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Essays on Empirical Models of Macroeconomics and Finance

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ABSTRACT OF THE DISSERTATION

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The dissertation offers insights into measuring and managing risk in financial institutions and the role of central banks as regulators and supervisors. Specifically, the first chapter 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.

The second chapter uses a big dataset of over one million observations on firm characteristics, bank balance sheets, and loan information to study the default risk of loans to small businesses under the Small Business Administration (SBA) loan guarantee program. Using a logistic model, we find that loan age is the most important predictor of loan default over the entire sample. This is also the case for the periods before, during, and after the 2008 financial crisis. The other important variables are bank capital and bank assets in predicting default risk before and during the crisis period. However, after the crisis, firm characteristics, such as earnings-to-assets and debt-to-assets, are the most important predictors after loan age. The results suggest that major post-crisis reforms in the banking industry may have improved the quality of bank balance sheets. Bank characteristics, therefore, have since become less crucial in determining the quality of loans after the crisis.

The third chapter investigates the effects of the Dodd-Frank Act Stress Test (DFAST) on bank equity risk and liquidity risk management of the 100 largest publicly traded banks in the U.S. based on their consolidated assets. Bank equity risk is derived from banks' daily stock returns. Exposure to liquidity risk is measured by the amount of bank equity capital, core deposits, and liquid assets since they act as buffers for banks when market liquidity becomes scarce. Using a difference in difference panel data model for the period between 2008Q1-2017Q4, the paper finds that the implementation of the DFAST significantly decreases bank equity risk and increases the amount of equity capital and core deposits held at stress-tested banks. The paper concludes that the stress test indeed has had a positive impact on banks' risk exposure and risk management.

Contents

List of Figures

List of Tables

Chapter 1

Firm Equity Risk, Bank Lending Standards, and the Macroeconomy

1.1 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 responsible for nearly half of total bank risk compared to other risks, such as operational and market risk (Kuritzkes and Schuermann, 2010). In addition, among financial instruments, loans account for the largest component of credit risk in commercial bank activities. Thus, measuring and managing credit risk associated with business loans is one of banks' primary concerns. The 2008 financial crisis also 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 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 goods markets and financial markets, it is important for central banks, commerical banks, and firms 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 credit 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. By construction, equity risk reflects volatility in a firm's stock price. Thus, firms with high levels of equity risk signal unstable future cash flows, having lower abilities to service their debts. This measure of firms' credit risk is better than nonperforming loans for a couple of reasons. Information on nonperforming loans is backward-looking as it reflects a firm's past performance. Thus, firms without a history of nonperforming loans do not necessarily imply that they are currently low risk. Equity risk, on the other hand, contains forward-looking information about a firm since stock returns reflect investors' expectations about a firm's future performance. As a result, equity risk is more suited for calculating the likelihood that a firm might default on its debt. 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.

1.2 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.

1.3 Theoretical Framework of a Structural FAVAR Model

1.3.1 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:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \nu_t \tag{1.1}$$

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:

$$X_t = \begin{bmatrix} \Lambda & \Gamma \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + e_t \tag{1.2}$$

where $\Lambda = \begin{pmatrix} \lambda_1 & ... & \lambda_N \end{pmatrix}'$ is an $N \times K$ matrix of factor loadings, $\Gamma = \begin{pmatrix} \gamma_1 & ... & \gamma_N \end{pmatrix}'$ is an $N \times M$ matrix, and $e_t = \begin{pmatrix} e_{1t} & ... & e_{Nt} \end{pmatrix}'$ 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.

1.3.2 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:

$$X_t = \Lambda F_t + \Gamma Y_t + e_t = (\Lambda M_{11})(M_{11}^{-1} F_t - M_{11}^{-1} M_{12} Y_t) + (\Gamma + \Lambda M_{12}) Y_t + e_t \tag{1.3}$$

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.

1.3.3 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:

$$\hat{C}_t = b_f \hat{F}_t^s + b_y Y_t + e_t \tag{1.4}$$

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 to shocks in the policy variable. This assumption is reasonable given that the latent factors

[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 $\hat{F}_t$.

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.

1.4 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.

1.4.1 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 banks credit standards for approving loan applications for C&I [commercial and industrial] loans or credit lines —excluding those to finance mergers and acquisitionschanged? 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.

1.4.2 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:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{1.5}$$

Thus, the residual is given by:

$$\hat{\varepsilon}_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{1.6}$$

The firm's equity risk is the quarterly standard deviation of the residuals. 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:

$$\sum_{i=1}^{N} w_{i,t} \times r_{i,t} \tag{1.7}$$

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.

1.4.3 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.

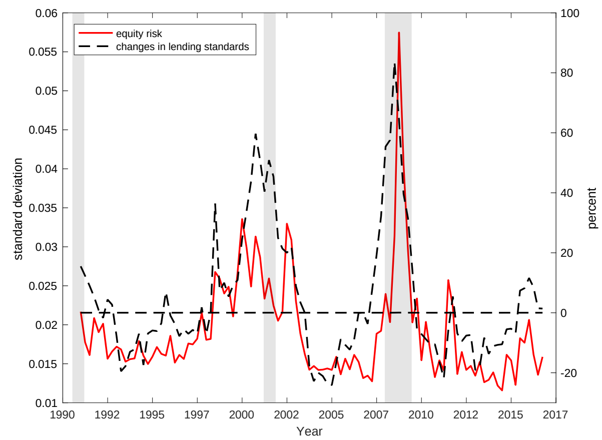
1.4.4 Relationship between Firm Risk and Bank Lending Standards from Analyzing the Data

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.

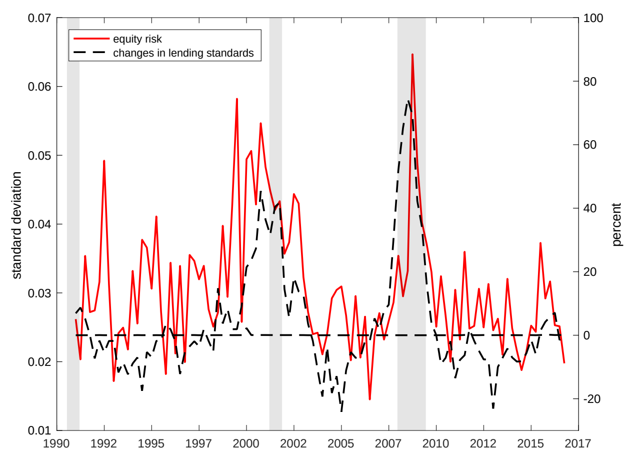
1.5 Estimated Results

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

Figure 1.1: Firm Equity Risk and Net Percentage of Banks Tightening Lending Standards



(a) Medium-Large Firms



(b) Small Firms

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 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 (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.

[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.

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

Table 1.1: 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

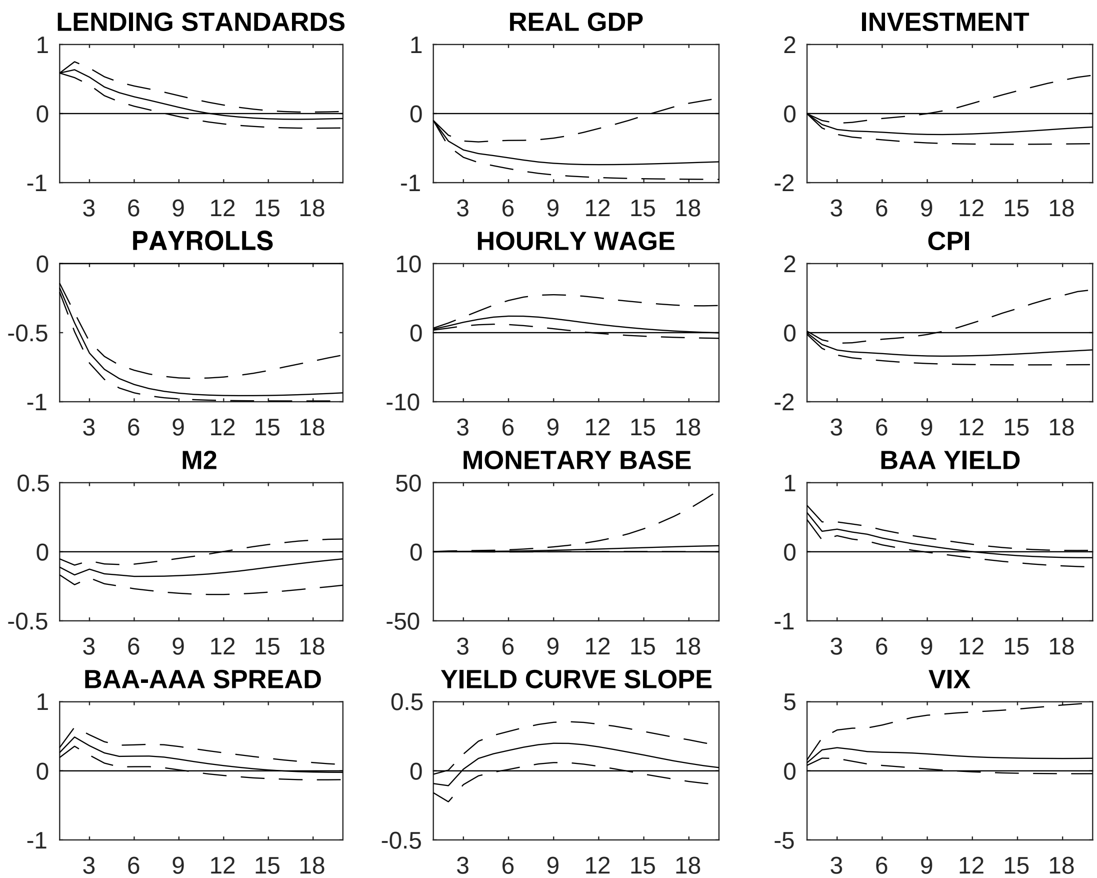
Notes: Variance decompositions are at the 20-quarter horizon.

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.

