Leading indicator properties of the US corporate spreads

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Abstract

The focus of this paper is on the leading indicator properties of high-yield corporate spreads regarding the level of real economic activity. This is motivated by the financial accelerator mechanism underlying business cycle fluctuations as suggested by Bernanke and Gertler (1989). We examine the out-of-sample forecast performance of high-yield 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 substantial gain from using a Dynamic Factor model fitted to 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.

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JEL codes: *C53, E32, C22.*

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 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 growth. This is motivated by the financial accelerator model developed by Bernanke and Gertler (1989). 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

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

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 approximate Dynamic Factor (DF) method developed by Stock and Watson (1998, 2002) to model the dynamics of various high-yield credit spreads through a relatively small set of common factors. 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 the DF model include those by Stock and Watson (2002) and by Forni, Hallin, Lippi and Reichlin (2003), among others. In particular, Stock and Watson (2002) use a large dataset of real and financial variables to forecast economic activity in the US, while Forni, Hallin, Lippi and Reichlin (2003) concentrate only on a dataset of monetary and financial variables to forecast economic activity and inflation in Europe. However, neither of these studies includes high-yield credit spread data in its information set. On the other hand, in this paper, given that our main motivation is to test the financial accelerator mechanism, our information set is focused more on financial variables and in particular on US corporate bonds rather than on a whole set of economic variables.

Secondly, we are not only interested in point forecast accuracy (as the existing literature has done), but we also focus on forecast accuracy regarding a contraction in the US economy. For this purpose, we use Monte Carlo simulation to produce probability forecasts of a contraction and we evaluate their accuracy. This probability forecast exercise is closely related to the work by Anderson and Vahid (2001), Garratt et al. (2003) and Galvão (2006). In these studies, the probability forecasts are obtained from a dynamic forecasting exercise. Our study makes a contribution to the above literature by being the first to produce probability forecasts using the h-step-ahead projection method.

The outline of the paper is as follows. In Section 2, we describe the dynamic factor method and 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[2]:

$$y_{t+h} = \alpha_h + \beta_h(L)x_t + \gamma_h(L)y_t + \varepsilon_{t+h} \qquad (1)$$

where $y_{t+h} \equiv \frac{1200}{h}[\ln(y_{t+h}) - \ln(y_t)]$ is an h-step ahead (scalar) variable to be forecasted. The latter can be either the employment or the industrial production series (in logs). 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 the dependent variable as well as the predictor variable, x_t. Moreover, $\beta_h(L) = (\beta_{h,0} + \beta_{h,1}L + ... + \beta_{h,p}L^p)$ and $\gamma_h(L) = (\gamma_{h,0} + \gamma_{h,1}L + ... + \gamma_{h,s}L^s)$ are lag polynomials 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 variable 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:

$$x_t = \Lambda F_t + e_t \qquad (2)$$

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

[2] Notice that the h-step-ahead projection approach contrasts with the iterated approach of estimating a one-step ahead model, then iterating that model forward to obtain h-step ahead predictions. There are two main advantages of the h-step-ahead projection approach. First, it eliminates the need for estimating additional equations for simultaneously forecasting x_t, e.g. by a VAR. Second, it can reduce the potential impact of specification error in the iterated model (including the equation of x_t) by using the same horizon for estimation as for forecasting.

analysis (see Stock and Watson, 1998, 2002).[3] More specifically, 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'. Principal component analysis gives a consistent estimation (for large N and T) of the space spanned by the static factors F_t. The model specification in (2) is the static representation of the Dynamic Factor model (see Stock and Watson, 1998, 2002), where the i^{th} series entering in the vector x_t given in equation (2) is described as follows:

$$x_{it} = \lambda_i(L) f_t + e_t \tag{3}$$

for $i = 1,...,N$. In Eq. (3), the lag polynomials $\lambda_i(L)$ are modelled as having finite orders of at most q, so $\lambda_i(L) = \sum_{j=0}^{q} \lambda_{ij} L^j$ and the vector of common dynamic factor f_t is modelled as having dimension $\bar{r}$. The relationship between the static and dynamic factors is given by $F_t = (f'_t,...,f'_{t-q})'$, and the dimension of the space spanned by the static factor is $r \le (q+1)\bar{r}$.

To produce h-step-ahead forecasts through the DF model 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

[3] It is important to point out that there are also alternative methods to the estimation of the static factors proposed by Forni et al. (2000) and by Kapetanios and Marcellino (2003). The former base its analysis on the frequency domain, whereas the latter is based upon a state space model.

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 $y_{2005:m4}$. 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 individual credit spreads 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.

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:

$$MSFE = \frac{1}{T_2 - T_1 - h + 1} \sum_{t=T_1}^{T_2 - h} (y_{t+h} - \hat{y}_{t+h|h})^2 \tag{4}$$

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 $t = T_1 + h, ..., T_2$. If the MSFE of the ARDL 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 Diebold and Mariano (1995) (DM) test.

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

$$y_{t+h} = \alpha + (1-\beta) y^a_{t+h} + \beta y^b_{t+h} + u_{t+h} \tag{5}$$

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. (5) 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]:

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

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

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 is correctly predicted. Also, we calculate the Pesaran and Timmermann (1992) nonparametric test (PT) of directional change.

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 events such as recessions. In this section, we compare models according to their ability to out-of-sample forecast bad outcomes related to contractionary periods in the real economic activity. Contractionary periods in real activity can be identified by using rules based on those employed in the algorithms to identify turning points of classical business cycles. Previous related work includes that by Fair (1993), Anderson and Vahid (2001) and Galvão (2006).

In particular, we focus on scenarios described as at least two consecutive negative quarterly growth rates in employment (or industrial production) over the next five quarters. For this purpose we use probability forecasts obtained by Monte Carlo simulation. In subsection 4.1 we explain the artificial generation of scenarios through stochastic simulation using the Dynamic Factor, ARDL and AR models. Then, in

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

subsection 4.2 we describe the indicators used to assess the accuracy of probability forecasts.

3.1 Stochastic Simulation of Models

Before describing the simulation experiment associated with the Dynamic Factor model, we explain how to account for the impact of the dynamic factors f_t on the h-step ahead projections. This is done following the suggestion by Forni, Lippi, Reichlin (2003) who use an eigenvalue-eigenvector decomposition of Σ. The latter is the covariance matrix of the r reduced form residuals ν obtained by fitting a VAR(1) on the r principal components. The eigenvalue-eigenvector decomposition is a factorisation of Σ that gives an $r \times q$ matrix R. The latter allows to measure the impact of the q dynamic factors (common shocks) on the r principal components. Any choice of q would imply a different coefficient matrix R such that the reduced form disturbances ν are unchanged. Therefore, given that the focus of this paper is on forecasting, what matters is the r (e.g., the dimension of the static factor space). Given r (obtained through recursive BIC), we fix q, the number of dynamic factors (common shocks) describing a specific scenario, to 1. This will allow us to keep the computational intensity of the Monte Carlo experiment limited to 10000 replications.

