to the Fisher equation, *the nominal interest rate reflects market expectations of both future inflation and the real rate for a given maturity.* The slope of the yield curve should therefore reflect expected changes in inflation and, in line with this, Mishkin [13, 14] finds that the yield spread contains information about future changes in US inflation. Schich [15], Berk and Bergeijk [16], and Estrella [17] also find yield spread as a reliable leading indicator of inflation. Tkacz [18] by testing the asymmetric relationship between inflation and yield spread using two-regime threshold models arrives at the same conclusion.

Although many empirical studies find yield spread as a good predictor of economic activity and inflation, however some studies reveal either no or very weak predictive content of yield spread (see [19, 20]). This lack of predictive ability has been attributed to several reasons; for example, heavy financial regulation by governments may not bring expectations into interest rates and then yield spreads may not contain information for predicting economic activity and inflation, asymmetric monetary policy [18], negligence of taking into account structural breaks in relationships [21], and time varying term premium which have also been found to diminish the predictive power of yield spreads [22].

A plethora of research on yield spread's predictive ability focuses on developed countries whereas its empirical verification has received the least attention in developing countries like India. Till recent past, interest rates in developing countries including India were highly regulated, which did not allow the emergence of market determined yield curve. In India, soon after the emergence of yield curve in 1996, a study conducted by Kanagasabapathy and Goyal [23] showed that yield spread has predictive information about future economic activity and recessions. On the other hand, Bhaduri and Saraogi [24] have shown that yield spread in India is able to time stock markets only using probit estimation method. The empirical validity of predictive power of the yield spread is still at the epicentre of controversy and economists have not reached precise conclusion yet.

The objective of this paper is to revisit the leading indicator property of yield spread for economic activity and inflation in India. We use conventional regression approach to study this property but fail to find any evidence. Since we fail to find the leading indicator property of yield spread using conventional method, we use quantile regression to reexamine this property. The use of quantile regression is motivated by the fact that if yield spread has predictive information for future recessions only (as proposed in literature), the predictive power of yield spread could be more obvious for the lower quantiles of output growth. Nevertheless, quantile regressions fail to provide any evidence of leading indicator property of yield spread.

Numerous authors have suggested that the true economic relationships among variables could hold at the disaggregated level rather than at the usual aggregation level (see [25, 26]). In fact, economic agents operate at different frequencies; for example, central banks have different objectives in the short and long run, and they operate at different time scales separately (see [27]). This operation of central banks at different time scales leads to heterogeneous frequency contents in the yield spreads. Similarly, monetary policy, which drives the most predictive power of the yield spread, is also a heterogeneous process. Therefore, economic agents operate at different frequencies or time scales. This warrants the relationship to be studied at different frequencies. To the best of our knowledge, couple of studies (see [28–30]) have used wavelet based frequency approach to unveil the predictive ability of yield spreads. We therefore assess the leading indicator property of yield spread at different frequencies of output growth and inflation in India using the multiscale regression based on wavelets. Using this novel approach, we are able to unveil the leading indicator property of yield spread for output growth at higher time scales but not for inflation.

The remainder of the paper is organised as follows. The theoretical model of this problem is described in Section 2. The quantile regression and wavelet based methodology used in the paper are described in Sections 3 and 4, respectively. The data description and the results of this analysis are discussed in Section 5 and finally Section 6 gathers the main conclusions.

2. Theoretical Model

The theoretical argument underlying the use of yield curve as a leading indicator for real growth as well as inflation is based on the combination of *Fisher equation* and *rational expectation hypothesis*. The rational expectation hypothesis of term structure states that *the yield to maturity of a bond with n-periods to maturity can be decomposed into expected one-period yields and a risk premium*. Mathematically,

$$R(n,t) = \frac{1}{n}\sum_{i=0}^{n-1} E_t R(1, t+i) + \Phi(n,t), \tag{1}$$

where E_t is the conditional expectation operator and $R(n,t)$ and $\Phi(n,t)$ refer to the yield to maturity of a bond with n-periods maturity and average risk premium on n-period bond until it matures, respectively. Using Fisher decomposition, (1) can be rewritten as

$$R(n,t) = E_t r(n,t) + E_t \pi(n,t) + \theta(n,t), \tag{2}$$

where $E_t r(n,t)$ and $E_t \pi(n,t)$ are average real interest rate over periods t to $(t+n-1)$ and the average expected inflation rate over the periods $(t+1)$ to $(t+n)$, respectively. Further, under rational expectations hypothesis theory of term structure, the risk premium is assumed to be constant over time (see [31]).

The slope of the yield curve between maturities "m" and "n" can be decomposed into change in real rate and expected inflation making use of (2). Therefore, considering (2) for long-term interest rate of maturity "n" and a short-term interest in maturity "m" and hence by subtracting the latter from former, the following equation emerges:

$$\begin{aligned} R(n,t) &- R(m,t) \\ &= E_t[r(n,t) - r(m,t)] + E_t[\pi(n,t) - \pi(m,t)] \\ &\quad + \theta(n,t) - \theta(m,t). \end{aligned} \tag{3}$$

Now, if the real activity is related to change in real interest rate and the term premium is kept constant, then (2) and (3) imply that the term spread should contain information about future economic activity through consumption and investment. Similar relation can be expected to hold between yield spread and inflation through inflation-growth nexus and the notion that yield spread is composed of real interest rate and expected inflation. Econometric analysts, therefore, look at the yield spread as a potential source of information about future economic activity and inflation. The predictive ability of yield spread for output and inflation could be modeled by the following equations:

$$\left(\frac{1200}{h}\right)(\ln y_{t+h} - \ln y_t) = \alpha + \beta \cdot \text{Spread} + \mu_{t+h}, \quad (4)$$

$$\left(\frac{1200}{h}\right)(\ln \pi_{t+h} - \ln \pi_t) = \alpha + \beta \cdot \text{Spread} + \mu_{t+h}, \quad (5)$$

where y_t and π_t are output and prices, respectively.

3. Quantile Regression

Quantile regression has been proposed as a way to discover more useful predictive relationships between variables in case where there is no relationship or only a weak relationship between the set of variables. The success of quantile regression in testing relationships has been attributed to the different factors leading to data with unequal variation of one variable for different ranges of another variable. Under the framework of quantile regression, each quantile regression characterizes a particular point of the conditional distribution. Moreover, when the conditional distribution is *heterogeneous,* allowing different quantile regressions together, further, proves to be quite useful. The method of quantile regression proposed by Koenker and Bassett [32] permits estimation of various quantile functions in a conditional distribution. The interest of empirical research lies with the analysis of the behavior of a dependent variable given the information contained in a set of explanatory variables. Since the underlying idea of this paper is to test the predictive ability of yield spread for economic activity and inflation in India, a quantile regression model is used to draw more insights into the relationship at different quantiles. Further, if the yield spread could predict recessions better than the upturns in the economic activity, the predictive power of yield spread will be more for the lower quantiles of output growth and inflation.

