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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 real-time and revised data on employment and industrial production in the US. We evaluate models 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, especially for employment, 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. Moreover, forecasts based on real-time data are generally comparable to forecasts based on revised data.

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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 for the last two recessions. Finally, Fama (1981) and Harvey (1988) argue 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. 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 model, respectively.

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

First, we are interested in assessing whether using the aggregate high-yield credit spread (as done previously in the literature) delivers better forecasts than using instead a pool of several 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 number of sector-specific high-yield credit spreads. These factors are then used to produce point forecasts for measures of real economic activity by using the h-step-ahead projection method.[2]

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 probability that the employment (or industrial production) annual growth is negative using Monte Carlo simulation. Our probability forecast exercise is related to the work by Anderson and Vahid (2001), Garratt et al. (2003) and Galvão (2006). While these studies obtain probability forecasts of recessions using quarterly GDP data, we retrieve probability forecast of annualised negative growth in employment (or industrial production) using data observed at monthly frequencies. 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.

Third, unlike the previous papers we evaluate forecasts using both revised and real-time data, which has become increasingly popular in the literature on macroeconomics and business cycle fluctuations (Croushore, 2001; Croushore and Stark, 2003; Orphanides and Van Norden, 2002, among others).

Our results are summarized as follows. We find that using information from a pool of several sector-specific high-yield credit spreads improves the out-of-sample forecasts for US activity. This result applies more to employment than to industrial production for which the forecasts are not always the best. We also find that there are no systematic differences between forecast results obtained from real-time and revised data.

The outline of the paper is as follows. Section 2 presents the forecasting models as well as the discussion of point and probability forecasts. In Section 3, we describe methods of evaluation of forecasts. Section 4 discusses the data and presents the results. 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

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[2] Other related applications of h-step-ahead forecast using factors extracted from large datasets include those by Stock and Watson (2002) and by Forni, Hallin, Lippi and Reichlin (2003) and Artis, Banerjee

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

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 an 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 the aggregate 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.[3]

To produce h-step-ahead forecasts through principal components we follow Stock and Watson and split the analysis in two stages. In the first stage, we retrieve the

and Marcellino (2005), among others.

[3] See Stock and Watson (1998, 2002), among others. Alternative methods to the estimation of common factors are the one proposed by Forni et al. (2005) and the one put forward by Kapetanios and Marcellino (2003).

principal components, $\hat{F}_t$. In the second stage, we run an OLS regression of y_{t+h} on a constant, on the principal components $\hat{F}_t$ and on y_t (and its lags), which produce the forecast of y_{t+h}. 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 as predictors x_t, we use the estimated OLS regression, $\hat{\alpha}_h + \hat{\beta}_h(L)x_t + \hat{\gamma}_h(L)y_t$.

Policy makers are often more interested in forecasts of future business cycles turning points than in point forecasts as described above. Therefore, we also compare models according to their ability to out-of-sample forecast the probability that the employment (or industrial production) annual growth is negative. For this purpose we use probability forecasts obtained by Monte Carlo simulation as follows.

To produce *h*-step-ahead probability forecasts through principal components we run the following regression under a specific scenario

$$y_{t+h/t} = \alpha_h + \beta_h(L)\left[F_t + \sigma^F_{t+h/t}\xi_{t+h/t}\right] + \gamma_h(L)y_t + \sigma_{t+h/t}\varepsilon_{t+h/t}, \qquad \text{for } h = 3, 6, 9 \text{ and } 12 \qquad (6)$$

where $\xi_{t+h/t}$ and $\varepsilon_{t+h/t}$ are the realisations for the *r* dimensional and one dimensional vectors of common and idiosyncratic shocks, respectively, using draws from a standardised Gaussian distribution. In order to get the un-standardised shock realisations, we multiply the standardised shock realisations by their corresponding sample standard deviations, $\hat{\sigma}^F_{t+h/t}$ and $\hat{\sigma}_{t+h/t}$ for the common and idiosyncratic shocks, respectively. The number of replications (draws) is 10000 and this gives 10000 forecasts corresponding to each scenario. We assign score one if $y_{t+h/t}$ is negative and zero otherwise. 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 would give the probability forecast that the employment (or industrial production) annual growth is negative. Then, we add one observation, re-estimate the model and repeat the same exercise, and so forth.

