Credit spreads, daily business cycle, and corporate bond returns predictability*

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Abstract

The part of credit spread that is not explained by corporate credit risk forecasts future economic activity. I show that the link with aggregate business risk and bond liquidity risk explains this finding. Once I project spreads on these two risk factors, which are readily measurable with the daily frequency, in addition to corporate credit risk, the forecasting power of the residual spread reduces substantially for some macro variables and disappears entirely for the others. Such residual, however, turns out to be an out-of-sample forecast of corporate bond market returns. An investment strategy based on such forecasts delivers risk-adjusted returns 50% higher than the corporate bond market.

JEL classification: E44, G12, G17.

Keywords: credit spreads, corporate bond returns, business cycle, predictability of returns.

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1. Introduction

Credit spreads forecast economic activity. Gilchrist and Zakrajšek (2012) elaborated on this statement; there is a particular portion of credit spreads that is of most importance for activity forecasts. It is a part of the spread that is *not* explained by corporate credit risk, called the credit risk premium or the excess bond premium (EBP). The first part of this paper shows what stands behind the forecasting power of the EBP.

I argue that the forecasting power of the EBP hinges on the information about aggregate business risk and bond liquidity risk contained in credit spreads and show how to extract this information using daily frequency. I construct a large bond-day panel of credit spreads from transactions recorded in TRACE and measure corporate credit risk, bond-specific liquidity risk, and aggregate business risk at the daily frequency. When I project spreads on corporate credit risk only (as in Gilchrist and Zakrajšek, 2012), I confirm that the residual forecasts future economic activity. However, when I further project spreads on aggregate business risk as measured by the Aruoba-Diebold-Scotti daily business conditions index (ADS index) and bond liquidity risk, as measured by the Amihud measure, the forecasting power of the residual portion of spreads for macroeconomic variables largely goes away.[1]

Following finance literature, I interpret the residual portion of credit spread unexplained by corporate credit risk, bond liquidity risk, and aggregate business risk as the *credit risk premium*. The second part of this paper demonstrates that my measure of the credit risk premium is a forecast of corporate bond market returns. The forecasting power is absent when one considers instead the residuals from the projection of spreads on corporate credit risk only. This result is robust to different estimation windows and different bond market portfolios. Moreover, the risk premium forecasts returns even when it is estimated in real time with the information available only on the estimation date.

I remain agnostic about what this return-forecasting component of credit spreads is.

[1]The ADS index does not contain any bond or stock market indicators as inputs.

Yet, I demonstrate what it is surely not. The paper shows that neither bond pricing factors of Bai, Bali, and Wen (2016), including contemporaneous bond market returns per se, nor stock market factors can explain the time series variation of my credit risk premium measure. The models with my credit risk premium on the right-hand side, in addition to other bond pricing factors, however, forecast returns on diverse size, maturity, and industry corporate bond portfolios better than the models without it. This result is robust to exclusion of the subprime crisis episode from the sample.

I exploit the forecasting power of the risk premium to construct a corporate bond market-timing strategy that delivers risk-return characteristics superior to the buy-and-hold market strategy. My strategy assumes weekly portfolio rebalancing and uses only one risky instrument, an investable aggregate corporate bond market index, which is bought and sold depending on predicted corporate bond market excess returns. On a testing sample, my predictive model successfully forecasts market returns out-of-sample, and the strategy delivers total return and a Sharpe ratio 1.5 times higher than the corporate bond market index.

The first part of this paper on macro forecasting properties of the EBP feeds into several discussions in the literature. From the perspective of EBP estimation and predictive power, this paper is related to the work by Gilchrist and Zakrajšek (2012), De Santis (2017), and Nozawa (2017). In particular, De Santis (2017) constructed a monthly credit risk premium free from aggregate business risk on European multi-country data but reached a different conclusion regarding its forecasting properties. From the perspective of empirical credit spread modeling, this paper contributes to the 'credit spread puzzle' literature stemming from Collin-Dufresne, Goldstein, and Martin (2001). I demonstrate that aggregate business risk, as measured by the daily business cycle index, is able to explain a significant portion of common variation in credit spreads at the daily frequency. In this respect, this paper is related to the results by d'Avernas (2017), who estimates a joint structural model of credit spreads and equity volatility to argue that firms time-varying aggregate asset volatility helps to explain both the dynamics of credit spreads and their forecasting power for economic activity. There are no direct references for the second part of this paper that investigates asset pricing properties of the EBP. To the best of my knowledge, this is the first study to establish the forecasting power of EBP for corporate bond market returns.

The paper is organized as follows. Section 2 discusses the data sample. Section 3 estimates the credit risk premium by fitting alternative models to the bond-day panel of credit spreads. Forecasting power of the risk premium for macroeconomic activity is discussed in Section 4. Section 5 shows that the EBP forecasts excess bond market returns, does multiple robustness tests, and presents an investment strategy to benefit from the forecasting power of the risk premium. Section 6 concludes the work.

2. Sample Characteristics

I merge daily bond trades from TRACE with bond characteristics from Mergent Fixed Income Securities Database (FISD) and issuing firm characteristics from Compustat and CRSP for senior unsecured corporate bonds with fixed coupon schedules. My data construction approach is presented in detail in Appendix B. The constructed sample is an unbalanced bond-day panel with around 2 million bond-day observations that span a period from Oct 2004 to Dec 2014. The number of bonds sampled per day is, on average, 823 with a standard deviation of 111. Summary statistics for the panel are presented in Table 1.

[Insert Table 1 near here]

An average bond in the sample has been issued approximately six years ago and has about nine years to maturity. It has an outstanding amount of about 600 million USD and pays a coupon of 6%. It is an investment-grade security rated between BBB+ and BBB and is traded six times per day. Its yield to maturity is about 5%, approximately 2.4% above its risk-free counterpart. The latter number is the credit spread measure constructed following Gilchrist and Zakrajšek (2012). I call it either the GZ spread or simply the spread.

To control for illiquidity, I use a daily Amihud measure AMH_t computed for each bond for each day t when the bond was traded:

$$AMH_t = \frac{1}{N_t} \sum_{j=1}^{N_t} \frac{|r_{t,j}|}{Q_{t,j}},$$

where $r_{t,j}$ is the price return of trade j of this bond on day t, $Q_{t,j}$ is the volume of a corresponding transaction, and N_t is a total number of trades of this bond per day.[2] This definition of the Amihud measure follows the approach of Dick-Nielsen, Feldhütter, and Lando (2012) with one modification. Their approach requires at least two trades per day to compute the Amihud measure; I compute it even for days with a single trade. In this case, the price return is relative to a previous trade whenever it occurred.[3] Table 1b presents median values of the Amihud measure in the sample by credit rating. Bonds of lower credit quality tend to be less liquid in the sample.

As Table 1b shows, A- and BBB-rated callable bonds are predominant in the sample. The spread measure is not option-adjusted by construction; as in Gilchrist and Zakrajšek (2012), I will control for that in the EBP calculations. The median GZ spread and distance-to-default are aligned with credit ratings in an intuitive way. The higher the rating, the 'farther' the default is and the lower the spread. Ratings are also aligned (except AAA-rated and almost defaulted bonds) with median coupons, durations, and total daily returns.

[**Insert Figure 1 near here**]

My aggregate spread measure constructed on the daily data is in line with the monthly measure of Gilchrist and Zakrajšek (2012), as Figure 1 demonstrates. The left panel is my daily time series. For each day, the aggregate spread is a simple cross-sectional average of GZ spreads across all bonds of all firms sampled on that day. The aggregate spread is non-

[2] To see how the Amihud measure behaves on daily frequency on TRACE data relative to other illiquidity measures see Schestag, Schuster, and Uhrig-Homburg (2016).

[3] I experimented with these two definitions and found that for bond-days with at least two trades per day two definitions give very close numerical measures.

stationary in levels. The right panel of Figure 1 compares the monthly mean and last values of my daily measure with the original monthly spread from Gilchrist and Zakrajšek (2012). The three series differ a bit only during the 2008-2009 crisis; otherwise, the fit is tight. Thus, at this stage, I have obtained a larger sample with the daily data and constructed the daily GZ-spread measure, which is very close to the monthly one presented in the literature.

3. Measuring Excess Bond Premium

Excess bond premium (EBP) is the portion of credit spread not explained by credit risk factors. Given a panel of bonds k issued by firms i and observed at times t, and given their GZ spreads $S^{GZ}_{i,t}[k]$, bond-level $EBP_{i,t}[k]$ is computed as follows:

$$
\begin{aligned}
\log\left(S^{GZ}_{i,t}[k]\right) &= \text{Factors of credit spreads} + \epsilon_{i,t}[k], \\
\hat{S}^{GZ}_{i,t}[k] &= \exp\left(\text{Part due to estimated factors} + \frac{\hat{\sigma}^2_{\epsilon_{i,t}[k]}}{2}\right), \\
EBP_{i,t}[k] &= S^{GZ}_{i,t}[k] - \hat{S}^{GZ}_{i,t}[k],
\end{aligned}
$$

where $\hat{\sigma}^2_{\epsilon_{i,t}[k]}$ is the variance of residuals of the log-spread-fitting regression above. In this paper, I am interested in the properties of the aggregate excess bond premium EBP_t defined for each day t as a simple cross-sectional average of $EBP_{i,t}[k]$ across all bonds of all firms.

I estimate the EBP on the daily data, unlike Gilchrist and Zakrajšek (2012) and De Santis (2017), who worked with bond–month panels. My major motivation is pronounced business cycle forecasting properties of monthly EBP established in the literature. Is it possible to extract the information about the future state of the economy beyond what we know from daily real activity measurements from credit spreads on a daily basis? Does this approach bring new information that is valuable for forecasting not only macroeconomic activity but also bond returns?

To answer these questions, I want to capture the portion of bond spreads *beyond* firm-specific credit risk, bond-specific liquidity risk, and economy-wide business risk. I directly control for bond-specific illiquidity with the daily Amihud measure and for aggregate business risk with a high-frequency *real activity* proxy. This is the daily ADS index computed and published in real time by the Philadelphia Fed.[4] The ADS index based on Aruoba, Diebold, and Scotti (2009) is a smoothed business cycle state derived from a mixed-frequency state-space linear model for six real-valued variables: initial jobless claims, payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and gross domestic product. The ADS index contains neither bond nor stock market data as inputs.

I benchmark my EBP measure on Gilchrist and Zakrajšek (2012). Their EBP is correlated with economy-wide business risk, and bond-specific illiquidity is controlled only with monthly bond characteristics. De Santis (2017) controlled for aggregate business risk when measuring EBP, but he estimated it on monthly European multi-country data. This summarizes the differences in my preferred spread-fitting model relative to the Gilchrist and Zakrajšek (2012) model:

Original GZ models:

$$\log\left(S_{it}^{GZ}[k]\right) = \beta \cdot DD_{it} + \text{(Proxies for recovery rate and liquidity)} + \text{(Call adjustment)} + \\ + \text{(Industry and rating FE)} + \epsilon_{it}[k].$$

My preferred models:

$$\log\left(S_{it}^{GZ}[k]\right) = \beta \cdot DD_{it} + \text{(Proxies for recovery rate and liquidity)} + \text{(Call adjustment)} + \\ + \underbrace{\gamma \cdot ADS_t + \eta \cdot AMH_{it}[k]}_{\text{Daily business cycle and liquidity}} + \text{(Industry and rating FE)} + \epsilon_{it}[k],$$

where DD_{it} is the distance-to-default of firm i at time t (proxy for idiosyncratic credit risk),

[4] For details on the ADS index see Appendix C and `https://goo.gl/mZJ5Sj`. Many alternative daily aggregate business risk proxies exist, for instance, the Economic Policy Uncertainty index of Baker, Bloom, and Davis (2016). I opted for the ADS mainly because of a long history of ADS vintages readily available at the Philadelphia Fed web page. These historical vintages allow me to perform out-of-sample analysis in Sections 5.2 and 5.4.

ADS_t is the aggregate business activity index at day t, and $AMH_{it}[k]$ is the Amihud measure. In the following sections, I apply both approaches on the bond-day panel and investigate the differences in the resulting EBPs.

[Insert Table 2 near here]

Table 2 presents the estimated models over the entire sample. Model 1 is the basic model with corporate credit risk factors on the right-hand side. In Models 2 and 3, I consecutively add aggregate business activity and liquidity factors. Models 1 to 3 have the simplest possible call option adjustment: a constant that is identical for all bonds at all times. Models 4 to 6 introduce interactions of call dummy with yield curve factors and bond characteristics to possibly better capture the time variation in the issuers desire to call an issue before maturity. Model 4 is the benchmark Gilchrist and Zakrajšek (2012) model. I see Model 6, which extends Model 4 with daily aggregate business activity and liquidity factors, as the alternative model.

All models in Table 2 have high explanatory power for log spreads. Even the simplest model, Model 1, explains around 72% of the log spreads variation in the data. More elaborate call option adjustment (Model 4) increases this share by 2.5 percentage points. Aggregate business activity and liquidity factors (Model 6) add another 4.5 percentage points to the share of explained log spreads variation, which reaches 79%.

As Table 2 shows, aggregate business risk and bond illiquidity are significant predictors of credit spreads. Coefficients on the ADS business cycle index and the Amihud measure are statistically significant across all specifications. They do not vary much from one model to another and have reasonable signs. Business cycle upturns are associated with lower credit spreads, and more illiquid bonds have higher spreads.

Most interaction variables of the call dummy with yield curve factors and bond characteristics introduced in Models 4–6 for the purpose of call option adjustment are statistically significant, as Table 2 shows. Observe for Models 5 and 6 that when the yield curve moves up and becomes steeper, the spreads tend to become lower. This finding can be explained as follows: the probability of an early call decreases when rates become higher (fewer incentives for an issuer to refinance at higher rates); hence, an early call premium drops and callable bonds tend to become more expensive. The importance and significance of call option adjustment make Gilchrist and Zakrajšek (2012) argue that Model 4 is superior to Model 1 on their data, I get the same result on my data. My primary interest, however, is in comparison of Models 4 and 6, which I turn to now.

[**Insert Figure 2 near here**]

Figure 2a compares the goodness of fit of Models 4 (benchmark Gilchrist and Zakrajšek, 2012) and 6 (my preferred model) to actual aggregate spreads. Model 6 captures time series variation in daily spreads much better than Model 4, especially in years 2008 and 2009, and this is due to only two additional factors: the state of the business cycle and bond liquidity. The left panel of Figure 2b presents the same result in terms of the EBP. An unexplained increase in credit spread during the subprime crisis is significantly smaller and shorter in time according to my preferred model; hence, the state of the business cycle is a factor of aggregate credit spread even on a daily frequency. The right panel of Figure 2b compares monthly EBP values of my preferred daily EBP (Model 6) with the original monthly EBP series from Gilchrist and Zakrajšek (2012) and confirms this finding.

[**Insert Table 3 near here**]

The significance of business cycle and liquidity as factors of credit spreads survives the truncation of the data sample. Table 3 compares performance of Models 4 and 6 in subsamples of either investment-grade or high-yield bonds. The models explain spreads of investment-grade bonds much better than high-yield ones. Spreads of the riskiest bonds are probably non-linear in the distance-to-default: coefficients on the DD variable in columns 3 and 4 (high-yield bonds) of Table 3 are roughly twice the corresponding coefficients in columns 1 and 2 (investment-grade bonds). Yet, business cycle and liquidity factors are still significant for both types of bonds, and coefficients on these variables are not much different from the full-sample specifications. More importantly, business cycle and liquidity factors survive complete deletion of observations between Jan 2008 and Dec 2008 (inclusive) from the sample. Columns 5 and 6 of Table 3 present these estimations. Both coefficients do not change much relative to full-sample specifications and improve the explanatory power of Model 6 as measured by the R^2 compared to Model 4.

An alternative way to establish the link between aggregate business risk and the portion of spreads beyond corporate bond credit risk is presented in Appendix D. There I first introduce, following d'Avernas (2017), time fixed effect in log spread fitting models (and remove the ADS). Then I project this estimated time fixed effect on the ADS in a univariate time-series regression to demonstrate that the latter explains significantly around 63% of the variation of the former on the daily frequency.

In this section, I have demonstrated that aggregate business risk and bond liquidity risk are significant factors of credit spreads in addition to corporate credit risk. Does the residual spread that is free from all these sources of risk (EBP of Model 6) still forecast macro as the benchmark EBP measure (Model 4)? Section 4 answers this question.

