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# Credit Constraints and Bank Failures: A Macroprudential Perspective on the U.S. Commercial Banking Sector

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**Abstract**

We examine the impact of economy wide credit tightening on bank failures and investigate the relationship between bank failures and tighter monetary policy while accounting for bank balance sheet variables. Using a sample of U.S. banks from 1984 to 2020, we find the following: i) increases in corporate credit spreads lead to a significant increase in aggregate bank failures; ii) lower aggregate bank return on equity and higher allowances for loan losses are associated with a higher incidence of bank failures; iii) no robust evidence suggesting that tighter monetary policy drives higher bank failures. Finally, we show that lower bank failures, contraction in corporate credit spreads, higher bank profitability, and higher stock market returns contribute to higher economic growth, highlighting the interconnectedness of banking, stock markets, credit availability, and the macro-economy. These results may have potential macro-prudential policy implications.

**Keywords**: Bank Failures; Corporate Bond Credit-Spreads; Stock Market Returns; Bank Profitability.

**JEL**: E51, E52, G21

## 1. Introduction

The connection between credit tightening and bank failures is currently debated due to recent bank failures and tightening monetary policy. The collapse of Silicon Valley Bank (SVB) due to balance sheet mismanagement highlights the potential for systemic bank failures, as identified by Diamond and Rajan (2005). In light of these concerns, the U.S. Federal Reserve has implemented measures such as enhanced deposit guarantees and the Bank Term Funding Program (BTFP) to mitigate systemic risks and minimize the impact of individual bank failures on the broader financial system. Building upon this background, the primary objective of this study is to investigate the impact of credit tightening on bank failures and to explore the potential relationship between bank failures and tighter monetary policy. We further examine the macroeconomic consequences of failed banks, as this analysis is crucial for policymakers, corporate managers, and investors.

Moving beyond idiosyncratic factors typically examined in existing literature (e.g., Imbierowicz and Rauch, 2014) and taking a macro perspective, we examine the macro-prudential implications of bank failures. Firstly, we define economy-wide bank failures as the ratio of failed banks to the total number of active banks in the U.S. commercial banking sector (FABR), providing insights into the overall state of the banking industry. We then investigate credit conditions strongly associated with FABR, considering important bank balance sheet variables. This approach is crucial as credit constraints can significantly impact bank balance sheets, and analyzing these variables helps identify potential indicators of future bank failures. Lastly, considering the endogenous evolution of bank failures, credit conditions, and bank balance sheet variables, we employ both standard vector autoregression (VAR) and Bayesian VAR (BVAR) methods to investigate the relationship. For the sample period from 1984 to 2020, and the main results are as follows.

First, the Granger causality results indicate that corporate credit spreads, stock market returns, and bank returns on equity Granger cause FABR, while there is no reverse causality. Additionally, FABR Granger causes the bank loan loss reserve ratio, and there is no reverse causality. Notably, corporate credit spreads Granger cause the bank loan loss reserve ratio, with no reverse causality observed. These complex Granger causality results show the endogenous relationship among the variables and support the selection of the VAR model to examine the relationship.

Second, depending on the VAR specifications, the forecast error variance decomposition (FEVD) reveals that approximately 30-40% of the FEVD of FABR can be attributed to corporate credit spreads as measured by the excess bond premium (EBP) (see, e.g., Gilchrist & Zakrajšek, 2012). Although bank balance sheet variables and other credit constraints, such as the Federal funds rate representing the monetary policy stance, also display significance, their contribution is comparatively smaller than that of EBP.

Third, while the FEVD indicates the relative importance of one variable in explaining the forecast error variance of another, it does not directly indicate the direction of impact of shocks from endogenous variables on that variable. Therefore, we examine the impulse responses of FABR to shocks from different variables. Our findings reveal that EBP serves as a highly informative leading indicator of FABR. For instance, an unexpected positive shock of one standard deviation in EBP results in an increase in FABR by approximately 0.25 percentage points over the subsequent ten quarters. Conversely, higher economy-wide bank returns on equity reduce FABR. In contrast, a higher loan loss reserve ratio and allowances for loan losses increase FABR. However, the impacts of shocks to other variables on FABR are lower than that of EBP. Importantly, we do not find robust evidence to support the notion that tighter monetary policy, as captured by the Federal funds rates, leads to an increase in bank failures.

Finally, we investigate the impact of bank failures on real GDP growth to examine the macroeconomic consequences of bank failures. This analysis is essential to establish a clear link between bank failures and their impact on the real economy. Our findings indicate that positive orthogonalized shocks of one standard deviation to EBP and FABR lead to a reduction in real GDP growth by over -0.8 and -0.2 percentage points, respectively, over a ten-quarter period. In contrast, positive shocks to stock market returns, bank net interest margin, and bank returns on equity also have a substantial positive impact on real GDP growth. Conversely, positive shocks to loan loss reserves have a negative impact on real GDP growth. These results highlight the significant role that credit constraints, bank failures, and various bank balance-sheet indicators play as leading indicators of real economic growth. Our findings contribute valuable insights to the existing literature in the following ways.

