4. IMPROVING THE PREDICTIVE POWER OF SPREADS FOR ECONOMIC ACTIVITY: A WAVELET METHOD

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Abstract

In this paper, we examine whether and to what extent the predictive power of credit spread for real economic activity can be enhanced by using additional information via wavelet approach. In doing so, we first apply the wavelet analysis to the Korean real GDP data, and present evidence that the business-cycle component of wavelet-filtered series closely resembles the series obtained from an approximate band-pass filter.

Given the recent empirical findings that the credit spread has a useful explanatory power for future economic fluctuations, we also suggest that the business-cycle component of the credit spread can better predict the probability of a recession than the usual time-domain analysis. The wavelet methodology used in this paper can naturally be applied to any sets of economic and financial time series to unveil their structures and hence to enhance their predictive contents.

Keywords: credit spread, business cycle, wavelet decomposition
JEL Classification: E32, E43, C25

I. Introduction

Following the early work by Stock and Watson (1989) and Estrella and Hardouvelis (1991), there has been an increasing interest in exploring the information content of financial indicators. In particular, many researchers have presented evidence that the term spread can predict future real economic activity. For instance, Plosser and Rouwenhorst (1994) found that the term structure contains information about future economic fluctuations, which is independent from information on current or future monetary policy. Haubrich and Dombrosky (1996) found that the predictive content of the yield curve has changed over time. Estrella and Mishkin (1997) confirmed that the basic results of Estrella and Hardouvelis (1991) continue to hold in many European

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countries as well as in the U.S. Dueker (1997) and Estrella and Mishkin (1998) presented evidence that the yield spread is a good predictor for the probability of a recession.

However, confidence in the predictive power of the term spread has been tempered by recent studies such as Dotsey (1998), and Mody and Taylor (2003), although there remains somewhat mixed evidence in the term-structure literature. Based on the theory of the financial accelerator, Gertler and Lown (1999) argue that the credit spread should also have the predictive content for real economic activity. Also presented is empirical evidence that the high-yield spread, the premium required on less than investment-grade corporate bonds, outperforms other leading financial indicators, including the term spread and the paper-bill spread.

In this paper, we first attempt to explore the predictive power of the credit spread by using the wavelet approach. In particular, we first adopt the multiresolution analysis, which is a useful tool for decomposing time series with various components such as trend, cycle, and seasonal fluctuation. Given the findings that the wavelet methodology is a powerful tool for capturing the business-cycle components of economic time series, while preserving information in time, we discuss whether and to what extent the predictive power of the credit spread for real economic activity can be enhanced by using additional information on the frequency domain. We further investigate the forecasting performance of the high-yield spread as compared to other indicators, such as the spread between the AA- grade corporate bonds and the government bond. We also considered a decomposition of the term spread into the expectations effect and the term premium based on the liquidity premium theory, and discussed evidence that the decomposition might lead to a better prediction for business-cycle fluctuations than the usual term spread.

This paper is organized as follows. In section 2, we give a brief overview on the basic tools of wavelet theory, and present evidence that the business-cycle component of wavelet-filtered series closely resembles the series obtained from an approximate band-pass filter. In section 3, we discuss the predictive contents of the high-yield spread, derived as the difference between the return on the BBB- class corporate bonds and the government bond rate, in comparison with the low-yield spread of the AA- grade corporate bonds. Section 4 examines whether the business-cycle component of the credit spread, derived from the wavelet decomposition, can better forecast the probability of a recession than the usual time-domain regression model. Concluding remarks are in section 5, which summarizes the significance of empirical results with a brief discussion about future research.

II. Wavelet Analysis

Wavelet analysis is a relatively new but powerful tool for analyzing the time and frequency properties of various time series data. In fact, the wavelet methodology has already shown diverse applications in many fields, such as medical sciences and physics, although it has received little attention in empirical analysis of economic and financial data. This section gives a brief overview on the basic tools of wavelet method, and discusses some new statistical results of wavelet analysis in decomposing time series data. In particular, we focus on two major facets of wavelet analysis. First, wavelets are localized in time, and hence are useful in handling a variety of nonstationary signals. Second, wavelets can separate a signal into multiresolution components.