4. Forecasting the Business Cycle

I explore the forecasting properties of the EBP with respect to business activity by running predictive models for monthly industrial production, payroll employment, and the unemployment rate similar to the ones in Gilchrist and Zakrajšek (2012). Here, I use month-end values of my daily EBP measures obtained in Section 3. The regressions are:

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \underbrace{\gamma_1 RFF_t + \gamma_2 TS_t}_{\text{Real Fed funds rate and term spread}} + \underbrace{\gamma_3 S_t^{GZ}}_{\text{True GZ spread}} + \epsilon_{t+h},$$

and:

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=1}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 RFF_t + \gamma_2 TS_t + \underbrace{\gamma_3 \hat{S}_t^{GZ} + \gamma_4 EBP_t}_{\text{Fitted GZ spread and EBP}} + \epsilon_{t+h},$$

where $\nabla^h Y_{t+h}$ is either $\log Y_{t+h} - \log Y_{t-1}$ the growth rate of industrial production/payroll employment or $Y_{t+h} - Y_{t-1}$ the change in unemployment rate. The right-hand side variables (apart from a constant and the dependent variable lags) capture different components of the real cost of borrowing through the corporate bond market for an average U.S. bond-issuing firm.[5]

The literature has established long ago that, in such models, credit spreads are significant predictors for different left-hand side indicators and forecasting horizons. Gilchrist and Zakrajšek (2012) demonstrated that the predictive power of spreads is rather due to the residual spread than the fitted spread component. I revisit this result with my preferred measure of the EBP.

[Insert Table 4 near here]

Table 4 demonstrates that high spreads today are indeed associated with lower future industrial production and higher future unemployment in my sample.[6] The columns titled '–' estimate models with GZ spread as an explanatory variable without splitting it into explained and unexplained parts. For the industrial production, the unemployment rate and the payroll employment on all horizons (except for one-year ahead industrial production), the spread is indeed a strong predictor of future macroeconomic activity with reasonable signs.[7]

As 'M4' columns of Table 4 show, the EBP computed as in Gilchrist and Zakrajšek (2012) is indeed a stronger predictor of future macro activity than the explained portion of spread ('fitted spread'). For the industrial production, the EBP of Model 4 is a significant predictor, and the fitted spread is not. Speaking about economic significance, the absolute value of

[5]For details on the right-hand side variables see Appendix C.

[6]This table echoes Table 6 of Gilchrist and Zakrajšek (2012).

[7]I use Newey and West (1987) heteroskedasticity and autocorrelation consistent standard errors in forecasting regressions with overlapping observations in Sections 4 and 5 of the paper. I also ran all the estimations with Hodrick (1992) standard errors instead and found that in my sample Newey-West standard errors are bigger than Hodrick's ones in vast majority of cases. Hence I reject the 'no predictability' null less frequently using the Newey-West errors.

the coefficients on EBP is 4-7 times higher depending on the forecasting horizon. For the employment-related variables, both the EBP and the fitted spread are statistically significant predictors, but the economic significance of changes in EBP for future employment trends is, again, substantially higher than of changes in fitted spreads, especially on longer horizons.

The predictive power of the EBP becomes considerably lower once I switch to residual spreads free from corporate default risk, aggregate business risk, and bond liquidity risk. This result is the most pronounced for the industrial production. Observe in the column titled 'M6' of Table 4a that for three-month ahead growth of the industrial production, the fitted spread is now a significant predictor, and the EBP is not. Compared to 'M4' column, not only the significance but also the magnitude of coefficients on the fitted spread and the EBP has changed considerably. The same result applies to the 6-month ahead industrial production, Table 4b shows. At the 12-month horizon, Table 4c, neither of the two components of the spread is a significant predictor of industrial production. Table 4 also presents similar results for the unemployment rate and the payroll employment. Here, in 'M6' columns, both components of the spread are still statistically significant predictors of employment trends, but the economic significance of the fitted spread is now much higher than of the EBP (especially on the 3-month horizon, where coefficients on the fitted spread are roughly twice higher in absolute value than the coefficients on the EBP). Hence, switching from Model 4 to Model 6 increases both statistical and economic significance of the fitted spread and shrinks the significance of the EBP in forecasting economic activity.[8]

The results discussed in this section so far go through if one compares instead predictive models with the fitted spread and the EBP of Models 1 and 3 of Table 2 (not reported). This case refers to the EBP estimations when call option adjustment is just the loading on the call dummy, same for all callable bond at all times. Hence, the reduction in predictive power of the EBP for future macroeconomic activity is not due to the chosen method of

[8]This result is reinforced by the lower variability of the EBP estimated by Model 6 compared to Model 4: large deviations of the EBP of Model 6 from its mean are less probable per se.

embedded call option adjustment.

I interpret the findings of this section as follows: the daily EBP measure contains information that is relevant for predicting the future state of the economy, but this information can be also derived from a readily available daily business activity measure, such as the ADS index. The forecasting power of the residual spread that is free from the corporate default risk only (EBP of Model 4 or Model 1) is mostly due to the persistence of the business cycle itself.[9] Once one further projects spreads on the aggregate activity and illiquidity measures, the forecasting power of the residual component (EBP of Model 6 or Model 3) goes away completely for some macro indicators and falls considerably for the others.[10]

[**Insert Figure 3 near here**]

Bi-variate monthly vector autoregression (VAR) models on the EBP and the ADS activity index provide supporting evidence for such an interpretation.[11] I estimate these VARs to capture possible time series interdependence of activity and the EBP. Figure 3 presents orthogonalized impulse response functions from the estimated models, with the EBPs of Models 1, 3, 4, and 6 on Figures 3a, 3b, 3c, and 3d correspondingly. The response of activity on the EBP shock on the left panel of Figure 3a (the EBP of Model 1) shows that unexpected jumps in the EBP today imply significantly lower business activity up to nine months ahead, and vice versa. The EBP-to-activity pass-through remains the same when I consider the EBP from Model 4 instead, Figure 3c shows, hence this finding is not due to the chosen method

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[9]For estimations of the U.S. business cycle persistence at monthly frequency see Mariano and Murasawa (2003).

[10]Gilchrist and Zakrajšek (2012) also considered structural shocks to their EBP measure in a quarterly eight-variable macro SVAR model and interpreted the shocks as 'EBP shocks orthogonal to the business cycle'. However, this interpretation hinges on the identification of the SVAR model by exclusion restrictions. Their identification yields significant effects of 'EBP shocks orthogonal to the business cycle' on activity. I believe that it is better to directly control for the state of the business cycle at the stage of the EBP estimation. This approach leads to a different conclusion regarding the forecasting power of the EBP relative to the fitted spread.

[11]On monthly frequency, both the ADS and the EBP are stationary time series over the years 2004–2014. I obtain monthly values of these series by taking the latest daily observation per month. Taking monthly means instead doesn't change the results.

of call option adjustment. However, once I consider the EBP free from liquidity risk and aggregate business risk (Models 3 and 6), the link between the EBP and activity breaks up. Figures 3b and 3d show that now shocks to the EBP do not affect activity significantly over horizons longer than several months (and over these shorter horizons the effect has a counter-intuitive sign). There is no significant effect in the opposite direction either. These results corroborate the findings of this chapter: the portion of credit spreads explained by firm-specific credit risk, economy-wide business risk and bond-specific liquidity risk does a good job in forecasting the future macroeconomic state, and the residual portion of spreads is less important for macro forecasting.

5. Forecasting Corporate Bond Returns

In this section, I investigate two questions: whether the EBP contains any information relevant for forecasting bond returns or not, and how the EBP relates to other known bond pricing factors. The motivation for this part comes from the decomposition of credit spreads by Nozawa (2017). This paper shows that the Campbell-Shiller decomposition applied to corporate bond spreads (under mild assumptions about losses in default) yields:

$$S_t = \underbrace{\mathbb{E}_t\left[\sum_{i=1}^{\infty}\rho^{i-1}r^e_{t+i}\right]}_{\text{Risk premium}} + \underbrace{\mathbb{E}_t\left[\sum_{i=1}^{\infty}\rho^{i-1}l_{t+i}\right]}_{\text{Expected credit loss}} + \text{Const},$$

where ρ is the steady-state price-coupon ratio, r^e is excess bond return and l is credit loss. I want to think of the empirical decomposition of GZ spreads into an explained part and the EBP as one particular model-based method to reinterpret the Campbell-Shiller decomposition above. The EBP is interpreted in this case as the credit risk premium (i.e., conditional expectation of future excess corporate bond returns). Then, it is natural to ask whether the EBP forecasts actual future returns.

5.1. *EBP and Excess Corporate Bond Market Returns*

Building on regression models of Section 4, I estimate the following forecasting models on the daily data:

$$R_{t:t+h} = \alpha + \beta R_{t-h:t} + \underbrace{\gamma_1 LVL_t + \gamma_2 SLP_t + \gamma_3 CRV_t}_{\text{level, slope and curvature factors}} + \underbrace{\gamma_4 S_t^{GZ}}_{\text{true GZ spread}} + \epsilon_{t+h},$$

and:

$$R_{t:t+h} = \alpha + \beta R_{t-h:t} + \gamma_1 LVL_t + \gamma_2 SLP_t + \gamma_3 CRV_t + \underbrace{\gamma_4 \hat{S}_t^{GZ} + \gamma_5 EBP_t}_{\text{Fitted GZ and EBP}} + \epsilon_{t+h},$$

where $R_{t:t+h} = \sum_{i=1}^{h} R_{t+i}$ are cumulative excess log returns on a diversified bond portfolio h days ahead.[12] I consider the range of horizons from 1 day to 90 days to ensure the stationarity of the returns series on the left-hand side.[13] The left-hand side returns are for one of the two alternative bond market portfolios: the value-weighted portfolio of in-sample TRACE bonds and the portfolio of investment-grade bonds in the Barclays Aggregate U.S. corporate bond index.[14]

[Insert Figure 4 near here]

My findings are as follows: the actual GZ spread is not a significant predictor of bond market returns. Figure 4a presents the estimates of the various parameters in the model with actual GZ spread on the right and their significance over different horizons. None of the factors significantly predicts cumulative returns in such a model on horizons up to 90 days.

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[12]Returns are total returns here, they account for both price changes and accrued interest.

[13]Cumulative returns are non-stationary on horizons beyond roughly 90 days. Hence one needs to test for cointegration between returns and potential predictors on these longer horizons instead. I did that, and the tests didn't reject the null (no cointegration, i.e. no predictability for returns coming from the fitted spread, the EBP, or the yield curve factors).

[14]All subsequent results were also obtained fot the equally-weighted portfolio of TRACE bonds (not presented here).

The residual spread free from corporate default risk only (EBP of Model 4) is not a predictor of bond market returns either. Figure 4b presents these estimations, and here, again, none of the factors is significant at horizons below 70 business days. For 70–90 days ahead the fitted spread is a significant in-sample predictor of cumulative returns, but, as I show later, this result is not robust to alternative specifications of market returns and the EBP. The bottom line of the estimations presented in Figure 4 is as follows: if there is any information in aggregate spreads relevant for forecasting future excess bond market returns at all, it can hardly be extracted using the EBP correlated with the state of the business cycle.

[**Insert Figure 5 near here**]

In contrast, once one switches to the residual spread free from aggregate business risk and bond liquidity risk (EBP of Model 6), such bond premiums, unlike the EBP of Gilchrist and Zakrajšek (2012), turn out to be a significant predictor of bond market returns. Figure 5a presents the results of such forecasting models. For all horizons between 40 and 60 days ahead, the EBP and only the EBP is a significant predictor of excess bond market returns. Economic significance of the EBP for future returns is high as well. A 10 basis points (b.p.) rise in the EBP today implies almost 40 b.p. of excess bond market return over the next two-three month. To give a sense of scale, the average absolute daily change in the EBP in my sample is 4 b.p. with a standard deviation of 5 b.p. The adjusted R^2 of return forecasting regression at the 50-day horizon is 0.52.

My preferred measure of the EBP remains a significant predictor of bond market returns when the market is the Barclays Aggregate U.S. corporate bond index.[15] On Figure 5b, I present these estimated forecasting regressions. Both statistical and economic significance of the EBP still holds, moreover, here the EBP is a significant predictor on all horizons from several weeks to several months ahead. In contrast, the fitted spread is nowhere significant.

[15] The correlation of excess returns on Barclays index with excess returns on our TRACE portfolio is 0.79.

The adjusted R^2 of return-forecasting regression at the 20-day horizon is 0.33. Appendix E demonstrates that the predictive power of the EBP for market returns remains if I control for the VIX levels in returns-forecasting regressions. To sum up, out of all considered factors the EBP free from aggregate business risk and bond liquidity risk is the only significant in-sample predictor of cumulative corporate bond market returns 1–3 months ahead.

5.2. 'Real-time' EBP as a Predictor of Market Returns

The EBP constructed and discussed in Sections 3 and 4 is the in-sample measure based on the entire dataset as of the end of 2016. A 'real-time' EBP might, in principle, be different from my full-sample measure because the whole historical path of the ADS index is re-estimated as new macroeconomic data become available (see Appendix C for details). In this section, I estimate a 'real-time' EBP, show that it is not much different from the full-sample measure, and demonstrate that the two have similar predictive power for bond market returns.

Computation of a 'real-time' EBP is possible for all dates starting from the end of 2008; this is when the historical vintages of the ADS become available.[16] For every single day t in the sample, I cut my bond-day data at day t, take the ADS vintage as of t, and re-run Model 6 of Table 2 on this dataset to obtain the real-time measure of EBP denoted $EBP^{RT}(t)$.[17] I will denote observations in this time series $EBP^{RT}_{\tau}(t)$, where $\tau \leq t$.

[Insert Figure 6 near here]

Real-time EBPs turn out to be not much different from the full-sample EBP starting from the year 2010, as charts on Figure 6 demonstrate. These charts present a collection of

[16] See the Philadelphia Fed web-page: `https://goo.gl/mZJ5Sj`.

[17] There is still one piece of information I use that could have not been available at day t, namely, accounting books used to compute the distance-to-default. I do not expect, however, real-time accounting books to diminish the explanatory power of the ADS index for credit spreads. Late dissemination of information about idiosyncratic credit risk would probably increase the loading on timely systematic business risk measure in explanatory regressions for credit spreads.

the last points of real-time EBPs: $\left\{EBP^{RT}_{\tau=t}(t)\right\}$. Here, I estimate $EBP^{RT}(t)$ with samples always starting on Oct 4, 2004, and ending on the estimation day t. There are periods of time in 2009 when real-time EBPs differ considerably from the full-sample EBP_t estimate; otherwise, the real-time and the full-sample measures are close. Hence, we may expect that whatever valuable information EBP_t contains, we can extract it in real time, unless we are in some very volatile period as 2009 was.

[**Insert Figure 7 near here**]

It's important to check, however, whether the predictive power of the EBP for corporate bond market returns holds when the full-sample estimate is replaced in forecasting regressions with real-time estimates. I demonstrate in Figure 7 that, ever since 2010, real-time EBP has mostly been a significant predictor for excess bond market returns. Here, I re-estimate for each day t two forecasting models for 50-days ahead excess cumulative bond market returns with the real-time EBP on the right:

$$R_{\tau:\tau+50} = \alpha + \gamma EBP^{RT}_{\tau}(t) + \epsilon_{\tau+50},$$

and:

$$R_{\tau:\tau+50} = \alpha + \beta R_{\tau-50:\tau} + \gamma_1 LVL_\tau + \gamma_2 SLP_\tau + \gamma_3 CRV_\tau + \gamma_4 EBP^{RT}_{\tau}(t) + \epsilon_{\tau+50}.$$

Figure 7 depicts estimated coefficients $\hat{\gamma}$ and $\hat{\gamma}_4$ and their confidence bounds for each estimation day t (on the horizontal axis). The left chart demonstrates that real-time EBP has significantly predicted excess bond market returns in-sample since 2010 in the univariate regression model. The right chart of Figure 7 indicates that this predictive power is not affected by the inclusion of additional yield curve factors in the model. Here, for almost all estimation days in 2010–2014, EBP is still a significant predictor of excess corporate bond returns 50 days ahead. A 10 b.p. rise in $EBP^{RT}_{\tau=t}(t)$ implies 25 to 40 b.p. extra excess cumulative bond market returns over $t : t + 50$ when t is in 2010–2014.

