

Credit Risk and the Macroeconomy: Evidence from an Estimated DSGE Model

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Abstract

Canonical macroeconomic models have a difficult time accounting for the severity of the feedback effects between financial conditions and the real economy during financial crisis. Embedded in these models is the assumption of frictionless financial markets, implying that the composition of borrowers' balance sheets has no effect on their spending decision. Financial frictions—reflecting agency problems in credit markets—provide a theoretical link between the agents' financial health and the amount of borrowing and hence economic activity in which they are able to engage. This paper attempts to quantify the role of such frictions in U.S. business cycle fluctuations during the 1973–2008 period by estimating a DSGE model with the financial accelerator mechanism. The main innovation of our approach is that we incorporate a high information-content credit spread, constructed directly from the secondary-market prices of outstanding corporate bonds, into the Bayesian ML estimation. This high information-content credit serves as a proxy for the fluctuations in the unobservable external finance premium, and its movements are used to identify the strength of the financial accelerator mechanism and to quantify the magnitude of financial sector shocks. Our results indicate that financial frictions are an economically important part of the propagation mechanism of business cycle shocks. An increase in the external finance premium causes a significant drop in both investment and output. The estimated effects of financial disturbances and their impact on the real economy also accord well with historical perceptions of the likely effects of financial conditions on economic activity during the 1973–2008 period.

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1 Introduction

The United States remains mired in the throes of an acute liquidity and credit crunch, by all accounts, the severest financial crisis since the Great Depression.¹ The roots of this crisis lie in the bursting of the housing bubble, sparked by an unprecedented and unexpected fall in house prices. The resulting financial turmoil in mortgage markets subsequently spread to a variety of other asset markets, causing enormous liquidity problems in interbank funding markets, a massive widening of yield-spreads on private debt instruments, a plunge in equity prices, and a severe tightening of credit conditions for both businesses and households, a confluence of factors that culminated in a sharp drop in economic activity. Indeed, by the summer of 2008, a combination of a rapidly weakening U.S. economy and continued turmoil in global credit markets led to a widespread loss of confidence in the financial sector, and in the early autumn, the U.S. government intervened in the financial system at an unprecedented scale in order to prevent the incipient financial meltdown from engulfing the real economy.²

The inability of canonical macroeconomic models to account for the severity of the feedback effects between financial conditions and the real economy during the current economic downturn (as well as previous financial crisis) should come as no surprise. Predicated on the Modigliani and Miller [1958] assumptions of frictionless financial markets, these models imply that the composition of agents' balance sheets has no effect on their optimal spending decision: Households make consumption decisions based solely on permanent income—the sum of their financial wealth and the per-period income obtained from the present discounted value of future wages. And firms make investment decisions by comparing the expected marginal profitability of new investment projects with the after-tax user-cost of capital, where the relevant interest rate reflects the maturity-adjusted risk-free rate of return appropriate to discount the future cash flows. Movements in financial asset prices thus affect agents' spending decisions insofar that they influence households' financial wealth, and changes in interest rates affect spending decisions because they alter the present dis-

¹See Brunnermeier [2009] for an early account of the current financial crisis.

²In September 2008, the government-sponsored enterprises Fannie Mae and Freddie Mac were placed into conservatorship by their regulator; Lehman Brothers Holdings filed for bankruptcy; and the insurance company American International Group Inc. (AIG) came under severe pressure, necessitating the Federal Reserve to provide substantial liquidity support to the company. At the same time, a number of other financial institutions failed or were acquired by competitors. In response, U.S. government entities took a number of measures to shore up financial markets, restore a degree of stability in the banking system, and support the flow of credit to businesses and households. In addition to large-scale capital injections, expansions of deposit insurance, and guarantees of some forms of bank debt, these measures also included the establishment of special lending programs to alleviate stresses in dollar funding markets, support the functioning of the commercial paper market, and restart certain securitization markets. For a history and a full description of these programs, see the Board of Governors' website "Credit and Liquidity Programs and the Balance Sheet," available at <http://www.federalreserve.gov/monetarypolicy/bst.htm>.

counted values and hence appropriately calculated user-costs for financing real consumption and investment expenditures.

Financial market imperfections—owing to asymmetric information or moral hazard on the part of borrowers vis-à-vis lenders—provide a theoretical link between the agents’ financial health and the amount of borrowing and hence economic activity in which they are able to engage. In general, contracts between borrowers and lenders require that borrowers post collateral or maintain some stake in the project in order to mitigate the agency problems associated with such financial market imperfections. For example, when the borrower’s net worth is low relative to the amount borrowed, the borrower has a greater incentive to default on the loan. Lenders recognize these incentive problems and, consequently, demand a premium to provide the necessary external funds. Because this external finance premium is increasing in the amount borrowed relative to the borrower’s net worth and because net worth is determined by the value of assets in place, declines in asset values during economic downturns result in a deterioration of borrowers’ balance sheets and a rise in the premiums charged on the various forms of external finance. The increases in external finance premiums, in turn, lead to further cuts in spending and production. The resulting slowdown in economic activity causes asset values to fall further and amplifies the economic downturn—the so-called financial accelerator mechanism emphasized by Bernanke, Gertler, and Gilchrist [1999] (BGG hereafter).³

In this paper, we attempt to quantify the role of the financial accelerator in U.S. business cycle fluctuations over the last three decades and a half. Our analysis consists of two parts. First, we provide new empirical evidence on the relationship between corporate credit spreads—the difference in yields between various corporate debt instruments

³Other formulations of financial market frictions in general equilibrium models include, for example, Fuerst [1995], Carlstrom and Fuerst [1997], Kiyotaki and Moore [1997], and Cooley, Marimon, and Quadrini [2004]. In general, the various mechanisms linking balance sheet conditions of borrowers to real activity fall under the guise of the “broad credit channel.” As underscored by the current financial crisis, financial firms are also likely to suffer from asymmetric information and moral hazard problems when raising funds to finance their lending activities. The focus of this so-called “narrow credit channel” is the health of financial intermediaries and its impact on the ability of financial institution to extend credit. As shown by Kashyap and Stein [2000], this narrow credit channel appears to have important effects on the lending behavior of smaller banks. Such banks, however, account for only a small fraction of total bank lending in the United States, which suggests that the narrow credit channel may not be a quantitatively important transmission mechanism of business cycle shocks. Reductions in bank capital during economic downturns can also reduce lending activity. Banks seeking to shore up their capital or to meet regulatory capital requirements may tighten their credit standards and cut back on lending, an inward shift in loan supply that curtails spending of bank-dependent borrowers (see, for example, Van den Heuvel [2007].) The strength of this so-called “capital channel” depends on the overall health of the banking sector and on the extent to which firms and households are bank dependent. As evidenced by the sharp pullback in lending by large commercial banks and nonbank financial institutions during the current financial crisis—owing to a lack of liquidity in the interbank funding markets and the tightening of credit conditions as these institutions sought to replenish depleted capital—the capital channel may have contributed importantly to the severity of the contraction in economic activity.

and government securities of comparable maturity—and macroeconomic outcomes. In the context of the financial accelerator, an increase in default-risk indicators such as corporate credit spreads curtails the ability of firms to obtain credit. The widening of credit spreads could reflect disruptions in the supply of credit resulting from the worsening in the quality of corporate balance sheets or the deterioration in the health of financial intermediaries that supply credit. The resulting contraction in credit supply causes asset values to fall, incentives to default to increase, and yield spreads on private debt instruments to widen further as lenders demand compensation for the expected increase in defaults.

Building on the recent work by Gilchrist, Yankov, and Zakrajšek [2009], we construct, using individual security-level data, a corporate credit spread index with a high information content for future economic activity. Our forecasting results indicate that the predictive content of this credit spread for various measures of economic activity significantly exceeds that of widely-used financial indicators such as the standard Baa-Treasury corporate credit spread and indicators of the stance of monetary policy such as the shape of the yield curve or the real federal funds rate. However, as showed recently by Philippon [2009], the predictive content of corporate bond spreads for economic activity could reflect—absent any financial market imperfections—the ability of the bond market to signal more accurately than the stock market a general decline in economic fundamentals stemming from a reduction in the expected present value of corporate cash flows prior to a cyclical downturn. This result underscores the difficult identification issue that plagues empirical research aimed at quantifying the implications of credit supply shocks on the real economy: a fall in output that follows a drop in lending associated with a major financial disruption reflects both supply and demand considerations.

In an attempt to disentangle movements in the supply and demand for credit, we impose a structural framework on macroeconomic data by incorporating financial market frictions into a dynamic stochastic general equilibrium (DSGE) model with a rich array of real and nominal rigidities. Specifically, we augment a dynamic New Keynesian model developed by Smets and Wouters [2007] with the financial accelerator mechanism of BGG. We then estimate the resulting model on U.S. quarterly data over the 1973–2008 period, an approach closely related to the recent work of Christiano, Motto, and Rostagno [2008], De Graeve [2008], Christensen and Dib [2008], and Queijo von Heideken [2008], who showed that the ability of DSGE models to fit macroeconomic data improves significantly if one allows for the presence of a BGG-type financial accelerator mechanism.

The main innovation of our approach is that we incorporate our high information-content credit spread directly in the Bayesian maximum likelihood (ML) estimation, where it serves as a proxy for the fluctuations in the unobservable external finance premium.⁴ De Graeve

⁴Whether observable credit spreads are a good proxy for the unobservable external finance premium

[2008] and Queijo von Heideken [2008], in contrast, estimated a DSGE model with the financial accelerator that is identified without the reliance on financial data and that does not allow for shocks to the financial sector, whereas Christiano, Motto, and Rostagno [2008], though allowing for a wide variety of shocks to the financial sector, did not estimate the parameters governing the strength of the financial accelerator mechanism. In our estimation approach, movements in the high information-content credit spread are used to identify the strength of the financial accelerator mechanism in the DSGE framework and to measure the extent to which disruptions in financial markets have contributed to fluctuations in the real economy during the last three and a half decades.

Our estimates indicate that financial disturbances have played an economically significant role in U.S. business cycle fluctuations over the 1973–2008 period. In particular, the model estimates suggest that financial disruptions are responsible for sharp declines in output growth during the last two recessions and that the easing of financial conditions during the second half of the last decade contributed importantly to the investment boom of the late 1990s. In addition, the model estimates imply that the current financial crisis—through its impact on business fixed investment—appears to be responsible for a considerable portion of the observed slowdown in economic activity.

The remainder of the papers is organized as follows. Section 2 describes the construction of our high information-content credit spread and compares its predictive power for economic activity to that of some standard financial indicators. In Section 3, we augment the Smets and Wouters [2007] model with the financial accelerator, discuss its estimation, and present our main findings. Section 4 concludes.

2 Corporate Credit Spreads and Economic Activity

Corporate credit spreads have long been used to gauge the degree of strains in the financial system. Moreover, because financial asset prices are forward looking, movements in credit spreads have been shown to be particularly useful for forecasting economic activity.⁵ Despite considerable success, results from this strand of research are often sensitive to the

is, of course, model dependent. Employing firm-level data on credit spreads, EDFs, and leverage Levin, Natalucci, and Zakrajsek [2006] estimated directly the structural parameters of the debt-contracting problem underlying the financial accelerator model of BGG. According to their results, movements in credit spreads are highly correlated—both across firms and across time—with fluctuations in the model-implied external finance premium.

⁵The forecasting power 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.

choice of a credit spread index under consideration, as credit spreads that contained useful information about macroeconomic outcomes in the past often lose their predictive power for the subsequent cyclical downturn.⁶ These mixed results are partly attributable to the rapid pace of financial innovation that likely alters the forecasting power of financial asset prices over time or results in one-off developments that may account for most of the forecasting power of a given credit spread index.

