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Forecasting sectorial profitability and credit spreads using bond yields

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ABSTRACT

While previous research has focused mainly on government bonds as economic predictors we provide evidence that corporate bonds can act as predictors as well. By analyzing data from the financial and industrial sectors, which are the main pillars of the economy, we show that corporate bonds can predict changes in corporate profits and stock price behavior in the sector they are affiliated with. In addition, the examination of the relationship between sectorial credit spreads and various states of the economy shows that the financial sector is more sensitive to economic deterioration than the industrial sector.

1. Introduction

Sectorial diversification is one of the common approaches in portfolio management. While previous research showed that government bonds could be employed as predictors of macroeconomic parameters (the leading one being Estrella & Hardouvelis, 1991, hereafter E&H), we attempt to use corporate bonds from various sectors to predict sectorial behavior. E&H established that the yield curve (YC) on US government bonds could help predict the future state of the economy. Basing their work on Fama (1984, 1990) who showed that the forward interest rate could forecast future changes in short-term interest rates, E&H's results imply that the greater the spread between the yields of long-term and short-term bonds, the higher the expected growth rate.

These results provide the foundation for the current research, which focuses on predicting sectorial behavior by using sectorial corporate bonds. Given that corporate bonds are considered more volatile than government bonds, we believe they can provide a more refined approach to predicting sectorial behavior thereby enabling the improvement of sectorial diversification. The results we obtained, shown later in this study, support this argument.

Before formulating our hypotheses we examined papers that focused on government YC behavior, including those of Cox, Ingersoll, and Ross (1985), Brandt and Kavajecz (2004), Tkacz (2004), Berardi and Torous (2005), Chun (2011), Duffee and Hopkins (2011), Goyenko, Subrahmanyam, and Ukhov (2011), Lettau and Wachter (2011), Kim and Orphanides (2012) and Lange (2013).

Prior studies that examined the behavior of corporate bonds include the following: Merton (1974), Altman (1987), Fons (1994), Jarrow, Lando, and Turnbull (1997), Duffie and Singleton (1999), Helwege and Turner (1999), Zhou (2001), Becker and Milbourn (2011), Bar-Isaac and Shapiro (2013), Huang and Huang (2012) and Pericoli and Taboga (2012). They find differences in the conception of credit risk and its implications for the slope of the YC of corporate bonds. We investigate this issue by using sectorial YCs and sectorial credit spreads as predictors of changes in corporate profits and the behavior of stock indices.

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While previous research attempts to predict macroeconomic behavior largely by using the government YC and its derivatives, we argue that by using sectorial corporate YCs and credit spreads we can predict sectorial behavior. We investigate this argument in the context of the financial and industrial sectors in the US economy. These two sectors are the main pillars[1] of the economy and have usually the richest available data. The findings in this study support the argument just stated above.

Finally, we use sectorial credit spreads to predict sectorial stock performance.

The relationship between the government YC and stock market behavior was examined in studies such as those of Campbell (1987), Campbell and Cochrane (1999) and Chen, Collin-Dufresne, and Goldstein (2009). These studies serve as a basis to examine the relationship between sectorial bonds and sectorial stock indices in this study.

We find that by using government and sectorial corporate YCs we are able to predict changes in corporate profits in both sectors. We also find that in weaker economic states, credit spreads are wider than in stronger economic states. Another result indicates that by using sectorial credit spreads we can predict substantial movements in the sectorial stock indices.

This study is organized as follows. Section 2 presents the theoretical framework. Section 3 describes the data used in the study. Section 4 examines whether sectorial corporate YCs are effective for forecasting changes in sectorial corporate profits in the relevant sector. Section 5 shows the behavior of sectorial corporate credit spreads in different states of the economy. Section 6 determines whether sectorial credit spreads are effective for predicting sectorial stock performance. Finally, Section 7 concludes the study.

2. Theoretical background

The basis for forecasting economic parameters by employing government bonds and the government YC stems from the direct relationship between the interest rate[2] and bond yields. The expectation for a drop in the interest rate causes bond yields to drop and YCs to flatten or even to flip to a declining state. Indeed, towards the end of 2008 expectations of a reduction in interest rates caused the US government YC to flip and decline from left to right before the US central bank reduced the interest rate to its lowest level ever in order to stimulate the growth of the economy. This relationship, which is documented in several papers, such as that of E&H, caused economists to use the YC of government bonds as a tool for forecasting the future macroeconomic state. E&H show that the slope of the government YC, representing the spread between yields in the long and short terms, has a positive relationship with the future growth rate. This relationship follows when a favorable macroeconomic state usually causes the central bank to increase the interest rate. Consequently, investors will demand higher returns for their long-term investments because the long-term interest rate is expected to be higher than its current levels.

While previous research utilized mainly government bonds in order to predict future economic parameters, we argue that by using corporate bonds we can refine our predictive ability. This refinement stems from the additional characteristics of corporate bonds such as credit risk and sectorial affiliation.

Bonds fall into three main groups: government bonds, investment grade bonds[3] and junk bonds.[4] We argue that one of the most important factors for bonds is the issuer's credit risk[5] — defined as the ability to repay one's obligations. The higher the credit rating, the lower the rate of return and the volatility of the bond (Altman, 1987). In a strong economic environment, investors are willing to take greater risks, so they invest in riskier instruments that offer a higher rate of return, such as low-rated bonds. In contrast, when they are concerned about the economic outlook, they seek refuge in less risky instruments such as high-rated bonds.

In addition, while government bonds are relevant for the entire economy, by using sectorial bonds we can estimate the behavior of a specific sector. This characteristic may enable a more refined approach that might help optimize the sectorial diversification of portfolios. The two sectors investigated in this study are the financial and industrial sectors, which are considered to be the main pillars of the economy and also have the richest available data.

3. Data description

3.1. Data

We collected data about the sectorial economic parameters and the sectorial yield curves from Bloomberg. The system includes consistent and reliable data about the sectors used in this study. In our research we used data from Q3/91 up to Q4/13 because the data for the sectors examined, which are the main pillars of the economy, is available since 1991. Yield curve data was collected from Bloomberg's fair market yield curves, which are considered to be option-free as they exclude regular callable bonds and include only make whole callable bonds.

Regular callable bonds entail prepayment risk (Bleaney, Mizen, & Veleanu, 2012) and therefore might impact the results we find. However, make whole callable bonds have a floating call price that is determined by a spread from the relevant Treasury bond. As a result, they make the bond holder "whole" when called, thereby eliminating most of the prepayment risk (Fabozzi, 2005). By using Bloomberg's option-free fair market yield curves we obtained a proper filtration of the data and eliminated potential prepayment risks.

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[1] The financial and industrial sectors have the largest number of companies in the S&P 500 index, represented by 85 and 76 companies, respectively.

[2] The Federal Funds Rate, the overnight interest rate at which depository institutions lend funds to one another, is determined by the Federal Reserve.

[3] Investment grade bonds are considered low risk bonds, and are rated *BBB*− (by S&P or Fitch) or *Baa3* (by Moody's) and above.

[4] Junk bonds are considered high risk bonds, and are rated lower than *BBB*− (by S&P or Fitch) or *Baa3* (by Moody's).

[5] The credit risk represents the probability that the issuer will not be able to pay all of its obligations when due.

Following Chun (2011), in order to provide continuous results, yield curve data was collected daily and used by calculating the average yield in the relevant quarter. Table 1 includes descriptive statistics about the most commonly used variables in the study.

3.2. Methodology

We use yield and credit spreads in order to predict changes in corporate profits and changes in sectorial stock indices by employing regression models.