First, the role of banks in economic growth (e.g., Bernanke and Blinder 1988; Bencivenga & Smith, 1991) is a well-researched topic. However, the existing banking literature (e.g., Bernanke & Lown, 1991; Kashyap & Stein, 1994) has provided inconclusive evidence regarding credit constraints by investigating the relationship between bank lending and economic activity. We contribute to this strand of literature by demonstrating that while higher Federal funds rates may have limited impact on bank failures, corporate credit spreads, as a proxy for economywide credit constraints, are positively associated with bank failures.

Second, we contribute to the existing literature (e.g., Gilchrist & Zakrajšek, 2012; Gertler & Gilchrist, 2018) that examines corporate credit spreads to evaluate financial accelerator and credit-cycle theories (e.g., Bernanke and Gertler, 1989, 1995; Kiyotaki & Moore, 1997; Bernanke et al., 1999). However, our analysis specifically focuses on the impact of EBP on the banking sector, particularly on bank failures. Lastly, while the literature (e.g., Levine, 1991; Levin & Zarvos, 1998) shows that both banks and a well-functioning stock market contribute to economic development, we establish the crucial linkages between the health of the banking sector, bank profitability, higher stock market returns, lower corporate credit spreads, and economic growth.

Future research can explore the generalizability of our findings by examining the relationship at the U.S. state level and in other countries. Additionally, investigating alternative measures for bank failures, such as total loss of failed bank assets, can provide deeper insights into the impact of credit constraints. These avenues would contribute to a better understanding of the dynamics between credit constraints, bank failures, and their implications for the banking sector and the broader macroeconomy.

The paper proceeds as follows: Section 2 describes the data sources, section 3 presents empirical methods and results, and section 4 concludes.

## 2. Data Sources and Characteristics

Our sample spans from the first quarter of 1984 through the fourth quarter of 2020. We collect bank and macroeconomic data, such as real GDP, from both the Federal Reserve Bank's (FRB) and the *Federal Deposit Insurance Corporation* (*FDIC*) databases, and stock market data from the Center for Research in Security Prices (CRSP). For monthly data, we compute quarterly variables by averaging monthly data over a three-month period starting from January of each year. Table 1 Panels A shows the summary statistics of quarterly failed banks to the total number of active banks (FABR) in the U.S. commercial banking sector. While FABR is our primary variable of interest, we also examine the relationship between FABR and real GDP growth, as bank failures are expected to impact the overall economic growth.

Banks can fail due to various factors, including both idiosyncratic and systematic reasons. Among the systematic factors, which is our focus, credit constraints play a significant role in determining the success or failure of banks. In this paper, we use the following credit constraints. We include the effective Federal funds rate (EFFR) as a measure of the monetary policy stance. The Treasury term spread (TS) and stock market returns (XMRET) are also included following the related literature (e.g., Estrella & Mishkin, 1998; Harvey, 1989; Stock & Watson, 2003). We further incorporate a corporate bond credit-spread measure proposed in Gilchrist and Zakrajšek (2012), specifically the excess bond premium (EBP). Since credit constraints impact bank balance sheets, we control for some of those variables that may be relevant for bank failures. Table 1 Panel B shows a brief description of credit constraints and bank balance sheet variables that are used in this study.

Table 1. Summary statistics

| Panel A: Frequency Distribution of FABR in % | |
|---|---|
| Mean | 0.12% |
| Std. Dev. | 0.15% |
| Median | 0.04% |
| Min. | 0.00% |
| Max. | 0.52% |

| Panel B: Bank Failures Determinants | | |
|---|---|---|
| Variables | Description | Federal Reserve Data Codes/Notes |
| XMRET(%) | Stock Market Excess Returns | CRSP |
| EBP (basis points) | Corporate Bond Credit Spreads | As per Gilchrist and Zakrajšek (2012) |
| TS (%) | Term Spread | Difference in yields between 10 year and 30 days U.S. Treasuries |
| ΔFED (%) | Changes in the Federal Funds Rate as the monetary policy indicator | FEDFUNDS |
| ROE (%) | Return on Average Equity | USROE |
| ΔLLRR(%) | Changes in Loan Loss Reserve to Total Loans | USLLRTL |
| NIM (%) | Net Interest Margin | USNIM |
| PLL(%) | Provision for Loan Losses to total loans | QBPQYLNLOSS |
| ALL(%) | Allowance for Loan Losses to total loans | ALLACBW027SBOG |
| ΔGDP | Log difference of real GDP | GDPC |

Panel C: Correlation Matrix

| | FABR | XMRET | EBP | TS | ΔFED | ROE | LLRR | NIM | PLL | ALL |
|---|---|---|---|---|---|---|---|---|---|---|
| XMRET | -0.011 | | | | | | | | | |
| EBP | 0.178 | 0.531 | | | | | | | | |
| TS | 0.156 | -0.072 | 0.021 | | | | | | | |
| ΔFED | 0.061 | 0.168 | -0.343 | -0.018 | | | | | | |
| ROE | -0.473 | 0.121 | -0.291 | -0.214 | 0.154 | | | | | |
| LLRR | 0.666 | 0.017 | 0.139 | 0.444 | -0.033 | -0.351 | | | | |
| NIM | 0.114 | 0.035 | -0.007 | 0.190 | 0.011 | -0.035 | 0.086 | | | |
| PLL | 0.151 | 0.181 | 0.084 | -0.059 | -0.048 | 0.107 | -0.109 | 0.056 | | |
| ALL | 0.126 | 0.136 | 0.143 | -0.014 | 0.211 | -0.041 | -0.151 | 0.067 | 0.831 | |
| ΔGDP | -0.026 | 0.301 | -0.323 | 0.051 | 0.244 | 0.229 | -0.046 | 0.177 | 0.001 | -0.001 |

*Note.* This table shows descriptive statistics. Panel A shows the descriptive statistics of Failed to Active Banks Ratio (FABR). Panel B shows the determinants of FABR used in this study. Bank variables are for all U.S. Commercial Banks. Panel C shows pairwise correlations. Quarterly sample is from 1984: Q1 to 2020: Q4.