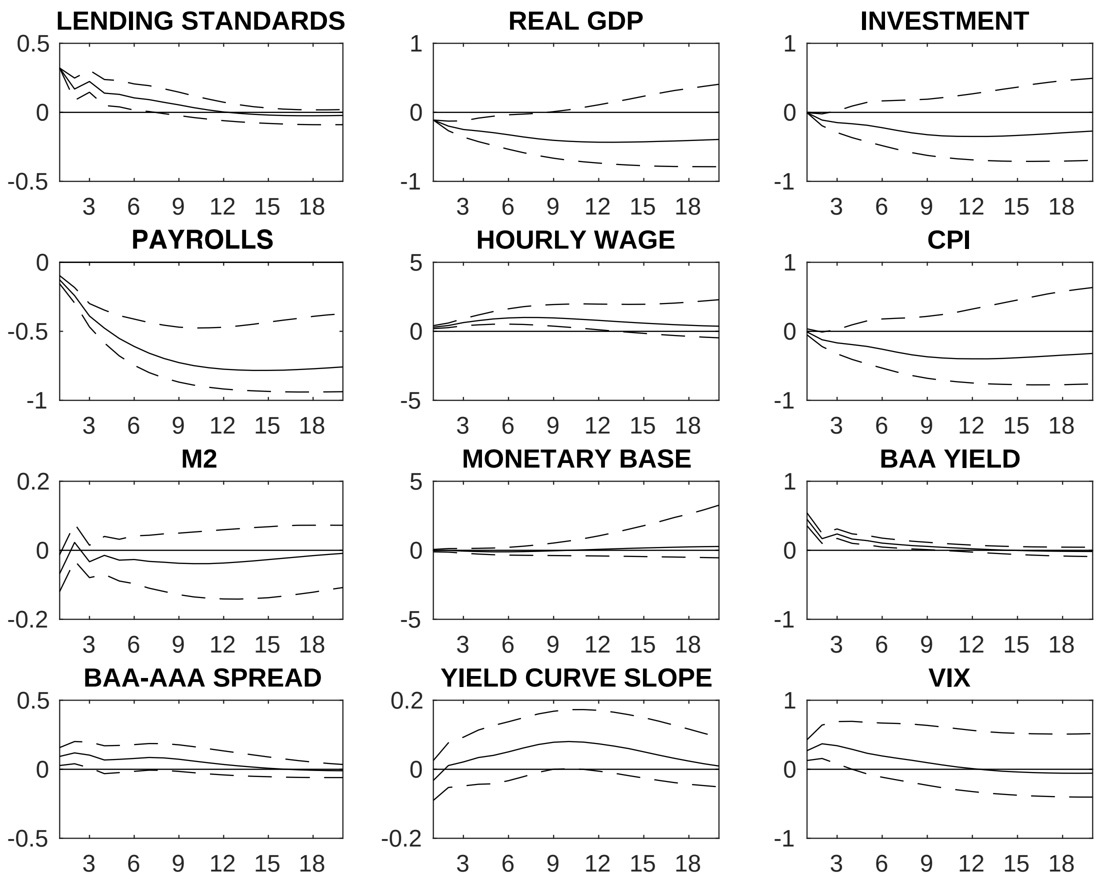
In addition, except for CPI, the shock in medium-large firm risk explains a significant amount of macroeconomic variables: about a third of real GDP and nonfarm payrolls, 13.85 percent of private investment, and 63.34 percent of hourly wages.

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

Figure 1.2: 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 1.2: 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.

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.

1.6 Concluding Remarks

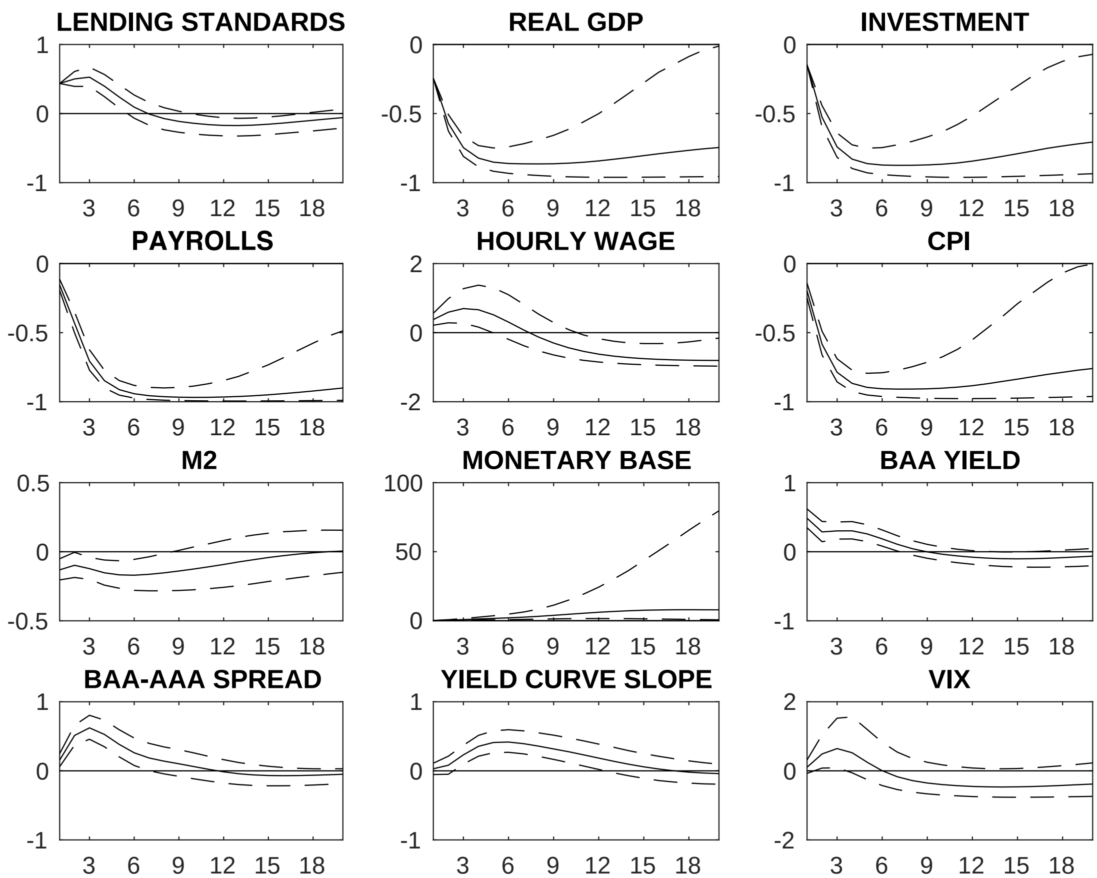
This paper analyzes the effect of U.S. firm risk on bank lending standards and the macroeconomy. To achieve this, we construct a firm equity risk index using firms' daily stock returns. The FAVAR model is then applied for 54 macroeconomic and financial time series from 1991Q1 to 2016Q4 . To the best 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.

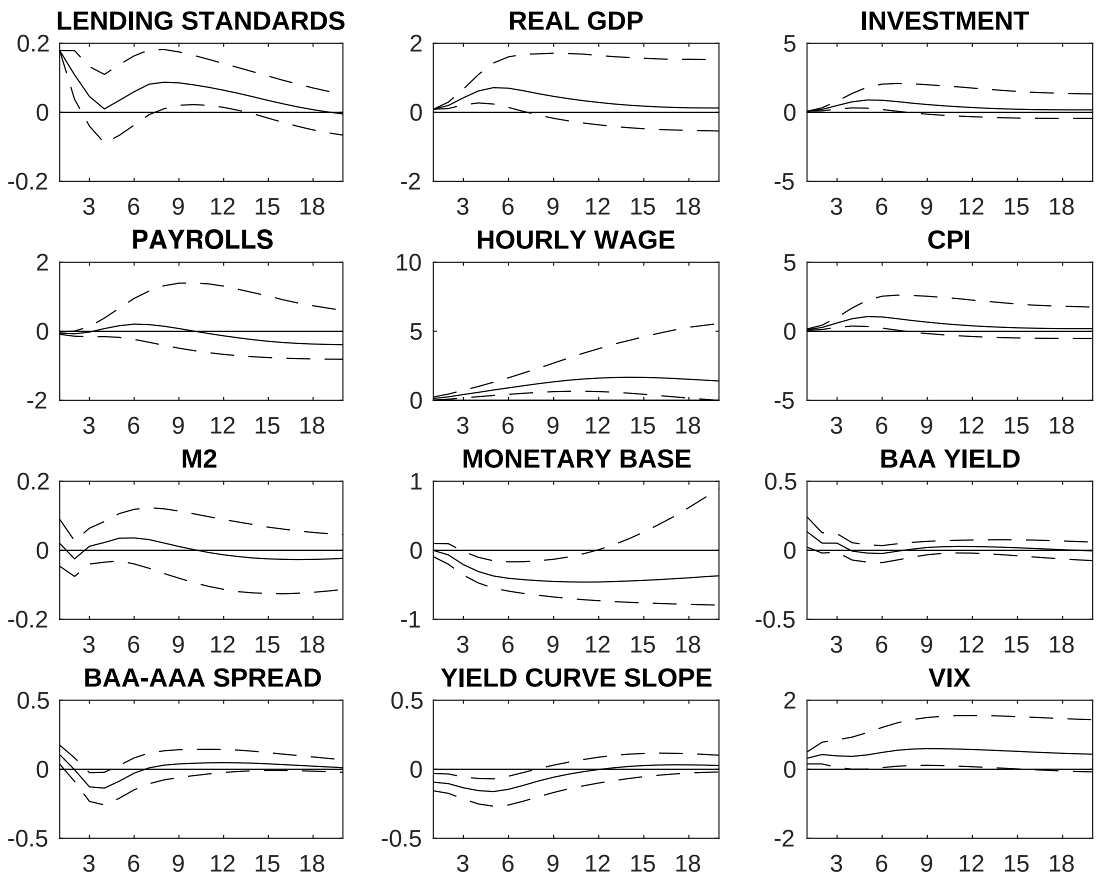
To investigate the effect of business cycle risk on bank lending practices, we segregate the sample into two periods using the NBER recession indicator: recession and expansion. The result is that the effect of firm risk on bank lending practices during a recession is much more pronounced than that during 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 1.3: Impulse Responses to a Shock in Firm Risk For Medium-Large Firms



