Credit Spreads as Predictors of Real-Time Economic Activity: A Bayesian Model-Averaging Approach

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Abstract

We use Bayesian Model Averaging (BMA) to forecast real-time measures of economic activity using a large set of possible predictors. The set of potential predictors includes option-adjusted credit spreads—in addition to a large number of other asset market indicators—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. nonfinancial corporations. Our results indicate that relative to a direct autoregression, BMA yields consistent improvements in the prediction of the growth rates of real GDP, industrial production, employment, and business fixed investment, 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 almost 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.

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Keywords: forecasting, real-time data, Bayesian Model Averaging, credit spreads

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1 Introduction

One area of agreement among economists at universities, central banks, and Wall Street is that forecasting future economic activity is hard. While the existing econometric models give us some ability to forecast economic developments for the current quarter and perhaps the quarter after that, their predictive power deteriorates rapidly as the forecast horizon extends beyond the very near term. Indeed, in predicting economic activity just a few quarters ahead, many researchers find it very difficult to beat the simplest time-series models—for example, a univariate autoregression—or even a forecast that is equal to the unconditional mean of the variable being forecasted; see, for example, Sims [2005]; Tulip [2005]; and Faust and Wright [2009].

Nevertheless, the idea of using information from financial markets—or assets markets more generally—to predict future economic activity remains alluring among both practitioners and policymakers. By their very nature, asset markets are forward looking. As a result, prices in these markets should impound information about investors' expectations of future economic outcomes, even if extracting that information is complicated by the existence of time-varying risk premiums.[1]

From a theoretical perspective, default-risk indicators such as corporate credit spreads—the difference in yields between various corporate debt instruments and government securities of comparable maturity—seem to be particularly well suited for forecasting future economic activity. Philippon [2009], for example, considers 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.

Despite their seeming advantage, the empirical success of using default-risk indicators to forecast economic activity is mixed, with results varying substantially across different credit spread indexes and across different time periods. For example, the "paper-bill" spread—the difference between yields on nonfinancial commercial paper and comparable-maturity Treasury bills—appears to have has lost much of its forecasting power since the early 1990s.

[1] Asset market 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]).

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 prior to the mid-1980s, have done particularly well at forecasting output growth during the previous decade, according to Gertler and Lown [1999] and Mody and Taylor [2004]. Stock and Watson [2003], however, find mixed evidence for the junk spread as a leading indicator during this period, largely because it falsely predicted an economic downturn in the autumn of 1998. This dichotomy of findings is perhaps not surprising, because as asset markets evolve, the information content of prices in these markets may change as well. The range of empirical findings may also reflect the fact that this research has generally relied on a single credit spread index, rather than on multiple indexes reflecting a broad cross-section—in terms of both default risk and maturity—of private debt instruments.

In part to address these problems, Gilchrist et al. [2009] (GYZ hereafter) constructed credit spreads directly from the monthly data on prices of individual senior unsecured corporate bonds trading in the secondary market. These micro-level credit spreads were then sorted into bond portfolios by the remaining term-to-maturity of the underlying bond issue and by the credit risk of the issuer as measured by its monthly expected default frequency (EDF) constructed by the Moody's/KMV. According to the results reported by GYZ, these portfolio credit spreads have substantial predictive power for the growth of payroll employment and industrial production—at both short- and longer-term horizons—and significantly outperform the predictive ability of the standard default-risk indicators. Moreover, GYZ results indicate that the information content of credit spreads is concentrated in portfolios consisting of long-maturity bonds issued by firms at a high-end of the credit-quality spectrum.

While certainly tantalizing, the economists' seemingly endless search for an asset price(s) that will consistently and accurately predict macroeconomic outcomes naturally raises concerns that the GYZ results are due to data mining. Even if asset prices had no true predictive power, a finding that a particular asset market indicator is a useful predictor of future economic activity would be bound to crop up from time to time. In this paper, we address these concerns through the use of Bayesian Model Averaging (BMA), a framework that explicitly takes into account model uncertainty. The BMA approach to economic forecasting involves using a potentially large number of possible models, one of which is considered to be the true data-generating process; using the BMA methodology, a researcher can then evaluate the posterior probability that each model is the "true model." In addition, the forecasts from the different models can be combined into a single forecast—the so-called BMA forecast—using the models' posterior probabilities as weights.

The contribution of our paper is not in the econometric methodology for forecasting with a large number of predictors—a literature that has been very active in recent years.

Rather, we are concerned about the choice of which variables are best suited for predicting economic activity in a data-rich environment. In particular, we consider a large number of asset prices, yields, and spreads as predictors of a wide variety of indicators of economic activity. In addition to the standard set of asset market indicators, we use the "bottom up" approach of GYZ to construct credit spreads for the bond portfolios sorted by the bond's remaining term-to-maturity and the issuer's credit quality, which are then included in the prediction exercise. We also adjust our portfolio credit spreads for the fact that a significant portion of the underlying securities are callable, a feature, as pointed out by Duffee [1998] and Duca [1999], with important consequences for the behavior of credit spreads over the course of the business cycle. Finally, the set of predictors also includes macroeconomic variables, and the forecasting methods are assessed in an out-of-sample prediction exercise conducted using real-time data.

Our results indicate that in forecasting the growth rates of real GDP, real business fixed investment, industrial production, and employment, as well as the change in the unemployment rate, the BMA approach assigns a high weight to our option-adjusted portfolio credit spreads. Moreover, the resulting BMA forecasts yield economically and statistically significant improvements in the forecast accuracy over a univariate autoregression, a standard benchmark in this sort of forecasting exercises. In contrast, if the portfolio credit spreads are omitted from the predictor set, the BMA forecasts are generally statistically indistinguishable from the forecasts based on the autoregressive benchmark.

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. Lastly, 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. nonfinancial corporations. Specifically, from the Lehman/Warga (LW) and Merrill Lynch (ML) databases, we obtained month-end prices of outstanding long-term corporate bonds that are actively traded in the secondary market.[2] To guarantee that we

[2]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. Focused on the most liquid securities in the secondary market, bonds in the ML database must have a remaining term-to-maturity of at least two years, a fixed coupon schedule, and a minimum amount outstanding of $100 million for below investment-grade and $150 million for investment-grade issuers. By contrast, the LW database of month-end bond prices has a somewhat broader coverage

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 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-to-maturity of less than one year or more than 30 years; calculating spreads for maturities of less than one year and more than 30 years would involve extrapolating the Treasury yield curve beyond its support.[3] These selection criteria yielded a sample of 5,896 individual securities between January 1986 and June 2010. 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 firms.

and is available from 1973 through mid-1998 (see Warga [1991] for details).

[3]We also eliminated a small number of putable 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.

Table 1: Summary Statistics of Corporate Bond Characteristics

Variable	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[a] ($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 effective yield (pct.)	7.30	3.04	0.60	6.93	44.3
Credit spread (bps.)	215	297	5	123	3,499

NOTE: Sample period: Jan1986–June2010; No. of bonds/firms = 5,896/1,104; Obs. = 305,412. Sample statistics are based on trimmed data (see text for details).

[a]Market value of the outstanding issue deflated by the CPI (1982–84 = 100).

Table 1 contains summary statistics for the key characteristics of bonds in our sample. Note that a typical firm has only a few senior unsecured issues outstanding at any point in time—the median firm, for example, has two such issues trading at any given month. This distribution, however, exhibits a significant positive skew, as some firms can have as many as 74 different senior unsecured bond issues trading in the market at a point in time. The distribution of the real market values of these issues is similarly skewed, with the range running from $1.2 million to more than $5.6 billion. Not surprisingly, the maturity of these debt instruments is fairly long, with the average maturity at issue of about 13 years. Because corporate bonds typically generate significant cash flow in the form of regular coupon payments, the effective duration is considerably shorter, with both the average and the median duration of about 6 years.

According to the S&P credit ratings, our sample spans the entire spectrum of credit quality, from "single D" to "triple A." At "BBB1," however, the median bond/month observation is still solidly in the investment-grade category. Turning to returns, the (nominal) coupon rate on these bonds averaged 7.30 percent during our sample period, while the average expected total return, as measured by the nominal effective yield, was 7.3 percent per annum. Reflecting the wide range of credit quality, the distribution of nominal yields is quite wide, with the minimum of 0.66 percent and the maximum of more than 44 percent. Relative to Treasuries, an average bond in our sample has an expected return of about 215 basis points above the comparable risk-free rate, with the standard deviation of 297 basis points.

