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Simon Gilchrist
Vladimir Yankov
Egon Zakrajsek

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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 30 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 1990–2008 period.

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

Vladimir Yankov
Department of Economics
Boston University
270 Bay State Road
Boston, MA 02215
yankov@bu.edu

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

1 Introduction

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 the 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.

This paper considers credit spreads constructed directly from monthly data on prices of senior unsecured corporate debt traded in the secondary market over the 1990–2008 period, issued by about 900 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 not affected 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 relevant market has undergone a significant structural change.

We exploit the cross-sectional heterogeneity of our data by constructing an array of credit-spread portfolios sorted 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 based on observable information in equity markets, EDFs provide a more timely and potentially more objective assessment of credit risk compared with the issuer's credit rating. Importantly, by building bond portfolios from the "ground up," we can also construct portfolios of stock returns—sorted by the same credit-risk categories—corresponding to the firms that issued those bonds. These matched portfolios of stock returns, in turn, serve as controls for news about firms' future earnings as these corporate borrowers experience shocks to their creditworthiness.

Two empirical methods are employed to assess the role of credit market factors in economic fluctuations. First, the analysis documents the predictive content of corporate bond spreads in our credit-risk portfolios for measures of economic activity such as 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. The results show that at shorter forecast horizons, the information content of credit spreads in our EDF-based bond portfolios for these monthly measures of economic activity is comparable to that of standard credit spread indexes. At longer forecast horizons, however, our portfolios of credit spreads outperform—both in-sample and out-of-sample—standard default-risk indicators by almost a factor of two. The results from these forecasting exercises indicate that the predictive power of corporate bond spreads comes from the middle of the credit-quality spectrum, a result also documented by Mueller [2007] who examines the predictive content of corporate bond spread indexes across different rating categories. Our results also indicate that at longer forecasting horizons, the predictive power of corporate bond spreads is concentrated at long maturities. At these forecasting horizons, the predictive content of publicly-available long maturity investment-grade corporate bond spread indexes—such as those rated between BBB and AA—is comparable to that of our low-risk long maturity EDF portfolios. All told, these results imply that the forecasting ability of credit spreads is well captured by a single index that measures credit spreads of long maturity bonds issued by firms with low to medium probability of default.

The second empirical approach 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. Within the FAVAR framework, we identify credit market shocks from the 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 results 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—predicts 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 30 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 1990–2008 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 [2007] 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 899 publicly-traded firms covered by the Center for Research in Security Prices (CRSP), month-end secondary market prices of their outstanding long-term corporate bonds were drawn 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, the analysis is restricted to senior unsecured issues only. For such securities with market prices in both the LW and LM databases, option-adjusted effective yields at month-end—a component of the bond's yield that is not attributable to embedded options—are spliced across the two data sources. To calculate the credit spread at each point in time, the resulting yield on *each* individual security issued by the firm is matched 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, the analysis eliminates all observations with credit spreads smaller than 10 basis points and with spreads greater than 5,000 basis points; in addition, eliminated were 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 5,045 individual securities, covering the period from January 1990 to September 2008.

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 the average firm has almost six 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	5.66	8.42	1.00	2.00	75.0
Mkt. Value of Issue[a] ($mil.)	312.0	318.8	1.11	234.5	6,657
Maturity at Issue (years)	13.7	9.3	1.0	10.0	50.0
Term to Maturity (years)	10.8	8.67	0.01	7.54	30.0
Duration (years)	5.95	3.27	0.00	5.40	26.4
S&P Credit Rating	-	-	D	BBB1	AAA
Coupon Rate (pct.)	7.60	2.00	0.00	7.38	15.9
Nominal Effective Yield (pct.)	7.46	3.16	1.20	7.08	57.4
Credit Spread[b] (bps.)	192	299	10	114	4,995

Panel Dimensions

Obs. $= 275,880$ $N = 5,045$ bonds

Min. Tenure = 1 Median Tenure = 48 Max. Tenure = 224

NOTE: Sample period: Monthly data from January 1990 to September 2008 for a sample of 899 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 5.95 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.

The coupon rate on our sample of bonds averaged 7.60 percent during the sample period, and the average total return, as measured by the nominal effective yield, was 7.46 percent per annum. Reflecting the wide range of credit quality, the distribution of yields is quite wide, with the minimum of about 1.2 percent and the maximum of more than 57 percent. Relative to Treasuries, an average bond in our sample generated a return of about 192 basis points above the comparable-maturity risk-free rate, with a standard deviation of 299 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—the “Expected Default Frequency” (EDF). This measure of default risk is constructed and marketed by the Moody's/KMV Corporation (MKMV). It measures 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; asset volatility; the risk-free interest rate and the firm's leverage.[5] These factors are combined into a single measure of default risk called *distance to default*, defined as

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

Because the market value of assets and the volatility of assets are not directly observable, 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.

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] These default-risk portfolios are constructed by sorting credit spreads and excess equity returns in

[5]In the original work of Merton [1974], the default point is equal to the book value of liabilities. Later structural default models relax this assumptions and allow for endogenous capital structure as well as strategic default. In these models, both the default time and default boundary are determined endogenously and depend on firm-specific as well as aggregate factors; the voluminous literature on structural default models is summarized by Duffie and Singleton [2003]. Recent theoretical work has examined the importance of aggregate risk and different specifications of investors' preferences for generating default-risk premiums and matching historical credit spreads; see, for example, Chen, Collin-Dufresne, and Goldstein [2008] and Chen [2008]. 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 × 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.

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

month t into five quintiles based on the distribution of EDFs in month $t-1$. To control for maturity, 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 then 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 20 bond portfolios of credit spreads (five EDF quintiles and four maturity categories) and five EDF-based stock portfolios of excess equity returns.

Table 2 contains summary statistics of our variables by the five EDF quintiles. 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. Consistent with the increase in the probability of default, both the average and the median credit spread increase monotonically across the five EDF quintiles in all four maturity categories. 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 riskiest 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. Excess return increase monotonically across the first four EDF quintiles, but the 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 1990–2008 period of only 0.24 percent.[8]

3 Credit Spreads and Economic Activity

This section examines the predictive power of credit spreads in our EDF-based bond portfolios and compare their forecasting performance—both in-sample and out-of-sample—with several commonly used credit spread indexes. Letting Y_t denote a measure of economic

[8] This paltry performance is especially stark when one considers the Sharpe ratio for this category of firms, which is considerably below that of the less risky portfolios. The finding is consistent with the distress risk anomaly documented by a large empirical literature that has used different measures of default risk; see, for example, Griffin and Lemmon [2002] and Campbell, Hilscher, and Szilagyi [2008].

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	0.46
EDF	3	0.24	0.19	-	0.05	0.19	0.90
EDF	4	0.55	0.42	-	0.08	0.38	2.07
EDF	5	4.70	3.02	-	0.61	3.76	15.5
Spread (under 3 yrs.)	1	0.79	0.38	2.09	0.32	0.69	2.69
Spread (under 3 yrs.)	2	1.03	0.49	2.10	0.41	0.89	3.44
Spread (under 3 yrs.)	3	1.21	0.55	2.22	0.50	1.09	3.30
Spread (under 3 yrs.)	4	1.84	1.00	1.84	0.67	1.54	5.13
Spread (under 3 yrs.)	5	5.28	3.74	1.41	1.16	3.79	22.3
Spread (3–7 yrs.)	1	0.92	0.33	2.75	0.52	0.85	2.56
Spread (3–7 yrs.)	2	1.26	0.49	2.58	0.52	1.17	3.32
Spread (3–7 yrs.)	3	1.52	0.55	2.75	0.71	1.38	3.57
Spread (3–7 yrs.)	4	2.20	0.93	2.37	1.15	1.91	5.05
Spread (3–7 yrs.)	5	5.69	2.87	1.98	1.99	4.83	16.4
Spread (7–15 yrs.)	1	0.86	0.38	2.29	0.38	0.74	2.49
Spread (7–15 yrs.)	2	1.15	0.51	2.27	0.49	1.04	3.04
Spread (7–15 yrs.)	3	1.38	0.58	2.37	0.67	1.21	3.09
Spread (7–15 yrs.)	4	2.00	0.85	2.35	0.81	1.73	5.27
Spread (7–15 yrs.)	5	5.20	3.24	1.61	1.59	4.19	18.8
Spread (above 15 yrs.)	1	1.02	0.41	2.47	0.45	0.92	2.38
Spread (above 15 yrs.)	2	1.28	0.47	2.72	0.58	1.22	3.07
Spread (above 15 yrs.)	3	1.45	0.56	2.60	0.55	1.32	2.91
Spread (above 15 yrs.)	4	2.11	0.84	2.51	0.93	1.91	4.96
Spread (above 15 yrs.)	5	3.79	2.03	1.87	1.10	3.41	12.0
Excess Equity Return	1	0.60	3.20	0.19	-11.5	0.77	11.5
Excess Equity Return	2	0.75	3.90	0.19	-14.5	1.03	12.5
Excess Equity Return	3	0.80	4.28	0.19	-16.3	0.92	13.1
Excess Equity Return	4	0.90	5.19	0.17	-19.5	1.16	15.6
Excess Equity Return	5	0.24	7.42	0.03	-28.1	0.78	30.7

NOTE: Sample period: Monthly data from February 1990 to September 2008. 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.

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. Nonfarm payroll employment (EMP) published monthly by the Bureau of Labor Statistics and the Federal Reserve's monthly index of industrial production (IP) are used to gauge the state of the economy. In addition, the analysis presents forecasting results for a broader index of economic activity that summarizes the eleven indicators of economic growth employed in our FAVAR analysis.

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

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

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

In the VAR forecasting system given by equations 1–2, Z_{1t} denotes a vector of standard 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.[9] The following three specifications are considered: (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 and 12 months, we estimate equations 1 and 2 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 $h + 1$.

The 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; (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 Trea-

[9] An alternative approach to the direct h-step ahead prediction method specified in equations 1–2 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.

sury 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.[10] 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.[11]

3.1 In-Sample Predictive Power of Credit Spreads

This section examines the in-sample predictive power of various credit spreads for our two measures of economic activity. The upper panel of Table 3 contains the results of this exercise for the short-run forecast horizon (3 months), whereas the lower panel contains results for the long-run forecast horizon (12 months). In both cases, 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 panels 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 3-month forecast horizon. As evidenced by the p-values reported in the upper panel of Table 3, both the standard credit spread indexes and credit spreads in each EDF quintile are statistically significant predictors of employment growth three 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, the specification that excludes all credit spreads yields an adjusted R^2 of 69 percent, only about 9 percentage points below the adjusted R^2 from a specification that includes standard credit spread indexes and credit spreads in the second EDF quintile.

The inclusion of credit spreads in the equation for industrial production, in contrast, leads to a substantial increase in predictive accuracy at the 3-month forecast horizon. Ac-

[10] 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.

[11] 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.

