# CREDIT SPREADS AS PREDICTORS OF REAL-TIME ECONOMIC ACTIVITY: A BAYESIAN MODEL-AVERAGING APPROACH

Jon Faust
Simon Gilchrist
Jonathan H. Wright
Egon Zakrajsek

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## ABSTRACT

Employing a large number of real and financial indicators, we use Bayesian Model Averaging (BMA) to forecast real-time measures of economic activity. Importantly, the predictor set includes option-adjusted credit spread indexes based on bond portfolios sorted by maturity and credit risk as measured by the issuer's "distance-to-default." The portfolios are constructed directly from the secondary market prices of outstanding senior unsecured bonds issued by a large number of U.S. corporations. Our results indicate that relative to an autoregressive benchmark, BMA yields consistent improvements in the prediction of the growth rates of real GDP, business fixed investment, industrial production, and employment, as well as of the changes in the unemployment rate, at horizons from the current quarter (i.e., "nowcasting") out to four quarters hence. The gains in forecast accuracy are statistically significant and economically important and owe exclusively to the inclusion of our portfolio credit spreads in the set of predictors—BMA consistently assigns a high posterior weight to models that include these financial indicators.

Jon Faust
Department of Economics

Mergenthaler Hall 456
3400 N. Charles Street
Baltimore, MD 25218
and NBER
faustj@jhu.edu

Simon Gilchrist
Department of Economics
Boston University
270 Bay State Road
Boston, MA 02215
and NBER
sgilchri@bu.edu

Jonathan H. Wright
Department of Economics
Johns Hopkins University
3400 N. Charles Street
Baltimore, MD 21218
and NBER
wrightj@jhu.edu

Egon Zakrajsek
Division of Monetary Affairs
Federal Reserve Board
20th Street & Constitution Avenue, NW
Washington, D.C. 20551
egon.zakrajsek@frb.gov

# 1 Introduction

One area of agreement among economists at universities, central banks, and Wall Street is that forecasting economic activity is hard. While the existing methods give us some ability to forecast economic developments for the current quarter and perhaps the quarter after that, their predictive power is modest at best and deteriorates rapidly as the forecast horizon extends beyond the very near term. Moreover, what little predictability there seems to be appears to be captured about as well by simple models—such as a univariate autogression—as by the large number of complex statistical and DSGE forecasting methods that have been proposed in the literature (cf. Sims [2005]; Tulip [2005]; Faust and Wright [2009]; and Edge and Gürkaynak [2010]).

Economists have long sought to improve on this record by using information from financial markets. Because they are inherently forward looking, the argument goes, financial market prices should impound information about investors' expectations of future economic outcomes.[1] From a theoretical perspective, default-risk indicators such as credit spreads—the difference in yields between various corporate debt instruments and government securities of comparable maturity—are particularly well suited for forecasting economic activity. Philippon [2009], for example, presents a model in which the decline in investment fundamentals, owing to a reduction in the expected present-value of corporate cash flows, leads to a widening of credit spreads prior to a cyclical downturn. As emphasized by Bernanke et al. [1999] and Gilchrist and Zakrajšek [2010], increases in credit spreads can also signal disruptions in the supply of credit resulting from the worsening in the quality of corporate balance sheets or from the deterioration in the health of financial intermediaries that supply credit.

The empirical success of default-risk indicators as predictors of economic activity is decidedly mixed, however, with results varying substantially across various credit spread indexes and different time periods. For example, the "paper-bill" spread—the difference between yields on nonfinancial commercial paper and comparable-maturity Treasury bills—had substantial forecasting power for economic activity during the 1970s and the 1980s, only to see its predictive ability vanish in the subsequent decade. In contrast, credit spreads based on indexes of speculative-grade (i.e., "junk") corporate bonds, which contain information from markets that were not in existence before the mid-1980s, have done particularly well at forecasting output growth during the 1990s, according to Gertler and Lown [1999] and Mody and Taylor [2004]. Stock and Watson [2003], however, show that the forecasting ability of this default-risk indicator is considerably more uneven.

In a recent paper, Gilchrist et al. [2009] (GYZ hereafter) argue that these mixed results may be

[1] Financial indicators considered in this vast literature include stock prices (Fama [1981] and Harvey [1989]); spreads between long and short-term risk-free interest rates (Harvey [1988]; Estrella and Hardouvelis [1991]; Estrella and Mishkin [1998]; and Hamilton and Kim [2002]); the term structure of interest rates more generally (Ang et al. [2006]); spreads between rates on short-term commercial paper and rates on Treasury bills (Bernanke [1990]; Friedman and Kuttner [1992, 1998]; and Emery [1999]); and yield spreads on longer-term corporate debt (Gertler and Lown [1999]; King et al. [2007]; Mueller [2007]; Gilchrist et al. [2009]; and Gilchrist and Zakrajšek [2010]).

due to the fact that the credit spread indexes used by researchers tend to be based on aggregates of returns on a mishmash of bonds with different duration, credit risk, and other characteristics. In part to address these problems, GYZ constructed 20 monthly credit spread indexes for different maturity and credit risk categories using secondary market prices of individual senior unsecured corporate bonds.[2] Their findings indicate that these credit spread indexes have substantial predictive power, at both short- and longer-term horizons, for the growth of payroll employment and industrial production. Moreover, they significantly outperform the predictive ability of the standard default-risk indicators, a result that suggests that using "cleaner" measures of credit spreads may, indeed, lead to more accurate forecasts of economic activity.

This paper extends the analysis of GYZ in several dimensions. Most importantly, we provide a thorough evaluation of the marginal information content of credit spreads in real-time economic forecasting. Given the extensive and ongoing search for consistent predictors of U.S. economic activity, the macroeconomics profession runs a substantial risk that results like those of GYZ are due to researchers stumbling on variables that just happen to fit the existing sample, but which, in reality, have no true predictive power. The regular breakdown of new forecasting relationships soon after they are documented confirms that this risk is real. Thus, it is especially important that any such analysis takes into account model search and selection issues.

To guard against the problem of selecting financial indicators that just happen to fit our sample, we adopt a Bayesian Model Averaging (BMA) approach. As explained more fully below, we add the new credit spread indexes to a predictor set containing over 100 financial indicators, as well as a large number of real variables, and begin with a prior that each predictor is equally likely to be useful in forecasting future economic activity. The posterior weight assigned to each predictor in period $t$ is then based on a Bayesian updating scheme that uses only the information available at time $t$. While our BMA scheme has, under certain conditions, a formal Bayesian justification, we follow a large and growing literature that takes a frequentist perspective and relies on the BMA framework as a pragmatic approach to data-based weighting of a large number of competing prediction models (e.g., Min and Zellner [1993]; Fernandez et al. [2001b]; Avramov [2002]; Cremers [2002]; Sala-i-Martin et al. [2004]; Koop and Potter [2004]; King et al. [2007]; and Wright [2008]).

While following GYZ's basic approach for constructing credit spread indexes, we also improve on their methodology by adjusting the underlying micro-level credit spreads for the call option embedded in many of the underlying securities. As pointed out by Duffee [1998] and Duca [1999], fluctuations in the value of embedded options—reflecting shifts in the term structure of risk-free rates—can substantially alter the information content of movements in corporate bond yields at business cycle frequencies.

Our results indicate that the new credit spread indexes have considerable marginal predictive power for economic activity. When using the entire set of predictors to forecast a wide array of

[2] GYZ measure the underlying credit risk by the issuer's expected default frequency (EDF™), a market-based default-risk indicator calculated by Moody's/KMV that is more timely that the issuer's credit rating.

economic activity indicators, the gains in the root mean square forecast error (RMSFE)—relative to a univariate autoregressive benchmark—are statistically significant and often substantial in magnitude: BMA forecasts generate 5 to 10 percent reductions in the RMSFEs at horizon zero (i.e., the "nowcast") and between 10 and 25 percent improvement in predictive accuracy when forecasting the cumulative growth of cyclically sensitive economic indicators four quarters into the future. Consumption growth is the main exception to this general result—there are no gains in predictive accuracy relative to our benchmark for this measure of economic activity.

When we omit the credit spread indexes from the predictor set and redo the analysis, we obtain the standard result, namely, that the predictive accuracy of the BMA method—like that of most other documented forecasting methods—is statistically indistinguishable from that of the univariate autoregressive benchmark. This result indicates that there is something different about the information content of credit spreads and that our BMA weighting scheme is able to pick out this difference in real-time from a large number of predictors, all of which were treated equally *ex ante*. Indeed, the analysis of the evolution of posterior weights that the BMA scheme assigns to various variables in the predictor set shows that it is economic downturns that lead to the majority of the posterior weight being placed on the credit spreads. This finding suggests that corporate bond spreads—when properly measured—may be one of the earliest and clearest aggregators of accumulating evidence of incipient recession.

Lastly, we examine the predictive power of the BMA model during the recent financial crisis. While the blowout in credit spreads following the collapse of Lehman Brothers in the early autumn of 2008 is ingrained in the minds of financial market participants, the standard macro predictions did not anticipate the severe slump in economic activity that ultimately transpired until about the end of 2008. Thus, it is seems reasonable to expect that a forecast incorporating the information content of credit spreads is likely to signal a very bad economic outcome before many standard models and forecasters. In fact, when we examine our real-time forecasts, we find that they predicted the downturn earlier than many standard macroeconomic forecasts. Nevertheless, our BMA forecasts still underestimated the severity of the downturn, a finding that is perhaps not too surprising given the extraordinary economic and financial turmoil surrounding that period.

The plan for the remainder of this paper is as follows. Section 2 describes our bond-level data and the construction of portfolios based on the option-adjusted credit spreads. In Section 3, we outline the econometric methodology used to combine forecasts by BMA. Section 4 contains our main empirical results. Section 5 concludes.

# 2 Data Sources and Methods

## 2.1 Credit Spreads

The key information for our analysis comes from a large sample of fixed income securities issued by U.S. corporations. Specifically, from the Lehman/Warga (LW) and Merrill Lynch (ML) databases, we extracted month-end prices of outstanding long-term corporate bonds that were actively traded in the secondary market between January 1986 and June 2010.[3] To guarantee that we are measuring borrowing costs of different firms at the same point in their capital structure, we restricted our sample to senior unsecured issues with a fixed coupon schedule only. For such securities, we spliced their month-end prices across the two data sources.

The micro-level aspect of our data set allows us to construct credit spreads that are not contaminated by the maturity/duration mismatch that plagues most commercially-available credit spread indexes. In particular, we construct for each individual bond issue a theoretical risk-free security that replicates exactly the promised cash-flows of the corresponding corporate debt instrument. For example, consider a corporate bond $k$ issued by firm $i$ that at time $t$ is promising a sequence of cash-flows $\{C(s) : s = 1, 2, \ldots, S\}$, consisting of the regular coupon payments and the repayment of the principle at maturity. The price of this bond in period $t$ is given by

$$P_{it}[k] = \sum_{s=1}^{S} C(s)D(t_s),$$

where $D(t) = e^{-r_t t}$ is the discount function in period $t$. To calculate the price of a corresponding risk-free security—denoted by $P_t^f[k]$—we discount the promised cash-flow sequence $\{C(s) : s = 1, 2, \ldots, S\}$ using continuously-compounded zero-coupon Treasury yields in period $t$, obtained from the daily estimates of the U.S. Treasury yield curve reported by Gürkaynak et al. [2007]. The resulting price $P_t^f[k]$ can then be used to calculate the yield—denoted by $y_t^f[k]$—of a hypothetical Treasury security with exactly the same cash-flows as the underlying corporate bond. The credit spread $S_{it}[k] = y_{it}[k] - y_t^f[k]$, where $y_{it}[k]$ denotes the yield of the corporate bond $k$, is thus free of the "duration mismatch" that would occur were the spreads computed simply by matching the corporate yield to the estimated yield of a zero-coupon Treasury security of the same maturity.

To ensure that our results are not driven by a small number of extreme observations, we eliminated all bond/month observations with credit spreads below 5 basis points and with spreads greater than 3,500 basis points. In addition, we dropped from our sample very small corporate issues—those with a par value of less than \$1 million—and all observations with a remaining term-

[3] These two data sources are used to construct benchmark corporate bond indexes used by market participants. Specifically, they contain secondary market prices for a vast majority of dollar-denominated bonds publicly issued in the U.S. corporate cash market. The ML database is a proprietary data source of daily bond prices that starts in 1997. The LW database of month-end bond prices is available from 1973 through mid-1998 (see Warga [1991] for details).

Table 1: Corporate Bond Characteristics by Type of Firm

| *Nonfinancial Firms* | | | | | |
|---|---|---|---|---|---|
| Bond Characteristics | Mean | SD | Min | P50 | Max |
| No. of bonds per firm/month | 3.08 | 3.75 | 1.00 | 2.00 | 74.0 |
| Mkt. value of issue ($mil.) | 334.7 | 327.6 | 1.22 | 248.3 | 5,628 |
| Maturity at issue (years) | 12.9 | 9.3 | 1.0 | 10.0 | 50.0 |
| Term to maturity (years) | 10.5 | 8.4 | 1.0 | 7.5 | 30.0 |
| Duration (years) | 6.29 | 3.26 | 0.91 | 5.75 | 15.8 |
| Credit rating (S&P) | - | - | D | BBB1 | AAA |
| Coupon rate (pct.) | 7.30 | 1.97 | 1.70 | 7.00 | 17.5 |
| Nominal yield to maturity (pct.) | 7.29 | 3.04 | 0.60 | 6.93 | 44.3 |
| Credit spread (bps.) | 215 | 297 | 5 | 123 | 3,499 |
| *Financial Firms* | | | | | |
| Bond Characteristic | Mean | SD | Min | P50 | Max |
| No. of bonds per firm/month | 3.03 | 3.49 | 1.00 | 2.00 | 26.0 |
| Mkt. value of issue ($mil.) | 471.0 | 554.9 | 9.11 | 266.1 | 4,351 |
| Maturity at issue (years) | 10.4 | 8.0 | 2.0 | 10.0 | 40.0 |
| Term to maturity (years) | 8.5 | 7.7 | 1.0 | 5.9 | 30.0 |
| Duration (years) | 5.47 | 3.17 | 0.90 | 4.77 | 15.3 |
| Credit rating (S&P) | - | - | CC | A2 | AAA |
| Coupon rate (pct.) | 6.89 | 1.94 | 2.25 | 6.63 | 15.8 |
| Nominal yield to maturity (pct.) | 6.72 | 2.73 | 1.01 | 6.40 | 41.2 |
| Credit spread (bps.) | 173 | 254 | 5 | 102 | 3,495 |

NOTE: Sample period: Jan1986–June2010. No. of nonfinancial firms/bonds = 1,104/5,896 (Obs. = 305,412); No. of financial firms/bonds = 193/886 (Obs. = 42,270). The market value of the bond issues is deflated by the CPI (1982–84 = 100). Sample statistics are based on trimmed data (see text for details).

to-maturity of less than one year or more than 30 years.[4] These selection criteria yielded a sample of 5,896 individual securities issued by firms in the nonfinancial sector and 886 securities issued by financial firms.[5] We matched these corporate securities with their issuer's quarterly income and balance sheet data from Compustat and daily data on equity valuations from CRSP, yielding a matched sample of 1,104 nonfinancial firms and 193 financial firms.