The model is briefly illustrated as follows. Suppose there is a linear specification for the conditional quantiles of Y; then

$$Y_t = X_t\beta + \mu_t, \quad (6)$$

where Y_t is the output growth of a country, X_t is lagged spread which is constant, β is the coefficients of the model that need to be estimated, and μ_t is the error term. The goal of the quantile regression model is therefore to estimate β for different conditional quantile functions.

Assume that the conditional mean of Y is $\mu(X) = X'\beta$; then the approach of ordinary least squares is to estimate the mean, $\min_{\mu\in\mathbb{R}} \sum_{t=1}^{n}(Y_t - \mu)^2$; that is,

$$\min_{\beta\in\mathbb{R}} \sum_{t=1}^{n} \left(Y_t - X_t'\beta\right)^2. \quad (7)$$

Solving the linear specification of (7) will give the estimation of median (0.5th quantile) function. We choose τ to denote the other quantile variables. Then, the conditional quantile function can also be expressed as

$$Q_E\left(\frac{\tau}{X}\right) = X'\beta(\tau). \quad (8)$$

Therefore, in order to obtain the estimation of the conditional quantile functions, we need to solve the following equation:

$$\min_{\beta\in\mathbb{R}} \sum_{t=1}^{n} \rho_\tau \left(Y_t - X_t'\beta\right)^2. \quad (9)$$

By following the minimization algorithm, we can minimize the above equation into

$$\min_{\beta} \left[\tau \sum_{E_t X_t'\widehat{\beta}} \left|Y_t - X_t'\widehat{\beta}\right| + (1-\tau) \sum_{Y_t \le X_t'\widehat{\beta}} \left|Y_t - X_t'\widehat{\beta}\right|\right], \quad (10)$$

where $X_t'\widehat{\beta}$ is an approximation to the τth conditional quantile of Y. By choosing τ very close to zero (one), $X_t'\widehat{\beta}$ characterizes the behavior of Y at the left (right) tail of the conditional distribution. Further, this minimization problem could be solved by using the linear programming method as proposed by Koenker and Orey [33].

4. Wavelet Analysis

Wavelet analysis is the outcome of multidisciplinary endeavor that brought together mathematicians, physicists, and engineers. This relationship created a flow of ideas that goes well beyond the construction of new transforms. Wavelet analysis shares several features in common with Fourier analysis but has the advantage of capturing features in the underlying series that vary across both time and frequency. Wavelets are mathematical functions that decompose data into different frequency components, after which each component is studied with a resolution matched to its scale. These functions are generated by the dyadic dilations and integer shifts a single function called a *mother wavelet*. The key feature of wavelets is the time-frequency localization. It means that most of the energy of the wavelet is restricted to a finite time interval and its Fourier transform is band limited. Therefore, as a result, it can reveal short-term transient components of data in shorter time intervals, as well as trends and patterns within longer time intervals.

The application of wavelet theory in modeling and analyzing economic data is a recent phenomenon and its applications in economics began in the late nineties by the contribution of Ramsay and his collaborators (see, e.g., [25, 26]). Since then wavelets have been used in many areas of economics and finance (see [30, 34–37]).

The mathematical theory behind wavelet analysis is briefly described here; an extensive summary of the motivation and details of wavelet analysis can be found in Daubechies [38], and an advanced treatment of the subject is provided in Gençay et al. [35]. Let $L^2(\mathbb{R})$ denote the space of all real-valued functions f to $\mathbb{R}$ such that the L^2 norm is finite:

$$f(t) \in L^2(\mathbb{R}) \quad \text{if and only if} \quad \left(\int_{-\infty}^{\infty} \left|f(t)\right|^2 dt\right)^{1/2} < \infty. \quad (11)$$

A wavelet for $L^2(\mathbb{R})$ is a square integrable function ψ such that the collection $\{\psi_{j,k} = 2^{j/2}\psi(2^j t - k) : j,k \in \mathbb{Z}\}$

forms an orthonormal basis for $L^2(\mathbb{R})$. One of the most useful methods to construct a wavelet is through the concept of *multiresolution analysis* (MRA) introduced by Mallat [39]. An MRA is an increasing family of closed subspaces $\{V_j : j \in \mathbb{Z}\}$ of $L^2(\mathbb{R})$ satisfying the properties (i) $V_j \subset V_{j+1}$, $j \in \mathbb{Z}$, (ii) $\bigcup_{j\in\mathbb{Z}} V_j$ is dense in $L^2(\mathbb{R})$ and $\bigcap_{j\in\mathbb{Z}} V_j = \{0\}$, (iii) $f(t) \in V_j$ if and only if $f(2t) \in V_{j+1}$, and (iv) there is a function $\phi \in V_0$, called the *scaling function*, such that $\{\phi(t-k) : k \in \mathbb{Z}\}$ form an orthonormal basis for V_0. In view of the translation invariant property (iv), it is possible to generate a set of functions $\phi_{j,k}$ in V_j, $j \in \mathbb{Z}$, such that $\{\phi_{j,k} = 2^{j/2}\phi(2^j t - k) : j,k \in \mathbb{Z}\}$ forms an orthonormal basis for V_j, $j \in \mathbb{Z}$.

Given an MRA $\{V_j : j \in \mathbb{Z}\}$, we define another sequence $\{W_j : j \in \mathbb{Z}\}$ of closed subspaces of $L^2(\mathbb{R})$ by $V_{j+1} = V_j \oplus W_j$, $j \in \mathbb{Z}$. These subspaces inherit the scaling property of $\{V_j : j \in \mathbb{Z}\}$; namely,

$$f(t) \in W_j \quad \text{if and only if } f(2t) \in W_{j+1}. \tag{12}$$

Moreover, the subspaces W_j are mutually orthogonal and we have the following orthogonal decompositions:

$$V_{j+1} = V_0 \oplus \left(\bigoplus_{j=0}^{\infty} W_j\right), \quad j = 0, 1, 2, 3, \ldots. \tag{13}$$

Since $V_0 = \oplus_{j=1}^{\infty} W_{-j}$, therefore an MRA produces an orthogonal direct decomposition of $L^2(\mathbb{R})$ as

$$L^2(\mathbb{R}) = \bigoplus_{j\in\mathbb{Z}} W_j. \tag{14}$$

Thus, in view of (12), it follows that if there exists a function $\psi \in W_0$ such that $\{\psi(t-k) : k \in \mathbb{Z}\}$ constitute an orthonormal basis for W_0, then $\{\psi_{j,k} = 2^{j/2}\psi(2^j t - k) : k \in \mathbb{Z}\}$ will be an orthonormal basis for W_j, $j \in \mathbb{Z}$. It is immediate from (14) that the family $\{\psi_{j,k} : j,k \in \mathbb{Z}\}$ will represent an orthonormal basis for $L^2(\mathbb{R})$. It is called an *orthonormal wavelet basis* with mother wavelet ψ.

