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The Predictive Power of the Yield Spread Under the Veil of Time

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Abstract

This paper studies the sources of cyclical information delivered by the term spread for output growth predictability in the U.S. I use a wavelet-based time-frequency decomposition to decompose the predictive power of the yield spread across time scales, both in-sample and out-of-sample, over various forecast horizons. Spreads between interest rates on 10-year and 3-month Treasuries have a predictive ability for output growth that changes largely over different time scales. I find evidence of a negative correlation between the spread and future GDP growth for fluctuations with a frequency of 4 to 8 years per cycle. A linear combination among filtered yield spreads shows a sizable improvement in forecasting out-of-sample. The time-frequency decomposition is also used to propose an interpretation for the breakdown of in-sample predictability documented by Dotsey (1998) that arises after 1985.

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1. Introduction

A large body of literature argues that the difference between long and short-term interest rates on government bonds - the so-called 'term spread' - reflects the expectations of financial markets about future macroeconomic conditions. This has provided the ground for empirical studies on the predictive ability of the yield spread. The seminal work by Estrella and Hardouvelis (1991) shows that the slope of the yield curve holds a consistently negative correlation with real GDP growth up to the following 6 quarter. Stock and Watson (2003) find that the yield spread is also a good predictor for future output growth out-of-sample. Two aspects of the predictive relationship are worth stressing. First, there is evidence of a drop of in-sample fit starting from 1985 (see Dotsey, 1998). Second, the estimated parameters of the predictive regressions are unstable over the full post-war sample (see Giacomini and Rossi, 2006).

This paper re-considers the predictive power of the yield curve across time-frequencies. The aim is to understand what components of the time pattern in the predictive relation explain its success or failure. I apply a multiresolution decomposition to the quarterly series for real GDP and the term spread in the United States. The data sample spans from the first quarter of 1954 to the second quarter of 2024. Then, I study the predictive regressions based on these filtered series. The methodological framework used here is not new. For instance, Verona and Faria (2023) use wavelet-based filtering to build predictors for the equity premium.

The results indicate that the predictive ability of the decomposed yield spread for unfiltered output growth varies largely across time scales. Using a linear combination of the decomposed spread as predictor for unfiltered GDP growth, I find a sizeable improvement in both in-sample and out-of-sample forecasts. I investigate the heterogeneity in predicting ability by regressing filtered output growth on the filtered yield spread at each time scale. A remarkable result emerges. For series that include cycles with frequency spanning from 4 to 8 years, the relation between future output growth and the slope of the yield curve is significantly negative over the full sample. Plots of the filtered series indicate that this is a key feature of the relation between output growth and the yield spread before 1985. For a subsample starting in 1985, the predictive relation has the expected positive sign. The decomposed series are also used for proposing a solution to the breakdown of in-sample fit documented by Dotsey (1998) that occurs after 1985.

This paper is organized as follows. Section 2 provides a broad overview of the technique of multiresolution decomposition used in the remaining sections. Section 3 describes the dataset and the properties of the filtered series. Then, I analyze the details of the predictive content of the filtered term spread both in-sample, and out-of-sample. In section 4, I discuss a possible resolution of the forecast breakdown after 1985 based on filtered regressors. Section 5 presents some concluding remarks.

2. A short review of multiresolution analysis

The following section provides a discussion of key aspects concerning the foundations of multiresolution analysis. I provide results on the connections between time-scale decomposition and wavelet functions. For a more thorough overview, the reader can refer to Debauchies (1992), which is the standard reference for the mathematical properties of multiresolution analysis through wavelets. A compact review of the topic with sample of economic applications can be found in Ramsey (1999) and Crowley (2005).

The purpose of multiresolution analysis consists in the approximation of signals. A time series is decomposed into a smooth component, that represents the long-run trend, and fluctuations or details, that identify the short-run movements. The distinction between the smooth and the fluctuating parts is determined by the resolution, that is the time scale below which the details cannot be detected. At each scale, the multiresolution decomposition approximates a time series by ignoring the details at the lower scales. The approximation of the signal improves by adding finer details at higher time scales.

In order to fix the notation, denote by $f(t)$ the signal to decompose. The time scale takes on values from $(1/2)^j$, where j is the (integer) resolution level. The j-level approximation of the signal is $f_j(t)$. The approximation at j+1 is a function of the detail level $d_j(t)$:

$$f_{j+1}(t)=f_j(t)+d_j(t) \tag{1}$$

Recursive substitution within this expression suggests the way of recovering the original signal. As the resolution goes to infinity, the raw signal is obtained.

The principles of multiresolution analysis generalize to function spaces. Let $L^2(\mathrm{R})$ denote the space of square-integrable functions. The multiresolution decomposition of $L^2(\mathrm{R})$ consists of the sequences of subspaces $\{W_k\}_{k=j}^{\infty}$ and V_j such that $f_j(t)\in V_j$ and $d_k(t)\in\{W_k\}_{k=j}^{\infty}$. The following theorem establishes the conditions of a multiresolution analysis.

Theorem 1: *A multiresolution analysis of* $L^2(R)$ *is a nested sequence of subspaces* $\{\mathrm{V_j}\}_{\mathrm{j}\in\mathrm{Z}}$ *such that:*

- *The information at level j is included in the information at finer resolutions:* $\ldots\subset V_{-1}\subset V_0\subset V_1\subset L^2(R)$
- *All the integrable functions should be included at the highest resolution:* $\cap_j V_j=\emptyset,\ \overline{\cup_j V_j}=L^2(R)$

- *(dilation invariance) Re-scaling from the central space* V_0 *generates all the spaces* $\{V_j\}_{j\in Z}$*:* $f(t)\in V_j \Leftrightarrow f(2t)\in V_j$
- *(translation invariance)* $f(t)\in V_0 \Rightarrow f(t-k)\in V_0$
- *There exists a scaling function* $\varphi(t)$ *such that* $\{\varphi(t-k)\}$ *is an orthonormal basis for* V_0.