Table 1 contains summary statistics for the key characteristics of bonds in our sample by the type of firm (nonfinancial vs. financial). Note that a typical firm has only a few senior unsecured

[4]We also eliminated a very small number of puttable bonds from our sample. In contrast, a significant fraction of the securities in our sample is callable, which raises an important issue of how to separate time-varying prepayment risk from the default risk premium. We address this issue in detail later in the paper.

[5]Government-sponsored entities, such as Fannie Mae and Freddie Mac, were excluded from the sample.

issues outstanding at any point in time—the median firm in both sectors, for example, has two such issues trading at any given month. The size of bond issues, measured by their market value, tend to be somewhat larger, on average, in the financial sector. Not surprisingly, the maturity of these debt instruments is fairly long, with the average maturity at issue of more than 10 years in both sectors. Because corporate bonds typically generate significant cash flow in the form of regular coupon payments, their effective duration is considerably shorter.

According to the S&P credit ratings, our sample spans the entire spectrum of credit quality, from "single D" to "triple A." At A2, the median bond/month observation in the financial sector is somewhat above that in the nonfinancial sector (i.e., BBB1), though they are both solidly in the investment-grade category. Turning to returns, the (nominal) coupon rate on the bonds issued by nonfinancial firms averaged 7.30 percent during our sample period, compared with 6.89 percent for bonds issued by their financial counterparts. The average expected total return was 7.29 percent per annum in the nonfinancial sector and 6.72 percent in the financial sector. Relative to Treasuries, an average bond issued by a nonfinancial firm has an expected return of about 215 basis points above the comparable risk-free rate. Reflecting their generally higher credit quality—at least as perceived by the ratings agencies—the average credit spread on a bond issued by a financial intermediary is 173 basis points.

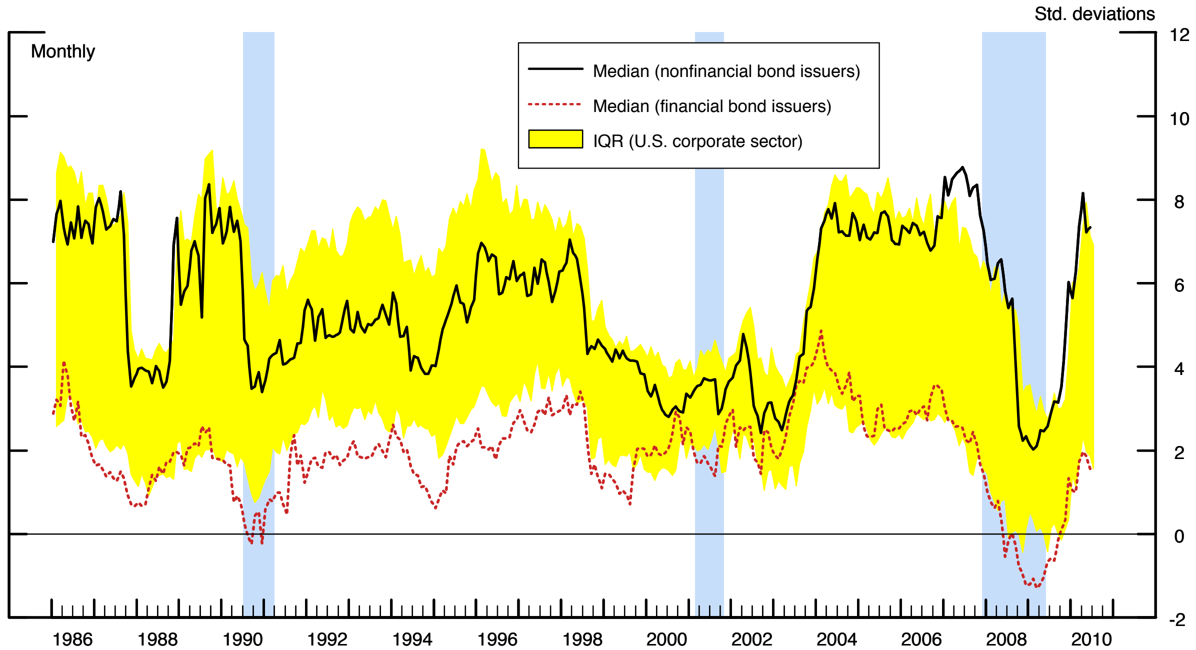
## 2.2 Default Risk

The measurement of firm-specific default risk is the crucial input in the construction of our bond portfolios. To measure an issuer's probability of default at each point in time, we employ the "distance-to-default" (DD) framework developed in the seminal work of Merton [1973, 1974]. The key insight of this contingent claims approach to corporate credit risk is that the equity of the firm can be viewed as a call option on the underlying value of the firm with a strike price equal to the face value of the firm's debt. Although neither the underlying value of the firm nor its volatility is directly observable, they can, under the assumptions of the model, be inferred from the value of the firm's equity, the volatility of its equity, and the firm's observed capital structure.

The procedure used to construct our market-based measure of default risk is described in detail by Bharath and Shumway [2008] and Gilchrist and Zakrajšek [2010]. Employing this methodology, we calculate the distance-to-default for all U.S. corporations covered by S&P's Compustat and CRSP (i.e., 14,446 firms over the Jan1986–June2010 period). Figure 1 plots the cross-sectional median of the DDs for the 1,104 nonfinancial and 193 financial bond issuers in our sample. As a point of comparison, the figure also depicts the cross-sectional interquartile range (IQR) of the DDs for the entire Compustat-CRSP matched sample.[6] According to this metric, the credit quality of the median nonfinancial bond issuer in our sample is, on average, higher than that of the median

[6]To ensure that our results were not driven by a small number of extreme observations, we eliminated from our sample all firm/month observations with a DD of more than 20 or less than -2, cutoffs corresponding roughly to the 99th and 1st percentiles of the DD distribution, respectively.

Figure 1: Distance-to-Default




NOTE: Sample period: Jan1986–June2010. The solid line depicts the weighted median DD of the 1,104 nonfinancial bond issuers in our sample; the dotted line depicts the weighted median DD of the 193 financial bond issuers. The shaded band depicts the weighted interquartile range of the DDs for the entire U.S. corporate sector; all percentiles are weighted by the firm's outstanding liabilities. The shaded vertical bars represent the NBER-dated recessions.

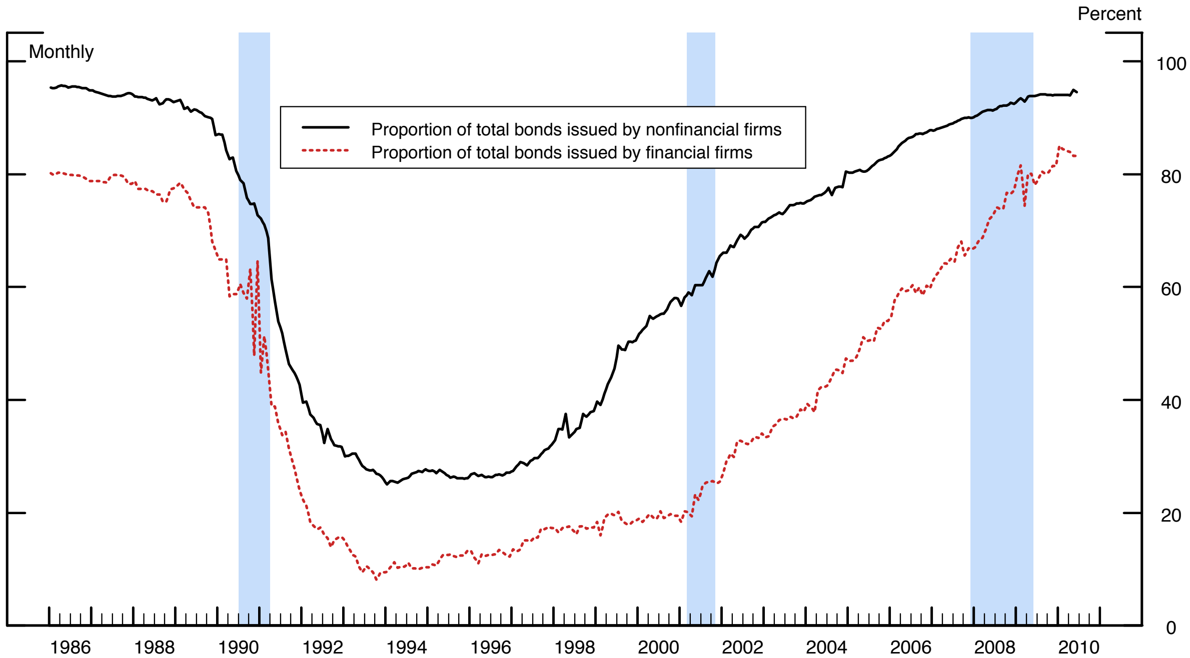
financial issuer, a result that is primarily due to the fact that financial firms tend to have higher leverage than their nonfinancial counterparts. More importantly, the median DD for both sets of firms is strongly procyclical, implying that market participants anticipate corporate defaults to increase during economic downturns. Indeed, during the height of the recent financial crisis in the autumn of 2008, both measures fell to very low levels by recent historical standards.

## 2.3 Call-Option Adjustment

Figure 2 shows the proportion of bonds in our sample that are callable—that is, the issuer has, under certain pre-specified conditions, the right to "call" (i.e., redeem) the security prior to its maturity. The share of senior unsecured bonds with embedded call options is, on average, substantial in both sectors.[7] Moreover, the proportion of callable debt has changed considerably over the course of our sample period, with almost all bonds being subject to a call provision at the start of our sample. In the late 1980s, however, the composition of debt began to shift noticeably toward noncallable

[7]The proportions and the U-pattern of the two series are virtually the same if the shares are weighted by the amount issued.

Figure 2: Proportion of Callable Corporate Bonds




NOTE: Sample period: Jan1986–June2010. The figure depicts the proportion of bonds in our sample that are callable. The shaded vertical bars represent the NBER-dated recessions.

debt, and by the mid-1990s, the majority of senior unsecured debt traded in the secondary market was in the form of noncallable securities. Over the past decade or so, this trend has been reversed, as firms resumed issuing large amounts of callable long-term debt.

As shown by Duffee [1998], if a firm's outstanding bonds are callable, movements in the risk-free rates—by changing the value of the embedded call option—will have an independent effect on bond prices, complicating the interpretation of the behavior of credit spreads. For example, as the general level of interest rates in the economy increases, the option to call becomes less valuable, which accentuates the price response of callable bonds relative to that of noncallable bonds. As a result, a rise in interest rates will, ceteris paribus, compress the credit spreads of callable bonds more than the credit spreads of their noncallable counterparts. In addition, prices of callable bonds are more sensitive to uncertainty regarding the future course of interest rates. On the other hand, to the extent that callable bonds are, in effect, of shorter duration, they may be less sensitive to changes in default risk.

To deal with this issue, we utilize the micro-level aspect of our bond data to adjust directly for the value of embedded options in callable bonds. In particular, we consider the following empirical pricing model for credit spreads:

$$\begin{aligned}\ln S_{it}[k] &= (1 + \mathit{CALL}_i[k]) \times (\alpha + \beta_1 \mathit{DD}_{it} + \beta_2 \mathit{DD}_{it}^2 + \gamma' X_{it}[k]) \\ &\quad + \mathit{CALL}_i[k] \times (\theta_1 \mathit{LEV}_t + \theta_2 \mathit{SLP}_t + \theta_3 \mathit{CRV}_t + \theta_4 \mathit{VOL}_t) + \mathit{RTG}_{it}[k] + \epsilon_{it}[k], \quad (1)\end{aligned}$$

where $\mathit{CALL}_i[k]$ is an indicator variable that equals one if bond $k$ (issued by firm $i$) is callable and zero otherwise, $\mathit{DD}_{it}$ denotes the estimated year-ahead distance-to-default for firm $i$, and $\epsilon_{it}[k]$ is a "bond-pricing error."[8] In this framework, the credit spreads of callable bonds are allowed to depend separately on the level ($\mathit{LEV}_t$), slope ($\mathit{SLP}_t$), and curvature ($\mathit{CRV}_t$) of the Treasury yield curve, the three factors that summarize the vast majority of the information in the Treasury term structure, according to Litterman and Scheinkman [1991] and Chen and Scott [1993].[9] The spreads of callable bonds are also influenced by the uncertainty regarding the path of long-term interest rates, as measured by the option-implied volatility on the 30-year Treasury bond futures ($\mathit{VOL}_t$).

We also allow for a nonlinear effect of default risk on credit spreads by including a quadratic term of $\mathit{DD}_{it}$ in the pricing regression, thereby accounting for the nonlinear relationship between credit spreads and leverage documented by Levin et al. [2004].[10] The vector $X_{it}[k]$, in contrast, controls for the bond-specific characteristics that could influence credit spreads through either term or liquidity premiums, including the bond's duration ($\ln \mathit{DUR}_{it}[k]$), the amount outstanding ($\ln \mathit{PAR}_{it}[k]$), and the bond's (fixed) coupon rate ($\ln \mathit{CPN}_i[k]$). The regression also includes credit rating fixed effects ($\mathit{RTG}_{it}[k]$), which capture the "soft information" regarding the firm's financial health, information that is complementary to our market-based measures of default risk; see, for example, Löffler [2004, 2007].