In part to address these problems, Gilchrist, Yankov, and Zakrajšek [2009] (GYZ hereafter) rely on the prices of individual senior unsecured corporate debt issues traded in the secondary market to construct a broad array of corporate bond spread indexes that vary across maturity and default risk. Compared with other corporate financial instruments, senior unsecured bonds represent a class of securities with a long history containing a number of business cycles, and the rapid pace of financial innovation over the past two decades has done little to alter the basic structure of these securities. Thus, the information content of spreads constructed from yields on senior unsecured corporate bonds is likely to provide more consistent signals regarding economic outcomes relative to spreads based on securities with a shorter history or securities whose structure or the relevant market has undergone a significant structural change. In addition, GYZ rely on the firm-specific expected default frequencies (EDFs) based on the option-theoretic framework of Merton [1974] provided by the Moody's/KMV corporation to construct their credit spread indexes. Because they are based primarily on observable information in equity markets, EDFs provide a more objective and more timely assessment of firm-specific credit risk compared with the issuer's senior unsecured credit rating.

The results of GYZ indicate that at longer forecast horizons (i.e., one- to two-year ahead), the predictive ability of their EDF-based portfolios of credit spreads significantly exceeds—both in-sample and out-of-sample—that of the commonly-used default-risk indicators, such as the paper-bill spread and the Baa or the high-yield corporate credit spread indexes. The predictive power of corporate bond spreads for economic activity comes from the upper-end and the middle of the credit quality spectrum and is concentrated in securities with a long remaining term-to-maturity. In this section, we construct such a high information-content default-risk indicator by constructing a credit spread of long-maturity bonds issued by firms with low to medium probability of default. We compare its forecasting

⁶For 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. Indeed, according to Thoma and Gray [1998] and Emery [1999], the predictive content of the paper-bill spread may have reflected a one-time event. Similarly, yield spreads based on indexes of high-yield corporate bonds, which contain information from markets that were not in existence prior to the mid-1980s, have done particularly well at forecasting output growth during the previous decade, according to Gertler and Lown [1999] and Mody and Taylor [2004]. Stock and Watson [2003], however, find mixed evidence for the high-yield spread as a leading indicator during this period, largely because it falsely predicted an economic downturn in the autumn of 1998.

ability over the 1973–2008 period to that of the standard Baa-Treasury credit spread and other financial indicators such as the slope of the yield curve and the federal funds rate. We then use our high information-content credit spread as a proxy for the unobservable external finance premium in the Bayesian ML estimation of a DSGE model that incorporates the financial accelerator mechanism.

2.1 Corporate Bond Spreads

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 926 publicly-traded firms covered by the Center for Research in Security Prices (CRSP) and S&P’s Compustat, 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 we are measuring long-term financing costs of different firms at the same point in their capital structure, we limited our sample to only senior unsecured issues. For the securities carrying the senior unsecured rating and with market prices in both the LW and LM databases, we spliced the option-adjusted effective yields at month-end—a component of the bond’s yield that is not attributable to embedded options—across the two data sources. To calculate the credit spreads at each point in time, we matched the yield on *each* individual security issued by the firm to the estimated yield on the Treasury coupon security of the same maturity. The month-end Treasury yields were taken from the daily estimates of the U.S. Treasury yield curve reported in Gürkaynak, Sack, and Wright [2007]. To mitigate the effect of outliers on our analysis, we eliminated all observations with credit spreads below 10 basis points and with spreads greater than 5,000 basis points. This selection criterion yielded a sample of 5,269 individual securities between January 1973 and December 2008.

Table 1 contains summary statistics for the key characteristics of bonds in our sample. Note that a typical firm has only a few senior unsecured issues outstanding at any point in time—the median firm, for example, has two such issues trading at any given month. This distribution, however, exhibits a significant positive skew, as some firms can have

as many as 75 different senior unsecured bond issues trading in the market at a point in time. The distribution of the real market values of these issues is similarly skewed, with the range running from \$1.1 million to more than \$6.6 billion. Not surprisingly, the maturity of these debt instruments is fairly long, with the average maturity at issue of 14 years. Because corporate bonds typically generate significant cash flow in the form of regular coupon payments, the effective duration is considerably shorter, with both the average and the median duration of about 6 years. Although our sample spans the entire spectrum of credit quality—from “single D” to “triple A”—the median bond/month observation, at “A3,” is solidly in the investment-grade category.

Turning to returns, the (nominal) coupon rate on these bonds averaged 7.77 percent during our sample period, while the average total nominal return, as measured by the nominal effective yield, was 8.26 percent per annum. Reflecting the wide range of credit quality, the distribution of nominal 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 178 basis points above the comparable-maturity risk-free rate, with the standard deviation of 275 basis points.

2.2 Credit Risk Indicators

As noted above, our aim is to construct a portfolio of long-maturity corporate bonds issued by firms with a low to medium probability of default. To measure a firm’s probability of default at each point in time, we employ the “distance-to-default” (DD) framework developed in the seminal work of Merton [1973, 1974]. The key insight of this approach is that the equity of the firm can be viewed as a call option on the underlying value of the firm with a strike price equal to the face value of the firm’s debt. Although neither the underlying value of the firm nor its volatility can be directly observed, they can, under the assumptions of the model, be inferred from the value of the firm’s equity, the volatility of its equity, and the firm’s observed capital structure.

The first critical assumption underlying the DD-framework is that the total value of the a firm—denoted by V —follows a geometric Brownian motion:

$$dV = \mu_V V dt + \sigma_V V dW, \quad (1)$$

where μ_V is the expected continuously compounded return on V ; σ_V is the volatility of firm value; and dW is an increment of the standard Weiner process. The second critical assumption pertains to the firm’s capital structure. In particular, it is assumed that the firm has just issued a single discount bond in the amount D that will mature in T periods. Together, these two assumption imply that the value of the firm’s equity E can be viewed as

a call option on the underlying value of the firm V with a strike price equal to the face value of the firm's debt D and a time-to-maturity of T . According to the Black-Scholes-Merton option-pricing framework, the value of the firm's equity then satisfies:

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

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

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

According to equation 2, the value of the firm's equity depends on the total value of the firm and time, a relationship that also underpins the link between volatility of the firm's value σ_V and the volatility of its equity σ_E . In particular, it follows from Ito's lemma that

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

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

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

From an operational standpoint, the most critical inputs to the Merton DD-model are clearly the market value of the equity E , the face value of the debt D , and the volatility of equity σ_E . Assuming a forecasting horizon of one year ($T = 1$), we implement the model in two steps: First, we estimate σ_E from historical daily stock returns. Second, we assume that the face value of the firm's debt D is equal to the sum of the firm's current liabilities and one-half of its long-term liabilities.⁷ Using the observed values of E , D , σ_E , and r (i.e., the one-year constant-maturity Treasury yield), equations 2 and 4 can be solved for V and σ_V using standard numerical techniques. However, as pointed out by Crosbie and Bohn [2003] and Vassalou and Xing [2004], the excessive volatility of market leverage (V/E) in equation 4 causes large swings in the estimated volatility of the firm's value σ_V , which are difficult to reconcile with the observed frequency of defaults and movements in financial asset prices.

⁷This assumption for the "default point" is also used by Moody's/KMV in the construction of their Expected Default Frequencies (EDFs) based on the Merton DD-model, and it reflects the finding that most defaults occur when the market value of the firm's assets drops below the sum of its current liabilities and one-half of its long-term liabilities. Both current and long-term liabilities are taken from quarterly Compustat files and interpolated to daily frequency using a step function.

To resolve this problem, we implement an iterative procedure recently proposed by Bharath and Shumway [2008].⁸ The resulting solutions of the Merton DD-model can be used to calculate the firm-specific distance-to-default over the one-year horizon as

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

where μ_V is an estimate of the expected annual return on the firm’s assets. The corresponding implied probability of default—the so-called EDF—is given by

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

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

2.3 High Information-Content Corporate Credit Spread

We construct a proxy for the external finance premium—namely, a medium-risk, long-maturity corporate credit spread—by sorting our sample of credit spreads into a “medium-risk” category based on the distribution of the estimated firm-specific DDs in month $t - 1$. In particular, for each month t , we calculate the 20th and 60th percentiles of the cross-sectional distribution of the distance-to-default using a sample of all publicly-traded firms in the matched CRSP/Compustat sample (more than 2,700 firms in an average month). The resulting time-varying thresholds define a “medium-risk” category for our sample of 926 bond issuers. Within this credit risk category, we then select all bonds with the remaining term-to-maturity of more than 15 years and compute an arithmetic average of credit spreads for each month t .

Figure 1 shows our medium-risk, long-maturity credit spread along with, for comparison purposes, the average credit spread for our sample of bonds, and the widely-used Baa corporate bond spread, defined as the difference between the yield on an index of seasoned long-term Baa-rated corporate bonds and the yield on the constant-maturity 10-year Treasury note.⁹ All three series show substantial variation and comovement over the business cycle. Whereas the Baa spread is highly correlated with the average credit spread for our

⁸Briefly, the procedure involves the following steps. Initialize the procedure by letting $\sigma_V = \sigma_E[D/(E + D)]$. Use this value of σ_V in equation 2 to infer the market value of the firm’s assets V for every day of the previous year. Then calculate the implied daily log-return on assets (i.e., $\Delta \ln V$) and use the resulting series to generate new estimates of σ_V and μ_V . Iterate on σ_V until convergence; see Bharath and Shumway [2008] for details.

⁹The source for all Treasury yields and the yield on Baa-rated long-term corporate bonds is “Selected Interest Rates” (H.15) Federal Reserve statistical release. Because the Baa yield is only available at quarterly frequency prior to 1986:Q1, we converted our monthly credit spreads to quarterly averages.

sample of bonds ($\rho = 0.79$), its correlation with the medium-risk, long maturity credit spread is much lower ($\rho = 0.55$). Both the average spread and its Baa counterpart appear considerably more volatile than the medium-risk, long maturity spread, especially during economic downturns. Focusing on the current period of financial turmoil, all three credit spreads started to move up noticeably in the second half of 2007, and they reached their respective historical peaks in the fourth quarter of 2008.

2.4 Forecasting Power of Credit Spreads for Economic Activity

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

$$\Delta^h Y_{t+h} \equiv \frac{400}{h} \ln \left(\frac{Y_{t+h}}{Y_t} \right),$$

where h denotes the forecast horizon. We estimate the following univariate forecasting specification:

$$\Delta^h Y_{t+h} = \alpha + \sum_{i=0}^{h-1} \beta_i \Delta Y_{t-i} + \gamma_1 TS_t^{3M-10Y} + \gamma_2 RFF_t + \gamma_3 CS_t + \epsilon_{t+h}, \quad (7)$$

where TS_t^{3M-10Y} denotes the “term spread”—that is, the slope of the Treasury yield curve defined as the difference between the three-month constant-maturity Treasury yield and the 10-year constant-maturity yield;¹⁰ RFF_t denotes the real federal funds rate;¹¹ CS_t denotes a credit spread; and ϵ_{t+h} is the forecast error. The forecasting regression given by equation 7 is estimated using OLS, and the serial correlation induced by overlapping forecast errors is taken into account by computing the covariance matrix of regression coefficients according to Newey and West [1987], with the “lag truncation” parameter equal to $h + 1$.

