The predictive power of the yield spread for future economic expansions: Evidence from a new approach*

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Abstract: We investigate the predictive power of the yield spread for future economic growth. The novel approach adopted here is to utilise its predictive ability for the whole distribution of future growth, rather than predicting the centre of this distribution directly. Our results confirm previous findings that the yield spread does contain additional information about future GDP growth, which varies over time. Most importantly, utilising the information contained in the whole conditional distribution of predicted GDP growth, rather than concentrating on the centre of it, provides additional forecasting power for shorter (3-9 months) horizons. This approach is also superior in forecasting future expansionary phases, notably a more common phenomenon than recessions for which the traditional, OLS-based forecasts seem to perform better.

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1. Introduction

The ability of the yield spread, defined as the difference between yields on long- versus short-term government bonds, to predict future economic activity has been intensely debated in the academic literature (see, e.g., Wheelock and Wohar, 2009, for a review of the literature). Numerous earlier empirical studies have reported the predictive power of the spread regarding future inflation, industrial production, and, most extensively, future growth rates of the economy. This relationship between the current spread and future economic variables has also been observed for many different countries[1] and varying across time and phases of the business cycle.[2]

In this paper, we propose a novel way to extract the predictive content of the spread, by obtaining forecasts of the whole distribution of future economic growth by means of quantile regressions and aggregating them into a single forecast of expected future growth. This approach differs from those employed in the literature which aim at forecasting future economic phenomena directly, and we find it empirically superior in forecasting over short-term horizons and future economic expansions.

Forecasting the whole distribution rather than merely its centre is better aligned with the original proposition by Granger (1969), who defines causality in terms of conditional *distributions* of variables, rather than its subsequent implementations which focus almost exclusively on conditional means. Predicting quantiles of the future distribution has been already shown to be largely successful for stock returns, and in particular, helping improve forecasts of the future centre of return distribution by utilising predictions of off-the-centre future returns (Cenesizoglou and Timmermann, 2008, Ma and Pohlman, 2008, Zhu, 2013,

[1] Examples of international studies include: Davis and Fagan (1997) and Berk and van Bergeijk (2001) for the EU countries, Kim and Limpaphayom (1997), and Nakaota (2005) for Japan, Harvey (1991), Hu (1993), Plosser and Rouwenhorst (1994), Benati and Goodhart (2008), Chinn and Kucko (2015), Schrimpf and Wang (2010), and Argyropoulos and Tzavalis (2016) for selected developed countries.
[2] Section 2 provides a review of theoretical and empirical literature on these issues.

Meligkotsidou et al., 2014, Pedersen, 2015). Therefore, we expect that the ability to predict the shape of the future distribution of economic growth using yield spread values would improve our knowledge about the future growth, and potentially our estimates of future expected growth rates. For instance, forecasts of different quantiles of future growth could be aggregated to obtain the forecasted centre of growth distribution. In addition, the widely reported higher predictive power of the spread for future recessions rather than booms could be just an artefact of higher predictive power for lower quantiles of the future growth distribution. Similarly, findings in the literature of the time-varying predictive power of the spread for future mean growth, which imply that the spread is an unreliable predictor, might be misleading if the spread could be demonstrated to predict other parts of the distribution of future growth, helping us to construct more reliable forecasts of that distribution's centre.

Overall, our results suggest that the yield spread does contain information about future GDP growth, and that its predictive ability varies over time, forecast horizons, and quantiles of future growth distribution. Most importantly, using quantile regressions to utilise information contained in the whole conditional distribution of predicted GDP growth, rather than directly concentrating on the centre of it, provides additional forecasting power for shorter (3-9 months) horizons. Another empirical contribution of our approach is that it is more effective to forecast future expansionary phases than OLS-based forecasts, notably a more common phenomenon than recessions, for which the latter seem to perform better.

Hence, this study advances the existing literature by making the following contributions. Methodologically, we propose a quantile regression approach to forecast the future distribution of GDP growth rates using current observations of the yield spread. Empirically, we demonstrate this approach to have superior forecasting performance over short horizons and for future expansions.

The remainder of this paper is organised as follows: Section 2 reviews the theoretical and empirical literature on the predictive power of the yield spread, data is discussed in Section 3, and Section 4 describes our methodology. Results are presented and discussed in Section 5, Section 6 reports outcomes of multiple robustness checks, and Section 7 concludes.

2. Literature Review

2.1. Theoretical Arguments

The literature discusses multiple potential reasons for the yield spread to contain information about future states of the economy. On the most basic level, according to the expectations theory of the yield curve (Modigliani and Sutch, 1966), the yield on bonds with long maturities equals the average of expected future nominal short-term yields. These nominal yields, in turn, are driven by expected future inflation and expected future real rates, with the former being historically higher in times of economic expansion. Hence, large spreads due to high yields on long term bonds indicate the market's expectation of high future inflation and/or real growth rates.

Estrella et al. (2003) further discuss several other explanations of the predictive power of the spread. First, they argue that it can be explained by the consumption CAPM of Campbell and Cochrane (1999) as, e.g., following negative news about future incomes, intertemporal consumption adjusts and gives way to short rates increasing more than long rates. Second, monetary policy can be argued to affect the current spread and future inflation/growth, e.g., lowering the rates can lead to lower short-term yields and higher future inflation or economic growth, i.e., higher future yields, resulting in a steeper yield curve. Third, they argue that short-term real shocks under the assumption of sticky prices will lead to fluctuations in real output, resulting in a decline in short-term yields when output declines.

Last, general equilibrium real business cycle models are argued to generate a link between expected productivity shocks and the slope of the yield curve.

Further, Adrian et al. (2010) propose that the balance sheet management of financial intermediaries, which borrow at short and lend at long rates, establishes a link between the yield spread and future economic activity, consistent with the “risk taking channel” of monetary policy (Adrian and Shin, 2009, Borio and Zhu, 2008). In Lint and Stolin’s (2003) model with endogenous production, a positive shock to production increases bond demand and the spread declines today, whereas future growth rates decline as the shock dies out, hence low current spread predicts lower growth in the future. Lastly, Benati and Goodhart (2008) argue that increases in marginal predictive content of spreads are observed in periods when the current (and future) monetary policy regime were most uncertain: if monetary policy is certain and known, most information about the future will be contained in current and past inflation, GDP, and short rates. However, uncertainty leads to higher long rates (a premium) and, hence, further suppresses future growth. Overall, given the above mentioned arguments, one would expect the yield spread to possess a fairly substantial degree of predictive power.

However, as it has been noted in even early studies and has become more apparent ever since, the predictive power of the spread has not been stable over time. This could be explained in light of the above mentioned theoretical arguments. For instance, changes in the monetary policy reaction function (emphasis on inflation vs. growth/employment) would theoretically and empirically affect the predictive power of the spread (e.g., Peel and Ioannidis 2003, Feroli, 2004, Estrella, 2005, Estrella and Trubin, 2006). Further, even changes in uncertainty about current (and future) monetary policy regimes would result in the Benati and Goodhart (2008) framework in changes of the predictive power of the spread (Bordo and Haubrich, 2008a, 2008b, demonstrate empirically that shifts in monetary policy credibility affect the predictive power of the spread). In addition, changes in the willingness (due to, e.g., changes in risk-attitudes) or ability of intertemporal consumption smoothing would also affect the link between the current spread and future economic activity. Price stickiness is also an important factor in some theoretical explanations, hence changes in this factor could also affect the spread's predictive power.

2.2. Empirical Evidence

The empirical literature on the predictive power of the spread is vast and we do not intend to give a comprehensive review here; rather, we point the reader towards some seminal papers in this area. For the US, there is strong evidence of predictive power of the spread. For instance, Dotsey (1998) employs single-equation regressions reports predictability of output for up to 24 months ahead, and Galbraith and Tkacz (2000) find evidence of asymmetries in the predictive regressions using linear and non-linear models. Estrella et al. (2003) and Jardet (2004) argue that predictability exists especially for one-year horizons, based on their results from single-equation and VECM models, and Stock and Watson (2003) utilise linear regression models and combination forecasts to confirm the predictive power of the spread for future growth until the mid-80s. Ang et al. (2006) employ single equation and VAR models and argue that the level of the short-term rate contains more predictive power for future growth than the spread does. However, the majority of studies still finds the spread to contain unique information about the future state of the US economy, at least in certain subperiods, e.g., D'Agostino et al. (2006), Giacomini and Rossi (2006), Aretz and Peel (2010), Benati and Goodhard (2008) and Bordo and Haubrich (2008 b). More recently, Chinn and Kucko (2015) find US industrial production to be predicted by the yield spread within a framework of linear regressions. Kao et al. (2013) test over 900 alternative predictive linear models for future US GDP growth and find those containing the spread to be among the best performers and Kurmann and Otrok (2013) demonstrate that the predictive power of the spread results from its link to future news about total factor productivity.

The predictive power of the yield spread has also been analysed in international markets. For instance, Davis and Fagan (1997) report only limited predictive power of the yield spread for EU countries based on VAR estimates, with Berk and van Bergeijk (2001) being equally sceptical based on their results from linear models. For Japan, Kim and Limpaphayom (1997) estimate simple regressions via GMM and find the spread to predict future economic activity in the subsample following financial market liberalization and interest rate deregulation, a result corroborated by Nakaota (2005). Harvey (1991) and Hu (1993) find the spread to possess significant predictive power in G-7 countries, while Plosser and Rouwenhorst (1994), Benati and Goodhart (2008), Chinn and Kucko (2015), Schrimpf and Wang (2010), and Argyropoulos and Tzavalis (2016) also report the ability of yield spread to forecast future economic activity to some extent in selected developed countries.

In line with theoretical considerations discussed in section 2.1., the empirical literature finds that the spread predicts future economic growth with varying degrees of success across time periods. Specifically, a substantial amount of evidence points towards a general decline in spread's predictive power since the mid-1980s.[3] The evidence remains rather strong, however, that the spread can predict future recessions much better than expansionary phases of the economy, across a sample of countries.[4] The reduced frequency of recessionary episodes in recent times is hypothesized in Schrimpf and Wang (2010) as a potential reason for poorer forecasting performance of the spread in recent years when measured jointly across both expansionary and recessionary times.