We now describe the artificial generation of scenarios using the Dynamic Factor model. After estimating the principal components and after fitting the VAR(1) on the principal components, we use the point estimates for the coefficients α_h, β_h, γ_h and the impact multiplier matrix R to produce the out-of-sample forecasts under a large number of scenarios. For this purpose, we use the following specification:

$$y_{t+h} = \alpha_h + \beta_h (F_t^* + R f_{t+h}) + \gamma_h (L) y_t + \varepsilon_{t+h} \qquad (6)$$

Equation (6) describes the h-step ahead forecast conditional on the information set at time t, associated with a specific scenario. The specific scenario is described by the joint realisations of the dynamic factor (common shock) f_{t+h} and of the idiosyncratic shock ε_{t+h}. Both shocks are assumed to be orthogonal to each other and they are obtained using random draws from an *iid* standardised Gaussian distribution. In particular, the number of replications (draws) is 10000 which gives 10000 forecasts corresponding to each scenario.

The artificial generation of scenarios using the ARDL with either the term spread or the individual credit spreads, and the AR models are similar. More specifically, after estimating recursively the coefficients of the models used to produce the point forecast conditional on the information set at time *t*, a scenario is artificially generated by the ARDL model is given by:

$$y_{t+h} = \alpha_h + \beta_h(L)x_t + \gamma_h(L)y_t + \varepsilon_{t+h}$$

whereas the stochastic simulation of the AR model is obtained from:

$$y_{t+h} = \alpha_h + \gamma_h(L)y_t + \varepsilon_{t+h}$$

Therefore, the only shock producing the various scenarios is the idiosyncratic innovation ε_{t+h} .

Given monthly observations, the actual realisations for a contraction in employment (or industrial production) are identified by at least two consecutive periods of negative quarterly growth rates in employment (or industrial production) over the next five quarters, and this is the case when[5]:

a) the 3-month differences y_{t+3}-y_t and y_{t+6}-y_{t+3} are both negative, or if:
b) the 3-month differences y_{t+6}-y_{t+3} and y_{t+9}-y_{t+6} are both negative, or if:
c) the 3-month differences y_{t+9}-y_{t+6} and y_{t+12}-y_{t+9} are both negative, or if:
d) the 3-month differences y_{t+12}-y_{t+9} and y_{t+15}-y_{t+12} are both negative

To our knowledge, probability forecasts so far have been obtained from a dynamic forecasting exercise (see, for instance, Anderson and Vahid, 2001, Garratt et al., 2003 and Galvão, 2006). In this respect, we contribute to the above studies by being the first to attempt to produce probability forecasts using the *h*-step-ahead projection method**.**

In order to compute the probability forecast of a contraction in employment (or industrial production) over the next five quarters conditioning on the information set

[5] This definition of a contraction in employment (or industrial production) can be seen as the classical definition of the business cycle.

dated 2000:m2, we first produce the following five forecasts under a specific scenario u:

$$y^u_{2000:m2+h} = \alpha_h + \beta_h(F_{2000:m2} + Rf_{\,t+h}) + \gamma_h(L)y_{2000:m2} + \varepsilon_{t+h}\text{, for } h = 3, 6, 9, 12 \text{ and } 15$$

The superscript u picks the specific scenario involved in the stochastic simulation experiment. Given the point forecast for the long differences $y^u_{2000:m2+3}$, $y^u_{2000:m2+6}$, $y^u_{2000:m2+9}$, $y^u_{2000:m2+12}$, $y^u_{2000:m2+15}$, it is possible to retrieve the conditional predictions for the quarterly growth rates in the next five quarters. In particular, a scenario u would identify a contraction if:

e) the forecasted quarterly growth rates $y^u_{2000:m2+3}$ and $y^u_{2000:m2+6} - y^u_{2000:m2+3}$ are both negative, or if:

f) the forecasted quarterly growth rates $y^u_{2000:m2+6} - y^u_{2000:m2+3}$ and $y^u_{2000:m2+9} - y^u_{2000:m2+6}$ are both negative, or if:

g) the forecasted quarterly growth rates $y^u_{2000:m2+9} - y^u_{2000:m2+6}$ and $y^u_{2000:m2+12} - y^u_{2000:m2+9}$ are both negative, or if:

h) the forecasted quarterly growth rates $y^u_{2000:m2+12} - y^u_{2000:m2+9}$ and $y^u_{2000:m2+15} - y^u_{2000:m2+12}$ are both negative.

We assign score one to a prediction of contraction in scenario u 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 gives the probability forecast regarding a contraction in employment (or industrial production) over the next five quarters, conditioning on the information set at 2000:m2. Then, we add one observation and repeat the same exercise to obtain the probability forecast regarding a contraction in employment over the next five quarters, conditioning on the information set at 2000:m3. We carry on until we reach the information set dated 2004:m1. This exercise will give 45 probability forecasts. This is due to the 60 observations describing the evaluation period for the point forecast (running from

2000:m5–2005:m4). Therefore, the information set common to the different forecast horizons consists of 45 observations, running 2000:m2–2004:m1.

3.2 Assessing Accuracy of Probability Forecasts

To evaluate these probabilities, we employ the quadratic probability score (QPS), and the log probability score (LPS), as suggested by Diebold and Rudebusch (1989). Let P_t be the probability forecast for the "contraction in employment (or industrial production)" by the model for the next five quarters conditional on the information set at time t. The variable R_t is binary and it takes value 1 if the contraction occurs in the actual data within the five quarters ahead period of time t, 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

The analysis was carried out using monthly data for the period 1993:m8-2005:m4. All the series including data on the term spread, the US non-farm payroll employment and industrial production were obtained from Datastream.

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. A careful inspection suggests the following results.

First, the Dynamic Factor model for credit spreads improves substantially upon the AR. In particular, as for the employment growth, the 3-, 6-, 9-, and 12-month-ahead MSFE values indicate a 32%, 48%, 61% and 66% improvement, respectively. For industrial production growth, the corresponding figures are 28%, 48%, 62% and

64%, respectively. Also, the Diebold-Mariano test suggests that, for employment, the forecast improvements are significant at 1% level for the 3- and 6-month horizons, and at 10% level for the 9-month horizon. As for the industrial production, the improvements are more modest (at 10% level for the 3-, 6- and 9-month horizons). Furthermore, the Dynamic Factor forecast encompasses the AR whereas the latter does not forecast encompass the former (the only exception is the 9-month horizon for employment growth). As for the Success Ratio, the results show that the Dynamic Factor model provides more accurate predictions than those corresponding to the AR.

Second, a number of sector-specific high-yield spreads (such as automotive, consumer cyclical, capital goods, finance, insurance, packaging, supermarkets, conglomerates) very often improve upon the AR and upon the term spread. However, the forecast performance of the individual spreads is not superior to the one associated with the Dynamic Factor. In particular, at 9- and 12-month horizons the Dynamic Factor model considerably improves upon the individual spreads in terms of the relative MSFEs and the Success Ratio.

Third, the aggregate high-yield corporate spread 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 Dynamic Factor 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.

Fourth, the forecasting performance of the term spread is of particular interest, given its prominence in the literature. It is possible to observe that the term spread forecasts (at the different horizons) are particularly poor relative to those of the Dynamic Factor in terms of all criteria and for both industrial production and employment growth. Also, even though the MSFEs produced by the term spread are lower than those associated with AR, the Diebold-Mariano test suggests that this improvement is not significant. Moreover, according to the Success Ratio, only the 3-month-ahead forecast of employment, and the 3-, 9-, and 12-month-ahead forecasts of industrial production are more accurate than those of the AR. According to the encompassing test, the term spread outperforms clearly the AR in five cases, except for 3- and 6- month-ahead forecasts of employment and for 12-month-ahead forecasts of industrial production. This is 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.