2.2 Default Risk

In this section, we describe the construction of variables used as proxies for the firm-specific default risk, the crucial input in the construction of our bond portfolios. To measure a firm'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 can be directly observed, 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 first critical assumption underlying the DD-framework is that the total value of the a firm—denoted by V—follows a geometric Brownian motion:

$$dV = \mu_V V dt + \sigma_V V dW, \tag{1}$$

where μ_V denotes the expected continuously-compounded return on V; σ_V is the volatility of firm value; and dW is an increment of the standard Weiner process. The second critical assumption pertains to the firm's capital structure. In particular, it is assumed that the firm has just issued a single discount bond in the amount D that will mature in T periods.[4] Together, these two assumption imply that the value of the firm's equity E can be viewed as a call option on the underlying value of the firm V with a strike price equal to the face value of the firm's debt D and a time-to-maturity of T. According to the Black-Scholes-Merton option-pricing framework, the value of the firm's equity then satisfies:

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2), \tag{2}$$

where r denotes the instantaneous risk-free interest rate, $\Phi(\cdot)$ is the cumulative standard normal distribution function, and

$$\delta_1 = \frac{\ln(V/D) + (r + 0.5\sigma_V^2)T}{\sigma_V^2\sqrt{T}} \quad \text{and} \quad \delta_2 = \delta_1 - \sigma_V\sqrt{T}.$$

According to equation (2), the value of the firm's equity depends on the total value of the firm and time, a relationship that also underpins the link between volatility of the firm's

[4]Recent structural default models relax this assumption and allow for endogenous capital structure as well as for strategic default. In these models, both the default time and default boundary are determined endogenously and depend on firm-specific as well as aggregate factors; the voluminous literature on structural default models is summarized by Duffie and Singleton [2003].

value σ_V and the volatility of its equity σ_E. In particular, it follows from Ito's lemma that

$$\sigma_E = \left[\frac{V}{E}\right] \frac{\partial E}{\partial V} \sigma_V. \tag{3}$$

Because under the Black-Scholes-Merton option-pricing framework $\frac{\partial E}{\partial V} = \Phi(\delta_1)$, the relationship between the volatility of the firm's value and the volatility of its equity is given by

$$\sigma_E = \left[\frac{V}{E}\right] \Phi(\delta_1) \sigma_V. \tag{4}$$

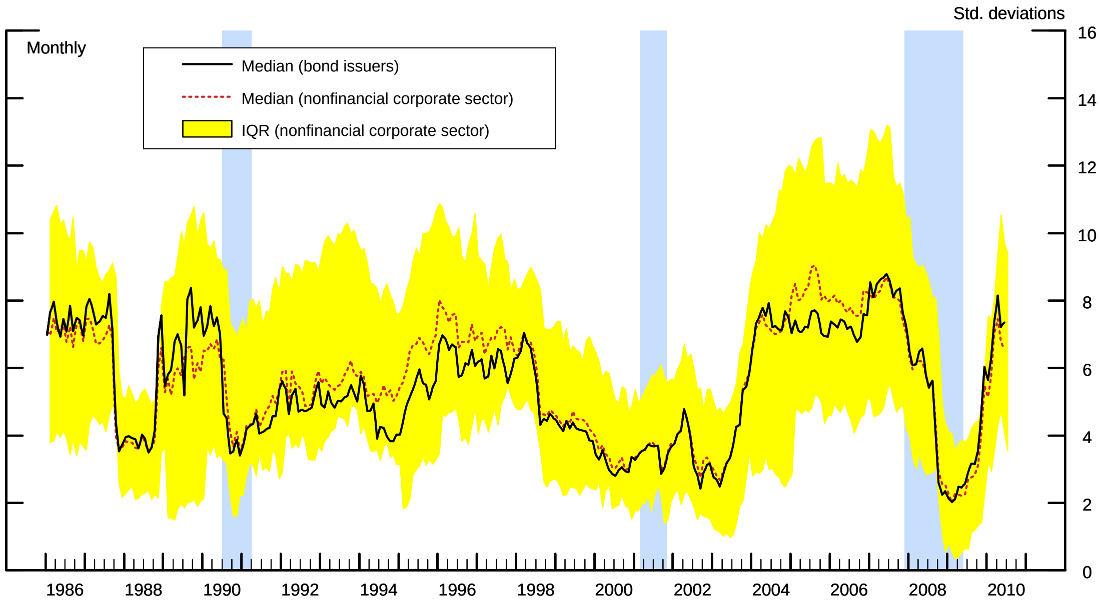
From an operational standpoint, the most critical inputs to the Merton DD-model are clearly the market value of the equity E, the face value of the debt D, and the volatility of equity σ_E. Assuming a forecasting horizon of one year (i.e., $T = 1$), we implement the model in two steps: First, we estimate σ_E from historical daily stock returns. Second, we assume that the face value of the firm's debt D is equal to the sum of the firm's current liabilities and one-half of its long-term liabilities.[5] Using the observed values of E, D, σ_E, and r (i.e., the 1-year constant-maturity Treasury yield), equations (2) and (4) can be solved for V and σ_V using standard numerical techniques. However, as pointed out by Crosbie and Bohn [2003] and Vassalou and Xing [2004], the excessive volatility of market leverage (V/E) in equation (4) causes large swings in the estimated volatility of the firm's value σ_V, which are difficult to reconcile with the observed frequency of defaults and movements in financial asset prices.

To resolve this problem, we implement an iterative procedure recently proposed by Bharath and Shumway [2008]. The procedure involves the following steps: First, we initialize the procedure by letting $\sigma_V = \sigma_E[D/(E + D)]$. We then use this value of σ_V in equation (2) to infer the market value of the firm's assets V for every day of the previous year. In the second step, we calculate the implied daily log-return on assets (i.e., $\Delta \ln V$) and use the resulting series to generate new estimates of σ_V and μ_V. We then iterate on σ_V until convergence. The resulting solutions of the Merton DD-model can be used to calculate the firm-specific DD over the one-year horizon as

$$DD = \frac{\ln(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}. \tag{5}$$

[5] This assumption for the "default point" is also used by Moody's/KMV in the construction of their Expected Default Frequencies (EDFs) based on the Merton DD-model, and it captures the notion that short-term debt requires a repayment of the principal relatively soon, whereas long-term debt requires the firm to meet only the coupon payments. Both current and long-term liabilities are taken from quarterly Compustat files and interpolated to daily frequency using a step function.

Figure 1: Distance-to-Default



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

The corresponding implied probability of default—the so-called EDF—is given by

$$EDF = \Phi(-DD) = \Phi\left(-\left(\frac{\ln(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}\right)\right), \tag{6}$$

which, under the assumptions of the Merton model, should be a sufficient statistic for predicting defaults.