As for the ARDL model with current and past values of either the term spread or the aggregate or a single credit spread as exogenous regressors, the projection conditional on a specific scenario is obtained by the following regression

$$y_{t+h/t} = \alpha_h + \beta_h(L)x_t + \gamma_h(L)y_t + \sigma_{t+h/t}\varepsilon_{t+h/t}, \qquad \text{for } h = 3, 6, 9 \text{ and } 12 \tag{7}$$

where $\hat{\sigma}_{t+h/t}$ is sample standard deviation of the idiosyncratic shock. In a similar fashion, the projection for the *AR* is obtained by

$$y_{t+h/t} = \alpha_h + \gamma_h(L)y_t + \sigma_{t+h/t}\varepsilon_{t+h/t}, \qquad \text{for } h = 3, 6, 9 \text{ and } 12 \tag{8}$$

where $\hat{\sigma}_{t+h/t}$ is sample standard deviation of the idiosyncratic shock from a regression that includes only lagged values of the dependent variable.

3. Forecast Evaluation Criteria

We evaluate the point forecasts according to the following criteria. First, we consider the Mean Square Forecast Error (MSFE), given by

$$MSFE = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} (y_{t+h} - \hat{y}_{t+h})^2 \tag{9}$$

where T_1 and $T_2 - h$ are respectively the first and last dates over which the out-of-sample forecast is computed. 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

$$y_{t+h} = \alpha + (1-\beta)\hat{y}^{a}_{t+h} + \beta\hat{y}^{b}_{t+h} + u_{t+h} \tag{10}$$

where $\hat{y}^{a}_{t+h}$ is the candidate h-step-ahead forecast and $\hat{y}^{b}_{t+h}$ is the benchmark h-step-ahead forecast obtained from the *AR* or ARDL model with the term spread as exogenous regressor. Given Eq. (10) 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]:

$$(y_{t+h} - \hat{y}^{a}_{t+h}) = \alpha + \beta(\hat{y}^{b}_{t+h} - \hat{y}^{a}_{t+h}) + u_{t+h} \tag{11a}$$

$$(y_{t+h} - \hat{y}^{b}_{t+h}) = \alpha + \beta(\hat{y}^{a}_{t+h} - \hat{y}^{b}_{t+h}) + u_{t+h} \tag{11b}$$

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

Third, we compare the sign of the forecasts with that of the actual realizations. This can be particularly relevant for economic activity forecasts as policy makers may be more interested in accurate forecasts of the direction in which, for example, the economy is moving than in the exact magnitude of the change. For this purpose, we report the so-called Success Ratio (the fraction of times the sign of the actual values is correctly predicted). We also calculate the Pesaran and Timmermann (1992) nonparametric test (PT) for comparison between the direction of change results, with the null hypothesis that each set of forecasts and the actual values are independently distributed.

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

To evaluate the probability forecasts, we employ the quadratic probability score (QPS) and the log probability score (LPS) (Diebold and Rudebusch, 1989, see also Galvao, 2006). Let P_{t+h} be the probability forecast that the employment (industrial production) annual growth is negative within the forecast horizon. The variable R_{t+h} 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,

$$QPS = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} 2(P_{t+h} - R_{t+h})^2$$

$$LPS = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} [(1 - R_{t+h}) \ln(1 - P_{t+h}) + R_{t+h} \ln(P_{t+h})]$$

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. 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. The sample contains the aggregate as well as 45 sector-specific high-yield corporate bonds, which are actively traded in the high-yield corporate bond market. The sector-specific series are listed in the Appendix. All 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 (revised data) as used in the estimated models, while Figure 3 plots the 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. On the other hand, the term structure turned negative only in late 2000 and after that became again positive.