[Insert Figure 8 near here]

The analysis so far focused on in-sample predictability. Now I use the two models of this paragraph to investigate out-of-sample predictability of corporate bond market returns with the real-time EBP estimates. Figure 8 presents out-of-sample predictive accuracy tests of Diebold and Mariano (1995) in which my models are tested against the no-predictability benchmark (zero expected excess corporate bond market returns) on forecasting horizons from 1 to 90 days ahead. The forecasts are constructed for all trading days in 2010–2014. The null states that candidate models are as accurate as zero excess return forecasts in this period. As Figure 8 shows, the null is rejected in favour of out-of-sample return predictability on horizons shorter than 10 days and longer than 45 days ahead when the EBP is the only predictor in the model.

These real-time estimations confirm that the EBP contains useful information for forecasting excess corporate bond market returns. The cheaper corporate bonds are relative to risk-free counterparts today (controlling for firm-specific credit risk, bond-specific liquidity risk, and aggregate business risk), the more they deliver on average over the next several months.

5.3. EBP and Other Corporate Bond Risk Factors

In this section, I demonstrate that the EBP is not explained by other corporate bond pricing factors, yet it improves their forecasting power with respect to diverse test portfolio returns. In particular, I compare the EBP to bond pricing factors derived by Bai et al. (2016) (referred to as 'BBW factors' herein). These factors are the 'market' factor, default risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF). These empirical factors are returns on factor-mimicking portfolios (see Appendix C for details about the construction of the factors). Bai et al. (2016) demonstrated that their four factors explain the major portion of variation of bond returns for size and maturity decile portfolios.

I do not have access to the original time series of the BBW factors, so I re-estimate them on my sample using the methodology by Bai et al. (2016). They compute the factors on the sample of TRACE bonds over a comparable time frame (Jul 2002 – Dec 2014) at a monthly frequency with monthly portfolio rebalancing. I compute the BBW factors either as in the original work with monthly portfolio rebalancing ('monthly factors') or, as a robustness check, with daily rebalancing ('daily factors').

[Insert Table 5 near here]

As Table 5 shows, the EBP is not strongly correlated with the bond risk factors, neither at the monthly nor the daily frequency. Likewise, the EBP is not linearly related to any stock market factor. The factors that are mildly correlated with the EBP on the monthly frequency are limited to bond credit risk and stock momentum factors. In the regression of daily EBP on BBW factors and a constant (not reported), none of the regressors has a significant coefficient, and the overall explanatory power of such a regression is low (adjusted R^2 is below 0.1). From this, I conclude that major empirical bond and stock pricing factors do not explain the time series variation of the EBP.

As Table 6 shows, the EBP does not add much to the BBW factors in explaining returns on Bai et al. (2016) test bond portfolios. Here, I consider monthly returns of size and maturity decile portfolios which I try to explain using candidate risk factors.[18] I also add industry portfolios to the analysis.[19] The 'Explanatory model' parts of Table 6 present R^2 from regressions of test portfolio returns on candidate risk factors. The columns titled BM and 4F refer to regressions with only the market factor and all the BBW factors correspondingly. The columns titled BM+ and 4F+ add the EBP as an explanatory variable to these baseline models. The market factor alone explains, on average, about 60-65% of variation of test portfolio returns. Three additional risk factors, DRF, CRF, and LRF, add 12–15% to the

[18] As in Section 6 of the work by Bai et al. (2016) I also tested 25 maturity-size quintile portfolios, but all the subsequent results are qualitatively similar for them, so they are not reported. For the same reason I am not reporting results obtained on the daily frequency.

[19] Eleven industry portfolios based on two-digit NAICS codes of the issuing firms.

R^2 of explanatory models on average. The EBP adds to that average virtually nothing. Based on these findings, I conclude that the EBP does not explain residual bond returns that are not explained by the BBW factors.

[Insert Table 6 near here]

However, when I run forecasting regressions for one-month ahead test portfolio returns, the EBP does much better than the BBW factors. Note first in the 'Forecasting model' parts of Table 6 that the market factor alone forecasts returns almost as good as the full Bai et al. (2016) four-factor model. This result holds for all industry portfolios and most size and maturity portfolios. That is why I use the 'BM' columns as benchmarks for return-forecasting regressions with the EBP added. The EBP improves the forecasting power of return-forecasting regressions across the board. Returns on all size, maturity, and industry portfolios are better forecasted once the EBP is included in the forecasting regressions. In addition, the increase in R^2 between BM and BM+ columns is pretty uniform across test portfolios. Hence, the strong forecasting power of the EBP is hardly due to any specific size, maturity, or industry group of bonds.

[Insert Table 7 near here]

Next, I check that the forecasting power of the EBP does not hinge on extreme return observations of the end of 2008. In Table 7, I compare for how many test portfolios of each type the coefficient on the EBP is significant in return forecasting-regressions both for the entire sample and for the sample with observations from Sep 2008 to Dec 2008 removed.[20] Table 7 demonstrates that the EBP remains a significant predictor of test portfolio returns at the 95% level, even with four extreme monthly observations removed. Removing years 2008 and 2009 completely makes this monthly time series very short, but even in this case (not reported), the EBP remains a significant predictor of returns at a 90% confidence level for most portfolios and for more portfolios than the market factor.

[20] These are the months with very low market returns and very high EBPs.

The logic behind the results of this section follows. Given the predictive power of the EBP for bond market returns discussed in Section 5, one should expect the EBP to forecast also whatever is strongly correlated with the market. As Table 6 shows, the market factor explains the major portion of variation of a broad range of test portfolio returns. Hence, one should expect the forecasting regressions in Table 7 to perform well, as they indeed do. It is important, though, that this result is not attainable with other bond pricing factors. The EBP outperforms DRF, LRF, and CRF factors in forecasting bond returns. In the next paragraph, I demonstrate how the predictive power of the EBP can be used to construct an investment strategy that outperforms the corporate bond market.

5.4. *Corporate Bond Market-timing Strategy*

I use the predictive power of the EBP for corporate bond market returns to design a market-timing strategy that delivers risk-return characteristics superior to the buy-and-hold the market strategy. My strategy uses only one risky instrument: the Barclays Aggregate U.S. corporate bond market index (investable; several replicating ETFs are available). The strategy consists of making one-week ahead forecasts of corporate bond market excess returns using recent observations of the EBP, fitted GZ spread, yield curve factors, and market returns. Based on these forecasts, an investor who has an amount of money W under management at the end of week t can take one of the following three positions for the week $t+1$:

- stay away from the corporate bond market and invest W in risk-free securities only (when low returns are forecasted);
- follow the market and invest W in the index ETF (when the model provides no clear signal about future returns);
- borrow a certain fraction α of W at the risk-free rate, and invest $(1+\alpha)W$ in the index ETF (when high positive returns are forecasted).

The forecasting model builds upon the results of Sections 5.1–5.3. The left-hand side variable is the *weekly* corporate bond market excess returns. The right-hand side variables are the five latest *daily* observations of the EBP, fitted GZ spread, three yield curve factors, and daily corporate bond market returns *one week prior to return observations.* Hence, there are 30 explanatory variables in total; selection among them is done by running LASSO estimations. The model is re-estimated every week w (using 'real-time' estimates of the EBP and fitted GZ spread of Section 5.2), and the LASSO penalty parameter λ is selected to minimize the root mean squared error (RMSE) of the out-of-sample forecasts with the 'leave-one-out' cross validation. Once the model is estimated, the forecast for the next week $w + 1$ is made using daily observations of predictors on week w.

[Insert Figure 9 near here]

The boundaries of the 'inaction region' in terms of predicted returns (when the investor simply holds W in the corporate bond market ETF) and the leverage ratio α are selected over the training sample, which is years 2009–2011. The selection problem is solved by maximizing the Sharpe ratio of the market-timing strategy on the training sample. The optimization is constrained, the lower bound of the inaction region is required to be negative, the upper bound positive, and $0 \leqslant \alpha \leqslant 0.5$. The left chart of Figure 9a presents the out-of-sample one-week ahead forecasts of market excess returns vis-a-vis actual excess returns. The two are significantly correlated: the correlation coefficient is 0.26, the regression coefficient is 0.96 (in the regression of actual returns on predicted ones), and both are significant at the 1%-level. Maximizing the Sharpe ratio yields $\alpha = 0.5$, the lower bound of the inaction region of -0.12%, and the upper bound of 0.06% (of predicted weekly market excess return). Table 8 and the right chart of Figure 9a show how the market-timing strategy performs on the training sample. It delivers 50% cumulative return over the three years (1.5 times more than the market) with a weekly Sharpe ratio of 0.37 (1.3 times higher than the market).

[Insert Table 8 near here]

As Figure 9b and Table 8 demonstrate, the strategy performs equally well on the testing sample, which is years 2012–2014 (with $\alpha = 0.5$ and inaction region bounds fixed at the values found on the training sample). Out-of-sample forecasts of market excess returns are again strongly correlated with actual returns; the correlation coefficient is 0.22, and the regression coefficient is 0.94, while both are significant at the 1%-level. Out of 155 weeks in the testing sample, an investor follows the market for 49 weeks, levers up for 93 weeks, and stays away from the market for 13 weeks. The strategy increases both mean weekly returns and the Sharpe ratio by roughly one-half relative to the buy-and-hold market strategy.[21] Cumulative returns of the strategy over the three testing years is 28% compared to 16% of the corporate bond market index.

6. Conclusion

In this paper, I explore the forecasting power of the aggregate corporate bond risk premium (EBP) with respect to the business cycle and corporate bond market returns. Unlike the closest study Gilchrist and Zakrajšek (2012), that defines the EBP as the portion of credit spread not explained by firm-specific credit risk, I additionally project spreads on bond-specific liquidity risk and economy-wide business risk. I do so using daily data constructed from tick-by-tick high-frequency data, while the literature works so far with historical monthly data.

The paper demonstrates that the forecasting power of the EBP for future economic activity depends on whether the EBP contains information about contemporaneous liquidity and aggregate business risks. The residual spread that is free from only corporate credit risk indeed forecasts activity, but this forecasting power mostly hinges on bond liquidity and aggregate business cycle states. The latter two are readily measurable with daily frequency. Once this information is taken away from credit spreads, both the statistical and the economic significance of the residual for the forecasts of macroeconomic activity reduces a lot.

[21] Transaction costs are not accounted for, but given that the strategy uses only one instrument, which is traded on the market, they will not considerably affect the results.

This residual spread, however, forecasts corporate bond market returns, unlike the EBP correlated with bond liquidity and aggregate business risks. The forecasting power is robust to different definitions of the bond market portfolio and to different estimation windows. I demonstrate that major stock and bond risk factors, including contemporaneous bond market returns per se, do not explain the time series variation of my risk premium measure. Moreover, its forecasting power is not concentrated in any particular size, maturity, or industry portfolio; the risk premium improves forecasts of corporate bond portfolios across the board.

One can profit from the forecasting power of the residual spread by investing according to the strategy designed to time the corporate bond market. The paper constructs the forecasting model for the corporate bond market excess returns that successfully forecasts returns out-of-sample. The strategy consists of staying away from the market when low negative returns are forecasted and levering up when high positive returns are forecasted; otherwise, an investor just follows the market. The strategy is implemented with only one risky instrument, an aggregate corporate bond market ETF, and delivers risk-adjusted returns 50% higher than the buy-and-hold market strategy.

Appendix A. Tables and Charts

Statistic	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Size, mln USD	594.71	549.50	1	282	500	750	15,000
Time to maturity, years	8.80	7.81	1.00	3.28	5.90	10.06	30.43
Age, years	5.72	4.95	0.00	2.05	4.22	7.84	49.66
Duration, years	6.19	4.10	0.94	3.02	5.03	8.00	19.64
Coupon rate, pct.	6.06	1.74	0.45	5.10	6.15	7.20	15.00
Credit rating	8.49	3.28	1	6	8	10	22
Trades per bond per day	6.18	12.33	1	2	3	6	1,861
Yield to maturity, pct.	5.07	2.82	0.19	3.22	5.09	6.27	39.42
Spread, pct.	2.38	2.41	0.05	1.04	1.68	2.86	35.00
Return, pct. per day	0.02	1.61	−11.77	−0.55	0.01	0.59	11.23
Distance-to-default (DD)	0.67	0.34	0.01	0.40	0.63	0.89	5.03
Amihud measure	0.60	1.06	0.00	0.03	0.21	0.68	8.87

(a) Full-sample descriptive statistics. The age variable represents time elapsed from issuance. Duration is the Macaulay duration. Ratings are in conventional numerical score; 'AAA' corresponds to 1, 'D' corresponds to 22. For spread 5 b.p. and 35% are truncation points. The Amihud price impact measure is computed as $\frac{1}{N_t}\sum_{j=1}^{N_t}\frac{|r_{t,j}|}{Q_{t,j}}$, where $r_{t,j}$ is the price return of trade j of this bond on day t, $Q_{t,j}$ is the volume of a corresponding transaction, and N_t is a total number of trades of this bond per day. The computation of the distance-to-default variable is detailed in Appendix B.2.

	AAA	AA	A	BBB	BB	B	CCC	CC	C	D
Size, mln USD	500.00	750.00	500.00	450.00	380.00	360.62	325.00	250.00	175.00	210.00
Time to maturity, years	6.01	4.56	5.68	6.16	6.16	5.98	5.63	5.36	6.08	18.91
Age, years	5.74	3.34	4.00	4.16	4.78	4.67	5.47	11.13	13.46	11.06
Duration, years	5.27	4.16	4.94	5.23	5.15	4.93	4.67	4.45	5.02	11.56
Coupon rate, pct.	5.15	4.88	5.60	6.20	7.12	7.75	7.86	7.70	9.00	7.12
Trades per bond per day	3.00	4.00	3.00	3.00	3.00	3.00	5.00	6.00	4.00	5.00
Yield to maturity, pct.	4.16	4.24	4.36	5.04	6.60	7.92	9.94	13.65	14.46	14.23
Spread, pct.	0.66	0.78	1.13	1.85	3.58	4.67	6.70	10.84	12.18	10.03
Return, pct. per annum	2.59	1.85	2.32	3.35	2.98	3.13	4.17	6.83	8.89	103.30
Distance-to-default (DD)	1.18	0.99	0.77	0.59	0.45	0.40	0.26	0.18	0.20	0.08
Amihud measure	0.29	0.17	0.19	0.21	0.23	0.24	0.42	0.74	0.69	1.08
% of total	0.56	5.91	34.98	39.10	11.30	5.46	2.21	0.26	0.19	0.03
% callable	24.62	67.17	83.02	86.49	81.42	78.52	66.73	39.72	37.60	28.64

(b) Median values by credit rating except for '% of total' and '% callable'. Here, numerical ratings of Table 1a are aggregated to 10 letter-coded bins. Median returns here are total returns expressed in *% per annum*.

Table 1: **Summary statistics**. The full sample is 2,032,455 bond-day observations that span a period from Oct 4, 2004 to Dec 23, 2014. The sample includes only senior unsecured non-convertible fixed coupon corporate bond issues with less than 30 years to maturity. The number of unique bonds/firms in sample is 4640/775. Appendix B.1 details the steps of data construction. The spread in both tables is the GZ spread from Gilchrist and Zakrajšek (2012): a difference in yields to maturity between a risky bond and an imaginary risk-free bond with the exact same cash flows.