We employ this methodology to calculate the distance-to-default for all U.S. nonfinancial corporations covered by the S&P's Compustat and CRSP (i.e., 11,886 firms over the Jan1986–June2010 period). Figure 1 plots the cross-sectional median of the DDs for the 1,104 bond issuers in our sample. As a point of comparison, the figure also depicts the cross-sectional median and interquartile range (IQR) of the DDs for the entire Compustat-CRSP matched sample of nonfinancial firms.[6] According to this metric, the credit quality of the median bond issuer in our sample is, on average, very close to that of the median nonfinancial firm, indicating that our sample of firms is representative of the broader economy. The

[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 the DD of more than 20 or less than -2, cutoffs corresponding roughly to the 99th and 1st percentiles of the DD distribution, respectively.

median DD for both groups of firms is strongly procyclical, implying that equity investors 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 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 four quartiles based on the distribution of the distance-to-default in month $t-1$. The distance-to-default portfolios are constructed by computing a weighted average of DDs in month t for each DD quartile, 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 DD quartile, with the weights equal to the market value of the firm's equity at the end of month $t-1$.[7]

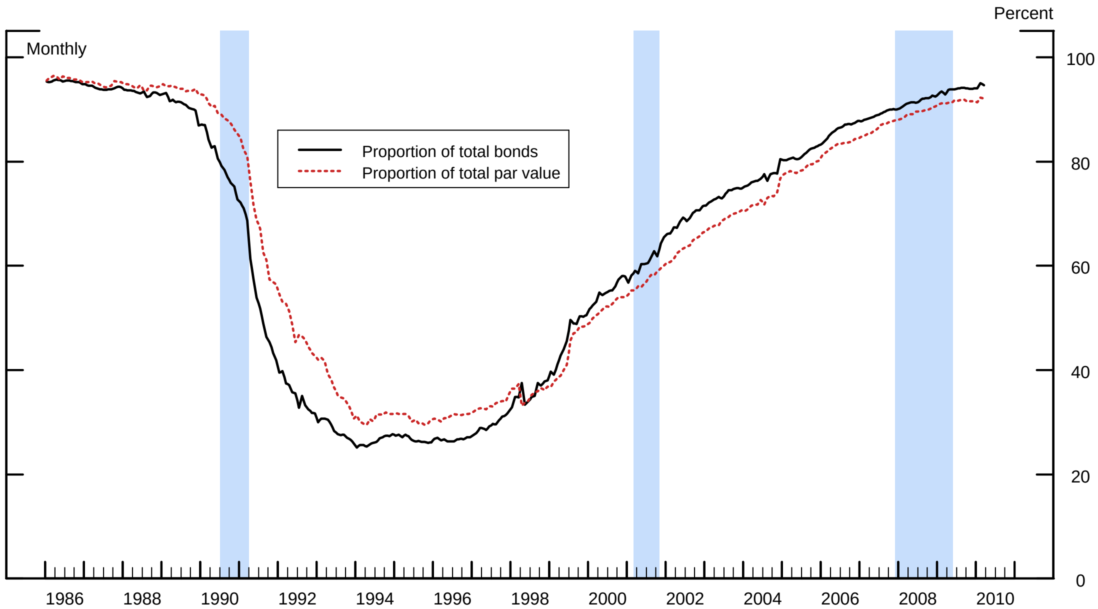
The construction of the corresponding bond portfolios is complicated by the fact that a significant portion of bonds in our sample are callable (see Figure 2). As shown by Duffee [1998], if the firm's outstanding bonds are callable, movements in the risk-free rates—by changing the value of the embedded 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 control directly for the effects of the Treasury term structure and interest rate uncertainty on the credit spreads of callable bonds when constructing bond portfolios. In particular, we consider the following empirical bond-pricing model:

$$\begin{aligned}\ln S_{it}[k] = {} & (1 + CALL_i[k]) \times (\alpha + \beta_1 DD_{it} + \beta_2 DD_{it}^2 + \gamma' X_{it}[k]) \\ & + CALL_i[k] \times (\theta_1 LEV_t + \theta_2 SLP_t + \theta_3 CRV_t + \theta_4 VOL_t) + RTG_{it}[k] + \epsilon_{it}[k], \quad (7)\end{aligned}$$

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

Figure 2: Callable Nonfinancial 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.

where $CALL_i[k]$ is an indicator variable that equals one if bond k (issued by firm i) is callable and zero otherwise, 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, credit spreads of callable bonds are allowed to depend separately on the level (LEV_t), slope (SLP_t), and curvature(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 credit 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 (VOL_t).

We also allow for a nonlinear effect of default risk on credit spreads by including a quadratic term of DD_{it} in the bond-pricing regression, thereby accounting for the nonlinear relationship between credit spreads and leverage documented by Levin et al. [2004].[10] The

[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.

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 ($\ln DUR_{it}[k]$), the amount outstanding ($\ln PAR_{it}[k]$), and the bond's (fixed) coupon rate ($\ln CPN_i[k]$). The bond-pricing regression also includes credit rating fixed effects ($RTG_{it}[k]$), which capture the "soft information" regarding the firm's financial health, information that is complementary to our option-theoretic measures of default risk; see, for example, Löffler [2004, 2007].

Using this framework, we adjust credit spreads on callable bonds (i.e., $CALL_i[k] = 1$) according to

$$\begin{aligned}\tilde{S}_{it}[k] = \exp\Big[&\ln S_{it}[k] - CALL_i[k] \times (\hat{\alpha} + \hat{\beta}_1 DD_{it} + \hat{\beta}_2 DD_{it}^2 + \hat{\gamma}' X_{it}[k]) \\ &- (\hat{\theta}_1 LEV_t + \hat{\theta}_2 SLP_t + \hat{\theta}_3 CRV_t + \hat{\theta}_4 VOL_t)\Big],\end{aligned}$$

where $\tilde{S}_{it}[k]$ is the option-adjusted spread on a callable bond k and $\hat{\alpha}, \hat{\beta}_1, \hat{\beta}_2$, and $\hat{\theta}_1, \ldots, \hat{\theta}_4$ denote OLS estimates of the corresponding parameters from the bond-pricing regression (7). 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. Consistent with the theoretical predictions, the effect of the distance-to-default on the credit spreads of callable bonds 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 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 51 basis points reduction in the credit spreads on callable bonds, while a one standard deviation increase in the slope factor lowers credit spreads on such bonds 32 basis points. 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 data set, calculated using both the raw and option-adjusted spreads. Although the two series are clearly highly correlated ($\rho = 0.88$) and are both strongly procyclical, there are a number of noticeable differences. First, the option-adjusted credit spreads are, on average, lower

Table 2: Selected Marginal Effects by Type of Bond

	Noncallable		Callable			
Marginal Effect	*Est.*	*S.E.*	*Est.*	*S.E.*	*Mean*[a]	*STD*[b]
Distance-to-default: DD_{it}	-0.227	0.013	-0.138	0.009	6.669	4.246
Term structure: LEV_t	-	-	-0.508	0.045	0.000	1.000
Term structure: SLP_t	-	-	-0.319	0.039	0.000	1.000
Term structure: CRV_t	-	-	-0.053	0.044	0.000	1.000
Term structure: VOL_t (%)	-	-	0.153	0.014	10.39	2.596
Obs. = 305,412						
No. of bonds/firms = 5,896/1,104						
Adjusted R^2 = 0.730						

NOTE: The table contains the estimates of the marginal effect of a one unit change in the specified variable on the level of credit spreads (in percentage points) for noncallable and callable bonds based on the bond-pricing regression (7). All marginal effects are evaluated at sample means; by construction, the level, slope, and curvature factors are standardized to have the mean equal to zero and the standard deviation equal to one. Robust asymptotic standard errors are double clustered in the firm (i) and time (t) dimensions; see Cameron et al. [2010] for details.

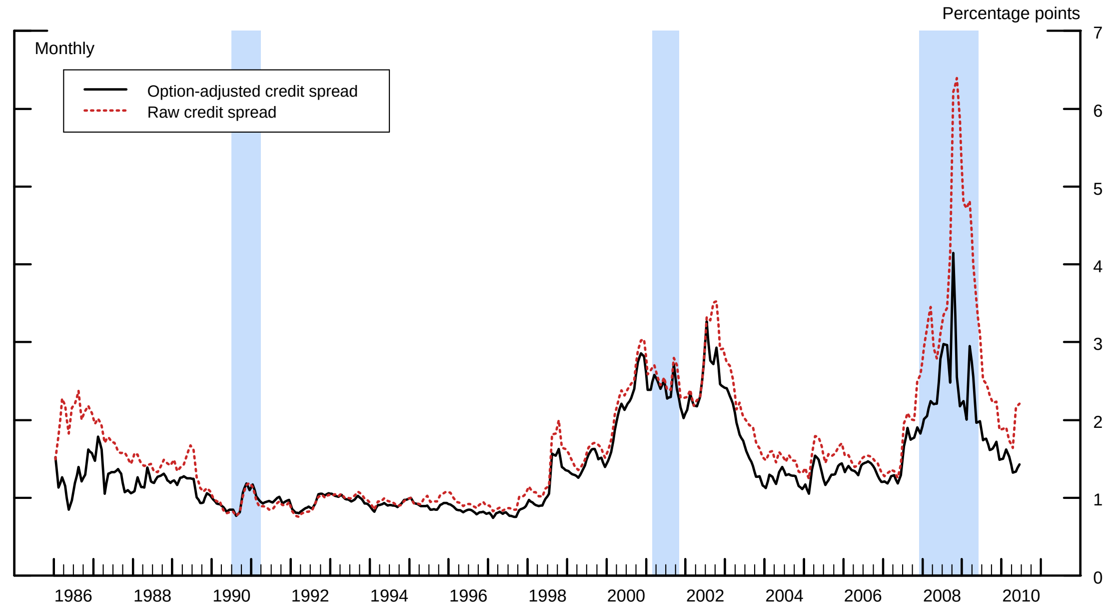
[a]Sample mean of the specified variable.

