Credit Spreads and Business Cycle Fluctuations

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Abstract

This paper re-examines the evidence on the relationship between credit spreads and economic activity. We construct a new credit spread index, employing an extensive micro-level data set of secondary market prices of outstanding senior unsecured bonds over the 1973–2009 period. Compared with the standard default-risk and other financial indicators, our credit spread index is a robust predictor of future economic growth across a variety of economic indicators, sample periods, and forecast horizons. Using an empirical bond-pricing framework, we also decompose our credit spread index into a predictable component that captures the available firm-specific information on expected defaults and a residual component—the excess bond premium—which we argue reflects the price of default risk rather than the risk of default. Our results indicate that a substantial portion of the predictive content of credit spreads for economic activity is due to the excess bond premium. Shocks to the excess bond premium that are orthogonal to the current state of the economy, the Treasury term structure, and stock returns are shown to cause significant declines in consumption, investment, and output as well as in equity prices. Overall, our findings are consistent with the notion that an increase in the excess bond premium reflects a reduction in the risk appetite of the financial sector and, as a result, a contraction in the supply of credit with significant adverse consequences for the macroeconomy.

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1 Introduction

Between the summer of 2007 and the spring of 2009, the U.S. economy was gripped by an acute liquidity and credit crunch, by all accounts, the most severe financial crisis since the Great Depression. At the height of the crisis in the autumn of 2008, the government, in an attempt to prevent the financial meltdown from engulfing the real economy, effectively assumed control of a number of systemically important financial institution; the Congress, faced with investors' rapidly deteriorating confidence in the financial sector, approved the plan to inject a massive amount of capital into the banking system; and the Federal Reserve dramatically expanded the number of emergency credit and liquidity facilities in an attempt to support the functioning of private debt markets.

Throughout this period of extreme financial turmoil, credit spreads—the difference in yields between various private debt instruments and government securities of comparable maturity—served as a crucial gauge of the degree of strains in the financial system. In addition, the movements in credit spreads were thought to contain important signals regarding the evolution of the real economy and risks to the economic outlook, a view supported by the insights from the large literature on the predictive content of credit spreads—or asset prices more generally—for future economic activity.[1]

The focus on credit spreads is motivated, in part, by financial theories that depart from the Modigliani and Miller [1958] paradigm of frictionless financial markets, theories that emphasize linkages between the quality of borrowers' balance sheets and their access to external finance. Movements in credit spreads may also reflect shifts in the effective supply of funds offered by financial intermediaries, which, in the presence of financial market frictions, have important implications for the usefulness of credit spreads as predictors of future economic activity. In the latter case, a deterioration in the balance sheets of financial intermediaries leads to a reduction in the supply of credit, causing an increase in the cost of debt finance—the widening of credit spreads—and a subsequent reduction in spending and production. In either case, credit spreads play a crucial role in the dynamic interaction of financial conditions with the real economy.

In this paper, we re-examine the evidence on the relationship between corporate bond credit spreads and economic activity. To do so, we first construct a credit spread index—the "GZ credit spread"—that has considerable predictive power for economic activity. Our

[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]; Mody and Taylor [2004]; King et al. [2007]; Mueller [2007]; Gilchrist et al. [2009]; and Faust et al. [2010]).

approach builds on the recent work of Gilchrist et al. [2009] (GYZ hereafter), in that we use prices of individual corporate bonds traded in the secondary market to construct this high-information content credit spread. According to our forecasting results, the predictive ability of the GZ credit spread for economic activity significantly exceeds that of the widely-used default-risk indicators such as the standard Baa-Aaa corporate bond credit spread and the "paper-bill" spread. Moreover, in predicting the volatile cyclical components of aggregate demand such as business fixed and inventory investment, the GZ credit spread significantly outperforms the standard indicators of the stance of monetary policy (e.g., the shape of the Treasury yield curve or the real federal funds rate).

As shown recently by Philippon [2009], the predictive content of corporate bond credit spreads for economic activity could reflect—absent any financial market frictions—the ability of the bond market to signal more accurately than the stock market a decline in economic fundamentals resulting from a reduction in the expected present-value of corporate cash flows prior to a cyclical downturn. To address this issue, we use a flexible empirical bond-pricing framework to decompose the GZ credit spread into two components: a component capturing the usual countercyclical movements in expected defaults; and a component representing the cyclical changes in the relationship between default risk and credit spreads—the so-called excess bond premium. We then examine the extent to which the forecasting power of the GZ credit spread is due to the measurable default component or the excess bond premium.

Our decomposition is motivated in part by the existence of the "credit spread puzzle," the well-known result from the corporate finance literature showing that less than one-half of the variation in corporate bond credit spreads can be attributed to the financial health of the issuer (e.g., Elton et al. [2001]). As shown by Collin-Dufresne et al. [2001], Houwelling et al. [2005], Driessen [2005], and Duffie et al. [2007], the unexplained portion of the variation in credit spreads appears to reflect some combination of time-varying liquidity premium, to some extent the tax treatment of corporate bonds, and, most importantly for our purposes, a default-risk factor.[2] Our results indicate that a substantial portion of

[2] Although corporate bonds are actively traded, the volume of transactions is far lower and transaction costs are much higher than in the Treasury market (e.g., Edwards et al. [2007]). Because the information content of prices tends to be lower for less actively traded securities and liquidity is an attractive feature of an asset class, the compensation for liquidity risk shows up in higher corporate bond credit spreads over otherwise comparable Treasuries. Relative to Treasuries, corporate bonds are also at a tax disadvantage, because their interest is taxed at the federal and state levels, whereas the interest earned on Treasuries is subject only to taxes at the federal level. This differential tax treatment should bias the prices of corporate bonds downward in order to equalize the after-tax return across the two asses classes. The implications of this tax effect for the ability of credit spreads to forecast economic activity, however, are likely to be negligible, because the marginal investor in the corporate cash market are banks, pension funds, insurance companies, and other institutional investors—that is, legal entities for which there is no difference in the tax treatment of interest income received from corporate bonds and Treasuries. In addition, major changes in tax laws are infrequent and unrelated to the large cyclical swings in corporate bond credit spreads.

the information content of the GZ credit spread can be attributed to the deviations in the pricing of corporate bonds relative to the expected default risk of the issuer. This finding suggests that changes in investor risk attitudes embedded in prices of corporate bonds may account for a significant fraction of the forecasting power of credit spreads for economic activity.

We examine the implications of this finding using an identified vector autoregression (VAR) framework. According to our analysis, shocks to the excess bond premium that are orthogonal to the current state of the economy, the Treasury term structure, and stock market returns cause economically and statistically significant declines in consumption, investment, and output as well as in equity prices. The confluence of our results is consistent with the notion that an increase in the excess bond premium reflects a reduction in the risk appetite of the financial sector and, as a result, a contraction in the supply of credit. Consistent with the financial accelerator mechanisms emphasized by Kiyotaki and Moore [1997], Bernanke et al. [1999], and Hall [2010], this reduction in credit availability augurs a change in financial conditions with significant adverse consequences for macroeconomic outcomes.

The remainder of the paper is organized as follows. Section 2 describes the construction of our high-information content credit spread index. In Section 3, we compare the forecasting power of the GZ credit spread to that of some standard financial indicators. In Section 4, we describe the methodology for decomposing credit spreads into a predicted component due to expected defaults and the excess bond premium. In Section 5, we evaluate the relative forecasting ability of the default component and the excess bond premium for future economic activity; we also analyze the effect of financial shocks—identified by orthogonalized movements in the excess bond premium—on the macroeconomy. Section 6 concludes.

2 A High-Information Content Credit Spread Index

Academics, business economists, and policymakers have long relied on credit spreads to gauge the degree of strains in the financial system. In addition, the forward-looking nature of financial markets should cause the information about investors' expectations of future economic outcomes to become embedded in asset prices, though obtaining an accurate reading of this information can be greatly complicated by the presence of time-varying risk premiums. Nonetheless, credit spreads on corporate debt instruments have been shown to be particularly useful for forecasting economic activity. Results from this strand of research, however, are often sensitive to the choice of a credit spread index under consideration. In particular, credit spreads that contained useful information about economic outcomes in the past often lose their predictive power for the subsequent cyclical downturn.[3] These mixed results are partly attributable to the rapid pace of financial innovation that likely alters the forecasting power of financial asset prices over time or results in one-off developments that may account for most of the forecasting power of a given financial indicator.

In part to address these problems, GYZ utilized secondary market prices of individual senior unsecured corporate bonds over the 1990–2007 period to construct a broad array of credit spread indexes that vary across maturity and default risk. As pointed out by GYZ, senior unsecured bonds, compared with other corporate debt instruments, represent a class of securities with a relatively long history containing a number of business cycles; moreover, the rapid pace of financial innovation over the past several decades has done little to alter the basic structure of these securities. Thus, the information content of spreads constructed from yields on senior unsecured corporate bonds is likely to provide more consistent signals regarding economic outcomes relative to spreads based on securities with a shorter history or securities whose structure or the relevant market has undergone a significant structural change. Indeed, the results of GYZ confirm this conjecture: At forecast horizons associated with business cycle fluctuations, the predictive ability of their portfolio credit spreads significantly exceeds—both in-sample and out-of-sample—that of the commonly-used default-risk indicators, such as the paper-bill spread or the Baa and the high-yield corporate credit spread indexes.

2.1 Data Sources and Methods

In this paper, we employ the same "bottom-up" approach to construct a credit spread index with a high-information content for future economic activity. Importantly, we extend the time span of the analysis back to the mid-1970s, thereby covering an appreciably greater number of business cycles, a consideration of particular importance when one is evaluating the predictive ability of financial indicators for economic activity. Specifically, for a sample of more than 1,100 U.S. nonfinancial firms covered by the S&P's Compustat and the Center for Research in Security Prices (CRSP), month-end secondary market prices of their outstanding securities were obtained from the Lehman/Warga (LW) and Merrill Lynch (ML) databases.[4] To ensure that we are measuring borrowing costs of different firms at the same

[3] For example, the paper-bill spread has lost much of its forecasting power since the early 1990s; indeed, according to Thoma and Gray [1998] and Emery [1999], the predictive content of the paper-bill spread may have reflected a one-time event. Similarly, yield spreads based on indexes of high-yield 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 high-yield spread as a leading indicator during this period, largely because it falsely predicted an economic downturn in the autumn of 1998.

[4] These two data sources include secondary market prices for a majority of dollar-denominated bonds publicly issued in the U.S. corporate cash market. The ML database is a proprietary data source of daily

point in their capital structure, we limited our sample to senior unsecured issues with a fixed coupon schedule only.

