

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

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Abstract

Embedded in canonical macroeconomic models is the assumption of frictionless financial markets, implying that the composition of borrowers' balance sheets has no effect on their spending decision. As a result, these models have a difficult time accounting for the feedback effects between financial conditions and the real economy during periods of financial turmoil. 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 business cycle fluctuations by estimating a DSGE model with the financial accelerator mechanism that links balance sheet conditions to the real economy through movements in the external finance premium. Our estimation methodology incorporates a high information-content credit spread—constructed directly from the secondary-market prices of outstanding corporate bonds—into the Bayesian ML estimation. This credit spread serves as a proxy for the unobservable external finance premium, an approach that allows us to estimate simultaneously the key parameters of the financial accelerator mechanism along with the shocks to the financial sector. Our results indicate the presence of an operative financial accelerator in U.S. cyclical fluctuations over the 1973–2009 period: Increases in the external finance premium cause significant and protracted declines in investment and output. The estimated effects of financial shocks and their impact on the macroeconomy also accord well with historical perceptions of the interaction between financial conditions and economic activity during cyclical fluctuations over the past three decades and a half.

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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 turmoil in mortgage markets subsequently spread to a variety of other asset classes, 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 financial crisis (as well as previous crises) 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 discounted values and hence appropriately calculated user-costs for financing real consumption and investment

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/monetarpolicy/bst.htm>.

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 and government securities of comparable maturity—and macroeconomic outcomes. In the

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.

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 version of the 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:Q1–2009:Q1 period, an approach closely related to the recent work of Christiano, Motto, and Rostagno [2008, 2009], 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 [2008]

⁴Whether observable credit spreads are a good proxy for the unobservable external finance premium is, of course, model dependent. Employing firm-level data on credit spreads, EDFs, and leverage Levin, Natalucci, and Zakrajšek [2006] estimated directly the structural parameters of the debt-contracting problem

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 [2009], though allowing for a wide variety of shocks to the financial sector, do 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 structural parameters 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 results identify the presence of an operative financial accelerator mechanism in U.S. cyclical fluctuations over the 1973–2009 period: Increases in the external finance premium cause significant and protracted declines in investment and output. Moreover, financial disturbances account for a significant portion of the decline in both investment and output during economic downturns since the mid-1970s. According to the historical decomposition of the model’s shocks, financial disruptions were mainly responsible for the sharp drop in both output and investment during the economic turmoil of the mid-1970s, and credit supply shocks have contributed importantly to the deceleration in output and the collapse of investment during the 1990–91 and 2001 recessions. On the other hand, the easing of financial conditions during the latter part of the 1990s provided a significant impetus to investment spending. Finally, our estimates imply that the current financial crisis—largely through its impact on 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

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,

Despite considerable success, results from this strand of research are often sensitive to the 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) relied 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 utilized 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 or the Baa and the high-yield corporate credit spread indexes. The predictive power of corporate bond spreads for economic activity comes from the middle of the credit quality spectrum and is concentrated in securities with a long

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.

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.

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 a medium probability of default. We compare its forecasting ability 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 Data Sources and Methods

2.1.1 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 927 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.⁷ 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 label 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 5,661 individual securities between January 1973 and March 2009.

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

⁷These 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).

as many as 76 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 six 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 7.67 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 183 basis points above the comparable-maturity risk-free rate, with the standard deviation of 283 basis points.

2.1.2 Credit Risk Indicators

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

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

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

where μ_V denotes the expected continuously compounded return on V ; σ_V is the volatility of firm value; and dW is an increment of the standard Weiner process. The second critical assumption pertains to the firm’s capital structure. In particular, it is assumed that the firm has just issued a single discount bond in the amount D that will mature in T periods.⁸

⁸Recent structural default models relax this assumption and allow for endogenous capital structure as

Together, these two assumptions 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.⁹ 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

well as for strategic default. In these models, both the default time and default boundary are determined endogenously and depend on firm-specific as well as aggregate factors; the voluminous literature on structural default models is summarized by Duffie and Singleton [2003] and Lando [2004] contains an excellent practical exposition of the contingent claims approach to corporate credit risk.

⁹This assumption for the "default point" is also used by Moody's/KMV in the construction of their Expected Default Frequencies (EDFs) based on the Merton DD-model, and it captures the notion that short-term debt requires a repayment of the principal relatively soon, whereas long-term debt requires the firm to meet only the coupon payments. Both current and long-term liabilities are taken from quarterly Compustat files and interpolated to daily frequency using a step function.

[2003] and Vassalou and Xing [2004], the excessive volatility of market leverage (V/E) in equation 4 causes large swings in the estimated volatility of the firm’s value σ_V , which are difficult to reconcile with the observed frequency of defaults and movements in financial asset prices.

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

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

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

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

which, under the assumptions of the Merton model, should be a sufficient statistic for predicting defaults.¹⁰

2.1.3 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 from the previous month. In particular, to construct the medium-risk, long-maturity credit spread for month t , we calculate the 25th and 75th percentiles of the cross-sectional distribution of the distance-to-default at the end of month $t - 1$, using the sample of all publicly-traded firms in the matched CRSP/Compustat databases (more than 2,700 firms in an average month). The resulting time-varying thresholds define the “medium-risk” category for our sample of 926 bond issuers in month t . Within this credit risk category, which is based on the information available through the end of month $t - 1$, we then select all bonds with the remaining term-to-maturity of more than 15 years and compute an arithmetic average of

¹⁰Note that, even if the EDF is not a sufficient statistic for predicting defaults, DD may still be a good indicator for ranking firms into different categories of risk. Indeed, that is essentially the operational philosophy used by Moody’s/KMV when constructing their EDFs; see Crosbie and Bohn [2003] for a complete discussion.

credit spreads for each month t .¹¹

Figure 1 shows our medium-risk, long-maturity credit spread, along with 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.¹² Both credit spread indexes show substantial variation and comovement over the business cycle, although the correlation between the two series is only 0.55. Note also that the Baa spread is noticeably more volatile than the medium-risk, long-maturity credit spread, especially during economic downturns. Focusing on the current period of financial turmoil, both 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.

2.2 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;¹³ RFF_t denotes the real federal funds rate;¹⁴ CS_t denotes a

¹¹In an average month, our portfolio of medium-risk, long-maturity bonds consists of about 130 different securities out of more than 800 different issues that are traded in the secondary market in a typical month.

¹²The 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.

¹³The 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].

¹⁴In calculating the real federal funds rate, we employed 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 in quarter $t - 1$ and its lagged value four quarters earlier. Of course, under the expectations hypothesis—and neglecting term premiums—the term spread is

credit spread; and ϵ_{t+h} is the forecast error. The forecasting regression given by equation 7 is estimated using OLS, and the $MA(h-1)$ structure of the error term induced by overlapping observations is taken into account by computing the covariance matrix of regression coefficients according to Hodrick [1992].¹⁵

Within this forecasting framework, we analyze the predictive content of financial asset prices for three broad categories of economic activity indicators. First, we examine the forecasting ability of financial indicators for changes in labor market conditions, specifically, the growth of private (nonfarm) payroll employment and the change in the (civilian) unemployment rate. Given the lagging nature of labor market indicators, we then turn to leading or coincident economic indicators, such as the growth in manufacturing industrial production and business inventories. Lastly, we consider the broadest measures of economic activity, namely the growth of real GDP and real business fixed investment. Focusing on the year-ahead horizon (i.e., $h = 4$), our first set of forecasting results utilizes data over the entire sample period (1973:Q1–2009:Q1). 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 over the post-1986 period, the so-called “Great Moderation.”

2.2.1 Forecasting Results: 1973–2009

The results in Table 2 detail the predictive power of various financial indicators for labor market developments. According to the baseline specification (column 1), the current slope of the yield curve is a statistically and economically significant predictor of future changes in labor market conditions, with the inversion of the yield curve signalling a slowdown in the pace of hiring and a rise in the unemployment rate. 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 and pushes the unemployment rate up by more than one-quarter 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 deterioration in

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.

¹⁵In a recent paper, Ang and Bekaert [2007] provided a systematic comparison of various HAC estimators of standard errors in the context of overlapping observations. According to their findings, the use of Newey and West [1987] standard errors leads to severe over-rejections of the null hypothesis of no predictability, whereas the standard errors developed by Hodrick [1992] retain the correct size even in relatively small samples. That said, all of our results were robust to the choice of Newey-West or Hodrick standard errors.

labor market conditions.

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—indeed, the effect of the Baa spread on both labor market indicators, though statistically significant, is of the wrong sign. In contrast, the credit spread based on long-maturity senior unsecured bonds issued by medium-risk firms (column 3) is a highly significant predictor of future labor market conditions: a one-percentage-point rise in the medium-risk, long-maturity spread in quarter t lowers employment growth over the subsequent four quarters by more than 1.5 percentage points and boosts the unemployment rate by more than one-half percentage points.

The results in Table 3 summarize the predictive power of these financial indicators for the growth in industrial output and business inventory investment. According to the entries in column 1 (top panel), the current shape of the yield curve and the real funds rate are both statistically and economically significant predictors of the subsequent growth in manufacturing industrial production. In contrast, neither financial indicator appears to contain much predictive content for the year-ahead growth in business inventories. The inclusion of the Baa credit spread in the forecasting regression (columns 2) yields a noticeable improvement in the goodness-of-fit for inventory investment over the subsequent four quarters, but does not improve the explanatory power of the regression for the year-ahead growth in manufacturing industrial production.

In contrast, our credit spread based on long-maturity senior unsecured bonds issued by medium-risk firms (column 3) is a highly significant predictor for these two volatile leading economic indicators: a one-percentage-point rise in the medium-risk, long-maturity spread in quarter t lowers the growth of industrial output over the subsequent four quarters by three and a half percentage points and cuts more than two percentage points from the year-ahead growth in business inventories. Moreover, in the case of inventory investment, the presence of this default-risk indicator in the forecasting regression yields a significantly larger increase in the explanatory power compared with the standard Baa credit spread.

Finally, Table 4 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 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. The standard Baa credit spread index (column 2) has no marginal predictive power for either of these two broad measures of economic activity, whereas our medium-risk, long-maturity credit spread (column 3) is, economically and statistically, a highly significant predictor in both forecasting regressions. For example, a one-percentage-point widening in

our credit spread leads to a more than one-percentage-point drop in economic growth over the subsequent four quarters. Movements in medium-risk, long-maturity credit spreads appear to be particularly informative about the future course of capital spending, as a one-percentage-point increase in such spreads is associated with a subsequent drop in the growth of real business fixed investment of more than a seven percentage points.

