Decoding Bank Profitability and Stability: An Examination of Key Drivers in the Financial Sector

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Introduction

Commercial banks are the backbone of financial systems, enabling and financing economic transactions from the individual to the corporate level. Maintaining the profitability and stability of banks is thus central to a stable and healthy financial system. Most recently, the banking crises of Spring 2023 have illustrated how financial markets and consumers can be significantly affected by failures of financial institutions. As such, what factors are predictive of the stability and profitability commercial banks is an important question for economists, policy makers, and consumers alike.

In this project, we approach this topic from two angles. First, we explore the question of what makes banks profitable. Profitability allows for the longevity and stability of a bank, and we work to identify what variables are predictive of bank profit. This could also help policymakers figure out what types of capital restrictions and regulations may affect profitability the most. This is currently a big question in the wake of proposed Basel III regulations and the banking industry's recent pushback against them where they cited concerns of profitability. Second, we ask what makes banks fail. In this analysis, we focus on fiscal quarters immediately preceding periods with high rates of bank failure, investigating what behaviors and characteristics may have predicted eventual bank collapse or instability. Our proxy for instability in this case will be a measure of deposit flight as banks see significantly higher rates of failure when deposits begin to leave the bank at high rates.

Data & EDA

Data

The data we use in this study is built from the Call Reports Data compiled by the FFIEC. This is a dataset made up of all banks' responses to the call report form from each quarter. This form provides itemized details on a bank's balance sheet, income statement, and other important characteristics. This is a notoriously hard to wrangle dataset. According to Sam Hanson at HBS and his PhD student, the Federal Reserve's cleaned version of this data and the version of this data used in some papers published in the Quarterly Journal of Economics are not fully correct (not merger adjusted using additional FFIEC Data, some variables are calculated incorrectly, etc.). After consultation with PhD students in the economics department, we believe our version is the most accurate version of this data that exists to date.

We built this dataset by taking the raw data from the FFIEC, calculating our needed variables using the Federal Reserve's Micro Data Reference Manual over time, and doing necessary merger adjustment and bank collapsing using additional tables from the FFIEC.

We have decided to restrict this dataset to banks with assets over $1 bn in the period 2002-2024. We decided to do this in order to focus on the banks that matter in our financial system today and to have the largest, most complete repertoire of variables available for our use. This is because some variables are only reported by banks with over $1 bn in assets.

Profitability EDA

For our analysis of bank profitability, the response variable we investigate is Net Interest Margin (NIM). A bank's NIM is the ratio between its net interest income and its average earning assets. NIM serves as a key profitability metric as it adjusts a bank's net interest income (its main form of profitability) by the amount of interest-earning assets it holds. Positive NIM values indicate a bank is profitable, while negative NIM values typically indicate that a bank is losing money. We will compute a bank's NIM according to the formula:

$$\text{NIM} = \frac{\text{Net Interest Income}}{\text{Average Earning Assets}} \cdot 400$$

Our call report data set contains net interest income (NII) values for the included banks. We compute a bank's average earning assets (AEA) from other data available in the dataset according the Federal Reserve's definition:

$$\begin{aligned}\text{Average Earning Assets} = \text{Interest Bearing Balances} + \text{Total Loan NEI} + \text{Trading Assets} + \text{Securities}\\ + \text{Repos Fed Fund Sold}\end{aligned}$$

In terms of predictors of bank profitability, we choose to include three categories of bank assets and the interest generated from these categories: securities, deposits, and loans. The call reports data set breaks these three assets down into categories according to type (e.g., Real Estate Loans, CRE Loans, C&I Loans) and duration (e.g., 0-3 month to 15+ year securities). We expect that a distribution of a bank's assets across these categories can be predictive of its profitability. In theory, holding longer duration loans and treasuries should correlate with a higher NIM, but it is unclear how the risk of these assets come into the picture. It would thus be interesting to see how the tradeoff between risk and higher interest spreads plays out in the average case for a bank. We also control for assets (bank size) and liabilities.

To get all these predictors on the same scale, we divided each of these variables by the total assets held by the bank and scaled by 100. Therefore, each of these predictors of profitability is now expressed as a percent of total held assets for each bank.

From Table 1, we note that we have complete observations for $n = 49,469$ for all predictors except for uninsured deposits and CRE loans. Additionally, we have near completeness for our response variable NIM (1923 missing observations out of 49,469). Most of these missing values (1913) come from banks who did not report net interest income values. The rest of the 10 missing values can be attributed to dividing by zero errors that arose during the NIM calculation. We will ignore those missing values in our analysis as we do not expect these banks to have missing values non-randomly.

