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Leading indicator properties of US high-yield credit spreads

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Abstract

In this paper we examine the out-of-sample forecast performance of high-yield credit spreads regarding employment and industrial production in the US, using both a point forecast and a probability forecast exercise. Our main findings suggest the use of few factors obtained by pooling information from a number of sector-specific high-yield credit spreads. This can be justified by observing that there is a gain from using a principal components model fitted to high-yield credit spreads compared to the prediction produced by benchmarks, such as an AR, and ARDL models that use either the term spread or the aggregate high-yield spread as exogenous regressor.

Keywords: *Credit spreads, principal components, forecasting.*
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1. Introduction

Previous literature that relates predictions of proxies for real economic activity to financial variables has focused mainly on the information from the government debt market, the corporate debt market and the stock market[1]. The prominent financial leading indicators for policy makers are the inverse of the slope of the nominal yield curve (e.g., term spread, defined as the difference between the 10-year Treasury bill rate and the 3-month Treasury bill rate), the paper-bill spread (defined as the difference between yields on the commercial paper and the Treasury bill) and the return on stock market indices.

It has been documented that these financial indicators have lost considerable forecasting power in recent years. More specifically, a worsening in the term spread predictive content regarding the US recession in the early 1990s has been documented by Haubrich and Dombrosky (1996) and by Dotsey (1998). More recently, Stock and Watson (2003b) find that although the term spread did turn negative in advance of the 2001 recession, this inversion, however, was small by historical standards. Furthermore, the study of Friedman and Kuttner (1998) shows a poor forecasting performance of the paper-bill spread. Finally, Fama (1981) and Harvey (1989) show that the linkage between stock market indicators and output growth is unclear, while Stock and Watson (1989, 1999) and Estrella and Mishkin (1998) find evidence of little marginal forecasting content in stock prices.

In this paper, in line with Gertler and Lown (1999), Mody and Taylor (2003, 2004) and Stock and Watson (2003b), we explore the leading indicator properties of high-yield corporate bond spreads regarding US employment and industrial production

[1] See Stock and Watson (2003a) for a comprehensive survey of the literature.

growth. The high-yield corporate bond spread is defined as the difference between yields on high-yield corporate bonds and the 10-year Treasury bill[2]. Gertler and Lown (1999), and Mody and Taylor (2004) present evidence of strong in-sample predictive power of the aggregate high-yield credit spread. Mody and Taylor (2003), and Stock and Watson (2003b) find good out-of-sample forecasting performance of the aggregate high-yield corporate spread relative to the term spread and to an AR, respectively.

This paper contributes to the small but fast growing literature on the leading indicator properties of credit spreads in the following two ways.

First, we are interested in assessing whether it is better to forecast economic activity using the aggregate high-yield spread (as previously done in this literature) or there is forecasting gain from pooling the information in a number of sector-specific high-yield spreads. For this purpose, we use the principal component method advocated by Stock and Watson (1998, 2002) to extract a handful of factors from a relatively large number of sector specific high-yield credit spreads documented in the Appendix. These factors are then used to produce point forecasts for the US real economic activity by using the h-step-ahead projection method. Other related applications of h-step-ahead forecast using factors extracted from a large dataset include those by Stock and Watson (2002) and by Forni, Hallin, Lippi and Reichlin (2003) and Artis, Banerjee and Marcellino (2005), among others.

Second, we are not only interested in point forecast accuracy (as the existing literature using credit spreads has done), but we also focus on the forecast accuracy regarding the 10% worst outcomes in US real economic activity (which includes the 2001 recession with its macroeconomic context) using Monte Carlo simulation. Our

[2] The high-yield credit spread data is obtained from Lehman Brothers via DATASTREAM.

probability forecast exercise is related to the work by Anderson and Vahid (2001), Garratt et al. (2003) and Galvão (2006), which obtain probability forecasts of recessions using quarterly GDP data. Our study differs from these studies in that it uses monthly employment and industrial production data, and therefore, it is hard to argue that the obtained probability forecasts would correspond to recessions using this data. Instead, our focus is on forecasting bad outcomes in the two indicators of economic activity. Furthermore, in the aforementioned studies, the probability forecasts are obtained from a dynamic forecasting exercise, while we produce probability forecasts using the *h*-step-ahead projection method.

Our main findings suggest that the use of a principal component model fitted to a number of US sector-specific high-yield credit spreads seems to improve upon various benchmark models in forecasting (out-of-sample) the US industrial production and employment growth. This can be explained by interpreting the common component to sector-specific high-yield corporate spreads (obtained through the principal component method) as a good proxy of the "systemic" default risk, enhancing the forecasting capabilities of the model relative to different benchmarks under investigation.

The outline of the paper is as follows. In Section 2, we describe the direct forecasting method through different ARDL model specifications, including the one based upon principal components. Furthermore, in Section 2 we also describe the point forecast exercise. Section 3 shows how to obtain probability forecasts by stochastic simulation and how to evaluate their accuracy. Section 4 presents the empirical analysis. Finally, Section 5 summarises the main findings of this paper and concludes them.

2. Empirical Methodology

For the purpose of forecasting, we use the *h*-step-ahead projection based upon the following autoregressive distributed lag (ARDL) model:

$$y_{t+h} = \alpha_h + \beta_h(L)x_t + \gamma_h(L)y_t + \varepsilon_{t+h}, \quad \text{for } h = 3, 6, 9 \text{ and } 12 \tag{1}$$

where $y_{t+h} \equiv \frac{1200}{h}[\ln(z_{t+h}) - \ln(z_t)]$ is an *h*-step ahead (scalar) variable to be forecasted, where z_t measures the levels of employment or industrial production. Therefore, the l.h.s of equation (1) measures annualised growth rates. The r.h.s. variables in (1) are current and past values of both the dependent variable and of x_t, which is exogenous predictor. Moreover, $\beta_h(L)$ and $\gamma_h(L)$ are lag polynomials (of order p and s, respectively) for the predictor variable and for the dependent variable, respectively. The subscript *h* denotes the dependence of the projection on the forecast horizon. As Stock and Watson (2003a) point out the inclusion of y_t with its past values is motivated by questioning whether x_t has predictive content for y_{t+h} above and beyond that contained in y_t (and its past values) since y_t is expected to be serial correlated.