We now briefly examine the predictive content of the medium-risk, long-maturity credit spread using pseudo out-of-sample forecasts. Specifically, we consider two forecasting specifications. In terms of financial indicators, the first specification includes the term spread, the real federal funds rate, and the standard Baa-Treasury credit spread (i.e., column 2 in the previous tables), whereas the medium-risk, long-maturity credit spread is the only financial indicator in the second specification. Focusing on the forecast horizon of four quarters, these two specifications are estimated using all available data through, and including, 1989:Q1. We then calculate the four-quarter ahead growth rates (or changes in the case of unemployment rate) for our set of economic indicators and the associated forecast errors. The forecast origin is then updated with an additional quarter of data, the regression parameters in both specifications 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 each measure of economic activity.

Tables 5 contains the results of this exercise.¹⁶ In all cases, the specification that includes the medium-risk, long-maturity credit spread yields substantial gains in out-of-sample predictive accuracy at the four-quarter forecast horizon, results consistent with the in-sample analysis presented above. Relative to the specification that includes the standard set of financial indicators, reductions in the MSFEs range from 40 percent in the case of employment growth to about 25 percent for fixed and inventory investment. Moreover, these improvements in predictive accuracy—with the exception of business fixed investment—are also highly statistically significant according to the Diebold-Mariano test.

¹⁶To quantify the pseudo out-of-sample forecasting performance of the two models, we report the square root of the mean squared forecast error in percentage points (RMSFE) for each specification. To compare the predictive accuracy of our medium-risk, long-maturity credit spreads with that of standard financial indicators, we then compute the ratio of the mean squared forecast error (MSFE) from the regression specification augmented with the medium-risk, long-maturity credit spread relative to the MSFE from the specification that includes the standard financial indicators; *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. Because the data in our forecasting specification are overlapping, the asymptotic (long-run) variance of the loss differential used to construct the Diebold-Mariano *S*-statistic allows for fourth-order serial correlation.

2.2.2 Forecasting Results: 1986–2009

As a robustness check, this section repeats the in-sample forecasting exercise 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.¹⁷

Table 6 contains our forecasting results based on the specification that includes our medium-risk, long-maturity credit spread for the post-1986 period. As evidenced by the entries in the table, our medium-risk, long-maturity credit spread continues to provide significant information for all six indicators of economic activity. Indeed, the estimated coefficients on the credit spread are noticeably larger (in absolute value) than those reported in Tables 2–4, and the associated confidence intervals are appreciably narrower compared with those estimated over the full sample period. In contrast, the standard Baa credit spread (not shown) generally remains an insignificant predictor—either statistically or economically—for all measures of economic activity, a result consistent with those reported in the previous section. Moreover, the presence of the medium-risk, long-maturity credit spread tends to eliminate the predictive content of the term spread and the real federal funds rate for a number of economic indicators.

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

¹⁷Although 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 Tables 2–3. However, we reject at conventional significance levels 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 4). Thus, this limited evidence suggests a stable relationship between our set of financial indicators and changes in labor market conditions as well as the growth in industrial output, inventories, and capital spending, but points to some structural instability in the relationship between financial indicators and the growth in real GDP.

is embedded in long-maturity bonds issued by firms in the middle of the credit quality spectrum. Such credit spreads hold substantial information content for leading, coincident, and lagging economic indicators 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, the real federal funds rate, and the standard default-risk indicators.

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. Following the work of Christiano, Eichenbaum, and Evans [2005], SW develop 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 capacity 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. Our modified version of the SW model also includes a shock to investment-specific technology, an important source of cyclical fluctuations, according to the recent work of Justiniano, Primiceri, and Tambalotti [2008]. 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.¹⁸

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 u_t , and an exogenous disturbance (i.e., government spending) to the resource constraint ε_t^g :

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

¹⁸As discussed above, our estimation strategy is very similar to that of Christiano, Motto, and Rostagno [2009], who also embed the BGG-type financial accelerator into an estimated DSGE model. Their framework includes all of the basic features that we have adopted, and it also allows for a fully-developed banking and monetary sector that includes cash-in-advance constraints and working capital loans. Christiano, Motto, and Rostagno [2009] estimate their model using 17 time series and allow for an equal number of structural disturbances. By simply adding the financial accelerator of BGG to the SW model, our approach is less ambitious in scope, however. It entails estimating the DSGE model with nine time series, allowing for nine structural shocks. A benefit of our approach is that it allows for a more direct comparison with the findings of both SW and the recent work by Primiceri, Schaumburg, and Tambalotti [2006] and Justiniano, Primiceri, and Tambalotti [2008], who highlighted the role of intertemporal disturbances as a driving force of business cycle fluctuations.

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 u_t , according to

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

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:

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

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; h 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 :

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

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 and a shock to the investment technology $\varepsilon_t^{\mathcal{I}}$:

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

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:

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

where R_*^K is the steady-state value of the return on capital and δ denotes the rate of capital depreciation. Lastly, the log-linearized equation for capital accumulation can be expressed as

$$k_t = \left[\frac{1 - \delta}{\gamma} \right] k_{t-1} + \left[1 - \frac{1 - \delta}{\gamma} \right] i_t + \left[1 - \frac{1 - \delta}{\gamma} \right] \left[1 + \beta\gamma^{(1-\sigma_c)} \right] \gamma^2 \varphi \varepsilon_t^{\mathcal{I}}. \quad (16)$$

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.¹⁹ Then,

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

and

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

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

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

¹⁹Note 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.

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 :

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

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 :

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

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

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

where R_*^K denotes the steady-state value of the return on capital in the model with the financial accelerator.²⁰

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

²⁰As 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 $\left(\frac{K}{N}\right)^\chi \frac{1}{\beta} \gamma^{\sigma_c} - (1 - \delta)$. In the flexible economy without the financial accelerator case $\chi = 0$.

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:

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

where the coefficient $\chi > 0$ measures the elasticity of the premium with respect to leverage $q_t + k_t - n_t$. 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 or a shock to the financial sector that boosts the external finance premium beyond the level warranted by the current economic conditions and the current stance of monetary policy.²¹ 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:

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

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

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

²¹Christiano, Motto, and Rostagno [2009] provided a structural interpretation of this shock, arguing that it represents an increase in the variance of idiosyncratic shocks affecting the firm's profitability, which exacerbates the costly-state verification problem faced by entrepreneurs. In the BGG model, this shock may also reflect an increase in the monitoring costs (i.e., a decline in recovery rates in the case of default). Such an interpretation is consistent with the work of Levin, Natalucci, and Zakrajšek [2006] who documented the importance of time-varying monitoring costs for the observed magnitude of corporate credit spreads.

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:

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

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.²² 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, and the capital-arbitrage equation 15 is replaced by equation 22.

3.3 Shocks, Data, and Estimation

The model is estimated using time-series data for the quarterly growth rate of real GDP, consumption, investment, and the average real wage, along with inflation, the log of average hours worked, and the effective nominal federal funds rate.²³ To quantify the strength of financial frictions and identify disturbances to the financial sector, our estimation procedure also includes two key variables of the financial accelerator mechanism: (1) the medium-risk, long-maturity corporate bond spread and (2) the average leverage based on the Merton DD-model. The medium-risk, long-maturity credit spread is used as a proxy for the unobservable external finance premium s_t , movements in which are related to fluctuations in the logarithm of leverage—that is $\ln(V_t/E_t)$ —an empirical counterpart to the model-implied leverage $q_t + k_t - n_t$.

Estimating the SW-model with the financial accelerator using Bayesian ML techniques requires one to specify a minimum of nine structural disturbances. In the absence of the

²²In 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.

²³Output, consumption, investment, the average hours worked, and the real wage are expressed in per capita terms; real personal consumption expenditures are defined as the chain-weighted aggregate of real personal expenditures on nondurable goods and services; real investment is defined as the chain-weighted aggregate of real personal consumption expenditures on durable goods and real gross private domestic investment; and inflation is measured by the GDP price deflator. Average hours worked and the average real wage per capita are for the nonfinancial business sector.

financial accelerator, the model described above includes shocks to both disembodied and investment-specific 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 nine structural shocks. 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 $[\eta_t^b, \eta_t^a, \eta_t^g, \eta_t^p, \eta_t^w, \eta_t^r, \eta_t^{\mathcal{F}}, \eta_t^{fd}, \eta_t^{mw}]$ denote a vector of mutually-uncorrelated i.i.d. shocks. The structural shocks to preferences (ε_t^b), disembodied technology (ε_t^a), monetary policy (ε_t^r), and investment-specific technology ($\varepsilon_t^{\mathcal{F}}$) are assumed to follow stationary AR(1) processes:

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

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 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 the shock to net worth (ε_t^{mw}) is i.i.d., whereas the credit-supply shock (ε_t^{fd}) is assumed to follow a stationary AR(1) process:

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

The estimation procedure relates the nine observable macroeconomic/financial series to

their theoretical counterparts through the following system of measurement equations:

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

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 $\bar{\gamma}$ in per capita output, consumption, investment, and real wages, 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.

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 exogenous share of government spending in GDP, the rate of capital depreciation δ , 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 $\theta = 0.99$ and the entrepreneurs' share of consumption $c_y^e = 0.01$. 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 our sample period (see Figure 2). Parameters to be estimated then include the structural parameters associated with the monetary policy rule $[\rho, r_\pi, r_y, r_{\Delta y}]$; parameters pertaining to the model specification without the financial accelerator, namely $[\gamma, \alpha, \phi_p, \beta, \sigma_c, \sigma_l, h, \xi_w, \xi_p, \iota_w, \iota_p, \varphi, \psi, \bar{l}, \bar{\pi}]$; and the parameters governing the time-series properties of the shock processes—that is, the persistence parameters $[\rho_a, \rho_b, \rho_r, \rho_g, \rho_{ga}, \rho_w, \rho_p, \rho_{qs}, \rho_{fd}, \mu_w, \mu_p]$ and standard deviations of the nine i.i.d. processes $[\sigma_a, \sigma_b, \sigma_g, \sigma_w, \sigma_p, \sigma_r, \sigma_{qs}, \sigma_{fd}, \sigma_{mw}]$.

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:Q1–2009:Q1 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 0.05, the calibrated elasticity used 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 7 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 8 reports the same results for the parameters pertaining to the shock processes. As indicated by the entries in Tables 7, our posterior estimates of the structural parameters are in most cases similar to those obtained by SW, 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. Similar to the results reported by SW, our model estimates imply only a minor role for price and wage indexation. 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 χ is estimated to be 0.01—significantly lower than its prior mean—but nonetheless statistically different from zero.