4.2 Empirical evidence

The out-of-sample forecasts are obtained using recursive OLS, where all parameters and the factors are estimated recursively. We first run the regressions over 1993:m8-2000:m5-*h*, and then produce out-of-sample forecasts for the period from 2000:m5 to 2005:m4. The dimension of the factor space and the order of the lag polynomials are selected using the recursive BIC criterion as in Stock and Watson (2002). The maximum orders for the factors and for the lag polynomials are set to 6 and 12, respectively. We followed this procedure using both revised data (latest vintage available) and real-time data (for which data revisions are possible as we roll forward each month using the next vintage associated with that month). In calculating forecast errors, we use the latest vintage (the revised data) to represent the true values of the observed series as in Croushore (2001).[6]

The point forecast results for the employment growth are reported in detail in Tables 1-2 and those for the industrial production (IP) growth are in Tables 3-4. In these

[5] For space considerations, the graphs as well as the results for the individual high-yield corporate bonds are not shown but are available from the authors upon request.
[6] We also experimented with real-time data as alternative choices for the true values of the observed series with the results remaining qualitatively similar.

tables we report the 3-, 6- and 12-month-ahead forecasts for the revised data (first panel) as well as the corresponding forecasts for the real-time data (second panel).[7] We evaluate the forecasting performance of the models by setting first the AR as the benchmark (Tables 1 and 3 for employment and IP, respectively) and then the term spread (TS) (Tables 2 and 4 for employment and IP, respectively). The results are summarized as follows.

First, the principal components model (PC) for credit spreads seems to improve upon the AR and TS model based predictions for both revised and real-time data. In particular, as for the employment growth, the 3-, 6-, and 12-month-ahead MSFE values indicate about 30%, 33% and 20% improvement, respectively. For industrial production growth, using revised data the corresponding figures are about 20-27% for the 3-, and 6-month-ahead horizons, whereas the 12-month-ahead MSFE value shows no improvement. Moreover, for employment using real-time data seems to yield lower relative MFSE than using revised data. The opposite is true in the case of industrial production. Furthermore, the (modified) Diebold-Mariano (DM) test suggests that, for employment the forecast improvements (upon either the AR or the term spread set as benchmark) are statistically significant for the 3-month horizon, and to less extent for the 6-month horizon, whereas for the 12-month horizon the improvement is not statistically significant. This holds for both revised and real-time data. As for the industrial production, there is no statistically significant improvement neither upon the AR nor the TS model for the different horizons.

Furthermore, apart from few exceptions the PC model forecast encompasses the benchmarks whereas the latter two do not forecast encompass the former. Again, this

[7] Results for 9-step-ahead forecasts are similar to those of 12-month-ahead forecasts. For space considerations we do not report these results, but these are available from the authors upon request.

result is robust to the data set being used. As for the ability of the models to predict directional changes, the Pesaran-Timmermann (PT) test and the Success Ratio, in general, show that the PC model provides more accurate predictions than the AR and TS (a notable exception is the case of industrial production for 12-month horizon). Also, using real-time data generally produces less accurate prediction of directional changes than using revised data.

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 is the 12-month horizon prediction for industrial production). This seems to hold across the two data sets being used (real-time vs. revised data). What is more surprising, however, is that the term spread hardly bits the AR model. For instance, even though the term spread MSFEs are generally lower than those of the AR, the improvement is small and only in 2 out of 12 cases statistically significant at 10% level (see the DM test results for the 12-month horizon in the case of employment). Based on the directional change criteria, the Success Ratio favours the term spread over the AR model, while the PT test yields mixed results. According to the encompassing test, the term spread generally forecast encompasses the AR (without the latter forecast encompassing the former) for industrial production. However, this does not apply to the employment results. 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 yields good leading indicator properties relative to the benchmarks. 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, the PC model delivers lower relative MSFEs than those corresponding to the aggregate high-yield spread, and it also shows a superior forecasting performance according to the other criteria used.

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 performance of the PC model versus the term spread. As for the comparison of the PC model versus the AR, in practice 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.[8] 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 candidate models with the AR), our findings regarding the relative MSFEs and the directional change criteria support the use of the principal component model.

It is also worth mentioning that for both revised and real-time data 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 two benchmarks. However, their forecast performance is not superior to the one associated with the PC model.[9]

We now turn our focus on the accuracy of probability forecasts. Table 5 (Table 6) report the QPS and LPS scores to evaluate the accuracy of forecasting the probability

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

that the employment (industrial production) annual growth is negative over the 3-, 6-, and 12-month-ahead horizons.[10]

As seen, using real-time data yields higher QPS and LPS values than using revised data. Nevertheless, regarding the performance of the models, the results are generally consistent with the point forecast results. In most cases and in particular for employment the PC model improves the probability fit compared to the other candidates and the benchmarks. For instance, the tables show that for revised employment data the 3-, 6-, and 12-month-ahead QPS values obtained from the PC model are about 40%, 30% and 25% (respectively) lower than those of the AR. The corresponding figures for real-time employment data are 45%, 26% and 20%. On the other hand, for industrial production using QPS values the PC model appears more accurate than the AR mainly for the 3-, and 6-month-ahead horizons. In terms of LPS, for revised employment data the PC model substantially improves the accuracy of forecasts at all horizons (the corresponding figures are about 22%, 55%, and 22% lower than those of the AR). Similar results are obtained for real-time employment data. However, for industrial production the LPS values of the PC model are generally higher than those of the AR.

