Credit Market Shocks: Evidence From Corporate Spreads and Defaults

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Abstract

Several recent papers have found that exogenous shocks to spreads paid in corporate credit markets are a substantial source of macroeconomic fluctuations. An alternative explanation of the data is that spreads respond endogenously to expectations of future default. We use a simple model of bond spreads to derive sign restrictions on the impulse-response functions of a VAR that identify credit shocks in the bond market, and compare them to results from a benchmark recursive VAR. We find that credit market shocks cause a persistent decline in output, prices and policy rates. Historical decompositions clearly show the negative effect of adverse credit market shocks on output in the recent recession. The identified credit shocks are unrelated to exogenous innovations to monetary policy and measures of bond market liquidity, but are related to measures of risk compensation. In contrast to results found using the benchmark restrictions, our identified credit shocks account for relatively little of the variance of output. Our results are consistent with a role for shocks in financial crises, but also with a lesser but non-zero role in normal business fluctuations.

Keywords: corporate bond spreads; default rates; sign restrictions; Bayesian vector autoregression.

JEL classification: C32, E32, E43, E44.

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Do credit market shocks drive output fluctuations? Recent experience during the financial crisis seems to show that they do: A graphic case was made for how a shock to the money markets, especially if it affects highly levered financial firms, can precipitate financial distress which is quickly transmitted to the real economy. But is the story always so simple? For non-financial firms, which tend to carry less leverage, there is usually scope to offset shocks to market credit by drawing upon alternative sources of funds, such as bank credit lines (Saidenberg and Strahan, 1999) or retained earnings. Further, because most borrowing by non-financial firms is long term in nature, a relatively small proportion of outstanding debt must be refinanced each month. Consequently a shock to the bond market might not be expected to have immediate effects on output. Moreover, shocks may be sufficiently infrequent that they play little role in the 'normal' ups and downs of the business cycle. Thus Bernanke and Gertler (1995, p. 43) argue that except in rare financial crises, credit is not a 'primitive driving force' of economic fluctuations[1].

In the absence of credit market shocks, changes in spreads would be driven by changes in default risk. Figure 1 depicts the spread on a broad index of speculative-grade (synonymously, 'high yield') bonds alongside default rates[2]. Periods of stress in the credit market, marked by higher default rates and wider spreads, are evident during recessions; for example, in the recent downturn the spread peaked at a little over two thousand basis points (hundredths of a percent), compared to six hundred basis points a year earlier. One hypothesis attributes a large portion of this increase to credit shocks. An alternative explanation of the data is that credit spreads responded endogenously to fundamental macroeconomic shocks that altered the expected likelihood of default. Understanding

[1] Cochrane (1994) strikes a similarly skeptical note on the importance of credit shocks for output fluctuations, although he too makes an allowance for the negative impact of banking crises. There is evidence from non-crisis periods that bank loan supply shocks do have a systematic impact on at least some components of GDP (Peek and Rosengren, 2000), but nagging problems of identification and measurement often remain.

[2] The spread is defined as the difference between the yield on a risky (defaultable) corporate bond, and the yield on a safe Treasury bond of equivalent time-to-maturity. Most high yield bonds are rated between BB and B, with the term 'junk' usually reserved for bonds rated CCC and below. Gertler and Lown (1999) argue that the speculative-grade bond spread is likely to proxy well for the cost of finance prevailing for more credit constrained firms in the economy, and thus is a good indicator of overall financial conditions. Some support for this conjecture comes from the close correlation between the default rate on high yield bonds and commercial banks' write-off rate on C&I loans.

which view has the most merit is of clear practical importance[3].

This paper sets out to gauge the effects of credit market shocks, with a focus on the market for high yield corporate bonds. Using monthly data from 1982-2009, we develop a joint vector autoregressive (VAR) model of credit spreads and default rates, along with a set of key macroeconomic indicators. In doing so, we build on the related work of Gertler and Lown (1999) and Balke (2000), who study the financial accelerator, and Friedman and Kuttner (1998), who use a VAR to decompose movements in the paper-bill spread. The paper closest to ours is Gilchrist, Yankov, and Zakrajšek (2009). They extract two credit market factors from a carefully constructed panel of bond spreads spanning the period between 1990 and 2008, and model them in a VAR. They report that a shock to their main bond market factor leads to lower output and lower real interest rates. Their findings also suggest that credit shocks are a significant factor in economic fluctuations, accounting for 30% of the variability of output, and a large fraction of the variability of spreads.

An advantage of the VAR approach is that it allows both for the direct effects of credit shocks on the macroeconomy, and for feedbacks from the macroeconomy to the credit market. To apply the VAR methodology to our question, the credit shock must be identified. In the past, this step has been left quite vague, with most researchers specifying a causal ordering of the variables based on an assumption on the timing of shocks. We depart from past studies by motivating identification from explicit economic assumptions. Using a simple model of bond prices, we show that fundamental shocks that cause movements in expected default can be separated from credit market shocks that do not, by imposing sign restrictions on the impulse-response functions of spreads and default rates. Throughout, we leave agnostically open the responses of output, monetary policy and other asset prices. As in Uhlig (2005), this approach leaves the data free to speak on the question of interest.

[3]To answer the question definitively, we would require a model that specifies the source of credit market shocks, and their transmission mechanism. Unfortunately, there is no widely agreed-upon integrated financial-macro model to provide such a description. However, the contributions of Nolan and Thoenissen (2009) and Jermann and Quadrini (2009) suggest that credit market shocks will play an important role in matching theoretical models to the data.

Our results confirm that credit market shocks lead to output recessions, declining interest rates and slow recoveries. We also find that the initial impact on output is negative and far from zero, contrary to the delayed response that has often been imposed. Historical decompositions show that the cumulative effect of credit shocks was a significant factor in both the 2001 and 2007-9 recessions. In the case of the most recent downturn, the effect of credit market shocks in driving up spreads prior to the start of the recession is particularly noteworthy. Under our sign restriction approach, we can attribute at most 15% of the variance of output to credit market shocks at one-to-two year horizons, and very little of the variation in spreads. The average contribution to output fluctuations is similar when we exclude the recent financial crisis from the sample. In sum, our main results show that credit shocks did play an independent role in the recent crisis, but contrary to the argument in Bernanke and Gertler (1995), they also appear to make a limited but non-zero contribution to macroeconomic fluctuations even in 'normal' times.

As a check, we compare our results to those obtained using a benchmark model that imposes a contemporaneously recursive identification structure, similar to that employed in previous studies. The conclusions reached using the benchmark identification are very different: we show that at one-to-two year horizons, three quarters of the variation in spreads, and a third of the variation in output is attributed to 'credit shocks'.

The reader should be aware of what we do not do in this paper. First, we do not claim to give a comprehensive account of credit market disruptions. The market for high yield bonds, although an important source of business finance, did not trigger the financial crisis which began in 2007. However, we argue that the deliberately narrow view of credit market disturbances adopted here has little risk of confounding the effects of macroeconomic shocks. Second, a number of studies have examined credit market shocks resulting from financial deregulation, such as the removal of interest rate ceilings, on macroeconomic performance and monetary policy (Benk et al. (2005); Mertens (2008)). However, the long-term structural consequences of regulatory changes are not the main focus of this paper. Such changes are unlikely to be unanticipated at monthly or quarterly frequencies, and indeed regulatory policy may be shaped in response to macroeconomic developments rather than being truly exogenous.

The remainder of the paper is organized as follows. Section 1 motivates the approach to identification by outlining an economic model of the spread. Our data are discussed in section 2.1, with a discussion of the results of an impulse-response analysis in section 2.2. The importance of credit market shocks in past recessions is detailed in section 2.3, and their overall role in macroeconomic fluctuations is related in section 2.4. We compare sign restrictions with recursive identification in section 3.1. Section 3.2 discusses external validation, and some caveats are outlined in section 3.3. Finally, section 4 concludes.

1 Identifying credit market shocks

Our first task is to disentangle shocks that arise from the corporate bond market from fundamental macroeconomic shocks. The tool we will use is a structural VAR, identified using sign restrictions on the response functions of credit variables. Identifying the effects of individual macroeconomic shocks, although possible in this framework, is not necessary to achieve our particular aim. Thus will we concern ourselves only with how to split out credit shocks from all the rest[4].

Structural identification requires that we take a stand on the behavioral relationships between variables. Some assumption is needed because the same reduced form relationship can be generated by many different behavioral models, but naturally a poor choice can lead us to draw erroneous conclusions. The assumption that has been used in the literature is that the variables in the VAR can be arranged in a Wold causal chain with bond spreads ordered last. A drawback of this approach is that economic theory does not usually deliver restrictions that take this form. Instead, we will adopt the assumption that fundamental macroeconomic shocks drive the corporate bond spread solely by altering the likelihood of future default. We will refer to movements in spreads that are caused by

[4] A detailed description of the sign restrictions approach to identification can be found in Canova and De Nicoló (2002) and Uhlig (2005). Peersman (2005) identifies all four structural macroeconomic shocks in a four-dimensional VAR.

changes in expected default rates as the 'default channel'. We will take residual changes in the spread, after purging the effect of expected default, to be 'purely financial' in origin. These will be labeled credit market shocks.

Two points are worth stressing about the proposed identification. First, separating the default component matters as it is widely recognized that the default channel does not fully account for changes in bond spreads. The approach of first purging the effect of default from the bond spread, and then examining the residual 'non-default' component, has been applied fruitfully in the finance literature. For example, Longstaff et al. (2005) use credit default swap (CDS) data to establish the existence of a time varying non-default component in spreads, which they attribute to liquidity effects. Collin-Dufresne et al. (2001) consider a range of variables that 'structural' models of default say explain changes in spreads. Their regression results show that these variables are able to capture only a quarter of the movements in spreads across a large panel of bonds, and they conclude that most variation is due to market-specific shocks[5]. Furthermore, in macroeconomics, the importance of the default channel in the link between credit spreads and real activity has been questioned. In their forecasting survey, Stock and Watson (2003) note that spreads 'have the potential to provide useful forecasts of real activity, and at times they have, but the obvious default risk channel appears not to be the relevant channel by which [they] have their predictive content.' Second, the assumption that fundamental macroeconomic shocks work through the default channel is consistent with popular models of financial frictions (Carlstrom and Fuerst (1997); Bernanke et al. (1999); De Graeve (2008)). Moreover, where we have external measures of macroeconomic shocks, the assumption is testable. This issue is taken up in section 3.2, which deals with model validation.