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 Figures 3–5.²⁴ A contractionary monetary policy shock (Figure 3) causes a rise in the nominal interest rate, a reduction in inflation, 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; the peak response in inflation occurs three quarters after the shock. These results are in line with the conventional wisdom regarding both the strength of the monetary transmission mechanism as well as the length of the average lag of the economy’s response to monetary policy actions. An unanticipated tightening of monetary policy also causes a decline in asset values, which boosts leverage and leads to an increase in the external finance premium. Thus, the impact of a contractionary monetary policy shock on the economy works, to some extent, by boosting the cost of external funds through the deterioration in the strength of borrowers’ balance sheets.

Adverse credit supply shocks (Figure 4) also result in a significant reduction in economic growth. A one-standard-deviation shock to the external finance premium (ε_t^{fd}) causes an increase of about 30 basis points in the credit spread, which depresses the level of output by about 10 basis points and the level of investment by 60 basis points relative to the steady state. Again, the response of both investment and output is hump-shaped, with the peak in the response occurring six to eight quarters after the impact of the financial shock. In contrast, disturbances to net worth (Figure 5) have more pronounced and longer-lasting effects. A one-standard-deviation shock to net worth (ε_t^{nw}) implies substantial declines in the levels of output and investment at the two- to three-year horizon. Indeed, with both the leverage and the credit spread significantly and persistently above their respective steady states, investment continues to fall for a substantial period after the initial impact of the shock to net worth. Overall, shocks to the external finance premium appear to capture relatively high frequency movements in investment and output, whereas net worth shocks imply stronger dynamics at lower frequencies.

To assess the historical relevance of disturbances in financial markets for macroeconomic performance over the 1973–2008 period, Figures 6–14 depict the decomposition of shocks implied by the model. These figures plot the time-paths of all estimated variables implied by each of the model shocks. For the purposes of exposition, the contribution of the two credit-supply shocks—that is, the shock to the credit spread and the shock to entrepreneurial net worth—has been combined into a single “financial” shock.

According to the historical decomposition, the dynamics of output and investment over

²⁴Recall that output, consumption, investment, and the real wage enter the system of measurement equations in log differences. For these four variables, we cumulate their impulse responses to depict the impact of shocks on levels of the variables.

the course of a business cycle are shaped importantly by shocks emanating from the financial sector (Figures 6–7). In particular, financial disturbances accounted for a significant portion of the drop in investment in each recession that has occurred over the 1973–2008 period, with the exception of the 1980–82 monetary-policy-induced downturn. These historical decompositions also accord well with the historical narrative regarding the role of monetary policy in determining economic outcomes (Figures 9–10). In particular, monetary policy is estimated to be expansionary relative to the estimated rule during the 1975–79 period and during the 1991–1993 and 2003–05 periods that followed periods of economic weakness. According to our estimates, monetary policy was restrictive during the 1979–1982 period—the so-called “Volcker deflation”—and also prior to the 1990–91 economic downturn.

Regarding the current financial crisis, our model estimates imply that the direction of financial shocks reversed course sharply with the onset of the financial crisis in late 2007—that is, from having a significantly expansionary effect on investment during the 2004–06 period to having a negative influence on investment spending by the end of 2007. Since then, deteriorating financial conditions have caused significant declines in investment spending, culminating in the drop of nearly 30 percentage points (at an annual rate) in investment activity observed during the last couple of quarters. This collapse in investment explains about two vast majority of the measured drop in output growth during that period. According to our estimates, the adverse effects of these financial shocks were offset, in part, by a positive shock to government spending, which may also proxy for the strength in net exports during this period. The remaining drop in output during this last quarter is explained by a collapse in consumption, reflecting a sharp increase in the desire of households to save rather than spend.

4 Conclusion

This paper provided evidence in support of the notion that financial frictions play an important role in U.S. cyclical fluctuations. Our first set of result showed that medium-risk, long-maturity corporate credit spreads are highly informative about the future course of a variety of indicators of economic activity. These forecasting results were robust to the inclusion of other financial market indicators that have been shown to have predictive power for economic activity, including the term spread, the real federal funds rate, and the widely-used Baa credit spread index. The predictive content of medium-risk, long-horizon corporate bond spreads appears to be the strongest since the mid-1980s, a period that coincides with a significant deregulation of financial markets.

Our second set of results provided a structural framework for our empirical results by using Bayesian methods to estimate a New Keynesian DSGE model that included the BGG-

type financial accelerator mechanism, an approach that allowed us to attribute movements in aggregate macroeconomic variables to various sources of disturbances. The main innovation of our approach was that we explicitly incorporated our high information-content credit spread into the Bayesian ML estimation, where it served as a proxy for the external finance premium. Fluctuations in this proxy for the external finance premium were used to identify the strength of the financial accelerator mechanism and to measure the extent to which disruptions in financial markets have contributed to cyclical fluctuations over the 1973:Q1–200:Q1 period.

Our estimates of the structural parameters governing the strength of the financial accelerator mechanism point to an important macroeconomic role for financial market frictions, which act as an amplification mechanism for real and nominal disturbances in the economy. Moreover, our results imply that a substantial fraction of cyclical fluctuations in output and investment over the past decades and a half can be attributed to disturbances that originated in the financial sector. These results reinforce the conclusions of Christiano, Motto, and Rostagno [2009], who showed that disruptions emanating from the financial sector accounted for an important fraction of investment activity in both the U.S. and in the Euro area. Overall, such findings indicate that a New Keynesian DSGE model augmented to include 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 past three decades and a half.

References

- ANG, A., AND G. BEKAERT (2007): “Stock Return Predictability: Is It There?,” *Review of Financial Studies*, 20, 651–707.
- ANG, A., M. PIAZZESI, AND M. WEI (2006): “What Does the Yield Curve Tell Us About GDP Growth?,” *Journal of Econometrics*, 131, 359–403.
- BERNANKE, B. S., M. GERTLER, AND S. GILCHRIST (1999): “The Financial Accelerator in a Quantitative Business Cycle Framework,” in *The Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, pp. 1341–1393. Elsevier Science B.V., Amsterdam.
- BHARATH, S. T., AND T. SHUMWAY (2008): “Forecasting Default with the Merton Distance to Default Model,” *Review of Financial Studies*, 21, 1339–1369.
- BRUNNERMEIER, M. K. (2009): “Deciphering the Liquidity and Credit Crunch 2007–08,” *Journal of Economic Perspectives*, 23, 77–100.
- CAMPBELL, J. Y., M. LETTAU, B. G. MALKIEL, AND Y. XU (2001): “Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk,” *Journal of Finance*, 56, 1–44.
- CARLSTROM, C. T., AND T. S. FUERST (1997): “Agency Costs, Net Worth, and Business Cycle Fluctuations: A Computable General Equilibrium Analysis,” *American Economic Review*, 87, 893–910.
- CHRISTENSEN, I., AND A. DIB (2008): “Monetary Policy in an Estimated DSGE Model with a Financial Accelerator,” *Review of Economic Dynamics*, 11, 155–178.
- CHRISTIANO, L. J., M. EICHENBAUM, AND C. L. EVANS (2005): “Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy,” *Journal of Political Economy*, 113, 1–45.
- CHRISTIANO, L. J., R. MOTTO, AND M. ROSTAGNO (2008): “Shocks, Structures, or Monetary Policies? The Euro Area and U.S. After 2001,” *Journal of Economic Dynamics and Control*, 32, 2476–2506.
- (2009): “Financial Factors in Economic Fluctuations,” Mimeo, Dept. of Economics, Northwestern University.
- CLARIDA, R., J. GALÍ, AND M. GERTLER (2000): “Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory,” *Quarterly Journal of Economics*, 115, 147–180.
- COOLEY, T. F., R. MARIMON, AND V. QUADRINI (2004): “Aggregate Consequences of Limited Contract Enforceability,” *Journal of Political Economy*, 112, 817–847.
- CROSBIE, P. J., AND J. R. BOHN (2003): “Modeling Default Risk,” Research Report, Moody’s|K-M-V Corporation.

- DE GRAEVE, F. (2008): “The External Finance Premium and the Macroeconomy: U.S. Post-WWII Evidence,” *Journal of Economic Dynamics and Control*, 32, 3415–3440.
- DIEBOLD, F. X., AND R. S. MARIANO (1995): “Comparing Predictive Accuracy,” *Journal of Business and Economic Statistics*, 13, 253–263.
- DOTSEY, M. (1998): “The Predictive Content of the Interest Rate Term Spread for Future Economic Growth,” *Federal Reserve Bank of Richmond Economic Quarterly*, 84, 31–51.
- DUCA, J. V. (1999): “An Overview of What Credit Market Indicators Tell Us,” *Economic and Financial Review, Federal Reserve Bank of Dallas*, Third Quarter, 2–13.
- DUFFIE, D., AND K. J. SINGLETON (2003): *Credit Risk*. Princeton University Press, Princeton, NJ.
- DYNAN, K. E., D. W. ELMENDORF, AND D. E. SICHEL (2006): “Can Financial Innovation Help Explain the Reduced Volatility of Economic Activity,” *Journal of Monetary Economics*, 53, 123–150.
- ELLIOTT, G., AND U. K. MÜLLER (2006): “Efficient Tests for General Persistent Time Variation in Regression Coefficients,” *Review of Economic Studies*, 73, 907–940.
- EMERY, K. M. (1999): “The Information Content of the Paper-Bill Spread,” *Journal of Business and Economic Statistics*, 48, 1–10.
- ESTRELLA, A., AND G. A. HARDOUVELIS (1991): “The Term Structure as Predictor of Real Economic Activity,” *Journal of Finance*, 46, 555–576.
- ESTRELLA, A., AND F. S. MISHKIN (1998): “Predicting U.S. Recessions: Financial Variables as Leading Indicators,” *Review of Economics and Statistics*, 80, 45–61.
- EWING, B. T., G. J. LYNCH, AND J. E. PAYNE (2003): “The Paper-Bill Spread and Real Output: What Matter More, a Change in the Paper Rate or a Change in the Bill Rate?,” *Journal of Financial Economics*, 12, 233–246.
- FRIEDMAN, B. M., AND K. N. KUTTNER (1998): “Indicator Properties of the Paper-Bill Spread: Lessons From Recent Experience,” *Review of Economics and Statistics*, 80, 34–44.
- FUERST, T. S. (1995): “Money and Financial Interactions in the Business Cycle,” *Journal of Money, Credit, and Banking*, 27, 1321–1338.
- GERTLER, M., AND C. S. LOWN (1999): “The Information in the High-Yield Bond Spread for the Business Cycle: Evidence and Some Implications,” *Oxford Review of Economic Policy*, 15, 132–150.
- GILCHRIST, S., V. YANKOV, AND E. ZAKRAJŠEK (2009): “Credit Market Shocks and Economic Fluctuations: Evidence From Corporate Bond and Stock Markets,” *Journal of Monetary Economics*, 56, 471–493.