Also, there are forecasting gains (particularly for employment) when the PC model is compared to the term spread. For example, for revised employment data (real-time employment data) the QPS values obtained from PC are 45%, 34% and 23% (48%, 30% and 18%) lower than those of the term spread at the 3-, 6- and 12-month-ahead horizons, respectively. In terms of LPS, similar results are obtained for both data sets and different horizons. Regarding industrial production, the results now are favourable to the PC model. For instance, in terms of QPS the PC bits the term spread model at the

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

3- and 6-month-ahead horizons while for the 12-step horizon the term spread has the best forecasting performance (both for revised and real-time data). On the other hand, using LPS the PC model admittedly delivers poor forecasts.

Furthermore, the PC model fares better when compared to the aggregate high-yield credit spread model. As seen, in the majority of cases and particularly for employment, it is more accurate in delivering probability forecasts than the aggregate high-yield spread. In this light, it is believed that the present work contributes to the literature by suggesting that there are gains in building forecasting models for economic activity based on a small number of factors that effectively summarise a large amount of information about the high-yield corporate bond market.

As in the case of point forecasts, even though the probability forecasts of some sector-specific high-yield spreads are more accurate than those corresponding to the AR and TS models, overall the PC model appears superior in forecasting the probability that the employment (or industrial production) annual growth rate is negative.[11]

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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[10] As in the case of point forecasts, results for 9-step-ahead probability forecasts are similar to those of 12-month-ahead horizon. For space considerations we do not report these results.

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 the leading indicator properties of high-yield corporate spreads regarding real-time and revised data on employment and industrial production in the US. We compare the high-yield spreads with other leading indicators (e.g., term spread) based on their ability to produce out-of-sample point and probability forecasts. Our empirical analysis leads to the following conclusions. Our point forecasts shows that high-yield credit spreads have a good predicting performance, which is in line with Gertler and Lown (1999) and Mody and Taylor (2003, 2004). However, our work goes one step further and suggests that rather than using the aggregate high-yield spread (as in the previous studies), forecasting can be improved, especially when the focus is on the employment growth, if one uses just a few factors extracted from a number of disaggregated high-yield credit spreads. The probability forecasts confirm this finding, particularly for the 3-, and 6-month-ahead horizons and for employment data. We also find that there are no systematic differences between forecast results obtained from real-time and revised data.

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[11] The results are not reported but are available upon request.

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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Table 1. Out-of-sample forecasting results for employment. Benchmark *AR*.

	Benchmark model	Candidate models		
	AR	HY (Principal components)	HY (Aggregate)	Term spread
Revised data				
3-step-ahead horizon				
Relative MSFE	1.000	0.703	0.859	1.030
Success Ratio	0.700	0.816	0.783	0.650
PT	2.883	4.813	4.278	2.001
DM		0.030	0.050	0.612
Encompassing		-1.450 [4.736]	-1.580 [4.424]	0.597 [0.559]
6-step-ahead horizon				
Relative MSFE	1.000	0.673	0.874	0.980
Success Ratio	0.666	0.733	0.650	0.650
PT	2.543	3.617	2.272	2.300
DM		0.070	0.029	0.383
Encompassing		-3.039 [7.635]	-1.296 [2.625]	-0.907 [1.675]
12-step-ahead horizon				
Relative MSFE	1.000	0.795	0.949	0.951
Success Ratio	0.466	0.650	0.483	0.550
PT	-0.657	2.321	-0.316	0.753
DM		0.215	0.350	0.054
Encompassing		-0.283 [3.329]	0.153 [1.126]	-3.347 [4.510]
Real-time data				
3-step-ahead horizon				
Relative MSFE	1.000	0.695	0.801	1.012
Success Ratio	0.600	0.816	0.683	0.633
PT	1.114	4.802	2.572	1.663
DM		0.011	0.005	0.565
Encompassing		-1.003 [4.430]	-2.673 [5.636]	0.556 [0.123]
6-step-ahead horizon				
Relative MSFE	1.000	0.672	0.825	0.955
Success Ratio	0.583	0.666	0.583	0.633
PT	1.194	2.654	1.187	2.122
DM		0.074	0.082	0.211
Encompassing		-2.006 [6.108]	-1.788 [3.385]	-1.524 [2.219]
12-step-ahead horizon				
Relative MSFE	1.000	0.754	0.932	0.946
Success Ratio	0.466	0.633	0.466	0.500
PT	-0.657	2.064	-0.593	-0.177
DM		0.171	0.336	0.036
Encompassing		-1.029 [4.134]	0.184 [1.244]	-2.796 [3.595]