We perform stationarity tests using two commonly employed methods: the Augmented Dickey-Fuller (ADF) unit-root test proposed by Dickey and Fuller (1979), and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test developed by Kwiatkowski et al. (1992). In cases where the variables are found to be nonstationary, we apply appropriate transformations to achieve stationarity. The transformed variables are denoted by the prefix 'Δ'. For example, ΔGDP is the percentage change of real GDP.

Table 1 Panel C presents the correlation matrix, which provides insights into the relationships among the variables. Several key observations can be made based on the correlation analysis. Firstly, we observe a high correlation between ALL and PLL. This finding is expected since PLL is one of the components of ALL, and the inclusion of PLL in ALL contributes to their strong positive correlation. Secondly, we find a positive correlation between FABR and LLRR, while FABR is negatively correlated with ROE. These correlations align with our expectations as an increase in economywide bank loan loss reserves tends to coincide with a higher frequency of bank failures. Similarly, a decrease in aggregate bank profitability (as indicated by ROE) is associated with an increase in bank failures. Additionally, we observe a positive correlation between EBP and FABR, implying that higher levels of corporate credit spreads are associated with an increased frequency of bank failures. On the other hand, XMRET exhibits a negative correlation with FABR, suggesting that higher stock market returns are associated with a lower frequency of bank failures. Since ALL and PLL exhibit a high correlation, we choose to focus on ALL for our analysis as it includes other variables that capture not only bank loan losses (and recovery) but also PLL. However, contemporaneous correlations may not hold in a predictive setup, which we investigate next.

## 3. Empirical Results

We begin our analysis to gain insights into the predictive relationship between the variables of interest, by conducting pairwise Granger causality tests. In this analysis, we utilize a standard vector autoregression (VAR) framework and determine an optimal lag length of one quarter based on both the Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC). Table 2 provides the results of the pairwise Granger causality tests for the selected variables. To save space, we present only a subset of the results, but the complete Granger causality results can be obtained upon request.

Table 2. Granger causality tests

| Panel D: Pairwise Granger Causality Tests | |
|---|---|
| Null Hypothesis: | p-value |
| XMRET does not Granger Cause FABR | 0.085* |
| FABR does not Granger Cause XMRET | 0.581 |
| EBP does not Granger Cause FABR | 0.000*** |
| FABR does not Granger Cause EBP | 0.170 |
| ROE does not Granger Cause FABR | 0.049** |
| FABR does not Granger Cause ROE | 0.261 |
| LLRR does not Granger Cause FABR | 0.449 |
| FABR does not Granger Cause LLRR | 0.003*** |
| NIM does not Granger Cause FABR | 0.019*** |
| FABR does not Granger Cause NIM | 0.061* |

*Note.* This table shows pairwise Granger Causality results for selected variables, where the optimal lag of "one" quarter was chosen in a VAR framework. Variables are described earlier. We do not present the Granger causality results for all variables for parsimony. Quarterly sample is from 1984:Q1 to 2020:Q4.

The results presented in Table 2 show that XMRET, EBP, and ROE Granger cause FABR, while there is no reverse Granger causality. That is, stock market returns, bank profitability and credit spreads contain leading information about bank failures. However, FABR Granger causes LLRR, with no evidence of reverse causality. Additionally, NIM and FABR Granger cause each other. Overall, these findings suggest that credit conditions, bank profitability along with stock market have future information about bank failures. It is important to note that these Granger causality results exhibit a complex interrelationship that evolves endogenously, necessitating a VAR analysis that accounts for endogeneity among the variables of interest. In addition, while the pairwise Granger causality results for a one-quarter lag are informative, they may not hold in a multivariate framework. Thus, we next examine the interrelationships within a VAR framework.

### *3.1 The VAR analysis of FABR with Credit Constraints*

We start our VAR analysis using the standard VAR approach, where the monetary policy variables are ordered first, followed by macro and micro variables, as suggested by the literature (e.g., Christiano et al., 1994, 1999, 2001). However, when considering bank-related variables, we give priority to the impact of credit constraints. This is because financial intermediaries, such as banks, primarily function by borrowing and lending, and credit constraints have a significant influence not only on the banking sector but also on bank balance sheets. Furthermore, we further place FABR after bank balance sheet variables since information about banks failures are in their balance sheet variables such as ROE or NIM. Hence, the endogenous VAR variables are arranged as follows: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET.