We estimate the pricing regression (1) separately for the sample of securities issued by nonfinancial firms and those issued by financial firms. Neglecting the effect of Jensen's inequality, the option-adjusted spread on a callable bond $k$ (i.e., $\mathit{CALL}_i[k] = 1$)—denoted by $\tilde{S}_{it}[k]$—is given by

$$\begin{aligned}\tilde{S}_{it}[k] = \exp \Big[ &\ln S_{it}[k] - \mathit{CALL}_i[k] \times (\hat{\alpha} + \hat{\beta}_1 \mathit{DD}_{it} + \hat{\beta}_2 \mathit{DD}_{it}^2 + \hat{\gamma}' X_{it}[k]) \\ &- (\hat{\theta}_1 \mathit{LEV}_t + \hat{\theta}_2 \mathit{SLP}_t + \hat{\theta}_3 \mathit{CRV}_t + \hat{\theta}_4 \mathit{VOL}_t) \Big],\end{aligned}$$

where $\hat{\alpha}, \hat{\beta}_1, \hat{\beta}_2$, $\hat{\gamma}$, and $\hat{\theta}_1, \ldots, \hat{\theta}_4$ denote the OLS estimates of the corresponding parameters from equation (1).

[8] Taking logs of credit spreads provides a useful transformation to control for heteroscedasticity, given that the distribution of credit spreads is highly skewed.

[9] The level, slope, and curvature factors correspond, respectively, to the first three principal components of nominal Treasury yields at 3-month, 6-month, 1-, 2-, 3-, 5-, 7-, 10-, 15-, and 30-year maturities. All yield series are monthly (at month-end) and with the exception of the 3- and 6-month bill rates are derived from the smoothed Treasury yield curve estimated by Gürkaynak et al. [2007].

[10] As a robustness check, we also considered higher-order polynomials of the distance-to-default, but the inclusion of cubic and quartic terms had virtually no effect on our results.

Table 2: Selected Marginal Effects by Type of Bond

| | *Nonfinancial Firms*[a] | | *Financial Firms*[b] | |
|---|---|---|---|---|
| Marginal Effect | $CALL = 0$ | $CALL = 1$ | $CALL = 0$ | $CALL = 1$ |
| Distance-to-default: $DD_{it}$ | -0.227 | -0.138 | -0.123 | -0.133 |
| | (0.013) | (0.009) | (0.029) | 0.016 |
| Term structure: $LEV_t$ | - | -0.508 | - | -0.480 |
| | | (0.045) | | (0.082) |
| Term structure: $SLP_t$ | - | -0.319 | - | -0.245 |
| | | (0.039) | | (0.052) |
| Term structure: $CRV_t$ | - | -0.052 | - | -0.086 |
| | | (0.044) | | (0.042) |
| Term structure: $VOL_t$ | - | 0.153 | - | 0.147 |
| | | (0.014) | | (0.017) |
| Adjusted $R^2$ | 0.730 | | 0.594 | |
| $\Pr > W^c$ | 0.000 | | 0.000 | |

NOTE: Sample period: Jan1986–Jun2010. Entries in the table denote the estimated marginal effects of a one unit change in the specified variable on the level of credit spreads (in percentage points) for noncallable ($CALL = 0$) and callable ($CALL = 1$) bonds based on the bond-pricing regression (1). All marginal effects are evaluated at their respective sample means (not reported). Robust asymptotic standard errors reported in parentheses are double clustered in the firm ($i$) and time ($t$) dimensions; see Cameron et al. [2010] for details.

[a]No. of firms/bonds = 1,104/5,896; Obs. = 305,412.

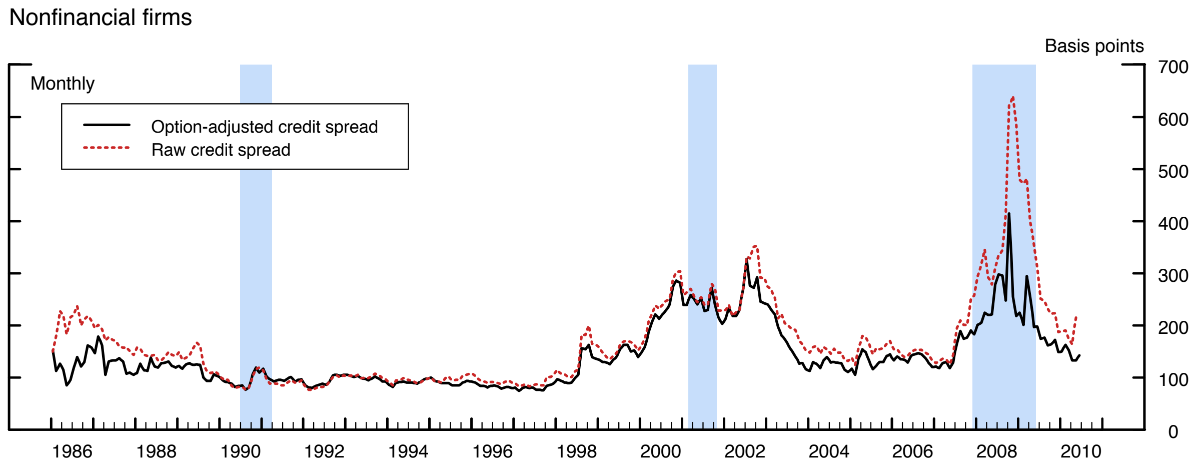
[b]No. of firms/bonds = 193/886; Obs. = 42,270.

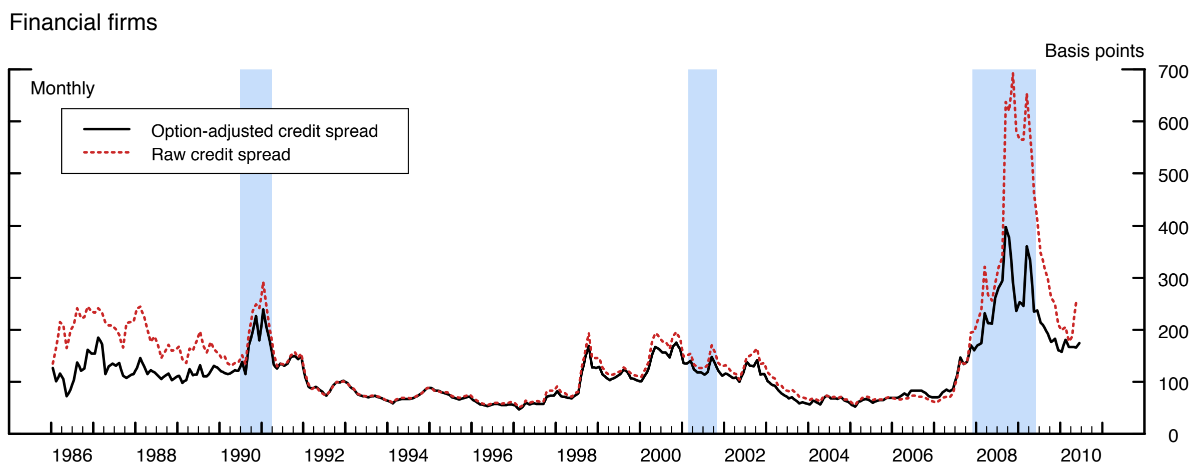
[c]$p$-value for the robust Wald test of the exclusion of credit rating fixed effects.

Table 2 translates the selected coefficients from the estimated log-spread pricing equation into the impact of variation in default risk (the sum of the linear and quadratic $DD$ terms), the shape of the term structure, and interest rate uncertainty on the *level* of credit spreads. For callable bonds issued by nonfinancial firms, the effect of the distance-to-default on credit spreads is significantly attenuated by the call-option mechanism: A one standard deviation increase in the distance-to-default—a signal of improving credit quality—implies a decrease of 23 basis points in the spreads of noncallable bonds, compared with a 14 basis points decline in the spreads of their callable counterparts. The same call-option mechanism, however, does not seem to be as important for bonds issued by financial intermediaries. In that case, a one standard deviation increase in the distance-to-default implies a narrowing of spreads of about 13 basis points for both types of bonds.

The estimates in Table 2 also indicate that the shape of the Treasury term structure and interest rate volatility have first-order effects on the credit spreads of callable bonds, which are consistent with the theoretical predictions. For example, a one standard deviation increase in the level factor implies a 50 basis points reduction in the credit spreads on callable bonds in both sectors.

Figure 3: Credit Spreads on Corporate Bonds




NOTE: Sample period: Jan1986–June2010. The solid line in each panel depicts the time-series of the weighted cross-sectional average of the option-adjusted credit spreads for our sample of bonds (see text for details); the dotted line depicts the time-series of the weighted cross-sectional average of the raw credit spreads. In all cases, the weights are equal to the market values of the underlying bond issues. The shaded vertical bars represent the NBER-dated recessions.

Similarly, an increase in the option-implied volatility on the long-term Treasury bond futures of one percentage point implies a widening of callable credit spreads of about 15 basis points, because the rise in interest rate uncertainty lowers the prices of callable bonds by boosting the value of the embedded call options.

The importance of the option-adjustment procedure over the entire sample period is illustrated in Figure 3, which shows the time path of the average credit spread in our two data sets, calculated using both the raw and option-adjusted spreads. Although the two series in each sector are clearly highly correlated ($\rho = 0.88$ for nonfinancial issuers and $\rho = 0.92$ for financial issuers) and are all strongly countercyclical, there are a number of noticeable differences. First, the option-adjusted credit spreads are, on average, lower than their unadjusted counterparts, reflecting the positive value of the embedded call options. By eliminating, at least in part, fluctuations in the call option values, the option-adjusted credit spreads are also less volatile, on average, than the raw credit spreads. Lastly, the largest differences between the two series occurred in the mid-1980s and during the recent financial crisis. The former period was characterized by a high general level of interest rates and relatively high uncertainty regarding the future course of long-term interest rates, whereas the difference during the latter period owes primarily to the plunge in interest rates and the steepening of the term structure that began with the onset of the financial crisis in the summer of 2007, two factors than more than offset the spike in interest rate volatility that occurred during that period.

### 2.4 Distance-to-Default Portfolios

We summarize the information contained in credit spreads, DDs, and excess equity returns for the sample of bond issuers by constructing portfolios based on expected default risk—as measured by our estimate of the distance-to-default—at the beginning of the period. These conditional DD-based portfolios are constructed by sorting the three financial indicators in month $t$ into bins based on the percentiles of the distribution of the distance-to-default in month $t-1$. Separate portfolios are formed for the financial and nonfinancial issuers.

The distance-to-default portfolios are constructed by computing a weighted average of DDs in month $t$ for each bin, with the weights equal to the book value of the firm's liabilities at the end of month $t-1$. Similarly, the stock portfolios are computed as a weighted average of excess equity returns in month $t$ for each bin, with the weights equal to the market value of the firm's equity at the end of month $t-1$.[11] Given the relatively large number of nonfinancial issuers, the bins for nonfinancial portfolios are based on the quartiles of the DD distribution, yielding four credit-risk categories, denoted by NFIN-DD1, NFIN-DD2, NFIN-DD3, and NFIN-DD4. The financial bond issuers, by contrast, are sorted into two credit-risk categories—denoted by FIN-DD1 and FIN-DD2—based on the median of the DD distribution.

To control for maturity, we further split each DD-based bin of nonfinancial credit spreads into four maturity categories: (1) NFIN-MTY1: credit spreads of bonds with the remaining term-to-maturity of more than 1 year but less than (or equal) to 5 years; (2) NFIN-MTY2: credit spreads of bonds with the remaining term-to-maturity of more than 5 years but less than (or equal) 10 years; (3) NFIN-MTY3: credit spreads of bonds with the remaining term-to-maturity of more than 10 years but less than (or equal) to 15 years; (4) NFIN-MTY4: credit spreads of bonds with the remaining term-to-maturity of more than 15 years. Given the substantially smaller sample of bonds issued by firms in the financial sector, we split the two credit-risk categories in this sector

[11]Excess equity returns, which include dividends and capital gains, are measured relative to the yield on 1-month Treasury bills.

into two maturity categories: (1) FIN-MTY1: credit spreads of bonds with the remaining term-to-maturity of more than 1 year but less than (or equal) to 5 years; and (2) FIN-MTY2: credit spreads of bonds with the remaining term-to-maturity of more than 5 years. All told, this gives us a total of 16 nonfinancial and 4 financial DD/maturity bond portfolios. Within each of these portfolios, we compute a weighted average of option-adjusted credit spreads in month $t$, with the weights equal to the market value of the outstanding issue. (The summary statistics of all DD-based portfolios are contained in Appendix A.)

The DD-based portfolios considered thus far were based on asset prices of a subset of U.S. corporations, namely firms with senior unsecured bonds that are traded in the secondary market. We also consider a broader set of DD-based financial indicators by constructing the same type of portfolios using the distance-to-default estimates and excess equity returns for the entire matched CRSP-Compustat sample of U.S. corporations. Given the large number of firms in any given month, we increase the number of bins by sorting—for both nonfinancial and financial firms separately—the DDs and excess equity returns in month $t$ into 10 deciles based on the distribution of the distance-to-default in month $t-1$. As before, the conditional DD portfolios are constructed by computing a weighted average of DDs in month $t$ for each DD decile, whereas the stock portfolios are computed as a weighted average of excess equity returns in month $t$. This procedure yields a total of 20 additional DD-based portfolios for the nonfinancial sector and another 20 portfolios for the financial sector.

# 3 Econometric Methodology

We examine the predictive content of the DD-based portfolios, as well as a large number of other predictors, within the Bayesian Model Averaging (BMA) framework, an approach that is particularly well-suited to deal with model uncertainty. Initially proposed by Leamer [1978], BMA has been used extensively in the statistics literature; see, for example, Raftery et al. [1997] and Chipman et al. [2001]. The BMA approach to model uncertainty has also found numerous econometric applications, including the forecasting of output growth (Min and Zellner [1993] and Koop and Potter [2004]); the forecasting of recession risk (King et al. [2007]); cross-country growth regressions (Fernandez et al. [2001b] and Sala-i-Martin et al. [2004]); exchange rate forecasting (Wright [2008]); and the predictability of stock returns (Avramov [2002] and Cremers [2002]).