[3] Examples include: Dotsey (1998), Stock and Watson (2003), Jardet (2004), Giacomini and Rossi (2006), D'Agostino et al. (2006), Benati and Goodhart (2008), Chinn and Kucko (2015). Wheelock and Wohar (2009) review the relevant literature.

[4] For instance, Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998), Bernard and Gerlach (1998), Estrella et al. (2003), Moneta (2005), Wright (2006), Chinn and Kucko (2015), Christiansen (2013).

The overwhelming majority of studies in this area uses single-equation or VAR/VECM models to investigate the forecasting power of the yield spread for future economic activity, mostly in-sample but also increasingly out-of-sample, while employing diverse robust estimates of standard errors (e.g., Newey-West, GARCH, or bootstrapped values).[5] These studies attempt to directly forecast the centre of the future distribution of GDP growth. Here is where the methodological contribution of our study lies: we forecast numerous points of that future distribution first, and aggregate them subsequently to obtain potentially more accurate forecasts of the centre of that future GDP growth distribution.

3. Data

Data for the US on 3-month and 10-year treasury rates, M2, GDP, and GDP deflator comes from FRED. The sample starts in Q1 1959, due to unavailability of data on M2 prior to that date, and runs until Q2 2015. Inflation is calculated as a percentage change in the GDP deflator. Spread is calculated as the difference between yields on 10-year versus 3-month bonds.[6] Future GDP growth rate is calculated for H=1, 2, …, 8 quarters (3, 6, 9, …, 21, 24 months) ahead, and annualised, i.e., $\Delta GDP_t^H = (400/H) * (GDP_{t+H} - GDP_t)/GDP_t$. The spread is stationary but the remaining variables of interest (3-month yield, GDP, M2, and inflation) are not. However, the growth rates of the 3-month yield ($\Delta 3MYIELD_t$), GDP (ΔGDP_t), M2 ($\Delta M2_t$), and inflation rate ($\Delta INFL_t$) are stationary and, hence, used in our models.

[5] Studies on forecasting future states of recession constitute a distinct class and employ mostly profit/logit models.

[6] There is a discussion in the literature whether real-time, rather than revised, data should be used when analysing the predictive power of variables (e.g., Rossi, 2013, Chinn and Kucko, 2015). However, virtually all of the yield spread literature uses revised data, hence we follow this approach as it allows for comparability of results. In addition, Chinn and Kucko (2015) found that using real-time, pre-revision data does not change conclusions regarding the predictive power of the yield spread. Rossi (2013) discusses relevant studies in a related area and concludes that using revised data either does not make any difference, or it allows to avoid finding of spurious predictability present in real-time data. Given these arguments, we follow the literature and employ revised data.

4. Methodology

When analysing the differences in forecasting power, the recursive predicting approach is employed, with the initial estimation period of 10 years and expanding by one quarter at a time. At every iteration, a one-step-ahead forecast for the future H-months ahead GDP growth rate is formed, resulting in quarterly series of forecasts from each forecasting model and for the future GDP growth at each horizon H. The forecasting models investigated are as follows:

<u>Historical mean (HM)</u>

We follow the literature on forecasting (e.g., Welch and Goyal, 2008, Campbell and Thompson, 2008, Rapach et al., 2010, Neely et al., 2014) and begin with the simplest benchmark forecasting model: for the annualised future GDP growth rate at horizon H, estimated at time t, this forecast is given by the average GDP growth rate up to and including time t, i.e.:[7]

$$\widehat{\Delta GDP}_t^H = t^{-1} \sum_{\tau=1}^{t} \Delta GDP_\tau. \quad (1)$$

<u>An OLS predictive regression without the spread</u>

This model utilises several macroeconomic variables,[8] but not the spread, to recursively generate predictions for one-step-ahead GDP growth at horizon H, i.e., at every iteration we estimate:

$$\Delta GDP_t^H = \beta_0 + \beta_1 \Delta GDP_t + \beta_2 \Delta 3MYIELD_t + \beta_3 \Delta INFL_t + \beta_4 \Delta M2_t + \epsilon_t. \quad (2)$$

Hence, the prediction made at time t for the H-quarters-ahead annualised GDP growth rate is given by: $\hat{\beta}_0 + \hat{\beta}_1 \Delta GDP_t + \hat{\beta}_2 \Delta 3MYIELD_t + \hat{\beta}_3 \Delta INFL_t + \hat{\beta}_4 \Delta M2_t$.

[7] This model is not our main benchmark, however. Rather, the main focus of the paper is on comparing quantiles-based vs. OLS-based forecasts.

[8] Surprisingly, most studies on the predictive power of the yield spread do not control for the potential predictive power of alternative factors such as macroeconomic variables the spread could be correlated with. Our choice of macroeconomic control variables follows those studies which did include controls in their predictive models, e.g., Stock and Watson (2003), Benati and Goodhard (2008), Bordo and Haubrich (2008a), Chinn and Kucko (2015). Inclusion of the contemporaneous (time *t*) GDP growth rate accounts for persistence and, hence, potential predictive power of GDP growth rates.

An OLS predictive regression with the spread

To analyse the incremental predictive content of the yield spread, i.e., over and above the predictive content of other macro variables, the forecasting performance of model (2) is compared to that containing the spread as an additional RHS variable, i.e.,

$$\Delta GDP_t^H = \beta_0 + \beta_1 \Delta GDP_t + \beta_2 \Delta 3MYIELD_t + \beta_3 \Delta INFL_t + \beta_4 \Delta M2_t + \beta_5 SPREAD_t + \epsilon_t \quad (3)$$

Quantile regression (QR) without the spread

Rather than attempting to directly predict the centre of the distribution of future GDP growth rates, ΔGDP_t^H, as is done in cases (1)-(3), we employ the quantile regression approach and, at each forecast formation time t, attempt to predict a range of quantiles of that distribution. Next, we combine those predicted quantiles to obtain a forecast of the future distribution's centre. The QR model without the spread, in analogy to (2), is:

$$\Delta GDP(\theta)_t^H = \beta_0^\theta + \beta_1^\theta \Delta GDP_t + \beta_2^\theta \Delta 3MYIELD_t + \beta_3^\theta \Delta INFL_t + \beta_4^\theta \Delta M2_t + \epsilon_t, \quad (4)$$

where $\Delta GDP(\theta)_t^H$ denotes the θ-th quantile of the conditional distribution of ΔGDP_t^H, and we generate those estimates for the following values of θ: 5%, 10%, 15%, …, 90%, 95%, at each point in time *t* when a forecast is formed. For instance, the H=3 quarters ahead of GDP growth at quantile θ =5% forecasted at time *t* will be given by:

$$\widehat{\Delta GDP}(\theta = .05)_t^{H=3} = \hat{\beta}_0^\theta + \hat{\beta}_1^\theta \Delta GDP_t + \hat{\beta}_2^\theta \Delta 3MYIELD_t + \hat{\beta}_3^\theta \Delta INFL_t + \hat{\beta}_4^\theta \Delta M2_t.$$

It should be noted that coefficients β not only change as the estimation window is being expanded over time, but also differ at each point in time across quantiles (hence, the superscript θ).

Once quantile estimates for the next-step-ahead GDP growth have been generated, they need to be aggregated to obtain a forecast for the centre of the future GDP growth distribution, at each point in time *t*. We perform this aggregation in three alternative ways:

a. Simple weighting

Under this scheme, 50% of the weight is attached to the predicted median (i.e., for θ= 50%), and the rest is distributed equally across the remaining (eighteen) predicted quantiles of $\widehat{\Delta GDP}(\theta)_t^H$, θ= 5%, …, 45%, 55%, …, 95%. Hence, the forecast is computed as:

$$\widehat{\Delta GDP}_t^H = .5 * \widehat{\Delta GDP}(\theta = .5)_t^H + .5 * \frac{1}{18} \sum_{\theta \neq .5,} \widehat{\Delta GDP}(\theta)_t^H \tag{5}$$

b. Model fit-based weighting

To account for the fact that quantile regressions at some quantiles fit the data better than at other quantiles, we design a weighting scheme which attributes higher weights to those quantiles θ for which model's (4) goodness of fit measure R^2 was higher, as those predictions can be considered to be based on more reliable models. This is done at every interaction of the recursive procedure. Hence, the forecast for the future GDP growth made at time t is given by:

$$\widehat{\Delta GDP}_t^H = \omega * \hat{y}(\theta = .5)_t^H + \sum_{i, \theta \neq .5,} \omega_\theta * \hat{y}_i(\theta)_t^H, \tag{6}$$

The variable $\hat{y}(\theta)$ denotes the predicted median only if $\theta = .5$ (first component of (6)), but otherwise measures the middle of the distance between two predicted quantiles situated symmetrically around the median, i.e., θ =5% and 95%, 10% and 90%, etc. Hence, $\hat{y}_i(\theta) = .5 * \left(\widehat{\Delta GDP}(1-\theta) + \widehat{\Delta GDP}(\theta)\right)$ for 0< $\theta < .5$, e.g., for the pair 5% and 95%, $\hat{y}_i = .5 * \left(\widehat{\Delta GDP}(\theta = .95) + \widehat{\Delta GDP}(\theta.05)\right)$.