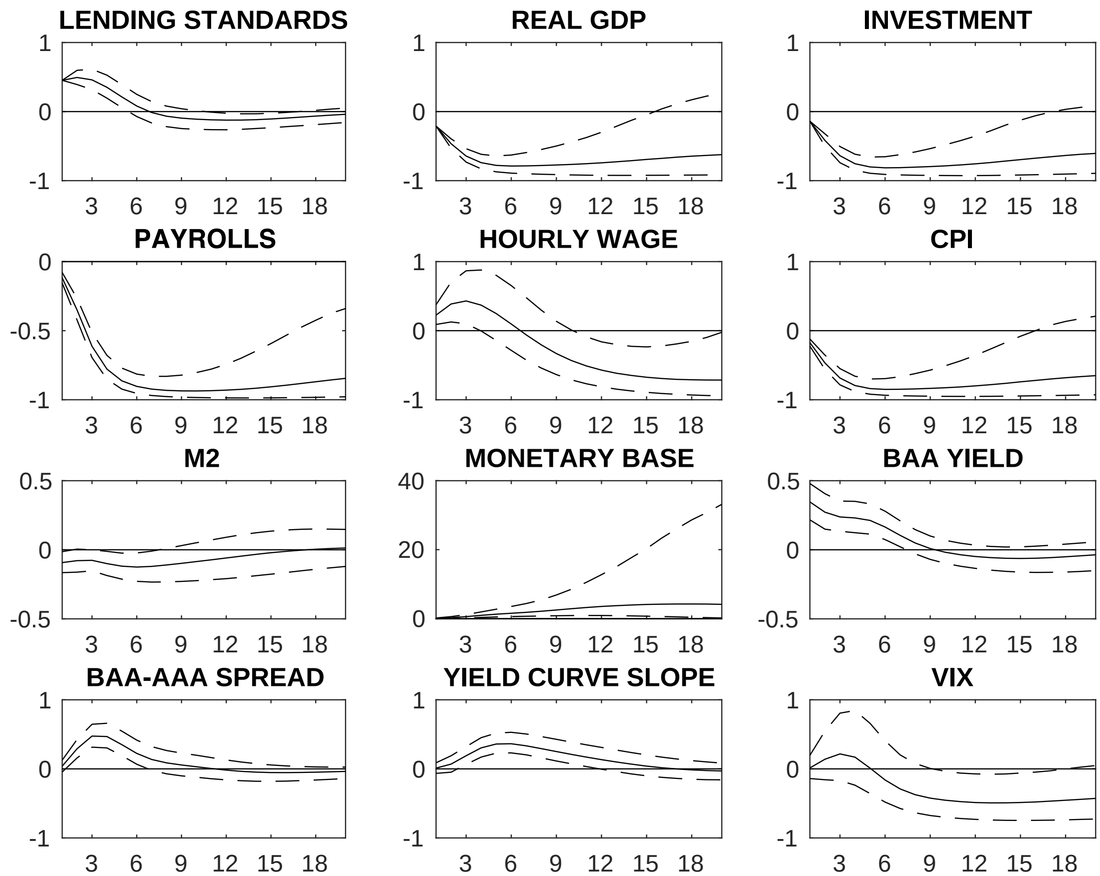
(a) Recessions



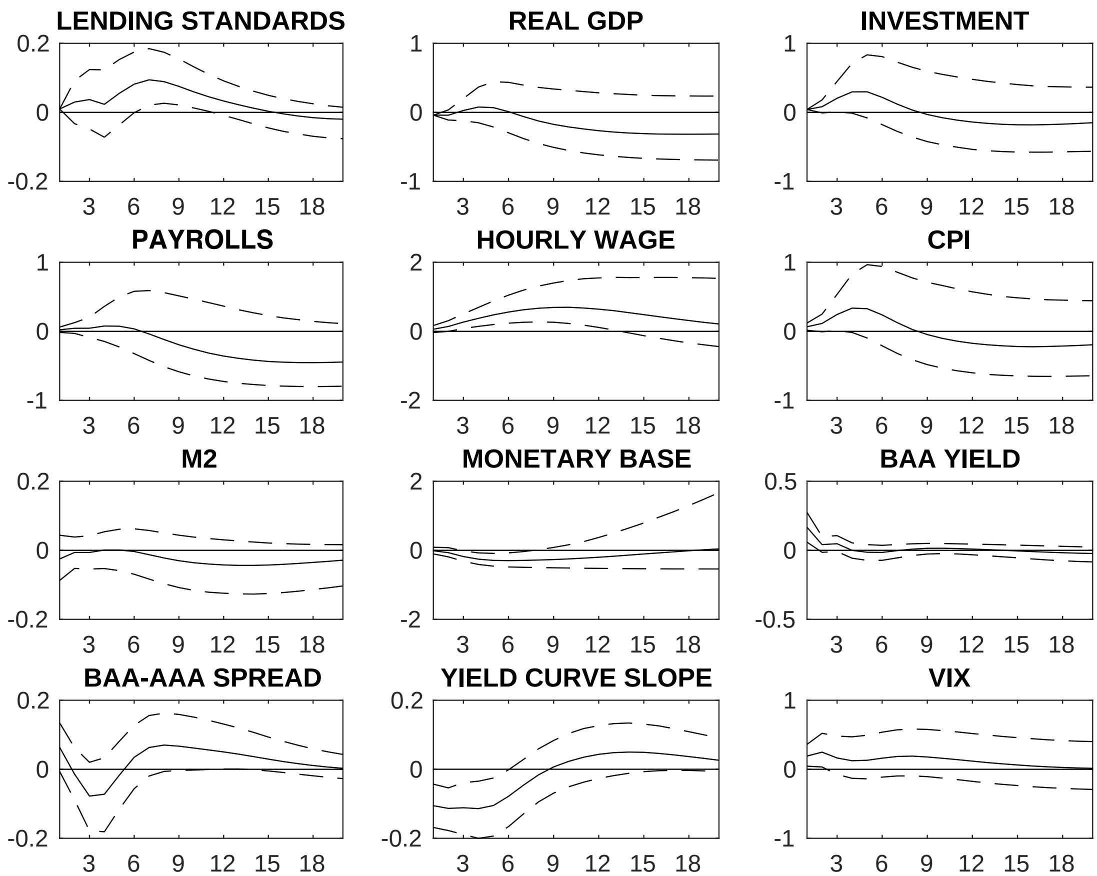
(b) Expansions

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 1.4: 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.

Chapter 2

Predicting Loan Default Risk to Small Businesses with Big Data

2.1 Introduction

Small businesses are generally defined as hiring fewer than 500 employees. They make up to 99 percent of total businesses in the U.S. Small businesses have become the economy's engine in terms of creating jobs and spurring economic growth. According to a recent report by the Small Business Administration (SBA), small businesses added 61.8 percent of newly created jobs between the third quarter of 1993 and the third quarter of 2016. Despite their important role, small businesses have a harder time obtaining loans from financial institutions for a couple of reasons. First, they, along with many start-up firms, do not have access to capital markets by issuing stocks and bonds. Second, financial institutions are more reluctant to lend money to small businesses due to the asymmetric information problems, adverse selection and moral hazard. Available information about small businesses is limited, posing challenges for lenders to accurately measure the credit risk associated with small business loans. Banks, therefore, rely on soft information about small businesses, such as personal relationships.

This paper predicts the default risk of more than one million loans to small businesses under the SBA loan guarantee program using a binary logit model. The main contribution of the paper to the existing literature is that it is the first to apply balance sheet information on firms and banks to predict the default rate of small business loans. Previous papers have focused on either the bankruptcy rate of small businesses or their credit availability. In this paper, I compile big datasets on characteristics of loans, borrowers, and banks to analyze the micro structure of loans to small businesses. In addition, the paper provides the power of predictors in forecasting the default rate of small business loans.

I find that loan age is the most important predictor in the model for all periods: before crisis (2001Q1-2006Q4), during crisis (2007Q1-2011Q4), and after the crisis (2012Q1-2016Q4). Bank balance sheet information, including bank capital and bank assets, plays a crucial role in predicting the default rate before and during the crisis. After the crisis, firm characteristics, earnings-to-assets and debt-to-assets, become the most important predictors after loan age. Since the SBA is required to share losses in the event of default with the lender, the paper provides insightful policy implications for the SBA. First, loans granted by big banks have less default risk than ones granted by small banks. Thus, approving loans underwritten by big banks can decrease credit risk for the SBA. Second, firm balance sheets are informative in measuring the default risk of loans to small businesses.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the SBA loan guarantee program. Section 4 discusses the model setup. Section 5 reports the results. Section 6 concludes.

2.2 Survey of the Literature

The literature on lending to small businesses can be summarized into two main strands, credit availability to small businesses and default rate of small business loans, with a major focus on the former. In the first strand, Peterson and Rajan (1994, 1995) study how small businesses' personal relationships with banks affect their access to credit. They argue that banks' familiarity with small firms reduces information asymmetry and monitoring costs. Using the National Survey of Small Business Finances (NSSBF), business relationship with banks is determined as: credit relationship (firms borrow from the bank), a service relationship (firms purchase financial services from the bank), or a deposit relationship (firms have a checking or savings account with the bank). The authors find that relationship with banks indeed helps small businesses attain better access to credit.

Peterson and Rajan(2002) study the role of physical distance between lenders and borrowers in small business lending. The result is that due to recent development of the financial sector, banks and firms communicate less in person and more digitally. As a result, physical distance with the bank does not significantly affect a firm's ability to acquire loans. Berger and Udell (1995) argue that the relationship variable used by Peterson and Rajan (1994) is misleading as some of the loans in the survey are mainly transaction-driven.

The authors, therefore, use the length of the relationship between firms and banks. The finding is that longer relationships with banks decrease the cost of borrowing for small businesses.

Peek and Rosengren (1996); Berger, Saunders, Scalise and Udell (1998); Berger, Goldberg and White (2001) study the effects of bank consolidation on small business lending. They find that the major mergers of the banking system reduced credit availability to small firms. Sskilahti (2016) investigates the effect of the 2008 financial crisis on the volume and prices of small business lending. The author concludes that the crisis drove up the average loan margins and decreased the volume of loans with a larger impact on the former.

The second strand of the literature focuses on the default of small businesses. Altman and Sabato (2007) study the default rate of small businesses by applying a number of methods, including multiple discriminant analysis technique (MDA) and logistic analysis. They find that with the same set of predictors, logistic models outperform MDA models in predicting the default rate of small businesses.

To the best of my knowledge, the closest study to my paper in the literature is the work of Glennon and Nigro (2005), in which they study the default rate of small business loans. They use data on loans originated under the SBA 7(a) loan guarantee program, which is designed to help small businesses obtain loans. The authors state that time should have an effect on the probability of default, using a discrete-time hazard procedure. The sample is from 1981 to 2000 and restricted to medium-maturity loans. The information on borrowers includes firm age, firm size (number of employees), corporate structure, location and Standard Industrial Classification (SIC). Lender information consists of banks or nonbanks.

Loan characteristics are the approval amount and interest rates. Key macroeconomic variables, such as employment growth rate and industry income, are also included in the model. The authors find that the SBA's exposure to default risk is an inverted U-shape. Default risk increases and reaches its maximum two years after the loan is originated and declines thereafter. Furthermore, the likelihood of SBA medium-maturity loans defaulting depends on characteristics of lenders, borrowers, loan characteristics and the macroeconomy. More specifically, new small businesses have a higher rate of default on their loans compared to established ones.

What distinguishes my paper from the study of Glennon and Nigro (2005) is that I apply big datasets on balance sheet information about firms and banks to examine the default rate of small business lending.

2.3 The SBA 7(A) Loan Guarantee Program

SBA 7(a) loans are the most common type of SBA loans. These loans go up to \$ 5,000,000 and can be used for working capital, to refinance debt, or to buy a business, real estate or equipment. The SBA 7(a) loan program is designed to help small businesses who are not qualified for conventional bank loans of equivalent terms, price and maturity. Under the program, the SBA offers loans to businesses through financial institutions, mainly banks. The lenders are responsible for choosing borrowers, initiating SBA involvement and monitoring the loans. To obtain a SBA 7(a) loan, a firm needs to meet the following three requirements. First, the firm could not qualify for credit on reasonable terms without the SBA guarantee. Second, the prospects for repayment are sound. Third, the firm must be considered small based on the number of employees and annual revenue.

The lenders submit SBA applications to the local SBA office to review. The SBA re-underwrites submitted applications and makes a final decision to approve or deny the loan. Once the loan is approved, the lender of the loan is responsible for loan servicing and reporting loan performance information to the SBA quarterly. Loans that are in arrears for 60 days or more are considered non-performing loans. The SBA is required to purchase them from the lender at a value equal to the guaranteed portion of the remaining outstanding balance and delinquent interest.

2.4 Model Lineup

This section presents the econometric model and data. The sample period is from 2001Q1 to 2016Q4. The starting point of the data period is determined by the availability of data on bank balance sheets. Information on loans to small businesses is downloaded from the SBA website. Data on small business balance sheets are from COMPUSTAT database. Bank balance sheet information comes from the Call Reports database. I combine the three separate datasets to obtain over one million observations. Table 1 provides the summary statistics.