Table 1: Frequency interpretation of time scales

Component	Quarterly-frequency resolution
D1	1-2 quarters
D2	2-4 quarters
D3	1-2 years
D4	2-4 years
D5	4-8 years

Through translation invariance, it is possible to generate a set of functions that are orthonormal basis for $\{V_j\}_{j\in Z}$:

$$\varphi_{j,k}(t) := 2^{j/2}\varphi\left(2^j t-k\right) \tag{2}$$

The level j controls the degree of stretching of the function. The larger the j, the more stretched is the basis function. The smaller the time scale, the higher the frequency of the decomposed series (see Table 1), the less stretched the basis function. The parameter k determines the location of the basis function. Time localization captures the information of each form of noise separately at each frequency. This property implies that any locally-inhomogenous behavior affects only a few coefficients of the transformation.

Let us assume that the detail spaces $\{W_j\}$ are orthogonal to each other. Like for the approximation spaces, we can define a sequence $\{\psi_{j,k}(t)\}_k$ of orthonormal basis functions that spans L^2 (R):

$$\psi_{j,k}(t) := 2^{j/2}\psi\left(2^j t-k\right) \tag{3}$$

The function $\psi_{j,k}(t)$ is called wavelet. Like the set of scaling functions, wavelets are generated by dilation and translation from a mother wavelet $\psi(t)$.

In the analysis presented in this paper, the assumption of orthogonality among detail spaces is relaxed, and biorthogonal wavelet functions are used. In order to allow the decomposition of a function space by linear combination of nonorthogonal basis, dual multiresolution analysis introduces the dual subspaces $\{\tilde{W}_k\}_{k=j}^{\infty}$ and $\{\tilde{V}_j\}_{j\in Z}$.

These are generated, respectively, from a dual scaling function $\tilde{\boldsymbol{\varphi}}(t)$ and a dual mother wavelet $\tilde{\boldsymbol{\psi}}(t)$. Given an inner product $<\cdot>$ on L^2 (R), the conditions for biorthogonality take the form:

$$\left\langle \tilde{\phi}_{j,k}\ \tilde{\phi}_{j,l} \right\rangle = \delta_{k,l} \tag{4}$$

$$\left\langle \tilde{\psi}_{j,k}\ \tilde{\psi}_{j',l} \right\rangle = \delta_{j,j'}\delta_{k,l} \tag{5}$$

$$\left\langle \tilde{\psi}_{j,k}\ \phi_{j,l} \right\rangle = 0 \tag{6}$$

$$\left\langle \tilde{\phi}_{j,k}\ \psi_{j,l} \right\rangle = 0 \tag{7}$$

where $\tilde{\phi}_{j,k}(t) := 2^{j/2}\tilde{\phi}\left(2^j t - k\right)$ and $\tilde{\psi}_{j,k}(t) := 2^{j/2}\tilde{\psi}\left(2^j t - k\right)$.

Summing up, the biorthogonal wavelet decomposition of a time series $f(t)$ can be written as:

$$f(t) = \sum_k s(J,k)\phi(t,J,k) + \sum_j \sum_k d(j,k)\psi(t,j,k) = A_J + D_J + D_{J-1} \ldots + D_1 \tag{8}$$

$$s(J,k) := \sum_t \phi(t,J,k) f(t) \tag{9}$$

$$d(j,k) := \sum_t \psi(t,j,k) f(t) \tag{10}$$

The discrete wavelet transform of (t) is summarized by the set $\{A_J, D_{J-1} \ldots, D_1\}$.

The term A_J is a level approximation that captures the long-run (trending) properties of the signal. Given a decomposition scaling function $\tilde{\boldsymbol{\varphi}}(\boldsymbol{t},\boldsymbol{J},\boldsymbol{k})$ and a reconstruction scaling function $\tilde{\boldsymbol{\psi}}(\boldsymbol{t},\boldsymbol{J},\boldsymbol{k})$, A_J can be written as:

$$A_J = \sum_k \left[\tilde{\phi}(t,J,k) f(t)\right] \tilde{\psi}(t,J,k) \tag{11}$$

The level details D_j focus on high-resolution properties of the series. They are constructed in a way analogous to that of the level approximation:

$$D_j = \sum_k \left[\varphi(t,j,k) f(t)\ \psi(t,j,k)\right] \tag{12}$$

The biorthogonal wavelet transform makes use of four types of functions. One type - decomposition scaling and decomposition wavelet function - is needed for decomposing the signal. The other type - reconstruction scale and reconstruction wavelet function - is used for reconstructing the series.

The choice of the wavelet filter should not affect the behavior of the series extracted at each time scale. The filter should also be sufficiently long so that no artificial properties are generated both for filtering and for reconstruction. Yogo (2008) finds that a lowpass filter with 17 periods as the length, and a high-pass filter with 11 periods performs quite well for the decomposition of real output. Consistently with these results, I apply the 17-11 filter bank.

