Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets

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Abstract

To identify disruptions in credit markets, research on the role of asset prices in economic fluctuations has focused on the information content of various corporate credit spreads. We re-examine this evidence using a broad array of credit spreads constructed directly from the secondary bond prices on outstanding senior unsecured debt issued by a large panel of nonfinancial firms. An advantage of our "ground-up" approach is that we are able to construct matched portfolios of equity returns, which allows us to examine the information content of bond spreads that is orthogonal to the information contained in stock prices of the same set of firms, as well as in macroeconomic variables measuring economic activity, inflation, interest rates, and other financial indicators. Our portfolio-based bond spreads contain substantial predictive power for economic activity and outperform—especially at longer horizons—standard default-risk indicators. Much of the predictive power of bond spreads for economic activity is embedded in securities issued by intermediate-risk rather than high-risk firms. According to impulse responses from a structural factor-augmented vector autoregression, unexpected increases in bond spreads cause large and persistent contractions in economic activity. Indeed, shocks emanating from the corporate bond market account for more than 20 percent of the forecast error variance in economic activity at the two- to four-year horizon. Overall, our results imply that credit market shocks have contributed significantly to U.S. economic fluctuations during the 1990–2007 period.

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1 Introduction

After markets for securitized credit products collapsed dramatically in the second half of 2007, growth in a number of industrialized economies slowed markedly, suggesting that disruptions in financial markets can have important macroeconomic consequences. The fact that sharp and sudden deteriorations in financial conditions are typically followed by a prolonged period of economic weakness is a feature of a growing number of economic downturns in the U.S. and abroad. During periods of credit market turmoil, financial asset prices, owing to their forward-looking nature, are especially informative of linkages between the real and financial sides of economy: Movements in asset prices can provide early-warning signals for such economic downturns and can be used to gauge the degree of strains in financial markets.

Past research on the role of asset prices in signaling future economic conditions and in propagating economic fluctuations has emphasized the information content of default-risk indicators such as corporate credit spreads—the difference in yields between various corporate debt instruments and government securities of comparable maturity—for the state of the economy and risks to the economic outlook.[1] In a recent paper, Philippon [2008] provides a theoretical framework in which the predictive content of corporate bond spreads for economic activity—absent any financial frictions—reflects a general decline in economic fundamentals stemming from a reduction in the expected present value of corporate cash flows prior to a cyclical downturn. Rising credit spreads can also reflect disruptions in the supply of credit resulting from the worsening in the quality of corporate balance sheets or from the deterioration in the health of financial intermediaries that supply credit—the financial accelerator mechanism emphasized by Bernanke, Gertler, and Gilchrist [1999]. In this context, a contraction in credit supply causes asset values to fall, incentives to default to increase, and yield spreads on private debt instruments to widen before economic downturns, as lenders demand compensation for the expected increase in defaults.

In terms of forecasting macroeconomic conditions, the empirical success of this vein of research is considerable. Nevertheless, results vary substantially across different financial

[1]The predictive content of various corporate credit spreads for economic activity has been analyzed, among other, by Stock and Watson [1989]; Friedman and Kuttner [1998]; Duca [1999]; Emery [1999]; Gertler and Lown [1999]; Ewing, Lynch, and Payne [2003]; Mody and Taylor [2004]; and Mueller [2007]. In addition, Stock and Watson [2002b] have pointed out the ability of credit spreads to forecast economic growth using dynamic factor analysis, and King, Levin, and Perli [2007] find that corporate bond spread indexes contain important information about the near-term likelihood of a recession. In a related vein, an extensive empirical literature has emphasized the extent to which the slope of the yield curve—the so-called term spread—provides a signal for forecasting economic growth or for assessing the near-term risk of recession; see, for example, Dotsey [1998], Estrella and Hardouvelis [1991], Estrella and Mishkin [1998], and Hamilton and Kim [2002]. More recent work on this topic includes Ang, Piazzesi, and Wei [2006] and Wright [2006]. A comprehensive review of the literature on the role of asset prices in forecasting macroeconomic outcomes is provided by Stock and Watson [2003a].

instruments underlying credit spreads under consideration as well as across different time periods. For example, the spread of yields between nonfinancial commercial paper and comparable-maturity Treasury bills—the so-called paper-bill spread—has lost much of its forecasting power since the early 1990s.[2] In contrast, 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 [2003b], 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. This dichotomy of findings is perhaps not surprising, because as financial markets evolve, the information content of specific financial assets prices may change as well. The fragility of results may also reflect the fact that this research has generally relied on a single credit spread index, rather than on multiple indexes reflecting a broad cross-section—in terms of both default risk and maturity—of private debt instruments.

In addition to focusing on a single credit spread index, researchers often ignore the information content of other asset prices when evaluating the forecasting ability of different default-risk indicators. Although it is straightforward to control for the general level of equity prices in such analysis, it is usually not possible to obtain equity valuations of the borrowers whose debt securities are used to construct the credit spreads under consideration.[3] Such information could potentially be used to distinguish movements in corporate credit spreads that are due to general trends in financial asset prices associated with a given class of borrowers from the movements in spreads that are specifically related to developments in credit markets.

When assessing the information content of corporate credit spreads for economic activity, it is also important to control accurately for the maturity structure of the underlying credit instruments. The widely used paper-bill spreads, for example, are based on short maturity instruments—typically between one and six months—whereas the specific maturity structure of corporate bond spread indexes such as the high-yield spread or Baa-Aaa spread—though much longer—is not generally known. In general, short-term credit instruments reflect near-term default risk, whereas longer-maturity instruments are likely better at capturing expectations about future economic conditions one to two years ahead, a forecast horizon typically associated with business cycle fluctuations. Thus, a correct assessment of the ability of credit spreads to forecast at business cycle frequencies likely requires careful

[2]Indeed, Thoma and Gray [1998] and Emery [1999] argue that the predictive content of the paper-bill spread may reflect one-time events.

[3]Fama [1981], Harvey [1989], Stock and Watson [1989, 1999], and Estrella and Mishkin [1998] examine the predictive content of various stock price indexes for economic activity and compare it to other financial and nonfinancial indicators.

attention to the maturity structure of securities used to construct credit spreads.

In this paper, we construct credit spreads using monthly data on prices of senior unsecured corporate debt traded in the secondary market over the 1990–2007 period, issued by nearly 1,000 U.S. nonfinancial corporations. In contrast to many other corporate financial instruments, long-term senior unsecured bonds represent a class of securities with a long history containing a number of business cycles, an attribute that is most useful in the valuation process of debt instruments. In addition, the rapid pace of financial innovation over the past twenty years 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 underwent a significant structural change. As a result, our measures of corporate bond spreads are less likely to capture "one-off" developments in the financial sector that can reduce the informational content of asset prices for future economic activity.

We exploit the cross-sectional heterogeneity of our data by constructing a broad array of credit spreads that vary across maturity and default risk. Because we observe prices of individual securities, we can assign each bond outstanding at each point in time to a specific category determined by the issuer's ex-ante expected probability of default and the bond's remaining term-to-maturity. In the construction of these "bond portfolios," we rely on the monthly firm-specific expected default frequencies (EDFs) constructed by the Moody's/KMV corporation. Because they are primarily based on observable information in equity markets, EDFs provide, arguably, a more objective—and certainly more timely—assessment of credit risk compared with the issuer's senior unsecured credit rating. Importantly, by building bond portfolios from the "ground up," we can also construct portfolios of stock returns corresponding to firms in the same credit-risk categories. These matched portfolios of stock returns, in turn, serve as controls for the news about firms' future earnings as these corporate borrowers experience shocks to their creditworthiness.

Using portfolios of bond and stock returns based on the riskiness of a borrower as measured by the EDFs, we employ a two-pronged empirical strategy to assess the role of credit market factors in economic fluctuations. First, we document the predictive content of corporate bond spreads in our credit-risk portfolios for both the growth of nonfarm payroll employment and industrial production, and we compare the forecasting power of credit spreads in our EDF-based bond portfolios to that of other default-risk indicators emphasized in the literature. We find that at shorter forecast horizons, the information content of credit spreads in our EDF-based bond portfolios for these two monthly measures of economic activity is comparable to that of standard credit spread indexes. At longer forecast horizons, however, our portfolio credit spreads outperform—both in-sample and out-of-sample—standard default-risk indicators by almost a factor of two. The results from forecasting exercises that rely on credit spreads in our EDF-based bond portfolios indicate that most of the predictive power of these default-risk indicators comes from the middle of the credit-quality spectrum, a result consistent with that of Mueller [2007] who examines the predictive content of corporate bond spread indexes across different rating categories.

The second prong of our empirical strategy assesses the impact on the macroeconomy of movements in credit spreads in our EDF-based bond portfolios within a structural factor-augmented vector autoregression (FAVAR) framework proposed by Bernanke and Boivin [2003], Bernanke, Boivin, and Eliasz [2005], and Stock and Watson [2005], an approach particularly well-suited to our case given the large number of variables under consideration. Our empirical strategy involves identifying credit market shocks—that is, shocks to corporate bond spreads—that are orthogonal to general measures of economic activity, inflation, real interest rates, and various financial indicators, as well as to equity returns of firms whose outstanding bonds were used to construct credit spreads in our EDF-based portfolios.

According to the result from our FAVAR analysis, an unanticipated worsening of business credit conditions—identified through the widening of corporate bond spreads that is orthogonal to other contemporaneous information—causes substantial and long-lasting declines in economic activity. The decomposition of the forecast error variance implies that these credit market shocks account, on average, for more than 20 percent of the variation in economic activity (as measured by industrial production) at the two- to four-year horizon. We also find that incorporating information from the stock market does not alter any of our conclusions. Thus to the extent that equity returns capture news about firms' future earnings, our FAVAR specification identifies shocks to credit spreads that are orthogonal to such news and hence are specific to events that lead to disruptions in the corporate bond market.[4] Overall, our results suggest that disturbances specific to credit markets account for a substantial fraction of the volatility in U.S. economic activity during the 1990–2007 period.

The remainder of the paper is organized as follows. Section 2 discusses the characteristics of our underlying security-level data, the construction of portfolios based on expected default risk, and presents the key summary statistics of and statistical relationships between our EDF-based financial indicators. Section 3 presents our forecasting exercises. Section 4 contains results of our FAVAR analysis. Section 5 concludes.

[4]By examining the joint behavior of stock prices and TFP, Beaudry and Portier [2006], identify a component in stock returns that captures news about future permanent changes in TFP; moreover, they show that movements in this component explains a significant portion of U.S. business cycle fluctuations. Jermann and Quadrini [2008] develop a theoretical framework in which news about future technological opportunities raises firms' current equity valuations, which relax credit constraints, thereby boosting current investment and output.

2 Data Description

The key information for our analysis comes from a large sample of fixed income securities issued by U.S. nonfinancial corporations. Specifically, for a sample of 944 publicly-traded firms covered by the Center for Research in Security Prices (CRSP), we obtained month-end secondary market prices of their outstanding long-term corporate bonds from the Lehman/Warga (LW) and Merrill Lynch (ML) databases. These two data sources include secondary market prices for a significant fraction of dollar-denominated bonds publicly issued in the U.S. corporate cash market. The ML database is a proprietary data source of *daily* bond prices that starts in 1997. Focused on the most liquid securities in the secondary market, bonds in the ML database must have a remaining term-to-maturity of at least two years, a fixed coupon schedule, and a minimum amount outstanding of $100 million for below investment-grade and $150 million for investment-grade issuers. By contrast, the LW database of *month-end* bond prices has a somewhat broader coverage and is available from 1973 through mid-1998 (see Warga [1991] for details).

To ensure that the bonds yields used to construct portfolios are obtained from comparable securities, we restricted our attention to senior unsecured issues only. For such securities with market prices in both the LW and LM databases, we spliced their option-adjusted effective yields at month-end—a component of the bond's yield that is not attributable to embedded options—across the two data sources. To calculate the credit spread at each point in time, we matched the resulting yield on *each* individual security issued by the firm to the estimated yield on the Treasury coupon security of the same maturity. The month-end Treasury coupon yields were taken from the daily estimates of the U.S. Treasury yield curve reported in Gürkaynak, Sack, and Wright [2006]. To mitigate the effect of outliers on our analysis, we eliminated all observations with credit spreads smaller than 10 basis points and with spreads greater than 5,000 basis points; in addition, we eliminated all issues with a par value of less than $1 million, as such small issues are likely plagued by significant liquidity concerns. These selection criteria yielded a sample of 5,321 individual securities, covering the period from January 1990 to December 2007.

Table 1 contains summary statistics for the selected characteristics of bonds in our sample. Note that a typical firm has only a few senior unsecured issues outstanding at any point in time—the median firm, for example, has two such issues trading in the secondary market at any given month. This distribution, however, exhibits a significant positive skew, as some firms can have more than 50 different senior unsecured bond issues trading in the market at a point in time. The distribution of the market values of these issues is similarly skewed, with the range running from $1.1 million to nearly $6.7 billion. Not surprisingly, the maturity of these debt instruments is fairly long, with the average maturity at issue

Table 1: Summary Statistics of Bond Characteristics

Bond Characteristic	Mean	SD	Min	P50	Max
# of bonds per firm/month	3.51	4.10	1.00	2.00	57.0
Mkt. Value of Issue[a] ($mil.)	307.9	309.3	1.11	233.6	6,658
Maturity at Issue (years)	13.8	9.4	1.0	10.0	50.0
Term to Maturity (years)	11.2	8.6	0.01	7.87	30.0
Duration (years)	6.17	3.18	0.00	5.61	26.4
S&P Credit Rating	-	-	D	BBB1	AAA
Coupon Rate (pct.)	7.56	2.02	0.00	7.38	16.5
Nominal Effective Yield (pct.)	7.54	2.94	1.47	7.17	57.4
Credit Spread[b] (bps.)	186	277	10	111	4,995

Panel Dimensions

Obs. $= 282,227$ $\quad N = 5,321$ bonds

Min. Tenure = 1 Median Tenure = 45 Max. Tenure = 215

NOTE: Sample period: Monthly data from January 1990 to December 2007 for a sample of 944 nonfinancial firms. Sample statistics are based on trimmed data (see text for details).

[a]Market value of the outstanding issue deflated by the CPI.

[b]Measured relative to comparable-maturity Treasury yield (see text for details).

of almost 14 years; the average term-to-maturity is about 11 years. Because corporate bonds typically generate significant cash flow in the form of regular coupon payments, the effective duration is considerably shorter, averaging about 6.2 years over the sample period. Although our sample spans the entire spectrum of credit quality—from "single D" to "triple A"—the median bond/month observation, at BBB1, is still solidly in the investment-grade category.

Turning to returns, the coupon rate on our sample of bonds averaged 7.56 percent during the sample period, and the average total return, as measured by the nominal effective yield, was 7.54 percent per annum. Reflecting the wide range of credit quality, the distribution of yields is quite wide, with the minimum of about 1.5 percent and the maximum of more than 57 percent. Relative to Treasuries, an average bond in our sample generated a return of about 186 basis points above the comparable-maturity risk-free rate, with the standard deviation of 277 basis points.

A portion of observed credit spreads reflects compensation demanded by investors for bearing the risk that a firm who issued the bonds will default on its payment obligations. To measures this firm-specific likelihood of default at each point in time, we employ a monthly indicator that is widely used by financial market participants. In particular, the "Expected Default Frequency" (EDF)—constructed and marketed by the Moody's/KMV Corporation

(MKMV)—gauges the probability of default over the subsequent twelve-month period. The theoretical underpinnings to these probabilities of default are provided by the seminal work of Merton [1973, 1974]. According to this option-theoretic approach, the probability that a firm will default on its debt obligations at any point in the future is determined by three major factors: the market value of the firm's assets; the standard deviation of the stochastic process for the market value of assets (i.e., asset volatility); and the firm's leverage. These three factors are combined into a single measure of default risk called *distance to default* defined as

$$\begin{bmatrix}\text{Distance}\\ \text{to Default}\end{bmatrix} = \frac{\begin{bmatrix}\text{Mkt. Value}\\ \text{of Assets}\end{bmatrix} - \begin{bmatrix}\text{Default}\\ \text{Point}\end{bmatrix}}{\begin{bmatrix}\text{Mkt. Value}\\ \text{of Assets}\end{bmatrix} \times \begin{bmatrix}\text{Asset}\\ \text{Volatility}\end{bmatrix}}.$$

In theory, the default point should equal to the book value of total liabilities, implying that the distance to default—essentially a volatility adjusted measure of market leverage—compares the net worth of the firm with the size of a one-standard-deviation move in the firm's asset value.[5] The market value of assets and the volatility of assets, however, are not directly observable, so they have to be computed in order to calculate the distance to default. Assuming that the firm's assets are traded, the market value of the firm's equity can be viewed as a call option on the firm's assets with the strike price equal to the current book value of the firm's total debt.[6] Using this insight, MKMV "backs out" the market value and the volatility of assets from a proprietary variant of the Black-Scholes-Merton option-pricing model, employing the observed book value of liabilities and the market value of equity as inputs (see Crosbie and Bohn [2003] for details).

In the final step, MKMV transforms the distance to default into an expected probability of default—the so-called EDF—using an empirical distribution of actual defaults. Specifically, MKMV estimates a mapping relating the likelihood of default over a particular horizon to various levels of distance to default, employing an extensive proprietary database of historical defaults and bankruptcies in the United States (see Dwyer and Qu [2007] for details). In our case, these EDFs are calculated monthly and measure the probability that a firm will default on its debt obligations over the next twelve months. One clear advantage of EDFs over the traditional measures of default risk based on credit ratings stems from the fact that the dynamics of EDFs are driven primarily by the movements in equity values. As a result, EDF-based measures of default risk can react more rapidly to deterioration

[5]Empirically, however, MKMV has found that most defaults occur when the market value of the firm's assets drops to the value equal to the sum of the firm's current liabilities and one-half of long-term liabilities (i.e., Default Point = Current Liabilities + $0.5 \times$ Long-Term Liabilities), and the default point is calibrated accordingly.

[6]The assumption that all of the firm's assets are traded is clearly inappropriate in most cases. Nevertheless, as shown by Ericsson and Reneby [2004], this approach is still valid provided that at least one of the firm's securities (e.g., equity) is traded.

in the firm's credit quality as well as reflect more promptly changes in aggregate economic conditions.