Table 3: In-Sample Predictive Content of Credit Spreads

	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	-	0.761	0.000	-	0.291
EDF-Q1	-	0.002	0.734	-	0.000	0.370
EDF-Q2	-	0.000	0.746	-	0.000	0.361
EDF-Q3	-	0.000	0.750	-	0.000	0.337
EDF-Q4	-	0.000	0.725	-	0.000	0.304
EDF-Q5	-	0.042	0.725	-	0.000	0.343
Standard & EDF-Q1	0.002	0.006	0.775	0.033	0.001	0.392
Standard & EDF-Q2	0.002	0.004	0.782	0.717	0.005	0.357
Standard & EDF-Q3	0.006	0.007	0.780	0.017	0.000	0.371
Standard & EDF-Q4	0.002	0.074	0.771	0.091	0.029	0.322
Standard & EDF-Q5	0.000	0.016	0.781	0.004	0.000	0.377
Memo: None	-	-	0.695	-	-	0.169
	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	0.003	-	0.665	0.109	-	0.200
EDF-Q1	-	0.000	0.727	-	0.000	0.563
EDF-Q2	-	0.000	0.759	-	0.000	0.641
EDF-Q3	-	0.000	0.739	-	0.000	0.528
EDF-Q4	-	0.000	0.704	-	0.000	0.439
EDF-Q5	-	0.000	0.685	-	0.000	0.420
Standard & EDF-Q1	0.000	0.000	0.809	0.297	0.000	0.585
Standard & EDF-Q2	0.016	0.000	0.817	0.128	0.000	0.677
Standard & EDF-Q3	0.000	0.000	0.816	0.000	0.000	0.645
Standard & EDF-Q4	0.000	0.000	0.795	0.021	0.000	0.552
Standard & EDF-Q5	0.000	0.000	0.791	0.015	0.000	0.499
Memo: None	-	-	0.537	-	-	0.042

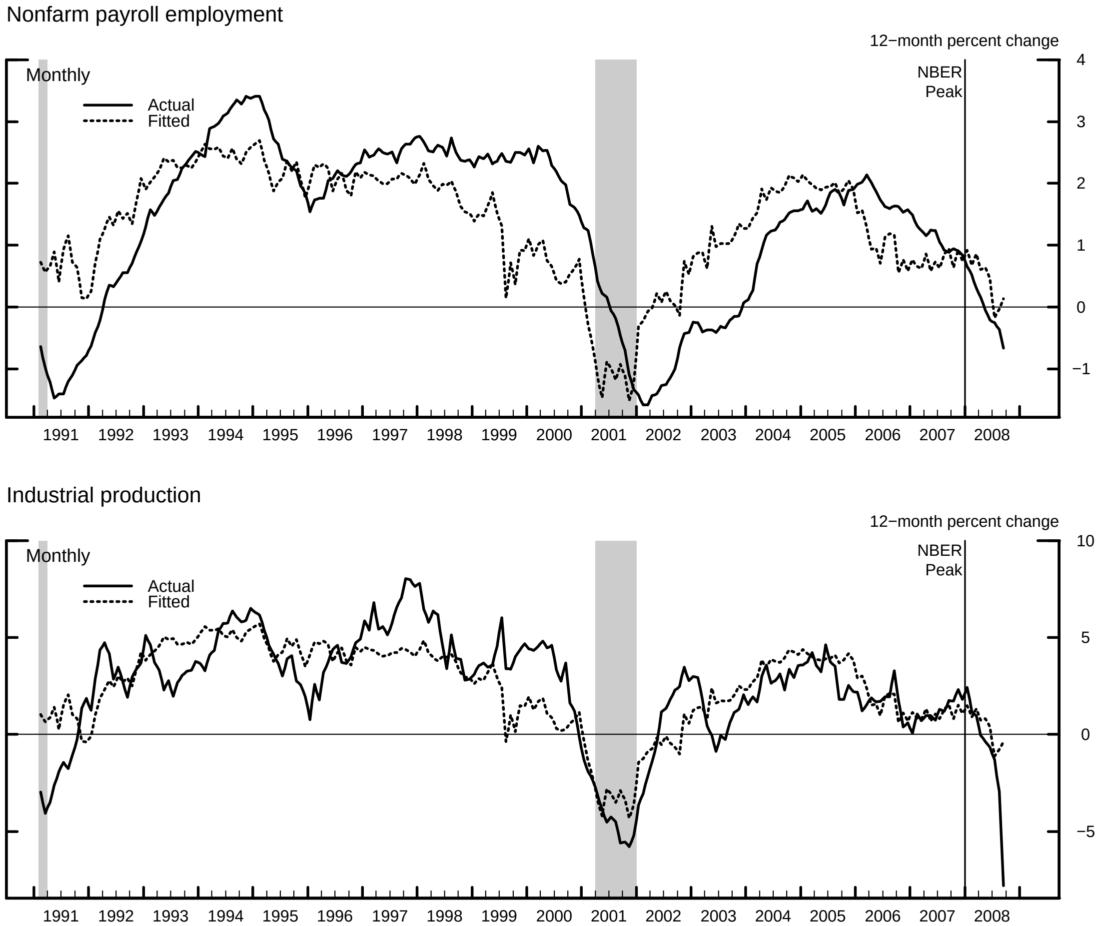
NOTE: Sample period: Monthly data from February 1990 to September 2008. Dependent variables in the VAR specification are $\nabla^h \text{EMP}_{t+h}$ and $\nabla^h \text{IP}_{t+h}$, where h is the forecast horizon. Each VAR specification also includes a constant, current, and 11 lags of ∇EMP_t and ∇IP_t (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.

cording to the *Memo* item, lags of industrial production and employment growth explain only about 17 percent of the variation in the growth of industrial output three months ahead. By including standard credit spread indexes in the forecasting VAR, the adjusted R^2 increases to almost 30 percent. Specifications that include credit spreads in our EDF-based portfolios yield even greater improvements in the in-sample fit. 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).

The lower panel of Table 3 examines the in-sample explanatory power of credit spreads at the 12-month horizon. At this longer horizon, 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 66 percent of the variation in the 12-month ahead growth rate, 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. The information content of our default-risk indicators for the growth of employment is highest for 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. 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 20 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 over 50 percent of the variation in the 12-month ahead growth rate of industrial output.

The results in Table 3 highlight the gains in in-sample predictive accuracy for employment and industrial output growth at longer forecast horizon obtained from conditioning on credit spreads in our EDF-based bond portfolios. The results of these forecasting exercises indicate that the information content of credit spreads is concentrated in the low to medium risk categories. As we show below, the predictive content of credit spreads is also concentrated at the long end of the maturity spectrum. This result is shown graphically in Figure 1, where the two panels depict the actual 12-month ahead growth of employment and industrial production along with their respective fitted values obtained from simple regressions of these two variables on the credit spreads in the very long maturity EDF-Q2 portfolio—that is, the portfolio with the highest overall predictive content, according to the results in Table 3. Note that these fitted values are a simple renormalization of the credit spread dated 12 months before the time period over which the growth in employment and industrial production was computed. Remarkably, this single credit spread forecasted employment growth throughout the 2001 recession and the subsequent recovery.

Figure 1: Long Maturity Credit Spreads and Economic Activity Indicators



NOTE: The solid lines in the two panels of the figure depict the actual 12-month growth in nonfarm payroll employment and industrial production. The dotted lines show the fitted values from a regression of each variable on a 12-month lag of very long credit spreads in the second EDF quintile (EDF-Q2). Shaded vertical bars correspond to NBER-dated recessions.

It also accurately predicted the current slowdown in employment growth, which peaked in January 2006. As shown in the bottom panel of Figure 1, the ability of this long-horizon relatively low-risk credit spread to predict accurately future economic activity as measured by the 12-month ahead growth in industrial production is even more striking.

3.2 Out-of-Sample Predictive Power of Credit Spreads

This section examines 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, the forecasting VAR given in equations 1–2 is estimated 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 4 contains the results of this exercise. To quantify the pseudo out-of-sample forecasting performance of the different VAR specifications, we report the square root of the mean squared forecast error in annualized percentage points (RMSFE) for each specification. To compare the predictive accuracy of credit spreads in our EDF-based bond portfolios with that of standard default-risk indicators, we then compute 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; p-values of the Diebold and Mariano [1995] test of equal predictive accuracy indicate whether the difference in predictive accuracy between these two non-nested models are statistically significant.[12]

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 than the specification augmented with standard credit spread indexes. At the 3-month forecast horizon, 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 by 20 to 25 percent, and these improvements in predictive accuracy are statistically significant at the 10 to 15 percent level. 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 the 3-month forecast horizon, although the differences in predictive accuracy are not statistically significant at conventional levels.

The gain in out-of-sample predictive accuracy at the 12-month forecast horizon is especially striking, a result consistent with the in-sample analysis of the previous section. 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), which yield reductions in the MSFEs on the order of 60 percent relative to the specification that includes the standard set of credit spread indexes. Moreover, these improvements in predictive accuract are also highly statistically significant according to the Diebold-Mariano test.

The results reported in Table 4 point to significant improvements in the out-of-sample

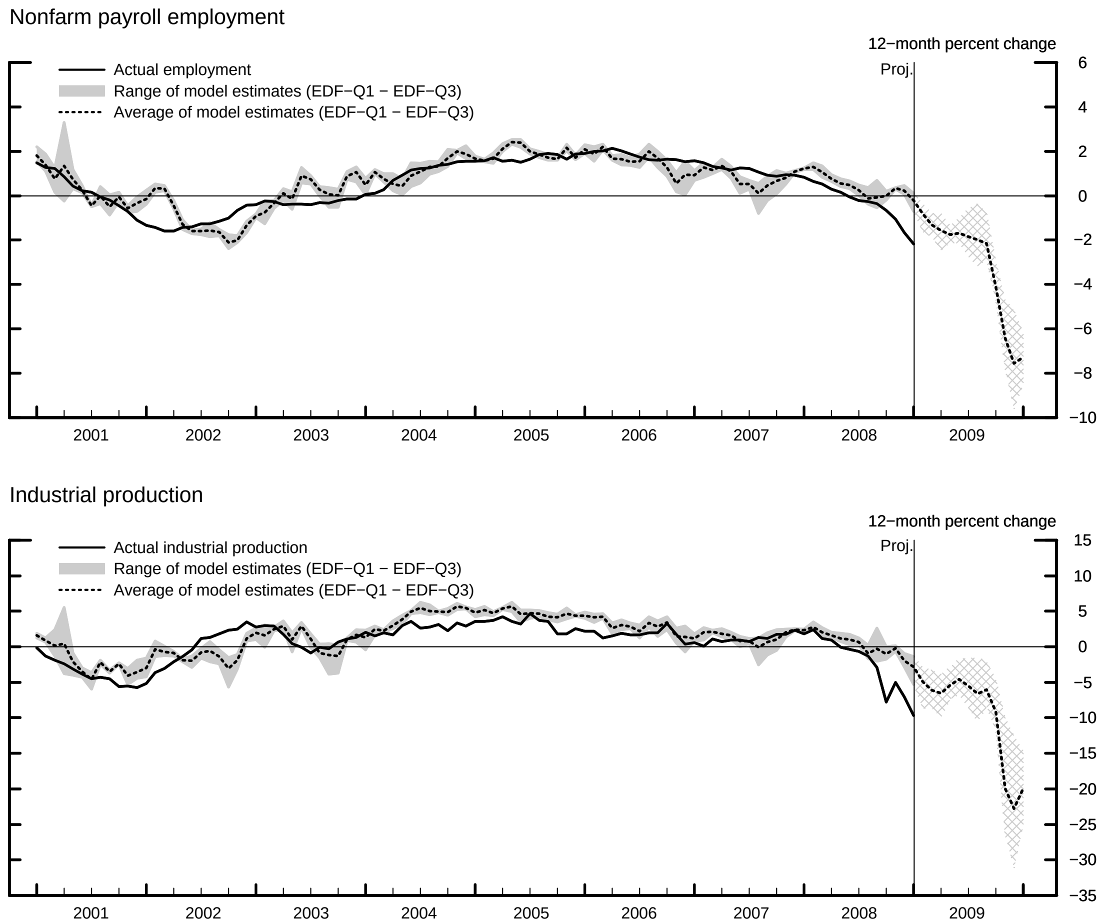
[12]Because the data in our forecasting VAR specification are overlapping, the asymptotic (long-run) variance of the loss differential used to construct the Diebold-Mariano S-statistic allows for serial correlation of order h.