2.4.1 Logistic Regression

I apply a logistic model to forecast the default rate of small business loans. Let y_t be a binary random variable that is equal to one if the loan is defaulted and zero otherwise. Let $x_t = (x_1 ... x_K)$ be a vector of K exogenous variables, including borrower, bank, loan

Table 2.1: Sample Summary Statistics

Variable	Mean	Std. Dev.	N
Panel A: Loan Characteristics			
Loan-Size-to-Assets	0.041	2.007	1,048,576
Loan Age (months)	99.759	11.604	1,048,576
Panel B: Borrower Characteristics			
Relationship	0.345	0.475	1,048,576
Business Type	0.744	0.436	1,048,576
Location	0.499	0.500	1,048,576
Firm Size	5.810	2.332	1,048,576
Liabilities-to-Assets	0.536	5.969	1,048,576
Debt-to-Assets	0.237	2.832	1,048,576
Earnings-to-Assets	0.731	12.824	1,048,576
Panel C: Bank Characteristics			
Bank Assets	14.687	3.228	1,048,576
Bank Capital	12.339	3.178	1,048,576
Bank ROA	0.007	0.007	1,048,576
Bank Liabilities	0.898	0.052	1,048,576
Panel D: Macroeconomic Variables			
Unemployment Rate	5.165	0.564	1,048,576
Slope of the Yield Curve	1.335	1.316	1,048,576

and macroeconomic variables. The logit model can be written as follows:

$$y_t = {x_t}'\beta + e_t \tag{2.1}$$

where e_t is the error term following an *i.i.d.* logistic distribution. The conditional probability of a defaulted loan any given observation is:

$$p(i) = E(y_t = 1|x_t) = \frac{exp({x_t}'\beta)}{1 + exp({x_t}'\beta)} \tag{2.2}$$

The estimates of the model parameters can be obtained by maximum likelihood methods (Green, 2011).

$$\hat{\beta} = \arg\max_{\beta} \left[\sum_t \left(y_t ln \frac{exp({x_t}'\beta)}{1 + exp({x_t}'\beta)} + (1 - y_t)\, ln \frac{1}{1 + exp({x_t}'\beta)} \right) \right] \tag{2.3}$$

2.4.2 The Dependent Variable: Loan Default

Loan status is reported in five different categories: undisbursed, paid in full, charged off, canceled, and exempt. In this paper, a small business defaults on its loan when its loan status is marked charged off. Loans are considered charged-off when all reasonable liquidity requests have been sent, and the cost of additional recovery is expected to exceed the recovery. The dependent variable in a dummy variable equal to one if the loan is default and zero otherwise.

2.4.3 Loan Characteristics

Loan-Size-to-Assets is the ratio of the size of a loan approved by the SBA to the firm's assets, signaling the firm's ability to repay its debts. The larger this ratio is, the more likely the firm will default on its debt. Thus, the potential effects of the variable on default rate should be positive. Loan age is the length of a loan, measured in months. Long-term loans might possess more risk, but they also can be safer since banks scan their borrowers more carefully for long-term loans. The coefficient of loan age could be either negative or positive.

2.4.4 Borrower Characteristics

Relationship with Bank is a dummy variable indicating whether firms and banks have a pre-existing relationship. It is equal to one if banks have granted loans to the same firms in the past. Banks with more inside information about firms can mitigate the adverse selection problem. As a result, the probability of firms defaulting on their loans is lower for firms who have previous lending relationships with the same banks. I expect the coefficient of this variable to be negative. Business type is dummy equal to one if a firm is a corporation. The effects of business type are expected to be negative. Corporations are more well-structured and informative than partnerships and individuals. Thus, loans to the first group are less risky than the other two groups.

Location is a binary dummy variable equal to one if the borrower is from the South or West, and zero otherwise. The rationale is that firms from these two regions have a higher chance of defaulting on their loans according to the data. The sign of the coefficient should be positive. Firm Size is the natural logarithm of firm's sales. Larger firms provide more assurance to banks that loans will be repaid. Thus, I expect a negative coefficient. Cash-to-Asset is the ratio between a firm's cash to its assets. More liquid firms have better ability to fulfill their debt payment. Hence, the effects of this variable on the default rate are predicted to be negative.

Liabilities-to-Assets is the ratio of a firm's current liabilities to its assets. Debt-to-Assets is a firm's long-term debt over its assets. Firms with higher debt ratios are more likely to experience financial distress and thus are more likely to default on their loans. I expect a positive coefficient. Earnings-to-Assets is the ratio is a firm's retained earnings to its assets. More profitable firms have stronger prospects of repaying their loans. I expect the coefficient to be negative.

2.4.5 Bank Characteristics

Bank Assets and Bank Capital are expressed as the natural logarithm of a bank's assets and capital, respectively. The effects of bank assets and bank capital on default rate are ambiguous. Large banks might have more resources to obtain information on small businesses thus encountering lower default risk on loans. Small banks, on the other hand, have more personal relationships with small firms, better assessing their prospects for loan repayment.

Bank Return-to-Assets is the ratio of a bank's net income to its total assets. More profitable banks could make safer loans. However, they might be more willing to engage in risky loans as they have the ability to absorb the loss. The effects of this variable on default rate are ambiguous. Bank Liabilities is a bank's current liabilities over its assets. More indebted banks are less likely to grant risky loans. I predict the coefficient to be negative.

2.4.6 Macroeconomic Variables

In addition to the borrower, bank and loan information, the slope of the yield curve (the yield spread between 10-year Treasury bonds and three-month Treasury bills) and unemployment rate are also included in the model. These variables are constant over loans but change across geographic areas during the life of the loan. I expect the coefficient of unemployment rate to be positive as when the economy is in downturn, firms are more likely to default on their loans. The effects of the slope of the yield curve on the default rate are predicted to be negative. A steeper yield curve signals that investors expect short-term interest rates and inflation rate to rise. Thus, the real value of loans decreases, making it easier for borrowers to repay their loans.

2.4.7 Figures

Figure 1 plots the total number of loans granted to small businesses from five largest states in the U.S., California, New York, Florida, Texas and Illinois, under the SBA 7(a) program. California takes the largest share of loans among other states. Figures 2-3 display the default rates of loans, which is the number of charged-off loans over the total number of loans, based on borrower state and loan age, respectively. The data show that Florida has the highest rate of default followed by California. Additionally, long-term loans are most risky compared to medium-term and short-term loans. The rates of default peaked in 2007 just before the financial crisis.

2.5 Empirical Results

Table 2 reports the estimates of the logistic regressions for the whole sample, before crisis, during crisis, and after crisis.

Table 2.2: Results from Logistic Models

	(1) Whole Sample	(2) Before Crisis	(3) During Crisis	(4) After Crisis
Panel A: Loan Characteristics				
Loan-Size-to-Assets	-0.009	0.024	0.087***	0.001**
	(0.006)	(0.006)	(0.027)	(0.008)
Loan Age (months)	-0.019***	-0.019***	-0.019***	-0.017**
	(0.000)	(0.000)	(0.001)	(0.004)
Panel B: Borrower Characteristics				
Relationship	-0.204***	-0.109***	-0.392***	-0.494
	(0.024)	(0.026)	(0.044)	(0.328)
Business Type	-0.098***	-0.156***	-0.042***	-0.593***
	(0.019)	(0.021)	(0.037)	(0.624)
Location	0.286***	0.211***	0.454***	0.367***
	(0.018)	(0.020)	(0.031)	(0.272)
Firm Size	0.042***	0.047***	0.005	0.049
	(0.004)	(0.005)	(0.007)	(0.106)
Liabilities-to-Assets	0.005***	0.011***	0.015***	0.012***
	(0.002)	(0.003)	(0.001)	(0.002)
Debt-to-Assets	0.010**	0.201***	0.023*	0.111*
	(0.004)	(0.044)	(0.015)	(0.065)
Earnings-to-Assets	-0.000	−0.001***	-0.004***	-0.003***
	(0.000)	(0.000)	(0.002)	(0.001)
Panel C: Bank Characteristics				
L. Bank Assets	-0.444***	-0.371***	-0.329***	-0.311***
	(0.039)	(0.042)	(0.015)	(0.562)
L. Bank Capital	0.479***	0.399***	0.346***	0.229
	(0.039)	(0.042)	(0.106)	(0.551)
Bank Return-to-Assets	- 0.83***	-0.896***	- 0.991	-0.381***
	(10.195)	(0.374)	(0.252)	(0.268)
Bank Liabilities	0.339	0.109	0.872	0.470
	(0.187)	(0.184)	(0 .666)	(0.267)
Panel D: Macroeconomic Variables				
Unemployment Rate	-0.002	0.214***	-0.176***	0.366*
	(0.028)	(0.037)	(0.062)	(0.067)
Slope of the Yield Curve	-0.236***	-0.300***	-0.307***	-0.249***
	(0.013)	(0.016)	(0.029)	(0.032)
Observations	1,048,576	638,860	204,857	104,967
Predictive ability, AUROC	0.7777	0.7794	0.7631	0.7774

*Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses.*

2.5.1 Loan Characteristics

The coefficient of Loan-Size-to-Assets is positive and significant for the entire sample. Firms with more loans relative to assets have less ability to fulfill their debt obligations. The effects are positive and significant for three subsamples as well, with larger effects during crisis and after crisis. Loan-Age has negative and significant impacts on the default rate. Longer loans are less risky as they are granted to more qualified borrowers. The impacts remain significant and negative in all models.

2.5.2 Borrower Characteristics

The pre-existing relationship of a firm to a bank lowers the default rate on loans. Banks which previously gave loans to small businesses have more accurate information about them, reducing the adverse selection problem. The effects are more substantial during a crisis. This finding is consistent with the hypothesis that lending to small businesses relies more on soft information compared with lending to large businesses. During crisis, banks are more reluctant to lend, especially to small firms, due to tight credit conditions and high uncertainty. As a result, personal relationships with firms play a more important role in terms of selecting good borrowers. The coefficient of relationship is significant before and during the crisis yet insignificant after the crisis. The result is in line with papers in the related literature, which find that thanks to substantial development of the financial sector, soft information about firms has become less important in lending to small businesses (Chen et al., 2015; Mills and McCarthy, 2014).

Business Type has negative and significant influences on the default rate as predicted. Loans to corporations are safer than loans to individuals and partnerships. Corporations are well-structured, and their decision-making process involves shareholders. Individuals and partnerships, on the other hand, are governed by one or more individuals. Thus, they carry more default risk.

Borrower Location offers important results. Borrowers from the South and West are more likely to default on their loans. The finding comports with the data, which shows that four out of five states with the lowest rates of SBA loan repayment are from the South and West. Firm Size and Earnings-to-Assets both reveal negative and significant effects on the default rate. Firms with more income and earnings are more likely to pay back their loans. Debt-to-Assets impacts the default rate positively and significantly. More indebted firms have trouble repaying their loans, particularly during the crisis. The effect during the crisis is almost twice that after the crisis.