As for the predictor x_t, we choose to work on either the term spread or on a single credit spread, or on *r* common factors to credit spreads. The latter are obtained by estimating the following factor model fitted to the standardised *N* dimensional vector x_t of credit spreads:

$$x_t = \Lambda F_t + e_t \tag{2}$$

where Λ is an $N \times r$ matrix of factor loadings and F_t describes the r dimensional vector of static factors. The factors estimates are obtained by principal component analysis. Recently, (see Stock and Watson, 1998, 2002, among the others), the extraction of factors (by minimising the noise to signal ratio) from large dataset has proven to be successful in forecasting output and prices.[3] The r principal components F_t^* are given by $T^{1/2}W$, where the matrix W is $T \times r$ and it has, on the columns, the eigenvectors corresponding to the r largest eigenvalues of the sample covariance matrix. The latter, given the $T \times N$ (standardised) panel X of credit spreads, is measured by XX'.

To produce h-step-ahead forecasts through the principal components we follow Stock and Watson and we split the analysis in two stages. In the first stage, we retrieve the principal components F_t^*. In the second stage, we run an OLS regression of y_{t+h} on a constant, on the principal components F_t^* and on y_t (and its lags). The resulting coefficient estimates are then able to produce the forecast of y_{t+h} as $\hat{\alpha}_h + \hat{\beta}_{h,0} F_t^* + \hat{\gamma}_h(L) y_t$. The out-of-sample forecasts are obtained using recursive OLS. We run the regressions for t = 1993:m8,…,2000:m2-h, then the values of the regressors at t = 2000:m2 are used to forecast $y_{2000:m2+h}$. All parameters, factors, and so forth are then re-estimated, information criteria are re-computed, and models were selected using data from 1993:m8 through 2000:m3, and forecasts from these models are then computed for $y_{2000:m3+h}$.The final out-of-sample forecast is made in 2005:m4-h for

[3] It is important to point out that there are also alternative methods to the estimation of latent factors from a large dimensional dataset as the one proposed by Forni et al. (2005) and also the one put forward by Kapetanios and Marcellino (2003).

$y_{2005:m4}$. Therefore the forecast evaluation period is made of the last 60 observations in the sample.

The dimension of the static factor space, *r*, and the order of the lag polynomial, $\gamma_h(L)$, are selected using the recursive BIC criterion as in Stock and Watson (2002). The maximum order for *r* and for the lag polynomial $\gamma_h(L)$ is set to 6 and 12, respectively.

To produce *h*-step-ahead forecasts through an ARDL model with either the term spread or the aggregate high-yield credit spread or sector specific high yield credit spreads (obtained from Lehman Brothers) as predictors x_t, we use the estimated regression, $\hat{\alpha}_h + \hat{\beta}_h(L)x_t + \hat{\gamma}_h(L)y_t$. The lag orders *p* and *s* for the polynomials in (1) are selected using the recursive BIC criterion assuming $p = s = 12$ as the maximum lag length.

2.1 Point Forecast Evaluation Criteria

In this section we describe how to evaluate the accuracy of point forecasts. First, we consider the Mean Square Forecast Error (MSFE), given by:

$$MSFE = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2-h} (y_{t+h} - \hat{y}_{t+h|h})^2 \tag{3}$$

where T_1 and $T_2{-}h$ are respectively the first and last dates over which the out-of-sample forecast is computed (so that forecasts are made for dates $t = T_1 + h, \ldots, T_2$. If the MSFE of the candidate model computed relative to the MSFE of the benchmark is less than 1, then the former performs better than the latter. In order to determine whether this difference is statistically significant, we report the modified Diebold-Mariano test put forward by Harvey et al. (1997) which provides a small sample correction of the original Diebold-Mariano (1995) test for equal predictive ability.

Second, we consider an encompassing test based upon the following regression:

$$y_{t+h} = \alpha + (1-\beta) y^{a}_{t+h} + \beta y^{b}_{t+h} + u_{t+h} \tag{4}$$

where y^{a}_{t+h} is the candidate h-step-ahead forecast and y^{b}_{t+h} is the benchmark h-step-ahead autoregressive forecast. Given Eq. (4) we test two null hypotheses. Specifically, if $\beta = 0$, then the candidate model forecast encompasses the benchmark; if $\beta = 1$, then the benchmark forecast encompasses the candidate. The two tests are implemented by checking the statistical significance of the slope coefficient in the following two regressions[4]:

$$(y_{t+h} - y^{a}_{t+h}) = \alpha + \beta (y^{b}_{t+h} - y^{a}_{t+h}) + u_{t+h} \tag{5a}$$

$$(y_{t+h} - y^{b}_{t+h}) = \alpha + \beta (y^{a}_{t+h} - y^{b}_{t+h}) + u_{t+h} \tag{5b}$$

Note that we include the intercept α to account for a forecast bias.

Finally, we compare the sign of the forecasts with that of the actual realizations. We report the Success Ratio, which is the fraction of times the sign of the actual values are correctly predicted.

[4] The t-ratios are computed by using a heteroscedastic autocorrelation robust (HAC) robust covariance estimator (see Newey-West, 1987).