The following are the explanatory variables we use in our models:

CrdtSprd(A) is the spread between corporate bonds that are rated A and government bonds. It is the difference between the yield of 10-year A-rated bonds and the yield of 10-year government bonds. For example, we define the A credit spread as:

$$CrdtSprd(A) = Y(A)_{(10Yr)}\text{-}Y(UST)_{(10Yr)}. \tag{1}$$

Sprd(*UST*) is the US government yield spread. It is defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ \mathrm{Yr})}$) and a 3-month government bond ($Y(UST)_{(0.25\ \mathrm{Yr})}$):

$$Sprd(UST) = Y(UST)_{(10\ \mathrm{Yr})}\text{-}Y(UST)_{(0.25\ \mathrm{Yr})}. \tag{2}$$

In our research we distinguish between the government predictive ability and the corporate predictive ability by calculating the following variables:

TtSprd(A) is the total spread of corporate bonds that are rated A. It is the difference between the yield to maturity on 10-year bonds ($Y(A)_{(10\ \mathrm{Yr})}$) and 3-month bonds ($Y(A)_{(0.25\ \mathrm{Yr})}$). Thus, for rating level A:

$$TtSprd(A) = Y(A)_{(10\ \mathrm{Yr})} - Y(A)_{(0.25\ \mathrm{Yr})}. \tag{3}$$

MrSprd(A) is the marginal spread of corporate bonds that are rated A. It is defined as the difference between the total spread of the A rating and the total spread of a rating that is higher than A by one rating level. For example, the A marginal spread is as follows:

$$MrSprd(A) = TtSprd(A) - Sprd(UST). \tag{4}$$

We chose *A* as the highest corporate rating rather than *AA* because data for *AA*-rated bonds exist only up to 2011. When conducting the research, we also ran tests for *AA*-rated bonds up to 2011. The results for the A-rated bonds were similar to those obtained for *AA*-rated bonds, so we use the former. We believe that the similar results stem from the similarities between the *A* and *AA* ratings, which are both considered to be high and relatively safe ratings. These additional analyses indicate that the results we obtained are robust and reliable.

Bloomberg calculates the corporate yields and credit spreads on an average basis. In addition, in order to neutralize inflation, the explained variables are in real terms. Similarly the explanatory variables are also considered in real terms because they are yield spreads.

In accordance with some of the studies described in the previous section, we lag the explanatory variables. By adopting this approach, we can examine the explanatory variables of time t with the economic performance of time $t + k$, where t is the current time, and k is the forecasting horizon. This approach allows us to investigate whether we can use the explanatory variables to predict future economic behavior.

Table 1
Descriptive statistics of bond yields.

Descriptive statistics					
	n	Minimum	Maximum	Mean	Std. deviation
Sprd(*UST*)	90	−.708	3.880	1.86451	1.243819
MrSprd(*A*)-IND	90	−.62	1.10	.2304	.38087
MrSprd(*A*)-FIN	90	−.71	2.56	.6094	.66112
CrdtSprd(*A*)-IND	90	.46	3.26	.9577	.46216
CrdtSprd(*A*)-FIN	90	.47	5.21	1.3683	.95201
Basic yield level	90	.025	6.260	3.00481	2.140530

Notes: Data was collected using Bloomberg's fair market option-free yield curves. The data is available from 1991 to 2013 for most bonds. The spreads denoted in the table are the most relevant bond levels used in the study.

4. Can spreads of sectorial corporate yield curves predict sectorial corporate profit changes?

Given that sectorial corporate bonds are more volatile than government bonds and each one of them is affiliated with a different sector, they provide a refined approach to forecasting the behavior of that sector. Thus, we posit that:

H1. Sectorial corporate YC spreads can predict changes in corporate profits in the sector.

4.1. Definitions

The first explained variable used in this section is Profit Changes which is a dummy variable that receives the value 1 if the sectorial corporate profits in the current quarter were higher than the corporate profits in the corresponding quarter in the previous year, and 0 otherwise. This variable determines whether the state of the corporations within the sector has improved. In order to provide an additional approach to investigating whether the sectorial corporate yield curves can predict sectorial profit changes, we defined *PrfPrChng* as the percentage change in sectorial profits compared with the corresponding quarter in the previous year. We then ran regressions on the Ln transformation of this variable.

Two sectors are examined here — the financial and the industrial.

4.2. Hypothesis testing: estimated equations and findings for H1

As discussed above, past research has shown that by using the government YC one can forecast future macroeconomic parameters such as the GDP growth rate. We argue that by adding corporate YCs we can provide a more refined approach that allows us to forecast the behavior of specific sectors. The first regression equation (Eq. (5)), shown below, attempts to predict a change in the profits of corporations by employing the government spread and the marginal spread defined above:

$$PrftChng_{t+k} = \frac{e^{\left(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t\right)}}{e^{\left(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t\right)}+1}, \tag{5}$$

where, $PrftChng_{t+k}$ is a dummy variable that receives the value 1 if the corporations' profits in the relevant sector increased compared with the corresponding quarter last year, and 0 otherwise.

The findings for Eq. (5) estimated for the financial sector and shown in Table 2 indicate that the government and corporate YCs can indeed predict changes in sectorial profits as the regression equation is significant for seven of the nine quarters examined. The highest R-Squared of the regression is in the second and third quarters (0.12). As expected, we found a significant positive relationship between the YC spreads and changes in profits. In other words, when the YC spread increases, corporate profits increase. This finding is in line with our expectations because both changes in profits and higher YC spreads are positive developments for the sector.

We also use Eq. (5) to estimate changes in the industrial sector. Here, the explanatory variables are the government spread and the marginal spread of A-rated industrial bonds while the explained variable is the changes in profits of industrial corporations.

The findings in Table 3 indicate that YC spreads can also predict changes in the profits of industrial corporations because the regression equation is significant for all of the nine quarters examined. Here too the relationship between the YC spreads and the changes in profits is positive as described above. The quarter with the highest R-Squared is the fifth, which has an R-Squared of 0.12. The comparison between Tables 2 and 3 indicates that when predicting changes in profits for the short term the prediction is weaker for industrial corporations than for the financial sector. Both tables also indicate that the coefficients for the marginal

Table 2
Predicted profit changes in financial corporations based on US government spreads and marginal spreads of US A-rated financial corporate bonds, Q3/1991–Q4/2013.

k	β_0	$Wald_{\beta_0}$	β_1	$Wald_{\beta_1}$	β_2	$Wald_{\beta_2}$	Cox&Snell R^2	Chi Square	Sig.	n
1	−0.475	1.038	0.418	4.460	1.052	5.444	0.114	10.775	0.005	89
2	−0.511	1.178	0.418	4.391	1.120	5.888	0.119	11.195	0.004	88
3	−0.545	1.350	0.462	5.338	1.011	4.842	0.119	10.977	0.004	87
4	−0.456	0.975	0.442	5.053	0.848	3.635	0.103	9.315	0.009	86
5	−0.244	0.289	0.393	4.116	0.649	2.277	0.077	6.819	0.033	85
6	−0.292	0.394	0.318	2.646	1.022	4.896	0.094	8.325	0.016	84
7	−0.161	0.115	0.231	1.354	1.194	6.056	0.099	8.643	0.013	83
8	0.143	0.095	0.165	0.727	0.830	3.432	0.055	4.626	0.099	82
9	0.401	0.774	0.079	0.176	0.539	1.702	0.025	2.036	0.361	81

Notes: Estimated model, Eq. (5): $PrftChng_{t+k} = \frac{e^{\left(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t\right)}}{e^{\left(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t\right)}+1}$, where $PrftChng_{t+k}$ receives the value of 1 when the financial corporations' profits in the current quarter are higher than those of the corresponding quarter, and 0 otherwise. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ Yr)}$) and a 3-month government bond ($Y(UST)_{(0.25\ Yr)}$) and $MrSprd(A)_t$ is the marginal yield difference in the financial sector, calculated by: $MrSprd(A) = TtSprd(A) - Sprd(UST)$.
The correlation between $Sprd(UST)_t$ and $MrSprd(A)_t$ is 0.09.

