An Empirical Investigation of Technical Analysis in Government Bond Markets

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Abstract

Technical analysis is a popular technique among investors, and a controversial one among economists. This paper investigates the central point of contention between these groups i.e. the extent to which chart patterns are capable of predicting the probability distributions asset prices, in this case the prices of government bonds. We use nonparametric kernel regressions, and local polynomial regressions, to identify standard chart patterns in times series of yields. By comparing the unconditional distributions of returns with those conditioned on the identified patterns we find that while charts contain information about subsequent returns this information cannot, in general, be exploited to yield excess profits. We also find that chart patterns can

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predict the distribution of the general level of yields but that they contain almost no information about movements in the slope of the yield curve.

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I Introduction

This paper extends the literature on technical analysis by investigating the presence, and information content, of chart patterns in government bond yields. The historical behaviour of yields, and particularly of yield spreads, is a cornerstone of the active management of bond portfolios.[1] We address the following questions: (i) How frequently do technical chart patterns appear in yields and yield-spreads? (ii) Do these patterns contain any information about subsequent yield behaviour (including the probability density function of future returns), and (iii) Can traders profit from this information?

We apply and extend the automated pattern recognition tool proposed by Lo, Mamasky and Wang (2000, LMW henceforth).[2] The main statistical tool used by LMW is the Nadaraya-Watson nonparametric kernel regression.[3] In this paper, we improve upon the nonparametric Nadaraya-Watson kernel regression by employing a local polynomial regression, which is known to ameliorate several biases embedded in the Nadaraya-Watson regression.

A significant amount of bond trading involves either a simple purchase of a bond for cash i.e. a bet on the direction of change of the bond's yields, or a purchase hedged with a short position in another bond i.e. a bet on direction of change the yield spread between the long and short positions; examples include curve, and swap, spreads[4] Most analyses of yield spreads are based

[1]See the bond analysis pages of investment tools such as Bloomberg.

[2]See also the discussion of LMW in Jegadeesh (2000).

[3]This approach has also been used in the construction of yield curves, see Tanggaard (1992), Gourieroux and Scaillet (1994) and Linton et al. (2001).

[4]Curve spreads enable investors to bet on changes in the slope of the yield curve.

on regression models (Prendergast (2000)) or on quantitative models (See, for example, Merton (1974), Duffie and Singleton (2003)). In this paper we analyze yields and yield curve spreads using technical chart patterns.

The literature on yield spread trading is sparse, which is one of the motivations for our work. Yield spreads have, however, been used to investigate the expectations hypothesis of the term structure (see for example, Cox, Ingersoll and Ross (1981), Campbell and Shiller (1987) and Longstaff (2000a,b)). Dolan (1999) provides a preliminary analysis of the predictability of the yield curve shapes: By choosing the Nelson-Siegel (1987) model as the benchmark tool, he shows that movements in the model's parameters are predictable, which has significance for the selection of bond portfolios. Despite the investigation of numerous arbitrage-free yield curve models in the literature, it is not clear whether any of them have good forecasting properties. Duffee (2002), for example, documents the fact that the three-factor affine term structure model cannot outperform a simple random walk model in forecasting future yields. Several authors have modelled sovereign spreads using an econometric. For example, Duffie, Pedersen and Singleton (2003) estimate the Russian yield spread relative to US Treasuries during the 1998 Russian debt default.

The rest of this paper is organised as follows: The first part of Section

Swap spreads relate to spread between interest rate swaps and government securities. See Duffie and Singleton (1997) and Brown, In and Fang (2002) for empirical analyses of swap spreads. Other fixed income spread trades include convergence trades, such as those involving mortgage-based securities (MBS) and US Treasuries. See Fung and Hsieh (2002) for an analysis of a range of spread-investment returns.

III briefly describes the use of nonparametric kernel and local polynomial regressions to identify chart patterns; the second part describes the patterns themselves. Section IV discusses our bond yield data and the probability-distribution tests. Section V presents our empirical results, and Section VI concludes.

II A Review of Previous Research.

Automated identification of chart patterns is not new. Girmes and Damant (1975), for example, use a gradient smoothing technique to investigate the frequency of Head-and-Shoulders patterns in stock prices. They find five times as many Head-and-Shoulders patterns in actual stock prices than in simulated data, suggesting that the movements of stock prices are subjected to human intervention. While such patterns may occur surprisingly often, earlier work, by Levy (1971), suggests that their profit-making ability is zero, concluding that (p.318) *"after taking transaction costs into account, none of the thirty-two patterns showed any evidence of profitable forecasting ability in either (bullish or bearish) direction."* Similarly, Olser (1998) tests the Head-and-Shoulders pattern in the US equity market and finds that this pattern lacks predictive power. Dempster and Jones (1998, 2002) automate the detection of Head-and-Shoulders and Channel patterns and find that that both produce trading losses, suggesting the presence of predictive value, but not in the direction that practitioners expect. Dawson and Steeley (2003) find that 10 chart patterns contain no incremental information when tested in UK equity markets. Chang and Osler (1999) look at Head-and-Shoulders patterns for six currency pairs: They find that for four of the six the pattern could generate no profits but that chart-based dollar-yen and dollar-mark trades were profitable, even after adjusting for interest rate differentials, risk, and transaction costs.

The overall conclusion from such tests is that chart patterns cannot be used to generate excess returns. The fact that market practitioners continue to use them is, therefore, something of a puzzle: Chang and Osler (1999) describe this persistence as *methodical madness*.[5] Part of the explanation may lie in the fact that, as empirical investigations have become more sophisticated, a number of studies have found evidence that charts may contain some predictive information, even if this information, in isolation, is not sufficient to suggest profitable trades.[6] In particular, LMW, conclude that using chart patterns as additional inputs to the investment process may be profitable in US equity markets. Using the same methodology as LMW, Savin, Weller and Zvingelis (2003) find that the Head-and-Shoulders pattern can predict

[5]Graphical charts available to investors include bar, line, point-and-figure and candlesticks. Each type of chart interprets asset prices in a different way and therefore offers different trading implications. Marshall, Young and Rose (2006) investigated the predictive property of candlestick charting in the US equity market over the period 1992-2002. Using the bootstrap methodology as in Brock, Lakonishok and LeBaron (1992), they report low predictive power for various candlestick patterns commonly advocated by technical analysts. Their results support the view that investors who base their trading decisions solely on candlestick patterns are unlikely to gain financially. See also Fock, Klein and Zwergel (2005).

[6]A number of authors provide theoretical explanations for the potential value of technical analysis, see Brown and Jennings (1989) for example.

excess returns, again in US equity markets. Another class of investigations that provides some support for technical analysis goes beyond the analysis of prices alone and looks at the extent to which charts may reveal information about stop-loss and take-profit orders (Osler (2003)) and market liquidity (Kavajecz and Odders-White (2004)).

III Identification of Technical Charts Patterns

A Nonparametric Kernel Regression

The object of technical analysis is to extract signals from noisy data. This is usually accomplished in two stages, with the search for patterns being applied after the raw data have been smoothed. This smoothing is undertaken to allow the pattern search to focus on 'large', less frequent, price movements. As in all signal extraction exercises a subjective element the smoothing process is unavoidable. In this paper we use two nonparametric smoothing methodologies: kernel regression, and local polynomial regression.

Assume that bond yields, y, are generated as follows:

$$y_t = f(x_t) + \epsilon_t \tag{1}$$

where $f(x)$ is an arbitrary, fixed, and unknown nonlinear function of state variable(s) x, and $\epsilon \sim iid(0,1)$. A smoothed estimator of $f(x)$, may be expressed as:

$$\hat{f}(x) = \frac{1}{T}\sum_{t=1}^{T}\omega_t(x)y_t \tag{2}$$

where the weights $\omega_t(x)$ are large for y_ts paired with x_ts near to the value x (the 'focal' point), and small for x_t far from x. The weight function $\omega_t(x)$ is constructed from a probability density function $K(x)$ (the 'kernel'), with the properties $K(x) \geq 0$ and $\int K(u)du = 1$.

The role of the kernel is to weight the data such that observations close to the focal point have more influence than those further away. (See, for example, Rosenblatt (1956), Hardle (1990), Campbell, Lo and Mackinlay (1997, Chapter 12) for a comprehensive review of these concepts.) By rescaling the kernel with an additional parameter $h > 0$, we can change its spread to $K_h(u) = \frac{1}{h}K(u/h)$ and $\int K_h(u)du = 1$. The weight function ω_t is then defined as:

$$\omega_{t,h}(x) = K_h(x - x_t)/g_h(x) \tag{3}$$

$$g_h(x) = \frac{1}{T}\sum_{t=1}^{T}K_h(x - x_t) \tag{4}$$

Substituting equations (3) and (4) into (2) yields the *Nadaraya-Watson* kernel estimator $\hat{f}_{NW}(x)$ of $f(x)$:

$$\hat{f}_{NW}(x) = \frac{\sum_{t=1}^{T}K_h(x - x_t)y_t}{\sum_{t=1}^{T}K_h(x - x_t)} \tag{5}$$

This expression allows us to estimate the kernel regression in any fixed length window of d observations. This can be written as:

$$\hat{f}_{NW}(\tau) \quad = \quad \frac{\sum_{s=t}^{t+d-1} K_h(\tau - s) y_s}{\sum_{s=t}^{t+d-1} K_h(\tau - s)}, \qquad t = 1, ..., T - (d + H - 1) \qquad (6)$$

where T is the number of observations in a yield series and H is the holding period over which we measure the conditional returns. In short, we apply the Nadaraya-Watson estimator to a series of fixed length, rolling windows from t to $t + d - 1$, where t begins at 1 and ends at $T - (d + H - 1)$.

We then identify a series of turning points by finding times $(\tau - 1)$ such that $\text{Sgn}(\hat{f}'_{NW}(\tau - 1) = -\text{Sgn}\hat{f}'_{NW}(\tau)$, where $\hat{f}'_{NW}(\tau)$ denotes the derivative of $\hat{f}_{NW}(\tau)$ with respect to τ and $\text{Sgn}(\cdot)$ is the signum function. If the signs of $\hat{f}'_{NW}(\tau - 1)$ and $\hat{f}'_{NW}(\tau)$ are $+1$ and -1 respectively, we have a local maximum, and if they are -1 and $+1$ we have a local minimum. These turning points provide the proximate information required for the identification of most chart patterns.

B Local Polynomial Regression

It is well-known that the Nadaraya-Watson estimators suffer from a large bias at the boundaries of the window. Although many ad-hoc proposals, such as boundary kernel methods, have been proposed to alleviate this problem, these are less efficient than a local linear fit. (See, for example, Fan and Gijbels (1996).) Thus we supplement the kernel approach with a local polynomial regression. An advantage of this method is that the biases along the boundary are similar to those in the interior, so reducing the need to use specific boundary kernels. Another advantage is that we can estimate the regression parameters using least squares. (See, for example, Fan and Gijbels (1996, Chapter 3) and Hastie, Tibshirani and Friedman (2001, Chapter 5).)

The starting point for a local polynomial regression is similar to that for a nonparametric kernel regression. Assume that the yields and spreads are generated by some nonlinear function $f(x)$ as in equation (1), and that the $(p+1)^{th}$ derivative of $f(x)$ at focal point x_0 exists. We can approximate the unknown regression function $f(x)$ locally by a polynomial of order p. A Taylor expansion for x in the neighborhood of x_0 gives:

$$f_{LP}(x) \approx f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2}(x - x_0)^2 + \ldots + \frac{f^{(p)}x_0}{p}(x - x_0)^p \quad (7)$$

This polynomial is fitted locally by a weighted least squares regression, minimizing the following function:

$$\min_{\beta} \sum_{i=1}^{d} \left[y_i - \sum_{j=0}^{p} \beta_j (x_i - x_0)^j \right]^2 K_h\left(\frac{x_i - x_0}{h}\right) \quad (8)$$

where $K_h(\cdot)$ is the kernel function assigning weights to each observation, and h is a bandwidth parameter that controls the size of the local neighborhood. Let $\hat{\beta}_j$ $(j = 0, ..., p)$ be the solution to this problem. It is clear from the Taylor expansion that $\hat{f}_j(x_0) = j!\hat{\beta}_j$ is an estimator for $f^{(j)}(x_0)$, for $j = 0, 1, ..., p$. If we denote $\mathbf{X}$ as the $(d \times p)$ design matrix:

$$\mathbf{X} = \begin{pmatrix} 1 & (x_1 - x_0) & \cdots & (x_1 - x_0)^p \\ 1 & (x_2 - x_0) & \cdots & (x_2 - x_0)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & (x_d - x_0) & \cdots & (x_d - x_0)^p \end{pmatrix} \tag{9}$$

and let $\mathbf{W}$ be a $(d \times d)$ diagonal matrix of weights,

$$\mathbf{W} = \operatorname{diag}\left(K_h \left(\frac{x_i - x_0}{h} \right) \right) \quad i = 1, ..., d \tag{10}$$

the weighted least squares problem (8) can be written as:

$$\min_{\beta} (\mathbf{y} - \mathbf{X}\beta)' \mathbf{W} (\mathbf{y} - \mathbf{X}\beta) \tag{11}$$

where $\hat{\beta} = (\beta_0, \beta_1, ..., \beta_p)'$ is the vector of parameters and $\mathbf{y}$ is a vector of yields or yield spreads. The solution is given by:

$$\hat{\beta} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1} \mathbf{X}'\mathbf{W}\mathbf{y} \tag{12}$$

if $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible. The estimator $\hat{f}_{LP}(\cdot)$ is the intercept term $\hat{\beta}_0$. To ensure that $(\mathbf{X}'\mathbf{W}\mathbf{X})$ is invertible, at least $(p+1)$ different points with positive weights are required. Essentially, $\mathbf{X}$ is a matrix of power functions of d yield observations to which we apply (12) in order to obtain d smoothed, or fitted, yields.