[5]It is important to distinguish between the contribution of default likelihood to *changes* in the spread, and to its *level*. In addition to compensation for default loss, the average level of the spread is explained by taxation effects and compensation for systematic risk (Elton et al., 2001). The 'non-default' component of spreads is found to be largest for investment-grade bonds.

1.1 The restrictions in detail

This section describes how our identifying assumption maps into sign restrictions on the impulse-response functions for the bond spread and default rate in a VAR. The intuition is fairly straightforward. At each point in time, the VAR gives us a projection for the path of future spreads and default rates. One way to think about the impulse-response function is as the revision made to this projection, conditional (in our case) on a credit market shock. Suppose the observed bond spread S_t increases. The default component of S_t can be shown to depend on the cumulative likelihood of default over some horizon h_d. If we revise upward our expectation of the cumulative likelihood of default, then we will attribute the increase in the measured spread to a fundamental shock operating through the default channel. By restricting the cumulative revision to default likelihood to be non-positive, we therefore isolate movements in the measured bond spread which are unrelated to default and are, under our assumptions, due to credit market shocks[6].

Matters can be clarified using a simple two-period example, in which investors are assumed to be risk-neutral, and defaulting bonds are assumed to have a zero recovery rate. Then the difference in yield between a defaultable and a risk-free bond with identical promised cash-flows can be thought of as the compensation investors demand to bear the risk of default over the lifetime or 'tenor' of the bond. Consider a zero-coupon bond that pays \$1 with certainty in two periods' time. If its price at time t is $P_t^{(2)}$, then its yield to maturity is defined by $y_t^{(2)} := -\log[P_t^{(2)}]$. The price of a risky claim to \$1 in two periods, denoted $Q_t^{(2)}$, is determined by its expected value given the random probabilities of default δ_{t+j} in periods $j = 1, 2$:

$$Q_t^{(2)} = \frac{\mathrm{E}_t[(1-\delta_{t+1})(1-\delta_{t+2})]}{1+Y_t^{(2)}}$$

which implies that the yield to maturity on the risky bond $r_t^{(2)} := -\log[Q_t^{(2)}]$ is given by

$$r_t^{(2)} = -\log\{\mathrm{E}_t[(1-\delta_{t+1})(1-\delta_{t+2})]\} + y_t^{(2)} \tag{1}$$

[6]A related approach to the one we describe is the present value VAR model proposed in Campbell and Shiller (1987). Their method would be applicable if we were to model the level of corporate bond yields, rather than the spread, and if the yields were I(1), or integrated of order one.

Denote the spread by $\tilde{S}_t^{(2)} := r_t^{(2)} - y_t^{(2)}$. We will think of $\tilde{S}_t$ as the component of the observed credit spread S_t that is due solely to expected default. When the default intensity is stochastic, an adjustment must be made for Jensen's inequality in order to pass the logarithm through the expectation in (1). A convenient formulation is for the default probabilities to be independent lognormal with constant second moments. In this case, when δ_s is not too large the spread is well approximated by

$$\tilde{S}_t^{(2)} \approx \mathrm{E}_t[\delta_{t+1}] + \mathrm{E}_t[\delta_{t+2}] + c \tag{2}$$

for some constant c depending on the variance of δ_s. The sign of the response of $\tilde{S}_t^{(2)}$ to credit shock can be seen to depend upon the sign of the cumulative change in expected defaults.

We can now distinguish between two cases. If a shock that increases measured bond spreads also leads us to revise upward our expectation of the cumulative default rate in equation (2), the sign of the response of S and for $\tilde{S}_t^{(2)}$ would also coincide. We will say that such a shock operates through the default channel. On the other hand, if a shock leads to wider measured spreads $S_t^{(2)} > 0$, but a lower cumulative likelihood of default $\tilde{S}_t^{(2)} < 0$, we will label it a credit shock. To make the sign restriction operational in the following sections, the two-period example is generalized in the obvious way to account for bonds with tenors of several years, by an appropriate choice of restriction horizon h_d. We specify how h_d is chosen in section 2.2, but turn now to a discussion of our data and results.

2 Data and Results

2.1 Data

Our data runs monthly from November 1982 to April 2009. These dates span a period from the end of the Volker-era non-borrowed reserves targeting to the start of 'credit easing' (Bernanke, 2009). Where the underlying observations are at a daily frequency, we use the data for the last day of the month. The first set of variables is reasonably standard for monetary economics. Output and prices are measured by the log industrial production (IP) index and the log core consumer price index (P) respectively, while policy is measured by the effective federal funds rate (FFR), and the log of real M1[7].

The second set consists of our credit and asset market variables. Monthly default rates are for the universe of Moody's rated U.S. speculative-grade corporate bonds[8]. Moody's defines default events broadly to include any missed payments of interest or principal, the initiation of bankruptcy or other legal blocks to payments, and distressed exchanges which reduce the issuer's financial obligations (for example, an exchange of a less senior for a more senior obligation). Denote the number of defaults in month t by d_t, and the total number of rated issues outstanding by N_t. An estimate of the marginal default likelihood at time t attaching to a broad portfolio of speculative grade bonds is constructed as the trailing 12-month cumulative default rate $D_t = \sum_{s=0}^{11} d_{t-s}/N_{t-11}$. It can be seen that D_t is the proportion of those issues outstanding 12 months ago that defaulted. The denominator N is adjusted for ratings withdrawals, due to scheduled repayments, calls, or mergers. The measure is issuer-based, meaning that the expected likelihood of default for a particular issue with a particular rating is expected to be the same regardless of its nominal size (see Hamilton and Cantor (2006) for details of Moody's methodology).

The bond spread (S_t) is measured as the difference between the yield to maturity on a value-weighted portfolio of cash-pay only corporate bonds and the yield to maturity on a closely-matching government bond. The corporate bond index covers a broad segment

[7]Other authors have favored monthly estimates of aggregate GDP over the IP index. The aggregate output measure that is most comparable is GDP for goods. It comprises durable and nondurable personal consumption expenditures, fixed investment, change in private inventories, and net exports (further explanation can be found on the BEA website). There is a debate on whether money is a necessary component in a VAR model. In this paper we chose to be inclusive, but for the purposes of identifying the credit shock, it made little difference to our conclusions if it were excluded, or if total and non-borrowed reserves were included instead of M1 (for the period November 1982 to December 2007).

[8]Moody's defines this universe as those senior unsecured bonds carrying a rating of Ba1 or lower (the Standard and Poor's equivalent rating is BB+). The equivalent series of speculative-grade default rates produced by Standard and Poor's has a correlation of .96 with the Moody's series. Other studies have made use of structural estimates of default likelihood, such as MKMV (e.g. Gilchrist et al. (2009)). Jarrow and Turnbull (2000) offer a detailed critique of these methods, and argue that they tend to under-predict the likelihood of default during recessions. Market-based measures such as credit default swap (CDS) rates are available for a limited number of the largest companies, and have a relatively short history (see Longstaff et al. (2005)).

of the U.S. high yield corporate market, so as to match as closely as possible the universe of bonds used in the default series[9]. The maturity of the portfolio, measured by its Macaulay duration, is almost constant over time at about 6 years. We nevertheless ensure that the yield spread is calculated with respect to the Treasury bond of equivalent time to maturity following each month's portfolio re-balancing, to avoid conflating movements in the corporate bond spread with changes in term premiums[10]. The average quality rating of the portfolio remains in the B1/B2 range, a category described by Moody's as being 'subject to high credit risk'. Because the bond index starts only in November 1984, we interpolate back an additional two years of data using a quarterly index from Gertler and Lown (1999) and a monthly index of Moodys Baa-rated bonds (none of the results are sensitive to excluding the interpolated data). Last, we include an equity price index (EQ_t) for mid-sized stocks, the S&P MidCap 400, to capture linkages between asset markets, and as a proxy for collateral values.

2.2 Impulse-responses

The baseline statistical model is a Bayesian VAR(6) with $\mathbf{y}_t = [\ln(\mathrm{IP}_t), \ln(\mathrm{P}_t), \mathrm{FFR}_t, \ln(\mathrm{M1}/\mathrm{P}_t), (\mathrm{EQ}_t), \mathrm{D}_t, \mathrm{S}_t]'$ (details of our estimation methods can be found in Appendix A). We begin with the results from the sign restrictions approach. Sign restrictions limit the way that expectations are revised relative to baseline, following a shock. We restrict the response of corporate bond spreads to be positive for $h_s = 6$ months, and the cumulative response of the default rate to be non-positive for $h_d = 48$ months. The results were not sensitive to imposing the second restriction for longer or shorter periods,

[9]The Merrill Lynch index is a widely-used benchmark for assessing portfolio performance. For inclusion in the index, bonds must be a year or more from maturity, be U.S. dollar denominated, and have at least $100 million face value outstanding. The 'cash pay' index excludes deferred interest and pay-in-kind issues. Full details of the calculations behind the index can be found in Galdi (1997).