2.5.3 Bank Characteristics

Bank Assets, Bank Capital, and Bank ROA negatively and significantly affect the default rate. The paper provides evidence that healthier banks make safer loans. Big banks normally lend to less risky borrowers (Jimenez et al., 2014) as they have a larger pool of borrowers to choose from than do small banks. Therefore, loans coming from larger banks have lower odds of default. Bank Liabilities positively affects the default rate, but the effects are never significant in all models.

2.5.4 Macroeconomic Variables

The unemployment rate does not have any significant effects on the default rate in the whole period. The slope of the yield curve, on the other hand, significantly influences the default rate. An increase in the slope results in a lower probability of loan defaults. When the yield curve is steep and upward-sloping, investors expect future interest rates and inflation rate to increase. An increase in the inflation rate benefits borrowers as the real value of their loans decreases. Consequentially, the chance of defaulting on their loans is lower.

2.5.5 Measure of Forecast Accuracy

To measure the predictive power of the model, I use the Receiver Operating Characteristic (ROC) curve to evaluate binary classification ability. The curve plots the true positive rate, $TP(c)$ against the false positive rate, $FP(c)$ for all thresholds c. Let $I(.)$ be the indicator function, and $\hat{p}$ be the linear prediction of the model which forms a continuous signal. When the threshold c gets large and negative, the classifier is very aggressive in making default calls, almost all signals are above the threshold. TP and FP converge to 1. When c gets large and positive, the classifier is very conservative in making default calls, almost all signals are below the threshold. TP and FP converge to 0. In between, an informative classifier should yield $TP > FP$. As a result, the ROC curve should be above the 45-degree line.

The area under the ROC curve (AUROC) provides a test of the predictive power of the model. The null value of the test is 0.5, which is the probability of accuracy of a completely random guess. The results of the AUROC test are reported in Table 2. Figures 4-7 plot the results of the test. Overall, the model performs relatively well in the whole sample and subsample periods. The model performs best before the crisis period.

2.5.6 Importance of Variables in Forecasting Loan Default Rates

To rank the importance of variables in predicting the default rate on small business loans, I use the standardized coefficients of the estimates of the predictors. The greater the absolute value of the standardized coefficient, the greater the predicted power in the probability of the outcome, given a one-standard deviation change in the corresponding predictor. Figures 8-11 show the results of the standardized coefficients. Loan age has the highest power of predicting the default rate among all predictors in the model. The result holds for all sample periods: before crisis, during crisis and after crisis. Bank Capital and Bank Assets follow Loan Age in ranking before and during the crisis. The finding supports that banks with strong balance sheets engage in less risky lending.

Among firm characteristics, firm location and firm size play the most important role in predicting the default before crisis. Moreover, relationships with banks become more dominant in determining the default rate of loans during a crisis compared to other periods. Noticeably, Earning-to-Assets and Debt-to-Assets surpass bank characteristics as the most important predictors after Loan Age after the crisis. After the most recent financial crisis, banks' risk appetite is reduced due to a number of regulations, such as the Dodd-Frank Act. Hence, the quality of banks' balance sheets improves after the crisis, making bank characteristics less important in affecting the quality of the loans to small businesses.

2.6 Conclusion

The paper studies the default rate of loans to small businesses under the SBA 7(a) loan guarantee program for the period 2001Q1-2016Q4. It is the first paper applying balance sheet information on firms and banks to analyze the default rate of small business loans. I split the sample into three periods: before crisis (2001Q1-2006Q4), during crisis (2007Q1-2011Q4) and after the crisis (2012Q1-2016Q4). A logistic model is employed to forecast loan default rates. I find that loan age has the most predictive power among all explanatory variables, and the finding holds for all periods. Moreover, bank capital and bank assets are the next most important predictors for before and during crisis.

Firm characteristics, earnings-to-assets and debt-to-assets, replace bank characteristics to be the most important predictors after loan age during post-crisis period. The results imply that healthy banks are more selective in choosing borrowers. After the Great Recession, major reforms in the banking industry improve bank balance sheets. Banks become more risk averse. As a result, bank characteristics are less crucial in determining the quality of loans. To test the forecast accuracy of the model, the area under the ROC curve (AUROC) is calculated. The result shows that the model performs relatively well in all periods.

The paper sheds some light on the SBA 7(a) loan guarantee program. First, loans granted by big banks have less default risk than those granted by small banks. Thus, cooperating with big banks to underwrite business loans can decrease credit risk for the SBA. Second, firm balance sheet variables are key predictors of the default rate of loans to small businesses, especially after the 2008 financial crisis.

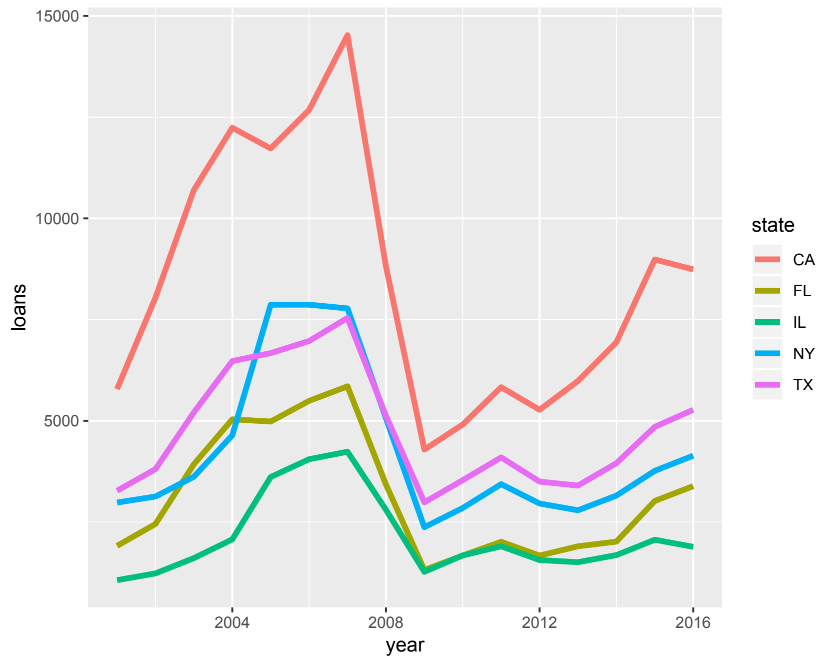


Figure 2.1: Total Number of Loans Granted

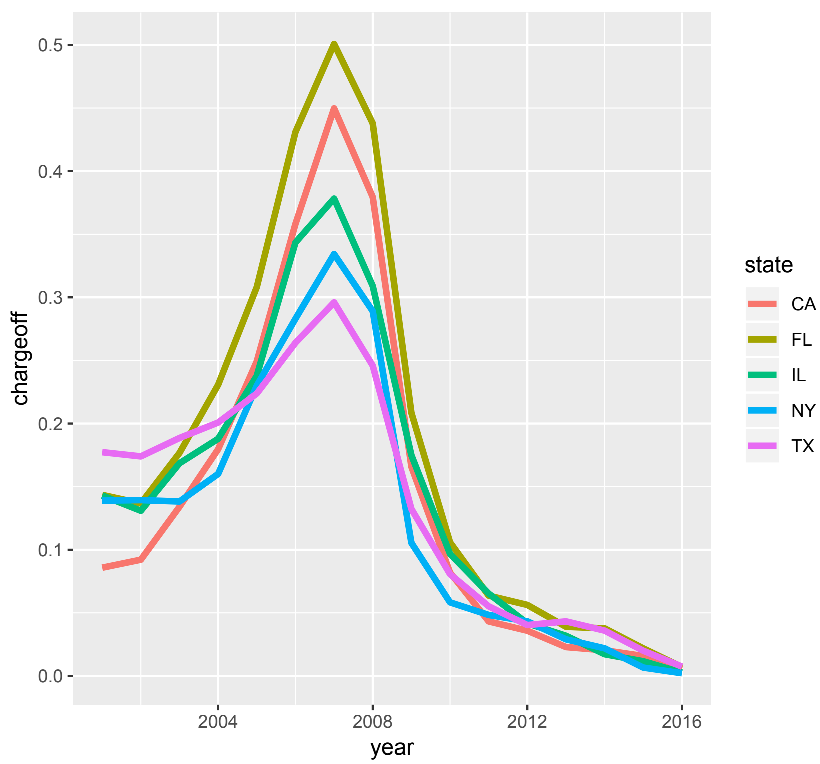


Figure 2.2: Default Rate by Borrower State

Figure 2.3: Default Rate by Loan Age

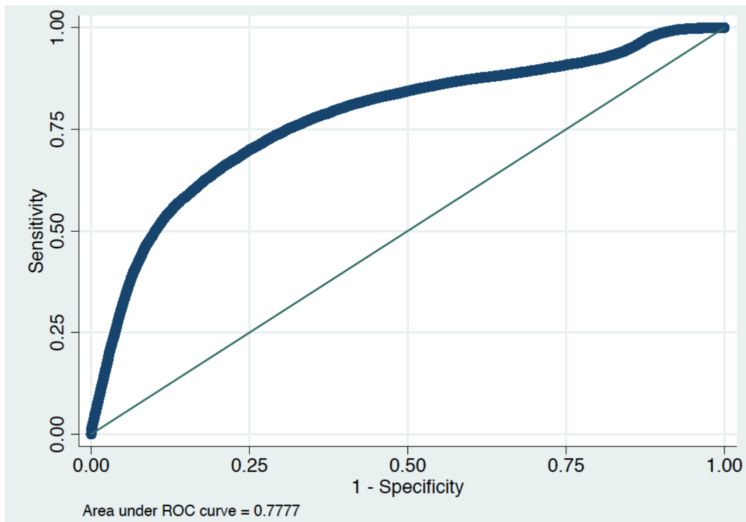


Figure 2.4: AUROC (Whole Sample)

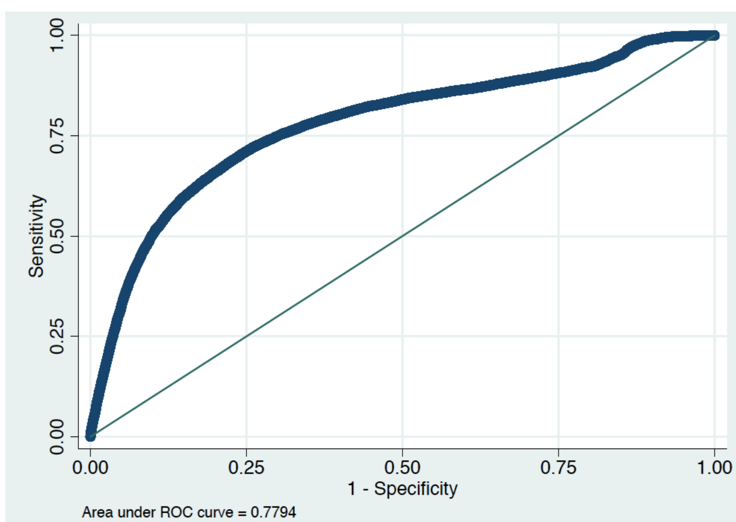


Figure 2.5: AUROC (Before Crisis)