The maxima and minima in a window are found from the signs of $\{\hat{f}'_{LP}(\tau)\}_{\tau=1}^{\tau=45}$. $\hat{f}'_{LP}(\cdot)$ is given by parameter $\hat{\beta}_1$ in equation (12). All extrema are obtained by checking for the sign of $\hat{f}'_{LP}(\tau)$ against $\hat{f}'_{LP}(\tau-1)$. If $\hat{f}'_{LP}(\tau) > 0$ and $\hat{f}'_{LP}(\tau-1) < 0$, there is a minimum at $(\tau-1)$ and *vice versa.* If $\hat{f}'_{LP}(\tau) = \hat{f}'_{LP}(\tau-1) = 0$, we work backwards for each $\beta_{1,\tau}$ to determine whether the current stationary point is a maximum or minimum since the extrema always generate an alternating max-min sequence. The asymptotic conditional bias for odd values of p is simpler than for even values. (See Simonoff (1996) and Fan and Gijbels (1996)) Consequently, we set $p = 1$ throughout.

C Choice of smoothing parameters.

C.1 Window length.

We set the rolling window sizes to $d = 45$ days (i.e. we use $\{y_t, ..., y_{t-44}\}$), and the holding period to $H = 1$ day, on the assumption that market practitioners should take no more than 1-day to recognize the completion of a pattern. The first window starts at $t = 1$ and ends at $d + H - 1$. Only patterns completed within $(d - H)$ days and with the final extremum occurring on the final day are selected since without this requirement the same pattern would be recorded several times while rolling the window forward. Our estimation strategy is as follow: (1) Estimate a 45-day window of smoothed prices using kernel and local polynomial regressions. (2) Check whether an extremum has occurred at day 44. (3) If an extremum exists on this day, check whether it is accompanied by a chart pattern. (4) If a chart pattern is confirmed, the one-day conditional bond return is measured from day 45 ($d+1$) to 46 ($d+2$). Where no chart pattern is confirmed, we move on to the next fixed-length window. This process gives us a clean out-of-sample bond return with which to measure the information value of chart patterns.

C.2 Kernel Function and Bandwidth.

We use the Epanechnikov kernel (Epanechnikov (1969)): [7]

$$K(z) = \frac{3}{4}(1 - z^2)_{|z|<1} \tag{13}$$

Fan and Gijbels (1996, Theorem 3.4) and Fan et al. (1995) show that the Epanechnikov is the optimal kernel for all orders of p in the local polynomial regression, in the sense that it provides the minimimum asymptotic mean squared error. To be consistent for both nonparametric regressions, we also apply this kernel function to the Nadaraya-Watson estimators.

We use a bandwidth parameter derived from the popular cross validation

[7] The Gaussian kernel is used by LMW and Dawson and Steely (2003), and defined as: $K_h(x) = \frac{1}{h\sqrt{2\pi}} \exp(-x^2/2h^2)$. For other kernel choices, see Silverman (1986) and Hardle (1990).

method, which minimizes the following function:[8]

$$CV_h = \frac{1}{d}\sum_{t=1}^{d}\left(y_t - \hat{f}_{h,t}\right)^2 \tag{14}$$

where $\hat{f}_{h,t} = \frac{1}{d-1}\sum_{\tau\neq t}^{d}\omega_{\tau,h}y_\tau$[9]

D Technical Chart Patterns

We search for six pairs of standard patterns: Head-and-Shoulders Top (HST) and Bottom (HSB), Broadening (BT, BB), Triangle (TT, TB), Rectangle (RT, RB), Double (DT, DB) and Triple (TPT,TPB). (For details see Edward and Magee (1966), Schwager (1996), Kaufman (2005) and Bulkowski (2005).) We denote the extrema identified by the regressions by $(e_1, e_2, ..., e_m)$ and their dates by $(t_1^*, t_2^*, ..., t_m^*)$. The technical patterns are identified by framing conditions on the final five extrema as follows:

Head-and-Shoulders

HST1 e_m is a maximum

HST2 $e_{m-2} > e_{m-4}$, $e_{m-2} > e_m$, $e_{m-4} > e_{m-3}$, and $e_m > e_{m-1}$

HST3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m$ and $\bar{e} = (e_{m-4} + e_m)/2$

[8] There are numerous alternative methods, including rule-of-thumb, cross-validation, nearest neighbours, and plug-ins. (See Simonoff (1996), Fan and Gijbels (1996) and Jones, Marion and Sheather (1996) for some extensive discussion of these methods.)

[9] The t^{th} observation is omitted thereby making the fitted value independent of the observed value y_t.

HST4 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

HSB1 e_m is a minimum

HSB2 $e_{m-2} < e_{m-4}$, $e_{m-2} < e_m$, $e_{m-3} > e_{m-4}$, and $e_{m-1} > e_m$

HSB3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m$ and $\bar{e} = (e_{m-4} + e_m)/2$

HSB4 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

Broadening

BT e_m is a maximum, $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} > e_{m-1}$

BB e_m is a minimum, $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} < e_{m-1}$

Triangle

TT e_m is a maximum, $e_{m-4} > e_{m-2} > e_m$ and $e_{m-3} < e_{m-1}$

TB e_m is a minimum, $e_{m-4} < e_{m-2} < e_m$ and $e_{m-3} > e_{m-1}$

Rectangle

RT1 e_m is a maximum

RT2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m-2, m$ and $\bar{e} = (e_{m-4} + e_{m-2} + e_m)/3$

RT3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

RT4 $\min(e_{m-4}, e_{m-2}, e_m) > \max(e_{m-3}, e_{m-1})$

RB1 e_1 is a minimum

RB2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-4, m-2, m$ and $\bar{e} = (e_{m-4} + e_{m-2} + e_m)/3$

RB3 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = m-3, m-1$ and $\bar{e} = (e_{m-3} + e_{m-1})/2$

RB4 $\max(e_{m-4}, e_{m-2}, e_m) < \min(e_{m-3}, e_{m-1})$

Double

Define,

$$e_a = \sup\{P^*_{t_k} : t^*_k > t^*_m\} \quad k = 2, ..., d \tag{15}$$

$$e_b = \inf\{P^*_{t_k} : t^*_k > t^*_m\} \quad k = 2, ..., d \tag{16}$$

then

DT1 e_m is a maximum

DT2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = (m, a)$ and $\bar{e} = (e_m + e_a)/2$

DT3 $t^*_a - t_m > 20$ days

DB1 e_m is a minimum

DB2 $\max|e_i - \bar{e}| = 0.010 \times \bar{e}$, where $i = (m, b)$ and $\bar{e} = (e_m + e_b)/2$

DB3 $t_b^* - t_m > 20$ days

Triple

TPT1 e_m is a maximum

TPT2 Select three of the highest maxima ($e_{\max 1} > e_{\max 2} > e_{\max 3}$) with corresponding time at ($t_{\max 1}, t_{\max 2}, t_{\max 3}$) respectively, one of the extrema must be e_m.

TPT3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$ for $i = (\max 1, \max 2, \max 3)$, where $\bar{e} = \frac{1}{3}(e_{\max 1} + e_{\max 2} + e_{\max 3})$

TPT4 $t_{\max 3} - t_{\max 1} > 25$ days

TPB1 e_m is a minimum

TPB2 Select three of the lowest maxima ($e_{\min 1} < e_{\min 2} < e_{\min 3}$) with corresponding time at ($t_{\min 1}, t_{\min 2}, t_{\min 3}$) respectively, one of the extrema must be e_5.

TPB3 $\max |e_i - \bar{e}| = 0.010 \times \bar{e}$ for $i = \min 1, \min 2, \min 3$, where $\bar{e} = \frac{1}{3}(e_{\min 1} + e_{\min 2} + e_{\min 3})$

TPB4 $t_{\min 3} - t_{\min 1} > 25$ days

IV Yield Data, Returns and Distribution Tests

A Government Benchmark Bond Yield Data

We use benchmark government bond yields from the US, UK, Germany, Japan, Australia, Canada and Hong Kong, and construct 45 yield spreads to give us a total of 262,170 daily observations. (See Table 1 for details.)

B Sampling Conditional and Unconditional Bond Returns

We approximate a bond's holding-period return (r^B) as:

$$r_t^B = -D \times \Delta y \tag{17}$$

where $\Delta y = y_t - y_{t-1}$ is the change in yield from time $t-1$ to t and D is the bond's duration.[10]

Yield-spread trading is aimed at exploiting changes in the slope of the yield curve, while minimising exposure to changes in its position. This requires opposite positions to be taken in bonds at different maturities, with position weights (α) such that the aggregate position is hedged against small and equal movements in the yields at the two maturities; a method known as 'duration weighting'. The resulting portfolio return (r^S)is a linear combi-

[10]We assume that benchmark bonds trade close to par in order to obtain the duration data. An alternative approach is derived by Shiller, Campbell and Schoenholtz (1983). See Campbell, Lo and Mackinlay (1997, p.408) for more details.

nation of the returns on the two bonds:

$$r_t^S = \alpha_1 r_{1t}^B + \alpha_2 r_{2t}^B \tag{18}$$

We search for patterns in both yields and spreads, and calculate the returns from investments suggested by any patterns that are identified. This gives us 12 sets of 'conditional' returns per series. We then compare these conditional returns with the unconditional returns based on the complete series, with the null hypothesis being that the population distributions of the conditional and unconditional series are identical.

To allow simple comparisons across markets i, we standardize returns (Z_i) for each series by subtracting the mean of the series and dividing by its standard deviation i.e.

$$Z_{i,t} = \frac{r_{i,t} - \text{Mean}(r_{i,t})}{\text{S.D.}(r_{i,t})} \tag{19}$$

C Distribution Tests

To test for differences between the conditional and unconditional returns we follow LMW, and use goodness-of-fit, and Kolmogorov-Smirnov tests.

The goodness-of-fit test compares the quantiles of the returns. The first step is to compute the deciles of unconditional returns and tabulate the relative frequency $\hat{\delta}_j$ of conditional returns that fall into decile j of the unconditional returns, $j = 1, ..., 10$:

$$\hat{\delta}_j = \frac{\text{Number of conditional bond returns in decile} \quad j}{\text{total number of conditional bond returns}} \tag{20}$$

The null hypothesis is that bond returns are independently and identically distributed so that the conditional and unconditional bond distributions are identical. The goodness-of-fit test statistic Q is given by:

$$\sqrt{N}(\hat{\delta}_j - \frac{1}{10}) \sim N(0, \frac{1}{10}(1 - \frac{1}{10})) \tag{21}$$

$$Q = \sum_{j=1}^{10} \frac{(N_j - \frac{1}{10}N)^2}{\frac{1}{10}N} \sim \chi_9^2 \tag{22}$$

where N_j is the number of (conditional) observations in decile j, N is the total number of (conditional) observations, and (21) is the asymptotic Z-value for each bin.

The Kolmogorov-Smirnov test is derived from the cumulative distribution functions $F_1(z)$ and $F_2(z)$ with the null hypothesis that $F_1 = F_2$. Denote the empirical cumulative distribution function $\hat{F}_j(z)$ of both samples:

$$\hat{F}_j(z) = \frac{1}{N_i} \sum_{k=1}^{N_i} I(Z_{ik} \leq z), \quad i = 1, 2 \tag{23}$$

where $I(\cdot)$ is the indicator function and $(Z_{1t})_{t=1}^{T_1}$ and $(Z_{2t})_{t=1}^{T_2}$ are the two iid samples. The Kolmogorov-Smirnov statistic and the associated p-values are given by the following expressions:

$$\gamma = \left(\frac{N_1 N_2}{N_1 + N_2}\right)^{1/2} \sup |\hat{F}_1(z) - \hat{F}_2(z)| \tag{24}$$

$$\text{Prob}(\gamma \leq x) = \sum_{k=-\infty}^{\infty} (-1)^k \exp(-2k^2x^2), \quad x > 0 \tag{25}$$

Under the null hypothesis, γ should be small. An approximate α-level test of the null hypothesis can be performed by computing the statistic and rejecting the null if it exceeds the upper 100αth percentile for the null distribution. (See Press et al. (2002, Section 14.3))

D Vasicek simulation as a benchmark.

To provide an illustrative benchmark for comparison, we apply the search and test procedures to data simulated using Vasicek's (1977) model.[11] The Vasicek model is given by:

$$dy_t = \lambda(\mu - y_t)dt + \sigma dW_t \tag{26}$$

where W_t is the standard Brownian motion and y_t is the yield at time t. The parameters λ governs the speed of reversion to the long run equilibrium μ, and σ is the volatility parameter. The parameters (μ, λ, σ) are estimated using maximum likelihood for each bond yield and yield spread, and an

[11] By its Gaussian property, the Vasicek model is able to generate negative values, which models the yield spread better than the square-root model. (Cox, Ingersoll and Ross (1985))

independent series is simulated for each series. (See, for example, Gourieroux and Jasiak (2001, Section 12.1) or Brigo and Mercurio (2001, p.54)) We then apply the pattern recognition algorithm to the simulated series. We do this only once for each series since the purpose here is not to construct a distribution of conditional returns but to provide a simple comparison between the simulated series and the actual yields.

E Addition of a moving average test.

The moving average is a popular technical indicator that appears to have predictive power for asset prices. (See Brock, Lakonishok and LeBaron (1992) and Levich and Thomas (1993)) Therefore, for each pattern found, we compute the 45-day moving average and include it as a further conditioning variable. The chart patterns are thus further separated into two categories, one where the last extrema e_m is *above* the moving average, and the other *below*.

V Empirical Results

A Bond Yields

Tables 2 and 3 display the pattern count from applying the Nadaraya-Watson and local polynomial regressions respectively. The first row is the total sample count, and the second gives the results from the simulation of a Vasicek model. The third and fourth rows are counts for e_m above and below the 45-day moving average. The most frequently occurring pattern using Nadaraya-Watson regressions is the Rectangle, with more than 3000 occurrences in each of its top and bottom forms, followed by the Head-and-Shoulders and Double, with more than 1000 occurrences each. The remaining patterns have counts between 600 and 800. This result differs from LMW, who find the Double to be the most frequent in US equities, and Dawson and Steeley (2003) who find the Head-and-Shoulders to be the most frequent in the UK equity market.