## 3.1 Bayesian Model Averaging

We begin with a brief review of the formal Bayesian justification for our model-averaging approach. The researcher starts with a set of $n$ possible models, where the $i$-th model, denoted by $M_i$, is parametrized by $\theta_i$. The researcher has prior beliefs about the probability that the $i$-th model is true—denoted by $P(M_i)$—observes data $D$, and updates her beliefs to compute the posterior probability that the $i$-th model is the true model according to

$$P(M_i|D) = \frac{P(D|M_i)P(M_i)}{\sum_{j=1}^{n} P(D|M_j)P(M_j)}, \tag{2}$$

where

$$P(D|M_i) = \int P(D|\theta_i, M_i)P(\theta_i|M_i)d\theta_i \tag{3}$$

is the marginal likelihood of the $i$-th model; $P(\theta_i|M_i)$ is the prior density of the parameter vector $\theta_i$ associated with the $i$-th model; and $P(D|\theta_i, M_i)$ is the likelihood function.

Each model also implies a forecast. In the presence of model uncertainty, the BMA forecast weights each of the individual forecasts by their respective posterior probabilities. To operationalize a BMA forecasting scheme, the researcher needs only to specify the set of models, the model priors $P(M_i)$, and the parameter priors $P(\theta_i|M_i)$. In this paper, we follow a growing literature that considers a large set of very simple models. In particular, the models are all linear regression models, with each model adding a single regressor to the baseline specification. More formally, the $i$-th model is given by

$$y_{t+h} = \beta_i X_{it} + \gamma' Z_t + \epsilon_{t+h}, \tag{4}$$

where $y_t$ is the variable that the researcher wishes to forecast at a horizon of $h$ periods; $X_{it}$ is the predictor specific to model $i$; $Z_t$ is a $(p \times 1)$-vector of predictors that are common to all models; and $\epsilon_{t+h} \overset{iid}{\sim} N(0, \sigma^2)$ is the forecast error. Without loss of generality, the model-specific predictor $X_{it}$ is assumed to be orthogonal to the common predictors $Z_t$. In our setup, the vector of parameters characterizing the $i$-th model is thus given by $\theta_i = (\beta_i\ \gamma'\ \sigma^2)'$.

In setting the model priors, we assume that all models are equally likely, implying that $P(M_i) = 1/n$. For the parameter priors, we follow the general trend of the BMA literature (e.g., Fernandez et al. [2001a]) in specifying that the prior for $\gamma$ and $\sigma^2$, denoted by $p(\gamma, \sigma)$, is uninformative and is proportional to $1/\sigma$, while using the $g$-prior specification of Zellner [1986] for $\beta_i$ conditional on $\sigma^2$. The $g$-prior is given by $N(0, \phi\sigma^2(X_i'X_i)^{-1})$, where the shrinkage hyperparameter $\phi > 0$ measures the strength of the prior—a smaller value of $\phi$ corresponds to a more dogmatic prior.

Letting $\hat{\beta}_i$ and $\hat{\gamma}$ denote the OLS estimates of the corresponding parameters in equation (4), the Bayesian $h$-period-ahead forecast made from model $M_i$ at time $T$ is given by

$$\tilde{y}^i_{T+h|T} = \tilde{\beta}_i X_{it} + \hat{\gamma}' Z_t, \tag{5}$$

where $\tilde{\beta}_i = \left(\frac{\phi}{\phi+1}\right)\hat{\beta}_i$ denotes the posterior mean of $\beta_i$. In our framework, the marginal likelihood of the $i$-th model reduces to

$$P(D|M_i) \propto \left[\frac{1}{1+\phi}\right]^{-\frac{1}{2}} \times \left[\frac{1}{1+\phi} SSR_i + \frac{\phi}{1+\phi} SSE_i\right]^{-\frac{(T-p)}{2}}, \tag{6}$$

where $SSR_i$ is the sum of squares from the $i$-th the regression and $SSE_i$ is the associated sum of squared errors. The posterior probabilities of the models can then be worked out from equation (2), and the final BMA forecast that takes into account model uncertainty is given by

$$\tilde{y}_{T+h|T} = \sum_{i=1}^{n} P(M_i|D)\tilde{y}^i_{T+h|T}. \tag{7}$$

Clearly, the BMA forecast in equation (7) will depend on the value of the shrinkage hyperparameter $\phi$. A small value of $\phi$ implies that the model likelihoods are roughly equal, and so the BMA forecast will resemble equal-weighted model averaging (cf. Bates and Granger [1969]). In contrast, a high value of $\phi$ amounts to weighting the models by their in-sample $R^2$ values, a procedure that is well known to generate poor out-of-sample forecasting performance. Because the relationship between the out-of-sample root mean square prediction error and the parameter $\phi$ is often U-shaped, the best out-of-sample forecasts are obtained when $\phi$ is neither too small nor too big. Our baseline results are based on a standard value ($\phi = 4$) taken from the aforementioned literature, but we also conduct sensitivity analysis, which shows that our key results are robust with respect to this choice.

We apply BMA to forecasting various indicators of economic activity using standard macroeconomic variables and financial asset prices as predictors. The common predictors $Z_t$ in the predictive regression (4) are a constant and lags of the dependent variable. It is worth emphasizing that we view the forecasting scheme proposed above as a pragmatic approach to data-based weighting of models and make no claim to its Bayesian optimality properties.[12]

## 3.2 The Forecasting Setup

We focus on forecasting real GDP, real personal consumption expenditures (PCE), real business fixed investment, industrial production, private payroll employment, the civilian unemployment rate, exports, and imports over the period from 1986:Q1 to 2010:Q2. All series are in quarter-over-quarter growth rates (actually 400 times log first differences), except for the unemployment rate, which is simply in first differences. Our objective is to forecast the cumulative growth rate (or the cumulative change in the case of the unemployment rate) for each of these macroeconomic variables from quarter $t-1$ through quarter $t+h$.

Specifically, let $y_t$ denote the growth rate in the variable from quarter $t-1$ to quarter $t$. (In

[12] As noted by a number of papers that employ the same data-based model averaging approach, several of the conditions for strict optimality are not met in typical macro time-series applications. First, the regressors are assumed to be strictly exogenous. And second, the forecasts are overlapping $h$-step ahead forecasts, so the forecast errors less than $h$ periods apart are bound to be serially correlated, even though it is assumed that they are i.i.d. normal. Nevertheless, BMA, like other methods that combine a large number of predictors to generate a forecast, may still have good forecasting properties, even if the premises underlying their theoretical justification are false (e.g., Stock and Watson [2005]). In fact, ability to provide accurate out-of-sample forecasts is a stringent test of the practical usefulness of BMA in forecasting.

case of the unemployment rate, $y_t$ denotes the first difference.) The average value of $y_t$ over the forecast horizon $h$ is denoted by $y^C_{t+h} = \frac{1}{h+1}\sum_{i=0}^{h} y_{t+i}$. The $i$-th forecasting model in our setup is given by:

$$y^C_{t+h} = \alpha + \beta_i x_{it} + \sum_{j=1}^{p} \gamma_j y_{t-j} + \epsilon_{t+h}, \tag{8}$$

where $x_{it}$ is one of the predictors listed in Table 3 and $p$, the number of lags, is determined by the Bayes Information Criterion (BIC). The set of possible predictors listed in Table 3 includes 15 different macroeconomic series and 110 financial indicators. The financial indicators include our 20 bond portfolios of option-adjusted credit spreads, as well as average DDs and excess equity returns for different default-risk portfolios; in addition, we consider the predictive content of the three Fama-French risk factors (i.e., the excess market return and the SMB and HML factors), a range of standard interest rates and interest rate spreads, implied volatilities from options quotes, commodity prices, and conventional credit spreads.

The timing convention in the forecasting regression (8) is as follows. We think of forecasts as being made in the middle month of each quarter. For macroeconomic variables, we use the February, May, August, and November vintages of data from the real-time data set compiled and maintained by the Federal Reserve Bank of Philadelphia; this includes data through the previous quarter for all the macroeconomic series that we consider. All asset prices are as of the end of the month from the *first* month of the current quarter and would have been available as of the middle month of the quarter.

The option-adjustment procedure is also implemented in real-time—that is, the parameters of the pricing regression (1) are estimated each month using only data available at that time. The resulting real-time coefficient estimates are used to compute the option-adjusted credit spreads, which are then sorted into the DD-based bond portfolios.[13] With these fully real-time data in hand, we then use BMA to construct forecasts of the values of the dependent variable for the current and next four quarters (i.e., $h = 0, 1, \dots, 4$). Thus, we are considering both "nowcasting" and prediction at horizons up to one year ahead. These forecasts are evaluated in a recursive out-of-sample forecast evaluation exercise, starting with the forecasts made in 1992:Q1 and continuing through to the end of the sample period in 2010:Q2.

An important issue in this type of real-time forecasting exercise is the definition of what constitutes the "actual" values with which to compare the BMA forecasts. The macroeconomic series that we are forecasting are subject to benchmark revisions, and some of the series are also subject to definitional and conceptual changes. None of these changes seem sensible to predict in a real-time forecasting exercise. Accordingly, we follow a standard convention (cf. Tulip [2005]; and Faust and Wright [2009]), which is to measure actual realized values from the data as recorded in

[13] Note that the real-time implementation of the option-adjustment procedure generates spreads that differ from the option-adjusted spreads underlying Figure 3, where the option-adjustment procedure was implemented using the full data set.

Table 3: Macroeconomic and Financial Predictors

| Predictor (# of series) | Data Transformation |
|---|---|
| *Macroeconomic Series* (15) | |
| GDP | log difference |
| PCE | log difference |
| PCE (durable goods) | log difference |
| Residential investment | log difference |
| Business fixed investment | log difference |
| Government spending | log difference |
| Exports | log difference |
| Imports | log difference |
| Nonfarm private payrolls | log difference |
| Civilian unemployment rate | difference |
| Industrial production | log difference |
| Single-family housing starts | log difference |
| GDP price deflator | log difference |
| Consumer price index | log difference |
| M2 | log difference |
| *Financial Indicators* (110) | |
| Credit spreads in DD-based bond portfolios (nonfinancial) (16) | level |
| Credit spreads in DD-based bond portfolios (financial) (4) | level |
| Avg. DD by DD percentile (nonfinancial bond issuers) (4) | level |
| Avg. DD by DD percentile (nonfinancial firms) (10) | level |
| Excess stock returns by DD percentile (nonfinancial bond issuers) (4) | level |
| Excess stock returns by DD percentile (nonfinancial firms) (10) | level |
| Avg. DD by DD percentile (financial bond issuers) (2) | level |
| Avg. DD by DD percentile (financial firms) (10) | level |
| Excess stock returns by DD percentile (financial bond issuers) (2) | level |
| Excess stock returns by DD percentile (financial firms) (10) | level |
| 3-month nonfinancial commercial paper rate | level |
| 3-month nonfinancial commercial paper rate | less 3-month Tbill rate |
| 3-month Eurodollar rate | level |
| 3-month Eurodollar rate | less 3-month Tbill rate |
| 3-month Treasury bill rate | level |
| Federal funds rate | level |
| 1- to 10-year Treasury yields[a] (10) | level |
| 1- to 10-year Treasury yields (10) | less 3-month Tbill rate |
| Fama-French risk factors (3) | level |
| S&P 100 futures implied volatility (VXO) | level |
| Treasury futures implied volatility (10 and 30 year) | level |
| Eurodollar futures implied volatility (3-month) | level |
| Gold price | 2nd difference of logs |
| Oil price | 2nd difference of logs |
| CRB commodity price index | 2nd difference of logs |
| S&P 500 dividend yield | log |
| Moody's Baa-Aaa credit spread | level |

NOTE: All macroeconomic series come from the real-time data set maintained by the Federal Reserve Bank of Philadelphia. The NIPA series are in real terms (c-w, $2000).

[a]The nominal Treasury yields between maturities of 1- and 10-years are taken from the Treasury yield curve estimated by Gürkaynak, Sack, and Wright [2007]

the real-time data set by the Philadelphia Fed two quarters after the quarter to which the data refer.

### 3.3 Inference

The accuracy of the BMA forecasts is evaluated by comparing the mean-square prediction error (MSPE) of the BMA forecast to that obtained from a univariate autoregression:[14]

$$y^C_{t+h} = \alpha + \sum_{j=1}^{p} \gamma_j y_{t-j} + \epsilon_{t+h}. \tag{9}$$

Unfortunately, evaluating the statistical significance of the difference in MSPEs from BMA and the direct autoregression is complicated by the fact that the forecasts are generated by nested models. As shown by Clark and McCracken [2001], the distribution of the Diebold and Mariano [1995] test statistic under the null hypothesis of equal forecast accuracy has a nonstandard distribution in this case. Accordingly, we use a bootstrap to approximate the limiting distribution of the Diebold-Mariano statistic under the null hypothesis. In the bootstrap, the predictors are, by construction, irrelevant—nevertheless, they have time-series and cross-sectional dependence properties that are designed to mimic those of the underlying data. The bootstrap hence allows us to test the null hypothesis of no improvement in forecast accuracy.

We consider two specific bootstrap re-sampling schemes to implement this idea. The first implementation of the bootstrap, henceforth referred to as **bootstrap B1**, involves fitting an AR(4) process to $y_t$ and separately estimating a dynamic factor model using the set of all predictors $X_t$:

$$X_t = \Lambda F_t + u_t; \tag{10}$$

and

$$F_t = \Phi F_{t-1} + v_t, \tag{11}$$

where the elements of the vector $F_t$ correspond to the first three principal components of $X_t$. In each bootstrap replication, we first re-sample with replacement from the residuals of the AR(4) process for $y_t$ to construct bootstrap samples of $y_t$. We then independently re-sample with replacement from the residuals in equations (10) and (11), thereby constructing bootstrap samples of $X_t$ for use in BMA; note that in this setup, the predictor set $X_t$ is, by construction, irrelevant for the forecasting of the dependent variable.