1. Multiresolution Analysis

There are two types of wavelets defined on different normalization rules; father wavelets ϕ and mother wavelets ψ. The father wavelet integrates to 1 and the mother wavelet integrates to 0: $\int\phi(t)dt=1$, $\int\psi(t)dt=0$. They are used in pairs within a family of wavelet functions, with father wavelets used for the trend components and the mother wavelets for all the deviations from the trend.

A two-dimensional family of functions to be represented by a wavelet analysis can be built up as a sequence of projections onto father and mother wavelets generated from ϕ and ψ through scaling and translation as follows:

$$\phi_{j,k}(t)=2^{-j/2}\phi(2^{-j}t-k)=2^{-j/2}\phi(\frac{t-2^{j}k}{2^{j}}) \tag{1}$$

$$\psi_{j,k}(t)=2^{-j/2}\psi(2^{-j}t-k)=2^{-j/2}\psi(\frac{t-2^{j}k}{2^{j}}) \tag{2}$$

where: 2^{j} is a sequence of scales. The term $2^{-j/2}$ maintains the norm of the basis functions $\phi(t)$ at 1. Using a wavelet filter, a time series or a signal $f(t)$ can be decomposed as:

$$f(t)=\sum_{k}s_{J,k}\phi_{J,k}(t)+\sum_{k}d_{J,k}\psi_{J,k}(t)+\sum_{k}d_{J-1,k}\psi_{J-1,k}(t)+\cdots+\sum_{k}d_{1,k}\psi_{1,k}(t) \tag{3}$$

where: J is the number of multiresolution components, and k ranges from 1 to the number of coefficients in the specified component. The basic functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ are the approximating wavelet functions generated as scaled and translated versions of ϕ and ψ, with scale factor 2^{j} and translation parameter $2^{j}k$, respectively. The scale factor 2^{j} is also called the dilation factor and the translation parameter $2^{j}k$ refers to the location. Here 2^{j} is a measure of the scale or width of the functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$. That is, the larger the index j, the larger the scale factor 2^{j}, and hence the function get shorter and more spread out. The translation parameter $2^{j}k$ is matched to the scale parameter 2^{j} in that as the functions $\phi_{J,k}(t)$ and $\psi_{j,k}(t)$ get wider, their translation steps are correspondingly larger.

The coefficients $s_{J,k}$, $d_{J,k},\cdots,d_{1,k}$ are the wavelet transform coefficients, the magnitude of which reflects a measure of the contribution of the corresponding wavelet function to the total signal. The coefficients $s_{J,k}$ are called the smooth coefficients, representing the underlying smooth behavior of the signal at the coarse scale 2^{J}. On the other hand, $d_{j,k}$ are called the detailed coefficients, representing deviations from the smooth behavior, where $d_{J,k}$ describe the coarse scale deviations and $d_{J-1,k}, \cdots, d_{1,k}$ provide progressively finer scale deviations.

Similarly to the wavelet representation (3), a time series *f*(*t*) can be expressed in terms of the signals:

$$f(t) = S_J(t) + D_J(t) + D_{J-1}(t) + \cdots + D_1(t) \tag{4}$$

where: the functions in (4) represent the product of the coefficients and the corresponding wavelet functions, namely:

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t) \tag{5}$$

$$D_j(t) = \sum_k d_{j,k}\psi_{J,k}(t) \quad \text{(for } j = 1,2,\ldots,J\text{)} \tag{6}$$

The functions (5) and (6) are called the smooth signal and the detail signals, respectively, which constitute a decomposition of a signal into orthogonal components at different scales. As each terms in (4) represent components of the signal *f*(*t*) at different resolutions, it is called a multiresolution decomposition.