Identified patterns appear with the greatest frequency in the UK with 2909 occurrences in 27848 observations (10%), and least frequency in Japan (4%) and Hong Kong (6%). When classified according to maturity brackets (short, medium and long) rather than by country, the Rectangle is the most common pattern for all three maturities, followed by Head-and-Shoulders and Double. Nearly all Double and Triple top patterns lie above the moving average, and nearly all Double and Triple bottom patterns lie below. The only top pattern found to be predominantly below the moving average is the Triangle.

The count for the local polynomial regression (21334) is higher than for the Nadaraya-Watson regression (16929) (see Tables 2 and Table 3). This suggests that the former generates more extrema near the boundary from which we can identify patterns. As with the Nadaraya-Watson regression, the most frequently observed pattern for the local polynomial regression is the Rectangle, followed by the Head-and-Shoulders and the Double. Aside from the greater frequency of patterns, the qualitative results are the same for both regressions.

The total count for the Vasicek series is higher than for the actual series in the UK, Germany, Japan and Australia markets, by a factor of 4 in the case of Japan. This may be due to the level of Japanese yields in our sample. During the nineties, the Japanese monetary authority followed a zero-interest rate policy for many years. With yields at near zero for such a considerable length of time, there were few yield movements and therefore little opportunity for the formation of chart patterns.[12] For the US, Canada and Hong Kong markets, the pattern count for actual yields is higher than for the simulated series. For all simulated Vasicek series, the most frequently detected chart pattern is the Rectangle, followed by the Head-and-Shoulders and Double; the same ordering as for the actual data. The Vasicek results suggest that the patterns in the actual data are likely to have arisen by chance and not as a result of the behaviour of technical traders themselves. While this is interesting in itself, the focus of our investigation is on the distribution of returns on the day after each pattern has appeared.

A.1 The Level of Post-Pattern Returns.

Tables 4 and 5 display summary statistics of one-day-post-pattern, or conditional, returns for the two nonparametric regressions methods. The asterisk

[12]The late nineties witnessed a series of failures of Japanese financial institutions, such as the Long-Term Credit Bank and Nippon Credit Bank. As a result, Moody downgraded Japan's sovereign credit rating from AAA in November in 1998 and further downgrades in September 2000 and November 2001.

(*) beside the mean return signifies that the return is significantly different from zero using standard 5% t-tests. The normalization of returns described above reduces the mean and standard deviation of all unconditional returns to zero and one respectively.

Seven out of 12 patterns exhibit statistically significant mean returns from the Nadaraya-Watson regression. With the larger set of conditional returns from the local polynomial regression, this falls to 5 out of 12. The signs of the statistically significant returns are as expected with the exception of those for Double-top in Germany and the US.[13] The signs of the mean returns across different countries and maturities does not yield any systematic pattern however. For example, the mean return Head-and-Shoulders pattern is statistically significant for US and UK, but not the rest of the markets. Conditioning on the moving average does offer some improvement in isolated cases (for the UK, for example, $e_m > MA$ produces more significant returns than does the unconditioned sample) but again there is no systematic pattern that would indicate a reliable conditioning in all circumstances.

A.2 Information-Test Results.

Tables 6 and 7 present the information-test results.[14] The goodness-of-fit null hypothesis is that each decile should contain 10% of the post-pattern observations and significant deviations from this indicate the presence of information in the chart patterns. The final column is the Q-statistic, and

[13] All top patterns are supposed to produce positive returns, and vice versa.

[14] In Tables 6 and 7 -99.00 indicates that fewer than three patterns were detected.

the numbers in parenthesis are the asymptotic z-values for each decile, and the p-value for the Q-statistics respectively. The results, from both regressions, suggest that there is information in the chart patterns. On the basis of the goodness-of-fit test 7 of the 12 patterns contain information using Nadaraya-Watson, and 8 using the local polynomial regressions. Using the Kolmogorov-Smirnov test 5 and 6 chart patterns appear to contain information for the two smoothing methods[15] for Nadaraya-Watson and local polynomial regression respectively. No pattern performs consistently well in any country with the exception of the HEad-and-Shoulders-Top in the US, which appears to reject both the goodness-of-fit and Kolmogorov-Smirnov null hypothesis for both regressions. The maturity of bond yields does not seem to have any effect on the results. Similarly, conditioning on the moving average does not improve the results systematically. To summarize, the chart patterns do appear to contain information about the distribution of returns. This information appears to be scattered randomly across countries and maturities however.

B Yield Spreads

Table 8 presents the pattern count for the Nadaraya-Watson kernel regression (Panel A) and local polynomial regression (Panel B) respectively. The top row is the aggregate count for all yield spreads. For all of the patterns the frequency of counts are substantially lower than for yield levels, despite the

[15] p-value < 0.1

number of raw observations being greater. From 262,170 observations, only 7209 and 9136 chart patterns are found by Nadaraya-Watson and local polynomial regression respectively, a considerably lower number than for bond yields. The most frequent patterns are the triangle and broadening, rather than rectangle, double or head-and-shoulders commonly found in equity or currency markets. The least frequent pattern is the triple. The country with the lowest pattern count is Australia. A comparison of the results from the Vasicek simulation series and actual bond yield spreads show no significant difference for any chart pattern. It appears from these results that the behaviour of yield spreads differs fundamentally from that of yield levels, stocks and currencies.

C Returns

Table 9 gives summary results for the unconditional and conditional yield spread return from the long-spread strategy.[16] All the yield spread returns from the long spread strategy have been normalized to zero mean and unit standard deviation. None of the country-aggregated mean returns is statistically significant from zero, with the single exception of the HST using the local polynomial regression, although there are isolated significant results for some of the individual countries.

[16] The mean, standard deviation and skewness results for the short-spread strategy have the opposite signs to the long spread strategy, but the values remain the same.

D Information-Test Results.

Tables 10 and 11 show the results for information tests from the two non-parametric regressions. Panel A of shows the goodness-of-fit test results, while panel B presents the results from the Kolmogorov-Smirnov test for all yield spreads. Four chart patterns contain information using the Nadaraya-Watson, and seven using the local polynomial regression.[17] The Kolmogorov-Smirnov test, however rejects the presence of predictive information for every pattern with the exception of the HST. Thus while there is some evidence that chart patterns contain information about yield spreads, this is considerably weaker than for the case of yields *per se*.

VI Conclusions

We have examined the information content of technical chart patterns in government bond yields for seven countries. To the best of our knowledge, this is the first systematic evaluation of technical analysis applied to yields.

We find that chart patterns arise frequently in yields, that they have an influence on conditional distributions of returns, and, in some cases, they influence holding-period returns. Substantially fewer patterns arise in yield-spreads however, suggesting a fundamental difference in the behaviour of spreads as opposed to individual yields, and (as found by others) to stock prices and exchange rates. While conditional returns obtained from spread

[17] At 5%.

patterns do appear to embody some information about the distributions of returns, the evidence here is substantially weaker than for yield levels. That is, chart patterns appear to be able to pick up the influence of otherwise unobservable fundamental factors that move the yield curve as a whole, but are less able to account for the factors that influence its slope.

This may be due to the fact that bond portfolio managers undertake many more spread trades than outright sales or purchases, with the result that any predictability in spreads is exploited by intra-day trading, leaving little information in the pattern of end-of-day prices. Outright trades are both less frequent and more risky, with the result that some potentially profitable positions may be left unexploited, with the related information retrievable from end-of-day prices. One way to test this would be to perform the search and information tests on intra-day data. Further investigation of the usefulness of the information that could be provided by patterns is another possible avenue for future research: As in the case profit signals it may be that the information in patterns of yield levels has little value, while that in spreads is valuable and leads to trading that removes the patterns from end-of-day prices.

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Table 1: Government Benchmark-Bond Yield Data

Markets	Bond Yield Maturities (yr)	Yield Spread Pairs (Short,Long)	Obs. (Bond Yield)	Obs. (Yield Spread)
US	1, 2, 3, 5, 7, 10, 30	(1,5),(1,7),(1,10),(1,30),(2,5),(2,7),(2,10),(2,30)	69,245(7)	116,147(13)
		(3,7),(3,10),(5,10),(5,30),(10,30)		
UK	2, 5, 7, 10	(2,5),(2,7),(2,10),(5,10)	27,848 (4)	27,848 (4)
Germany	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	25,500 (5)	30,104 (6)
Japan	2, 3, 5, 10	(2,5),(2,10),(3,10),(5,10)	21,000 (4)	21,000 (4)
Australia	2, 3, 5, 10	(2,5),(2,10)(3,10),(5,10)	20,548 (4)	20,548 (4)
Canada	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	25,785 (5)	30,942 (6)
Hong Kong	2, 3, 5, 7, 10	(2,5),(2,7),(2,10),(3,7),(3,10),(5,10)	14,890 (5)	15,581 (6)
Total			204,816 (34)	262,170 (52)

This Table provides description of the sample data. The second column gives the yield maturities; the third gives the set of maturity pairings used in the spread trades, all of which are extensions i.e. we short bonds of the first maturity and buy bonds of the second. The final columns give the numbers of observations of yields and spreads respectively, with the numbers of yield maturities and spread pairs in parentheses.

Table 2: Pattern Counts for Yields (Nadaraya-Watson Kernel Regression)

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
All Yields													
Actual	16929	1841	634	736	3200	1180	645	1760	762	666	3552	1237	716
Vasicek	19962	2092	1063	976	3735	1350	751	2114	1066	933	3735	1458	689
$e_m > MA$	7846	1100	572	227	1993	1177	638	582	54	428	1071	0	4
$e_m < MA$	9083	741	62	509	1207	3	7	1178	708	238	2481	1237	712
US, All Maturities													
Actual	5520	599	187	221	1090	442	222	605	223	186	1125	389	231
Vasicek	5183	546	375	334	793	368	179	549	359	317	793	410	160
$e_m > MA$	2649	360	170	75	684	441	219	210	21	113	355	0	1
$e_m < MA$	2871	239	17	146	406	1	3	395	202	73	770	389	230
UK, All Maturities													
Actual	2909	328	84	113	603	162	88	302	101	107	703	186	132
Vasicek	3015	312	158	133	578	193	102	352	148	110	604	224	101
$e_m > MA$	1344	209	77	36	387	162	87	112	4	66	203	0	1
$e_m < MA$	1565	119	7	77	216	0	1	190	97	41	500	186	131
Germany, All Maturities													
Actual	2496	299	83	105	476	146	92	275	110	89	534	186	101
Vasicek	3616	389	149	122	805	241	149	365	138	134	767	235	122
$e_m > MA$	1119	189	66	29	279	146	92	87	9	62	160	0	0
$e_m < MA$	1377	110	17	76	197	0	0	188	101	27	374	186	101
Japan, All Maturities													
Actual	858	75	64	63	110	70	31	76	71	61	140	73	24
Vasicek	3226	326	98	108	707	179	126	358	112	90	758	207	157
$e_m > MA$	402	41	60	24	67	68	31	23	4	39	43	0	2
$e_m < MA$	456	34	4	39	43	2	0	53	67	22	97	73	22
Australia, All Maturities													
Actual	1863	201	70	42	319	145	95	178	101	60	419	146	87
Vasicek	2226	251	93	97	431	148	99	232	114	86	438	172	65
$e_m > MA$	892	129	67	11	214	145	93	60	4	43	126	0	0
$e_m < MA$	971	72	3	31	105	0	2	118	97	17	293	146	87
Canada, All Maturities													
Actual	2289	257	93	126	433	144	77	225	110	108	445	172	99
Vasicek	2128	233	115	112	372	182	85	217	126	121	332	164	69
$e_m > MA$	1004	131	83	31	267	144	76	65	8	71	128	0	0
$e_m < MA$	1285	126	10	95	166	0	1	160	102	37	317	172	99
Hong Kong, All Maturities													

continued

(*continued*)

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Actual	994	82	53	66	169	71	40	99	46	55	186	85	42
Vasicek	568	35	75	70	49	39	11	41	69	75	43	46	15
$e_m > MA$	436	41	49	21	95	71	40	25	4	34	56	0	0
$e_m < MA$	558	41	4	45	74	0	0	74	42	21	130	85	42
Short Maturities (1-, 2- and 3-year)													
Actual	6156	623	281	301	1136	444	227	639	326	284	1230	432	233
Vasicek	7415	722	423	415	1331	494	280	754	433	398	1334	553	278
$e_m > MA$	2850	363	251	94	689	443	221	215	27	181	364	0	2
$e_m < MA$	3306	260	30	207	447	1	6	424	299	103	866	432	231
Medium Maturities (5- and 7-year)													
Actual	6048	662	201	278	1175	403	219	637	245	229	1298	440	261
Vasicek	7043	772	382	333	1313	493	254	760	383	316	1288	518	231
$e_m > MA$	2785	410	179	84	740	403	219	208	15	148	377	0	2
$e_m < MA$	3263	252	22	194	435	0	0	429	230	81	921	440	259
Long Maturities (10- and 30-year)													
Actual	4725	556	152	157	889	333	199	484	191	153	1024	365	222
Vasicek	5504	598	258	228	1091	363	217	600	250	219	1113	387	180
$e_m > MA$	2211	327	142	49	564	331	198	159	12	99	330	0	0
$e_m < MA$	2514	229	10	108	325	2	1	325	179	54	694	365	222

This Table presents the pattern count from applying the Nadaraya-Watson. This Table presents the pattern count from applying the local polynomial regressions. The first row is the total number of each pattern in the sample (sample sizes are given in Table VI), and the second gives the results from the simulation of a Vasicek model. The third and fourth rows are counts for e_m above and below the 45-day moving average. See Table 3 for the equivalent local polynomial regressions results.