Table 3
Predicted profit changes in industrial corporations based on US government spreads and marginal spreads of US A-rated industrial corporate bonds, Q3/1991–Q4/2013.

k	β_0	$Wald_{\beta_0}$	β_1	$Wald_{\beta_1}$	β_2	$Wald_{\beta_2}$	Cox&Snell R^2	Chi Square	Sig.	n
1	−0.067	0.018	0.395	3.340	1.617	4.971	0.072	6.646	0.036	89
2	−0.171	0.119	0.443	4.044	1.725	5.400	0.082	7.527	0.023	88
3	−0.348	0.496	0.572	6.471	1.466	3.857	0.092	8.383	0.015	87
4	−0.410	0.683	0.608	7.169	1.432	3.605	0.099	8.959	0.011	86
5	−0.486	0.934	0.690	8.524	1.453	3.443	0.116	10.479	0.005	85
6	−0.398	0.636	0.625	7.285	1.450	3.453	0.102	9.062	0.011	84
7	−0.377	0.550	0.612	6.565	1.840	4.960	0.107	9.408	0.009	83
8	−0.290	0.327	0.555	5.541	1.814	4.807	0.096	8.267	0.016	82
9	−0.285	0.310	0.534	5.030	2.009	5.555	0.099	8.456	0.015	81

Notes: estimated model, Eq. (5): $PrftChng_{t+k} = \frac{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(A)_t+\varepsilon_t)}+1}$, where $PrftChng_{t+k}$ receives the value of 1 when the industrial corporations' profits in the current quarter are higher than those of the corresponding quarter, and 0 otherwise. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ Yr)}$) and a 3-month government bond ($Y(UST)_{(0.25\ Yr)}$) and $MrSprd(A)_t$ is the marginal yield difference in the industrial sector, calculated by: $MrSprd(A) = TtSprd(A) - Sprd(UST)$.
The correlation between $Sprd(UST)_t$ and $MrSprd(A)_t$ is −0.31.

corporate spreads are substantially larger in absolute value compared with the coefficients for the government spread. These results confirm H1, because we found that the government and sectorial corporate spreads can predict changes in corporate profits. The logical explanation for these results is that when the state of the economy is expected to deteriorate, investors believe that the central bank will lower interest rates to ease the economy, and these expectations cause the YCs to flatten. On the other hand, in times of high growth the central bank is expected to raise rates and cause the YCs to be steeper. Employing the slopes of both the government and corporate YCs enabled us to use the basic yield levels, as they can be found implicitly in the slopes.

One of the most important characteristics of corporate bonds is their credit rating, which differs from one issuer to another. When examining this issue for the financial sector, we modified Eq. (5) to include the marginal spread of investment grade bonds. Data about high yield bonds was available only from 2005. Therefore, we did not use it in this scenario. The results of this regression are presented in Table 4.

As Table 4 indicates, the inclusion of *BBB*-rated bonds, which comprised the investment grade rating with the *A*-rated bonds, improved the prediction slightly in the short-term but degraded it a bit in the long-term. We then investigated this issue for the industrial sector. Here we added the high yield bonds represented by the *BB*-rating, which is the lowest rating for which we had data.

The results in Table 5 are consistent with those of Table 4, as the use of *BBB*-rated bonds improved the prediction in the short-term a bit but disrupted the prediction in the long-term. Another interesting phenomenon in Table 5 indicates that the low-rated bonds are insignificant when forecasting the future profit changes in the sector.

In order to investigate our hypothesis from another angle we used the *PrfPrChng* variable, defined above as the explained variable in the linear regression of the following form:

$$Ln(Prf\,PrChng)_{t+k} = \beta_0 + \beta_1 Sprd(UST)_t + \beta_2 MrSprd(A)_t + \varepsilon_t, \tag{6}$$

Table 4
Predicted profit changes in financial corporations based on US government spreads and marginal spreads of US financial corporate bonds rated *A* and *BBB*, Q3/1991–Q1/2013.

k	β_0	$Wald_{\beta_0}$	β_1	$Wald_{\beta_1}$	β_2	$Wald_{\beta_2}$	Cox&Snell R^2	Chi Square	Sig.	n*
1	−0.547	1.368	0.458	5.062	1.010	6.323	0.132	12.328	0.002	87
2	−0.514	1.222	0.450	4.955	0.959	5.912	0.126	11.678	0.003	87
3	−0.600	1.647	0.505	6.084	0.955	5.733	0.135	12.622	0.002	87
4	−0.571	1.504	0.492	5.859	0.912	5.263	0.129	11.832	0.003	86
5	−0.238	0.282	0.412	4.460	0.548	2.363	0.079	7.037	0.030	85
6	−0.219	0.229	0.337	2.965	0.767	3.976	0.084	7.378	0.025	84
7	−0.113	0.058	0.261	1.705	0.961	5.314	0.092	7.966	0.019	83
8	0.180	0.153	0.186	0.922	0.661	2.973	0.050	4.236	0.120	82
9	0.455	1.018	0.092	0.237	0.375	1.194	0.018	1.511	0.470	81

Notes: estimated model, Eq. (5): $PrftChng_{t+k} = \frac{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(IG)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(IG)_t+\varepsilon_t)}+1}$, where $PrftChng_{t+k}$ receives the value of 1 when the financial corporations' profits in the current quarter are higher than those of the corresponding quarter, and 0 otherwise. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ Yr)}$) and a 3-month government bond ($Y(UST)_{(0.25\ Yr)}$) and $MrSprd(IG)_t$ is the marginal yield difference in the financial sector, calculated by:$MrSprd(IG) = TtSprd(BBB) - Sprd(UST)$.
The correlation between $Sprd(UST)_t$ and $MrSprd(IG)_t$ is 0.02.

* The data for 10 Yr *BBB* bonds exist only until Q1/13. As a result the first three horizons have a similar number of observations.

Table 5
Predicted profit changes in industrial corporations based on US government spreads and marginal spreads of US industrial corporate bonds rated *A*, *BBB* and *BB*, Q1/1992–Q4/2013.

k	β_0	$Wald_{\beta_0}$	β_1	$Wald_{\beta_1}$	β_2	$Wald_{\beta_2}$	β_3	$Wald_{\beta_3}$	Cox&Snell R^2	Chi Square	Sig.	n
1	−0.960	1.246	0.740	4.574	2.106	6.715	0.393	0.486	0.103	9.393	0.024	86
2	−0.844	0.898	0.775	4.591	2.022	5.549	0.133	0.052	0.110	9.953	0.019	85
3	−1.112	1.418	0.949	5.966	2.245	5.785	0.029	0.002	0.147	13.355	0.004	84
4	−0.134	0.019	0.686	3.281	1.347	1.948	−0.754	1.293	0.156	14.035	0.003	83
5	−0.538	0.315	0.819	4.470	1.568	2.624	−0.410	0.411	0.147	13.043	0.005	82
6	−0.390	0.183	0.687	3.605	1.220	1.811	−0.176	0.084	0.097	8.303	0.040	81
7	−0.092	0.011	0.541	2.392	1.155	1.681	−0.334	0.304	0.080	6.711	0.082	80
8	0.420	0.217	0.376	1.232	0.414	0.211	−0.459	0.548	0.062	5.05	0.168	79
9	0.746	0.636	0.300	0.753	0.316	0.114	−0.736	1.259	0.070	5.697	0.127	78

Notes: estimated model, Eq. (5): $PrftChng_{t+k} = \frac{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(IG)_t+\beta_3 MrSprd(BB)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 Sprd(UST)_t+\beta_2 MrSprd(IG)_t+\beta_3 MrSprd(BB)_t+\varepsilon_t)}+1}$, where $PrftChng_{t+k}$ receives the value of 1 when the industrial corporations' profits in the current quarter are higher than those of the corresponding quarter, and 0 otherwise. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\text{ Yr})}$) and a 3-month government bond ($Y(UST)_{(0.25\text{ Yr})}$).
MrSprd (*IG*) and *MrSprd* (*BB*) are the marginal yield differences, calculated by $MrSprd(IG) = TtSprd(BBB) - Sprd(UST)MrSprd(BB) = TtSprd(BB) - TtSprd(BBB)$.
The correlation coefficients for the three explanatory variables are: −0.50, −0.453, and −0.185 for the following three pair correlations, respectively: Sprd(*UST*)–*MrSprd*(*IG*), *Sprd*(*UST*)–*MrSprd*(*BB*) and *MrSprd*(*IG*)–*MrSprd*(*BB*).
The data for *BB* industrial bonds exist only from Q1/92.

where $Ln(Prf\,Pr\,Chng)_{t+k}$ is a log transformation of the profit change percentage variable. When estimating an OLS regression, the overlapping data creates a moving average error of order $k-1$ where k is the forecasting horizon. We use the Newey–West method to adjust the standard errors by using the lag length of $k-1$ because of the moving average error order.