3. Probability Forecasts

The point forecast exercise described in the previous section is useful for model selection, but it does not address directly the interests of forecast users. Policy makers are typically more interested in forecasts of future turning points or prediction of bad outcomes in the series. In this section, we compare models according to their ability to out-of-sample forecast bad outcomes related to 10% worst outcomes observed during the forecast evaluation period (which, as specified above includes the last 60 observations in the sample, and, in particular, the 2001 recession with its macroeconomic context) in the real economic activity. The distressful event is observed whenever the annualised growth rate (over h months) is less or equal than $thres_h$, which is the sixth smallest observed annualised growth rate (over h months) in the forecast evaluation period. For this purpose we use probability forecasts obtained by Monte Carlo simulation. In subsection 3.1 we explain the artificial generation of scenarios through stochastic simulation using the Dynamic Factor, ARDL and AR models. Then, in subsection 3.2 we describe the indicators used to assess the accuracy of probability forecasts.

3.1 Stochastic Simulation of Models

In order to compute, through the ARDL model with principal components of high yield of credit spreads as exogenous regressors, the probability forecast of the worst outcomes (given by 10% of the observations in the forecast evaluation period) for the annualised growth rate in employment (or industrial production) we proceed as follows. First, we condition on the information set dated 2000:m2, and we obtain the coefficients estimates α_h^{PC}, β_h^{PC} and $\gamma_h^{PC}(L)$ and we produce the following forecasts under a specific scenario *m*:

$$y_{2000:m2+h}^{m} = \alpha_h^{PC} + \beta_h^{PC}\left\lfloor F_{2000:m2} + std(F_{1993m8:2000m2})\xi^{m}\right\rfloor + \gamma_h^{PC}(L)y_{2000:m2} + std(\varepsilon_{1993m8:2000m2}^{PC})\varepsilon_{t+h}^{m} \quad (6)$$

for h = 3, 6, 9 and 12

where ξ_{t+h}^{m} and ε_{t+h}^{m} are the realisations for the *r* dimensional and for the one dimensional vectors of common and idiosyncratic shocks, respectively, using draws from a standardised Gaussian distribution. In order to get the un-standardised shocks realisation, we multiply the standardised shocks realisation by the corresponding standard deviations. Specifically, the idiosyncratic shock standard deviation is proxied by $std(\left(\varepsilon_{1993m8:2000m2}^{PC}\right)$, which is the sample standard deviation of the estimated residuals from the regressions given in (1), using the principal components as exogenous regressors and the information set dated 2000:m2. The common shocks standard deviations are those obtained by computing $std(F_{1993:m8;2000:2})$, which are the sample standard deviation of the *r* principal components using the information set dated 2000:m2. The number of replications (draws) is 10000 and this gives 10000 forecasts corresponding to each scenario. We assign score one if $y_{2000m2+h}^{m}$ is less than or equal to $thres_h$ defined above. We repeat the exercise for each of the 10000 draws, and finally, we divide the sum of the scored ones by the total number of scenarios. This number gives the probability forecast (conditional on the information set dated 2000:m2) regarding the 10% worst outcomes for the annualised growth rate over *h* months in employment (or industrial production). Then, we add one observation, re-estimate the coefficients and repeat the same exercise to obtain the probability forecast regarding the 10% worst outcome for each of the aforementioned annualised growth rates, conditioning on the information set at 2000:m3. We carry on until we produce the 10000 scenarios using the out-of-sample point forecast made in 2005:m4-*h* for $y_{2005:m4}$.

As for the ARDL model with current and past values of each single high yield spread as exogenous regressors, the projection conditional on scenario *m* and on the information set dated 2000:m2 is obtained by focussing on:

$$\begin{aligned} y^{m}_{2000:m2+h} &= \alpha^{ARDL}_{h} + \beta^{ARDL}_{h}(L)x_{2000:m2} + \gamma^{ARDL}_{h}(L)y_{2000:m2} + \\ &std(\varepsilon^{ARDL}_{1993m8:2000m2})\varepsilon^{m}_{t+h} \end{aligned} \tag{7}$$

where $std(\varepsilon^{ARDL}_{1993m8:2000m2})$ is the sample standard deviation of the estimated residuals from the regressions given in (1), using current and past values of each single high yield spread as exogenous regressors and the information set dated 2000:m2. The projection conditional on scenario *m* and on the information set dated 2000:m2 obtained through the *AR* are given by:

$$y^{m}_{2000:m2+h} = \alpha^{AR}_{h} + \gamma^{AR}_{h}(L)y_{2000:m2} + std(\varepsilon^{AR}_{1993m8:2000m2})\varepsilon^{m}_{t+h} \tag{8}$$

where $std(\varepsilon^{ARDL}_{1993m8:2000m2})$ is the sample standard deviation of the estimated residuals from the regressions given in (1), using only lagged values of the dependent variable and the information set dated 2000:m2.

By adding one observation to the information set, re-estimating coefficients and by repeating the same exercise we obtain the probability forecasts using the aforementioned benchmark models.

3.2 Assessing Accuracy of Probability Forecasts

To evaluate these probabilities, we employ the quadratic probability score (QPS) and the log probability score (LPS) (Diebold and Rudebusch, 1989, see also Galvao, 2006). Let P_t be the probability forecast conditional on the information set at time t, regarding a bad outcome affecting, within the forecast horizon, employment growth (or industrial production growth). The variable R_t is binary and it takes value 1 if the bad outcome occurs in the actual data within the forecast horizon, and it is equal to 0 otherwise. Then the QPS and LPS are written as:

$$QPS = \frac{1}{T}\sum_{t=1}^{T} 2(P_t - R_t)^2$$

$$LPS = -\frac{1}{T}\sum_{t=1}^{T}[(1-R_t)\ln(1-P_t) + R_t \ln(P_t)]$$

The *QPS* score ranges from 0 to 2, with 0 being perfect accuracy. The second one ranges from 0 to ∞. *LPS* and *QPS* imply different loss functions with large mistakes more heavily penalized under LPS.