Notice that the Diebold-Mariano and the forecast encompassing tests can be used use to compare non-nested models. However, in our work 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 ARDL candidate models[6]. We argue that, even though, we should interpret with caution the Diebold-Mariano and encompassing tests results, the relative MSFEs and the directional changes support some candidate ARDL, particularly, the Dynamic Factor model.

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 a contraction in employment and industrial production over the next five quarters. Overall, the results are consistent with the point forecast findings. More specifically, there are substantial gains when using an ARDL model with Dynamic Factors. For instance, for a contraction in employment the probability forecasts obtained from the Dynamic Factor model are 21% and 24% (in terms of QPS and LPS, respectively) more accurate than those of the AR; while for a contraction in industrial production there is a 20% and 46% improvement relative to the AR.

Also, there are gains when the Dynamic Factor model is compared to the term spread. For example, for employment, the scores obtained from Dynamic Factor are 22% and 10% lower than those from the term spread; while**,** for industrial production**,** there is 13% and 40% improvement upon the AR.

Furthermore, the Dynamic Factor for credit spreads is more accurate than the aggregate high-yield credit spread in predicting contraction events. In particular, for employment the accuracy gains are of 22% and 21%, while for industrial production the there are of 32% and 46%. In this light, it is believed that the present work contributes to the literature by suggesting that to test the financial accelerator mechanism 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.

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[6] See also Stock and Watson (2003b) for a similar argument.

Finally, even though some sector-specific high-yield spreads forecasts are more accurate than those corresponding to the AR and the term spread, overall the Dynamic Factor model is the best in predicting contraction events in employment and industrial production.

5. Conclusions

The focus of this paper is on testing the financial accelerator mechanism (see Bernanke and Gertler, 1989) by 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 strong evidence of the financial accelerator mechanism (see Bernanke and Gertler, 1989). Our work, however, goes one step further and suggests that rather using the aggregate high-yield spread (as in the previous studies aforementioned), it is better to use few factors extracted from a number of disaggregated high-yield credit spreads. As shown, there is a substantial improvement in the forecasting performance of the Dynamic Factor 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 a contraction in the real economic activity. To our knowledge, the present study is the first attempt in the literature to produce probability forecasts using the h-step-ahead projection method. Finally, the superior forecasting performance of the Dynamic Factor model can be explained by recognizing that the factor extraction is obtained by averaging out noisy information contaminating the empirical observed sector-specific credit spreads.

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.767	4.081		
Term spread	1.027	0.783	4.288	0.581	0.572 [0.932]
HY Corporate spread models					
HY (Dynamic factor)	0.679	0.867	5.613	0.010	-0.838 [6.544]
HY (Aggregate)	0.865	0.850	5.348	0.151	-0.559 [3.421]
HY (Aerospace)	0.992	0.850	5.346	0.458	0.090 [1.149]
HY (Automotive)	0.770	0.817	4.817	0.085	-0.193 [7.070]
HY (Building materials)	0.965	0.800	4.532	0.398	0.280 [1.974]
HY (Banking)	0.995	0.800	4.553	0.486	0.861 [1.376]
HY (Consumer cyclical)	0.904	0.817	4.802	0.234	-0.461 [3.089]
HY (Capital goods)	0.848	0.834	5.081	0.171	-0.460 [4.691]
HY (Chemicals)	0.871	0.834	5.074	0.160	-0.627 [3.704]
HY (Construction machinery)	0.926	0.834	5.074	0.219	-0.715 [2.595]
HY (Consumer products)	0.894	0.767	4.021	0.073	-2.064 [4.856]
HY (Electric)	0.962	0.817	4.847	0.328	0.315 [1.274]
HY (Energy)	1.045	0.850	5.346	0.709	0.986 [0.010]
HY (Entertainment)	0.899	0.817	4.817	0.149	-0.739 [3.055]
HY (Finance)	0.912	0.817	4.813	0.188	0.109 [2.605]
HY (Insurance)	0.928	0.817	4.847	0.263	1.525 [3.385]
HY (Media-cable)	0.912	0.900	6.248	0.239	0.351 [2.258]
HY (Metals)	0.884	0.800	4.531	0.235	-0.620 [3.888]
HY (Media-noncable)	0.908	0.833	5.081	0.275	0.177 [2.652]
HY (Natural gas)	1.005	0.833	5.081	0.520	0.333 [1.467]
HY (Oil field services)	1.017	0.833	5.135	0.583	0.726 [0.582]
HY (Paper)	0.943	0.883	5.883	0.239	-1.409 [3.430]
HY (Packaging)	0.684	0.833	5.184	0.021	-1.084 [7.384]
HY (Pharmaceuticals)	0.976	0.867	5.624	0.367	0.222 [1.562]
HY (Railroads)	0.955	0.833	5.093	0.166	-0.428 [2.770]
HY (Retailers)	0.925	0.783	4.288	0.289	-0.228 [2.780]
HY (Services)	0.936	0.850	5.346	0.289	-0.578 [2.653]
HY (Supermarkets)	0.837	0.850	5.348	0.127	-0.582 [3.470]
HY (Technology)	0.879	0.900	6.188	0.116	-0.334 [3.302]
HY (Telecommunications)	0.887	0.833	5.074	0.141	0.394 [3.224]
HY (Transportation)	0.964	0.850	5.348	0.322	0.925 [1.946]
HY (Textile)	0.893	0.850	5.348	0.121	0.504 [3.770]
HY (Utility)	1.034	0.850	5.375	0.649	0.898 [0.217]
HY (Airlines)	1.045	0.833	5.074	0.718	1.246 [-0.048]
HY (Conglomerates)	0.701	0.767	4.021	0.047	1.085 [7.261]
HY (Consumer noncyclical)	0.948	0.817	4.817	0.275	-0.957 [3.581]
HY (Environmental)	1.077	0.850	5.346	0.767	1.324 [-0.175]
HY (Independent energy)	1.045	0.833	5.081	0.705	0.943 [0.043]
HY (Finance composite)	0.965	0.800	4.561	0.339	0.292 [1.455]
HY (Gaming)	1.005	0.783	4.259	0.524	-0.063 [1.506]
HY (Health care)	0.972	0.867	5.613	0.361	-0.518 [2.443]
HY (Home construction)	0.940	0.817	4.847	0.232	-0.233 [2.658]
HY (Industrial)	0.852	0.867	5.613	0.123	-1.071 [4.250]
HY (Lodging)	1.022	0.850	5.346	0.587	0.565 [0.878]
HY (Natural gas distribution)	1.005	0.817	4.817	0.525	-0.008 [1.424]
HY (Natural gas pipeline)	0.992	0.833	5.081	0.463	0.165 [2.375]
HY (Refining)	1.033	0.817	4.803	0.697	0.963 [0.135]

Notes: *MSFE* is the mean square forecast error relative to the MSFE for the univariate autoregression; 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) test; the null hypothesis is that each set of forecasts and the actual values are independently distributed; this statistic is asymptotically normal; *Encompassing* tests the null hypothesis that the credit spread model forecast encompasses the benchmark *AR* (first *t*-ratio of slope coefficient in regression 4a) and the benchmark *AR* forecast encompasses the credit spread model (second *t*-ratio (in brackets) of slope coefficient in regression 4b).