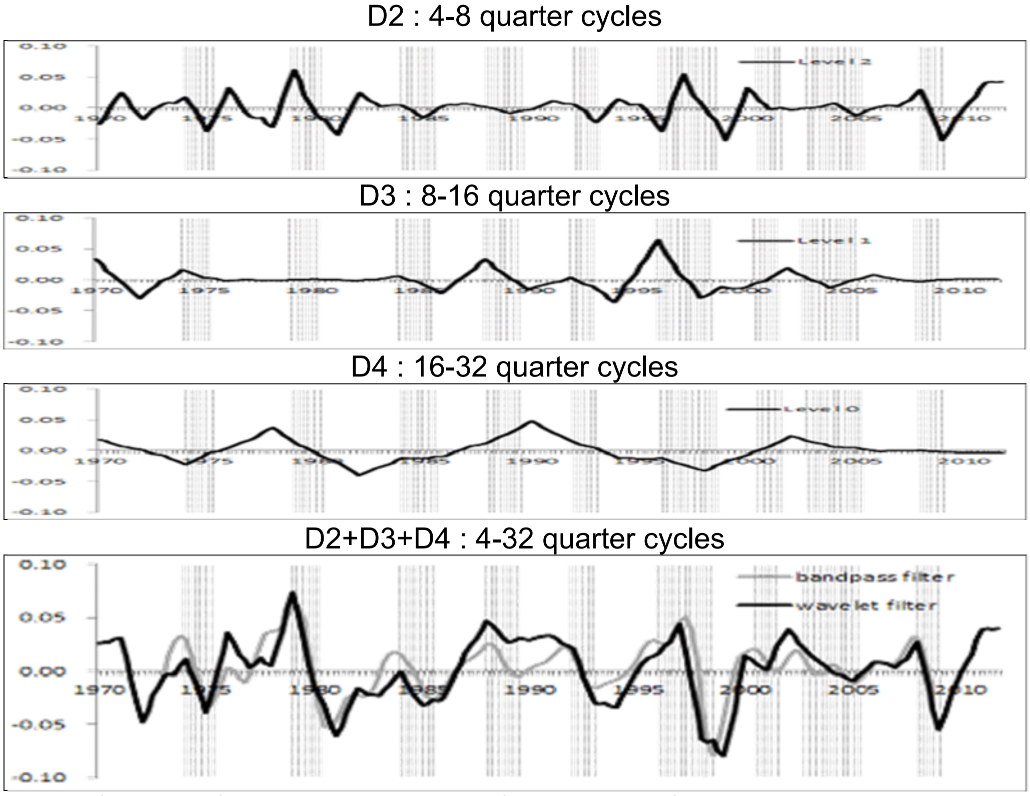
When *J* = 4, for instance, $S_4(t)$ represents the smooth signal, and $D_j(t)$ denotes coarse scale deviations with periodicity between 2^j and 2^{j+1} periods. As for quarterly data, $S_4(t)$ captures the long-run trend with cycles longer than 32 quarters, whereas $D_1(t)$ denotes high frequency fluctuations occurring with periodicity of less than four quarters. The busyness-cycle components with periodicities of 4-8, 8-16, and 16-32 quarters, respective, are captured by $D_2(t)$, $D_3(t)$, and $D_4(t)$.

2. Measuring Business Cycles

Applying the wavelet multiresolution analysis to the US real GDP, Yogo (2008) shows that the wavelet filtering is a useful alternative to the band-pass filter. Similar evidence is presented here for the Korean real GDP data, in that the business-cycle component of wavelet-filtered series closely resembles the series obtained from an approximate band-pass filter. Figure 1 shows cyclical variations of GDP at different scales obtained from a biorthogonal bs2.4 filter. The top three panels show the three business-cycle scales of details in the wavelet decomposition. The details at scales 2 through 4 correspond to the business-cycle components of GDP at 4-8, 8-16, and 16-32 quarter cycles, respectively. The bottom panel of Figure 1 shows the cyclical variations with periodicity of 4-32 quarters, which is close to the business-cycle components discussed in Baxter and King (1999). As a comparison, also shown is the graph of fluctuations in real GDP filtered by the approximate band-pass filter. The two filtered series are quite close to each other, with almost similar local minima and maxima, corresponding to the business cycle announced by the Statistics Korea, the governmental statistical institute in Korea.

Figure 1

Business-cycle Component of Korean Real GDP



Notes : 1) The log of seasonally adjusted data for Korean real GDP is used.
2) Shaded regions denote recession periods dated by the Statistics Korea.