Based on both the Schwarz information criterion (SIC) and the Akaike information criterion (AIC), we find an optimal lag length of "one" quarter. To assess the VAR(1) results, we analyze both the forecast error variance decomposition (FEVD) and the accumulated impulse response functions (IRFs) of the variables of interest over a period of ten quarters. We do not report the VAR(1) coefficient estimates for the sake of parsimony. We further do not report the impulse response functions of FABR to all shocks or FEVDs of all variables, but these results are available on request. Table 2 presents the FEVD of FABR.

Table 3. Forecast Error Variance of Bank Failure Rates using Standard VAR

| Panel A: Forecast Error Variance Decomposition of FABR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Period | S.E. | EFFR | ΔGDP | TS | EBP | NIM | ALL | LLRR | ROE | FABR | XMRET |
| 1 | 0.51 | 1.76 | 0.08 | 0.00 | 16.01 | 0.24 | 0.48 | 1.39 | 0.55 | 79.49 | 0.00 |
| 2 | 0.53 | 1.43 | 0.15 | 0.00 | 19.47 | 0.21 | 1.89 | 1.58 | 0.45 | 74.14 | 0.67 |
| 3 | 0.54 | 1.62 | 0.14 | 0.00 | 22.79 | 0.18 | 4.65 | 1.79 | 0.67 | 67.08 | 1.07 |
| 4 | 0.54 | 1.94 | 0.11 | 0.01 | 26.33 | 0.17 | 7.28 | 2.05 | 0.86 | 60.11 | 1.15 |
| 5 | 0.54 | 2.26 | 0.12 | 0.03 | 29.57 | 0.17 | 9.62 | 2.18 | 0.98 | 53.95 | 1.11 |
| 6 | 0.55 | 2.49 | 0.12 | 0.07 | 32.65 | 0.18 | 11.17 | 2.27 | 1.04 | 48.99 | 1.03 |
| 7 | 0.55 | 2.64 | 0.14 | 0.14 | 35.40 | 0.20 | 12.20 | 2.29 | 1.06 | 45.00 | 0.93 |
| 8 | 0.55 | 2.74 | 0.16 | 0.22 | 37.85 | 0.23 | 12.79 | 2.29 | 1.06 | 41.83 | 0.84 |
| 9 | 0.55 | 2.79 | 0.19 | 0.32 | 39.96 | 0.26 | 13.11 | 2.27 | 1.06 | 39.28 | 0.76 |
| 10 | 0.55 | 2.80 | 0.22 | 0.43 | 41.77 | 0.30 | 13.26 | 2.25 | 1.05 | 37.22 | 0.70 |

*Note.* This table shows the forecast error variance decomposition (FEVD) of FABR for the VAR (1) model with the following endogenous variables: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The FEVD of FABR is shown for 10 quarters is shown in %; the FEVDs for other variables are not shown for parsimony. Quarterly sample 1984: Q1 to 2020: Q4.

The first column of Table 3 represents the standard errors (S.E.), while the subsequent columns show the contributions of each variable to the FEVD of FABR, with the contributions summing up to 100% at each quarter. Examining the first row of the results, we observe that approximately 80% of the FEVD of FABR is attributable to FABR itself after one quarter. Moving to the last row, after ten quarters, EFFR contributes approximately 2.8%, and EBP accounts for around 41.77% of the FEVD of FABR. Among the bank balance sheet variables, ALL emerges as the most significant contributor. On the other hand, the contributions of other variables, such as TS or NIM, are significantly lower compared to EBP, highlighting the importance of EBP in forecasting FABR. Since the FEVD analysis does not provide information about the direction of impact of shocks on the endogenous VAR variables, to complement the FEVD analysis, we investigate the IRFs of FABR in response to various shocks. In Figure 1A, we show IRFs of FABR to selected orthogonalized Cholesky shocks.

Looking at the left three plots from the top to bottom, we find that an unexpected one standard deviation orthogonalized positive Cholesky shock to EFFR leads to a decrease in FABR of approximately 0.08 percentage points. Conversely, an unexpected one standard deviation orthogonalized positive shock to EBP and LLRR results in an increase in FABR of approximately 0.25 and 0.05 percentage points over the next ten quarters. Looking next at other IRFs, the impulse response functions for shocks to bank variables align with expectations to varying degrees, but their impacts are considerably lower compared to that of EBP. For instance, positive shocks to NIM and ROE result in a reduction in FABR, while positive shocks to LLRR and ALL lead to an increase in FABR. However, we find a counterintuitive positive relationship between XMRET and FABR, and this result do not align with the pairwise contemporaneous correlation results between these two variables.

Overall, these findings indicate that EBP has a significantly stronger impact on FABR compared to other shocks, suggesting that as credit spreads increase and credit availability becomes scarce, the likelihood of bank failures rises. These results conform to the FEVD results we presented earlier, reinforcing the importance of EBP in predicting FABR.