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; the PT presents values of the statistic of Pesaran and Timmermann (1992) to test the null hypothesis that each set of forecasts and the actual values are independently distributed (this statistic is asymptotically normal); *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 11a) and the benchmark forecast encompasses the candidate model (second figure (in brackets) is *t*-ratio of slope coefficient in regression 11b).

Table 2. Out-of-sample forecasting results for employment. Benchmark Term Spread.

	Benchmark model	Candidate models	
	Term spread	HY (Principal components)	HY (Aggregate)
Revised data			
3-step-ahead horizon			
Relative MSFE	1.000	0.687	0.833
Success Ratio	0.650	0.816	0.783
PT	2.001	4.813	4.278
DM		0.035	0.035
Encompassing		-0.487 [5.666]	-2.008 [4.458]
6-step-ahead horizon			
Relative MSFE	1.000	0.665	0.891
Success Ratio	0.650	0.733	0.650
PT	2.300	3.617	2.272
DM		0.048	0.165
Encompassing		-1.878 [11.81]	-0.827 [2.138]
12-step-ahead horizon			
Relative MSFE	1.000	0.800	0.997
Success Ratio	0.550	0.650	0.483
PT	0.753	2.321	-0.316
DM		0.153	0.495
Encompassing		-2.440 [24.29]	1.802 [-0.457]
Real-time data			
3-step-ahead horizon			
Relative MSFE	1.000	0.687	0.791
Success Ratio	0.633	0.816	0.683
PT	1.663	4.802	2.572
DM		0.048	0.013
Encompassing		-1.009 [4.461]	-2.291 [4.327]
6-step-ahead horizon			
Relative MSFE	1.000	0.704	0.864
Success Ratio	0.633	0.666	0.583
PT	2.122	2.654	1.187
DM		0.063	0.087
Encompassing		-1.335 [4.791]	-1.208 [2.529]
12-step-ahead horizon			
Relative MSFE	1.000	0.797	0.985
Success Ratio	0.500	0.633	0.466
PT	-0.177	2.064	-0.593
DM		0.213	0.463
Encompassing		-0.374 [3.346]	1.637 [-0.367]

Notes: See notes to Table 1.

Table 3. Out-of-sample forecasting results for industrial production. Benchmark *AR*.

	Benchmark model	Candidate models		
	AR	HY (Principal components)	HY (Aggregate)	Term spread
Revised data				
3-step-ahead horizon				
Relative MSFE	1.000	0.789	0.856	0.953
Success Ratio	0.533	0.700	0.600	0.566
PT	0.149	3.053	1.448	0.749
DM		0.124	0.061	0.293
Encompassing		0.831 [5.729]	-0.969 [3.510]	-1.443 [2.769]
6-step-ahead horizon				
Relative MSFE	1.000	0.783	0.916	0.948
Success Ratio	0.383	0.583	0.450	0.466
PT	-2.525	1.090	-0.969	-1.273
DM		0.163	0.219	0.294
Encompassing		0.262 [5.087]	-0.195 [1.687]	-1.468 [2.428]
12-step-ahead horizon				
Relative MSFE	1.000	1.031	1.079	0.967
Success Ratio	0.583	0.466	0.383	0.566
PT	-0.473	-1.517	-2.444	-1.576
DM		0.581	0.616	0.160
Encompassing		3.702 [0.857]	3.401 [-1.069]	-1.618 [2.880]
Real-time data				
3-step-ahead horizon				
Relative MSFE	1.000	0.868	0.904	0.962
Success Ratio	0.533	0.600	0.600	0.516
PT	0.149	1.415	1.415	-0.259
DM		0.156	0.123	0.344
Encompassing		1.460 [4.822]	0.332 [3.169]	-0.163 [1.531]
6-step-ahead horizon				
Relative MSFE	1.000	0.883	0.980	0.940
Success Ratio	0.366	0.533	0.466	0.433
PT	-2.907	0.252	-0.829	-2.331
DM		0.268	0.417	0.261
Encompassing		1.516 [3.749]	1.079 [0.738]	-1.442 [2.983]
12-step-ahead horizon				
Relative MSFE	1.000	1.148	1.133	0.952
Success Ratio	0.566	0.483	0.366	0.633
PT	-0.148	-1.101	-2.469	1.041
DM		-	0.739	0.116
Encompassing		4.120 [0.057]	3.930 [-1.431]	-1.173 [2.993]