III. Business Cycles and Credit Spread

Earlier studies have shown that the credit spread has a predictive power for future economic activity. Given the recent empirical evidence that the high-yield spread has borne a systematic relationship to subsequent fluctuations in real economic activity, we focus on the business-cycle predictability of the high-yield spread.

1. Data

Our data sets used in this empirical analysis are composed of monthly observations on the return on corporate bonds of BBB- and AA- classes together with the government bond rate of three year maturity. The credit spreads are derived as the difference between the return on corporate bonds of each class and the government bond rate. As discussed in Kim and Lee (2011), the sample period used for the BBB- class corporate bonds starts from January 2002, whereas that for AA- class is from January 1998. In order to examine the predictive content of credit spread for business-cycle fluctuations, the composite concurrent index is used to reflect the real economic activity.

The definition of each data is presented in Table 1 together with their summary statistics. The return on the BBB- class corporate bonds is much larger than that on the AA- class, and the former shows a larger volatility than the latter. Although the standard deviation of the AA- class bonds appears to be larger than that of the BBB- class, it is because the data for the former includes a highly volatile period during the Korean financial crisis in 1998. When we focus on the same sample period, the BBB- class corporate bonds show a larger volatility than the AA- class corporate bonds.

Table 1

Data Definition and Summary Statistics

variable name	definition	Mean	max	min	standard deviation
Ycba	Return on AA- class corporate bonds of 3 year maturity (%)	6.66	23.36	3.73	3.04
		5.62*	8.64*	3.73*	0.92*
Ycbb	Return on BBB- class corporate bonds of 3 year maturity (%)	9.66	12.40	7.72	1.23
Tb	Government bond rate of 3 year maturity (%)	5.64	17.13	3.24	2.59
ycbatb3	Spread_A = Ycba – Tb (%)	1.03	8.36	0.27	0.89
ycbbtb3	Spread_B = Ycbb – Tb (%)	5.17	8.62	3.10	1.56
CCI	Composite concurrent index (2005=100)	100.5	144.0	59.6	24.8

Note: The asterisk (*) denotes the summary statistics of ycba (AA- class) for the period from January 2002 to June 2012, which are reported here for direct comparison with those for ycbb (BBB- class).

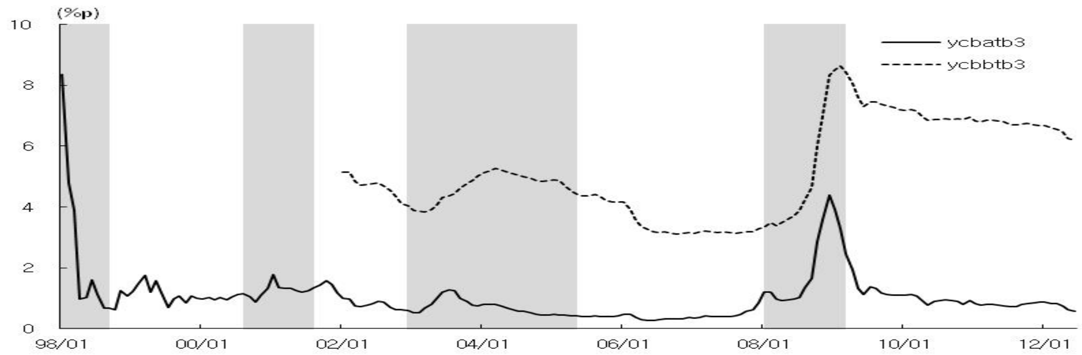
2. Credit Spread and Business Cycles

Earlier studies have found the term spread to contain information with respect to future economic activity. The theoretical underpinning of the credit spread as a predictor of real economic activity primarily relates to the theory of the financial accelerator (see, for example, Bernanke and Gertler, 1995, and the references therein). As discussed in Friedman and Kuttner (1991), the predictive properties of the credit spread can be explained in term of monetary policy. That is, a tightening of monetary policy causes banks demand for loans to shift inward, which results in a higher loan rate and a smaller loan quantity. Hence the quantity of paper issued rises, as does the commercial paper interest rate.

