Firm Equity Risk, Bank Lending Standards, and the Macroeconomy

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Abstract

This paper analyzes the impact of U.S. firms' equity risk on bank lending standards and on the macroeconomy, considering two groups: small firms and medium-large firms. Using firms' daily stock returns, we construct a firm equity risk index for each group based on 30,000 firms over 104 quarters. Once the indices are constructed, they are analyzed with a large dataset of over 50 macroeconomic and financial time series using the Factor-Augmented Vector Autoregressive (FAVAR) framework. The results indicate that a higher level of firm risk leads to a higher percentage of banks tightening their lending standards on commercial and industrial (C&I) loans. The effect of firm risk on bank lending standards for medium-large firms is twice that for small firms. In addition, we find that greater firm risk results in an inversion of the yield curve, an increase in the corporate bond risk premium, and a decrease in real GDP. Lastly, the effect of an increase in firm risk on bank lending standards and the economy is larger during recessions than in expansions.

Keywords: Credit Risk, Risk Management, Macroeconomics, Financial Markets
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1 Introduction

Banks are an important channel of funds for firms, especially for those with limited or no access to capital markets. At the same time, credit risk, the risk of borrowers defaulting on their debt, is the main source of potential losses in commercial bank activities (Kuritzkes and Schuermann, 2010). Thus, measuring and managing credit risk associated with business loans is one of banks' primary concerns. The 2008 financial crisis showed that bank risk from different instruments can quickly transmit to each other, affecting bank balance sheets, and sending shock waves to the rest of the economy.

This paper uses firm equity risk as a measure of credit risk associated with business lending. It aims to provide an extensive analysis of the links among firm risk, bank lending standards, and the macroeconomy for the period from 1991Q1 to 2016Q4. In detail, firm equity risk is calculated as the standard deviation of the residual of regression of firms' daily stock returns on daily market returns. Considering the potential effect of firm risk on the economy depending on firm size, we classify a big dataset of over 30,000 firms into two groups, medium-large and small, based on their total sales. Next, the firm equity risk index for each group is constructed and analyzed together with over 50 macroeconomic and financial time series using a Factor-Augmented Vector Autoregressive (FAVAR) model. Multiple imputation methods are applied to treat missing variable problems. Additionally, we examine the potential impact across recession and expansion phases in order to take into account business cycle risk.

This paper is closely related to the following two strands in the literature. One uses micro-level data on firms and banks to investigate the effect of firm risk and monetary policy on bank lending. Firm risk is measured as the number of firm nonperforming loans. Keeton (1999), Gambacorta (2009), and Behr et al., (2007) find that banks are less likey to grant loans to risky firms. Borio and Zhu (2012) argue that during an expansionary monetary policy, when interest rates are low, banks have incentive to seek high-yielding assets, engaging in riskier investments. The mechanism in which banks are more willing to grant loans to risky firms due to low short-term interest rates is called the risk taking channel of monetary policy. It is studied in Jimenez et al. (2014) and Bruno and Shin (2015).

The second strand uses macro-level data on bank lending standards and the economy to analyze their relationships, generally using standard low-dimension vector autoregressive (VAR) models. Lown et al. (2000) investigate the impact of bank lending standards on macroeconomic variables. They find that a tightening shock in lending standards decreases real GDP and the federal funds rate (FFR). Lown and Morgan (2006) study the connection between credit cycles and bank lending standards and conclude that the feedback of loans to shocks in lending standards reveals a credit cycle. Bassett et al. (2014) introduce a new method to measure changes in bank lending standards. They find that a tightening shock in lending standards decreases real GDP and the FFR. These effects are more substantial compared to those in Lown et al. (2000).

A plethora of papers have focused on either the relationship between firm risk and bank lending activities at the micro level, or the relationship between lending standards and the economy at the macro level. However, to our knowledge, no research has been done on how firm risk affects bank lending standards and the macroeconomy. How important is firm risk in determining banks' decisions to tighten or ease their lending standards? What role does it play in economic activities, monetary aggregates, and financial markets? The goal of this paper is to provide answers to these questions.

This paper contributes to the literature of economics and finance in three ways. First, this is the first paper investigating the effect of firm risk on bank lending standards and the macroeconomy. Given the critical role this risk may play in financial markets and monetary aggregates, it is important to understand the mechanism through which risk is transferred from firms to the economy. Second, most papers in closely related literature use firm nonperforming loans to measure risk. This paper uses firm equity risk instead, which is calculated as the standard deviation of the error term in the regression of a firm's daily stock returns on market returns. This measure of firm risk has been widely used in the finance literature (Schwert, 1989; Rego et al., 2009) for a couple of reasons. Since data on stock returns are publicly available with high frequency and easy to obtain, banks can watch them closely to determine changes in the risk associated with their loans to firms. Nonperforming loans, on the other hand, are only available with a lag of three months. It takes 90 days after debtors fail to make payment for those to be classified as nonperforming. In addition, firms without a history of nonperforming loans do not necessarily imply that they are currently low risk. Another rationale for choosing firm equity risk is that stock returns have been shown to be related to economic activities (Fama, 1981; Lee, 1992; Jones et al., 2017).

Finally, this is the first paper employing a FAVAR model to gauge the interactions among firm risk, bank lending standards, and the rest of the economy. We collect and treat a huge amount of data at the micro level on firms, then compare that with a number of economic time series at the macro level. Consequently, traditional VAR models cannot be applied in this analysis. Bernanke, Boivin, and Eliasz (BBE 2005) point out that FAVAR models are superior to VAR models in macroeconomic studies because they overcome the VAR's biggest weakness related to the curse of dimensionality. While previous studies in the related literature include fewer than eight variables in their VAR models, this paper uses information on thousands of firms and 54 macroeconomic and financial time series over 25 years. The inclusion of variables containing important information about the economy can mitigate the dimension and mismeasurement problems that commonly occur in the traditional VAR method.

The main results of this paper are as follows. First, a one standard-deviation increase in firm risk causes more banks to significantly tighten their lending standards to both groups of firms, medium-large and small. However, the effect for medium-large firms is twice as large as that for small firms. The finding provides support to the Risk Management Hypothesis, under which banks decrease lending to risky borrowers to reduce credit risk. In addition, the variance decomposition results show that firm risk explains a major share of the variability of changes in lending standards for both groups of firms. Second, the economy responds negatively to a higher level of firm risk with a decline in real GDP and employment. The corporate bond risk premium, measured by the yield spread between BAA and AAA corporate bonds, increases with a positive shock in firm risk. Additionally, the slope of the yield curve (the yield spread between 10-year Treasury bonds and three-month Treasury bills) decreases with an unexpected increase in firm risk. Lastly, the impact of an increase in firm risk on bank lending practices and the economy is larger during recessions than in expansions. These findings shed light on how firm risk affects credit availability to businesses and on how banks' risk appetite changes over business cycles.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 introduces the econometric framework of the FAVAR model. Section 4 describes the data. Section 5 discusses the estimated results. Section 6 concludes.

2 Survey of Related Literature

There is extensive literature on the relationships among credit risk, bank lending practices, and the macroeconomy. The first strand of articles uses micro-level data on firms and banks to investigate the effect of firm risk and monetary policy risk on bank lending. They argue that banks lending money to firms is subject not only to firm characteristics but also to changes in monetary policy conducted by central banks. During an expansionary monetary policy when interest rates are low, banks have incentive to seek high-yielding assets, engaging in riskier investments. The mechanism in which banks are more willing to grant loans to risky firms due to a lax monetary policy is called the risk taking channel of monetary policy (Borio and Zhu, 2012).