- GÜRKAYNAK, R. S., B. SACK, AND J. H. WRIGHT (2007): “The U.S. Treasury Yield Curve: 1961 to the Present,” *Journal of Monetary Economics*, 54, 2291–2304.
- HAMILTON, J. D., AND D. H. KIM (2002): “A Reexamination of the Predictability of Economic Activity Using the Yield Spread,” *Journal of Money, Credit, and Banking*, 34, 340–360.
- HODRICK, R. J. (1992): “Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement,” *Review of Financial Studies*, 5, 357–386.
- JUSTINIANO, A., G. E. PRIMICERI, AND A. TAMBALOTTI (2008): “Investment Shocks and Business Cycles,” Federal Reserve Bank of Chicago Working Paper No. 12.
- KASHYAP, A. K., AND J. C. STEIN (2000): “What Do a Million Observations on Banks Say About the Transmission of Monetary Policy?,” *American Economic Review*, 90, 407–428.
- KING, T. B., A. T. LEVIN, AND R. PERLI (2007): “Financial Market Perceptions of Recession Risk,” Finance and Economics Discussion Series Paper No. 57, Federal Reserve Board.
- KIYOTAKI, N., AND J. H. MOORE (1997): “Credit Cycles,” *Journal of Political Economy*, 105, 211–248.
- LANDO, D. (2004): *Credit Risk Modeling: Theory and Applications*. Princeton Series in Finance, Princeton University Press, Princeton, NJ.
- LEVIN, A. T., F. M. NATALUCCI, AND E. ZAKRAJŠEK (2006): “The Magnitude and Cyclical Behavior of Financial Market Frictions,” Mimeo, Federal Reserve Board.
- MERTON, R. C. (1973): “A Rational Theory of Option Pricing,” *Bell Journal of Economics and Management Science*, 4, 141–183.
- (1974): “On the Pricing of Corporate Debt: The Risk Structure of Interest Rates,” *Journal of Finance*, 29, 449–470.
- MODIGLIANI, F., AND M. H. MILLER (1958): “The Cost of Capital, Corporation Finance, and the Theory of Investment,” *American Economic Review*, 38, 261–297.
- MODY, A., AND M. P. TAYLOR (2004): “Financial Predictors of Real Activity and the Financial Accelerator,” *Economic Letters*, 82, 167–172.
- MUELLER, P. (2007): “Credit Spreads and Real Activity,” Mimeo, Columbia Business School.
- NEWBY, W. K., AND K. D. WEST (1987): “A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix,” *Econometrica*, 55, 703–708.
- PHILIPPON, T. (2009): “The Bond Market’s Q,” *Quarterly Journal of Economics*, forthcoming.

- PRIMICERI, G. E., E. SCHAUMBURG, AND A. TAMBALOTTI (2006): “Intertemporal Disturbances,” NBER Working Paper No. 12243.
- QUEIJO VON HEIDEKEN, V. (2008): “How Important are Financial Frictions in the U.S. and the Euro Area?,” Sveriges Riksbank Working Paper No. 223.
- SMETS, F., AND R. WOUTERS (2007): “Shocks and Frictions in U.S. Business Cycle: A Bayesian DSGE Approach,” *American Economic Review*, 97, 586–606.
- STOCK, J. H., AND M. W. WATSON (1989): “New Indexes of Coincident and Leading Economic Indicators,” in *NBER Macroeconomics Annual*, ed. by O. J. Blanchard, and S. Fischer, pp. 351–394. The MIT Press, Cambridge.
- (2002a): “Has the Business Cycle Changed and Why?,” in *NBER Macroeconomics Annual*, ed. by M. Gertler, and K. Rogoff, pp. 159–218. The University of Chicago Press, Chicago.
- (2002b): “Macroeconomic Forecasting Using Diffusion Indexes,” *Journal of Business and Economic Statistics*, 20, 147–162.
- (2003): “How Did Leading Indicators Forecasts Perform During the 2001 Recessions?,” *Federal Reserve Bank of Richmond Economic Quarterly*, 89, 71–90.
- THOMA, M. A., AND J. A. GRAY (1998): “Financial Market Variables Do Not Predict Real Activity,” *Economic Inquiry*, 36, 522–539.
- VAN DEN HEUVEL, S. J. (2007): “The Bank Capital Channel of Monetary Policy,” Mimeo, The Wharton School, University of Pennsylvania.
- VASSALOU, M., AND Y. XING (2004): “Default Risk and Equity Returns,” *Journal of Finance*, 59, 831–868.
- WARGA, A. D. (1991): “A Fixed Income Database,” Mimeo, University of Houston.
- WRIGHT, J. H. (2006): “The Yield Curve and Predicting Recessions,” Finance and Economics Discussion Series Paper No. 7, Federal Reserve Board.

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	3.27	3.85	1.00	2.00	60.0
Mkt. Value of Issue ^a (\$mil.)	294.0	308.3	1.11	220.4	6,657
Maturity at Issue (years)	13.9	9.4	1.0	10.0	50.0
Term to Maturity (years)	11.8	8.62	0.01	8.63	30.0
Duration (years)	6.25	3.14	0.00	6.01	24.4
S&P Credit Rating	-	-	D	A3	AAA
Coupon Rate (pct.)	7.67	2.18	0.00	7.38	17.5
Nominal Effective Yield (pct.)	8.25	3.40	1.20	7.74	57.4
Credit Spread ^b (bps.)	184	283	10	112	4,995

Panel Dimensions

Obs. = 364,403 $N = 5,661$ bonds

Min. Tenure = 1 Median Tenure = 54 Max. Tenure = 294

NOTE: Sample period: Monthly data from January 1973 to March 2009 for a sample of 927 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 Indicators and Labor Market Conditions (1973–2009)

<i>Private Payroll Employment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	-0.418 (0.108)	-0.363 (0.108)	-0.268 (0.108)
Real Federal Funds Rate	-0.243 (0.067)	-0.258 (0.068)	-0.227 (0.060)
Baa Credit Spread	-	0.613 (0.236)	-
M-R/L-M Credit Spread	-	-	-1.652 (0.244)
Adj. R^2	0.495	0.502	0.598
<i>Unemployment Rate</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	0.314 (0.021)	0.289 (0.019)	0.268 (0.020)
Real Federal Funds Rate	0.088 (0.012)	0.093 (0.012)	0.085 (0.011)
Baa Credit Spread	-	-0.169 (0.046)	-
M-R/L-M Credit Spread	-	-	0.639 (0.039)
Adj. R^2	0.400	0.399	0.473

NOTE: Sample period: Quarterly data from 1973:Q1 to 2009:Q1 ($T = 141$). Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes a labor market indicator (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 Hodrick [1992] and are reported in parentheses.

Table 3: Financial Indicators, Production, and Inventories (1973–2009)

<i>Manufacturing Industrial Production</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	-1.248 (0.408)	-1.218 (0.358)	-1.009 (0.424)
Real Federal Funds Rate	-0.502 (0.211)	-0.506 (0.208)	-0.474 (0.193)
Baa Credit Spread	-	0.202 (0.937)	-
M-R/L-M Credit Spread	-	-	-3.540 (0.974)
Adj. R^2	0.316	0.312	0.412
<i>Real Business Inventories</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	-0.284 (0.157)	-0.432 (0.139)	-0.048 (0.165)
Real Federal Funds Rate	-0.154 (0.097)	-0.140 (0.084)	-0.149 (0.089)
Baa Credit Spread	-	-1.785 (0.318)	-
M-R/L-M Credit Spread	-	-	-2.323 (0.393)
Adj. R^2	0.226	0.362	0.459

NOTE: Sample period: Quarterly data from 1973:Q1 to 2009:Q1 ($T = 141$). Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes a production indicator (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 Hodrick [1992] and are reported in parentheses.

Table 4: Financial Indicators, Output, and Investment (1973–2009)

<i>Real GDP</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	-0.635 (0.211)	-0.581 (0.206)	-0.557 (0.222)
Real Federal Funds Rate	-0.135 (0.140)	-0.139 (0.138)	-0.132 (0.129)
Baa Credit Spread	-	0.364 (0.482)	-
M-R/L-M Credit Spread	-	-	-1.205 (0.537)
Adj. R^2	0.285	0.297	0.345
<i>Real Business Fixed Investment</i>			
Financial Indicator	(1)	(2)	(3)
Term Spread (3m–10y)	-0.703 (0.548)	-0.912 (0.533)	0.070 (0.589)
Real Federal Funds Rate	-0.924 (0.322)	-0.875 (0.292)	-0.848 (0.300)
Baa Credit Spread	-	-2.565 (1.465)	-
M-R/L-M Credit Spread	-	-	-7.508 (1.324)
Adj. R^2	0.339	0.352	0.533

NOTE: Sample period: Quarterly data from 1973:Q1 to 2009:Q1 ($T = 141$). 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 Hodrick [1992] and are reported in parentheses.

Table 5: Comparison of Out-of-Sample Predictive Accuracy

Economic Activity Indicator	RMSFE-1 ^a	RMSFE-2 ^b	Ratio	Pr > S
Private Payroll Employment	1.597	0.949	0.594	0.019
Unemployment Rate	0.840	0.562	0.669	0.022
Mfg. Industrial Production	4.693	3.132	0.667	0.007
Real Business Inventories	2.146	1.631	0.760	0.011
Real GDP	1.917	1.177	0.614	0.001
Real Business Fixed Investment	5.858	4.561	0.779	0.114

NOTE: Sample period: Quarterly data from 1973:Q1 to 2009:Q1. Forecast origin date = 1989:Q4 ($N = 73$). Dependent variable in each regression specification is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms if necessary). In addition to the specified financial indicators, each regression specification also includes a constant, current, and 3 lags of ΔY_t . “Ratio” denotes the ratio of RMSFE-2 to RMSFE-1; Pr > |S| denotes the p -value for the Diebold and Mariano [1995] test of the null hypothesis that the difference between the MSFEs from the two models is equal to zero (see text for details).

^aRMSFE from the specification that includes the term spread, the real federal funds rate, and the Baa credit spread.

^bRMSFE from the specification that includes the medium-risk, long-maturity credit spread.

Table 6: Financial Indicators and Economic Activity (1986–2009)

Financial Indicator	<i>Economic Activity Indicator</i>					
	EMP	UE	IP	INV	GDP	BFI
Term Spread	-0.356 (0.095)	0.189 (0.018)	-0.778 (0.357)	-0.467 (0.212)	-0.201 (0.249)	0.556 (0.683)
Real FFR	-0.015 (0.077)	0.002 (0.013)	0.791 (0.305)	0.297 (0.166)	0.192 (0.178)	0.023 (0.534)
M-R/L-M Credit Spread	-1.456 (0.181)	0.726 (0.042)	-6.790 (0.699)	-2.572 (0.475)	-1.954 (0.356)	-11.00 (1.434)
Adj. R^2	0.758	0.545	0.517	0.544	0.386	0.683

NOTE: Sample period: Quarterly data from 1986:Q1 to 2009:Q1 ($T = 89$). Dependent variable is $\Delta^4 Y_{t+4}$, where Y_t denotes an indicator of economic activity (in logarithms if necessary). EMP = private payroll employment; UE = unemployment rate; IP = manufacturing industrial production; INV = real business inventories; GDP = real GDP; and BFI = real business fixed investment. 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 Hodrick [1992] and are reported in parentheses.