Table 3: Pattern Count for Yields (Local Polynomial Kernel Regression)

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
All Yields													
Actual	21334	2297	831	893	4016	1483	818	2215	998	834	4462	1585	902
Vasicek	25178	2645	1380	1127	4693	1724	968	2639	1385	1139	4668	1911	899
$e_m > MA$	9910	1368	750	287	2526	1479	810	734	75	537	1340	0	4
$e_m < MA$	11424	929	81	606	1490	4	8	1481	923	297	3122	1585	898
US, All Maturities													
Actual	7025	749	246	269	1379	540	283	757	306	235	1444	516	301
Vasicek	6462	666	476	385	989	461	239	669	468	402	959	542	206
$e_m > MA$	3356	459	221	92	882	539	279	261	27	140	454	0	2
$e_m < MA$	3669	290	25	177	497	1	4	496	279	95	990	516	299
UK, All Maturities													
Actual	3680	407	108	137	771	214	117	362	143	143	871	242	165
Vasicek	3784	401	200	160	725	240	133	429	195	131	739	294	137
$e_m > MA$	1700	256	99	45	489	214	116	129	6	92	254	0	0
$e_m < MA$	1980	151	9	92	282	0	1	233	137	51	617	242	165
Germany, All Maturities													
Actual	3075	373	117	125	597	184	129	314	137	103	653	224	119
Vasicek	4530	477	189	144	997	295	186	453	176	158	973	317	165
$e_m > MA$	1412	223	94	40	364	184	129	99	12	70	197	0	0
$e_m < MA$	1663	150	23	85	233	0	0	215	125	33	456	224	119
Japan, All Maturities													
Actual	1101	95	80	77	136	88	39	106	96	78	170	104	32
Vasicek	4105	421	123	115	894	231	161	459	142	107	974	277	201
$e_m > MA$	519	57	75	30	82	86	39	36	9	49	54	0	2
$e_m < MA$	582	38	5	47	54	2	0	70	87	29	116	104	30
Australia, All Maturities													
Actual	2387	256	104	58	416	182	112	236	128	74	525	184	112
Vasicek	2838	329	132	114	551	202	124	288	149	115	537	210	87
$e_m > MA$	1138	161	99	15	277	181	110	78	7	53	157	0	0
$e_m < MA$	1249	95	5	43	139	1	2	158	121	21	368	184	112
Canada, All Maturities													
Actual	2810	308	115	142	510	190	93	300	129	132	562	203	126
Vasicek	2728	303	160	129	478	238	109	285	158	138	432	213	85
$e_m > MA$	1248	160	104	37	320	190	92	91	9	88	157	0	0
$e_m < MA$	1562	148	11	105	190	0	1	209	120	44	405	203	126
Hong Kong, All Maturities													

continued

(*continued*)

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Actual	1256	109	61	85	207	85	45	140	59	69	237	112	47
Vasicek	731	48	100	80	59	57	16	56	97	88	54	58	18
$e_m > MA$	537	52	58	28	112	85	45	40	5	45	67	0	0
$e_m < MA$	719	57	3	57	95	0	0	100	54	24	170	112	47
Short Maturities (1-, 2- and 3-year)													
Actual	7745	769	371	365	1404	561	275	807	415	351	1572	547	308
Vasicek	9333	906	558	472	1656	647	355	970	557	484	1660	718	350
$e_m > MA$	3579	442	333	123	859	559	269	267	34	230	460	0	3
$e_m < MA$	4166	327	38	242	545	2	6	540	381	121	1112	547	305
Medium Maturities (5- and 7-year)													
Actual	7626	836	264	328	1461	505	282	805	331	292	1636	559	327
Vasicek	8989	980	503	383	1682	640	340	933	514	380	1621	696	317
$e_m > MA$	3516	511	236	99	923	505	282	267	27	187	478	0	1
$e_m < MA$	4110	325	28	229	538	0	0	538	304	105	1158	559	326
Long Maturities (10- and 30-year)													
Actual	5963	692	196	200	1151	417	261	603	252	191	1254	479	267
Vasicek	6856	759	319	272	1355	437	273	736	314	275	1387	497	232
$e_m > MA$	2815	415	181	65	744	415	259	200	14	120	402	0	0
$e_m < MA$	3148	277	15	135	407	2	2	403	238	71	852	479	267

This Table presents the pattern count from applying the local polynomial regressions. The first row is the total number of each pattern in the sample (sample sizes are given in Table VI), and the second gives the results from the simulation of a Vasicek model. The third and fourth rows are counts for e_m above and below the 45-day moving average. See Table and 2 for the equivalent Nadaraya-Watson results.

Table 4: Summary Statistics for Unconditional and Conditional Bond Returns
(Nadaraya-Watson Kernel Regression)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
All Bond Yields													
Mean	0.000	0.051*	-0.006	0.112*	0.068*	-0.037	-0.039	-0.059*	0.067*	-0.155*	-0.023*	0.005	-0.001
S.D.	1.00000	0.920	1.033	0.847	0.837	0.839	0.957	0.869	0.958	1.003	0.802	0.866	0.775
Skew.	-0.1375	-0.852	-0.922	-0.218	-0.448	-1.114	-2.198	0.142	0.668	-0.675	-0.172	0.728	-0.641
Kurtosis	17.4359	18.010	10.670	3.073	8.411	9.705	19.560	6.088	10.640	5.028	3.340	10.800	4.117
$e_m > MA$	0.0000	0.055*	-0.013	0.145*	0.044*	-0.038	-0.047	-0.095*	0.342*	-0.221*	-0.052*	-	0.618
$e_m < MA$	0.0000	0.044	0.050	0.097*	0.108*	0.447	0.739	-0.042	0.046	-0.037	-0.011	0.005	-0.004
US, All Maturities													
Mean	0.0000	0.093*	-0.011	0.117*	0.097*	-0.068*	-0.172*	-0.040	0.008	-0.221*	-0.021	-0.123*	-0.093
S.D.	1.0000	1.081	1.054	0.872	0.877	0.843	0.963	0.815	0.970	1.040	0.771	0.851	0.775
Skew.	0.2348	-1.712	0.608	0.158	-0.108	-2.525	-2.795	0.147	-0.651	-1.176	-0.274	-0.186	-1.575
Kurtosis	10.3536	26.690	8.066	3.008	10.640	20.500	21.260	2.464	4.540	5.101	4.406	6.607	8.994
$e_m > MA$	0.0000	0.0961	-0.006	0.117	0.075*	-0.069*	-0.177*	-0.037	0.419	-0.311*	-0.012	-	0.001
$e_m < MA$	0.0000	0.0879	-0.067	0.117	0.132*	0.130	0.167*	-0.042	-0.035	-0.084	-0.026	-0.123*	-0.094*
UK, All Maturities													
Mean	0.0000	0.092*	0.155	0.118	0.112*	0.154*	0.112	-0.087*	0.117	-0.183	-0.067*	0.060	0.034
S.D.	1.0000	0.817	1.080	0.984	0.894	0.864	0.706	0.762	0.841	1.193	0.807	0.823	0.795
Skew.	0.1680	-0.143	-4.025	0.163	-1.010	0.783	-0.156	-0.316	0.569	-1.882	-0.236	0.469	0.139
Kurtosis	7.4571	1.545	28.080	1.254	9.450	1.830	0.785	1.487	0.975	5.151	2.269	1.860	0.314
$e_m > MA$	0.0000	0.070	0.144	0.445*	0.088*	0.154*	0.110	-0.133*	-0.355*	-0.373*	-0.139*	-	-0.016
$e_m < MA$	0.0000	0.131*	0.286	-0.035	0.155*	-	0.276	-0.060	0.136	0.122	-0.038	0.060	0.035
Germany, All Maturities													
Mean	0.0000	-0.009	0.067	0.119*	0.004	-0.185*	-0.096	-0.152*	-0.008	-0.130	-0.020	0.063	-0.023
S.D.	1.0000	0.849	0.957	0.704	0.770	0.927	0.981	0.888	0.934	0.805	0.778	0.787	0.747
Skew.	-0.3819	-0.256	-0.988	0.008	-0.382	-0.667	0.085	-1.136	0.472	-0.606	-0.202	-0.083	-0.438
Kurtosis	19.7031	5.010	4.171	0.294	3.289	2.164	0.314	6.076	1.716	1.092	2.062	1.804	1.890
$e_m > MA$	0.0000	-0.035	0.094	0.294*	-0.037	-0.185*	-0.096	-0.245*	0.424	-0.202*	-0.050	-	-
$e_m < MA$	0.0000	0.036	-0.040	0.052	0.062	-	-	-0.109	-0.046	0.035	-0.008	0.063	-0.023
Japan, All Maturities													
Mean	0.0000	0.036	0.010	0.067	-0.018	-0.058	-0.261	0.092	0.074	-0.029	-0.077	0.009	0.242
S.D.	1.0000	0.827	1.017	0.790	0.711	0.726	1.852	1.063	0.752	0.912	0.619	0.681	0.816
Skew.	-0.5683	-0.109	-0.471	-0.732	-1.164	0.117	-3.261	4.736	0.094	1.311	-0.147	-0.546	-1.270
Kurtosis	10.1088	3.031	1.471	2.786	7.016	0.070	13.610	32.500	0.094	6.551	2.879	2.469	3.605
$e_m > MA$	0.0000	0.001	0.038	0.108	-0.021	-0.078	-0.261	-0.159	0.516*	0.086	-0.212*	-	1.244*

continued

(*continued*)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
$e_m < MA$	0.0000	0.079	-0.398	0.043	-0.013	0.606	-	0.200	0.047	-0.235	-0.018	0.009	0.151
Australia, All Maturities													
Mean	0.0000	-0.041	-0.087	0.149	0.048	0.009	0.136	0.045	0.076	-0.144	0.090*	0.070	0.136
S.D.	1.0000	0.860	0.836	1.085	0.843	0.900	0.943	1.020	1.007	0.986	0.936	0.776	0.901
Skew.	-0.3079	0.474	0.038	-0.382	-0.887	-0.862	0.076	0.179	-1.117	0.378	0.125	-0.472	0.042
Kurtosis	5.5083	5.104	0.338	1.875	6.016	3.381	3.522	1.062	4.642	2.559	3.084	2.391	1.453
$e_m > MA$	0.0000	-0.077	-0.104	0.386	-0.003	0.009	0.095	0.027	-0.012	-0.244	0.026	-	-
$e_m < MA$	0.0000	0.023	0.302	0.065	0.153*	-	2.011	0.054	0.079	0.108	0.117*	0.070	0.136
Canada, All Maturities													
Mean	0.0000	0.037	-0.061	0.015	0.053	-0.055	0.055	-0.154*	0.153*	-0.063	-0.076*	0.039	-0.028
S.D.	1.0000	0.883	1.220	0.747	0.805	0.760	0.758	0.978	0.869	0.876	0.884	1.007	0.723
Skew.	-0.2826	0.303	-1.686	-1.357	-0.192	-0.423	-0.108	-0.460	0.133	0.523	-0.168	0.059	-0.893
Kurtosis	6.9883	1.172	11.710	8.908	4.517	3.344	1.916	1.680	1.742	2.651	2.529	1.407	1.461
$e_m > MA$	0.0000	0.157*	-0.089	-0.127	0.063	-0.055	0.051	-0.224*	0.349	-0.115	-0.016	-	-
$e_m < MA$	0.0000	-0.089	0.166	0.061	0.036	-	0.373	-0.126	0.137	0.036	-0.099	0.039	-0.028
Hong Kong, All Maturities													
Mean	0.0000	0.075	-0.179	0.280	0.042	-0.008	0.078	0.074	0.195	-0.249	0.033	0.151	0.089
S.D.	1.0000	0.521	0.894	0.786*	0.664	0.612	0.547	0.651	1.474	1.127	0.564	1.095	0.506
Skew.	-0.9280	0.727	0.411	-0.999	-0.407	0.238	0.600	0.490	4.141	0.815	-1.261	5.542	0.690
Kurtosis	110.0890	1.262	3.232	1.926	3.879	1.299	2.978	3.384	22.040	3.832	5.863	41.360	0.753
$e_m > MA$	0.0000	0.183*	-0.233*	-0.157	-0.025	-0.008	0.078	0.215*	0.623*	-0.209	-0.127	-	-
$e_m < MA$	0.0000	-0.034	0.489	0.484*	0.129*	-	-	0.026	0.154	-0.314	0.103*	0.151	0.089
Short Maturities (1-, 2- and 3-year)													
Mean	0.0000	0.009	0.041	0.093*	0.052*	-0.003	0.067	-0.089*	0.065	-0.111*	-0.012	-0.027	-0.038
S.D.	1.0000	0.960	1.089	0.810	0.718	0.798	0.872	0.836	1.000	0.924	0.719	0.907	0.730
Skew.	-0.2170	-2.458	-0.508	-0.132	-0.101	-0.350	0.220	-0.183	1.499	-0.463	0.233	1.801	-1.380
Kurtosis	19.1048	39.800	10.640	5.538	6.144	5.373	2.636	5.334	18.770	5.323	2.588	23.380	12.460
$e_m > MA$	0.0000	0.029	0.036	0.052	0.024	-0.004	0.047	-0.104*	0.206	-0.152	-0.083	-	0.418
$e_m < MA$	0.0000	-0.019	0.082	0.111*	0.095*	0.130	0.816	-0.081*	0.052	-0.040	0.018	-0.027	-0.042
Medium Maturities (5- and 7-year)													
Mean	0.0000	0.101*	-0.047	0.100*	0.069*	-0.048	-0.077	-0.038	0.073	-0.181*	-0.031	0.017	0.055
S.D.	1.0000	0.851	0.954	0.919	0.888	0.883	1.127	0.915	0.889	1.005	0.829	0.815	0.746
Skew.	-0.0893	0.633	-2.573	-0.358	-1.094	-2.270	-3.969	0.639	-0.268	-0.524	-0.203	0.186	-0.288
Kurtosis	22.7280	3.747	17.680	2.204	12.540	18.180	27.880	9.303	4.142	3.670	4.213	1.297	1.436
$e_m > MA$	0.0000	0.119*	-0.052	0.090	0.064*	-0.048	-0.077	-0.116*	0.764*	-0.257*	-0.054	-	0.818
$e_m < MA$	0.0000	0.072	-0.006	0.104*	0.077*	-	-	-0.000	0.028	-0.041	-0.022	0.017	0.050

continued

(*continued*)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
						Long Maturities (10- and 30-year)							
Mean	0.0000	0.037	-0.040	0.171*	0.088*	-0.068	-0.117*	-0.049	0.064	-0.198*	-0.027	0.026	-0.029
S.D.	1.0000	0.950	1.029	0.783	0.907	0.839	0.830	0.848	0.977	1.136	0.859	0.876	0.849
Skew.	-0.0687	-0.221	-0.132	0.048	0.130	-0.327	-0.226	-0.290	0.051	-0.978	-0.407	-0.143	-0.412
Kurtosis	6.8821	2.342	3.065	-0.259	3.355	1.377	0.893	0.930	0.681	5.360	2.443	2.288	0.848
$e_m > MA$	0.0000	0.005	-0.049	0.419*	0.042	-0.072	-0.119*	-0.055	0.121	-0.293*	-0.015	-	-
$e_m < MA$	0.0000	0.083	0.080	0.059	0.167*	0.606	0.276	-0.047	0.061	-0.025	-0.032	0.026	-0.029

This Table presents summary statistics for full-sample and one-day-post-pattern, or conditional, returns for the Nadaraya-Watson regressions. An asterisk (*) beside the mean return signifies that the return is significantly different from zero using standard 5% t-tests. The normalization of returns described above reduces the mean and standard deviation of all unconditional returns to zero and one respectively. The returns are calculated as proportionate one-day price changes and normalized such that the full-sample series have zero mean and unit standard deviation. See Table 5 for equivalent results for the local polynomial regressions.