2.1 Default-Risk Based Portfolios

We summarize the information contained in bond spreads and excess equity returns for our sample of firms by constructing portfolios based on expected default risk.[7] Specifically, we sort credit spreads and excess equity returns in month t into five quintiles based on the distribution of EDFs in month $t-1$. To control for the maturity differences in the capital structure of our firms, we split each EDF-based quintile of credit spreads into four maturity categories: (1) *short maturity*: credit spreads of bonds with the remaining term-to-maturity of less than (or equal) to 3 years; (2) *intermediate maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 3 years but less than (or equal) 7 years; (3) *long maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 7 years but less than (or equal) to 15 years; (4) *very long maturity*: credit spreads of bonds with the remaining term-to-maturity of more than 15 years. We than compute an arithmetic average of credit spreads in month t for each EDF/maturity portfolio and an arithmetic average of excess equity returns in month t for each EDF portfolio. This procedure yields a monthly time series of credit spreads for each of the 20 EDF-based bond portfolios (five EDF quintiles and four maturity categories) and a monthly time series of excess equity returns for each of the five EDF-based stock portfolios.

Table 2 contains summary statistics of our variables by the five EDF quintiles. The entries in the top panel of the table represent summary statistics for the average EDF—our measure of default risk—in each quintile. As evidenced by both the mean and the median, the average expected probability of default increases in a roughly linear fashion between the first and the fourth quintiles before jumping sharply for firms in the fifth quintile—that is, for the riskiest firms. The next three panels of the table contain the same descriptive statistics for our twenty EDF/maturity bond portfolios. Not surprisingly, both the average and the median credit spread increase monotonically across the five EDF quintiles in all four maturity categories. In terms of reward-to-variability trade-off, the Sharpe ratio within each maturity category is fairly constant for the portfolio of bonds in the first three EDF quintiles. However, the Sharpe ratio drops markedly for portfolios containing bonds issued by the higher risk firms.

The bottom panel of Table 2 examines the time-series characteristics of monthly excess equity returns of firms in our five credit-risk categories. Both the average and the median excess equity return increase monotonically across the first four EDF quintiles, but the

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

Table 2: Summary Statistics of Financial Indicators by EDF Quintile

Financial Indicator	Quintile[a]	Mean	SD	S-R[b]	Min	P50	Max
EDF	1	0.05	0.03	-	0.01	0.04	0.14
EDF	2	0.12	0.09	-	0.03	0.10	0.43
EDF	3	0.25	0.19	-	0.05	0.19	0.88
EDF	4	0.57	0.41	-	0.08	0.42	1.92
EDF	5	4.98	2.98	-	0.67	3.95	16.6
Spread (under 3 yrs.)	1	0.75	0.29	2.62	0.31	0.69	1.88
Spread (under 3 yrs.)	2	0.98	0.38	2.62	0.40	0.91	2.13
Spread (under 3 yrs.)	3	1.17	0.48	2.45	0.50	1.03	2.57
Spread (under 3 yrs.)	4	1.86	1.03	1.03	0.61	1.67	5.87
Spread (under 3 yrs.)	5	5.30	3.34	1.59	1.44	4.40	17.4
Spread (3–7 yrs.)	1	0.88	0.26	3.35	0.48	0.87	1.85
Spread (3–7 yrs.)	2	0.98	0.38	3.21	0.53	1.12	2.10
Spread (3–7 yrs.)	3	1.47	0.48	3.08	0.75	1.37	2.86
Spread (3–7 yrs.)	4	2.17	0.89	0.89	1.09	1.94	5.40
Spread (3–7 yrs.)	5	5.75	2.71	2.12	2.08	4.99	14.4
Spread (7–15 yrs.)	1	0.81	0.32	2.55	0.38	0.73	1.91
Spread (7–15 yrs.)	2	1.07	0.41	2.60	0.41	0.96	2.40
Spread (7–15 yrs.)	3	1.36	0.54	2.52	0.66	1.21	2.77
Spread (7–15 yrs.)	4	1.97	0.78	0.78	0.91	1.70	4.47
Spread (7–15 yrs.)	5	4.87	2.48	1.96	1.82	4.19	15.4
Spread (above 15 yrs.)	1	1.01	0.39	2.60	0.48	0.92	2.29
Spread (above 15 yrs.)	2	1.23	0.44	2.77	0.56	1.15	2.57
Spread (above 15 yrs.)	3	1.41	0.53	2.67	0.59	1.27	2.82
Spread (above 15 yrs.)	4	2.08	0.85	0.85	0.93	1.87	4.61
Spread (above 15 yrs.)	5	3.79	2.03	1.87	1.15	3.32	13.5
Excess Equity Return	1	0.67	3.13	0.22	-10.9	0.85	10.7
Excess Equity Return	2	0.82	3.79	0.22	-14.3	0.95	13.0
Excess Equity Return	3	0.85	4.17	0.20	-16.6	1.10	12.9
Excess Equity Return	4	1.07	4.87	0.22	-18.5	1.18	13.0
Excess Equity Return	5	0.46	7.22	0.06	-26.6	0.31	31.3

Note: Sample period: Monthly data from February 1990 to December 2007. Credit spreads are expressed in percentage points; EDFs are expressed in percent; and excess equity returns are expressed in percent.

[a]The average of financial indicators in month t in each quintile is based on the EDF distribution in month $t-1$ (see text for details).

[b]Sharpe ratio.

Sharpe ratios associated with these four stock portfolios are essentially constant. By contrast, firms in the fifth EDF quintile registered considerably lower returns relative to their less risky counterparts, with an average (monthly) excess return over the 1990–2007 period of less than 0.5 percent. This paltry performance is especially stark when one considers the volatility of returns, as evidenced by the fact that the Sharpe ratio on the portfolio of stocks associated with firms in the fifth EDF quintile is considerably below that of the less risky portfolios.

The next set of descriptive statistics focuses on the relationship between returns and credit risk. In particular, we estimate the following time-series regression between returns in our portfolios and expected default risk:

$$R^e_{it} = \alpha_i + \beta_i \mathrm{EDF}_{i,t-1} + \epsilon_{it}; \quad i = 1, \ldots, 5, \tag{1}$$

where R^e_{it} denotes the average credit spread or the average excess equity return in the EDF quintile i in month t, and $\mathrm{EDF}_{i,t-1}$ denotes the average year-ahead expected probability of default at the end of month $t-1$ in the same quintile. For returns in both our bond and stock portfolios, the system of five equations corresponding to the five EDF quintiles is estimated by OLS in a SUR framework to take into account the correlation of regression errors across the different credit-risk categories; we allow for serial correlation of order 12 in the error term ϵ_{it} when computing the Newey and West [1987] covariance matrix of regression coefficients. Table 3 contains the results of this exercise for credit spreads in our EDF-based bond portfolios, and Table 4 contains the results for the excess equity returns. In both tables, we report standardized estimates of the coefficient β_i in equation 1 to facilitate the comparison of coefficients across the different portfolios, which differ markedly in their volatilities.

As evidenced by the entries in Table 3, there is a strong positive relationship between measures of default risk based on the information from the corporate bond market and measures based on the information from the equity market summarized in the expected default frequencies. The standardized estimates of coefficients associated with the average EDF in each quintile are economically large and highly statistically significant, an indication that this relationship holds across the cross-sectional distribution of credit risk as well as across the maturity of corporate debt instruments. In the credit-risk dimension, the EDFs explain, on balance, the least variation in credit spreads of portfolios containing bonds issued by the least risky firms—those in the first EDF quintile—a category of firms characterized by a relatively stable credit outlook. The explanatory power of the EDFs for credit spreads also diminishes somewhat for portfolios of longer maturity bonds. Judging by the in-sample fit, however, these equity-based indicators of default risk, despite their relatively short year-ahead horizon, contain substantial information regarding credit risk at longer horizons.

Table 3: Relationship Between Credit Spreads and EDFs
(By Maturity and EDF Quintile)

Short Maturity (less than 3 years) Corporate Bonds

Variable	EDF Q1	EDF Q2	EDF Q3	EDF Q4	EDF Q5
Constant	0.532	0.634	0.735	0.980	0.870
	[11.48]	[12.03]	[12.55]	[7.68]	[3.20]
EDF_{t-1}	0.530	0.838	0.901	0.765	1.237
	[8.04]	[12.24]	[14.34]	[13.04]	[17.53]
Adj. R^2	0.207	0.406	0.448	0.367	0.593

Intermediate Maturity (3–7 years) Corporate Bonds

Variable	EDF Q1	EDF Q2	EDF Q3	EDF Q4	EDF Q5
Constant	0.610	0.811	0.987	1.228	1.944
	[23.99]	[20.19]	[26.60]	[16.79]	[12.99]
EDF_{t-1}	0.877	0.965	1.102	1.111	1.593
	[25.45]	[16.83]	[24.35]	[22.41]	[28.38]
Adj. R^2	0.428	0.470	0.539	0.543	0.716

Long Maturity (7–15 years) Corporate Bonds

Variable	EDF Q1	EDF Q2	EDF Q3	EDF Q4	EDF Q5
Constant	0.530	0.724	0.850	1.152	1.655
	[23.43]	[24.25]	[19.16]	[19.88]	[9.88]
EDF_{t-1}	0.643	0.686	0.875	1.046	1.313
	[16.73]	[21.22]	[30.12]	[30.18]	[15.94]
Adj. R^2	0.302	0.314	0.417	0.511	0.653

Very Long Maturity (greater than 15 years) Corporate Bonds

Variable	EDF Q1	EDF Q2	EDF Q3	EDF Q4	EDF Q5
Constant	0.725	0.856	0.937	1.381	1.448
	[28.19]	[27.87]	[29.59]	[15.03]	[7.84]
EDF_{t-1}	0.493	0.704	0.855	0.636	0.908
	[14.15]	[18.62]	[26.17]	[14.88]	[19.45]
Adj. R^2	0.179	0.311	0.405	0.257	0.446

NOTE: Sample period: Monthly data from February 1990 to December 2007 ($T = 214$). Dependent variable in each regression is the average credit spread in month t in the specified EDF quintile. Estimates of parameters corresponding to the explanatory variable EDF_{t-1} in each quintile are standardized. Absolute t-statistics based on a heteroscedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West [1987] are reported in brackets.

Table 4: Relationship Between Excess Equity Returns and EDFs
(By EDF Quintile)

Variable	EDF Q1	EDF Q2	EDF Q3	EDF Q4	EDF Q5
Constant	1.076	0.689	0.577	0.605	-0.476
	[4.68]	[3.69]	[2.94]	[2.36]	[0.99]
EDF_{t-1}	-0.090	0.021	0.048	0.070	0.083
	[3.21]	[0.85]	[2.15]	[3.26]	[2.82]
Adj. R^2	0.007	-0.005	-0.003	-0.000	0.006

NOTE: Sample period: Monthly data from February 1990 to December 2007 ($T = 214$). Dependent variable in each regression is the average excess equity return in month t in the specified EDF quintile. Estimates of parameters corresponding to the explanatory variable EDF_{t-1} in each quintile are standardized. Absolute t-statistics based on a heteroscedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West [1987] are reported in brackets.

In contrast, as shown in Table 4, excess equity returns appear to be completely unrelated to expected default risk. Although estimates of the coefficients associated with the average EDF in each quintile are statistically significant at conventional levels for four out of five EDF-based stock portfolios, they are economically small, and movements in expected default risk explain virtually none of the time-series variation in excess equity returns across the spectrum of credit quality. This finding suggests that, for the portfolios under consideration, the price of risk in excess equity returns is unrelated to systematic movements in expected default risk within different credit-risk categories.

3 Credit Spreads and Economic Activity

We now turn to the information content of credit spreads for economic activity. Specifically, we examine the predictive power of several commonly used credit spread indexes, and we compare their forecasting performance—both in-sample and out-of-sample—with the predictive content of credit spreads in our EDF-based bond portfolios. Letting Y_t denote a measure of economic activity in month t, we define

$$\nabla^h Y_{t+h} \equiv \frac{1200}{h} \ln\left(\frac{Y_{t+h}}{Y_t}\right),$$

where h denotes the forecast horizon and $\nabla^1 \equiv \nabla$. (The factor $1200/h$ standardizes the units to annual percentage growth rates.) Because we are using monthly data, real GDP is not readily available as a measure of economic activity. As an alternative, we use nonfarm payroll employment (EMP) published monthly by the Bureau of Labor Statistics and the Federal Reserve's monthly index of industrial production (IP) to gauge the state of the economy. Because credit spreads in our EDF-based portfolios rely on secondary market prices of bonds issued by firms in the nonfinancial corporate sector, the growth in industrial output is likely the most pertinent measure of economic activity for our purposes. Nevertheless, we also consider the information content of credit spreads for the growth of employment, a considerably less volatile and a broader indicator of economywide trends.

For these two measures of economic activity, we estimate the following bivariate vector autoregression (VAR), augmented with two sets of credit spreads:

$$\nabla^h \mathrm{EMP}_{t+h} = \beta_0 + \sum_{i=0}^{11} \beta_{1i} \nabla \mathrm{EMP}_{t-i} + \sum_{i=0}^{11} \beta_{2i} \nabla \mathrm{IP}_{t-i} + \eta_1' Z_{1t} + \eta_2' Z_{2t} + \epsilon_{1,t+h}; \quad (2)$$

$$\nabla^h \mathrm{IP}_{t+h} = \gamma_0 + \sum_{i=0}^{11} \gamma_{1i} \nabla \mathrm{EMP}_{t-i} + \sum_{i=0}^{11} \gamma_{2i} \nabla \mathrm{IP}_{t-i} + \theta_1' Z_{1t} + \theta_2' Z_{2t} + \epsilon_{2,t+h}. \quad (3)$$

In the VAR forecasting system given by equations 2–3, Z_{1t} denotes a vector of standard—that is, widely used—credit spreads indexes; Z_{2t} is a vector of credit spreads in the four maturity categories associated with a particular EDF quintile; and $\epsilon_{1,t+h}$ and $\epsilon_{2,t+h}$ are the forecast errors.[8] We consider the following three VAR specifications: (1) a benchmark specification that includes only the vector of standard credit spread indexes Z_{1t}; (2) an alternative specification that includes only the vector Z_{2t}, elements of which correspond to credit spreads in the four maturity categories of an EDF quintile; and (3) a specification that includes both the vector of standard credit spread indexes Z_{1t} and the vector of spreads in a particular EDF quintile Z_{2t}. For each specification and a forecast horizon of 3, 6, 12, and 24 months, we estimate equations 2 and 3 by OLS. To take into account serial correlation induced by overlapping forecast errors, the estimated covariance matrix is computed according to Newey and West [1987], with the "lag truncation" parameter equal to $h + 1$.

Our set of standard default-risk indicators—the vector Z_{1t}—consists of four credit spread indexes, all of which have been used extensively to forecast real economic activity; see Stock and Watson [2003a] for a comprehensive review. Specifically, we consider: (1) *paper-bill spread*: the difference between the yield on one-month nonfinancial AA-rated commercial paper and the yield on the constant maturity one-month Treasury bill; (2) *Aaa corporate bond spread*: the difference between the yield on an index of seasoned long-term Aaa-rated corporate bonds and the yield on the constant maturity ten-year Treasury note;

[8] An alternative approach to the direct h-step ahead prediction method specified in equations 2–3 would be to specify a VAR—or some other joint one-step ahead model for employment growth, industrial production, and credit spreads—and then iterate this model forward h periods. If the one-period ahead joint model is correctly specified, iterated forecasts are more efficient, whereas the direct h-step ahead forecasts are more robust to model misspecification; see Marcellino, Stock, and Watson [2006] for details.

(3) *Baa corporate bond spread*: the difference between the yield on an index of seasoned long-term Baa-rated corporate bonds and the yield on the constant maturity ten-year Treasury note; and (4) *high-yield corporate bond spread*: the difference between the yield on an index of long-term speculative-grade corporate bonds and the yield on the constant maturity ten-year Treasury note.[9] Note that by including a paper-bill spread with spreads on long-term corporate bonds, our set of standard credit spread indexes captures the information content of default-risk indicators at both short and long horizons.[10]

To preview briefly our results, we find that at short-run forecast horizons, both the standard set of credit spread indexes and spreads in our EDF-based bond portfolios provide a noticeable improvement in the in-sample fit relative to the specification that contains no default-risk indicators. Neither set of default-risk indicators, however, clearly outperforms each other when predicting economic activity three to six months ahead. At the one- to two-year forecast horizon, by contrast, spreads in our EDF-based bond portfolios generate improvements in the in-sample fit of a factor of two relative to the specification that includes only standard credit spread indexes, a gain in predictive accuracy that is is also evident when forecasting out-of-sample.

3.1 In-Sample Predictive Power of Credit Spreads

We first examine the in-sample predictive power of various credit spreads for our two measures of economic activity. Table 5 contains the results of this exercise for the short-run forecast horizons (3 and 6 months), whereas Table 6 contains the results for the long-run horizons (12 and 24 months). In both tables, we report p-values associated with the exclusion tests on the two sets of credit spreads along with the explanatory power of each forecasting equation as measured by the adjusted R^2. As a benchmark, the *Memo* item in both tables contains the in-sample fit from the VAR specification that excludes all credit spreads.

When forecasting employment growth, the inclusion of credit spreads leads only to a modest improvement in the in-sample fit at the three- to six-month forecast horizon. As

[9] Commercial paper rates are taken from the "Commercial Paper Rates and Outstanding" Federal Reserve statistical release. The source of Treasury yields and yields on Aaa- and Baa-rated corporate bonds is "Selected Interest Rates" (H.15) Federal Reserve statistical release. To construct the high-yield spread, we use the High-Yield Master II index, a commonly used benchmark index for long-term speculative-grade corporate bonds administered by Merrill Lynch.