Once we have constructed our *mother* and *father wavelets*, then we can represent a given signal $f(t) \in L^2(\mathbb{R})$ as a series of mother and father wavelets as

$$\begin{aligned} f(t) = {} & \sum_k a_{J,k}\phi_{J,k}(t) + \sum_k d_{J,k}\psi_{J,k}(t) \\ & + \sum_k d_{J-1,k}\psi_{J-1,k}(t) + \cdots + \sum_k d_{1,k}\psi_{1,k}(t), \end{aligned} \tag{15}$$

where J is the number of multiresolution components or scales and k ranges from 1 to the number of coefficients in the specified components. The coefficients $a_{J,k}$; $d_{J,k} \cdots d_{2,k}, d_{1,k}$ in (15) are the *wavelet transform coefficients* and can be approximated by the following relations:

$$a_{J,k} = \int_{-\infty}^{\infty} f(t)\,\phi_{J,k}(t)\,dt, \qquad d_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)\,dt, \qquad j = 1, 2, \ldots, J. \tag{16}$$

The coefficients $a_{J,k}$, known as the *smooth coefficients,* represent the underlying smooth behaviour of the time series at the coarse scale 2^J, while $d_{j,k}$, known as the *detailed coefficients,* describe the coarse scale deviations from the smooth behaviour and $d_{J-1,k} \cdots d_{2,k}, d_{1,k}$ provides progressively finer scale deviations from the smooth behaviour. The actual derivation of the smooth and detailed coefficients may be done via the so-called *discrete wavelet transform* (DWT), which can be computed in several alternative ways. The intuitively most appealing procedure is the pyramid algorithm, suggested in Mallat [40] (and fully explained in [34]). In this context, the Daubechies family of wavelets is very useful because the mother wavelets in this family have compact support. Therefore, with these wavelets, the size of $a_{J,k}$ and $d_{j,k}$ decreases rapidly as j increases for the DWT of most signals. These coefficients are fully equivalent to the information contained in the original series and the time series can be perfectly reconstructed from its DWT coefficients. Thus, the wavelet representation in (15) can also be expressed as

$$f(t) = A_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t), \tag{17}$$

where $A_J(t) = \sum_k a_{J,k}\phi_{J,k}(t)$ and $D_j(t) = \sum_k d_{j,k}\psi_{j,k}(t)$, $j = 1, 2, \ldots, J$, are called the *smooth* and *detail signals,* respectively. The sequential set of terms $(A_J, D_J, D_{J-1}, \ldots, D_1)$ in (17) represents a set of orthogonal signal components that represent the signal at resolutions 1 to J. Each D_{J-1} provides the orthogonal increment to the representation of the function $f(t)$ at the scale 2^{J-1}.

The DWT introduced earlier is often referred to as the *decimated transform* as the pyramid algorithm arises from a successive downsampling process, in which only alternate observations are picked up at each subsampling stage. However, for many economic and financial applications, an *undecimated* DWT is more appropriate, and this is furnished by the so-called *maximum overlap discrete wavelet transform* (MODWT), described in Percival and Walden [34]. It is similar to the discrete wavelet transform, but it gives up the orthogonality property of the DWT to gain other features that are far more desirable in economic applications. For example, the MODWT can handle input data of any length, not just powers of two; it is translation invariant—that is, a shift in the time series results in an equivalent shift in the transform; it also has increased resolution at lower scales since it oversamples data (meaning that more information is captured at each scale); the choice of a particular wavelet filter is not so crucial if MODWT is used and, finally, excepting the last few coefficients, the MODWT is not affected by the arrival of new information.

Let $\mathbf{X} = (X_0, X_1, X_2, \ldots, X_{N-1})$ be an N-dimensional vector where the sample size N is any positive integer. Then, for any positive integer, the MODWT of $\mathbf{X}$ is a transform consisting of the $J+1$ vectors $\widetilde{\mathbf{W}}_1, \widetilde{\mathbf{W}}_2, \ldots, \widetilde{\mathbf{W}}_J$, and $\widetilde{\mathbf{V}}_J$ all of which have the dimension N. Here, the vector $\widetilde{\mathbf{W}}_J$ contains the MODWT wavelet coefficients associated with changes at scale 2^{j-1}, $j = 1, 2, \ldots, J$ while $\widetilde{\mathbf{V}}_J$ contains

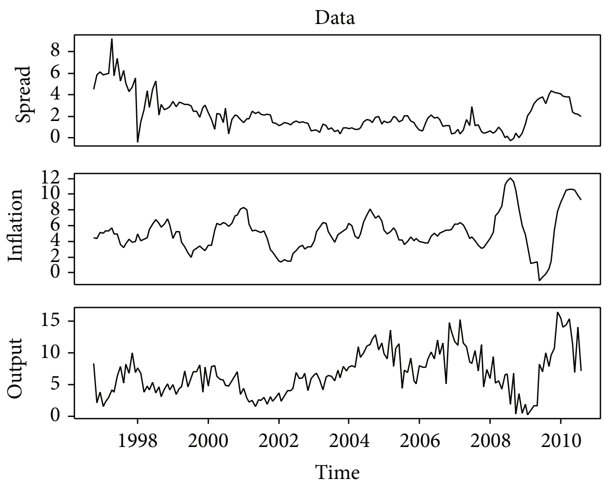

Figure 1: Plot of the output, inflation, and yield spread.

MODWT scaling coefficients associated with averages at scale 2^J. Mathematically, it can be represented as

$$\widetilde{\mathbf{W}}_j = \widetilde{\mathcal{W}}_j \mathbf{X}, \qquad \widetilde{\mathbf{V}}_J = \widetilde{\mathcal{V}}_J \mathbf{X}, \tag{18}$$

where $\widetilde{\mathcal{W}}_j$ and $\widetilde{\mathcal{V}}_J$ are $N \times N$ matrices. Furthermore, if $h = (h_l : l = 0, 1, \ldots, L-1)$ represents the wavelet filter associated with the Daubechies wavelet of unit scale, then clearly

$$\begin{gathered} h_{j,l} = 0, \quad \text{for } l > L, \qquad \sum_{l=0}^{L-1} h_l = 0, \\ \sum_{l=0}^{L-1} g_l g_{l+2n} = \begin{cases} 1, & \text{if } n = 0 \\ 0, & \text{if } n \neq 0, \end{cases} \end{gathered} \tag{19}$$

where g_l is the DWT scaling filter defined in terms of wavelet filter as

$$g_l = (-1)^{l+1} h_{L-1-l}. \tag{20}$$

Now corresponding to $h_{j,l}$ and $g_{j,l}$, the jth level MODWT wavelet and scaling filters are given by

$$\tilde{h}_{j,l} = \frac{h_{j,l}}{2^{j/2}}, \qquad \tilde{g}_{j,l} = \frac{g_{j,l}}{2^{j/2}}. \tag{21}$$

Now, in view of (18), the elements of $\widetilde{\mathbf{W}}_j$ and $\widetilde{\mathbf{V}}_J$ can be expressed as

$$\begin{gathered} \widetilde{W}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{h}_{j,l} X_{t-l \bmod N}, \quad t = 0, 1, \ldots, N-1, \\ \widetilde{V}_{j,t} = \sum_{l=0}^{L_j-1} \tilde{g}_{j,l} X_{t-l \bmod N}, \quad t = 0, 1, \ldots, N-1, \end{gathered} \tag{22}$$

where $L_j = (2^j - 1)(L-1) + 1$ is the width of each MODWT wavelet filter.