The second implementation of the bootstrap, henceforth referred to as **bootstrap B2**, follows Clark and McCracken [2010] and Gonçalves and Perron [2010]. Specifically, we estimate two mod-

[14]Note that this is a direct autoregression that projects $y^C_{t+h}$ onto $p$ lags of $y_t$. An alternative would be to estimate an AR($p$) model for $y_t$ and then iterate it forward to construct the forecasts. This approach yielded very similar results.

els: a *restricted* model that involves estimating an AR(4) process for $y_t$ and an *unrestricted* model that consists of a regression of $y_t$ on four lags of itself and the first three principal components of $X_t$. In each bootstrap replication, we then re-sample from the residuals of the unrestricted model using a wild bootstrap and then construct a bootstrap sample of $y_t$ using these re-sampled residuals together with the coefficients from the restricted model (see Clark and McCracken [2010] for details); meanwhile, the predictor set $X_t$ is held fixed. As with bootstrap B1, the predictors are again, by construction, irrelevant for the forecasting of the dependent variable in all samples. Compared with bootstrap B1, bootstrap B2 has the advantage of preserving any conditional heteroscedasticity in the data.

# 4 Results

Table 4 contains the relative out-of-sample MSPEs of the BMA forecasts, using the benchmark value of the shrinkage parameter $\phi = 4$. Bootstrapped $p$-values testing the null hypothesis that the relative mean-square prediction error is equal to 1.0, are shown in round and square brackets for bootstraps B1 and B2, respectively; as evidenced by the entries in the table, the two $p$-values are generally consistent. For real GDP growth, the MSPEs from the BMA forecasts relative to those from the direct autoregression are around 0.8 at all forecast horizons beyond the current quarter. Judging from the associated $p$-values, these improvements in forecast accuracy are all statistically significant, at least at the 5 percent level.

The relative accuracy of BMA in forecasting output growth appears to reflect, in part, its ability to predict the growth of business fixed investment. In addition, BMA also does well in forecasting the external dimension of U.S. economic performance, namely the growth of both exports and imports. Personal consumption expenditures, in contrast, are considerably less predictable. Although BMA is noticeably more accurate than the direct autoregression in forecasting consumption growth over the very near term, the relative MSPEs are statistically indistinguishable from 1.0 at the two- to four-quarter-ahead horizons.

Our BMA setup also implies economically and statistically significant gains in accuracy when predicting the growth of industrial production and changes in labor market conditions at both the near- and longer-term forecast horizons. In the case of industrial production, the relative MSPEs lie between 0.87 and 0.97, improvements that are borderline statistically significant. The relative MSPEs in the case of employment growth and changes in the unemployment rate are mostly around 0.8, values that are all significantly below 1.0 at a 5 percent significance level.

Overall, our first set of results indicates that for forecasting a range of real economic activity indicators, BMA—with (option-adjusted) portfolio credit spreads in the set of predictors—yields improvements relative to the univariate benchmark that are both economically and statistically significant. The gains in forecasting accuracy are most pronounced for cyclically sensitive indicators of economic activity, such as the growth of business fixed investment, industrial production, and

Table 4: BMA Out-of-Sample Predictive Accuracy
(Predictor Set: All Variables)

| | Forecast Horizon ($h$ quarters) | | | | |
|---|---|---|---|---|---|
| Economic Activity Indicator | $h = 0$ | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ |
| GDP | 0.94 | 0.82 | 0.73 | 0.79 | 0.85 |
| | (0.01) | (0.00) | (0.00) | (0.01) | (0.03) |
| | [0.04] | [0.01] | [0.00] | [0.02] | [0.05] |
| Personal consumption expenditures | 0.79 | 0.86 | 0.96 | 1.07 | 1.14 |
| | (0.00) | (0.02) | (0.16) | (0.61) | (0.70) |
| | [0.01] | [0.06] | [0.16] | [0.29] | [0.35] |
| Business fixed investment | 0.89 | 0.70 | 0.87 | 0.87 | 0.86 |
| | (0.00) | (0.00) | (0.02) | (0.03) | (0.04) |
| | [0.01] | [0.00] | [0.02] | [0.03] | [0.03] |
| Industrial production | 0.97 | 0.95 | 0.95 | 0.93 | 0.87 |
| | (0.04) | (0.04) | (0.07) | (0.06) | (0.04) |
| | [0.06] | [0.06] | [0.07] | [0.08] | [0.06] |
| Private employment | 0.88 | 0.79 | 0.83 | 0.89 | 0.84 |
| | (0.00) | (0.01) | (0.01) | (0.04) | (0.03) |
| | [0.01] | [0.00] | [0.01] | [0.05] | [0.03] |
| Unemployment rate | 0.92 | 0.78 | 0.73 | 0.74 | 0.77 |
| | (0.00) | (0.00) | (0.00) | (0.01) | (0.02) |
| | [0.01] | [0.00] | [0.00] | [0.00] | [0.02] |
| Exports | 0.96 | 0.92 | 0.88 | 0.89 | 0.89 |
| | (0.01) | (0.01) | (0.01) | (0.02) | (0.05) |
| | [0.00] | [0.00] | [0.00] | [0.01] | [0.02] |
| Imports | 0.91 | 0.90 | 0.94 | 0.91 | 0.92 |
| | (0.00) | (0.00) | (0.03) | (0.03) | (0.06) |
| | [0.00] | [0.01] | [0.05] | [0.05] | [0.08] |

NOTE: Sample period: 1986:Q1–2010:Q2. The jump-off date for the out-of-sample recursive forecasts is 1992:Q1. The forecasted variable is the cumulative growth rate (or change in the case of unemployment rate) of each economic activity indicator over the specified forecast horizon. Entries in the table denote the ratio of the MSPE from the BMA forecast to the MSPE from a direct autoregression. Each model in the BMA forecast consists of a direct autoregression augmented with one predictor. Bootstrapped $p$-values (500 replications) for the test of the null hypothesis that the ratio of the MSPEs is equal to one are shown in round and square brackets, using bootstraps B1 and B2, respectively (see text for details).

private employment.[15]

To gauge the information content of credit spreads in predicting economic activity, we repeat the above analysis, except that we exclude the 20 models that utilize the credit spreads in the

[15] As a robustness check, we also considered other methods for forecasting in a data-rich environment, including a factor-augmented autoregression and an equally-weighted average of OLS-based forecasts. In general, BMA outperformed these methods.

Table 5: BMA Out-of-Sample Predictive Accuracy
(Predictor Set: All Variables Except Option-Adjusted Credit Spreads)

| | Forecast Horizon ($h$ quarters) | | | | |
|---|---|---|---|---|---|
| Economic Activity Indicator | $h = 0$ | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ |
| GDP | 0.96 | 0.95 | 0.95 | 0.98 | 0.98 |
| | (0.03) | (0.05) | (0.08) | (0.14) | (0.15) |
| | [0.12] | [0.11] | [0.12] | [0.13] | [0.14] |
| Personal consumption expenditures | 0.95 | 0.92 | 0.99 | 1.06 | 1.13 |
| | (0.06) | (0.06) | (0.21) | (0.57) | (0.68) |
| | [0.12] | [0.11] | [0.20] | [0.32] | [0.43] |
| Business fixed investment | 0.90 | 0.91 | 0.92 | 0.96 | 0.92 |
| | (0.00) | (0.02) | (0.04) | (0.11) | (0.08) |
| | [0.01] | [0.04] | [0.07] | [0.10] | [0.07] |
| Industrial production | 0.98 | 1.04 | 1.11 | 1.11 | 1.07 |
| | (0.07) | (0.70) | (0.83) | (0.72) | (0.50) |
| | [0.10] | [0.51] | [0.63] | [0.50] | [0.32] |
| Private employment | 0.97 | 1.00 | 1.09 | 1.13 | 1.07 |
| | (0.06) | (0.20) | (0.72) | (0.71) | (0.42) |
| | [0.07] | [0.23] | [0.53] | [0.45] | [0.24] |
| Unemployment rate | 0.93 | 0.94 | 1.04 | 1.11 | 1.08 |
| | (0.01) | (0.03) | (0.54) | (0.71) | (0.55) |
| | [0.01] | [0.02] | [0.32] | [0.47] | [0.28] |
| Exports | 0.97 | 1.05 | 0.99 | 0.97 | 0.97 |
| | (0.01) | (0.80) | (0.15) | (0.09) | (0.12) |
| | [0.01] | [0.59] | [0.07] | [0.05] | [0.07] |
| Imports | 0.91 | 0.94 | 1.01 | 1.08 | 1.07 |
| | (0.00) | (0.01) | (0.24) | (0.53) | (0.45) |
| | [0.00] | [0.04] | [0.16] | [0.27] | [0.25] |

NOTE: Sample period: 1986:Q1–2010:Q2. The jump-off date for the out-of-sample recursive forecasts is 1992:Q1. The forecasted variable is the cumulative growth rate (or change in the case of unemployment rate) of each economic activity indicator over the specified forecast horizon. Entries in the table denote the ratio of the MSPE from the BMA forecast to the MSPE from a direct autoregression. Each model in the BMA forecast consists of a direct autoregression augmented with one predictor. Bootstrapped $p$-values (500 replications) for the test of the null hypothesis that the ratio of the MSPEs is equal to one are shown in round and square brackets, using bootstraps B1 and B2, respectively (see text for details).

DD-based bond portfolios from the pool of prediction models. As shown in Table 5, very few of the entries are less than 0.95, and, especially at longer forecast horizons, most entries are greater than 1.0. This finding is consistent with the standard result that a majority of forecasting methods perform about as well as a univariate autoregression. These results also illustrate a sense of how the information content of our credit spread indexes differs from that of the other real and financial

Table 6: BMA Out-of-Sample Predictive Accuracy
(Predictor Set: Option-Adjusted Credit Spreads Only)

| | Forecast Horizon ($h$ quarters) | | | | |
|---|---|---|---|---|---|
| Economic Activity Indicator | $h = 0$ | $h = 1$ | $h = 2$ | $h = 3$ | $h = 4$ |
| GDP | 0.88 | 0.83 | 0.80 | 0.89 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.02) | (0.24) |
| | [0.00] | [0.00] | [0.01] | [0.02] | [0.06] |
| Personal consumption expenditures | 0.77 | 0.76 | 0.92 | 1.01 | 1.08 |
| | (0.00) | (0.00) | (0.07) | (0.30) | (0.66) |
| | [0.00] | [0.01] | [0.08] | [0.16] | [0.26] |
| Business fixed investment | 0.84 | 0.69 | 0.85 | 0.85 | 0.86 |
| | (0.00) | (0.00) | (0.01) | (0.02) | (0.03) |
| | [0.00] | [0.00] | [0.02] | [0.02] | [0.04] |
| Industrial production | 0.92 | 0.90 | 0.94 | 0.96 | 0.89 |
| | (0.01) | (0.01) | (0.05) | (0.08) | (0.04) |
| | [0.02] | [0.03] | [0.08] | [0.10] | [0.08] |
| Private employment | 0.85 | 0.78 | 0.81 | 0.84 | 0.78 |
| | (0.00) | (0.00) | (0.01) | (0.02) | (0.02) |
| | [0.00] | [0.00] | [0.00] | [0.01] | [0.01] |
| Unemployment rate | 0.86 | 0.76 | 0.69 | 0.70 | 0.70 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| | [0.00] | [0.00] | [0.00] | [0.00] | [0.00] |
| Exports | 0.96 | 0.94 | 0.99 | 1.07 | 1.13 |
| | (0.01) | (0.02) | (0.15) | (0.68) | (0.82) |
| | [0.00] | [0.00] | [0.01] | [0.14] | [0.28] |
| Imports | 0.90 | 0.84 | 0.84 | 0.88 | 0.89 |
| | (0.00) | (0.00) | (0.00) | (0.02) | (0.03) |
| | [0.00] | [0.00] | [0.02] | [0.05] | [0.08] |

NOTE: Sample period: 1986:Q1–2010:Q2. The jump-off date for the out-of-sample recursive forecasts is 1992:Q1. The forecasted variable is the cumulative growth rate (or change in the case of unemployment rate) of each economic activity indicator over the specified forecast horizon. Entries in the table denote the ratio of the MSPE from the BMA forecast to the MSPE from a direct autoregression. Each model in the BMA forecast consists of a direct autoregression augmented with one predictor. Bootstrapped $p$-values (500 replications) for the test of the null hypothesis that the ratio of the MSPEs is equal to one are shown in round and square brackets, using bootstraps B1 and B2, respectively (see text for details).

indicators in the predictor set: When assigning the weight to a predictor using only information available at the time of the forecast, the BMA method singles out portfolio-based credit spreads and is able to exploit their predictive ability for economic activity to improve significantly on the benchmark forecast.

Another way to highlight the predictive ability of credit spreads is shown in Table 6, which contains the results of the forecasting exercise based *only* on models that include portfolio credit spreads as predictors. These results are very comparable to those reported in Table 4, which utilize the information content of the entire predictor set. Although restricting the predictor set to only DD-based portfolio credit spreads leads to some loss of predictive accuracy for real GDP growth, it actually improves the accuracy of the BMA forecasts of labor market indicators and business fixed investment. Because all of our models embed the autoregressive benchmark, the results in Tables 5–6 together imply that any forecasting gains over the univariate autoregression are, in general, due to the information content of credit spreads in the DD-based portfolios.