[10] Note that we construct our standard corporate bond spread indexes using the ten-year Treasury yield. 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 spreads measured relative to the yield on Aaa-rated bonds are more reflective of default risk than those measured relative to comparable-maturity Treasuries, which makes the former spreads more correlated with economic downturns. For comparison, we computed the Baa and the high-yield bond spread relative to the Aaa yield, and our results were virtually identical.

evidenced by the p-values reported in Table 5, both the standard credit spread indexes and credit spreads in each EDF quintile are statistically significant predictors of employment growth three and six months ahead. Moreover, when both sets of credit spreads are included in the forecasting VAR, they all tend to remain statistically significant. Nevertheless, adding either set of credit spreads to the VAR results only in a relatively modest improvement in the explanatory power of the equation for employment growth. For example, at the three-month horizon, the specification that excludes all credit spreads yields an adjusted R^2 of 72 percent, only about 8 percentage points below the adjusted R^2 from a specification that includes standard credit spread indexes and credit spreads in the fifth EDF quintile. At the six-month horizon, the marginal improvement in the in-sample fit from including credit spreads in the forecasting VAR is somewhat larger, but, again, the gains in performance relative to the specification that omits all default-risk indicators are still relatively small.

The inclusion of credit spreads in the equation for industrial production, in contrast, leads to a substantial increase in predictive accuracy at the three- to six-month forecast horizon. According to the *Memo* item, lags of industrial production and employment growth explain only about 15 percent of the variation in the growth of industrial output three and six months ahead. By including standard credit spread indexes in the forecasting VAR, the adjusted R^2 increases to almost 30 percent at the three-month horizon and to 35 percent at the six-month horizon. Specifications that include credit spreads in our EDF-based portfolios yield even greater improvements in the in-sample fit, especially at the six-month forecast horizon. Note also that the best in-sample fit comes from specifications that include credit spreads in the lowest two quintiles of the EDF distribution (EDF-Q1 and EDF-Q2).

Table 6 examines the in-sample explanatory power of credit spreads at longer forecast horizons, namely 12 and 24 months. At these longer horizons, the information content of credit spreads for both measures of economic activity is considerable. In the case of nonfarm payroll employment, for example, standard credit spread indexes explain about 70 percent of the variation in the 12-month ahead growth rate and about 63 percent in the 24-month ahead growth rate, results representing a significant increases in the goodness-of-fit relative to the specification that relies only on lags of employment growth and lags of the growth rate in industrial production. Credit spreads in our EDF-based bond portfolios do even better, especially at the 24-month ahead forecast horizon. The information content of our default-risk indicators for the growth of employment is concentrated in the second and third EDF quintiles (EDF-Q2 and EDF-Q3), with the average spreads in these two quintiles yielding adjusted R^2s of about 75 percent and 85 percent at the 12-month and 24-month forecast horizons, respectively. The in-sample fit, however, deteriorates noticeably for the average credit spreads based on portfolios of bonds issued by the riskiest firms in our sample (EDF-Q4 and EDF-Q5).

Table 5: In-Sample Predictive Content of Credit Spreads for Economic Activity (Short-Run Forecast Horizons)

	Forecast Horizon $h = 3$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2
Standard	0.000	-	0.771	0.000	-	0.293
EDF-Q1	-	0.015	0.739	-	0.000	0.342
EDF-Q2	-	0.004	0.757	-	0.000	0.309
EDF-Q3	-	0.000	0.754	-	0.000	0.295
EDF-Q4	-	0.002	0.753	-	0.000	0.288
EDF-Q5	-	0.026	0.747	-	0.000	0.344
Standard & EDF-Q1	0.000	0.011	0.786	0.021	0.003	0.367
Standard & EDF-Q2	0.000	0.001	0.796	0.308	0.172	0.323
Standard & EDF-Q3	0.025	0.142	0.781	0.020	0.007	0.362
Standard & EDF-Q4	0.004	0.014	0.787	0.018	0.010	0.358
Standard & EDF-Q5	0.000	0.000	0.798	0.000	0.000	0.432
Memo: None	-	-	0.720	-	-	0.148

	Forecast Horizon $h = 6$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2
Standard	0.000	-	0.782	0.000	-	0.350
EDF-Q1	-	0.000	0.748	-	0.000	0.453
EDF-Q2	-	0.000	0.766	-	0.000	0.443
EDF-Q3	-	0.000	0.770	-	0.000	0.395
EDF-Q4	-	0.000	0.742	-	0.001	0.374
EDF-Q5	-	0.000	0.775	-	0.000	0.428
Standard & EDF-Q1	0.000	0.000	0.832	0.028	0.000	0.500
Standard & EDF-Q2	0.000	0.000	0.829	0.205	0.001	0.466
Standard & EDF-Q3	0.000	0.002	0.824	0.023	0.000	0.489
Standard & EDF-Q4	0.002	0.004	0.821	0.031	0.016	0.460
Standard & EDF-Q5	0.000	0.000	0.840	0.011	0.000	0.504
Memo: None	-	-	0.676	-	-	0.163

NOTE: Sample period: Monthly data from February 1990 to December 2007. Dependent variables in the VAR specification are $\nabla^h \text{EMP}_{t+h}$ and $\nabla^h \text{IP}_{t+h}$, where h is the forecast horizon. Each VAR specification also includes a constant, current, and 11 lags of of ∇EMP_t and ∇IP_t (see text for details). $\Pr > W_1$ denotes the p-value for the robust Wald test of the null hypothesis that coefficients on standard credit spread indexes are jointly equal to zero; $\Pr > W_2$ denotes the p-value for the robust Wald test of the null hypothesis that coefficients on EDF-based credit spreads in a particular quintile are jointly equal to zero.

Table 6: In-Sample Predictive Content of Credit Spreads for Economic Activity
(Long-Run Forecast Horizons)

	Forecast Horizon $h = 12$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2
Standard	0.000	-	0.703	0.014	-	0.305
EDF-Q1	-	0.000	0.719	-	0.000	0.578
EDF-Q2	-	0.000	0.756	-	0.000	0.604
EDF-Q3	-	0.000	0.762	-	0.000	0.541
EDF-Q4	-	0.000	0.686	-	0.000	0.373
EDF-Q5	-	0.000	0.721	-	0.000	0.386
Standard & EDF-Q1	0.000	0.013	0.832	0.177	0.000	0.638
Standard & EDF-Q2	0.002	0.000	0.817	0.393	0.000	0.638
Standard & EDF-Q3	0.000	0.000	0.827	0.000	0.000	0.656
Standard & EDF-Q4	0.000	0.000	0.808	0.082	0.000	0.520
Standard & EDF-Q5	0.000	0.000	0.817	0.048	0.000	0.516
Memo: None	-	-	0.523	-	-	0.014
	Forecast Horizon $h = 24$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2	$\Pr > W_1$	$\Pr > W_2$	Adj. R^2
Standard	0.000	-	0.633	0.002	-	0.349
EDF-Q1	-	0.000	0.801	-	0.000	0.687
EDF-Q2	-	0.000	0.854	-	0.000	0.770
EDF-Q3	-	0.000	0.832	-	0.000	0.681
EDF-Q4	-	0.000	0.675	-	0.000	0.480
EDF-Q5	-	0.000	0.636	-	0.000	0.335
Standard & EDF-Q1	0.000	0.000	0.858	0.029	0.000	0.707
Standard & EDF-Q2	0.005	0.000	0.878	0.148	0.000	0.795
Standard & EDF-Q3	0.000	0.000	0.874	0.004	0.000	0.722
Standard & EDF-Q4	0.000	0.000	0.792	0.045	0.000	0.586
Standard & EDF-Q5	0.000	0.000	0.775	0.000	0.000	0.504
Memo: None	-	-	0.367	-	-	-0.009

NOTE: Sample period: Monthly data from February 1990 to December 2007. Dependent variables in the VAR specification are $\nabla^h \text{EMP}_{t+h}$ and $\nabla^h \text{IP}_{t+h}$, where h is the forecast horizon. Each VAR specification also includes a constant, current, and 11 lags of of ∇EMP_t and ∇IP_t (see text for details). $\Pr > W_1$ denotes the p-value for the robust Wald test of the null hypothesis that coefficients on standard credit spread indexes are jointly equal to zero; $\Pr > W_2$ denotes the p-value for the robust Wald test of the null hypothesis that coefficients on EDF-based credit spreads in a particular quintile are jointly equal to zero.

Results are even more striking in the case of industrial production, a measure of economic activity for which the explanatory power of our portfolio credit spreads significantly exceeds that of standard default-risk indicators. Whereas standard credit spread indexes explain about 30 percent of the variation in the 12-month ahead growth of industrial production, credit spreads associated with the first three EDF quintiles (EDF-Q1–EDF-Q3) explain close to 60 percent of the variation in the 12-month ahead growth rate of industrial output; at the 24-month ahead forecast horizon, credit spreads in the first three EDF quintiles explain around 70 percent of the variation in the 24-month growth rate of industrial production, double the adjusted R^2 obtained from specification that includes only standard credit spread indexes.

The results in Table 6 highlight the gains in in-sample predictive accuracy for employment and industrial output growth at longer forecast horizons obtained from conditioning on credit spreads in our EDF-based bond portfolios. These forecast exercises utilize the information content of credit spreads across the maturity and credit-risk spectrum. To determine more precisely the location of the predictive content of credit spreads in the maturity-risk space, Table 7 contains the results from regressions of the 12-month ahead growth in employment and industrial production (i.e., $\nabla^{12}\text{EMP}_{t+12}$ and $\nabla^{12}\text{IP}_{t+12}$) on one 12-month lag of itself and a single default-risk indicator in month t, chosen from our set of standard credit spread indexes or from the credit spreads in our EDF-based bond portfolios. As evidenced by the first four lines of the table, the high-yield credit spread index has the highest explanatory power for the 12-month ahead growth in nonfarm payroll employment among standard default-risk indicators, with an adjusted R^2 of about 67 percent. Several spreads in our EDF-based bond portfolios provide as good, if not better, in-sample fit however. Spreads containing the greatest predictive content for employment growth lie at the very long-end of the maturity spectrum and are concentrated in the center of the credit-risk distribution—that is, portfolios containing bonds with a remaining term-to-maturity greater than 15 years that were issued by firms in the second and third quintiles of the EDF distribution.

Among standard default-risk indicators, the high-yield credit spread index—with an adjusted R^2 of about 33 percent—also provides the best in-sample fit for the 12-month ahead growth in industrial production. This is substantially below the goodness-of-fit obtained from specifications that rely on longer-maturity credit spreads in our EDF-based bond portfolios, a number of which yield an adjusted R^2 in excess of 50 percent. Consistent with the findings for employment growth, the predictive content for industrial production of credit spreads in our EDF-based bond portfolios is again concentrated at longer maturities and the high to middle range of the credit-quality spectrum.

In sum, the results in Tables 5–6 indicate that the information content for the growth

Table 7: Predictive Content of Credit Spreads for Economic Activity
(12-Month Forecast Horizon)

	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spread	Estimate	t-stat	Adj. R^2	Estimate	t-stat	Adj. R^2
CP1m − Treas1m	-0.314	-2.269	0.363	-0.182	-1.508	0.087
Aaa − Treas10y	-0.253	-0.863	0.318	-0.430	-1.936	0.083
Baa − Treas10y	-0.363	-1.756	0.347	-0.460	-2.500	0.103
HighYield − Treas10y	-1.239	-6.706	0.674	-0.917	-4.413	0.334
EDF-Q1 (under 3 yrs.)	-0.446	-1.927	0.396	-0.611	-3.138	0.233
EDF-Q1 (3–7 yrs.)	-0.712	-4.729	0.553	-1.079	-4.729	0.478
EDF-Q1 (7–15 yrs.)	-0.940	-7.360	0.655	-1.129	-7.040	0.552
EDF-Q1 (above 15 yrs.)	-0.921	-5.966	0.653	-0.867	-4.726	0.501
EDF-Q2 (under 3 yrs.)	-0.493	-2.676	0.431	-0.713	-3.933	0.283
EDF-Q2 (3–7 yrs.)	-0.571	-3.708	0.500	-0.894	-4.150	0.423
EDF-Q2 (7–15 yrs.)	-0.914	-6.608	0.651	-1.112	-6.964	0.552
EDF-Q2 (above 15 yrs.)	-1.154	-7.120	0.721	-1.024	-5.187	0.557
EDF-Q3 (under 3 yrs.)	-0.646	-3.516	0.476	-0.784	-3.813	0.301
EDF-Q3 (3–7 yrs.)	-0.728	-3.679	0.499	-1.040	-4.105	0.389
EDF-Q3 (7–15 yrs.)	-0.591	-5.155	0.591	-1.107	-5.748	0.487
EDF-Q3 (above 15 yrs.)	-1.289	-8.959	0.737	-1.057	-5.074	0.526
EDF-Q4 (under 3 yrs.)	-0.769	-3.466	0.461	-0.796	-3.549	0.257
EDF-Q4 (3–7 yrs.)	-0.627	-2.434	0.408	-0.739	-2.718	0.216
EDF-Q4 (7–15 yrs.)	-0.669	-3.028	0.468	-0.857	-3.742	0.309
EDF-Q4 (above 15 yrs.)	-0.674	-3.201	0.475	-0.766	-3.108	0.287
EDF-Q5 (under 3 yrs.)	-0.449	-1.940	0.361	-0.451	-2.247	0.119
EDF-Q5 (3–7 yrs.)	-0.790	-3.613	0.385	-0.733	-3.551	0.122
EDF-Q5 (7–15 yrs.)	-0.791	-4.867	0.494	-0.797	-4.118	0.232
EDF-Q5 (above 15 yrs.)	-0.895	-6.497	0.555	-0.936	-5.541	0.334

NOTE: Sample period: Monthly data from February 1990 to December 2007 (T = 203). Dependent variables in the bivariate system are $\nabla^{12}\text{EMP}_{t+12}$ and $\nabla^{12}\text{IP}_{t+12}$. Each regression specification includes a credit spread, a 12-month lag of the respective dependent variable, and a constant term (the latter two effects are not reported). The bivariate system is estimated by OLS in a SUR framework. Estimates of parameters corresponding to credit spreads are standardized; t-statistics are based on a heteroscedasticity- and autocorrelation-consistent asymptotic covariance matrix computed according to Newey and West [1987].

of employment of credit spreads in our EDF-based bond portfolios is comparable to that of commonly used default-risk indicators at short-run forecast horizons (3 and 6 months), whereas at longer horizons (12 and 24 months), EDF-based credit spreads tend to outperform significantly—as measured by the adjusted R^2—standard credit spread indexes. The greater in-sample predictive accuracy of credit spreads in our EDF-based bond portfolios is particularly apparent in the case of industrial production, an indicator of economic activity for which our default-risk indicators yield, at longer forecast horizons, adjusted R^2s double that of standard credit spread indexes. Also of interest is the fact that for both employment and industrial output growth, the greatest predictive power of credit spreads in our EDF-based portfolios appears to be embedded in the prices of bonds issued by firms in the upper end and the middle of the credit-quality spectrum—that is, firms in the first three quintiles of the EDF distribution.

3.2 Out-of-Sample Predictive Power of Credit Spreads

We now examine the predictive content of credit spreads for our two measures of economic activity using pseudo out-of-sample forecasts. Specifically, for each forecast horizon h, we estimate the forecasting VAR given in equations 2–3 using all available data through, and including, November 1999. We then calculate the (annualized) h-month ahead growth rates of nonfarm payroll employment and industrial production and the associated forecast errors. The forecast origin—that is, November 1999—is then updated with an additional month of data, the VAR parameters are re-estimated using this new larger observation window, and new forecasts are generated. This procedure is repeated through the end of the sample, thereby generating a sequence of pseudo out-of-sample forecasts for the two measures of economic activity.

Tables 8–9 contain the results of this exercise; the results for the short-run forecast horizons (3 and 6 months) are presented in Table 8, whereas Table 9 contains the results for the long-run forecast horizons (12 and 24 months). To quantify the pseudo out-of-sample forecasting performance of the different VAR specifications, the entries under the column heading "RMSFE"report the square root of the mean squared forecast error (in annualized percentage points) for each specification. To compare the predictive accuracy of credit spreads in our EDF-based bond portfolios with that of standard default-risk indicators, the entries under the column heading "Ratio" contain the ratio of the mean squared forecast error (MSFE) of the VAR specification augmented with EDF-based credit spreads with the MSFE of the specification that includes only standard credit spread indexes. To gauge whether the difference in predictive accuracy between these two non-nested models is statistically significant, the entries under the column heading "Pr $> |S|$" contain the p-values of the Diebold and Mariano [1995] test of the null hypothesis of equal predictive accuracy.[11]

In the case of employment growth, the VAR specifications that include credit spreads in our EDF-based bond portfolios yield lower MSFEs at short-run forecast horizons (Table 8)

[11]Because the data in our forecasting VAR specification are overlapping, the asymptotic (long-run) variance of the loss differential used to construct the Diebold-Mariano S-statistic allows for serial correlation of order h.

Table 8: Out-of-Sample Predictive Content of Credit Spreads for Economic Activity (Short-Run Forecast Horizons)

	Forecast Horizon $h = 3$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	$\Pr > \|S\|$	RMSFE	Ratio	$\Pr > \|S\|$
Standard	0.889	-	-	4.820	-	-
EDF-Q1	0.742	0.696	0.079	4.367	0.821	0.278
EDF-Q2	0.748	0.708	0.069	4.544	0.889	0.395
EDF-Q3	0.768	0.747	0.089	4.468	0.859	0.404
EDF-Q4	0.899	1.021	0.928	4.357	0.817	0.409
EDF-Q5	0.848	0.910	0.644	4.191	0.756	0.228
Standard & EDF-Q1	0.858	0.931	-	4.652	0.931	-
Standard & EDF-Q2	0.848	0.909	-	4.919	1.041	-
Standard & EDF-Q3	0.885	0.990	-	4.683	0.944	-
Standard & EDF-Q4	0.885	0.990	-	4.837	1.007	-
Standard & EDF-Q5	0.838	0.888	-	4.580	0.903	-
Memo: None	0.795	-	-	4.883	-	-

	Forecast Horizon $h = 6$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	$\Pr > \|S\|$	RMSFE	Ratio	$\Pr > \|S\|$
Standard	0.907	-	-	3.998	-	-
EDF-Q1	0.705	0.603	0.071	3.328	0.693	0.070
EDF-Q2	0.695	0.587	0.057	3.338	0.697	0.049
EDF-Q3	0.718	0.626	0.033	3.474	0.755	0.238
EDF-Q4	0.909	1.003	0.992	3.528	0.779	0.372
EDF-Q5	0.720	0.629	0.055	3.356	0.705	0.246
Standard & EDF-Q1	0.776	0.732	-	3.506	0.769	-
Standard & EDF-Q2	0.799	0.777	-	3.604	0.813	-
Standard & EDF-Q3	0.809	0.795	-	3.519	0.777	-
Standard & EDF-Q4	0.851	0.880	-	3.725	0.868	-
Standard & EDF-Q5	0.774	0.727	-	3.691	0.852	-
Memo: None	0.853	-	-	4.166	-	-

Note: Sample period: Monthly data from February 1990 to December 2007. Dependent variables in the VAR specification are $\nabla^h \mathrm{EMP}_{t+h}$ and $\nabla^h \mathrm{IP}_{t+h}$, where h is the forecast horizon. Each VAR specification also includes a constant, current, and 11 lags of of $\nabla\mathrm{EMP}_t$ and $\nabla\mathrm{IP}_t$ (see text for details). "Ratio" denotes the ratio of the MSFE of each model relative to the MSFE of the model that includes standard credit spreads; $\Pr > |S|$ denotes the p-value for the Diebold and Mariano [1995] test of the null hypothesis that the difference between the MSFE from the model that includes standard credit spreads and the MSFE from the model that includes EDF-based credit spreads is equal to zero.