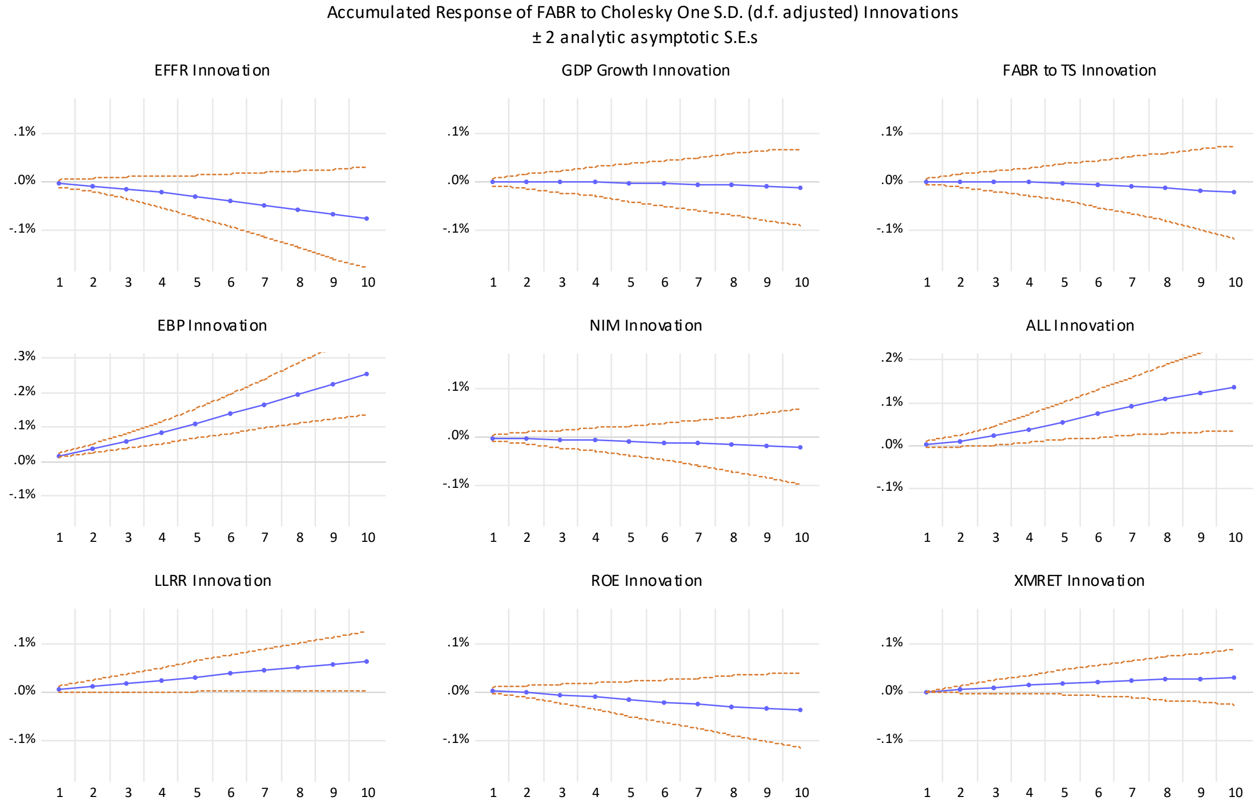


Figure 1A: IRFs to Cholesky shocks

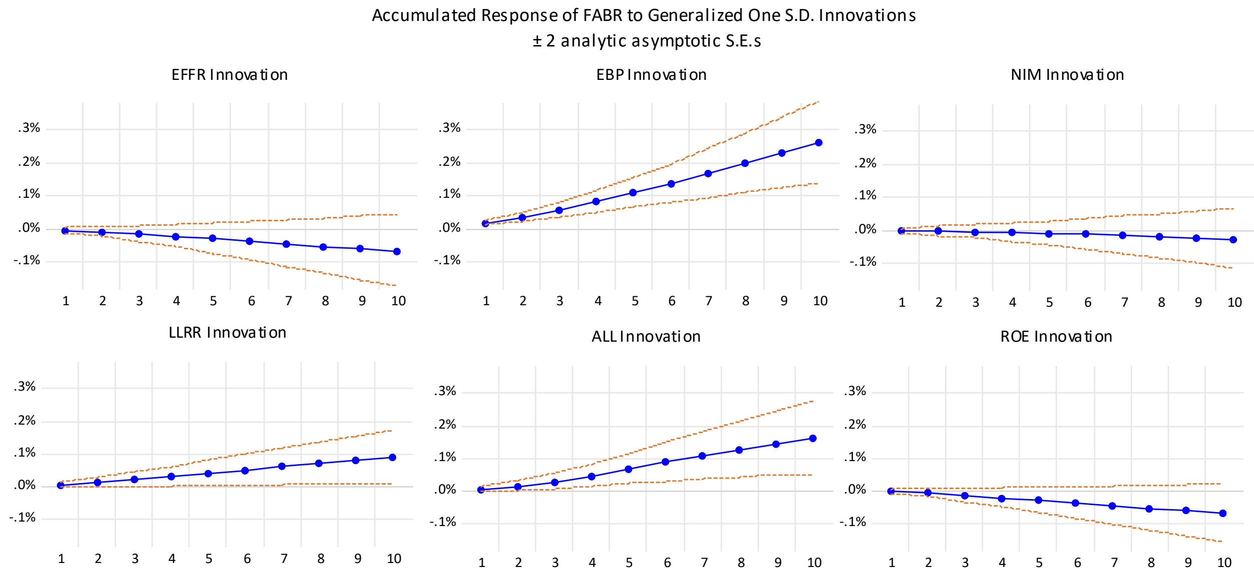


Figure 1B. IRFs to generalized shocks

Figure 1. Impulse Responses of FABR to Different Shocks using Standard VAR

*Note.* This table shows the impulse response functions (IRFs) of FABR for the VAR(1) model with the following endogenous variables:

EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The IRFs of FABR are shown for 10 quarters in % points; Figure 1A shows the IRFs under Cholesky shocks; Figure 1B shows the IRFs under generalized shocks, where the IRFs for other variables are not shown for parsimony. Quarterly sample 1984: Q1 to 2020: Q4.