The results in Table 6 that refer to the financial sector indicate similar but weaker results than those obtained by the logistic regression. For the first three forecasting horizons we found the regression to be significant and demonstrating a positive relationship between both yield spreads and a positive change in the profits of financial corporations. We conducted the same test for the industrial sector as well, and its results are presented in Table 7.

The results imply that the regression is significant for the six forecasting horizons. However, the corporate marginal spread is not efficient in predicting the percentage change in profits.

The comparison between the linear analysis and the logistic regressions conducted earlier indicates that the corporate yield spreads are more efficient in predicting trends such as profit growth or contraction than predicting the actual rate of change in corporate profits. Still, we confirmed our hypothesis that corporate spreads can predict sectorial profit changes.

We also estimated an additional regression that accounts for the fixed effects of each sector. By using the average recovery ratings for each sector, taken from Moody's DRS, we were able to include both sectors in the same regression, thereby doubling the number of observations. The regression equation is similar to Eq. (5) with the additional recovery rates predictor, which is higher for industrial corporations and lower for financial corporations. The results of this regression are presented in Table 8.

Table 8 also provides important results indicating that the increase in the number of observations improved the predictions compared with Tables 2 and 3. In addition, we can see a positive relationship between the recovery rates and profit growth, which indicates that in industrial corporations profit growth is more common.

Further validation of our results comes from an out-of-sample analysis of the linear regressions we ran. In order to establish a reliable out-of-sample analysis we defined the period from the start of the data until the end of 2010 as the estimation period, while the remaining observations were defined as the prediction period. This type of analysis allows us to compare the predictions of our models with the real data from the prediction period. The out-of-sample analyses for the financial and industrial sectors appear in Figs. 1 and 2, respectively.

Table 6
Predicted percentage of profit changes in financial corporations based on US government spreads and marginal spreads of US A-rated financial corporate bonds, Q3/1991–Q4/2013.

k	β_0	t_{β_0}	β_1	t_{β_1}	β_2	t_{β_2}	R^2	F	Sig.	n
1	−0.151	−2.86	0.054	2.92	0.155	2.89	0.219	7.40	0.001	89
2	−0.150	−2.15	0.065	2.63	0.118	1.86	0.183	4.35	0.016	88
3	−0.136	−1.67	0.072	2.34	0.068	1.26	0.147	3.13	0.049	87
4	−0.114	−1.21	0.069	1.82	0.041	0.78	0.115	2.05	0.136	86
5	−0.078	−0.73	0.059	1.36	0.018	0.36	0.080	1.17	0.315	85
6	−0.041	−0.34	0.037	0.85	0.024	0.47	0.036	0.54	0.584	84

Notes: estimated model, Eq. (6): $Ln(Prf\,Pr\,Chng)_{t+k} = \beta_0 + \beta_1 Sprd(UST)_t + \beta_2 MrSprd(A)_t + \varepsilon_t$, where $Ln(Prf\,Pr\,Chng)_{t+k}$ is a log transformation of the percentage change in the financial corporations' profits in the current quarter compared with those of the corresponding quarter. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\text{ Yr})}$) and a 3-month government bond ($Y(UST)_{(0.25\text{ Yr})}$) and $MrSprd(A)_t$ is the marginal yield difference in the financial sector, calculated by: $MrSprd(A) = TtSprd(A) - Sprd(UST)$.
The correlation between $Sprd(UST)_t$ and $MrSprd(A)_t$ is 0.09.

Table 7
Predicted percentage of profit changes in industrial corporations based on US government spreads and marginal spreads of US A-rated industrial corporate bonds, Q3/1991–Q4/2013.

k	β_0	t_{β_0}	β_1	t_{β_1}	β_2	t_{β_2}	R^2	F	Sig.	n
1	−0.034	−1.18	0.038	3.75	0.040	1.00	0.130	7.58	0.001	89
2	−0.051	−1.40	0.049	3.81	0.029	0.61	0.233	9.65	0.000	88
3	−0.061	−1.68	0.057	4.29	0.006	0.15	0.326	13.30	0.000	87
4	−0.064	−1.86	0.060	4.57	0.000	0.01	0.359	13.15	0.000	86
5	−0.064	−1.81	0.060	4.51	−0.002	−0.06	0.375	13.67	0.000	85
6	−0.067	−1.88	0.060	4.19	0.009	0.28	0.359	10.35	0.000	84

Notes: estimated model, Eq. (6): $Ln(Prf\ \mathrm{Pr}\ Chng)_{t+k} = \beta_0 + \beta_1 Sprd(UST)_t + \beta_2 MrSprd(A)_t + \varepsilon_t$, where $Ln(Prf\ \mathrm{Pr}\ Chng)_{t+k}$ is a log transformation of the percentage change in the industrial corporations' profits in the current quarter compared with those of the corresponding quarter. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ \mathrm{Yr})}$) and a 3-month government bond ($Y(UST)_{(0.25\ \mathrm{Yr})}$) and $MrSprd(A)_t$ is the marginal yield difference in the industrial sector, calculated by: $MrSprd(A) = TtSprd(A) - Sprd(UST)$.
The correlation between $Sprd(UST)_t$ and $MrSprd(A)_t$ is −0.31.

As the figures imply, the out-of-sample analysis shows a small RMSE, indicating an effective prediction of the future profit changes. Using these various tools, we were able to achieve a robust affirmation of our first hypothesis that sectorial corporate bonds can predict future sectorial profit changes.

5. The relationship between the state of the economy and sectorial credit spreads

Here we investigate the behavior of sectorial credit spreads during different states of the economy. Credit spreads, which were defined in the methodology section, indicate the additional yield investors demand in order to invest in corporate bonds in relation to government bonds of the same maturity. Therefore, when the economy is weak, we expect credit spreads to be greater because of the greater risk. We posit that:

H2. The weaker the economy, the greater the credit spreads will be.

5.1. Definitions

Below are the different states of the economy used to test the credit spreads: Economic Boom, Economic Cooldown, Stagnation and Recession.

Economic Boom is a dummy variable that receives the value 1 if the real GDP growth rate (g) is higher than 2.5%, and 0 otherwise. We chose 2.5% because the mean annual growth rate of the US economy between 1980 and 2013 was approximately 2.5%.
Economic Cooldown is a dummy variable that receives the value 1 if the real GDP growth rate in the current quarter is lower than the g of the previous quarter, and 0 otherwise. This variable indicates whether the economy is slowing down.
Economic Stagnation is a dummy variable that receives the value 1 if g is less than 2%, and 0 otherwise. The variable, which is a middle ground between boom and recession, can help determine whether the economy is stagnating and

Table 8
Predicted profit changes in both sectors based on US government spreads, marginal spreads of US A-rated sectorial corporate bonds and average sectorial recovery rates, Q3/1991–Q4/2013.