### 4.1 Which Predictors are the Most Informative?

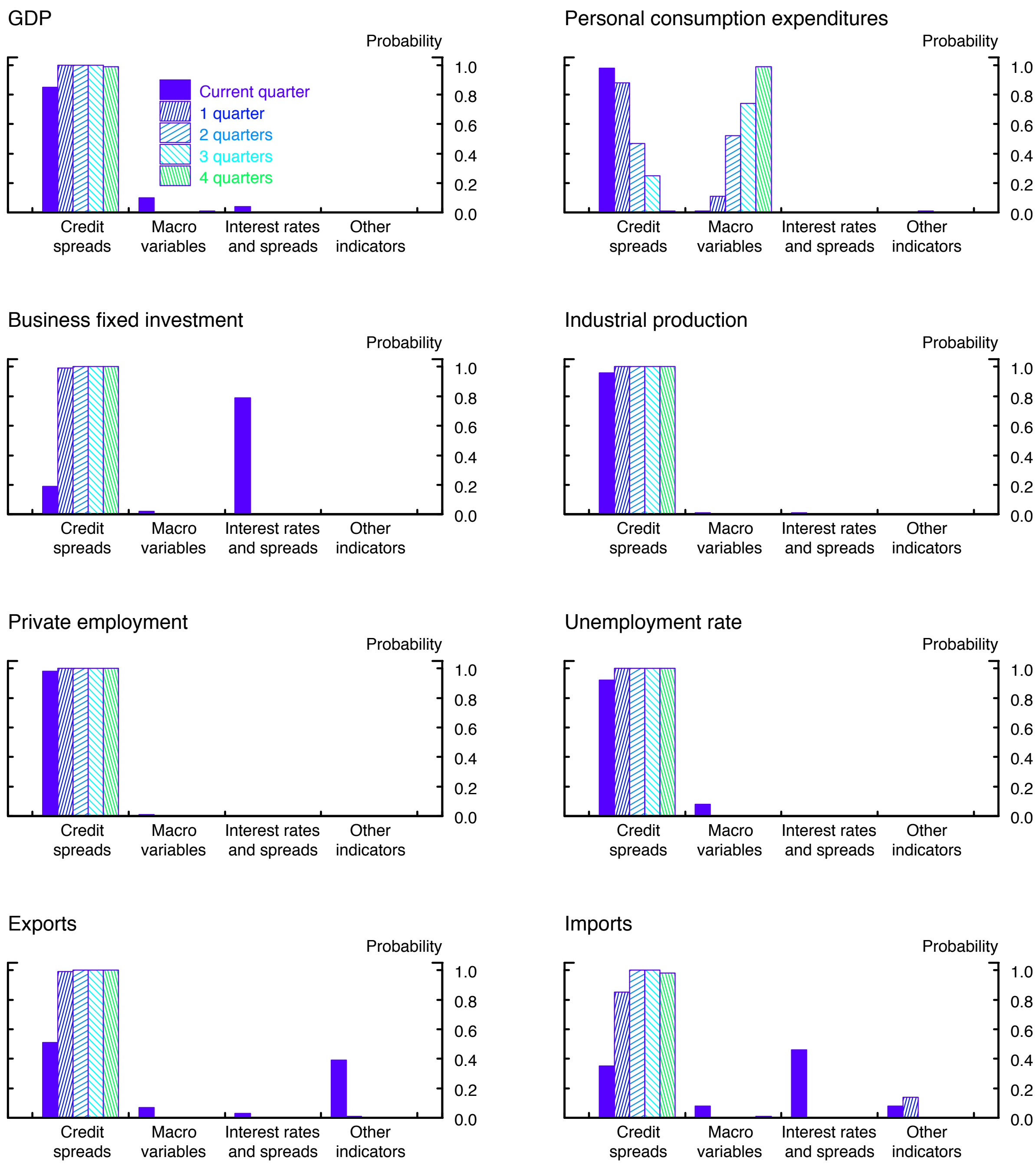
The vertical bars in Figure 4 depict the final total weights—that is, the sum of posterior probabilities—that BMA assigns to variables in the following predictor subsets: (1) option-adjusted credit spreads in the DD-based bond portfolios; (2) macroeconomic variables; (3) other interest rates and spreads; and (4) all other asset market indicators. Results are shown for all the forecast horizons considered and for each of the eight different indicators of economic activity. Note that, by construction, these probabilities sum up to one at each forecast horizon.

These results provide a visual confirmation of the information content of the option-adjusted credit spreads in our DD-based bond portfolios. With the exception of consumption growth, BMA assigns the vast majority of the posterior weight to credit spreads in our DD-based portfolios. But even in that case, most of the posterior weight for the near-term forecasts of the growth in PCE (i.e., $h = 0, 1, 2$) is assigned to the portfolio credit spreads; at longer horizons (i.e., $h = 3, 4$), BMA forecasts of consumption growth assign some weight to the macroeconomic variables, but the accuracy of these forecasts is statistically indistinguishable from those made by the benchmark autoregression, according to Table 4.

It should be emphasized, however, that Figure 4 shows the posterior probabilities for the different types of predictors as of 2010:Q2, that is, at the *end* of our sample period. In our real-time forecasting exercise, these posterior probabilities were updated each time a new forecast was made and thus, in principle, could have changed over time. Figure 5 illustrates how these probabilities evolved over time. Specifically, for each indicator of economic activity, the figure plots the total posterior weight attributed to the option-adjusted credit spreads in our 20 DD-based portfolios against the time that the forecast was made. (For parsimony, we show the posterior probabilities for the four-quarter-ahead forecast horizon only.)

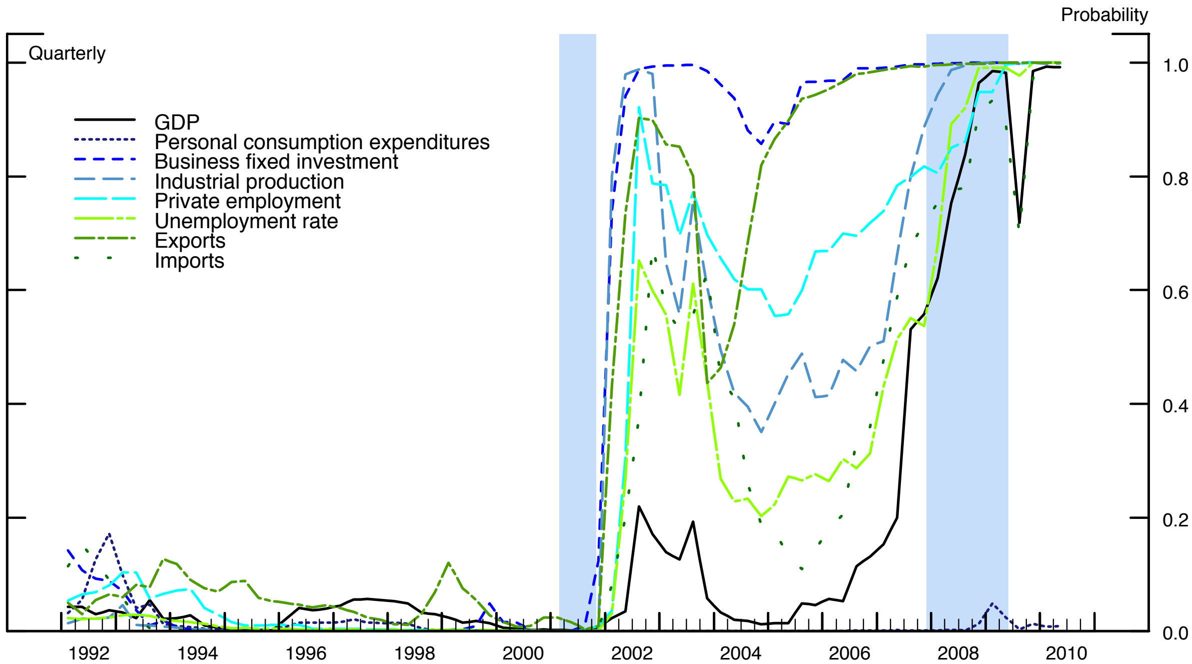
In line with the specified prior, forecasts made in the 1990s assigned very little weight to the portfolio credit spreads. The macroeconomic performance during the 2000–01 cyclical cyclical downturn led BMA to significantly increase—relative to other predictors—the posterior weight on the portfolio credit spreads, a pattern that was further reinforced by the 2007–09 financial crisis. In fact, by the end of our sample period, BMA assigns the vast majority of the posterior weight

Figure 4: BMA Posterior Probabilities by Predictor Type




NOTE: The figure depicts the sum of posterior probabilities that BMA assigns to variables in the following predictor sets: (1) option-adjusted credit spreads in the DD-based bond portfolios; (2) macroeconomic variables; (3) other interest rates and interest rate spreads; and (4) all other asset market indicators.

Figure 5: Evolution of BMA Posterior Probabilities for Bond Portfolios
(Four-Quarter-Ahead Forecast Horizon)



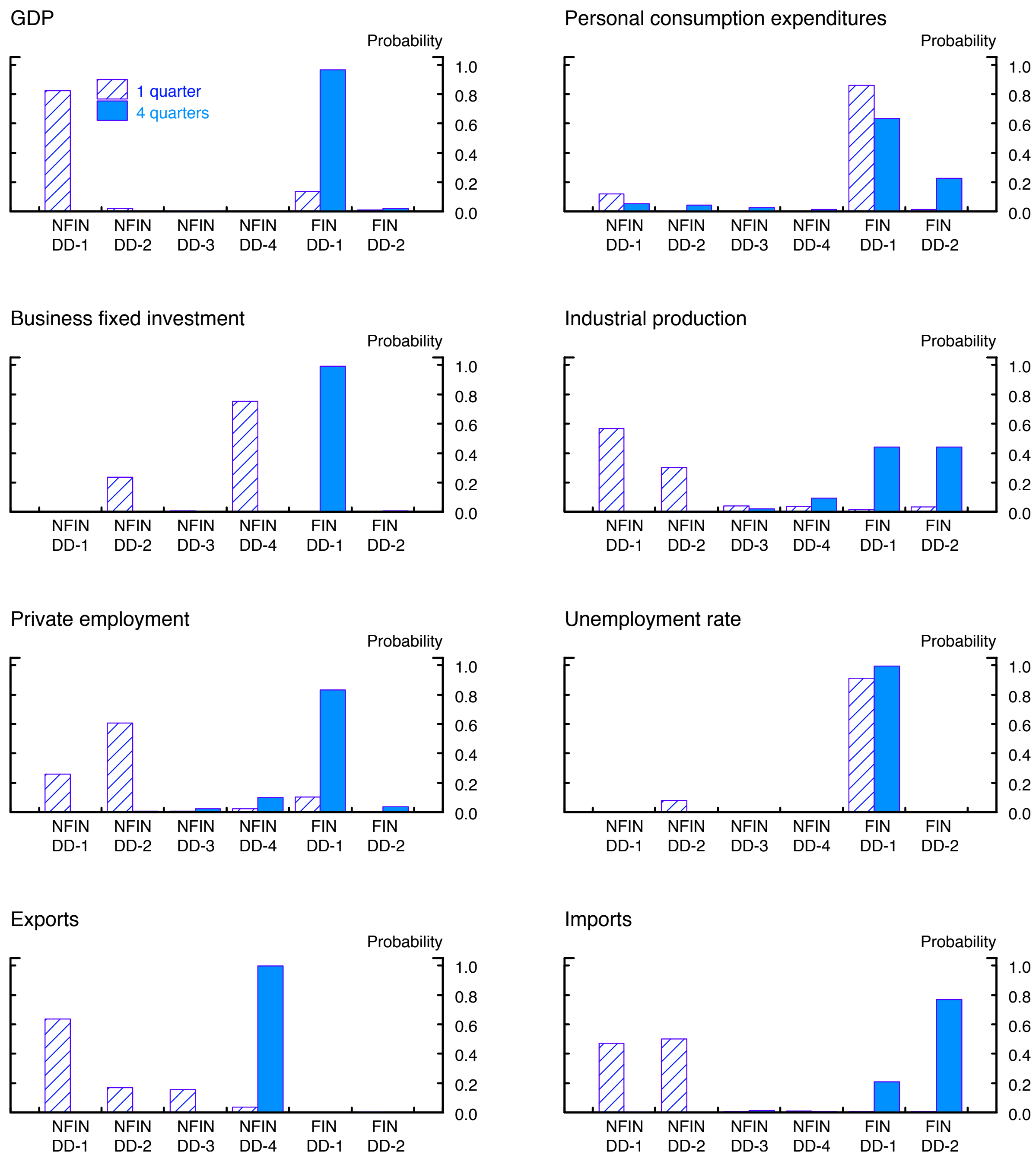

NOTE: The figure depicts the real-time evolution of the sum of posterior probabilities that BMA assigns to the option-adjusted credit spreads in the DD-based bond portfolios. The results shown are for the four-quarter-ahead forecast horizon (i.e., $h = 4$). The posterior probabilities for the 20 portfolios—16 in the case of nonfinancial portfolios and four in the case of financial portfolios—have been added together. The shaded vertical bars represent NBER-dated recessions.

to the information content of credit spreads in the DD-based portfolios, a result consistent with those shown in Figure 4. However, it is important to note that during the 1990s—a portion of the sample period that is included in the forecast evaluation—the real-time BMA forecasts of economic activity based on the entire predictor set would have differed markedly from those based only on the portfolio credit spreads.

The time-series evolution of posterior weights is important because the prediction of cyclical turning points is of special interest in many forecasting applications. As emphasized by Philippon [2009], the anticipation of rising defaults associated with economic downturns may make corporate bond spreads a particularly timely indicator of an incipient recession. The result is also consistent with the recent work by Gertler and Kiyotaki [2009] and Gertler and Karadi [2010], who introduce macroeconomic models in which shocks to the value of assets held by financial intermediaries—by reducing the supply of credit—have independent effects on the real economy.

Next, we examine the posterior weights implied by the forecasting exercise shown in Table 5, a case in which the predictor set includes only the option-adjusted credit spreads in the 20 DD-based

Figure 6: BMA Posterior Probabilities for Bond Portfolios by DD Category




NOTE: The figure depicts the sum of posterior probabilities that BMA assigns to the option-adjusted credit spreads in the DD-based bond portfolios. The results shown are for the case in which the predictor set includes only the option-adjusted credit spreads (see Table 5). The posterior probabilities for maturity categories within each DD bin—four in the case of nonfinancial portfolios and two in the case of financial portfolios—have been added together.

bond portfolios. Figure 6 depicts the total posterior probabilities that BMA assigns to nonfinancial portfolios in each DD quartile (NFIN-DD1, NFIN-DD2, NFIN-DD3, and NFIN-DD4) and the posterior probabilities assigned to the financial portfolios in the two halves of the DD distribution (FIN-DD1 and FIN-DD2). Results are shown for the one-quarter-ahead and four-quarter-ahead forecast horizons only. For the ease of presentation, we also summed up the posterior probabilities across the maturity categories within each DD-based portfolio—by construction, therefore, these six posterior probabilities must sum to one.

In forecasting economic activity over the subsequent quarter (i.e., $h = 1$), BMA tends to place most posterior weight on credit spreads based on portfolios that contain bonds issued by nonfinancial firms. At the four-quarter-ahead forecast horizon, in contrast, the posterior probabilities are concentrated on credit spreads based on portfolios that contain bonds issued by financial firms in the lower half of the credit-quality spectrum; though not reported, most of that posterior probability is assigned to portfolios that contain longer maturity bonds (i.e., FIN-DD1-MTY2).