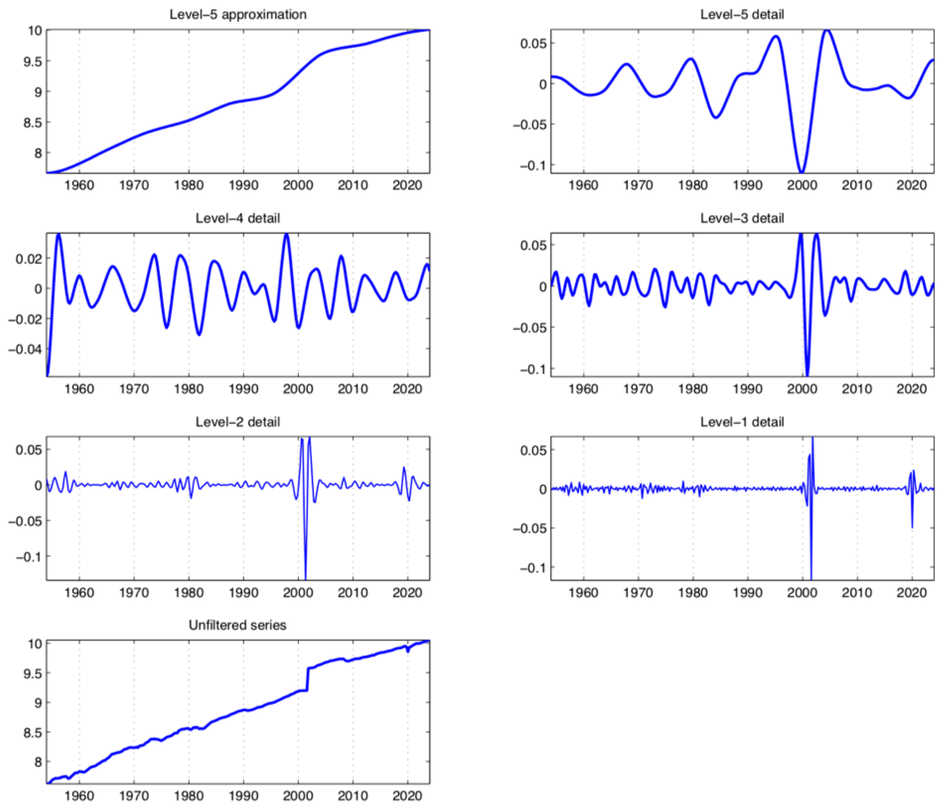

Figure 1: Time-scale decomposition for the 10-year yield spread

3. Dataset

I use quarterly data obtained from the FREDII online database of the Federal Reserve Bank of St. Louis. The sample spans from the first quarter of 1954 to the second quarter of 2024. The yield spread is computed as the difference between the 10-year yield and the 3-month yield on constant-maturity Treasury bonds. This definition of the spread has been standard practice since the seminal work of Estrella and Hardouvelis (1991), and is applied here for comparison with the literature.
The wavelet decomposition is applied to the seasonally-adjusted level of the real GDP (in billions of chained 2000 U.S. Dollars), and to each of the bond yields separately. The filtered series for GDP growth and the yield spread at every predictive horizon are computed afterwards. By applying the wavelet filter on the raw data rather on differenced series, I avoid the non-standard problems that would arise otherwise.

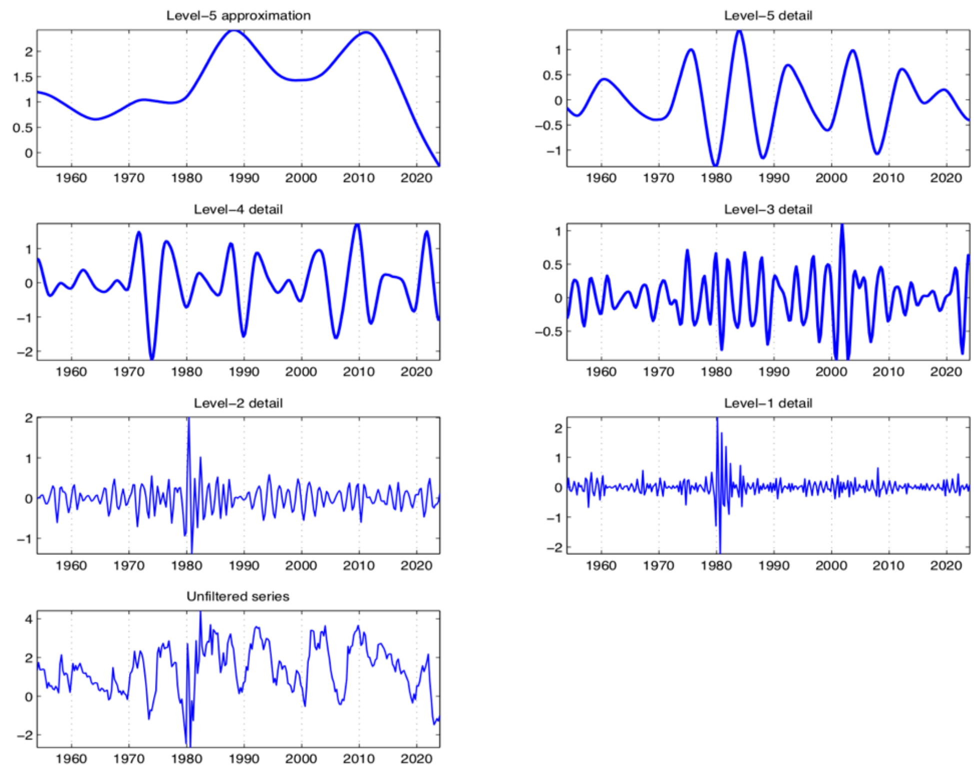

Figure 2: Time-scale decomposition for the level of GDP

The discrete wavelet transform can be applied to sample sizes that are multiples of *m* power of 2. The sample size is 282, which suggests that decompositions up to level 5 is feasible. Finally, I should point out that the wavelet decomposition introduces some distortion at the end of the filtered series. The reason lies in the wave-like periodic shape of the transformation, which is interrupted independently from the location along the wave. Like most empirical studies, I disregard this issue. Figures 1 and 2 show the decomposition of the series. As expected, details at level 1 and 2 identify the noisiest components. The approximations pick up the (possibly nonlinear) trends. The level decomposition from 1 to 3 captures the large outliers in the interest rate series in coincidence with the two episodes of large inversion of the yield curve in the first half of the 1980s.