Table 9: Out-of-Sample Predictive Content of Credit Spreads for Economic Activity (Long-Run Forecast Horizons)

	Forecast Horizon $h = 12$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	Pr > $\|S\|$	RMSFE	Ratio	Pr > $\|S\|$
Standard	1.069	-	-	3.393	-	-
EDF-Q1	0.666	0.382	0.001	1.886	0.309	0.000
EDF-Q2	0.639	0.358	0.001	1.994	0.345	0.000
EDF-Q3	0.685	0.411	0.001	2.174	0.410	0.001
EDF-Q4	0.988	0.854	0.617	3.006	0.785	0.400
EDF-Q5	0.783	0.537	0.033	2.605	0.589	0.051
Standard & EDF-Q1	0.780	0.533	-	2.328	0.471	-
Standard & EDF-Q2	0.829	0.602	-	2.361	0.484	-
Standard & EDF-Q3	0.796	0.555	-	2.242	0.437	-
Standard & EDF-Q4	0.872	0.666	-	2.824	0.693	-
Standard & EDF-Q5	0.816	0.583	-	2.906	0.733	-
Memo: None	1.044	-	-	3.530	-	-
	Forecast Horizon $h = 24$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	Pr > $\|S\|$	RMSFE	Ratio	Pr > $\|S\|$
Standard	1.036	-	-	2.244	-	-
EDF-Q1	0.512	0.244	0.004	1.494	0.444	0.014
EDF-Q2	0.476	0.211	0.000	1.278	0.324	0.001
EDF-Q3	0.557	0.289	0.005	1.566	0.487	0.011
EDF-Q4	0.918	0.785	0.089	2.140	0.910	0.779
EDF-Q5	0.954	0.848	0.428	2.321	1.070	0.853
Standard & EDF-Q1	0.653	0.397	-	1.638	0.533	-
Standard & EDF-Q2	0.584	0.318	-	1.293	0.332	-
Standard & EDF-Q3	0.580	0.313	-	1.494	0.443	-
Standard & EDF-Q4	0.801	0.598	-	1.940	0.747	-
Standard & EDF-Q5	0.831	0.643	-	2.144	0.914	-
Memo: None	1.195	-	-	2.620	-	-

NOTE: Sample period: Monthly data from February 1990 to December 2007. Dependent variables in the VAR specification are $\nabla^h \text{EMP}_{t+h}$ and $\nabla^h \text{IP}_{t+h}$, where h is the forecast horizon. Each VAR specification also includes a constant, current, and 11 lags of of ∇EMP_t and ∇IP_t (see text for details). "Ratio" denotes the ratio of the MSFE of each model relative to the MSFE of the model that includes standard credit spreads; Pr > $|S|$ denotes the p-value for the Diebold and Mariano [1995] test of the null hypothesis that the difference between the MSFE from the model that includes standard credit spreads and the MSFE from the model that includes EDF-based credit spreads is equal to zero.

than the specification augmented with standard credit spread indexes. At the three- and six-month forecast horizons, the out-of-sample forecasting performance of credit spreads in the first three EDF quintiles (EDF-Q1–EDF-Q3) for employment growth exceeds that of standard credit spread indexes between 25 and 40 percent, and these improvements in predictive accuracy are statistically significant at the 10 percent level. Indeed, at short-run forecast horizons, the specification that includes standard default-risk indicators yields RMSFEs for employment growth that are larger than those obtained from a VAR that excludes all default-risk indicators (see the *Memo* item).

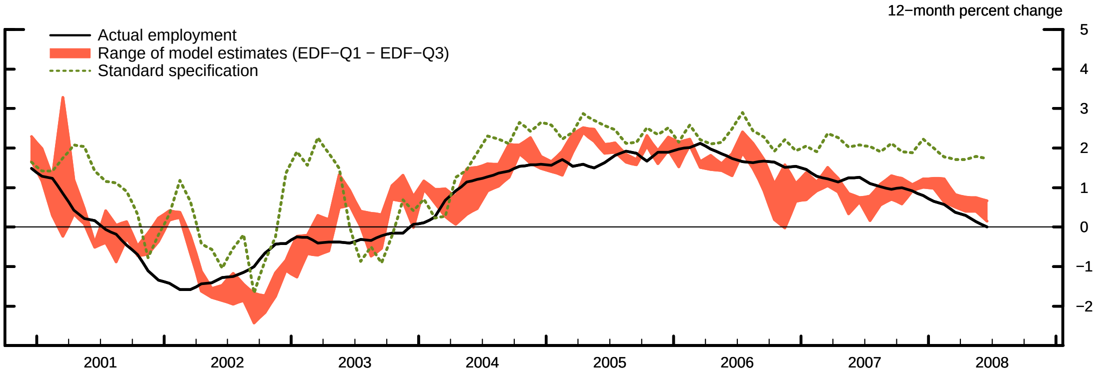
The out-of-sample forecasting performance of credit spreads in our EDF-based bond portfolios for the growth of industrial production also exceeds that of standard default-risk indicators at short-horizons, although at the three-month forecast horizon, the differences in predictive accuracy are not statistically significant at conventional levels. At the six-month horizon, however, the predictive accuracy of portfolio credit spreads associated with the first two EDF quintiles (EDF-Q1 and EDF-Q2) exceeds that of standard credit spread indexes by about 30 percent, improvements that are statistically significant at the 10 percent level.

Whereas short-run forecasts of employment and industrial output growth that rely on credit spreads in our EDF-based bond portfolios tend to be only somewhat more accurate than those based on standard default-risk indicators, gains in out-of-sample predictive accuracy at longer forecast horizons are especially striking, a result consistent with the in-sample analysis of the previous section. According to the entries in Table 9, credit spreads in our EDF-based bond portfolios have a significantly higher out-of-sample predictive power for the growth of employment and industrial output than standard default-risk indicators at both the 12-month and 24-month ahead forecast horizons. The predictive content of our portfolio credit spreads is again concentrated among firms in the first three quintiles of the EDF distribution (EDF-Q1–EDF-Q3). In the case of the 12-month horizon, credit spreads associated with the first three quintiles yield a reduction in the MSFE on the order of 60 percent relative to the specification that includes the standard set of credit spread indexes. At the 24-month horizon, the reduction in the MSFE is on the order of 70 percent, depending on the exact specification. Moreover, not only are these gains in forecasting power large in economic terms, they are also highly statistically significant according to the Diebold-Mariano test.

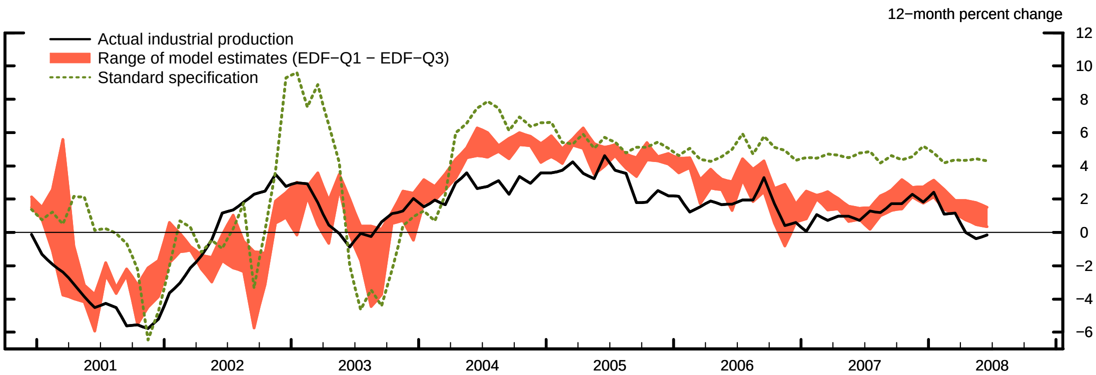
The results reported in Tables 8–9 indicate significant improvements in the out-of-sample forecasting performance of VAR specifications that rely on corporate bond spreads constructed from the low to middle ranges of the credit-risk distribution. To assess whether these improvements are due to a specific subperiod or a “one-time” event, Figure 1 plots the realized values of the 12-month growth in nonfarm payroll employment and industrial production, along with the range of their respective out-of-sample forecasts over the

Figure 1: Out-of-Sample Forecasts of Economic Activity Indicators

Nonfarm payroll employment



Industrial production



NOTE: The panels of the figure depict pseudo out-of-sample forecasts of the 12-month growth in nonfarm payroll employment and industrial production. The solid line shows the actual data; the shaded band shows the range of forecasts based on VAR specifications augmented with credit spreads in the first three quintiles of the EDF distribution (EDF-Q1–EDF-Q3); and the dotted line shows the forecast based on the VAR specification that includes standard default-risk indicators (see text for details).

1999:1–2008:6 period, where the range of forecasts for both variables is based on the VAR specifications that include credit spreads in portfolios corresponding to EDF quintiles one to three (EDF-Q1–EDF-Q3); each panel of the figure also depicts the forecast from the VAR specification augmented with the standard set of default-risk indicators (i.e., the standard specification).[12]

As indicated by the narrow shaded band, forecasts of employment and industrial output growth based on credit spreads in our EDF-based bond portfolios track quite well year-

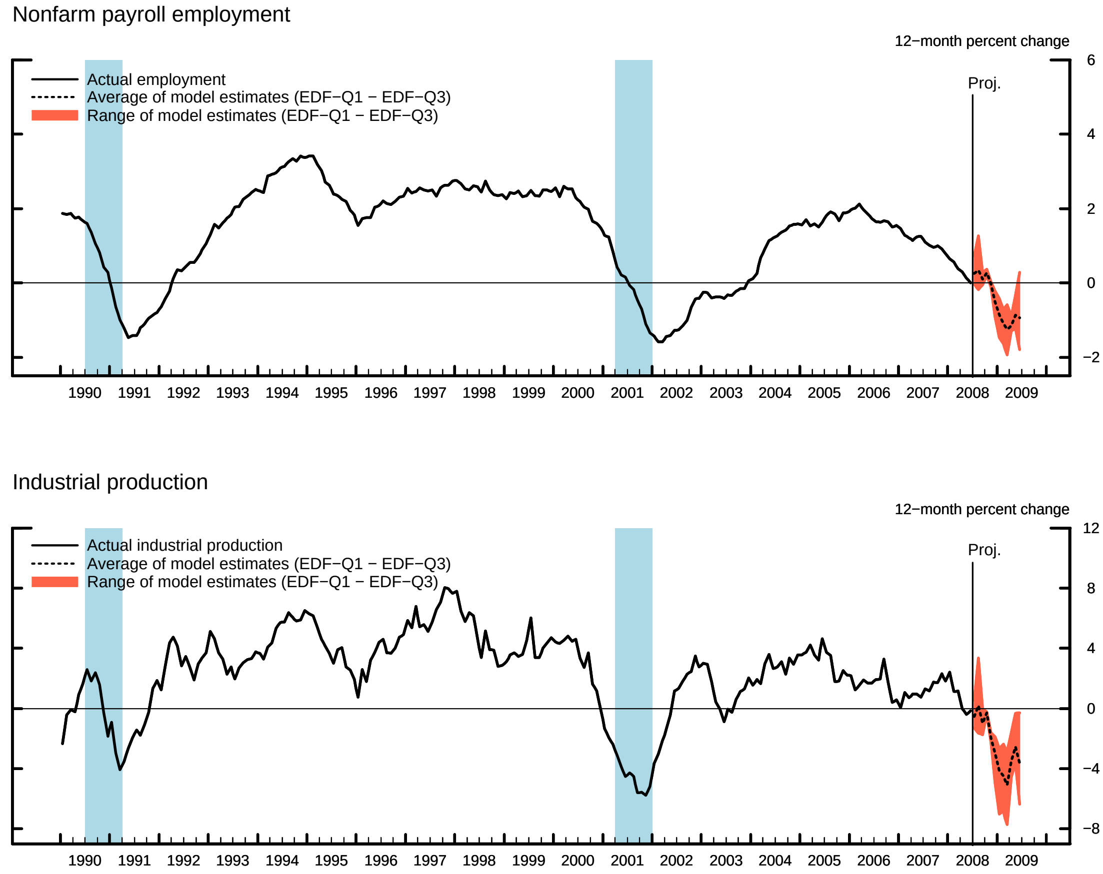
[12]Note that this analysis is based on additional six months of data, relative to the results reported earlier. For most of the analysis in the paper, the end-period of our sample (December 2007) is dictated by the availability of the firm-level stock price data from CRSP.

over-year growth in the actual series in both recessionary and expansionary times. In addition, the substantial gain in predictive accuracy obtained from using credit spreads in our EDF-based portfolios rather than standard default-risk indicators does not seem to reflect any "one-time" event or a specific subperiod. Importantly, our EDF-based forecasts capture much better the slowdown in economic activity associated with the 2001 recession relative to the specification based on standard default-risk indicators. Although forecasts based on both the standard set of credit spread indexes and spreads in our EDF-based bond portfolios miss somewhat the subsequent cyclical recovery, the VAR specification that includes standard default-risk indicators over-predicts the rebound in economic activity by a much wider margin than specification that relies on our portfolio credit spreads. Finally, the forecast based on standard credit spread indexes completely misses the slowdown in economic activity that has emerged since late 2006, whereas the EDF-based forecasts predict this slowdown with high degree of accuracy.

In light of the ongoing turmoil in financial markets, investors and policymakers are obviously concerned with the near-term economic outlook. Figure 2 depicts the realized values of the 12-month growth rate in employment and industrial production along with their respective forecast through mid-2009. As before, the shaded band depicts a range of forecasts based on the VAR specifications augmented with credit spreads in portfolios corresponding to the first three quintiles of the EDF distribution (EDF-Q1–EDF-Q3); the dotted lines in the two panels of the figure show the simple arithmetic average of these three forecasts. Given data through June 2008, the average of the three EDF-based forecasts implies a substantial contraction in economic activity as measured by year-over-year growth in both employment and industrial output: The average of the three EDF-based forecasts indicates that over the 12 months ending in June 2009, U.S. nonfarm payrolls will fall about 1.25 percent, while industrial production is projected to drop almost 4 percent, declines comparable to those experienced during the 2001 recession. Tempering somewhat this bleak economic outlook is the relatively wide range of estimates across the three different EDF quintiles, a finding that perhaps is not too surprising because at turning points, out-of-sample forecasts are likely to differ substantially across risk categories.

In summary, our out-of-sample forecasting analysis is consistent with the in-sample results presented in the previous section. At short-run forecast horizons, the information content of credit spreads in the EDF-based bond portfolios is somewhat higher than that of commonly-used default-risk indicators. At longer horizons, however, credit spreads in our bond portfolios have a significantly better forecasting power. Also of interest is the fact that for both employment and industrial output growth, the greatest predictive content appears to be embedded in the prices of bonds issued by firms in lower risk categories—that is, firms in the first three quintiles of the EDF distribution.

Figure 2: Credit Spreads and the Near-Term Economic Outlook



NOTE: The panels of the figure depict forecasts of the 12-month growth in nonfarm payroll employment and industrial production for the 12 months ending in June 2009. The solid line shows the actual data, which extend through June 2008; the shaded band shows the range of projections based on VAR specifications augmented with credit spreads in the first three quintiles of the EDF distribution (EDF-Q1–EDF-Q3); and the dotted line shows the average forecast (see text for details). Shaded vertical bars correspond to NBER-dated recessions.

4 Factor-Augmented VAR Analysis

In this section, we use the factor-augmented vector autoregression (FAVAR) methodology proposed by Bernanke and Boivin [2003] and Bernanke, Boivin, and Eliasz [2005] to identify shocks to corporate bond spreads and to trace out their dynamic effect on a broad set of macroeconomic variables. In particular, we examine the interaction between credit spreads in our EDF-based bond portfolios and measures of economic activity and inflation, the monetary policy rate, yields on Treasury securities of various maturities, excess returns on the matched EDF-based portfolios of stocks, and other financial indicators. Using factor analysis, we summarize the large number of macroeconomic and financial time series by a small number of unobservable (latent) factors. We associate a subset of these latent factors—referred to as "credit factors"—with the corporate bond market, in the sense that these credit factors capture information in corporate bond spreads that is orthogonal to the information content of factors that summarize the remaining macroeconomic and financial indicators. To identify structural shocks associated with the credit factors, we rely on standard recursive identification scheme, an approach that enables us to examine the impact of an orthogonalized shock to corporate bond spreads on the macroeconomy.

4.1 Specification, Identification, and Estimation

Let X_t, $t = 1, 2, \dots, T$, denote a $(n \times 1)$ vector of observations on all the variables in the FAVAR system in month t. We assume that X_t can be partitioned as $X_t = [X'_{1t}\ X'_{2t}]'$, where X_{1t} is the $(n_1 \times 1)$ vector whose elements correspond to measures of economic activity and inflation, Treasury yields, excess equity returns, and other financial indicators, and elements of the $(n_2 \times 1)$ vector X_{2t} correspond to credit spreads in our EDF-based bond portfolios. We assume that the information in the vector of observable variables X_t can be summarized by a small set of latent factors denoted by the $(k \times 1)$ vector F_t, with $k < n$. We make the following assumption with regards to this latent factor structure: A subset of factors—denoted by the $(k_1 \times 1)$ vector F_{1t}—spans all the information contained in the observed vector X_t, whereas the remaining factors, denoted by the $(k_2 \times 1)$ vector F_{2t}, are specific to credit spreads in our EDF-based portfolios—the so-called credit factors.