In addition to predicting output and business fixed investment, we also consider labor market and production indicators, such as private nonfarm payroll employment, the unemployment rate, and the index of manufacturing industrial production. Focusing on the year-ahead horizon (i.e., $h = 4$), our first set of forecasting results uses data over the en-

¹⁰The role of the term spread in forecasting economic growth or for assessing the near-term risk of recession has been analyzed by 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].

¹¹In calculating the real federal funds rate, we employ a simplifying assumption that the expected inflation is equal to lagged core PCE inflation. Specifically, real funds rate in quarter t is defined as the average effective federal funds rate during quarter t less realized inflation, where realized inflation is given by the log-difference between the core PCE price index and its lagged value 4 quarters earlier.

tire sample period (1973–2008). In light of the well-documented decline in macroeconomic volatility since the mid-1980s, we also examine the predictive power of these financial indicators for economic activity during the so-called “Great Moderation,” namely over the 1986–2008 period.

2.4.1 Results: Sample Period 1973–2008

The results in Table 2 examine the predictive power of various financial asset prices for labor market and production indicators over the entire sample period. According to the baseline specification—shown in column 1—the slope of the yield curve is statistically and economically significant predictor for all three measures of economic activity, with the inversion of the yield curve signalling a slowdown in future economic activity. For example, a one-percentage-point decline in the term spread in quarter t reduces the year-ahead employment growth by almost one-half percentage points, pushes the unemployment rate up by more than one-quarter percentage points, and depresses the growth in industrial output by about 1.2 percentage points. Conditional on the shape of the yield curve, tight monetary policy, as measured by the real federal funds rate, is also predictive of a subsequent slowdown in economic activity.¹²

Column 2 shows the results in which the baseline specification is augmented with the standard Baa corporate credit spread index. As evidenced by the entries in the table, the Baa spread has no marginal predictive power for any of the three measures of economic activity. In contrast, the credit spread based on long-maturity senior unsecured bonds issued by medium-risk firms—column 3—is a highly significant predictor for both labor market indicators and the growth of industrial output: a one-percentage-point rise in the medium-risk, long-maturity spread in quarter t lowers employment growth over the subsequent four quarters by almost 1.25 percentage points, boosts the unemployment rate up by almost one-half percentage points, and cuts almost 2.5 percentage points from the year-ahead growth in manufacturing industrial production.

Table 3 examines the predictive contents of these financial indicators for the growth of real GDP and real business fixed investment. According to the results in column 1, the shape of the yield curve contains substantial predictive power for the year-ahead growth

¹²Under the expectations hypothesis and neglecting term premiums, the term spread is an indicator of the stance of monetary policy—the higher the term spread, the more restrictive is the current stance of monetary policy and, hence, the more likely is economy to decelerate in subsequent quarters. In general, however, the shape of the yield curve contains information about term premiums and the average of expected future short-term interest rates over a relatively long horizon. As emphasized by Hamilton and Kim [2002] and Ang, Piazzesi, and Wei [2006], the term premium and expectations hypothesis components of the term spread have very different correlations with future economic growth. The federal funds rate, in contrast, is a measure of the stance of monetary policy that is relatively unadulterated by the effects of time-varying term premiums.

in real output, whereas the current stance of monetary policy—as measured by the real federal funds rate—is highly informative for the subsequent growth in capital expenditures. As before, the standard Baa credit spread index—column 2—has no marginal predictive power for either activity indicator, whereas our medium-risk, long-maturity credit spread—column 3—appears to be a particularly good predictor of the growth in business fixed investment. For example, a one-percentage-point widening in our credit spread leads to a six-percentage-point drop in the year-ahead growth in real business fixed investment. In contrast, the coefficient on the medium-risk, long-maturity credit spread in the forecasting regression for output growth, although economically significant, is estimated rather imprecisely.

2.4.2 Results: Sample Period 1986–2008

In this section, we repeat our forecasting exercises for the Great Moderation period, namely from 1986:Q1 onward. Although no clear consensus has emerged regarding the dominant cause(s) of the striking decline in macroeconomic volatility since the mid-1980s, changes in the conduct of monetary policy appear to be at least partly responsible for the significantly diminished variability of both output and inflation over the past two decades; see, for example, Clarida, Galí, and Gertler [2000] and Stock and Watson [2002a]. Because monetary policy affects the real economy by influencing financial asset prices, the change in the monetary policy regime may have also altered the predictive content of various financial indicators for economic activity. Moreover, as emphasized by Dynan, Elmendorf, and Sichel [2006], the rapid pace of financial innovation since the mid-1980s—namely, the deepening and emergence of lending practices and credit markets that have enhanced the ability of households and firms to borrow and changes in government policy such as the demise of Regulation Q—may have also changed the information content of financial asset prices for macroeconomic outcomes.¹³

Tables 4 and 5 contain our forecasting results for the 1986–2008 subperiod. As evidenced by the entries in column 2 of Table 4, the standard Baa credit spread remains an insignificant predictor—both statistically and economically—of all three measures of economic activity, a result consistent with that reported in Table 2. In contrast, our medium-risk, long-

¹³Although a full formal investigation of potential parameter instability is beyond the scope of this paper, we tested for time variation in the coefficients associated with financial indicators in the forecasting equation 7 using the methodology proposed by Elliott and Müller [2006]. These tests do not reject—even at the 10 percent level—the null hypothesis of fixed regression coefficients on financial indicators for all specifications reported in Table 2. However, we reject at the 5 percent (or higher) significance level the null hypothesis of fixed coefficients on financial indicators in the forecasting regressions for output growth and very much fail to reject the same null in the forecasting regressions for the growth in business fixed investment (Table 3). Thus the evidence suggests a stable relationship between our set of financial indicators and changes in labor market conditions as well as growth in industrial output and investment, but points to some structural instability in the relationship between asset prices and the growth in real GDP.

maturity credit spread—column 3—continues to provide significant information for the future changes in labor market conditions and growth in industrial output. Indeed, the estimated coefficients on the medium-risk, long-maturity credit spread are noticeably larger (in absolute value) than those reported in Table 2, and the associated confidence intervals are appreciably narrower compared with those estimated over the full sample period.

A similar pattern emerges when forecasting the growth of real GDP and business fixed investment. As shown in column 3 of Table 5, the inclusion of the medium-risk, long-maturity credit spread in the baseline specification for the year-ahead growth in both output and investment yields a substantial improvement in the adjusted R^2 s, and the credit spread enters both specifications with a coefficients that is economically and statistically highly significant. Moreover, the presence of the medium-risk, long-maturity credit spread eliminates any predictive content of the term spread and the real federal funds rate for both measures of economic activity. The inclusion of the standard Baa credit spread index, in contrast, yields no improvement in the in-sample fit. All told, these results are consistent with those reported by GYZ for the 1990-2008 period: The information content of corporate credit spreads for macroeconomic outcomes is embedded in long-maturity bonds issued by firms in the middle and the upper-end of the credit quality spectrum. Such credit spreads hold substantial information content for broad measures of economic activity and are especially good predictors of economic activity during the Great Moderation, a period in which they significantly outperform the forecasting ability of other financial indicators such as the shape of the yield curve and the real federal funds rate.

3 An Estimated DSGE Model with Financial Frictions

In this section, we describe the log-linearized version of the Smets and Wouters [2007] (SW hereafter) DSGE model extended to include the financial accelerator outlined in BGG. The SW-model is a variant of a New Keynesian model that incorporates a rich array of nominal and real rigidities, such as habit formation on the part of households, higher-order adjustment costs to investment, variable utilization in production, and Calvo-style nominal price and wage rigidities with partial indexation. Monetary policy in the model is conducted according to a Taylor-type rule for the nominal interest rate. We first outline the basic model without financial frictions and then describe the extension of the model that includes the financial accelerator mechanism. We then discuss the estimation strategy and present our main results.

3.1 The SW-Model without the Financial Accelerator

The resource constraint stipulates that the aggregate output y_t depends on consumption c_t , investment i_t , resources lost owing to variable capital utilization z_t , and an exogenous disturbance (i.e., government spending) to the resource constraint ε_t^g :

$$y_t = c_y c_t + i_y i_t + z_y z_t + \varepsilon_t^g. \quad (8)$$

The Cobb-Douglas production function relates output to a weighted average of capital services k_t^s , labor inputs l_t , and an exogenous level of disembodied technology ε_t^a :

$$y_t = \phi_p [\alpha k_t^s + (1 - \alpha) l_t + \varepsilon_t^a], \quad (9)$$

where α measures the share of capital in production and ϕ_p equals one plus the share of fixed costs in production. Capital services depend on the existing stock of capital k_{t-1} and the capital-utilization rate z_t , according to

$$k_t^s = k_{t-1} + z_t. \quad (10)$$

Under cost minimization, the marginal product of capital depends on the capital-labor ratio and the real wage:

$$mpk_t = -(k_t^s - l_t) + w_t, \quad (11)$$

whereas optimal capital utilization determines the relationship between the utilization rate and the marginal product of capital:

$$z_t = \left[\frac{1 - \psi}{\psi} \right] mpk_t; \quad (12)$$

the parameter ψ in equation 12 determines the elasticity of utilization costs with respect to capital inputs.

The demand-side of the model specifies the two intertemporal Euler equations that determine the optimal consumption and investment decisions. In particular, let σ_c denote the intertemporal elasticity of substitution; λ the degree of habit formation; β the household's discount factor; γ the trend growth rate of technology; φ the cost of adjusting the rate of investment; and $\frac{W_*^h L_*}{C_*}$ the steady-state ratio of labor income to consumption. Then the log-linearized consumption Euler equation implies that a weighted average of current, past, and expected future consumption and labor is a function of the real interest rate ($r_t - E_t(\pi_{t+1})$)

and the intertemporal shock to preferences ε_t^b :

$$c_t - \left[\frac{\frac{\lambda}{\gamma}}{1 + \frac{\lambda}{\gamma}} \right] c_{t-1} - \left[\frac{1}{1 + \frac{\lambda}{\gamma}} \right] E_t c_{t+1} - \left[\frac{(\sigma_c - 1) \left(\frac{W_*^h L_*}{C_*} \right)}{\sigma_c \left(1 + \frac{\lambda}{\gamma} \right)} \right] (l_t - E_t l_{t+1}) = \\ - \left[\frac{1 - \frac{\lambda}{\gamma}}{\sigma_c \left(1 + \frac{\lambda}{\gamma} \right)} \right] (r_t - E_t \pi_{t+1}) + \varepsilon_t^b. \quad (13)$$

Similarly, the Euler equation specifying the optimal investment trajectory implies that a weighted average of past, current, and future investment depends on the value of installed capital q_t :

$$i_t - \left[\frac{1}{1 + \beta \gamma^{(1-\sigma_c)}} \right] i_{t-1} - \left[\frac{\beta \gamma^{(1-\sigma_c)}}{1 + \beta \gamma^{(1-\sigma_c)}} \right] E_t i_{t+1} = \left[\frac{1}{1 + \beta \gamma^{(1-\sigma_c)}} \frac{1}{(\gamma^2 \varphi)} \right] q_t. \quad (14)$$

The arbitrage condition for the value of installed capital states that the value of capital today depends positively on the expected future marginal product of capital and the expected future value of capital and negatively on the rate of return required by the households—that is, the real interest rate relative to the intertemporal shock to preferences:

$$q_t = \left[\frac{R_*^K}{R_*^K + (1 - \delta)} \right] E_t mpk_{t+1} + \left[\frac{1 - \delta}{R_*^K + (1 - \delta)} \right] E_t q_{t+1} \\ - (r_t - E_t \pi_{t+1}) + \left[\frac{\sigma_c \left(1 + \frac{\lambda}{\gamma} \right)}{1 - \frac{\lambda}{\gamma}} \right] \varepsilon_t^b, \quad (15)$$

where δ denotes the rate of capital depreciation. Lastly, the log-linearized equation for capital accumulation can be expressed as

$$k_t = \left[\frac{1 - \delta}{\gamma} \right] k_{t-1} + \left[1 - \frac{1 - \delta}{\gamma} \right] i_t. \quad (16)$$