Figure 2 provides a visual representation of the predictive power of the credit spread. We can see that the spread shows a rapid increase at an early stage of each recession, and that it remains wide during recession. The association between the credit spread and the recession is particularly strong during the Korean financial crisis in 1998, and also during the global financial crisis in 2008.

Figure 2

Fluctuations in Spreads and Business Cycle



Note : The shaded regions denote recessions dated by Statistics Korea.

3. Predictive Power of Credit Spread

As discussed in Estrella and Hardouvellis (1991), the linear regression model and the probit model are often used in much empirical analysis on the predictive power of the term structure and/or the credit spread. In order to examine extra predictive content of the business-cycle component of the wavelet-filtered series over the time-domain spread, the probit model is used in this paper (see Lee, 2012, for additional results on various regression analyses).

The probit model is useful in forecasting the turning points of a business cycle and the probability of a recession. Under the normal distribution, the probability of recession can be expressed as a function of the spread as:

$$P(Y_t = 1 | Spread_{t-k}) = F(\alpha + \beta\, Spread_{t-k}) \qquad (7)$$

where: $F(\cdot)$ denotes the CDF (cumulative distribution function) of the normal distribution, and Y_t is an index indicating whether the economy is in recession $(Y_t = 1)$ or in boom period $(Y_t = 0)$. Hence the left hand side of equation (7) shows the probability of a recession given the observation on the spread. Equation (7) states that an increase in the credit spread implies an increase in the probability of a recession k months later.

Table 2 provides the regression results for different lags k, and the *pseudo*-R^2 values are compared. The *pseudo*-R^2 is a measure of the overall fit of the equation, like the R^2 in OLS regression. Its value lies between 0 and 1, and corresponds roughly to the degree of association between the credit spread and the probability of a recession. As for both the AA- and BBB- class corporate bonds, the relation between the probability of a recession and the spread is statistically significant for $k = 1$. Although the relation appears to be significant at larger lags for the spread of the AA- class, the estimate of

β has a wrong sign, and they cannot be interpreted as a predictive content for future business-cycle movements.[3]

Table 2

Probit Regression for the Credit Spread

Lag		Spread_A			Spread_B	
k	*β*	*z-statistic*	*Pseudo-R²*	*β*	*z-statistic*	*Pseudo-R²*
1	0.38*	2.42	0.03	0.16*	2.17	0.03
2	0.26*	1.95	0.02	0.12	1.65	0.02
3	0.15	1.26	0.01	0.08	1.14	0.01
4	0.08	0.73	0.00	0.06	0.81	0.00
5	0.04	0.37	0.00	0.05	0.62	0.00
6	-0.03	-0.29	0.00	0.04	0.60	0.00
7	-0.12	-1.02	0.01	0.05	0.62	0.00
8	-0.45*	-2.51	0.04	0.05	0.68	0.00
9	-0.46*	-2.57	0.04	0.06	0.76	0.00
10	-0.46*	-2.55	0.04	0.07	0.87	0.00
11	-0.46*	-2.56	0.04	0.08	1.03	0.01
12	-0.45*	-2.54	0.04	0.09	1.20	0.01

Note: The asterisk (*) denotes the significance of the regression estimate at 5% level.

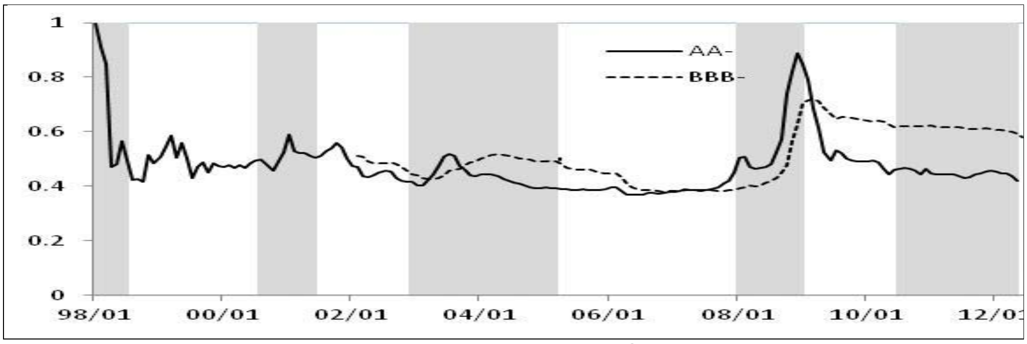
As the relation between the credit spread and the probability of a recession estimated in equation (7) is nonlinear, it is difficult to assess the quantitative association. Figure 3 plots the estimated probability of a recession derived from the historical data on the spread lagged one month, using the parameter estimates of equations (7). The forecasted probability of a recession denotes the within-sample fit of a probit model. It provides clearer information on the economic importance of the forecasting ability of the credit spread. In Figure 3, the shaded regions denote periods of actual recessions dated by the Statistics Korea.