The micro-level aspect of our data allows us to construct credit spreads that are not subject to the "duration mismatch" that plagues most commercially-available credit spread indexes. We do so by constructing for each individual corporate issue a synthetic risk-free security that mimics exactly the cash-flows of the corresponding corporate debt instrument. Specifically, 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 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 the corresponding risk-free security—denoted by $P_t^f[k]$—we discount the cash-flow sequence $\{C(s) : s = 1, 2, \ldots, S\}$ using continuously-compounded zero-coupon Treasury yields in period t, obtained from the U.S. Treasury yield curve estimated daily 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 resulting 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 bias that would occur were the spreads computed simply by matching the corporate yield to the estimated yield of a 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.[5] These selection criteria yielded a sample of 5,937 individual securities for the period between January 1973 and December 2009. We matched these corporate securities with their issuer's quarterly income and balance sheet

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

[5] 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

Bond Characteristic	Mean	SD	Min	P50	Max
No. of bonds per firm/month	2.87	3.54	1.00	2.00	74.0
Mkt. value of issue[a] ($mil.)	311.2	313.5	1.22	231.7	5,628
Maturity at issue (years)	13.0	9.4	1.0	10.0	50.0
Term to maturity (years)	11.4	8.5	1.0	8.3	30.0
Duration (years)	6.59	3.17	0.91	6.10	15.6
Credit rating (S&P)	-	-	D	BBB1	AAA
Coupon rate (pct.)	7.34	1.99	1.80	7.00	17.5
Nominal effective yield (pct.)	7.82	3.22	1.03	7.25	44.3
Credit spread (bps.)	201	283	5	115	3,499

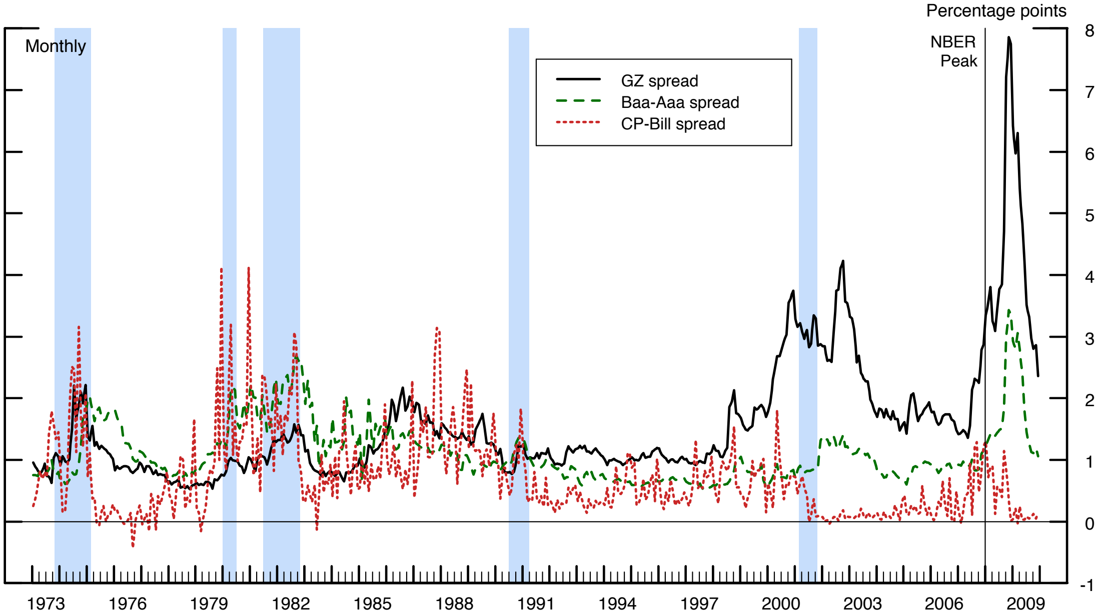
NOTE: Sample period: Jan1973–Dec2009; Obs. = 330,029; No. of bonds = 5,937; No. of firms = 1,111. Sample statistics are based on trimmed data (see text for details).
[a]Market value of the outstanding issue deflated by the CPI (1982–84 = 100).

data from Compustat and daily data on equity valuations from CRSP, yielding a matched sample of 1,111 firms.

Table 1 contains summary statistics for the key characteristics of bonds in our sample. Note that a typical firm in our sample has only a few senior unsecured issues outstanding at any point in time—the median firm, for example, has two such issues trading in 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 13 years; the average remaining term-to-maturity in our sample is 11.4 years. However, because corporate bonds typically generate significant cash flow in the form of regular coupon payments, their duration is considerably shorter, with both the average and the median duration of a bit more than 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 observation is still solidly in the investment-grade category. Turning to returns, the (nominal) coupon rate on these bonds averaged 7.34 percent during our sample period, while the average nominal effective yield was 7.82 percent per annum. Reflecting the wide range of credit quality, the distribution of nominal yields is quite wide, with the minimum of 1.03 percent and the maximum of more than 44 percent. Relative to Treasuries, an average bond in our sample has an expected return of 201 basis points above the comparable risk-free rate, with the

Figure 1: Selected Corporate Credit Spreads



NOTE: Sample period: Jan1973–Dec2009. The figure depicts the following default-risk indicators: GZ spread = average credit spread on senior unsecured bonds issued by nonfinancial firms in our sample (the solid line); Baa-Aaa = the spread between yields on Baa- and Aaa-rated long-term industrial corporate bonds (the dashed line); and CP-Bill = the spread between the yield on 1-month A1/P1 nonfinancial commercial paper and the 1-month Treasury yield (the dotted line). The shaded vertical bars represent the NBER-dated recessions.

standard deviation of 283 basis points.

Using this micro-level data set, we construct a simple credit spread index that is representative of the entire maturity spectrum and the range of credit quality in the corporate cash market. Specifically, the GZ credit spread is calculated as

$$S_t^{GZ} = \frac{1}{N_t} \sum_i \sum_k S_{it}[k], \tag{1}$$

where N_t is the number of bond/firm observations in month t—that is, the GZ credit spread in month t is simply an arithmetic average of the credit spreads on outstanding bonds in that month. Figure 1 shows the GZ credit spread along with two widely-used default-risk indicators that are also available over our sample period: the yield spread between 1-month A1/P1-rated nonfinancial commercial paper and the 1-month Treasury yield (i.e., the paper-bill spread) and the spread between yields on indexes of Baa- and Aaa-rated seasoned industrial corporate bonds.[6]

[6]Other than than the GZ credit spread, all yields are taken from the “Selected Interest Rates” (H.15)

All three credit spreads are clearly countercyclical, rising prior to and during economic downturns. Nonetheless, the pair-wise correlations between the three series are fairly small and do not exhibit much of a systematic pattern. For example, the correlation between the paper-bill and the Baa-Aaa spread is 0.21, whereas the paper-bill and the GZ spread are slightly negatively correlated, with the correlation coefficient of -0.16. Perhaps not too surprising, the highest correlation, 0.37, is between the two corporate bond credit spread indexes. Regarding their variability, the Baa-Aaa and the paper-bill spreads are the least volatile, with the standard deviations of 50 and 67 basis points, respectively.[7] Reflecting its broader coverage, both in terms of credit quality and maturity, the standard deviation of the GZ credit spread—at about 100 basis points—is considerably higher.

3 Credit Spreads and Economic Activity

This section examines the predictive power of the GZ credit spread for various measures of economic activity and compares its forecasting performance with that of several commonly-used financial indicators. Letting Y_t denote a measure of economic activity in period t, we define

$$\nabla^h Y_{t+h} \equiv \frac{c}{h} \ln\left(\frac{Y_{t+h}}{Y_t}\right),$$

where h denotes the forecast horizon and c is a scaling constant that depends on the frequency of the data (i.e., $c = 1,200$ for monthly data and $c = 400$ for quarterly data). We estimate the following univariate forecasting specification:

$$\nabla^h Y_{t+h} = \alpha + \sum_{i=0}^{p} \beta_i \nabla Y_{t-i} + \gamma_1 TS_t + \gamma_2 RFF_t + \gamma_3 CS_t + \epsilon_{t+h}, \tag{2}$$

where TS_t denotes the "term spread"—that is, the slope of the Treasury yield curve, defined as the difference between the three-month constant-maturity Treasury yield and the 10-year constant-maturity yield; RFF_t denotes the real federal funds rate; CS_t denotes a credit

statistical release published by the Federal Reserve Board. Note that the GZ credit spread is measured relative to Treasury yields, whereas the Baa-Aaa spread is defined as the difference between yields on long-term corporate debt instruments of varying credit quality. As emphasized by Duffee [1998], the corporate-Treasury yield spreads can be influenced significantly by time-varying prepayment risk premiums, reflecting the call provisions on corporate issues. According to Duca [1999], corporate bond spread indexes measured relative to the yield on Aaa-rated bonds are more reflective of default risk than those measured relative to comparable-maturity Treasuries.

[7] A significant portion of the volatility in the paper-bill spread reflects year-end funding pressures. These pressures can arise as the maturity of the paper crosses over year-end, and investors demand a premium to hold paper over the turn of the year. Trends in business sector credit quality and the amount of outstanding commercial paper are important determinants of year-end pressures.

spread; and ϵ_{t+h} is the forecast error.[8] The forecasting regression (2) is estimated by OLS, and the lag length p of each specification is determined by the Akaike Information Criterion (AIC). For the forecasting horizons $h > 1$, the MA($h-1$) structure of the error term ϵ_{t+h} induced by overlapping observations is taken into account by computing the covariance matrix of regression coefficients according to Hodrick [1992].[9]

Within this framework, we analyze the information content of the three credit spreads shown in Figure 1 for future economic growth. First, we examine the ability of these credit spreads to forecast the key monthly indicators of economic activity: the growth of private (nonfarm) payroll employment and the growth in manufacturing industrial production. Using quarterly data, we also consider the predictive content of these default-risk indicators for the broadest measure of economic activity, namely the growth rate of real GDP as well as its main components.

3.1 Forecasting Results

The results in Table 2 detail the predictive power of various financial indicators for the two monthly measures of economic activity. We focus on two forecast horizons: 3- and 12-month ahead and report standardized estimates of the coefficients associated with the financial indicators as well as the in-sample goodness-of-fit as measured by the adjusted R^2. The first column in each panel of the table contains results from our baseline specification, which includes the term spread and the real federal funds rate, along with the current and p lags of ∇Y_t, as predictors. Consistent with previous findings, the shape of the Treasury term structure has significant predictive content for the two economic indicators at both forecast horizons, with a flat or inverted yield curve signalling a slowdown in labor demand and a deceleration in industrial output. The real federal funds rate has some additional predictive power for changes in the labor market conditions at both the 3- and 12-month forecast horizons but has no explanatory power for the growth of industrial production at either horizon.

The remaining three columns in each panel contain results from our baseline specification augmented with the three default-risk indicators. Relative to the baseline, the paper-bill spread forecasts both economic indicators at the 3-month horizon; at the year-

[8] In calculating the real federal funds rate, we employ a simplifying assumption that the expected inflation is equal to lagged core PCE inflation. Specifically, real funds rate in period t is defined as the average effective federal funds rate during period t less realized inflation, where realized inflation is given by the log-difference between the core PCE price index in period $t-1$ and its lagged value a year earlier.

[9] Ang and Bekaert [2007] compare the performance of various HAC estimators of standard errors in the context of overlapping observations. According to their findings, the standard errors developed by Hodrick [1992] retain the correct size even in relatively small samples. In the case of non-overlapping data (i.e., $h = 1$), our inference is based on the heteroscedasticity-consistent asymptotic covariance matrix (HC3) computed according to MacKinnon and White [1985].