The relationship between the observed variables in X_t and the latent factors $F_t = [F'_{1t}\ F'_{2t}]'$ is linear and is given by the observation equation:

$$\begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \mathbf{\Lambda}_{11} & \mathbf{\Lambda}_{12} \\ \mathbf{\Lambda}_{21} & \mathbf{\Lambda}_{22} \end{bmatrix} \begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} + \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix}, \tag{4}$$

where $\mathbf{\Lambda}_{ij}$, $i, j = 1, 2$, are conformable matrices of factor loadings, and $\nu_t = [\nu'_{1t}\ \nu'_{2t}]'$ denotes the $(n \times 1)$ vector of idiosyncratic measurement errors. Consistent with the assumptions underlying approximate factor models, the process for the vector of measurement errors ν_t can be weakly serially correlated and exhibit some degree of cross-sectional dependence (see, for example, Bai and Ng [2002]). Because the latent factors enter equation 4 without lags, the above specification corresponds to the static form of a dynamic factor model. However, as discussed by Stock and Watson [2005], this is not a restrictive assumption, because the static factors can, in principle, contain an arbitrary number of lags of some underlying dynamic factors.

The dynamics of the latent factors are described by an autoregressive process of the form

$$\begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} = \mathbf{\Phi}(L) \begin{bmatrix} F_{1,t-1} \\ F_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}, \tag{5}$$

where $\mathbf{\Phi}(L)$ denotes a matrix polynomial in the lag operator L of finite order p, and $\epsilon_t = [\epsilon_{1t}' \ \epsilon_{2t}']'$ is the $(k \times 1)$ vector of reduced-form VAR disturbances with a covariance matrix $\mathbf{\Sigma} = E[\epsilon_t \epsilon_t']$. Following standard practices, we assume that the idiosyncratic measurement errors are uncorrelated with VAR innovations—that is, $E[\nu_{it}\epsilon_{jt}] = 0$, for $t = 1, \ldots, T$; $i = 1, \ldots, n$; and $j = 1, \ldots, k$. To identify the vector of credit factors F_{2t}, we impose the following restrictions on the system of equation 4 and 5. First, we assume that $\mathbf{\Lambda}_{12} = \mathbf{0}$ in equation 4. This restriction on the factor loadings implies that once we have conditioned on the factors in F_{1t}, the remaining information content of credit spreads in our EDF-based portfolios has a systematic component specific to the corporate bond market that is reflected in its own factor structure. Although the credit factors in F_{2t} have no contemporaneous effect on the vector X_{1t}, they affect the factors in F_{1t}—and, by extension, the vector of observed variables X_{1t}—with a lag through the dynamics of the VAR equation 5. The second identifying assumption is that the factors in F_{1t} and F_{2t} are orthogonal, an assumption that separates the residual information content from the corporate bond market from the factors summarizing the state of the economy.

In principle, all the parameters of the FAVAR model given by equations 4–5 can be estimated by maximum likelihood using the Kalman filter to construct the likelihood function. However, in the presence of identifying restrictions and when the dimension of X_t is large, this method is computationally infeasible. Accordingly, we employ a five-step estimation procedure that is computationally easy to implement and that imposes restrictions needed to identify the credit factors. The five steps of our procedure are as follows:

1. Estimate the $(T \times k_1)$ matrix of factors $\mathbf{F}_1$ as the first k_1 principle components of the $(T \times n_1)$ data matrix $\mathbf{X}_1$ corresponding to the vector of variables X_{1t}.

2. Regress each column of the $(T \times n_2)$ data matrix $\mathbf{X}_2$ corresponding to the vector of variables in X_{2t}—that is, credit spreads associated with our EDF-based bond portfolios—on the k_1 factors in $\mathbf{F}_1$, and let $\widehat{\mathbf{E}}$ denote the corresponding $(T \times n_2)$ matrix of OLS residuals.

3. Estimate the $(T \times k_2)$ matrix of factors $\mathbf{F}_2$ as the first k_2 principle components of the data matrix $\widehat{\mathbf{E}}$ from step 2.

4. Estimate factor loadings by regressing each column of the $(T \times n)$ data matrix $\mathbf{X}$ on the estimated factors $\mathbf{F}_1$ and $\mathbf{F}_2$, imposing the restriction $\mathbf{\Lambda}_{12} = \mathbf{0}$.

5. Using the identified factors, estimate the VAR(p) model in equation 5 by OLS.

The latent factors $\mathbf{F}_1$ and $\mathbf{F}_2$ in steps 1 and 3 are estimated using asymptotic principal components, the method whose properties are discussed in detail by Stock and Watson [2002a] and Bai and Ng [2002]. Note that the residuals from step 2 are, by construction, orthogonal to $\mathbf{F}_1$, implying that the estimated factors $\mathbf{F}_2$ from step 3 are also orthogonal to $\mathbf{F}_1$. In step 4, we impose the identifying assumption that variables in X_{1t} do not respond contemporaneously to movements in F_{2t}—that is, the matrix of factor loadings $\mathbf{\Lambda}_{12} = \mathbf{0}$. In step 5, we estimate the VAR(p) in the identified factors F_{1t} and F_{2t}, which summarizes in a parsimonious way the dynamic interactions between the unobserved factors.

We identify structural shocks affecting the vector of credit factors F_{2t} using the Cholesky decomposition of $\mathbf{\Sigma}$, the covariance matrix of the reduced-form VAR disturbances in equation 5. In computing the Cholesky decomposition, the credit factors are ordered last, and the individual components of F_{2t} are ordered in descending order with respect to their associated eigenvalues. Thus identified "credit market shocks" correspond to unexpected movements in corporate bond spreads that are contemporaneously uncorrelated with indicators of economic activity and inflation, interest rates, and other financial indicators as summarized by the vector of factors F_{1t}.

As noted above, the vector X_{1t} contains a broad set of macroeconomic and financial variables, whereas elements of the vector X_{2t} correspond to credit spreads in our EDF-based bond portfolios. The variables included in X_{1t} can be classified into five broad categories: economic activity indicators, inflation indicators, risk-free interest rates, equity market indicators, and other financial indicators. We briefly discuss each in turn.

- **Economic activity**: We include the following 11 monthly indicators of economic activity in our FAVAR specification: (1) the difference of the civilian unemployment rate; (2) the log-difference of nonfarm payroll employment; (3) the log-difference of industrial production index; (4) the difference in capacity utilization index; (5) the log-difference of real durable goods orders; (6) the log-difference of real nondurable good orders; (7) the Institute for Supply Management (ISM) diffusion index of activity in the manufacturing sector; (8) the log-difference of real personal consumption expenditures (retail control category); (9) the log-difference of real disposable personal income; (10) the log-difference of housing starts; (11) and the log-difference of Conference Board's leading economic indicator index.

- **Inflation**: Price developments are summarized by the following 6 inflation indicators: (1) the log-difference of the Consumer Price index (CPI); (2) the log-difference of the core CPI; (3) the log-difference of the Producer Price index (PPI); (4) the log-difference of the core PPI; (5) the log-difference of the Journal of Commerce index of (spot) commodity prices; (6) the log-difference of the price of oil as measured by price of a barrel of West Texas Intermediate (WTI) crude.

- **Interest rates**: Our FAVAR specification also includes the entire term structure of interest rates, starting at the short end with the effective federal funds rate and continuing with the constant maturity Treasury yields at 6-month, 1-year, 2-year, 3-year, 5-year, and 10-year horizons, for a total of 7 interest rates. Because nominal yields exhibit a discernible downward trend over our sample period (1990–2007), we convert them into real terms to ensure their approximate stationarity. To do so, we utilize both the realized inflation and survey measures of inflation expectations reported by the Survey of Professional Forecasters (SPF).[13] Specifically, the real federal funds rate is measured as the difference between the nominal rate and realized inflation, where the realized inflation is given by the the difference between the log of the core CPI price index and its lagged value 12 months earlier. The real 6-month Treasury yield is measured as the difference between the nominal yield and the equally-weighted average of the realized inflation given above and the one-year ahead expected CPI inflation as reported in the SPF. For the remaining Treasury yields, we construct the expected inflation at each specific horizon by calculating the appropriately weighted average of the one-year ahead and the ten-year ahead expected CPI inflation reported in the SPF.[14]

- **Equity returns**: Developments in equity markets are summarized by the following 8 series: (1) the total value-weighted excess market return from CRSP; (2) the excess equity returns of firms in our five EDF-based stock portfolios; and (3) the Fama-French "SMB" and "HML" factors to account for the different dynamics of equity returns in our EDF-based stock portfolios.

- **Financial indicators**: The final group of variables in the vector X_{1t}—4 series—includes: (1) the implied volatility on the S&P 500 index options (VIX) to capture uncertainty in the equity market;[15] (2) the implied volatilities on Eurodollar and ten-year Treasury note futures, measures of uncertainty associated with movements in short- and long-term interest rates, respectively; and (3) the log-difference of the trade-weighted exchange value of the dollar against major currencies to control for the international dimension of the U.S. financial system.

[13] The SPF is conducted at a quarterly frequency. We obtain monthly estimates of inflation expectations from a linear interpolation of quarterly values.

[14] For example, in calculating the 5-year real Treasury yield, we employ a simplifying assumption that the expected inflation over the next five years is equal to an equally-weighted average of one-year ahead and ten-year ahead expected inflation as reported in the SPF.

[15] The link between equity volatility and prices of corporate debt is central to options-based models of corporate bond yields such as Merton [1974]. Campbell and Taksler [2003] examine empirically the relationship between the large increase in idiosyncratic firm volatility and a rise in corporate bonds yields observed in the late 1990s. By including a measure of stock market uncertainty in our FAVAR specification, we are attempting to control for the general increase in idiosyncratic volatility that has occurred during our sample period.

Thus in our baseline specification, the vector X_{1t} contains 36 monthly macroeconomic and financial time series, and the 20 elements of vector X_{2t} correspond to the average credit spreads in the 20 corporate bond portfolios classified by maturity and default risk.[16] With this specification, our assumptions identify credit market shocks that are orthogonal to the excess equity returns of firms whose outstanding bonds are used to construct the EDF-based bond portfolios underlying the information content of the vector X_{2t}. Hence, we are tracing out the effect of a shock to corporate bond spreads that is unrelated to news contained in stock returns of the same set of firms.

The remaining question concerns the number of latent factors (k_1 and k_2) and the order of the VAR system p. In our baseline specification, we set $k_1 = 4$ and $k_2 = 2$.[17] Under this parametrization, we are assuming that four common factors—denoted by $F_{1t} = [F^1_{1t}\ F^2_{1t}\ F^3_{1t}\ F^4_{1t}]'$—summarize the information contained in the vector X_{1t}, whereas the residual component of credit spreads in our EDF-based bond portfolios can be represented by two factors, denoted by $F_{2t} = [F^1_{2t}\ F^2_{2t}]'$. We set the order of the VAR system $p = 6$, a lag length chosen according to the Akaike information criterion (AIC) with two additional lags to preclude any potential under-fitting. Using this FAVAR specification, we present two sets of results. First, we compute impulse responses of the variables in vector X_t resulting from a shock to the first credit factor—that is, F^1_{2t}. Second, for selected macroeconomic and financial series, we calculate the fraction of their forecast error variance that is attributable to our identified credit shocks, an alternative metric by which we gauge the economic significance of disturbances in credit markets.

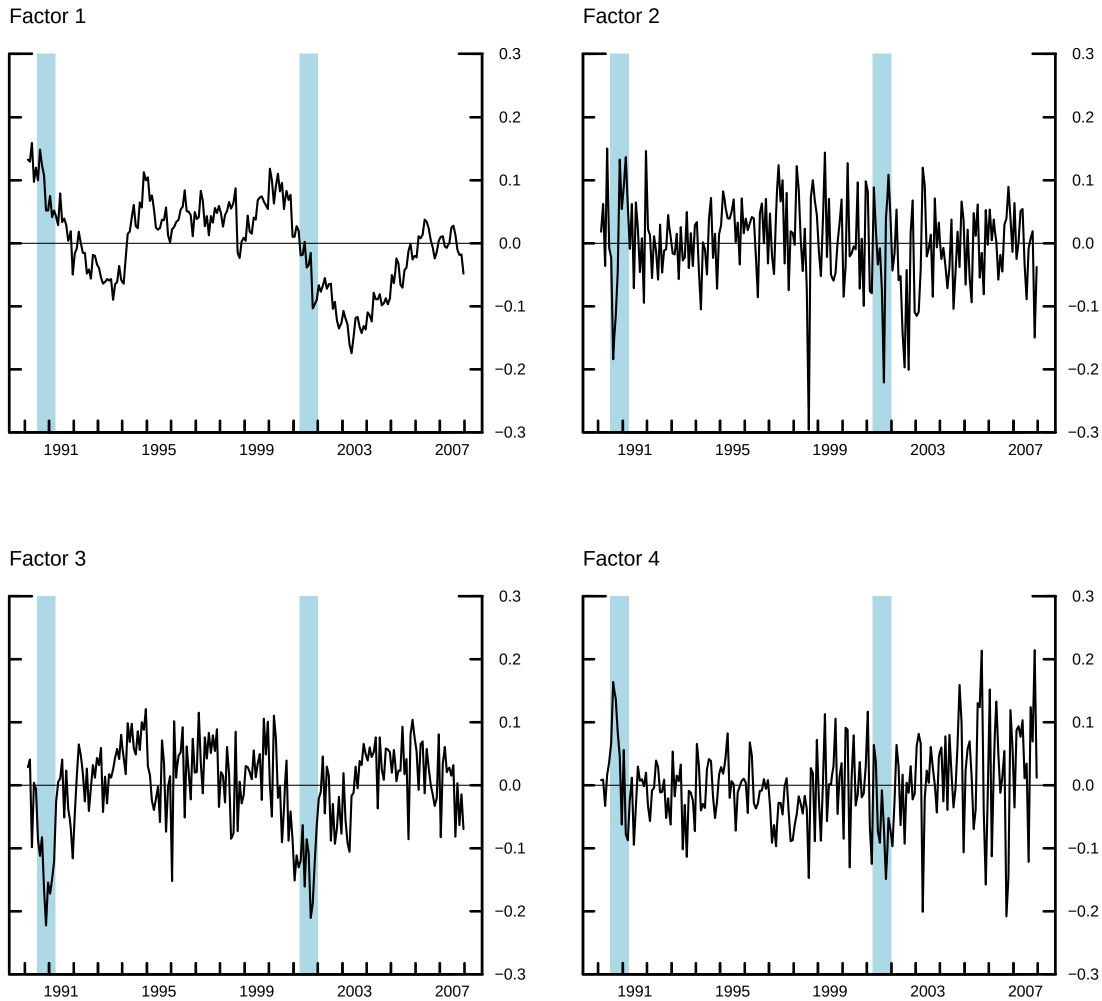
4.2 Shocks to Corporate Bond Spreads

Before turning to our main results, we briefly discuss the estimates of the factors $F_{1t} = [F^1_{1t}\ F^2_{1t}\ F^3_{1t}\ F^4_{1t}]'$ and credit factors $F_{2t} = [F^1_{1t}\ F^2_{1t}]'$ from our baseline specification. Figure 3 depicts the four factors associated with macroeconomic and financial variables contained

[16] The cross-sectional dimensions of our FAVAR specification—a total of 56 series—may appear modest when compared with recent applications of "large-dimensional" approximate factor models, where more than 100 or even several hundred series have been used to identify a small number of common factors. However, as pointed out by Boivin and Ng [2006], increasing the cross-sectional dimension beyond a certain point may be undesirable. Indeed, according to their results, factors extracted from as few as 40 series generally do better in terms of forecasting key macroeconomic series than the ones extracted from very large panels.

[17] Recently, Bai and Ng [2002, 2007] and Stock and Watson [2005] have proposed several methods of how to select formally the number of factors in such models. Because of the added complexity reflecting our identification procedure, we adopted a more informal approach. Specifically, employing reasoning similar to that of Forni, Giannone, Lippi, and Reichlin [2005] and Giannone, Reichlin, and Sala [2005], we picked k_1 by looking at the increase in the explained variation of the 36 macroeconomic and financial series in X_{1t} that resulted from increasing the number of factors in F_{1t}. Given our choice of k_1, we selected the number of credit factors k_2 using the same approach. As a robustness check, we increased the number of factors extracted from the data matrix $\mathbf{X}_1$ from four to five, and to six, and we increased the number of factors extracted from the data matrix $\mathbf{X}_2$ to three. None of the resulting FAVAR specifications yielded materially different conclusions.

Figure 3: Macroeconomic and Financial Factors
(Baseline Specification)

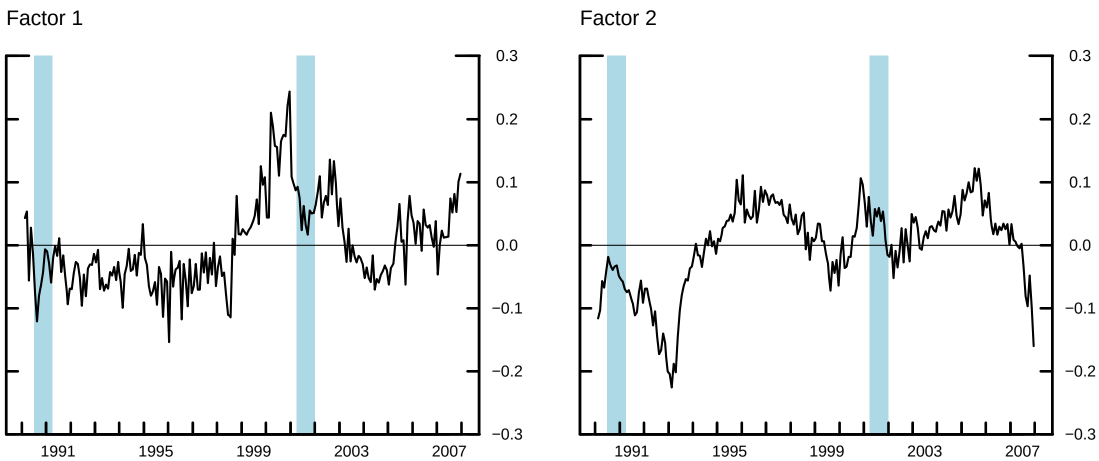


NOTE: The panels of the figure depict estimates of the four factors from the baseline FAVAR specification. The four factors summarize the 36 macroeconomic and financial variables included in the vector X_{1t} (see text for details). Shaded vertical bars correspond to NBER-dated recessions.

in the vector X_{1t}, and Figure 4 shows the estimates of the two credit factors identified using the information from the corporate bond market. (Tables summarizing correlations between the six factors and all the variables in X_t are shown in Appendix A.)