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.750	3.870		
Term spread	0.997	0.717	3.414	0.490	-0.193 [1.183]
HY Corporate spread models					
HY (Dynamic factor)	0.517	0.833	5.424	0.008	- 1.314 [10.80]
HY (Aggregate)	0.798	0.817	4.935	0.001	-1.297 [4.312]
HY (Aerospace)	0.979	0.817	4.902	0.342	-0.311 [1.593]
HY (Automotive)	0.661	0.817	4.935	0.045	-0.911 [7.797]
HY (Building materials)	0.927	0.750	3.908	0.192	-1.033 [2.749]
HY (Banking)	0.894	0.733	3.662	0.205	-0.965 [4.536]
HY (Consumer cyclical)	0.802	0.750	3.908	0.013	-2.090 [6.361]
HY (Capital goods)	0.787	0.800	4.651	0.003	-2.156 [7.137]
HY (Chemicals)	0.807	0.767	4.122	0.017	-2.258 [5.997]
HY (Construction machinery)	0.850	0.750	3.870	0.016	-1.549 [3.529]
HY (Consumer products)	0.763	0.717	3.414	0.020	-3.776 [6.726]
HY (Electric)	0.941	0.817	4.892	0.241	0.497 [1.874]
HY (Energy)	1.012	0.783	4.402	0.582	0.439 [0.346]
HY (Entertainment)	0.774	0.700	3.164	0.072	-1.453 [5.621]
HY (Finance)	0.832	0.800	4.636	0.143	0.559 [4.145]
HY (Insurance)	0.790	0.867	5.678	0.086	0.587 [3.643]
HY (Media-cable)	0.881	0.883	5.941	0.234	-0.010 [3.029]
HY (Metals)	0.790	0.750	3.870	0.032	-1.853 [5.767]
HY (Media-noncable)	0.888	0.850	5.427	0.013	-0.499 [3.266]
HY (Natural gas)	0.964	0.750	3.908	0.308	-1.163 [5.645]
HY (Oil field services)	1.008	0.800	4.633	0.583	0.851 [0.301]
HY (Paper)	0.914	0.817	4.935	0.055	-2.318 [4.198]
HY (Packaging)	0.668	0.783	4.527	0.030	-0.598 [5.892]
HY (Pharmaceuticals)	0.967	0.817	4.902	0.185	-0.379 [2.526]
HY (Railroads)	0.889	0.817	4.892	0.081	-2.727 [4.922]
HY (Retailers)	0.854	0.667	2.654	0.176	-0.957 [4.750]
HY (Services)	0.885	0.767	4.155	0.023	-1.397 [3.653]
HY (Supermarkets)	0.684	0.783	4.402	0.044	-0.976 [8.885]
HY (Technology)	0.771	0.900	6.193	0.011	-0.839 [3.803]
HY (Telecommunications)	0.886	0.900	6.236	0.234	0.559 [3.127]
HY (Transportation)	0.934	0.783	4.376	0.243	0.200 [1.865]
HY (Textile)	0.768	0.817	4.892	0.063	-1.653 [5.264]
HY (Utility)	1.012	0.817	4.902	0.571	0.761 [0.374]
HY (Airlines)	1.013	0.783	4.402	0.611	0.980 [0.157]
HY (Conglomerates)	0.590	0.767	4.571	0.054	0.308 [7.814]
HY (Consumer noncyclical)	0.840	0.683	2.911	0.112	-2.127 [5.509]
HY (Environmental)	1.029	0.750	3.908	0.656	0.888 [-0.089]
HY (Independent energy)	1.015	0.750	3.908	0.602	0.504 [0.251]
HY (Finance composite)	0.835	0.800	4.660	0.140	-0.080 [3.818]
HY (Gaming)	0.959	0.733	3.662	0.216	-1.442 [3.101]
HY (Health care)	0.905	0.716	3.414	0.157	-1.965 [3.981]
HY (Home construction)	0.863	0.767	4.122	0.008	-1.520 [4.459]
HY (Industrial)	0.763	0.833	5.179	0.001	-2.147 [5.671]
HY (Lodging)	0.992	0.783	4.402	0.447	-0.072 [1.395]
HY (Natural gas distribution)	0.945	0.733	3.662	0.196	-3.671 [5.446]
HY (Natural gas pipeline)	0.924	0.750	3.908	0.119	-1.459 [3.688]
HY (Refining)	0.950	0.750	3.908	0.259	-0.267 [3.262]

Notes: See the notes to Table 1a.

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.750	3.951		
Term spread	0.980	0.650	2.494	0.404	-0.824 [2.195]
HY Corporate spread models					
HY (Dynamic factor)	0.387	0.900	6.318	0.066	-2.099 [16.21]
HY (Aggregate)	0.753	0.800	4.675	0.038	-1.092 [3.722]
HY (Aerospace)	0.990	0.767	4.151	0.431	0.191 [0.891]
HY (Automotive)	0.679	0.800	4.795	0.129	-0.390 [6.595]
HY (Building materials)	0.909	0.683	2.924	-	-1.640 [3.830]
HY (Banking)	0.863	0.617	1.909	0.098	-1.260 [5.489]
HY (Consumer cyclical)	0.728	0.783	4.432	0.026	-2.074 [6.006]
HY (Capital goods)	0.732	0.800	4.796	0.017	-2.410 [7.159]
HY (Chemicals)	0.753	0.767	4.191	0.076	-2.898 [7.603]
HY (Construction machinery)	0.831	0.733	3.659	0.115	-1.356 [3.437]
HY (Consumer products)	0.737	0.683	2.924	0.066	-5.343 [8.883]
HY (Electric)	0.866	0.783	4.399	0.209	0.055 [2.694]
HY (Energy)	1.038	0.733	3.659	0.710	1.613 [-0.800]
HY (Entertainment)	0.698	0.717	3.473	0.128	-1.548 [6.445]
HY (Finance)	0.773	0.817	4.911	0.213	0.410 [4.237]
HY (Insurance)	0.740	0.883	5.945	0.168	0.679 [3.678]
HY (Media-cable)	0.916	0.850	5.428	0.380	0.846 [2.288]
HY (Metals)	0.737	0.767	4.254	0.073	-1.940 [6.475]
HY (Media-noncable)	0.897	0.767	4.191	0.000	-0.145 [2.669]
HY (Natural gas)	0.978	0.733	3.659	0.355	-1.426 [4.632]
HY (Oil field services)	1.035	0.767	4.151	0.846	2.269 [-0.808]
HY (Paper)	0.902	0.783	4.488	0.064	-2.381 [4.347]
HY (Packaging)	0.653	0.800	5.038	0.104	0.087 [6.630]
HY (Pharmaceuticals)	0.984	0.767	4.151	0.277	0.626 [2.110]
HY (Railroads)	0.904	0.733	3.626	0.131	-1.824 [3.709]
HY (Retailers)	0.729	0.683	3.198	0.012	-1.646 [6.479]
HY (Services)	0.882	0.700	3.170	-	-1.369 [3.632]
HY (Supermarkets)	0.630	0.717	3.415	0.111	-0.546 [8.875]
HY (Technology)	0.795	0.817	4.921	0.064	-0.145 [3.263]
HY (Telecommunications)	0.890	0.900	6.248	0.307	0.620 [2.605]
HY (Transportation)	0.924	0.750	3.904	0.320	0.378 [1.809]
HY (Textile)	0.777	0.750	3.877	0.222	-1.069 [3.711]
HY (Utility)	1.026	0.767	4.151	0.681	1.587 [-0.168]
HY (Airlines)	1.039	0.767	4.151	0.777	2.024 [-0.914]
HY (Conglomerates)	0.617	0.750	4.420	0.120	0.690 [5.637]
HY (Consumer noncyclical)	0.787	0.667	2.676	0.074	-2.188 [5.929]
HY (Environmental)	1.046	0.700	3.170	0.745	1.771 [-0.989]
HY (Independent energy)	1.042	0.700	3.170	0.729	1.729 [-1.022]
HY (Finance composite)	0.785	0.783	4.421	0.247	0.042 [3.940]
HY (Gaming)	0.991	0.700	3.232	0.420	-0.249 [1.768]
HY (Health care)	0.887	0.683	2.924	0.031	-1.723 [3.899]
HY (Home construction)	0.863	0.700	3.170	0.040	-2.016 [5.240]
HY (Industrial)	0.722	0.817	4.960	0.018	-1.911 [5.350]
HY (Lodging)	1.015	0.700	3.170	0.602	0.835 [0.212]
HY (Natural gas distribution)	0.946	0.683	2.989	0.075	-2.964 [4.405]
HY (Natural gas pipeline)	0.921	0.717	3.415	0.048	-1.693 [3.209]
HY (Refining)	0.927	0.717	3.415	0.165	-0.535 [4.114]