[10]We calculated spreads against zero-coupon Treasury yields estimated from a Svensson yield curve from the Federal Reserve Board. This measure of the spread is not fully satisfactory as the returns on a coupon bearing bond and a zero coupon bond of identical Macaulay durations will be equal only up to a first-order, and only for a level shift in the yield curve. However, in the absence of information on coupon schedules it is likely to be a reasonable approximation, and it is widely used in the literature. Gilchrist et al. (2009) investigated the properties of the similar Merrill Lynch Master II index as a comparator, but calculated the spread relative to a 10-year government bond, rather than adjusting for duration each month as we do here.

although in order for our identification to be sensible, it was thought that imposing the sign restriction for less than three years was undesirable as the average Macaulay duration of the bond portfolio is around six years. Imposing the restriction for more than five years has little effect since default risk at very long horizons is not greatly influenced by current macroeconomic conditions.

The estimated responses to a one standard deviation adverse credit market shock (one that raises the credit spread) are shown in figure 2. The solid line shows the median value of the impulse-response function distribution for each horizon h across all posterior draws. The dashed lines give the 16th and 84th percentiles of the impulse-response function distribution at each h. Output is estimated to drop sharply on impact, and is expected to remain low for a protracted period, beginning to recover only after a year. The error band indicates that with high probability, output remains below its baseline value for a full two years following the shock, indicating that credit-induced recessions may be followed by sluggish recoveries. The responses of the funds rate and of money are consistent with a systematic easing of monetary policy in reaction to a combination of lower output and lower prices. The fall in output occurs for the usual reasons: Because firms face a higher cost of market funds and thus higher effective input costs, standard theory predicts lower input demand and lower output[11].

Default rates also decrease on impact. The initial fall of roughly a quarter of a percentage point is followed by a slow increase as defaults respond endogenously to lower real activity. The rate levels off after a year, when output begins to recover. There are several reasons underlying the lower default rates. Firstly, firms under financial stress are known to take a variety of steps to improve their creditworthiness. Asquith et al.'s (1994) study of junk bond issuers presents evidence that firms respond to a higher cost of funds by raising cash through asset sales, which reduce productive capacity but improve liquidity, and by outright mergers[12]. On the other side of their balance sheets, firms

[11] In the presence of financial frictions, alternative means of financing are imperfectly substitutable, giving rise to 'financial accelerator' effects (Bernanke and Gertler (1995); Gertler and Lown (1999)).

[12] Mergers, in which the acquiring firm generally assumes the debt of the target, can be thought of as a 100 percent asset sale.

make important changes to their private (i.e. bank) liabilities, which are designed to alleviate near term stress and at the same time improve creditworthiness. These margins of adjustment can lead to fewer outright defaults, even as output is cut. Secondly, if firms respond to the credit shock by delaying new debt issues, lower aggregate default rates can be explained by the well-known 'aging effect' (Helwege and Kleiman, 1996). Historically, more recently-issued bonds have experienced a higher frequency of default than seasoned bonds, so fewer new issues would mean lower average default rates[13].

The negative effect on output is present even though no restrictions are placed on the sign or shape of its response function (or that of any non-credit-related variable) under our approach. By contrast, the initial drop seen in figure 2 is ruled out by recursive identification schemes, where it is assumed that the response occurs only with a delay[14]. We take up the discussion of this point in section 3.1 below.

2.3 Historical decomposition

Further insight into the effects of credit market shocks can be gained by considering the historical contributions they have made to fluctuations in output and spreads. Results are shown for the median model (see Appendix A). The top panel of figure 3 shows the deviation of actual industrial production from a projection based on pre-sample data, and the contribution of credit shocks to this deviation. The lower panel of figure 3 shows the same information for the high-yield bond spread. The net contribution of all the other (unidentified) shocks is then the difference between the two lines in each of these figures. Naturally, without identifying the other shocks we are unable to say whether credit played the dominant role in a particular episode, but we can gauge its absolute importance.

The recessions of the early 1990s, of 2001 and of 2007-9 are marked by clear declines

[13]As noted in the minutes of the October 2008 FOMC meeting, new issuance of speculative-grade bonds all but ceased in the fall of 2008. McDonald and Van de Gucht (1999) document that the default likelihood of a new issue increases sharply at two years and then steadily declines, such that an issue that has survived for five years is about half as likely to default as an issue that has survived only two years.

[14]The sign restriction approach allows for the possibility of delayed responses, which correspond to the case of the rotation matrix **Q** given in Appendix A being close to diagonal.

in industrial output. In the last two cases, the cumulative effect of credit market shocks during these episodes was negative for industrial production. However, credit market shocks did not cause the 1990-1 recession. Although spreads were higher than in the base projection, the model attributes most of the increase to higher expected defaults, defaults which did transpire (see figure 1). By contrast, the 2001 recession was driven in part by credit shocks. From the peak of the business cycle in February 2001, to the trough of the recession in November, industrial production contracted 5.2% (relative to a baseline projection) of which 3.3%, or roughly two thirds, was due to credit shocks[15]. Spreads peaked in September 2001, at 2.3 percentage points (pp) above pre-recession levels. Credit shocks made a 3.4pp contribution, one-and-a-half times the total increase (meaning that the combined effects of other shocks was to lower spreads over this period).

The largest absolute effects, unsurprisingly, are seen during the 2007-9 recession. From the business cycle peak in November 2007 to the end of the first quarter of 2009, industrial production contracted 16%. Credit shocks account for a 6.7% decline, just over two fifths of the total. From the onset of the subprime crisis in June 2007, through to the start of the recession in December 2007, credit shocks raised spreads by a cumulative 1.1pp out of a total increase of 3pp. This accords well with the pattern of defaults over that period, which hit an all time *low* of 1% in December, and with narrative accounts that show that over this period, the full extent of the crisis was hardly imagined. On the eve of the crisis, The Economist called corporate debt defaults 'the mosquito that did not bite in the night', and asked when the default cycle would turn, while S&P's issued upgrades for a large number of junk bonds[16]. Anecdotal evidence would seem to agree with what our model-based forecasts tell us, namely that in the earlier stages of the crisis spreads were driven higher by credit market shocks. Once the recession got underway, spreads rose by a further 13.8pp, of which 6.3pp were due to credit shocks. With default rates forecast to reach double digits, more than half of the increase in spreads over this period was an

[15]By this we mean that under a counterfactual scenario in which credit shocks were zero over the same period, but all other shocks took the same values, four fifths of the decline in output would not have occurred.

[16]'Unsinkable junk', The Economist, June 24, 2007; 'S&P upgrades 1,500 junk bonds and loans', Financial Times, June 7, 2007.

endogenous response to expected credit losses.

2.4 Variance decomposition

In this section, we report variance decompositions for macroeconomic and credit variables over the 1982–2009 period. Arguably, the period from June 2007 has been far from average, and so we compute the same statistics on a shorter sample which omits it[17]. We should keep in mind when looking at these results that the particular type of credit disturbance we have identified may be only one of several ways in which credit shocks might impinge on the economy. There may well be other distinct, uncorrelated credit disturbances which we do not measure here, the most obvious arising from the banking sector, or as recently, from markets for securitized credit products[18]. For that reason, the results we obtain are best regarded as giving a lower bound for the contribution of credit market shocks to the business cycle.

Table 1 reports the percentage contribution of credit market shocks to the total mean square prediction error in output, default rates and spreads at various horizons. The left panels report our results under sign restrictions. On the full sample, the median proportion of output variation accounted for at the one-year horizon is 15%, with the 68% probability interval extending from 3% to 36%. On the sub-sample that excludes the 2007-9 crisis period, the median contribution is 21%, somewhat higher, while the range of uncertainty is wider, from 7% to 46%. As overall output volatility was significantly lower in the pre-crisis sample, mechanically the finding that credit market shocks contributed more to volatility in the earlier period must mean that the pre-crisis shocks were not much smaller on average than those during the crisis.

Estimates for the contribution of credit market shocks to the variance of spreads are small in both full and sub-samples. On the full sample, their average contribution is

[17] We date May 2007 as the end of the 'normal' period, as June saw the closure of two hedge funds managed by Bear Stearns that specialized in subprime asset-backed securities, the first such collapse of the crisis.

[18] Spreads on speculative-grade bonds are not likely to be informative about the state of the banking sector. As of December 2008, none of the 50 largest bank holding companies had debt rated below Baa. Furthermore, regulatory rules prohibit banks from holding below investment grade debt.

never far above 7% at any horizon. Spreads are highly volatile, and credit market shocks are small, thus the bulk of the variation in spreads is due to other disturbances[19]. In line with previous studies, it appears that for high yield corporate bonds, 'non-default' shocks do not account for much of the variation in spreads. The estimated credit shocks unsurprisingly account for only a small part of the variation in default rates at business cycle frequencies.

The results just outlined lend support to the view that credit market shocks do play a role in business cycle fluctuations. As is usual in this type of analysis, we cannot gauge the magnitude of their contribution to output fluctuations with high precision, but at the one-to-two year horizon it is probably about 15%. Even in 'normal' times, credit shocks matter, but their contribution is well below that reported in recent VAR studies. The following section investigates why this might be.

3 Further discussion

3.1 Why do conventional restrictions give such different results?

We now consider a recursive identification strategy similar to that used in several previous studies. As we use monthly rather than quarterly data, the timing restriction imposed by recursiveness may not be thought particularly strict. However, we show that it materially alters the conclusions drawn from the data[20]. The causal ordering broadly follows that used by Friedman and Kuttner (1998), Gertler and Lown (1999), Balke (2000) and others. It implies that innovations to output and prices can affect monetary policy within the month. It also implies that all the macroeconomic variables feedback to the credit market within the month, but not vice versa. In particular, innovations to the spread cannot affect the effective funds rate, equity prices or the likelihood of default within the month[21].

[19] Figure 2 shows that a one standard deviation credit shock raises spreads by 10-20bp.

[20] All the results reported in this section are based on the same posterior draws as for the sign restrictions results above.

[21] The conclusions of this section are not affected by changing the ordering of the VAR so that defaults are ordered after spreads, and can react on impact to the spread shock.