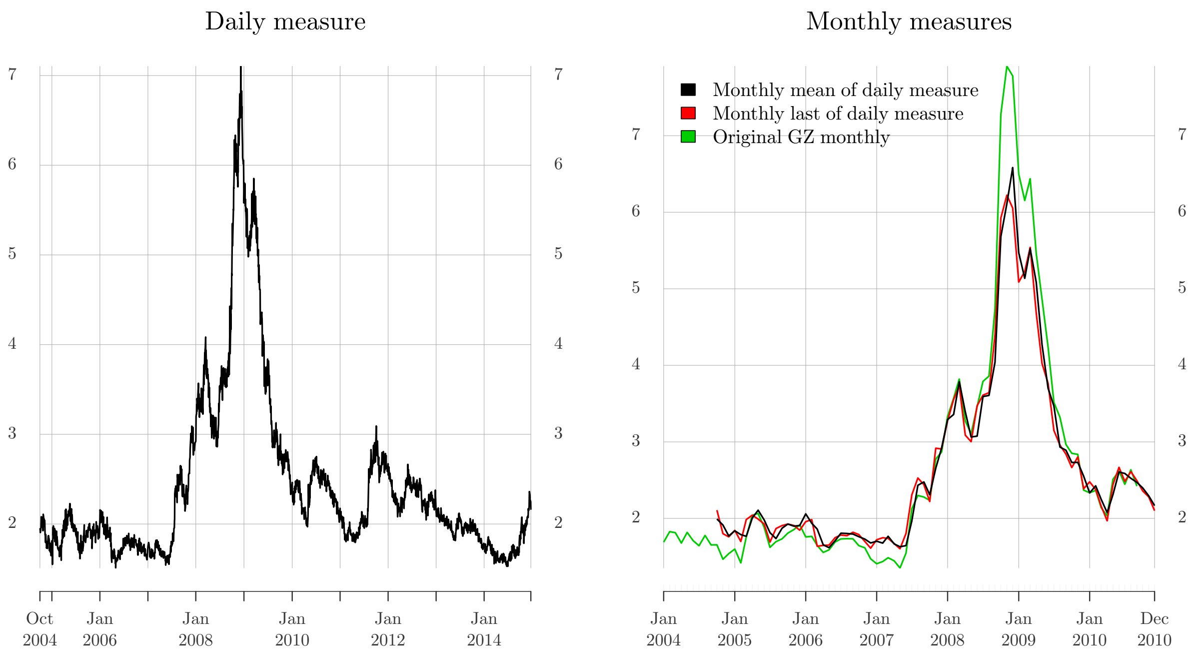
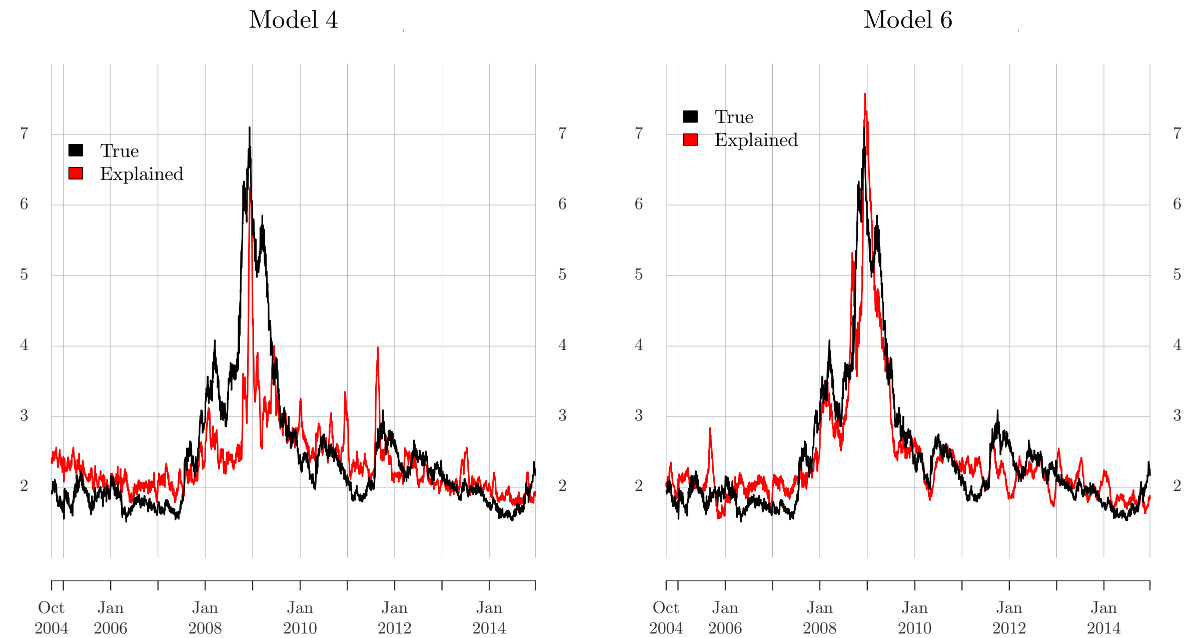


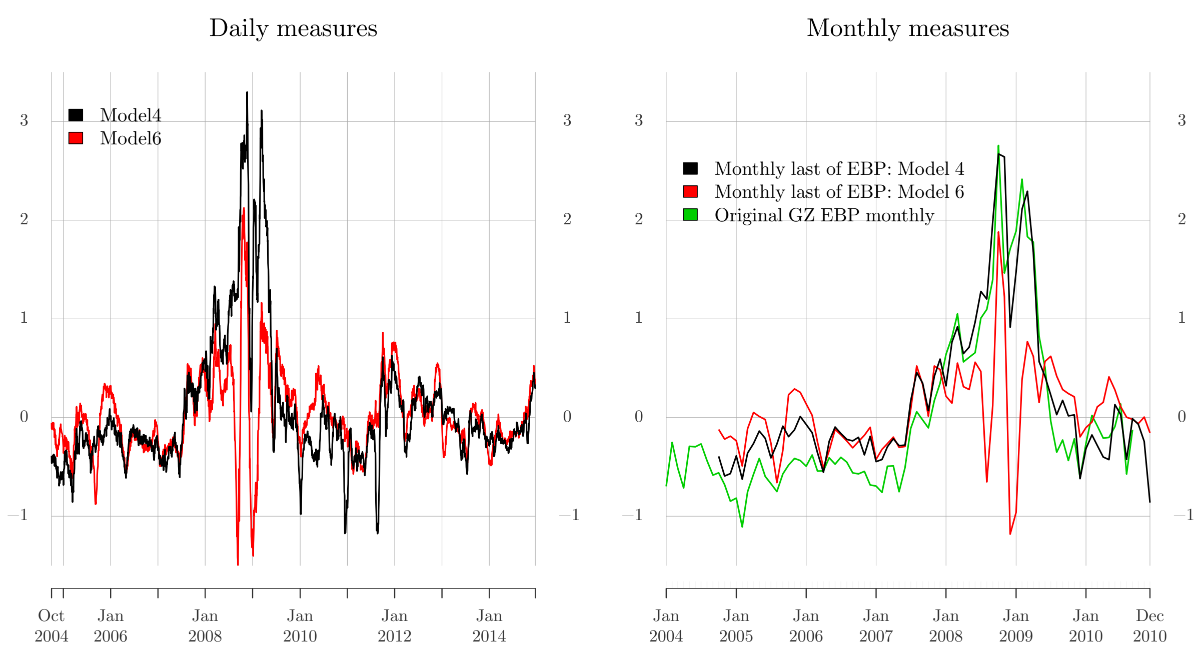
Fig. 1. **Daily and monthly measures of the aggregate GZ spread** (simple cross-sectional average of the GZ spread across all bonds for each time observation). The left chart shows daily GZ spread obtained on the daily TRACE-based sample. The right chart compares it with the original monthly GZ spread from Gilchrist and Zakrajšek (2012).

	Dependent variable: $\log(Spread_{it}[k])$					
	(1)	(2)	(3)	(4)	(5)	(6)
$-DD_{it}$	0.765***	0.543***	0.537***	0.633***	0.443***	0.434***
	(0.034)	(0.030)	(0.030)	(0.054)	(0.050)	(0.049)
$\log(DUR_{it}[k])$	0.097***	0.109***	0.099***	0.061***	0.068***	0.055***
	(0.010)	(0.009)	(0.009)	(0.021)	(0.020)	(0.019)
$\log(PAR_{it}[k])$	−0.073***	−0.073***	−0.068***	−0.038**	−0.043***	−0.038**
	(0.012)	(0.011)	(0.011)	(0.016)	(0.016)	(0.016)
$\log(CPN_i[k])$	0.631***	0.554***	0.554***	0.626***	0.563***	0.560***
	(0.020)	(0.019)	(0.018)	(0.068)	(0.063)	(0.062)
$\log(AGE_{it}[k])$	0.005	0.021***	0.016***	0.042	0.064***	0.061**
	(0.006)	(0.005)	(0.005)	(0.027)	(0.024)	(0.024)
$CALL_i[k]$	0.034*	0.038**	0.041**	0.406*	0.564**	0.584**
	(0.020)	(0.018)	(0.018)	(0.233)	(0.234)	(0.231)
ADS_t		−0.247***	−0.243***		−0.235***	−0.231***
		(0.007)	(0.007)		(0.006)	(0.006)
$AMH_{it}[k]$			0.037***			0.039***
			(0.002)			(0.002)
$-DD_{it} \cdot CALL_i[k]$				0.022	0.017	0.021
				(0.057)	(0.053)	(0.053)
$\log(DUR_{it}[k]) \cdot CALL_i[k]$				0.054***	0.048***	0.052***
				(0.020)	(0.019)	(0.018)
$\log(PAR_{it}[k]) \cdot CALL_i[k]$				−0.046***	−0.045***	−0.046***
				(0.017)	(0.017)	(0.017)
$\log(CPN_i[k]) \cdot CALL_i[k]$				−0.028	0.022	0.026
				(0.070)	(0.065)	(0.064)
$\log(AGE_{it}[k]) \cdot CALL_i[k]$				−0.032	−0.052**	−0.055**
				(0.027)	(0.023)	(0.023)
$LEV_t \cdot CALL_i[k]$				0.006	−0.021***	−0.023***
				(0.008)	(0.008)	(0.008)
$SLP_t \cdot CALL_i[k]$				−0.045***	−0.047***	−0.048***
				(0.010)	(0.008)	(0.008)
$CRV_t \cdot CALL_i[k]$				−0.068***	−0.100***	−0.100***
				(0.014)	(0.011)	(0.011)
$VOL_t \cdot CALL_i[k]$				2.142***	0.743***	0.727***
				(0.097)	(0.055)	(0.055)
Industry FE	YES	YES	YES	YES	YES	YES
Credit rating FE	YES	YES	YES	YES	YES	YES
Observations	2,032,455	2,032,455	2,032,455	2,032,455	2,032,455	2,032,455
Adjusted R^2	0.719	0.780	0.783	0.745	0.788	0.791
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 2: **Candidate explanatory models for the** bond k of firm i – day t **panel of credit spreads** for the entire sample (Oct 4, 2004 – Dec 23, 2014). The dependent variable is the log of GZ spread. DD is the distance-to-default, DUR is duration, PAR is amount outstanding, CPN is the coupon rate, AGE is time elapsed from issuance, and $CALL$ is a callable bond dummy. ADS is the Aruoba-Diebold and Scotti aggregate activity index, AMH is the Amihud liquidity measure. LEV, SLP, and CRV are correspondingly level, slope, and curvature yield curve factors, and VOL is the realized volatility of the 10-year rate (30-day moving average). See Appendix C for the details on explanatory variables. All models include industry (the first two digits of the NAICS code) and credit rating (22-grade numeric scale) fixed effects. Standard errors are clustered in both firm i and time t dimensions. Model (4) is a benchmark model (Gilchrist and Zakrajšek, 2012), Model (6) is used as an alternative model throughout the rest of the paper.



(a) Daily time series of true and fitted GZ spread from by Model 4 on the left (Gilchrist and Zakrajšek, 2012) and Model 6 on the right (my preferred model).



(b) Monthly time series of EBP from alternative models.

Fig. 2. **Fitted spread and EBP** (the residual portion of spread) that are computed with different models of Table 2 in comparison with the original Gilchrist and Zakrajšek (2012) EBP measure.

	Dependent variable: $\log\left(S_{it}^{GZ}[k]\right)$					
	M4	M6	M4	M6	M4	M6
	IG bonds: all years		HY bonds: all years		All bonds, ex. year 2008	
$-DD_{it}$	0.617***	0.403***	1.141***	0.987***	0.551***	0.422***
	(0.053)	(0.045)	(0.156)	(0.145)	(0.055)	(0.050)
$\log(DUR_{it}[k])$	0.053**	0.050**	0.077***	0.068***	0.078***	0.070***
	(0.024)	(0.021)	(0.025)	(0.025)	(0.022)	(0.021)
$\log(PAR_{it}[k])$	−0.067***	−0.066***	0.017	0.019	−0.043***	−0.039**
	(0.017)	(0.017)	(0.021)	(0.021)	(0.016)	(0.016)
$\log(CPN_i[k])$	0.632***	0.561***	0.563***	0.509***	0.569***	0.535***
	(0.064)	(0.059)	(0.130)	(0.124)	(0.066)	(0.063)
$\log(AGE_{it}[k])$	0.048*	0.068***	−0.050	−0.027	0.064**	0.072***
	(0.029)	(0.025)	(0.032)	(0.026)	(0.027)	(0.025)
$CALL_i[k]$	0.171	0.361	0.215	0.438	0.555**	0.669***
	(0.246)	(0.243)	(0.409)	(0.404)	(0.239)	(0.236)
ADS_t		−0.236***		−0.191***		−0.198***
		(0.007)		(0.011)		(0.008)
$AMH_{it}[k]$		0.036***		0.036***		0.040***
		(0.002)		(0.004)		(0.002)
$-DD_{it} \cdot CALL_i[k]$	0.052	0.049	−0.356***	−0.318**	0.039	0.030
	(0.060)	(0.054)	(0.137)	(0.130)	(0.057)	(0.054)
$\log(DUR_{it}[k]) \cdot CALL_i[k]$	0.070***	0.065***	−0.003	0.006	0.049**	0.050***
	(0.022)	(0.019)	(0.025)	(0.025)	(0.020)	(0.019)
$\log(PAR_{it}[k]) \cdot CALL_i[k]$	−0.024	−0.025	−0.045*	−0.051**	−0.049***	−0.049***
	(0.018)	(0.019)	(0.025)	(0.025)	(0.017)	(0.018)
$\log(CPN_i[k]) \cdot CALL_i[k]$	−0.055	0.006	−0.042	0.015	0.023	0.050
	(0.065)	(0.061)	(0.131)	(0.125)	(0.068)	(0.065)
$\log(AGE_{it}[k]) \cdot CALL_i[k]$	−0.038	−0.060**	0.052	0.020	−0.055**	−0.068***
	(0.029)	(0.025)	(0.033)	(0.027)	(0.026)	(0.024)
$LEV_t \cdot CALL_i[k]$	0.020**	−0.011	−0.031**	−0.052***	−0.023***	−0.036***
	(0.009)	(0.008)	(0.016)	(0.015)	(0.008)	(0.007)
$SLP_t \cdot CALL_i[k]$	−0.059***	−0.063***	−0.005	−0.007	−0.075***	−0.059***
	(0.011)	(0.009)	(0.016)	(0.014)	(0.010)	(0.009)
$CRV_t \cdot CALL_i[k]$	−0.060***	−0.101***	−0.079***	−0.085***	−0.103***	−0.106***
	(0.015)	(0.011)	(0.024)	(0.022)	(0.013)	(0.012)
$VOL_t \cdot CALL_i[k]$	2.124***	0.685***	2.210***	1.052***	1.989***	0.807***
	(0.101)	(0.054)	(0.114)	(0.099)	(0.094)	(0.053)
Industry FE	YES	YES	YES	YES	YES	YES
Credit rating FE	YES	YES	YES	YES	YES	YES
Observations	1,637,136	1,637,136	395,319	395,319	1,887,091	1,887,091
Adjusted R^2	0.646	0.716	0.580	0.632	0.762	0.789
Note:	*p<0.1; **p<0.05; ***p<0.01					

Table 3: Model 4 (M4 columns) and Model 6 (M6 columns) from Table 2 recomputed over **different sub-samples of the entire sample**. The first two columns are only investment-grade bonds over the entire sample, the second two columns are high-yield bonds over the entire sample, and the last two columns are all bonds but excluding all days in year 2008. Dependent variable is the log of GZ spread. Explanatory variables are as in Table 2. Standard errors are clustered in both firm i and time t dimensions.