Notes: See notes to Table 1; (-) denotes the test cannot be calculated.

Table 4. Out-of-sample forecasting results for industrial production. Benchmark Term Spread.

	Benchmark model	Candidate models	
	Term spread	HY (Principal components)	HY (Aggregate)
Revised data			
3-step-ahead horizon			
Relative MSFE	1.000	0.837	0.898
Success Ratio	0.566	0.700	0.600
PT	0.749	3.053	1.448
DM		0.122	0.210
Encompassing		0.627 [3.806]	0.849 [1.939]
6-step-ahead horizon			
Relative MSFE	1.000	0.828	0.966
Success Ratio	0.466	0.583	0.450
PT	-1.273	1.090	-0.969
DM		0.159	0.387
Encompassing		0.253 [3.276]	1.444 [0.699]
12-step-ahead horizon			
Relative MSFE	1.000	1.065	1.115
Success Ratio	0.566	0.466	0.383
PT	-1.576	-1.517	-2.444
DM		0.667	0.661
Encompassing		3.560 [-0.269]	5.496 [-2.524]
Real-time data			
3-step-ahead horizon			
Relative MSFE	1.000	0.901	0.940
Success Ratio	0.516	0.600	0.600
PT	-0.259	1.415	1.415
DM		0.188	0.302
Encompassing		1.657 [3.050]	1.237 [1.186]
6-step-ahead horizon			
Relative MSFE	1.000	0.939	1.041
Success Ratio	0.433	0.533	0.466
PT	-2.331	0.252	-0.829
DM		0.347	0.647
Encompassing		1.813 [1.739]	2.237 [-0.258]
12-step-ahead horizon			
Relative MSFE	1.000	1.206	1.190
Success Ratio	0.633	0.483	0.366
PT	1.041	-1.101	-2.469
DM		-	0.803
Encompassing		4.516 [-1.333]	5.833 [-2.797]

Notes: See notes to Table 1; (-) denotes the test cannot be calculated.

Table 5: Measures of out-of-sample performance of the probability that the employment annual growth rate is negative

	QPS			*LPS*		
	3-step	6-step	12-step	3-step	6-step	12-step
Revised data						
AR	0.393	0.517	0.838	0.696	1.402	3.570
HY (Principal components)	0.232	0.357	0.633	0.542	0.630	2.789
HY (Aggregate)	0.301	0.514	0.892	0.453	1.109	3.471
Term spread	0.424	0.541	0.817	0.737	1.435	3.418
Real-time data						
AR	0.524	0.606	0.868	0.872	1.612	3.674
HY (Principal components)	0.290	0.446	0.702	0.546	0.767	3.276
HY (Aggregate)	0.387	0.629	0.911	0.562	1.218	3.554
Term spread	0.558	0.637	0.860	0.948	1.763	3.646

Notes: Forecasting period 2000:m5-2005:m4; *QPS* is the quadratic probability score; *LPS* is the log probability score.

Table 6: Measures of out-of-sample performance of the probability that the industrial production annual growth rate is negative

	QPS			*LPS*		
	3-step	6-step	12-step	3-step	6-step	12-step
Revised data						
AR	0.713	0.936	0.698	1.099	1.753	2.517
HY (Principal components)	0.488	0.717	0.977	1.010	2.456	3.661
HY (Aggregate)	0.546	0.856	0.981	0.817	1.544	2.599
Term spread	0.674	0.876	0.696	1.062	1.733	2.617
Real-time data						
AR	0.776	0.981	0.725	1.255	1.929	3.265
HY (Principal components)	0.632	0.806	0.989	1.287	3.041	4.165
HY (Aggregate)	0.642	0.929	1.032	1.044	2.013	3.784
Term spread	0.766	0.930	0.703	1.176	1.906	3.180

Notes: See notes to Table 5.