We now consider the setting of prices and wages under the assumption of Calvo-type adjustment mechanisms with partial indexation. Let μ_t^p and μ_t^w denote the price and wage markups, respectively, both of which are determined under monopolistic competition.¹⁴ Then,

$$\mu_t^p \equiv mpl_t - w_t = \alpha(k_t^s - l_t) + \varepsilon_t^a - w_t; \quad (17)$$

¹⁴Note that $\mu_t^p = -mc_t$, where mc_t denotes real marginal costs—that is, the price mark-up is inversely related to marginal costs.

and

$$\mu_t^w \equiv w_t - mrs_t = w_t - \left[\sigma_l l_t + \frac{1}{1 - \frac{\lambda}{\gamma}} \left(c_t - \frac{\lambda}{\gamma} c_{t-1} \right) \right]. \quad (18)$$

Note that the wage mark-up in equation 18 measures the gap between the real wage and the households' marginal rate of substitution between consumption and leisure. Letting ι_p and ι_w measure the degree of price and wage indexation, respectively, then the New Keynesian Phillips curve implies that a weighted-average of current, past, and expected future inflation depends on the price markup and an exogenous cost-push shock to prices ε_t^p , according to

$$\begin{aligned} \pi_t = & \left[\frac{\iota_p}{1 + \beta\gamma^{(1-\sigma_c)\iota_p}} \right] \pi_{t-1} + \left[\frac{\beta\gamma^{(1-\sigma_c)}}{1 + \beta\gamma^{(1-\sigma_c)\iota_p}} \right] E_t \pi_{t+1} \\ & - \left[\left(\frac{1}{1 + \beta\gamma^{(1-\sigma_c)\iota_p}} \right) \left(\frac{(1 - \xi_p)(1 - \beta\gamma^{(1-\sigma_c)}\xi_p)}{\xi_p((\phi_p - 1)\epsilon_p + 1)} \right) \right] \mu_t^p + \varepsilon_t^p. \end{aligned} \quad (19)$$

Similarly, Calvo-style wage setting implies that a weighted-average of current, past, and expected future wages depends on the wage-markup, inflation, and a cost-push shock to wages ε_t^w :

$$\begin{aligned} w_t = & \left[\frac{1}{1 + \beta\gamma^{(1-\sigma_c)}} \right] w_{t-1} + \left[\frac{\beta\gamma^{(1-\sigma_c)}}{1 + \beta\gamma^{(1-\sigma_c)}} \right] (E_t w_{t+1} + E_t \pi_{t+1}) \\ & - \left[\frac{1 + \beta\gamma^{(1-\sigma_c)\iota_w}}{1 + \beta\gamma^{(1-\sigma_c)}} \right] \pi_t + \left[\frac{\iota_w}{1 + \beta\gamma^{(1-\sigma_c)}} \right] \pi_{t-1} \\ & - \left[\left(\frac{1}{1 + \beta\gamma^{(1-\sigma_c)}} \right) \left(\frac{(1 - \xi_w)(1 - \beta\gamma^{(1-\sigma_c)}\xi_w)}{\xi_w((\phi_w - 1)\epsilon_w + 1)} \right) \right] \mu_t^w + \varepsilon_t^w. \end{aligned} \quad (20)$$

Finally, the model stipulates that the monetary authority follows a rule in setting the short-term nominal interest rate r_t . Specifically, the monetary policy rule allows the current interest rate to respond to lagged interest rates, current inflation, the current level and change in the output gap, and an exogenous policy disturbance ε_t^r :

$$r_t = \rho r_{t-1} + (1 - \rho) \left[r_\pi \pi_t + r_y (y_t - y_t^f) \right] + r_{\Delta y} \left[(y_t - y_t^f) - (y_{t-1} - y_{t-1}^f) \right] + \varepsilon_t^r, \quad (21)$$

where y_t^f denotes potential output, defined as the output that would be obtained under fully flexible wages and prices.

3.2 Augmenting the SW-Model with the Financial Accelerator

The financial accelerator model in BGG centers on the entrepreneurial sector that buys capital at price q_t in period t and uses that capital in production in period $t + 1$. At

$t + 1$, entrepreneurs receive the proceeds—the marginal product of capital mpk_{t+1} —from operating their capital, which is then resold at price q_{t+1} . Under these assumptions, the capital-arbitrage equation implies that the expected rate of return on capital in the entrepreneurial sector is given by

$$E_t r_{t+1}^k = \left[\frac{1 - \delta}{R_*^K + (1 - \delta)} \right] E_t q_{t+1} + \left[\frac{R_*^K}{R_*^K + (1 - \delta)} \right] E_t mpk_{t+1} - q_t, \quad (22)$$

where R_*^K denotes the steady-state value of the return on capital in the model with the financial accelerator.¹⁵

Entrepreneurs are assumed to be risk neutral and, owing to an exogenous survival rate, discount the future more heavily than the households. Entrepreneurs have access to net worth n_t , which they may use to finance a portion of their capital expenditures ($q_t k_t$). Financial frictions—reflecting the costly-state verification problem between entrepreneurs and risk-neutral financial intermediaries—imply that entrepreneurs face an external finance premium s_t that drives a wedge between the expected return on capital and the expected return demanded by households:

$$s_t = E_t r_{t+1}^k - (r_t - E_t \pi_{t+1}) \quad (23)$$

The presence of financial frictions also implies that the size of the external finance premium is negatively related to the strength of entrepreneurs' balance sheets:

$$s_t = -\chi (n_t - q_t - k_t) + \varepsilon_t^{fd}, \quad (24)$$

where the coefficient $\chi > 0$ measures the elasticity of the premium with respect to leverage. We assume that the external finance premium also depends on an exogenous financial disturbance ε_t^{fd} , which may be thought of as a shock to the supply of credit that captures changes in the efficiency of the financial intermediation process. Equation 24 also implies that the entrepreneurial sector leverages up to the point where the expected return on capital equals the cost of borrowing in the external credit market.

Because we assumed that entrepreneurs are long-lived but discount the future more heavily than households, entrepreneurial net worth depends on past net worth and on the return on capital relative to the expected return:

$$n_t = \frac{K}{N} r_t^k - \left(\frac{K}{N} - 1 \right) (s_{t-1} + r_{t-1} - \pi_t) + \theta n_{t-1} + \varepsilon_t^{nw}, \quad (25)$$

¹⁵As discussed in the appendix, in the case of the financial accelerator, the steady-state values are modified because R_*^K changes from $\frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta)$ to $\left(\frac{K}{N} \right)^x \frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta)$. In the flexible economy without the financial accelerator case $\chi^f = 0$.

where K/N denotes the steady-state ratio of capital expenditures to entrepreneurial net worth and θ is the survival rate of entrepreneurs. The first term in equation 25 reflects the leveraged realized return on net worth, whereas the second term represents the required payment to the holders of debt. Rearranging, one can see that

$$n_t = \frac{K}{N} \left(r_t^k - E_{t-1} r_t^k \right) + E_{t-1} r_t^k + \theta n_{t-1} + \varepsilon_t^{nw}.$$

In the BGG framework, the presence of leverage thus magnifies the effect of unexpected changes in the return on capital on entrepreneurs' net worth.

Finally, entrepreneurs that do not survive a given period are assumed to consume their net worth:

$$c_t^e = n_t, \tag{26}$$

which implies the following modification of the constraint on aggregate resources:

$$y_t = c_y c_t + c_y^e c_t^e + i_y i_t + z_y z_t + \varepsilon_t^g, \tag{27}$$

where c_y^e denotes the consumption-output ratio of entrepreneurs. In practice, however, this consumption-output ratio is small, so that movements in net worth have a negligible effect on the resource constraint.¹⁶ To summarize, augmenting the SW-model with the financial accelerator includes the addition of the equations that determine the external finance premium—that is, equations 23 and 24—along with equation 25 that specifies the evolution of net worth. In addition, the original resource constraint equation 8 is modified according to equation 27.

3.3 Shocks, Data, and Estimation

As in Smets and Wouters [2007], the model is estimated using time-series data for the quarterly growth rate of real output, consumption, investment, and real wages, along with inflation, the log of hours worked, and the effective nominal federal funds rate. To quantify the strength of financial frictions and identify disturbances to the financial sector, our estimation procedure also includes the medium-risk, long-maturity corporate bond spread discussed above. This high information-content financial indicator is used as a proxy for the unobservable external finance premium s_t . Because corporate credit spreads exhibit a discernible upward trend over our sample period, we linearly detrended our proxy for the

¹⁶In the BGG framework, a portion of aggregate resources is lost due to the monitoring of entrepreneurs that face bankruptcy in a given period. Again, the importance of this term in practice is of second order, and, therefore, it is not included in the resource constraint equation.

external finance premium.¹⁷

Estimating the SW-model with the financial accelerator using Bayesian ML techniques requires one to specify a minimum of eight structural disturbances. In the absence of the financial accelerator, the model described above includes shocks to disembodied technology, intertemporal preferences, government spending, price and wage markups, and the nominal interest rate. With the financial accelerator, the model also includes shocks to the external finance premium and entrepreneurs' net worth, for a total of eight structural shocks. In their original formulation, Smets and Wouters [2007] estimated the model using the seven macroeconomic time-series discussed above, and they allowed for a shock to investment-specific technology. However, as emphasized by Justiniano, Primiceri, and Tambalotti [2008], the investment-specific technology shock may also be viewed as a disturbance to the financial sector. Because we are interested in determining the extent to which movements in investment and output may be due to financial factors, we therefore omit the investment-specific technology shock and replace it with the shock to entrepreneurial net worth.