Most notably, Jimenez et al. (2014) use a comprehensive set of firm and bank level data on loan applications and outcomes for Spanish firms from 2002 to 2009. The authors apply a two-stage model, which in the first stage the dependent variable is one if a firm receives a loan and zero otherwise. In the second stage, the dependent variable is the amount of the loans granted to firms in stage one. Firm risk is measured as the number of firm nonperforming loans over the sample time period. A number of interaction terms of monetary policy (proxied by the Euro Overnight Index Average rate) with firm risk and bank capital are included in each stage. Jimenez et al. find that when the overnight interest rate is low, more loans are granted to risky firms. Controlling for bank capital, they conclude that low-capital banks are more willing to provide loans to risky firms given a low interest rate. The results confirm the existence of risk taking channel of monetary policy in bank lending activities. The findings of their paper are in line with other articles in the literature that also use micro-level data on firms, banks, and interest rates (Gambacorta, 2009; Demiroglu, C., et al, 2012; Keeton, 1999; Behr et al., 2007; Bruno and Shin, 2015). However, the analysis of Jimenez et al. (2014) stands out due to its incorporation of all micro information on firms, banks, and monetary conditions in a single economic model.

The second strand of papers collects macro-level data on bank lending standards and the economy to analyze their interrelationships. The standard VAR framework is employed in most studies. Lown et al. (2000) investigate the impact of bank lending standards on macroeconomic variables. They use the percentage of banks tightening their lending standards on commercial and industrial (C&I) loans drawn from the Federal Reserve's Senior Loan Officer Opinion Survey (SLOOS). Other macroeconomic variables, real GDP, GDP deflator, commodity price, and the FFR are also included in the VAR model. The authors find that a tightening shock in lending standards decreases real GDP and the FFR. The result implies that when banks decrease their credit supply, the economy slows down, leading the Federal Reserve to lower the FFR to spur economic growth.

Lown and Morgan (2006) study the connection between credit cycles and bank lending standards. The volume of commerical loans at banks and the net percentage of banks tightening their lending standards are used to model credit cycles. The finding is that the feedback of loans to shocks in lending standards reveals a credit cycle. A higher amount of loans leads to tighter lending standards. Tighter lending standards, in return, result in fewer loans, causing lending standards to ease and the number of loans to increase extensively.

Bassett et al. (2014) argue that the percentage of banks tightening their lending standards taken from the SLOOS might not be an accurate measure of changes in credit supply since part of the changes might come from demand for loans and other macroeconomic factors.

As a result, the authors use data on banks, loans, and bank lending standards to construct an index for changes in credit supply. Applying a VAR model, Bassett et al. (2014) find that a tightening shock in lending standards decreases real GDP and the FFR. These effects are more substantial compared to those in Lown et al. (2000), which use the original data on changes in lending standards from the SLOOS.

Our paper will fill the gap in the literature by analyzing the relationships among firm risk, bank lending standards, and the marcoeconomy to a gain better understanding of how firm risk influences business lending and the rest of the economy.

3 Theoretical Framework of a Structural FAVAR Model

3.1 Model Setup

Let Y_t be an $M \times 1$ vector of observable economic variables and F_t be an $K \times 1$ vector of latent factors. Assume that Y_t and F_t follow a VAR model:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi\left(L\right) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{1}$$

where $\Phi(L)$ is a matrix of coefficients, and ν_t is an error term with mean zero and covariance matrix Q. Since the latent factors F_t are not observable, equation (1) cannot be estimated. The FAVAR model further assumes that there exist N observable informational time series X_t that can be used to extract the latent factors F_t. N is assumed to be large and much larger than the total number of factors and observable variables, $K + M$. Suppose X_t is related to F_t and Y_t by a factor model:

$$X_t = \begin{bmatrix} \Lambda & \Gamma \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + e_t \tag{2}$$

where $\Lambda = \begin{pmatrix} \lambda_1 & \dots & \lambda_N \end{pmatrix}'$ is an $N \times K$ matrix of factor loadings, $\Gamma = \begin{pmatrix} \gamma_1 & \dots & \gamma_N \end{pmatrix}'$ is an $N \times M$ matrix, and $e_t = \begin{pmatrix} e_{1t} & \dots & e_{Nt} \end{pmatrix}'$ is an $N \times 1$ matrix of idiosyncratic errors. The error terms e_t are assumed to have mean zero and be weakly correlated. The latent factors F_t usually capture the information in some important structural shocks to the economy. These shocks are represented by a large number of macroeconomic series. Thus, by including a significantly larger amount of variables, the FAVAR model can solve the VAR's mismeasurement problem.

3.2 Model Identification

Model (1)-(2) cannot be identified without imposing further restrictions. The number of restrictions needed can be estimated by rewriting the model as:

$$X_t = \Lambda F_t + \Gamma Y_t + e_t = (\Lambda M_{11})(M_{11}^{-1} F_t - M_{11}^{-1} M_{12} Y_t) + (\Gamma + \Lambda M_{12}) Y_t + e_t \tag{3}$$

where M_{11} is an invertible $K \times K$ matrix, and M_{12} is an $K \times M$ matrix. The number of restrictions imposing on the FAVAR model is equal to the number of free parameters of M_{11} and M_{12}, which is $K^2 + K \times M$ (Bai et al., 2016).

BBE (2005) introduce an identification scheme by partitioning all variables into three groups: slow moving variables, the policy variable, and fast moving variables. Based on this method, within a period the structural shocks in the slow group can affect all the variables. The structural shock in the policy variable affects all but slow moving variables. Lastly, the structural shocks in the fast group affect only the remaining fast variables.

3.3 Model Estimation

Model (1)-(2) can be estimated using a two-step principal components method as in standard FAVAR literature. The first step involves obtaining the estimate of the latent factors, $\hat{F}_t$. The unobservable common components, C_t from all variables in X_t are estimated using the first $K + M$ principal components of X_t. The number of factors, K is determined according to the information criteria IC_1, IC_2, and IC_3 proposed by Bai and Ng (2002). Using an asymptotic principal component analysis[1](Stock and Watson, 2002), the latent factors, $\hat{F}_t$ can be estimated by removing Y_t from $\hat{C}_t$. To achieve that, all variables in X_t are divided into two groups, slow-moving variables and fast-moving variables. The policy variable is included in Y_t. The slow common factors, $\hat{F}_t^s$ are extracted from the slow-moving variable group and estimated using the principal components analysis. Next, the following equation is estimated:

$$\hat{C}_t = b_f \hat{F}_t^s + b_y Y_t + e_t \tag{4}$$

Thus, the estimated latent factors $\hat{F}_t$ are $\hat{C}_t - \hat{b}_y Y_t$. In the second step, F_t is replaced by $\hat{F}_t$ in equation (1) to obtain the estimates of the FAVAR model. The policy rate is ordered last in the VAR framework assuming that the latent factors do not contemporaneously respond

[1]when N is large and the number of principal components used is at least as large as the true number of factors, the principal components consistently recover the space spanned by both F_t and Y_t. Hence, the part of space covered in $\hat{C}_t$ that is not covered in Y_t is $\hat{F}_t$.

to shocks in the policy variable. This assumption is reasonable given that the latent factors obtained from the first step mainly contain information in the slow-moving variables. The number of lags in the VAR model is determined using the Akaike information criterion.

4 Data

The data on firm risk, changes in bank lending standards, and other macroeconomic variables are constructed quarterly from 1991Q1 to 2016Q4. The starting point of the dataset is determined by the availability of data on bank lending standards. For identification purposes in the FAVAR model, we follow BBE (2005) to divide all time series into three different blocks: slow-moving variables, policy variable, and fast-moving variables. The policy variable is the constructed firm equity risk index. The main variable of interest, changes in lending standards, is placed in the fast-moving variable block as banks can observe information on key economic indicators in the slow-moving variables and firm risk before deciding to ease, tighten, or unchange their lending standards to firms. Daily and monthly time series are converted to quarterly by taking averages. All series are transformed by logarithms, first differencing and/or first differencing of logarithms to be approximately stationary. Details are in Appendix A.