[b]Sample standard deviation of the specified variable.

than their unadjusted counterparts—140 basis points compared with 168 basis points—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 most 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 (long-term) interest rate volatility that occurred during that period.

We use the option-adjusted credit spreads to construct the DD-based bond portfolios. To control for maturity, we also split each conditional DD quartile of credit spreads into four maturity categories: (1) *short maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 1 year but less than (or equal) to 5 years; (2) *intermediate maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 5 years but less than (or equal) 10 years; (3) *long maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 10 years but less than (or equal) to 15 years;

Figure 3: Credit Spreads on Nonfinancial Corporate Bonds



NOTE: Sample period: Jan1986–June2010. The solid line depicts the time-series of the weighted 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 average of the raw credit spreads. In both cases, the weights are equal to the market values of the underlying bond issues. The shaded vertical bars represent the NBER-dated recessions.

(4) *very long maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 15 years. We then compute a weighted average of credit spreads in month t for each DD/maturity portfolio, with the weights equal to the market value of the outstanding issue; this procedure yields 16 bond portfolios of credit spreads (four DD quartiles and four maturity categories).

Table 3 contains summary statistics of the DDs, credit spreads, and excess equity returns in the DD-based portfolios. Not surprisingly, the average distance-to-default increases across the four conditional DD quartiles. 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 the most risky 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 four conditional DD quartiles in all four maturity categories. The Sharpe ratio within each maturity category is fairly constant for the portfolio of bonds in the first three DD quartiles. However, the Sharpe ratio drops markedly for portfolios containing bonds issued by the riskiest firms.

The time-series characteristics of excess equity returns of firms in our four default-risk

Table 3: Summary Statistics of Financial Indicators in DD-Based Portfolios

Financial Indicator	DD Quartile[a]	Mean	SD	S-R[b]	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

NOTE: Sample period: Jan1986–June2010. Distances-to-default are in units of standard deviations, credit spreads are in percentage points, and (monthly) excess equity returns are in percent.

[a]The (weighted) average of financial indicators in month t in each quartile is based on the distance-to-default (DD) distribution in month $t-1$ (see text for details).

[b]Sharpe ratio.

categories, by contrast, do not exhibit much of a systematic pattern. Portfolios based on returns of firms from the center of the credit quality spectrum (i.e., DD quartiles 2 and 3) have identical Sharpe ratios, whereas the least risky firms (i.e., DD quartile 4) have an appreciably better reward-to-variability ratio, a result that largely reflects the absence of very large negative returns associated with the recent financial crisis. In contrast, firms in the first DD quartile 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.[11]

The DD-based portfolios considered thus far were based on asset prices of a subset of nonfinancial 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. nonfinancial corporations. Given the large number of firms in any given month, we increase the granularity of the portfolios by sorting 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, a procedure yielding 20 additional DD-based portfolios of financial indicators.

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 application, 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

In using the BMA approach, the researcher considers a set of n possible models, where the i-th model, denoted by M_i, is characterized by the parameter vector θ_i. One of these models is the true model, but the researcher does not know which one. 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

[11] Although financial theory predicts a positive relationship between default risk and equity returns, empirically, stocks of firms with a high likelihood of default have anomalously low returns; see, for example, Griffin and Lemmon [2002] and Campbell et al. [2008]

true model according to

$$P(M_i|D) = \frac{P(D|M_i)P(M_i)}{\sum_{j=1}^{n} P(D|M_j)P(M_j)}, \tag{8}$$

where

$$P(D|M_i) = \int P(D|\theta_i, M_i)P(\theta_i|M_i)d\theta_i \tag{9}$$

is the marginal likelihood of the i-th model; $P(\theta_i|M_i)$ is the prior density of the parameter vector θ_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 BMA, 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, all the models considered are linear regressions. Specifically, the i-th model is given by

$$y_{t+h} = \beta_i' X_{it} + \gamma' Z_t + \epsilon_{t+h}, \tag{10}$$

where y_t is the variable that the researcher wishes to forecast at a horizon of h periods; X_{it} is a $(p_i \times 1)$-vector of predictors that are specific to model i; Z_t is a $(p_0 \times 1)$-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 predictors X_{it} are 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 γ and σ^2, denoted by $p(\gamma, \sigma)$, is uninformative and is proportional to $1/\sigma$, while using the g-prior specification of Zellner [1986] for β_i conditional on σ^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 ϕ corresponds to a more dogmatic prior. Letting $\hat{\beta}_i$ and $\hat{\gamma}$ denote the OLS estimates of the parameters in equation (10), respectively, then the Bayesian h-period-ahead forecast made from model M_i at time T is

$$\tilde{y}^i_{T+h|T} = \tilde{\beta}_i' X_{it} + \hat{\gamma}' Z_t, \tag{11}$$

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

$$P(D|M_i) \propto \left[\frac{1}{1+\phi}\right]^{-\frac{p_i}{2}} \times \left[\frac{1}{1+\phi} SSR_i + \frac{\phi}{1+\phi} SSE_i\right]^{-\frac{(T-p_0)}{2}}, \tag{12}$$

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 (8), and the final BMA forecast that takes into account model uncertainty is given by

$$\tilde{y}_{T+h|T} = \sum_{i=1}^{n} P(M_i|D)\tilde{y}^{i}_{T+h|T}. \tag{13}$$

Clearly, the BMA forecast in equation (13) will depend on the value of the shrinkage hyperparameter ϕ. A small value of ϕ 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 ϕ 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 ϕ is often U-shaped, the best out-of-sample forecasts are obtained when ϕ is neither too small nor too big.

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 our regression equation (10) are a constant and lags of the dependent variable. In our application, as well as in nearly any macro-finance application, the assumptions used in deriving equation (12) are clearly false in two respects. First, the regressors are assumed to be strictly exogenous; that said, many of the commonly-used methods for combining a large number of variables in forecasting exercises, including bagging and empirical Bayes methods, likewise have a theoretical justification that relies on strict exogeneity of the regressors. 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.

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, and the civilian unemployment rate over the period from 1986:Q1 to 2010:Q1. 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 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:

$$y^C_{t+h} = \alpha + \beta_i x_{it} + \sum_{j=1}^{p} \gamma_j y_{t-i} + \epsilon_{t+h}, \tag{14}$$

where x_{it} is one of the predictors listed in Table 4 and p, the number of lags, is determined by the Bayes Information Criterion (BIC). The set of possible predictors listed in Table 4 includes 15 different macroeconomic series and 80 asset market indicators. The asset market indicators include our 16 bond portfolios of options-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, a range of standard interest rates and interest rate spreads, implied volatilities from options quotes, and commodity prices.

The timing convention in the forecasting regression (14) 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. Importantly, all of these data would have been available at the time that the Philadelphia Fed assembled its mid-quarter vintage data set.

The option-adjustment procedure is also implemented in real-time—that is, the parameters of the bond-pricing regression (7) 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.[12] 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., $h = 0, 1, \ldots, 4$). 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:Q1.

[12] 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 4: Predictor Set

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
Asset Market Indicators (80)	
Credit spreads in DD-based bond portfolios (16)	level
Avg. DD by DD quartile (bond issuers) (4)	level
Avg. DD by DD decile (nonfinancial firms) (10)	level
Excess stock returns by DD quartile (bond issuers) (4)	level
Excess stock returns by DD decile (nonfinancial 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 implied volatility	level
10- and 30-year Treasury futures implied volatility (2)	level
Eurodollar futures implied volatility	level
Gold spot price	second difference of logs
Oil spot price	second difference of logs
CRB commodity spot price index	second difference of logs

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]

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

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:[13]

$$y_{t+h}^{C} = \alpha + \sum_{j=1}^{p} \gamma_j y_{t-i} + \epsilon_{t+h}. \tag{15}$$

Unfortunately, evaluating the statistical significance of the difference in root 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. 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 mimic those of the underlying data. The bootstrap hence allows us to test the null hypothesis of no improvement in forecast accuracy.