According to the correlations in Table A-1, the four factors shown in Figure 3 have a clear economic interpretation: Factor 1 is most highly correlated with real short-term interest rates; factor 2 captures the excess stock market return; factor 3 summarizes the various measures of economic activity; and factor 4 is a summary statistics for inflation

Figure 4: Credit Factors
(Baseline Specification)



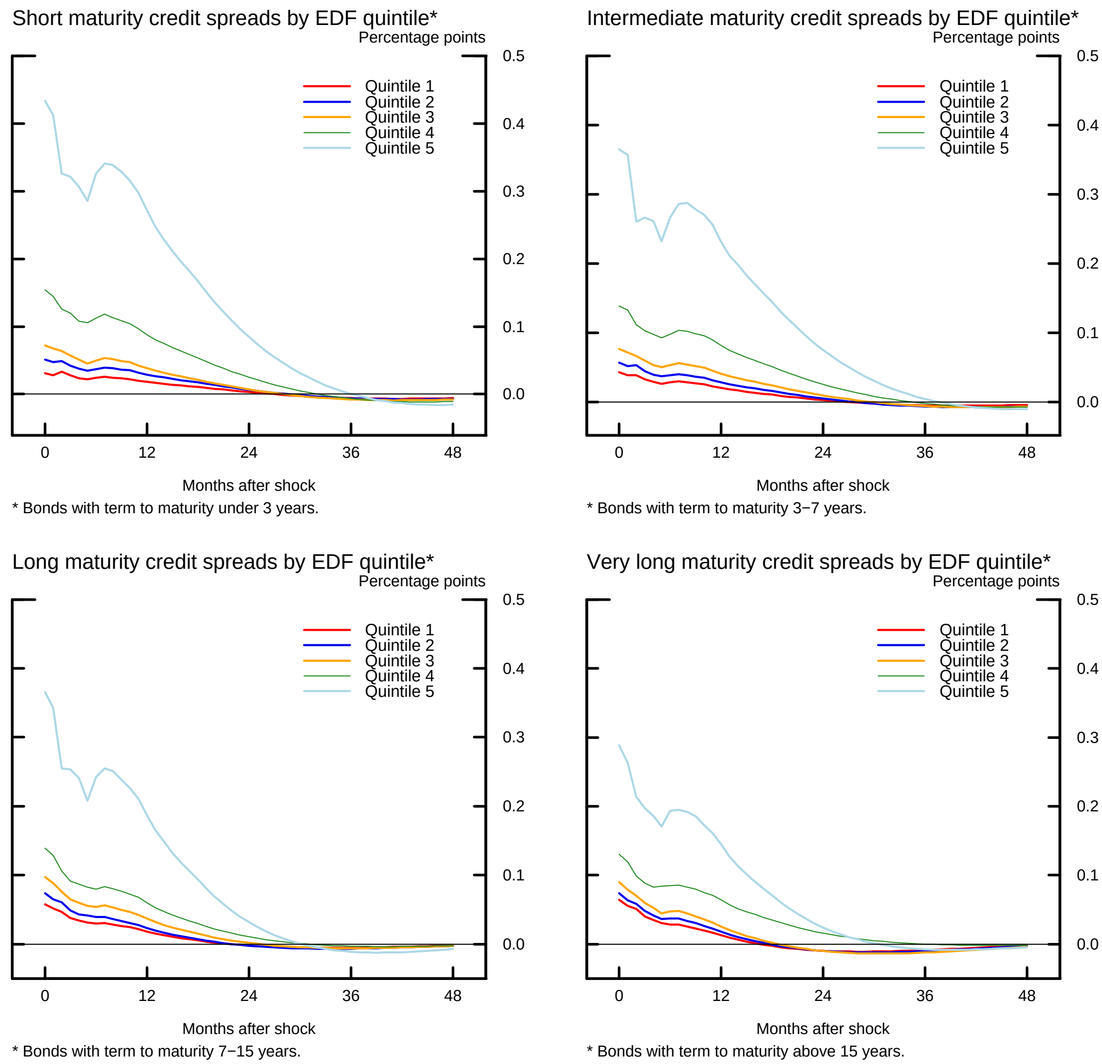
NOTE: The panels of the figure depict estimates of the two credit factors from the baseline FAVAR specification. The two credit factors summarize the residual information content of credit spreads in the 20 EDF-based bond portfolios included in the vector X_{2t} (see text for details). Shaded vertical bars correspond to NBER-dated recessions.

developments. Figure 4 depicts the estimates of the two credit factors obtained using the variation in credit spreads across the 20 EDF-based bond portfolios. The first credit factor corresponds most closely to credit spreads in the long-maturity bond portfolios in the middle of the credit-quality spectrum. Recall that these are the portfolios that contained the greatest predictive power for the growth of employment and industrial production at longer forecast horizons, according to the results of our forecasting analysis. The interpretation of the second credit factor, by contrast, is less clear. According to the correlations in Table A-2, the second credit factor is negatively correlated with shorter-term credit spreads in the first two EDF quintiles and positively correlated with longer-term credit spreads in higher default-risk portfolios. Thus the second credit factor appears to capture differences between high- and low-risk firms and differences between near- and longer-term credit risk.

Figure 5 depicts responses of credit spreads in the 20 bond portfolios to a one standard deviation orthogonalized shock to the first credit factor. (Impulse responses for all the variables in our baseline specification, along with their respective 95-percent confidence intervals, are shown in Appendix B.[18]) This credit market shock causes corporate bond

[18] The confidence intervals of the impulse response functions are based on a two-stage bootstrap procedure that takes into account both the serial correlation and cross-sectional dependence of the measurement errors in equation 4. In particular, we first estimate the factors and factor loadings following the estimation procedure described above. We then perform a sieve bootstrap on the residuals of the observation equation 4. For each bootstrapped sample, we also re-estimate the factors $\mathbf{F}_1$ and $\mathbf{F}_2$, thereby taking into account that

Figure 5: Response of Corporate Bond Spreads
(Baseline Specification)



NOTE: The panels of the figure depict the effect of an orthogonalized one standard deviation shock to credit factor 1 on corporate bond spreads in the 20 EDF-based bond portfolios (see text for details).

spreads to widen across the entire spectrum of credit quality and across all maturities. The response of credit spreads associated with riskier bond portfolios is significantly greater than that of the less risky portfolios and is also more persistent. Furthermore, the jump in

the factors appear as generated regressors in equation 5. Second, for each bootstrap loop of the observation equation, we apply the "bootstrap-after-bootstrap" procedure of Kilian [1998] to the state-space equation 5 using the bootstrapped factors. This procedure is designed to take into account the small sample bias, the lack of scale invariance, and the skewness of the distribution of the impulse response functions of the VAR system.

the riskiest corporate bond spreads is somewhat more pronounced at the short end of the maturity spectrum.

The impact of this credit shock on selected macroeconomic variables is shown in Figure 6. A shock to credit factor 1 is clearly contractionary, as evidenced by the fact that industrial production declines about 0.4 percentage points over a 24-month period.[19] In addition to being statistically significant, the cumulative contraction in industrial output in response to a credit shock is economically significant, especially given that the response of credit spreads is in the order of only 10-15 basis points for most of the credit-risk distribution. The increasing slack in resource utilization following a shock to the corporate bond market is associated with a modest decline in the level of core CPI prices. These macroeconomic developments, in turn, lead to a fall in the general level of real interest rates. In particular, real short-term interest rates decline about 10 basis points at the trough, but longer-term real Treasury yields fall somewhat less along the path, implying a steepening of the real Treasury yield curve in response to the innovation in the corporate bond spreads.[20]

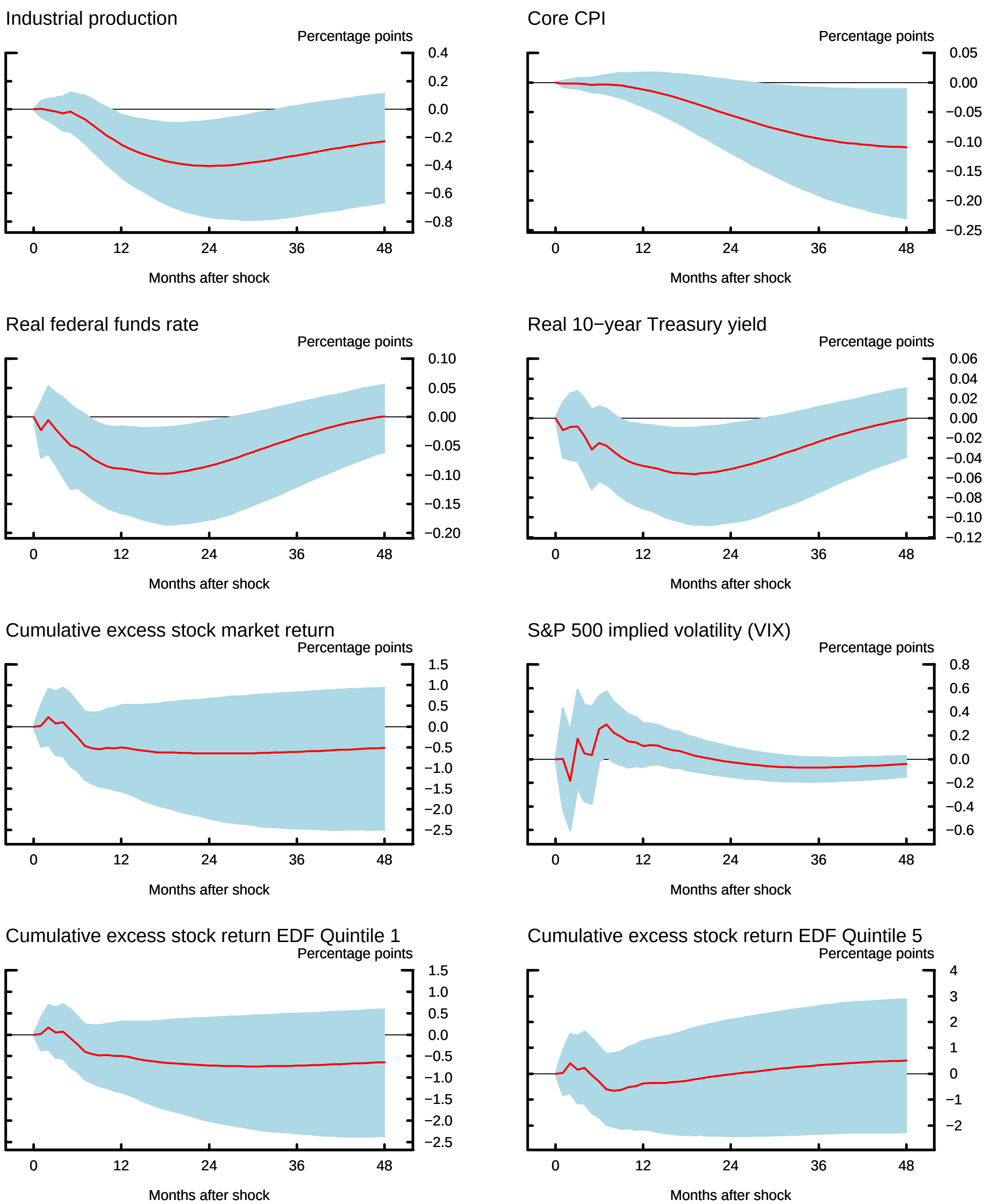
The contractionary effects of this credit market shock, however, are not evident in the stock market. Although the market excess return exhibits a cumulative decline of about 0.5 percentage points over the horizon shown, the fall in the stock market is statistically not different from zero. The cumulative excess equity returns of the least and the most risky firms also fall initially, but again, these declines are statistically indistinguishable from zero. Evidently, the decline in long-term real interest rates partly offsets the effect of the deterioration in the economic outlook. Nevertheless, the impact of this adverse credit market shock is reflected in stock market uncertainty, as the option-implied volatility on the S&P 500 (VIX) increases notably in the first six months after the shock. All told, a shock to the first credit factor implies a modest increase in the overall level of corporate bond spreads that leads to a sizable contraction in industrial output, a deceleration in core prices, lower real interest rates, and a rise in stock market uncertainty.

We now examine the importance of credit market shocks by calculating the proportion of the forecast error variance attributable to the innovations associated with credit factor 1, an alternative metric by which to gauge the economic significance of disruption in credit markets. Figure 7 reports the average proportion of the forecast error variance at different horizons for selected variables in our FAVAR specification that is explained by our identified

[19] As discussed above, the macroeconomic and financial variables contained in the vector X_{1t} were, if necessary, transformed using log or simple differencing to ensure their stationarity. In such a case, we cumulate their impulse responses to depict the impact of the credit market shock on levels of these variables; similarly, we compute and show the cumulative responses of both the excess market return and the excess equity returns of firms in the five EDF quintiles.

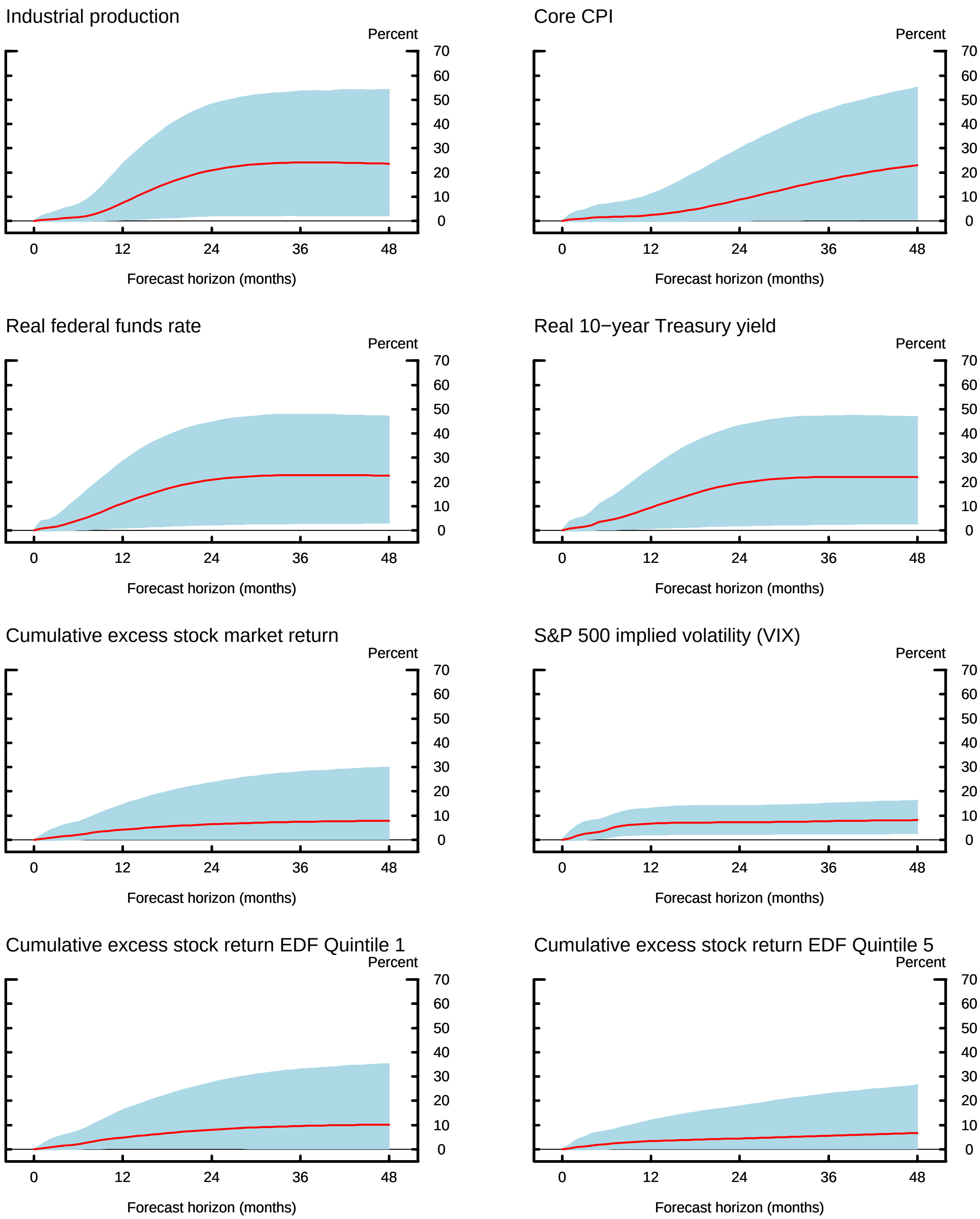
[20] As shown in Figure B-3 in Appendix B, the innovation in the corporate bond spreads is also associated with a decrease in the uncertainty regarding the path for short-term interest rates and with an increase regarding the path for long-term government bond yields.

Figure 6: Response of Selected Macroeconomic and Financial Variables
(Baseline Specification)



Note: The panels of the figure depict the effect of an orthogonalized one standard deviation shock to credit factor 1 on selected macroeconomic and financial variables (see text for details). The shaded bands represent the 95-percent confidence intervals computed using a sieve bootstrap with 10,000 replications.