4. Predicting over the full sample

This section studies the predictive relation between future output growth and the yield spread at each level of decomposition over the entire sample. The model takes the standard regression form:

$$\left(\frac{400}{h}\right)\ln\left[\frac{y_{t+h}}{y_t}\right]=\alpha+\beta s_t+\varepsilon_{t+h} \quad (13)$$

where and st is the term spread. Standard errors are estimated through the covariance estimator proposed by Newey and West (1987).[2]

4.1 Global predictability

The first column of Table 2 displays the well-known result of in-sample predictability for the unfiltered data. All the estimates of the slope coefficients are statistically significant and have the expected positive sign. The estimated R^2 statistics are somewhat lower than what found in previous studies like Estrella and Hardouvelis (1991). This is due to the fact that the sample used here includes the period of predictability breakdown starting in 1985 (see Dotsey, 1998).

The rest of Table 2 shows the results from regressing unfiltered future output growth on the filtered yield spread at each decomposition level. It is clear that the pattern of predictability is not homogenous across time scales. The slope coefficients for the regressions at the levels A5, D1 and D5 are statistically not different from zero for all the predictive horizons. The yield spread at the levels D4 and D5 appear as good predictors, both in terms of statistical significance of the relation and in terms of R^2. The long-term relationship between the term spread and future output growth at A5 is negative, although not significant.

[2] The potential issues arising in this application arise from a small-sample bias, and from size distortions in inference based on asymptotic distribution theory. As suggested in Kilian (1999), I could address this problem by computing bootstrapped *p*-values. However, since the application of the wavelet filter might create nonstandard statistical problems, I disregard these issues.

Table 2: Predictive models with level regressors, full sample

	Unfiltered series	A5	D1	D2	D3	D4	D5
h: 2							
α	2.15(4.83)	4.98(4.22)	4.38(9.90)	4.38(10.11)	4.43(9.97)	4.43(11.27)	3.10(10.14)
β	0.91(4.97)	-0.50(−0.82)	(0.68)0.44	1.92(2.61)	0.94(1.07)	1.81(5.93)	0.88(1.86)
R^2	0.12	0.02	0.002	0.05	0.02	0.14	0.03
h: 2							
α	2.20(4.96)	4.99(4.38)	4.43(10.23)	4.44(10.40)	4.43(10.44)	4.46(12.55)	4.45(10.89)
β	0.89(4.00)	-0.50(−0.82)	-0.06(−0.25)	0.97(2.02)	1.63(2.11)	1.88(5.41)	1.05(2.60)
R^2	0.19	0.02	0.00002	0.02	0.04	0.25	0.06
h: 2							
α	2.43(5.40)	4.95(4.65)	4.43(10.92)	4.43(10.91)	4.38(10.83)	4.45(12.82)	4.44(12.27)
β	0.87(4.62)	- 0.68(−0.84)	-0.06(−0.45)	(0.88)0.25	1.38(1.81)	1.63(6.87)	1.19(2.83)
R^2	0.21	0.02	0.0002	0.002	0.04	0.27	0.12
h: 2							
α	2.50(5.87)	4.92(4.96)	4.38(11.54)	4.38(11.53)	4.38(11.51)	4.43(12.61)	4.43(14.50)
β	0.63(4.46)	-0.50(−0.87)	0.06(0.63)	0.15(0.63)	0.69(1.26)	1.23(5.81)	1.27(4.22)
R^2	0.19	0.02	0.0002	0.002	0.02	0.22	0.18
h: 2							
α	2.81(6.80)	4.91(5.17)	4.43(12.55)	4.43(12.12)	4.43(12.12)	4.43(12.45)	4.43(14.89)
β	0.67(2.93)	-0.64(−0.89)	-0.02(−0.17)	0.14(0.81)	0.41(0.80)	0.82(4.19)	1.28(4.64)
R^2	0.14	0.02	0.00002	0.002	0.0002	0.13	0.25
h: 2							
α	2.85(5.61)	4.89(5.38)	4.43(12.63)	4.43(12.64)	4.43(12.62)	4.38(12.63)	4.43(15.69)
β	0.46(2.63)	-0.63(−0.90)	0.05(0.83)	0.25(1.58)	0.28(0.85)	0.64(2.50)	1.24(4.18)
R^2	0.11	0.03	0.0002	0.004	0.005	0.05	0.29

Legend: Round brackets indicate *t*-values.

Table 3: Predictive models with filtered regressors, full sample

	h					
	2^a	4^b	6^c	8^c	10^d	12^a
α	4.45(11.67)	4.47(14.87)	4.45(14.99)	4.43(15.20)	4.43(15.09)	4.43(14.84)
β	1.50(5.38)	1.50(6.52)	1.64(6.57)	1.20(6.47)	1.02(5.64)	0.82(4.86)
R^2	0.20	0.45	0.63	0.62	0.46	0.26

Legend: The regressors are obtained by summing the explanatory variables in table 2 that are significant at the 5% level for each predictive h. ^{a}Sum between crystals at D2, D4 and D5. ^{b}Sum between crystals at D2, D3, D4 and D5. ^{c}Sum between crystals at D3, D4 and D5. ^{d}Sum between crystals at D4 and D5. Round brackets indicate *t*-ratios.