Hence, each pair (and the median) of predicted future growth rates generates a prediction of the centre of the distribution, and those predictions are aggregated as in (6). The weights add up to one ($\omega + \sum \omega_\theta = 1$), and are computed depending on the R^2 measures of quantile regressions as follows: if we denote $R^2(\theta)$ as goodness of fit of the quantile regression for quantile θ, then:

$$\omega = \omega_\theta = \frac{\emptyset R_i^2}{\sum \emptyset R_i^2}$$

where $\emptyset R_i^2$ is the average R^2 measure for each pair $\{\theta, 1-\theta\}$ of predicted quantile returns, except for the median ($\theta = .5$) where it is just the R^2 measure from the QR for the median. In this way, predictions for future GDP growth based on QR models with better fits (higher values of R^2) carry more weight.

c. Model fit-based weighting, without the median

Here, a weighting scheme as in b. but without the forecasts for the median (QR for $\theta = .5$) is employed. This is to concentrate on predictive content of the quantiles in the shoulders and the tails of the distribution, to further differentiate the QR approach from the OLS one, which focuses on the distribution's centre directly.[9]

Quantile regression with the spread

The same steps a. to c. as above are conducted for QR models with the spread variable added to the econometric model (4), resulting in the following model:

$$\Delta GDP(\theta)_t^H = \\ = \beta_0^\theta + \beta_1^\theta \Delta GDP_t + \beta_2^\theta \Delta 3MYIELD_t + \beta_3^\theta \Delta INFL_t + \beta_4^\theta \Delta M2_t + \beta_5^\theta SPREAD_t + \epsilon_t. \quad (7)$$

To evaluate the in-sample incremental predictive content of the yield spread, we calculate the mean squared prediction error (MSE) and the mean absolute prediction error (MAE) for each model. In order to test for the significance of differences in predictive power across models, we follow the recommendation of West (2006) and regress the differences in squared (or absolute) prediction errors from two models at a time on a constant, its sign and significance (based on HAC standard errors where required) can be used to infer about the relative predictive performance of models analysed. Where nested competing forecasting

[9] It should be noted that our aggregation approaches do not utilize the knowledge of which quantile is more predictable; they simply account for the fact that quantiles other than the mean could be more predictable and, when combined in a certain way, could help to obtain superior forecasts of the future mean/median. Attaching bigger weights to those future quantiles which are known/expected to be more predictable could result in a further improvement of the forecasting performance of the aggregated forecast for future mean/median.

models can be clearly identified, the Clark and West (2007) test (CW07, for short) is used (as in, e.g., Bordo and Haubrich, 2008a).

5. Empirical results

5.1. In-sample predictability

We start by analysing the in-sample predictive ability of the spread, to compare our sample with those employed in the literature (this is achieved by fitting each relevant model to the whole sample of data). In OLS regressions, the spread possesses significant explanatory power in the whole sample for all time horizons considered, as shown in the left panel of Table 1. This is not just a statistical artefact of the spread's correlation with other variables which themselves can predict future growth. When we control for the lagged growth, money supply, inflation, and short-term rate (model (3)), the coefficients on yield spread remain significant for all horizons (the right panel of Table 1).

[Table 1 around here]

However, QR estimation results (model (7)) reveal that this in-sample predictive power of the spread is not constant across quantiles of the conditional distribution of future GDP growth (Figure 1). For all horizons H, values of the spread coefficient are positive for low quantiles and decline almost monotonically as we move towards higher quantiles, reaching negative values in some cases. For horizons of 15 months and longer, yield coefficients are insignificant from around quantile .55, whereas for shorter horizons they remain significant until they reach quantile .70-.80, with those for a 3-month horizon predictions being insignificant already beyond quantile .38. Overall, one can conclude that the distribution of future growth is a significantly predictable in-sample by the yield spread if one analyses longer horizons and if conditional values of future growth are not too high. This corresponds well with previous findings in the literature reporting superior predictive power of the spread for future recessions, i.e., when the future growth rates of the GDP are exceptionally low.

[Figure 1 around here]

It is a well-established empirical fact in the literature that the predictive power of the yield spread varies across time (see, e.g., Chinn and Kucko, 2015, for most recent evidence, and Wheelock and Wohar, 2009, for a review of previous studies). To investigate whether the time-varying nature of predictability is also present in quantiles, we start by estimating the OLS regression model (3) within a moving window framework, with overlapping windows including 10 years of data at a time.[10] The results (shown in Figure 2) confirm previous findings that the predictive power of the yield spread is time-varying. More specifically, in the early period of our sample (for windows ending around the mid-70s and earlier) the yield spread has no predictive power for future GDP growth in-sample at any horizon. However, for 10-year-long windows ending between the mid-70s and the mid-90s, coefficients on the yield spread are positive and significant, indicating its predictive power. This seems to have been declining gradually from the late 70s, however. The yield spread regains its predictive ability for windows ending around 2007, mostly for longer-term forecast horizons, most likely due to the tightening of the monetary policy preceding the 2008 recession. These results are very similar across all forecasting horizons, from 3 to 24 months ahead. This pattern is roughly in line with results reported by Chinn and Kucko (2015) for simple regressions of the future GDP growth on spread alone.

[Figure 2 around here]

Our further analysis reveals that the predictive power of the spread for specific quantiles of the (conditional) future growth distribution is also time-varying. Here, we only comment on quantile results for H=6, 12, and 24 months-ahead forecasts and for selected quantiles, to conserve space (for illustration, we report selected results for H=12 months in Figure 3). For the 6-months ahead forecasts, the predictive ability across all quantiles roughly follows that

[10] Windows of 15 years generate qualitatively similar results; those are not reported to conserve space.

observed for OLS regressions, i.e., spread coefficients are significant in windows ending between the mid-70s and the mid-90s, and seem to regain some of their predictive content in the final part of our sample, except for those in low quantiles. For the 12-months ahead forecasts, the predictive ability of the yield spread follows a similar pattern. However, coefficients for low and central quantiles tend to be significant also in the early periods, which corresponds well with the previous finding that in the whole sample spread coefficients are significant until they reach quantile .70-.80. The values of those significant coefficients seem to be of similar magnitude across quantiles, however. Hence, the finding of declining spread coefficient values as one moves from low to high quantiles in the whole sample is not due to the fact that those in lower quantiles were of higher magnitude in periods when they were significant. Rather, they were significant for longer periods of time, which results in higher coefficient values when measured over the entire sample, as the whole-sample estimates be thought of as coefficients averaged over all subsamples. For the 24-months ahead forecasts, the overall pattern is similar to that for the 12-months horizon, with an exception of quantiles .15 (.25) for which the predictive power of the spread is observed almost continuously from the early 80s (mid-90s). Overall, the in-sample predictive power of the spread for future quantiles of growth distribution appears to vary over time, but not dramatically across quantiles and not so much across forecast horizons.

[Figure 3 around here]

5.2. Out-of-sample forecasting performance

5.2.1. Moving window OLS-based results

The existence of predictive power in-sample does not imply that the spread possesses unique information content about the future economic growth; however, economic agents could not have known and acted upon the in-sample predictive power as knowledge about its existence would not have been available before the end of that sample. To circumvent this potential "look-ahead" bias, the forecasting literature employs out-of-sample analysis to establish a genuine forecasting power of any variable in question. In addition, if the underlying relationship between the yield spread and future growth is unstable, as our moving window analysis shows it is, any in-sample predictive power might be short-lived and fail to provide a basis for reliable out-of-sample forecasts; out-of-sample analysis also addresses this issue. We investigate the time-varying nature of the out-of-sample forecasting power of the spread by performing the CW07 test in moving windows of 10 years of width each. In each window, the first five years form the estimation period and the remaining five years are used to generate and compare forecasts, recursively.[11] This test for encompassing performance compares forecasts generated by the full model (3), which includes macroeconomic variables and the spread, with those stemming from a reduced model (2), containing only the macroeconomic variables but no spread. The null hypothesis in our case implies that the spread possesses no incremental forecasting power beyond that contained in other macro variables, while the alternative hypothesis states that the yield spread does possess unique information, which helps to improve GDP growth forecasts.

Figure 4 presents p-values of the CW07 test executed in rolling windows. The results indicate that, for 10-year long rolling subsamples ending between the 1970s and the mid-1990s, the spread has had out-of-sample forecasting power for future growth beyond that potentially contained in other macroeconomic variables, as p-values of the CW07 statistic are below the 10% level. This period of forecasting power ends abruptly for all horizons around the mid-90s, which is in line with our results obtained in-sample. For some horizons, this period of forecasting ability starts around the mid-70s, as in-sample results suggested, but for

[11] It should be noted that the CW07 test is usually employed over the whole sample, recursively, to answer the question of the overall superior forecasting power of one (encompassing) model vs. another (reduced) one. This generates one test statistic for the entire sample. However, we are interested in how the forecasting power of the spread varied across time. Hence, the CW07 test is employed repeatedly, in subsamples/windows moving over time, and generates a time series of test statistics. This allows us to observe movements in the forecasting performance of the yield spread over time.

other horizons it starts a few years earlier (H=9 to 12 months) or later (H=21 to 24 months). In addition, in-sample results indicate that the spread possesses predictive ability in subsamples ending around 2007 and later, mostly for longer-term forecast horizons. As far as the out-of-sample forecasting ability is concerned, there is also some significant predictive power of the spread around the end of the sample (except for 3 months ahead growth forecasts). For horizons 6-12 months, this predictability disappears for windows ending in 2011 and beyond, but it appears to be sustained from around 1997 (windows ending around 2007) until the sample's end for horizons of 15 months and above. Overall, the in-sample predictability tends to translate well into out-of-sample forecasting ability of the yield spread.

[Figure 4 around here]

5.2.2. Recursive forecast test results: OLS models

Next, we turn our attention to the *relative* out-of-sample forecasting power of various models, with and without the yield spread, as discussed in Section 4, now applied to the entire sample in the recursive set-up. The initial estimation window is restricted to the first 10 years of data and is being expanded by one quarter at a time, generating a future GDP growth forecast in each iteration. This spawns a time series of forecasts for each model.

To get an initial overview of the results, we compared model (3), i.e., the OLS regression with the yield spread and other macroeconomic variables, with model (2) (without the spread) and model (1) (historical average) by simply comparing their respective forecast errors, as measured by MSE and MAE values (results not reported but available on request). Forecasts based on OLS models perform better than those utilising the historical average values of GDP growth, as indicated by lower values of prediction errors, and those employing the spread perform better than those without the spread (lower MSE and MAE values). This implies that macroeconomic variables used here (inflation, M2, short-term rate, and lagged growth) do possess predictive content for future GDP growth rates for horizons between 3 and 24 months and, more importantly, that the yield spread possesses an incremental predictive content, after accounting for that contained in other macroeconomic variables.