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

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.733	3.712		
Term spread	1.004	0.650	2.588	-	-0.628 [2.159]
HY Corporate spread models					
HY (Dynamic factor)	0.344	0.883	6.015	0.155	-1.665 [22.32]
HY (Aggregate)	0.800	0.750	3.904	0.230	-0.253 [2.823]
HY (Aerospace)	0.993	0.683	2.879	0.427	0.290 [1.151]
HY (Automotive)	0.747	0.733	3.891	0.257	1.300 [6.977]
HY (Building materials)	0.909	0.633	2.121	0.117	-1.030 [3.365]
HY (Banking)	0.838	0.583	1.422	0.066	-1.070 [7.593]
HY (Consumer cyclical)	0.735	0.700	3.317	0.183	-1.233 [6.267]
HY (Capital goods)	0.756	0.733	3.788	0.164	-1.275 [5.942]
HY (Chemicals)	0.726	0.700	3.128	0.191	-2.251 [8.327]
HY (Construction machinery)	0.821	0.667	2.628	0.238	-1.188 [3.869]
HY (Consumer products)	0.703	0.733	3.788	0.152	-5.547 [10.35]
HY (Electric)	0.844	0.766	4.130	0.292	0.371 [2.275]
HY (Energy)	1.030	0.700	3.170	0.718	1.096 [-0.121]
HY (Entertainment)	0.606	0.767	4.254	0.197	-0.969 [7.545]
HY (Finance)	0.700	0.800	4.647	0.261	0.502 [4.553]
HY (Insurance)	0.750	0.850	5.428	0.302	1.245 [3.531]
HY (Media-cable)	0.986	0.817	4.911	0.485	1.950 [1.242]
HY (Metals)	0.715	0.767	4.465	0.172	-1.232 [6.230]
HY (Media-noncable)	0.959	0.700	3.128	0.300	0.879 [1.921]
HY (Natural gas)	0.970	0.733	3.712	-	-1.671 [3.869]
HY (Oil field services)	1.036	0.717	3.377	0.889	2.036 [-0.342]
HY (Paper)	0.935	0.750	3.951	0.048	-0.915 [2.806]
HY (Packaging)	0.716	0.800	5.038	0.194	0.566 [5.517]
HY (Pharmaceuticals)	0.978	0.717	3.377	0.398	0.530 [1.307]
HY (Railroads)	0.894	0.733	3.659	0.178	-2.043 [4.361]
HY (Retailers)	0.706	0.683	3.360	0.161	-1.421 [8.374]
HY (Services)	0.903	0.650	2.376	0.142	-0.857 [3.723]
HY (Supermarkets)	0.635	0.650	2.376	0.228	0.627 [9.319]
HY (Technology)	0.858	0.750	3.951	0.234	0.560 [2.677]
HY (Telecommunications)	0.948	0.850	5.487	0.415	1.384 [1.266]
HY (Transportation)	0.899	0.767	4.130	0.367	0.662 [1.607]
HY (Textile)	0.737	0.800	4.647	0.285	-1.310 [5.537]
HY (Utility)	1.045	0.717	3.377	0.787	1.795 [-0.438]
HY (Airlines)	1.002	0.717	3.377	0.516	1.280 [0.040]
HY (Conglomerates)	0.624	0.800	5.038	0.207	1.134 [6.069]
HY (Consumer noncyclical)	0.761	0.650	2.494	0.204	-1.866 [6.398]
HY (Environmental)	1.044	0.717	3.473	0.750	0.946 [-0.046]
HY (Independent energy)	1.034	0.717	3.473	0.741	1.085 [-0.160]
HY (Finance composite)	0.655	0.817	4.911	0.239	0.076 [5.731]
HY (Gaming)	1.010	0.683	3.078	-	0.210 [1.672]
HY (Health care)	0.873	0.617	1.975	0.229	-0.937 [3.723]
HY (Home construction)	0.891	0.667	2.676	0.153	-1.078 [4.055]
HY (Industrial)	0.758	0.783	4.432	0.177	-1.057 [4.222]
HY (Lodging)	1.032	0.650	2.425	0.759	1.155 [0.173]
HY (Natural gas distribution)	0.867	0.633	2.238	0.081	-2.630 [6.167]
HY (Natural gas pipeline)	0.891	0.750	4.021	0.124	-2.339 [3.757]
HY (Refining)	0.897	0.683	2.924	0.229	0.035 [4.358]