Table 4: Out-of-Sample Predictive Content of Credit Spreads

	Forecast Horizon $h = 3$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	$\Pr > \|S\|$	RMSFE	Ratio	$\Pr > \|S\|$
Standard	0.947	-	-	5.211	-	-
EDF-Q1	0.824	0.757	0.106	4.592	0.777	0.153
EDF-Q2	0.842	0.791	0.160	4.667	0.802	0.093
EDF-Q3	0.826	0.761	0.069	4.644	0.794	0.180
EDF-Q4	0.946	0.999	0.996	4.647	0.795	0.219
EDF-Q5	0.956	1.019	0.902	4.779	0.841	0.360
Standard & EDF-Q1	0.932	0.968	-	4.904	0.886	-
Standard & EDF-Q2	0.924	0.953	-	5.040	0.936	-
Standard & EDF-Q3	0.926	0.957	-	4.994	0.918	-
Standard & EDF-Q4	0.951	1.010	-	5.397	1.073	-
Standard & EDF-Q5	0.922	0.948	-	5.226	1.006	-
Memo: None	0.925	-	-	5.513	-	-
	Forecast Horizon $h = 12$ (months)					
	Nonfarm Employment (EMP)			Industrial Production (IP)		
Credit Spreads	RMSFE	Ratio	$\Pr > \|S\|$	RMSFE	Ratio	$\Pr > \|S\|$
Standard	1.113	-	-	3.676	-	-
EDF-Q1	0.693	0.387	0.002	2.089	0.323	0.000
EDF-Q2	0.667	0.359	0.001	2.004	0.297	0.000
EDF-Q3	0.740	0.442	0.000	2.279	0.384	0.000
EDF-Q4	0.902	0.657	0.094	2.704	0.541	0.004
EDF-Q5	0.872	0.613	0.092	2.574	0.490	0.001
Standard & EDF-Q1	0.827	0.552	-	2.571	0.489	-
Standard & EDF-Q2	0.816	0.537	-	2.238	0.371	-
Standard & EDF-Q3	0.814	0.535	-	2.376	0.418	-
Standard & EDF-Q4	0.869	0.609	-	2.686	0.534	-
Standard & EDF-Q5	0.864	0.602	-	2.948	0.643	-
Memo: None	1.115	-	-	3.882	-	-

NOTE: Sample period: Monthly data from February 1990 to September 2008. 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 ∇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.

Figure 2: Out-of-Sample Forecasts of Economic Activity Indicators



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 average of the three forecasts (see text for details).

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 2 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 based on the VAR specifications that include credit spreads in portfolios corresponding to the first three EDF quintiles (EDF-Q1–EDF-Q3); the dotted line in each panel depicts the average of these forecast.

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-over-year growth in the actual series in both recessionary and expansionary times. In addition, the predictive accuracy obtained from using credit spreads in our EDF-based portfolios does not seem to reflect any "one-time" event or a specific subperiod. Importantly, our EDF-based forecasts capture the slowdown in economic activity associated with the 2001 recession as well as the subsequent recovery. These EDF-based forecasts also predict the slowdown in economic activity that has emerged since late 2006 with a 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 also depicts the forecasts for these two measures of economic activity through December 2009.[13] The average of the three EDF-based forecasts indicates that over the 12 months ending in December 2009, U.S. nonfarm payrolls will fall about 7.5 percent, while industrial production is projected to drop around 20 percent, declines that are four times greater than those experienced during the 2001 recession.

3.3 Predicting an Index of Economic Activity

The previous results focused on forecasting the growth employment and industrial output. In the FAVAR analysis below, real economic activity is summarized by a factor that relies, in addition to the growth in employment and industrial production, on nine additional macroeconomic indicators that measure economic activity. Some of these series are leading indicators, or forward-looking variables such as new manufacturing orders, whereas other series such as unemployment are relatively sluggish. To assess the ability of credit spreads to forecast this broader set of economic indicators, we construct an index of economic activity, defined as the first principal component of these 11 time-series.

Table 5 reports both the in-sample and out-of-sample results obtained from univariate forecasting specifications that include credit spread indexes along with the 12 monthly lags of the economic activity index. These results are very similar to those obtained using growth in payroll employment and industrial production: Specifications that include credit spreads in the lowest three EDF quintiles provide modest improvements in out-of-sample forecasting performance at the 3-month horizon, and quantitatively large and statistically significant gains—both in-sample and out-of-sample—at the 12-month horizon.

As a final exercise, we explore the extent to which the predictive content of credit spreads depends on the maturity structure of the underlying securities. Because our credit spreads rely on proprietary measures of default risk and issue-specific bond yields, we are also interested in determining whether ratings-based credit spreads yield similar forecasting

[13] The year-over-year forecasts for December 2009 are based on the realized values of the two forecasting variables through December 2008, but we only use data through September 2008 to compute these forecasts.

Table 5: Predictive Content of Credit Spreads for Economic Activity Index

	Forecast Horizon $h = 3$ (months)					
	In-Sample			Out-of-Sample		
Credit Spreads	Pr $> W_1$	Pr $> W_2$	Adj. R^2	RMSFE	Ratio	Pr $> \|S\|$
Standard	0.000	-	0.525	0.841	-	-
EDF-Q1	-	0.000	0.520	0.716	0.726	0.135
EDF-Q2	-	0.000	0.527	0.722	0.739	0.096
EDF-Q3	-	0.000	0.511	0.730	0.754	0.107
EDF-Q4	-	0.000	0.457	0.874	1.081	0.626
EDF-Q5	-	0.000	0.495	0.780	0.860	0.410
Standard & EDF-Q1	0.000	0.002	0.605	0.763	0.824	-
Standard & EDF-Q2	0.060	0.000	0.577	0.820	0.951	-
Standard & EDF-Q3	0.000	0.004	0.575	0.820	0.951	-
Standard & EDF-Q4	0.000	0.009	0.549	0.864	1.056	-
Standard & EDF-Q5	0.000	0.000	0.585	0.762	0.821	-
Memo: None	-	-	0.393	0.852	-	-

	Forecast Horizon $h = 12$ (months)					
	In-Sample			Out-of-Sample		
Credit Spreads	Pr $> W_1$	Pr $> W_2$	Adj. R^2	RMSFE	Ratio	Pr $> \|S\|$
Standard	0.004	-	0.407	1.132	-	-
EDF-Q1	-	0.000	0.607	0.568	0.252	0.000
EDF-Q2	-	0.000	0.618	0.574	0.257	0.000
EDF-Q3	-	0.000	0.591	0.650	0.330	0.000
EDF-Q4	-	0.000	0.455	0.985	0.757	0.300
EDF-Q5	-	0.000	0.381	0.945	0.697	0.270
Standard & EDF-Q1	0.000	0.000	0.726	0.724	0.409	-
Standard & EDF-Q2	0.000	0.000	0.742	0.690	0.372	-
Standard & EDF-Q3	0.000	0.000	0.732	0.706	0.384	-
Standard & EDF-Q4	0.000	0.000	0.677	0.809	0.511	-
Standard & EDF-Q5	0.000	0.000	0.617	0.884	0.610	-
Memo: None	-	-	0.178	1.065	-	-

NOTE: Sample period: Monthly data from February 1990 to September 2008. Dependent variable is the h-month moving average of the index of real economic activity, where h is the forecast horizon. Each regression specification includes a constant, current, and 11 lags of the economic activity index (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. "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 6: Credit Spreads and Index of Real Economic Activity
(12-Month Forecast Horizon)

Credit Spreads (by maturity & risk)	Estimate	t-stat	Adj. R^2	Pr > SW^a
Short Maturity (less than 3 years)				
EDF-Q1	-0.236	-0.841	0.088	0.000
EDF-Q2	-0.456	-1.533	0.163	0.001
EDF-Q3	-0.573	-1.866	0.200	0.004
EDF-Q4	-0.604	-1.976	0.235	0.000
EDF-Q5	-0.563	-2.369	0.220	0.000
AA-rated	-0.296	-1.729	0.109	0.000
BBB-rated	-0.143	-0.681	0.055	0.000
Intermediate Maturity (3–7 years)				
EDF-Q1	-0.910	-3.542	0.410	0.001
EDF-Q2	-0.604	-2.243	0.261	0.031
EDF-Q3	-0.734	-2.634	0.313	0.059
EDF-Q4	-0.561	-1.756	0.230	0.021
EDF-Q5	-0.674	-2.093	0.261	0.000
AA-rated	-1.489	-7.313	0.676	0.136
BBB-rated	-0.765	-2.439	0.287	0.001
Long Maturity (7–15 years)				
EDF-Q1	-1.260	-6.370	0.613	0.062
EDF-Q2	-1.155	-5.553	0.575	0.003
EDF-Q3	-1.183	-5.345	0.569	0.042
EDF-Q4	-0.851	-3.468	0.424	0.191
EDF-Q5	-0.765	-3.078	0.342	0.000
AA-rated	-1.473	-6.404	0.690	0.001
BBB-rated	-1.150	-4.975	0.520	0.054
Very Long Maturity (greater than 15 years)				
EDF-Q1	-1.354	-7.326	0.655	0.143
EDF-Q2	-1.378	-6.881	0.654	0.159
EDF-Q3	-1.349	-6.584	0.634	0.087
EDF-Q4	-0.669	-2.521	0.318	0.075
EDF-Q5	-0.726	-2.987	0.353	0.001
AA-rated	-1.331	-6.183	0.649	0.099
BBB-rated	-1.270	-5.795	0.606	0.096

NOTE: Sample period: Monthly data from April 1991 to September 2008 ($T = 198$). The dependent variable is the 12-month moving average of the index of economic activity (see text for details). Each regression specification includes a credit spread, a 12-month lag of the dependent variable, and a constant term (the latter two effects are not reported) and is estimated by OLS. 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].

[a] p-value for the Shapiro-Wilk test of the null hypothesis that the OLS residuals are normally distributed.

performance once one controls for maturity. These two issues are addressed by considering a simple in-sample forecasting exercise, in which the 12-month change in the index of economic activity is regressed on a 12-month lag of itself and a single credit spread index. We consider separately the credit spreads in our 20 bond portfolios as well as AA-rated and BBB-rated credit spreads for the same four maturity categories based on the Bloomberg Fair Value (BFV) model.[14]

The results of this exercise, which are reported in Table 6, again indicate that long maturity low to medium risk credit spreads provide substantial gains in predictive content relative to short maturity credit spreads. The adjusted R^2's from the regressions of the 12-month change in the economic activity index on the very long maturity credit spreads in the first three EDF quintiles (EDF-Q1–EDF-Q3) are about 65 percent, whereas those that rely on short maturity credit spreads are below 25 percent. At shorter maturities, the information content of credit spreads in our EDF-based portfolios exceeds that of the AA- and BBB-rated counterparts. At longer maturities, the information content of our EDF-based credit spreads is essentially the same as that of spreads in the two rating categories. These findings suggest that EDF-based measures of default risk provide timely information that is especially useful for forecasting at shorter horizons.

4 Factor-Augmented VAR Analysis

This section examines the interaction between the credit spreads in our EDF-based bond portfolios and a wide range of 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. We use the factor-augmented vector autoregression (FAVAR) methodology proposed by Bernanke and Boivin [2003] and Bernanke, Boivin, and Eliasz [2005] to summarize a large number of macroeconomic and financial time series by a small number of unobservable (latent) factors. This methodology is then used to identify shocks to corporate bond spreads and trace out their dynamic effect on the macroeconomy.