Except for the two financial shocks, our specification of the model uses the same stochastic representation of structural disturbances as the SW-model. Specifically, let $[\eta_t^b, \eta_t^a, \eta_t^g, \eta_t^p, \eta_t^w, \eta_t^r, \eta_t^{fd}, \eta_t^{nw}]'$ denote a vector of mutually-uncorrelated i.i.d. shocks. The structural shocks to preferences (ε_t^b) and technology (ε_t^a) are assumed to follow stationary AR(1) processes:

$$\begin{aligned}\varepsilon_t^b &= \rho_b \varepsilon_{t-1}^b + \eta_t^b; \\ \varepsilon_t^a &= \rho_a \varepsilon_{t-1}^a + \eta_t^a,\end{aligned}$$

whereas the government spending shock (ε_t^g) follows a stationary AR(1) process that responds to an exogenous shock η_t^g and the shock to technology η_t^a :

$$\varepsilon_t^g = \rho_g \varepsilon_{t-1}^g + \eta_t^g + \rho_{ga} \eta_t^a.$$

The cost-push shocks to the price and wage equations (ε_t^p and ε_t^w) are parametrized as

¹⁷The secular rise in corporate credit spreads is consistent with the deepening of the markets for corporate debt—for example, the emergence of the “junk bond” market—which allowed higher-risk firms to tap the long-term cash market. The upward trend in credit spreads is also consistent with the secular increase in idiosyncratic volatility over the last four decades documented by Campbell, Lettau, Malkiel, and Xu [2001]. To ensure that our estimates of this secular trend were not driven by the outsize widening of credit spreads since the second half of 2008, we estimated the trend using an outlier-resistant M -regression.

stationary ARMA(1,1) processes:

$$\begin{aligned}\varepsilon_t^p &= \rho_p \varepsilon_{t-1}^p + \eta_t^p - \mu_p \eta_{t-1}^p; \\ \varepsilon_t^w &= \rho_w \varepsilon_{t-1}^w + \eta_t^w - \mu_w \eta_{t-1}^w.\end{aligned}$$

Regarding shocks to the financial sector, we assume that both financial shocks (ε_t^{fd} and ε_t^{mw}) follow stationary AR(1) processes:

$$\begin{aligned}\varepsilon_t^{fd} &= \rho_{fd} \varepsilon_{t-1}^{fd} + \eta_t^{fd}; \\ \varepsilon_t^{mw} &= \rho_{mw} \varepsilon_{t-1}^{mw} + \eta_t^{mw}.\end{aligned}$$

The estimation procedure relates observable data on the growth rates of output, consumption, investment, real wages (all in per capita terms), and prices, along with the nominal short-term interest rate and the credit spread to model variables through the following system of measurement equations:

$$\mathbf{Y}_t = \begin{bmatrix} \Delta \ln GDP_t \\ \Delta \ln CONS_t \\ \Delta \ln INV_t \\ \Delta \ln W_t \\ \ln HRS_t \\ \Delta \ln P_t \\ FF_t \\ CS_t \end{bmatrix} = \begin{bmatrix} \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{\gamma} \\ \bar{l} \\ \bar{\pi} \\ \bar{r} \\ 0 \end{bmatrix} + \begin{bmatrix} y_t - y_{t-1} \\ c_t - c_{t-1} \\ i_t - i_{t-1} \\ w_t - w_{t-1} \\ l_t \\ \pi_t \\ r_t \\ s_t \end{bmatrix},$$

where

$$\begin{aligned}\bar{\gamma} &= 100(\gamma - 1); \\ \bar{\pi} &= 100(\Pi_* - 1); \\ \bar{r} &= 100 \left(\frac{\Pi_*}{\beta} \gamma^{\sigma_c} - 1 \right).\end{aligned}$$

This specification allows for a common trend $\bar{\gamma}$ that is estimated from the data in the growth rates of real GDP, consumption, investment, and the real wage, as well as in the long-run inflation rate of Π_* . The long-run level of the nominal interest rate is then determined by the model-implied real interest rate in the steady state. Because our proxy for the external finance premium was linearly detrended, we impose a mean of zero on s_t in our estimation procedure.

The estimation procedure specifies a mix of structural parameters that are calibrated, and a set of structural parameters that are estimated using Bayesian ML methods. Following SW, we calibrate the rate of capital depreciation δ , the parameter governing the size of fixed costs in production ϕ_p , the exogenous share of government spending in GDP, the steady-state wage mark-up λ_w , and the curvature parameters of the Kimball aggregators in the goods and labor markets ϵ_p and ϵ_w , respectively; the calibrated values of these parameters are the same as those in SW. We also calibrate the entrepreneurial survival probability θ , to the value used by BGG. Finally, we set the steady-state value of the leverage ratio $K/N = 1.7$, the value that corresponds to the average leverage ratio in the U.S. nonfinancial corporate sector over the 1973–2008 period (see Figure 2). Estimated parameters then include the structural parameters pertaining to the the model without the financial accelerator, namely the vector $[\gamma, \alpha, \beta, \sigma_c, \sigma_l, \lambda, \xi_w, \xi_p, \epsilon_w, \epsilon_p, \iota_w, \iota_p, \varphi, \psi]'$, and the vector of parameters governing the time-series properties of the shock processes—that is, the persistence parameters $[\rho_a, \rho_b, \rho_g, \rho_w, \rho_p, \rho_{fd}, \rho_{mw}, \mu_w, \mu_p]'$ and the vector of standard deviations of the eight i.i.d. processes $[\sigma_a, \sigma_b, \sigma_g, \sigma_w, \sigma_p, \sigma_r, \sigma_{fd}, \sigma_{mw}]'$.

In addition to the above set of parameters, we also estimate the key parameter that govern the strength of the financial accelerator: χ , the elasticity of the external finance premium with respect to leverage. If $\chi = 0$ then, in the absence of shocks to ε_t^{fd} , the premium on external finance $s_t = 0$. In this case, there is no feedback from financial conditions to the real economy and hence no financial accelerator. By estimating this parameter, our procedure allows the model to determine the degree of financial market frictions necessary to explain the cyclical dynamics of the U.S. economy over the 1973–2008 period.

The Bayesian ML estimation procedure requires the specification of a prior distribution for each parameter estimated. For all parameters that are common to the SW-model, we adopt their priors for estimation purposes. The additional priors correspond to the parameter determining the elasticity of the external finance premium χ and the parameters governing the time-series properties of the two financial shocks. We set the prior for χ to a Beta distribution, with prior mean equal to the elasticity calibrated by BGG. Following the convention in SW, we set the prior distribution of the AR coefficients on the financial shock processes to a Beta distribution with prior mean equal to 0.5; similarly, the prior distribution for the standard deviation of the financial shocks is set to an Inverse Gamma distribution with prior mean equal to 0.1.

3.4 Results

3.4.1 Parameter Estimates

Table 6 contains our assumed prior distributions, along with the selected moments of the posterior distribution obtained from estimation, for the structural parameters of the model, whereas Table 7 reports the same results for the parameters pertaining to the shock processes. As indicated by the entries in Tables 6, our posterior estimates of the structural parameters are in most cases similar to those obtained by Smets and Wouters [2007], though there are some noticeable differences. For example, our estimates for both the degree of habit formation and the investment adjustment cost are somewhat higher, as is the intertemporal elasticity of substitution. Similar to the results reported by SW, our model estimates imply only a minor role for price and wage indexation, but they imply greater wage rigidity as measured by the Calvo wage-setting parameter. Finally, our estimated monetary policy rule is less responsive to both inflation and the output gap than the estimates obtained by SW, differences that may partly reflect the shorter sample period used in our estimation. The elasticity of the external finance premium is estimated to be 0.04—somewhat lower than its prior mean—but nonetheless substantially greater than zero and in the mid-range of previous estimates in the literature, a result pointing to a significant role of financial frictions in the model.

3.4.2 Impulse Responses and Historical Shock Decomposition

To assess the model’s performance, we report impulse response function to monetary and financial shocks in Figure 3–5. A contractionary monetary policy shock (Figure 3) causes a rise in the nominal interest rate and a deceleration in output and investment. Owing to habit formation and adjustment costs, the peak response in the level of output occurs about four quarters after the shock. These results are in line with the conventional wisdom on both the strength of the monetary transmission mechanism as well as the length of the average lag of the economy’s the response to monetary policy actions. The tightening of monetary policy also causes a decline in asset values and an increase in the external finance premium. Thus, monetary policy works in part by causing an increase in the cost of external funds through the deterioration in the strength of borrowers’ balance sheets.

Adverse credit supply shocks (Figure 4) also cause a significant reduction in economic activity. A one-standard-deviation increase in the shock to the external finance premium (ε_t^{fd}) causes an increase of about 25 basis points in the credit spread, which depresses the level of output by about 15 basis points and the level of investment by 75 basis points. Again, the responses of both the level of investment and output are hump-shaped with the peak response occurring eight to 10 quarters after the impact of the financial shock. Shocks

to net worth (Figure 5) have more pronounced and longer-lasting effects. A one-standard-deviation decline in net worth (ε_t^{nw}) implies substantial fluctuations in the levels of output and investment at the two- to three-year horizon. The long-lasting decline in investment implies a significant reduction in the supply of capital, which leads to rising marginal costs. As a result, model estimates imply that adverse shocks to net worth are inflationary and therefore may represent a significant tradeoff between inflation and output for the monetary authority.

To assess the relevance of disturbances in financial markets for economic outcomes, Figures 6–9 report the historical shock decomposition implied by the model. These figures plot the time-path of output, investment, the nominal interest rate, and the credit spread implied by each of the model shocks. Overall, these results accord well with the historical narrative regarding the role of monetary policy and financial conditions in determining economic outcomes. Monetary policy is estimated to be expansionary relative to the estimated rule during the 1975–79 period and again during the 2004–05 period. Monetary policy was significantly contractionary during the 1979–1982 period, the so-called “Volcker deflation”—and prior to the 1990–91 recession.

According to our shock decomposition, a significant fraction of investment and output dynamics are determined by shocks that emanate from the financial sector. In particular, financial disturbances account for nearly all of the investment declines in each recession that has occurred over the 1973–2008 period. Interestingly, financial shocks had a positive effect on investment during the 1980–82 economic downturn, a finding that is consistent with the view that financial deregulation during this time period helped to spur economic activity.

Regarding the current financial crisis, our model estimates imply that the direction of financial shocks reversed sharply in 2006, that is, from having a significantly expansionary effect on investment during 2005 to having a negative influence on investment spending by mid-2006. From this point onwards, deteriorating financial conditions have caused further declines in investment spending, culminating in the 10 percent drop in investment activity observed during the last quarter of 2008. This collapse in investment activity explains about two percentage points of the measured drop in output growth during 2008:Q4. According to our estimates, this adverse effect was partially offset by a positive shock to government spending, which may also proxy for the strength in the net export activity during this period. The remaining drop in output during this last quarter is explained by a drop in consumption, owing to a sharp increase in the desire of households to save rather than spend.

4 Conclusion

This paper provides compelling evidence of a systematic relationship between financial factors and the macroeconomy. Medium-risk, long-maturity corporate credit spreads are highly informative about the future course of economic activity. When used in an estimated DSGE framework, these credit spreads imply that a substantial fraction of cyclical fluctuations in output and investment over the 1973–2008 period can be attributed to disturbances that originated in the financial sector. Overall, our estimates imply that a New Keynesian DSGE model with the financial accelerator—when estimated using both real and financial market data—does well at capturing much of the historical narrative regarding the conduct of monetary policy and developments in financial markets that led to episodes of financial excess and distress over the last three decades and a half.

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Appendices

A Steady State of the Model

The following relations are derived from the steady state of the model without the financial accelerator:

$$R_*^K = \frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta); \quad (\text{A.1})$$

$$W = \left[\frac{\alpha^\alpha (1 - \alpha)^{(1-\alpha)}}{\phi_p (R_*^K)^\alpha} \right]; \quad (\text{A.2})$$

$$\frac{i}{k} = \gamma - (1 - \delta); \quad (\text{A.3})$$

$$\frac{l}{k} = \left[\frac{1 - \alpha}{\alpha} \right] \frac{R_*^K}{W}; \quad (\text{A.4})$$

$$\frac{k}{y} = \phi_p \left(\frac{l}{k} \right)^{(\alpha-1)}; \quad (\text{A.5})$$

$$i_y \equiv \frac{i}{y} = \left(\frac{i}{k} \right) \left(\frac{k}{y} \right); \quad (\text{A.6})$$

$$c_y \equiv \frac{c}{y} = 1 - g - \frac{i}{y}; \quad (\text{A.7})$$

$$z_y \equiv \frac{z}{y} = R_*^K \left(\frac{k}{y} \right); \quad (\text{A.8})$$

$$\frac{W_*^h L_*}{C_*} = \frac{1}{\phi_w} \frac{(1 - \alpha)}{\alpha} \left(\frac{z}{y} \right) \left(\frac{y}{c} \right). \quad (\text{A.9})$$

In the model without financial frictions, the required return on capital in steady state is given by

$$R_*^K = \frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta).$$

The addition of financial market frictions implies that

$$R_*^K = \left(\frac{K}{N} \right)^\chi \frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta); \quad \chi > 0,$$

and the steady-state equations A.1–A.9 are modified accordingly.