Table 2: Financial Indicators and Economic Activity (1973–2009)

Private Payroll Employment

Financial Indicator	Forecast Horizon: 3 months				Forecast Horizon: 12 months			
Term spread	-0.080	-0.085	-0.084	-0.096	-0.240	-0.241	-0.220	-0.263
	[1.92]	[2.03]	[2.04]	[2.34]	[4.81]	[4.78]	[4.72]	[5.41]
Real FFR	-0.079	-0.009	-0.075	-0.128	-0.122	-0.108	-0.157	-0.208
	[1.75]	[0.14]	[1.62]	[2.79]	[2.34]	[1.71]	[3.15]	[4.09]
CP-bill spread	-	-0.108	-	-	-	-0.023	-	-
		[2.41]				[0.68]		
Baa-Aaa spread	-	-	-0.019	-	-	-	0.108	-
			[0.49]				[2.20]	
GZ spread	-	-	-	-0.272	-	-	-	-0.462
				[6.64]				[14.0]
Adj. R^2	0.661	0.668	0.661	0.705	0.432	0.431	0.441	0.583

Manufacturing Industrial Production

Financial Indicator	Forecast Horizon: 3 months				Forecast Horizon: 12 months			
Term spread	-0.144	-0.166	-0.174	-0.186	-0.332	-0.346	-0.323	-0.368
	[2.15]	[2.48]	[2.72]	[2.84]	[3.95]	[4.12]	[3.88]	[4.44]
Real FFR	-0.070	-0.117	-0.048	-0.145	-0.099	0.016	-0.107	-0.189
	[0.97]	[1.28]	[0.67]	[2.09]	[1.08]	[0.15]	[1.20]	[2.14]
CP-bill spread	-	-0.285	-	-	-	-0.179	-	-
		[4.23]				[3.02]		
Baa-Aaa spread	-	-	-0.108	-	-	-	0.032	-
			[1.63]				[0.39]	
GZ spread	-	-	-	-0.353	-	-	-	-0.417
				[4.88]				[6.06]
Adj. R^2	0.276	0.325	0.283	0.363	0.225	0.243	0.224	0.363

NOTE: Sample period: Jan1973–Dec2009. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of an indicator of economic activity in month t and h is the forecast horizon. In addition to the specified financial indicator in month t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator; absolute t-statistics reported in brackets are based on the asymptotic covariance matrix computed according to Hodrick [1992].

ahead forecast horizon, in contrast, the paper-bill spread has predictive content only for the growth in industrial production. Note also that the addition of the paper-bill spread—where statistically significant—results only in a modest increase in the adjusted R^2 relative to the baseline specification. The forecasting ability of the Baa-Aaa spread appears to be equally unimpressive. At the 3-month horizon, the coefficients on the Baa-Aaa credit

Table 3: Financial Indicators and Real GDP (1973–2009)

Financial Indicator	Forecast Horizon: 1 quarter				Forecast Horizon: 4 quarters			
Term spread	-0.148	-0.179	-0.185	-0.200	-0.380	-0.384	-0.369	-0.415
	[1.43]	[1.68]	[1.65]	[1.97]	[2.85]	[2.84]	[2.60]	[3.31]
Real FFR	-0.112	0.104	-0.074	-0.175	-0.073	-0.033	-0.081	-0.154
	[1.06]	[0.72]	[0.68]	[1.71]	[0.54]	[0.20]	[0.60]	[1.17]
CP-bill spread	-	-0.264	-	-	-	-0.057	-	-
		[2.40]				[0.49]		
Baa-Aaa spread	-	-	-0.112	-	-	-	0.054	-
			[1.00]				[0.43]	
GZ spread	-	-	-	-0.335	-	-	-	-0.352
				[3.69]				[3.68]
Adj. R^2	0.171	0.192	0.165	0.239	0.235	0.232	0.232	0.333

NOTE: Sample period: 1973:Q1–2009:Q4. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of real GDP in quarter t and h is the forecast horizon. In addition to the specified financial indicator in quarter t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator. For the 1-quarter horizon, absolute t-statistics reported in brackets are based on the asymptotic covariance matrix (HC3) computed according MacKinnon and White [1985]; for the 4-quarter horizon, absolute t-statistics are computed according to Hodrick [1992].

spread are statistically insignificant in both forecasting regression. At the 12-month horizon, the Baa-Aaa spread has significant explanatory power for the year-ahead growth in payroll employment—however, an increase in the Baa-Aaa spread, conditional on the stance of monetary policy, predicts an *increase* in employment growth over the subsequent year.

In contrast to the results obtained with the two standard default-risk indicators, the GZ credit spread is statistically a highly significant predictor of these two measures of economic activity at both the short and longer-term forecast horizons. Moreover, the magnitude of the estimated coefficients implies an economically significant negative relationship between credit spreads and future economic activity. For example, an increase of 100 basis point in the GZ credit spread in month t implies a 2.75 percentage points (annualized) drop in the growth rate of industrial output over the subsequent three months. The predictive content of the GZ credit spread is particularly apparent at the year-ahead horizon, where the increases in the in-sample fit range from 25 percent in the case of payroll employment to almost 35 percent in the case of manufacturing industrial production.

Table 3 summarizes the predictive content of these financial indicators for the growth of real GDP. According to the entries in the table, the current stance of monetary policy—measured by either the slope of the Treasury yield curve or the real federal funds rate—has

Table 4: Financial Indicators and Components of Aggregate Demand (1973-2009)

	Forecast Horizon: 1 quarter						
Financial Indicator	C-NDS	C-D	I-RES	I-ES	I-HT	I-NRS	INV
Term spread	-0.220	-0.289	-0.304	-0.171	-0.059	0.152	-0.052
	[2.26]	[2.82]	[3.76]	[1.88]	[0.65]	[1.75]	[0.59]
Real FFR	-0.071	-0.099	-0.162	-0.184	0.013	-0.133	-0.008
	[0.69]	[1.02]	[1.92]	[2.29]	[0.11]	[1.41]	[0.09]
GZ spread	-0.214	-0.187	-0.208	-0.462	-0.329	-0.327	-0.345
	[2.65]	[2.27]	[1.83]	[3.01]	[3.04]	[2.09]	[5.88]
Adj. R^2	0.372	0.095	0.471	0.319	0.339	0.282	0.448
	Forecast Horizon: 4 quarters						
Financial Indicator	C-NDS	C-D	I-RES	I-ES	I-HT	I-NRS	INV
Term spread	-0.422	-0.501	-0.560	-0.354	-0.077	0.309	-0.164
	[3.91]	[2.64]	[5.59]	[3.11]	[0.73]	[2.66]	[1.86]
Real FFR	0.069	0.063	0.005	-0.251	-0.179	-0.331	-0.213
	[0.72]	[0.39]	[0.05]	[2.59]	[1.41]	[2.74]	[2.33]
GZ spread	-0.243	-0.080	-0.149	-0.493	-0.558	-0.465	-0.570
	[2.96]	[0.61]	[1.98]	[4.42]	[7.19]	[4.07]	[9.82]
Adj. R^2	0.360	0.189	0.395	0.490	0.440	0.392	0.464

NOTE: Sample period: 1973:Q1–2009:Q4. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of the component of private (real) aggregate demand in quarter t and h is the forecast horizon: C-D = PCE on durable goods; C-NDS = PCE on nondurable goods & services; I-RES = residential investment; I-ES = business fixed investment in E&S (excl. high tech); I-HT = business fixed investment in high-tech equipment; I-NRS = business fixed investment in structures; INV = business inventories. In addition to the specified financial indicators in quarter t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator. For the 1-quarter horizon, absolute t-statistics reported in brackets are based on the asymptotic covariance matrix (HC3) computed according MacKinnon and White [1985]; for the 4-quarter horizon, absolute t-statistics are computed according to Hodrick [1992].

no predictive power for the next quarter's economic growth, although the term spread is economically and statistically a highly significant predictor of the year-ahead growth in real output. The paper-bill spread contains some information about the near-term growth prospects, but the signalling ability of this default-risk indicator vanishes at longer horizons. Regardless of the forecast horizon, the Baa-Aaa credit spread is uninformative about the economic outlook, a finding consistent with those reported in Table 2. In contrast, the GZ credit spread is a highly significant predictor of real GDP growth at both the 1- and 4-quarter forecast horizons—an increase of 100 basis points in the GZ credit spread in quarter

t leads to a deceleration in real GDP of more than 0.75 percentage point over the subsequent four quarters.

Table 4 examines the predictive content of the GZ credit spread for the main categories of personal consumption expenditures and private investment. At the 1-quarter horizon, the GZ credit spread is a significant predictor of all major components of private aggregate demand, with the exception of residential investment. At the 4-quarter horizon, the GZ credit spread remains a highly significant—both economically and statistically—predictor of the growth in all the major categories of business spending, and it also retains its predictive ability for the growth of personal consumption expenditures on nondurable goods and services.

In summary, the results in Tables 2–4 indicate a robust and economically significant negative relationship between a credit spread index constructed as a cross-sectional average of properly measured spreads on individual senior unsecured corporate bonds and various measures of economic activity. At both the short- and longer-term forecast horizons, the predictive ability of the GZ credit spread substantially exceeds that of the standard default-risk indicators. Compared with the indicators of the stance of monetary policy, the GZ credit spread has significantly greater information content for the cyclically-sensitive indicators of economic activity such industrial production, the main categories of capital spending, and business inventory investment.

4 The Excess Bond Premium

In this section, we exploit the micro-level aspect of our data to decompose the GZ credit spread into two components: a component that captures the systematic movements in default risk of individual firms and a residual component, which we label the *excess bond premium*. Our empirical methodology is based on the standard bond-pricing framework, where the log of the credit spread on bond k (issued by firm i) at time t is related to a firm-specific measure of expected default DFT_{it}, a vector of additional bond-specific controls $Z_{it}[k]$, and a residual component $\epsilon_{it}[k]$:[10]

$$\ln S_{it}[k] = \beta_0 + \beta_1 DFT_{it} + \beta_2' Z_{it}[k] + \epsilon_{it}[k]. \tag{3}$$

The empirical bond-pricing equation (3) is estimated by OLS. Given the estimated parameter vector $(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2')$, we then calculate the predicted *level* of the spread for bond k of firm

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

i at time t—denoted by $\widehat{S}_{it}[k]$—as:

$$\widehat{S}_{it}[k] = \hat{\theta}\tilde{S}_{it}[k],$$

where $\tilde{S}_{it}[k] = \exp(\hat{\beta}_0 + \hat{\beta}_1 DFT_{it} + \hat{\beta}_3' Z_{it})$, and $\hat{\theta}$ is the OLS estimate of the slope coefficient from the pooled regression (without the constant term) of $S_{it}[k]$ on $\tilde{S}_{it}[k]$.[11]

By averaging across bonds/firms at time t, we can define the predicted component of the GZ credit spread as

$$\widehat{S}_t^{GZ} = \frac{1}{N_t}\sum_i \sum_k \widehat{S}_{it}[k].$$

The excess bond premium in period t is then defined by the following linear decomposition:

$$EBP_t = S_t^{GZ} - \widehat{S}_t^{GZ}.$$

Within this framework, we are interested in determining the extent to which the forecasting power of the GZ credit spread is due to the information content of the expected default component $\widehat{S}_t^{GZ}$, versus the movements in the excess bond premium EBP_t.

4.1 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 the excess bond premium. 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:

$$dV = \mu_V V dt + \sigma_V V dW, \tag{4}$$

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

[11] The parameter θ plays the same role as the variance-adjustment term in the standard formula $\exp(\hat{\beta}_0 + \hat{\beta}_1 DFT_{it} + \hat{\beta}_3' Z_{it} + 0.5\hat{\sigma}_\epsilon)$ used to obtain the predicted level of spreads under the assumption of log-normality.

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.[12] 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:

$$E = V\Phi(\delta_1) - e^{-rT} D\Phi(\delta_2), \tag{5}$$

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

$$\sigma_E = \left[\frac{V}{E}\right] \frac{\partial E}{\partial V} \sigma_V. \tag{6}$$

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

$$\sigma_E = \left[\frac{V}{E}\right] \Phi(\delta_1)\sigma_V. \tag{7}$$

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.[13] Using the observed values of E, D, σ_E,

[12] 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]; Lando [2004] contains an excellent practical exposition of the contingent claims approach to corporate credit risk.