4. Empirical Analysis

4.1 Data

The analysis was carried out using monthly data for the period 1993:m8-2005:m4. The reason we consider this period is due to the availability of the high-yield corporate bond data. Furthermore, the high-yield corporate bond market was relatively small until the 1980s. Since the early 1990s the market has broadened and is considered reasonably liquid with issue sizes of over $100 million. Contrary to the previous studies (see above) on forecasting US real economic activity through credit spreads, we do not consider only the high yield credit spread, which, in our study, is given by the Lehman aggregate high yield credit spread. We also consider 45 sector-specific high-yield corporate bonds which are actively traded in the high yield corporate bond market and they are obtained from Lehman Brothers (via DATASTREAM). The series are listed in the Appendix. All the series including data on the term spread, the US non-farm payroll employment (SA) and industrial production (SA) were obtained from DATASTREAM. Figures 1-2 graph the employment and industrial production series as used in the estimated models, while Figure 3 plots the Lehman aggregate high-yield spread and the term spread[5]. As seen, the aggregate high-yield spread increased substantially during the 1999-2003 period, a period which includes the 2001 recession with its macroeconomic context. On the other hand, the term structure turned negative only in late 2000 and after that became again positive.

4.2 Empirical evidence

The point forecast results for the employment growth are reported in detail in Tables 1a-1d and those for the industrial production growth are in Tables 2a-2d. In these tables we report the 3-, 6-, 9-, and 12-month-ahead forecasts for the period 2000:m5-2005:m4. We evaluate the forecasting performance of the models by setting first the AR as the

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[5] For space considerations, the graphs as well as the results for the individual high-yield corporate bonds are not reported but are available from the authors upon request.

benchmark (first panel of the tables) and then the term spread (TS) (second panel of tables). A careful inspection suggests the following results.

First, the principal components model for credit spreads seems to improve upon the AR model based predictions. In particular, as for the employment growth, the 3-, 6-, 9-, and 12-month-ahead MSFE values indicate about 30%, 34%, 30% and 20% improvement, respectively. For industrial production growth, the corresponding figures are about 19%, 20%, 4% for 3-, 6-, and 9-month-ahead horizons, whereas the 12-month-ahead MSFE value shows no improvement. Furthermore, the (modified) Diebold-Mariano (DM) test suggests that, for employment, the forecast improvements (upon either an AR or a terms spread set as benchmark) are statistically significant mainly for the 3- and 6-month horizons. As for the industrial production, there is no statistically significant improvement neither upon the AR or the TS model for the different horizons. Furthermore, apart from few exceptions the PC model forecast encompasses the two benchmarks whereas the latter does not forecast encompass the former. As for the Success Ratio, the results show that the PC model provides more accurate predictions than the AR and TS (the only exception is the 12-month horizon where the best is the AR).

Second, the forecasting performance of the term spread is of particular interest, given its prominence in the literature. As seen before**,** the term spread forecasts (at the different horizons) are poor relative to those of the PC model in terms of most criteria and for both industrial production and employment growth (the only notable exception are the long term horizon prediction for industrial production). What is more surprising, however, is that the term spread does not perform well even when compared to the AR. For instance, even though its MSFEs are generally lower than those associated with AR, the improvement is small and only in very few cases statistically significant (according to the DM test). Moreover, according to the Success Ratio, only the 12-month-ahead forecast of employment, and the 3-, and 6-month-ahead forecasts of industrial production seem more accurate than those of the AR. According to the encompassing test, although the term spread forecast encompasses the AR (without the latter forecast encompassing the former) for industrial production, this seems not the case for employment. These findings are consistent with the recent empirical studies reviewed in the introduction, which found a deterioration of the forecasting performance of the term spread as a predictor of output growth in the US since 1985.

Third, the aggregate high-yield corporate spread in the majority of cases shows good leading indicator properties relative to the AR and to the term spread. This result is in line with Stock and Watson (2003b) and Mody and Taylor (2003, 2004). Interestingly, the PC model still has the best forecasting performance. For instance, it delivers substantially lower relative MSFEs than those corresponding to the aggregate high-yield spread at all horizons.

Notice that the (modified) DM and the forecast encompassing tests can be used to compare non-nested models. This is the case when we compare the point forecast performance of the PC model versus the term spread. As for the comparison of the PC model versus the AR, we observe that the evidence is mixed since the recursive BIC criterion used for model selection suggests the choice of a benchmark AR, which in some periods is nested but in other periods is not nested in the various PC models[6]. We argue that, even though, we should interpret with caution the DM and encompassing tests results (when the focus is on the comparison of the the PC model versus the term

[6] See also Stock and Watson (2003b) for a similar argument. Results for the lag selection based on BIC are available upon request.

spread), the relative MSFEs and the directional changes support the use of the principal component model.

It is also worth mentioning that we found a number of sector-specific high-yield spreads (such as automotive, consumer cyclical, capital goods, finance, insurance, packaging, supermarkets, conglomerates) that perform well and very often improve upon the AR and upon the term spread. However, their forecast performance is not superior to the one associated with the PC model[7].

We now turn our focus on the accuracy of probability forecasts. Tables 3a-3b report the QPS and LPS scores to evaluate the accuracy of the probability forecasts regarding the 10% worst outcomes in employment and industrial production.

Overall, the results are consistent with the point forecast findings. For instance, from the graphs it can be seen that the PC model in the majority of cases and in particular for the 3- and 6-month-ahead horizons improves the probability fit compared to the AR and the other candidates. Moreover, the tables show that for employment the 3-, 6-, and 9-month-ahead QPS values obtained from the PC model are about 38%, 21% and 2% (respectively) lower than those of the AR. For industrial production, however, the PC model appears more accurate than the AR only for the 3-month-ahead horizon. In terms of LPS, for employment the PC model improves the accuracy of forecasts at all horizons (corresponding figures are about 55%, 77%, 50% and 14% lower than those of the AR). For industrial production, the LPS values of the PC model are lower than the AR by about 64%, 53% and 44% for the 3-, 6-, and 9-month-ahead horizons.