Observe that all peaks in the estimated probability were associated with a recession. The result here obtained from the usual time-domain regression seems to suggest that the association between the credit spread of the AA- class corporate bonds is stronger than that for the BBB- class corporate bonds during the global financial crisis in 2008. Notice that the estimated probability of recession stays low during the recent 2010-2012 period, for which business-cycle turning points are not officially dated yet.

3 According to the economic theory or empirical result, the term or credit spread gets larger during recession. The positive (+) sign of β implies that the probability of recession increases as spread becomes larger. Hence, the negative (-) sign of β in this case does not correspond to the economic theory and/or preceding empirical evidence.

Figure 3

Credit Spreads and Probability of Recession



Note: The shaded regions denote recessions dated by the Statistics Korea. The black line shows the estimated probability of a recession using the spread of the AA- class corporate bonds, whereas the gray line shows the probability of a recession estimated from the spread of the BBB- class corporate bonds.

IV. Predictive Power of Wavelet-Filtered Credit Spread

Previous studies presented evidence that the credit spread has a predictive power for future economic activity. Given the recent findings that the wavelet methodology is a powerful tool for capturing the business-cycle components of economic time series, this section further explores the marginal explanatory power of the credit spread for cyclical activity, using the wavelet approach.

Tables 3 and 4 (in the annex) report the regression results for different timescales obtained from the wavelet decomposition of the AA- and BBB- spreads, respectively. As for both the AA- and BBB- class corporate bonds, the details at scales 3 through 5, corresponding to the business-cycle components of the spread at 8-64 month cycles, show higher estimates of the *pseudo*-R^2 values with more significant regression coefficients, compared to other time-scales.[4]

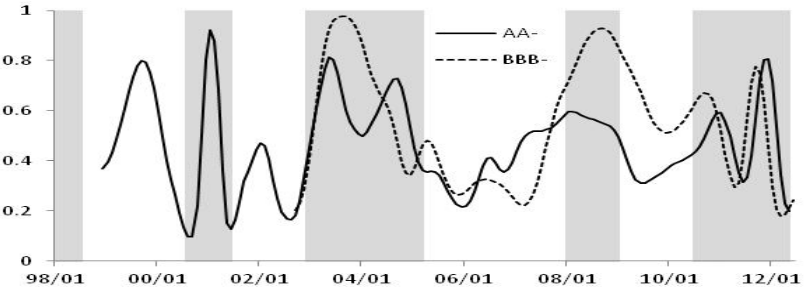
As it is difficult to assess the quantitative association of the estimates in Tables 3 and 4, we need to further estimate the probability of a recession as discussed in the previous section. In this case, the parameter estimates for the details at scales 3 through 5 are employed, as they correspond to the business-cycle components of the spread at 8-64 month cycles. In particular, the models with k =12 lags and 8 lags are used for the AA- and BBB- spreads, respectively, which show the highest estimates of the *pseudo*-R^2 values. Using the within-sample fit of the probit model, the forecasted probabilities of recession are derived, which are presented in Figure 4.