Can the finding on time-heterogeneity be used to improve the in-sample fit of the predictive model? In order to answer this question, I study the predictive relation between prices and dividend-price ratios of stocks. The intuition goes as follows. Since the statistical properties of the predictive models for output growth vary across time scales, I can look for a linear combination among the level components of the yield spread that have a statistically significant predictive power. In other words, the aim is that of finding a filtered regressor that removes the 'noisy' components of the predictive regressor at each time scale. I compute this filtered regressor as the sum of level components whose estimated slopes are statistically significant at the 5% level. This variable is then used to predict unfiltered output growth. For instance, predictions for two quarters ahead use the sum between crystals at levels D2, D4 and D5 as the regressor. Table 3 shows that there are large gains from following this strategy. First, the proposed filtered predictors perform very well in-sample even at long predictive horizons. Second, the sum among the statistically significant regressors has a predictive power larger than that of each level regressor from Table 2.

The subsequent question of interest is whether the filtered series can be used for forecasting out-of-sample. Thus, I compute the tests for forecasting comparisons of nested models proposed by Clark and McCracken (2001). Like in Stock and Watson (2003), the nested model postulates that output growth is unpredictable in that it follows a random walk. This idea is formalized by imposing $\hat{\alpha} = \hat{\beta} = 0$. The forecast-encompassing tests are applied to split-sample, recursive and rolling forecasting schemes. The null is that the nested and non-nested model have equal predictive ability.[3]

Encompassing tests cannot be applied to nonstationary data (see Kilian, 1999). Hence, I apply the variants of the tests of Dickey and Fuller (1979) and Phillips and Perron (1988) proposed by Perron and Ng (1996, 2001) for the null of a unit root. These tests retain power in small samples through the use of a set of selection

[3] I do not report the results from the tests of Diebold and Mariano (1995) for they do not apply to comparisons between nested models.

criteria for the order of the underlying autoregression. The results are reported in a statistical annex available upon request. They indicate strong rejections of the null of a unit root for the unfiltered yield spread at all predictive horizons. There is evidence of nonstationarity for the raw series of output growth only up to a predictive horizon of 4 quarters ahead. I calculate the first difference of the variables that are nonstationary before computing the nested models.

Table 4: Predictability tests on models based on the full sample

Statistic	**Unfiltered regressors**						**Filtered regressors**					
	h						*h*					
	2	4	6	8	10	12	2[a]	4[b]	6[c]	8[c]	10[d]	12[a]
QLR	34.14	54.17	9.23	14.50	6.69	14.86	24.41	22.1	41.13	24.64	12.54	11.27
p-value	0	0	0.21	0.04	0.5	0.03	0	0	0	0	0.06	0.1
Exp-W	12.43	22.65	2.2	4.81	1.23	2.87	5.49	6.68	15.82	8.69	2.69	1.84
p-value	0	0	0.38	0.07	0.81	0.18	0	0	0	0	0.24	0.67
Nyblom	4.64	6.69	0.61	1	0.47	0.38	0.88	1.6	4.64	1.41	0.54	0.41
p-value	0	0	0.62	0.13	0.86	0.84	0.26	0.02	0	0.04	0.51	0.85
ENCsp	172.09*	199.07*	-5.55	-5.69	-1.65	25.85*	19.96*	30.19*	170*	116.06*	122.19*	19.21*
ENCre	225.1*	414.94*	-0.95	-2.99	4.13*	30.23*	21.19*	39.14*	210.50*	111.67*	138.64*	45.97*
ENCro	240.48*	444.52*	-1.82	-3	6.04*	30.17*	22.12*	41.93*	240*	105.29*	124.65*	40.03*

Legend: Models for predictive *h*s from 1 to 5 quarters ahead, and for 11 quarters ahead use non-differenced variables. All other models are based on data in first difference. The filtered regressors are obtained by summing the explanatory variables from the level regressions that are significant at the 5% level for each predictive *h*. [a]Sum between crystals at D2, D4 and D5. [b]Sum between crystals at D2, D3, D4 and D5. [c]Sum between crystals at D3, D4 and D5. [d]Sum between crystals at D4 and D5. This table reports the following test statistics and p-values. A series of tests for a one-time structural break: Andrews (1993) test, labeled QLR, Andrews and Ploberger (1993) tests, labeled Exp-W and Mean-W, Nyblom (1989) test, labeled Nyblom. A series of tests for out-of-sample relative forecast comparisons: the test for forecasting comparisons for nested models discussed by Clark and McCracken (2001), labeled ENC-NEW. The latter tests are applied to rolling, recursive and fixed forecasting schemes, respectively labeled with the following subscripts: roll, rec, and fix. *Significant at the 1% level. **Significant at the 5% level. ***Significant at the 10% level.

Table 4 reports the results from a battery of tests for a one-time structural break, namely the tests of Andrews (1993), Andrews and Ploberger (1993) and Nyblom (1989). The null is that of parameter stability. The low p-values suggest that both models with unfiltered and filtered regressors suffer from structural instability. Hence, the reader should focus on the forecast-encompassing tests based on rolling-windows estimates, which are known to be robust to parameter instability. Unfiltered regressors have no predictive power out-of-sample for 6 and 8 quarters ahead (see Table 4). The use of the predictive regressors restores the predictive power over all the horizons.