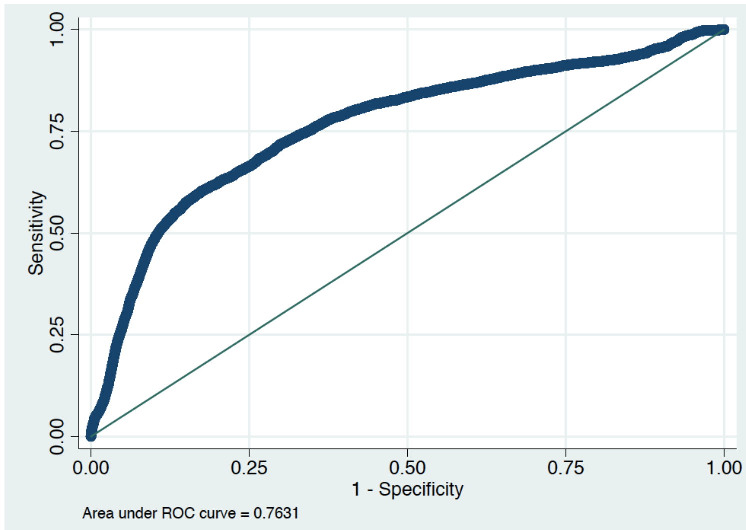


Figure 2.6: AUROC (During Crisis)

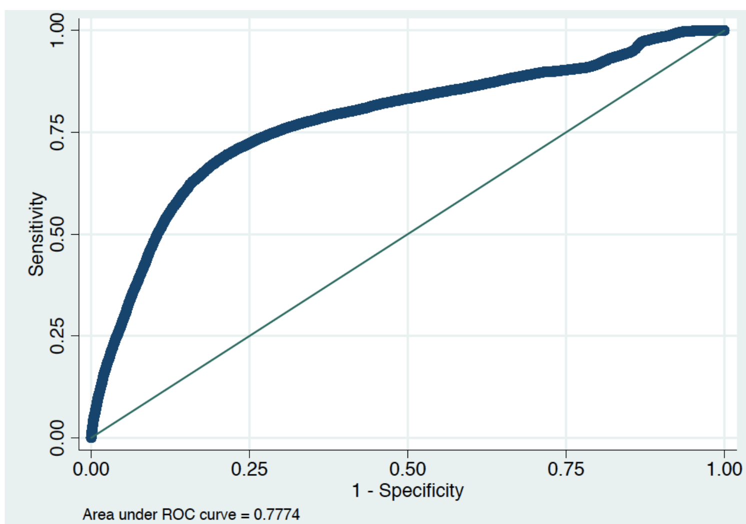


Figure 2.7: AUROC (After Crisis)

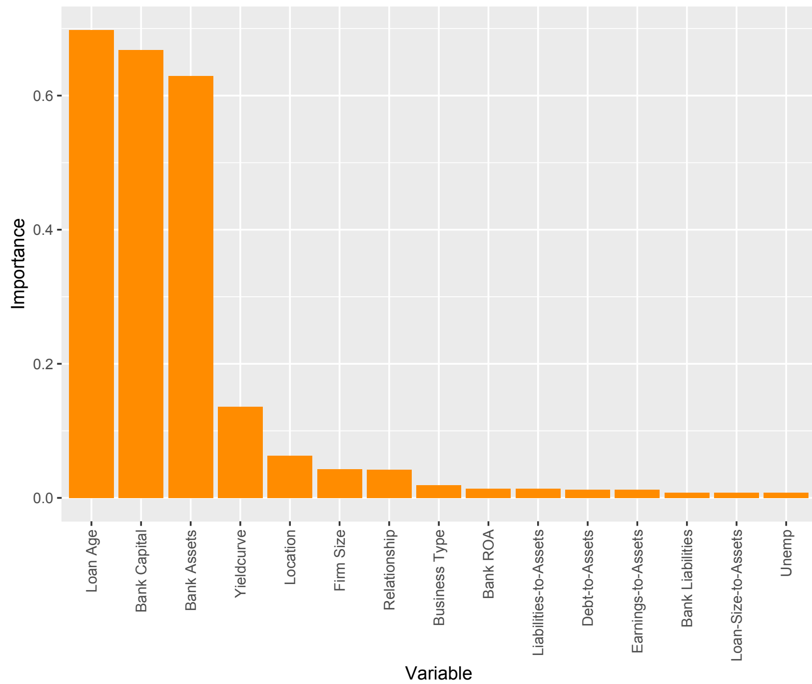


Figure 2.8: Importance of Variables (Whole Sample)

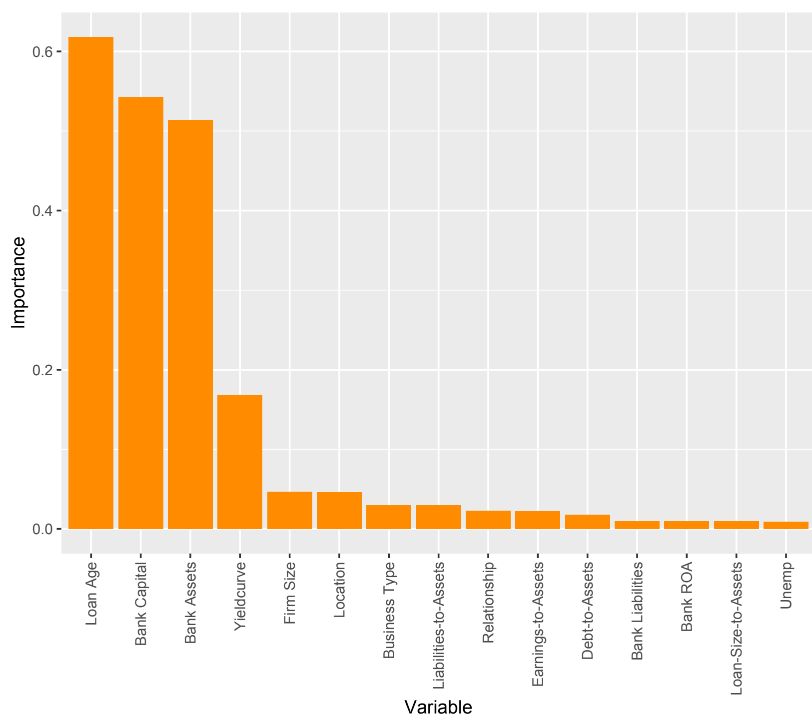


Figure 2.9: Importance of Variables (Before Crisis)

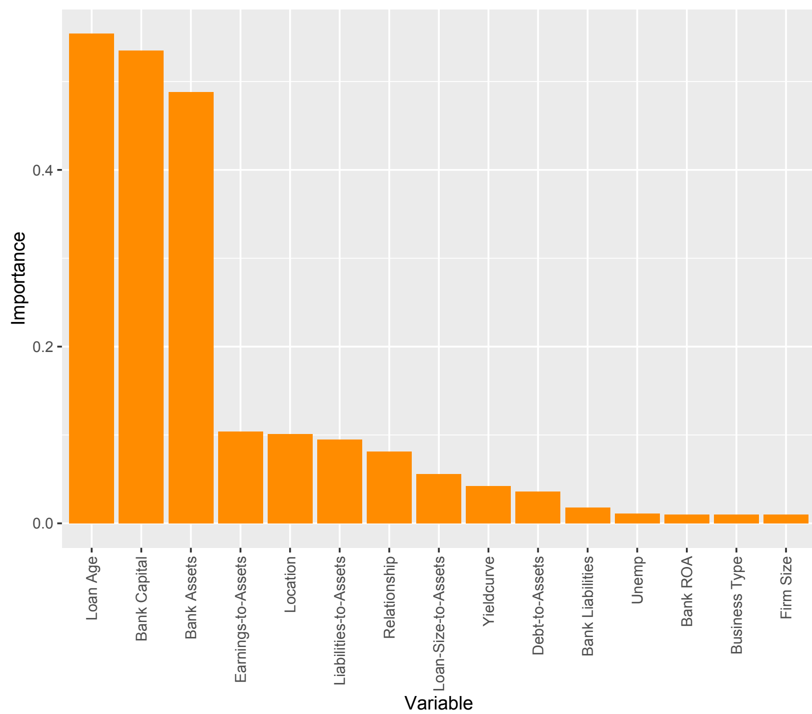


Figure 2.10: Importance of Variables (During Crisis)

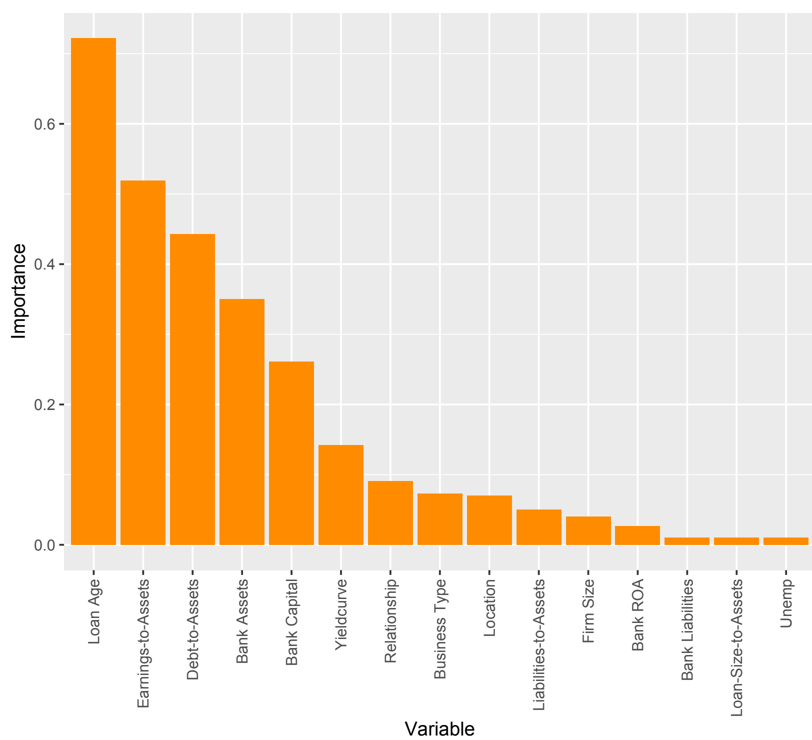


Figure 2.11: Importance of Variables (After Crisis)

Chapter 3

Does the Dodd-Frank Act Stress Test Improve Bank Equity Risk and Liquidity Risk?

3.1 Introduction

The financial crisis of 2008 raised attention to the catastrophic consequences of systemic risk in the financial sector. Prominent banks had become “too big to fail, imposing severe risk in the financial sector and the whole economy as a result. In response to the crisis, Congress passed the Dodd-Frank Wall Street Reform and Consumer Protection Act (hereby the Dodd-Frank Act) in 2010, offering substantial changes in regulation and supervision of financial institutions. Starting from 2013, banks with total consolidated assets of more than $10 billion are required to conduct an annual stress test given by the Federal Reserve.