Next, we note that the response variable NIM has a large range (from -22.2 to 30) but a relatively small standard deviation of 2. This suggests that the distribution of NIM mostly contains values clustered around its mean of 4 while also containing a few extremely high and low outliers. Indeed, this heavy-tailedness in the distribution of NIM is quite apparent in Figure 1. These features of the distribution make sense: even within this dataset of large banks with over $1 billion in assets, we expect a few banks to perform extremely well and poorly relative to the rest. When building our regression model, we are largely interested in how the typical bank performs, not in extremely high or low outliers. Therefore, we will focus on banks with NIM values roughly within three standard deviations of the mean ([-10.0, 10.0]).

We hypothesize that banks which hold more of their assets in high duration assets (high duration securities or loans) are going to be less profitable. We believe that this is the case because of the risk dynamics inherent to these assets: we believe banks have played too risky with respect to the market and that their gambles have not paid off, especially with respect to financial crises that have occurred in the span of our dataset. It also could be that this risky behavior is correlated with some other characteristic of a bank that is negatively correlated with profitability (e.g. a bad risk management department).

Table 1: Summary Statistics for Profitability Analysis

	Non-missing Obs	Missing Obs	Mean	Median	Standard Deviation	Interquartile Range	Min	Max
Securities	49469	0	20.1	18.1	12.8	15.2	0.0	99.4
Securities 3mo	49469	0	1.5	0.5	3.2	1.5	0.0	57.7
Securities 3-12mo	49469	0	1.0	0.4	1.9	1.0	0.0	51.8
Securities 1-3 Yr	49469	0	2.2	1.0	3.4	2.4	0.0	68.1
Securities 3-5 Yr	49469	0	1.8	1.0	2.7	2.1	0.0	50.1
Securities 5-15 Yr	49469	0	5.9	4.3	5.8	6.4	0.0	48.1
Securities 15 Yr	49469	0	3.3	1.6	4.7	4.1	0.0	62.5
Demand Dep	49469	0	11.6	7.6	11.6	10.1	0.0	97.4
Nonint. Dep	49469	0	17.4	16.3	10.7	13.6	0.0	97.7
Dep	49469	0	79.8	82.0	10.8	9.5	0.0	103.3
Uninsured Dep	44637	4832	24.9	23.5	13.5	17.8	0.0	90.7
Liabilities	49469	0	89.3	89.9	4.4	3.0	3.9	108.6
Loan Total	49468	1	65.3	67.7	14.7	16.3	0.0	98.2
RE Loan	49469	0	46.2	48.1	17.5	20.5	0.0	95.0
CRE Loan	41812	7657	20.9	20.6	10.9	12.9	0.0	74.4
C&I Loan	49469	0	11.5	9.6	8.7	9.1	0.0	95.9
Personal Loan	49469	0	5.0	1.5	11.9	3.8	0.0	102.4
Other Loans	49469	0	1.2	0.2	3.1	0.9	0.0	58.2
Loans 3mo	49469	0	20.4	17.2	14.3	17.5	0.0	100.9
Loans 3-12mo	49469	0	6.4	5.4	5.0	5.4	0.0	96.0
Loans 1-3 Yr	49469	0	11.1	10.5	6.6	7.8	0.0	96.2
Loans 3-5 Yr	49469	0	12.1	11.5	6.9	8.8	0.0	81.8
Loans 5-15 Yr	49469	0	10.7	9.4	7.8	9.5	0.0	85.1
Loans 15 Yr	49469	0	4.9	2.6	6.4	5.6	0.0	82.2
Ln(Assets)	49469	0	15.1	14.6	1.3	1.5	13.8	22.0
NIM	47546	1923	3.7	3.5	1.7	0.9	-22.2	30.0

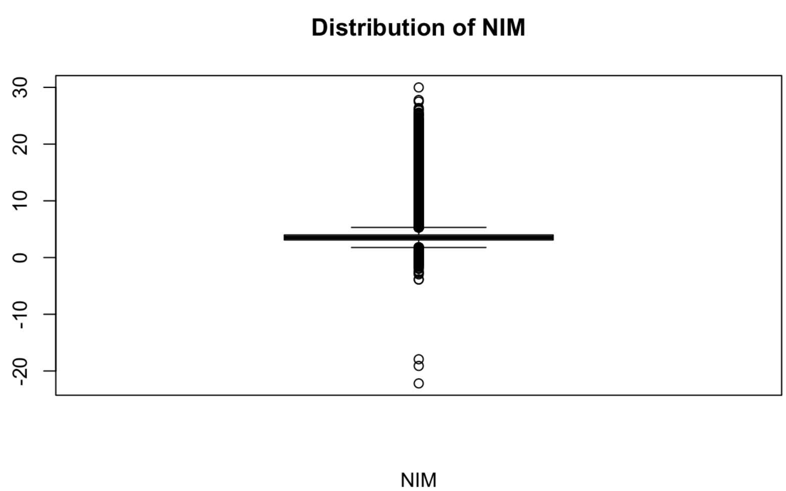

Figure 1: Boxplot Distribution of NIM

Bank Stability EDA

For this analysis, we consider the response variable to be Deposit Flight, defined as the percentage change in deposits from one quarter to the next, often considered a key metric of bank stability. We calculate this variable as:

$$\text{Deposit Flight} = \frac{\text{Current Deposit} - \text{Previous Deposit}}{\text{Previous Deposit}} \times 100$$

In our regression, we will lag the predictors of deposit flight (described below) one financial quarter behind the deposit flight response variable. This lagging reflects the intuition that deposit flight responds not to a bank's current holdings but its past holdings. In addition, if we did not lag our variables, our coefficients would be muddled by an issue reverse causality. For example, it would be obvious that the current period's assets would increase if deposit inflows increased at the same time because assets mechanically increase with an increase in deposits. By lagging, we will hopefully be able to avoid this issue of reverse causality and isolate the effect of a bank's holding composition on what depositors do in the next period.

In terms of predictors toward bank stability, we chose to include that were able to capture dimensions of liquidity, investment risk, profitability, and loan portfolios. Key predictor categories include:

Liquidity and Deposit Composition: Uninsured deposit ratio, interest- and non-interest-bearing deposits, brokered deposits (insured and uninsured), cash holdings, total domestic deposits.

Investment Risk: Ratio of hold-to-maturity (HTM) to available-for-sale (AFS) treasuries, percent of total securities which are HTM, total securities, total fair value (FV) AFS securities, total amortized cost (AC) AFS securities, and long-term securities (5-15 yr and 15+ yr).

Profitability: Net interest margin, average interest rate paid on deposits.

Loan Portfolio and Risk: Total net loans, commercial real estate (CRE) loans, consumer and industrial (C&I) loans, and long-term loans (5-15 yr and 15+ yr).

Bank Characteristics: Bank size as represented by ln(assets).

As in our profitability analysis, we divide the majority of our non-rate variables by total assets to standardize them. One key distinction is that, in this analysis, we divide our deposit variables by total deposits rather than total assets. This is because we are more interested in how a bank's deposit franchise strategy affects deposit flight. For example, we want to know whether banks that work with more uninsured deposits as a percent of their deposit franchise see greater deposit flight rather than know whether banks that simply have higher uninsured deposits as a percent of their assets see deposit flight.

In terms of missingness, aside from certain variables that were excluded due to the majority of their observations lacking data, all rows with any missing values were removed. This process reduced the dataset from an initial $n = 49,469$ observations to a final total of $n = 35,490$. Table 2 illustrates where the missingness primarily occurred and provides us a distribution of our given predictors and response.

Notably in Table 2, we see that that the response variable Deposit Flight has a extremely large range (-76 to 4465) and a large standard deviation of 73 with a mean of 3, median of 1, and IQR of 5.0. From this, we can infer that the distribution of Deposit Flight primarily clusters within a very limited range around 0 with very large outliers skewing our distribution. As such, we decided to limit the possible values of this variable. When devising our regression model, we are primarily interested in banks that are seeing deposit outflows that threaten stability, not banks who see huge deposit inflows (over 100%) as a result of some outside factors. Thus, with such rationale, we will limit the range of the Deposit Flight response variable to [-100,100].

We hypothesize that banks with higher uninsured deposit ratios and brokered deposits are more likely to experience deposit flight. We believe this is the case because these deposits are more volatile and prone to withdrawal during periods of financial uncertainty. Additionally, banks with higher allocations to hold-to-maturity (HTM) securities and long-term assets may face liquidity constraints, as these assets are less marketable and more sensitive to interest rate risk. This perceived illiquidity could erode depositor confidence, especially during times of market stress. It may also be that these characteristics are correlated with broader structural issues, such as weaker risk management practices or lower overall financial health, further exacerbating deposit flight risk.