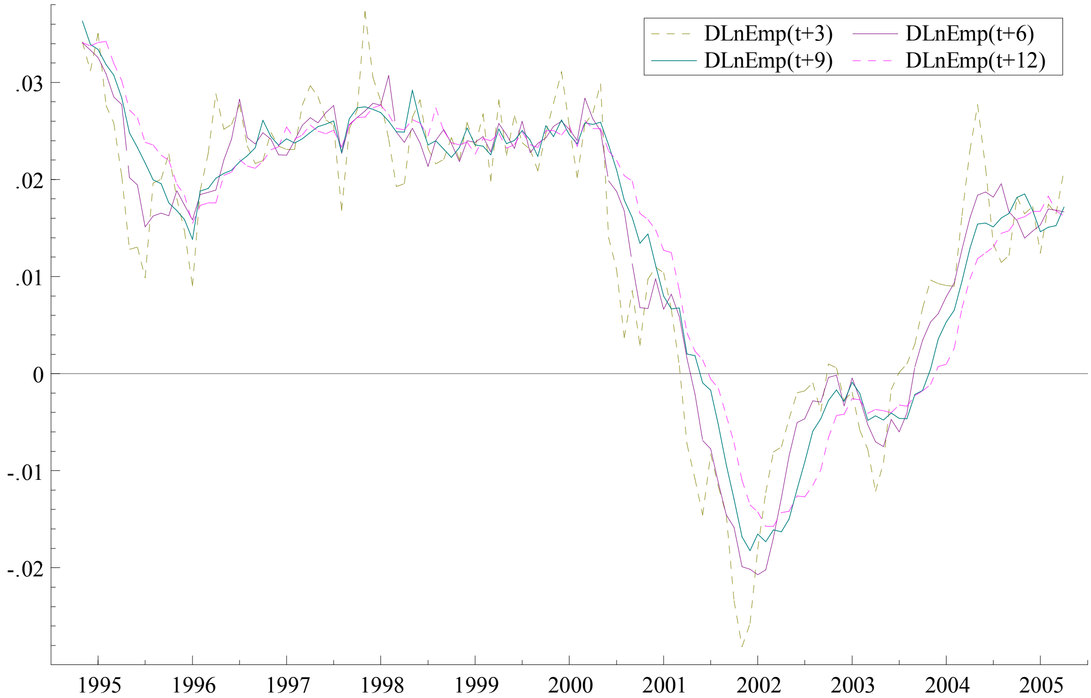

Fig. 1. Three-month difference *DLnEmp* (t+3), six-month difference *DLnEmp*(t+6), nine-month difference *DLnEmp*(t+9) and twelve-month difference *DLnEmp*(t+12) of the logarithm of US non-farm payroll employment (SA).