k	β_0	Wald_{β_0}	β_1	Wald_{β_1}	β_2	Wald_{β_2}	β_3	Wald_{β_3}	Cox&Snell R^2	Chi Square	Sig.	n
1	−1.344	2.381	0.389	7.344	1.223	9.952	3.380	2.050	0.092	17.120	0.001	178
2	−1.440	2.696	0.412	7.990	1.302	10.671	3.471	2.138	0.100	18.449	0.000	176
3	−1.455	2.709	0.501	11.601	1.138	8.186	3.191	1.785	0.105	19.296	0.000	174
4	−1.357	2.360	0.501	11.843	0.999	6.517	2.979	1.554	0.099	17.951	0.000	172
5	−1.172	1.735	0.501	11.850	0.828	4.542	2.716	1.265	0.091	16.212	0.001	170
6	−1.324	2.219	0.450	9.457	1.117	7.512	3.138	1.690	0.094	16.590	0.001	168
7	−1.343	2.238	0.392	6.896	1.350	9.759	3.468	2.011	0.096	16.725	0.001	166
8	−0.853	0.915	0.313	4.694	1.051	6.529	2.659	1.196	0.064	10.913	0.012	164
9	−0.565	0.407	0.229	2.674	0.827	4.480	2.357	0.948	0.042	6.956	0.073	162

Notes: estimated model, Eq. (5): $PrftChng_{t+k} = \frac{e^{(\beta_0 + \beta_1 Sprd(UST)_t + \beta_2 MrSprd(A)_t + \beta_3 Rcvr + \varepsilon_t)}}{e^{(\beta_0 + \beta_1 Sprd(UST)_t + \beta_2 MrSprd(A)_t + \beta_3 Rcvr + \varepsilon_t)} + 1}$, where $PrftChng_{t+k}$ receives the value of 1 when the sectorial corporations' profits in the current quarter are higher than those of the corresponding quarter, and 0 otherwise. $Sprd(UST)_t$ is the US government yield spread, defined as the difference between the yield to maturity of a 10-year government bond ($Y(UST)_{(10\ \mathrm{Yr})}$) and a 3-month government bond ($Y(UST)_{(0.25\ \mathrm{Yr})}$) and $MrSprd(A)_t$ is the marginal yield difference in both sectors, calculated by: $MrSprd(A) = TtSprd(A) - Sprd(UST)$.
Rcvr is the average sectorial recovery rates taken from Moody's DRS.
The correlation between $Sprd(UST)_t$ and $MrSprd(A)_t$ is 0.05.

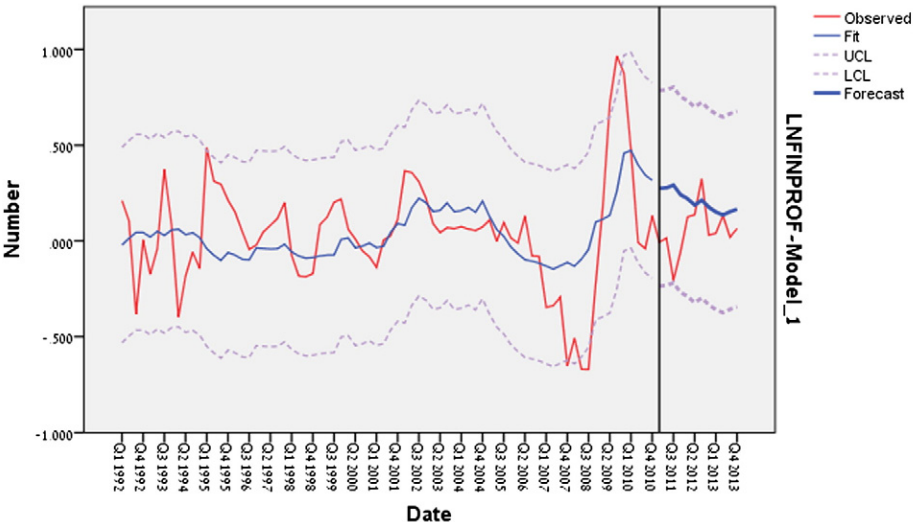

Fig. 1. Out-of-sample forecasting profit changes in financial corporations based on US government spreads and marginal spreads of US A-rated financial corporate bonds. Notes: The data was divided into an estimation period (Q1/1992–Q4/2010) and a prediction period (Q1/2011–Q4/2013). By employing two of the estimated predictors, $Sprd(UST)_2$ and $MrSprd(A)_2$, we forecasted the expected values for the prediction period, and compared them with the observed values. The RMSE of this comparison is 0.256.

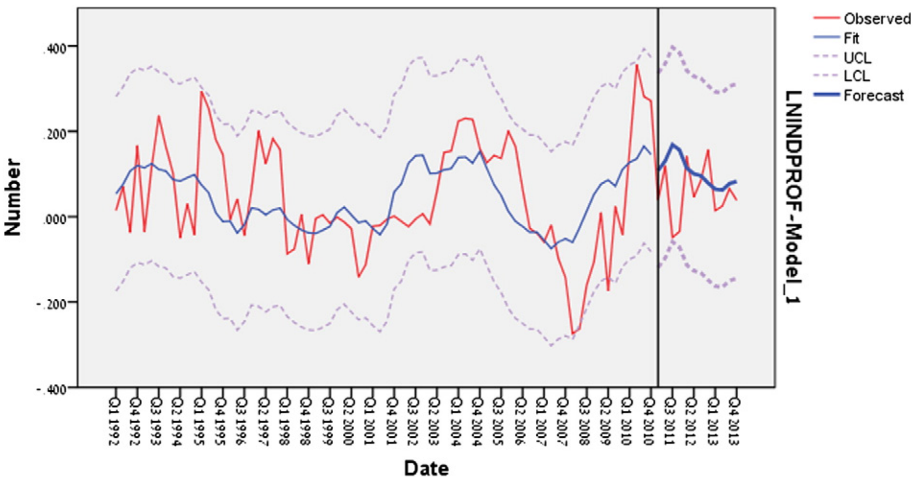

Fig. 2. Out-of-sample forecasting profit changes in industrial corporations based on US government spreads and marginal spreads of US A-Rated industrial corporate bonds. Notes: The data was divided into an estimation period (Q1/1992–Q4/2010) and a prediction period (Q1/2011–Q4/2013). By employing two of the estimated predictors, $Sprd(UST)_2$ and $MrSprd(A)_2$, we forecasted the expected values for the prediction period, and compared them with the observed values. The RMSE of this comparison is 0.114.

growing slowly. We calculate this variable using the standard definition of stagnation as explained in financial books and websites.[6]

Economic Recession is a dummy variable that receives the value 1 if g is negative, and 0 otherwise. This variable represents the worst cases in which the real GDP is in decline. We calculate this variable using the standard definition in the financial literature and websites.[7]

5.2. The findings for H2

The analysis shown in Table 9 was conducted using sensitivity analyses that investigate whether the credit spreads of both sectors are significantly different in a specific state of the economy compared with other states. For example, Table 9(B) shows that in times of

[6] See, e.g., Investopedia.com.
[7] See, e.g., Investopedia.com.

Table 9
Sensitivity analysis of the changes in the credit spread of US A-rated corporate bonds in the financial and industrial sectors, Q3/1991–Q4/2013.

(A): Mean comparison of the credit spread of US A-rated corporate bonds in relation to economic boom

	Boom	n	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	0	38	1.842	1.200	0.195
	1	52	1.022	0.497	0.069
Industrial: *CrdtSprd*(*A*)	0	38	1.197	0.547	0.089
	1	52	0.783	0.286	0.040

(B): Mean comparison of the credit spread of US A-rated corporate bonds in relation to economic cooldown

	CoolDown	n	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	0	43	1.194	0.718	0.109
	1	47	1.528	1.108	0.162
Industrial: *CrdtSprd*(*A*)	0	43	0.822	0.267	0.041
	1	47	1.082	0.562	0.082

(C): Mean comparison of the credit spread of US A-rated corporate bonds in relation to economic stagnation

	Stagnation	n	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	0	66	1.075	0.512	0.063
	1	24	2.174	1.357	0.277
Industrial: *CrdtSprd*(*A*)	0	66	0.816	0.289	0.035
	1	24	1.347	0.612	0.125

(D): Mean comparison of the credit spread of US A-rated corporate bonds in relation to economic recession

	Recession	n	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	0	83	1.177	0.541	0.059
	1	7	3.640	1.709	0.646
Industrial: *CrdtSprd*(*A*)	0	83	0.879	0.306	0.034
	1	7	1.889	0.889	0.336

(E) The Credit Spread Change across the four economic states for the financial and industrial sectors

	Financial: *CrdtSprd*(*A*) Change	Industrial: *CrdtSprd*(*A*) Change
Boom	−44%	−34%
Cooldown	+28%	+32%
Stagnation	+102%	+65%
Recession	+209%	+114%

* The difference between the mean credit spread for the two dichotomist cases (represented by the values of one and zero for the dummy variable) is statistically significant at less than 3% for the industrial sector at all four economic states in Table 9(A)–(D). For the financial sector the difference between the mean credit spread is statistically significant at less than 3% for all but the cooldown economic state. For the cooldown state the difference is significant at less than 10% level.

cooldown both financial and industrial credit spreads are higher than when the economy is heating up, meaning the economy is growing at a higher rate than the previous quarter.