Table 5: Summary Statistics for Unconditional and Conditional Bond Return
(Local Polynomial Kernel Regression)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
						All Bond Yields							
Mean	0.0000	0.063*	0.017	0.110*	0.064*	-0.022	-0.023	-0.044*	0.045	-0.096*	-0.015	0.007	-0.004
S.D.	1.0000	0.919	1.043	0.823	0.847	0.859	0.949	0.861	0.959	0.965	0.811	0.848	0.779
Skew.	-0.1375	-1.016	-0.910	-0.019	-0.728	-0.907	-2.109	0.174	0.542	-0.222	-0.042	0.772	0.238
Kurtosis	17.4359	18.730	9.478	2.754	10.410	7.920	18.350	5.720	8.944	4.418	3.623	10.750	4.652
$e_m > MA$	0.0000	0.065*	0.018	0.129*	0.041*	-0.023	-0.029	-0.072*	0.261*	-0.166*	-0.042*	-	0.538
$e_m < MA$	0.0000	0.060*	0.003	0.101*	0.102*	0.330	0.665	-0.030	0.028	0.030	-0.004	0.007	-0.006
						US, All Maturities							
Mean	0.0000	0.099*	-0.015	0.112*	0.073*	-0.062*	-0.145*	-0.022	-0.011	-0.123*	-0.009	-0.109*	-0.069
S.D.	1.0000	1.097	1.024	0.836	0.897	0.813	0.992	0.810	0.958	0.922	0.788	0.854	0.799
Skew.	0.2348	-1.940	0.472	0.143	-1.031	-2.266	-2.898	0.199	-0.232	-0.520	0.067	0.435	1.000
Kurtosis	10.3536	26.010	7.112	3.132	16.170	19.510	19.580	2.891	4.515	2.041	4.915	9.464	10.620
$e_m > MA$	0.0000	0.093	-0.002	0.066	0.050	-0.062*	-0.149*	-0.003	0.492*	-0.239*	-0.006	-	-0.168
$e_m < MA$	0.0000	0.109*	-0.131	0.137*	0.112*	0.130	0.162*	-0.032	-0.060	0.049	-0.011	-0.109*	-0.068
						UK, All Maturities							
Mean	0.0000	0.082*	0.236*	0.076	0.097*	0.127*	0.097	-0.039	0.061	-0.177*	-0.094*	0.032	-0.056
S.D.	1.0000	0.815	1.069	0.919	0.868	0.912	0.700	0.780	0.929	1.127	0.801	0.768	0.805
Skew.	0.1680	-0.397	-3.076	0.190	-0.903	0.161	-0.112	-0.087	0.220	-1.585	-0.452	0.414	0.039
Kurtosis	7.4571	2.230	24.320	1.589	8.487	1.791	0.397	0.985	3.083	4.956	2.558	2.103	0.315
$e_m > MA$	0.0000	0.054	0.228*	0.377*	0.082*	0.127*	0.095	-0.134*	-0.478*	-0.323*	-0.127*	-	-
$e_m < MA$	0.0000	0.129*	0.325*	-0.071	0.123*	-	0.276	0.013	0.084	0.088	-0.081*	0.032	-0.056
						Germany, All Maturities							
Mean	0.0000	0.026	0.029	0.110	0.021	-0.158*	-0.058	-0.105*	-0.034	-0.132	0.014	0.050	0.046
S.D.	1.0000	0.845	1.099	0.738	0.766	0.904	0.937	0.891	0.955	0.826	0.805	0.768	0.766
Skew.	-0.3819	-0.170	-1.731	0.179	-0.193	-0.625	0.038	-0.907	0.288	-0.353	-0.112	-0.363	-0.305
Kurtosis	19.7031	4.220	8.987	1.398	3.667	1.912	0.332	5.702	1.202	1.000	2.195	0.884	1.670
$e_m > MA$	0.0000	0.021	0.073	0.129	-0.025	-0.158*	-0.058	-0.186*	0.345	-0.194*	-0.041	-	-
$e_m < MA$	0.0000	0.032	-0.149	0.102	0.094*	-	-	-0.067	-0.070	-0.001	0.038	0.050	0.046
						Japan, All Maturities							
Mean	0.0000	0.004	0.120	0.091	-0.001	-0.013	-0.279	0.081	0.017	0.036	-0.055	-0.006	0.161
S.D.	1.0000	0.770	1.051	0.728	0.694	0.756	1.653	0.941	0.800	0.872	0.612	0.740	0.750
Skew.	-0.5684	-0.044	-0.217	-0.584	-0.844	-0.399	-3.635	4.872	-0.469	1.067	-0.145	-0.742	-1.000
Kurtosis	10.1088	3.366	1.207	3.421	6.703	0.645	17.310	38.650	1.532	5.774	2.629	2.246	3.487
$e_m > MA$	0.0000	-0.023	0.127	0.098	0.038	-0.027	-0.279	-0.099	0.092	0.103	-0.186*	-	1.244*

continued

(*continued*)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
$e_m < MA$	0.0000	0.046	0.015	0.086	-0.059	0.606	-	0.173	0.010	-0.078	0.006	-0.006	0.088
Australia, All Maturities													
Mean	0.0000	-0.047	-0.067	0.241	0.091*	0.022	0.175*	-0.013	0.064	-0.043	0.106*	0.121*	0.144
S.D.	1.0000	0.801	0.939	1.120	0.900	1.055	0.972	1.028	0.959	1.102	0.945	0.812	0.870
Skew.	-0.3079	0.467	-0.482	0.086	-0.453	-0.501	0.221	0.451	-1.231	1.275	0.065	-0.113	-0.074
Kurtosis	5.5083	5.570	1.931	1.881	4.632	3.295	3.025	1.737	5.088	5.388	2.557	2.930	1.413
$e_m > MA$	0.0000	-0.100	-0.098	0.653	0.055	0.022	0.142	0.016	-0.249	-0.111	0.048	-	-
$e_m < MA$	0.0000	0.042	0.540	0.097	0.161*	-0.022	2.011	-0.027	0.082	0.129	0.131*	0.121*	0.144
Canada, All Maturities													
Mean	0.0000	0.098*	-0.040	0.027	0.044	0.006	0.087	-0.125*	0.192*	-0.046	-0.064*	0.086	-0.030
S.D.	1.0000	0.904	1.164	0.726	0.830	0.807	0.782	0.954	0.906	0.835	0.879	0.978	0.700
Skew.	-0.2826	0.515	-1.595	-0.638	-0.247	-0.320	0.273	-0.574	0.306	0.505	0.210	0.038	-0.590
Kurtosis	6.9883	1.941	11.530	3.501	3.878	3.087	2.365	2.304	1.409	2.792	3.517	1.439	1.512
$e_m > MA$	0.0000	0.227*	-0.049	-0.057	0.028	0.006	0.084	-0.192*	0.366	-0.078	-0.022	-	-
$e_m < MA$	0.0000	-0.043	0.044	0.057	0.070	-	0.373	-0.097	0.179*	0.016	-0.080*	0.086	-0.030
Hong Kong, All Maturities													
Mean	0.0000	0.087*	-0.155	0.224*	0.039	-0.007	0.040	-0.007	0.165	-0.089	0.030	0.080	0.073
S.D.	1.0000	0.509	0.837	0.738	0.645	0.571	0.457	0.648	1.325	1.114	0.564	0.979	0.485
Skew.	-0.9280	0.574	0.348	-0.861	-0.517	0.072	-0.196	0.113	4.464	0.732	-1.032	6.029	0.776
Kurtosis	110.0890	0.831	3.959	1.920	3.851	1.535	1.661	3.345	27.020	3.325	5.430	51.160	1.105
$e_m > MA$	0.0000	0.172*	-0.175	-0.059	0.005	-0.007	0.040	0.084	0.535*	-0.104	-0.110	-	-
$e_m < MA$	0.0000	0.009	0.245	0.363*	0.080	-	-	-0.044	0.131	-0.060	0.086*	0.080	0.073
Short Maturities (1-, 2- and 3-year)													
Mean	0.0000	0.001	0.037	0.064	0.036*	-0.006	0.051	-0.061*	0.059	-0.081	-0.007	-0.005	0.016
S.D.	1.0000	0.981	1.016	0.794	0.757	0.836	0.843	0.833	0.966	0.915	0.760	0.896	0.736
Skew.	-0.2170	-2.689	-0.478	-0.282	-1.339	-0.351	0.131	0.070	1.189	0.015	0.294	2.053	1.761
Kurtosis	19.1048	38.480	10.850	5.818	17.650	4.824	2.680	5.511	17.200	6.803	4.544	22.760	14.150
$e_m > MA$	0.0000	0.012	0.033	0.032	-0.004	-0.006	0.033	-0.082*	0.132	-0.128*	-0.089*	-	0.167
$e_m < MA$	0.0000	-0.014	0.072	0.081	0.099*	0.054	0.816	-0.051	0.052	0.010	0.028	-0.005	0.014
Medium Maturities (5- and 7-year)													
Mean	0.0000	0.128*	0.048*	0.121	0.075*	-0.010	-0.054	-0.009	0.050	-0.107*	-0.015	-0.024	0.007
S.D.	1.0000	0.841	1.047	0.868	0.883	0.886	1.130	0.908	0.918	0.995	0.825	0.798	0.755
Skew.	-0.0893	0.628	-2.042	0.051	-1.116	-1.795	-3.586	0.526	0.214	-0.401	-0.020	0.090	-0.277
Kurtosis	22.7280	3.511	14.140	0.892	12.230	14.800	24.500	8.138	4.561	3.145	3.902	1.426	1.239
$e_m > MA$	0.0000	0.143*	0.063	0.105	0.074*	-0.010	-0.054	-0.072	0.445*	-0.189*	-0.030	-	1.652
$e_m < MA$	0.0000	0.105*	-0.076	0.127*	0.075*	-	-	0.022	0.015	0.039	-0.009	-0.024	0.002
Long Maturities (10- and 30-year)													

continued

(*continued*)

Statistics	Unconditional Returns	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Mean	0.0000	0.054	-0.064	0.176*	0.083*	-0.058	-0.066	-0.067*	0.016	-0.109	-0.027	0.056	-0.041
S.D.	1.0000	0.935	1.090	0.799	0.902	0.858	0.831	0.833	1.003	1.010	0.853	0.846	0.854
Skew.	-0.0686	-0.244	-0.202	0.290	0.158	-0.415	-0.173	-0.328	-0.074	-0.270	-0.358	-0.311	-0.422
Kurtosis	6.88212	2.439	2.411	1.186	3.086	2.248	1.578	1.026	0.989	3.048	2.378	1.990	0.693
$e_m > MA$	0.0000	0.026	-0.067	0.349*	0.051	-0.061	-0.068	-0.059	0.223	-0.203*	-0.003	-	-
$e_m < MA$	0.0000	0.096*	-0.026	0.093	0.143*	0.606	0.211*	-0.071	0.004	0.050	-0.038	0.056	-0.041

This Table presents summary statistics for full-sample and one-day-post-pattern, or conditional, returns for the local polynomial regressions. An asterisk (*) beside the mean return signifies that the return is significantly different from zero using standard 5% t-tests. The normalization of returns described above reduces the mean and standard deviation of all unconditional returns to zero and one respectively. The returns are calculated as proportionate one-day price changes and normalized such that the full-sample series have zero mean and unit standard deviation. See Table 4 for equivalent results for the Nadaraya-Watson regressions.