4.1 Federal Reserve's Loan Officer Opinion Survey on Bank Lending Standards

The Federal Reserve collects information on changes in bank lending standards by sending out a quarterly survey to a group of selected domestic banks across the U.S. Participants are normally the largest banks of the twelve Federal Reserve Districts, aggregating nearly 60 percent of all loans made by U.S. banks. The number of participating banks was roughly 120 in early years but gradually declined over time to around 60 banks today. The response rate of banks is close to 100 percent. Twenty-one questions are asked on changes in bank lending standards and in demand for loans to business owners and households. In this paper, we will use the answers to the following question in the survey:

> "Over the past three months, how have your bank's credit standards for approving loan applications for C&I [commercial and industrial] loans or credit lines —excluding those to finance mergers and acquisitions—changed? 1) tightened considerably, 2) tightened somewhat, 3) remained basically unchanged, 4) eased somewhat, 5) eased considerably."

The answers show the number of banks reporting changes in their lending standards in the five different categories above. Next, the net percentage of banks tightening their lending standards is calculated as the number of banks reporting tightening less the number banks easing standards, divided by the total number of banks reporting. The survey also separates firms into two groups based on their total sales: medium-large firms whose total sales are greater than 50 million dollars, and small firms whose total sales are less than or equal to 50 million dollars. A a result, we have two different time series on changes in bank lending standards for two groups of firms. The data are taken from the Federal Reserve's website.

4.2 Firm Equity Risk

Daily stock returns for all firms in the sample and daily market returns are downloaded from the Center for Research in Security Prices (CRSP) database. A firm's daily stock returns R_{it} are regressed on daily market returns, S&P 500 index, as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{5}$$

Thus, the residual is given by:

$$\hat{\varepsilon}_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{6}$$

The firm's equity risk is the standard deviation of the residual, and its quarterly equity risk is the simple average of daily risk. Next, we match the firm's calculated equity risk to its financial variables, which come from the COMPUSTAT database. To construct the firm risk index for the whole group of medium-large or small firms, each firm's total sales is used to measure its weight in the index. The firm risk index is obtained according to:

$$\sum_{i=1}^{N} w_{i,t} \times r_{i,t} \tag{7}$$

where $w_{i,t}$ is the weight of firm i at quarter t, and $r_{i,t}$ is the equity risk for firm i at quarter t.

4.3 Macroeconomic and Financial Indicators

Besides the firm risk index and changes in lending standards, the model also includes 52 other macroeconomic and financial time series . Although the biggest innovation of a FAVAR model is its large dimension, more data as always better may not be true in practice. Boivin and Ng (2006) point out that adding too much data of the same type, such as real economic activities, can create noise in the model. As a result, the average common component would become smaller and/or the residual cross-correlation would eventually be larger than that warranted by theory. All macroeconomic and financial indicators in our model are selected according two criteria: fitness in the firm risk and lending standard context and availability within the sample period. The S&P 500 index is taken from the Yahoo Finance website. The rest of the variables are downloaded from the Federal Reserve Economic Data (FRED) website of the Federal Reserve Bank of St. Louis.

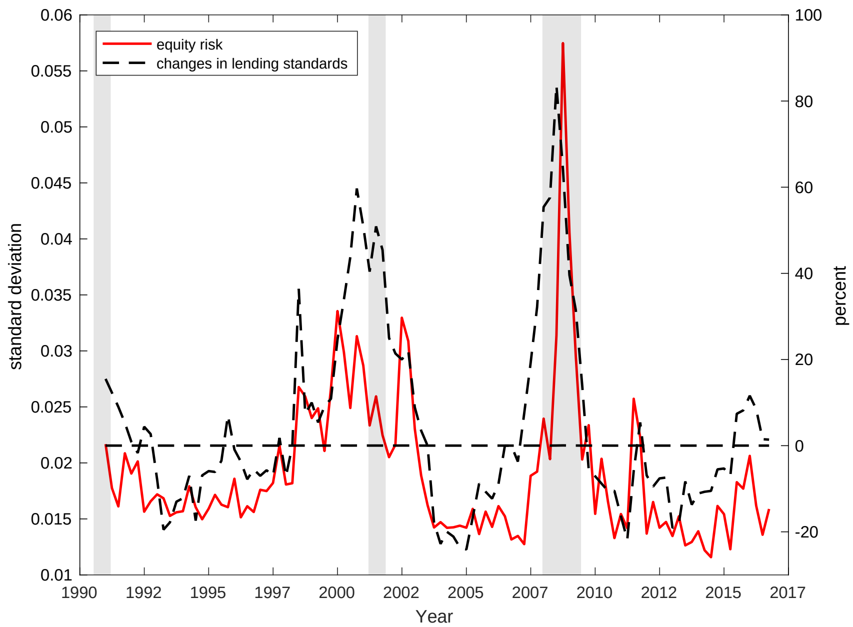
4.4 Relationship between Firm Risk and Bank Lending Standards from Analyzing the Data

Figure 1 plots the firm risk index and net percentage of loan officers tightening their lending standards on C&I loans to medium-large firms and small firms for the period 1991Q1-2016Q4. For both groups of firms, the two time series move closely together: a higher risk index, more banks strengthening lending standards and vice versa. During an economic expansion, firm risk reduces significantly, banks hence are more willing to lend to firms. When a recession hits the economy, financial markets become more volatile and firms possess more risk. Banks impose more restrictions on lending. Noticeably, in the fourth quarter of 2007 just before the financial crisis, the peak in the risk index explains a record-high number of 83.6 percent of banks tightening their lending standards for medium-large firms, and 75 percent for small firms.

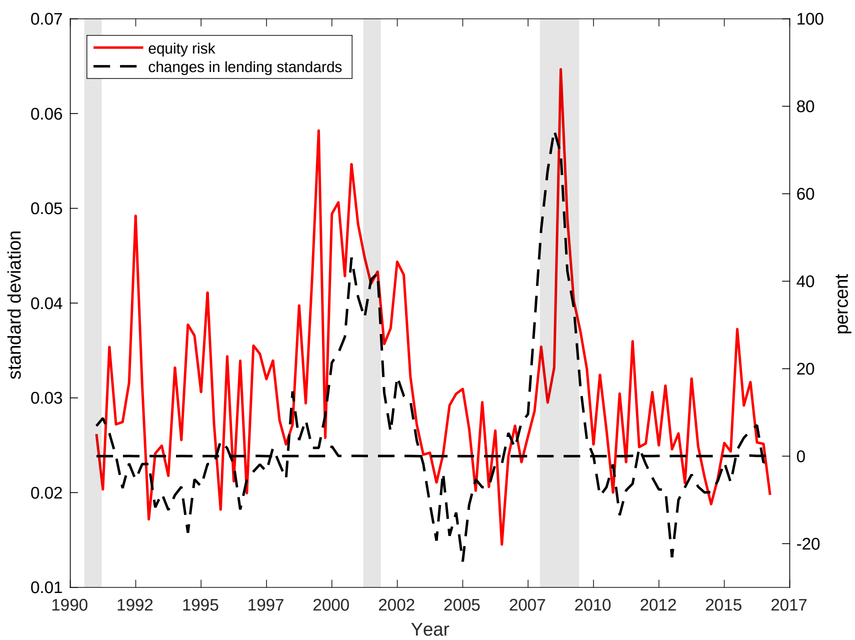
5 Estimated Results

The FAVAR model is estimated using the two-step principal components method. The information criteria IC_1, IC_2, and IC_3 all yield four factors in the factor equation. There are two lags in the VAR equation, based on the Akaike information criterion. The single shock in the FAVAR model is defined as a one standard-deviation increase in firm risk. Figure 2 displays the impulse response functions (IRF) of 12 selected variables due to the shock for the group of medium-large firms and small firms. The IRFs are in standard deviation units with their respective 90 percent confidence bands, and are plotted over a 20 quarter horizon. Our primary focus is the IRF of net percentage of banks tightening their lending due to a positive shock in firm risk. As firm risk increases for medium-large firms, the

Figure 1: Firm Equity Risk and Net Percentage of Banks Tightening Lending Standards



(a) Medium-Large Firms



(b) Small Firms

percentage of banks tightening their lending standards increases by 0.6 standard deviation immediately. However, the effect gradually decreases over two years before it dies out. This finding confirms our conclusion from analyzing the data. When firms reveal a higher level of risk, banks strengthen their lending criteria considerably.