The response to an orthogonal innovation to spreads under the recursive identification scheme is shown in figure 4. An increased spread leads to lower real activity and to somewhat easier monetary policy as the funds rate is lowered and real balances rise. Equity prices undergo a significant and protracted decline. Such responses are broadly similar to type of picture seen for example in Balke (2000, Fig. 2) or Gilchrist et al. (2009, Fig. 5). The most important difference compared to sign restrictions is that the shock is associated with substantially higher default rates over the two following years which, by causing an endogenous rise in spreads through the default channel, tends to amplify its effects.

Variance decompositions under the recursive identification scheme are shown in the right panels of table 1. There are some marked differences with the sign restrictions results. First, the contribution of credit market shocks to output variation is substantially greater than under sign restrictions, and peaks at business cycle rather than short frequencies. This is the case in both samples, although the ex-crisis results show lower contributions than the full sample. At one-to-two years, they account for around a third of the fluctuations in output. The probability intervals are as wide as under sign restrictions at the longer horizons, even though credit shocks make no contribution to fluctuations at $h = 0$ by construction. In fact, for 16% of draws, more than half of output variance is attributed to credit market shocks at horizons over two years.

Second, most of the variation in credit spreads is attributed to credit *shocks*. Their contribution is 73% at one year, and remains above 50% even after five years. The variance of default rates is also strongly affected by the recursively-identified credit shocks at horizons over a year. An implication is that credit spreads barely register the effect of macroeconomic shocks, even over longer horizons. The size of the contribution made by credit market shocks to the variance decompositions of output and credit variables is something of a surprise. Gilchrist et al. (2009) argue that large effects may be explicable if bond spreads mainly reflect premiums on risk and liquidity, an issue we take up below. An alternative explanation is that the recursive scheme confounds financial shocks with fundamental macro shocks. Indeed, the sign pattern of responses for output, prices and monetary policy shown in figure 4 are often taken to identify an adverse demand shock (see, for example, Peersman (2005)).

3.2 Are the identified shocks reasonable?

This section returns to the VAR identified using sign restrictions, as discussed in section 1. We undertake to validate our results using information from outside the VAR, as a way of building confidence and gaining insight into the model [22]. The estimated credit shocks for the median model are shown in figure 5. The terrorist attacks of September 2001, and the market freeze following the failure of Lehman Brothers in September 2008 manifest as large spikes in the series.

Although these shocks appear to be reasonable, an important motivation for our identification scheme was that it should not confound credit market and macroeconomic shocks. The first check we perform tests whether our estimated credit market shocks satisfy that basic assumption. Second, the discussion in section 1 abstracted from liquidity effects, which empirical studies of corporate bond markets often find are important, and it assumed that investors were risk neutral, whereas in practice, there is good evidence to suggest that they demand a premium for bearing default risk. We examine each of these issues in turn.

Monetary Policy Shocks: Surprise moves in monetary policy are often taken to be a fundamental driver of macroeconomic fluctuations. They are also an obvious source of high-frequency variation in interest rates that should be unrelated to credit shocks. We calculated monetary policy shocks derived from movements in the Federal Funds Futures (FFF) rate for each month in which there was a scheduled FOMC meeting[23]. We have approximately 16 years of data, starting in 1992, and after allowing for months in

[22]For a critique of the structural VAR method in another context, see Rudebusch (1998).

[23]For full details of how we constructed the policy shocks, see Faust et al. (2004). Note that the match between our credit shocks, which correspond to end-of-month data, and the policy shocks, which correspond to meeting day data, is somewhat imperfect.

which there was no scheduled policy meeting are left with 131 data points. Figure 6 plots monetary policy shocks against the VAR-based credit market shocks (where the latter are rescaled so both series have the same variance). Bars join observations on a given date to make the association clearer. It does not appear to be a close one: for example, in September and October 2008 there were two large adverse credit shocks; in September the futures market was surprised by monetary policy being 5bp tighter than anticipated, but in October policy was 6bp looser. To investigate further, we regressed the estimated credit shock $\hat{v}_t$ on the monetary policy shock. The results were as follows (t-statistics in parentheses):

$$\hat{v}_t = \underset{(1.65)}{-.196} + \underset{(.492)}{1.19}\ \hat{\varepsilon}_t^{FFF}, \qquad R^2 = .00188, \quad N = 131$$

The regression reveals no statistical association between our estimated credit market shocks, and the independently measured exogenous monetary policy shocks. This finding adds confidence to the identifying assumptions adopted in section 1. It also suggests that the degree of error in our measurement of the bond spread is not too large.

Liquidity Shocks: Chen et al. (2007) investigate bond-specific liquidity effects using detailed quote data, which includes liquidity proxies such as the size of the bid-ask spread, and the occurrence of zero returns. They find that the liquidity of individual bond issues is a significant determinant of changes in their spreads, after controlling for ratings effects, firm-specific characteristics and certain key interest rates. Another possibility is that changes in the liquidity of the government bond market drive changes in the spread. Government bonds carry a significant liquidity premium, particularly on-the-run Treasury issues[24], a factor that gives rise to their 'specialness'. However, Collin-Dufresne et al. (2001) report that aggregate liquidity proxies such as the on-the-run/off-the-run spread do not explain spread changes. Lacking a measure of liquidity premiums in corporate bond markets, we examined premiums on government bonds. To arrive at a measure of

[24]The most recently issued and so most liquid Treasury bond of a particular maturity. Secondary market 'off-the-run' Treasury bonds are less liquid.

liquidity shocks, we projected the on-the-run/off-the-run spread, denoted *ONOFF*, on six own lags and six lags of all the explanatory variables used in the VAR. We then ran an OLS regression of our credit market shocks on the liquidity shocks. The results were as follows:

$$\hat{v}_t = - \underset{(.925)}{.0887} - \underset{(.0102)}{.0349} \hat{\varepsilon}_t^{ONOFF}, \qquad \underset{1984:5-2009:4}{R^2 = .0}$$

Liquidity shocks have no statistical association with credit shocks. Naturally, this result does not rule out an independent role for liquidity shocks as a driver of changes in bond spreads, but it does indicate that the variation in spreads that we identify is not primarily liquidity-related.

Risk premium shocks: Changes in the non-default component of the spread may be driven by shocks to risk premiums. Theoretically, even if diversification of risk means that investors' risk-neutral assessment of default likelihood coincides with the actual ('physical') likelihood we model in the VAR, actual and risk-neutral bond prices need not coincide as pricing is done under the risk-neutral probability measure[25]. This means that changes in risk premiums could be behind non-default moves in spreads. Elton et al. (2001) find that a significant portion of time series variation in spreads is due to variations in the compensation required for bearing systematic risk, by regressing the 'residual' spread, after accounting for default, on the Fama-French factors[26]. Unfortunately, risk premiums are hard to measure, and no ready empirical proxy exists. One imperfect possibility is to use the CBOE's VIX index, a measure of expected 30 day volatility in the S&P equity index based on index option prices. The VIX can be thought of as primarily reflecting the price of protecting investor portfolios against loss, and as such captures shifting demand for 'insurance' that is likely linked to risk premiums. To construct a risk premium shock, we projected the logarithm of the VIX index on six own lags and six lags

[25]See Duffie and Singleton (2003) for a discussion of this point.

[26]These are returns on small versus large stocks, high versus low book-to-market stocks, and excess returns on the market. Elton et al. abstract from liquidity effects.

of the other variables. We then ran an OLS regression of our credit market shocks on the risk shocks with the following results:

$$\hat{v}_t = -\underset{(1.26)}{.0999} + \underset{(6.27)}{4.29}\,\hat{\varepsilon}_t^{VIX} \qquad \underset{1990:7-2009:4}{R^2 = .149}$$

The strong statistical association between VIX shocks and credit shocks provides support for the finding in Campbell and Taksler (2003) that equity volatility has explanatory power for corporate bond spreads.

3.3 Caveats

An advantage of our VAR-based model of bond spreads is that it does not tie us to a particular class of parametric term structure model. Further, by allowing for credit and macro variables to be jointly determined, it explicitly allows for feedback effects from credit markets to the macroeconomy. However, several potential weaknesses in the approach should be dealt with. First, there may be other disruptions to credit markets that lead to simultaneous increases in both spreads and default risk, which we cannot easily separate from other macroeconomic shocks. An example is the 'credit shock' modeled by Nolan and Thoenissen (2009) as an exogenous change in collateral values (formally, the net worth of the firms facing financial constraints). Of course, our investigation remains worthwhile, as we cannot know *a priori* which shock is the most relevant one for understanding credit market disruptions.

A second consideration is the familiar Peso problem, the possibility that investors might rationally believe there is a small probability of visiting states where they would suffer large losses, but these states did not occur during the sample period under study. Bekaert, Hodrick, and Marshall (2001) are able to estimate the Peso effect in U.S. Treasury bonds using multi-country data, but the extension to corporate bonds, although interesting, is beyond the scope of the present study.

Perhaps more serious is the possibility that, because of segmentation between the markets for various asset classes, endogenous changes in the quantities of corporate bonds outstanding are an important driver of spreads[27]. If firms issue bonds in anticipation of a favorable economic climate, this will tend to raise their required yield without necessarily raising the likelihood of default, and that would interfere with our inference[28]. However, Korajczyk and Levy (2003) find that firms that are relatively financially constrained - such as those who cannot tap the investment grade bond market - are less able to alter their capital structures in response to favorable macroeconomic conditions in this way. Another reason for an increased supply of speculative-grade bonds could be increased downgrades of investment-grade bonds, perhaps as a result of poor economic news. In this case, although high-yield spreads may increase on the back of increased supply, a worsening macroeconomic outlook would mean that default risk would also be higher.