Table 1: Unit root test.

Variable	ADF test	PP test
Output growth	-2.262^{**}	-5.55^{*}
Inflation	-2.946^{**}	-3.46^{*}
Yield spread	-2.93^{**}	-3.48^{*}

$*$, $**$, and $***$ denote significance at 1%, 5%, and 10%, respectively.

Table 2: Estimation results of output growth and inflation prediction using yield spread.

Months	Coefficient	Output growth	Inflation
$h = 2$	β	−0.15 (0.19)	0.04 (0.04)
	R^2	0.00	−0.00
$h = 4$	β	−0.09 (0.19)	−0.01 (0.04)
	R^2	−0.00	−0.00
$h = 6$	β	−0.01 (0.20)	−0.05 (0.05)
	R^2	−0.00	0.00
$h = 8$	β	0.06 (0.22)	0.04 (0.07)
	R^2	−0.00	−0.00

5. Data, Empirical Results, and Discussion

In this empirical work, monthly data for the period from October 1996 to August 2010 has been used to test the predictability of yield spreads. The data has been collected from the database on Indian economy from the *Reserve Bank of India* website http://www.rbi.org.in/. The selection of sample period is dictated by the fact that administered interest rate regime did not allow the emergence of a market determined yield curve and it began to emerge only after 1996 in India. A resurgent bond market developed in India as reflected in increase in volumes, variety of instruments, and number of participants justifies our choice of the sample period to be taken from October 1996 to August 2010 for this study. This gives the data window size of 167 observations plotted in Figure 1. Index for industrial production (IIP) and whole sale price index (WPI) are considered to derive the output growth and inflation. Further, the spread is constructed as a difference of yield on ten-year government bond rate and three-month treasury bill rate. We first examine the stationary property of the time series by using *Augmented Dickey-Fuller* and *Phillips-Perron* tests. The results are presented in Table 1 and it shows that all series are stationary at levels. We run the regressions of two, four, six, and eight months ahead output growth and inflation on the yield spread using (4) and (5). The estimated coefficients and standard errors of (4) and (5) are shown in Table 2, and none of the coefficients is found to be significant from two to eight months ahead. This means that the yield spread does not have any predictive information for future output growth and inflation. A plethora of literature suggests that yield spread has predictive information for future recessions (see literature in Section 1). If this assertion is true, then the predictive power of yield spread could be more obvious for the lower quantiles of output growth. We therefore use quantile regression to assess the predictive ability of yield spread for lower quantiles of output growth.

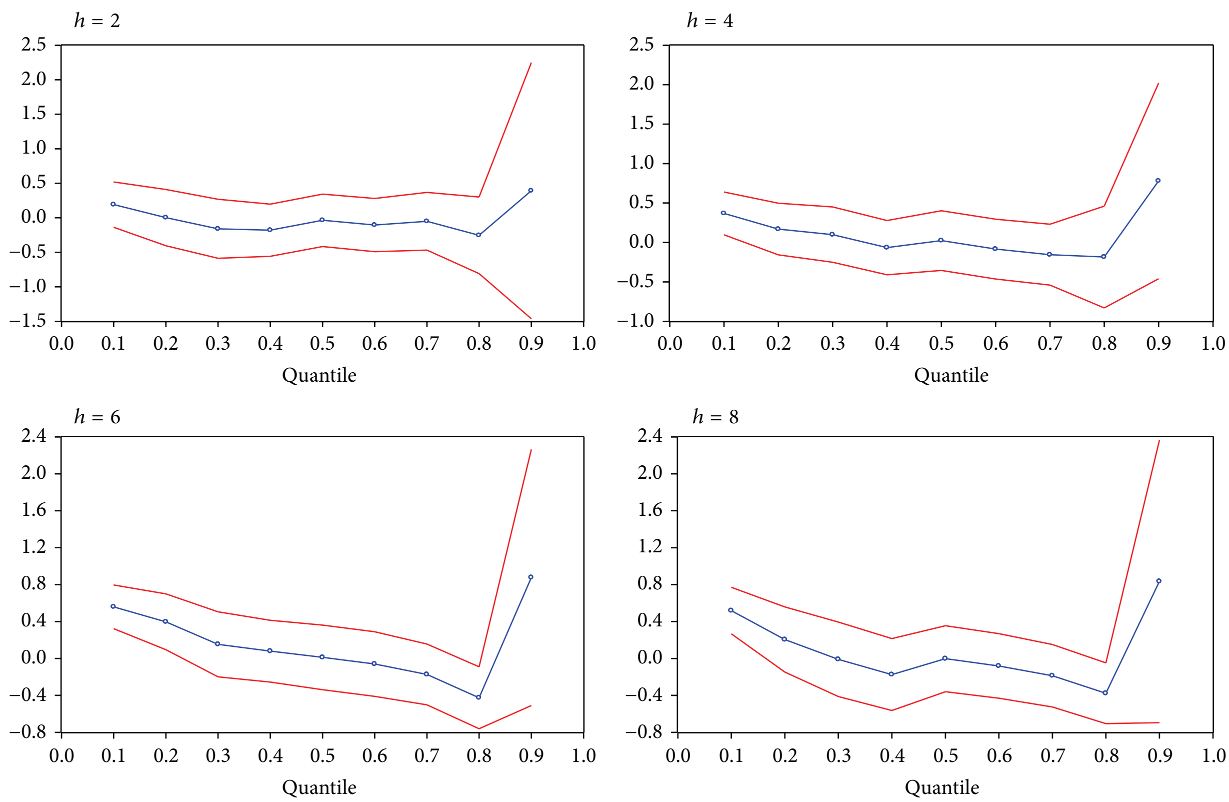

FIGURE 2: Quantile process estimates (with 95% CI) of yield spread for (4).