Further, we investigate if these differences in MSE (MAE) are statistically significant by regressing the differences in squared (absolute) forecast errors of any two models on a constant and calculating the corresponding HAC standard errors (this effectively amounts to applying the Diebold-Mariano (1995) test). These test results are reported in Table 2. Model (3) (OLS with spread) beats model (1) (historical mean) when both MSE and MAE are used to measure the forecasting performance, although most results for MAE are not significant (*Case 1*). Model (3) also produces lower prediction errors than model (2) (OLS without the spread) when MSE is used (*Case 2*), although these results are only significant for horizons *H* of 15 months and longer, i.e., there is some evidence of an increase in predictive ability of the OLS model resulting from inclusion of the spread. Results based on MAE, although not significant, are of the “correct” sign as well, suggesting that model (3) outperforms model (2) across the board. This consistency of results (i.e., lower prediction errors) further suggests that the spread contains information about the future GDP not carried by other variables, even if this forecasting improvement is not always significant when tested separately for individual horizons and using the MAE as a forecast performance measure.

[Table 2 around here]

5.2.3. Recursive forecast tests results: Quantile Regressions (QS) and OLS models

Next, we analyse the forecasting performance of the QR model which includes the spread (7) and uses a simple weighting of quantile forecasts, compared, first, against the QR simply-weighted forecasts from models without the spread (4), second, against the OLS model (3) with the spread, and third, against a simple historical average (1). The QR models with spread produce the lowest forecast errors in all but one cases when MAE is used, and also outperform these alternative three predictors when MSE is used for horizons 3, 6, and 9 months. QR models with spread tend to show significant forecasting improvements vis-à-vis the historical mean when using both the MSE and the MAE (*Case 3*), but there are only few cases of significant improvements as compared to the OLS models (*Case 4*, for horizons 3-9 months when MAE is used) and no significant result when compared to the QR models without the spread (*Case 5*); albeit the observed signs are "correct", i.e., suggest lower forecasting errors when spread is used in the model. Hence, simple weighting of quantile forecasts does not seem to be generating widespread improvements in incremental forecasting performance of the yield spread.

Using R^2-based rather than simple weights for quantile predictions appears to utilise the out-of-sample predictive content of the yield slightly better when MSE are used to evaluate forecasting performance. MSE values are lower for R^2-based than simply-weighted QR forecasts (*Case 7*), although they tend to be individually significantly lower only for the longest forecast horizon (24 months). When MAE is used, however, simple weighting of QR forecasts tend to generate more accurate forecasts than the R^2-based scheme (albeit no difference is significant here). Further, R^2-based forecasts outperform the OLS-based ones (*Case 6*) only for short horizons (up to 9 months), and significantly so only when MAE is used. Hence the R^2-based approach is comparable and not superior to the simple weighting approach.

Dropping the predicted median from the QR R^2-based forecast aggregation improves the predictive ability vis-à-vis the approach with the predicted median included (*Case 9*) only when MSE is used and only for the 24 months ahead prediction. These no-median predictions also outperform the OLS ones (*Case 8*) at shorter horizons when MSE is used, albeit not significantly so. However, when MAE is used, forecasts from the weighting scheme without the median are overall inferior to those obtained when median was used. Even then, however, the OLS-based forecasts can still be significantly outperformed at shorter horizons (3 to 9 months).

5.3. Forecasting performance across the business cycle

Numerous studies report that the yield spread possesses superior predictive ability regarding future recessions, as compared to future economic expansions (see, e.g., Wheelock and Wohar, 2009, and for a review). Hence, we further investigate whether the performance of QR-based forecasts, as compared to the OLS ones, differs when it comes to predicting future GDP growth during different stages of the business cycle. Specifically, for each forecast horizon H we estimate the following model:

$$RPRED_t = \alpha_0(1 - FR_t) + \alpha_1 FR_t + \epsilon_t, \quad (8)$$

where $RPRED_t$ denotes the relative predictive power of one approach versus the other (either a difference in squared prediction errors or absolute prediction errors), and FR_t is a dummy equal to one if there is a recession in the *future* period for which the GDP growth forecast is formed (any quarter of it), and zero otherwise. Recessions are as defined by the NBER. Hence, α_0 (α_1) measures the relative forecasting performance of one model against the other during expansions (recessions), and their significance is evaluated utilising the corresponding HAC standard errors. For instance, $\hat{\alpha}_0 < 0$ would indicate that one model possesses superior forecasting performance for future expansions, as its MSE (MAE) is lower.

The results (Table 3) first indicate that simple-weighted QR forecasts outperform those produced by historical means (*Case 1*), as they produce significantly better forecasts for future recessions (while not being outperformed by the historical mean in predicting future expansions), as indicated by negative and significant values of $\hat{\alpha}_1$. This is not surprising, especially given that the moving average of past growth rates would be biased towards the more frequently observed and persistent expansionary periods and, hence, struggle to predict the less frequent economic downturns. As compared to OLS forecasts (*Case 2*), those based on a QR simple weighting scheme perform significantly better when predicting GDP during future expansionary phases (but OLS tends to predict GDP growth in future recessions significantly better). To investigate whether it is the QR approach or the predictive content of the yield which helps to produce superior forecasts for expansionary periods, we compare the QR-based simply-weighted forecasts with and without the spread as a RHS variable (*Case 3*). The QR model with the yield spread performs better when predicting future recessions, i.e., the yield's information content appears to be related to future recessionary phases, as the OLS results in the literature suggest. When predicting future expansions, however, inclusion of the spread into the predictive QR models does not make a significant difference. Hence, it is the QR approach which helps to extract information from the spread about future expansions and, hence, to improve the forecasting ability for future expansionary phases over that obtained from the same set of variables in an OLS forecasting setup. Once adopted, the QR approach can also extract information from the spread about future recessions.

[Table 3 around here]

Switching to R^2-based weighting further improves the performance of QR models, mostly regarding future recessions, but this effect is limited to selected horizons. Compared with OLS-generated forecasts (*Case 4*), these R^2-based QR approaches continue to perform significantly better when predicting future economic expansions, but are beaten by OLS-based forecasts when there are recessions 15 months and more ahead. Compared to simple-weighted QR forecasts, those based on R^2-derived weights tend to do better mostly in the case of future recessions (*Case 5*). Lastly, dropping the predicted median from the forecast formation procedure does not change the pattern of relative forecasting performance as compared to the OLS method (*Case 6*), but shows some improvements for forecasting future recessions vis-à-vis the QR approach which does utilizes the predicted medians (*Case 7*).

Overall these results suggest that the yield spread does contain additional information about the future GDP growth, but its predictive content varies over time, forecast horizons, and quantiles of the future growth. In addition, utilising the information contained in the whole conditional distribution of predicted GDP growth, rather than concentrating on the centre of it, provides additional forecasting power for shorter (3-9 months) horizons, as compared to OLS-based forecasts. Most importantly, this QR-based approach is especially effective to forecast future expansionary phases using the yield spread, notably a more common phenomenon than recessions for which the OLS-based forecasts seem to perform better.

6. Robustness Checks

We have also undertaken a series of further empirical checks to scrutinise the robustness of our result.[12] Here, we concentrate on the main result, presented in Table 3, *Case 6*, which indicates that forecasts using forecasted return quantiles (except the forecasted median) and derived from a model with the yield spread display superior performance when predicting future economic expansions. First, we investigate whether the 2007-2009 global financial crisis was the main driving force behind our results, i.e., if the predictive power of the yield in QR approach was observable in the period prior to the crisis' outbreak. To this end, we limit our sample to the period ending in the second quarter of 2007, and test for predictive power of the yield in QR vs OLS setup (equivalent of *Case 6* in Table 3). The results, reported in Table 4, Panel A, are qualitatively identical with those obtained for the whole sample: QR-based forecasts outperform those derived from OLS models for future expansionary periods, and OLS forecasts do better in forecasting future recession over long horizons. Hence, our main result was not driven by the "outlier" of the 2007-2009 crisis.

[Table 4 around here]

[12] We thank anonymous reviewers for suggesting these extensions.

Second, in line with the literature which suggest the predictive power of the yield curve depends on monetary policy regime (or whether policy-makers prioritise low inflation over short-term employment and growth, e.g., Giacomini and Rossi, 2006, Bordo and Haubrich, 2004, 2008a, b, Benati and Goodhard, 2008), we differentiate between active/passive, or "hawkish"/"dovish", monetary policy regimes following the dating results in Davig and Doh (2014). The results for the regime where stronger emphasis is placed on achieving target inflation (active, or "hawkish") are reported in Table 4, Panel B, and show a high degree of similarity with our baseline result (for all observations). In fact, the QR-based predictions show more cases of superiority for short-term forecasts of economic expansions then was the case in the whole sample. For the "dovish" regime (Panel C), the superior predictive power of QR (OLS) forecasts remains for long-horizon forecasts of future expansions (recessions), but is weaker for shorter horizons (however, QR forecasts gain predictive superiority for H=9 months ahead recession).

Further, we analyse if the predictive content of the spread, i.e., the slope of the yield curve, is not encompassed by other market-related factors. First, the literature has suggested that other features of the yield spread, in addition to its slope, could also contain information about future economic events beyond what is captured by the spread.[13] Hence, we investigate if the level and the curvature of the yield curve contain additional information about future growth not contained in the spread. To this end, we test if using the level and the curvature of the yield curve helps to reduce forecast errors as compared to a model without those variables (we estimate an equivalent of model (4) with the spread and macroeconomic controls, and an extended model, equivalent to model (7), which adds the level and the curvature variable as predictors). We estimate the level and the curvature proxy as suggested in Diebold et al.

[13] Examples of research incorporating the level and curvature of the yield curve include: Moneta (2005), Chinn and Kucko (2015), Stock and Watson (2003), Benati and Goodhard (2008), Ang, Piazzesi, and Wei (2006), Hännikäinen (2017). Overall, the spread appears to have stronger predictive power that the level or the curvature factor (Hännikäinen, 2017).