4

Table 6: Goodness-of-Fit and Kolmogorov-Smirnov Tests (Nadaraya-Watson Kernel Regression) for yields

Panel A: Goodness-of-Fit Test

Chart Patterns	Deciles 1	2	3	4	5	6	7	8	9	10	Q-Statistic
HST	7.88	9.94	9.45	10.80	8.96	9.67	11.00	11.10	11.70	9.51	22.20
(p-value)	(-3.04)	(-0.09)	(-0.78)	(1.08)	(-1.48)	(-0.47)	(1.47)	(1.55)	(2.48)	(-0.71)	(0.008)
BT	9.62	8.83	12.00	11.50	7.89	9.15	9.94	10.10	10.60	10.40	8.52
(p-value)	(-0.32)	(-0.98)	(1.67)	(1.27)	(-1.77)	(-0.71)	(-0.05)	(0.08)	(0.48)	(0.34)	(0.482)
TT	6.93	8.29	9.24	10.50	8.70	11.10	8.56	13.50	11.50	11.70	26.00
(p-value)	(-2.78)	(-1.55)	(-0.69)	(0.42)	(-1.18)	(1.03)	(-1.30)	(3.12)	(1.40)	(1.52)	(0.002)
RT	6.50	8.28	10.10	11.70	9.38	11.80	10.90	11.30	11.30	8.84	86.50
(p-value)	(-6.60)	(-3.24)	(0.12)	(3.12)	(-1.18)	(3.36)	(1.71)	(2.53)	(2.36)	(-2.18)	(0.000)
DT	8.57	10.70	10.40	12.00	9.84	11.20	9.75	10.00	9.50	8.06	14.30
(p-value)	(-1.64)	(0.79)	(0.50)	(2.24)	(-0.18)	(1.37)	(-0.28)	(0.01)	(-0.57)	(-2.22)	(0.113)
TPT	9.61	10.40	9.15	9.92	11.00	12.60	8.99	10.20	9.61	8.53	7.73
(p-value)	(-0.33)	(0.33)	(-0.72)	(-0.07)	(0.85)	(2.17)	(-0.85)	(0.20)	(-0.33)	(-1.25)	(0.438)
HSB	10.10	11.20	10.60	10.40	10.30	10.70	10.80	9.49	8.69	7.78	17.60
(p-value)	(0.16)	(1.67)	(0.79)	(0.56)	(0.40)	(0.95)	(1.11)	(-0.72)	(-1.83)	(-3.10)	(0.041)
BB	9.20	9.20	9.59	10.20	9.33	8.67	10.40	11.40	11.00	10.90	5.85
(p-value)	(-0.74)	(-0.74)	(-0.37)	(0.23)	(-0.62)	(-1.22)	(0.35)	(1.32)	(0.95)	(0.83)	(0.255)
TB	13.80	11.70	11.10	9.01	11.00	9.16	6.16	10.10	11.00	7.06	30.40
(p-value)	(3.28)	(1.47)	(0.96)	(-0.85)	(0.83)	(-0.72)	(-3.31)	(0.05)	(0.83)	(-2.53)	(0.000)
RB	7.85	10.50	11.00	12.10	10.20	10.10	11.30	10.60	9.07	7.18	75.50
(p-value)	(-4.26)	(0.94)	(2.06)	(4.24)	(0.38)	(0.16)	(2.67)	(1.28)	(-1.86)	(-5.60)	(0.000)
DB	9.05	9.46	11.00	12.40	9.22	10.00	9.78	10.90	9.14	8.97	14.20
(p-value)	(-1.11)	(-0.63)	(1.17)	(2.87)	(-0.92)	(0.03)	(-0.26)	(1.07)	(-1.01)	(-1.20)	(0.116)
TPB	6.99	8.25	11.20	13.40	9.79	12.00	11.30	8.25	10.60	8.11	27.30
(p-value)	(-2.68)	(-1.56)	(1.06)	(3.05)	(-0.19)	(1.81)	(1.18)	(-1.56)	(0.56)	(-1.68)	(0.001)

Panel B: Kolmogorov-Smirnov Test

Statistics	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
All Bond Yields												
γ	1.206	0.319	1.292*	2.689*	0.821	0.535	1.544*	0.378	1.334*	1.866*	0.652	0.649
γ ($\nearrow$) MA	1.096	0.214	1.024	1.577*	0.839	0.661	2.248*	1.292*	1.809*	1.608*	-99.000	0.499
γ ($\searrow$) MA	1.144	0.381	0.860	2.222*	-99.000	1.185	0.597	0.292	0.427	1.484*	0.652	0.646
US, All Maturities												
γ	1.640*	0.358	0.609	2.150*	0.553	0.838	0.686	0.237	0.790	1.136	1.047	0.859
γ ($\nearrow$) MA	1.307*	0.357	0.923	1.576*	0.547	0.815	1.286*	0.921	1.204	1.383*	-99.000	-99.000
γ ($\searrow$) MA	0.960	0.401	0.572	1.117	-99.000	-99.000	0.371	0.444	0.475	1.112	1.047	0.850

continued

(*continued*)

UK, All Maturities											
γ	0.893	0.877	0.509	1.151	0.496	0.715	1.002	0.504	0.477	1.364*	0.280	0.402
γ ($\nearrow$) MA	0.569	0.792	0.582	0.623	0.496	0.704	1.400*	0.256	0.778	1.420*	-99.000	-99.000
γ ($\searrow$) MA	0.793	0.332	0.268	1.442*	-99.000	-99.000	0.452	0.542	0.379	0.689	0.280	0.395
Germany, All Maturities												
γ	0.944	0.477	0.789	1.075	1.102	0.654	1.317*	0.741	0.607	1.236*	0.242	0.474
γ ($\nearrow$) MA	0.920	0.562	0.327	0.944	1.102	0.654	1.017	0.516	0.973	0.282	-99.000	-99.000
γ ($\searrow$) MA	0.638	0.429	0.554	0.994	-99.000	-99.000	0.870	0.616	0.326	1.282*	0.242	0.474
Japan, All Maturities												
γ	0.172	0.735	0.232	0.581	0.377	0.610	0.305	0.200	0.528	1.173	0.325	0.530
γ ($\nearrow$) MA	0.153	0.470	0.339	0.858	0.418	0.610	0.787	0.281	0.230	1.224*	-99.000	-99.000
γ ($\searrow$) MA	0.264	0.751	0.160	0.323	-99.000	-99.000	0.380	0.328	1.097	0.515	0.325	0.467
Australia, All Maturities												
γ	0.463	0.821	0.611	1.283*	0.429	0.733	0.575	0.689	0.852	0.817	0.686	0.878
γ ($\nearrow$) MA	0.369	0.871	0.363	0.828	0.429	0.677	0.410	0.022	1.082	0.642	-99.000	-99.000
γ ($\searrow$) MA	0.265	-99.000	0.319	0.535	-99.000	-99.000	0.492	0.765	0.491	1.179	0.686	0.878
Canada, All Maturities												
γ	0.199	0.706	0.992	0.647	1.143	0.468	1.048	0.824	0.489	0.929	0.565	0.465
γ ($\nearrow$) MA	0.876	0.747	0.478	0.553	1.143	0.452	1.002	0.409	0.659	0.617	-99.000	-99.000
γ ($\searrow$) MA	0.686	0.290	0.766	0.740	-99.000	-99.000	0.762	0.898	0.626	0.681	0.565	0.465
Hong Kong, All Maturities												
γ	0.564	0.773	1.228*	0.307	0.450	0.508	0.470	0.494	1.386*	1.142	0.469	0.413
γ ($\nearrow$) MA	0.523	1.032	0.761	0.134	0.450	0.508	0.761	0.361	1.091	0.449	-99.000	-99.000
γ ($\searrow$) MA	0.571	0.447	2.025*	0.683	-99.000	-99.000	0.478	0.656	0.763	1.215	0.469	0.413
Short Maturities (1-, 2- and 3-year)												
γ	0.615	0.207	0.896	2.146*	0.651	0.537	1.052	0.339	0.758	1.152	0.750	0.830
γ ($\nearrow$) MA	0.391	0.258	0.136	1.201	0.643	0.407	1.274*	0.453	0.646	1.474*	-99.000	-99.000
γ ($\searrow$) MA	0.695	0.324	0.716	1.522*	-99.000	1.064	0.578	0.302	0.527	0.825	0.750	0.881
Medium Maturities (5- and 7-year)												
γ	1.150	0.348	0.756	1.643*	0.711	0.492	0.499	0.347	1.314*	1.135	0.343	1.051
γ ($\nearrow$) MA	0.868	0.410	0.569	1.301*	0.711	0.492	1.214	1.359*	1.341*	0.881	-99.000	-99.000
γ ($\searrow$) MA	0.852	0.211	0.446	1.232*	-99.000	-99.000	0.466	0.242	0.470	0.805	0.343	1.032
Long Maturities (10- and 30-year)												
γ	1.128	0.339	0.802	1.078	0.777	0.816	0.628	0.464	0.648	0.963	0.346	0.520
γ ($\nearrow$) MA	0.335	0.362	1.492*	0.613	0.797	0.797	0.909	0.402	0.919	0.395	-99.000	-99.000
γ ($\searrow$) MA	1.181	0.111	0.412	1.266*	-99.000	-99.000	0.436	0.411	0.408	0.866	0.346	0.520

This Table presents information-test results.(-99.00 indicates that fewer than three patterns were detected.) The goodness-of-fit null hypothesis is that each decile should contain 10% of the post-pattern observations and significant deviations from this indicate the presence of information in the chart patterns. The final column is the Q-statistic, and the numbers in parenthesis are the asymptotic z-values for each decile, and the p-value for the Q-statistics respectively.

Table 7: Goodness-of-Fit and Kolmogorov-Smirnov Tests (Local Polynomial Kernel Regression)

Panel A: Goodness-of-Fit Test

	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HST	7.49	9.71	9.53	10.40	9.32	9.75	10.70	11.00	12.50	9.58	34.90
(p-value)	(-4.01)	(-0.47)	(-0.74)	(0.72)	(-1.09)	(-0.40)	(1.13)	(1.55)	(3.99)	(-0.67)	(0.000)
BT	9.99	8.42	11.00	11.10	8.30	9.75	10.10	9.39	10.30	11.70	8.96
(p-value)	(-0.01)	(-1.51)	(0.91)	(1.03)	(-1.63)	(-0.24)	(0.10)	(-0.59)	(0.34)	(1.61)	(0.441)
TT	6.72	8.40	8.85	10.50	9.41	11.80	8.73	12.90	12.00	10.80	29.30
(p-value)	(-3.27)	(-1.60)	(-1.15)	(0.52)	(-0.59)	(1.75)	(-1.26)	(2.87)	(1.97)	(0.75)	(0.001)
RT	6.65	8.22	10.00	11.10	9.56	11.90	11.30	11.30	11.10	8.76	104.00
(p-value)	-7.08)	(-3.77)	(0.02)	(2.39)	(-0.93)	(4.07)	(2.76)	(2.76)	(2.39)	(-2.61)	(0.000)
DT	8.70	10.60	10.60	10.60	9.24	10.90	9.78	11.20	10.20	8.16	13.50
(p-value)	(-1.67)	(0.75)	(0.75)	(0.75)	(-0.98)	(1.19)	(-0.29)	(1.53)	(0.32)	(-2.36)	(0.142)
TPT	9.17	9.41	9.90	9.78	10.80	11.90	10.10	10.30	9.78	8.92	5.25
(p-value)	(-0.79)	(-0.56)	(-0.09)	(-0.21)	(0.72)	(1.77)	(0.14)	(0.26)	(-0.21)	(-1.03)	(0.188)
HSB	9.98	10.90	9.89	11.10	9.62	11.40	10.60	9.62	9.16	7.77	22.70
(p-value)	(-0.04)	(1.38)	(-0.18)	(1.74)	(-0.60)	(2.16)	(0.96)	(-0.60)	(-1.31)	(-3.51)	(0.007)
BB	9.52	8.92	9.52	11.40	9.12	8.62	9.82	11.80	11.00	10.20	10.80
(p-value)	(-0.51)	(-1.14)	(-0.51)	(1.50)	(-0.93)	(-1.46)	(-0.19)	(1.92)	(1.08)	(0.23)	(0.291)
TB	12.40	11.80	11.00	9.59	9.47	9.71	6.71	10.20	11.50	7.67	23.9
(p-value)	(2.26)	(1.69)	(0.99)	(-0.39)	(-0.51)	(-0.28)	(-3.16)	(0.18)	(1.45)	(-2.24)	(0.004)
RB	7.87	10.20	10.80	12.10	10.20	10.40	11.30	10.80	8.92	7.33	92.40
(p-value)	(-4.75)	(0.39)	(1.89)	(4.73)	(0.44)	(0.99)	(2.93)	(1.74)	(-2.41)	(-5.95)	(0.000)
DB	8.64	9.53	10.90	12.30	8.96	10.20	10.90	10.50	9.65	8.39	20.80
(p-value)	(-1.80)	(-0.63)	(1.21)	(3.06)	(-1.38)	(0.29)	(1.21)	(0.63)	(-0.46)	(-2.14)	(0.014)
TPB	7.87	8.65	11.00	12.10	9.65	12.00	12.00	9.31	9.76	7.76	22.70
(p-value)	(-2.13)	(-1.35)	(0.98)	(2.09)	(-0.36)	(1.98)	(1.98)	(-0.69)	(-0.24)	(-2.24)	(0.007)

Panel B: Kolmogorov-Smirnov Test

Statistics	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
All Bond Yields												
γ	1.645*	0.669	1.633*	2.345*	0.764	0.371	1.53*1	0.345	1.562*	2.192*	0.739	0.824
γ ($\nearrow$) MA	1.384*	0.647	1.049	1.457*	0.776	0.339	1.345*	1.388*	1.699*	1.766*	-99.000	0.262
γ ($\searrow$) MA	1.522*	0.499	1.066	2.403*	0.442	1.315*	0.528	0.266	0.946	1.723*	0.739	0.847
US, All Maturities												
γ	1.928*	0.157	0.814	1.237*	0.728	0.660	0.737	0.262	0.738	1.425*	1.169	0.799
γ ($\nearrow$) MA	1.500*	0.162	0.295	0.815	0.727	0.630	1.013	1.179	0.844	1.499*	-99.000	-99.000
γ ($\searrow$) MA	1.209	0.679	0.682	1.247*	-99.000	0.751	0.357	0.484	0.708	1.239*	1.169	0.791

continued

(*continued*)