Table 7: Prior and Posterior Distributions of Structural Parameters

Parameter	<i>Prior</i>			<i>Posterior</i>			
	Distribution	Mean	SD	Mode	Mean	P5	P95
χ	Beta	0.05	0.02	0.01	0.01	0.01	0.01
φ	Normal	4.00	1.50	4.62	6.98	5.43	8.56
σ_c	Normal	1.50	0.37	0.98	0.95	0.88	1.02
h	Beta	0.70	0.10	0.90	0.92	0.89	0.95
ξ_w	Beta	0.50	0.10	0.94	0.77	0.68	0.87
σ_l	Normal	2.00	0.75	2.36	1.43	0.25	2.73
ξ_p	Beta	0.50	0.10	0.72	0.74	0.68	0.80
ι_w	Beta	0.50	0.15	0.38	0.46	0.25	0.67
ι_p	Beta	0.50	0.15	0.65	0.38	0.19	0.61
ψ	Beta	0.50	0.15	0.36	0.57	0.44	0.71
ϕ_p	Normal	1.25	0.12	1.70	1.49	1.36	1.64
r_π	Normal	1.50	0.25	1.10	1.72	1.45	1.97
ρ	Beta	0.75	0.10	0.74	0.79	0.75	0.84
r_y	Normal	0.12	0.05	0.001	0.08	0.04	0.12
$r_{\Delta y}$	Normal	0.12	0.05	0.14	0.17	0.12	0.23
$\bar{\pi}$	Gamma	0.62	0.10	0.88	0.77	0.61	0.94
$100(\beta^{-1} - 1)$	Gamma	0.25	0.10	0.34	0.27	0.14	0.43
\bar{l}	Normal	0.00	2.00	-5.61	-4.61	-5.56	-3.70
$\bar{\gamma}$	Normal	0.40	0.10	0.33	0.36	0.33	0.39
α	Normal	0.30	0.05	0.26	0.20	0.17	0.23
\bar{z}	Normal	52.0	10.0	45.7	45.3	40.6	50.3
\bar{s}	Normal	0.39	0.10	0.35	0.34	0.26	0.41

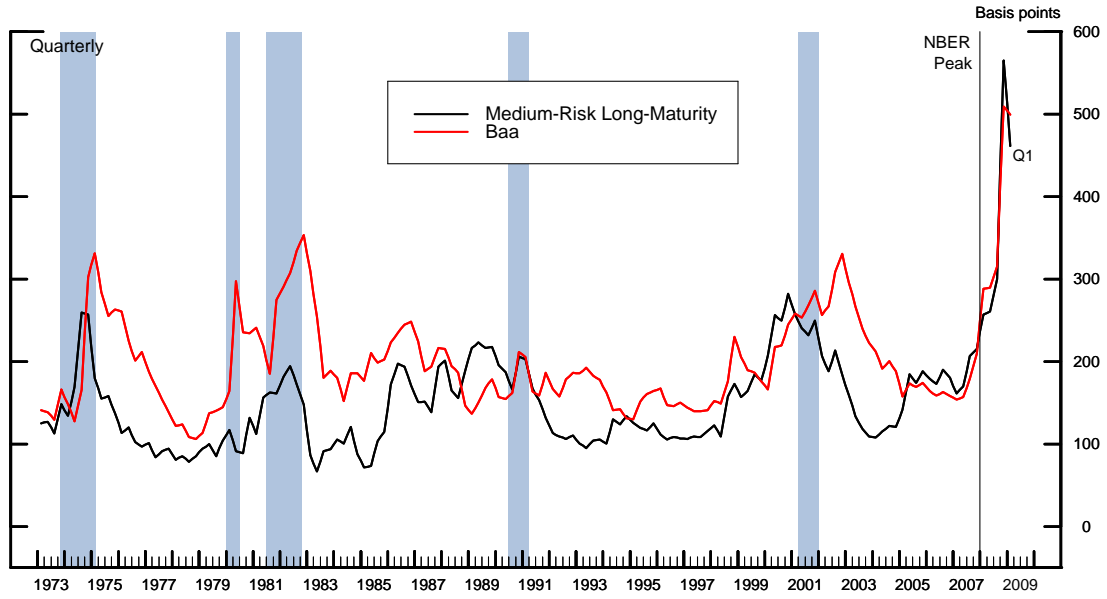
NOTE: Entries under the heading *Priors* specify the mean and the standard deviation of the prior distribution for the model's estimated structural parameters (see text for details). Entries under the heading *Posterior* denote the Bayesian ML estimates of the mean and the mode, along with the 5th (P5)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

Table 8: Prior and Posterior Distributions of Structural Shock Processes

Parameter	<i>Prior</i>			<i>Posterior</i>			
	Distribution	Mean	SD	Mode	Mean	P5	P95
σ_n	Inv. Gamma	0.10	2.00	7.88	8.15	7.38	8.91
σ_{fd}	Inv. Gamma	0.10	2.00	0.08	0.08	0.07	0.09
σ_{qs}	Inv. Gamma	0.10	2.00	0.56	0.47	0.33	0.59
σ_a	Inv. Gamma	0.10	2.00	0.41	0.41	0.37	0.46
σ_b	Inv. Gamma	0.10	2.00	0.14	0.12	0.09	0.15
σ_g	Inv. Gamma	0.10	2.00	0.50	0.50	0.45	0.55
σ_r	Inv. Gamma	0.10	2.00	0.25	0.25	0.22	0.28
σ_p	Inv. Gamma	0.10	2.00	0.20	0.18	0.12	0.23
σ_w	Inv. Gamma	0.10	2.00	0.21	0.23	0.18	0.27
ρ_{fd}	Beta	0.50	0.20	0.84	0.84	0.79	0.89
ρ_{qs}	Beta	0.50	0.20	0.61	0.74	0.61	0.87
ρ_a	Beta	0.50	0.20	0.92	0.84	0.75	0.93
ρ_b	Beta	0.50	0.20	0.29	0.52	0.37	0.68
ρ_g	Beta	0.50	0.20	0.89	0.89	0.82	0.96
ρ_r	Beta	0.50	0.20	0.22	0.19	0.07	0.30
ρ_p	Beta	0.50	0.20	0.64	0.82	0.71	0.94
ρ_w	Beta	0.50	0.20	0.80	0.88	0.80	0.96
μ_p	Beta	0.50	0.20	0.89	0.82	0.64	0.99
μ_w	Beta	0.50	0.20	0.72	0.75	0.61	0.89
ρ_{ga}	Beta	0.50	0.20	0.62	0.47	0.30	0.65

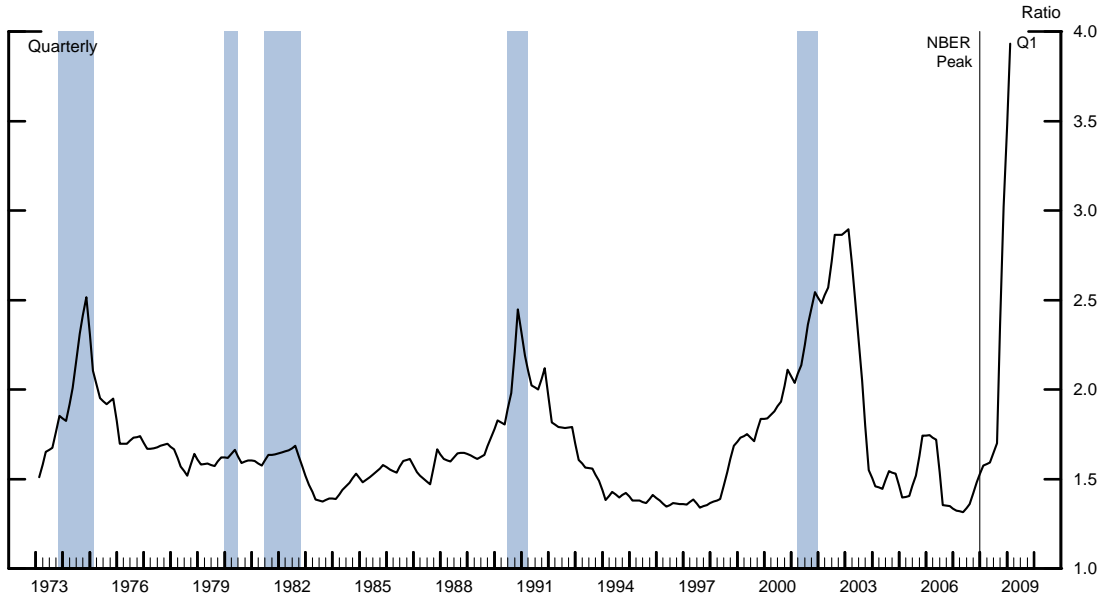
NOTE: Entries under the heading *Priors* specify the mean and the standard deviation of the prior distribution for the parameters governing the time-series properties of the model's structural shocks (see text for details). Entries under the heading *Posterior* denote the Bayesian ML estimates of the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