(2006) and Afonso and Martins (2012); the former is computed as (y(3) + y(36) + y(120)) / 3, with y(*k*) denoting the yield of a bond with maturity of *k* months, whereas the latter is calculated as 2*y(36) - y(120) - y(3). We use *k*=36 due to data availability and because it is the average of values suggested in Diebold et al. (2006) and Afonso and Martins (2012). The results reported in Table 4, Panel D show that using the level and the curvature of the yield curve in addition to its slope (the spread) does not generate significantly better forecasts as a model with the spread being the only yield curve-derived predictor, as all test statistics are insignificant. Hence, we can conclude that there is no evidence in our sample that the level or the curvature of the yield curve capture information which would not be contained in the spread already.

Lastly, we investigate whether the information contained in the spread is unique to the bond market or whether it can also be extracted from movements on the stock market. To that end, we add returns on the DJIA index to models (4) and (7) as an additional "macroeconomic" control. The results reported in Table 4, Panel E, show that the model which also contains the spread significantly outperforms the one without the spread across a number of instances (negative test statistic signs indicate lower forecast errors for models with the spread). This is mostly observable for predictions of future recessions, and in line with the literature which reports the superior forecasting ability of the spread regarding future economic downturns. Spread-based forecasts are generally not outperformed by the stock market-based ones for future expansions, either, making the spread an overall superior predictor. Hence, our results demonstrate that the spread contains unique information about future recessions which is not captured by the stock market return variable.

Overall, our robustness checks indicate that the QR-based approach can extract useful information uniquely contained in the yield curve slope (the spread) about future economic expansionary periods and that this result is not driven by the 2007-2009 crisis, and is stronger in “hawkish” monetary regimes. In addition, there is no evidence in our sample that the level or the curvature of the yield curve captures information that would not be contained in the spread already, and the spread is shown to contain unique information about future recessions which is not captured by stock market index returns.

7. Conclusions

In this paper, we analyse the issue of the predictive ability of the yield spread from a new angle. Rather than following the existing literature and investigating its ability to directly forecast the centre of the future economic growth variable, we examine the spread’s predictive ability regarding the whole distribution of future economic growth, not just the centre of that distribution. We confirm previous findings based on OLS forecasts that the spread possesses predictive power for future growth in-sample, and that this power varies over time. We further unveil new evidence. First, the yield spread has more predictive power for lower quantiles of future growth. This forms an empirical basis for our further steps, where we investigate if forecasts of different quantiles can be effectively aggregated into a superior forecast of the future mean/median growth (as compared to those methods which only attempt to forecast the future mean/median directly). Second, the spread’s ability to predict quantiles of future growth varies over time, and less so over forecasting horizons or quantiles. Third, quantiles-based predictions, when aggregated to yield forecasts for the centre of the future growth distribution, significantly outperform those based on the OLS approach for horizons of three to nine months ahead. Lastly, predictions of future growth based on quantile forecasts significantly outperform OLS-based predictions when forecasting growth in expansionary phases of the economy. Hence, we uncover an additional, previously unreported, information content contained in current yield spreads, which can be extracted using a quantile regressions-based forecasting approach. Utilising other methods of aggregation of quantile predictions could have a potential to extract further predictive contents of the yield spread. We leave these investigations for further research.

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Figure 1: Quantile regression estimates for the spread coefficient, model (7), whole sample period.

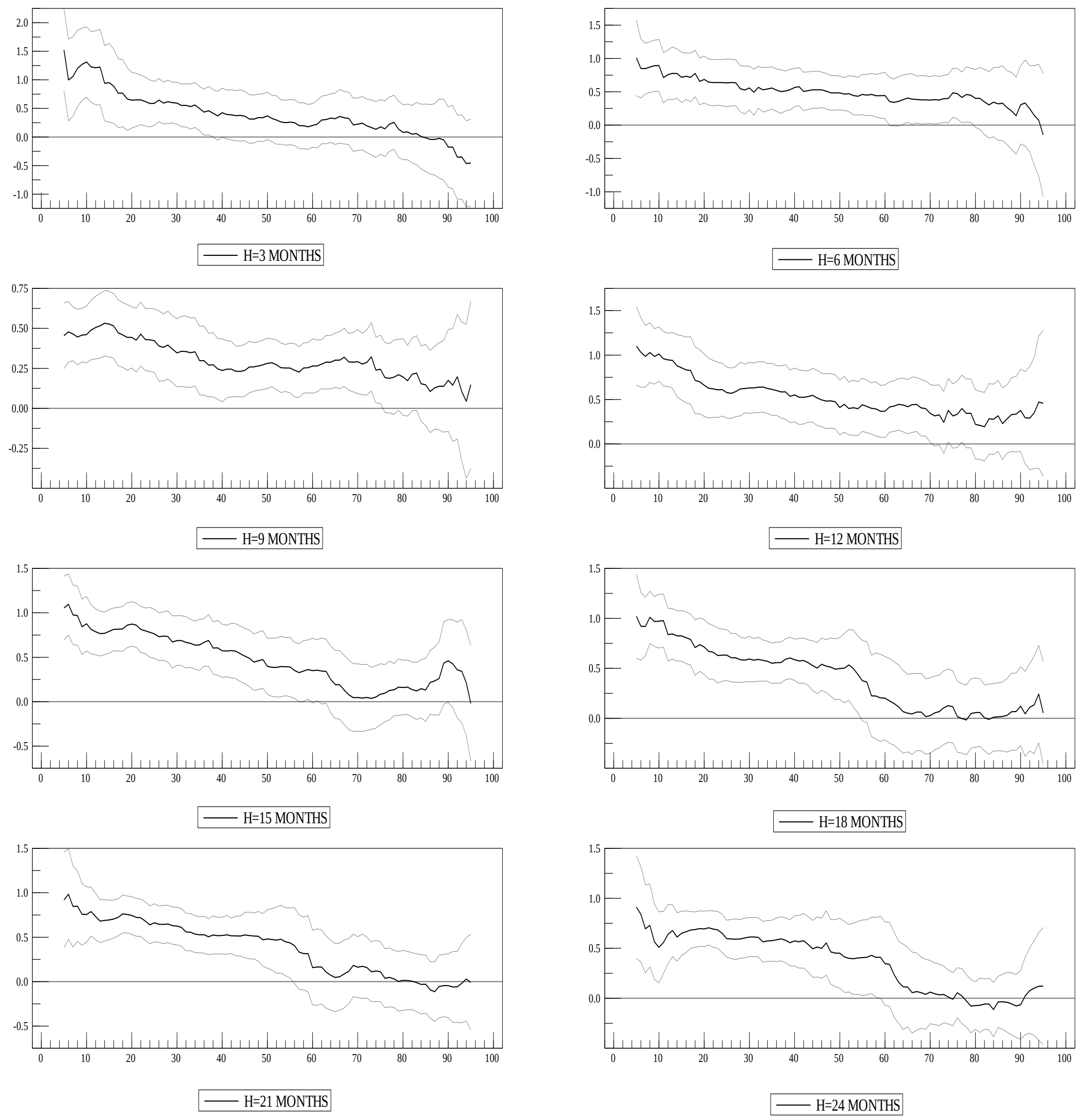

Figure 2: OLS estimates for the spread coefficient, model (3), rolling windows (length: 10 years), HAC standard errors.

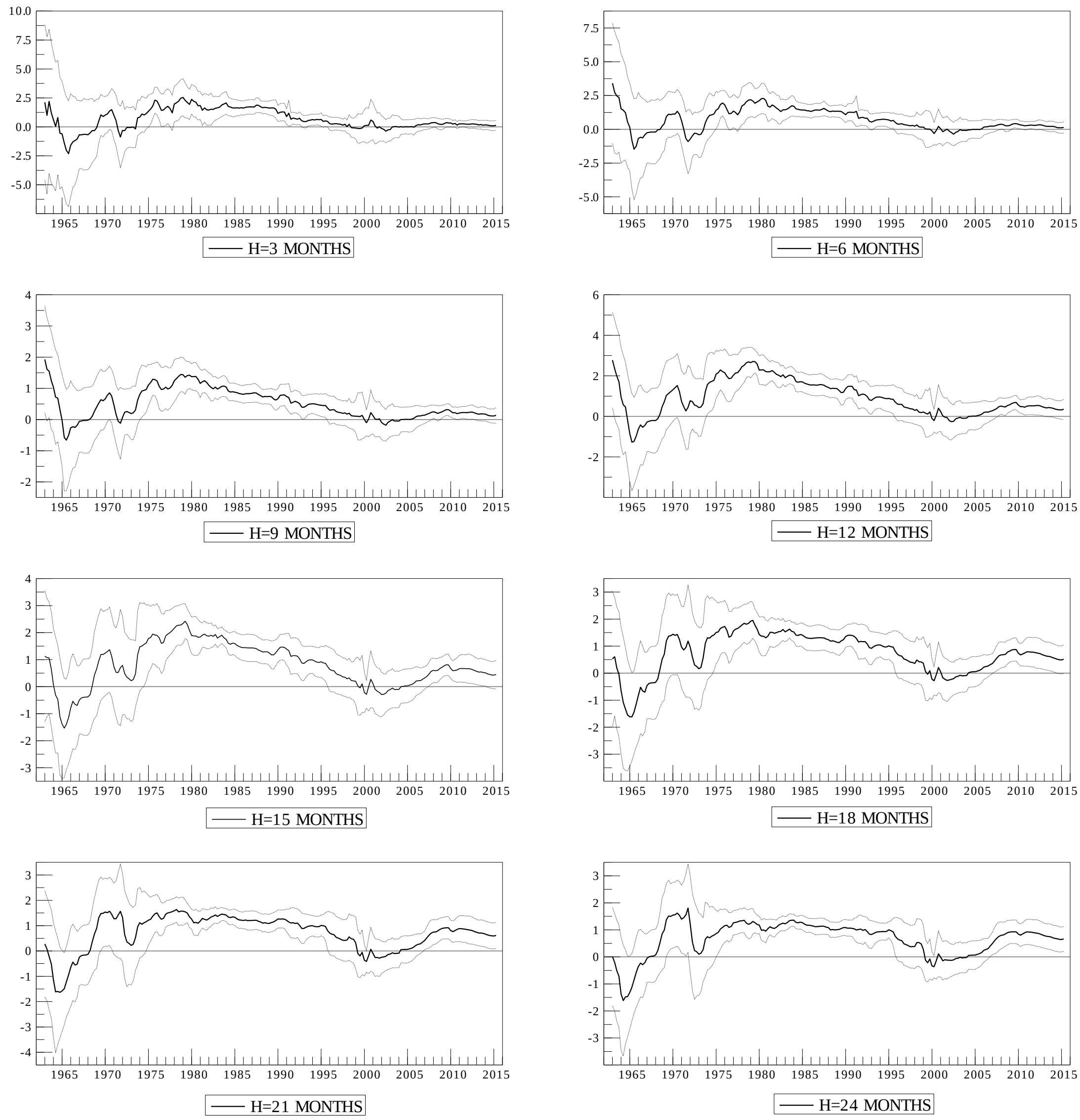

Figure 3: Time variations in estimated spread parameters in QRs (moving windows of 10 years, X axis: end of the window)