A final concern is that we require a linear VAR to provide a good enough approximation to the data generating process both for the macroeconomic variables, and importantly for bond yields as well. An extension to the linear VAR framework that we do not pursue here is to allow for conditional mean shifts driven by credit regimes, as in Balke (2000). He finds that the propagation of shocks is dependent on prevailing credit conditions, with substantial amplification of shocks in his 'tight credit' regime, compared to normal times. If these effects were important in our sample, we would tend to underestimate the contractionary effect of credit market shocks in stressed conditions[29].

4 Conclusion

Do credit market shocks drive output fluctuations? We investigated this question focusing on the market for speculative-grade corporate bonds. The view we took was deliberately narrow, in order to avoid conflating credit market shocks with fundamental

[27] In the case of the paper-bill spread, this possibility has been studied in detail by Friedman and Kuttner (1998). Note that regulatory changes enacted in the wake of the savings and loan crisis mean that some investors are unable to hold high yield bonds, and so face a perfectly segmented debt market.

[28] Although in light of the 'aging effect' (section 2.2), we might expect a wave of new issues to raise expected default likelihoods.

[29] Rubio-Ramírez et al. (2005) discuss identification of Markov-switching VARs using sign restrictions. We judged that nonlinearities in higher moments, such as stochastic volatility, were less important for modeling yield spreads than is the case for yield levels.

macroeconomic shocks. Our approach made use of a VAR to model the joint behavior of the macroeconomy and the credit market as in Friedman and Kuttner (1998), Balke (2000) and Gilchrist et al. (2009). Unlike previous studies, our approach to identification was motivated by explicit economic assumptions. An important component of our strategy was to account for default risk by modeling historical default rates together with spreads. This allowed us to purge the effects of expected default from the spread, and in so doing, isolate the effects of financial shocks. As in Uhlig (2005), we left the question of the effects of credit shocks agnostically open by using sign restrictions on credit spreads and default rates, while leaving output and other financial market prices unrestricted.

We find that shocks to lending spreads in the market for long-term corporate debt cause immediate and prolonged contractions in output. Credit market shocks were found to have had a negative impact in the 2001 and 2007-9 recessions. However, the average size of the sector's contribution to business cycle fluctuations is much more modest than several recent papers have estimated, contributing around 15% to the variance of output at the one year horizon. To generate large contributions, a recursive identification scheme which has little theoretical support must be assumed. Nevertheless, our research lends empirical support to recent theoretical models where financial shocks are an independent source of business cycle fluctuations.

A Estimation, Inference and Model Selection

This section outlines the specification and estimation of our baseline statistical model, and reviews the sign restriction approach to identification. We follow a conventional estimation strategy, choosing the familiar reduced-form linear VAR(p), written

$$\mathbf{B}(L)\mathbf{y}_t = \mathbf{u}_t \tag{3}$$

where $\mathbf{y}_t$ is an n-vector of variables of interest, and $\mathbf{B}(L)$ is a lag polynomial of order p with $\mathbf{B}_0 = \mathbf{I}_n$. We take a Bayesian perspective to inference, and do not include any deterministic components, such as a constant or trend. We adopt the uninformative priors for $(\mathbf{B}, \mathbf{\Sigma})$ described by Uhlig (2005, Appendix B). Lag length p was set to 6 months, although the choice of either 12 months or 3 months was not found to greatly affect the results. The solution to the VAR is the vector moving average process

$$\mathbf{y}_t = \mathbf{C}(L)\mathbf{u}_t \tag{4}$$

It is usual to transform the reduced form innovations $\mathbf{u}_t$ to orthogonality to see the 'distinct patterns of movement' in the system. A common approach is to assume a contemporaneously recursive structure by using the lower triangular Choleski factor of the covariance matrix $\mathbf{\Sigma}$, denoted $\mathbf{A}_0$, which gives the transformation

$$\mathbf{u}_t = \mathbf{A}_0\mathbf{v}_t^* \qquad \mathrm{E}[\mathbf{v}_t^*\mathbf{v}_t^{*'}] = \mathbf{I} \tag{5}$$

where $\mathbf{v}_t^*$ are the Choleski-orthogonalized residuals. It is straightforward to see that this factorization of $\mathbf{\Sigma}$ is not unique. For any nonsingular matrix $\mathbf{Q}$, we can form a new impact matrix $\mathbf{A} = \mathbf{A}_0\mathbf{Q}$ and associated structural shocks $\mathbf{v}_t = \mathbf{Q}^{-1}\mathbf{v}_t^*$ such that the reduced form covariance structure is preserved. Supposing we choose $\mathbf{Q}$ to be an orthogonal matrix, such that $\mathbf{Q}^{-1} = \mathbf{Q}'$, then we may write

$$\mathbf{u}_t = \mathbf{A}\mathbf{v}_t := \mathbf{A}_0\mathbf{Q}\mathbf{Q}'\mathbf{v}_t^* \qquad \mathrm{E}[\mathbf{A}\mathbf{v}_t\mathbf{v}_t'\mathbf{A}'] = \mathbf{A}\mathbf{A}' = \mathbf{\Sigma} \tag{6}$$

There are many candidate structural VMA representations, each given by an $\mathbf{A}$ in

$$\mathbf{y}_t = \mathbf{C}(L)\mathbf{A}\mathbf{v}_t \tag{7}$$

and we select amongst them according to prior sign restrictions placed on the impulse-response functions. If the matrices $\mathbf{C}_i$ in the reduced form moving average representation are stacked, then the response vectors up to horizon h for a particular model given by $\mathbf{A}_0\mathbf{Q}$ are straightforwardly found as the $n(h+1)\times n$ matrix

$$\mathbf{R}(h) = [\mathbf{A}_0' \quad \mathbf{A}_0'\mathbf{C}_1' \quad \mathbf{A}_0'\mathbf{C}_2' \quad \ldots \quad \mathbf{A}_0'\mathbf{C}_h']'\,\mathbf{Q} \tag{8}$$

The sign restrictions that we will impose on the impulse responses are then restrictions on the columns of this matrix. Some blocks will be unrestricted; for example, if a set of sign restrictions hold only contemporaneously, then only columns of $\mathbf{A}_0\mathbf{Q}$ need be considered. Similarly, if the sign of the response of variable i is free under every restriction vector, then rows $(i, i+n, i+2n, \ldots, i+hn)$ will be unrestricted. The advantage of the sign restrictions approach is that the tasks of orthogonalizing the VAR residuals and of ensuring that they obey theoretical priors are separated.

The computational approach is described in Rubio-Ramírez et al. (2005, Algorithm 2): for each posterior draw of $(\mathbf{B}, \mathbf{\Sigma})$, we draw a $\mathbf{Q}$ matrix and check if our sign priors are satisfied for every shock that is to be identified; if they are not, we draw another $\mathbf{Q}$ and so on until a one is found that does. To obtain $\mathbf{Q}$, we draw an $(n\times n)$ Gaussian matrix, and then compute the orthogonal-triangular or QR decomposition to obtain the orthonormal matrix $\mathbf{Q}$. Because $\mathbf{Q}$ is orthonormal, each column satisfies $\|q_i\| = 1$ and $q_i'q_j = 0$ for all $i \neq j$. As there exists a $\mathbf{Q}$ such that $\mathrm{a}_i = \mathbf{A}_0 q_i$, this method provides a constructive means to find a set of n impulse vectors $\mathbf{A} = [\mathrm{a}_1, \ldots, \mathrm{a}_n]$.

Fry and Pagan (2007) have cautioned against certain innovation accounting methods that fail to preserve the orthogonality between structural shocks. Following their lead, the 'median model' mentioned in the text is found as follows. A single model from the posterior set is chosen that has an impulse-response function closest to the median response for each variable and at every horizon. Define the stacked and standardized impulse response function for model k by $\phi^{(k)} = (\mathrm{vec}[R(h)^{(k)} - \bar{R}(h)])/\mathrm{std}[R(h)]$. Then the model that generates the smallest deviation from the median response solves

$$k_{(2)} = \arg\min_{k}\{\|\phi^{(k)}\|_2\} \tag{9}$$

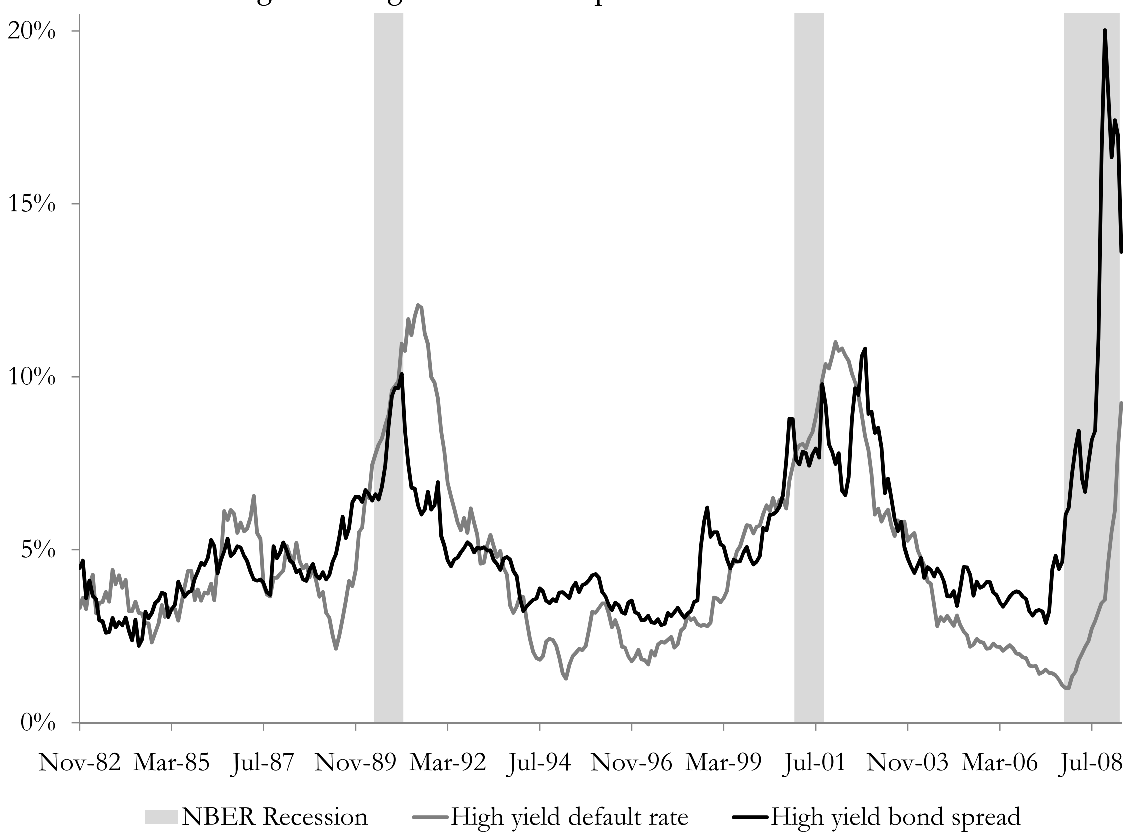
where $\|.\|_2$ denotes the usual Euclidean norm, and we set $h = 48$. The impulse-responses from the selected model are shown in figure 7.