However, the ordering of the VAR variables is a matter of concern, and there are no established economic guidelines for ordering bank balance sheet variables. To address this issue and ensure robustness of our results, we adopt a generalized impulse definition. Pesaran and Shin (1998) have shown that generalized impulse definitions do not require a specific ordering of the VAR variables. In Figure 1B, we show the IRFs of FABR to selected generalized positive shocks to save space.

Figure 1B illustrates that an unexpected positive shock of one standard deviation in the EFFR leads to a decrease in FABR by approximately 0.1 percentage points. On the other hand, an unexpected positive shock of one standard deviation in EBP results in an increase in FABR by approximately 0.25 percentage points over the subsequent ten quarters. The results for other impulse response functions (IRFs) align with our earlier findings, confirming the robustness of our previous results. However, regardless of the impulse definitions used, we find a small yet negative relationship between EFFR and FABR. This suggests that higher monetary policy rates are associated with a slight decrease in bank failures, which may seem counterintuitive. Overall, the above analysis confirms the robustness of the results. To maintain consistency, we use generalized impulses for the remaining analysis.

To ensure further robustness, we next conduct a Bayesian vector autoregression (BVAR) analysis. Koop and Korobilis (2010) argue that Bayesian methods are a superior approach for addressing the issue of over-parameterization when the time-series data is limited. Bayesian methods may become particularly valuable when the ratio of endogenous variables to observations increases. Thus, we examine whether BVAR method, as opposed to standard VAR, alters our results. We conduct the BVAR analysis with a "Minnesota prior" as recommended by the related literature (e.g., Litterman 1986). The BVAR specification includes the same endogenous variables that we used in the standard VAR. Table 4 presents the FEVD of FABR using the BVAR(1) specification. The results of the FEVD of FABR in Table 4 demonstrate that the BVAR(1) specification does not qualitatively alter the main conclusions obtained from the standard VAR(1) analysis and EBP remains one of the most important variables.

Table 4. Forecast Error Variance of Bank Failure Rates using Bayesian VAR

| Forecast Error Variance Decomposition of FABR | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Period | S.E. | EFFR | ΔGDP | TS | EBP | NIM | ALL | LLRR | ROE | FABR | XMRET |
| 1 | 0.52 | 2.15 | 0.24 | 0.10 | 14.50 | 0.27 | 0.20 | 1.43 | 0.47 | 80.63 | 0.00 |
| 2 | 0.60 | 2.22 | 0.16 | 0.11 | 16.96 | 0.27 | 0.53 | 2.12 | 0.25 | 77.27 | 0.10 |
| 3 | 0.62 | 2.48 | 0.13 | 0.11 | 19.50 | 0.28 | 1.30 | 2.68 | 0.22 | 73.03 | 0.26 |
| 4 | 0.63 | 2.77 | 0.13 | 0.09 | 22.07 | 0.28 | 2.42 | 3.10 | 0.29 | 68.43 | 0.41 |
| 5 | 0.63 | 3.03 | 0.13 | 0.08 | 24.62 | 0.30 | 3.65 | 3.40 | 0.39 | 63.88 | 0.52 |
| 6 | 0.63 | 3.22 | 0.14 | 0.07 | 27.09 | 0.32 | 4.85 | 3.60 | 0.51 | 59.63 | 0.58 |
| 7 | 0.63 | 3.33 | 0.15 | 0.07 | 29.43 | 0.34 | 5.92 | 3.72 | 0.61 | 55.81 | 0.60 |
| 8 | 0.63 | 3.39 | 0.16 | 0.09 | 31.62 | 0.37 | 6.82 | 3.79 | 0.70 | 52.45 | 0.60 |
| 9 | 0.64 | 3.39 | 0.18 | 0.13 | 33.63 | 0.41 | 7.55 | 3.82 | 0.77 | 49.53 | 0.58 |
| 10 | 0.64 | 3.36 | 0.19 | 0.19 | 35.45 | 0.45 | 8.13 | 3.82 | 0.83 | 47.02 | 0.56 |

*Note.* This table shows the forecast error variance decomposition (FEVD) of FABR for the BVAR models with the following endogenous variables: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The FEVD of FABR is shown for 10 quarters is shown in %; the FEVDs for other variables are not shown for parsimony. Quarterly sample 1984:Q1 to 2020:Q4.

In Figure 2, we show the IRFs of FABR to various generalized positive shocks using the BVAR(1) specification. To facilitate comparison and visual clarity, the IRFs are presented in a single plot without the inclusion of standard error (S.E.) bands. The IRFs show that shocks to EBP, ROE, ALL, and LLRR have the most significant impact on FABR, consistent with our previous findings in the standard VAR(1) model. Interestingly, we continue to observe a counterintuitive positive relationship between XMRET and FABR and this indicate that stock market returns may not be a valuable indicator of bank failures. The notable exception is that we observe a positive shock to EFFR leads to an approximate 0.016 percentage points increase in FABR. This finding suggests that higher policy rates, albeit very small, may have a positive impact on bank failures.