Also, there are gains (particularly for the 3-, and 6-month-ahead horizons) when the PC model is compared to the term spread. For example, for employment the QPS

[7] For space considerations, the results are not reported but are available from the authors upon request.

obtained from PC are 40% and 16% lower than those of the term spread at the 3- and 6-month-ahead horizons, respectively. In terms of LPS, the improvement is 62%, 70%, 48% and 10% for the 3-, 6-, 9, and 12-month-ahead horizons. As for industrial production, the picture is similar, that is, the findings favour again the PC model mostly for 3-, and 6-month-ahead horizons.

Furthermore, the PC model fares better when compared to the aggregate high-yield credit spread model. As seen, it is more accurate in predicting the 10% worst outcomes in the majority of cases. In this light, it is believed that the present work contributes to the literature by suggesting that it is better to build forecasting models for economic activity based on a small number of factors that effectively summarise large amount of information about the high-yield corporate bond market.

Finally, even though some sector-specific high-yield spreads forecasts are more accurate than those corresponding to the AR and even the term spread, overall the PC model is the best in predicting the 10% worst outcomes in the series[8].

The empirical findings can be interpreted as follows. First, the high predictive content in high-yield credit spreads can be explained only if the latter are largely determined by default risk. It is important to observe that, the assumption of the spreads measuring default risk has been questioned by the study of Elton et al. (2001), among the others. Only recently, Huang and Huang (2003) have reached robust conclusions regarding the default risk component of credit spreads. In particular, the authors (op. cit.) find that the default risk accounts for a small fraction of the observed corporate-Treasure yield spread only for investment grade bonds, whereas it accounts for a much higher fraction of yield spreads for high-yield corporate bonds. Second, in order to

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[8] The results are not reported but are available from the authors upon request.

predict the future state of the economy, we need to retrieve the "systemic" default risk component in the spreads. Our empirical findings suggest that it is not the aggregate high-yield, but the common component to a number of sector-specific high-yield corporate spreads (obtained via the principal components method), that could be a good proxy of "systemic" default risk. Consequently, this is expected to enhance the forecasting capabilities of the principal components model relative to the different benchmarks, including the one using the aggregate high-yield spread as a predictor.

5. Conclusions

The focus of this paper is on investigating (out-of-sample) the leading indicator properties of high-yield corporate spreads regarding the level of real economic activity. Our empirical analysis leads to the following conclusions. In line with Gertler and Lown (1999) and Mody and Taylor (2003, 2004) we find that high-yield credit spread spreads have a good predicting performance regarding US industrial production and employment growth. Our work, however, goes one step further and suggests that rather using the aggregate high-yield spread (as in the previous studies aforementioned), forecasting can be improved if one uses few factors extracted from a number of disaggregated high-yield credit spreads. As shown, there is an improvement in the forecasting performance of the principal components model compared to the one corresponding to AR models or to ARDL models where the exogenous regressor is either the term spread or the individual credit spread. Also, we focus on the prediction of average, using a point forecast analysis, but also of "adverse" scenarios, computing probability forecasts regarding the 10% worst outcomes affecting US real economic activity. The probability forecast results show that there are gains from using the principal components model particularly for the 3-, and 6-month-ahead horizons. Finally, the superior forecasting performance of the principal components model can be explained by recognizing that the factor extraction is obtained by averaging out noisy idiosyncratic information contaminating the empirical observed sector-specific credit spreads. Consequently, the principal components method allows to obtain a "systemic" default risk proxy whose predictive performance (regarding the future real economic activity in the US) compares favorably relative to a number of benchmarks (including the high yield aggregate credit spread).