The results in Table 9 indicate a significant difference in credit spreads between two states of the economy for each of the sectors examined.

Table 9(A)–(D) can be summarized as follows. During economic booms the credit spreads for the financial and industrial sectors decline by 44% and 34%, respectively. During economic cooldowns the relevant credit spreads rise by 28% for the financial sector and 32% for the industrial. During times of stagnation the financial and industrial spreads rise by 102% and 65%, respectively and during

Table 10(A)
Predicted substantial negative financial stock index change based on US financial A-rated bonds' 10-year credit spreads, Q3/1991–Q4/2013.

k	β_0	Wald$_{\beta_0}$	β_1	Wald$_{\beta_1}$	Cox&Snell R^2	Chi Square	Sig.	n
1	−3.118	24.952	1.142	10.421	0.167	16.210	0.000	89
2	−2.513	23.377	0.764	7.506	0.097	8.968	0.003	88
3	−2.173	20.427	0.557	4.867	0.057	5.069	0.024	87
4	−1.832	16.006	0.346	2.027	0.022	1.943	0.163	86
5	−1.602	12.570	0.203	0.668	0.007	0.634	0.426	85
6	−1.405	9.634	0.076	0.085	0.001	0.083	0.773	84

Notes: estimated model, Eq. (7): $SbsNg_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}+1}$, where $SbsNg_{t+k}$ receives the value of 1 when the financial stock index in a given quarter decreases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. *CrdtSprd*(*A*) is the yield difference between 10-year A-rated financial corporate bonds and 10-year Treasury bonds.

Table 10(B)
Mean comparison of the credit spread of US A-rated financial corporate bonds in relation to substantial negative financial stock index change, Q3/1991–Q4/2013.

	SbsNg	N	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	1	18	2.441	1.429	0.337
	0	72	1.100	0.531	0.063

* The difference between the mean credit spread for the two dichotomist cases (represented by the values of one and zero for the dummy variable) is statistically significant at less than 1%.

Table 11(A)
Predicted substantial positive financial stock index change based on US financial A-rated bonds' 10-year credit spreads, Q3/1991–Q4/2013.

k	β_0	Wald_{β_0}	β_1	Wald_{β_1}	Cox&Snell R^2	Chi Square	Sig.	n
1	0.987	4.992	−0.695	5.192	0.076	6.987	0.008	89
2	0.562	2.021	−0.383	2.317	0.029	2.619	0.106	88
3	0.228	0.368	−0.150	0.438	0.005	0.447	0.504	87
4	0.034	0.008	−0.025	0.013	0.000	0.013	0.911	86
5	0.025	0.005	−0.036	0.026	0.000	0.026	0.873	85
6	−0.059	0.025	0.009	0.002	0.000	0.002	0.969	84

Notes: estimated model, Eq. (8): $SbsPs_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}+1}$, where $SbsPs_{t+k}$ receives the value of 1 when the financial stock index in a given quarter increases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. *CrdtSprd*(*A*) is the yield difference between 10-year A-rated financial corporate bonds and 10-year Treasury bonds.

recessions the spreads rise by 209% for the financial sector and 114% for the industrial sector. These results are summarized in Table 9(E), which illustrates that the weaker the economy is, the higher the credit spreads are in both sectors. This finding confirms H2. Another result indicates that in all economic states credit spreads for the financial sector are higher than credit spreads for the industrial sector. In addition, the table illustrates a very interest phenomenon in which the rate of change in the industrial sector generally remains the same, while the change in the financial sector becomes steeper and steeper.

One explanation for this phenomenon is that the beginning of an economic downturn affects all companies in a similar manner in that it diminishes future growth. However, a sustained economic downturn has a stronger effect on financial corporations that are highly leveraged because of their main activity of loaning money. In times of crisis, such as 2008, financial corporations face heavy losses when borrowers cannot repay their loans. In contrast, industrial firms are less exposed to these problems. Thus, as Table 9(E) demonstrates, an anticipated steep downturn in the economy is expected to cause less harm to these corporations. From these results we can conclude that in times of crisis we should turn to industrial corporate bonds rather than financial corporate bonds. In addition, if the downturn is expected to be minimal, such as a cooldown, the differences between the two sectors are negligible.

Another result we see in Table 9(E) is that during economic booms the change in the credit spread for both sectors is negative, implying a decline in the credit spread. The results we obtained in this section confirm H2, because, as demonstrated in Table 9(E), weaker economic states are associated with higher credit spreads.

6. Can sectorial credit spreads predict sectorial stock performance?

The question examined below is whether sectorial corporate credit spreads can forecast sectorial stock performance. We investigate this question by estimating regression equations that link the sectorial credit spread to the performance of the sectorial stock index. We posit that:

H3. Sectorial corporate credit spreads can predict substantial changes in the relevant stock indices.

6.1. Definitions

For this section we define the following explained variables:

SbsNg is a dummy variable that receives the value of 1 when the sectorial stock index[8] in a given quarter declines by more than 10% in real terms relative to the corresponding quarter in the previous year, and 0 otherwise. As noted above, we used the rate of 10% because of the S&P 500's average rate of return from 1980 up to 2013.

SbsPs is a dummy variable that receives the value of 1 when the sectorial stock index in a given quarter increases by more than 10% in real terms relative to the corresponding quarter in the previous year, and 0 otherwise. As with the variable above, we selected

[8] The sectorial indices are subsets of the S&P 500.

Table 11(B)
Mean comparison of the credit spread of US A-rated financial corporate bonds in relation to substantial positive financial stock index change, Q3/1991–Q4/2013.

	SbsPs	N	Mean*	Std. deviation	Std. error mean
Financial: *CrdtSprd*(*A*)	1	47	1.076	0.550	0.080
	0	43	1.688	1.179	0.180

* The difference between the mean credit spread for the two dichotomist cases (represented by the values of one and zero for the dummy variable) is statistically significant at less than 1%.

the rate of 10% as the annual average yield of the S&P 500 from 1980 up to 2013 was approximately 10%. Therefore, a higher than average yearly return indicates a significant rise in the stock index.

6.2. Hypothesis testing: estimated equations and findings for H3

Eq. (7) below represents the estimated regression equation of the relationship between a substantial negative change in the sectorial stock index and the sectorial credit spread:

$$SbsNg_{t+k} = \frac{e^{\left(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t\right)}}{e^{\left(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t\right)}+1}, \tag{7}$$

where $SbsNg_{t+k}$ is a dummy variable that receives the value 1 if the sectorial stock index declined more than 10% in real terms relative to the corresponding quarter in the previous year, and 0 otherwise.

Eq. (8) below is similar to Eq. (7) except it represents a substantial positive change in the sectorial stock index:

$$SbsPs_{t+k} = \frac{e^{\left(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t\right)}}{e^{\left(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t\right)}+1}, \tag{8}$$

where $SbsPs_{t+k}$ is a dummy variable that receives the value 1 if the sectorial stock index increased by more than 10% in real terms relative to the corresponding quarter in the previous year, and 0 otherwise.

The findings for Eqs. (7) and (8) for the financial sector appear in Tables 10(A), 10(B), 11(A) and 11(B), respectively, while the corresponding findings for the industrial sector appear in Tables 12(A), 12(B), 13(A) and 13(B).