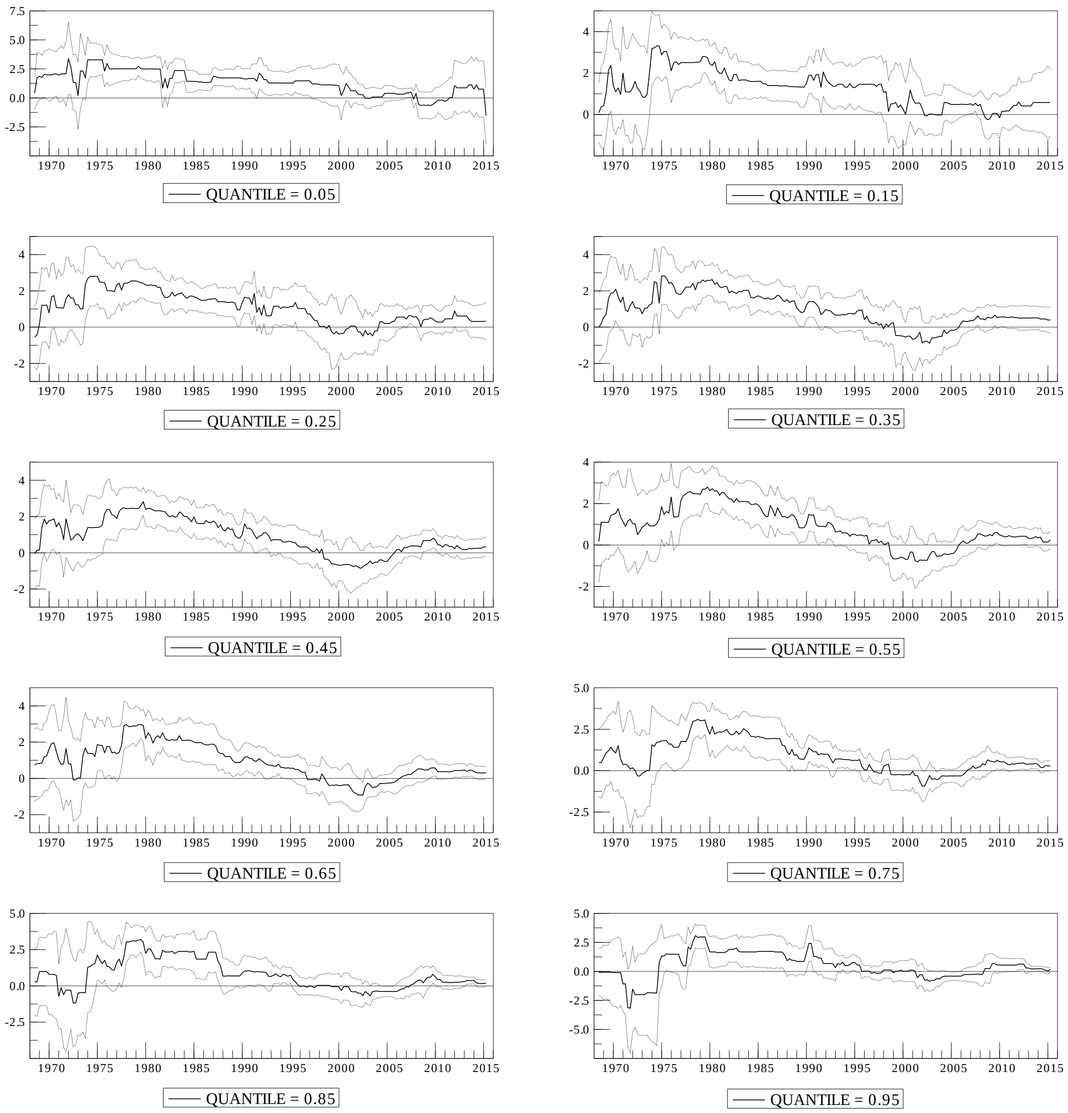

Figure 4: P-values from the CW07 test (moving windows of 10 years, X axis: end of the window).

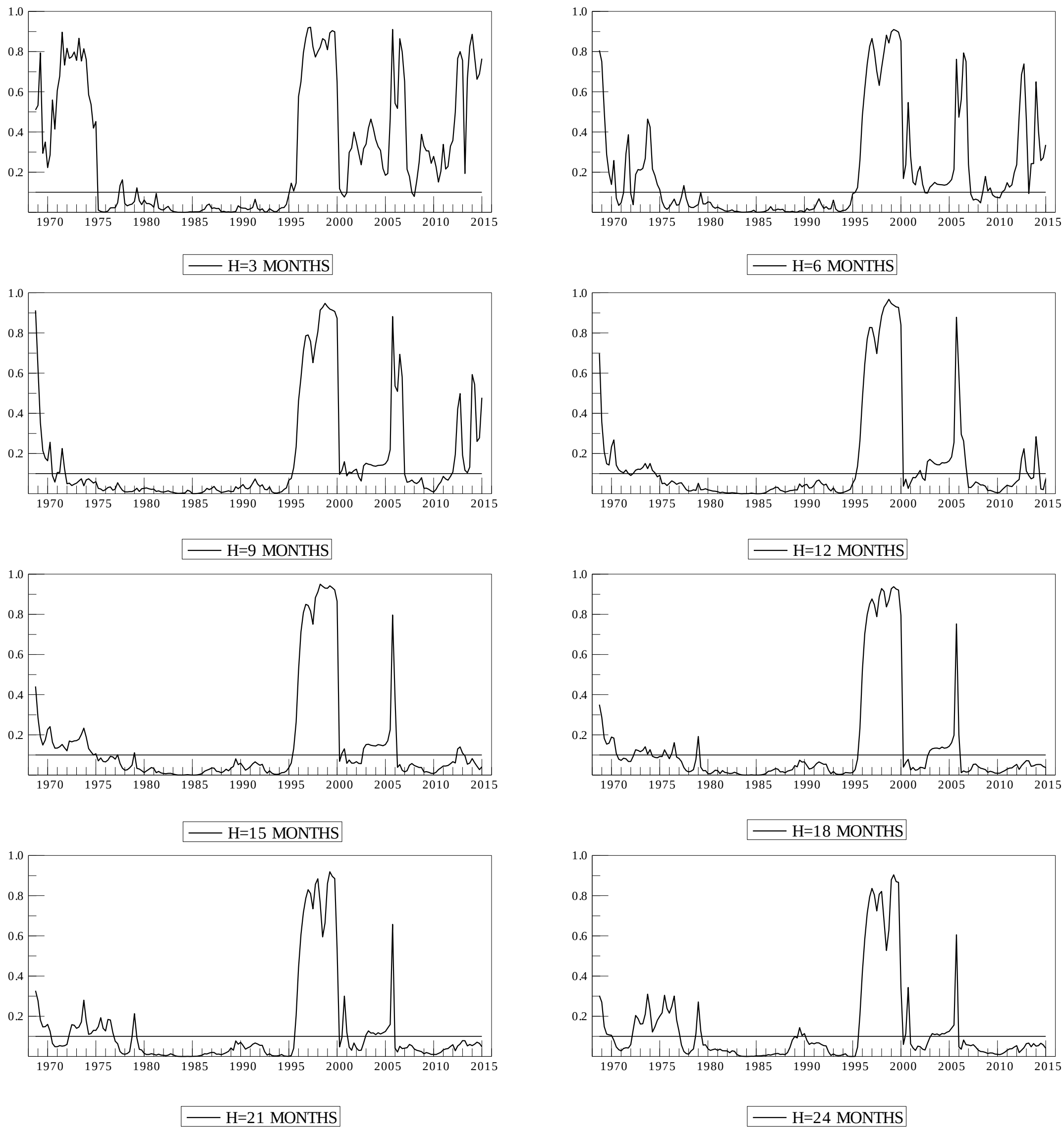

Table 1: OLS whole sample regression results.