Table 1: Summary Statistics of Bond Characteristics

Bond Characteristic	Mean	SD	Min	P50	Max
# of bonds per firm/month	5.77	8.84	1.00	2.00	75.0
Mkt. Value of Issue ^a (\$mil.)	290.7	306.7	1.11	218.2	6,657
Maturity at Issue (years)	14.0	9.4	1.0	10.0	50.0
Term to Maturity (years)	11.8	8.61	0.01	8.62	30.0
Duration (years)	6.25	3.14	0.00	6.00	24.4
S&P Credit Rating	-	-	D	A3	AAA
Coupon Rate (pct.)	7.77	2.19	0.00	7.50	17.5
Nominal Effective Yield (pct.)	8.26	3.37	1.20	7.76	57.4
Credit Spread ^b (bps.)	178	275	10	110	4,995

*Panel Dimensions*Obs. = 360,996 $N = 5,269$ bonds

Min. Tenure = 1 Median Tenure = 59 Max. Tenure = 294

NOTE: Sample period: Monthly data from January 1973 to December 2008 for a sample of 926 nonfinancial firms. Sample statistics are based on trimmed data (see text for details).

^aMarket value of the outstanding issue deflated by the CPI (1982-84 = 100).

^bMeasured relative to comparable maturity Treasury yield (see text for details).

Table 2: Financial Asset Prices and Labor Market and Production Indicators

<i>Activity Indicator: Private Nonfarm Payroll Employment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.407 (0.148)	-0.422 (0.158)	-0.273 (0.161)
Real Federal Funds Rate	-0.258 (0.129)	-0.256 (0.131)	-0.233 (0.128)
Baa Credit Spread	-	-0.123 (0.539)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-1.247 (0.459)
Adj. R^2	0.508	0.505	0.554
<i>Activity Indicator: Unemployment Rate</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	0.307 (0.088)	0.283 (0.086)	0.263 (0.091)
Real Federal Funds Rate	0.098 (0.066)	0.098 (0.057)	0.090 (0.057)
Baa Credit Spread	-	-0.135 (0.233)	-
Medium-Risk Long-Maturity Credit Spread	-	-	0.461 (0.219)
Adj. R^2	0.434	0.434	0.461
<i>Activity Indicator: Manufacturing Industrial Production</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-1.207 (0.425)	-1.117 (0.395)	-0.982 (0.468)
Real Federal Funds Rate	-0.559 (0.220)	-0.560 (0.225)	-0.512 (0.231)
Baa Credit Spread	-	-0.514 (1.268)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-2.453 (1.062)
Adj. R^2	0.358	0.356	0.393

NOTE: Sample period: 1973:Q1 to 2008:Q4 ($T = 140$). Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms if necessary). Each specification also includes a constant, current, and three lags of ΔY_t and is estimated by OLS. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West [1987] and are reported in parentheses (see text for details).

Table 3: Financial Asset Prices, Output, and Investment

<i>Activity Indicator: Real GDP</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.625 (0.215)	-0.607 (0.210)	-0.564 (0.228)
Real Federal Funds Rate	-0.155 (0.129)	-0.154 (0.131)	-0.144 (0.131)
Baa Credit Spread	-	0.102 (0.467)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-0.675 (0.478)
Adj. R^2	0.302	0.297	0.313
<i>Activity Indicator: Real Business Fixed Investment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.656 (0.606)	-0.830 (0.689)	0.062 (0.673)
Real Federal Funds Rate	-1.012 (0.353)	-1.003 (0.351)	-0.877 (0.375)
Baa Credit Spread	-	-1.531 (2.017)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-6.094 (2.039)
Adj. R^2	0.371	0.375	0.472

NOTE: Sample period: 1973:Q1 to 2008:Q4 ($T = 140$). Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms). Each specification also includes a constant, current, and three lags of ΔY_t and is estimated by OLS. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West [1987] and are reported in parentheses (see text for details).

Table 4: Financial Asset Prices and Labor Market and Production Indicators

<i>Activity Indicator: Private Nonfarm Payroll Employment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.432 (0.132)	-0.453 (0.142)	-0.337 (0.129)
Real Federal Funds Rate	-0.216 (0.118)	-0.219 (0.117)	-0.027 (0.123)
Baa Credit Spread	-	-0.318 (0.453)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-1.319 (0.309)
Adj. R^2	0.699	0.700	0.750
<i>Activity Indicator: Unemployment Rate</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	0.246 (0.095)	0.250 (0.094)	0.182 (0.086)
Real Federal Funds Rate	0.071 (0.061)	0.080 (0.066)	0.009 (0.065)
Baa Credit Spread	-	0.137 (0.243)	-
Medium-Risk Long-Maturity Credit Spread	-	-	0.600 (0.177)
Adj. R^2	0.492	0.491	0.553
<i>Activity Indicator: Manufacturing Industrial Production</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.951 (0.490)	-1.127 (0.538)	-0.611 (0.388)
Real Federal Funds Rate	-0.062 (0.325)	-0.113 (0.339)	0.852 (0.370)
Baa Credit Spread	-	-1.700 (1.341)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-6.518 (1.209)
Adj. R^2	0.215	0.237	0.471

NOTE: Sample period: 1986:Q1 to 2008:Q4 $T = 88$. Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms if necessary). Each specification also includes a constant, current, and three lags of ΔY_t and is estimated by OLS. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West [1987] and are reported in parentheses (see text for details).

Table 5: Financial Asset Prices, Output, and Investment

<i>Activity Indicator: Real GDP</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-0.312 (0.175)	-0.377 (0.200)	-0.161 (0.203)
Real Federal Funds Rate	-0.008 (0.149)	-0.018 (0.150)	0.226 (0.177)
Baa Credit Spread	-	-0.198 (0.491)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-2.001 (0.407)
Adj. R^2	0.109	0.101	0.319
<i>Activity Indicator: Real Business Fixed Investment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3-month – 10-year)	-1.393 (0.636)	-1.243 (0.485)	0.215 (0.729)
Real Federal Funds Rate	-0.654 (0.400)	-1.003 (0.432)	0.341 (0.463)
Baa Credit Spread	-	-5.241 (2.757)	-
Medium-Risk Long-Maturity Credit Spread	-	-	-10.21 (2.127)
Adj. R^2	0.431	0.508	0.633

NOTE: Sample period: 1986:Q1 to 2008:Q4 $T = 88$. Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms). Each specification also includes a constant, current, and three lags of ΔY_t and is estimated by OLS. Heteroscedasticity- and autocorrelation-consistent asymptotic standard errors are computed according to Newey and West [1987] and are reported in parentheses (see text for details).

Table 6: Prior and Posterior Distributions of Structural Parameters

Parameter	<i>Prior</i>			<i>Posterior</i>			
	Distribution	Mean	SD	Mode	Mean	P5	P95
χ	Beta	0.07	0.02	0.04	0.04	0.03	0.05
φ	Normal	4.00	1.50	6.53	6.75	5.45	7.83
σ_c	Normal	1.50	0.37	1.10	1.11	1.00	1.21
λ	Beta	0.70	0.10	0.79	0.81	0.77	0.85
ξ_w	Beta	0.50	0.10	0.94	0.93	0.92	0.95
σ_l	Normal	2.00	0.75	2.26	2.41	1.90	2.86
ξ_p	Beta	0.50	0.10	0.76	0.74	0.70	0.78
ι_w	Beta	0.50	0.15	0.26	0.23	0.12	0.36
ι_p	Beta	0.50	0.15	0.22	0.23	0.14	0.40
ψ	Beta	0.50	0.15	0.34	0.30	0.20	0.39
ϕ_p	Normal	1.25	0.12	1.62	1.65	1.58	1.71
r_π	Normal	1.50	0.25	1.12	1.12	1.05	1.20
ρ	Beta	0.75	0.10	0.73	0.72	0.67	0.76
r_y	Normal	0.12	0.05	0.01	0.01	0.00	0.01
$r_{\Delta y}$	Normal	0.12	0.05	0.11	0.09	0.07	0.13
$\overline{\pi}$	Gamma	0.62	0.10	0.65	0.68	0.58	0.76
$100(\beta^{-1} - 1)$	Gamma	0.25	0.10	0.80	0.76	0.69	0.84
$\bar{l}$	Normal	0.00	2.00	-1.06	-0.85	-2.27	0.74
$\overline{\gamma}$	Normal	0.40	0.10	0.42	0.43	0.41	0.45
α	Normal	0.30	0.05	0.26	0.26	0.22	0.30

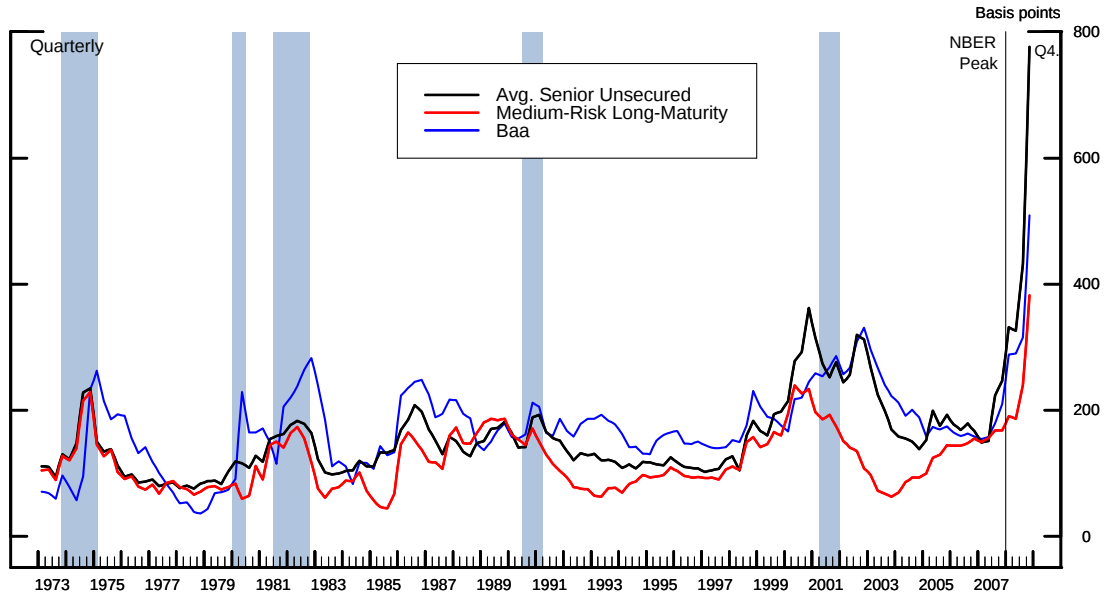
NOTE: Entries under the heading *Priors* specify the mean and the standard deviation of the prior distribution for the model's estimated structural parameters (see text for details). Entries under the heading *Posterior* denote the Bayesian ML estimates of the mean and the mode, along with the 5th (P5) and 95th percentiles (P95), of the posterior distribution.