[13] 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.

and r (i.e., the 1-year constant-maturity Treasury yield), equations (5) and (7) 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 (7) 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 (5) 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

$$DD = \frac{\ln(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}. \tag{8}$$

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

$$EDF = \Phi(-DD) = \Phi\left(-\left(\frac{\ln(V/D) + (\mu_V - 0.5\sigma_V^2)}{\sigma_V}\right)\right), \tag{9}$$

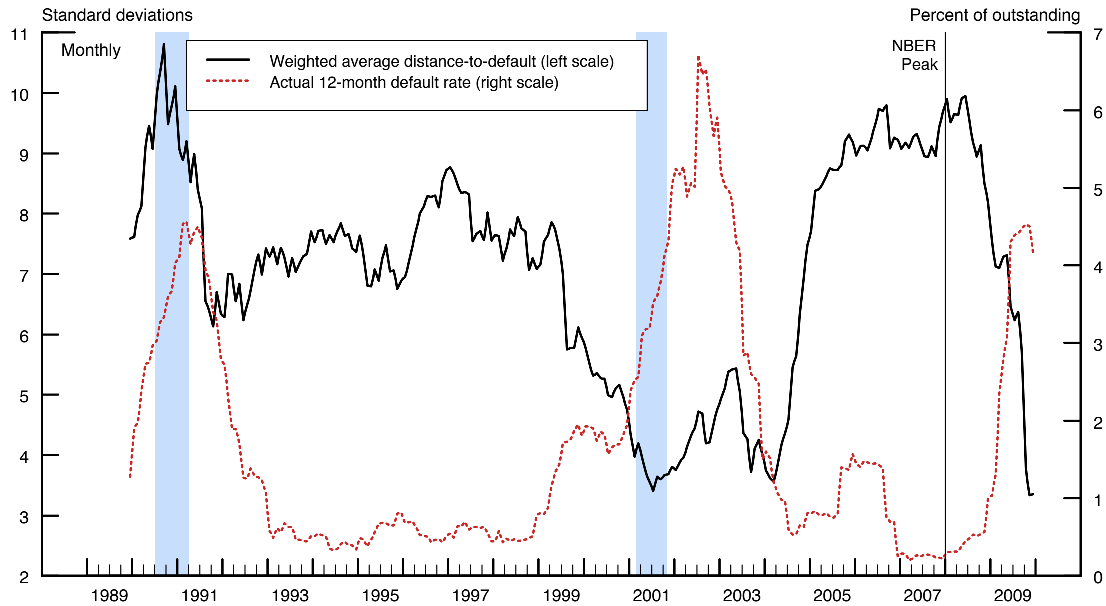
which, under the assumptions of the Merton model, should be a sufficient statistic for predicting defaults.

Using this methodology, we compute the year-ahead DD for all U.S. nonfinancial corporations covered by the S&P's Compustat and CRSP (i.e., 14,397 firms) over the 1973–2009 period.[14] To assess the empirical relevance of the Merton DD-model, Figure 2 shows the cross-sectional (weighted) average of the firm-specific DDs in month t against the realized nonfinancial bond default rate over the subsequent 12 months. As evidenced by the strong negative correlation between the two series ($\rho = -0.50$), the available evidence suggests that the average DD contains substantial information regarding the near-term likelihood of default in the nonfinancial corporate sector. One notable exception is the onset of the economic downturn in the early 1990s, a period during which the average DD increased appreciably—a signal of improving credit quality—while the actual bond default rate rose sharply.

In Figure 3, we plot the cross-sectional median and the interquartile range of the DD

[14]To ensure that our results were not unduly influenced 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.

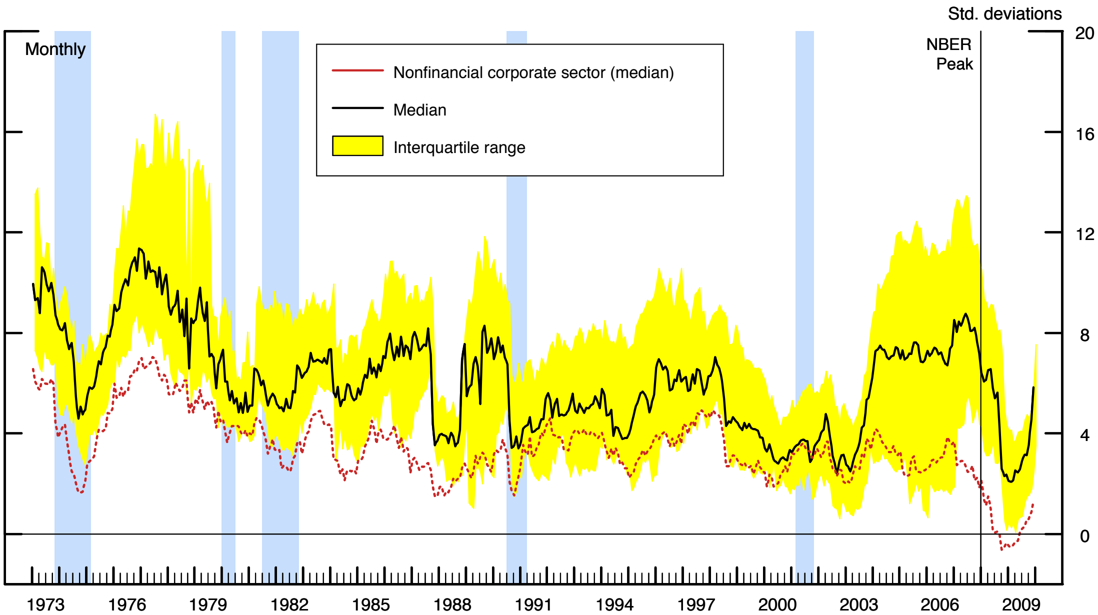
Figure 2: Distance-to-Default and Actual Corporate Bond Defaults



NOTE: Sample period: Dec1989–Dec2009. The solid line depicts the (weighted) average distance-to-default (DD) for the U.S. nonfinancial corporate sector in month $t - 12$, calculated using the Merton [1974] model (see text for details); the firm-level estimates of the year-ahead DD are weighted by firm liabilities. The dotted line depicts the nonfinancial bond default rate in month t, calculated as the 12-month trailing sum of defaults divided by the amount outstanding at $t - 12$. The shaded vertical bars represent the NBER-dated recessions.

for the 1,111 bond issuers in our sample. As a point of comparison, the figure also depicts the cross-sectional median of the DD for the entire Compustat-CRSP matched sample of nonfinancial firms. Over the 1973–2009 period, the median DDs for the both sets of firms are strongly procyclical, implying that investors generally expect an increase in defaults during economic downturns. Indeed, during the height of the recent financial crisis in the autumn of 2008, both measures fell to record lows, a pattern consistent with the jump in the GZ credit spread shown in Figure 1. Note also that according to this metric, the credit quality of the median bond issuer in our sample is, on average, higher than that of the median nonfinancial firm, reflecting the fact that firms with the access to the unsecured corporate cash market tend to be more creditworthy than the typical nonfinancial firm. Nevertheless, the width of the interquartile range indicates a considerable dispersion in the credit quality of firms whose senior unsecured debt is traded in the secondary market.

Figure 3: Distance-to-Default



NOTE: Sample period: Jan1973–Dec2009. The figure depicts the distance-to-default (DD) calculated using the Merton [1974] model (see text for details). The solid line depicts the (weighted) median DD of the firms in our sample, and the shaded band depicts the corresponding (weighted) interquartile range. The dotted line depicts the (weighted) median DD in the U.S. nonfinancial corporate sector; all percentiles are weighted by the firm's outstanding liabilities. The shaded vertical bars represent the NBER-dated recessions.

4.2 Credit Spreads and Default Risk

The insights of the Merton DD-model are used regularly by the financial industry to provide creditors and financial regulators with the information used to assess and monitor corporate credit risk. Most notably, the Moody's/KMV Corporation (MKMV) employs a proprietary version of the Black-Scholes-Merton pricing model to calculate the firm-specific DDs, which are then mapped to "physical" probabilities of default using an extensive historical database of corporate defaults and bankruptcies; see Crosbie and Bohn [2003] for details. Thus, when analyzing the information content for corporate bond spreads of market-based indicators of default risk, it is natural to begin with a direct comparison of the MKMV's EDFs and our estimate of the distance-to-default from equation (8).

Table 5 reports the estimates of the key coefficients from this comparison. In both panels of the table, the dependent variable, as shown by equation (3), is $\ln S_{it}[k]$, the logarithm of the credit spread for the bond issue k of firm i in month t. In the top panel, the log credit spread is regressed on the MKMV's estimate of expected default risk EDF_{it}, whereas in the bottom panel, the default risk is captured by our estimate of the distance-to-default DD_{it}.

Table 5: Comparison of Market-Based Measures of Default Risk

EDF Specification				
EDF_{it}	0.099	0.095	0.061	0.159
	(0.005)	(0.005)	(0.003)	(0.008)
EDF_{it}^2	-	-	-	-0.004
				(0.000)
Adj. R^2	0.395	0.436	0.627	0.644
Industry Effects[a]	-	0.000	0.000	0.000
Credit Rating Effects[b]	-	-	0.000	0.000
DD Specification				
$-DD_{it}$	0.127	0.124	0.084	0.200
	(0.004)	(0.004)	(0.003)	(0.007)
$(-DD_{it})^2$	-	-	-	0.007
				(0.000)
Adj. R^2	0.521	0.545	0.682	0.707
Industry Effects	-	0.000	0.000	0.000
Credit Rating Effects	-	-	0.000	0.000

NOTE: Sample period: Feb1990–Dec2009. Obs. = 276,954; No. of bonds/firms = 5,616/1,046. Dependent variable is $\ln(S_{it}[k])$. All specifications include a constant term (not reported) and are estimated by OLS. Robust asymptotic standard errors are clustered at the firm level and are reported in parentheses.

[a] p-value for the robust Wald statistics of the exclusion test of industry fixed effects.

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

All specifications are estimated by OLS over the period from February 1990 to December 2009, the time range over which both the DDs and EDFs are available. In all specifications, we also control for the bond-specific characteristics that could influence bond yields through either term or liquidity premiums, including the bond's duration ($\ln DUR_{it}[k]$), the amount outstanding ($\ln PAR_{it}[k]$), the bond's (fixed) coupon rate ($\ln CPN_i[k]$), and an indicator variable that equals one if the bond is callable and zero otherwise ($CALL_i[k]$).

As shown in the first column, both market-based measures of default risk are statistically highly significant predictors of the log credit spreads. The estimated coefficients imply that an increase of one percentage point in the year-ahead EDF boosts the level of credit spreads about 20 basis points. In comparison, a decrease of one standard deviation in the year-ahead DD predicts a widening of credit spreads of about 28 basis points. Importantly, our DD measure explains a considerably greater fraction of the variability in the log credit spreads—52 percent compared with about 40 percent when using the MKMV's EDFs as a proxy for expected defaults.

In the remaining columns, we control for systematic differences across (3-digit NAICS) industries, external credit ratings, and nonlinear effects of default risk. As shown in the third column, the inclusion of the credit rating (S&P) fixed effects leads to a substantial improvement in the goodness-of-fit in both specifications. This improvement likely reflects the fact that the external ratings of senior unsecured debt are based, in part, on 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].

The final specification allows for a nonlinear effect of default risk on credit spreads by including a quadratic term of either EDF_{it} or DD_{it} in the bond-pricing regression. Consistent with the nonlinear relationship between credit spreads and leverage documented by Levin et al. [2004], the quadratic terms are highly statistically significant in both specifications. Moreover, the magnitude of the coefficients on the corresponding linear terms increases significantly, an indication that the linear specifications are inadequate to capture the relationship between log credit spreads and expected defaults.[15] Overall, these results imply that the distance-to-default—rather than the MKMV's EDF—yields a better fit of the bond-pricing equation.