Variable:	Constant	$SPREAD_t$	Constant	$SPREAD_t$	ΔGDP_t	$\Delta 3MYIELD_t$	$\Delta INFL_t$	$\Delta M2_t$
Horizon H=3 months								
Estimate	2.4081***	0.4158*	0.3124	0.4366**	0.2932***	0.2782	0.2360	67.7339***
t-value	4.76	1.74	0.57	2.49	3.38	0.38	1.49	3.47
Horizon H=6 months								
Estimate	2.2296***	0.5347**	0.1567	0.5418***	0.2621***	-0.0196	0.1963	74.7667***
t-value	4.36	2.24	0.31	2.89	3.42	-0.04	1.36	4.55
Horizon H=9 months								
Estimate	1.2397***	0.3184**	0.2139	0.3199***	0.1176***	-0.0227	0.0786	39.4294***
t-value	4.42	2.50	0.81	3.10	2.95	-0.07	1.39	4.44
Horizon H=12 months								
Estimate	2.1958***	0.5861***	0.5437	0.5845***	0.1828***	-0.1627	0.0996	64.7876***
t-value	4.52	2.71	1.21	3.24	2.84	-0.38	1.61	4.34
Horizon H=15 months								
Estimate	2.2164***	0.5815***	0.8255*	0.5870***	0.1446**	-0.3439	0.1789***	56.0475***
t-value	4.67	2.80	1.84	3.32	2.53	-0.92	2.57	3.65
Horizon H=18 months								
Estimate	2.2790***	0.5513***	1.0406**	0.5552***	0.1192**	-0.3235	0.1625**	51.7033***
t-value	4.94	2.79	2.31	3.22	2.15	-0.95	2.46	3.38
Horizon H=21 months								
Estimate	2.3432***	0.5222***	1.2610***	0.5292***	0.0959*	-0.2497	0.1688***	46.6124***
t-value	5.25	2.78	2.77	3.17	1.76	-0.74	2.57	3.01
Horizon H=24 months								
Estimate	2.4330***	0.4779***	1.5062***	0.4820***	0.0819	-0.3883	0.1633**	40.2860**
t-value	5.60	2.65	3.26	2.98	1.43	-1.23	2.07	2.52

Note: The left-hand side panel present results from whole sample OLS estimations of the following model: $\Delta GDP_t^H = \beta_0 + \beta_1 \Delta GDP_t + \epsilon_t$. The right-hand side panel present analogous estimations from the following model: $\Delta GDP_t^H = \beta_0 + \beta_1 \Delta GDP_t + \beta_2 \Delta 3MYIELD_t + \beta_3 \Delta INFL_t + \beta_4 \Delta M2_t + \beta_5 SPREAD_t + \epsilon_t$. *,**,*** denotes significance at 10%, 5%, and 1%, respectively, based on HAC standard errors.

Table 2. Tests of the relative predictive performance of the yield spread.

Horizon H (months):	3	6	9	12	15	18	21	24
Case 1: OLS vs HM								
Estimate for MSE	-2.7623***	-2.2543***	-0.5836**	-1.5763**	-1.3299**	-1.2047**	-1.0562**	-0.8820**
t-value	-2.84	-2.76	-2.42	-2.23	-2.11	-2.22	-2.21	-2.05
Estimate for MAE	-0.1854	-0.2649**	-0.1360*	-0.2120	-0.1964	-0.1919	-0.1860	-0.1611
t-value	-1.42	-1.96	-1.72	-1.47	-1.37	-1.36	-1.31	-1.16
Case 2: OLS vs OLS without spread								
Estimate for MSE	-0.6840	-0.6377	-0.2235	-0.6983	-0.7105*	-0.6510*	-0.6151*	-0.5283*
t-value	-1.45	-1.42	-1.38	-1.47	-1.72	-1.76	-1.87	-1.83
Estimate for MAE	-0.0384	-0.0776	-0.0546	-0.0765	-0.1036	-0.0872	-0.0916	-0.0873
t-value	-0.49	-0.85	-0.99	-0.76	-1.08	-0.92	-1.01	-1.04
Case 3: QR vs HM								
Estimate for MSE	-2.9227***	-2.3225***	-0.6147***	-1.4069**	-1.1837**	-1.1176**	-0.9103*	-0.6382
t-value	-3.19	-2.63	-2.62	-2.04	-1.99	-2.16	-1.91	-1.40
Estimate for MAE	-0.2942**	-0.3291**	-0.1759**	-0.2613*	-0.2250*	-0.2216	-0.1989	-0.1439
t-value	-2.36	-2.32	-2.28	-1.86	-1.68	-1.62	-1.41	-1.00
Case 4: QR simple weights vs OLS								
Estimate for MSE	-0.1604	-0.0682	-0.0311	0.1694	0.1462	0.0871	0.1459	0.2438**
t-value	-0.64	-0.39	-0.79	0.88	0.87	0.85	1.61	2.01
Estimate for MAE	-0.1088***	-0.0643**	-0.0399***	-0.0493	-0.0286	-0.0297	-0.0129	0.0172
t-value	-3.01	-2.01	-2.70	-1.39	-0.90	-1.21	-0.55	0.73
Case 5: QR vs QR without spread								
Estimate for MSE	-0.5465	-0.6776	-0.2153	-0.4533	-0.4485	-0.5031	-0.4125	-0.3018
t-value	-1.10	-1.41	-1.39	-1.10	-1.27	-1.53	-1.32	-1.05
Estimate for MAE	-0.0569	-0.1099	-0.0656	-0.0859	-0.0885	-0.0812	-0.0692	-0.0615
t-value	-0.82	-1.15	-1.23	-0.97	-1.04	-0.93	-0.78	-0.71
Case 6: QR-R^2 vs OLS								
Estimate for MSE	-0.2629	-0.1442	-0.0454	0.0943	0.1322	0.0535	0.0793	0.1378
t-value	-1.59	-1.13	-1.23	0.61	0.92	0.52	0.86	1.57
Estimate for MAE	-0.0829***	-0.0602**	-0.0349**	-0.0295	-0.0173	-0.0300	-0.0223	0.0061
t-value	-2.95	-2.30	-2.50	-1.08	-0.65	-1.26	-0.98	0.31
Case 7: QR-R^2 vs QR simple weights								
Estimate for MSE	-0.1025	-0.0760	-0.0143	-0.0751	-0.0141	-0.0336	-0.0666	-0.1060**
t-value	-0.70	-0.91	-0.82	-1.16	-0.33	-1.04	-1.42	-2.51
Estimate for MAE	0.0258	0.0041	0.0050	0.0198	0.0113	-0.0003	-0.0094	-0.0111
t-value	1.58	0.26	0.75	1.34	0.93	-0.03	-0.81	-1.22
Case 8: QR-R^2 (no median) vs OLS								
Estimate for MSE	-0.2629	-0.1548	-0.0484	0.0833	0.1350	0.0531	0.0652	0.1003
t-value	-1.62	-1.29	-1.29	0.56	0.97	0.50	0.67	1.30
Estimate for MAE	-0.0741***	-0.0583**	-0.0333**	-0.0228	-0.0134	-0.0288	-0.0234	0.0023
t-value	-2.75	-2.25	-2.33	-0.88	-0.52	-1.18	-0.99	0.12
Case 9: QR-R^2 (no median) vs QR-R^2								
Estimate for MSE	0.0000	-0.0105	-0.0030	-0.0110	0.0028	-0.0004	-0.0142	-0.0375**
t-value	0.00	-0.45	-0.60	-0.68	0.22	-0.04	-0.96	-2.42
Estimate for MAE	0.0088**	0.0019	0.0016	0.0067*	0.0039	0.0012	-0.0012	-0.0038
t-value	2.04	0.43	0.90	1.73	1.07	0.40	-0.32	-1.07

Note: This table reports estimates of the following model: $RPRED_t = \alpha + \epsilon_t$, where $RPRED_t$ denotes the relative predictive power of one approach versus the other (a difference in squared prediction errors (MSE) or in absolute prediction errors (MAE)). HM stands for the historical mean model and QR stands for quantile regression. t-values are based on HAC standard errors. ***, **, and * indicates significance at 10%, 5%, and 1% level, respectively (all two-sided tests).

Table 3: The relative predictive performance of the yield spread for future economic expansions and recessions.