	Industrial production			Unemployment rate			Payroll employment		
	–	M4	M6	–	M4	M6	–	M4	M6
Real Fed funds rate	0.51	0.23	0.56	0.06	0.07*	0.05	−0.09*	−0.09**	−0.09*
	(0.36)	(0.21)	(0.42)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Term spread	−0.90*	−0.39	−0.94*	0.04	0.02	0.04	0.06	0.07	0.06
	(0.47)	(0.33)	(0.50)	(0.06)	(0.04)	(0.05)	(0.06)	(0.04)	(0.06)
GZ spread	−1.84***			0.54***			−0.66***		
	(0.40)			(0.05)			(0.05)		
Fitted GZ		−0.70	−2.18***		0.46***	0.60***		−0.59***	−0.74***
		(0.54)	(0.35)		(0.08)	(0.04)		(0.11)	(0.06)
EBP		−2.85***	−0.82		0.59***	0.33***		−0.70***	−0.46***
		(0.60)	(0.66)		(0.07)	(0.10)		(0.07)	(0.08)
Adjusted R^2	0.61	0.68	0.64	0.76	0.76	0.79	0.89	0.89	0.91
Note:	*p<0.1; **p<0.05; ***p<0.01								

(a) **3 months ahead**

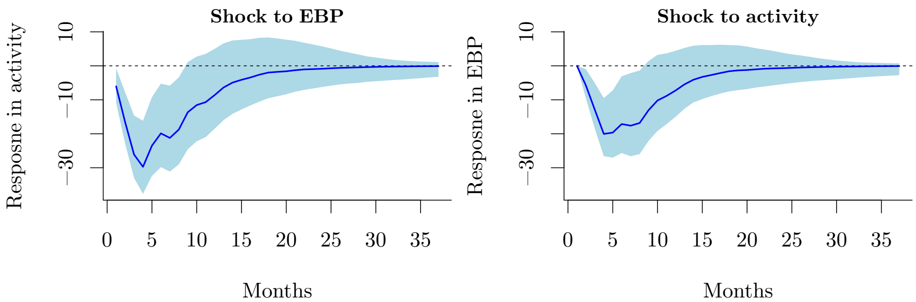
	Industrial production			Unemployment rate			Payroll employment		
	–	M4	M6	–	M4	M6	–	M4	M6
Real Fed funds rate	1.02	0.48	1.08	0.04	0.06	0.03	−0.07	−0.09	−0.07
	(0.71)	(0.43)	(0.70)	(0.11)	(0.07)	(0.12)	(0.15)	(0.11)	(0.15)
Term spread	−1.65**	−0.71	−1.69**	0.17	0.12*	0.17	−0.04	0.02	−0.03
	(0.76)	(0.61)	(0.71)	(0.11)	(0.07)	(0.12)	(0.17)	(0.11)	(0.17)
GZ spread	−2.58***			0.83***			−1.09***		
	(0.91)			(0.10)			(0.06)		
Fitted GZ		−0.78	−2.92***		0.57***	0.88***		−0.80***	−1.17***
		(0.81)	(1.09)		(0.16)	(0.14)		(0.27)	(0.14)
EBP		−4.77***	−1.55		0.99***	0.65***		−1.27***	−0.89***
		(1.24)	(1.29)		(0.20)	(0.15)		(0.17)	(0.15)
Adjusted R^2	0.50	0.57	0.51	0.75	0.77	0.75	0.83	0.84	0.84
Note:	*p<0.1; **p<0.05; ***p<0.01								

(b) **6 months ahead**

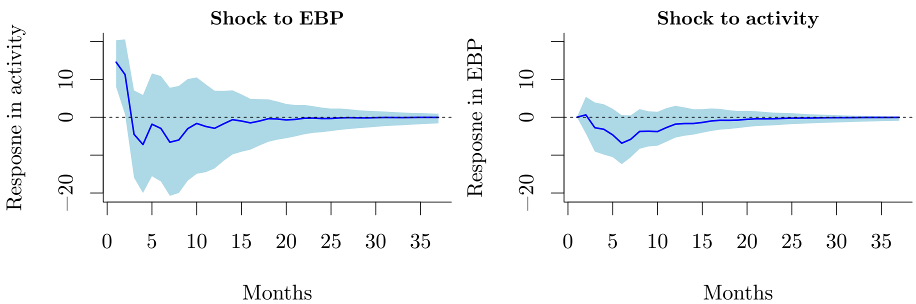
	Industrial production			Unemployment rate			Payroll employment		
	–	M4	M6	–	M4	M6	–	M4	M6
Real Fed funds rate	1.47	0.36	1.45*	0.02	0.05	0.02	−0.05	−0.09	−0.05
	(0.94)	(0.45)	(0.87)	(0.21)	(0.15)	(0.19)	(0.30)	(0.21)	(0.29)
Term spread	−2.99**	−1.21	−2.97**	0.47**	0.39**	0.47**	−0.35	−0.24	−0.35
	(1.37)	(0.87)	(1.28)	(0.23)	(0.16)	(0.21)	(0.38)	(0.24)	(0.37)
GZ spread	−3.16			1.24***			−1.84***		
	(2.44)			(0.34)			(0.30)		
Fitted GZ		−1.00	−3.02		0.78***	1.25***		−1.25**	−1.88***
		(1.79)	(2.09)		(0.26)	(0.37)		(0.52)	(0.38)
EBP		−8.08**	−3.57		1.51***	1.18***		−2.20***	−1.74***
		(3.45)	(3.58)		(0.49)	(0.40)		(0.53)	(0.41)
Adjusted R^2	0.29	0.40	0.28	0.58	0.60	0.58	0.67	0.68	0.67
Note:	*p<0.1; **p<0.05; ***p<0.01								

(c) **12 months ahead**

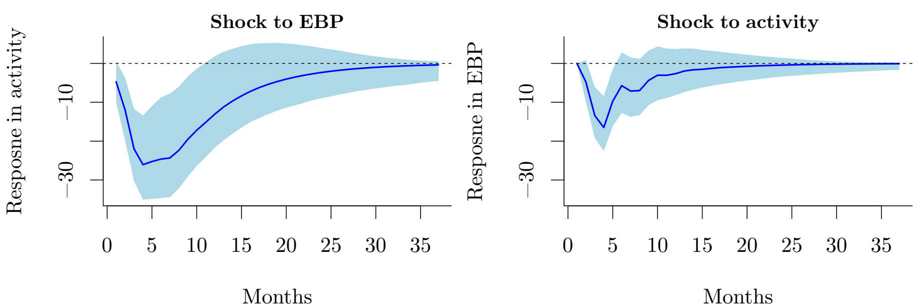
Table 4: **Forecasting regressions for** the log growth rate of **industrial production**, change in the **unemployment rate**, and the log growth rate of **payroll employment** on different horizons (*not* annualized) with either true spread or fitted spread and the EBP (excess bond premium) as explanatory variables. The EBP is from two alternative models of Table 2: Models 4 and 6 (columns 'M4' and 'M6' correspondingly). Real Federal funds rate is the difference between nominal rate and realized 12-month inflation (one month prior to a rate observation), Term spread is the difference between 3-month and 10-year Treasury zero coupon rates. See Appendix C for the details on explanatory variables. Each regression also has a constant and an automatically selected number of lags (based on the AIC) of the dependent variable (also not reported). Sample period is monthly from Oct 2004 to Dec 2014. Standard errors are Newey and West (1987) HAC estimates.



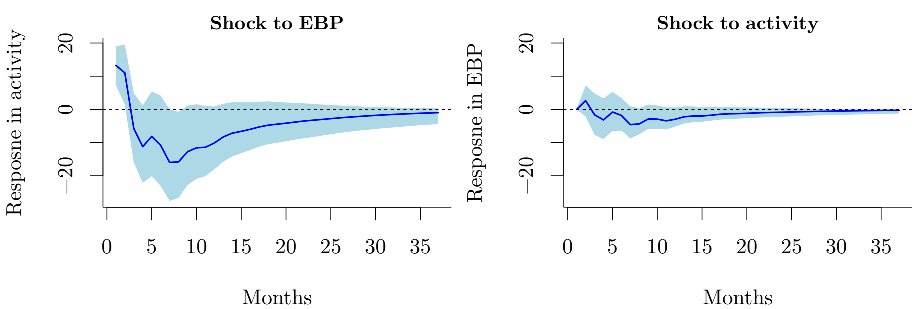
(a) Here EBP is computed with **Model 1** of Table 2.



(b) Here EBP is computed with **Model 3** of Table 2.



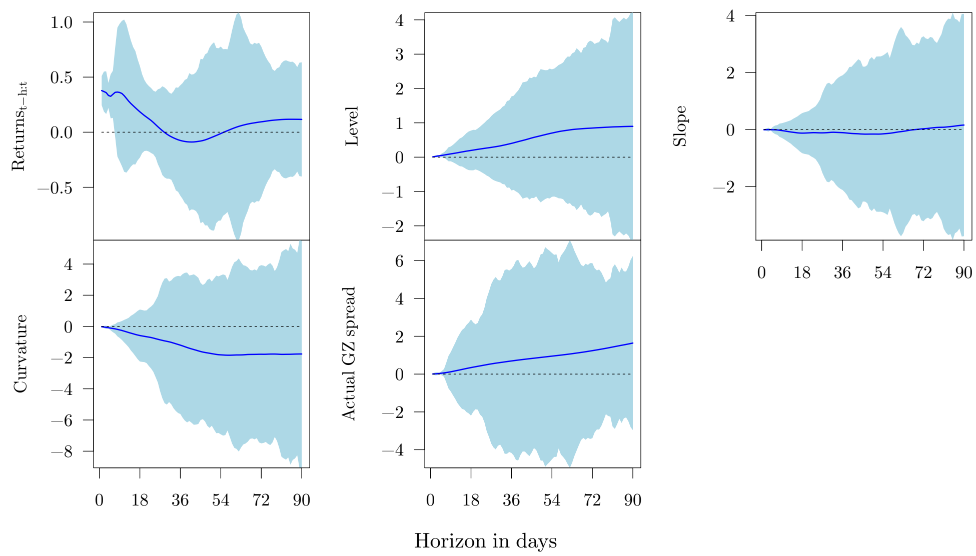
(c) Here EBP is computed with **Model 4** of Table 2.



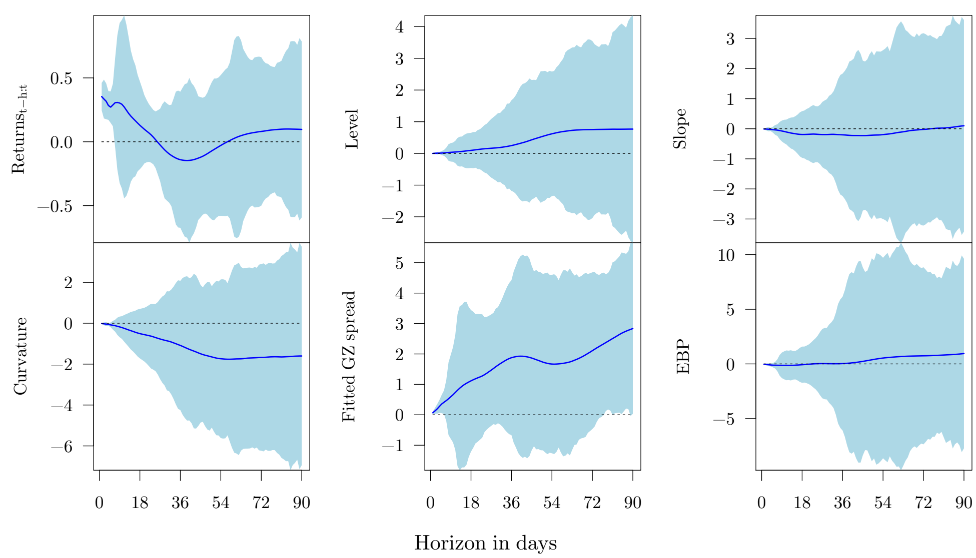
(d) Here EBP is computed with **Model 6** of Table 2.

Fig. 3. Orthogonalized impulse-response functions (IRFs) to one standard deviation shocks from bi-variate monthly **VAR models of business activity (the ADS index) and the EBP**. Monthly ADS and EBP are the latest daily observations per month. The models include a number of lags selected by AIC (required to be less or equal to 12) and a constant. The EBP is based on Models 1, 3, 4, and 6 of Table 2. Shaded areas are 95% bootstrapped confidence bands (10'000 runs). Sample period is from Oct 2004 to Dec 2014.

Parameter estimates for cumulative returns on different horizons



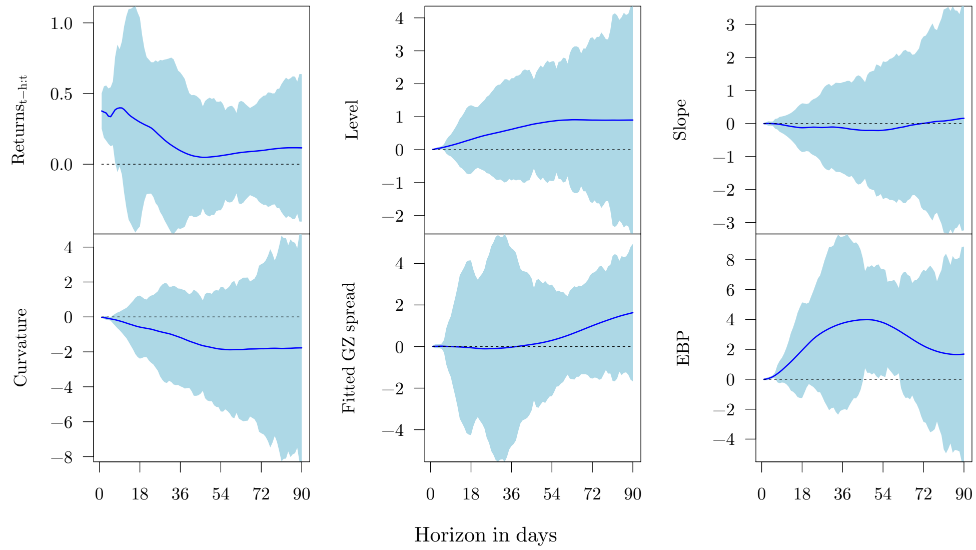
(a) Dependent variable: returns on **TRACE portfolio** of bonds; actual GZ spread as one of explanatory variables.



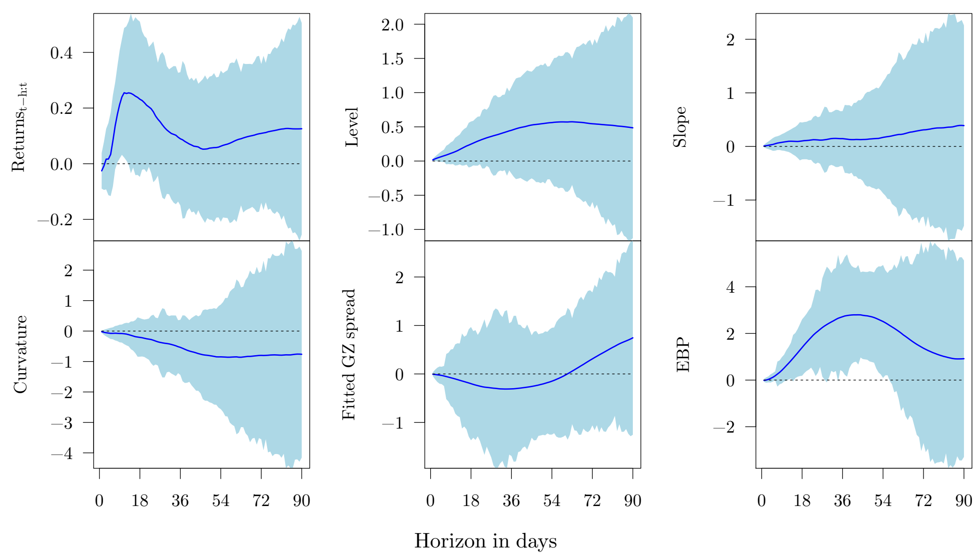
(b) Dependent variable: returns on **TRACE portfolio** of bonds; fitted GZ spread and EBP of **Model 4** as explanatory variables.

Fig. 4. Estimated **forecasting regressions for cumulative bond market excess returns**. Forecasting horizons are on horizontal axes. Market returns are log returns (*not* annualized) on the value-weighted portfolio of TRACE bonds. Explanatory variables are on vertical axes. See Appendix C for the details on explanatory variables. Each point on a solid line on each chart is the OLS-estimate from a corresponding regression. Shaded areas around are two standard errors of the estimates. The standard errors are heteroskedasticity and autocorrelation consistent estimates of Newey and West (1987). Each model also includes a constant (not reported). The sample is daily from Oct 4, 2004 to Dec 23, 2014.

Parameter estimates for cumulative returns on different horizons



(a) Dependent variable: returns on **TRACE portfolio** of bonds; fitted GZ spread and EBP of **Model 6** as explanatory variables.



(b) Dependent variable: returns on **Barclays Aggregate U.S. corporate bond index**; fitted GZ spread and EBP of **Model 6** as explanatory variables.