The findings in Tables 10(A) and 10(B) indicate that the credit spread for the financial sector can predict a substantial decline in the financial sector. More specifically, three of the regression equations in Table 10(A) are significant, and the significance level is particularly high for short-term horizons (quarters one–two). In addition, the relationship between the sectorial credit spread and a substantial sectorial stock index decline is positive. In other words, the greater the credit spread, the greater the likelihood of a substantial decline in stock prices.

Table 12(A)
Predicted substantial negative industrial stock index change based on US industrial A-rated bonds' 10-year credit spreads, Q3/1991–Q4/2013.

k	β_0	$Wald_{\beta_0}$	β_1	$Wald_{\beta_1}$	Cox&Snell R^2	Chi Square	Sig.	n
1	−7.666	18.297	4.933	12.570	0.282	29.509	0.000	89
2	−6.890	18.918	4.314	12.107	0.257	26.142	0.000	88
3	−5.052	20.227	2.798	9.739	0.174	16.615	0.000	87
4	−3.530	20.354	1.497	5.957	0.075	6.679	0.010	86
5	−3.111	18.400	1.140	4.010	0.046	3.973	0.046	85
6	−2.811	16.109	0.883	2.509	0.028	2.345	0.126	84

Notes: estimated model, Eq. (7): $SbsNg_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}+1}$, where $SbsNg_{t+k}$ receives the value of 1 when the industrial stock index in a given quarter decreases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. *CrdtSprd*(*A*) is the yield difference between 10-year A-rated industrial corporate bonds and 10-year Treasury bonds.

Table 12(B)
Mean comparison of the credit spread of US A-rated industrial corporate bonds in relation to substantial negative industrial stock index change, Q3/1991–Q4/2013.

	SbsNg	n	Mean*	Std. deviation	Std. error mean
Industrial: *CrdtSprd*(*A*)	1	11	1.683	0.746	0.225
	0	79	0.857	0.296	0.033

* The difference between the mean credit spread for the two dichotomist cases (represented by the values of one and zero for the dummy variable) is statistically significant at less than 1%.

Table 13(A)
Predicted substantial positive industrial stock index change based on US industrial A-rated bonds' 10-year credit spreads, Q3/1991–Q4/2013.

k	β_0	Wald_{β_0}	β_1	Wald_{β_1}	Cox&Snell R^2	Chi Square	Sig.	n
1	2.218	9.891	−2.266	9.323	0.141	13.543	0.000	89
2	1.767	7.308	−1.791	7.005	0.104	9.669	0.002	88
3	1.174	4.186	−1.115	3.828	0.053	4.697	0.030	87
4	0.593	1.361	−0.471	0.965	0.012	1.011	0.315	86
5	0.470	0.881	−0.316	0.457	0.005	0.465	0.495	85
6	0.312	0.395	−0.125	0.074	0.001	0.074	0.786	84

Notes: estimated model, Eq. (8): $SbsPs_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\varepsilon_t)}+1}$, where $SbsPs_{t+k}$ receives the value of 1 when the industrial stock index in a given quarter increases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. $CrdtSprd(A)$ is the yield difference between 10-year A-rated industrial corporate bonds and 10-year Treasury bonds.

Table 10(B) demonstrates another aspect of the phenomenon detected. When the sectorial stock index declines by more than 10% (i.e. its dummy variable receives the value of 1) the mean credit spread is equal to 2.441%. In contrast, when the sectorial stock index does not decline substantially, the mean credit spread is equal to just 1.100%. In addition, the difference between these two mean credit spreads is significant at the 1% significance level.

The next regression is given by Eq. (8), in which the explanatory variable is the same as in Eq. (7). However, here the explained variable is the SbsPs, which is a dummy variable receiving the value of 1 when the sectorial stock index in a given quarter increases in real terms by more than 10% relative to the corresponding quarter in the previous year, and 0 otherwise.

Tables 11(A) and 11(B) present the findings for the case where the change in the sectorial stock index is substantially positive (greater than 10%). Compared with the regression results for the previous case of a substantial decline, the results for a substantial positive incline are weaker. For only the first time horizon is the relationship between the credit spread and the substantial positive change significant. It should be noted that in this case of a positive change in stock prices (rather than the negative change in the previous case) the relationship should be negative, as also indicated by the results in Table 11(A). However, as in the previous case of a negative change, the difference between the mean credit spread for the two dichotomist cases (one and zero) is significant. In other words, the mean credit spread is higher when the change in the sectorial stock prices is not substantially positive. These findings support hypothesis H3. A possible reason for the weaker results for the case of the positive change in the stock index might stem from the fact that stock price declines are usually steeper than stock price upturns.

The findings for the industrial sector are presented in Tables 12(A), 12(B), 13(A) and 13(B).

Tables 12(A) and 12(B) imply that the relationship between the sectorial credit spread and substantial sectorial stock price declines is statistically positive. A similar result appears in Table 12(B), according to which, the mean value of the credit spread for substantial stock price declines is significantly higher than for the alternative case (when the dummy variable is equal to zero).

As Tables 13(A) and 13(B) indicate the results for the industrial sector are slightly better compared with those of the financial sector when forecasting substantial positive changes in stock prices.

The comparison of the findings in Tables 12(A), 12(B), 13(A) and 13(B) with the findings in Tables 10(A), 10(B), 11(A) and 11(B) for the financial sector indicates a stronger and more significant relationship between the credit spread and sectorial stock price performance for the industrial sector than for the financial sector.

The differences between the two substantial sectorial stock price changes – the negative (*SbsNg*) and the positive (*SbsPs*) – as well as between the two sectors – the financial and the industrial – can be summarized as follows:

To be recalled, *SbsNg* is a dummy variable that receives the value of 1 when the sectorial stock index declines by more than 10%, and 0 otherwise. The variable *SbsPs* receives the value of 1 when the sectorial stock index increases by more than 10%, and 0 otherwise. Starting with the financial sector, the rate of change in the credit spread for the dichotomist values of the *SbsNg* variable is 121% (i.e., 2.441/1.100–1) compared with −36% (i.e., 1.076/1.688–1) for the *SbsPs* variable. These two values imply that the results are stronger for negative outcomes than for positive outcomes.

For the industrial sector, the corresponding findings are 96% and −31% for the *SbsNg* and *SbsPs* variables respectively. These findings imply that the sensitivity of the financial sector is higher.

As in the previous section, we estimated an additional regression that uses the average recovery ratings for each sector. Using this method, we predicted both the *SbsNg* and the *SbsPs* variables. The results for the *SbsNg* variable are presented in Table 14.

Table 14 indicates that the average recovery rates do not have a significant relationship with negative stock performance. A similar estimation conducted for the *SbsPs* variable is presented in Table 15.

Table 13(B)
Mean comparison of the credit spread of US A-rated industrial corporate bonds in relation to substantial positive industrial stock index change, Q3/1991–Q4/2013.

	SbsPs	n	Mean*	Std. deviation	Std. error mean
Industrial: $CrdtSprd(A)$	1	48	0.791	0.225	0.032
	0	42	1.148	0.580	0.089

* The difference between the mean credit spread for the two dichotomist cases (represented by the values of one and zero for the dummy variable) is statistically significant at less than 1%.

Table 14
Predicted substantial negative sectorial stock index change based on US sectorial A-rated bonds' 10-year credit spreads and average sectorial recovery rates, Q3/1991–Q4/2013.

k	β_0	Wald_{β_0}	β_1	Wald_{β_1}	β_2	Wald_{β_2}	Cox&Snell R^2	Chi Square	Sig.	n
1	−4.402	10.464	1.742	20.461	1.392	0.173	0.187	36.874	0.000	178
2	−3.218	7.140	1.231	15.446	−0.078	0.001	0.130	24.458	0.000	176
3	−2.387	4.533	0.873	10.996	−1.123	0.139	0.085	15.425	0.000	174
4	−1.541	2.100	0.524	5.217	−2.265	0.590	0.042	7.307	0.026	172
5	−1.102	1.114	0.348	2.389	−2.875	0.978	0.025	4.340	0.114	170
6	−0.750	0.527	0.204	0.789	−3.357	1.350	0.017	2.810	0.245	168

Notes: estimated model, Eq. (7): $SbsNg_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\beta_2 Rcvr+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\beta_2 Rcvr+\varepsilon_t)}+1}$, where $SbsNg_{t\,+\,k}$ receives the value of 1 when the sectorial stock index in a given quarter decreases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. $CrdtSprd(A)$ is the yield difference between 10-year A-rated corporate bonds and 10-year Treasury bonds and $Rcvr$ is the sectorial average recovery rate taken from Moody's DRS.