For the group of small firms, a shock in risk leads to a 0.3 standard-deviation increase in banks tightening their lending. This effect is half the effect for medium-large firms. Loans to medium-large firms are normally larger in size compared to loans to small firms. If the former group possesses more risk, banks act quickly to scale back their lending due to potential losses. Moreover, banks face asymmetric information when lending to small businesses. They need to use soft information, such as their personal relationships with firms, to assess the credit risk (Peterson and Rajan, 2002; Cole, 2004). Consequently, a rise in small firms' risk is not as critical as in medium-large firms' risk for banks to re-evaluate their lending. Indeed, upon the same shock to firm risk, the percentage of banks changing their lending standards to small businesses is less than that to medium-large firms.

Moving to other macroeconomic variables, we find that a one standard-deviation shock in firm risk results in an instantaneous decline in real GDP for both groups of firms. However, the impact of the shock on real GDP is significantly greater for medium-large firms in comparison to small firms. Also, the impact remains significant for four years after the shock for the former group while only two years for the latter group. Medium-large firms, whose total sales are more than 50 million dollars, collectively contribute a bigger share to GDP than small firms do. Hence, a decrease in the total sales of the former group due to tighter lending standards has a larger effect on the economy compared to the latter group. Similarly, private investment and nonfarm payrolls negatively respond to a positive shock in firm risk. In addition, the reduction in the number of employees in the nonfarm payrolls is identical across two groups. This finding is consistent with the fact that despite the size, small businesses added 61.8 percent of newly created jobs between the third quarter of 1993 to the third quarter of 2016 in the U.S. (Report by the small business association (SBA), 2017).

Hourly earnings are upward for the whole time horizon. Since firms lay off workers after the shock, the total number of working hours in the economy decreases, increasing the average hourly wage. Furthermore, the "price puzzle,"[2] which is a common issue in VAR models, does not appear in our model. When firms reveal more risk, banks limit their lending to firms and the money supply decreases. As a result, the consumer price index

[2]Price puzzle found in the VAR literature is that a contractionary monetary policy shock results in an increase in the price level, rather than a decrease as standard economic theory would predict.

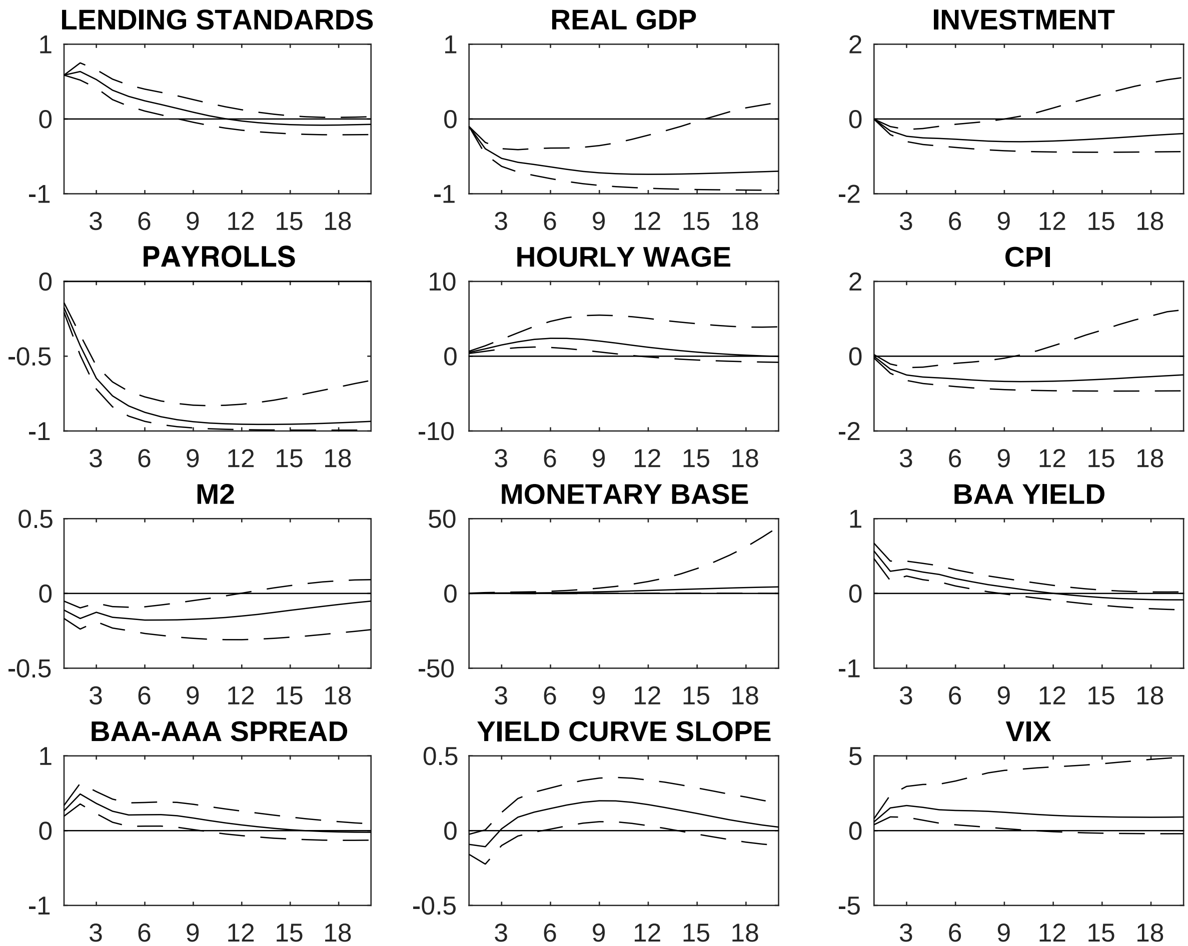
(CPI) declines for both groups of firms. This finding again proves the superiority of FAVAR models as opposed to VAR models. The inclusion of more than 50 time series in our model eliminates the mismeasurement problem found in VAR models.

Next, we analyze the effect of a shock in firm risk on money aggregates and financial markets. For both groups of firms, the influence of the shock in firm risk on the money supply, M2 is significant and negative, but it is more long-lasting for the medium-large group. The decrease in the money supply is due to bank scaling back their lending to firms as risk increases. The monetary base stays nearly unchanged after the shock as currency in circulation and total bank reserves in the economy are not affected by bank lending.