The bootstrap involves fitting an AR(4) process to y_t and separately estimating a dynamic factor model using the set of all predictors X_t:

$$X_t = \Lambda F_t + u_t; \tag{16}$$

and

$$F_t = \Phi F_{t-1} + v_t, \tag{17}$$

where F_t denotes the first three principal components of X_t. In each bootstrap replication, we first re-sample with replacement from the residuals of y_t to construct bootstrap samples of y_t. We then independently re-sample with replacement from the residuals in equations (16) and (17), thereby constructing bootstrap samples of X_t for use in BMA; note that in this

[13] Note that this is a direct autoregression that projects y_{t+h}^{C} onto four 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.

Table 5: BMA Out-of-Sample Predictive Accuracy

Predictors: Macroeconomic Variables & Asset Market Indicators					
	Forecast Horizon (h quarters)				
Economic Activity Indicator	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
GDP	0.95	0.87	0.78	0.81	0.81
	[0.04]	[0.01]	[0.00]	[0.01]	[0.01]
Personal consumption expenditures	0.91	0.89	0.92	0.98	1.03
	[0.02]	[0.04]	[0.08]	[0.17]	[0.33]
Business fixed investment	0.87	0.72	0.70	0.71	0.74
	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]
Industrial production	0.95	0.85	0.84	0.84	0.80
	[0.02]	[0.00]	[0.00]	[0.01]	[0.01]
Private employment	0.88	0.73	0.80	0.81	0.77
	[0.00]	[0.00]	[0.00]	[0.02]	[0.01]
Unemployment rate	0.92	0.80	0.86	0.94	0.93
	[0.00]	[0.00]	[0.01]	[0.09]	[0.08]

NOTE: Sample period: 1986:Q1–2010:Q1. 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 brackets.

setup, the predictor set X_t is, by construction, irrelevant for the forecasting of the dependent variable.

4 Results

Table 5 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 one, are shown in brackets. 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 bootstrapped 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. For this volatile and cyclically important indicator of economic activity, the BMA forecast improves on the direct autoregression by almost 30 percent at forecast horizons of one to four quarters. The growth of personal consumption expenditures, in contrast, is 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 one 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 0.80 and 0.95, improvements that are statistically highly significant. The relative MSPEs in the case of employment growth are between 0.73 and 0.88, values that are again all below one at conventional significance levels. For changes in the unemployment rate, the BMA forecast is more accurate than the univariate autoregression at all horizons, but the improvements are only statistically significant at the shorter horizons. Overall, our results indicate 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 private employment.[14]

To gauge the information content of credit spreads in predicting economic outcomes, we first repeat the forecast comparison exercise by using *only* the credit spreads in the 16 DD-based bond portfolios in the set of predictors and then by using all predictors *except* for the credit spreads. The results of this exercise are shown in the top and bottom panels of Table 6, respectively. According to the top panel, the accuracy of the BMA forecasts based only on credit spreads is very similar to that reported in Table 5 for most economic indicators and forecast horizons. Although restricting the predictor set to only credit spreads in our DD-based portfolios does lead to a loss of forecast accuracy for output and consumption growth at longer horizons, using only credit spreads as predictors actually improves the accuracy of the BMA forecast of the change in the unemployment rate.

In contrast, the exclusion of the DD-based portfolios of credit spreads from the predictor set results in a substantial deterioration in the predictive accuracy of the BMA forecasts.

[14]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. By construction, factors are designed to explain the maximum amount of the cross-sectional variation in the set of predictors, which is not the same thing as predicting future economic activity. Equally-weighted average of the OLS-based forecasts works relatively well, but it assumes away the possibility that some variables may be more useful for forecasting economic activity than others.

Table 6: The Information Content of Credit Spreads
(BMA Out-of-Sample Predictive Accuracy)

Predictors: Option-Adjusted Credit Spreads Only

	Forecast Horizon (h quarters)				
Economic Activity Indicator	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
GDP	0.91	0.88	0.89	1.00	1.03
	[0.02]	[0.01]	[0.03]	[0.26]	[0.41]
Personal consumption expenditures	0.87	0.88	1.03	1.14	1.19
	[0.00]	[0.03]	[0.53]	[0.87]	[0.89]
Business fixed investment	0.85	0.69	0.71	0.74	0.77
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Industrial production	0.91	0.79	0.84	0.90	0.86
	[0.00]	[0.00]	[0.00]	[0.03]	[0.02]
Private employment	0.84	0.70	0.72	0.73	0.71
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Unemployment rate	0.86	0.71	0.74	0.79	0.78
	[0.00]	[0.00]	[0.00]	[0.01]	[0.01]

Predictors: 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	0.96	0.96	0.95
	[0.05]	[0.06]	[0.08]	[0.10]	[0.09]
Personal consumption expenditures	0.97	0.90	0.92	0.96	1.02
	[0.12]	[0.04]	[0.07]	[0.14]	[0.28]
Business fixed investment	0.93	0.91	0.93	0.95	0.92
	[0.01]	[0.01]	[0.04]	[0.10]	[0.08]
Industrial production	0.98	1.03	1.12	1.13	1.16
	[0.06]	[0.64]	[0.89]	[0.80]	[0.80]
Private employment	0.98	1.01	1.09	1.10	1.07
	[0.11]	[0.35]	[0.73]	[0.65]	[0.48]
Unemployment rate	0.92	0.94	1.07	1.10	1.05
	[0.01]	[0.04]	[0.74]	[0.69]	[0.44]

NOTE: Sample period: 1986:Q1–2010:Q1. 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 brackets.

As shown in the bottom panel of Table 6, for the current-quarter forecasts, BMA yields only small improvements in forecast accuracy relative to the univariate benchmark. Moreover, the relative MSPEs of BMA forecasts at horizons beyond the current quarter are statistically indistinguishable from one in nearly all cases. In summary, absent the information content of credit spreads in our DD-based bond portfolios, the evidence of predictability of economic activity beyond the current quarter appears to be quite weak and inconsistent.