	UK, All Maturities											
γ	1.454*	1.197	0.219	1.238*	0.872	0.630	0.869	0.257	0.781	1.751*	0.464	0.468
γ ($\nearrow$) MA	0.816	1.099	0.732	0.760	0.872	0.620	1.375*	0.139	1.083	1.554*	-99.000	-99.000
γ ($\searrow$) MA	1.308*	0.445	0.451	1.055	-99.000	-99.000	0.428	0.461	0.340	1.064	0.464	0.468
	Germany, All Maturities											
γ	0.601	0.518	0.773	1.262*	0.982	0.510	1.296*	0.416	0.904	1.057	0.329	0.526
γ ($\nearrow$) MA	0.631	0.529	0.410	1.270*	0.982	0.510	0.693	0.652	1.134	0.428	-99.000	-99.000
γ ($\searrow$) MA	0.498	0.797	0.737	1.146	-99.000	-99.000	0.973	0.415	0.333	1.024	0.329	0.526
	Japan, All Maturities											
γ	0.307	0.772	0.463	0.732	0.433	0.555	0.585	0.235	0.324	1.247*	0.401	0.384
γ ($\nearrow$) MA	0.289	0.797	0.561	0.615	0.481	0.555	0.741	0.365	0.160	1.377*	-99.000	-99.000
γ ($\searrow$) MA	0.405	0.628	0.388	0.565	-99.000	-99.000	0.781	0.222	0.664	0.764	0.401	0.322
	Australia, All Maturities											
γ	0.767	0.488	0.595	1.400*	0.383	0.712	0.866	0.718	0.769	1.233*	1.162	1.098
γ ($\nearrow$) MA	0.761	0.602	0.706	0.961	0.361	0.662	0.743	0.484	0.995	0.140	-99.000	-99.000
γ ($\searrow$) MA	0.509	0.342	0.335	0.694	-99.000	-99.000	0.436	0.721	0.597	1.521*	1.162	1.098
	Canada, All Maturities											
γ	0.427	0.483	0.665	0.616	0.756	0.558	1.391*	0.916	0.555	1.175	0.632	0.567
γ ($\nearrow$) MA	1.201	0.452	0.490	0.672	0.756	0.544	0.768	0.338	0.622	0.618	-99.000	-99.000
γ ($\searrow$) MA	0.558	0.126	0.652	0.562	-99.000	-99.000	0.771	0.970	0.653	0.893	0.632	0.567
	Hong Kong, All Maturities											
γ	0.739	0.833	1.214	0.518	0.509	0.645	0.525	0.321	0.960	1.337*	0.541	0.454
γ ($\nearrow$) MA	0.719	0.978	0.597	0.190	0.509	0.645	0.331	0.483	0.689	0.522	-99.000	-99.000
γ ($\searrow$) MA	0.620	-99.000	1.440*	0.621	-99.000	-99.000	0.504	0.488	0.445	0.867	0.541	0.454
	Short Maturities (1-, 2- and 3-year)											
γ	0.681	0.249	0.872	1.640*	0.497	0.613	0.942	0.668	0.477	1.236*	0.822	0.560
γ ($\nearrow$) MA	0.372	0.245	0.426	1.014	0.482	0.496	1.287*	0.637	0.533	1.393*	-99.000	-99.000
γ ($\searrow$) MA	0.685	0.709	0.743	1.614*	-99.000	1.064	0.469	0.668	0.524	0.855	0.822	0.543
	Medium Maturities (5- and 7-year)											
γ	1.484*	0.896	1.007	2.028*	0.582	0.462	0.453	0.277	1.218	1.402*	0.831	0.785
γ ($\nearrow$) MA	1.270*	1.053	0.838	1.608*	0.582	0.462	0.605	1.031	1.242*	0.935	-99.000	-99.000
γ ($\searrow$) MA	1.129	0.302	0.551	1.321*	-99.000	-99.000	0.426	0.335	0.488	1.077	0.831	0.776
	Long Maturities (10- and 30-year)											
γ	1.359*	0.458	0.937	1.188	0.721	0.695	1.101	0.372	1.254*	1.167	0.883	0.571
γ ($\nearrow$) MA	0.273	0.398	1.338*	0.734	0.714	0.673	0.948	0.758	1.470*	0.482	-99.000	-99.000
γ ($\searrow$) MA	1.408*	0.478	0.385	1.205	-99.000	-99.000	0.871	0.349	0.747	1.125	0.883	0.571

This Table presents information-test results.(-99.00 indicates that fewer than three patterns were detected.) The goodness-of-fit null hypothesis is that each decile should contain 10% of the post-pattern observations and significant deviations from this indicate the presence of information in the chart patterns. The final column is the Q-statistic, and the numbers in parenthesis are the asymptotic z-values for each decile, and the p-value for the Q-statistics respectively.

Table 8: Technical Pattern Count for Yield Spreads

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Panel A: Nadaraya-Watson Kernel Regression													
All Yield Spreads													
Actual	7209	409	983	1031	387	614	144	394	1124	1071	403	508	141
Vasicek	7223	318	1357	1177	217	506	77	273	1362	1183	222	449	82
US, All Spreads													
Actual	3141	211	397	425	196	259	61	206	497	412	186	230	61
Vasicek	3103	117	600	522	66	220	32	104	607	522	79	203	31
UK, All Spreads													
Actual	445	13	85	90	7	32	8	7	85	85	10	19	4
Vasicek	597	8	123	133	5	27	1	8	136	142	3	10	1
Germany, All Spreads													
Actual	1124	75	134	155	72	88	21	81	144	168	91	76	19
Vasicek	1162	83	173	135	70	101	20	74	174	127	84	97	24
Japan, All Spreads													
Actual	695	42	68	74	52	76	21	50	76	80	57	75	24
Vasicek	853	80	123	94	64	59	16	62	114	92	49	81	19
Australia, All Spreads													
Actual	393	5	71	56	11	46	8	4	77	85	0	23	7
Vasicek	474	11	111	104	3	25	1	7	98	94	1	17	2
Canada, All Spreads													
Actual	1019	45	170	178	32	75	15	31	187	176	43	50	17
Vasicek	680	10	161	127	4	47	3	14	149	141	2	19	3
Hong Kong, All Spreads													
Actual	392	18	58	53	17	38	10	15	58	65	16	35	9
Vasicek	354	9	66	62	5	27	4	4	84	65	4	22	2
Panel B: Local Polynomial Regression													
All Spreads													
Actual	9136	511	1315	1254	488	813	194	481	1430	1283	518	674	175
Vasicek	9022	403	1744	1405	291	628	109	359	1685	1437	292	563	106
US, All Spreads													
Actual	3992	264	521	536	243	346	84	252	624	503	244	297	78
Vasicek	3870	158	756	629	96	267	43	135	758	641	102	244	41
UK, All Spreads													
Actual	571	17	111	113	9	39	8	7	115	107	15	25	5
Vasicek	744	8	164	156	5	35	2	10	178	164	5	15	2
Germany, All Spreads													
Actual	1401	89	179	182	94	119	30	90	182	197	114	102	23

continued

(*continued*)

Sample	Total	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Vasicek	1444	106	211	160	94	122	28	100	206	157	105	124	31
Japan, All Spreads													
Actual	873	54	87	96	61	94	26	65	90	100	71	99	30
Vasicek	1077	96	166	108	81	83	23	81	132	113	66	105	23
Australia, All Spreads													
Actual	525	10	112	64	16	62	12	5	100	92	4	39	9
Vasicek	598	12	145	126	3	31	1	9	125	117	2	24	3
Canada, All Spreads													
Actual	1266	54	228	200	43	96	20	41	245	206	49	65	19
Vasicek	844	13	203	149	7	55	6	18	187	170	5	27	4
Hong Kong, All Spreads													
Actual	508	23	77	63	22	57	14	21	74	78	21	47	11
Vasicek	445	10	99	77	5	35	6	6	99	75	7	24	2

This Table presents the pattern count from applying the Nadaraya-Watson and local polynomial regressions. The first row is the total number of each pattern in the sample (sample sizes are given in Table VI), and the second gives the results from the simulation of a Vasicek model.

Table 9: Summary Statistics for Conditional Spread Returns

Statistics	Unconditional Return	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Panel A: Nadaraya-Watson Kernel Regression													
All Spreads, All Spreads													
Mean	0.0000	0.060	-0.004	0.023	0.024	0.038	0.018	0.032	-0.016	0.014	0.008	0.007	0.022
S.D.	1.0000	0.742	0.944	0.897	0.763	0.888	0.718	0.669	0.947	0.908	0.588	0.718	0.723
Skew.	0.1200	0.222	-1.449	-0.364	-1.140	-1.761	-0.008	0.108	-0.724	0.365	0.072	0.732	2.143
Kurtosis	38.7293	8.523	11.020	11.350	8.396	21.830	0.739	3.862	12.410	6.965	1.309	5.953	12.670
US, All Spreads													
Mean	0.0000	0.053	-0.012	0.041	0.066	0.011	0.111	0.068*	-0.077	0.071	0.030	0.005	0.027
S.D.	1.0000	0.752	1.016	0.914	0.879	0.883	0.819	0.739	1.004	0.858	0.619	0.738	0.598
Skew.	0.1030	0.014	-1.096	0.616	-1.075	-1.222	0.124	-0.186	-1.757	0.099	-0.261	1.335	0.254
Kurtosis	11.5246	3.371	5.683	7.407	7.168	9.387	-0.010	3.075	15.180	5.779	0.500	6.849	0.088
UK, All Spreads													
Mean	0.0000	0.563	0.204*	-0.071	0.024	0.050	-0.042	-0.497	-0.062	0.060	-0.152	0.080	0.092
S.D.	1.0000	1.412	0.719	1.304	0.831	0.624	0.701	0.847	0.905	1.196	0.449	0.766	0.671
Skew.	2.2468	2.664	0.586	-2.227	0.298	0.849	0.913	-1.880	-1.678	0.049	-0.367	-0.316	0.458
Kurtosis	68.6957	5.940	2.387	16.250	-0.890	0.595	0.068	1.801	7.610	7.016	-0.404	-0.424	-0.953
Germany, All Spreads													
Mean	0.0000	-0.078	-0.163	0.094	-0.136	0.174*	0.060	0.046	0.012	-0.068	-0.020	-0.082	-0.019
S.D.	1.0000	0.722	1.144	0.723	0.728	0.802	0.697	0.536	0.988	0.905	0.532	0.691	0.870
Skew.	-0.6763	-2.339	-2.663	1.280	-2.256	1.167	-0.957	1.160	-0.367	1.167	-0.196	-1.090	0.417
Kurtosis	68.7458	9.662	19.800	4.330	9.028	2.064	1.742	4.025	5.551	15.200	1.467	3.092	-0.140
Japan, All Spreads													
Mean	0.0000	0.156	-0.065	-0.088	0.011	0.041	-0.168	0.003	0.176	0.106	-0.061	-0.069	-0.014
S.D.	1.0000	0.641	0.842	0.750	0.466	0.738	0.757	0.592	0.969	1.103	0.676	0.722	0.560
Skew.	-0.0591	0.897	-2.468	-0.473	-0.351	-0.123	-0.548	1.366	0.598	0.991	1.099	-0.474	-0.277
Kurtosis	26.8662	2.367	12.430	-0.133	0.917	0.615	0.560	5.268	2.252	1.599	3.291	4.085	-0.091
Australia, All Spreads													
Mean	0.0000	-0.374	0.028	-0.034	0.178	0.288*	-0.136	-0.283	0.007	-0.000	-	0.316	0.445
S.D.	1.0000	1.305	0.725	0.693	0.974	0.984	0.449	0.587	0.631	0.846	-	0.893	2.030
Skew.	-0.3493	-0.968	-0.580	-0.153	0.423	2.119	0.288	0.108	-0.218	0.661	-	2.284	1.661
Kurtosis	13.8816	-0.468	7.309	1.535	-0.140	7.320	-1.104	-1.597	2.500	2.045	-	6.907	1.315
Canada, All Spreads													
Mean	0.0000	0.133*	0.047	0.109	0.184*	-0.153	-0.062	-0.057	0.062	-0.027	0.061	0.055	-0.051
S.D.	1.0000	0.432	0.892	0.897	0.411	1.261	0.448	0.638	0.975	0.848	0.517	0.547	0.269
Skew.	-0.1623	-0.902	-0.445	-0.319	-0.068	-4.450	-0.802	0.894	1.852	0.082	0.519	-0.003	-0.381
Kurtosis	24.6661	0.968	4.671	3.520	-0.200	30.110	0.327	5.621	10.270	3.407	-0.007	1.867	0.394

continued

(*continued*)