## 4.2 Robustness Checks

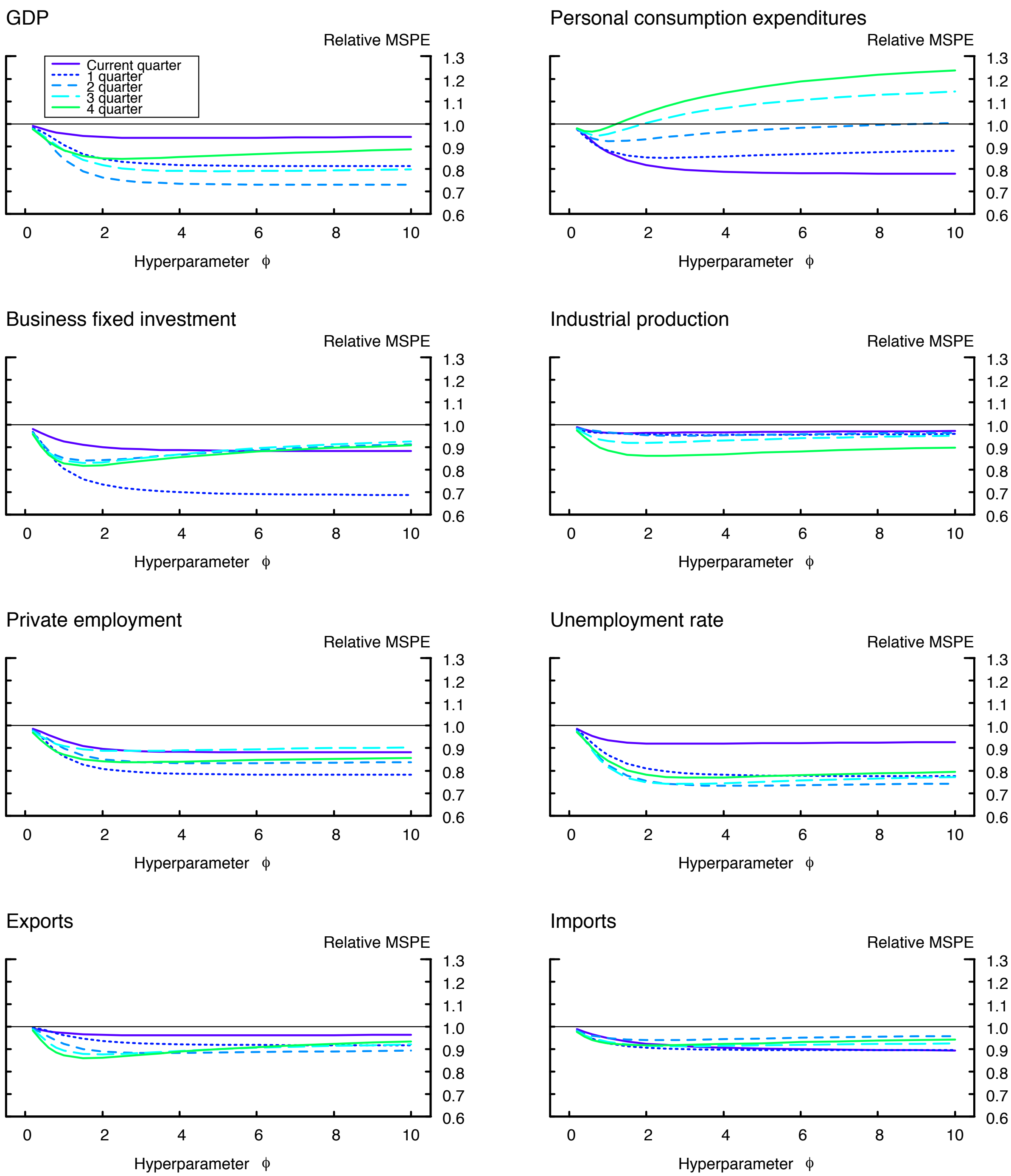
### 4.2.1 Varying the Hyperparameter $\phi$

The results reported thus far were based on the value of the shrinkage hyperparameter $\phi = 4$. In this section, we examine the robustness of our results to different values of $\phi$, the parameter governing the strength of the $g$-prior. Figure 7 plots the MSPE of the BMA forecast—relative to the MSPE from a direct autoregression—as a function of $\phi$ for all six economic indicators and all five forecast horizons. Our BMA forecasting setup delivers substantial gains in forecast accuracy relative to the direct autoregression for a wide range of values of $\phi$; in fact, the qualitative nature of our results appears to be fairly insensitive to the choice of the shrinkage parameter. In some cases, the relative MSPE decreases monotonically in $\phi$ (at least over the range of values of $\phi$ considered). In others, the relationship between the MSPE and $\phi$ is U-shaped, and the best forecasts are consequently obtained with a small or intermediate value of $\phi$.

With a sufficiently small value of $\phi$—implying a very informative prior—BMA outperforms the univariate time-series benchmark in all cases considered in this paper. This is an attractive feature of BMA with a sufficiently informative prior, at least in this data set.[16] Overall, setting $\phi = 4$ as our benchmark seems to be a good choice, because it gives relative MSPEs that are less than one in nearly all cases, and it often yields substantial gains in forecast accuracy. Nevertheless, our conclusions appear to be quite robust to a wide range of choices of $\phi$.

[16]Note that in the limit, as $\phi$ goes to zero, the BMA forecast is, by construction, equivalent to the forecast from a direct autoregression.

Figure 7: BMA Forecasting Performance and the Informativeness of the $g$-Prior




NOTE: The figure depicts the ratio of the MSPE of the BMA forecast to the MSPE from a direct autoregression for the different values of the shrinkage hyperparameter $\phi$.

### 4.2.2 Raw vs. Option-Adjusted Credit Spreads

An important feature of our DD-based bond portfolios is that they are based on option-adjusted credit spreads. As shown in Figure 3, the option-adjustment procedure significantly alters the time-series characteristics of the average credit spread across our 20 bond portfolios; indeed, the real-time option adjustment makes an even bigger difference in the case of individual bond portfolios. Thus one might naturally wonder to what extent our option-adjustment procedure influences the ability of credit spreads to forecast economic activity. Accordingly, we re-did our forecasting exercise using all the predictors as before, except with the DD-based bond portfolios now based on raw credit spreads, instead of their option-adjusted counterparts. The results of this exercise are shown in Table 7.

According to entries in the table, the BMA forecasts that use raw credit spreads continue to be more accurate than the forecasts obtained from direct autoregressions, at least at shorter horizons. Although gains in forecast accuracy are economically and statistically significant in some cases, they are neither as large nor as consistent—both across economic indicators and horizons—as those that relied on the option-adjusted credit spreads. For example, in forecasting the growth of private payroll employment, the BMA forecast that uses the option-adjusted credit spreads is considerably more accurate than the forecast from the direct autoregression at all forecast horizons. But when raw spreads are used instead, the BMA forecast is actually less accurate than our univariate benchmark at horizons of two quarters and beyond.

These results suggest that the information content of credit spreads on corporate bonds is significantly influenced by fluctuations in the values of embedded options, fluctuations that lower the signal-to-noise ratio of credit spreads for future economic outcomes. Given the fact the standard credit spread indexes are constructed using prices on both callable and non-callable bonds and that the portion of callable corporate debt is changing over time, our findings may also help explain the uneven forecasting performance of these default-risk indicators for future economic activity.

## 5 Prediction During the 2007–09 Financial Crisis

At the end of 2007, the U.S. economy entered the longest and most severe recession of the postwar period. This episode of extreme financial turmoil raises a natural question of the accuracy of our BMA forecasts during that period. The dashed lines in Figures 8–9 depict the realized growth rates—from quarter $t-1$ to quarter $t+h$—of the variables being forecasted and the level of the unemployment rate in quarter $t+h$ for $h=1$ (Figure 8) and $h=4$ (Figure 9). The solid lines depict the corresponding BMA point forecasts (using only the 20 DD-based portfolios of option-adjusted credit spreads) made in quarter $t$, while the shaded bands represent the respective BMA predictive densities. The data are plotted as of quarter $t+h$, so for the four-quarter-ahead case, the data for 2010:Q2 show actual growth rates of economic activity from 2009:Q1 to 2010:Q2 and forecasts for

Table 7: BMA Out-of-Sample Predictive Accuracy
(Predictor Set: All Variables with Raw Credit Spreads)

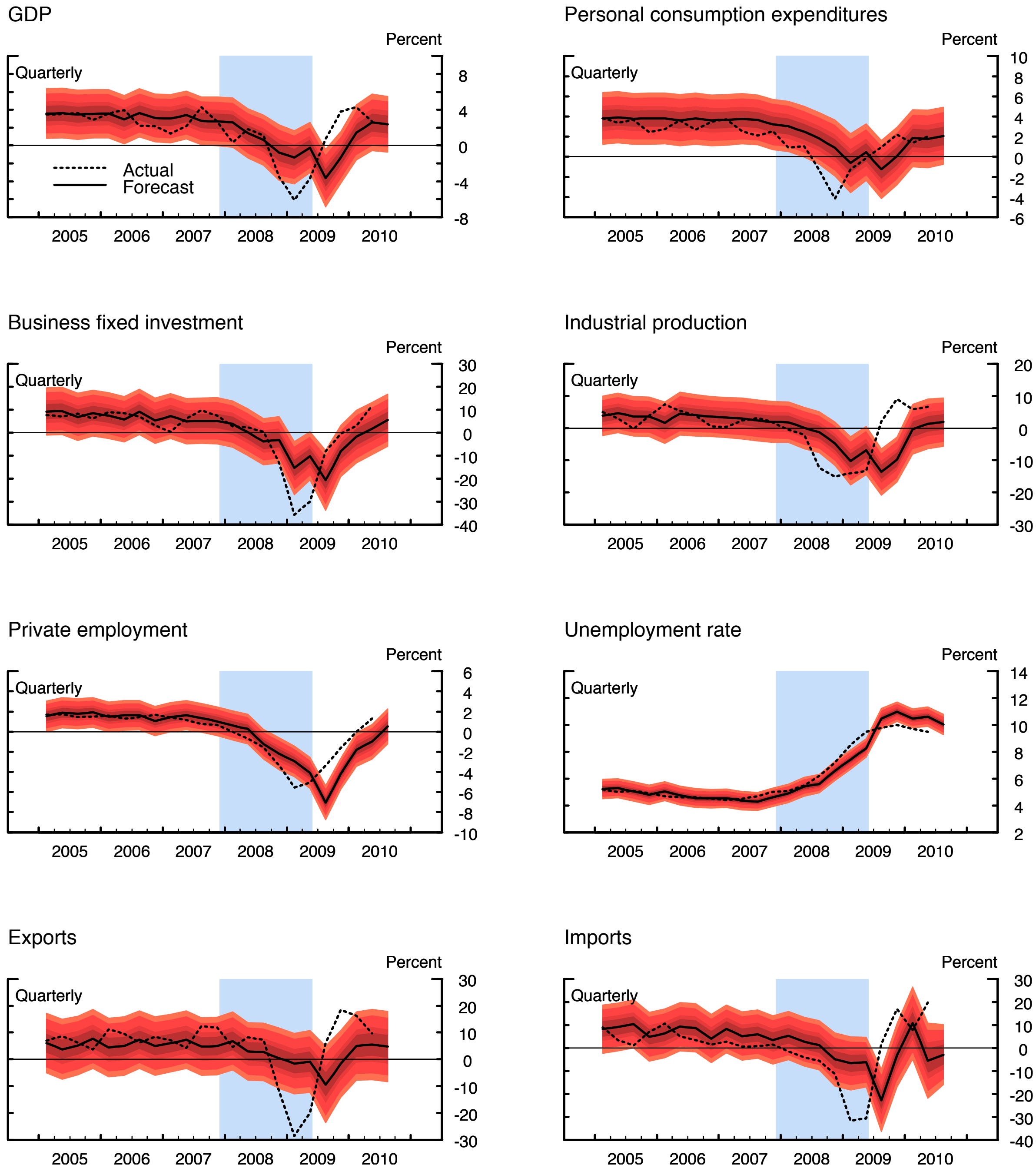
| | Forecast Horizon ($h$ quarters) | | | | |
|---|---|---|---|---|---|
| Economic Activity Indicator | $h=0$ | $h=1$ | $h=2$ | $h=3$ | $h=4$ |
| GDP | 0.94 | 0.92 | 0.87 | 0.94 | 0.89 |
| | (0.02) | (0.01) | (0.01) | (0.06) | (0.04) |
| | [0.05] | [0.04] | [0.04] | [0.08] | [0.05] |
| Personal consumption expenditures | 0.92 | 0.92 | 1.00 | 1.09 | 1.19 |
| | (0.03) | (0.07) | (0.26) | (0.69) | (0.80) |
| | [0.06] | [0.12] | [0.22] | [0.31] | [0.45] |
| Business fixed investment | 0.87 | 0.79 | 0.92 | 0.93 | 0.91 |
| | (0.00) | (0.00) | (0.05) | (0.07) | (0.08) |
| | [0.01] | [0.01] | [0.06] | [0.07] | [0.06] |
| Industrial production | 0.96 | 0.97 | 1.09 | 1.10 | 1.10 |
| | (0.03) | (0.08) | (0.75) | (0.64) | (0.58) |
| | [0.06] | [0.10] | [0.50] | [0.41] | [0.37] |
| Private employment | 0.94 | 0.95 | 1.09 | 1.23 | 1.20 |
| | (0.02) | (0.06) | (0.72) | (0.87) | (0.77) |
| | [0.03] | [0.08] | [0.43] | [0.55] | [0.40] |
| Unemployment rate | 0.91 | 0.95 | 1.11 | 1.21 | 1.15 |
| | (0.00) | (0.06) | (0.84) | (0.88) | (0.72) |
| | [0.00] | [0.03] | [0.49] | [0.57] | [0.32] |
| Exports | 0.96 | 0.94 | 1.01 | 1.02 | 0.88 |
| | (0.00) | (0.02) | (0.26) | (0.28) | (0.05) |
| | [0.00] | [0.01] | [0.08] | [0.09] | [0.01] |
| Imports | 0.91 | 0.93 | 0.97 | 1.03 | 0.99 |
| | (0.00) | (0.01) | (0.07) | (0.27) | (0.15) |
| | [0.00] | [0.02] | [0.07] | [0.16] | [0.13] |

NOTE: Sample period: 1986:Q1–2010:Q2. The jump-off date for the out-of-sample recursive forecasts is 1992:Q1. The forecasted variable is the cumulative growth rate (or change in the case of unemployment rate) of each economic activity indicator over the specified forecast horizon. Entries in the table denote the ratio of the MSPE from the BMA forecast to the MSPE from a direct autoregression (see text for details). Each model in the BMA forecast consists of a direct autoregression augmented with one predictor. Bootstrapped $p$-values (500 replications) for the test of the null hypothesis that the ratio of the MSPEs is equal to one are shown in round and square brackets, using bootstraps B1 and B2, respectively (see text for details).

growth over the same period. The real-time nature of our exercise implies that these forecasts were made in 2009:Q2. If the BMA predictions had perfect foresight, then the predicted and realized values would coincide.