Table 1: Forecast Error Variance Decomposition

	Sign Restrictions						Recursive Restriction					
Sample 1982:11 - 2009:4												
h	3	6	12	24	36	60	3	6	12	24	36	60
IP	12.9	15.2	15.1	11.5	10.1	10.8	10.8	21.2	31.6	36.0	35.5	31.1
	(3 – 33)	(4 – 36)	(3 – 36)	(2 – 34)	(2 – 34)	(3 – 33)	(7 – 15)	(14 – 29)	(21 – 42)	(22 – 50)	(20 – 52)	(16 – 50)
D	11.9	9.6	6.8	5.2	5.3	6.5	1.1	5.7	21.7	36.3	36.4	36.7
	(2 - 35)	(2 – 30)	(2 – 20)	(1 – 13)	(2 –13)	(2 – 16)	(0 – 3)	(2 – 11)	(12 – 34)	(20 – 52)	(20 – 52)	(21 – 51)
S	7.1	6.4	5.5	5.5	6.1	6.6	82.5	79.5	73.1	66.8	62.2	57.5
	(2 – 19)	(2 – 18)	(2 – 17)	(2 – 16)	(2 – 17)	(2 – 18)	(76 – 88)	(72 – 86)	(63 – 82)	(54 – 77)	(49 – 74)	(43 – 70)
Sample 1982:11 - 2007:5												
h	3	6	12	24	36	60	3	6	12	24	36	60
IP	17.3	21.0	21.2	16.3	13.3	11.6	10.3	16.4	20.7	22.8	24.1	22.9
	(4 – 44)	(7 – 47)	(7 – 46)	(4 – 39)	(4 – 35)	(4 – 31)	(7 – 15)	(11 – 24)	(12 – 31)	(12 – 35)	(12 – 38)	(11 – 38)
D	5.1	4.5	4.3	4.0	5.5	7.7	4.5	13.2	26.9	25.2	22.0	20.3
	(1 – 19)	(1 – 14)	(1 – 10)	(2 – 9)	(2 – 12)	(3 – 18)	(2 – 8)	(7 – 20)	(17 – 38)	(15 – 38)	(12 – 34)	(11 – 31)
S	12.0	9.5	8.0	6.8	8.0	9.4	73.1	64.6	52.1	43.4	38.2	32.8
	(4 – 27)	(3 – 22)	(3 – 17)	(3 – 15)	(4 – 17)	(4 – 17)	(65 – 81)	(53 – 75)	(40 – 64)	(31 – 56)	(27 – 51)	(22 – 45)

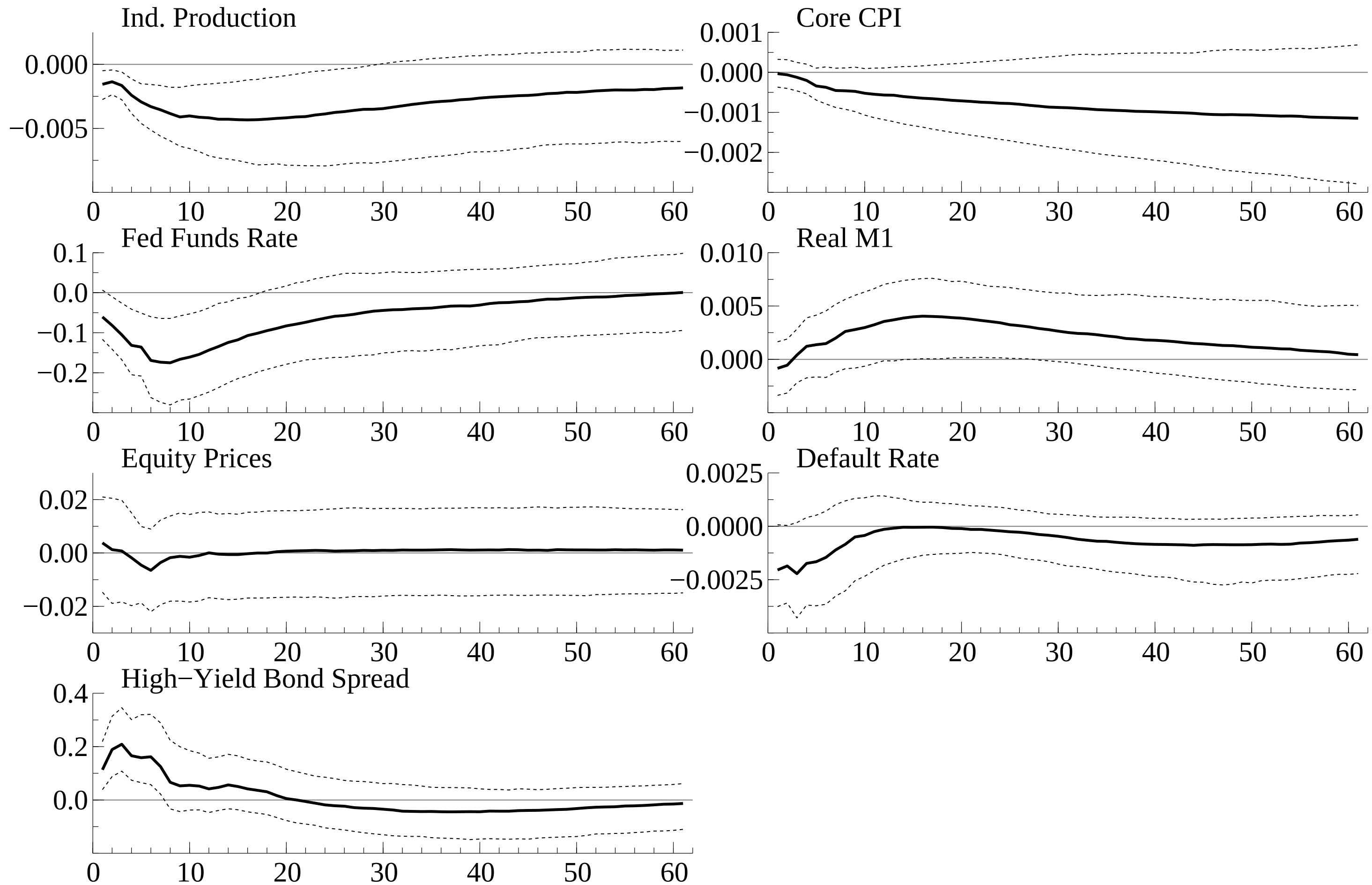
Note: Estimated median percentage share of total horizon-h forecast error variance attributed to credit market shocks in each sub-sample and under each identification scheme. The 16th and 84th percentiles of the distribution of the horizon h variance share in parentheses. *IP* industrial production, *D* default rate on high yield corporate bonds, *S* yield spread between high yield corporate bonds and Treasuries. The recursive ordering places spreads last in the causal chain.

Figure 1: High-Yield Bond Spread and Default Rate



Note: Spread is in annual percentage points; default rate is the percent of bonds outstanding 12 months ago that subsequently defaulted, weighted by issuer. The shaded rectangles represent NBER defined recessions. See Section 2.1 for details of data construction.

Figure 2: Impulse-responses: Sign restrictions



Note: Solid line is the posterior median of the impulse response function distribution at each horizon. Dashed lines are the 16th and 84th percentiles of the posterior distribution of the impulse response function at each horizon. Figure shows a one standard deviation credit market shock. Model is a VAR(6), sample is 1982:11 - 2009:4.