4.1 Which Predictors are the Most Informative?

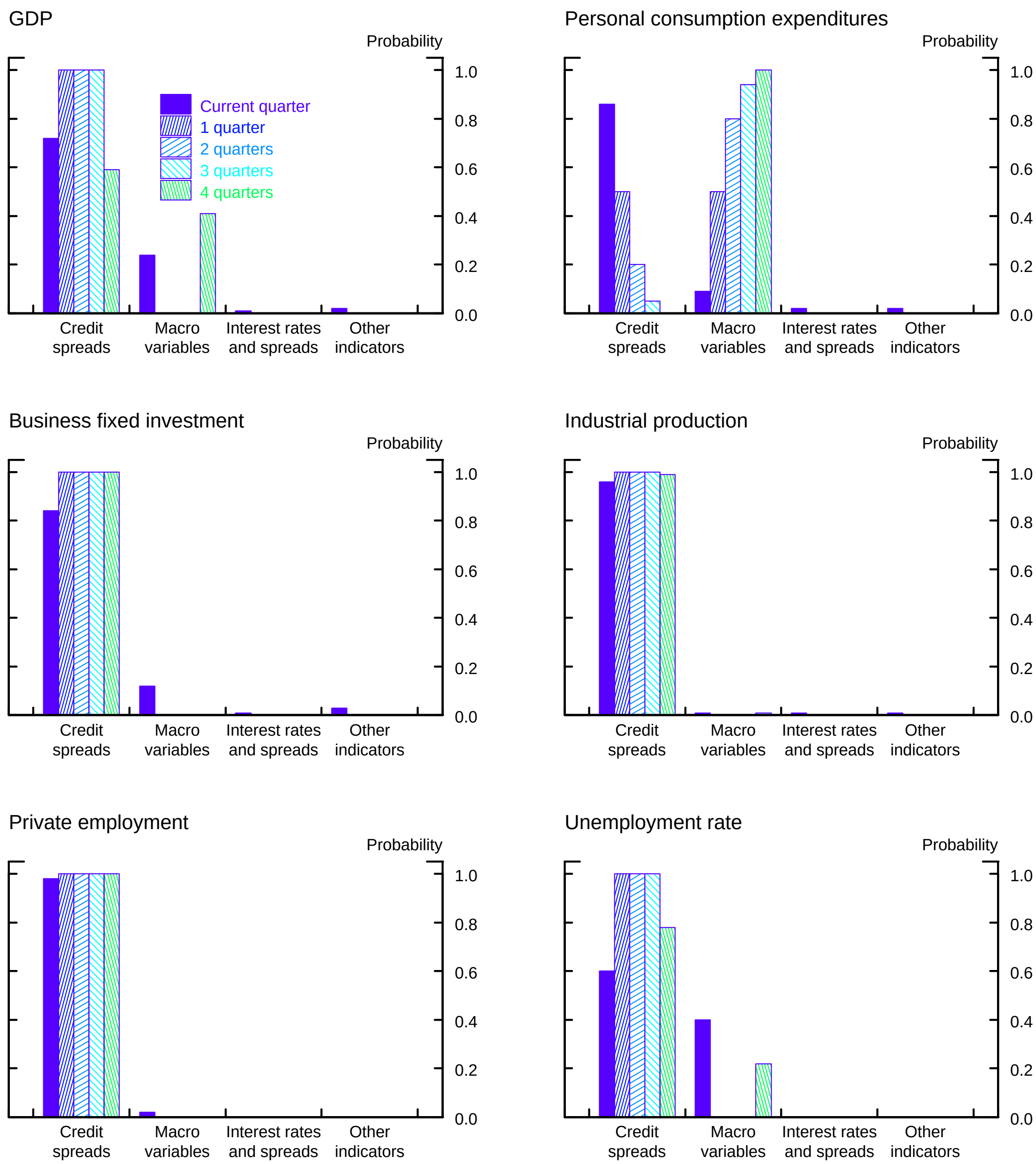
Figure 4 depicts the total weights—that is, the sum of posterior probabilities—that BMA assigns to variables in the following predictor subsets: (1) option-adjusted credit spreads in the DD-based bond portfolios; (2) macroeconomic variables; (3) Treasury yields and the associated interest rate spreads; and (4) all other asset market indicators. Results are shown for all forecast horizons considered and for each of the six different indicators of economic activity that we forecast.

According to these results, BMA assigns some weight to the macroeconomic variables in a number of cases. But, generally, BMA ascribes the vast majority of the posterior weight to the information content of option-adjusted credit spreads in our DD-based bond portfolios. Figure 5 depicts the posterior probabilities that BMA assigns to each of the 16 different DD-based bond portfolios when forecasting at the four-quarter-ahead horizon, using only these credit spreads as predictors. Note that, by construction, the posterior probabilities must sum to one for each indicator of economic activity.

Within the different bond portfolios, BMA assigns substantial posterior probabilities to multiple credit spreads, so it represents a genuine model combination exercise, as opposed to model selection. In general, credit spreads based on portfolios of long-maturity bonds (i.e., securities with the remaining term-to-maturity between 5 and 10 years) appear to be the most informative about the economic outlook, as these long-maturity credit spreads are consistently assigned a high posterior weight.

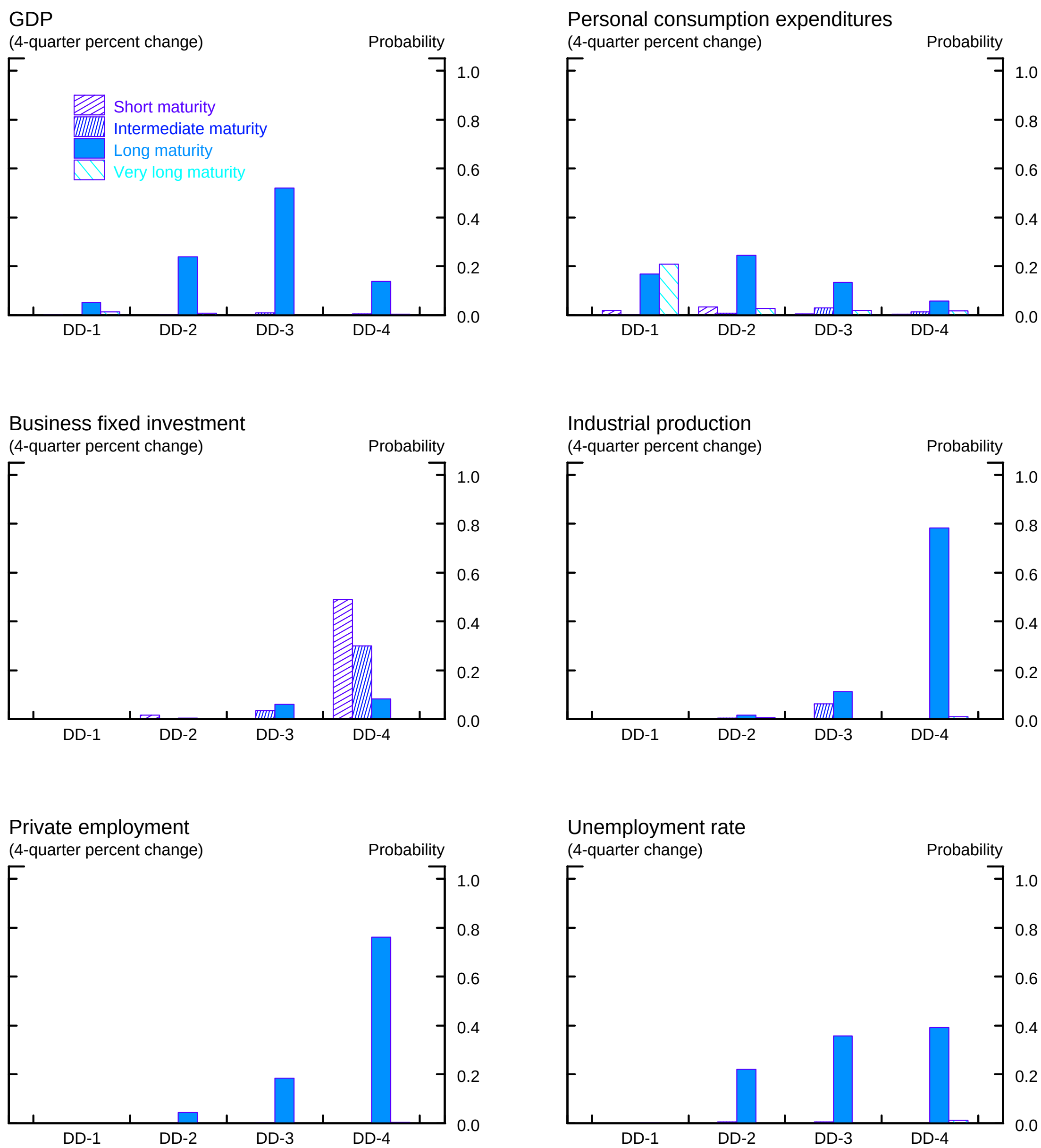
With regards to credit quality, BMA tends to place most posterior weight on credit spreads in portfolios containing securities issued by firms in the upper half of the credit quality distribution—that is, portfolios corresponding to the third and fourth quartile of the DD distribution. The exceptions seem to be the forecasts of output and consumption growth, two economic indicators for which BMA assigns a noticeable weight credit spreads associated with somewhat riskier firms. All told, these results are broadly consistent with those of Gilchrist et al. [2009] who find that the information content of credit spreads is concentrated in portfolios consisting of long-maturity bonds issued by firms at the middle and upper end of the credit-quality spectrum.

Figure 4: BMA Posterior Probabilities by Predictor Type



NOTE: The figure depicts the total weight (i.e., 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) Treasury yields and the associated interest rate spreads; and (5) all other asset market indicators. The entire set of predictors is listed in Table 4.