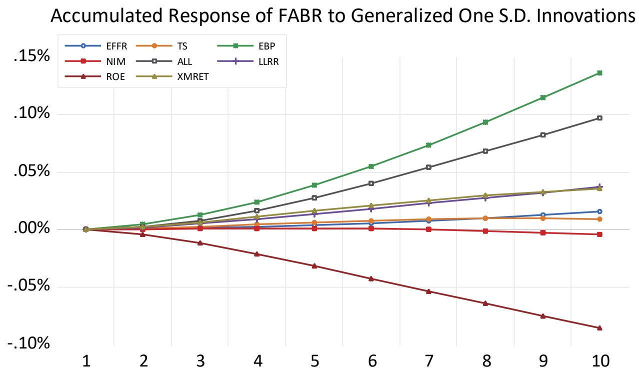


Figure 2. Impulse Responses of FABR to Different Shocks using Bayesian VAR

*Note.* This table shows the impulse response functions (IRFs) of FABR for the BVAR(1) model with the following endogenous variables: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The IRFs of FABR are shown for 10 quarters in % points. Standard error bands for the IRFs are not shown for visual clarity. Quarterly sample 1984:Q1 to 2020:Q4. Top of Form Bottom of Form

In summary, our main conclusion remains unchanged regardless of the definition of shocks (Cholesky or generalized) and the VAR models used (standard or Bayesian). Higher corporate credit spreads and lower bank profitability consistently emerge as significant factors contributing to an increased likelihood of bank failures at the economywide aggregate level.

### *3.2 Macroeconomic Consequences: Real GDP Growth, Bank Failures, and Credit Constraints*

In this section, we examine the macroeconomic consequences of failed banks, as these consequences have wide-ranging implications for various aspects of the economy. Failed banks affect financial stability, credit availability, economic growth, investor sentiment, and government finances. It is vital for policymakers, regulators, and market participants to comprehend and address these consequences in order to maintain a stable and resilient financial system while fostering sustainable economic development. Importantly, a large body of research (e.g., Bencivenga and Smith 1991; Levine 1991, among others) has consistently highlighted the importance of banking in driving economic growth. Consequently, we investigate the impact of bank failures and credit constraints on real GDP growth. Without this analysis, it would be difficult to convincingly argue that bank failures have a significant effect on overall economic growth.

Given that our earlier findings indicate the relative effectiveness of a VAR(1) model compared to its BVAR counterparts, we use the VAR(1) model with the following endogenous variables that we used earlier: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Table 5 presents the forecast error variance decomposition (FEVD) of ΔGDP.

Table 5. Forecast Error Variance of real GDP Growth

| Forecast Error Variance Decomposition of real GDP Growth | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Period | S.E. | EFFR | ΔGDP | TS | EBP | NIM | ALL | LLRR | ROE | FABR | XMRET |
| 1 | 0.75 | 4.05 | 95.95 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 2 | 0.80 | 3.26 | 81.66 | 0.32 | 0.22 | 0.93 | 0.64 | 0.00 | 0.37 | 0.66 | 11.94 |
| 3 | 0.82 | 3.79 | 79.39 | 0.69 | 0.92 | 1.05 | 0.77 | 0.09 | 0.61 | 0.75 | 11.93 |
| 4 | 0.83 | 5.58 | 74.23 | 2.27 | 1.34 | 0.98 | 3.07 | 0.08 | 0.57 | 0.72 | 11.15 |
| 5 | 0.84 | 5.53 | 73.10 | 2.66 | 2.08 | 1.08 | 3.11 | 0.10 | 0.60 | 0.78 | 10.96 |
| 6 | 0.85 | 5.99 | 71.84 | 2.96 | 2.29 | 1.14 | 3.41 | 0.11 | 0.63 | 0.84 | 10.79 |
| 7 | 0.85 | 6.03 | 70.98 | 3.10 | 2.39 | 1.24 | 3.82 | 0.13 | 0.68 | 0.96 | 10.67 |
| 8 | 0.85 | 6.02 | 70.47 | 3.13 | 2.43 | 1.35 | 4.01 | 0.15 | 0.71 | 1.11 | 10.62 |
| 9 | 0.85 | 6.02 | 70.09 | 3.13 | 2.43 | 1.42 | 4.19 | 0.17 | 0.73 | 1.24 | 10.60 |
| 10 | 0.86 | 6.00 | 69.89 | 3.12 | 2.42 | 1.47 | 4.24 | 0.18 | 0.73 | 1.36 | 10.59 |

*Note.* This table shows the forecast error variance decomposition (FEVD) of ΔGDP for the VAR (1) model with the following endogenous variables: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The FEVD of

FABR is shown for 10 quarters is shown in %; the FEVDs for other variables are not shown for parsimony. Quarterly sample 1984: Q1 to 2020: Q4.