[14]The BFV model provides daily estimates of the corporate bond yield curve utilizing prices of bonds with similar characteristics (i.e., currency, market type, industry, and credit rating). For comparability with our bond-level data, the sample is restricted to dollar-denominated bonds issued by industrial firms. For this segment of the corporate bond market, zero-coupon yields for AA- and BBB-rating categories at the maturities of 3-month, 6-month, 1-year, 2-year, 3-year, 4-year, 5-year, 7-year, 10-year, 15-year, 20-year, and 30-year were obtained from the Bloomberg BFV data base. These two rating categories represent the highest and lowest ratings for which spreads at all maturities are available since April 1991, the starting date of the Bloomberg data. Credit spreads at all maturities are computed by utilizing daily Treasury yields of the same maturities, derived from the estimates of the zero-coupon Treasury yield curve (see Gürkaynak, Sack, and Wright [2006]). For each rating categories, we then constructed the same four maturity categories as for our EDF-based portfolio and averaged the spreads in each maturity category.

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 set of latent factors denoted by the $(k \times 1)$ vector F_t, with $k < n$. The following assumption are made 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:

$$\begin{bmatrix} X_{1t} \\ X_{2t} \end{bmatrix} = \begin{bmatrix} \mathbf{\Lambda}_{11} & \mathbf{\Lambda}_{12} \\ \mathbf{\Lambda}_{21} & \mathbf{\Lambda}_{22} \end{bmatrix} \begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} + \begin{bmatrix} \nu_{1t} \\ \nu_{2t} \end{bmatrix}, \tag{3}$$

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.[15] The dynamics of the latent factors are described by an autoregressive process of the form

$$\begin{bmatrix} F_{1t} \\ F_{2t} \end{bmatrix} = \mathbf{\Phi}(L) \begin{bmatrix} F_{1,t-1} \\ F_{2,t-1} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{bmatrix}, \tag{4}$$

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 $t = 1, \dots, T$; $i = 1, \dots, n$; and $j = 1, \dots, k$.

To identify the vector of credit factors F_{2t}, we impose the following restrictions on the system of equation 3 and 4. First, we assume that $\mathbf{\Lambda}_{12} = \mathbf{0}$ in equation 3. 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

[15] 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 3 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.

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 4. 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.

A five-step estimation procedure that is computationally easy to implement and that imposes the specified restrictions is used to estimate and identify the credit factors. First, the $(T \times k_1)$ matrix of factors $\mathbf{F}_1$ is estimated 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}. Second, 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—is regressed on the k_1 factors in $\mathbf{F}_1$, with $\widehat{\mathbf{E}}$ denoting the corresponding $(T \times n_2)$ matrix of OLS residuals. Third, the $(T \times k_2)$ matrix of factors $\mathbf{F}_2$ is estimated as the first k_2 principle components of the data matrix $\widehat{\mathbf{E}}$ from the second step. Fourth, factor loadings are estimated 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 $\mathbf{\Lambda}_{12} = \mathbf{0}$. And fifth, the VAR($p$) model in equation 4 is estimated by OLS using the estimated factors.[16]

Structural shocks affecting the vector of credit factors F_{2t} are identified using the Cholesky decomposition of $\mathbf{\Sigma}$, the covariance matrix of the reduced-form VAR disturbances in equation 4. 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. In particular, the following 11 monthly indicators of economic activity are included in our FAVAR specification: (1) the difference of the civilian unemployment rate; (2) the log-difference of nonfarm payroll employment; (3)

[16] The latent factors $\mathbf{F}_1$ and $\mathbf{F}_2$ 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 the second step, by construction, orthogonal to $\mathbf{F}_1$, implying that the estimated factors $\mathbf{F}_2$ are also orthogonal to $\mathbf{F}_1$.

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.

Price developments are summarized by the following six 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.

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 seven interest rates. Because nominal yields exhibit a discernible downward trend over our sample period (1990–2008), they are converted into real terms to ensure their approximate stationarity.[17]

Developments in equity markets are summarized by the following eight 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. The final group of variables in the vector X_{1t}—six series—includes: (1) the implied volatility on the S&P 500 index options (VIX) to capture uncertainty in the equity market; (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; (3) the log-difference of the trade-weighted exchange value of the dollar against major cur-

[17]To do so, we utilize both the realized inflation and survey measures of inflation expectations reported by the Survey of Professional Forecasters (SPF). Because the SPF is conducted at a quarterly frequency, monthly estimates of inflation expectations are obtained from a linear interpolation of quarterly values. 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, the expected inflation at each specific horizon is constructed by calculating the appropriately weighted average of the one-year ahead and the ten-year ahead expected CPI inflation reported in the SPF. 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.

rencies to control for the international dimension of the U.S. financial system; and (4) two standard measures of liquidity—namely, the difference in the yields between the "off-the-run" and "on-the-run" 10-year Treasury note and the difference between the 5-year swap rate and the yield on the 5-year Treasury note.

Thus in our baseline specification, the vector X_{1t} contains 38 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. 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, the FAVAR traces 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, $k_1 = 4$ and $k_2 = 2$.[18] Under this parametrization, four common factors—denoted by $F_{1t} = [F_{1t}^1\ F_{1t}^2\ F_{1t}^3\ F_{1t}^4]'$—are assumed to 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 $F_{2t} = [F_{2t}^1\ F_{2t}^2]'$. The order of the VAR system is set to $p = 6$, a lag length chosen according to the Akaike information criterion (AIC).

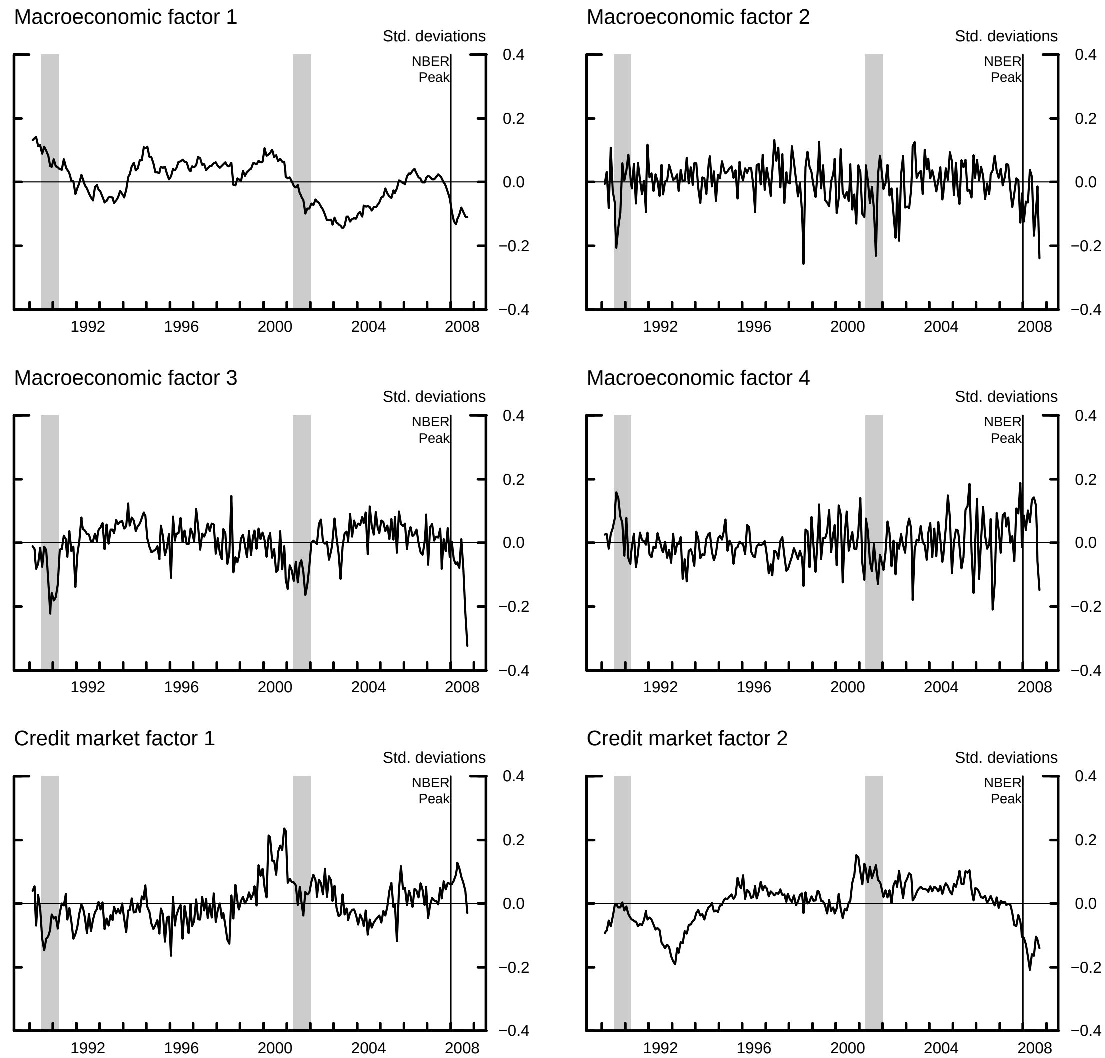
4.2 Shocks to Corporate Bond Spreads

Before turning to our main results, we briefly discuss the estimates of the factors $F_{1t} = [F_{1t}^1\ F_{1t}^2\ F_{1t}^3\ F_{1t}^4]'$ and credit factors $F_{2t} = [F_{1t}^1\ F_{1t}^2]'$ from the baseline specification. The first four panels of Figure 3 depict the four factors associated with macroeconomic and financial variables contained in the vector X_{1t}, and the bottom two panels show 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 between the estimated factors and macroeconomic variables, the first four factors shown in Figure 3 have a clear economic interpretation: Factor 1

[18] 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], k_1 was chosen by looking at the increase in the explained variation of the 38 macroeconomic and financial series in X_{1t} that resulted from increasing the number of factors in F_{1t}. Given our choice of k_1, the number of credit factors k_2 was selected 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.