The purpose of the Dodd-Frank Act stress tests (DFAST) is to gauge if banks have enough capital to survive unfavorable economic conditions while still being able to provide credit to the economy. Three hypothetical scenarios are designed: baseline, adverse, and severely adverse. The severely adverse scenario is close to a financial criss in which the economy experiences a high unemployment rate and a negative economic growth rate. In order to pass the stress tests, banks have to have at least the minimum ratio of capital determined by the Federal Reserve in the severely adverse situation. The results of the stress tests are released in June each year to the public, providing transparent information about big banks in the economy. Therefore, investors and consumers gain a better understanding of the current health of stress-tested banks and the banking industry as a whole.

This paper provides new evidence that the DFAST help improve bank equity risk. Banks are exposed to a number of risk, including credit risk, liquidity risk, and equity risk. Given that credit is still banks' most important source of risk (Kuritzkes and Schuermann, 2010), there are plenty of papers that study the effect of the DFAST on the availability of credit (Acharyam, Berger and Roman, 2018; Cortes et al., 2017; Basett and Berrospide, 2017). Liquidity risk also draws a substantial amount of attention in the literature (Acharyam, Berger and Roman, 2018; Cortes et al., 2017; Acharya, Engle and Pierret, 2014). The effect of the policy on bank equity risk, however, has not been done to the best of my knowledge. It is important to study changes in bank equity risk due to the implementation of the DFAST as they can affect the decision-making process of investors, borrowers, and regulators in the economy.This paper focuses on idiosyncratic equity risk instead of systematic equity risk since the DFAST is concerned with the performance of individual banks. In detail, bank idiosyncratic equity risk is measured as the standard deviation of error terms in the regression of banks' daily stock returns on daily market returns. By doing it, I am able to extract idiosyncratic risk from systematic risk in banks' total equity risk. For the rest of the paper, bank idiosyncratic equity risk is referred to as bank equity risk. A standard difference in difference (DID) model is used to study the effect of the stress tests on bank equity risk. I find that banks participating in the stress tests experience less equity risk. In addition to the effects of the DFAST on bank equity risk, I also investigate how the tests affect banks' liquidity risk buffers, including core deposits and liquid assets. Deposits are a stable source of financing for banks especially during a crisis when market liquidity dries up. Liquid assets are desirable during a crisis as they are easy to be converted into cash. The findings are that the DFAST have a positive and significant effect on the deposits of stress-tested banks. However, it does not have any significant impact on liquid assets of these banks. Overall, the DFAST improve banks' liquidity risk management.

The rest of the paper is organized as follows. Section 2 reviews the literature. Section 3 introduces the DFAST. Section 4 discusses the model and data. Section 5 reports the results. Section 6 concludes.

3.2 Stress Test Related Literature

A number of studies have been done on the effects of stress tests on the banking industry. The first strand of the literature focuses on how stress tests affect banks' risk management, mainly credit risk and liquidity risk. Acharyam, Berger and Roman (2018) investigate whether stress tests reduce loan supply to large corporates and increase loan prices to risky borrowers. A difference in difference model is applied to estimate the effects of stress tests on the amount of loans and price of loans to large businesses.They find that due to the implementation of stress tests, credit supply to large corporates is negatively affected, especially to risky borrowers. Their finding is consistent with the Risk Management Hypothesis, under which banks decrease lending to risky borrowers to reduce credit risk. Cortes et al. (2017) examine the consequences of stress tests on lending to small businesses. They calculate the stress-test exposure, which is the difference between the starting value of the capital ratio at the begining of the test and the minimum capital ratio projected by the severely adverse scenario. The result is that stress tests decrease credit supply to all small businesses with a larger effect on risky borrowers. Additionally, due to stress tests, small businesses experience higher interest rates on loans. Calem, Correa, and Lee (2016) provide similar evidence in the market for jumbo mortgages as the share of jumbo mortgage originations and approval rates decline at stress-tested banks. Basett and Berrospide (2017) study the impact of stress tests on loan growth rate. They construct a stress test measure, which is the difference between the minimum capital ratios in the supervisory and the bank holding companies' (BHCs) own stress tests. The result is that stress tests do not have any significant effect on the growth rate of loans.

Another strand of the literature pays attention to the reactions of financial markets to the release of the stress test results. Goldstein and Leitner (2018) develop a theoretical model to study if disclosing stress test results is optimal for financial markets. They find that during normal times no disclosure is optimal as too much information destroys risksharing opportunities. However, during bad times partial disclosure is optimal since it helps prevent a market turmoil. The closest paper to mine is the study of Peristian et al. (2014). They use standard event study techniques to assess the impact of stress tests on banks' daily stock returns. The event is the release of the first stress test results in 2009. Average cumulative abnormal returns (CAR) of each bank's stocks is calculated over three days: day before the event, event day, and day after the event. For 18 stress-tested banks, the authors separate them into two groups: banks passing the test and banks not passing the test. For the latter group, capital gap is calculated as the difference between the projected capital level obtained from the stress test under the adverse scenario minus the standard capital ratio determined by supervisors for each bank. Peristian et al. (2010) find that larger capital gaps result in more negative abnormal returns for banks. The finding suggests that stress tests are informative to investors and help mitigate bank's opacity. Petrella and Resti (2013) confirm the results found in Peristian et al.(2010), yet their study is for European Union stress tests. Fernandes, Igan and Pinheiro (2015), on the hand, also apply the event study techniques but find that public disclosure of stress tests does not improve information asymmetry and uncertainty in financial markets. In this paper, I contribute to the literature by addressing the effect of DFA stress tests on bank equity risk. Instead of using the event study techniques for one year of the stress tests, I apply an econometric model to estimate the effects of the DFAST on bank equity risk and liquidity risk management over a period of time.

3.3 The Dodd-Frank Act Stress Tests

The DFA requires the Federal Reserve to conduct annual stress tests on state nonmember banks and state savings associations whose total consolidated assets are more than $10 billion. The test is designed to assess how well large banks in the economy would absorb potential losses under unfavorable economic conditions, while still having the ability to fulfill their debt obligations and continue to lend to households and businesses. The stress test started with 18 BHCs and increased to 34 BHCs in 2017. Participants of the test include domestic as well as foreign-owned banks in the U.S. Table 1 lists the BHCs included in the stress tests from 2008 to 2017. On the test, the Federal Reserve designs three hypothetical economic scenarios: baseline, adverse, and severely adverse. Each scenario includes 28 variables capturing economic activities in the economy, such as real gross domestic products (GDP), asset prices, interest rates, and U.S./foreign currency exchange rates. To take into account the integration of the global economy, economic variables in the Euro area, the United Kingdom, Japan, and developing Asia are included as well.

The adverse scenario

The U.S. economy experiences a moderate recession in which real GDP decreases by 2 percent, the unemployment rate increases by 7 percent. In addition, the recession is accompanied by higher long-term interest rates, steeper yield curves in the U.S. and all other countries in the sample. Asset prices fall by nearly 40 percent and volatility rises in the equity market. In the housing market, house prices decline by 12 percent, and real estate prices fall by 15 percent. Global demand decreases, leading to a lower rate of inflation in all foreign countries. The U.S. dollar appreciates against the euro, the pound, the currencies of developing Asia, whereas it depreciates against the yen. The U.S. economy recovers after four quarters in this scenario.

The severely adverse scenario

The global economy is in a severe recession. The U.S. economy experiences a 6 percent decrease in real GDP, 10 percent increase in unemployment rate. Asset prices drop by 50 percent. House prices and real estate prices fall by 25 percent and 35 percent, respectively. This scenario is also featured by a sharper increase in long-term interest rates and a steeper yield curve compared to the adverse scenario. Exchange rates of the U.S. dollar and other foreign currencies move in the same directions yet with a larger magnitude in relation with the adverse scenario. The recession lasts for four quarters.

Analytical Framework and Models

The effects of the adverse and severely adverse scenarios on the regulatory capital ratios of all participating BHCs are estimated. The Federal Reserve predicts changes in the balance sheet, risk-weighted assets (RWAs), net income, and resulting capital of the BHCs due to changes in economic conditions under each scenario. To get the projection of net income, BHCs' revenues, expenses, and losses of loans are estimated. Two methods are applied to measure losses on loan portfolio. The first method calculates the default probabilities on loans, losses given default, and exposure at default under the macroeconomic conditions in each hypothetical scenario. The expected losses are the product of these components. The second method uses the history of how net charge-offs on loans behave as the macroeconomic and financial environment changes. The projected impact of the scenarios on the balance sheet growth is obtained using a common framework , which incorporates historical data on bank balance sheets from the Federal Reserve. BHCs subject to the stress test are required to submit data on their balance sheets, loans, and securities material information for all portfolios through the Capital Assessment and Stress Testing (FR Y-14A/Q/M) by the end of the prior year to the release of the test results. Five regulatory capital measures in the stress test are the common equity tier 1, tier 1 risk-based capital, total risk-based capital, tier 1 leverage, and supplementary leverage ratios. The projections of loan losses, revenue, net income, and capital measures are reported for the two scenarios, adverse and severely adverse. To pass the test, BHCs have to meet the minimum requirements of all five capital ratios.

3.4 Data and Model Specification

3.4.1 Data

To examine the effects of DFAST on bank equity risk, I select a sample of 100 largest publicly traded banks in the U.S. based on their consolidated assets at the beginning of each year from 2008 to 2017. All the Dodd-Frank stress-tested banks during this time period are included in the sample. There are a couple of reasons for choosing large banks. First, all the stress-tested banks are the largest in the U.S. Thus, comparing them to the next largest ones provides the most accurate estimate of the effect of the tests. Second, daily stock returns of large banks are available and reliable given the trade frequency. After selecting the top 100 banks, I exclude banks that participated in a merger or acquisition (M&A) during the year of the deal. Speculation about M&A deals can potentially generate

Table 3.1: List of Participants in DFA Stress Tests between 2013-2017

BHC Name	2013	2014	2015	2016	2017
Ally	1	1	1	1	1
American Express	1	1	1	1	1
BancWest	0	0	0	1	1
Bank of America	1	1	1	1	1
Bank of NY-Mellon	1	1	1	1	1
BB&T	1	1	1	1	1
BBVA	0	1	1	1	1
BMO	0	1	1	1	1
Capital One	1	1	1	1	1
CIT	0	0	0	1	1
Citigroup	1	1	1	1	1
Citizens	0	1	1	1	1
Comerica	0	1	1	1	1
DBTC	0	0	0	1	1
Deutsche Bank Trust Corporation	0	0	1	1	0
Discover	0	1	1	1	1
Fifth Third	1	1	1	1	1
Goldman Sachs	1	1	1	1	1
HSBC	0	1	1	1	1
Huntington	0	1	1	1	1
JPMorgan Chase	1	1	1	1	1
KeyCorp	1	1	1	1	1
M&T	0	1	1	1	1
Morgan Stanley	1	1	1	1	1
MUFG Americas	0	1	1	1	1
Northern Trust	0	1	1	1	1
PNC	1	1	1	1	1
Regions	1	1	1	1	1
Santander	0	1	1	1	1
State Street	1	1	1	1	1
SunTrust	1	1	1	1	1
TD Group	0	0	0	1	1
U.S. Bancorp	1	1	1	1	1
Wells Fargo	1	1	1	1	1
Zions	0	1	1	1	1