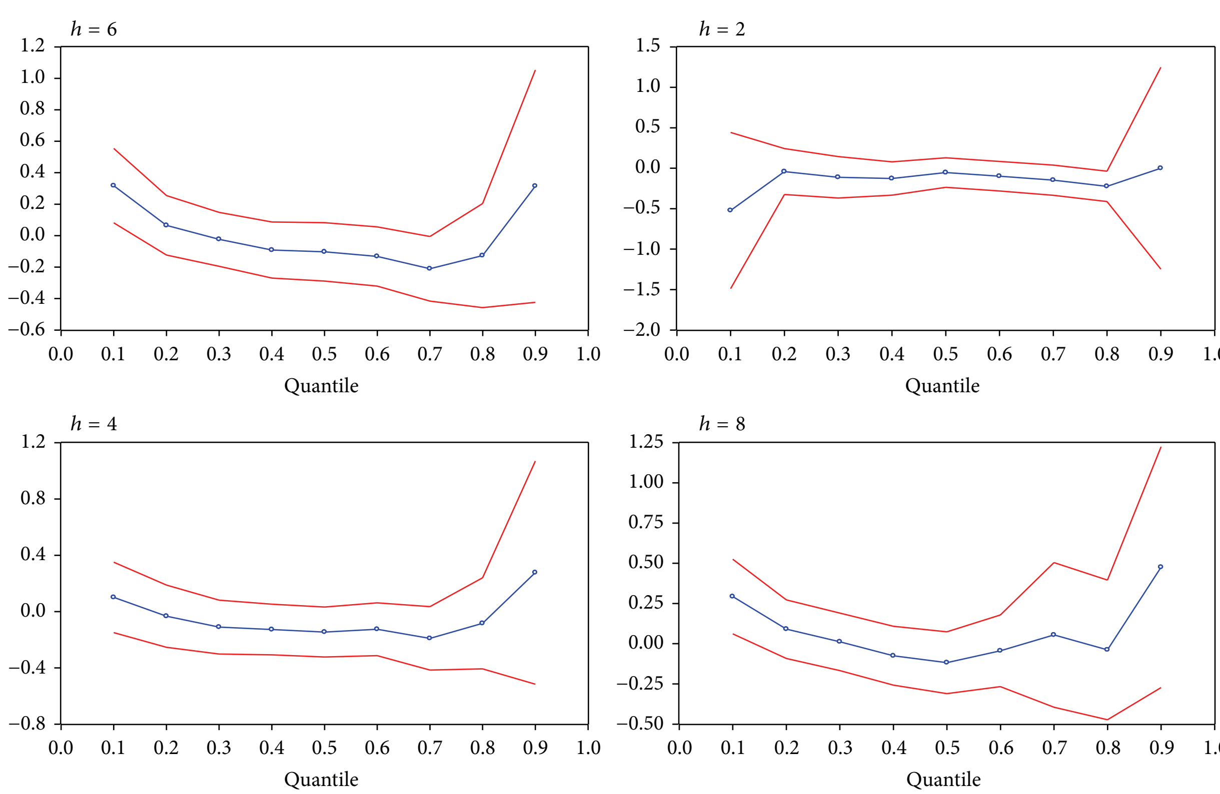

FIGURE 3: Quantile process estimates (with 95% CI) of yield spread for (5).

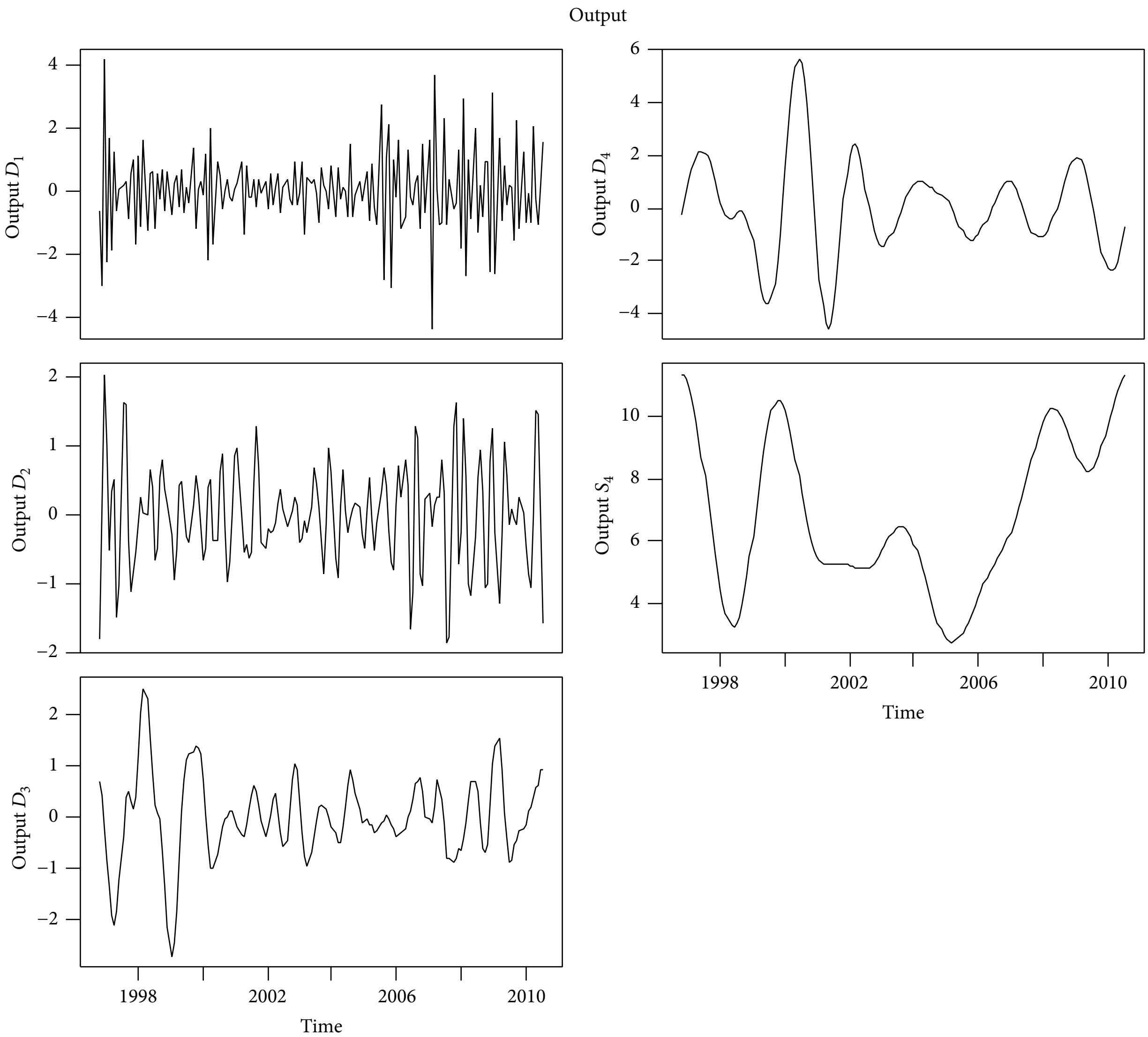

FIGURE 4: Plot of wavelet decomposed series of output into different frequency bands.