Fig. 5. Estimated **forecasting regressions for cumulative bond market excess returns**. Forecasting horizons are on horizontal axes. Market returns are log returns (*not* annualized) on the value-weighted portfolio of TRACE bonds (upper panel) or the Barclays Aggregate corporate bond market index (lower panel). Explanatory variables are on vertical axes. See Appendix C for the details on explanatory variables. Each point on a solid line on each chart is the OLS-estimate from a corresponding regression. Shaded areas around are two standard errors of estimates. The standard errors are heteroskedasticity and autocorrelation consistent estimates of Newey and West (1987). Each model also includes a constant (not reported). The sample is daily from Oct 4, 2004 to Dec 23, 2014.

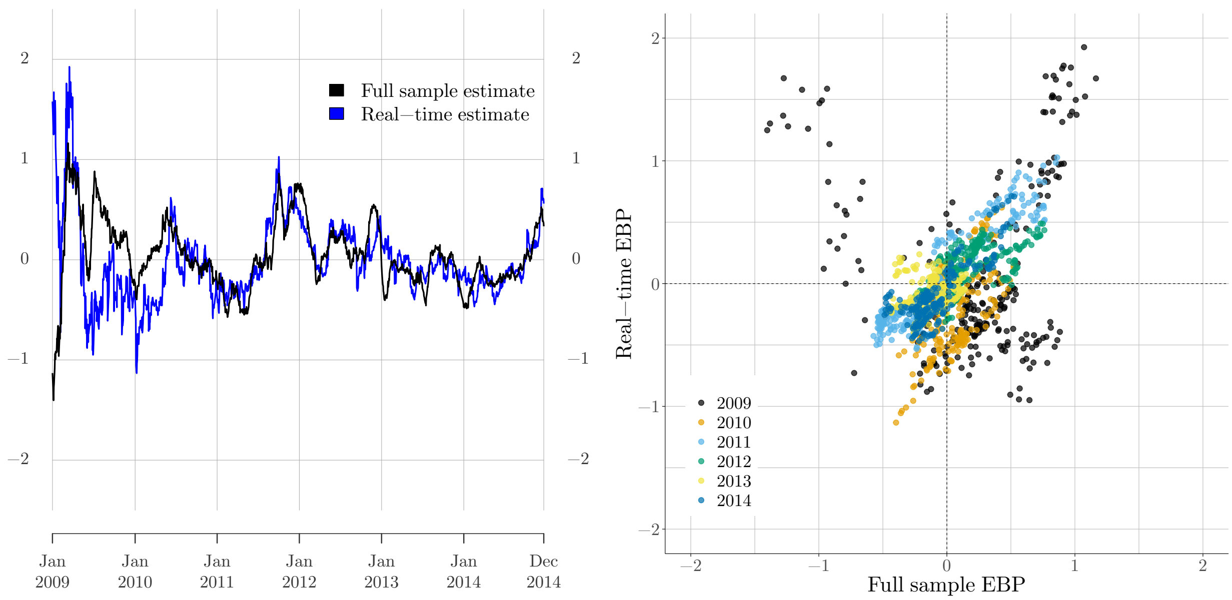


Fig. 6. **Real-time daily EBP measures** computed with only aggregate activity data available on each estimation day, in comparison with full-sample EBP estimates (same as 'Model 6' on the bottom-left panel of Figure 2); time-series on the left and scatter plot on the right. Each daily observation of the real-time EBP is computed by re-estimating Model 6 of Table 2 for log spreads with a historical ADS vintage available on that particular day, and taking the latest EBP observation. Re-estimations are performed on expanding samples; each spans a period from Oct 4, 2004 to the estimation day.

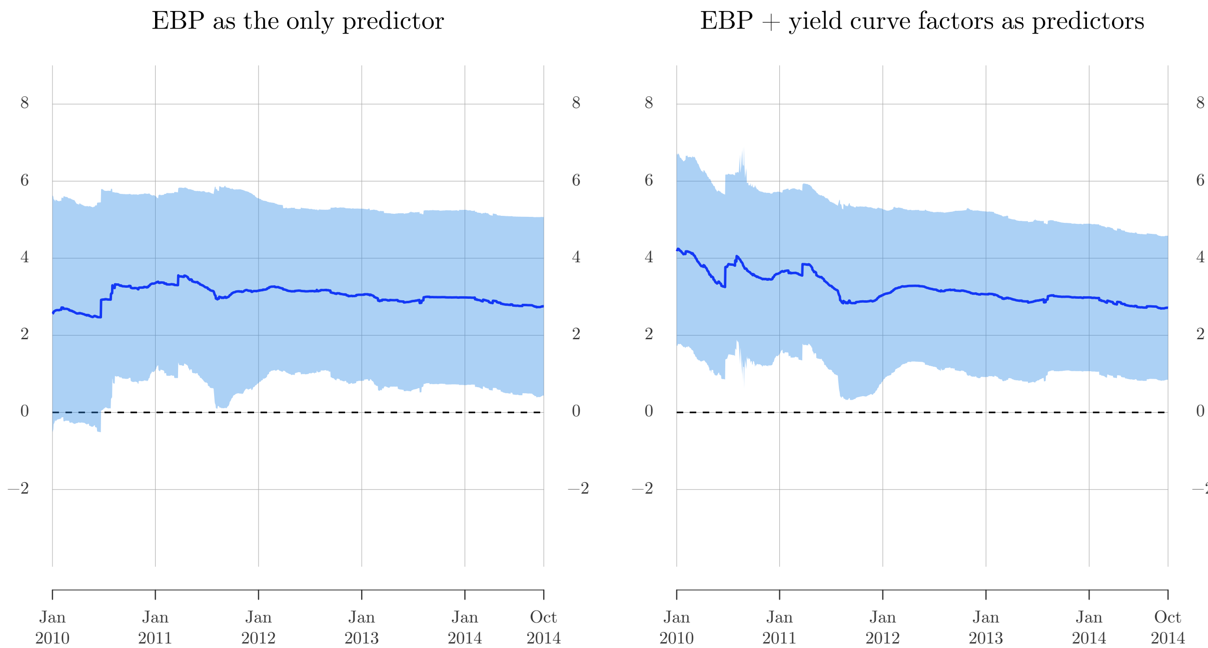


Fig. 7. **Coefficients on real-time EBP in cumulative excess corporate bond market return forecasting regressions**. The dependent variable is the cumulative 50-day ahead log return on the value-weighted portfolio of TRACE bonds, *not* annualized. The left chart presents the estimates from the model with real-time EBP as the only predictor. The right chart presents the estimates from the model that also includes yield curve factors (level, slope, and curvature) and one lagged cumulative bond market return as predictors. The underlying samples expand from Oct 4, 2004 to estimation dates, which are on the horizontal axes of the charts. Lines are OLS-estimates of the coefficients on EBP from corresponding regressions. Shaded areas are two standard errors of estimates. The standard errors are heteroskedasticity and autocorrelation consistent estimates of Newey and West (1987).

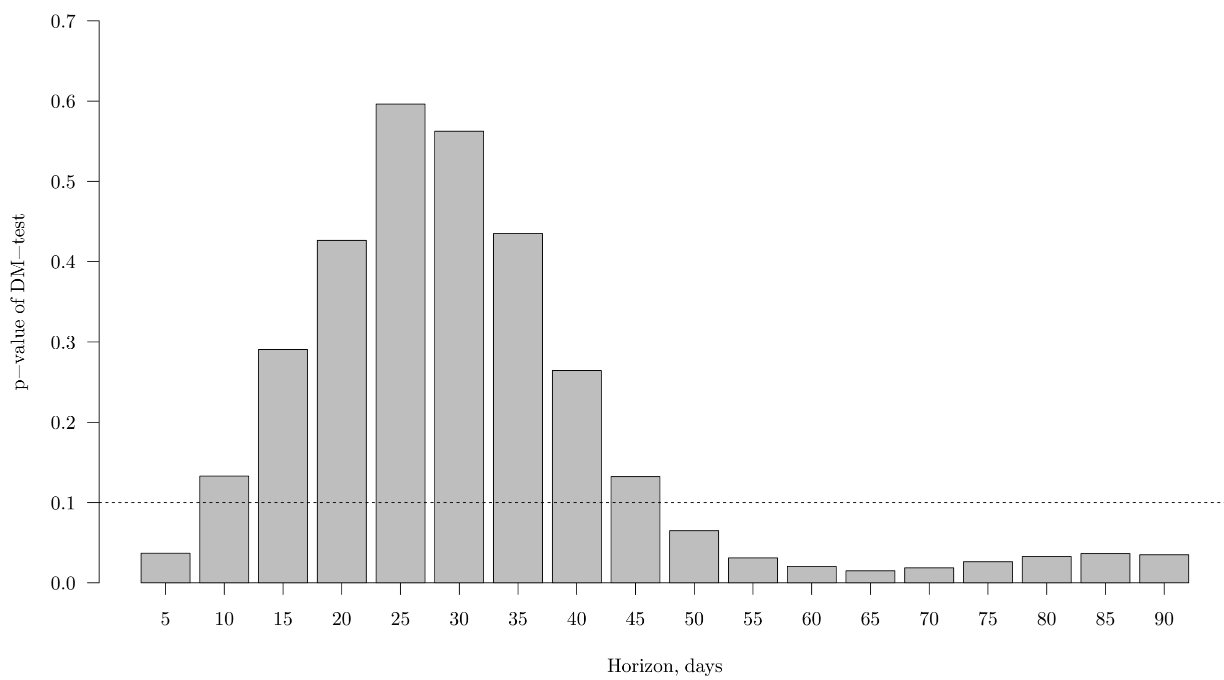


Fig. 8. **Diebold-Mariano (DM) out-of-sample predictive accuracy test of return-forecasting models** relative to no-predictability (zero expected excess return) benchmark on different forecasting horizons. Candidate predictive models for cumulative corporate bond market all have the real-time EBP as the only predictor. The forecasting horizon is on the horizontal axis. The null is equal predictive accuracy with zero excess-return benchmark. The alternative hypothesis is greater out-of-sample predictive accuracy of a considered return forecasting model. P-values of the DM test are on the vertical axis. Values below 0.1 indicate rejection of the null at the 90% confidence level. The bond market is the Barclays IG portfolio of bonds. DM test statistics are computed using forecast errors for all trading days between Jan 4, 2010 and Dec 23, 2014.

	EBP	BM	DRF	CRF	LRF	SM	SMB	HML
EBP								
BM	0.02							
DRF	-0.06**	0.28***						
CRF	-0.08**	-0.36***	0.08**					
LRF	0.05*	0.20***	0.47***	-0.06*				
SM	-0.01	-0.28***	0.03	0.41***	-0.02			
SMB	0.00	-0.08***	0.00	0.14***	-0.02	0.33***		
HML	0.01	-0.14***	0.00	0.18***	-0.02	0.44***	0.09***	
UMD	-0.03	0.09***	-0.04	-0.17***	-0.01	-0.38***	-0.05*	-0.59***

(a) Correlation matrix of **risk factors on the daily frequency**. Underlying portfolio rebalancing in construction of the corporate bond risk factors is also daily. The sample starts on Mar 10, 2005, because first 100 days are needed to compute the first observation of the DRF factor.

	EBP	BM	DRF	CRF	LRF	SM	SMB	HML
EBP								
BM	0.18							
DRF	-0.14	0.47***						
CRF	-0.22*	-0.04	-0.15					
LRF	0.03	0.04	0.37***	-0.07				
SM	-0.01	-0.14	0.03	-0.13	0.11			
SMB	0.13	0.02	-0.13	-0.09	0.19*	0.08		
HML	0.15	-0.17	-0.16	-0.20*	0.11	0.56***	-0.05	
UMD	-0.27**	-0.05	0.03	0.03	-0.01	-0.41***	0.10	-0.50***

(b) Correlation matrix of **risk factors on the monthly frequency**. Portfolio rebalancing frequency in construction of risk factors is monthly. EBP is monthly means of the daily series. The sample starts on Oct 2007, because first three years are needed to compute the first observation of the DRF factor.

Table 5: **Correlations of the EBP with corporate bond risk factors** from Bai et al. (2016), and stock market risk factors. The EBP is a full sample estimate from Model 6 of Table 2. The upper panel uses daily time series of the EBP; lower panel uses monthly averages of the EBP. BM stands for excess returns on the aggregate bond market index (Barclays IG), DRF for the default risk factor, CRF for the credit risk factor, and LRF for the liquidity risk factor. Construction methodology for the risk factors is similar to Bai et al. (2016), the details are provided in Appendix C. The difference between the upper and the lower panels is a frequency of portfolio rebalancing for the construction of bond risk factors. The last four rows of correlation matrices refer to the Fama-French stock market risk factors: SM is excess market return, SMB is the small-minus-big factor, HML is the high-minus-low factor, and UMD is the momentum factor. Significance code: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Explanatory model				Forecasting model			
	BM	4F	BM+	4F+	BM	4F	BM+	4F+
D1	0.28	0.59	0.29	0.59	0.36	0.33	0.41	0.38
D2	0.51	0.73	0.51	0.74	0.31	0.30	0.43	0.44
D3	0.54	0.72	0.53	0.71	0.21	0.18	0.30	0.27
D4	0.65	0.80	0.65	0.80	0.18	0.22	0.30	0.32
D5	0.61	0.70	0.61	0.70	0.14	0.11	0.23	0.18
D6	0.69	0.81	0.69	0.81	0.14	0.14	0.24	0.24
D7	0.74	0.84	0.74	0.84	0.07	0.13	0.20	0.22
D8	0.76	0.87	0.76	0.87	0.06	0.10	0.19	0.18
D9	0.79	0.89	0.79	0.89	0.04	0.09	0.16	0.15
D10	0.71	0.87	0.71	0.87	0.00	0.03	0.09	0.07
Average	0.63	0.78	0.63	0.78	0.15	0.16	0.26	0.25

(a) Maturity decile portfolios (D1 – shortest, D10 – longest).

	Explanatory model				Forecasting model			
	BM	4F	BM+	4F+	BM	4F	BM+	4F+
D1	0.37	0.71	0.36	0.71	0.24	0.17	0.26	0.19
D2	0.48	0.78	0.48	0.78	0.20	0.17	0.24	0.19
D3	0.61	0.82	0.61	0.81	0.20	0.21	0.28	0.26
D4	0.50	0.57	0.52	0.59	0.10	0.10	0.17	0.12
D5	0.66	0.81	0.66	0.80	0.11	0.11	0.19	0.16
D6	0.74	0.84	0.73	0.84	0.10	0.12	0.22	0.20
D7	0.78	0.86	0.78	0.87	0.07	0.08	0.19	0.17
D8	0.75	0.85	0.75	0.86	0.04	0.04	0.12	0.11
D9	0.82	0.88	0.82	0.87	0.03	0.09	0.19	0.20
D10	0.84	0.89	0.84	0.90	0.02	0.09	0.15	0.17
Average	0.65	0.80	0.65	0.80	0.11	0.12	0.20	0.18

(b) Size decile portfolios (D1 – smallest, D10 – largest).

	Explanatory model				Forecasting model			
	BM	4F	BM+	4F+	BM	4F	BM+	4F+
Mining, Quarrying, and Oil and Gas Extraction	0.72	0.82	0.72	0.82	0.09	0.06	0.18	0.12
Utilities	0.68	0.81	0.69	0.81	0.17	0.16	0.26	0.23
Construction	0.34	0.44	0.34	0.45	0.06	0.11	0.12	0.11
Manufacturing	0.73	0.87	0.73	0.87	0.08	0.10	0.20	0.18
Wholesale Trade	0.73	0.82	0.73	0.84	0.12	0.12	0.20	0.16
Retail Trade	0.70	0.80	0.70	0.79	0.07	0.09	0.18	0.15
Transportation and Warehousing	0.62	0.82	0.62	0.82	0.13	0.09	0.20	0.14
Information	0.76	0.86	0.76	0.86	0.09	0.07	0.17	0.13
Professional, Scientific, and Technical Services	0.20	0.28	0.20	0.28	0.02	0.04	0.03	0.03
Administrative and Support etc. Services	0.42	0.59	0.43	0.59	0.02	0.12	0.24	0.26
Accommodation and Food Services	0.57	0.65	0.57	0.65	0.10	0.10	0.18	0.16
Average	0.59	0.71	0.59	0.71	0.09	0.10	0.18	0.15

(c) Industry portfolios (2-digit NAICS codes).