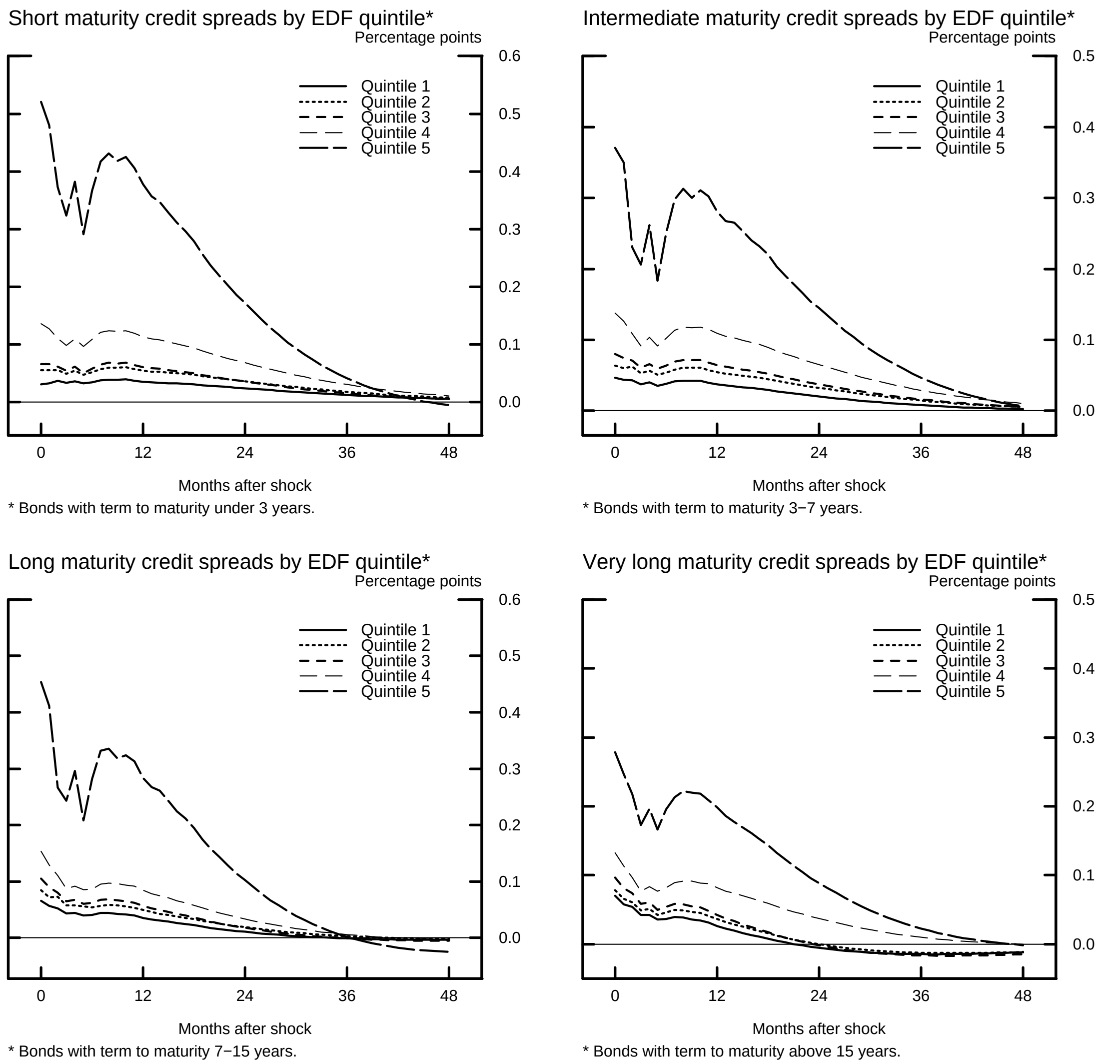
Figure 3: Macroeconomic and Credit Market Factors
(Baseline Specification)



NOTE: The panels of the figure depict estimates of the six factors from the baseline FAVAR specification. The first four factors summarize the 38 macroeconomic and financial variables included in the vector X_{1t}, and the last two 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.

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 developments. 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

Figure 4: 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).

predictive power for the growth of employment and industrial production at longer forecast horizons, according to the results of our forecasting analysis. The second credit factor appears to capture differences between high- and low-risk firms and differences between near- and longer-term credit risk.

Figure 4 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.[19]) This credit market shock widens corporate bond spreads 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 riskiest corporate bond spreads is somewhat more pronounced at the short end of the maturity spectrum.

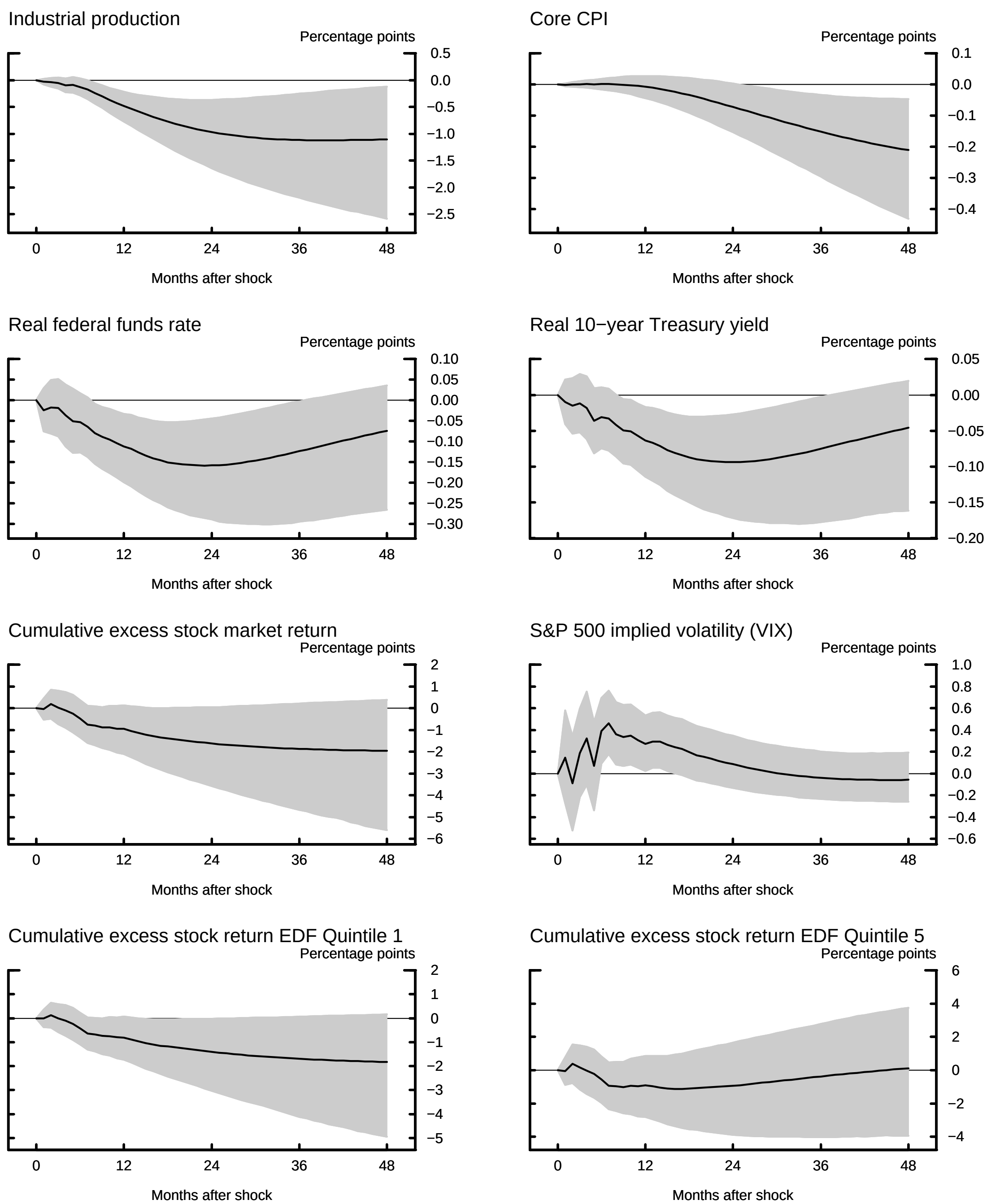
The impact of this credit shock on selected macroeconomic variables is shown in Figure 5. A shock to the first credit factor is clearly contractionary, as evidenced by the fact that industrial production declines about 1 percentage points over a 24-month period.[20] In addition to being statistically 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 10-50 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 15 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.

The contractionary effects of this credit market shock implies a cumulative decline in the excess stock market return of about 2 percentage points over the horizon shown. The cumulative excess equity returns of the least and the most risky firms also fall initially, though the latter effect is statistically indistinguishable from zero. The impact of this adverse credit market shock is also 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. In summary, 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 equity returns, and a rise in stock

[19]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 3. 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 3. For each bootstrapped sample, we also re-estimate the factors $\mathbf{F}_1$ and $\mathbf{F}_2$, thereby taking into account that the factors appear as generated regressors in equation 4. Second, for each bootstrap loop of the observation equation, we apply the "bootstrap-after-bootstrap" procedure of Kilian [1998] to the state-space equation 4 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.

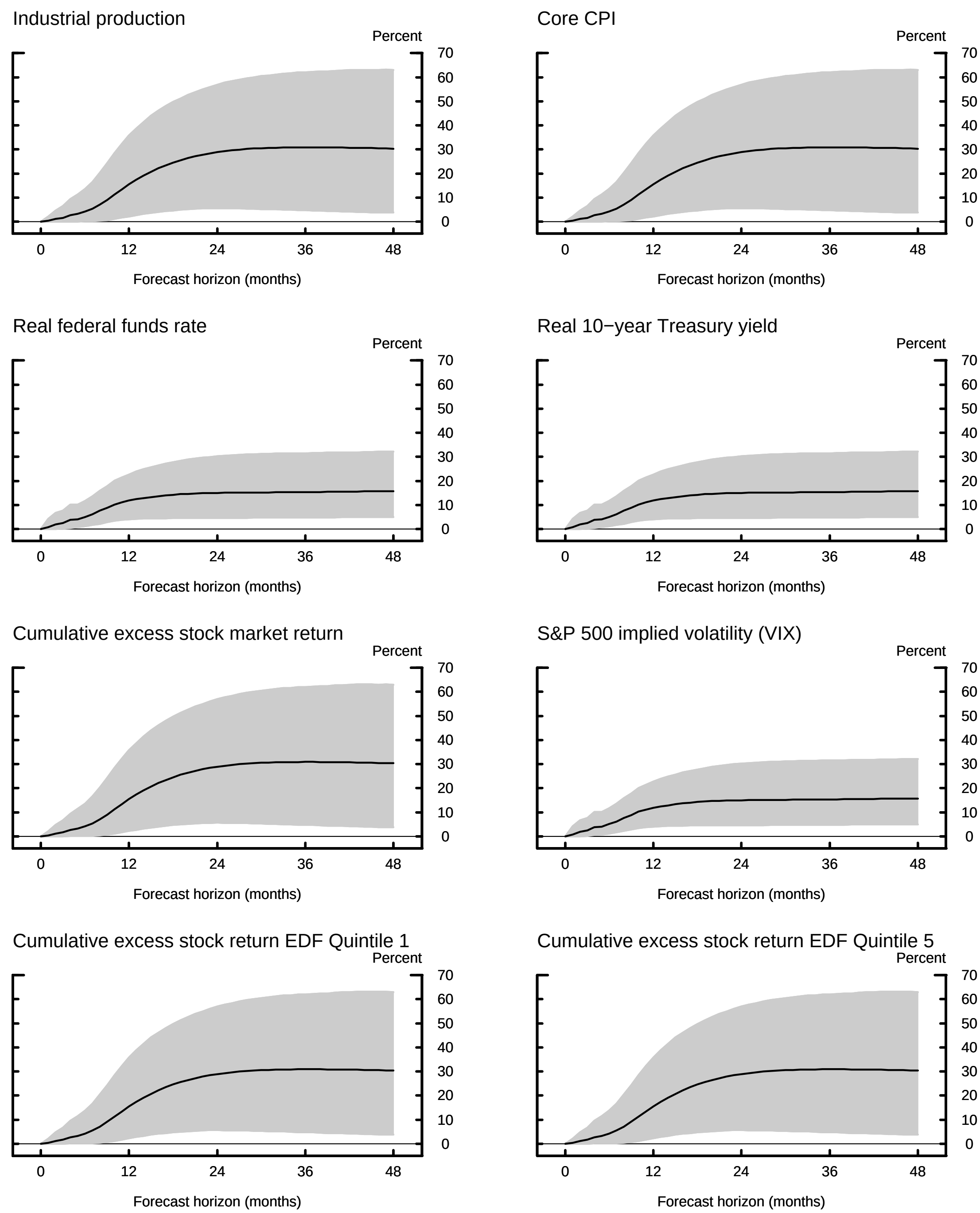
[20]As discussed above, the macroeconomic and financial variables contained in the vector X_{1t} were, if necessary, transformed using log or simple differencing to ensure their stationarity. In such a case, we cumulate their impulse responses to depict the impact of the credit market shock on levels 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.