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APPENDIX

HIGH YIELD CORPARATE BONDS	Code
1. HIGH YIELD: *AEROSPACE* - RED. YIELD	LHHYAER(RY)
2. HIGH YIELD: *AUTOMOTIVE* - RED. YIELD	LHHYAUT(RY)
3. HIGH YIELD: *BUILDING MATS.* - RED. YIELD	LHHYBDM(RY)
4. HIGH YIELD: *BANKING* - RED. YIELD	LHHYBNK(RY)
5. HIGH YIELD: *CNSM.CYCLICAL* - RED. YIELD	LHHYCCY(RY)
6. HIGH YIELD: *CAPITAL GOODS* - RED. YIELD	LHHYCGS(RY)
7. HIGH YIELD: *CHEMICALS* - RED. YIELD	LHHYCHM(RY)
8. HIGH YIELD: *CNSTR.MACHINERY* - RED. YIELD	LHHYCNM(RY)
9. HIGH YIELD: *CNSM.PRODUCTS* - RED. YIELD	LHHYCNP(RY)
10. HIGH YIELD: *ELECTRIC* - RED. YIELD	LHHYELE(RY)
11. HIGH YIELD: *ENERGY* - RED. YIELD	LHHYENE(RY)
12. HIGH YIELD: *ENTERTAINMENT* - RED. YIELD	LHHYENT(RY)
13. HIGH YIELD: *FINANCE* - RED. YIELD	LHHYFIN(RY)
14. HIGH YIELD: *INSURANCE* - RED. YIELD	LHHYINS(RY)
15. HIGH YIELD: *MEDIA* – CABLE	LHHYMDC(RY)
16. HIGH YIELD: *METALS* - RED. YIELD	LHHYMET(RY)
17. HIGH YIELD: *MEDIA* – NONCABLE	LHHYMNC(RY)
18. HIGH YIELD: *NATURAL GAS* - RED. YIELD	LHHYNGS(RY)
19. HIGH YIELD: *OIL FIELD SRVS.* - RED. YIELD	LHHYOFS(RY)
20. HIGH YIELD: *PAPER* - RED. YIELD	LHHYPAP(RY)
21. HIGH YIELD: *PACKAGING* - RED. YIELD	LHHYPCK(RY)
22. HIGH YIELD: *PHARMACEUTICALS* - RED. YIELD	LHHYPHM(RY)
23. HIGH YIELD: *RAILROADS* - RED. YIELD	LHHYRAL(RY)
24. HIGH YIELD: *RETAILERS* - RED. YIELD	LHHYRET(RY)
25. HIGH YIELD: *SERVICES* - RED. YIELD	LHHYSVC(RY)
26. HIGH YIELD: *SUPERMARKETS* - RED. YIELD	LHHYSMK(RY)
27. HIGH YIELD: *TECHNOLOGY* - RED. YIELD	LHHYTEC(RY)
28. HIGH YIELD: *TELECOMM.* - RED. YIELD	LHHYTEL(RY)
29. HIGH YIELD: *TRANSPORTATION* - RED. YIELD	LHHYTRN(RY)
30. HIGH YIELD: *TEXTILE* - RED. YIELD	LHHYTXT(RY)
31. HIGH YIELD: *UTILITY* - RED. YIELD	LHHYUTL(RY)
32. HIGH YIELD: *AIRLINES* - RED. YIELD	LHHYAIR(RY)
33. HIGH YIELD: *CONGLOMERATES* - RED. YIELD	LHHYCOG(RY)
34. HIGH YIELD: *CNSM.NONCYCLICAL* - RED. YIELD	LHHYCNC(RY)
35. HIGH YIELD: *ENVIROMENTAL* - RED. YIELD	LHHYENV(RY)
36. HIGH YIELD: *INDEP.ENERGY* - RED. YIELD	LHHYIEN(RY)
37. HIGH YIELD: *FINANCE COMP.* - RED. YIELD	LHHYFCM(RY)
38. HIGH YIELD: *GAMING* - RED. YIELD	LHHYGAM(RY)
39. HIGH YIELD: *HEALTH CARE* - RED. YIELD	LHHYHTC(RY)
40. HIGH YIELD: *HOME CNSTR.* - RED. YIELD	LHHYHCN(RY)
41. HIGH YIELD: *INDUSTRIAL* - RED. YIELD	LHHYIND(RY)
42. HIGH YIELD: *LODGING* - RED. YIELD	LHHYLOG(RY)
43. HIGH YIELD: *NAT.GAS - DISTR.*	LHHYNGD(RY)
44. HIGH YIELD: *NAT.GAS – PIPELINE*	LHHYNGP(RY)
45. HIGH YIELD: *REFINING* - RED. YIELD	LHHYREF(RY)

Notes: Datasource is DATASTREAM.

Table 1a. Out-of-sample forecasting results: Employment, 3-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.700		
Candidate models				
HY (Principal components)	0.703	0.816	0.030	-1.450 [4.736]
HY (Aggregate)	0.859	0.783	0.050	-1.580 [4.424]
Term spread	1.030	0.650	0.612	0.597 [0.559]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.650		
Candidate models				
HY (Dynamic factor)	0.687	0.850	0.035	-0.487 [5.666]
HY (Aggregate)	0.833	0.783	0.035	-2.008 [4.584]

Notes: Forecasting period 2000:m5-2005:m4; *Relative MSFE* is the mean square forecast error (MSFE) of the candidate model relative to the MSFE for the benchmark model; the *Success Ratio* gives the number of correct forecasts over the total number of observations; ***DM*** is the p-value of modified DM test (see Harvey et al, 1997) to tests the null hypothesis that the MSFE of the candidate model does not improve over the MSFE obtained from benchmark.*Encompassing* tests the null hypothesis that the candidate model forecast encompasses the benchmark (first figure is *t*-ratio of slope coefficient in regression 5a) and the benchmark forecast encompasses the candidate model (second figure (in brackets) is *t*-ratio of slope coefficient in regression 5b).

Table 1b: Out-of-sample forecasting results: Employment, 6-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.650		
Candidate models				
HY (Principal components)	0.673	0.733	0.070	-3.039 [7.635]
HY (Aggregate)	0.874	0.650	0.029	-1.296 [2.625]
Term spread	0.980	0.650	0.383	-0.907 [1.675]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.650		
Candidate models				
HY (Principal components)	0.665	0.733	0.048	-1.878 [11.81]
HY (Aggregate)	0.891	0.650	0.165	-0.827 [2.138]

Notes: See the notes to Table 1a.

Table 1c: Out-of-sample forecasting results: Employment, 9-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.616		
Candidate models				
HY (Principal components)	0.752	0.700	0.162	-1.101 [4.259]
HY (Aggregate)	0.912	0.600	0.224	-0.558 [1.771]
Term spread	0.945	0.616	0.006	-3.304 [4.358]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.616		
Candidate models				
HY (Principal components)	0.710	0.700	0.086	-2.827 [19.43]
HY (Aggregate)	0.964	0.600	0.386	0.483 [0.714]

Notes: See the notes to Table 1a.

Table 1d: Out-of-sample forecasting results: Employment, 12-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.466		
Candidate models				
HY (Principal components)	0.795	0.650	0.215	-0.283 [3.329]
HY (Aggregate)	0.949	0.483	0.350	0.153 [1.126]
Term spread	0.951	0.550	0.054	-3.347 [4.510]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.550		
Candidate models				
HY (Principal components)	0.800	0.650	0.153	-2.440 [24.29]
HY (Aggregate)	0.997	0.483	0.495	1.802 [-0.457]

Notes: See the notes to Table 1a.

Table 2a: Out-of-sample forecasting results: Industrial production, 3-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.500		
Candidate models				
HY (Principal components)	0.789	0.700	0.124	0.831 [5.729]
HY (Aggregate)	0.856	0.600	0.061	-0.969 [3.510]
Term spread	0.953	0.566	0.293	-1.443 [2.769]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.566		
Candidate models				
HY (Principal components)	0.837	0.700	0.122	0.627 [3.806]
HY (Aggregate)	0.898	0.600	0.210	0.849 [1.939]

Notes: See the notes to Table 1a.