The results of quantile regression for (4) and (5) are presented in Table 3 and their plots are shown in Figures 2 and 3. Our results based on quantile regression do not show any evidence for the predictive ability of yield spread for the different quantiles of output growth as well as inflation.

As proposed in the literature, the true economic relationships among variables can be expected to hold at the disaggregated level rather than at the usual aggregation. To use the spread as a predictor of future economic activity and inflation in India, we must look at different frequencies of output growth, inflation, and term spread. We, therefore, use the wavelet based methodology described in Section 3 to decompose a given time series into number of details and a single smooth vector. This avoids the time-horizon aggregation problem which is generally omitted in standard time series analysis. We choose the *maximal overlap discrete wavelet transform* (MODWT) over the more conventional orthogonal DWT because, by giving up orthogonality, the MODWT gains attributes that are far more desirable in economic applications (see wavelet methodology for details).

The application of the MODWT with a number of scales $J = 4$ produces four MODWT detail vectors D_1, D_2, D_3, and D_4 and one smooth vector A_4, where each wavelet scale is associated with a particular time period $[2^J - 2^{J-1}]$.(The Daubechies least asymmetric (LA) wavelet filter of length $L = 4$, commonly denoted as LA(4), in particular is used to decompose the output growth and yield spreads. This filter is favored because of our small sample size. Given the maximum decomposition level $\log_2(T)$ and sample size of 167, we could have attained the maximum level of seven decompositions. However, the number of feasible wavelet coefficients gets small for higher levels; we therefore chose to carry out the wavelet analysis with $J = 4$ so that four wavelet coefficients D_1, D_2, D_3, and D_4 and one scaling coefficient A_4, respectively, were produced.) The time dynamics of each detail vector and smooth vector is given in Table 5 of appendix. Plots of these different period oscillations are shown in Figures 4, 5, and 6 of appendix. Thus, the detail levels D_1 and D_2 represent the very short run dynamics of a signal

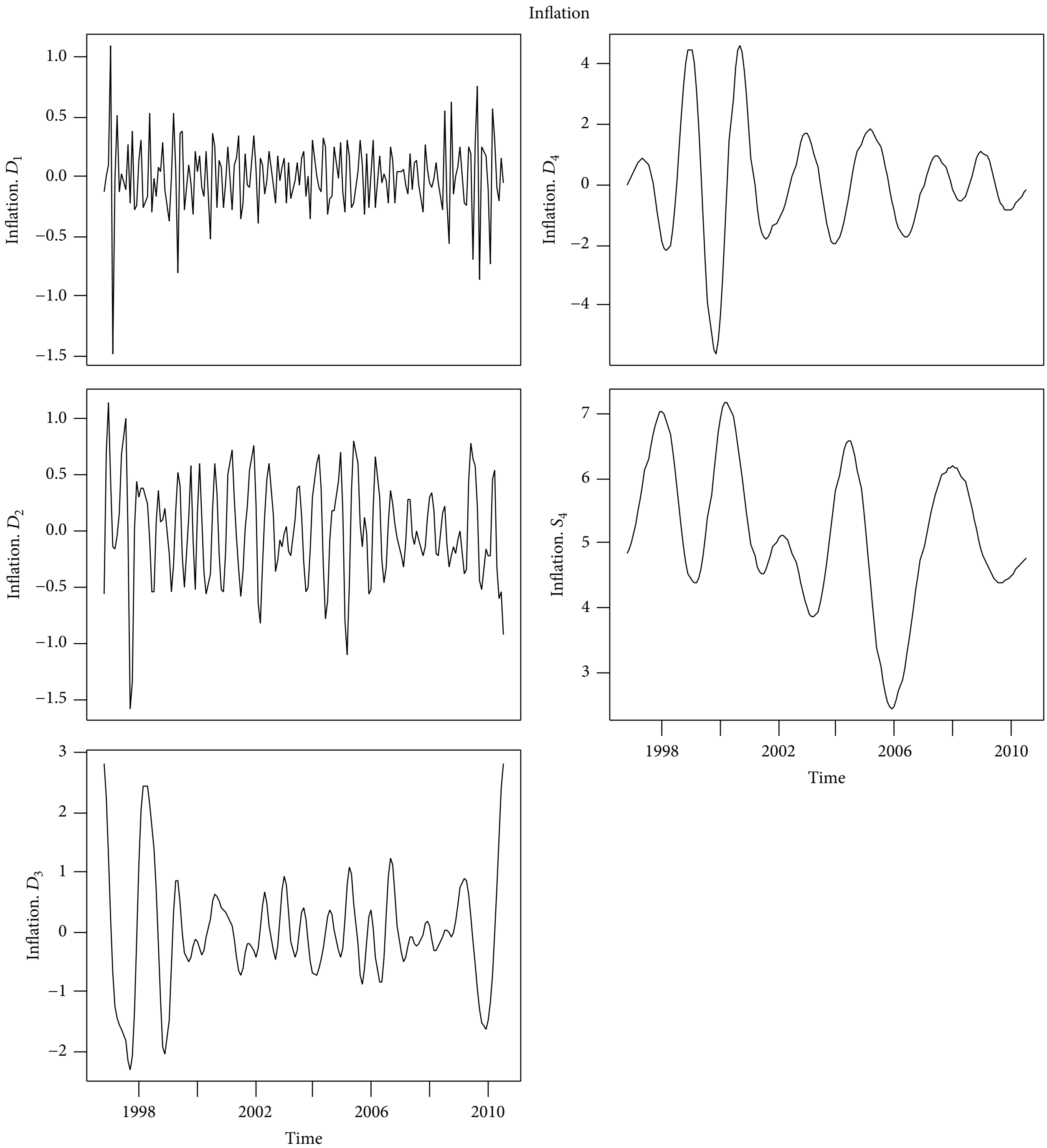

Figure 5: Plot of wavelet decomposed series of inflation into different frequency bands.

or time series (with D_1 containing most of the noise of the signal); detail levels D_3 and D_4 roughly correspond to the standard definition of business cycle. The estimated results of (4) and (5) using decomposed series of output, inflation and yield spread shown in Table 4 and Table 6 indicate that there is no predictive power in the lower scales (high frequency), whereas the scales corresponding to D_3 and D_4 show that yield spreads significantly predict economic activity. The term spread consistently predicts output but not inflation up to eight months ahead at D_3 and D_4 time scales. We can infer that the lack of predictive power of the unfiltered regression is due to the higher frequency resolutions. For inflation multiscale decomposition however fails to yield any conclusion. Yield spread is not found to predict inflation at any time scale, except for the scales D_3 and D_4, where it unusually predicts inflation negatively. These results should, nevertheless, not be surprising. Inflation-growth nexus is often evasive or absent for developing countries. Specifically, in India, studies have found the negative relation between inflation and output; Rangarajan [41], Bhattacharya and Lodh

Table 3: Estimation results of different quantiles of output growth and inflation prediction using yield spreads.