4.3 The Benchmark Estimate of the Excess Bond Premium

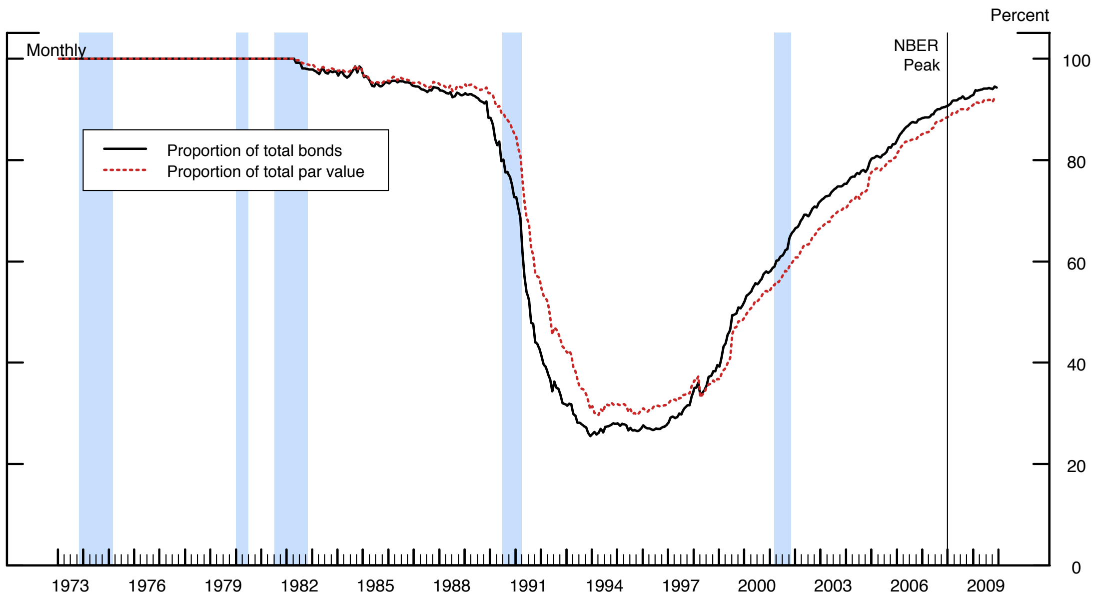
In this section, we describe the construction of our benchmark estimate of the excess bond premium over the 1973–2009 period. Recall that according to the Merton model, the distance-to-default should summarize all available information regarding the risk of default. Consequently, movements in the risk-free interest rates should affect credit spreads only insofar that they change the expected future cash flows and, as a result, the distance-to-default.

As shown by Duffee [1998], if the firm's outstanding bonds are callable, then 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.[16] In addition, callable bonds are more sensitive to uncertainty

[15] We also considered higher-order polynomials of the two default-risk indicators. The inclusion of cubic and quartic terms, however, had virtually no effect on any of our results.

[16] In fact, Duffee [1998] finds a strong negative correlation between Treasury yields and credit spreads based on commonly-used corporate bond yield indexes, which are constructed using both callable and noncallable

Figure 4: Callable Senior Unsecured Corporate Bonds



NOTE: Sample period: Jan1973–Dec2009. The figure depicts the proportion of bonds in our sample that are callable. The shaded vertical bars represent the NBER-dated recessions.

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.

One possible way to deal with this issue would be to confine the analysis to a sub-sample of noncallable bonds. However, as shown in Figure 4, callable debt accounts for a substantial portion of the debt traded in the secondary market for most of our sample period. Thus, restricting the sample to noncallable bonds only would severely limit the time span of our data, essentially making it impossible to shed much light on the recent financial crisis.

As an alternative, we control directly for the effects of the Treasury term structure and interest rate volatility on the credit spreads of callable bonds when estimating the excess bond premium. Specifically, the credit spreads of callable bonds are allowed to depend on the level, slope, and curvature 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]. The credit spreads of callable bonds are also allowed to depend on the realized monthly volatility of the daily 10-year Treasury yield, a proxy for interest rate uncertainty.[17]

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bonds. Moreover, the relation between Treasury yields and credit spreads on callable bonds is much more strongly negative that it is for noncallable bonds, a pattern consistent with the theoretical predictions.

[17] The level, slope, and curvature factors correspond, respectively, to the first three principal components

Table 6: Credit Spreads and Default Risk (1973–2009)

Explanatory Variable	*Est.*	*S.E.*	*Est.*	*S.E.*	*Est.*	*S.E.*
$-DD_{it}$	0.190	0.007	0.215	0.013	0.223	0.014
$(-DD_{it})^2$	0.007	0.000	0.008	0.001	0.008	0.001
$\ln(DUR_{it}[k])$	0.100	0.012	0.189	0.015	0.182	0.016
$\ln(PAR_{it}[k])$	0.134	0.014	0.125	0.020	0.111	0.021
$\ln(CPN_i[k])$	0.474	0.058	0.159	0.049	0.222	0.049
$CALL_i[k]$	0.262	0.017	-0.508	0.226	-1.105	0.196
$-DD_{it} \times CALL_i[k]$	-	-	-0.038	0.014	-0.070	0.014
$(-DD_{it})^2 \times CALL_i[k]$	-	-	-0.001	0.001	-0.003	0.001
$\ln(DUR_{it}[k]) \times CALL_i[k]$	-	-	-0.147	0.021	-0.103	0.019
$\ln(PAR_{it}[k]) \times CALL_i[k]$	-	-	0.011	0.021	-0.121	0.024
$\ln(CPN_i[k]) \times CALL_i[k]$	-	-	0.397	0.072	0.737	0.066
$LEV_t \times CALL_i[k]$	-	-	-	-	-0.364	0.014
$SLP_t \times CALL_i[k]$	-	-	-	-	-0.084	0.008
$CRV_t \times CALL_i[k]$	-	-	-	-	-0.038	0.005
$VOL_t \times CALL_i[k]$	-	-	-	-	0.126	0.004
Adj. R^2	0.663		0.666		0.705	
Industry Effects[a]	0.000		0.000		0.000	
Credit Rating Effects[b]	0.000		0.000		0.000	

NOTE: Sample period: Jan1973–Dec2009. Obs. = 330,029; No. of bonds/firms = 5,937/1,111. Dependent variable is $\ln(S_{it}[k])$. The Treasury term structure is represented by the following three factors: LEV_t = level; SLP_t = slope; and CRV_t = curvature. VOL_t = annualized realized monthly volatility of the daily 10-year Treasury yield. All specifications include a constant term (not reported) and are estimated by OLS. Robust asymptotic standard errors are clustered at the firm level.

[a] p-value for the robust Wald statistics of the exclusion test of industry fixed effects.

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

The results of this exercise are reported in Table 6. For comparison purposes, the first two columns contain the estimation results from the same specification as that reported in column 4 in the bottom panel of Table 5, except that the results in Table 6 are based on the full sample period. The estimates of coefficients on the distance-to-default—both the linear and quadratic terms—are virtually identical to those reported in Table 5. Moreover, the overall fit of the regression is highly comparable across the two estimation periods, indicating that our estimate of the distance-to-default is an informative and consistent indicator of default risk over the entire sample period.

The middle two columns of Table 6 report the estimation results from the specification

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].

Table 7: Selected Marginal Effects by Type of Bond

Variable	Noncallable Est.	Noncallable S.E.	Callable Est.	Callable S.E.	*Mean*[a]	*STD*[b]
Distance-to-default: $-DD_{it}$	0.230	0.010	0.160	0.005	6.574	3.953
Term structure: LEV_t	-	-	-0.733	0.029	0.000	1.000
Term structure: SLP_t	-	-	-0.170	0.016	0.000	1.000
Term structure: CRV_t	-	-	-0.076	0.010	0.000	1.000
Term structure: VOL_t (%)	-	-	0.254	0.008	1.866	1.249

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 parameter estimates reported in Table 6. 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 computed according to the delta method.

[a]Sample mean of the specified variable.

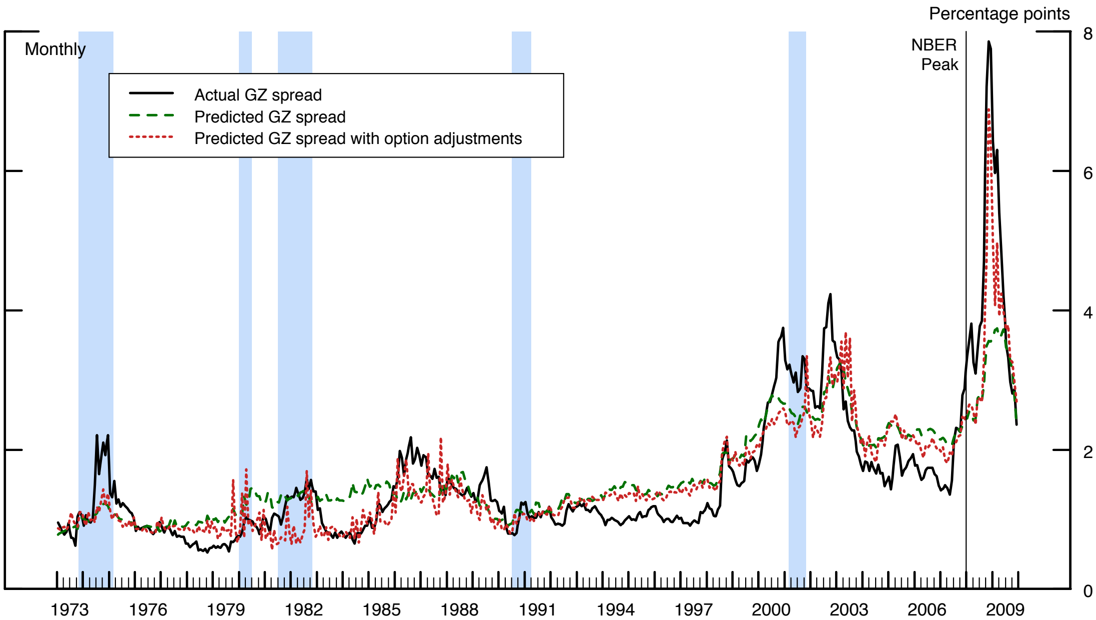
[b]Sample standard deviation of the specified variable.

that allows for the call-option interaction with the linear and quadratic DD terms and the bond-specific control variables. Consistent with the theoretical predictions, callable bonds are somewhat less sensitive to movements in default risk. Allowing for this interaction, however, result in a negligible improvement in the fit of the bond-pricing regression.

The results in the last two columns are based on the specification that controls for the effects of the Treasury term structure and interest rate volatility on the spreads of callable bonds. As predicted by the theory, an increase in the general level of interest rates and the steepening of the Treasury term structure—the effects captured by the level and slope factors, respectively—lead to a narrowing of the credit spreads of callable bonds. In contrast, an increase in the realized volatility of longer-term Treasury yields boosts the spreads of callable bonds. Importantly, the inclusion of the term structure and volatility factors noticeably improves the fit of the bond-pricing regression.

In Table 7, we translate the coefficients from the estimated log-spread pricing equation into the impact of variation in default risk, the shape of the term structure, and interest rate volatility 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, with a one standard deviation decline in the distance-to-default implying an increase of 23 basis points in the spreads of noncallable bonds, compared with a 16 basis points rise in the spreads of their callable counterparts. Consistent with the results of Duffee [1998], our estimates also imply that the shape of the

Figure 5: Actual and Predicted Credit Spreads



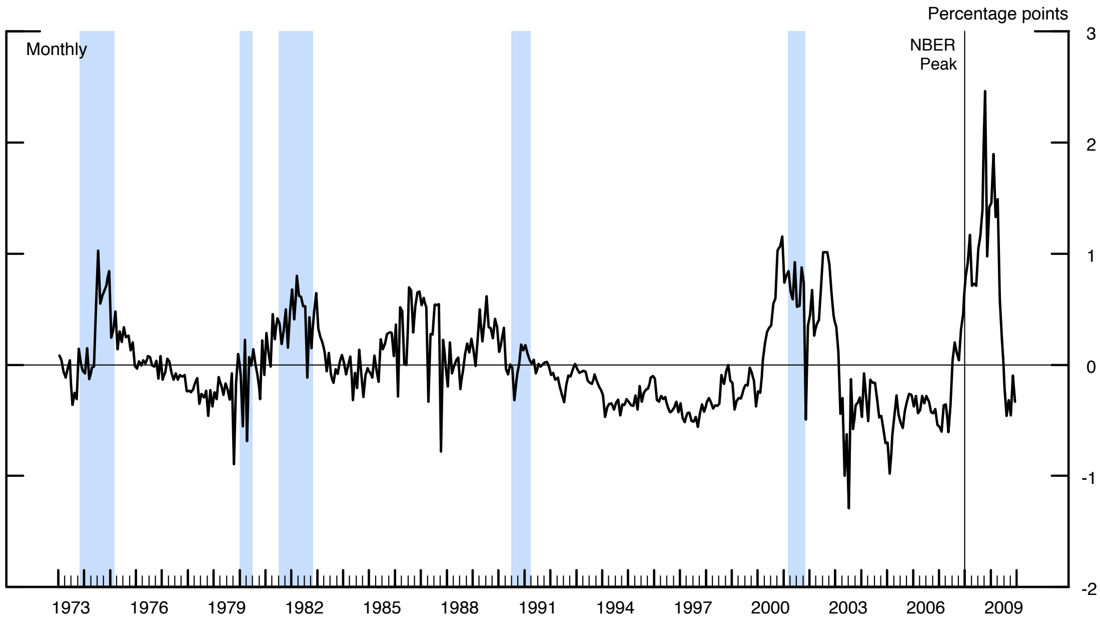
NOTE: Sample period: Jan1973–Dec2009. The solid line depicts the actual GZ credit spread. The dashed line depicts the predicted GZ credit spread based on the specification that excludes the option-adjustment terms; the dotted line depicts the predicted GZ credit spread based on the specification includes the option-adjustment terms (see text for details). The shaded vertical bars represent the NBER-dated recessions.