Figure 1: Selected Corporate Bond Spreads



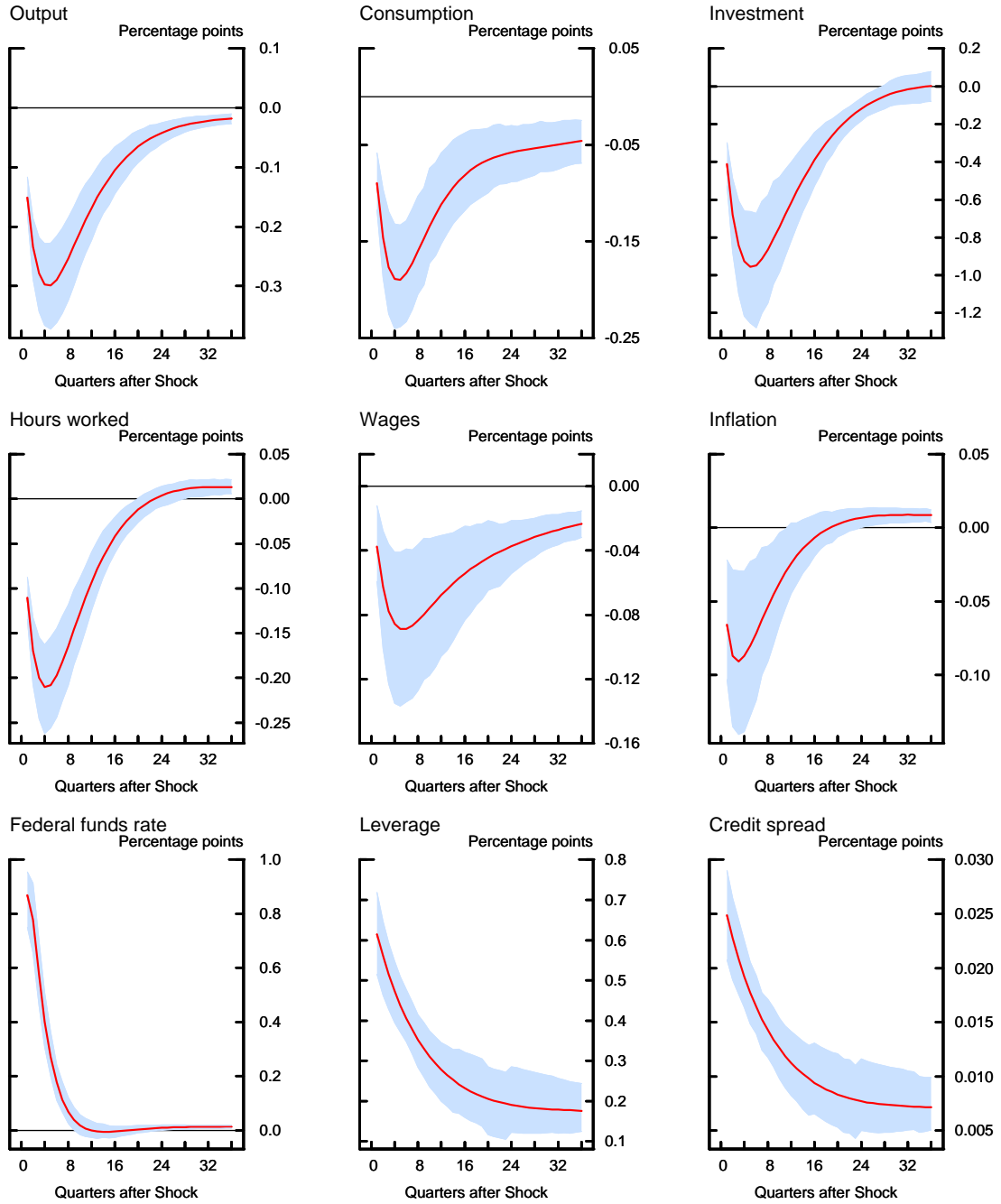
NOTE: The black line depicts the average credit spread associated with very long maturity corporate bonds issued by firms with low to medium probability of default (see text for details); the red line depicts the standard Baa credit spread, measured relative to the 10-year Treasury yield. The shaded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

Figure 2: Leverage Ratio



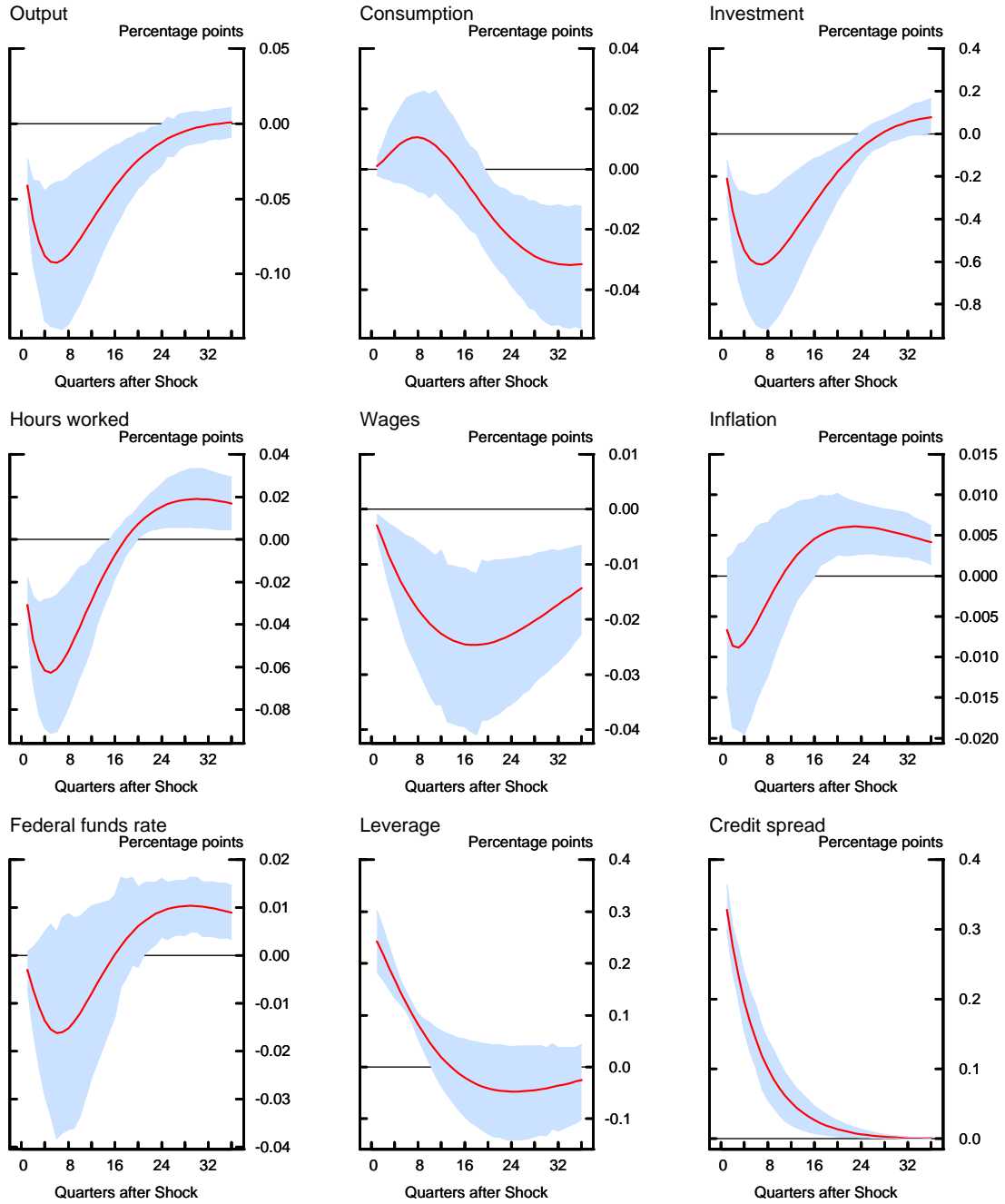
NOTE: The black line depicts the time-series of the cross-sectional averages of the leverage ratio for U.S. nonfinancial corporations. Leverage is defined as the ratio of the market-value of the firm's total assets (V) to the market-value of the firm's common equity (E), where the market-value of the 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



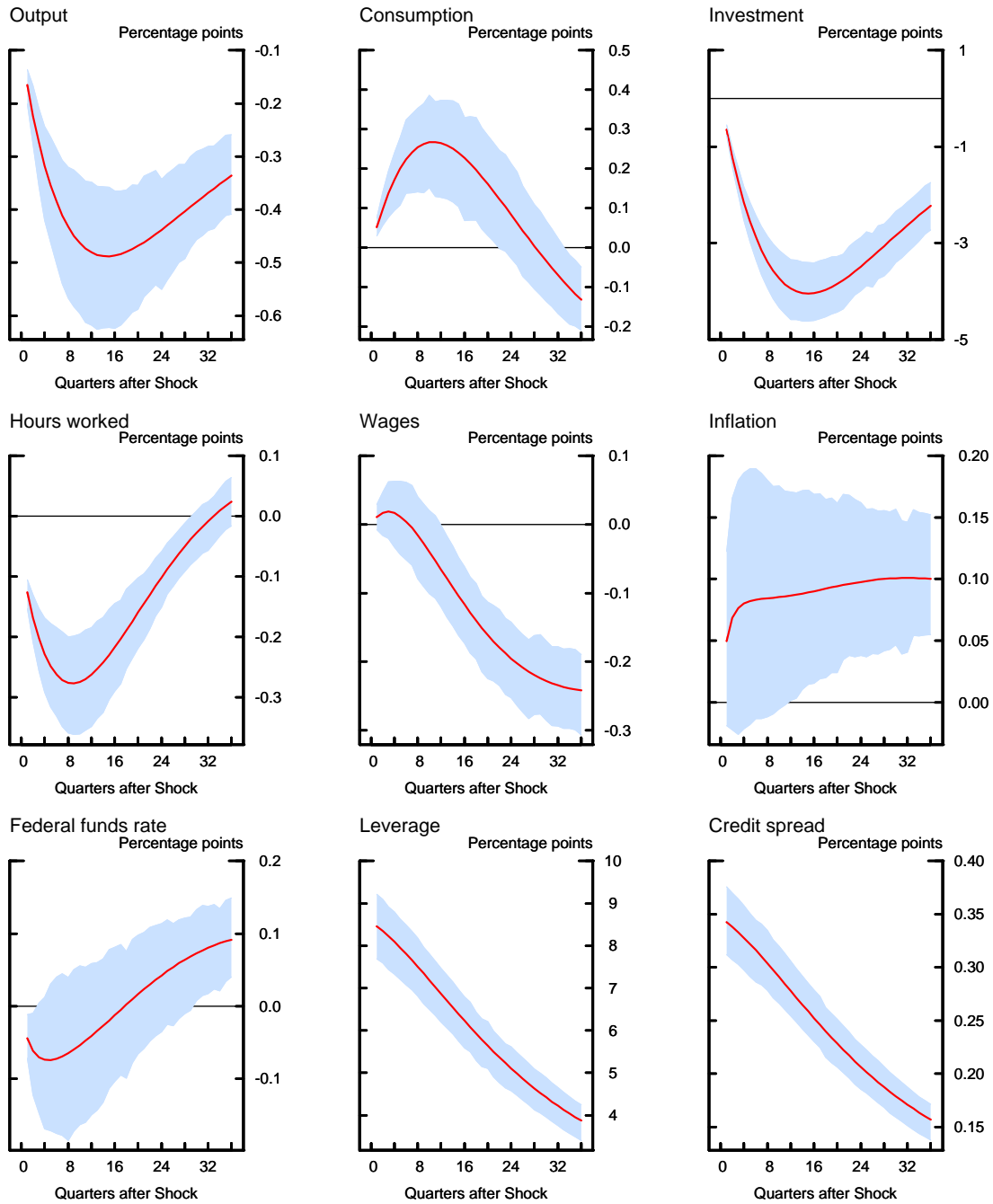
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation monetary policy shock. The shaded bands denote the 80 percent confidence intervals.