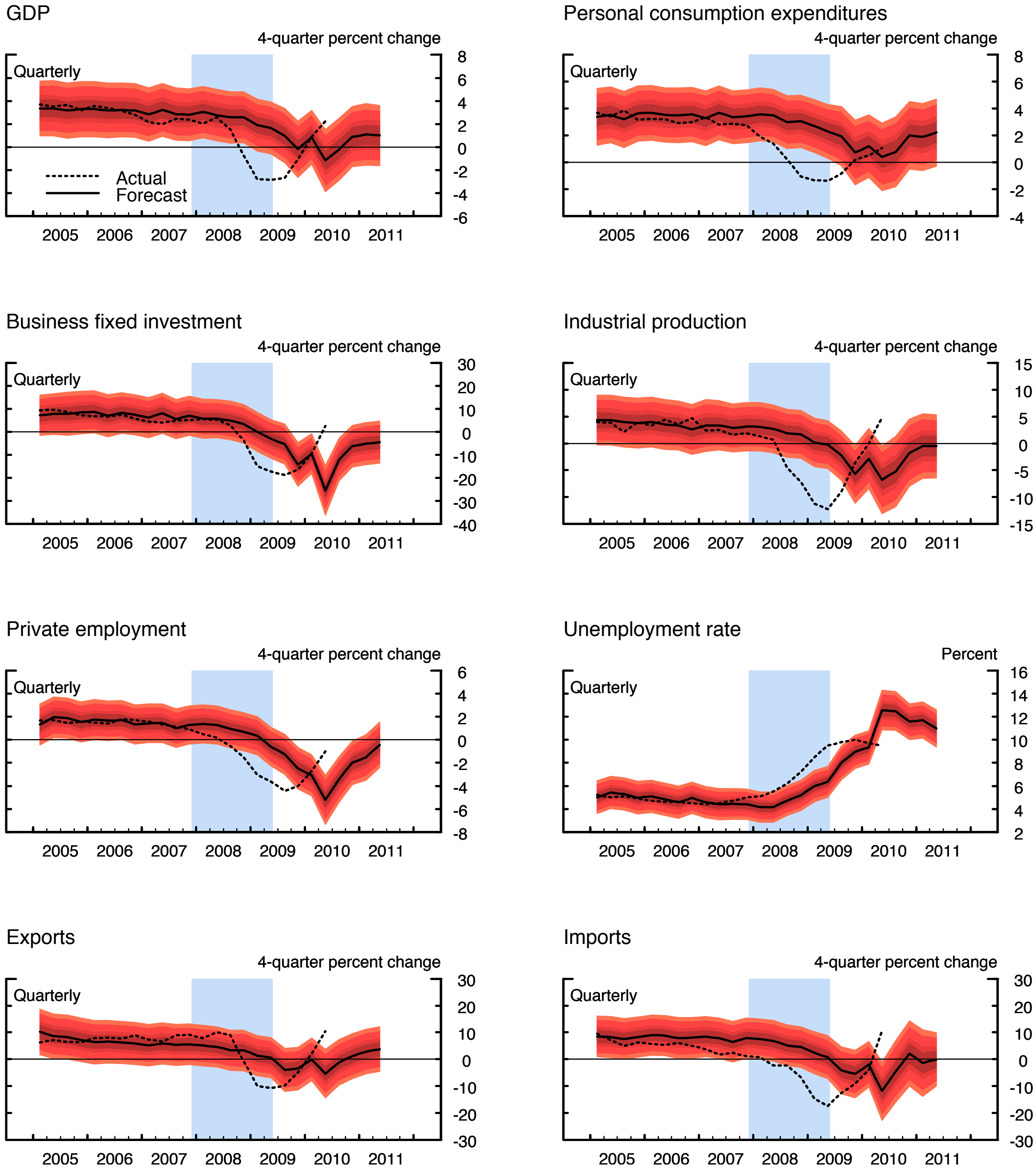
According to Figure 3, credit spreads started to widen significantly in the second half of 2007,

Figure 8: Real-Time Forecasts of the 2007–09 Financial Crisis
(One-Quarter-Ahead BMA Forecast)




NOTE: The solid line in each panel depicts the real-time BMA point forecast—using the 20 DD-based portfolios of option-adjusted credit spreads—of the specified variable for the one-quarter-ahead forecast horizon; the dashed line depicts the realized values of the corresponding variable; and the shaded bands represent the 50-, 68-, 90-, and 95-percent percentiles of the predictive density (see text for details). The shaded vertical bar denotes the 2007–09 NBER-dated recession.

Figure 9: Real-Time Forecasts of the 2007–09 Financial Crisis
(Four-Quarter-Ahead BMA Forecast)




NOTE: The solid line in each panel depicts the real-time BMA point forecast—using the 20 DD-based portfolios of option-adjusted credit spreads—of the specified variable for the four-quarter-ahead forecast horizon; the dashed line depicts the realized values of the corresponding variable; and the shaded bands represent the 50-, 68-, 90-, and 95-percent percentiles of the predictive density (see text for details). The shaded vertical bar denotes the 2007–09 NBER-dated recession.

concomitant with the slowdown in economic activity predicted by the BMA forecasts. With credit spreads continuing to move higher, the forecast for economic growth became progressively more pessimistic, reaching its nadir in 2008:Q4, a period when spreads skyrocketed to a record level after the collapse of Lehman Brothers. These real-time projections turned out to be quite accurate, especially at the one-quarter-ahead forecast horizon (Figure 8). The four-quarter-ahead BMA forecast (Figure 9) also did reasonably well, although it missed the timing of the recession by a couple of quarters. At this longer forecast horizon, the most pessimistic forecasts were also made in 2008:Q4—applying to the period ending in 2009:Q4—while the realized economic indicators were generally at their worst in 2009:Q2.

## 6 Conclusion

This paper has revisited the forecasting of real-time economic activity using a large number of macroeconomic and financial predictors. Our contribution involved expanding the set of financial predictors with corporate credit spreads based on bond portfolios sorted by the instrument's maturity and credit risk as measured by the issuer's distance-to-default. These portfolio credit spreads were constructed directly from the secondary market prices of a large number of senior unsecured bonds issued by U.S. financial and nonfinancial corporations. Using a flexible empirical bond-pricing framework, the micro-level credit spreads were adjusted for the callability of the underlying issue, a pervasive feature of the corporate cash market and one that significantly influences the information content of credit spreads for future economic activity.

To take explicitly into account model selection issues, we employed Bayesian model averaging techniques to combine the information content of variables in our predictor set, an approach that helps to mitigate concerns about data mining. Our results indicate that the accuracy of the BMA forecasts significantly exceeds—both economically and statistically—the accuracy of the forecasts obtained from a univariate direct autoregression, a benchmark that has proven to be quite difficult to beat when forecasting real-time economic activity.

The gains in forecasting accuracy stem almost exclusively from the inclusion of the option-adjusted portfolio credit spreads in the set of predictors—Bayesian model averaging consistently assigns high posterior probabilities to models that include these financial indicators. In contrast, if the portfolio credit spreads are omitted from the predictor set, the BMA forecasts of future economic activity are generally statistically indistinguishable from the forecasts obtained from a direct autoregression. This finding highlights the rich amount of information contained in corporate bond spreads, information, as argued by Gilchrist and Zakrajšek [2010], that may be particularly useful for identifying the importance of credit supply shocks in the determination of macroeconomic outcomes.

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# Appendices

## A DD-Based Portfolios

Table A-1 contains summary statistics of the distances-to-default, credit spreads, and excess equity returns in the DD-based portfolios; the top panel covers portfolios constructed using asset prices of nonfinancial firms, while the bottom panel corresponds to their financial counterparts. Not surprisingly, the average distance-to-default increases across the conditional DD bins in both sectors. The time-series volatility of this default-risk indicator, as measured by its standard deviation, also increases with the improvement in credit quality, indicating that the DDs of riskier firms fluctuate less than those of their more creditworthy counterparts. Consistent with the increase in the likelihood of default, both the average and the median credit spread decline monotonically across the conditional DD bins in all maturity categories.

The time-series characteristics of excess equity returns of firms in the different default-risk categories, by contrast, do not exhibit much of a systematic pattern. In general, less creditworthy firms registered an exceptionally weak performance over the 1986–2010 period, a finding consistent with the distress risk anomaly documented by the empirical asset-pricing literature (cf. Griffin and Lemmon [2002] and Campbell et al. [2008]).

Table A-1: Summary Statistics of DD-Based Portfolios by Type of Firm

| **Nonfinancial Firms** | DD Bin | Mean | SD | S-R[a] | Min | P50 | Max |
|---|---|---|---|---|---|---|---|
| Distance-to-default | 1 | 2.12 | 1.02 | - | -0.83 | 2.22 | 4.83 |
| Distance-to-default | 2 | 5.26 | 1.73 | - | 0.50 | 5.63 | 8.63 |
| Distance-to-default | 3 | 7.62 | 2.15 | - | 2.23 | 8.17 | 11.3 |
| Distance-to-default | 4 | 11.2 | 2.86 | - | 4.87 | 11.6 | 16.7 |
| Credit spread (1–5 yr.) | 1 | 2.77 | 1.82 | 1.52 | 0.73 | 2.27 | 12.1 |
| Credit spread (1–5 yr.) | 2 | 1.29 | 0.69 | 1.88 | 0.44 | 1.11 | 5.16 |
| Credit spread (1–5 yr.) | 3 | 0.94 | 0.48 | 1.94 | 0.29 | 0.85 | 3.65 |
| Credit spread (1–5 yr.) | 4 | 0.68 | 0.36 | 1.88 | 0.22 | 0.58 | 2.52 |
| Credit spread (5–10 yr.) | 1 | 2.97 | 1.65 | 1.80 | 0.93 | 2.35 | 9.65 |
| Credit spread (5–10 yr.) | 2 | 1.48 | 0.67 | 2.21 | 0.59 | 1.22 | 4.54 |
| Credit spread (5–10 yr.) | 3 | 0.99 | 0.45 | 2.20 | 0.45 | 0.86 | 3.33 |
| Credit spread (5–10 yr.) | 4 | 0.69 | 0.33 | 2.08 | 0.22 | 0.54 | 2.15 |
| Credit spread (10–15 yr.) | 1 | 2.51 | 1.67 | 1.50 | 0.87 | 1.98 | 13.2 |
| Credit spread (10–15 yr.) | 2 | 1.35 | 0.72 | 1.87 | 0.31 | 1.09 | 4.81 |
| Credit spread (10–15 yr.) | 3 | 0.90 | 0.48 | 1.89 | 0.25 | 0.79 | 3.45 |
| Credit spread (10–15 yr.) | 4 | 0.65 | 0.34 | 1.92 | 0.21 | 0.52 | 1.85 |
| Credit spread ($>$ 15 yr.) | 1 | 2.69 | 1.61 | 1.67 | 0.67 | 2.34 | 12.3 |
| Credit spread ($>$ 15 yr.) | 2 | 1.50 | 0.55 | 2.74 | 0.84 | 1.33 | 3.80 |
| Credit spread ($>$ 15 yr.) | 3 | 1.10 | 0.42 | 2.59 | 0.51 | 0.98 | 3.09 |
| Credit spread ($>$ 15 yr.) | 4 | 0.82 | 0.31 | 2.66 | 0.37 | 0.74 | 1.98 |
| Excess Equity Return | 1 | -0.31 | 8.11 | -0.04 | -58.0 | 0.66 | 28.8 |
| Excess Equity Return | 2 | 0.08 | 6.12 | 0.01 | -44.8 | 0.55 | 17.3 |
| Excess Equity Return | 3 | 0.05 | 4.91 | 0.01 | -31.0 | 0.64 | 14.8 |
| Excess Equity Return | 4 | 0.19 | 4.14 | 0.05 | -24.6 | 0.78 | 11.2 |
| **Financial Firms** | DD Bin | Mean | SD | S-R | Min | P50 | Max |
| Distance-to-default | 1 | 1.88 | 1.22 | - | -1.33 | 1.82 | 4.54 |
| Distance-to-default | 2 | 6.26 | 3.10 | - | 0.48 | 6.07 | 13.4 |
| Credit spread (1–5 yr.) | 1 | 1.10 | 0.78 | 1.41 | 0.28 | 0.98 | 5.38 |
| Credit spread (1–5 yr.) | 2 | 0.91 | 0.49 | 1.88 | 0.22 | 0.88 | 3.14 |
| Credit spread ($>$ 5 yr.) | 1 | 1.25 | 0.57 | 2.18 | 0.58 | 1.10 | 3.98 |
| Credit spread ($>$ 5 yr.) | 2 | 1.16 | 0.37 | 3.16 | 0.59 | 1.09 | 2.54 |
| Excess Equity Return | 1 | -0.13 | 8.30 | -0.02 | -42.8 | 0.74 | 22.1 |
| Excess Equity Return | 2 | 0.11 | 6.51 | 0.02 | -46.4 | 0.74 | 15.3 |

NOTE: Sample period: Jan1986–June2010. DDs are in units of standard deviations, credit spreads are in percentage points, and (monthly) excess equity returns are in percent. The (weighted) average of indicators in month $t$ in each DD bin is based on the DD distribution in month $t-1$. The four DD binds for the nonfinancial firms are based on the quartiles of the distribution; the two DD bins for the financial firms are based on the median of the distribution (see text for details).

[a]Sharpe ratio.