[4] *Baxter and King (1999) define the business cycle as cycles with periodicity of 6-32 quarters. As the scales in wavelet filters are dyadic in nature, cycles with periodicity of 8-64 months are used here to derive the business-cycle components. As discussed in Yogo (2008), the difference in obscured in practice.*

We can first see that all peaks in the estimated probability were associated with a recession. Note also that the peaks in the estimated probability of a recession obtained from the spread of the BBB- class bonds are higher than those for the AA- class bonds. This observation seems to indicate that the association between the high-yield spread and the probability of a recession is stronger than that for the low-yield spread. These results are in contrast to those obtained from the usual time-domain regression in previous section that the AA- class bonds shows a higher association with the probability of recession than the other.

Figure 4

Wavelet-filtered Credit Spreads and Probability of Recession



Note: See note to Figure 3.

Whereas the estimated probability of a recession in the previous section was low during the recent 2010-2012 period, the estimates for the probability of a recession during the same period display clear peaks and troughs, when the business-cycle component of the spread are used. Although the business-cycle turning points are not officially dated for the recent 2010-2012 period, sharp drops in the estimated probability of a recession indicate that at least one trough should be dated during this period.

Given the findings that the wavelet methodology is a powerful tool for capturing the business-cycle components of economic time series, the results in this section seem to suggest that the predictive power of the credit spread can be enhanced by using its business-cycle component, derived from the wavelet decomposition. The wavelet approach also confirms that the high-yield spread appears to have a better explanatory power than the low-yield spread.

V. Concluding Remarks

Although many researchers have suggested that the term spread can predict future real economic activity, such evidence on the predictive power of the term spread has been tempered by more recent studies. Instead, an increasing attention has been given in recent literature to the forecasting performance of the credit spread. In particular, empirical evidence is presented that the high-yield spread, the premium required on less than investment-grade corporate bonds, outperforms other leading financial indicators, including the term spread and the paper-bill spread.

In this paper, we attempt to further explore the predictive content of the credit spread by using the wavelet approach. As the wavelet methodology is a powerful tool for capturing the business-cycle components of economic time series, while preserving information in time, we can discuss whether and to what extent the predictive power of the credit spread for real economic activity can be enhanced by using additional information on the frequency domain, derived from the wavelet decomposition.

Applying the wavelet method to the fluctuations in the real GDP, we first present evidence that the business-cycle component of wavelet-filtered series closely resembles the series obtained from an approximate band-pass filter. We also show that the business-cycle component of the credit spread, derived from the wavelet decomposition, has extra predictive power for future economic activity over the credit spread in the usual time-domain regression model. The wavelet approach also confirms that the high-yield spread, derived as the difference between the return on the BBB-class corporate bonds and the government bond rate, outperforms forecasts obtained from the low-yield spread of the AA- grade corporate bonds.

Although some interesting results are presented here to show that the predictive power of the credit spread for real economic activity can be enhanced by using additional information on the frequency domain, there still remains much room for potential application. First of all, while the wavelet methodology is used here to decompose time series data, we also need to consider an alternative decomposition method. For example, the term spread can be decomposed into the expectations effect and the term premium, based on the liquidity premium theory, as discussed in Hwang and Lee (2015).

Second, the wavelet methodology can naturally be applied to any sets of economic time series to unveil their structures and relationships between them. In fact, the wavelet analysis is much more powerful in signal processing than what is discussed in this paper.

The wavelet methodology has not been so popular in economics, and hence wavelets have received little attention in empirical analysis of economic and financial data. The applications of the wavelet approach in economics and finance are now growing fast, and will be growing faster as potential application areas should get wider in the future (see, for example, Gençay *et al*., 2001; Lee, 2001; and the references therein). Hence the wavelet approach can naturally be applied to any sets of economic and financial time series to unveil their structures and hence to enhance their predictive contents.