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

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.600	1.388		
Term spread	0.951	0.633	1.949	0.320	-1.234 [2.748]
HY Corporate spread models					
HY (Dynamic factor)	0.712	0.833	5.170	0.092	0.739 [8.911]
HY (Aggregate)	0.836	0.733	3.555	0.088	-0.560 [3.356]
HY (Aerospace)	0.967	0.633	1.949	0.251	-0.487 [1.508]
HY (Automotive)	0.807	0.683	2.818	0.110	0.645 [4.191]
HY (Building materials)	0.875	0.667	2.483	0.077	-1.355 [2.960]
HY (Banking)	0.856	0.633	1.949	0.126	-2.446 [5.816]
HY (Consumer cyclical)	0.857	0.683	2.754	0.109	-0.944 [3.375]
HY (Capital goods)	0.820	0.717	3.305	0.075	-0.686 [3.929]
HY (Chemicals)	0.844	0.700	3.017	0.058	-1.800 [4.314]
HY (Construction machinery)	0.889	0.667	2.483	0.062	-2.116 [3.822]
HY (Consumer products)	0.943	0.633	1.932	0.096	-1.983 [2.871]
HY (Electric)	0.897	0.700	3.091	0.208	0.718 [3.463]
HY (Energy)	0.977	0.617	1.670	0.131	-0.998 [1.789]
HY (Entertainment)	0.820	0.700	3.017	0.092	-2.705 [5.845]
HY (Finance)	0.881	0.750	4.034	0.271	0.471 [2.621]
HY (Insurance)	0.900	0.750	3.955	0.338	1.099 [2.467]
HY (Media-cable)	0.958	0.683	2.856	0.411	0.641 [1.892]
HY (Metals)	0.830	0.650	2.210	0.115	-0.282 [4.015]
HY (Media-noncable)	0.875	0.717	3.301	0.086	-0.402 [3.241]
HY (Natural gas)	0.958	0.650	2.209	0.119	-2.198 [2.876]
HY (Oil field services)	0.976	0.650	2.253	0.366	0.911 [1.582]
HY (Paper)	0.917	0.717	3.287	0.125	-0.710 [2.207]
HY (Packaging)	0.826	0.700	3.042	0.096	0.412 [3.104]
HY (Pharmaceuticals)	0.921	0.667	2.531	0.157	-1.016 [2.489]
HY (Railroads)	0.924	0.683	2.756	0.163	-0.869 [3.006]
HY (Retailers)	0.845	0.633	1.949	0.112	-1.353 [4.727]
HY (Services)	0.899	0.683	2.748	0.065	-1.116 [3.355]
HY (Supermarkets)	0.794	0.750	3.825	0.096	-0.844 [4.765]
HY (Technology)	0.883	0.767	4.085	0.038	-0.461 [3.550]
HY (Telecommunications)	0.947	0.667	2.483	0.358	0.404 [1.205]
HY (Transportation)	0.952	0.683	2.810	0.371	0.705 [2.324]
HY (Textile)	0.953	0.650	2.226	0.357	0.136 [1.035]
HY (Utility)	0.939	0.683	2.777	0.152	-0.057 [3.505]
HY (Airlines)	0.991	0.633	1.949	0.392	0.937 [0.410]
HY (Conglomerates)	0.853	0.717	3.343	0.202	0.737 [2.636]
HY (Consumer noncyclical)	0.865	0.683	2.748	0.082	-2.172 [4.338]
HY (Environmental)	0.988	0.583	1.102	0.352	-0.775 [1.889]
HY (Independent energy)	0.982	0.617	1.670	0.237	-0.758 [1.726]
HY (Finance composite)	0.891	0.667	2.624	0.243	-0.132 [2.666]
HY (Gaming)	0.978	0.567	0.809	0.317	-0.431 [1.398]
HY (Health care)	0.867	0.683	2.748	0.051	-2.711 [4.652]
HY (Home construction)	0.942	0.633	1.932	0.233	-0.322 [2.415]
HY (Industrial)	0.834	0.733	3.555	0.081	-0.660 [3.460]
HY (Lodging)	0.975	0.633	1.949	0.338	0.086 [1.319]
HY (Natural gas distribution)	0.934	0.617	1.652	0.076	-2.601 [3.495]
HY (Natural gas pipeline)	0.960	0.650	2.203	0.225	-0.659 [1.574]
HY (Refining)	0.982	0.600	1.388	0.288	-0.473 [0.940]

Notes: See the notes to Table 1a.

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.650	2.110		
Term spread	0.955	0.633	1.808	0.363	-1.110 [2.487]
HY Corporate spread models					
HY (Dynamic factor)	0.518	0.883	5.904	0.092	-0.525 [11.05]
HY (Aggregate)	0.812	0.717	3.260	0.110	-0.819 [3.566]
HY (Aerospace)	0.957	0.633	1.843	0.274	-0.530 [1.642]
HY (Automotive)	0.808	0.667	2.397	0.120	-0.143 [3.525]
HY (Building materials)	0.883	0.650	2.162	0.078	-2.146 [3.591]
HY (Banking)	0.847	0.667	2.416	0.185	-2.544 [6.086]
HY (Consumer cyclical)	0.816	0.733	3.502	0.145	-1.544 [4.031]
HY (Capital goods)	0.786	0.733	3.502	0.078	-1.581 [4.427]
HY (Chemicals)	0.824	0.717	3.224	0.078	-2.354 [4.904]
HY (Construction machinery)	0.884	0.650	2.162	0.124	-1.502 [3.085]
HY (Consumer products)	0.902	0.667	2.389	0.066	-2.737 [3.711]
HY (Electric)	0.898	0.667	2.607	0.278	1.416 [3.743]
HY (Energy)	0.986	0.650	2.131	0.276	-0.257 [0.895]
HY (Entertainment)	0.746	0.717	3.235	0.120	-2.891 [6.683]
HY (Finance)	0.802	0.717	3.510	0.248	-0.029 [3.589]
HY (Insurance)	0.803	0.783	4.399	0.276	0.647 [3.375]
HY (Media-cable)	0.941	0.683	2.834	0.398	0.697 [2.188]
HY (Metals)	0.776	0.700	2.949	0.082	-1.345 [4.229]
HY (Media-noncable)	0.894	0.700	2.980	0.104	-0.688 [3.276]
HY (Natural gas)	0.955	0.650	2.131	0.125	-2.851 [3.373]
HY (Oil field services)	0.976	0.633	1.915	0.394	1.022 [1.359]
HY (Paper)	0.915	0.717	3.231	0.124	-1.208 [2.531]
HY (Packaging)	0.802	0.717	3.231	0.114	0.001 [2.946]
HY (Pharmaceuticals)	0.921	0.683	2.732	0.193	-0.711 [2.592]
HY (Railroads)	0.898	0.700	2.949	0.116	-1.912 [4.749]
HY (Retailers)	0.771	0.667	2.424	0.125	-2.507 [6.601]
HY (Services)	0.864	0.717	3.259	0.029	-2.684 [5.169]
HY (Supermarkets)	0.731	0.750	3.771	0.142	-0.452 [4.767]
HY (Technology)	0.877	0.750	3.771	0.054	-0.360 [3.537]
HY (Telecommunications)	0.923	0.733	3.498	0.322	0.087 [1.511]
HY (Transportation)	0.942	0.683	2.834	0.398	0.903 [2.226]
HY (Textile)	0.952	0.667	2.490	0.413	0.285 [0.915]
HY (Utility)	0.954	0.667	2.448	0.243	0.986 [2.884]
HY (Airlines)	1.001	0.650	2.162	0.513	1.685 [0.066]
HY (Conglomerates)	0.826	0.733	3.527	0.246	0.713 [2.649]
HY (Consumer noncyclical)	0.827	0.700	2.957	0.116	-2.510 [4.961]
HY (Environmental)	0.987	0.650	2.111	0.278	-1.103 [1.931]
HY (Independent energy)	0.986	0.650	2.111	0.269	-0.378 [0.964]
HY (Finance composite)	0.823	0.700	3.205	0.248	-0.464 [3.549]
HY (Gaming)	0.986	0.600	1.251	0.403	-0.240 [1.111]
HY (Health care)	0.853	0.666	2.416	0.098	-2.480 [4.379]
HY (Home construction)	0.920	0.683	2.680	0.248	-0.563 [2.467]
HY (Industrial)	0.804	0.750	3.771	0.097	-1.077 [3.851]
HY (Lodging)	0.971	0.617	1.585	0.351	-0.159 [1.159]
HY (Natural gas distribution)	0.925	0.617	1.523	0.153	-1.821 [2.661]
HY (Natural gas pipeline)	0.948	0.667	2.396	0.246	-0.989 [1.812]
HY (Refining)	0.993	0.617	1.550	0.376	-0.362 [0.938]

Notes: See the notes to Table 1a.