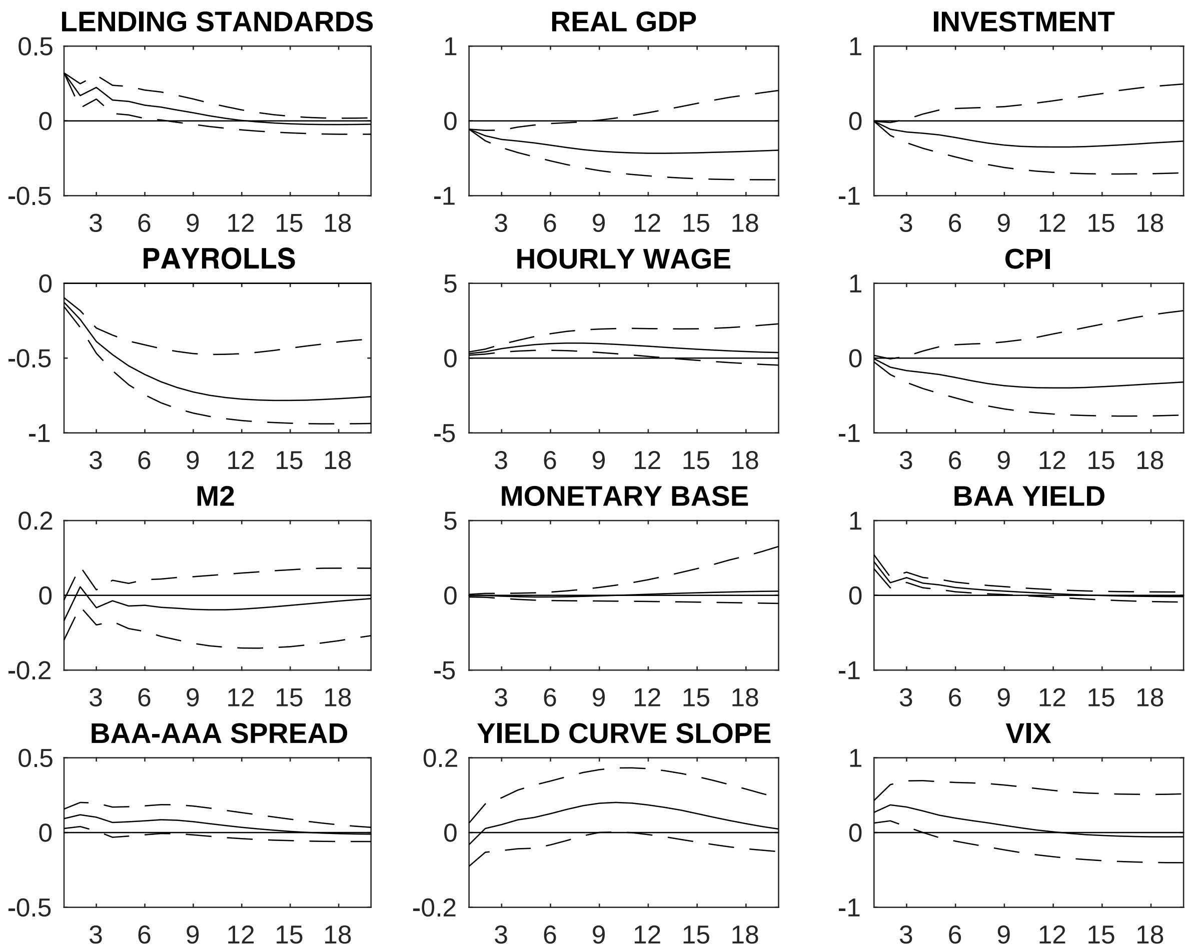
The IRFs of the financial variables to a positive shock in firm risk show interesting results. The BAA corporate bond yield positively responds to the shock in both groups, medium-large and small firms. Risk increases makes it more difficult for firms to obtain loans from banks. Firms, thus, rely more on capital markets to borrow money by issuing long-term corporate bonds (Becker and Ivashina, 2014). To make their bonds more attractive to investors, firms need to offer a higher yield. Moreover, the corporate bond default risk premium, the spread between BAA and AAA corporate bond yields, is larger. When firms carry more risk, the probability of their defaulting on loans is higher for both BAA and AAA firms, more so for the former group. Next, the slope of the yield curve, the yield spread between 10-year Treasury bonds and three-month Treasury bills, decreases after the shock. The economy slows down as the result of an increase in firm risk. Investors in bonds market see less future growth in the economy, causing a decrease in the yield spread. Lastly, the VIX volatility index increases due to a positive shock in firm risk.

Besides the IRFs, variance decomposition provides important information on the contribution of the policy shock to the forecast error of a variable. The variance decompositions for the same 12 selected variables are recorded in Tables 1 and 2. The second column contains the contribution of the shock in firm risk to variances of forecasts of the selected variables. The next four columns report the contributions of four latent factors in the FAVAR model to the variability of these variables. The shock to firm risk explains almost 68 percent and 42 percent of changes in bank lending standards for medium-large and small firms, respectively. These numbers indicate that banks heavily rely on firm risk when making their lending decisions.

Figure 2: Impulse Responses to a Shock in Firm Risk



(a) Medium-Large Firms



(b) Small Firms

Notes: Impulse Responses are generated from the FAVAR model with four latent factors and estimated by principal components with two-step bootstrap and their respective 90 percent confidence bands. All the responses are in standard deviation units.

Table 1: Variance Decompositions for Medium-Large Firms

Variables	Fraction of variance explained by				
	Firm Risk	Factor 1	Factor 2	Factor 3	Factor 4
Lending standards	67.49	7.53	4.90	8.72	11.40
Real GDP	25.47	22.08	31.82	13.56	7.08
Investment	13.85	41.29	28.71	7.40	8.74
Payrolls	29.32	13.20	40.59	8.59	8.30
Hourly wage	63.34	2.89	19.01	7.62	7.14
CPI	6.39	24.68	34.14	7.96	26.82
M2	39.86	13.83	20.97	19.96	5.28
Monetary base	0.00	3.88	94.02	2.05	0.00
BAA yield	3.67	13.31	17.81	49.71	15.51
BAA-AAA spread	2.31	20.30	51.14	13.83	12.43
Yield curve slope	0.76	8.45	60.01	20.90	9.89
VIX index	58.67	6.78	14.26	16.31	3.97

Notes: Variance decompositions are at the 20-quarter horizon.

Table 2: Variance Decompositions for Small Firms

Variables	Fraction of variance explained by				
	Firm Risk	Factor 1	Factor 2	Factor 3	Factor 4
Lending standards	42.01	20.89	20.51	9.17	7.41
Real GDP	10.10	31.30	34.32	16.71	7.57
Investment	3.89	48.32	29.83	7.89	10.07
Payrolls	20.91	17.84	42.86	9.56	8.82
Hourly wage	29.43	3.48	37.13	17.50	12.47
CPI	0.26	40.40	18.48	9.22	31.64
M2	1.39	34.80	31.83	24.95	7.03
Monetary base	0.00	49.17	27.38	13.33	10.57
BAA yield	1.80	10.11	20.48	53.48	14.13
BAA.AAA spread	0.28	29.67	44.62	15.45	9.98
Yield curve slope	0.26	8.91	61.88	20.53	8.53
VIX index	27.29	17.12	29.08	19.25	7.17

Notes: Variance decompositions are at the 20-quarter horizon.

In addition, except for CPI, the shock in medium-large firm risk explains a significant amount of macroeconomic variables: about a third of real GDP and nonfarm payrolls, 13.85 percent of private investment, and 63.34 percent of hourly wages.

Apart from the slope of the yield curve, the shock in medium-large firms contributes a small but nontrivial amount of variability of all financial variables. The shock in small firms, in contrast, contributes about half of the contribution of the shock in medium-large firms for most macroeconomic and financial variables. Indeed, the size of a firm determines its influence on the economy: bigger firm, bigger role. In addition, other structural shocks in the economy, which are captured in four factors, explain most of the variability of selected variables for small firms. This result once again confirms the advantage of a high dimensional FAVAR model. Having a wide selection of variables in the model allows one to fully capture important information in the economy.

In the next step, we split the whole dataset into two subsets, recession and expansion, using the recession indicator published by the National Bureau of Economic Research (NBER). Given the time period from 1991Q1 to 2016Q4, the economy experienced three recessions in 1991, 2001, and 2008. The purpose of this exercise is to investigate whether business cycle risk amplifies the effect of firm risk on the economy. The IRFs of the same 12 variables due to a one standard-deviation shock in firm risk when the economy is in recessions or expansions are reported in Figures 3 and 4. According to the results, as firm risk increases, the responses of banks during a recession are much more pronounced than those during an expansion. The percentage of banks imposing higher lending standards on firms during an economic downturn doubles that during an economic expansion. This finding applies for both groups of firms. As uncertainty increases, the shock in firm risk during a recession should have a greater impact on bank behavior than during an expansion.