Figure 5: 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 6: 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.

market uncertainty.[21]

To examine the economic importance of credit market shocks, we calculate the proportion of the forecast error variance attributable to the innovations associated with the first credit market factor. Figure 6 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 credit market shock, along with the respective 95-percent confidence intervals. According to results in Figure 6, shocks to corporate bond spreads account, on average, for more than 30 percent of the variation in the growth of 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 and accounts for 30 percent 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

The baseline FAVAR specification 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, this section examines 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.

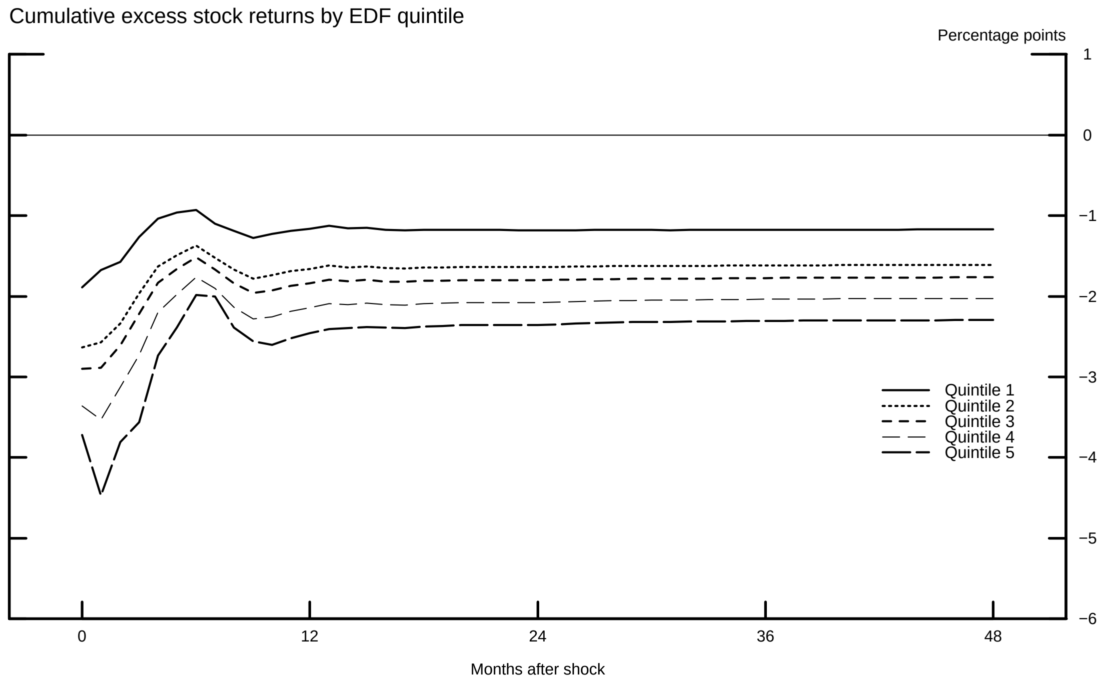
To do so, we consider an alternative FAVAR specification that relies only on excess equity returns in our EDF-based stock portfolios to identify a shock to financial markets. Specifically, instead of the 20 credit spreads associated with our EDF-based bond portfolios, the elements of the vector X_{2t} in this alternative specification 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.[22] 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.[23]

[21] In contrast, the orthogonalized shock to the second credit factor has a statistically and economically insignificant effect on real economic activity.

[22] The same identification scheme as in the baseline specification is employed to identify credit shocks; in addition, $k_1 = 4$, $k_2 = 2$, and $p = 6$, exactly the same as in the baseline case.

[23] We have also considered a specification that that includes both the stock returns and the corporate bond

Figure 7: Response of Excess Equity Returns
(Alternative Specification)

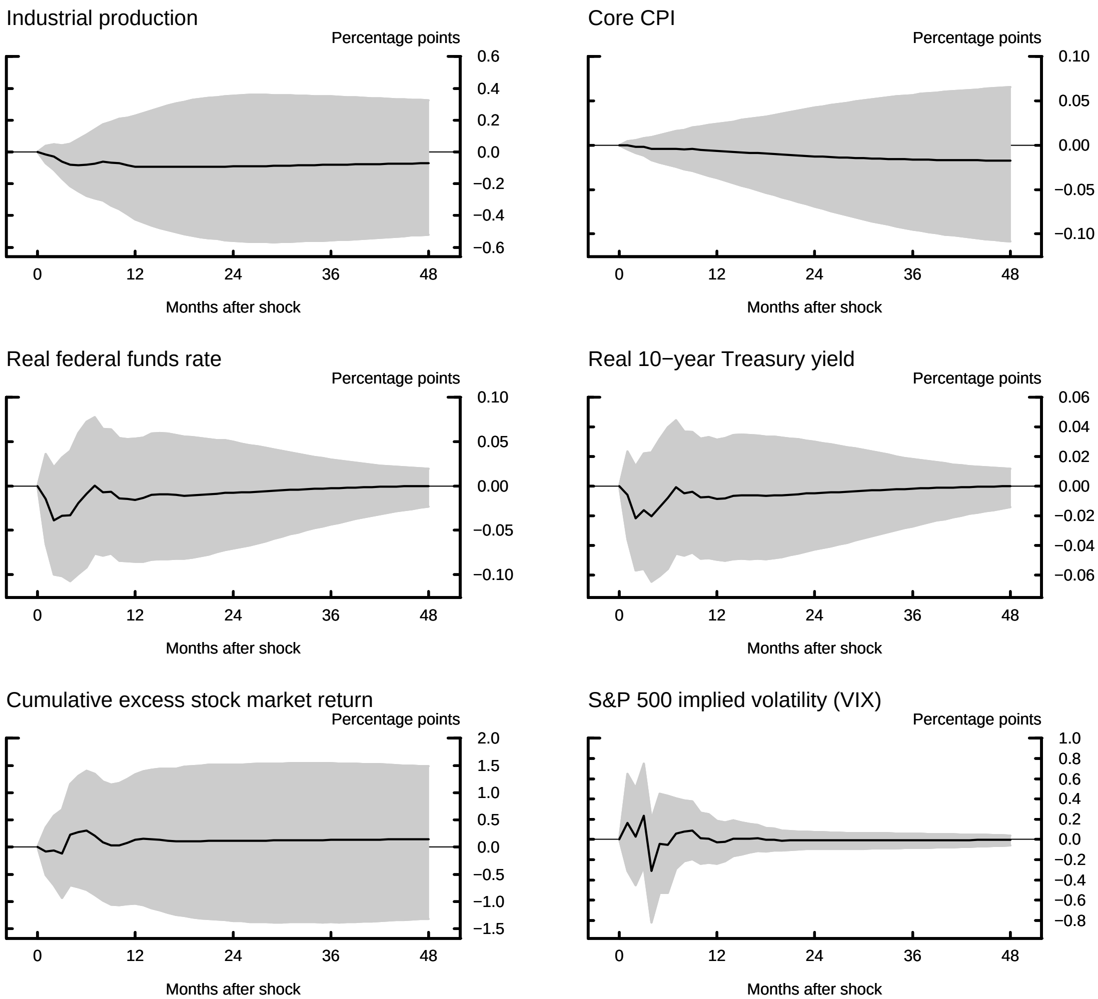


NOTE: The panels of the figure depict the effect of an orthogonalized one standard deviation shock to financial factor 1 on excess equity returns in the five EDF-based stock portfolios (see text for details).

Figure 7 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. This shock has clear negative 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. As shown in Figure 8, the macroeconomic implications of this shock—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 equity returns have little systematic component and largely reflect idiosyncratic news about earnings growth.

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.

Figure 8: 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.

5 Conclusion

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. Such credit market shocks 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 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 imply developments in corporate credit markets provide important information regarding the future course of economic activity.[24]

We offer two alternative explanations for our results. First, the recent empirical and theoretical asset pricing literature has emphasized the inability of standard structural models of default to explain both the level and movements in credit spreads (see, for example, Collin-Dufresne, Goldstein, and Martin [2001]). According to this literature, a large part of the variation in credit spreads is due to macroeconomic factors, particularly to liquidity and risk premiums. In the corporate bond market, the key investors are banks, insurance companies, and other financial intermediaries. To the extent that financial markets are segmented, the risk attitude of the marginal corporate bond investor may reflect the willingness or ability of these institutions to bear risk. Thus, as conditions in the financial sector deteriorate, the premium on the risk of default rises, which causes a drop in investment spending and a contraction in future economic activity, an argument consistent with the results of Philippon [2008] who finds that corporate bond spreads do particularly well at forecasting business fixed investment.

Second, the financial sector creates direct linkages between the banking sector and nonbank financial activity. For example, the ability of nonfinancial corporations to finance short-term liquidity needs by issuing commercial paper relies importantly on the ability of these firms to obtain back-up lines of credit from banks. As monetary policy tightens, or financial conditions in the banking sector deteriorate, banks may be forced to cut back on their lines of credit. More generally, the process of credit disintermediation may increase

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

liquidity risk for nonfinancial firms, which, in the case of a severe deterioration in economic and financial conditions, may turn into insolvency risk. Again, disturbances emanating from the financial sector would cause a rise in the cost of credit for nonfinancial firms. In addition, to the extent that monetary policy shocks are not fully summarized by movements in the Federal funds rate, these credit market disturbances may also reflect the anticipated tightening of monetary policy, which manifests itself in the disintermediation process sooner than it is reflected in the observable movements in standard indicators of monetary policy. This alternative is consistent with the findings of Gertler and Lown [1999] and Mueller [2007] who document a close relationship between changes in bank lending standards and credit market conditions over the course of the business cycle.

As emphasized by Primiceri, Schaumburg, and Tambalotti [2006], there is strong empirical evidence supporting the notion that "intertemporal disturbances" are a major source of business cycle fluctuations. In dynamic stochastic general equilibrium models that allow for financial accelerator mechanisms, such as those developed by Kiyotaki and Moore [1997] and Bernanke, Gertler, and Gilchrist [1999], these disturbances may be linked directly to changes in credit conditions. The rich amount of information contained in corporate bond spreads may be particularly useful for measuring and identifying the importance of these financial mechanisms. To understand the inter-related effects of movements in risk premiums, changes in the health of financial institutions, and economic activity would require extending these models to include financial market participants and changing risk attitudes in a fully-specified general equilibrium framework.

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Appendices

A Factors and Macroeconomic and Financial Variables

Table A-1 contains correlations between the six latent factors and the 38 macroeconomic and financial time series included in the vector X_{1t} in the 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 correlations are computed over the sample period from February 1990 to September 2008.