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.583	0.310		
Term spread	0.937	0.717	2.748	0.314	-1.276 [2.639]
HY Corporate spread models					
HY (Dynamic factor)	0.375	0.917	6.377	0.101	-0.444 [15.88]
HY (Aggregate)	0.759	0.733	3.392	0.146	-0.524 [3.082]
HY (Aerospace)	0.912	0.567	0.379	0.208	-1.217 [2.792]
HY (Automotive)	0.772	0.717	2.754	0.166	0.144 [3.706]
HY (Building materials)	0.835	0.700	2.574	0.119	-3.422 [5.645]
HY (Banking)	0.801	0.733	3.222	0.194	-2.922 [7.998]
HY (Consumer cyclical)	0.712	0.783	4.053	0.169	-2.549 [6.713]
HY (Capital goods)	0.696	0.750	3.476	0.098	-2.128 [5.768]
HY (Chemicals)	0.763	0.683	2.518	0.147	-1.961 [5.043]
HY (Construction machinery)	0.834	0.667	2.298	0.210	-1.236 [3.209]
HY (Consumer products)	0.842	0.650	1.548	0.101	-5.413 [7.394]
HY (Electric)	0.887	0.683	3.022	0.356	1.750 [3.023]
HY (Energy)	0.968	0.600	0.819	0.265	0.031 [0.845]
HY (Entertainment)	0.649	0.783	4.102	0.158	-2.692 [8.366]
HY (Finance)	0.705	0.650	2.342	0.229	-0.171 [5.021]
HY (Insurance)	0.728	0.700	2.957	0.243	1.069 [4.869]
HY (Media-cable)	0.927	0.683	3.022	0.387	1.306 [2.483]
HY (Metals)	0.687	0.733	3.111	0.076	-1.637 [4.965]
HY (Media-noncable)	0.882	0.700	2.653	0.092	-0.158 [2.419]
HY (Natural gas)	0.928	0.600	0.948	0.193	-1.690 [2.412]
HY (Oil field services)	0.978	0.567	0.519	0.418	1.761 [0.814]
HY (Paper)	0.873	0.667	1.989	0.076	-1.626 [3.313]
HY (Packaging)	0.757	0.750	3.476	0.148	0.206 [3.195]
HY (Pharmaceuticals)	0.904	0.650	1.966	0.261	-0.002 [1.750]
HY (Railroads)	0.890	0.683	2.416	0.140	-1.670 [3.579]
HY (Retailers)	0.657	0.800	4.555	0.117	-4.640 [12.77]
HY (Services)	0.838	0.733	3.082	0.073	-2.690 [5.405]
HY (Supermarkets)	0.686	0.750	3.430	0.198	0.047 [5.518]
HY (Technology)	0.857	0.700	2.653	0.039	0.086 [2.956]
HY (Telecommunications)	0.880	0.733	3.300	0.286	0.259 [2.138]
HY (Transportation)	0.946	0.667	2.680	0.439	1.171 [1.615]
HY (Textile)	0.903	0.667	2.543	0.394	0.405 [1.411]
HY (Utility)	0.955	0.617	1.540	0.302	1.408 [1.791]
HY (Airlines)	0.994	0.600	1.075	0.466	1.998 [0.060]
HY (Conglomerates)	0.814	0.783	4.024	0.261	1.195 [2.823]
HY (Consumer noncyclical)	0.752	0.750	3.405	0.158	-3.582 [8.013]
HY (Environmental)	0.972	0.617	0.929	0.245	-1.267 [2.098]
HY (Independent energy)	0.972	0.633	1.293	0.255	-0.026 [0.860]
HY (Finance composite)	0.744	0.683	2.879	0.243	-0.617 [4.886]
HY (Gaming)	0.953	0.650	1.453	0.301	-0.916 [1.811]
HY (Health care)	0.806	0.717	2.835	0.156	-2.114 [4.739]
HY (Home construction)	0.846	0.700	2.450	0.187	-2.291 [4.976]
HY (Industrial)	0.737	0.733	3.300	0.111	-0.911 [3.740]
HY (Lodging)	0.943	0.550	0.019	0.319	-0.274 [1.462]
HY (Natural gas distribution)	0.874	0.683	2.055	0.169	-1.980 [3.209]
HY (Natural gas pipeline)	0.901	0.633	1.516	0.247	-1.928 [3.093]
HY (Refining)	0.981	0.617	0.929	0.299	-0.760 [1.757]

Notes: See the notes to Table 1a.