Table 15 implies that the average recovery rates do not have a significant relationship with positive stock performance. The results of Tables 14 and 15 contribute to our understanding by showing once again the predictive ability of sectorial credit spreads when forecasting negative stock behavior.

The results in this section indicate that sectorial credit spreads can be used to forecast the short-term behavior of sectorial stock performance. We can also see that predicting negative events is more efficient than forecasting positive events. Nevertheless, the predictive ability was evident in both sectors.

As with the tests we ran in the previous section, we validated our results even further with an out-of-sample analysis of the negative stock behavior logistic regressions. Here too, we defined the period from the start of the data until the end of 2010 as the estimation period, and the remaining observations were defined as the prediction period. The out-of-sample analyses for the financial and industrial sectors appear in Tables 16 and 17 respectively.

The out-of-sample analysis shows that the logistic regressions were good at predicting significant negative stock performance. Indeed, the out-of-sample classification tables show better results than the in-sample classification tables. These findings validate our results once again and contribute to the understanding that sectorial credit spreads can forecast negative stock performance in the short-term.

7. Concluding remarks

This study examines whether sectorial corporate yield curves (YCs) and sectorial credit spreads can provide a refined approach to forecasting specific sectorial behavior. Two key sectors were examined — the financial and industrial. They are considered the main pillars of the economy and have the richest data available.

When the central bank believes that a slowdown is on the horizon, it usually lowers the interest rate in order to stimulate growth in the economy. The basis for using YCs to forecast the future state on the economy is based on the direct relationship between the central bank's interest rate and bond yields. The expectation for a drop in the interest rate causes bond yields to drop and YCs to flatten or even to flip to a declining state. Therefore, we can use YCs, which generally react faster than actual interest rate changes, to predict future economic factors. Credit spreads represent the difference between corporate and government bond yields. Thus, the higher the risk level of the asset (company or industry) the higher the required yield on that asset. Therefore high credit spreads are negative indicators.

Using the results of linear and logistic regressions as well as mean comparisons with data about the U.S. economy from 1991 to 2013, we arrive at several important conclusions when employing YCs and credit spreads in order to predict sectorial economic indicators.

Table 15
Predicted substantial positive sectorial stock index change based on US sectorial A-rated bonds' 10-year credit spreads and average sectorial recovery rates, Q3/1991–Q4/2013.

k	β_0	Wald_{β_0}	β_1	Wald_{β_1}	β_2	Wald_{β_2}	Cox&Snell R^2	Chi Square	Sig.	n
1	1.908	4.818	−1.029	11.285	−2.047	0.893	0.087	16.182	0.000	178
2	1.200	2.122	−0.636	6.251	−1.253	0.349	0.044	7.849	0.020	176
3	0.508	0.405	−0.319	2.173	−0.217	0.011	0.014	2.436	0.296	174
4	−0.013	0.000	−0.108	0.286	0.641	0.093	0.003	0.499	0.779	172
5	−0.157	0.039	−0.089	0.193	1.020	0.232	0.003	0.572	0.751	170
6	−0.411	0.265	−0.017	0.007	1.547	0.527	0.004	0.603	0.740	168

Notes: estimated model, Eq. (8): $SbsPs_{t+k} = \frac{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\beta_2 Rcvr+\varepsilon_t)}}{e^{(\beta_0+\beta_1 CrdtSprd(A)_t+\beta_2 Rcvr+\varepsilon_t)}+1}$, where $SbsPs_{t\,+\,k}$ receives the value of 1 when the sectorial stock index in a given quarter increases by more than 10% in real terms relative to the corresponding quarter, and 0 otherwise. $CrdtSprd(A)$ is the yield difference between 10-year A-rated corporate bonds and 10-year Treasury bonds and $Rcvr$ is the sectorial average recovery rate taken from Moody's DRS.

Table 16
Out-of-sample forecasting substantial negative financial stock index change based on US financial A-rated bonds' 10-year credit spreads.

Variables in the equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1[a]	*CrdtSprd*	0.815	0.298	7.490	1	0.006	2.259
	Constant	−2.492	0.530	22.082	1	0.000	0.083

Classification table[b]

Observed			Predicted *SbsNg* .000	Predicted *SbsNg* 1.000	Percentage correct
Out of sample prediction:					
Step 1	*SbsNg*	.000	10	0	100
		1.000	2	0	0
	Overall percentage				83.3
In sample prediction:					
Step 1	*SbsNg*	.000	68	2	97.1
		1.000	16	2	11.1
	Overall percentage				79.5

Notes: forecasting horizon, $k = 2$. Estimation period, Q1/1992–Q4/2010. Prediction period, Q1/2011–Q4/2013. Predictors: $CrdtSprd_2$.
[a] Variable(s) entered on step 1: *CrdtSprd*.
[b] The cut value is .500.

First, we can predict changes in the corporate profits of specific sectors. We found that the marginal yield spread of sectorial corporate bonds has a generally significant positive relationship with changes in profits. These results hold for both the financial and industrial sectors.

In addition, we found that high yield bonds differ from investment grade bonds as they have difficulty forecasting future sectorial profit changes. This result is in line with expectations because of the different characteristics of high yield bonds.

The mean comparisons we conducted about sectorial credit spreads also show that there indeed is a negative relationship between the credit spreads and the state of the economy. In addition, in times of cooldown, which indicates the beginning of economic deterioration, both sectors behave similarly. However, when the economic deterioration is steeper, the sensitivity of the financial sector is greater than that of the industrial sector.

We also investigated the relationship between sectorial credit spreads and sectorial stock price performance. Our findings demonstrate that sectorial credit spreads can predict short-term movements defined above as “substantial” in sectorial stock price indices. This result holds for both sectors. In addition, the tests show that the predictive ability in both sectors is much better when predicting

Table 17
Out-of-sample forecasting substantial negative industrial stock index change based on US industrial A-rated bonds' 10-year credit spreads.

Variables in the equation

		B	S.E.	Wald	Df	Sig.	Exp(B)
Step 1[a]	*CrdtSprd*	4.079	1.192	11.713	1	.001	59.079
	Constant	−6.412	1.520	17.789	1	.000	.002

Classification table[b]

Observed			Predicted *SbsNg* .000	Predicted *SbsNg* 1.000	Percentage correct
Out of sample prediction:					
Step 1	*SbsNg*	.000	12	0	100
		1.000	0	0	0
	Overall percentage				100
In sample prediction:					
Step 1	*SbsNg*	.000	74	3	96.1
		1.000	8	3	27.3
	Overall percentage				87.5

Notes: forecasting horizon, $k = 2$. Estimation period, Q1/1992–Q4/2010. Prediction period, Q1/2011–Q4/2013. Predictors: $CrdtSprd_2$.
[a] Variable(s) entered on step 1: *CrdtSprd*.
[b] The cut value is .500.

negative rather than positive future stock behavior. The reason for this difference may stem from the fact that downturns are usually steeper than upturns.

Our study consisted of a vast number of tools and out-of-sample analyses in order to ensure the validity of our results. By using these tools we could reach our conclusions that the employment of sectorial corporate YCs and credit spreads can improve the prediction of sectorial indicators such as changes in corporate profits and stock price performance.

Therefore, corporate bonds might help investors and financial professionals predict sectorial behavior and optimize sectorial differentiation in their portfolios.

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