Table A-1: Correlations between Estimated Factors and Macroeconomic Series
(Baseline FAVAR 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	0.07	-0.54	0.12	-0.13	-0.01
Payroll Employment (Δln)	0.20	0.11	0.71	-0.01	-0.02	-0.06
Capacity Utilization (Δ)	-0.13	-0.23	0.75	-0.08	0.18	0.13
Industrial Production (Δln)	0.06	-0.18	0.74	-0.14	0.15	0.09
ISM Mfg. Activity Index	-0.12	-0.08	0.71	0.10	-0.05	-0.07
Leading Indicator Index (Δln)	-0.34	0.17	0.46	-0.36	0.08	0.09
Real Durable Goods Orders (Δln)	-0.05	-0.02	0.34	-0.16	0.15	0.04
Real Nondurable Goods Orders (Δln)	-0.06	-0.16	0.31	0.44	0.09	0.04
Real PCE (Δln)	-0.09	-0.04	0.22	0.44	0.08	-0.07
Real DPI (Δln)	0.01	0.08	0.07	-0.25	0.01	-0.06
Housing Starts (Δln)	-0.14	-0.03	0.05	-0.12	-0.05	-0.03
Consumer Price Index (Δln)	0.19	-0.22	0.00	0.75	-0.07	0.12
Core Consumer Price Index (Δln)	0.42	0.06	-0.13	0.05	-0.14	0.37
Producer Price Index (Δln)	0.03	-0.24	0.08	0.84	0.04	0.02
Core Producer Price Index (Δln)	0.18	0.05	-0.05	0.41	-0.09	0.09
Commodity Price Index (Δln)	-0.12	0.02	0.25	0.25	0.13	-0.03
Price of WTI Crude (Δln)	0.01	-0.14	0.16	0.36	0.01	-0.02
Real Federal Funds Rate	0.83	0.14	0.03	0.07	0.09	-0.30
Real 6-month Treasury Yield	0.90	0.20	0.09	0.05	0.12	-0.25
Real 1-year Treasury Yield	0.94	0.22	0.07	0.02	0.07	-0.14
Real 2-year Treasury Yield	0.96	0.22	0.10	-0.02	0.03	-0.06
Real 3-year Treasury Yield	0.95	0.22	0.10	-0.05	-0.01	0.02
Real 5-year Treasury Yield	0.92	0.19	0.08	-0.08	-0.05	0.16
Real 10-year Treasury Yield	0.82	0.14	0.03	-0.10	-0.09	0.32
Excess Equity Return EDF-Q1	-0.16	0.87	0.05	0.03	0.01	0.01
Excess Equity Return EDF-Q2	-0.25	0.89	0.01	0.07	0.10	-0.01
Excess Equity Return EDF-Q3	-0.27	0.89	0.01	0.09	0.14	-0.02
Excess Equity Return EDF-Q4	-0.30	0.89	-0.01	0.08	0.11	-0.01
Excess Equity Return EDF-Q5	-0.27	0.81	0.01	0.14	-0.01	0.07
Excess Market Return	-0.20	0.90	0.01	0.09	-0.02	0.04
Fama-French HML Factor	-0.02	-0.28	0.09	-0.13	0.12	-0.05
Fama-French SMB Factor	-0.15	0.19	-0.08	0.10	0.01	0.04
S&P 500 Implied Volatility (VIX)	0.11	-0.33	-0.42	-0.09	0.30	-0.09
3-month Eurodollar Implied Volatility	0.75	0.11	-0.06	-0.04	-0.09	0.39
10-year Treasury Note Implied Volatility	-0.29	-0.18	-0.14	-0.05	0.07	0.26
Exchange Value of the Dollar (Δln)	0.17	-0.03	0.01	-0.43	-0.01	-0.06
On/Off-the-run Treasury Premium (10-year)	-0.16	-0.11	-0.22	-0.07	0.26	0.25
Swap-Treasury Spread (5-year)	0.29	-0.09	-0.44	0.09	0.65	-0.14

Table A-2: Correlations between Estimated Factors and Credit Spreads
(Baseline FAVAR 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	-0.13	-0.16	-0.39	0.01	0.35	0.76
EDF-Q2/Short Maturity	-0.26	-0.23	-0.53	-0.02	0.51	0.51
EDF-Q3/Short Maturity	-0.18	-0.21	-0.58	-0.08	0.54	0.43
EDF-Q4/Short Maturity	-0.31	-0.30	-0.54	-0.01	0.62	0.17
EDF-Q5/Short Maturity	-0.17	-0.20	-0.54	-0.04	0.60	-0.05
EDF-Q1/Intermediate Maturity	-0.05	-0.22	-0.58	0.01	0.67	0.32
EDF-Q2/Intermediate Maturity	-0.17	-0.22	-0.53	0.03	0.62	0.42
EDF-Q3/Intermediate Maturity	-0.22	-0.26	-0.56	-0.01	0.67	0.25
EDF-Q4/Intermediate Maturity	-0.36	-0.26	-0.53	-0.01	0.67	-0.05
EDF-Q5/Intermediate Maturity	-0.29	-0.21	-0.54	-0.11	0.58	-0.16
EDF-Q1/Long Maturity	0.19	-0.16	-0.46	0.03	0.78	-0.12
EDF-Q2/Long Maturity	0.10	-0.16	-0.43	0.12	0.76	-0.13
EDF-Q3/Long Maturity	0.04	-0.19	-0.48	0.02	0.77	-0.22
EDF-Q4/Long Maturity	-0.11	-0.21	-0.45	0.02	0.77	-0.27
EDF-Q5/Long Maturity	-0.13	-0.23	-0.51	-0.08	0.61	-0.30
EDF-Q1/Very Long Maturity	0.47	-0.06	-0.38	0.04	0.70	-0.14
EDF-Q2/Very Long Maturity	0.34	-0.12	-0.47	0.09	0.70	-0.20
EDF-Q3/Very Long Maturity	0.32	-0.11	-0.5	0.04	0.71	-0.19
EDF-Q4/Very Long Maturity	-0.23	-0.24	-0.45	0.07	0.68	-0.29
EDF-Q5/Very Long Maturity	-0.18	-0.16	-0.47	0.13	0.61	-0.27

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 38 macroeconomic and financial time series included in the vector X_{1t} in the 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 (see main text for details).

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

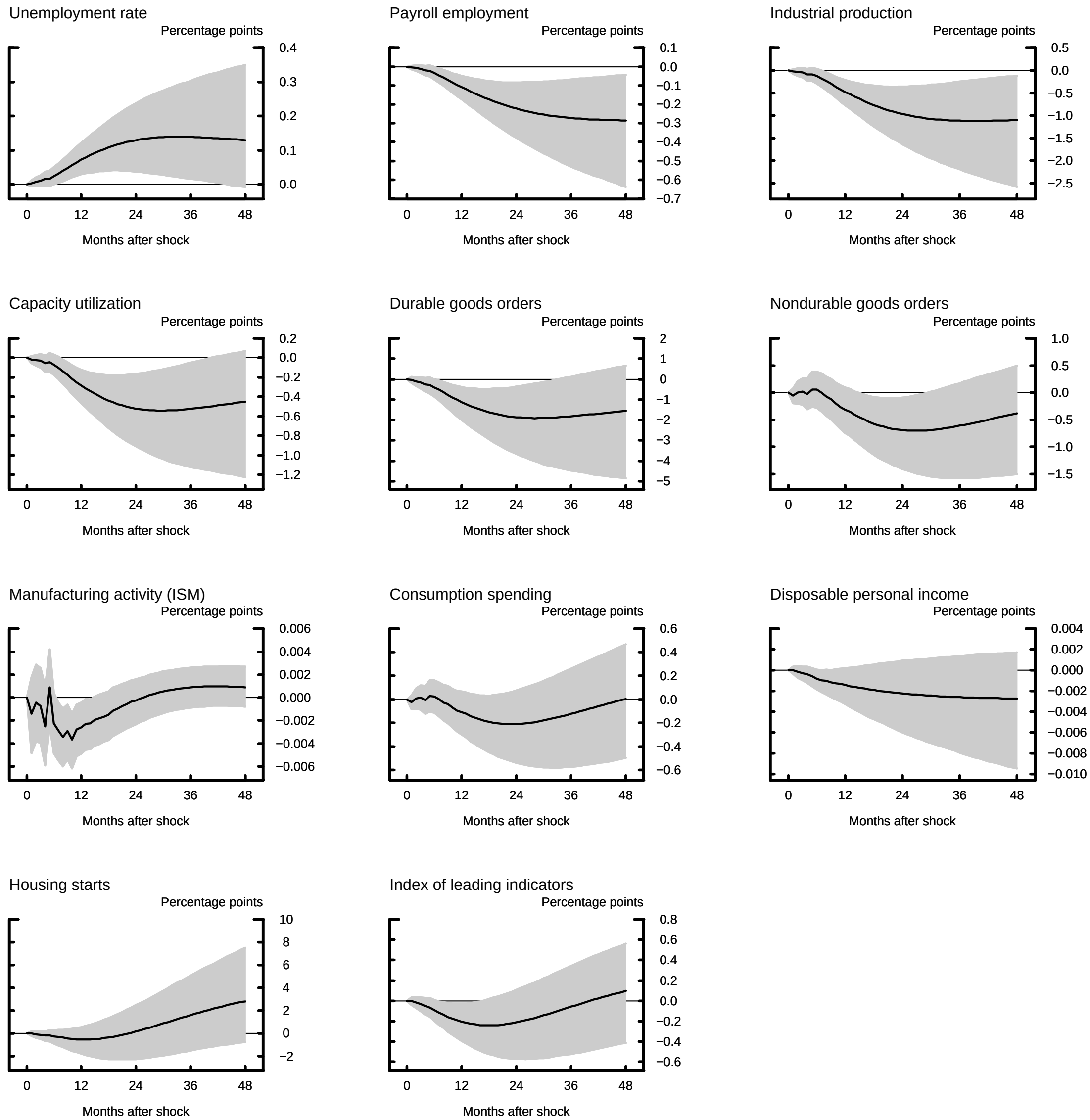

Figure B-2: Inflation Indicators and the Exchange Value of the Dollar
(Baseline FAVAR Specification)

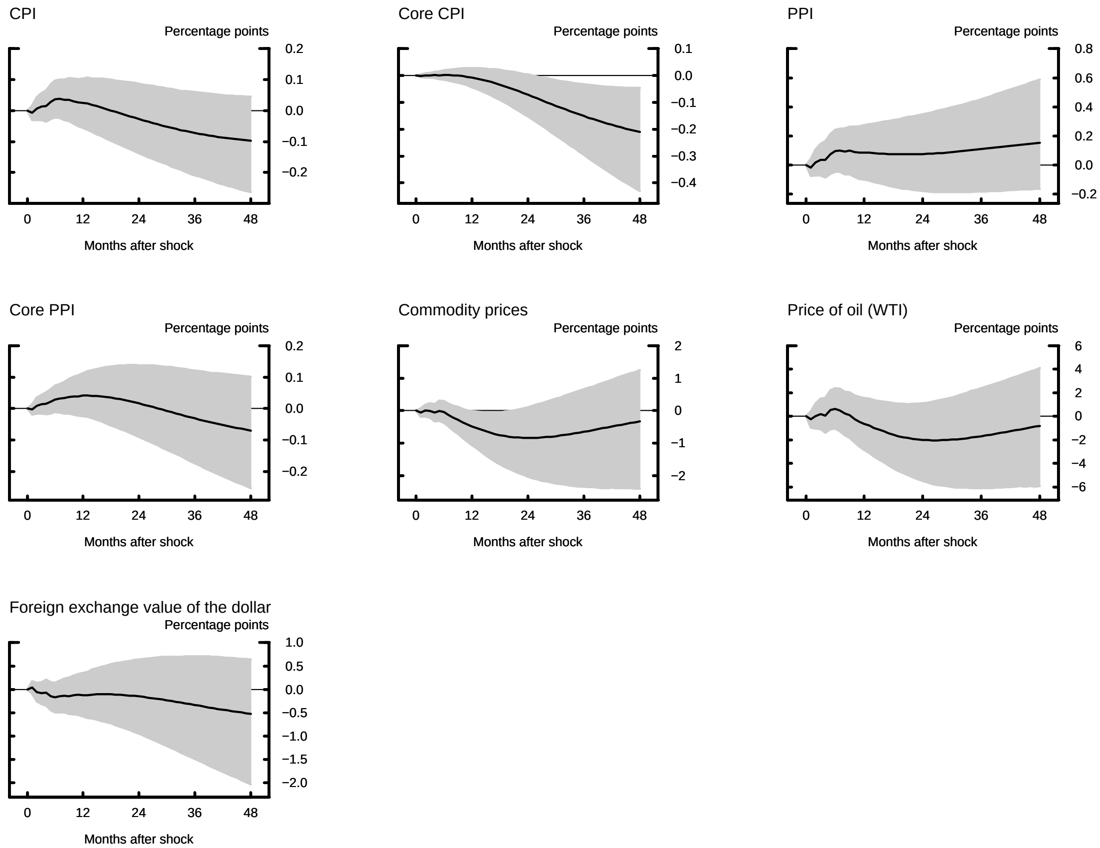

Figure B-3: Interest Rates, Interest Rate Uncertainty, and Liquidity Indicators
(Baseline FAVAR Specification)