Figure 5: BMA Posterior Probabilities for Option-Adjusted Credit Spreads



Note: The figure depicts the total weight (i.e., posterior probability) that BMA assigns to the 16 DD-based bond portfolios consisting of the option-adjusted credit spreads. The results shown are for the four-quarter-ahead forecast horizon and for the case in which the predictor set includes only the option-adjusted credit spreads (see the top panel of Table 6); as a result, the posterior probabilities sum to one for each indicator of economic activity.

4.2 Robustness Checks

4.2.1 Varying the Priors

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 ϕ, the parameter governing the strength of the g-prior. Figure 6 plots the MSPE of the BMA forecast—relative to the MSPE from a direct autoregression—as a function of ϕ 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 ϕ; 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 ϕ (at least over the range of values of ϕ considered). In others, the relationship between the MSPE and ϕ is U-shaped, and the best forecasts are consequently obtained with a small or intermediate value of ϕ.

With a sufficiently small value of ϕ—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.[15] 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 ϕ.

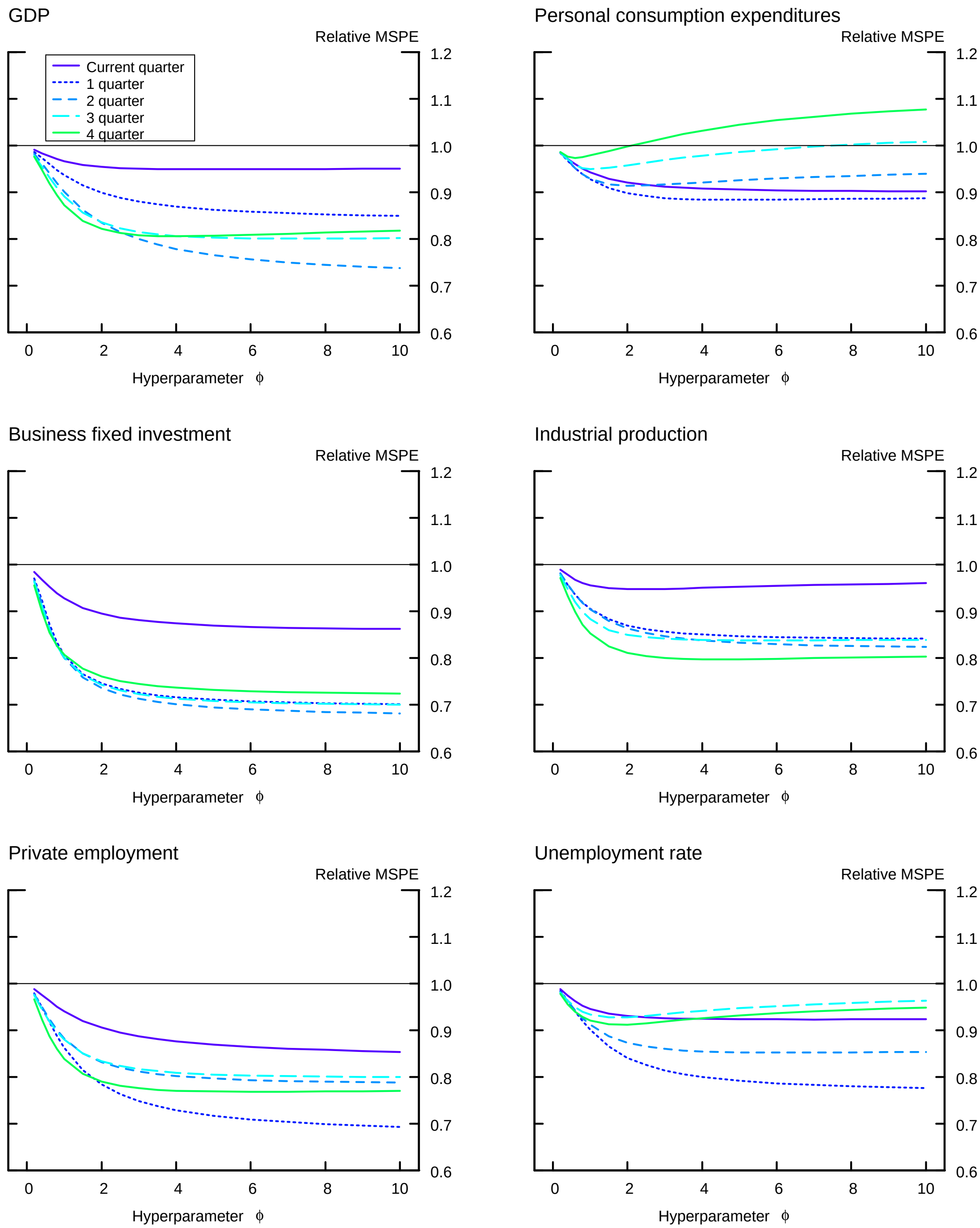
4.2.2 Raw vs. Option-Adjusted Credit Spreads

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 16 bond portfolios; indeed, the real-time option adjustment makes even a 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 is 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 statistically and economically

[15] Note that in the limit, as ϕ goes to zero, the BMA forecast is, by construction, equivalent to the forecast from a direct autoregression.

Figure 6: 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 ϕ (see text for details).

Table 7: BMA Out-of-Sample Predictive Accuracy
(Without Option Adjustment)

Predictors: Macroeconomic Variables & Asset Market Indicators					
	Forecast Horizon (h quarters)				
Economic Activity Indicator	$h = 0$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
GDP	0.95	0.89	0.82	0.82	0.78
	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]
Personal consumption expenditures	0.94	0.91	0.94	0.99	1.06
	[0.03]	[0.06]	[0.10]	[0.20]	[0.47]
Business fixed investment	0.89	0.85	0.86	0.83	0.76
	[0.00]	[0.01]	[0.02]	[0.02]	[0.01]
Industrial production	0.95	0.95	1.04	0.94	0.97
	[0.01]	[0.03]	[0.50]	[0.06]	[0.13]
Private employment	0.90	0.92	1.09	1.13	1.05
	[0.01]	[0.03]	[0.71]	[0.72]	[0.39]
Unemployment rate	0.92	0.91	1.12	1.17	1.11
	[0.01]	[0.03]	[0.85]	[0.86]	[0.63]

Note: Sample period: 1986:Q1–2010:Q1. 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 brackets.

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.

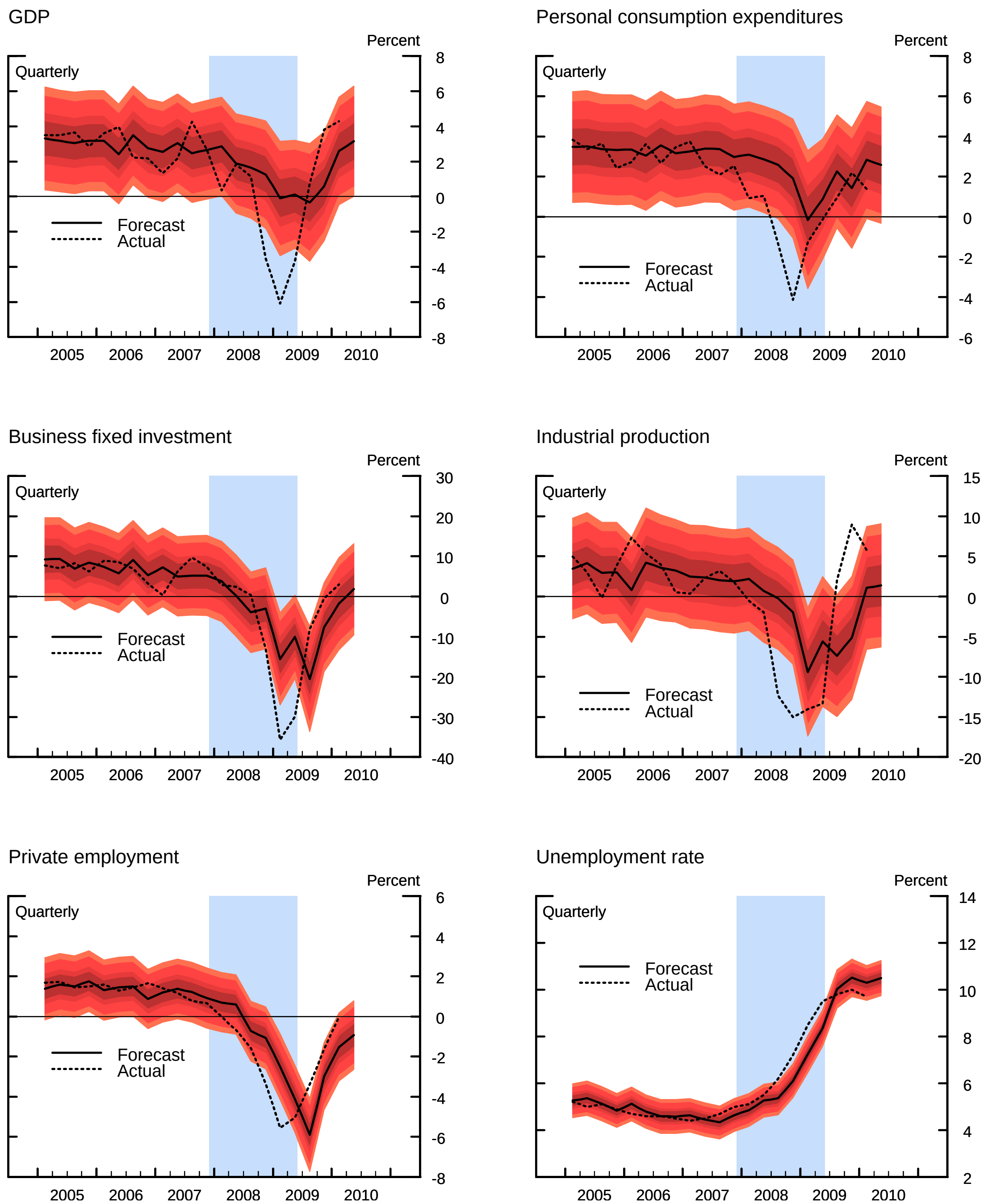
5 Predicting the 2007–09 Financial Crisis