Horizon (months):	3		6		9		12		15		18		21		24	
Parameter:	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$
Phase:	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession
Case 1: QR vs HM																
Estimate for MSE	-1.6003**	-11.0397***	-0.6467	-10.1428***	-0.1326	-2.3858***	-0.1627	-5.0899***	-0.3105	-3.2980***	-0.4415	-2.5018***	-0.3522	-1.8809**	-0.3019	-1.1358
t-value	-2.04	-3.80	-0.92	-3.79	-0.66	-4.25	-0.26	-3.55	-0.53	-2.88	-0.83	-2.79	-0.68	-2.41	-0.59	-1.49
Estimate for MAE	-0.1662	-1.0800***	-0.1184	-1.3124***	-0.0427	-0.6655***	-0.0381	-0.9218***	-0.0465	-0.6570***	-0.0585	-0.5556***	-0.0504	-0.4571***	-0.0053	-0.3491**
t-value	-1.33	-3.73	-0.85	-4.11	-0.55	-4.74	-0.26	-4.00	-0.30	-3.48	-0.35	-3.20	-0.27	-2.75	-0.03	-2.00
Case 2: QR vs OLS																
Estimate for MSE	-0.4475*	1.6016**	-0.0800	-0.0130	-0.0948***	0.2031*	-0.1272	1.0471**	-0.2180**	1.0280**	-0.2165***	0.7088***	-0.1027*	0.5783***	-0.0131	0.6240**
t-value	-1.86	1.94	-0.45	-0.03	-3.25	1.70	-0.92	1.96	-2.18	2.44	-3.02	3.56	-1.95	3.07	-0.26	2.42
Estimate for MAE	-0.1382***	0.0722	-0.0716**	-0.0301	-0.0607***	0.0365	-0.1048***	0.1150	-0.1014***	0.1476***	-0.0899***	0.0937***	-0.0762***	0.0973***	-0.0325	0.0907**
t-value	-3.46	0.80	-2.09	-0.40	-4.10	1.08	-3.12	1.49	-3.24	2.65	-3.23	2.62	-2.76	3.16	-1.43	2.28
Case 3: QR vs QR without spread																
Estimate for MSE	-0.8056*	1.0440	-0.4554	-1.7147	-0.0269	-0.9075*	0.1124	-2.1276*	0.1777	-1.9647**	0.1666	-1.8746***	0.2121	-1.4988**	0.2479	-1.1153**
t-value	-1.70	0.51	-1.08	-0.93	-0.23	-1.67	0.34	-1.91	0.69	-2.36	0.70	-2.88	0.90	-2.58	1.10	-2.16
Estimate for MAE	-0.0979	0.1947	-0.0675	-0.3081	-0.0043	-0.2908**	0.0001	-0.3406**	0.0237	-0.3602**	0.0658	-0.3821***	0.0679	-0.3075**	0.0959	-0.2944**
t-value	-1.28	0.82	-0.70	-1.18	-0.08	-2.08	0.00	-2.19	0.25	-2.48	0.71	-3.08	0.69	-2.44	1.01	-2.37
Case 4: QR-R^2 vs OLS																
Estimate for MSE	-0.3404**	0.2124	-0.1129	-0.2906	-0.0835***	0.0948	-0.1261	0.7465	-0.1836**	0.8965**	-0.2461***	0.6669***	-0.1964***	0.5589***	-0.0811**	0.4617***
t-value	-2.00	0.36	-0.91	-0.68	-2.84	0.77	-1.30	1.53	-2.22	2.47	-3.77	3.32	-3.98	3.25	-1.99	2.67
Estimate for MAE	-0.0891***	-0.0447	-0.0582**	-0.0693	-0.0471***	0.0101	-0.0688***	0.0868	-0.0772***	0.1278***	-0.0924***	0.0980***	-0.0898***	0.0952***	-0.0429**	0.0786***
t-value	-2.83	-0.62	-2.12	-0.95	-3.34	0.28	-2.68	1.32	-2.94	2.87	-3.69	3.04	-3.62	3.93	-2.09	2.85
Case 5: QR-R^2 vs QR simple weights																
Estimate for MSE	0.1072	-1.3892***	-0.0328	-0.2775	0.0113	-0.1083**	0.0011	-0.3006***	0.0345	-0.1315	-0.0295	-0.0419	-0.0937**	-0.0195	-0.0680**	-0.1623*
t-value	0.79	-3.21	-0.39	-0.98	0.71	-2.26	0.02	-3.01	0.75	-1.48	-1.37	-0.48	-2.48	-0.19	-2.27	-1.76
Estimate for MAE	0.0491***	-0.1169**	0.0134	-0.0392	0.0136*	-0.0264	0.0360**	-0.0282	0.0242	-0.0198	-0.0025	0.0043	-0.0135	-0.0021	-0.0104	-0.0120
t-value	2.88	-2.41	0.80	-0.89	1.95	-1.53	2.21	-1.21	1.59	-1.21	-0.25	0.24	-1.09	-0.09	-0.94	-0.77
Case 6: QR-R^2 (no median) vs OLS																
Estimate for MSE	-0.2848*	-0.1287	-0.1166	-0.3329	-0.0810***	0.0714	-0.1172	0.6769	-0.1681**	0.8688**	-0.2499***	0.6736***	-0.2178***	0.5573***	-0.1061***	0.4057***
t-value	-1.70	-0.22	-1.02	-0.77	-2.58	0.57	-1.27	1.42	-2.04	2.52	-3.84	3.22	-4.05	3.16	-2.56	2.83
Estimate for MAE	-0.0738**	-0.0758	-0.0549**	-0.0744	-0.0438***	0.0053	-0.0578**	0.0806	-0.0702***	0.1240***	-0.0923***	0.1014***	-0.0922***	0.0962***	-0.0475**	0.0759***
t-value	-2.45	-1.03	-2.02	-0.98	-3.00	0.14	-2.33	1.28	-2.68	3.00	-3.69	3.05	-3.68	3.74	-2.24	3.21
Case 7: QR-R^2 (no median) vs QR-R^2																
Estimate for MSE	0.0556**	-0.3412***	-0.0037	-0.0423	0.0025	-0.0234*	0.0088	-0.0696**	0.0154	-0.0277	-0.0039	0.0067	-0.0214**	-0.0015	-0.0250**	-0.0560*
t-value	2.22	-2.79	-0.15	-0.60	0.50	-1.85	0.53	-2.51	1.14	-0.98	-0.62	0.21	-2.03	-0.04	-2.18	-1.65
Estimate for MAE	0.0153***	-0.0311**	0.0033	-0.0050	0.0034*	-0.0048	0.0111***	-0.0062	0.0071	-0.0038	0.0001	0.0034	-0.0024	0.0010	-0.0046	-0.0027
t-value	3.57	-2.01	0.70	-0.49	1.66	-1.17	2.61	-0.95	1.54	-0.69	0.03	0.58	-0.63	0.13	-1.08	-0.42

Note: This table reports estimates of model (8): $RPRED_t = \alpha_0(1 - FR_t) + \alpha_1 FR_t + \epsilon_t$, where $RPRED_t$ denotes the relative predictive power of one approach versus the other (a difference in squared prediction errors (MSE) or in absolute prediction errors (MAE)), and FR_t is a dummy equal to one if there is a recession in the *future* period for which the GDP growth forecast is formed (any quarter of it), and zero otherwise. Recessions are as defined by the NBER. HM stands for the historical mean model and QR stands for quantile regression. t-values are based on HAC standard errors. ***, **, and * indicates significance at 10%, 5%, and 1% level, respectively (all two-sided tests).

Table 4: Robustness checks of the relative predictive performance of the yield spread.

Horizon (months):	3		6		9		12		15		18		21		24	
Parameter:	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\alpha}_0$	$\hat{\alpha}_1$
Phase:	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession	Boom	Recession
Panel A: Sample period prior to Q3:2007																
Estimate for MSE	-0.1388	-0.4669	-0.0311	-0.6242	-0.0565**	-0.0729	-0.0850	0.0717	-0.1573**	0.4414***	-0.2072***	0.4799***	-0.1984***	0.4266***	-0.1060**	0.2976**
t-value	-0.87	-0.74	-0.28	-1.33	-2.27	-1.10	-1.36	0.54	-2.54	3.76	-3.83	2.90	-3.78	2.70	-2.54	2.33
Estimate for MAE	-0.0480*	-0.1314*	-0.0429*	-0.1222	-0.0368***	-0.0313	-0.0456**	0.0078	-0.0623***	0.0790***	-0.0762***	0.0803**	-0.0783***	0.0829***	-0.0474**	0.0621***
t-value	-1.85	-1.76	-1.67	-1.44	-3.27	-1.12	-2.42	0.23	-2.88	3.35	-3.57	2.48	-3.50	3.14	-2.22	2.70
Panel B: Hawkish regime																
Estimate for MSE	-0.2977*	-0.4242	-0.1675*	-0.1106	-0.0651***	0.0666	-0.0986	0.1041	-0.1322**	0.3497***	-0.1893***	0.2657***	-0.1630***	0.2530***	-0.0942*	0.2600***
t-value	-1.93	-0.96	-1.83	-0.68	-2.88	1.08	-1.56	0.57	-2.00	3.28	-3.47	3.08	-3.05	2.58	-1.90	2.97
Estimate for MAE	-0.0703**	-0.1117**	-0.0608**	-0.0056	-0.0387***	0.0317	-0.0499**	0.0199	-0.0676***	0.0847***	-0.0807***	0.0655***	-0.0696***	0.0571***	-0.0542**	0.0726***
t-value	-2.23	-2.29	-2.04	-0.14	-2.90	1.07	-2.25	0.38	-2.83	3.38	-3.49	2.63	-2.92	2.85	-2.14	5.07
Panel C: Dovish regime																
Estimate for MSE	0.2621	-0.4944	0.3282	-0.9867	-0.0329	-0.1845	-0.0462	0.0435	-0.2326*	0.5260***	-0.2622**	0.6941**	-0.3099***	0.6117**	-0.1439**	0.3399
t-value	0.73	-0.50	1.18	-1.35	-0.49	-2.32**	-0.29	0.23	-1.81	2.57	-1.98	2.41	-2.72	2.14	-1.97	1.35
Estimate for MAE	0.0082	-0.1440	0.0043	-0.2044	-0.0317	-0.0817***	-0.0332	-0.0028	-0.0465	0.0738*	-0.0626	0.0951	-0.1056**	0.1104**	-0.0253	0.0503
t-value	0.22	-1.24	0.10	-1.61	-1.55	-2.74	-0.93	-0.07	-0.97	1.84	-1.20	1.59	-2.02	2.33	-0.68	1.07
Panel D: Predictive content of the level and the curvature of the yield curve (beyond that of the spread)																
Estimate for MSE	0.7446	-2.0347	0.8342	-1.5318	0.1375	-0.2437	-0.1495	-0.1889	-0.0900	-0.1130	0.0428	-0.1482	-0.1293	-0.5297	-0.1536	-0.3434
t-value	1.07	-0.99	1.28	-0.95	0.84	-0.63	-0.38	-0.18	-0.30	-0.10	0.14	-0.12	-0.48	-0.43	-0.54	-0.27
Estimate for MAE	0.1297	-0.2902	0.0984	-0.2406	0.0126	-0.1101	-0.1228	-0.0008	-0.0804	-0.0157	-0.0522	-0.0186	-0.0689	-0.0252	-0.0638	-0.0343
t-value	1.40	-1.51	1.09	-0.93	0.23	-0.77	-1.24	0.00	-0.91	-0.07	-0.57	-0.08	-0.74	-0.10	-0.62	-0.12
Panel E: Predictive content of the spread after accounting for the forecasting power of stock market index returns (DJIA)																
Estimate for MSE	-0.1552	-2.7599*	0.1409	-6.0862***	0.1132	-1.8352***	0.4310	-4.4235***	0.2657	-2.7611***	0.2468	-2.2887***	0.2870	-1.6981***	0.3324*	-1.2925**
t-value	-0.44	-1.76	0.35	-2.63	0.99	-3.51	1.49	-4.02	1.06	-3.65	1.06	-4.07	1.34	-3.08	1.93	-2.51
Estimate for MAE	-0.0215	-0.2353**	0.0853	-0.7861***	0.0680	-0.4488***	0.1221	-0.6622***	0.0852	-0.4482***	0.1346*	-0.3593***	0.1254	-0.3445***	0.1471*	-0.2850***
t-value	-0.31	-2.00	0.98	-3.01	1.41	-4.18	1.47	-4.15	1.08	-3.72	1.76	-3.63	1.57	-2.92	1.95	-2.74

Note: This table reports estimates of model (8): $RPRED_t = \alpha_0(1 - FR_t) + \alpha_1 FR_t + \epsilon_t$, where $RPRED_t$ denotes the relative predictive power of one approach versus the other (a difference in squared prediction errors (MSE) or in absolute prediction errors (MAE)), and FR_t is a dummy equal to one if there is a recession in the *future* period for which the GDP growth forecast is formed (any quarter of it), and zero otherwise. Recessions are as defined by the NBER. t-values are based on HAC standard errors. ***, **, and * indicates significance at 10%, 5%, and 1% level, respectively (all two-sided tests).