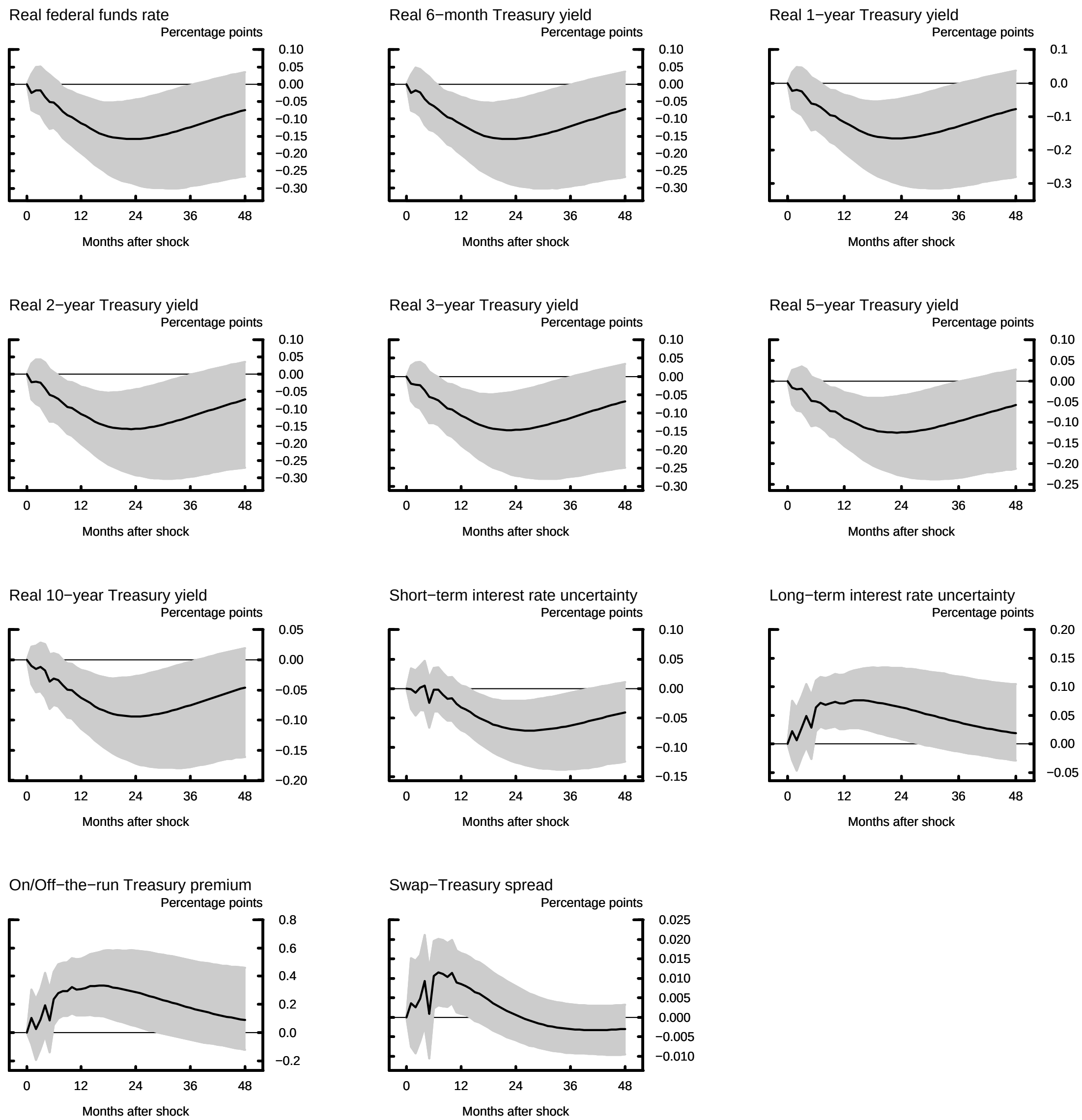

Figure B-4: Equity Market Indicators
(Baseline FAVAR Specification)

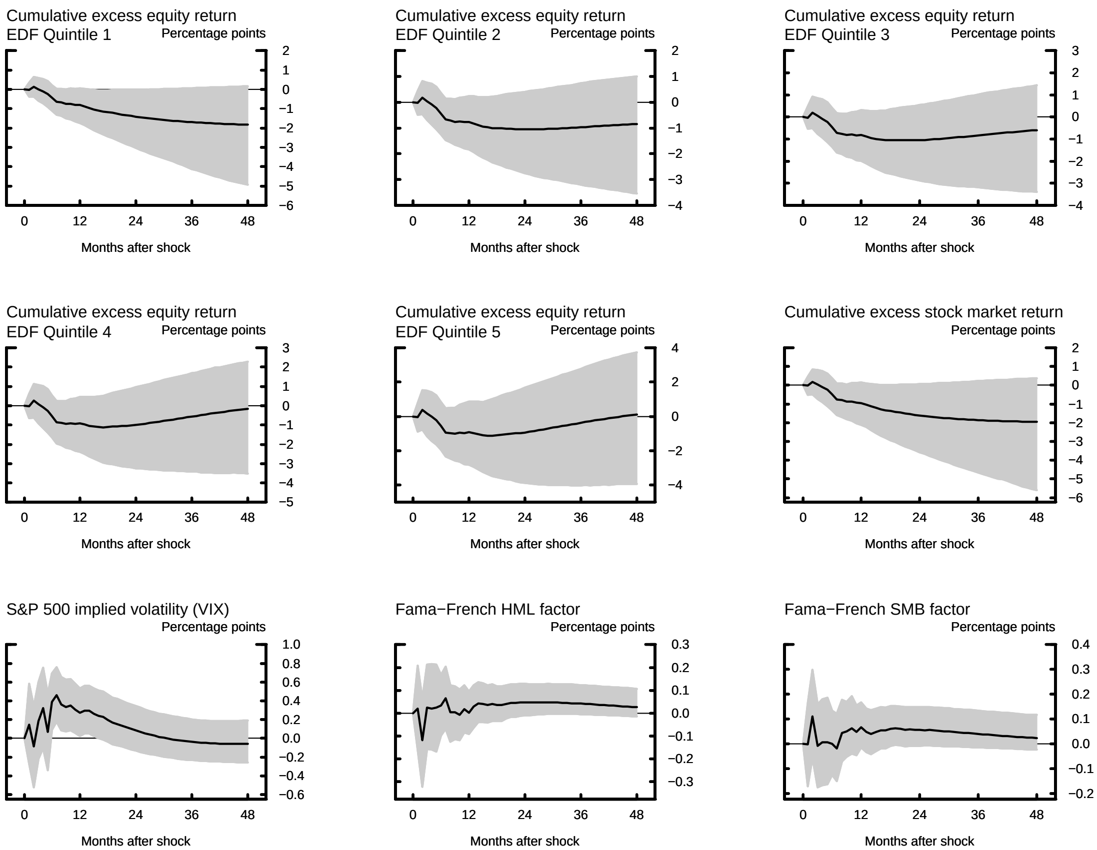

Figure B-5: Short and Intermediate Maturity Credit Spreads
(Baseline FAVAR Specification)

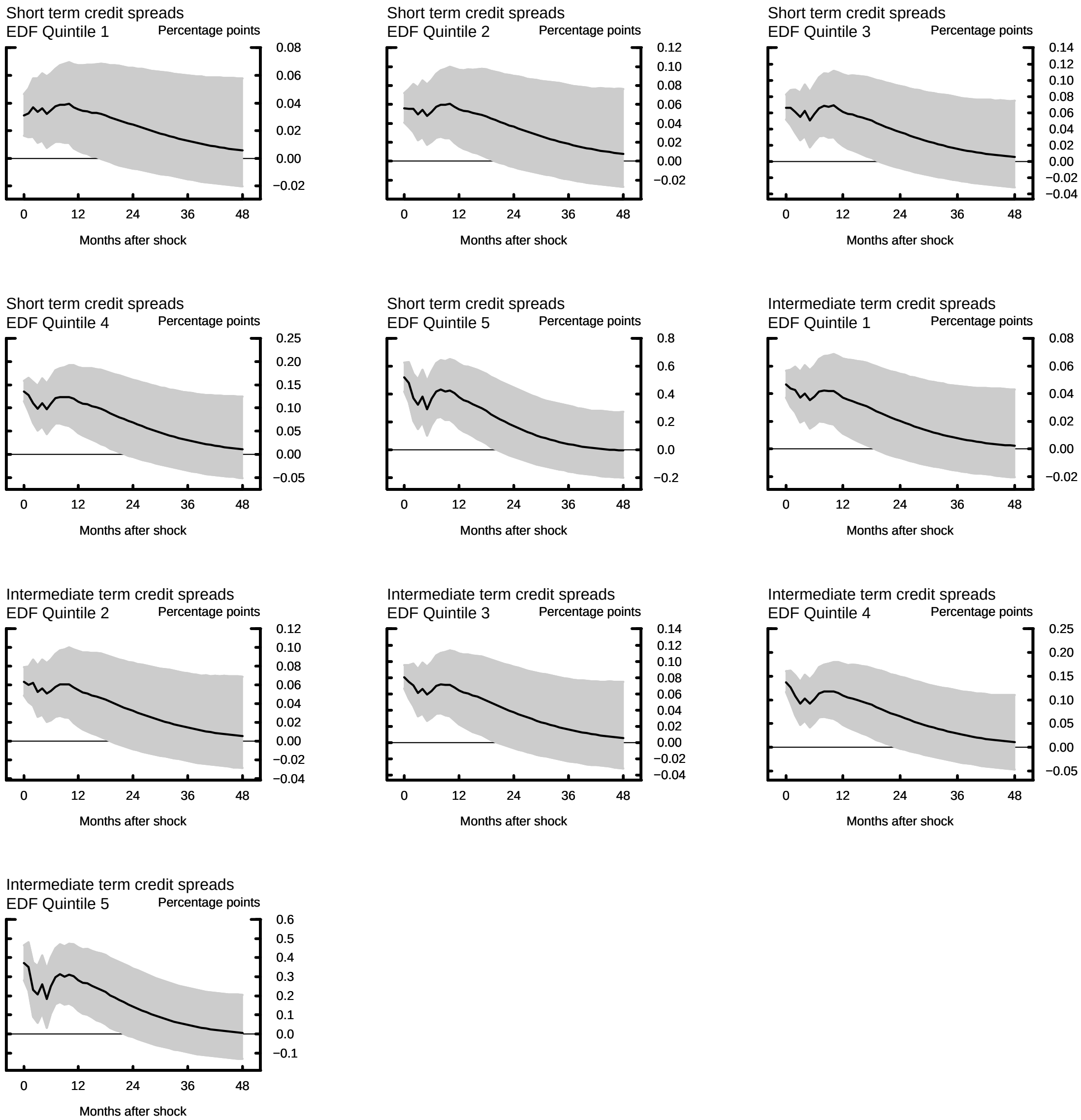

Figure B-6: Long and Very Long Maturity Credit Spreads
(Baseline FAVAR Specification)