Treasury term structure and interest rate volatility have economically significant effects on the credit spreads of callable bonds. For example, a one standard deviation increase in the level factor implies a reduction in the credit spreads on callable bonds of almost 75 basis points, while a one standard deviation increase in the slope factor lowers credit spreads on such bonds 17 basis points; an increase in the realized (annualized) monthly volatility of the daily 10-year Treasury yield of one percentage point implies a widening of callable credit spreads of about 25 basis points.

Figure 5 shows the GZ credit spread along with the fitted values from the last two specifications of the bond-pricing equation in Table 6. Over most of our sample period, the option adjustment has had relatively little effect. One exception is the 1979–82 period of nonborrowed reserves targeting, a period characterized by a substantial volatility in nominal interest rates. Given that most of the bonds in our sample during that period were callable, increased interest rate volatility implies a higher fitted average spread, relative to the fitted value that does not control for interest rate volatility; in addition, the excessive volatility of credit spreads during this period implies a more volatile fitted values.

The option adjustment also had a significant effect during the recent financial crisis,

Figure 6: Option-Adjusted Excess Bond Premium



NOTE: Sample period: Jan1973–Dec2009. The figure depicts our benchmark estimate of the excess bond premium. The shaded vertical bars represent the NBER-dated recessions.

reflecting the fact that the general level of interest rates fell to a historically low level. Because a low level of interest rates implies higher predicted values for the credit spreads of callable bonds, our option-adjustment procedure accounts for about 200 basis points of the total increase in the GZ credit spread during the height of the financial crisis in the autumn of 2008. Overall, the fitted values from this specification capture a substantial fraction of the movements in the GZ credit spread.

Figure 6 shows our benchmark estimate of the excess bond premium—that is, the difference between the GZ credit spread and the fitted value from the option-adjusted specification on Table 6.[18] With the exception of the 1990–91 recession, our benchmark estimate of

[18] According to equation (8), the distance-to-default consists of three terms: the log of leverage, the expected return on assets, and the volatility of asset returns. In the estimation of the excess bond premium, these three terms are constrained to enter the bond-pricing regression through their effect on the distance-to-default. To the extent that the distance-to-default is not a sufficient statistic for default risk, these terms may have independent effects on the credit spreads that should be accounted for when estimating the excess bond premium. As a robustness check, we estimated a specification in which the three components of the distance-to-default—both the linear and quadratic terms—were allowed to separately affect the log credit spreads; all of these terms were also interacted with the call-option indicator to capture their differential impact on the spreads of callable and noncallable bonds. All the estimated coefficients were statistically and economically highly significant and had a correct sign relative to the theoretical predictions. However, the improvement in the goodness-of-fit was negligible ($\bar{R}^2$ of 0.708 vs. $\bar{R}^2$ of 0.705 reported in Table 6), and the excess bond premium implied by this more general specification was virtually identical to that shown in Figure 6, indicating no further need for generalization.

the excess bond premium increased significantly during all cyclical downturns. The excess bond premium fell to a historically low level in the latter part of 2003 and remained low during the following several years, the period that, at least in retrospect, has been characterized by lax credit standards, excessive credit growth, and unsustainable asset price appreciation. The intensification of credit concerns in U.S. and foreign financial markets during the summer of 2007 precipitated a sharp increase in the excess bond premium, which continued to increase throughout the subsequent financial crisis, reaching a record high of almost 250 basis points in October 2008. Although conditions in financial markets improved somewhat over the remainder of 2008, investors' concern in early 2009 about the viability of major financial institutions led to another surge in the excess bond premium. Since then, the excess bond premium has reversed all of its run-up, a pattern consistent with the improved economic outlook and the easing of strains in financial markets.

5 The Excess Bond Premium and Economic Activity

Our decomposition of the GZ credit spread implies that an important component of the variation in corporate credit spreads is due to fluctuations in the excess bond premium, movements that arguably reflect variation in the pricing of default risk rather than variation in the risk of default. We now examine whether or not these movements in the excess bond premium provides independent information about future economic activity. We do so in two steps. First, we examine the extent to which the forecasting power of the GZ credit spread documented in Section 3 is attributable to the predicted component ($\widehat{S}_t^{GZ}$), versus the residual component—that is, the excess bond premium (EBP_t). We then add our benchmark estimate of the excess bond premium to an otherwise standard macroeconomic VAR and examine the implications of the orthogonalized shocks to the excess bond premium for the real economy and asset prices more generally.

5.1 Forecasting Results: 1973–2009

Table 8 reports the results for the monthly indicators of economic activity, based on the specification in which the two components of the GZ credit spread—$\widehat{S}_t^{GZ}$ and EBP_t—are allowed to enter the forecasting regression (2) separately.[19] According to our estimates, both the excess bond premium and the predicted GZ credit spread contains significant independent explanatory power for all three economic indicators, at both the 3- and 12-month forecast horizons. Moreover, the (absolute) magnitude of the estimated coefficients and the

[19]For completeness, this set of forecasting exercises also adds the change in the (civilian) unemployment rate to our monthly indicators of economic activity. Because the unemployment rate is already expressed in percent, it enters the forecasting equation (2) in simple annualized changes, rather than in log-differences.

Table 8: Excess Bond Premium and Economic Activity (1973–2009)

	Forecast Horizon: 3 months			Forecast Horizon: 12 months		
Financial Indicator	EMP	UER	IPM	EMP	UER	IPM
Term spread	-0.099	0.174	-0.201	-0.269	0.410	-0.387
	[2.43]	[6.40]	[3.05]	[5.54]	[48.6]	[4.49]
Real FFR	-0.112	0.106	-0.105	-0.188	0.096	-0.148
	[2.30]	[3.34]	[1.42]	[3.62]	[11.6]	[1.65]
Predicted GZ spread	-0.182	0.186	-0.205	-0.332	0.228	-0.268
	[4.42]	[8.13]	[3.00]	[8.62]	[39.5]	[3.87
Excess bond premium	-0.172	0.236	-0.277	-0.281	0.345	-0.314
	[6.17]	[12.1]	[4.46]	[11.4]	[74.1]	[4.54]
Adj. R^2	0.708	0.424	0.376	0.586	0.443	0.374

Note: Sample period: Jan1973–Dec2009. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes an indicator of economic activity in month t and h is the forecast horizon: EMP = log of private nonfarm payroll employment; UER = civilian unemployment rate; and IPM = log of the index of manufacturing industrial production. In addition to the specified financial indicators in month t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table denote standardized estimates of the OLS coefficients associated with each financial indicator; absolute t-statistics reported in brackets are based on the asymptotic covariance matrix computed according to Hodrick [1992].

associated t-statistics are roughly equivalent across the two predictors in all forecasting specifications.

In Table 9, we repeat this forecasting exercise for the growth rate of real GDP. Again, the results indicate that the excess bond premium is economically and statistically a highly significant predictor of output growth at both the short- and longer-term forecast horizons. The coefficient estimates imply that an increase in the excess bond premium of 100 basis points in quarter t leads to a drop in real GDP growth of more than 2.0 percentage points (annualized) in the subsequent quarter and 1.25 percentage points over the subsequent four quarters. The impact on economic growth of a similarly-sized move in the predicted component of the GZ credit spread is considerably smaller—a 100 basis points increase leads to a deceleration in real GDP of about 0.75 percentage point at both the 1- and 4-quarter forecast horizons.

The results reported in Table 10 focus on the main components of private aggregate demand. At the 1-quarter horizon, the excess bond premium has substantial predictive content for all components of business investment as well as for the growth of personal consumption expenditures on durable goods. The predicted GZ credit spread, in contrast, appears to be informative mainly for the near-term growth of residential investment, the

Table 9: Excess Bond Premium and Real GDP (1973–2009)

Financial Indicator	Forecast Horizon: 1 quarter	Forecast Horizon: 4 quarters
Term spread	-0.214	-0.423
	[2.09]	[3.30]
Real FFR	-0.134	-0.135
	[1.24]	[0.97]
Predicted GZ spread	-0.170	-0.237
	[1.85]	[2.31]
Excess bond premium	-0.267	-0.217
	[3.50]	[2.62]
Adj. R^2	0.250	0.333

NOTE: Sample period: 1973:Q1–2009:Q4. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of real GDP in quarter t and h is the forecast horizon. In addition to the specified financial indicator in quarter t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator. For the 1-quarter horizon, absolute t-statistics reported in brackets are based on the asymptotic covariance matrix (HC3) computed according MacKinnon and White [1985]; for the 4-quarter horizon, absolute t-statistics are computed according to Hodrick [1992].

growth of E&S spending, and the growth of business inventories. Moreover, in the case of business investment, the coefficients on the predicted component of the GZ spread are considerably smaller in (absolute value) than the respective coefficients on the excess bond premium, indicating that movements in the excess bond premium have, in economic terms, a greater impact on these cyclically-sensitive indicators of economic activity.

The forecasting power of the predicted component of the GZ spread improves noticeably at the year-ahead forecast horizon. However, the excess bond premium remains, statistically and economically, a highly significant predictor of the growth of business spending on fixed capital and inventories. Indeed, for the most cyclically volatile series such as inventory investment and spending on E&S and nonresidential structures, the economic impact of the excess bond premium is about twice as large as that of the predicted component of the GZ credit spread.