The shock has negative effects on real GDP, private investment, and nonfarm payrolls during recessions, yet positive effects during expansions. A healthy economy can absorb more adverse shocks without catastrophic consequences. We also find a fall in M2 during recessions while an increase during expansions. As the economy grows, banks and other financial institutions expand their lending to firms and consumers, raising M2. During an economic turmoil, banks as well as other financial institutions scale back their lending to firms, causing M2 to fall.

In the financial markets, we find that after the shock the corporate bond default risk premium increases more during recessions than expansions. Investors do not expect firms to default during good economic conditions. When bad economic conditions occur, firms, especially BAA rated ones, are more likely to default on their loans, increasing the credit spread. Furthermore, the slope of the yield curve declines during expansions while increases during recessions. This result is consistent with the recession predicting power of the slope found in the literature (Chauvet and Senyuz, 2016). An inverted yield curve (a negative slope) occurs when the Federal Reserve raises short-term interest rates to calm down the overheating economy. It happens about two years before a recession. The slope then starts to increase as the economy dips into a recession. The Federal Reserve has to lower short-term interest rates to stimulate the economy. In addition, investors demand a higher return on long-term bonds due to a poor economic outlook. The VIX index increases in both sub-periods, recession and expansion.

6 Concluding Remarks

This paper analyzes the effect of U.S. firm risk on bank lending standards and the macroeconomy. To achieve this, we construct a firm equity risk index using firms' daily stock returns. The FAVAR model is then applied for 54 macroeconomic and financial time series from 1991Q1 to 2016Q4 . To the best of our knowledge, this is the first paper studying the effect of firm risk on bank lending standards and the economy. In addition, taking into account the dependence of the impact of firm risk on the economy on firm size, over 30,000 firms in the sample are separated into two groups, medium-large and small, based on their total sales.

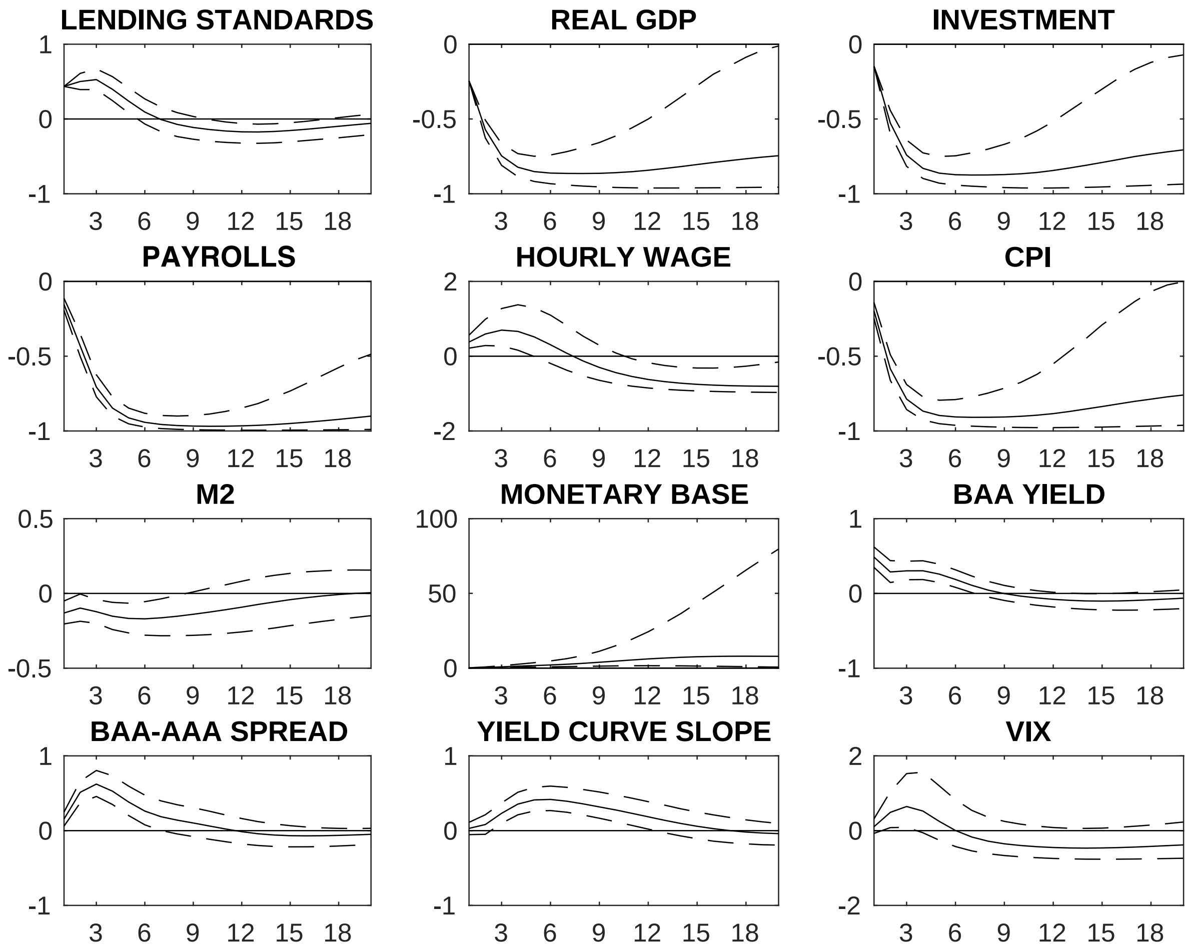
The main results show that an increase in firm risk leads to a higher percentage of banks tightening their lending standards for both groups of firms. However, the effect of the shock on lending standards for medium-large firms doubles that for small firms. The finding confirms the necessity to conduct our study in two groups. Loans to small firms are smaller in size compared to loans to medium-large firms. Thus, banks are more concerned about the latter group defaulting on their loans. In addition, because of incomplete information, banks evaluate loan applications of small firms based not only on firm risk but also on their past relationships with firms. This behavior is less common for medium-large firms. For macroeconomic variables, a one standard-deviation increase in firm risk results in a decrease in real GDP, private investment, and nonfarm payrolls. Financial variables also respond significantly to the shock in firm risk. Specifically, the shock causes a decrease in the money supply, M2 and the slope of the yield curve, as well as an increase in the corporate bond default risk premium.

To investigate the effect of business cycle risk on bank lending practices, we segregate the sample into two periods using the NBER recession indicator: recession and expansion.