Notes: The table displays a value of 1 if a BHC participated in a given stress test and 0 otherwise.

a great amount of stock volatility for acquires and targets that is unrelated to banks' basic risks, such as liquidity risk and credit risk, and the implementation of the stress tests. Quarterly data on banks are downloaded from the Call Reports. Data on banks' daily stock returns and market returns are obtained from the Center for Research in Security Prices (CRSP) database. Table 2 summarizes the statistics for all variables included in the regression

3.4.2 Model Specification

I apply a difference in difference (DID) model to examine the effects of the DFAST on bank equity risk. This approach is widely used in the recent banking literature (Duchin and Sosyura, 2014; Berger, Roman, et al.,2017, Acharya, Berger, and Roman, 2018) to study the impact of policy changes on banks' performances. The treated group is the equity risk of all BHCs that are subject to the DFAST, and the control group is the equity risk of remaining banks in the selected 100 banks. The following regression for equity risk of bank i at time t is estimated:

$$
\begin{aligned}
Risk_{it} = {} & \beta_0 + \beta_1 \times \textit{Stress-Tested Bank}_i \times Time + \beta_2 \; Log\,(Assets) \\
& + \beta_3 \; \textit{Liquid Assets} + \beta_4 \; \textit{Illiquid Assets} + \beta_5 \; Credit + \beta_6 \; Deposits \\
& + \beta_7 \; \textit{Commitment Ratio} + \beta_8 \; \textit{Equity Capital} + \beta_9 \; \textit{Bank FE} \\
& + \beta_{10} \; \textit{Quarter FE} + \varepsilon_{it}
\end{aligned}
\tag{3.1}
$$

3.4.3 Dependent Variable: Bank Equity risk

A bank's daily stock returns, R_{it}, are regressed on daily market returns, S&P 500 index, as follows:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \tag{3.2}$$

Thus, the residuals are given by:

$$\hat{\varepsilon}_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{3.3}$$

Next, the standard deviation of the residuals is calculated. It is a bank's idiosyncratic equity risk, which is used as the measure of bank equity risk in this paper.

3.4.4 Explainatory Variables

$Stress\text{-}Test\ Bank_i \times Time$ is the main variable of interest. *Stress-Test Bank* is a dummy variable, which is equal to one if a bank is required to take the DFAST and zero otherwise. *Time* is a dummy equal to one in 2013-2017, the period after the implementation of the stress tests, and zero otherwise. I expect the coefficient of the interaction term, β_1, to be negative. Stress tests provide investors with transparent information about the health of participating banks, improving the incomplete information problem. As a result, the introduction of the DFAST should reduce banks' stock volatility or equity risk. $Log\ (Assets)$ is expected to have a negative effect on bank equity risk as banks with more assets signal positive future earnings and their ability to weather adversaries. Next, two measures of bank liquidity risk management, including *Liquid Assets* and *Deposits*, should negatively impact bank equity risk. They act as buffers to prevent banks from facing a liquidity crisis and provide a stable source of financing during a crisis. *Commitment Ratio*, on the other hand,

Table 3.2: Data Description

Variable	Observations	Mean	Standard Deviation
Equity Risk	3870	0.02	0.02
Stress-Tested Bank × Time	3870	0.18	0.38
Log (Assets)	3870	7.54	0.93
Liquid Assets	3870	0.02	0.19
Illiquid Assets	3870	0.67	0.22
Credit	3870	0.64	0.22
Deposits	3870	0.61	0.19
Commitment Ratio	3870	0.21	0.22
Equity Capital	3870	0.13	0.13

exposes banks more to liquidity risk. Banks with many unused loan commitments might experience an unexpected increase in demand for loans by many borrowers simultaneously, especially during a crisis when the availability of liquidity market dries up. Banks with more illiquid assets should experience more equity risk since illiquid assets are more difficult to convert into cash, sending a negative signal about a bank's solvency. Thus, β_4 is expected to be positive.

3.5 Empirical Results

Table 3 reports the results of the DFAST on bank equity risk. The sign of the estimate of the interaction term $Stress\text{-}Test\ Bank_i \times Time$ is negative as expected. Banks subject to the stress tests experience less equity risk. This finding is consistent with the literature (Peristian et al., 2010; Petrella and Resti, 2013). The stress tests require banks to hold an adequate ratio of capital in order to survive adverse economic circumstances.

Stress-tested banks appear safer and more transparent to investors given that the results of the stress tests are publicly available. As a result, the banks' stock volatility or equity risk decreases. Moreover, the effect of the stress tests on bank equity risk is significant at one percent level. Assets also have a negative influence on bank equity risk as predicted. Banks with more assets possess less equity risk. Liquid assets, on the other hand, does not significantly affect bank equity risk. The finding implies that holding more liquid assets might help with managing liquidity risk but not equity risk. Strikingly, the effect of illiquid assets on bank equity risk is negative and significant. This result can be explained by the fact that illiquid signal a strong future earnings for banks. Banks with a large amount of loans and mortgage-backed securities have high potential earnings. Thus, the volatility of stock returns is less. Credit and commitment ratio both have insignificant impacts on bank equity risk. Having many unused loan commitments might expose banks to more liquidity risk, not equity risk. Lastly, banks holding more equity capital enjoys less equity risk. Equity capital is the margin by which creditors will be covered if a banks assets were liquidated. Thus, investors treat equity capital as one of the leading indicators of a bank's safety. When equity capital increases, investors consider the bank less risky, resulting in less volatility in stock returns.

Table 4 shows the estimates of the effects of the DFAST on core deposits. The stress tests have a significant and positive impact on deposits. Core deposits act as a buffer for banks when market liquidity becomes scarce. Thus, the tests encourage banks to hold more deposits to help them cope with unfavorable economic conditions that could lead to a liquidity crisis. Additionally, an increase in illiquid assets results in an increase in core deposits. As banks decide make more loans or invest in illiquid assets such as mortgage-back securities, they need to attract more deposits to finance these investments. Consider equity capital, I find that it positively affects deposits. Banks with more equity capital attract more deposits as they appear safer and more reliable to depositors . However, the effect is not significant. Lastly, credit, commitment ratio, assets, and liquid assets do not have any significant influence on core deposits.

The results of the regression on liquid assets are presented in Table 5. The DFAST do not have any significant effect on the amount of liquid assets that banks hold. An increase in bank assets, however, decreases liquid assets. Besides minimizing liquidity risk, banks also seek high returns on their investments. Liquid assets normally offer low returns. Therefore, banks with plenty of assets are considered safe banks, and they tend to have fewer liquid assets. Deposits have a positive and significant effect on liquid assets. Banks with more deposits hold more liquid assets. Furthermore, illiquid assets negatively impact liquid assets as they are considered substitutes. Similarly, credit and commitment ratios reduce the amount of liquid assets since they both include illiquid assets. Finally, equity capital has a positive and significant influence on liquid assets. Bank equity capital and liquid assets are considered safety guards for banks against liquidity risk. Thus, banks with more capital are more willing to run down their other liquid buffer, liquid assets.

Table 3.3: Effects of DFA Stress Tests on Bank Equity Risk

Variable	Estimate
Stress-Tested Bank x Time	-0.01***
Log(Assets)	-0.01***
Liquid Assets	-0.00
Illiquid Assets	-0.01*
Credit	0.01
Deposits	-0.06***
Commitment Ratio	0.01
Equity Capital	-0.03***

Notes: ***, **, * denote significance at the 1% level, 5% level, 10 % level, respectively.

Table 3.4: Effects of DFA Stress Tests on Core Deposits

Variable	Estimate
Stress-Tested Bank x Time	0.09***
Log(Assets)	0.03
Liquid Assets	0.13
Illiquid Assets	0.23***
Credit	-0.04
Commitment Ratio	-0.00
Equity Capital	0.04

Notes: ***, **, * denote significance at the 1% level, 5% level, 10 % level, respectively.

Table 3.5: Effects of DFA Stress Tests on Liquid Assets

Variable	Estimate
Stress-Tested Bank x Time	0.00
Log(Assets)	-0.03***
Deposits	0.10*
Illiquid Assets	-0.67***
Credit	-0.18***
Commitment Ratio	-0.09*
Equity Capital	-0.08**

Notes: ***, **, * denote significance at the 1% level, 5% level, 10 % level, respectively.

3.6 Conclusion

The financial crisis 2008 has put the banking industry on the spot light and posed the imminent need for new laws that could properly regulate banks, especially the "too big to fail" ones. The Dodd-Frank Act was passed in Congress in July 2010, providing a series of broad reforms in financial markets. This paper focuses on the Dodd-Frank Act stress test designed by the Federal Reserve to assess whether large BHCs have sufficient amount of capital to weather adverse economic conditions. Banks whose consolidated assets of more than 10 billion dollars are subject to the test. Banks are exposed to a number of risk, including credit risk, liquidity risk, equity risk, and market risk. In this paper, I focus on the effect of the DFAST on bank equity risk. The public release of the stress test results provides investors and banks' stockholders more information about banks, affecting the volatility of banks' stock returns. To measure bank equity risk, I regress banks' daily stock returns on market returns. Bank equity risk is the standard deviation of the error terms of the regression. A Difference in Difference model is applied to study the impact of the implementation of the DFAST on bank equity risk. The result is that the stress test significantly helps reduce bank equity risk. Moreover, I investigate if the stress test improves banks' liquidity risk buffers, including deposits and liquid assets. Deposits are a stable source of funding for banks. Thus, banks with more deposits have a better chance of surviving unfavorable economic conditions. Liquid assets also measure the liquidity of a bank during a crisis. I find that the stress test encourages banks to hold more core deposits. It, however, does not have any significant effect on liquid assets.

The debates over the necessity of the Dodd-Frank Act are current. Some economists and policymakers believe that the Act indeed imposes necessary regulations on banks and other financial institutions to improve transparency and safety in the banking industry and financial markets. Opponents of the Act argue that the policy burdens the banking sector with excessive rules and regulations, violating the free market principles, and hurting economic growth. My paper sheds some light on the effectiveness of the Dodd-Frank stress test on improving bank equity risk and liquidity risk management.

Conclusions

The dissertation sheds lights on how risks affect the banking industry and the rest of the economy. First, it shows that the Risk Management Hypothesis holds true as banks scale back their lending when businesses become riskier. Second, the dissertation provides a new assessment of the SBA lending program to small businesses by modeling the default rates on loans using the most complete set of information. The results suggest that the 2008 financial crisis changes the risk structure of loans, and major post-crisis reforms have improved the quality of bank balance sheets. Lastly, the dissertation addresses the role of central banks in regulating the banking industry by studying the impact of the Dodd-Frank Act Stress Test on bank equity risk, core deposits, and liquid assets. The findings reveal that the Stress Test has a positive impact on banks risk exposure and risk management.

Nowadays, a huge amount of new data at the disaggregated level is becoming available with the collection of information from the internet. By the same token, statistical tools are being developed and designed to study them that can trace these micro actions and their aggregated effects. Further research needs to be conducted using data science methods on large datasets of macroeconomics and financial economics to unveil the relationships between risks and the economy.

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