5.2 Forecasting Results: 1985–2009

As a robustness check, this section repeats our forecasting exercises for the 1985–2009 period. Although no clear consensus has emerged regarding the dominant cause(s) of the perceived decline in macroeconomic volatility since the mid-1980s, changes in the conduct of monetary policy appear to be at least partly responsible for the significantly diminished variability of both output and inflation over the past two and a half decades; see, for example, Clarida

Table 10: Excess Bond Premium and Components of Aggregate Demand (1973-2009)

	Forecast Horizon: 1 quarter						
Financial Indicator	C-NDS	C-D	I-RES	I-ES	I-HT	I-NRS	INV
Term spread	-0.222	-0.304	-0.299	-0.199	-0.069	0.151	-0.030
	[2.23]	[2.88]	[3.69]	[2.16]	[0.77]	[1.78]	[0.36]
Real FFR	-0.065	-0.049	-0.180	-0.095	0.070	-0.087	0.031
	[0.58]	[0.46]	[2.08]	[1.24]	[0.62]	[0.95]	[0.36]
Predicted GZ spread	-0.157	-0.022	-0.208	-0.228	-0.144	-0.154	-0.173
	[1.93]	[0.28]	[2.09]	[1.93]	[1.48]	[1.23]	[2.69]
Excess bond premium	-0.104	-0.234	-0.030	-0.458	-0.306	-0.274	-0.289
	[1.46]	[2.49]	[0.39]	[4.90]	[3.37]	[2.82]	[3.78]
Adj. R^2	0.368	0.115	0.471	0.364	0.362	0.296	0.474
	Forecast Horizon: 4 quarters						
Financial Indicator	C-NDS	C-D	I-RES	I-ES	I-HT	I-NRS	INV
Term spread	-0.418	-0.503	-0.545	-0.344	-0.086	0.313	-0.144
	[3.86]	[2.62]	[5.51]	[3.22]	[0.81]	[2.75]	[1.68]
Real FFR	0.061	0.070	-0.046	-0.161	-0.144	-0.214	-0.118
	[0.62]	[0.41]	[0.41]	[1.54]	[1.11]	[1.77]	[1.32]
Predicted GZ spread	-0.210	-0.049	-0.241	-0.255	-0.374	-0.138	-0.272
	[2.41]	[0.39]	[2.98]	[2.62]	[4.13]	[1.47]	[4.31]
Excess bond premium	-0.082	-0.056	0.093	-0.462	-0.349	-0.522	-0.536
	[1.13]	[0.41]	[1.39]	[4.53]	[4.45]	[5.00]	[7.39]
Adj. R^2	0.356	0.183	0.420	0.540	0.448	0.493	0.537

NOTE: Sample period: 1973:Q1–2009:Q4. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of the component of private (real) aggregate demand in quarter t and h is the forecast horizon: C-D = PCE on durable goods; C-NDS = PCE on nondurable goods & services; I-RES = residential investment; I-ES = business fixed investment in E&S (excl. high tech); I-HT = business fixed investment in high-tech equipment; I-NRS = business fixed investment in structures; INV = business inventories. In addition to the specified financial indicators in quarter t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator. For the 1-quarter horizon, absolute t-statistics reported in brackets are based on the asymptotic covariance matrix (HC3) computed according MacKinnon and White [1985]; for the 4-quarter horizon, absolute t-statistics are computed according to Hodrick [1992].

et al. [2000] and Stock and Watson [2002]. Because monetary policy affects the real economy by influencing asset prices, the change in the monetary policy regime may have also altered the predictive content of various financial indicators for economic activity. Moreover, as emphasized by Dynan et al. [2006], the rapid pace of financial innovation since the mid-1980s—namely, the deepening and emergence of lending practices and credit markets that

Table 11: Excess Bond Premium and Economic Activity (1985–2009)

	Forecast Horizon: 3 months			Forecast Horizon: 12 months		
Financial Indicator	EMP	UER	IPM	EMP	UER	IPM
Term spread	-0.103	0.134	-0.158	-0.286	0.345	-0.323
	[2.94]	[4.06]	[1.86]	[8.13]	[37.1]	[3.74]
Real FFR	0.057	-0.044	0.091	0.104	-0.147	0.182
	[1.34]	[1.09]	[0.83]	[2.65]	[15.6]	[1.81]
Predicted GZ spread	-0.071	0.147	-0.174	-0.062	0.067	-0.167
	[1.66]	[4.16]	[1.55]	[1.76]	[8.66]	[2.08]
Excess bond premium	-0.189	0.319	-0.397	-0.321	0.434	-0.482
	[5.68]	[12.0]	[4.26]	[11.1]	[75.0]	[5.25]
Adj. R^2	0.825	0.505	0.447	0.721	0.553	0.398

NOTE: Sample period: Jan1985–Dec2009. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes an indicator of economic activity in month t and h is the forecast horizon: EMP = log of private nonfarm payroll employment; UER = civilian unemployment rate; and IPM = log of the index of manufacturing industrial production. In addition to the specified financial indicators in month t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table denote standardized estimates of the OLS coefficients associated with each financial indicator; absolute t-statistics reported in brackets are based on the asymptotic covariance matrix computed according to Hodrick [1992].

have enhanced the ability of households and firms to borrow and changes in government policy such as the demise of Regulation Q—may have also changed the information content of financial indicators for macroeconomic outcomes.

As shown in Table 11, the predictive content of the excess bond premium for the monthly indicators of economic activity over the 1985–2009 period is, if anything, greater than that obtained for the full sample period. Compared with the predicted component of the GZ credit spread, the excess bond premium provides substantially greater explanatory power for changes in labor market conditions and for the growth of industrial production at both the 3- and 12-month forecast horizons.

The predictive content of the excess bond premium over the 1985–2009 period is especially striking in the case of real GDP growth. According to Table 12, the predicted component of the GZ credit spread has no forecasting power for the growth of real GDP over this period, while the excess bond premium continues to provide economically and statistically highly significant signals regarding economic growth prospects. Indeed, the coefficients on the excess bond premium estimated over the 1985–2009 period are noticeably higher (in absolute value) than those reported in Table 9. The estimates based on the 1985–2009 period imply that a 100 basis points increase in the excess bond premium in quarter

Table 12: Excess Bond Premium and Real GDP (1985–2009)

Financial Indicator	Forecast Horizon: 1 quarter	Forecast Horizon: 4 quarters
Term spread	-0.313	-0.455
	[2.00]	[3.44]
Real FFR	-0.343	-0.402
	[1.57]	[2.51]
Predicted GZ spread	-0.059	-0.081
	[0.27]	[0.59]
Excess bond premium	-0.507	-0.504
	[3.72]	[4.12]
Adj. R^2	0.315	0.328

NOTE: Sample period: 1985:Q1–2009:Q4. Dependent variable is $\nabla^h Y_{t+h}$, where Y_t denotes the log of real GDP in quarter t and h is the forecast horizon. In addition to the specified financial indicator in quarter t, each specification also includes a constant, current, and p lags of ∇Y_t (not reported), where p is determined by the AIC. Entries in the table are the standardized estimates of the OLS coefficients associated with each financial indicator. For the 1-quarter horizon, absolute t-statistics reported in brackets are based on the asymptotic covariance matrix (HC3) computed according MacKinnon and White [1985]; for the 4-quarter horizon, absolute t-statistics are computed according to Hodrick [1992].

t lowers output growth 2.6 percentage points (annualized) in the subsequent quarter and almost 2.0 percentage points over the next four quarters.

In summary, the above analysis indicates that our benchmark estimate of the excess bond premium is a robust predictor of future economic activity. This finding holds true across a variety of economic indicators, short- and longer-term forecast horizons, and sample periods. Furthermore, our forecasting results imply that over the 1985–2009 period, most of the predictive content of the GZ credit spread for economic activity can be attributed to variation in the excess bond premium rather than to variation in default risk, as measured by the predicted component of the GZ credit spread.

5.3 Macroeconomic Implications

In this section, we examine macroeconomic consequences of shocks to the excess bond premium. We do so by adding our benchmark estimate of the excess bond premium to an otherwise standard VAR. Using this framework, we consider the effects of a shock to the excess bond premium that is orthogonal to measures of economic activity and inflation, the stance of monetary policy, and returns on other financial assets.

Our VAR specification includes the following endogenous variables: (1) log-difference of real personal consumption expenditures (PCE); (2) log-difference of real business fixed investment (BFI); (3) log-difference of real GDP; (4) inflation as measured by the log-difference of the GDP price deflator; (5) the quarterly value-weighted excess stock market return from CRSP; (6) the 10-year (nominal) Treasury yield; (7) the effective (nominal) federal funds rate; and (8) the excess bond premium. By including short- and long-term interest rates along with the stock market return, we are considering shocks to the excess bond premium that are orthogonal to the information embedded in the level and slope of the Treasury yield curve and to the information content of equity prices. We estimate the VAR over the 1973–2009 period, using two lags of each endogenous variable.

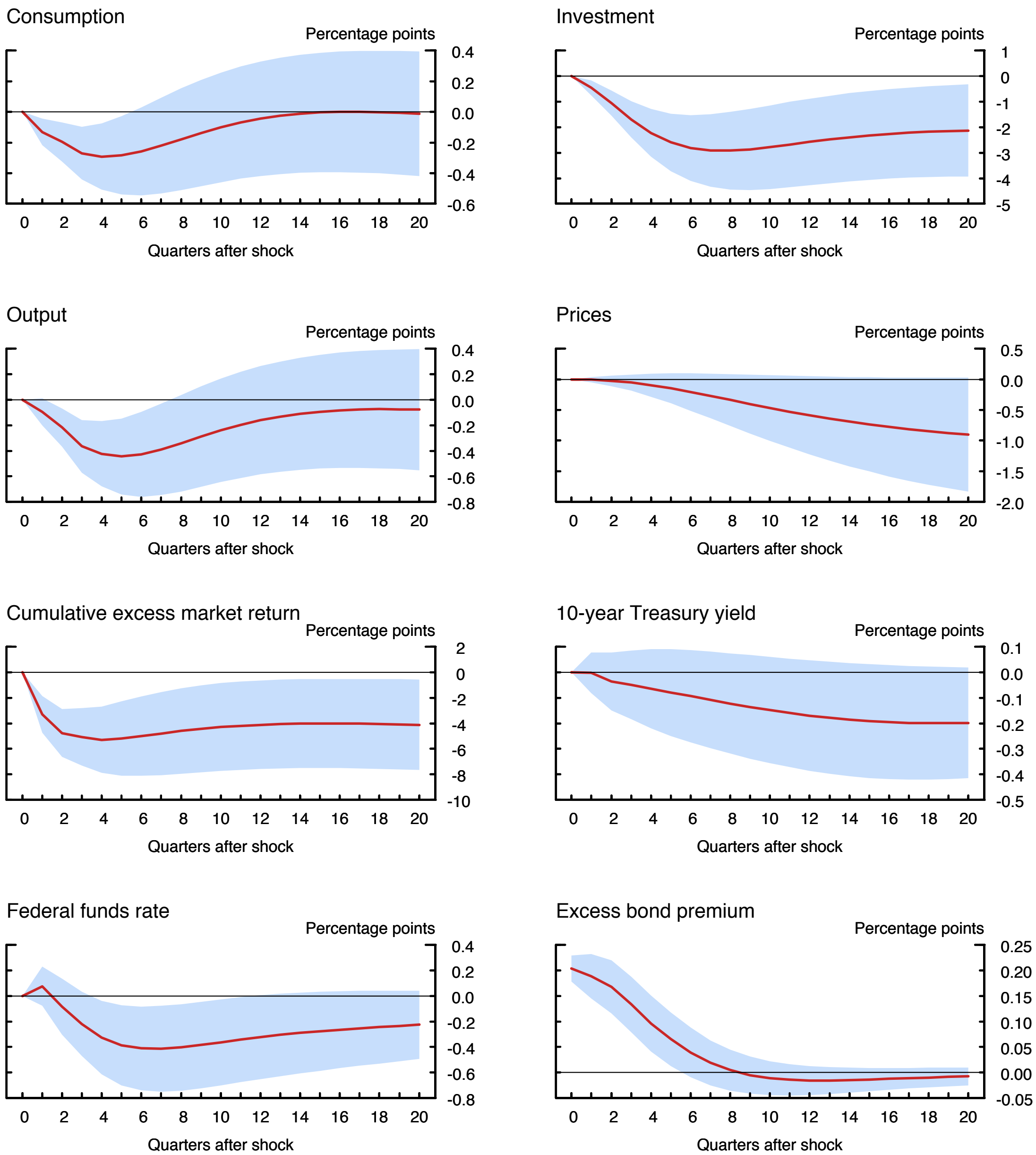
Figure 7 depicts the impulse response functions of the endogenous variables to an orthogonalized shock to the excess bond premium. An unanticipated increase of one standard deviation in the excess bond premium—about 20 basis points—causes a significant reduction in real economic activity, with consumption, investment, and output all falling over the next several quarters. The implications for economic growth of this adverse financial shock are substantial: The level of real GDP bottoms out almost 0.5 percentage point below trend about five quarters after the shock, while the drop in investment is much more severe and persistent. The resulting economic slack leads to a substantial disinflation and elicits a significant easing of monetary policy, as evidenced by the decline in the federal funds rate. Despite falling short-term interest rates, the stock market experiences a significant drop, with the cumulative decline of about 5 percentage points relative to trend growth.