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

Forecasting period 2000:m5-2005:m4	*MSFE relative to AR*	*Success Ratio*	*PT*	*DM*	*Encompassing*
Benchmark models					
AR	1.000	0.567	-0.268		
Term spread	0.933	0.700	2.722	0.331	-2.142 [3.510]
HY Corporate spread models					
HY (Dynamic factor)	0.359	0.833	4.913	0.150	0.221 [18.23]
HY (Aggregate)	0.761	0.650	1.966	0.259	0.149 [2.219]
HY (Aerospace)	0.896	0.533	-0.718	0.224	-0.799 [2.407]
HY (Automotive)	0.793	0.683	2.104	0.237	0.696 [2.970]
HY (Building materials)	0.791	0.633	1.072	0.173	-3.480 [6.623]
HY (Banking)	0.770	0.767	3.753	0.233	-2.790 [9.641]
HY (Consumer cyclical)	0.662	0.750	3.430	0.228	-1.927 [6.811]
HY (Capital goods)	0.686	0.683	2.104	0.178	-1.294 [5.028]
HY (Chemicals)	0.726	0.633	1.404	0.222	-0.967 [4.321]
HY (Construction machinery)	0.814	0.617	1.172	0.280	-0.678 [2.785]
HY (Consumer products)	0.812	0.667	1.678	0.169	-4.883 [6.966]
HY (Electric)	0.873	0.650	1.966	0.381	1.999 [2.230]
HY (Energy)	0.947	0.533	-0.718	0.278	0.482 [0.544]
HY (Entertainment)	0.565	0.783	4.056	0.207	-1.342 [8.799]
HY (Finance)	0.646	0.666	2.543	0.263	1.072 [5.631]
HY (Insurance)	0.737	0.717	3.171	0.313	1.892 [3.983]
HY (Media-cable)	0.930	0.583	1.562	0.397	2.574 [1.650]
HY (Metals)	0.683	0.717	2.748	0.117	-0.977 [4.255]
HY (Media-noncable)	0.905	0.600	0.687	0.236	0.626 [1.428]
HY (Natural gas)	0.916	0.517	-0.734	0.287	-0.409 [1.482]
HY (Oil field services)	0.963	0.483	-1.133	0.388	2.097 [0.080]
HY (Paper)	0.868	0.583	0.456	0.151	-0.948 [2.347]
HY (Packaging)	0.778	0.633	1.404	0.207	0.668 [2.503]
HY (Pharmaceuticals)	0.884	0.517	-0.393	0.314	0.553 [1.262]
HY (Railroads)	0.875	0.633	1.293	0.157	-1.210 [2.743]
HY (Retailers)	0.621	0.817	4.825	0.190	-3.218 [12.84]
HY (Services)	0.857	0.650	1.197	0.208	-2.264 [5.198]
HY (Supermarkets)	0.694	0.767	3.718	0.272	1.130 [5.246]
HY (Technology)	0.880	0.600	0.819	0.229	1.077 [1.751]
HY (Telecommunications)	0.881	0.633	1.751	0.264	1.170 [1.453]
HY (Transportation)	0.924	0.600	1.204	0.440	1.559 [1.048]
HY (Textile)	0.847	0.567	0.657	0.376	0.815 [1.478]
HY (Utility)	0.954	0.533	-0.190	0.315	1.616 [0.866]
HY (Airlines)	0.973	0.467	-1.327	0.419	2.602 [-0.787]
HY (Conglomerates)	0.831	0.783	4.024	0.280	1.696 [2.375]
HY (Consumer noncyclical)	0.716	0.750	3.440	0.237	-2.453 [7.773]
HY (Environmental)	0.960	0.583	0.152	0.260	-1.340 [2.120]
HY (Independent energy)	0.961	0.567	-0.268	0.282	0.667 [0.362]
HY (Finance composite)	0.666	0.650	2.342	0.254	0.558 [5.697]
HY (Gaming)	0.945	0.617	0.670	0.323	-0.957 [1.816]
HY (Health care)	0.773	0.633	0.959	0.244	-1.139 [4.073]
HY (Home construction)	0.840	0.667	1.630	0.263	-2.210 [5.329]
HY (Industrial)	0.734	0.650	1.854	0.217	-0.250 [2.650]
HY (Lodging)	0.927	0.550	-0.499	0.333	-0.102 [1.379]
HY (Natural gas distribution)	0.826	0.683	2.032	0.225	-1.364 [2.897]
HY (Natural gas pipeline)	0.850	0.533	-0.351	0.260	-0.967 [2.337]
HY (Refining)	0.958	0.567	-0.268	0.296	-1.127 [2.829]

Notes: See the notes to Table 1a.

Table 3a: Measures of out-of-sample forecasting performance of the probability of contraction in employment

Forecasting period 2000:m5-2005:m4	*QPS*	*LPS*
Benchmark models		
AR	0.870	1.290
Term spread	0.785	1.086
HY Corporate spread models		
HY (Dynamic factor)	0.690	0.980
HY (Aggregate)	0.883	1.259
HY (Aerospace)	0.895	1.301
HY (Automotive)	0.665	1.014
HY (Building materials)	0.873	1.277
HY (Banking)	0.788	1.143
HY (Consumer cyclical)	0.798	1.148
HY (Capital goods)	0.821	1.195
HY (Chemicals)	0.817	1.182
HY (Construction machinery)	0.854	1.245
HY (Consumer products)	0.777	1.134
HY (Electric)	0.948	1.332
HY (Energy)	0.866	1.246
HY (Entertainment)	0.748	1.090
HY (Finance)	0.875	1.216
HY (Insurance)	0.907	1.284
HY (Media-cable)	0.928	1.337
HY (Metals)	0.768	1.146
HY (Media-noncable)	0.943	1.350
HY (Natural gas)	0.883	1.304
HY (Oil field services)	0.900	1.288
HY (Paper)	0.883	1.290
HY (Packaging)	0.669	1.012
HY (Pharmaceuticals)	0.931	1.361
HY (Railroads)	0.843	1.227
HY (Retailers)	0.801	1.176
HY (Services)	0.881	1.275
HY (Supermarkets)	0.763	1.120
HY (Technology)	0.860	1.242
HY (Telecommunications)	0.905	1.287
HY (Transportation)	0.897	1.266
HY (Textile)	0.827	1.177
HY (Utility)	0.932	1.353
HY (Airlines)	0.870	1.228
HY (Conglomerates)	0.655	1.010
HY (Consumer noncyclical)	0.799	1.169
HY (Environmental)	0.882	1.301
HY (Independent energy)	0.882	1.294
HY (Finance composite)	0.865	1.216
HY (Gaming)	0.858	1.252
HY (Health care)	0.805	1.165
HY (Home construction)	0.846	1.212
HY (Industrial)	0.847	1.216
HY (Lodging)	0.877	1.270
HY (Natural gas distribution)	0.818	1.192
HY (Natural gas pipeline)	0.868	1.278
HY (Refining)	0.785	1.117

Notes: *QPS* is the quadratic probability score; *LPS* is the log probability score; contraction in employment is defined in section 4.1.

Table 3b: Measures of out-of-sample forecasting performance of the probability of contraction in industrial production

Forecasting period 2000:m5-2005:m4	*QPS*	*LPS*
Benchmark models		
AR	0.909	2.129
Term spread	0.837	1.864
HY Corporate spread models		
HY (Dynamic factor)	0.731	1.143
HY (Aggregate)	1.076	2.098
HY (Aerospace)	0.922	1.946
HY (Automotive)	0.887	2.051
HY (Building materials)	0.868	1.973
HY (Banking)	0.802	1.652
HY (Consumer cyclical)	0.840	1.670
HY (Capital goods)	0.923	1.907
HY (Chemicals)	0.965	2.019
HY (Construction machinery)	1.035	2.262
HY (Consumer products)	0.859	1.953
HY (Electric)	1.208	2.979
HY (Energy)	0.884	1.676
HY (Entertainment)	0.779	1.422
HY (Finance)	0.881	1.522
HY (Insurance)	0.881	1.918
HY (Media-cable)	1.081	2.078
HY (Metals)	0.891	2.074
HY (Media-noncable)	1.093	2.168
HY (Natural gas)	0.915	2.078
HY (Oil field services)	1.055	1.793
HY (Paper)	0.928	2.051
HY (Packaging)	0.808	1.675
HY (Pharmaceuticals)	1.086	2.386
HY (Railroads)	0.871	1.469
HY (Retailers)	0.891	1.966
HY (Services)	0.961	2.042
HY (Supermarkets)	0.995	2.060
HY (Technology)	1.151	2.177
HY (Telecommunications)	0.977	2.086
HY (Transportation)	1.066	2.126
HY (Textile)	0.891	1.984
HY (Utility)	1.141	2.435
HY (Airlines)	1.039	1.700
HY (Conglomerates)	0.716	1.774
HY (Consumer noncyclical)	0.953	2.082
HY (Environmental)	0.864	2.000
HY (Independent energy)	0.873	1.796
HY (Finance composite)	1.025	1.814
HY (Gaming)	0.851	1.669
HY (Health care)	0.947	1.612
HY (Home construction)	0.871	1.675
HY (Industrial)	1.028	2.012
HY (Lodging)	0.887	1.798
HY (Natural gas distribution)	0.843	1.617
HY (Natural gas pipeline)	0.866	1.915
HY (Refining)	0.837	1.917

Notes: See the notes to Table 3a.