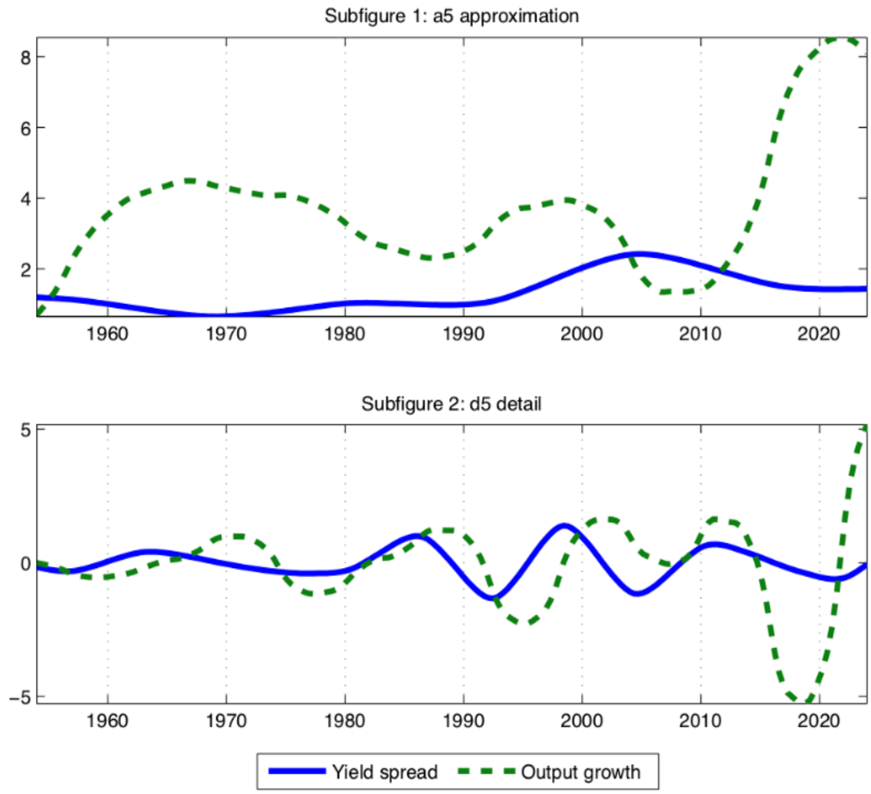

Figure 3: Plots of decompositions at A5 and D5

4.2 A negative slope in the long run

The previous section has established that the predictive power of the yield spread for unfiltered output growth varies across time scales. In this section, I investigate further the implications of the heterogeneity in the predictive relation. I regress filtered output growth on the filtered yield spread at each level. Table 5 shows that the quality of the predictive relation changes largely over time scales.

Differently from the standard results, for a time scale between 4 and 8 years, the slope of the predictive regressions are negative and largely significant (see Table 5). This result holds both for the detail D5 and the level approximation A5, that is both for details at long cycles and for the trend. In the former, the elasticity of future output growth to the yield spread is negative. In the latter, the elasticity is positive over all the predictive horizons owing to the large estimated constant terms.

Table 5: Level regressions, full sample

	A5	**D1**	**D2**	**D3**	**D4**	**D5**
h: 2						
α	4.95(15.60)	0.002(0.03)	-0.02(−0.11)	0.02(0.02)	0.13(0.68)	0.03(0.26)
β	-0.64(−4.50)	0.45(1.56)	1.45(2.96)	1.04(1.84)	1.17(4.89)	0.49(1.97)
R^2	0.23	0.02	0.11	0.03	0.21	0.05
h: 4						
α	4.98(14.14)	0.002(0.10)	0.02(0.25)	-0.02(−0.09)	0.13(0.63)	0.05(0.28)
β	−0.65(−4.81)	-0.10(−1.15)	0.81(2.67)	1.80(2.57)	1.47(5.67)	0.59(4.02)
R^2	0.26	0.02	0.15	0.12	0.38	0.13
h: 6						
α	4.00(12.55)	0.0002(0.02)	0.002(0.07)	-0.03(−0.45)	0.10(0.57)	0.05(0.38)
β	-0.50(−4.26)	−0.05(−0.81)	0.22(2.46)	1.50(2.99)	1.45(6.12)	0.87(4.81)
R^2	0.28	0.004	0.05	0.17	0.49	0.22
h: 8						
α	4.02(11.65)	-0.002(−0.20)	-0.004(−0.67)	-0.02(−0.45)	0.06(0.63)	0.06(0.46)
β	-0.50(−2.99)	0.05(1.00)	0.23(2.89)	0.86(2.63)	1.15(6.27)	0.91(5.51)
R^2	0.40	0.02	0.07	0.12	0.48	0.43
h: 10						
α	4.03(11.09)	0.0002(0.10)	-0.002(−0.29)	-0.0002(−0.10)	0.03(0.26)	0.06(0.61)
β	−0.50(−2.83)	-0.02(−0.65)	0.24(2.64)	0.45(1.57)	0.83(5.64)	1.00(10.67)
R^2	0.41	0.002	0.11	0.04	0.40	0.64
h: 12						
α	4.04(10.83)	−0.0003(−0.13)	0.002(0.49)	-0.0003(−0.17)	0.02(0.14)	0.06(0.50)
β	−0.65(−2.82)	0.04(1.87)	0.20(2.05)	0.20(1.18)	0.50(4.40)	1.05(14.14)
R^2	0.43	0.02	0.10	0.03	0.16	0.54

Legend: Round brackets indicate *t*-values.

Figure 3 indicates that, for the A5 components, the negative relation between output growth and the yield spread is an evident feature of the data until 1985. For the D5 components there appears to be a cyclical pattern in sign of the slope of the predictive model. For instance, from 1955 to 1960, and from 1965 to 1970, the slope evidently takes a negative sign. Instead, from 1960 to 1965, and from 1970 to 1975, the slope should be positive. Following this hint, I compute the level regressions for both the pre-1985 and the post-1985 period. Table 6 replicates all the findings that emerge from table 5. Since the results from the pre-1985 regressions are standard (included in the unpublished appendix), I can conclude that the negative slope of the predictive model is due to features of the data that are present only in the pre-1985 subsample.