Table 2b: Out-of-sample forecasting results: Industrial production, 6-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.416		
Candidate models				
HY (Principal components)	0.783	0.583	0.163	0.262 [5.087]
HY (Aggregate)	0.916	0.450	0.219	-0.195 [1.687]
Term spread	0.948	0.466	0.294	-1.468 [2.428]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.466		
Candidate models				
HY (Principal components)	0.828	0.583	0.159	0.253[3.276]
HY (Aggregate)	0.966	0.450	0.387	1.444 [0.699]

Notes: See the notes to Table 1a.

Table 2c: Out-of-sample forecasting results: Industrial production, 9-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.450		
Candidate models				
HY (Principal components)	0.986	0.516	0.466	2.166 [1.013]
HY (Aggregate)	1.014	0.466	0.528	1.400 [0.270]
Term spread	0.964	0.450	0.312	-1.047 [2.093]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.450		
Candidate models				
HY (Principal components)	0.957	0.516	0.422	2.192 [1.975]
HY (Aggregate)	1.052	0.466	0.607	2.747 [-0.572]

Notes: See the notes to Table 1a.

Table 2d: Out-of-sample forecasting results: Industrial production, 12-step-ahead horizon

	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
AR	1.000	0.633		
Candidate models				
HY (Principal components)	1.031	0.466	0.581	3.702 [0.857]
HY (Aggregate)	1.079	0.383	0.616	3.401 [-1.069]
Term spread	0.967	0.566	0.160	-1.618 [2.880]
	Relative MSFE	*Success Ratio*	*DM*	*Encompassing*
Benchmark model				
Term spread	1.000	0.566		
Candidate models				
HY (Principal components)	1.065	0.450	0.667	3.560 [-0.269]
HY (Aggregate)	1.115	0.383	0.661	5.496 [-2.524]

Notes: See the notes to Table 1a.

Table 3a: Measures of out-of-sample performance of the probability forecast regarding the 10% worst outcomes in employment

	QPS				*LPS*			
	3-step	6-step	9-step	12-step	3-step	6-step	9-step	12-step
AR	0.301	0.321	0.284	0.290	0.661	1.346	1.513	1.525
HY (Principal components)	0.187	0.253	0.278	0.309	0.297	0.445	0.771	1.319
HY (Aggregate)	0.280	0.279	0.244	0.277	0.602	1.179	1.463	1.514
Term spread	0.309	0.301	0.253	0.251	0.773	1.449	1.468	1.470

Notes: Forecasting period 2000:m5-2005:m4; *QPS* is the quadratic probability score; *LPS* is the log probability score; 10% worst outcomes for employment are defined in section 3.1.

Table 3b: Measures of out-of-sample performance of the probability forecast regarding the 10% worst outcomes in industrial production

	QPS				*LPS*			
	3-step	6-step	9-step	12-step	3-step	6-step	9-step	12-step
AR	0.200	0.219	0.213	0.204	0.588	1.204	1.426	1.408
HY (Principal components)	0.167	0.235	0.269	0.302	0.275	0.572	0.944	1.549
HY (Aggregate)	0.185	0.241	0.252	0.250	0.456	1.017	1.323	1.468
Term spread	0.183	0.206	0.206	0.202	0.484	1.143	1.332	1.400

Notes: See the notes to Table 3a.

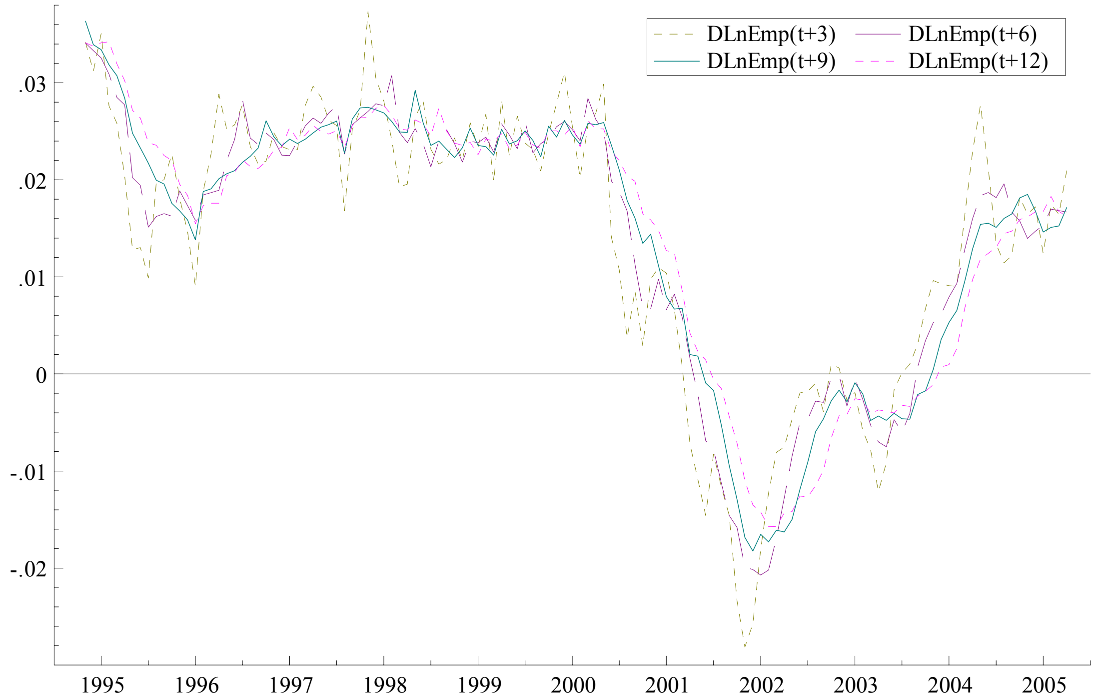

Fig. 1. Three-month difference *DLnEmp* (t+3), six-month difference *DLnEmp*(t+6), nine-month difference *DLnEmp*(t+9) and twelve-month difference *DLnEmp*(t+12) of the logarithm of US non-farm payroll employment (SA).