Figure 8 shows the amount of variation of the variables in the VAR explained by orthogonalized shocks to the excess bond premium. These financial shocks account for about 10 percent of the variation in output and 20 percent of the variation in investment at business cycle frequencies, proportions that exceed the amount of variation typically explained by monetary policy shocks. In addition, shocks to the excess bond premium explain a significant portion of the variation in equity prices.

These results are consistent with the notion that the excess bond premium provides a useful gauge of credit-supply conditions. A reduction in the supply of credit—an increase in the excess bond premium—causes a drop in asset prices and a contraction in economic activity through the financial accelerator mechanisms emphasized by Kiyotaki and Moore [1997], Bernanke et al. [1999], and Hall [2010]. Our findings are also consistent with the recent work by Gertler and Karadi [2009] and Gertler and Kiyotaki [2009], 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 economic activity.

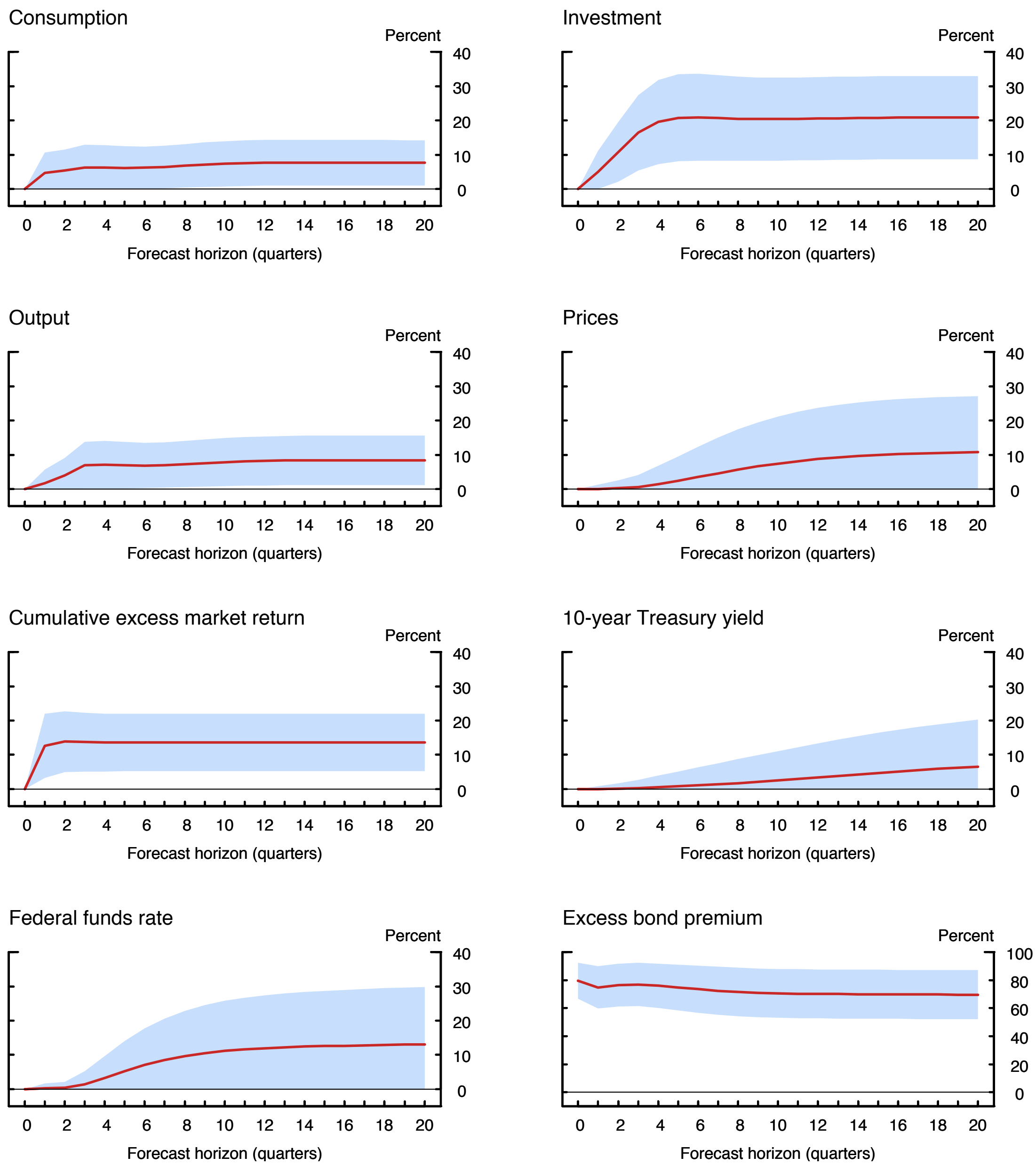
To the extent that financial shocks cause variation in the risk attitudes of the marginal investors pricing corporate bonds, shifting risk attitudes of these intermediaries may also influence the supply of credit available through the corporate bond market. By and large, the corporate bond market is dominated by institutional investors such as large banks, insurance companies, and pensions funds, intermediaries that possess specialized knowledge

Figure 7: Macroeconomic Implications of a Shock to the Excess Bond Premium



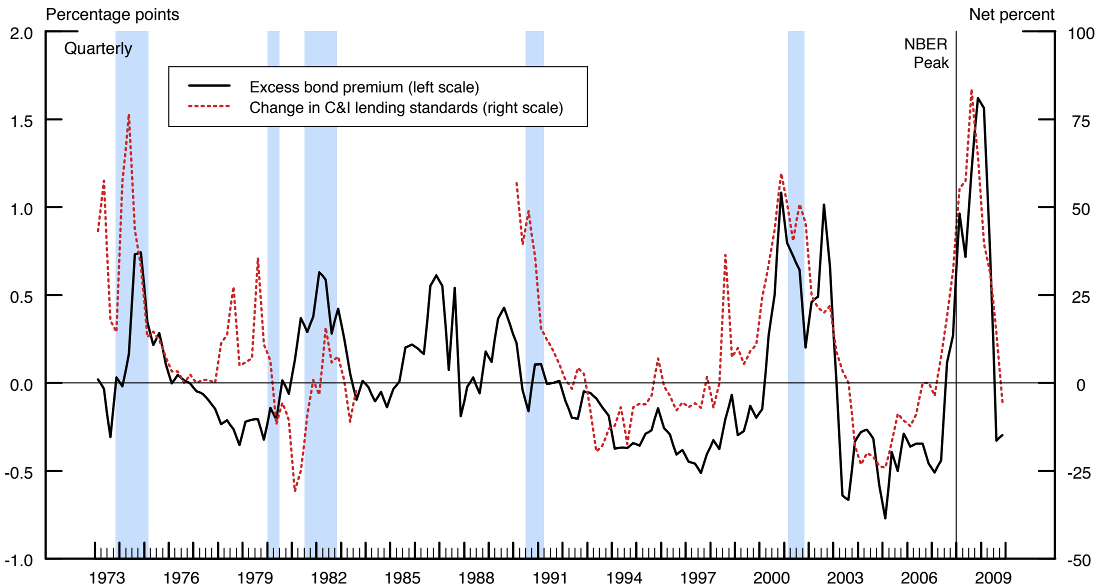
NOTE: Sample period: 1973:Q1–2009:Q4. The figure depicts the impulse responses to a one standard deviation orthogonalized shock to the excess bond premium. The VAR(2) is ordered as follows: (1) log-difference of real PCE; (2) log-difference of real BFI; (3) log-difference of real GDP; (4) log-difference of the GDP price deflator; (5) value-weighted excess stock market return; (6) 10-year Treasury yield; (7) federal funds rate; and (8) excess bond premium. The responses of consumption, investment, and output growth and that of the excess market return have been accumulated. Shaded bands denote 95-percent confidence intervals based on 2,000 bootstrap replications.

Figure 8: Forecast Error Variance Decomposition



NOTE: Sample period: 1973:Q1–2009:Q4. The figure depicts the forecast error variance decomposition from a one standard deviation orthogonalized shock to the excess bond premium. The VAR(2) is ordered as follows: (1) log-difference of real PCE; (2) log-difference of real BFI; (3) log-difference of real GDP; (4) log-difference of the GDP price deflator; (5) value-weighted excess stock market return; (6) 10-year Treasury yield; (7) federal funds rate; and (8) excess bond premium. The forecast error variance decomposition of consumption, investment, and output growth and that of the excess market return is based on the level of the variables. Shaded bands denote 95-percent confidence intervals based on 2,000 bootstrap replications.

Figure 9: Excess Bond Premium and Changes in Bank Credit Standards



NOTE: The solid line depicts our benchmark estimate of the excess bond premium. The dotted line depicts the net percent of respondents to the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices that reported tightening their credit standards on C&I loans to large and middle-market firms over the quarter. Reported net percent equals the percent of banks that reported tightening their standards minus the percent that reported easing their standards. (There was no survey conducted during the 1984-89 period.) The shaded vertical bars denote NBER-dated recessions.

pertinent to the corporate bond market. However, these investors also face—either explicit or implicit—capital requirements, and as their financial capital becomes impaired, they act in a more risk-averse manner. This shift in risk attitudes leads to an increase in the excess bond premium and a reduction in the supply of credit available to potential borrowers—both within the banking system and to those who rely on the corporate cash market—resulting in the type of asset market dynamics analyzed by He and Krishnamurthy [2010] and Adrian et al. [2010].

Figure 9 provides one piece of evidence in favor of such credit-supply mechanisms. It plots our benchmark estimate of the excess bond premium against the diffusion index of the change in credit standards on commercial and industrial (C&I) loans at U.S. commercial banks obtained from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices.[20] The correlation between these two series—one obtained from a survey of banks and the other obtained from market prices—is strikingly high. In effect,

[20]The change in credit standards is available from 1973 to 1984 and again during the 1990–2009 period; see Lown and Morgan [2006] for detailed description of the diffusion index and its role in economic fluctuations.

the willingness of commercial banks to make C&I loans comoves strongly with the supply conditions in corporate bond market as measured by the excess bond premium.

6 Conclusion

In this paper, we re-examine the role that corporate bond credit spreads play in determining macroeconomic outcomes. We do so by constructing a new corporate bond credit spread index—the GZ credit spread—employing an extensive micro-level data set of secondary market prices of outstanding senior unsecured bonds for a large panel of U.S. nonfinancial corporation. Compared with the widely-used credit spread indexes such as the Baa-Aaa corporate bond spread and the paper-bill spread, the GZ credit spread is shown to be a robust predictor of future economic activity across a variety of economic indicators, sample periods, and forecast horizons.

Using a flexible empirical bond-pricing framework, we then decompose the GZ credit spread into two parts: a component that reflects all available firm-specific information on default risk and a residual component—the excess bond premium—that plausibly reflects variation in the pricing of default risk. According to our results, a substantial portion of the predictive content of the GZ credit spread for economic activity is accounted for by movements in the excess bond premium—indeed, over the 1985–2009 period, the excess bond premium accounts for all of the predictive content of the GZ credit spread. Finally, shocks to the excess bond premium that are orthogonal to the current state of the economy, the information contained in the term structure of interest rates, and news embedded in stock returns are shown to cause substantial and protracted contractions in economic activity. All told, our findings are consistent with the notion that a rise in the excess bond premium reflects a reduction in the risk appetite of the financial sector and, as a result, a contraction in the supply of credit with significant adverse consequences for the macroeconomy.

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