Figure 4: Model Responses to an Adverse Credit Supply Shock



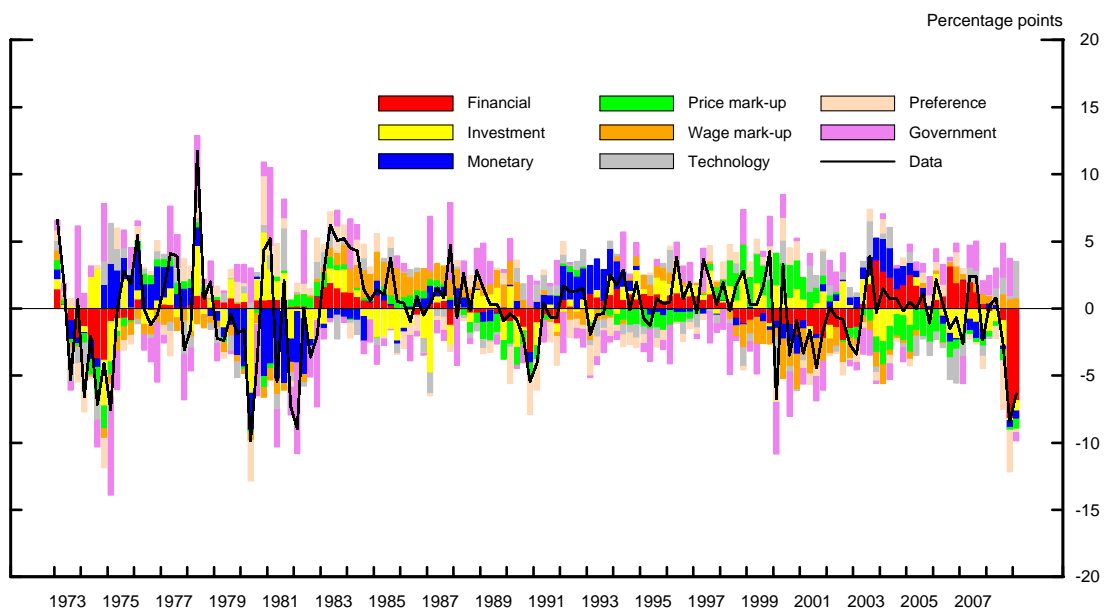
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation credit supply shock. The shaded bands denote the 80 percent confidence intervals.

Figure 5: Model Responses to an Adverse Net Worth Shock



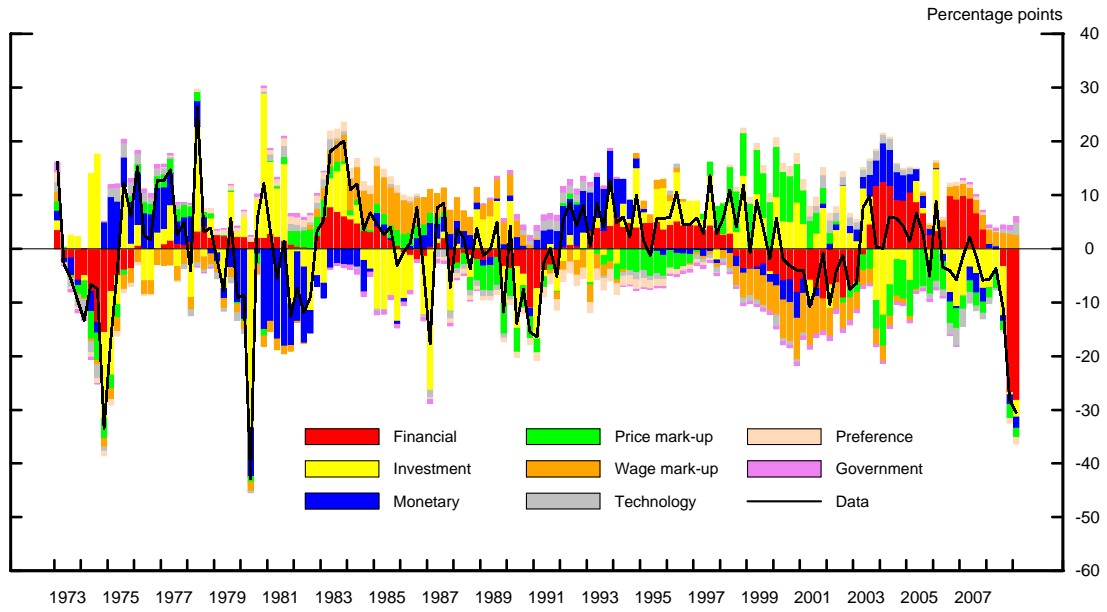
NOTE: The red lines in each panel depicts the estimated impulse responses of the model's variables to a one-standard-deviation net worth shock. The shaded bands denote the 80 percent confidence intervals.

Figure 6: Historical Decomposition of Output Growth



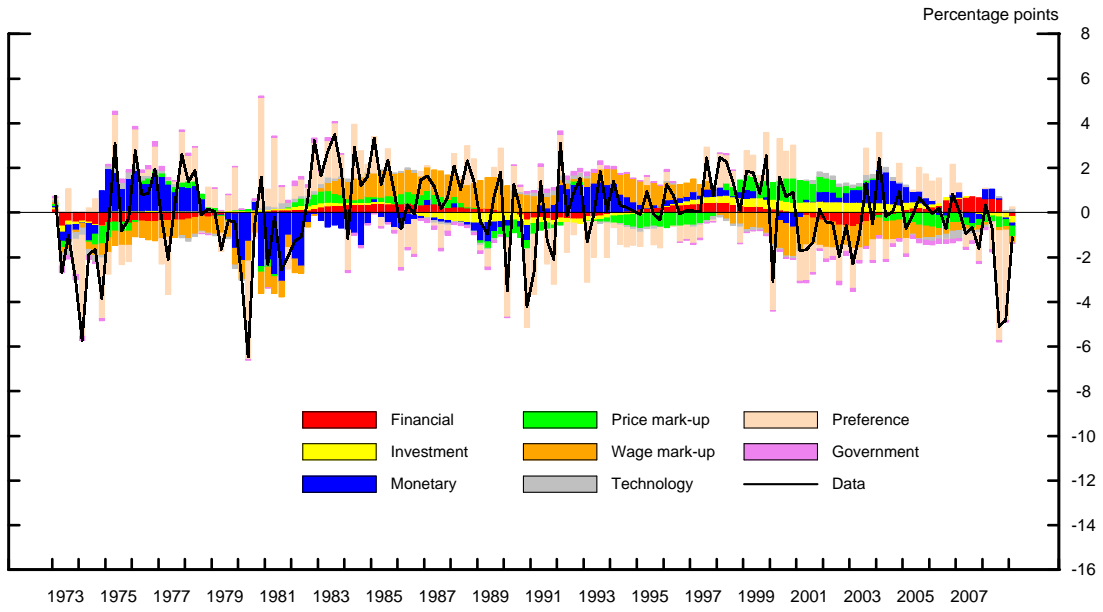
NOTE: The solid black line depicts the annualized quarterly growth rate in real GDP per capita, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 7: Historical Decomposition of Investment Growth



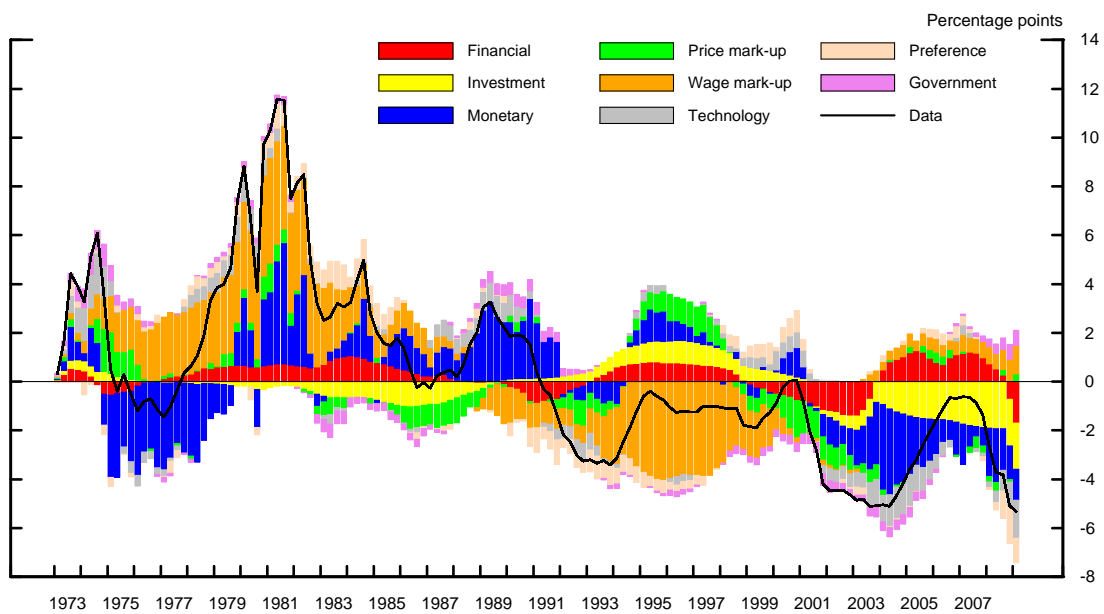
NOTE: The solid black line depicts the annualized quarterly growth rate in real fixed investment per capita, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 8: Historical Decomposition of Consumption Growth