Figure 3: Historical contributions of credit market shocks

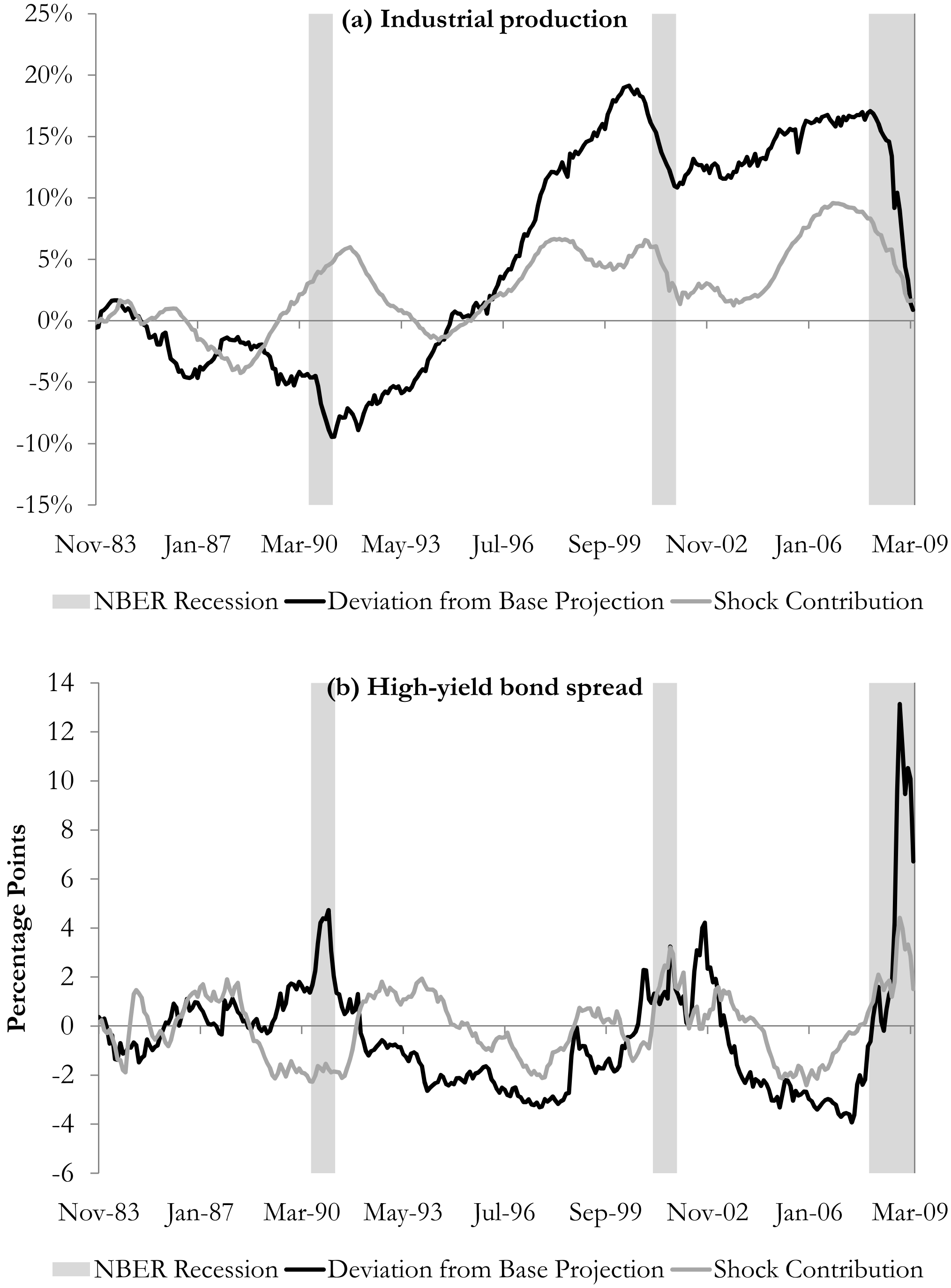
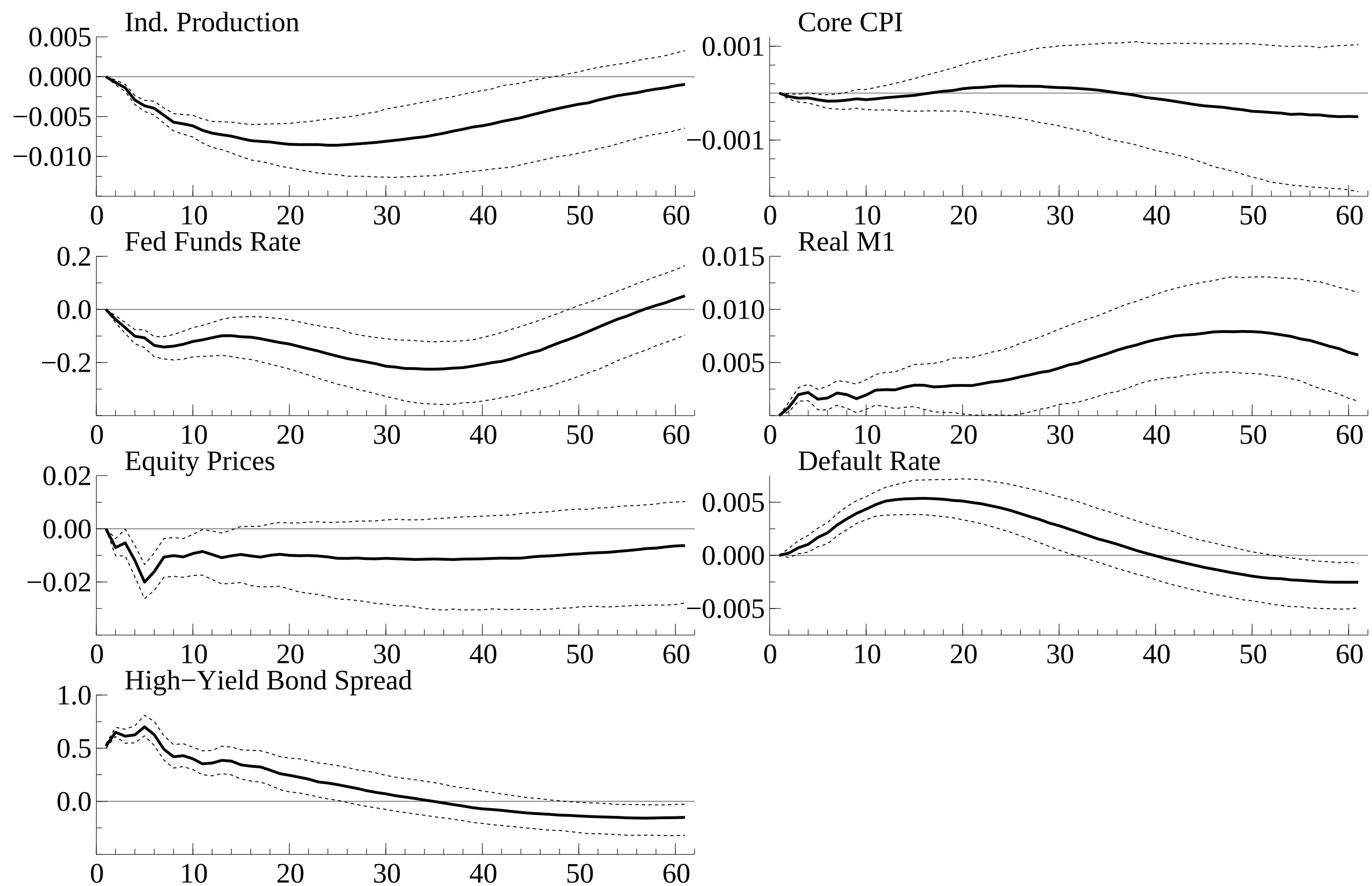
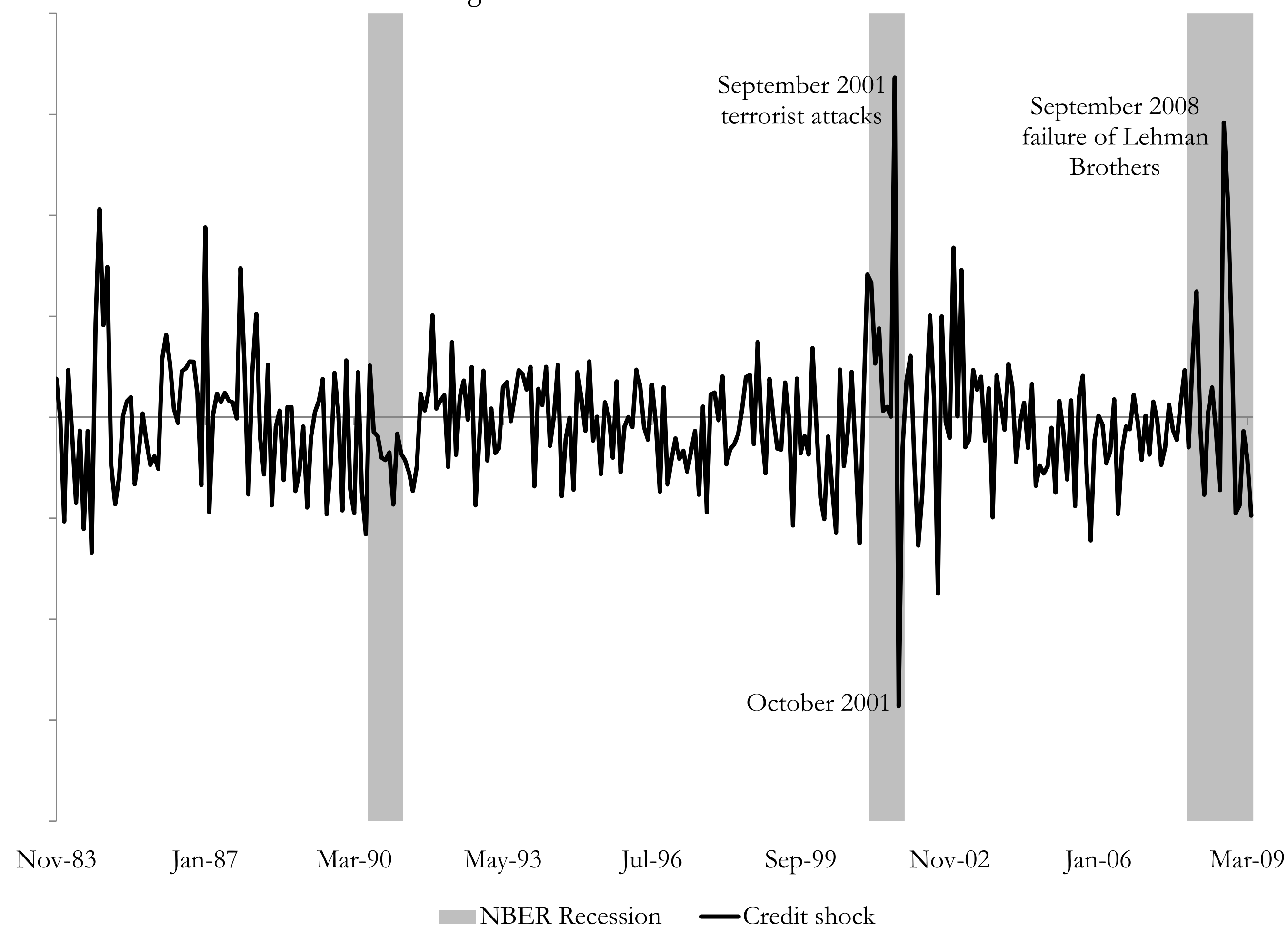