	Quantile	Output growth			Inflation		
		Coefficient	St. error	P value	Coefficient	St. error	P value
$h = 2$	0.2	0.00	0.20	0.99	−0.04	0.14	0.77
	0.4	−0.17	0.19	0.35	−0.12	0.10	0.22
	0.6	−0.10	0.19	0.59	−0.09	0.09	0.29
	0.8	−0.25	0.28	0.36	−0.22**	0.09	0.02
$h = 4$	0.2	0.16	0.16	0.30	−0.03	0.11	0.76
	0.4	−0.06	0.17	0.70	−0.12	0.09	0.16
	0.6	−0.08	0.19	0.66	−0.12	0.09	0.19
	0.8	−0.18	0.32	0.57	−0.08	0.16	0.61
$h = 6$	0.2	0.39*	0.15	0.01	0.06	0.09	0.49
	0.4	0.07	0.17	0.64	−0.09	0.09	0.31
	0.6	−0.06	0.17	0.73	−0.13	0.09	0.16
	0.8	−0.42	0.17	0.01	−0.12	0.16	0.45
$h = 8$	0.2	0.20	0.17	0.25	0.09	0.09	0.33
	0.4	−0.17	0.19	0.38	−0.07	0.09	0.42
	0.6	−0.08	0.17	0.64	−0.04	0.11	0.70
	0.8	−0.37	0.16	0.02	−0.03	0.22	0.86**

∗∗ represents the significance at 5% level.

Table 4: Estimation results of output growth prediction using yield spread at different time scales.

Months	Coefficient	D_1	D_2	D_3	D_4	A_4
$h = 2$	β	−0.02 (0.25)	0.20 (0.18)	0.35 (0.21)***	0.59 (0.52)	−0.11 (0.24)
	R^2	−0.00	0.00	0.02	0.03	−0.00
$h = 4$	β	−0.12 (0.30)	−0.03 (0.19)	0.83 (0.24)*	1.71 (0.51)*	−0.15 (0.23)
	R^2	−0.00	−0.00	0.19	0.26	0.00
$h = 6$	β	−0.14 (0.23)	0.04 (0.11)	0.86 (0.26)*	2.22 (0.47)*	−0.21 (0.22)
	R^2	0.00	−0.00	0.21	0.46	0.00
$h = 8$	β	−0.06 (0.18)	0.04 (0.15)	0.52 (0.22)**	1.99 (0.42)*	−0.29 (0.21)
	R^2	−0.00	−0.00	0.08	0.38	0.02

Standard errors are in parentheses. ∗, ∗∗, and ∗ ∗ ∗ denote significance at 1%, 5%, and 10%, respectively. R^2 refers to the coefficient of determination.

Table 5: Frequency interpretation of MRA scale levels.

Scale	Monthly frequency
D_1	2–4 months
D_2	4–8 months
D_3	8–16 months
D_4	16–32 months
A_4	More than 32 months

(1984), Ghani [42], Blakrishnan [43], Nachane and Laxmi [44], Brahmananda and Nagaraju [45], Virmani and Kapoor [46], Virmani [47], Bhalla [48], and Dholakia [49] assert that Indian economy does not seem to face any tradeoff between inflation and unemployment. Since inflation is related to yield spread through economic activity, one would therefore expect yield spread to predict economic activity but not inflation. Overall, we find that the use of multiscale decompositions therefore proves useful at least for predicting output growth.

6. Conclusion

We used conventional ordinary least squares to study the leading indicator property of yield spread for inflation and output growth in India. Our results based on the conventional method showed that there is no predictive information in the yield spreads for future economic activity and inflation. We therefore provided the reassessment of the predictive ability of yield spread using quantile regression. Results based on quantile regression also failed to provide any evidence of leading indicator property of yield spread. As proposed in literature that the true economic relationships between variables can be expected to hold at the disaggregated level rather than at the usual aggregation level, we estimated the predictive ability of yield spread for future economic activity and inflation at different time scales using the methodology of wavelets. Our results showed that yield spread has useful information about future output growth at higher time scales or lower frequencies but not about inflation. The use of wavelet methodology thus proved to be of immense value

Table 6: Estimation results of inflation prediction using yield spread at different time scales.

Months	Coefficient	D_1	D_2	D_3	D_4	A_4
$h = 2$	β	0.04 (0.04)	−0.18 (0.12)	0.28 (0.24)	−1.65 (0.39)*	0.02 (0.13)
	R^2	−0.00	0.01	0.01	0.26	−0.00
$h = 4$	β	−0.01 (0.04)	−0.03 (0.13)	0.32 (0.30)	−0.88 (0.36)*	−0.01 (0.12)
	R^2	−0.00	−0.00	0.01	0.07	−0.00
$h = 6$	β	−0.05 (0.05)	−0.05 (0.10)	0.12 (0.23)	−0.00 (0.49)	−0.04 (0.11)
	R^2	0.00	−0.00	−0.00	−0.00	−0.00
$h = 8$	β	0.04 (0.07)	−0.07 (0.10)	0.07 (0.26)	0.74 (0.61)	−0.06 (0.10)
	R^2	−0.00	−0.00	−0.00	0.04	−0.00

Standard errors are in parentheses. $*$, $**$, and $***$ denote significance at 1%, 5%, and 10%, respectively. R^2 refers to the coefficient of determination.