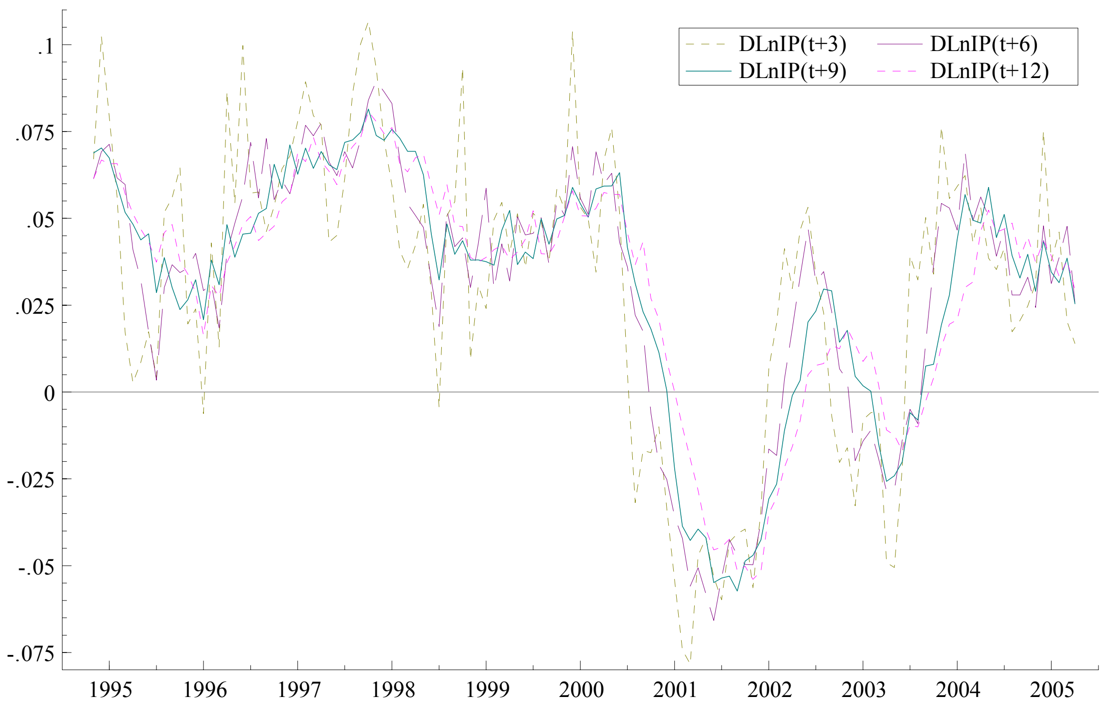

Fig. 2. Three-month difference *DLnIP*(t+3), six-month difference *DLnIP*(t+6), nine-month difference *DLnIP*(t+9) and twelve-month difference *DLnIP*(t+12) of the logarithm of US industrial production (SA).

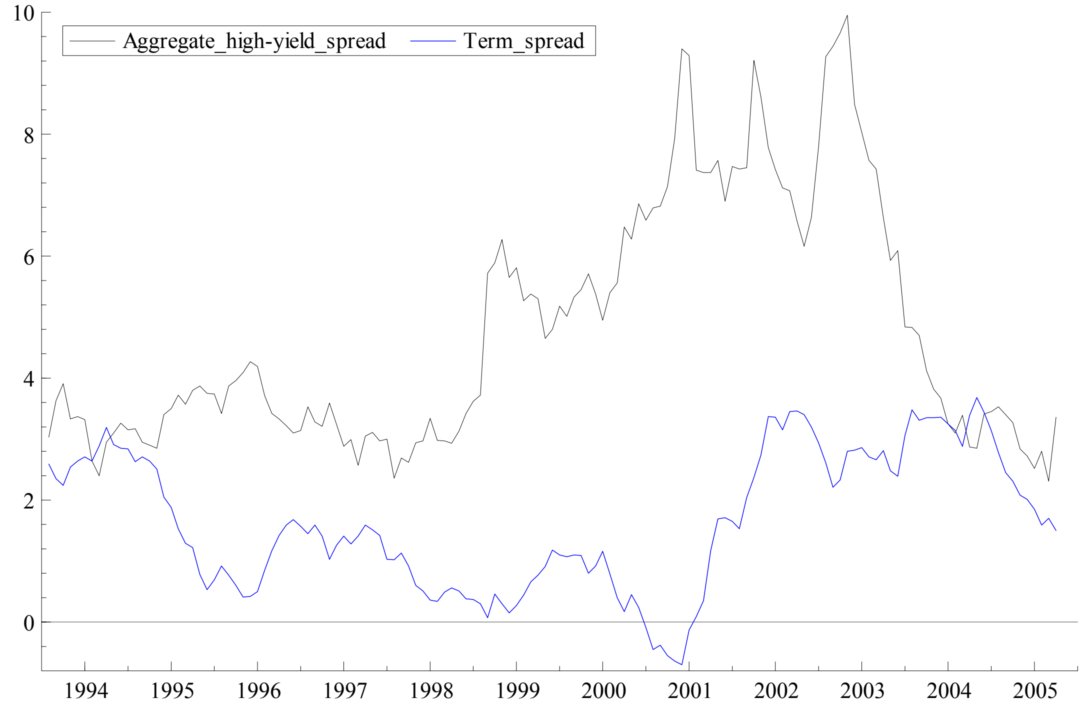

Fig. 3. Aggregate high-yield credit spread and term spread.

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