Table 6: Level regressions, pre-1985 subsample

	A5	D1	D2	D3	D4	D5
h: 2						
α	4.67(20.19)	0.002(0.03)	-0.02(−0.07)	0.02(0.04)	(0.87)0.24	-0.09(−0.67)
β	-1.43(−6.23)	0.61(1.89)	1.97(4.94)	1.58(1.40)	1.59(4.85)	0.65(2.21)
R^2	0.63	0.03	0.19	0.04	0.28	0.11
h: 4						
α	4.67(16.10)	0.002(0.12)	0.02(0.47)	-0.00(−0.02)	0.20(0.86)	−0.07(−0.51)
β	-1.38(−5.03)	−0.09(−0.86)	1.17(4.52)	4.04(2.55)	1.86(5.10)	0.65(4.41)
R^2	0.65	0.02	0.27	0.20	0.49	0.23
h: 6						
α	4.50(14.18)	0.0005(0.05)	0.003(0.21)	-0.02(−0.13)	0.16(0.68)	−0.07(−0.63)
β	-1.40(−4.68)	-0.04(−0.60)	0.41(4.41)	2.83(4.16)	1.68(5.15)	0.82(5.53)
R^2	0.67	0.003	0.10	0.41	0.65	0.47
h: 8						
α	4.64(14.07)	0.00002(0.003)	−0.004(−0.45)	−0.02(−0.25)	0.10(0.54)	−0.06(−0.49)
β	−1.28(−4.19)	0.07(1.64)	0.38(4.50)	1.61(4.21)	1.60(5.12)	0.95(9.67)
R^2	0.68	0.02	0.13	0.24	0.63	0.51
h: 10						
α	4.63(12.44)	0.0002(0.06)	−0.002(−0.18)	−0.02(−0.43)	0.06(0.48)	-0.04(−0.45)
β	-1.25(−4.02)	−0.006(−0.21)	0.43(4.07)	0.69(2.25)	1.00(4.58)	1.05(14.97)
R^2	0.69	0.0002	0.20	0.10	0.43	0.64
h: 12						
α	4.60(11.83)	0.0003(0.10)	0.004(0.56)	−0.02(−0.50)	0.03(0.25)	−0.03(−0.40)
β	-1.22(−4.90)	0.05(2.15)	0.29(4.50)	0.63(1.67)	0.59(4.65)	1.09(16.59)
R^2	0.69	0.02	0.19	0.07	0.17	0.84

Legend: Round brackets indicate *t*-values.

Can the finding of the negative slope be reconciled with the available theories on the term structure of interest rates? The conventional wisdom on the predictive power of the yield spread suggests that the slope the yield curve reflects both current and expected monetary policy actions. A monetary tightening raises both nominal and real short-term interest rates in the presence of nominal price rigidity. The opportunity cost of real investment increases, thus making future output fall. Since long-term rates are unchanged, the yield curve flattens (see Estrella and Hardouvelis, 1991).

A different line of explanation relies on the expectations hypothesis of the term structure. This theory postulates that long-term rates are the average of expected interest rates at short maturities. If financial markets predict a boom, and expected

monetary policy is countercyclical, then the expected short-term rates rise (see Rudebusch, 1995). Since current short-term rates do not change, the yield curve becomes steeper. However, as discussed in Chapter 7 of Mishkin (1989), the expectations hypothesis is characterized by several flaws.
Mishkin (1990) argues that the measure of yield spread used in this paper corresponds to a forward interest rate from 3 months to 10 years in the future. This rate can be decomposed into an expected real interest rate and a component of expected inflation. The expected real rate is related to the expectations of monetary policy. Furthermore, inflation and output growth are positively correlated, and so are expected inflation and expected output growth (see Estrella and Mishkin, 1996). Overall, the available theories are unable to account for a negative relationship between the slope of the yield curve and future output. However, they indicate that the expectations of the monetary policy stance play a key role for the result of predictability. This raises the issue of whether the negative slope is related to the course of monetary policy. Estrella and Hardouvelis (1991) suggest to include the federal funds rate among the predictive variables, and check whether the estimated coefficient $\hat{\beta}$ on the yield spread is statistically-significant. The model becomes:

$$\left(\frac{400}{h}\right)\ln\left[\frac{y_{t+h}}{y_t}\right]=\alpha+\beta s_t+\gamma ffr_t+\varepsilon_{t+h} \qquad (14)$$

where ffr_t is the nominal federal funds rate.

The models estimated on unfiltered data indicate that increases in the federal funds rate are negatively correlated with future output growth (see Table 7). Like in Estrella and Hardouvelis (1991), the information in the Fed funds rate does not exhaust the predictive content of the yield spread. However, at the A5 and D5 levels, the current stance of monetary policy in uninformative, with the exception of the A5 level for predictions two quarters ahead. This suggests that the negative relation between the yield spread and future output growth in the long run is determined by factors other than monetary policy.