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Annex

Table 3

Probit Regression for Wavelet-Filtered Credit Spread of AA- Class

Lag	d1-d2 (1-8 months)			d3-d5 (8-64 months)		
k	*β*	*z-statistic*	*Pseudo-R^2*	*β*	*z-statistic*	*Pseudo-R^2*
1	0.09	0.43	0.00	-0.31	-2.01**	0.02
2	0.09	0.44	0.00	-0.30	-2.00**	0.02
3	0.10	0.49	0.00	-0.27	-1.85*	0.01
4	-0.17	-0.93	0.00	-0.20	-1.35	0.01
5	-0.06	-0.30	0.00	-0.07	-0.45	0.00
6	-0.03	-0.15	0.00	0.11	0.77	0.00
7	-0.04	-0.20	0.00	0.32	2.14**	0.02
8	0.00	-0.01	0.00	0.50	3.22***	0.05
9	0.05	0.24	0.00	0.62	3.78***	0.07
10	0.05	0.26	0.00	0.68	4.01***	0.09
11	0.05	0.25	0.00	0.71	3.93***	0.09
12	0.03	0.14	0.00	0.74	3.90***	0.10

Lag	d6-d7 (64-256 months)			s7 (over 256 months)		
k	*β*	*z-statistic*	*Pseudo-R^2*	*β*	*z-statistic*	*Pseudo-R^2*
1	0.09	0.33	0.00	7.56	2.92***	0.04
2	0.01	0.05	0.00	7.13	2.74***	0.03
3	-0.06	-0.21	0.00	6.66	2.55**	0.03
4	-0.12	-0.46	0.00	6.16	2.35**	0.02
5	-0.18	-0.67	0.00	5.62	2.14**	0.02
6	-0.24	-0.86	0.00	5.04	1.91*	0.02
7	-0.28	-1.02	0.00	4.44	1.67*	0.01
8	-0.32	-1.14	0.01	3.80	1.43	0.01
9	-0.33	-1.21	0.01	3.77	1.41	0.01
10	-0.35	-1.26	0.01	3.73	1.39	0.01
11	-0.36	-1.31	0.01	3.69	1.36	0.01
12	-0.37	-1.36	0.01	3.63	1.33	0.01

Note: The asterisks *, **, *** denote the significance of the estimate at the 10, 5, and 1% level.

Table 4

Probit Regression for Wavelet-Filtered Credit Spread of BBB- Class

Lag *k*	d1-d2 (1-8 months)			d3-d5 (8-64 months)		
	β	*z-statistic*	*Pseudo-R^2*	*β*	*z-statistic*	*Pseudo-R^2*
1	-0.23	-0.25	0.00	0.06	0.51	0.00
2	0.12	0.14	0.00	0.19	1.53	0.01
3	-0.05	-0.05	0.00	0.33	2.61**	0.04
4	-0.36	-0.39	0.00	0.47	3.66***	0.07
5	-0.66	-0.73	0.00	0.60	4.54***	0.10
6	-0.71	-0.78	0.00	0.71	5.12***	0.14
7	-0.37	-0.40	0.00	0.79	5.40***	0.16
8	-0.14	-0.15	0.00	0.84	5.46***	0.18
9	0.89	0.99	0.01	0.85	5.36***	0.18
10	1.27	1.41	0.01	0.84	5.13***	0.18
11	0.96	1.08	0.01	0.80	4.79***	0.16
12	0.12	0.13	0.00	0.74	4.38***	0.15
Lag *k*	**d6 (64-128 months)**			**S6 (over 128 months)**		
	β	*z-statistic*	*Pseudo-R^2*	*β*	*z-statistic*	*Pseudo-R^2*
1	-0.65	-5.01***	0.16	-0.06	-0.41	0.00
2	-0.63	-4.90***	0.16	-0.09	-0.64	0.00
3	-0.61	-4.78***	0.15	-0.12	-0.87	0.00
4	-0.59	-4.64***	0.14	-0.16	-1.11	0.01
5	-0.56	-4.49***	0.13	-0.19	-1.36	0.01
6	-0.54	-4.33***	0.12	-0.23	-1.62	0.02
7	-0.51	-4.15***	0.12	-0.27	-1.88*	0.02
8	-0.48	-3.97***	0.11	-0.31	-2.16**	0.03
9	-0.46	-3.77***	0.10	-0.36	-2.44**	0.04
10	-0.43	-3.57***	0.09	-0.41	-2.73***	0.05
11	-0.40	-3.37***	0.08	-0.46	-3.03***	0.06
12	-0.37	-3.16***	0.07	-0.51	-3.34***	0.08

Note: See note to Table 3.