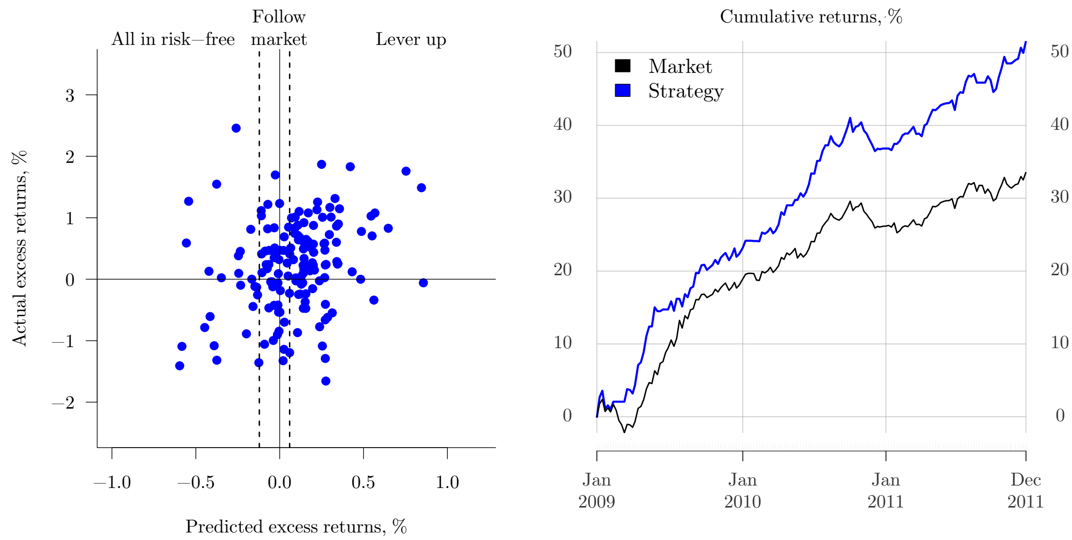
Table 6: **Adjusted R^2 of explanatory and forecasting regressions** for monthly returns on size decile, maturity decile, and industry portfolios. In explanatory models returns and risk factors are contemporaneous, in forecasting models returns are one month ahead. The sample is monthly from Oct 2007 to Dec 2014. Four alternative models are considered: BM has the bond market risk factor as the only explanatory variable, 4F has DRF, CRF, and LRF factors in addition, BM+ has the market factor and the EBP, and 4F+ has four aforementioned factors and the EBP.

	Full sample			Excl. Sep-Dec'08		
	Maturity	Size	Industry	Maturity	Size	Industry
BMarket	8	7	9	6	6	6
EBP	10	10	10	10	9	11
Memo: # of portf.	10	10	11	10	10	11

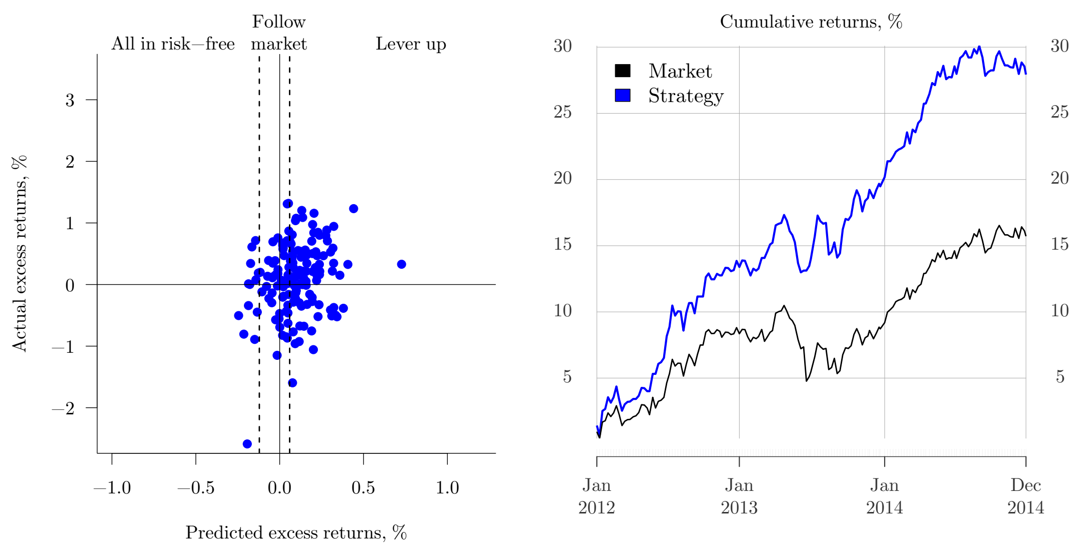
Table 7: **Significance of explanatory variables** in BM+ return-forecasting models from Table 6 at the 95%-level . A number in row i of column j shows for how many portfolios of type j factor i is a significant one-month ahead predictor of returns. Total number of portfolios of type j is given in the last line of the table. The left three columns build forecasting models over the full sample (Oct 2007 – Dec 2014), while the right three columns drop the period from Sep 2008 to Dec 2008 inclusive.

	Train (2009–2011)		Test (2012–2014)	
	Market	Strategy	Market	Strategy
Mean excess return	0.21	0.33	0.10	0.18
Standard devaition	0.75	0.88	0.59	0.72
Sharpe ratio	0.28	0.37	0.17	0.25
Information ratio		0.25		0.24
Max. excess return	2.46	2.80	1.32	1.85
Min. excess return	-1.66	-2.48	-2.59	-2.39

Table 8: **Comparative performance of the corporate bond market** (Barclays Aggregate U.S. corporate bond index, investable) **and a proposed market timing strategy**. Returns and standard deviations are in *% per week*, not annualized. The strategy consists in making 1-week ahead forecasts of market excess returns and taking positions in a market ETF based on these forecasts. Three options are available: invest all in risk-free bonds (low expected excess returns), follow the market (mediocre expected returns), lever up and invest more in the market (high expected returns). Separation bounds in terms of expected returns are determined by maximizing the strategy Sharpe ratio of the strategy over the training sample (see Figure 9 also). The leverage ratio is 0.5, meaning that 50% of the accumulated asset value is borrowed for one week and invested in the market whenever the strategy prescribes to lever up. The return-forecasting model is a 'leave-one-out' cross-validated LASSO regression with the penalty parameter selected to minimize the out-of-sample RMSE at each re-estimation date, which is weekly. The dependent variable is weekly excess corporate bond market returns. The regressors are 5 latest *daily* observations of excess returns, yield curve factors (level, slope, and curvature), fitted GZ spreads, the EBP, and a month dummy *all one week prior to return observations.* The EBP and the GZ spread are real time expanding sample estimates of Section 5.2. The information ratio in the table is relative to the corporate bond market returns. Transaction costs are not accounted for.



(a) **Training sample: 2009 – 2011**. Expected return bounds (vertical dashed lines) that determine investments for a week ahead (actions that are taken are given at the top of the left chart) are selected to maximize the Sharpe ratio of the strategy. The leverage ratio is 0.5.



(b) **Testing sample: 2012 – 2014**. Expected return bounds (vertical dashed lines) and 0.5 leverage ratio are as determined on the training sample.

Fig. 9. **Out-of-sample forecasts** of corporate bond market excess returns vis-a-vis actual returns, **and comparative performance of the market timing strategy** based on these forecasts. The return forecasting model is a 'leave-one-out' cross-validated LASSO regression with the penalty parameter selected to minimize the out-of-sample RMSE at each re-estimation date, which is weekly. The dependent variable is weekly excess corporate bond market returns. The regressors are 5 latest *daily* observations of excess returns, yield curve factors (level, slope, and curvature), fitted GZ spreads, and the EBP, *all one week prior to returns observations.* The EBP and the GZ spread are real-time expanding sample estimates of Section 5.2. Transaction costs are not accounted for.

Appendix B. Constructing the Dataset

B.1. Data Sources

This appendix describes step by step how the sample is constructed. Since I work in this paper on the daily frequency, sample construction methodology differs in certain aspects from that for the monthly frequency.

Step 1. I start with the Enhanced TRACE intra-day bond market transactional data. The main difference of the Enhanced TRACE from regular TRACE is no cap on the reported transaction volume. This comes at a cost of a reporting lag. As of spring 2017 the Enhanced TRACE data are available through the WRDS only till the end of 2014, while plain TRACE data are available till the end of 2016. For the purpose of this study, it is not critical, though, to work with the most recent data; to have data on the exact transaction volume is more important. Full transaction volume allows me to compute bond liquidity measures. To ensure representativeness of the data I look at the so-called 'Phase 3' of the TRACE only (from October 2004 onwards). For detailed quantitative comparison of different phases of the TRACE see Asquith, Covert, and Pathak (2013).

The Enhanced TRACE data needs to be cleaned of trade cancellations, reversals, corrections and agency transactions. The cleaning procedure I follow is described in Dick-Nielsen (2014). I also apply price filters to the data. All transactions with reported bond prices below 1 or above 500, as well as transactions with absolute returns above 20% (to a previous trade) are removed. Then I compute a daily average volume-weighted bond price and daily liquidity measures for each bond.[22] From this point onwards I work with the daily data.

Step 2. To obtain characteristics of the bonds I match securities from TRACE with Mergent FISD by CUSIP numbers. Once this is done, I reduce the sample to only **non-convertible senior unsecured corporate bonds** with less than 30 years to maturity. Callable bonds are not removed from the sample, but remaining outstanding amounts are

[22] I re-did the study for simple daily average prices and daily last prices; it doesn't affect the results.

tracked thanks to the file with historical outstanding amounts that is available in Mergent FISD.

Next, I determine for each bond for each day the exact remaining coupon payment/principal repayment schedule. This allows to compute daily prices of risk-free counterparts of the bonds by discounting remaining cash flows with Treasury zero-coupon rates for each particular day.[23] Then, observed bond prices and the prices of their risk-free counterparts are converted into yields to maturity. The difference in yields to maturity is the GZ spread (after Gilchrist and Zakrajšek, 2012).

I also obtain the history of credit rating revisions from Mergent FISD and add credit ratings to the sample. Throughout the paper I use a numerical rating scale: 1 corresponds to 'AAA', 2 corresponds to 'AAA-', and so on, up to 22 that corresponds to 'D'.

Step 3. In this step, I add issuing firms' characteristics to the data. For this purpose, I match the issuers with the firms in CRSP and Compustat. By matching on either tickers, or trade symbols, or 6-digit CUSIP numbers I am able to get the characteristics of issuing firms for more than 95% of the bonds (the rest are removed from the sample).

The ultimate goal of this step is to compute the Merton (1974) distance-to-default variable for each issuing firm for each day. For that I need firm equity value, volatility, and indebtedness for each day (see computational details in Appendix B.2). I obtain equity characteristics on the daily frequency from CRSP. Equity volatility is computed as the standard deviation of daily returns in the one-year rolling window. Firm indebtedness for each day is the latest available quarterly observation from Compustat carried forward. The default threshold needed to compute the distance-to-default is defined as all short-term debt and half of the long-term debt. Since the distance-to-default is a numerical solution to a system of equations, I remove bond(firm)-day observations for which this system doesn't

[23] These historical yield curves constructed as in Gürkaynak, Sack, and Wright (2007) are readily available via Quandl, `https://www.quandl.com/`. Here, the yield curve construction method is a modified Nelson-Siegel approach with additional parameters included to better fit the long end of the curve – the so-called 'Nelson-Siegel-Svensson' method.

have a solution with reasonable starting values.

Step 4. This is the step when I apply a number of final filters to the bond-day data. Below is the list of criteria according to which I remove observations from the sample. I remove:

- issuing firms from the financial and the real estate industry;
- bonds with less than one year to maturity;
- days with abnormally few trades;[24]
- observations in the 1st and the 99th percentiles of daily total returns;
- observations with the GZ spread below 5 b.p. or above 35%;[25]
- observations in the 99th percentile according to the Amihud illiquidity measure.

B.2. Daily Measure of Merton's Distance-to-default

In the Merton (1974) model firm's default probability at time t is determined by:

$$\mathbb{P}\left[V_A \leq D\right] = \Phi\left(-DD\right) = \Phi\left(d_1\right) = \Phi\left(-\frac{\log\left(\frac{V_A}{D}\right) + \left(r - \frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A\sqrt{T-t}}\right),$$

where V_A is the value of firm's assets, D is the default threshold, σ_A is the volatility of V_A, $T-t$ is the time to maturity, r is the discount rate, and $\Phi(\cdot)$ is the standard normal c.d.f.

To compute the DD variable one needs to know V_A and σ_A that are unobserved (unlike other parameters). There exist multiple methods to estimate these parameters, see Duan and Wang (2012) for a detailed overview. In this paper, I use the 'volatility restriction' method that consists in solving for V_A and σ_A the following system of equations:

$$0 = V_A\Phi(d_1) - \exp\left\{-r(T-t)\right\} D\Phi(d_2) - V_E,$$

[24] These are the days with total number of trades per day at least 20% lower than the average daily number of trades over a 30-day rolling window. This criteria is reverse engineered – it allows to remove pre-holiday trading days. Cross-sectional distributions of bond prices and spreads on these days were found to be very different from the ones on regular days.

[25] Same filter as in Gilchrist and Zakrajšek (2012).

$$0 = \frac{V_A}{V_E}\Phi(d_1)\sigma_A - \sigma_E,$$

where $d_2 = d_1 - \sigma_A\sqrt{T-t}$, and V_E and σ_E are correspondingly the value of the firm's equity and its volatility (these parameters are observed). I didn't use the transformed-data MLE approach to estimate the distance-to-default and opted for the volatility restriction method instead in order to speed up the computations. Solving numerically the system of equations above is orders of magnitude faster than running MLE estimations for each firm for each day. Experiments on a small sub-sample of the data didn't give considerably different results for the two methods.

In Section 2, I solve for V_A and σ_A for each firm for each day. V_E is the value of firm's equity from CRSP. σ_E is the standard deviation of daily equity returns from CRSP estimated over a backward-looking one-year long window. D is all short-term debt (less than one year to maturity) plus half of the long-term debt. Starting values for the solution algorithm are always $V_A[0] = V_E$ and $\sigma_A[0] = \sigma_E$. I disregard all firm-days when this approach doesn't lead to a reasonable solution.

Appendix C. Explanatory Variables

Here is the list of explanatory variables used in Sections 3–5.

- DD, the distance-to-default computed as presented in Appendix B.2. The values presented in Table 1 and further used in the analysis are scaled by 1000.
- DUR, the Macaulay duration.
- PAR, outstanding amount of a bond issue in mln USD. This variable contains the history of changes in the outstanding amount for each bond; a corresponding historical file is included in Mergent FISD (available through the WRDS server).
- CPN, a coupon rate of a bond, in % per annum.
- AGE, time elapsed since a bond was issued, in years.
- $CALL$, a call option dummy; equals to 1 if the bond issue is redeemable and to 0 otherwise.
- ADS, Aruoba et al. (2009) daily aggregate activity index for the US computed by the Philadelphia Fed and available (with historical vintages) at `https://goo.gl/mZJ5Sj`. This is a smoothed business cycle signal derived from 6 real activity series of different reporting frequency: weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, and manufacturing and trade sales, and quarterly real GDP. Since the index is obtained by running the Kalman smoother, its historical paths change a little bit as the new data become available.
- AMH, the Amihud liquidity measure, computed as presented in Section 2.
- LEV, an empirical proxy for the 'level' of the yield curve: 10-year zero-coupon rate y_{10Y}.
- SLP, an empirical proxy for the 'slope' of the yield curve: the difference between 10-year and 3-month zero-coupon rates $y_{10Y} - y_{3M}$.
- CRV, an empirical proxy for the 'curvature' of the yield curve: $2y_{2Y} - y_{10Y} - y_{3M}$.
- VOL, volatility of the long-rate: the standard deviation of the 10-year zero coupon

rate computed over the 30-day rolling window.