Table 7: Prior and Posterior Distributions of Structural Shock Processes

Parameter	<i>Prior</i>			<i>Posterior</i>			
	Distribution	Mean	SD	Mode	Mean	P5	P95
σ_{nw}	Inv. Gamma	0.10	2.00	0.87	0.86	0.68	1.05
σ_{fd}	Inv. Gamma	0.10	2.00	0.06	0.06	0.06	0.07
σ_a	Inv. Gamma	0.10	2.00	0.41	0.42	0.38	0.46
σ_b	Inv. Gamma	0.10	2.00	0.22	0.22	0.18	0.26
σ_g	Inv. Gamma	0.10	2.00	0.49	0.50	0.45	0.55
σ_r	Inv. Gamma	0.10	2.00	0.24	0.25	0.22	0.27
σ_p	Inv. Gamma	0.10	2.00	0.14	0.14	0.11	0.16
σ_w	Inv. Gamma	0.10	2.00	0.24	0.23	0.20	0.26
ρ_{nw}	Beta	0.50	0.20	0.98	0.97	0.95	0.99
ρ_{fd}	Beta	0.50	0.20	0.90	0.88	0.84	0.92
ρ_a	Beta	0.50	0.20	0.93	0.93	0.89	0.96
ρ_b	Beta	0.50	0.20	0.22	0.23	0.08	0.34
ρ_g	Beta	0.50	0.20	0.99	0.99	0.99	0.99
ρ_r	Beta	0.50	0.20	0.22	0.28	0.16	0.40
ρ_p	Beta	0.50	0.20	0.76	0.72	0.61	0.83
ρ_w	Beta	0.50	0.20	0.91	0.90	0.85	0.95
μ_p	Beta	0.50	0.20	0.55	0.48	0.33	0.67
μ_w	Beta	0.50	0.20	0.89	0.86	0.79	0.93
ρ_{ga}	Beta	0.50	0.20	0.59	0.66	0.54	0.80

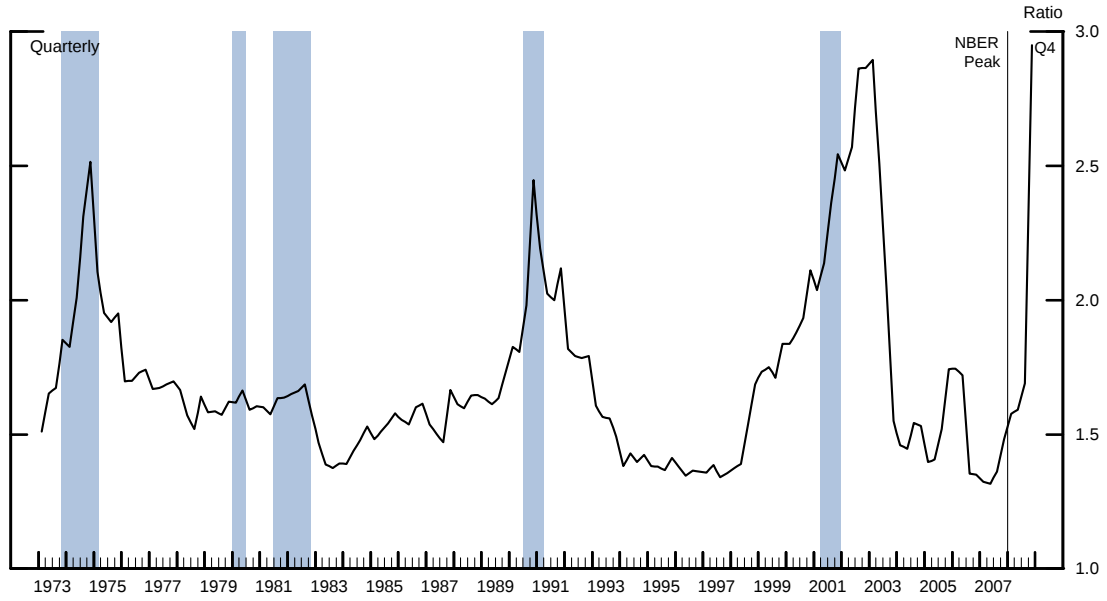
NOTE: Entries under the heading *Priors* specify the mean and the standard deviation of the prior distribution for the parameters governing the time-series properties of the model's structural shocks (see text for details). Entries under the heading *Posterior* denote the Bayesian ML estimates of the mean and the mode, along with the 5th (P5) and 95th percentiles (P95), of the posterior distribution.

Figure 1: Selected Corporate Bond Spreads



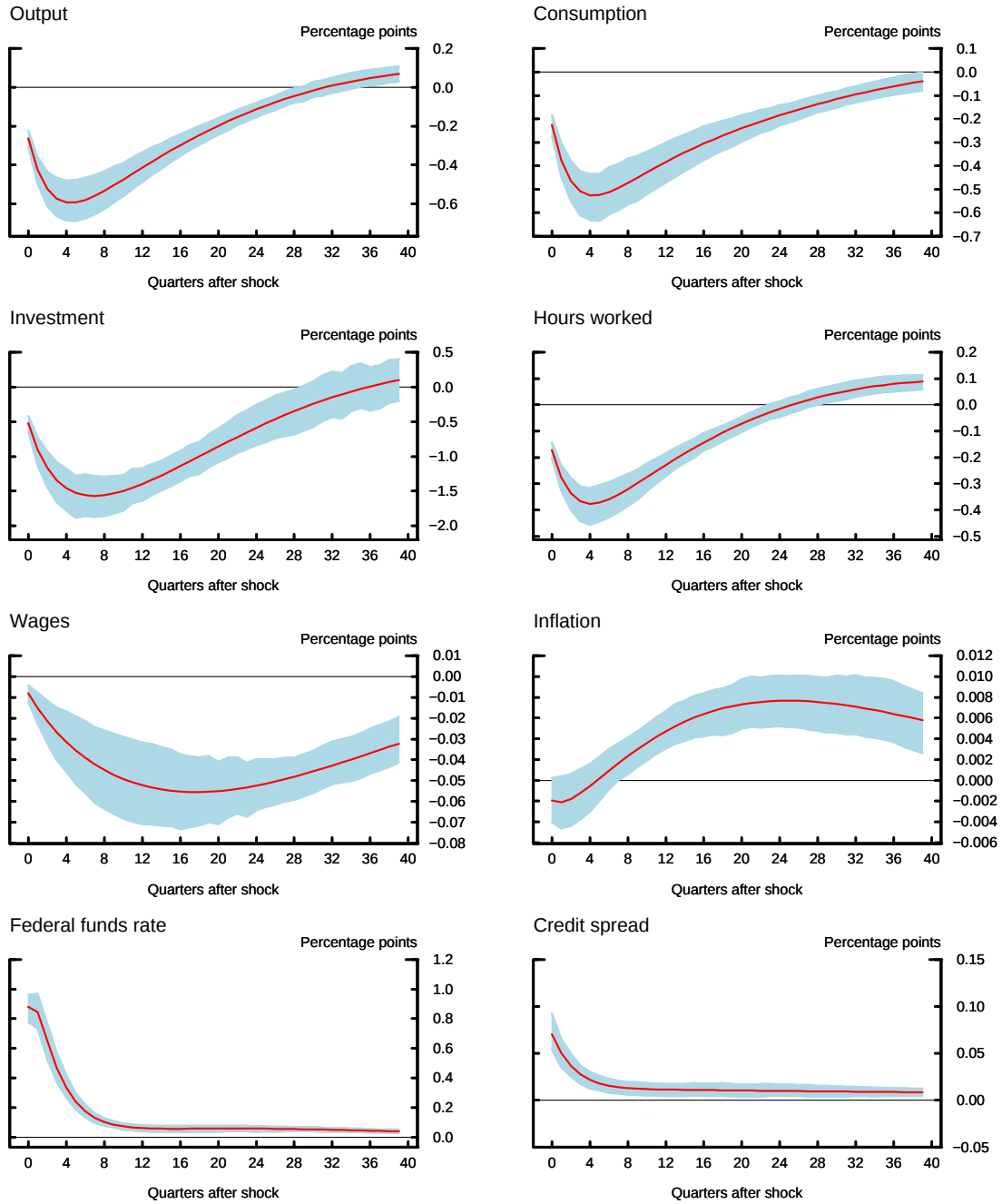
NOTE: The black line depicts the average credit spread for our sample of 5,269 senior unsecured corporate bonds; the red line depicts the average credit spread associated with very long maturity corporate bonds issued by firms with low to medium probability of default (see text for details); and the blue line depicts the standard Baa credit spread, measured relative to the 10-year Treasury yield. The shaded vertical bars denote NBER-dated recessions.

Figure 2: Leverage Ratio



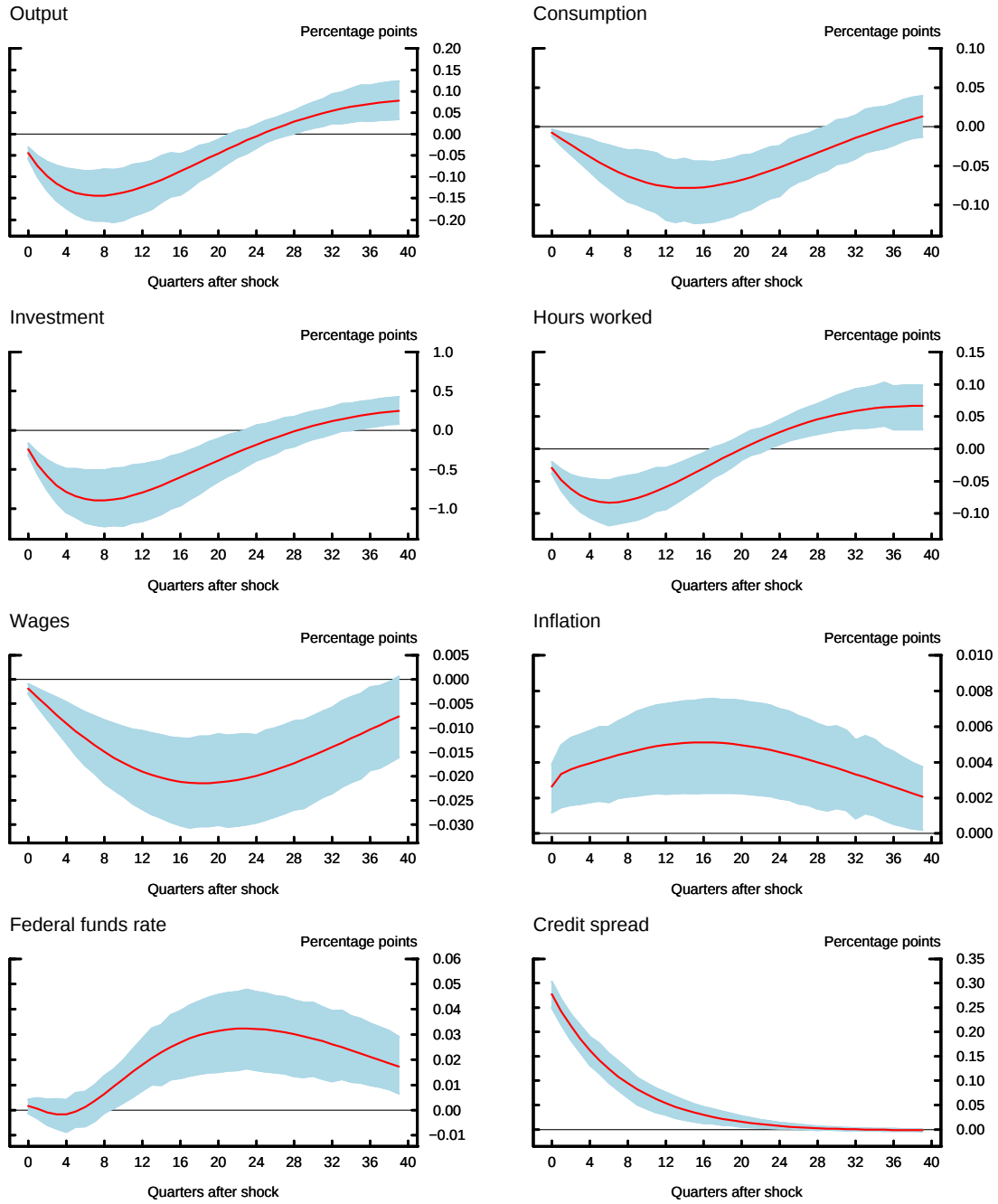
NOTE: The black line depicts the time-series of the cross-sectional averages of the leverage ratio for U.S. nonfinancial corporations. Leverage is defined as the ratio of the market-value of the firm's total assets (V) to the market-value of the firm's common equity (E), where the market-value of the firm's total assets is calculated using the Merton-DD model (see text for details). The shaded vertical bars denote NBER-dated recessions.