Statistics	Unconditional Return	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
					Hong Kong, All Spreads								
Mean	0.0000	0.066	-0.015	-0.248*	-0.143	-0.040	0.048	0.079	-0.025	-0.183*	0.100	0.066	-0.056
S.D.	1.0000	0.540	0.633	0.686	0.390	0.342	0.579	0.484	0.538	0.728	0.448	0.686	0.511
Skew.	-0.5951	-0.658	-1.187	-2.458	-0.023	0.430	0.656	-0.002	-0.543	-2.225	-0.533	1.580	-0.856
Kurtosis	206.748	0.591	4.480	10.280	-1.005	0.692	-0.137	-0.067	3.023	6.529	0.366	4.262	-0.573
					Panel B: Local Polynomial Regression								
					Long Spread, All Spreads								
Mean	0.0000	0.059*	-0.001	0.002	0.032	0.038	0.070	0.032	-0.045	0.025	0.016	0.024	0.021
S.D.	1.0000	0.732	0.938	0.879	0.755	0.799	0.756	0.670	0.976	0.954	0.643	0.759	0.684
Skew.	0.1200	0.065	-1.200	-0.504	-0.923	0.141	0.432	0.015	-1.210	0.445	-0.333	0.644	2.065
Kurtosis	38.7293	7.513	10.260	11.460	7.564	8.156	2.110	3.811	13.000	8.380	2.622	5.628	12.860
					US, All Spreads								
Mean	0.0000	0.055	-0.056	0.041	0.085	-0.007	0.219*	0.053	-0.118*	0.064	0.060	0.022	-0.016
S.D.	1.0000	0.758	1.014	0.899	0.874	0.871	0.865	0.741	1.028	1.033	0.659	0.748	0.591
Skew.	0.1030	-0.101	-1.223	0.482	-0.871	-0.709	0.532	-0.160	-1.929	0.505	-0.049	1.021	0.414
Kurtosis	11.5246	2.802	5.780	6.953	6.499	8.696	1.045	2.883	14.000	8.488	0.633	5.123	0.020
					UK, All Spreads								
Mean	0.0000	0.378	0.125*	-0.071	-0.301	-0.017	-0.042	-0.497	-0.051	0.004	-0.067	0.200	-0.005
S.D.	1.0000	1.284	0.709	1.280	1.000	0.625	0.701	0.847	0.871	1.162	0.632	0.955	0.620
Skew.	2.2468	2.994	0.799	-2.494	0.063	0.619	0.913	-1.880	-1.079	0.005	0.031	0.557	0.817
Kurtosis	68.7458	8.377	2.444	16.190	-0.648	0.819	0.068	1.801	7.257	6.395	-0.339	0.245	-0.523
					Germany, All Spreads								
Mean	0.0000	-0.080	-0.050	0.051	-0.085	0.060	-0.073	0.042	-0.031	-0.034	0.052	-0.015	0.012
S.D.	1.0000	0.722	1.087	0.711	0.723	0.764	0.664	0.538	1.083	0.891	0.507	0.653	0.803
Skew.	-0.6763	-2.122	-2.397	1.229	-1.799	1.207	-0.601	1.201	-2.001	0.820	-0.193	-1.170	0.344
Kurtosis	68.7458	8.703	19.200	4.231	7.646	2.429	0.975	3.687	14.770	14.060	1.596	3.595	0.159
					Japan, All Spreads								
Mean	0.0000	0.152*	0.030	-0.073	0.026	0.098	-0.008	-0.009	0.176*	0.178*	-0.187*	-0.144	0.046
S.D.	1.0000	0.591	0.960	0.721	0.453	0.677	0.723	0.664	0.953	1.036	0.801	0.800	0.544
Skew.	-0.0591	0.918	-1.608	-0.455	-0.468	0.413	1.135	0.001	0.333	0.865	-0.281	-0.747	-0.392
Kurtosis	26.8662	2.833	7.614	-0.111	0.572	1.089	2.182	5.256	2.307	1.630	3.845	2.924	-0.040
					Australia, All Spreads								
Mean	0.0000	-0.054	0.080	-0.084	0.054	0.275*	-0.079	-0.273	-0.060	0.005	-0.750	0.226	0.331
S.D.	1.0000	0.989	0.686	0.661	0.847	0.895	0.387	0.494	0.856	0.900	1.380	1.057	1.786
Skew.	-0.3493	-1.661	-0.146	-0.483	0.785	1.985	-0.048	-0.087	-1.257	0.555	-1.142	1.111	1.978
Kurtosis	13.8816	1.924	6.573	0.504	0.645	8.482	-0.894	-1.327	5.924	1.591	-0.677	4.952	2.724
					Canada, All Spreads								

continued

(*continued*)

Statistics	Unconditional Return	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
Mean	0.0000	0.113*	0.053	0.042	0.148*	-0.008	-0.105	0.008	0.039	-0.015	0.079	0.118	-0.044
S.D.	1.0000	0.480	0.920	0.854	0.395	0.833	0.713	0.551	0.955	0.724	0.551	0.710	0.294
Skew.	-0.1624	-1.336	0.383	-0.312	-0.023	0.930	-1.966	1.724	1.491	-0.188	0.429	2.393	-0.342
Kurtosis	24.6661	2.610	7.237	3.744	-0.222	7.325	4.392	5.289	9.192	5.499	-0.412	12.050	-0.352
Hong Kong, All Spreads													
Mean	0.0000	0.112	-0.016	-0.271*	-0.143	0.024	0.070	0.155	0.016	-0.113	0.067	0.074	0.111
S.D.	1.0000	0.521	0.589	0.703	0.349	0.423	0.563	0.426	0.520	0.699	0.358	0.541	0.426
Skew.	-0.5951	-0.700	-1.053	-2.152	-0.028	0.476	0.470	-0.437	-0.349	-2.221	-1.101	0.900	-1.243
Kurtosis	206.748	0.600	4.592	7.748	-0.638	0.128	-0.557	0.576	3.307	7.270	1.148	1.826	1.783

The returns are calculated as proportionate one-day price changes and normalized such that the full-sample series have zero mean and unit standard deviation.

Table 10: Information Tests for Bond Yield Spreads (Nadaraya-Watson Kernel Regression)

Panel A: Goodness-of-Fit Test (Long Spread)

	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HST	5.38	9.05	9.29	8.07	10.80	12.50	12.70	13.90	11.20	7.09	27.00
p-value	(-3.12)	(-0.64)	(-0.48)	(-1.30)	(0.51)	(1.66)	(1.83)	(2.65)	(0.84)	(-1.96)	(0.001)
BT	9.36	11.00	9.05	7.73	9.77	9.56	11.00	11.00	12.10	9.46	14.10
p-value	(-0.67)	(1.03)	(-0.99)	(-2.37)	(-0.24)	(-0.46)	(1.03)	(1.03)	(2.20)	(-0.56)	(0.119)
TT	7.95	11.50	10.30	9.21	9.21	10.90	10.30	10.60	11.10	9.02	11.50
p-value	(-2.19)	(1.65)	(0.30)	(-0.84)	(-0.84)	(0.92)	(0.30)	(0.61)	(1.13)	(-1.05)	(0.246)
RT	7.49	7.49	9.30	9.04	13.20	12.90	10.60	10.60	10.90	8.53	14.01
p-value	(-1.64)	(-1.64)	(-0.46)	(-0.63)	(2.08)	(1.91)	(0.39)	(0.39)	(0.56)	(-0.97)	(0.122)
DT	7.82	9.45	9.77	9.61	13.80	10.10	8.96	10.60	10.10	9.77	13.20
p-value	(-1.80)	(-0.46)	(-0.19)	(-0.32)	(3.17)	(0.08)	(-0.86)	(0.48)	(0.08)	(-0.19)	(0.152)
TPT	8.33	12.50	5.56	10.40	14.60	9.03	10.40	9.72	7.64	11.80	8.64
p-value	(-0.67)	(1.00)	(-1.78)	(0.17)	(1.83)	(-0.39)	(0.17)	(-0.11)	(-0.94)	(0.72)	(0.471)
HSB	4.82	10.20	11.90	10.20	13.20	11.20	9.90	11.40	10.40	6.85	21.40
p-value	(-3.43)	(0.10)	(1.28)	(0.10)	(2.12)	(0.77)	(-0.07)	(0.94)	(0.27)	(-2.08)	(0.011)
BB	10.10	10.60	10.10	10.20	9.25	9.70	9.25	11.90	8.81	10.10	7.58
p-value	(0.16)	(0.66)	(0.06)	(0.26)	(-0.84)	(-0.34)	(-0.84)	(2.15)	(-1.33)	(0.06)	(0.423)
TB	9.43	11.70	9.24	7.84	10.60	10.60	9.80	11.00	10.20	9.62	11.00
p-value	(-0.62)	(1.82)	(-0.83)	(-2.35)	(0.60)	(0.70)	(-0.21)	(1.11)	(0.19)	(-0.42)	(0.273)
RB	5.96	9.93	11.70	7.94	12.20	12.20	11.40	15.60	7.20	5.96	36.50
p-value	(-2.71)	(-0.05)	(1.11)	(-1.38)	(1.44)	(1.44)	(0.95)	(3.77)	(-1.88)	(-2.71)	(0.000)
DB	7.09	11.80	11.00	9.65	11.20	9.65	11.00	8.86	13.60	6.10	22.80
p-value	(-2.19)	(1.36)	(0.77)	(-0.27)	(0.92)	(-0.27)	(0.77)	(-0.86)	(2.69)	(-2.93)	(0.007)
TPB	6.38	12.10	9.22	7.80	15.60	15.60	7.80	7.80	10.60	7.09	14.70
p-value	(-1.43)	(0.81)	(-0.31)	(-0.87)	(2.22)	(2.22)	(-0.87)	(-0.87)	(0.25)	(-1.15)	(0.100)

Panel B: Kolmogorov-Smirnov Test

Statistics	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
γ	1.118	0.280	0.484	0.943	0.526	0.268	1.057	0.282	0.698	0.985	0.761	0.422
p-value	(0.164)	(1.000)	(0.974)	(0.336)	(0.945)	(1.000)	(0.214)	(1.000)	(0.715)	(0.286)	(0.609)	(0.994)

This Table presents information-test results.(-99.00 indicates that fewer than three patterns were detected.) The goodness-of-fit null hypothesis is that each decile should contain 10% of the post-pattern observations and significant deviations from this indicate the presence of information in the chart patterns. The final column is the Q-statistic, and the numbers in parenthesis are the asymptotic z-values for each decile, and the p-value for the Q-statistics respectively.

Table 11: Information Tests for Spreads (Local Polynomial Kernel Regression)

Panel A: Goodness-of-Fit Test (Long Spread Strategy)

	Deciles										
Patterns	1	2	3	4	5	6	7	8	9	10	Q-Statistic
HST	5.87	8.61	9.59	7.83	10.80	11.70	11.90	14.50	11.90	7.24	32.00
p-value	(-3.11)	(-1.05)	(-0.31)	(-1.64)	(0.58)	(1.31)	(1.46)	(3.38)	(1.46)	(-2.08)	(0.000)
BT	8.75	10.90	10.30	7.91	9.28	9.58	11.60	10.60	11.40	9.66	16.70
p-value	(-1.52)	(1.06)	(0.32)	(-2.53)	(-0.87)	(-0.51)	(1.98)	(0.78)	(1.70)	(-0.41)	(0.054)
TT	8.37	11.20	11.10	9.57	8.21	10.80	10.80	10.40	11.30	8.37	17.90
p-value	(-1.92)	(1.37)	(1.28)	(-0.51)	(-2.11)	(0.90)	(0.90)	(0.43)	(1.56)	(-1.92)	(0.037)
RT	7.38	6.76	10.20	9.22	13.50	11.90	10.00	11.30	11.90	7.79	21.50
p-value	(-1.93)	(-2.38)	(0.18)	(-0.57)	(2.60)	(1.39)	(0.03)	(0.94)	(1.39)	(-1.63)	(0.011)
DT	7.38	10.80	9.96	9.84	12.90	9.72	9.72	10.70	9.84	9.10	14.30
p-value	(-2.49)	(0.78)	(-0.04)	(-0.15)	(2.77)	(-0.27)	(-0.27)	(0.67)	(-0.15)	(-0.85)	(0.113)
TPT	7.22	11.90	4.12	12.90	12.90	9.28	11.90	9.79	8.25	11.90	14.10
p-value	(-1.29)	(0.86)	(-2.73)	(1.34)	(1.34)	(-0.34)	(0.86)	(-0.10)	(-0.81)	(0.86)	(0.117)
HSB	4.57	10.20	11.60	10.60	13.10	11.00	9.98	12.50	9.36	7.07	28.00
p-value	(-3.97)	(0.14)	(1.20)	(0.44)	(2.26)	(0.74)	(-0.02)	(1.81)	(-0.47)	(-2.14)	(0.001)
BB	10.30	10.80	10.10	10.10	9.16	10.30	9.44	11.50	8.67	9.58	8.64
p-value	(0.44)	(1.06)	(0.18)	(0.09)	(-1.06)	(0.35)	(-0.71)	(1.85)	(-1.67)	(-0.53)	(0.471)
TB	9.43	10.70	9.51	7.56	10.80	10.60	10.20	10.20	11.30	9.74	12.50
p-value	(-0.68)	(0.81)	(-0.59)	(-2.91)	(0.90)	(0.72)	(0.25)	(0.25)	(1.55)	(-0.31)	(0.186)
RB	6.95	9.27	10.20	7.72	12.50	11.80	11.00	15.80	7.34	7.34	38.30
p-value	(-2.31)	(-0.56)	(0.18)	(-1.73)	(1.93)	(1.35)	(0.76)	(4.42)	(-2.02)	(-2.02)	(0.000)
DB	7.12	11.60	9.79	9.64	11.40	9.94	11.00	9.64	13.20	6.68	23.80
p-value	(-2.49)	(1.36)	(-0.18)	(-0.31)	(1.23)	(-0.05)	(0.85)	(-0.31)	(2.77)	(-2.88)	(0.005)
TPB	5.14	13.10	10.90	6.86	13.70	14.90	8.57	9.71	10.90	6.29	17.20
p-value	(-2.14)	(1.39)	(0.38)	(-1.39)	(1.64)	(2.14)	(-0.63)	(-0.13)	(0.38)	(-1.64)	(0.046)

Panel B: Kolmogorov-Smirnov Test

Statistics	HST	BT	TT	RT	DT	TPT	HSB	BB	TB	RB	DB	TPB
γ	1.426*	0.171	0.357	0.790	0.863	0.326	1.089	0.184	1.140	0.916	0.663	0.514
p-value	(0.034)	(1.000)	(1.000)	(0.560)	(0.445)	(1.000)	(0.186)	(1.000)	(0.149)	(0.371)	(0.771)	(0.954)

This Table presents information-test results.(-99.00 indicates that fewer than three patterns were detected.) The goodness-of-fit null hypothesis is that each decile should contain 10% of the post-pattern observations and significant deviations from this indicate the presence of information in the chart patterns. The final column is the Q-statistic, and the numbers in parenthesis are the asymptotic z-values for each decile, and the p-value for the Q-statistics respectively.