At a one-quarter forecast horizon, we find that the forecast error variance is mainly attributed to EFFR (4.05%) and ΔGDP (95.95%). However, looking at the results for ten quarters, we find that ΔGDP accounts for approximately 69.89% of the FEVD. Among the other variables, EFFR, TS, EBP, and XMRET contribute around 6%, 3.12%, 2.42%, and 10.59%, respectively, to the FEVD after ten quarters. On the other hand, the banking variables such as FABR and ALL make varying degrees of contributions, explaining a portion of the FEVD. These results underscore the significance of credit availability, in conjunction with the banking sector, for fostering economic growth. Having examined the FEVD of ΔGDP, we next investigate the IRFs of ΔGDP to different generalized shocks to ensure that the ordering of the VAR variable is unimportant for this analysis. To facilitate comparison and visual clarity, we show the IRFs in a single plot and do not show the standard error (S.E.) bands.

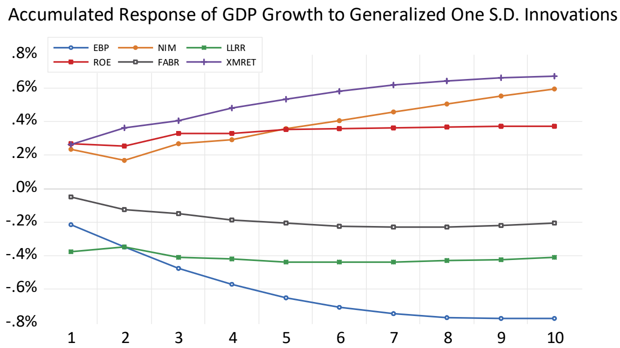


Figure 3. Macroeconomic Implications: Impulse Responses of real GDP Growth

*Note.* This table shows the impulse response functions (IRFs) of ΔGDP for the VAR (1) model with the following endogenous variables: EFFR, ΔGDP, TS, EBP, NIM, ALL, LLRR, ROE, FABR, and XMRET. Variables are explained in the previous table. The IRFs of ΔGDP are shown for 10 quarters in % points; the IRFs for other variables are not shown for parsimony. Standard error bands for the IRFs are not shown for visual clarity. Quarterly sample 1984: Q1 to 2020: Q4.

Figure 3 illustrates that a one standard deviation positive generalized shock in EBP has a substantial impact of approximately -0.8 percentage points on ΔGDP. Similarly, a comparable shock to XMRET results in an impact of about 0.6 percentage points. These results align with the findings in the existing literature (e.g., Gilchrist & Zakrajšek, 2012; Levin & Zarvos, 1998). In contrast, shocks to FABR lead to a reduction in ΔGDP by approximately -0.2 percentage points. Additionally, NIM, ROE, and LLRR, while substantial, have impacts that are relatively lower compared to XMRET and EBP. In summary, the evidence from the above analysis strongly supports the significant role of the banking sector, specifically bank profitability and failures, corporate credit spreads, and stock market returns, in driving economic growth.

## 4. Conclusions

Recent bank failures and the tightening of monetary policy have raised concerns about a potential banking crisis. This study investigates the impact of credit tightening on bank failures and explores the relationship between bank failures and tighter monetary policy. Our analysis takes a macro perspective and extends beyond the typical examination of idiosyncratic factors in existing literature (e.g., Imbierowicz & Rauch, 2014).

Our findings show that corporate credit spreads, stock market returns, and bank returns on equity possess leading information about bank failures. Additionally, we observe that higher loan loss reserve ratios and allowances for loan losses contribute to increased bank failures, while the impact of tighter monetary policy, represented by the Federal funds rate, seems to be limited.

Furthermore, we delve into the macroeconomic consequences of bank failures on real GDP growth. We ascertain that positive shocks to corporate credit spreads and bank failures lead to a contraction in real GDP growth, while positive shocks to stock market returns, bank net interest margin, and bank returns on equity have a positive impact on economic growth. Conversely, positive shocks to loan loss reserves adversely affect real GDP growth. These findings underscore the interdependencies between the health of the banking sector, stock market returns, corporate credit spreads, and overall economic development. Our results significantly contribute to the literature.

Firstly, we contribute to the literature (e.g., Bernanke & Lown, 1991; Kashyap & Stein, 1994) that investigates the link between bank lending and economic activity and finds no evidence of a "credit crunch." We demonstrate the positive association between corporate credit spreads, as a proxy for economywide credit constraints, and bank failures. Secondly, our analysis contributes to the literature on financial accelerator and credit-cycle theories (e.g., Gilchrist & Zakrajšek, 2012; Bernanke & Gertler, 1989, 1995; Kiyotaki & Moore, 1997) by examining the impact of EBP on the banking sector, specifically focusing on bank failures. Finally, we contribute to the literature on the relationship between banking, stock market, and economic development (e.g., Levine, 1991; Levin & Zarvos, 1998) by highlighting the interconnectedness of bank profitability and failures, stock market returns, and economic development.

In future research, it would be beneficial to explore the relationship we investigated in other countries to enhance the generalizability of our findings. Additionally, examining alternative measures for bank failures, such as the total loss of failed bank assets, could provide deeper insights into the impact of credit constraints on the broader macro-economy.

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**Authors contributions**

Dr. Chatterjee and Dr. Hervani were responsible for study design and revising. Dr. Downs was responsible for data collection and manuscript preparation. Dr. Chatterjee drafted the manuscript and Dr. French revised it. All authors read and approved the final manuscript.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

**Data sharing statement**

No additional data are available.

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