Figure 3: Model Responses to a Contractionary Monetary Policy Shock



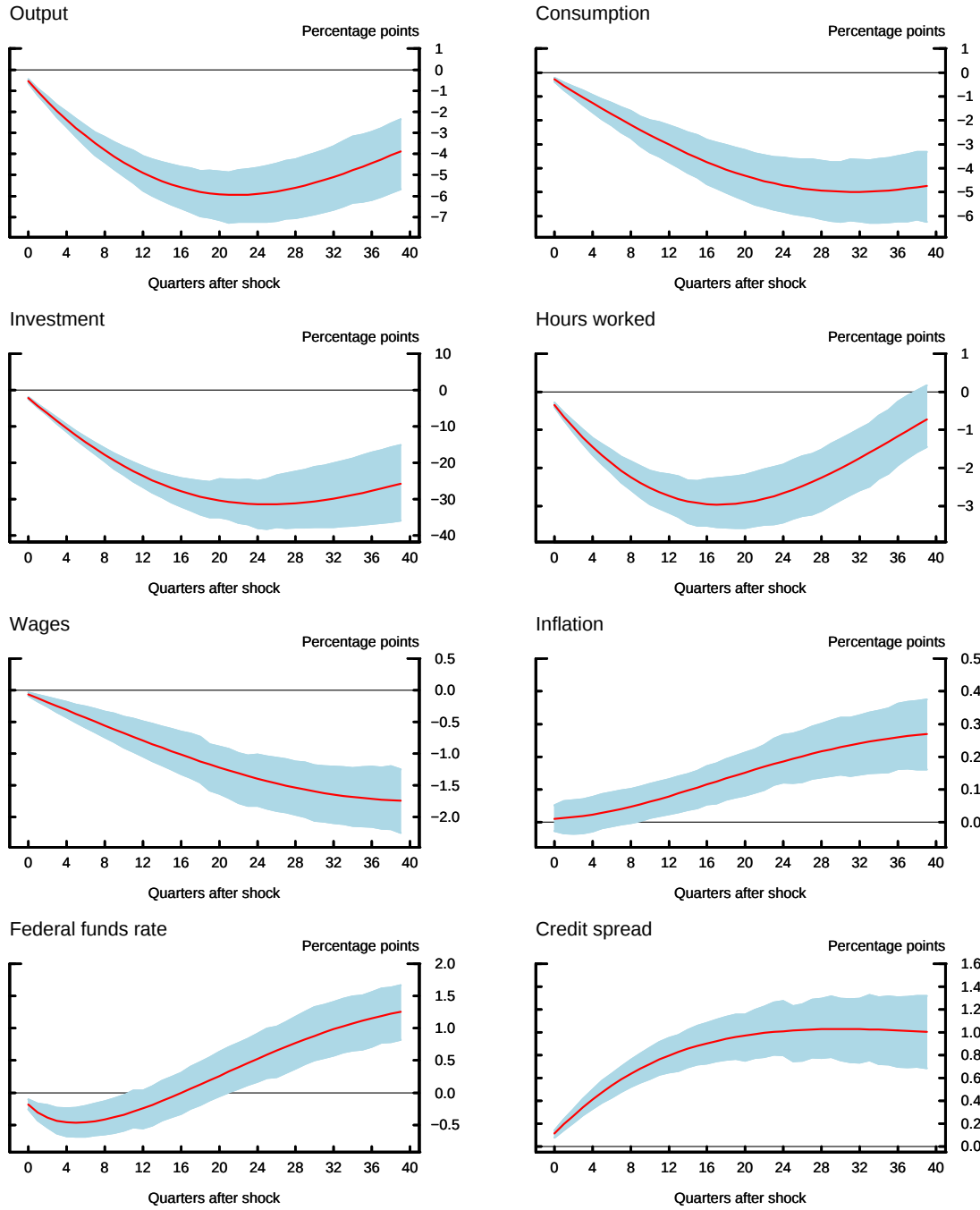
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation monetary policy shock. The shaded bands denote the 80 percent confidence intervals.

Figure 4: Model Responses to an Adverse Credit Supply Shock



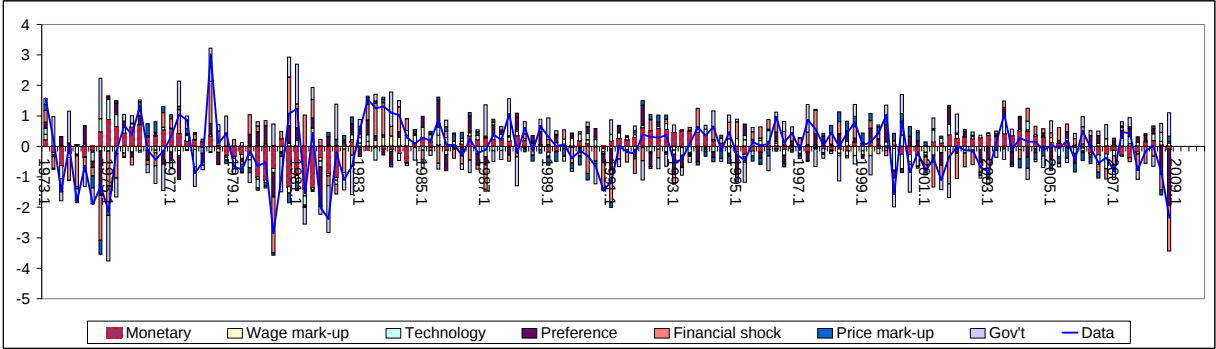
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation credit supply shock. The shaded bands denote the 80 percent confidence intervals.

Figure 5: Model Responses to an Adverse Network Shock



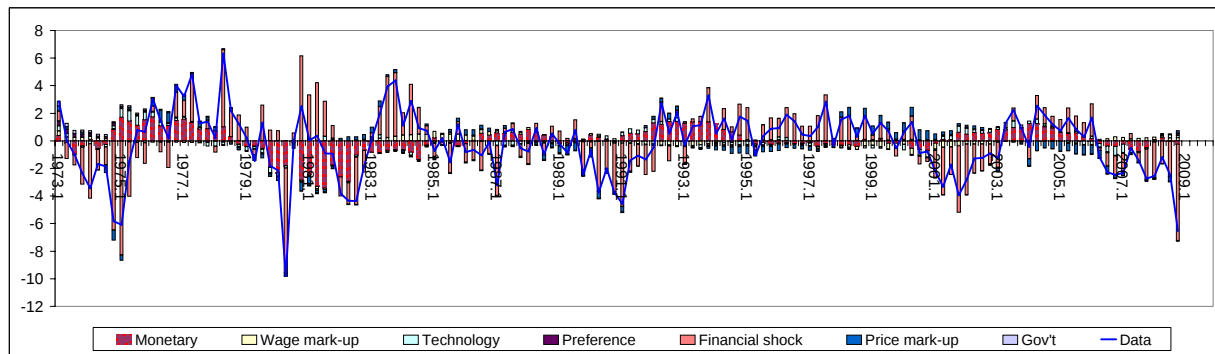
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation network shock. The shaded bands denote the 80 percent confidence intervals.

Figure 6: Historical Decomposition of Output Growth



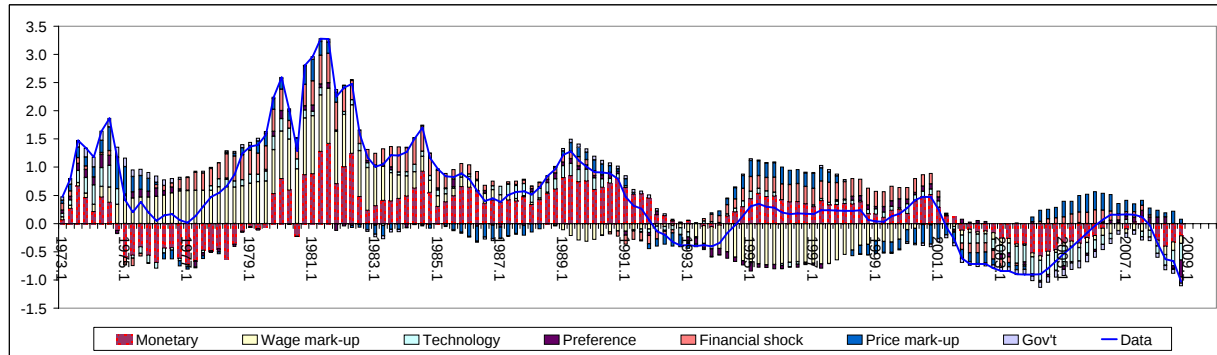
NOTE: The solid blue line depicts the behavior of actual variables expressed in percentage point deviations from steady state, while the colored portion in each column indicate the estimated contribution of the specific shock.

Figure 7: Historical Decomposition of Investment Growth



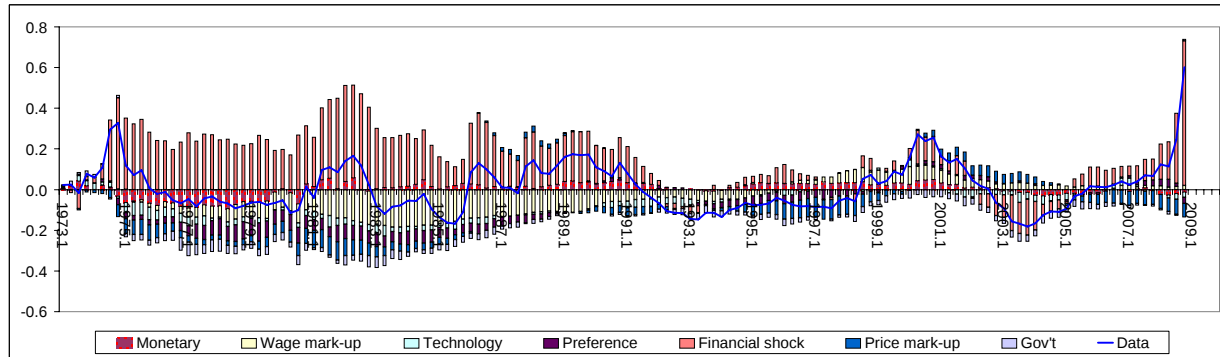
NOTE: The solid blue line depicts the behavior of actual variables expressed in percentage point deviations from steady state, while the colored portion in each column indicate the estimated contribution of the specific shock.

Figure 8: Historical Decomposition of the Federal Funds Rate



NOTE: The solid blue line depicts the behavior of actual variables expressed in percentage point deviations from steady state, while the colored portion in each column indicate the estimated contribution of the specific shock.

Figure 9: Historical Decomposition of the Credit Spread



NOTE: The solid blue line depicts the behavior of actual variables expressed in percentage point deviations from steady state, while the colored portion in each column indicate the estimated contribution of the specific shock.