The U.S. economy had generally performed well during the first half of 2007. After mid-year, however, the economic landscape was reshaped dramatically by the intensifying downturn in the housing market and the emergence of significant strains in the financial markets in the United States and abroad. Indeed, in December of 2007, the U.S. economy officially entered the longest and most severe recession of the postwar period. In this section, we examine the real-time accuracy of our BMA forecasts for this extraordinary episode of economic and financial turmoil.

The dashed lines in Figures 7–8 show the realized (annualized) growth rates from quarter $t-1$ to quarter $t+h$ of real GDP, PCE, business fixed investment, industrial production, private payroll employment, along with the level of the unemployment rate at $t+h$, since the beginning of 2005; Figure 7 considers the case of $h = 1$—that is, the one-quarter-ahead forecast horizon—whereas Figure 8 corresponds to the case of $h = 4$, that is, the four-quarter-ahead forecast horizon. The solid line in each panel depicts the corresponding real-time BMA point forecast—made in quarter t—using our DD-based portfolios of option-adjusted spreads. The shaded bands depict the 50-, 68-, 90-, and 95-percentiles of the associated predictive densities. The data are plotted as of quarter $t+h$. Thus in the four-quarter-ahead case, the data for 2010:Q1 show the actual growth rates of economic activity from 2008:Q4 to 2010:Q1 and the BMA forecasts for the growth over the same period, where the forecasts would have been made in 2009:Q1. Note that if the BMA predictions had perfect foresight, then the predicted and realized values would be equal.

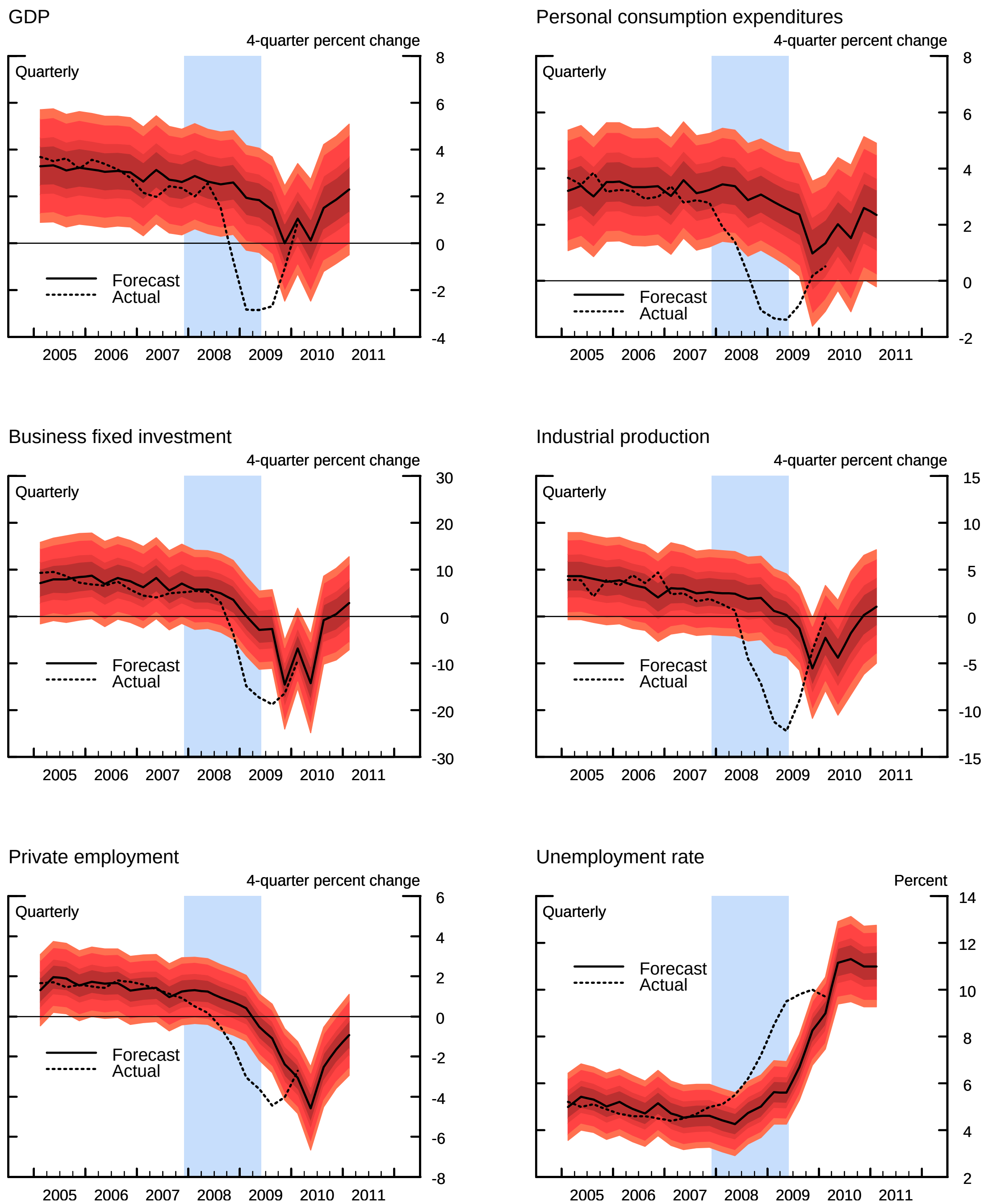
According to Figure 3, credit spreads started to widen significantly in the second half of 2007, concomitant with the slowdown in economic activity predicted by the BMA forecasts. With credit spreads continuing to move higher, the forecast for economic growth became progressively more pessimistic, reaching its nadir in 2008:Q4, a period when spreads sky-rocketed to 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 7). The four-quarter-ahead BMA forecast based on credit spreads (Figure 8) 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 2009Q4—while the realized economic indicators were generally at their worst in 2009:Q2.

Figure 7: Recent Predictive Accuracy of Credit Spreads
(One-Quarter-Ahead BMA Forecast)



Note: The solid line in each panel depicts the real-time BMA point forecast—using the 16 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 8: Recent Predictive Accuracy of Credit Spreads
(Four-Quarters-Ahead BMA Forecast)



NOTE: The solid line in each panel depicts the real-time BMA point forecast—using the 16 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.

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. 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 uncertainty, 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 statistically and economically—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 default-risk 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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