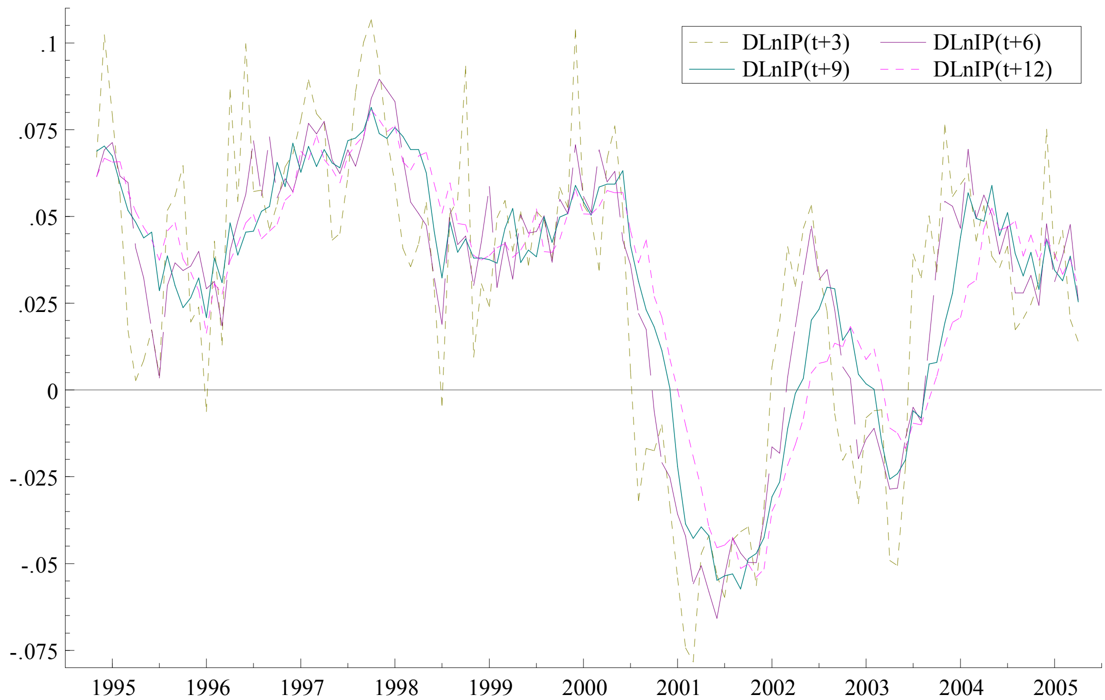

Fig. 2. Three-month difference *DLnIP*(t+3), six-month difference *DLnIP*(t+6), nine-month difference *DLnIP*(t+9) and twelve-month difference *DLnIP*(t+12) of the logarithm of US industrial production (SA).

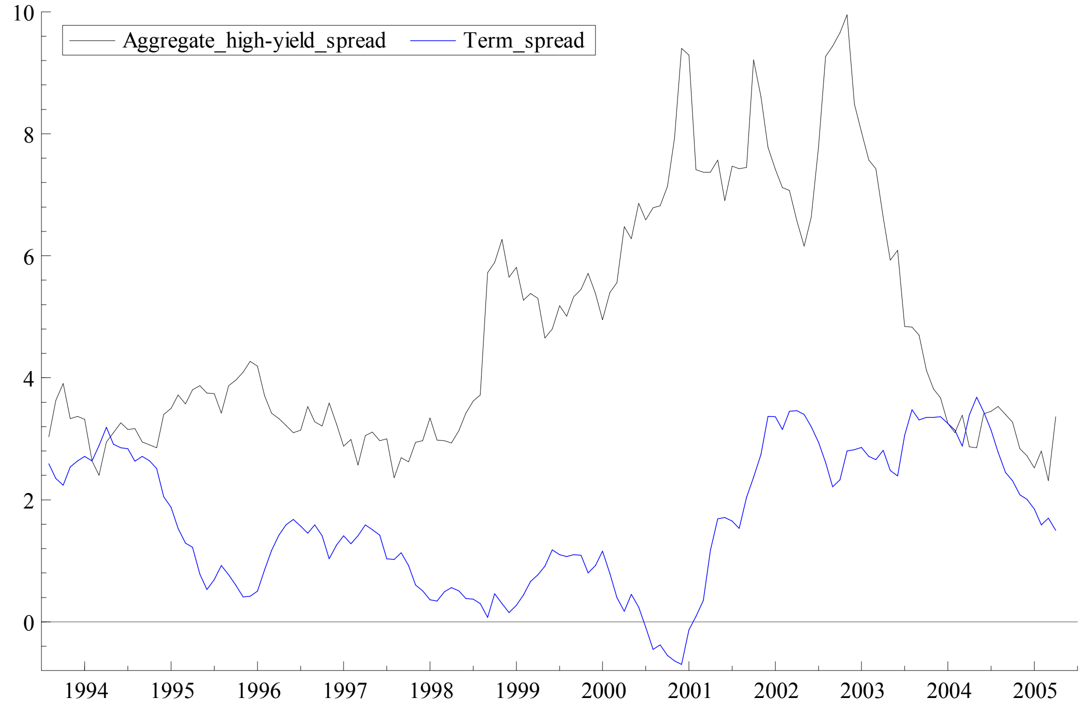

Fig. 3. Aggregate high-yield credit spread and term spread.

APPENDIX

HIGH YIELD CORPORATE 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: Lehman Brothers high-yield corporate bonds; data source is DataStream.