- RFF, *Real Federal funds rate*, the difference between nominal effective Federal funds rate and realized (one month prior to a rate observation) 12-month CPI growth rate.
- TS, *Term spread*, same as the yield curve slope SLP.
- *GZ spread*, the corporate bond spread computed as in Gilchrist and Zakrajšek (2012).
- *Fitted GZ spread*, the portion of GZ spread explained by one the models of Table 2.
- EBP, excess bond premium, the difference between GZ spread and Fitted GZ spread.
- DRF, the default risk factor of Bai et al. (2016). This is the value-weighted average return difference between the highest-VaR quintile portfolio and the lowest-VaR quintile portfolio within each rating quintile portfolio. VaR is computed at the 5% level. For daily-rebalanced portfolios VaR is computed over the latest 100 days, for monthly-rebalanced portfolios over the latest 36 months.
- CRF, the credit risk factor of Bai et al. (2016). This is the value-weighted average return difference between the lowest-rating quintile portfolio and the highest-rating quinitle portfolio within each illiquidity quintile portfolio. Illiquidity portfolios are formed using the Amihud measure, unlike Bai et al. (2016), who use negative covariance between daily price changes as a low-frequency illiquidity proxy.
- LRF, the liquidity risk bond pricing factors of Bai et al. (2016). This is the value-weighted average return difference between the highest-illiquidity quintile portfolio and the lowest-illiquidity quintile portfolio within each rating quintile portfolio.
- SMB, HML, and UMD, are, correspondingly, small-minus-big, high-minus-low, and momentum stock pricing factors. Available from the Ken French's database via Quandl at: `https://www.quandl.com/data/KFRENCH-Ken-French`.

Appendix D. Time fixed effects in regressions for spreads

Here I consider alternative specifications for log spread fitting models with the time fixed effect TFE_t included:

$$\log\left(S_{it}^{GZ}[k]\right) = \beta \cdot DD_{it} + (\text{Proxies for recovery rate and liquidity}) + (\text{Call adjustment}) + \\ + \eta \cdot AMH_{it}[k] + (\text{Industry and rating FE}) + TFE_t + \epsilon_{it}[k].$$

Compared to specifications in Section 3, this specification replaces ADS_t with TFE_t. Otherwise, the models are identical. As d'Avernas (2017) discusses in his Appendix E, such specification provides unbiased parameter estimates, unlike the benchmark Gilchrist and Zakrajšek (2012) model. My goal here is to extract the time fixed effect and investigate to what extent it is explained by aggregate business activity as measured by the ADS index.

Table 9 presents the estimated models with time fixed effects. The first two columns correspond to a simple option adjustment with the same call dummy for all callable bonds (as Models 1–3 in Table 2), the last two columns also control for the interactions of a call dummy with the yield curve and bond-specific factors (correspond to Models 4–6 in Table 2). Note that the time fixed effect improves the overall fit of the models (compared to the specifications with the ADS index in Table 2). The models in Table 9 capture more than 80% of the variation of log spreads. The coefficients on the Amihud measure in Tables 2 and 9 are very close. However, the coefficients on the distance-to-default are considerably lower when the time fixed effect is included, in line with d'Avernas (2017) arguments.

Estimated TFEs from four alternative models are almost identical, the left chart on Figure 10 shows. I will work with the TFE from Model 4 of Table 9 since this model is the closest analogue of my preferred Model 6 of Table 2. To investigate the relationship between the TFE and the ADS I first run a standard OLS of the TFE on the ADS and a constant on the daily sample from Oct 2004 to Dec 2014. Such model has an R^2 of 0.63. The explained portion of the TFE is presented on the right chart of Figure 10. To be sure

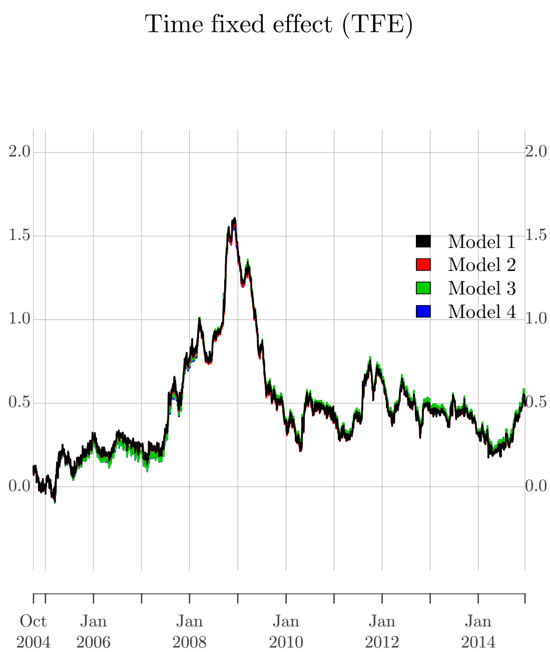
	Dependent variable: $\log(Spread_{it}[k])$			
	(1)	(2)	(3)	(4)
$-DD_{it}$	0.234***	0.234***	0.120**	0.119**
	(0.045)	(0.045)	(0.060)	(0.060)
$\log(DUR_{it}[k])$	0.106***	0.098***	0.057***	0.046**
	(0.009)	(0.008)	(0.019)	(0.018)
$\log(PAR_{it}[k])$	−0.085***	−0.081***	−0.062***	−0.057***
	(0.011)	(0.011)	(0.017)	(0.017)
$\log(CPN_i[k])$	0.581***	0.582***	0.685***	0.683***
	(0.019)	(0.019)	(0.056)	(0.055)
$\log(AGE_{it}[k])$	0.011**	0.007	0.005	0.002
	(0.005)	(0.005)	(0.021)	(0.021)
$CALL_i[k]$	0.012	0.014	0.541**	0.550**
	(0.017)	(0.016)	(0.246)	(0.243)
$AMH_{it}[k]$		0.030***		0.031***
		(0.002)		(0.002)
$-DD_{it} \cdot CALL_i[k]$			0.145***	0.147***
			(0.056)	(0.055)
$\log(DUR_{it}[k]) \cdot CALL_i[k]$			0.065***	0.069***
			(0.017)	(0.017)
$\log(PAR_{it}[k]) \cdot CALL_i[k]$			−0.029	−0.030*
			(0.018)	(0.018)
$\log(CPN_i[k]) \cdot CALL_i[k]$			−0.126**	−0.123**
			(0.057)	(0.056)
$\log(AGE_{it}[k]) \cdot CALL_i[k]$			0.010	0.009
			(0.021)	(0.021)
$LEV_t \cdot CALL_i[k]$			0.018	0.018
			(0.012)	(0.012)
$SLP_t \cdot CALL_i[k]$			−0.022**	−0.022**
			(0.011)	(0.011)
$CRV_t \cdot CALL_i[k]$			−0.016	−0.017
			(0.019)	(0.019)
$VOL_t \cdot CALL_i[k]$			0.102	0.104
			(0.082)	(0.081)
Time FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Credit rating FE	YES	YES	YES	YES
Observations	2,032,455	2,032,455	2,032,455	2,032,455
Adjusted R^2	0.822	0.824	0.823	0.825
Note:	*p<0.1; **p<0.05; ***p<0.01			

Table 9: Explanatory models for the bond k of firm i – day t panel of credit spreads for the entire sample (Oct 4, 2004 – Dec 23, 2014) with the time fixed effect included. The dependent variable is the log of GZ spread. DD is the distance-to-default, DUR is duration, PAR is amount outstanding, CPN is the coupon rate, AGE is time elapsed from issuance, and $CALL$ is a callable bond dummy. AMH is the Amihud liquidity measure. LEV, SLP, and CRV are correspondingly level, slope, and curvature yield curve factors, and VOL is the realized volatility of the 10-year rate (30-day moving average). See Appendix C for the details on explanatory variables. All models include also industry (the first two digits of the NAICS code) and credit rating (22-grade numeric scale) fixed effects. Standard errors are clustered in both firm i and time t dimensions.

that the result is not spurious I also do the Johansen cointegration test for the TFE and the ADS and estimate a corresponding error-correction model.[26]

Table 10 demonstrates that the strong link between the TFE and the ADS is not spurious.

[26] Both the TFE and the ADS are $I(1)$ over 2004–2014 period.



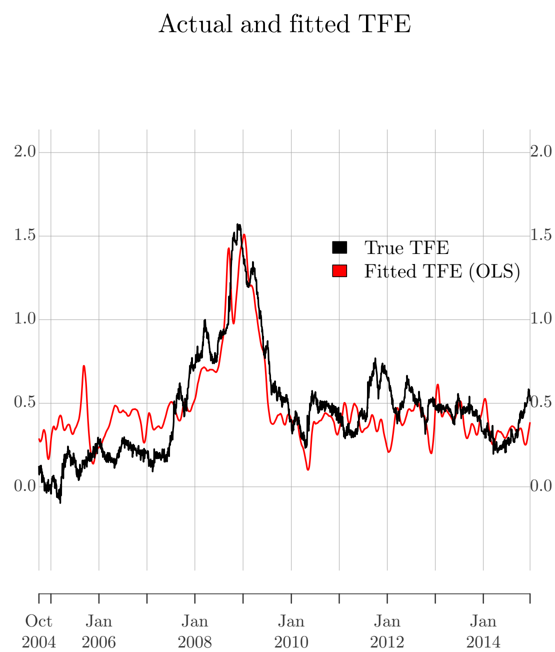


Fig. 10. Time fixed effect (TFE) extracted from the models of Table 9. The left chart presents four alternative daily time-series of the TFE. The right chart plots the TFE from Model 4 vis-a-vis its fitted counterpart from the regression of the TFE on a constant and the ADS index. The sample is daily from Oct 4, 2003 to Dec 23, 2014.

The Johansen test (Table 10a) rejects no-cointegration null at the 95% confidence level when more than two lags are included (the optimal number of lags is 15 according to the AIC). The estimated cointegration vector (Table 10b) is statistically significant and economically reasonable. When the ADS drops from zero ('normal' times) to negative values (low activity states), the TFE jumps above its mean of 34 b.p.

In economic terms, the TFE absorbs time-varying portions of the remuneration for credit risk and of the credit risk premium. In this appendix, I demonstrated that this time-varying object is explained to a large extent by the aggregate business risk fluctuations as measured by the ADS index. This finding is in line with the results of Section 3 of the main text that emphasises aggregate business risk as the factor of credit spreads.

$\mathscr{H}_0$	Lag length 2	3	15	Critical values 90%	95%	99%
$r = 1$	1.96	2.35	3.53	7.52	9.24	12.97
$r = 0$	13.78	22.11	27.68	17.85	19.96	24.60

(a) Johansen cointegration test with trace-type test statistics. Lag length of 15 is optimal according to AIC. The null is in the leftmost column (r is the number of cointegration vectors). The null is rejected when the test statistics exceeds the critical value (the rightmost part of the table).

	TFE	ADS	Const
$\hat{\beta}^T$	1	0.38	-0.34
	–	(8.49)	(-8.3)
$\hat{\alpha}^T$	-0.01	-0.01	–
	(-2.7)	(-4.2)	–

(b) Cointegration vectors $\hat{\beta}$ and coefficients on the error-correction terms $\hat{\alpha}$ in the VECM with 15 lags. t-stats are in parenthesis.

Table 10: Cointegration tests and vectors for the vector error-correction model (VECM) of daily TFE (Model 4 of Table 9) and the ADS index. The sample is daily from Oct 4, 2003 to Dec 23, 2014.

Appendix E. EBP and VIX as predictors of returns

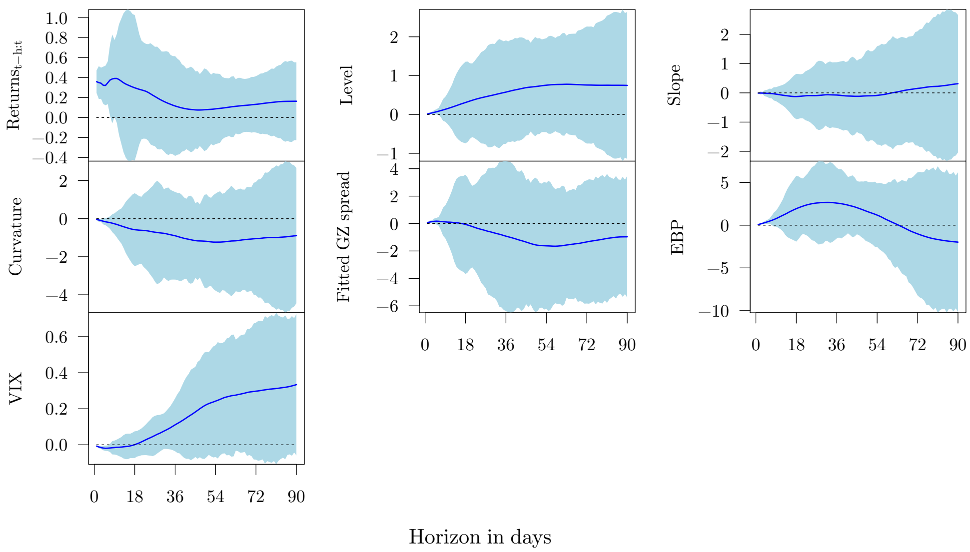
Here I show that the predictive power of EBP for corporate bond market returns is immune to the inclusion of the VIX index in return forecasting regressions of Section 5.1. Estimation results are presented in Figure 11. It is analogous to Figure 5, and the only difference is the VIX added to the right-hand side of forecasting models. On the top panel, Figure 11a, the bond market is the TRACE portfolio of bonds, while on the bottom panel, Figure 11b, the market is the Barclays Aggregate index.

As Figure 11 demonstrates, the VIX itself predicts market returns significantly only on horizons more than 50 days and only when the market is the TRACE portfolio. When the market is restricted to investment-grade bonds of the Barclays index only, the VIX is not significant on any horizon.

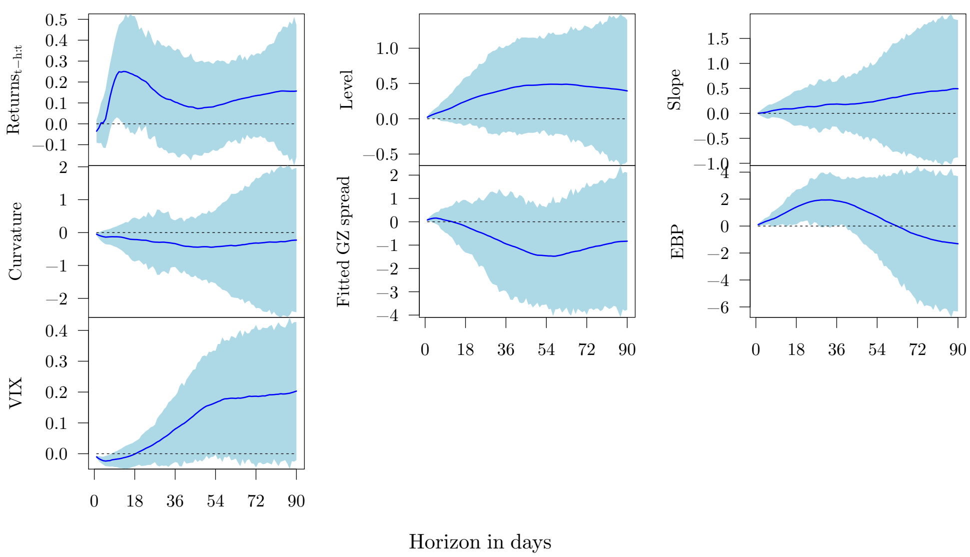
The coefficients on EBP remain significant for a wide range of forecasting horizons in the models with the VIX index added. When the market is the investment-grade index (Figure 11b), EBP significantly predicts excess market returns on horizons up to several months, and the economic significance is only marginally lower than in regressions without VIX in Figure 5. This result applies to the TRACE portfolio as well, but here the addition of VIX compromises statistical significance on shorter horizons.

Daily VIX is a difference-stationary variable over the years 2004–2014, while the EBP is a level-stationary series. Replacing the levels of VIX in return-forecasting models by its first differences doesn't undermine the predictive power of EBP for market returns (not reported). Same applies to regressions with only the EBP and the VIX or its first differences on the right-hand side (also not reported). To sum up, even though the VIX might be a predictor of corporate bond market returns on some horizons, it doesn't stand behind the forecasting power of EBP for market returns.

Parameter estimates for cumulative returns on different horizons



(a) Dependent variable: returns on **TRACE portfolio** of bonds; fitted GZ spread and EBP of **Model 6** as explanatory variables.



(b) Dependent variable: returns on **Barclays Aggregate U.S. corporate bond index**; fitted GZ spread and EBP of **Model 6** as explanatory variables.

Fig. 11. Estimated forecasting regressions for **cumulative bond market excess returns**. Same explanatory variables as in Figure 5, plus the VIX index.

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