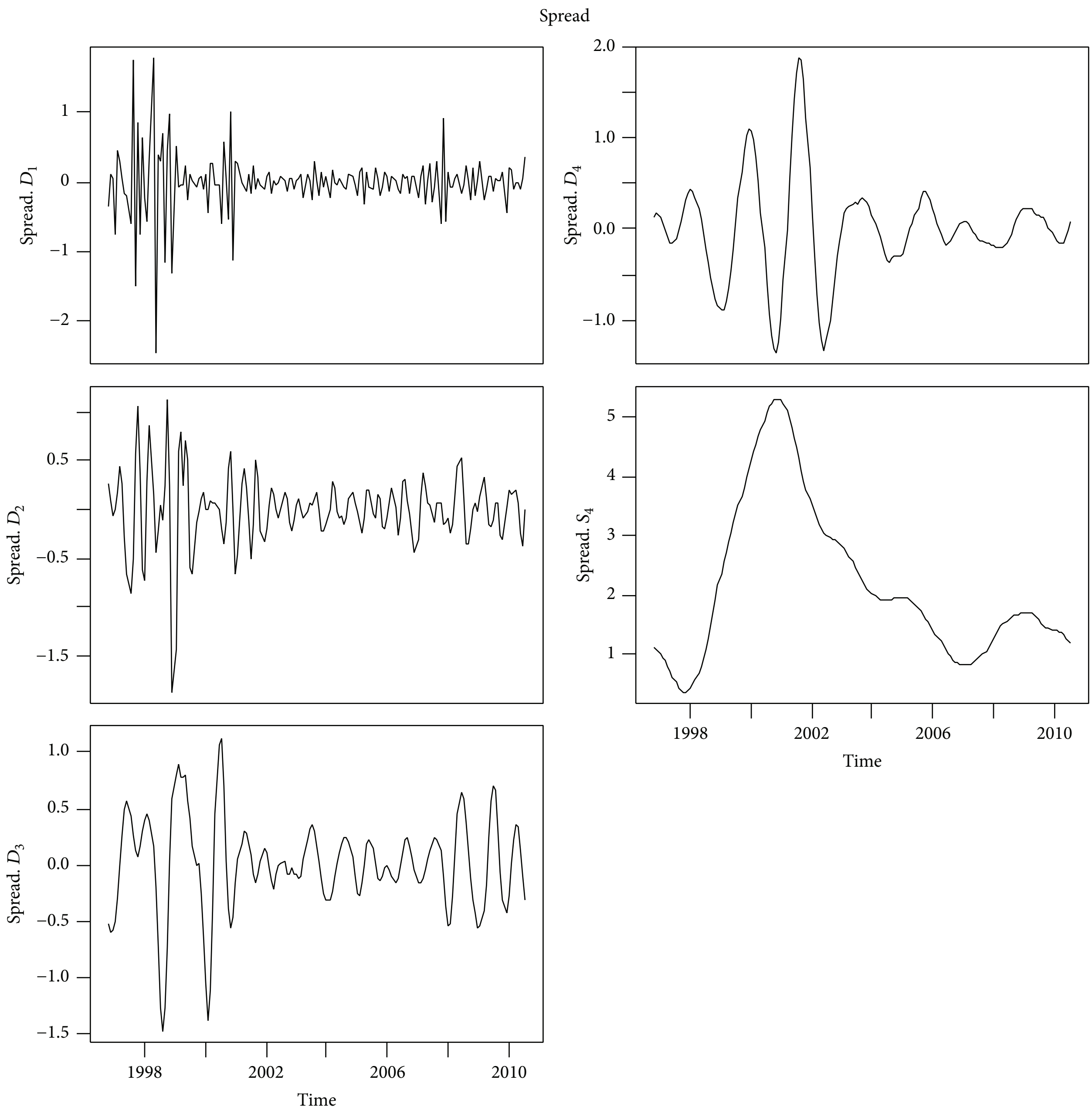

Figure 6: Plot of wavelet decomposed series of yield spread into different frequency bands.

because, with this decomposition, it was possible to show that corresponding to higher time scales, yield spread has a predictive power at least for economic activity. The use of wavelets helped to unravel economic time-frequency relations that otherwise would have remained hidden.

Appendix

See Table 5 and Figures 4, 5, and 6.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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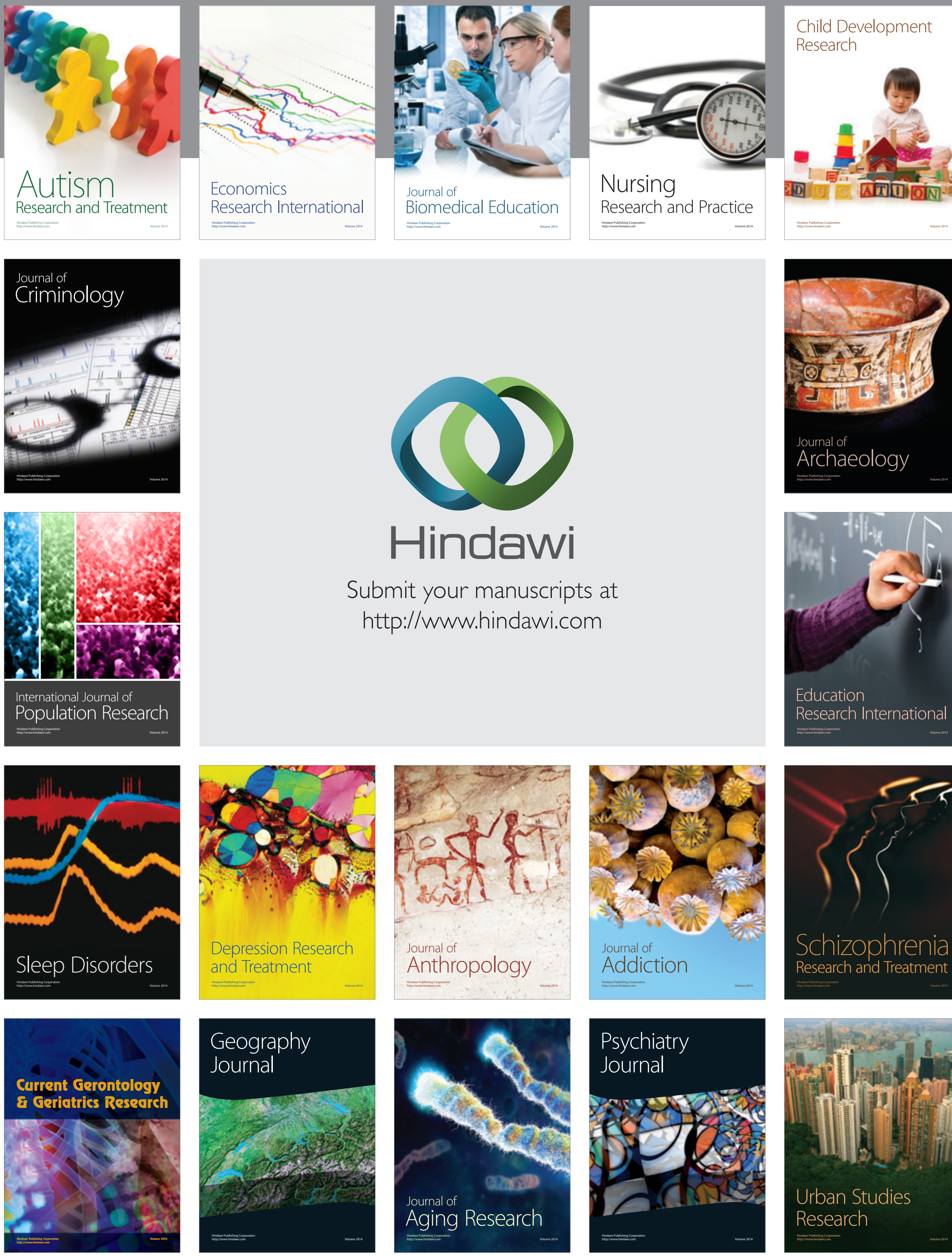
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