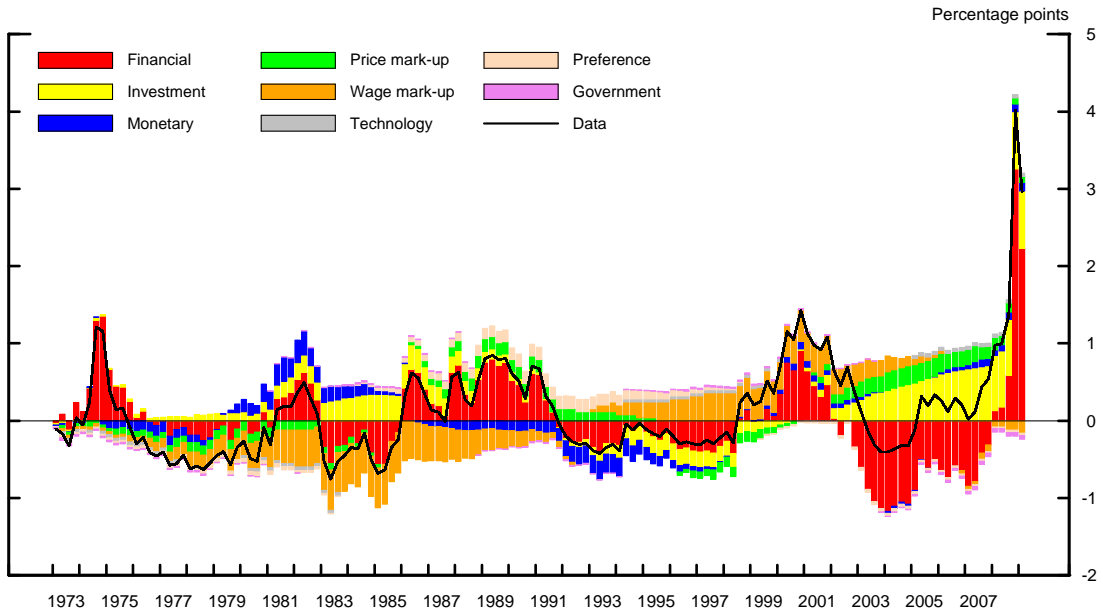
NOTE: The solid black line depicts the annualized quarterly growth rate in real personal consumption expenditures per capita, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 9: Historical Decomposition of Federal Funds Rate



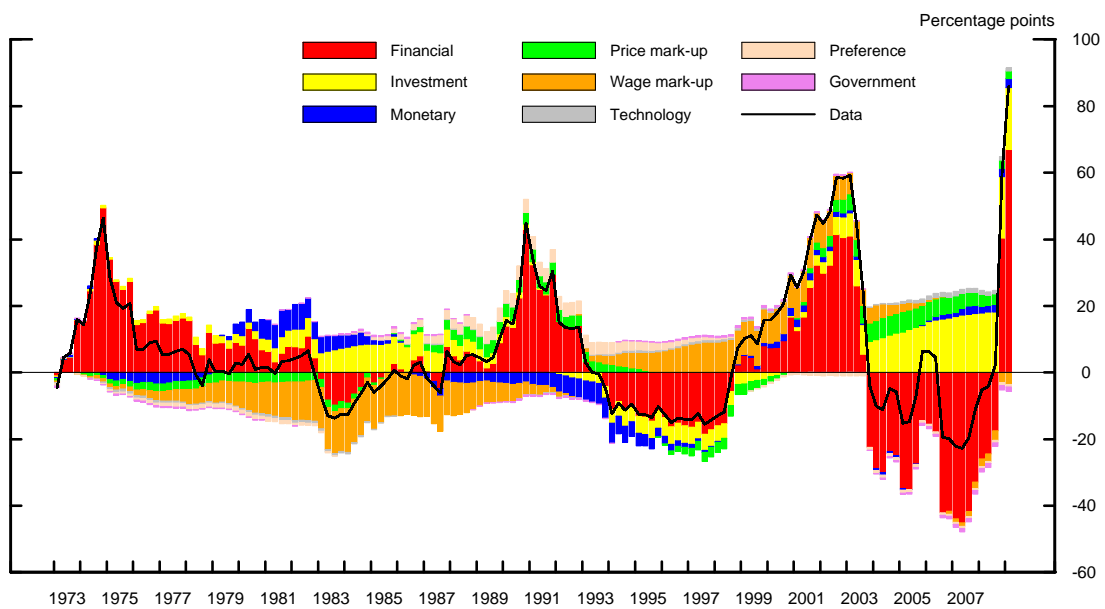
NOTE: The solid black line depicts the annualized effective federal funds rate, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 10: Historical Decomposition of Credit Spreads



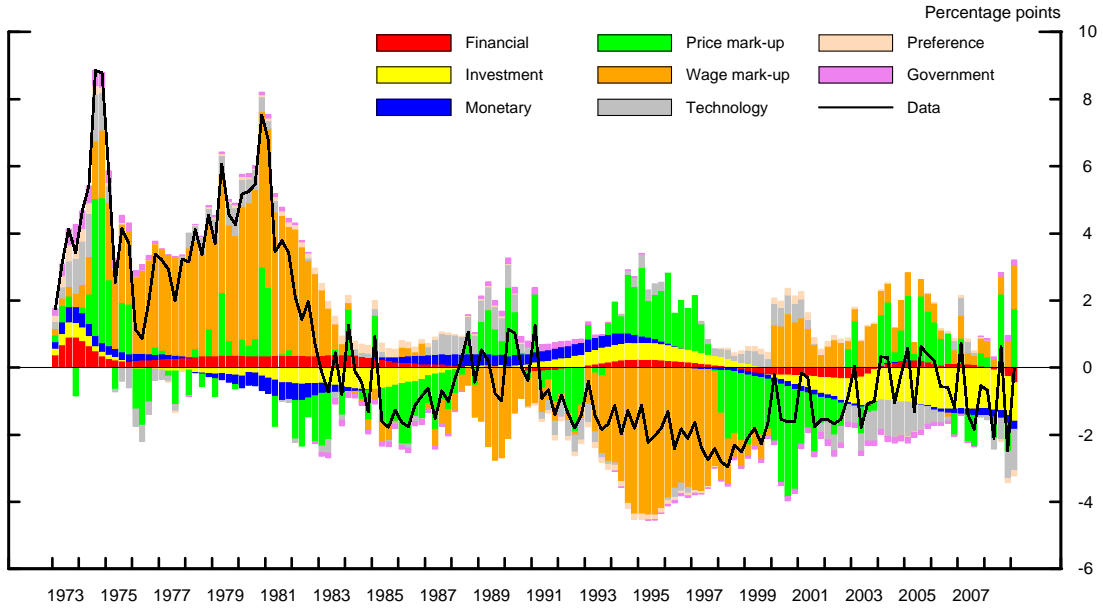
NOTE: The solid black line depicts the annualized medium-risk, long-maturity credit spread, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 11: Historical Decomposition of Leverage



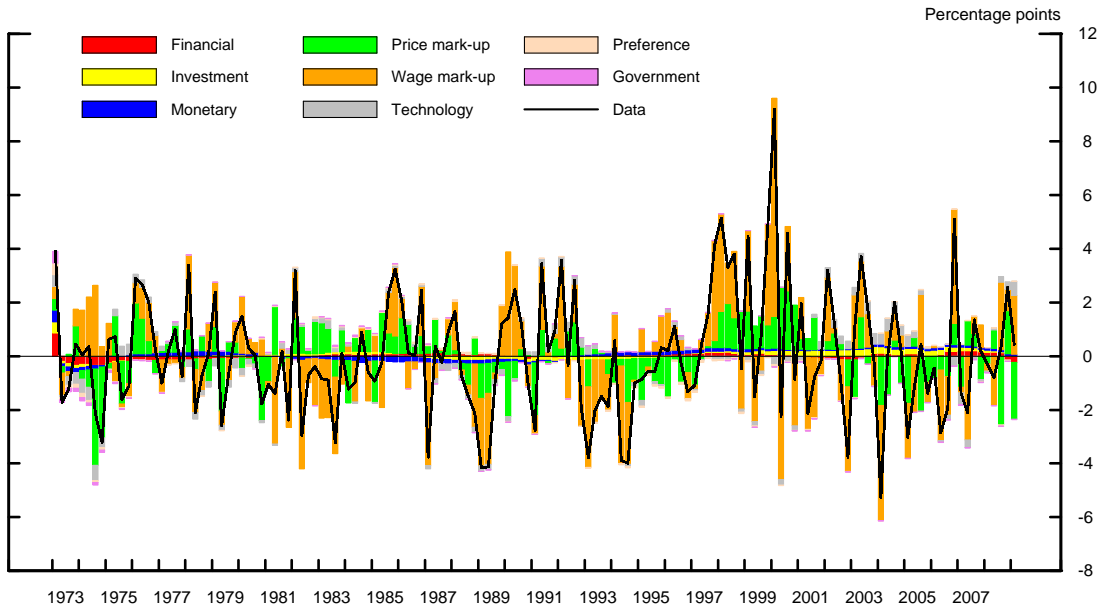
NOTE: The solid black line depicts the logarithm of leverage ratio, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 12: Historical Decomposition of Price Inflation



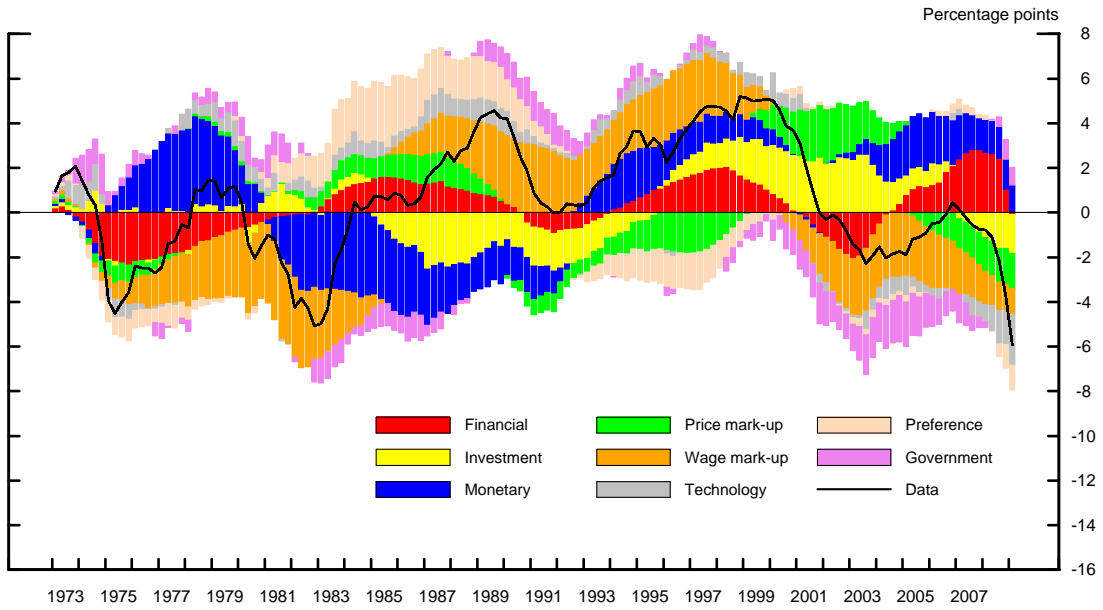
NOTE: The solid black line depicts the annualized GDP price inflation, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 13: Historical Decomposition of Real Wage Growth



NOTE: The solid black line depicts the annualized growth in real wages per capita, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).

Figure 14: Historical Decomposition of Aggregate Hours Worked



NOTE: The solid black line depicts the logarithm of the aggregate hours per capita, expressed in percentage point deviations from the model's steady state. The colored bars depict the estimated contributions of the various shocks (see text for details).