Figure 7: Forecast Error Variance Decomposition of a Credit Market Shock
(Baseline Specification)



NOTE: The panels of the figure depict the fraction of the forecast error variance for selected macroeconomic and financial variables that is attributed to an orthogonalized one standard deviation shock to credit factor 1. The shaded bands represent the 95-percent confidence intervals computed using a sieve bootstrap with 10,000 replications.

credit market shock, along with the respective 95-percent confidence intervals. According to results in Figure 7, shocks to corporate bond spreads account, on average, for more than 20 percent of the variation in the growth of nonfarm payroll employment and industrial production at the two- to four-year forecast horizon. The shock to the first credit factor also explains a significant fraction of the variation in both short- and long-term real interest rates but accounts for relatively little of the forecast error variance in the excess equity returns. This credit market shock also accounts for a large fraction of the variation in corporate bond spreads but at a higher frequency. Thus, variation in corporate bond spreads at the one- to two-year horizon appears to explain a substantial fraction of the variation in both real activity and real interest rates at the two- to four-year forecast horizon, a result consistent with the predictive power for economic activity of corporate bond spread at long-run forecast horizons.

4.3 Shocks to Excess Equity Returns

In our baseline specification, we analyzed the information content of corporate bond spreads that is orthogonal to both the aggregate stock market return and the average of excess returns of firms in our EDF-based stock portfolios. As a point of comparison, we now examine whether excess equity returns in our EDF-based stock portfolios also contain information regarding economic activity that is not captured by either standard macroeconomic indicators or the aggregate stock market return.

To do so, we consider an alternative FAVAR specification that relies only on excess equity returns in our EDF-based stock portfolios to identify a shock to financial markets. Specifically, instead of the 20 credit spreads associated with our EDF-based bond portfolios, we let the elements of the vector X_{2t} correspond to the (average) excess equity returns in our five EDF-based stock portfolios. The elements of the vector X_{1t}, except for removing the excess equity returns in the five EDF-based portfolios, are left unchanged.[21] This alternative FAVAR specification thus identifies shocks to firms' earnings contained in our EDF-based stock portfolios that are orthogonal to indicators of economic activity and inflation, real interest rates, and aggregate stock market developments.[22]

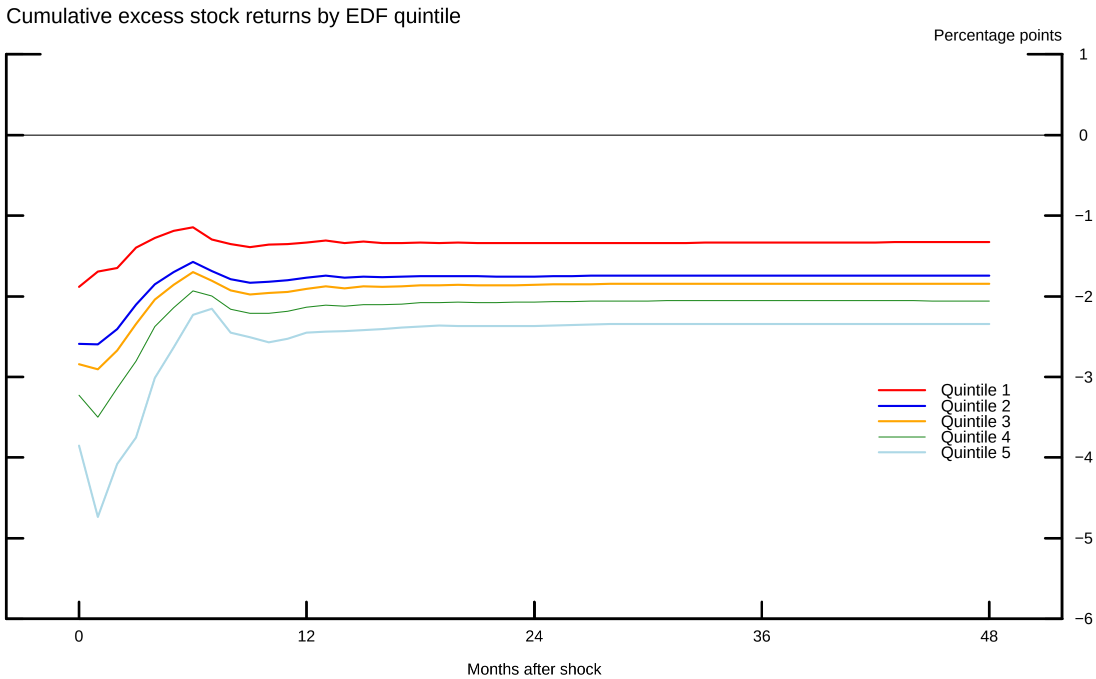
Figure 8 depicts the effect of a one standard deviation orthogonalized shock to the first factor—identified using excess stock returns—on the average excess equity return in each of the five quintiles of the credit-risk distribution.[23] This shock has clear negative

[21]We employ the same identification scheme as in our baseline specification to identify credit shocks, and we again set $k_1 = 4$, $k_2 = 2$, and $p = 6$.

[22]We have also considered a specification that that includes both the stock returns and the corporate bond spreads in the vector X_{2t}. These results are very similar to our baseline specification, a result that provides further evidence that corporate bond spreads contain unique information not captured by other financial asset prices.

[23]Note that under our identifying assumptions, the estimated macroeconomic and financial factors $\mathbf{F}_1$

Figure 8: Response of Excess Equity Returns
(Alternative Specification)

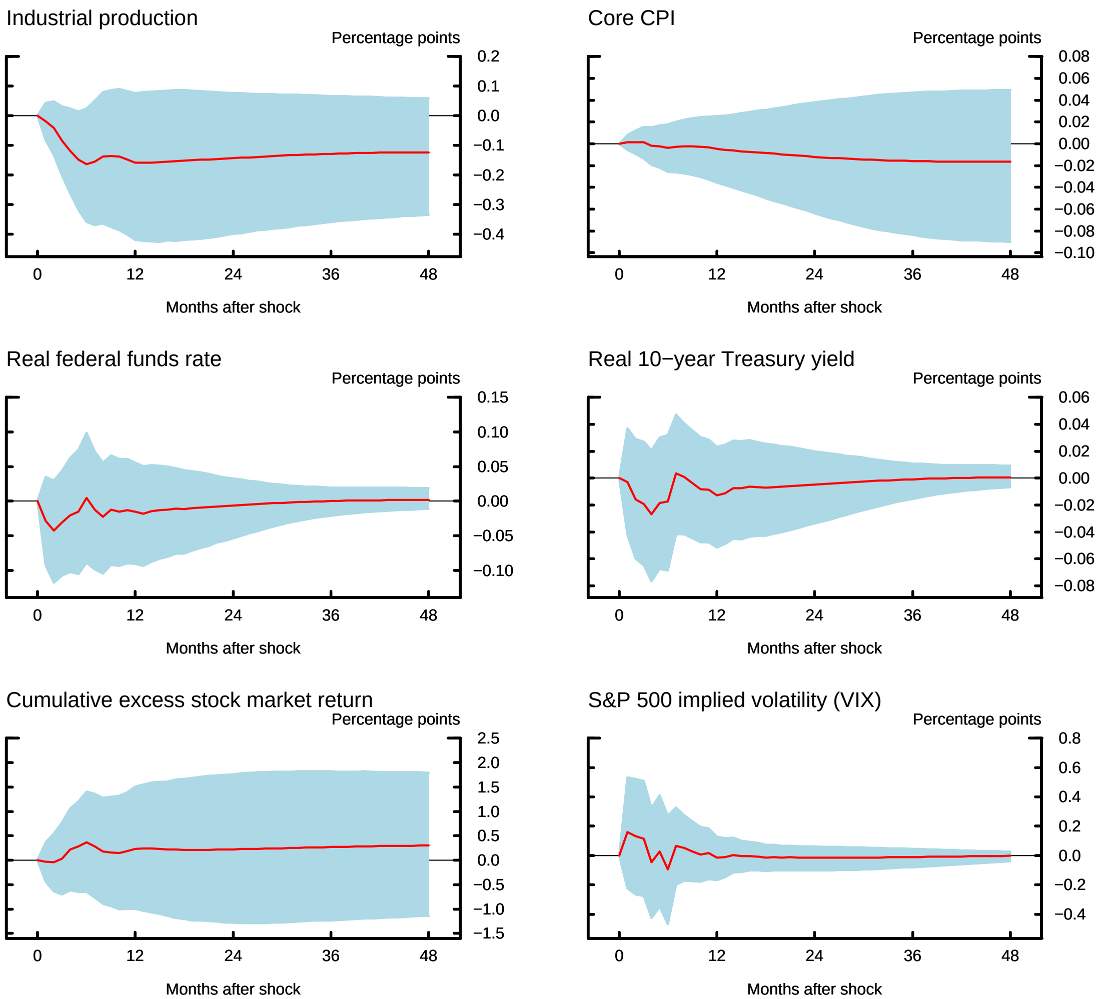


NOTE: The panels of the figure depict the effect of an orthogonalized one standard deviation shock to financial factor 1 on excess equity returns in the five EDF-based stock portfolios (see text for details).

implications for stock returns of firms across the spectrum of credit quality. Upon its impact, excess stock returns in our EDF-based stock portfolios fall between 2 and 4 percentage points, with returns of the riskiest firms registering the largest decline. However, compared with the shock to corporate bond spreads, the shock to excess equity returns is far less persistent, and the level of stock prices—though permanently lower—is back to steady state about six months after the shock. As shown in Figure 9, the macroeconomic implications of this shocks—given the width of the 95-percent confidence intervals—are ambiguous, a result suggesting that the two factors extracted from the residual component of excess

from this alternative specification can, in principle, differ from those in our baseline specification. As in the baseline specification, however, the four estimated factors summarizing the information content of the vector X_{1t} from the alternative specification correspond to real short-term interest rates, economic activity, inflation, and broad stock market developments. The two factors in $\mathbf{F}_2$ also have a similar interpretation: The first factor from this alternative specification captures movements in the residual component of excess equity returns across the five EDF quintiles; the second factor is negatively correlated with the average excess return of the least risky firms—those in the first quintile of the EDF distribution—and positively correlated with in the average excess return of the most risky firms—those in the fifth quintile. The second credit factor, therefore, appears to capture differences in the idiosyncratic components of excess stock returns between high- and low-risk firms.

Figure 9: Response of Selected Macroeconomic and Financial Variables (Alternative Specification)



NOTE: The panels of the figure depict the effect of an orthogonalized one standard deviation shock to financial factor 1 on selected macroeconomic and financial variables (see text for details). The shaded bands represent the 95-percent confidence intervals computed using a sieve bootstrap with 10,000 replications.

equity returns have little systematic component and largely reflect idiosyncratic news about earnings growth.

5 Conclusion

In this paper, we examined the forecasting performance and information content of credit spreads for macroeconomic outcomes. To control properly for risk and maturity of corporate debt instruments, we constructed credit spreads directly from the secondary prices of outstanding senior unsecured corporate bonds issued by a large panel of nonfinancial firms. By restricting our analysis to senior unsecured corporate bonds, we were able to avoid some of the pitfalls that rapid financial innovation may impart on the information content of financial asset prices over time. An additional benefit of our "ground-up" approach is that we were able to construct matched portfolios of equity returns, which allowed us to examine the information content of corporate bond spreads that is orthogonal to information contained in stock prices of the same set of firms, as well as to macroeconomic factors associated with economic activity, real risk-free interest rates, and inflation.

Our results indicate that credit spreads on senior unsecured corporate debt have a substantial predictive power for future economic activity relative to that of previously used default-risk indicators such as the paper-bill spread or the high-yield credit spread. This improvement in forecasting performance reflects the information content of spreads on longer-maturity bonds issued by firms at the high-end and middle of the credit-quality spectrum. According to our FAVAR results, shocks to corporate bond spreads lead to quantitatively large swings in economic activity and real interest rates, and, although such credit market shocks do not appear to be very important at high frequencies, they explain a sizable fraction of the variance in economic activity at the two- to four-year horizon. These findings are consistent with the notion that an unexpected worsening of conditions in credit markets can cause a long-lasting economic downturn and that shocks to credit markets have played an important role in business cycle fluctuations during the previous decade and a half.

The fact that our credit market shocks generate such large effects may come as a bit of surprise. One possibility is that credit markets provide better signals regarding future prospects of firms than does the stock market. In that case, a shock to credit markets may still reflect news regarding underlying cash flows rather than a disruption in the supply of credit. But we are then left with the puzzle as to why stock prices do not incorporate all the relevant information about the firms' profit opportunities? Although various theories of stock market behavior that emphasize departures from the standard efficient markets paradigm may help justify these findings, our results nonetheless imply that understanding and tracking developments in corporate credit markets provides important information regarding the future course of economic activity.[24] In addition, both our forecasting results and FAVAR analysis suggest that corporate bond spreads of different maturities and credit risk contain distinct information about macroeconomic outcomes, a finding that highlights the strength of our approach, which focused on a broad array of default-risk indicators to extract information from corporate credit markets.

[24]See Philippon [2008] for an overview of such theories and their potential implications for the information content of stock and bond returns.

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Appendices

A Factors and Macroeconomic and Financial Variables

Table A-1 contains correlations between the six latent factors and the 36 macroeconomic and financial time series included in the vector X_{1t} in our baseline FAVAR specification; Table A-2 contain correlations between the six latent factors and credit spreads in the 20 EDF-based bond portfolios included in the vector X_{2t}. All correlation are computed over the sample period February 1990 to December 2007.

Table A-1: Correlations between Factors and Macroeconomic Series
(Baseline Specification)

Variable (data transformation)	F_1^1	F_1^2	F_1^3	F_1^4	F_2^1	F_2^2
Unemployment Rate (Δ)	0.01	-0.09	0.55	-0.15	0.05	-0.01
Payroll Employment (Δln)	-0.23	-0.08	-0.69	0.03	0.11	0.08
Capacity Utilization (Δ)	0.10	0.27	-0.75	0.07	-0.08	-0.15
Industrial Production (Δln)	-0.09	0.22	-0.75	0.12	-0.06	-0.11
ISM Mfg. Activity Index	0.09	0.11	-0.71	-0.09	0.12	0.05
Leading Indicator Index (Δln)	0.31	-0.15	-0.49	0.35	0.01	-0.13
Real Durable Goods Orders (Δln)	0.04	0.03	-0.36	0.13	-0.11	-0.06
Real Nondurable Goods Orders (Δln)	0.05	0.17	-0.32	-0.46	-0.05	-0.00
Real PCE (Δln)	0.07	0.03	-0.25	-0.45	-0.06	0.06
Real DPI (Δln)	-0.02	-0.08	-0.11	0.25	-0.00	0.01
Housing Starts (Δln)	0.12	0.02	-0.05	0.10	0.08	0.05
Consumer Price Index (Δln)	-0.18	0.22	0.03	-0.74	0.04	-0.07
Core Consumer Price Index (Δln)	-0.41	-0.04	0.20	-0.08	0.14	-0.34
Producer Price Index (Δln)	-0.02	0.24	-0.08	-0.83	-0.04	0.02
Core Producer Price Index (Δln)	-0.17	-0.04	0.09	-0.42	0.08	-0.08
Commodity Price Index (Δln)	0.13	-0.02	-0.26	-0.25	-0.09	0.01
Price of WTI Crude (Δln)	-0.00	0.15	-0.17	-0.36	-0.01	0.01
Real Federal Funds Rate	-0.83	-0.15	-0.03	-0.04	-0.11	0.29
Real 6-month Treasury Yield	-0.89	-0.20	-0.09	-0.04	-0.14	0.23
Real 1-year Treasury Yield	-0.94	-0.21	-0.07	-0.01	-0.10	0.13
Real 2-year Treasury Yield	-0.96	-0.21	-0.09	0.01	-0.04	0.06
Real 3-year Treasury Yield	-0.96	-0.20	-0.08	0.03	0.00	-0.01
Real 5-year Treasury Yield	-0.92	-0.18	-0.06	0.06	0.05	-0.13
Real 10-year Treasury Yield	-0.84	-0.13	0.00	0.05	0.10	-0.28
Excess Equity Return EDF-Q1	0.14	-0.86	-0.09	-0.04	0.01	0.00
Excess Equity Return EDF-Q2	0.23	-0.90	-0.06	-0.08	-0.08	-0.00
Excess Equity Return EDF-Q3	0.28	-0.89	-0.06	-0.10	-0.08	0.01
Excess Equity Return EDF-Q4	0.29	-0.89	-0.05	-0.06	-0.08	0.01
Excess Equity Return EDF-Q5	0.25	-0.81	-0.01	-0.10	-0.01	-0.04
Excess Market Return	0.18	-0.90	-0.06	-0.09	0.04	-0.04
Fama-French HML Factor	0.03	0.27	-0.07	0.13	-0.08	0.05
Fama-French SMB Factor	0.15	-0.19	0.07	-0.09	-0.01	-0.02
S&P 500 Implied Volatility (VIX)	-0.09	0.33	0.37	0.12	-0.39	0.09
3-month Eurodollar Implied Volatility	-0.75	-0.09	0.13	0.01	0.08	-0.33
10-year Treasury Note Implied Volatility	0.29	0.17	0.14	0.01	-0.07	-0.21
Exchange Value of the Dollar (Δln)	-0.17	0.03	0.00	0.43	0.01	0.08

Table A-2: Correlations between Factors and Credit Spreads
(Baseline Specification)

EDF Quintile/Maturity Category	F_1^1	F_1^2	F_1^3	F_1^4	F_2^1	F_2^2
EDF-Q1/Short Maturity	0.14	0.17	0.46	-0.05	-0.45	-0.65
EDF-Q2/Short Maturity	0.25	0.19	0.5	0.00	-0.59	-0.45
EDF-Q3/Short Maturity	0.19	0.20	0.51	0.05	-0.67	-0.31
EDF-Q4/Short Maturity	0.34	0.28	0.47	0.00	-0.67	-0.08
EDF-Q5/Short Maturity	0.39	0.21	0.41	0.01	-0.59	0.18
EDF-Q1/Intermediate Maturity	0.12	0.18	0.52	-0.02	-0.72	-0.33
EDF-Q2/Intermediate Maturity	0.19	0.19	0.48	-0.04	-0.69	-0.40
EDF-Q3/Intermediate Maturity	0.27	0.23	0.50	0.01	-0.72	-0.23
EDF-Q4/Intermediate Maturity	0.42	0.23	0.44	0.02	-0.71	0.04
EDF-Q5/Intermediate Maturity	0.42	0.21	0.42	0.08	-0.62	0.24
EDF-Q1/Long Maturity	-0.12	0.12	0.36	-0.02	-0.84	0.06
EDF-Q2/Long Maturity	-0.09	0.12	0.32	-0.09	-0.83	0.05
EDF-Q3/Long Maturity	0.04	0.15	0.36	-0.01	-0.84	0.17
EDF-Q4/Long Maturity	0.18	0.17	0.35	-0.01	-0.82	0.25
EDF-Q5/Long Maturity	0.21	0.19	0.42	0.05	-0.68	0.33
EDF-Q1/Very Long Maturity	-0.39	0.04	0.27	-0.03	-0.78	0.10
EDF-Q2/Very Long Maturity	-0.32	0.08	0.36	-0.06	-0.78	0.12
EDF-Q3/Very Long Maturity	-0.27	0.09	0.43	-0.02	-0.79	0.12
EDF-Q4/Very Long Maturity	0.31	0.20	0.33	-0.08	-0.72	0.30
EDF-Q5/Very Long Maturity	0.20	0.14	0.41	-0.06	-0.66	0.32

B Impulse Response Functions

Figures B-1–B-4 depict the impact of an orthogonalized one standard deviation shock to credit factor 1 on the 36 macroeconomic and financial time series included in the vector X_{1t} in our baseline FAVAR specification; Figures B-5–B-6 depict the impact of an orthogonalized one standard deviation shock to credit factor 1 on credit spreads in the 20 EDF-based bond portfolios included in the vector X_{2t}. The shaded bands represent the 95-percent confidence intervals computed using a nonparametric sieve bootstrap with 10,000 replications.