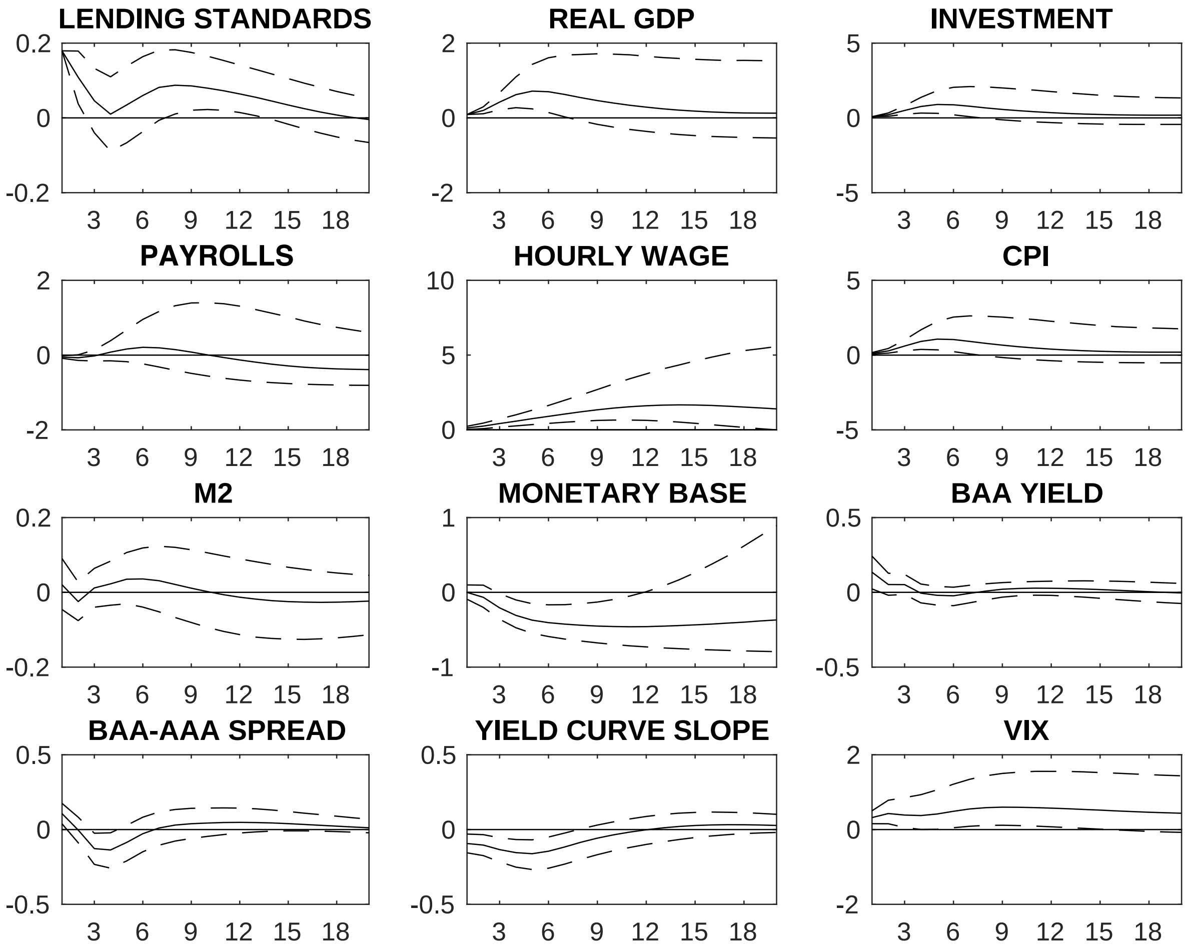
The result is that the effect of firm risk on bank lending practices during a recession is much more pronounced than that during an expansion. When the economy is healthy, a positive shock in firm risk leading to stronger bank lending standards is well absorbed. Hence, the consequence of the shock on the economy is modest and short-lived. In contrast, the consequence of the same shock is substantial and long-lasting during an economic downturn. In addition to the IRFs, variance decompositions are also calculated. We find that firm risk accounts for a major share of the variability in changes in bank lending standards for both groups of firms.

In summary, this paper provides a comprehensive study of the effect of firm risk on bank lending standards and the macroeconomy. Given that credit risk is still banks' most important risk, the paper provides insights on how firm risk affects bank lending and the rest of the economy over business cycles.