Table 7: Level regressions with the federal funds rate, full sample

	Unfiltered Series	Level Regressions					
		A5	D1	D2	D3	D4	D5
h: 2							
α	4.61 (5.12)	4.69 (14.06)	-0.004 (−0.02)	0.02 (0.23)	−0.02 (−0.07)	(0.51) 0.09	0.03 (0.26)
β	0.80 (2.84)	0.84 (−5.52) −	−0.05 (−0.13)	0.86 (2.44)	−0.05 (−0.14)	(0.87) 0.43	−0.60 (−1.84)
γ	−0.43 (−4.47)	0.09 (1.93)	−0.81 (−2.83)	−0.86 (−2.60)	−1.53 (−5.90)	(−2.20) −0.56	−0.52 (−5.85)
R^2	0.24	0.44	0.06	0.17	0.64	0.26	0.26
h: 4							
α	4.99 (5.13)	4.89 (10.82)	-0.002 (−0.03)	0.02 (0.40)	-0.002 (−0.04)	(0.63) 0.07	0.04 (0.29)
β	0.81 (2.84)	−0.80 (−4.12)	−0.22 (−1.86)	0.88 (2.29)	0.64 (1.60)	(2.83) 1.03	−0.11 (−0.64)
γ	-0.26 (−4.64)	0.07 (1.20)	−0.23 (−2.21)	−0.04 (−0.47)	−1.29 (−9.67)	(−0.89) −0.19	−0.50 (−4.48)
R^2	0.41	0.43	0.03	0.15	0.55	0.43	0.40
h: 6							
α	4.68 (4.80)	4.88 (9.83)	-0.005 (−0.18)	-0.002 (−0.24)	−0.02 (−0.40)	(0.49) 0.06	0.05 (0.44)
β	0.63 (2.80)	−0.87 (−4.63)	−0.11 (−0.85)	0.21 (2.17)	0.81 (2.25)	(4.59) 1.51	0.17 (0.81)
γ	−0.20 (−2.67)	) 0.05 (0.86)	−0.12 (−0.87)	−0.02 (−0.21)	−0.84 (−6.84)	(0.86) 0.17	−0.60 (−4.87)
R^2	0.41	0.43	0.02	0.06	0.50	0.61	0.46
h: 8							
α	4.52 (4.65)	4.95 (9.23)	-0.002 (−0.41)	0.002 (0.02)	−0.02 (−0.19)	(0.29) 0.03	0.06 (0.49)
β	0.53 (2.62)	−0.83 (−4.00)	0.04 (0.65)	0.12 (1.57)	0.51 (1.61)	(6.14) 1.81	0.62 (2.58)
γ	−0.15 (−1.87)	0.03 (0.64)	-0.002 (−0.03)	−0.15 (−2.51)	−0.49 (−4.86)	(4.06) 0.65	−0.38 (−4.44)
R^2	0.27	0.44	0.02	0.13	0.27	0.68	0.63
h: 10							
α	4.67 (4.61)	4.03 (8.99)	-0.006 (−0.07)	0.003 (0.52)	0.002 (−0.11)	(0.13) 0.02	0.06 (0.637)
β	0.60 (2.27)	−0.69 (−2.81)	−0.07 (−1.40)	0.17 (1.67)	0.25 (1.12)	(6.53) 1.62	0.65 (5.06)
γ	−0.11 (−1.44)	0.02 (0.16)	−0.11 (−1.54)	−0.09 (−2.00)	−0.12 (−1.65)	(4.683) 0.59	−0.23 (−2.80)
R^2	0.20	0.45	0.03	0.15	0.07	0.51	0.50
h: 12							
α	4.62 (4.48)	4.09 (8.91)	0.002 (0.19)	0.004 (0.68)	−0.02 (−0.38)	0.00 (−0.03)	0.06 (0.67)
β	0.41 (1.88)	−0.65 (−2.69)	0.03 (1.04)	0.20 (1.90)	0.16 (0.89)	1.41 (5.68)	0.83 (8.43)
γ	(−1.02) −0.07	−0.02 (−0.07)	−0.02 (−0.21)	0.002 (−0.10)	−0.07 (−1.61)	0.59 (4.27)	−0.15 (−2.02)
R^2	0.15	0.46	0.02	0.10	0.05	0.67	0.56

Legend: Round brackets indicate *t*-values.

5. A post-1985 predictability breakdown

Dotsey (1998) and Haubrich and Dombrosky (1996) report substantial evidence of a fall in the predictive power of the term spread since 1985. Ang et al. (2006) show that the short-term rate is a better predictor for output growth than the yield spread during the 1990s. In what follows, I investigate the question of forecast breakdown from a time-scale perspective. I divide the full sample into pre-1985 and post-1985 subsamples, and compute predictive regressions along the lines developed in the previous sections.

Like for the full sample, table 8 shows that the statistical significance of the regressions with filtered yield spread varies largely over time scales. This suggests a way out of the in-sample predictive breakdown after 1985, namely that of using an appropriate level component for the term spread in the predictive model. In particular, the table indicates that the D4-component of the yield spread is the best candidate, in that it is a significant predictor for output growth for up to 10 quarters ahead. I have also checked whether in-sample fit can be improved by regressing the unfiltered output growth on the sum of level regressors whose estimated regression slopes are significant at the 5% level. Differently from the full sample, no relevant results have emerged.

The issue is whether the filtered yield spread can help predicting out-of-sample. Both the tests for structural stability and the forecast-encompassing tests suggest that no gains in terms of out-of-sample forecasts are achieved by using filtered regressors.

6. Conclusion

In this paper, I revisit the relation of predictability between the yield spread and output growth at several forecasting horizons. I show that the predictive relation is heterogeneous across time scales. For a time scale between 4 to 8 years, a negative slope of the yield curve translates into positive GDP growth in the future in contrast to the existing literature. There is a linear combination of decomposed series for the yield spread that predicts output growth out-of-sample more accurately than the unfiltered regressor. Finally, I propose a solution to the breakdown of in-sample fit after 1985 through the use of a filtered regressor.

Several extensions are on the agenda. The question of primary interest is why the negative slope in the very long run explains future changes in output well. The issue of parameter instability is not solved through wavelet-filtered regressors. Giacomini and Rossi (2006) argue that the instability in predicting growth can be related to monetary policy conduct of the Fed. It would be interesting to check whether their conjecture applies to the analysis of monetary policy over time scales.

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