Figure B-1: Economic Activity Indicators
(Baseline Specification)

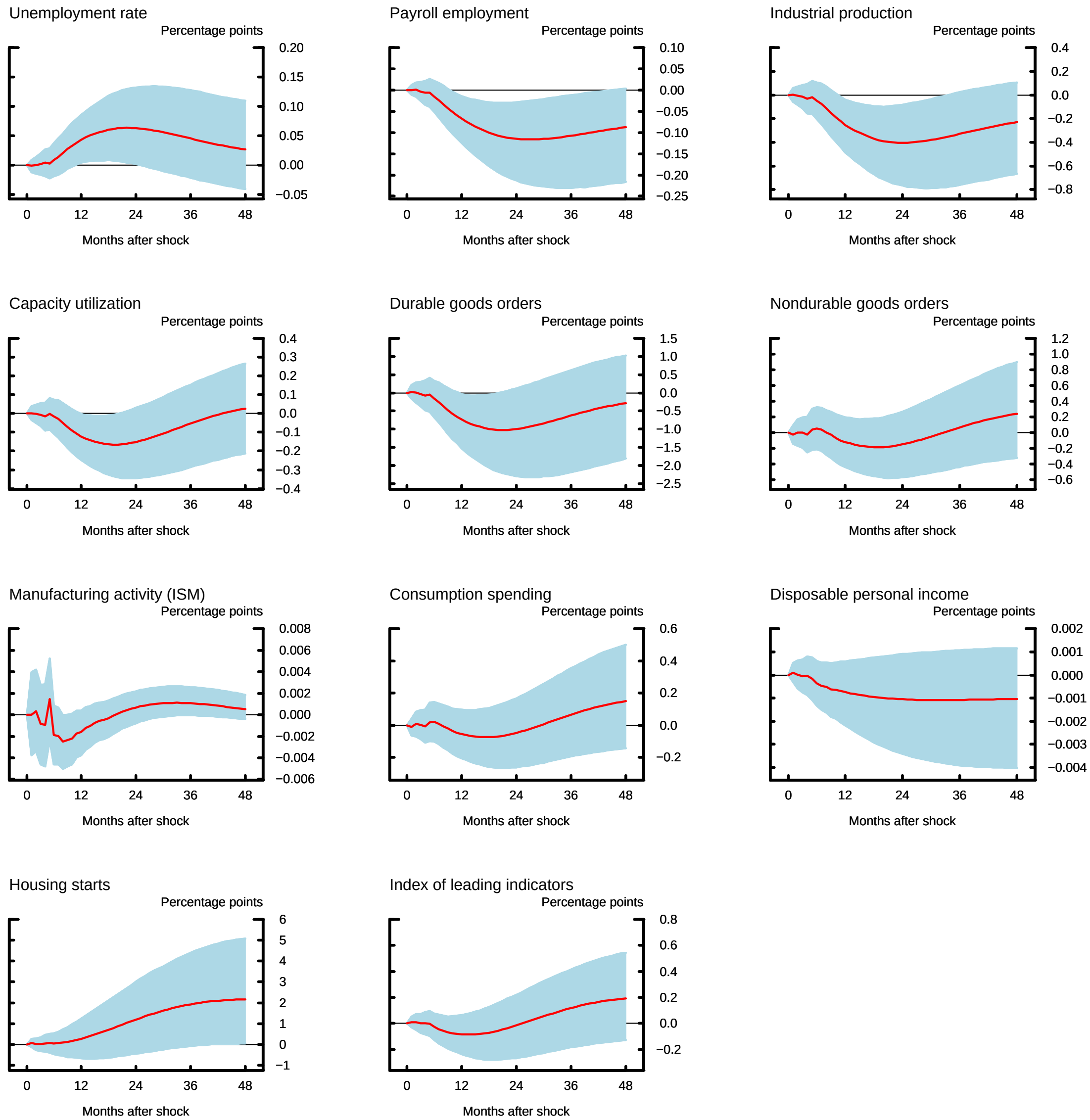

Figure B-2: Inflation Indicators
(Baseline Specification)

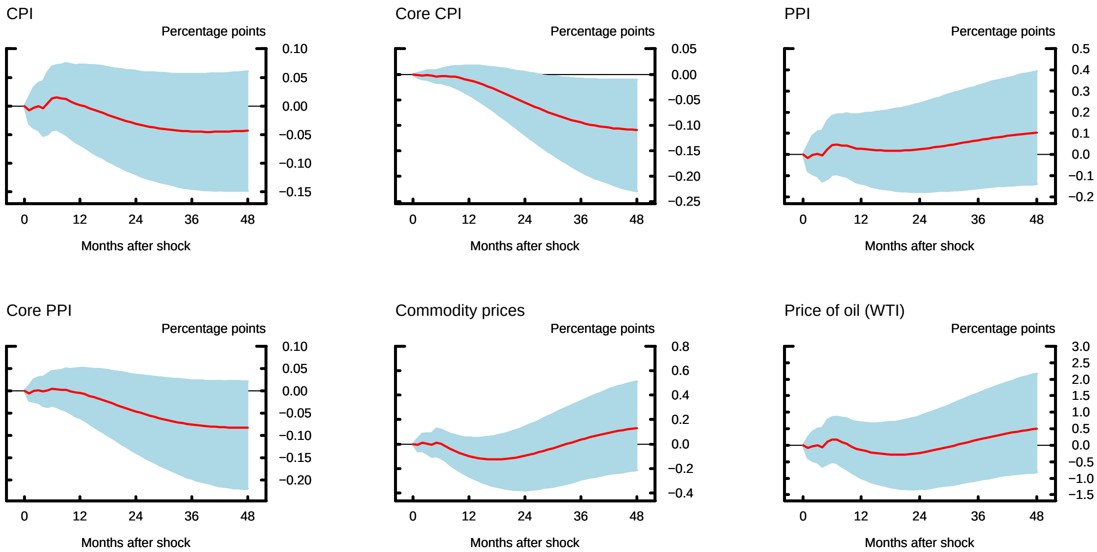

Figure B-3: Interest Rates and Interest Rate Uncertainty
(Baseline Specification)

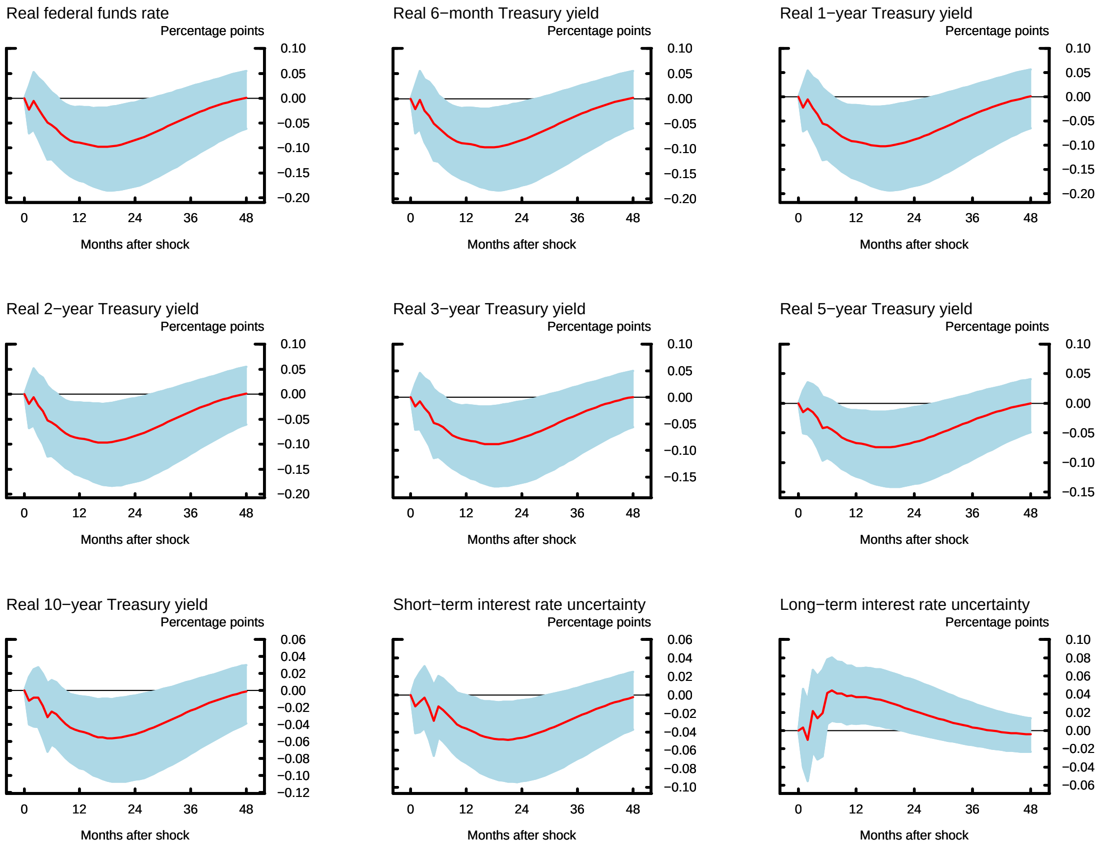

Figure B-4: Equity Market Indicators and Exchange Rates
(Baseline Specification)

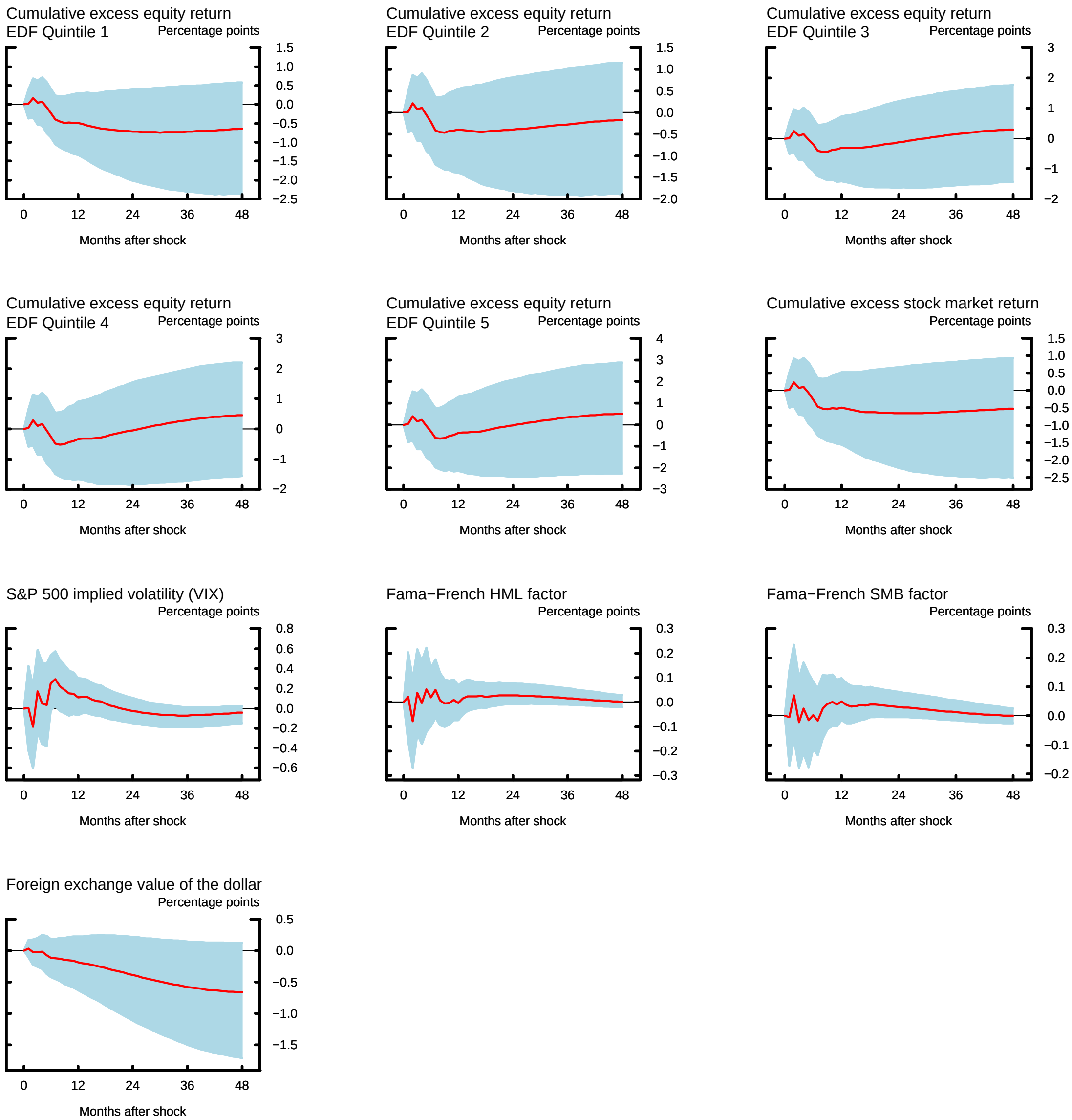

Figure B-5: Short and Intermediate Maturity Credit Spreads
(Baseline Specification)

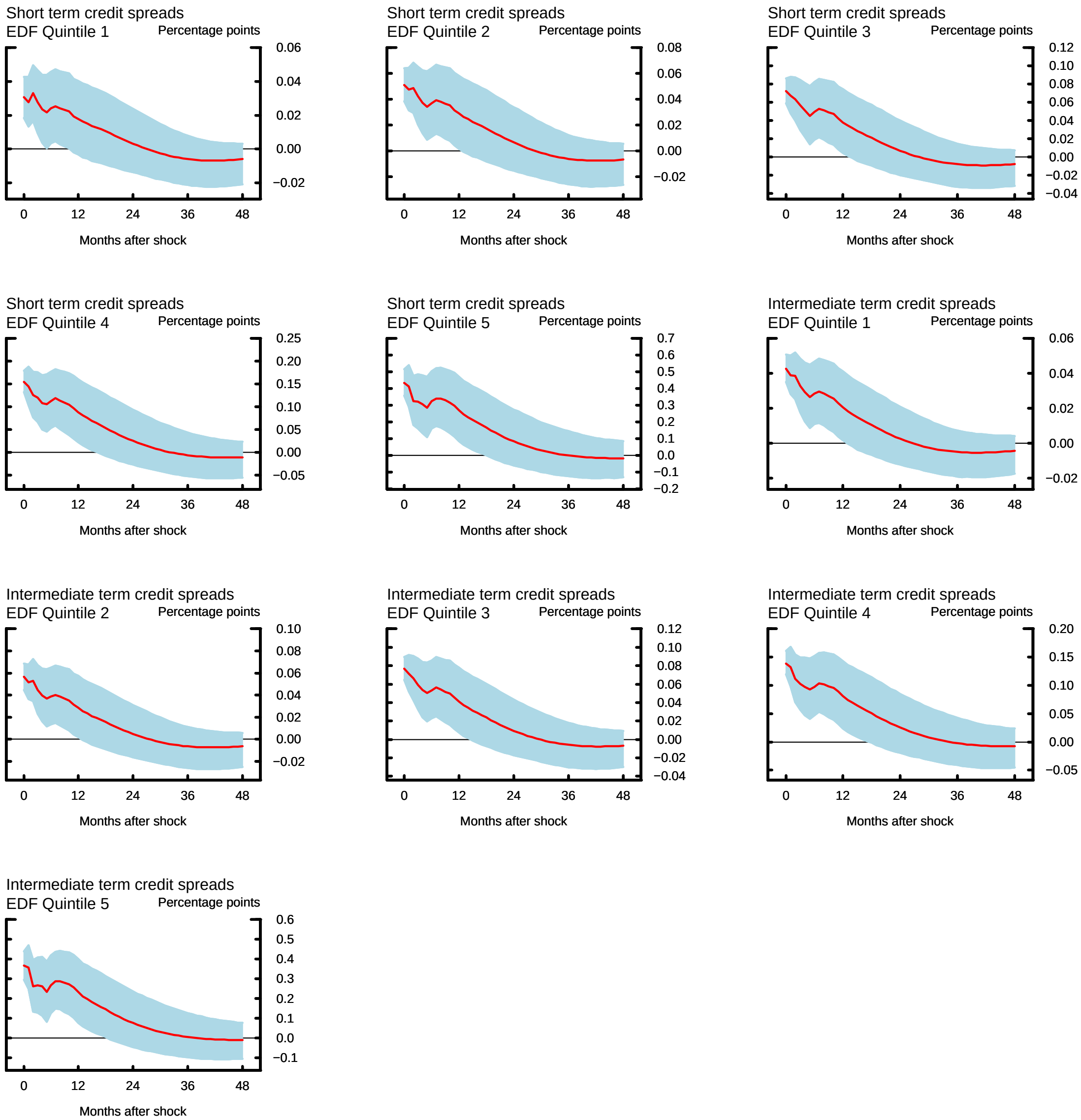

Figure B-6: Long and Very Long Maturity Credit Spreads
(Baseline Specification)