Figure 3: Impulse Responses to a Shock in Firm Risk For Medium-Large Firms



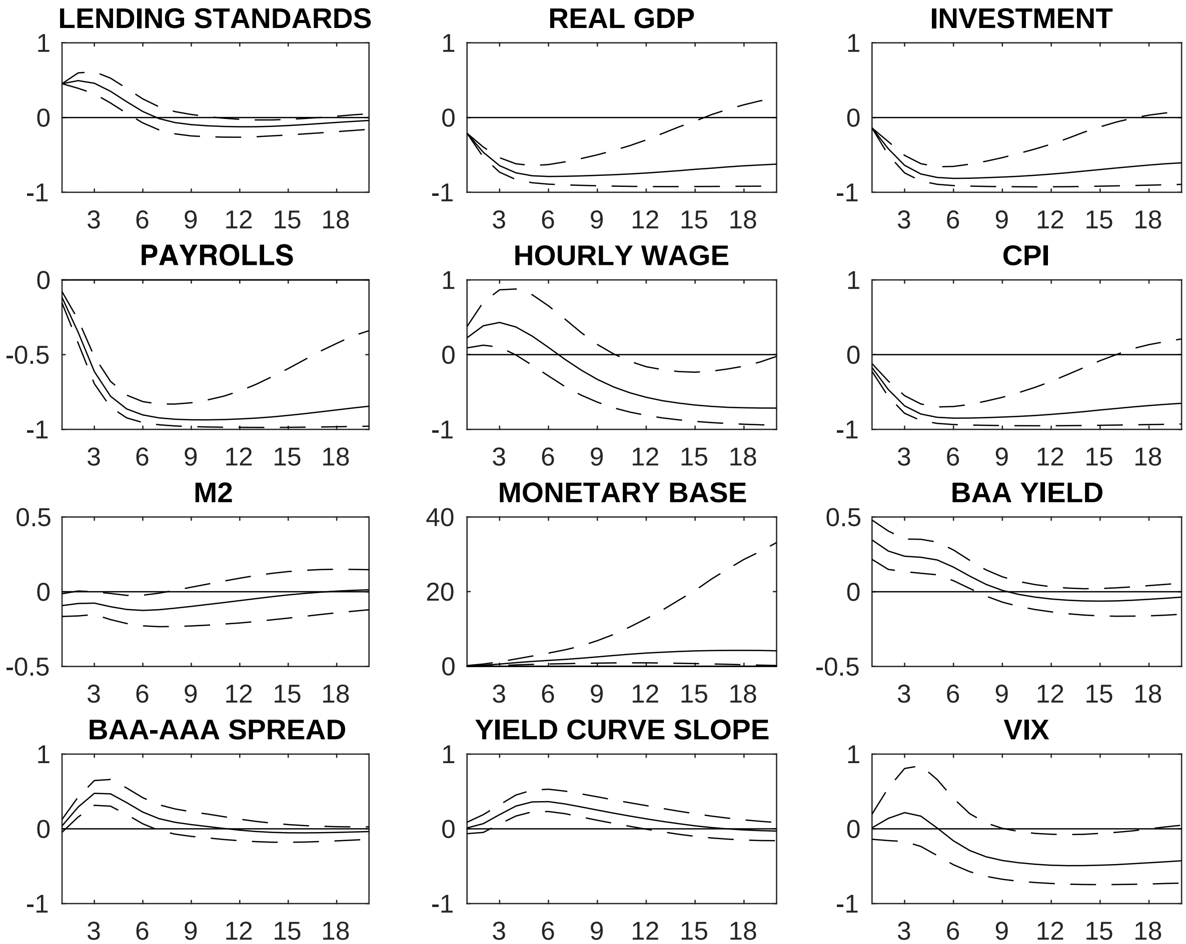
(a) Recessions



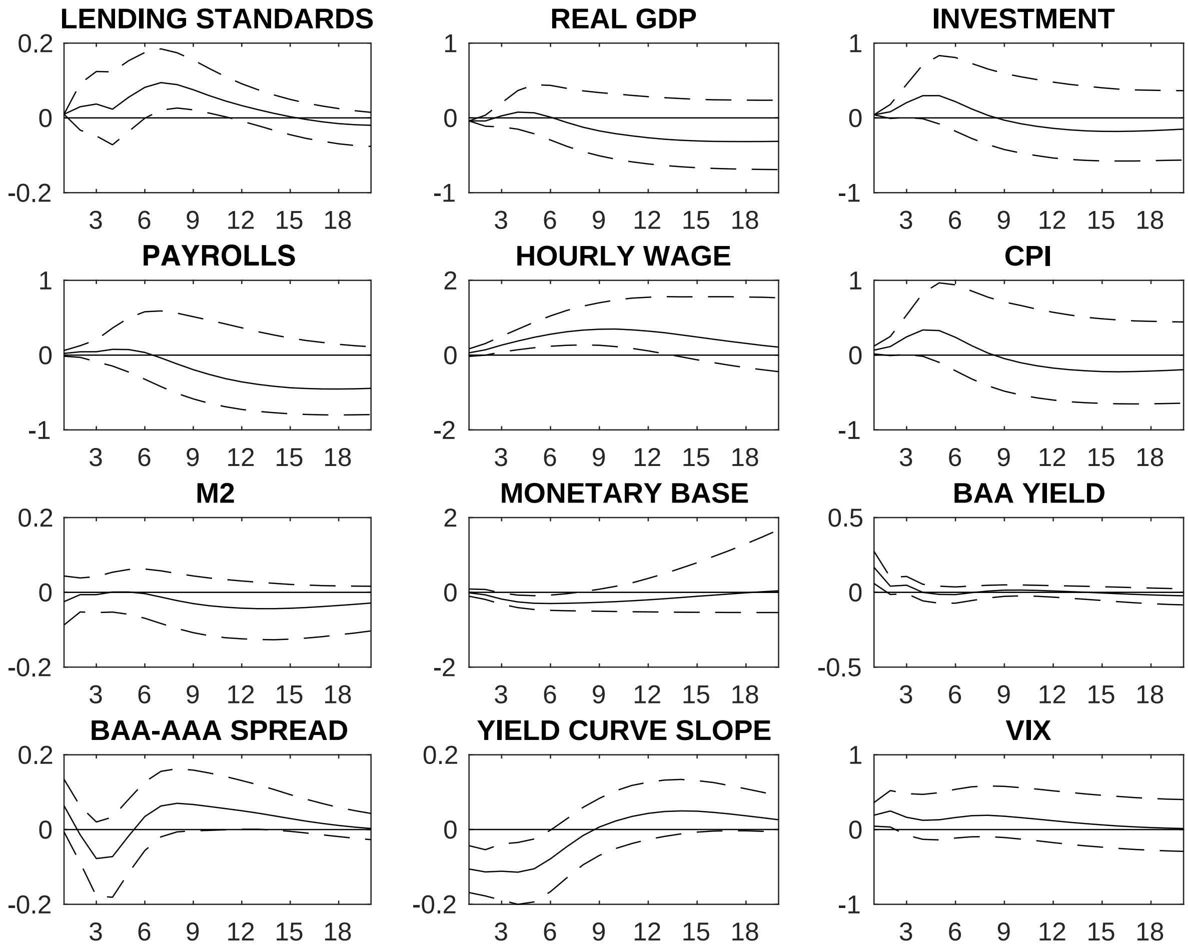
(b) Expansions

Notes: Impulse Responses are generated from the FAVAR model with four latent factors and estimated by principal components with two-step bootstrap and their respective 90 percent confidence bands. All the responses are in standard deviation units.

Figure 4: Impulse Responses to a Shock in Firm Risk for Small Firms



(a) Recessions



(b) Expansions

Notes: Impulse Responses are generated from the FAVAR model with four latent factors and estimated by principal components with two-step bootstrap and their respective 90 percent confidence bands. All the responses are in standard deviation units.

Appendix A: Data Description

Mnemonic	**Name**	**Transformation Code**	**Slow or Fast**
DRTSCILM	Percentage of banks tightening lending standards (NSA)	1	Fast
GDPC	Real GDP (Chained, Bil 2009 $, SA)	3	Slow
GPDI	Gross Private Investment, Bil 2009 $, SA	3	Slow
INDPRO	Industrial Production Index: Total (2012=100, SA)	3	Slow
IPDCONGD	Industrial Production Index: Durable Cons. Goods (2012=100, SA)	3	Slow
IPB51000NQ	Industrial Production Index: Cons. Goods (2012=100, SA)	3	Slow
IPDMAT	Industrial Production Index: Durable Materials (2012=100, SA)	3	Slow
IPB00004NQ	Industrial Production Index: Manufacturing (2012=100, SA)	3	Slow
IPB53000SQ	Industrial Production Index: Materials (2012=100, SA)	3	Slow
IPBUSEQ	Industrial Production Index: Business Equipment (2012=100, SA)	3	Slow
IPB50002SQ	Industrial Production Index: Final Products (2012=100, SA)	3	Slow
IPNMAT	Industrial Production Index: Nondurable Materials (2012=100, SA)	3	Slow
IPFUELS	Industrial Production Index: Fuels (2012=100, SA)	3	Slow
UNRATE	Civilian Unemployment Rate (%, SA)	3	Slow
PAYEMS	All Employees: Total Nonfarm Payrolls (Thous.,SA)	3	Slow
USCONS	All Employees: Construction (Thous.,SA)	3	Slow
DMANEMP	All Employees: Durable Goods (Thous.,SA)	3	Slow
USGOOD	All Employees: Goods-Producing Industries (Thous.,SA)	3	Slow
MANEMP	All Employees: Manufacturing (Thous.,SA)	3	Slow
USMINE	All Employees: Mining and Logging (Thous.,SA)	3	Slow
NDMANEMP	All Employees: Nondurable Goods (Thous.,SA)	3	Slow
USTRADE	All Employees: Retail Trade(Thous.,SA)	3	Slow
SRVPRD	All Employees: Service-Providing Industries(Thous.,SA)	3	Slow
USTPU	All Employees: Trade, Transportation and Utilities (Thous.,SA)	3	Slow
USWTRADE	All Employees: Wholesale Trade (Thous.,SA)	3	Slow
PCECC96	Real Personal Consumption Expenditures (Chained, Bil 2009 $, SA)	3	Slow
HOUST	Housing Starts: Total (Thous.,SA)	2	Fast
HOUSTNE	Housing Starts: Northeast (Thous.,SA)	2	Fast
HOUSTMW	Housing Starts: Midwest (Thous.,SA)	2	Fast
HOUSTW	Housing Starts: West (Thous.,SA)	2	Fast
HOUSTS	Housing Starts: South (Thous.,SA)	2	Fast
M1SL	Money Supply: M1 (Bil$, SA)	3	Fast
M2SL	Money Supply:M2 (Bil$, SA)	3	Fast
BOGMBASE	Monetary Base: Total (Mil $ NA)	3	Fast
PPIACO	Producer Price Index for All Commodities (100=1982, NSA)	3	Slow
CPALTT	CPI: Total All Items (100=2010, SA)	3	Slow
CES3	Average Hourly Earnings of All Employees: Manufacturing ($, SA)	3	Slow
CES05	Average Hourly Earnings of All Employees: Total Private($, SA)	3	Slow
BAA	Yield Spread: Moody's Seasoned BAA Corporate Bonds (%, NSA)	1	Fast
BAA.AAA	Yield Spread: Moody's Seasoned BAA and AAA Corporate Bonds (%, NSA)	1	Fast
T10Y3MM	Yield Spread: 10-year and 3-month Treasury Bills (%, NSA)	1	Fast
AAAFFM	Moody's Seasoned AAA Corporate Bond Minus FFR (%, NSA)	1	Fast
BAAFFM	Moody's Seasoned BAA Corporate Bond Minus FFR (%, NSA)	1	Fast
T1YFFM	1-Year Treasury Constant Maturity Minus FFR (%, NSA)	1	Fast
T5YFFM	5-Year Treasury Constant Maturity Minus FFR (%, NSA)	1	Fast
T10YFFM	10-Year Treasury Constant Maturity Minus FFR (%, NSA)	1	Fast
T3MFFM	3-Month Treasury Constant Maturity Minus FFR (%, NSA)	1	Fast
T6MFFM	6-Month Treasury Constant Maturity Minus FFR (%, NSA)	1	Fast
TB6MS	6-Month Treasury Bill: Secondary Market Rate (%, NSA)	1	Fast
TB3MS	3-Month Treasury Bill: Secondary Market Rate (%, NSA)	1	Fast
BAA10YT	Yield Spread:Moody's Seasoned BAA to 10-Year Treasury (%, NSA)	3	Fast
BAA3MT	Yield Spread:Moody's Seasoned BAA to 3-Month Treasury (%, NSA)	3	Fast
GSPC	S&P 500 ($, NSA)	3	Fast
VIXCLS	CBOE Volatility Index (NSA)	3	Fast

Notes: Transformation codes are: 1=no transformation; 2=logarithm; 3=first difference of logarithm. SA=seasonally adjusted; NSA= not seasonally adjusted.

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