Figure 4: Impulse-responses: Recursive identification



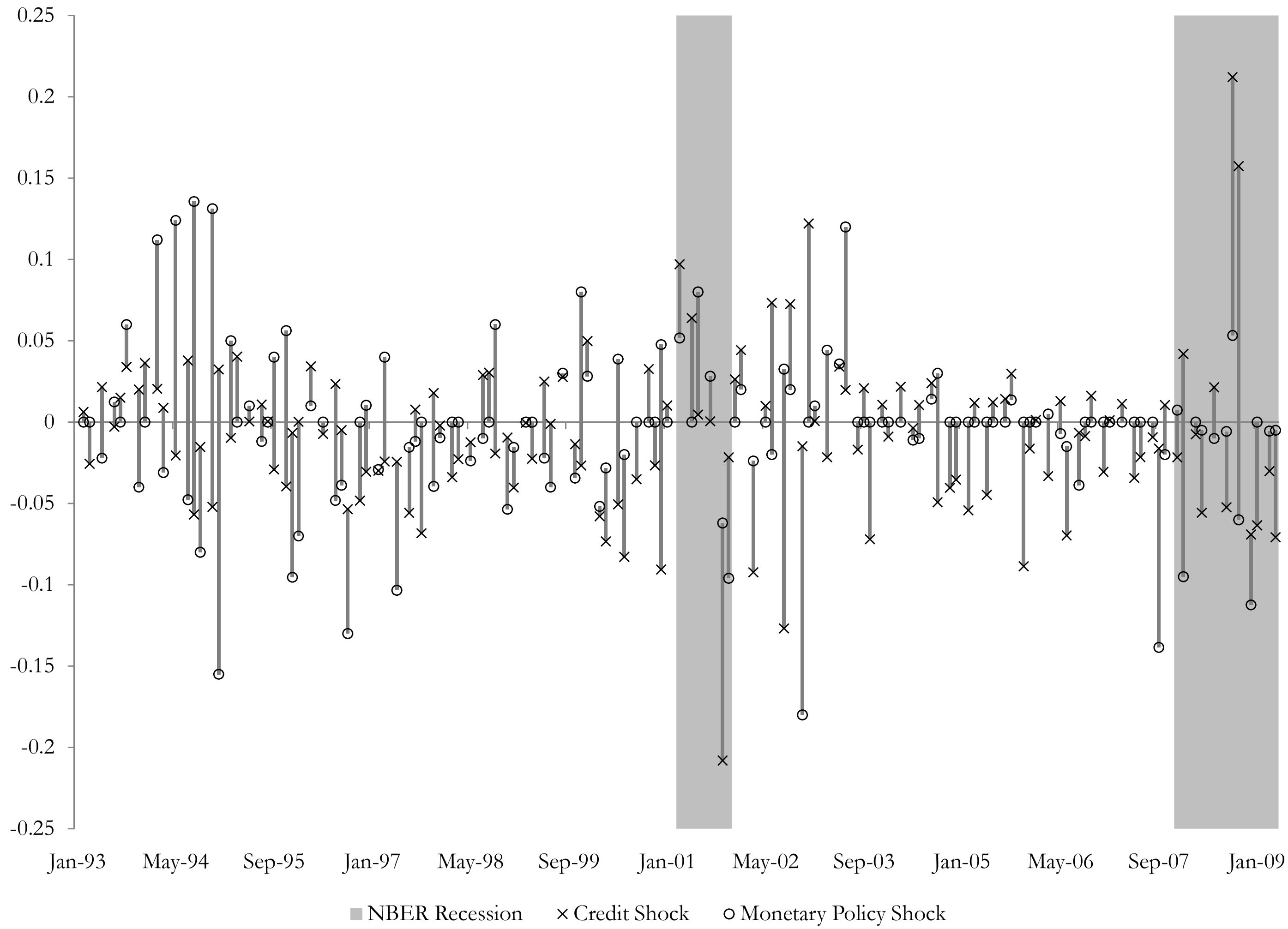
Note: Solid line is the posterior median of the impulse response function distribution at each horizon. Dashed lines are the 16th and 84th percentiles of the posterior distribution of the impulse response function at each horizon. Figure shows a one standard deviation shock to corporate bond spreads, which are ordered at the bottom of the Wold causal chain. Model is a VAR(6), sample is 1982:11 - 2009:4. Note that these responses are computed using the same posterior draws as in Figure 2.

Figure 5: Estimated credit shocks



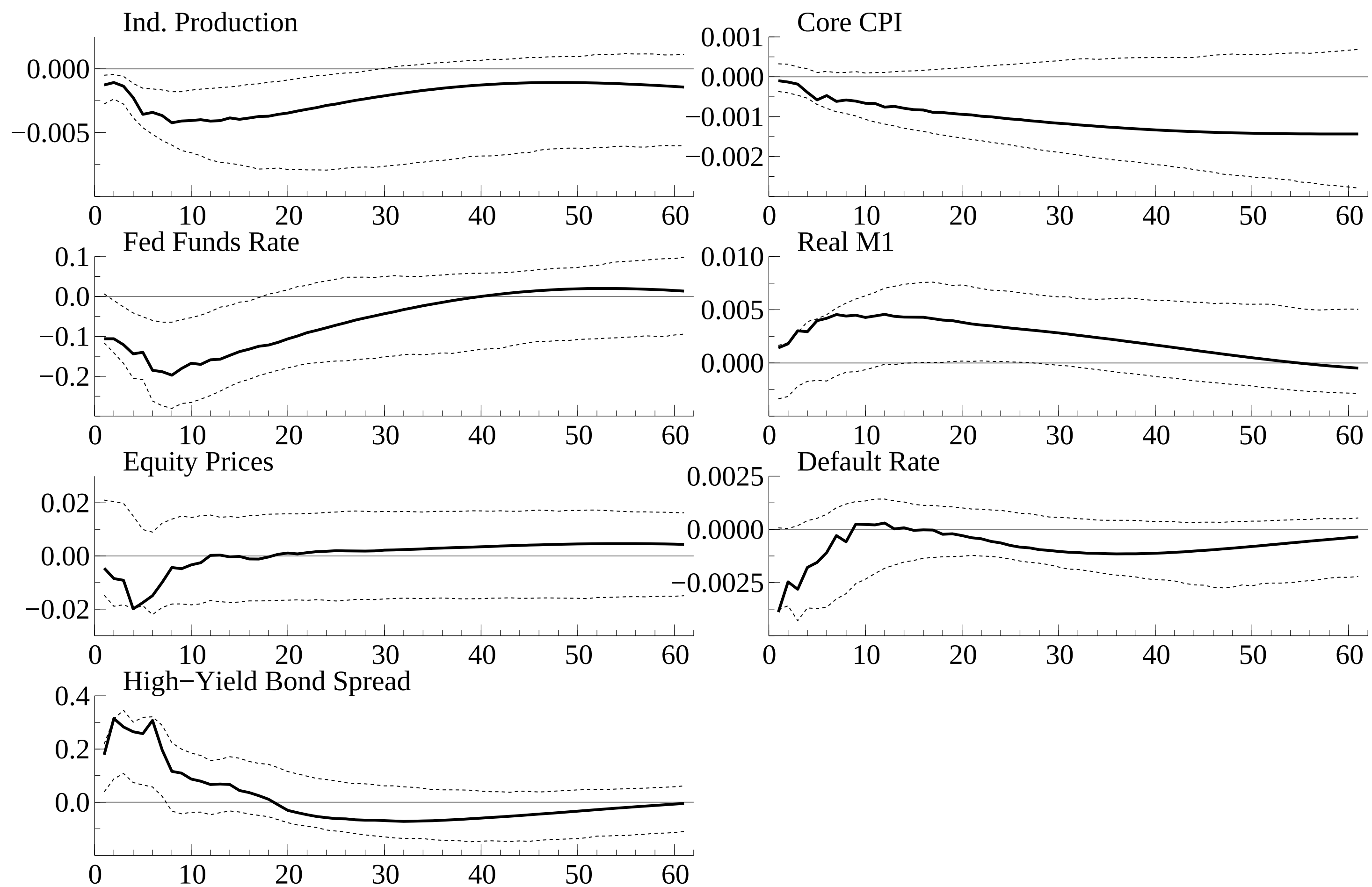
Note: Time series of structural credit shocks for the median model (described in Appendix A).

Figure 6: Monetary policy shocks and estimated credit shocks



Note: Chart shows futures-derived monetary policy shocks for scheduled FOMC meetings calculated using the method of Faust et al. (2004), plotted against VAR-based credit shocks generated by the median model (described in Appendix A). For each month in which a monetary policy shock is observed, the corresponding credit shock is plotted. A bar connects shocks that occur in the same month. The vertical scale is in percentage points for the monetary policy shock, and the credit shocks have been rescaled so that both series have the same variance. Note that there are a large number of months in which monetary policy shocks were exactly zero.

Figure 7: Impulse-responses: Median model



Note: Solid line is the impulse response function corresponding to posterior draw $k_{(2)}$ defined in equation (9). Dashed lines are the 16th and 84th percentiles of the posterior distribution of the impulse response function at each horizon. Figure shows a one standard deviation credit market shock. Model is a VAR(6), sample is 1982:11 - 2009:4.

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