Table 2: Summary Statistics for Stability Analysis

	Non-missing Obs	Missing Obs	Mean	Median	Standard Deviation	Interquartile Range
Deposit Flight	47014.0	2455.0	3.0	1.0	73.0	5.0
Ln(Assets)	47141.0	2328.0	15.0	15.0	1.0	1.0
Uninsured Ratio	42471.0	6998.0	31.0	30.0	17.0	22.0
Non-interest Deposit	45139.0	4330.0	21.0	20.0	13.0	16.0
Interest Deposit	45139.0	4330.0	77.0	79.0	14.0	17.0
Brokered Deposit	45139.0	4330.0	7.0	2.0	15.0	7.0
Insured Brokered Deposit	45139.0	4330.0	7.0	1.0	14.0	6.0
Cash	47141.0	2328.0	7.0	4.0	8.0	6.0
HTM to Total Ratio	46962.0	2507.0	1.0	0.0	6.0	0.0
Treasuries AFS FV	47141.0	2328.0	1.0	0.0	3.0	0.0
Treasuries AFS AC	47141.0	2328.0	1.0	0.0	3.0	0.0
Securities 5-15 Year	47141.0	2328.0	6.0	4.0	6.0	6.0
Securities 15 Year	47141.0	2328.0	3.0	2.0	5.0	4.0
Net Interest Margin	45226.0	4243.0	4.0	4.0	2.0	1.0
Deposit Rate	45139.0	4330.0	1.0	1.0	1.0	1.0
Loan Total Net	47140.0	2329.0	65.0	68.0	15.0	16.0
CRE Loan	39599.0	9870.0	21.0	21.0	11.0	13.0
CI Loan	47141.0	2328.0	12.0	10.0	9.0	9.0
Loan 5-15 Year	47141.0	2328.0	11.0	9.0	8.0	9.0
Loan 15 Year	47141.0	2328.0	5.0	3.0	6.0	6.0

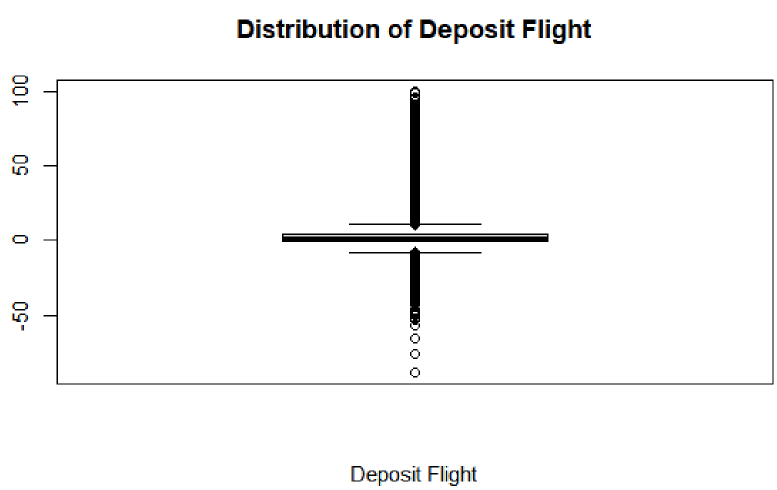

Figure 2: Boxplot Distribution of Deposit Flight

Methods

Baseline Regression Models

Ordinary Least-Squares (OLS) Regression models were fit using the `lm` function in `R`. Our baseline regression models for both bank profitability and stability were OLS models. Recall that in the OLS model, the loss function that is minimized is

$$L(\beta) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

The variables we use for this baseline model are the same as those mentioned in the EDA. In subject-specific formalism, the specific model we use is here is:

$$Y_{i,t} = \beta_0 + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_p x_{p,i,t} + \epsilon_{it},$$

where i represents an individual bank and t represents a given financial quarter. Thus, each value $x_{j,i,t}$ represents the value of the j^{th} predictor for bank i at time t. $\epsilon_{i,t}$ is a random error term for each observation assumed to be normally distributed with homogeneous variance across observations.

Ridge and LASSO Regression

After fitting these baseline OLS models using sets of predictors we expected to be predictive of profitability and stability, we assessed our variable selection using Ridge and LASSO regression. Identifying the slope parameter estimates that were significantly shrunk using these regularization methods can identify unnecessary variables included in our baseline regressions that do not contribute much explanatory power to the models.

These regressions were implemented using the `glmnet` package. First, optimal shrinkage parameter estimates λ that minimized mean squared error (MSE) were found via cross validation using the `cv.glmnet` function. With this optimal shrinkage parameter estimate, the regularized model was fit using the `glmnet` function.

We use both a Ridge and LASSO method since both provide us with valuable information. LASSO helps with interpretability by zeroing out coefficients. Ridge retains all features, which may hinder interpretability, but can perform better than LASSO. Ridge also works better with correlated features as it distributes its shrinkage across all correlated predictors instead of arbitrarily zeroing out some of them. The loss function minimized for LASSO is:

$$L_{\text{LASSO}}(\beta) = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j|$$

and for Ridge it is:

$$L_{\text{Ridge}}(\beta) = \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} \beta_j x_{ij} \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

Fixed Effects Regression

We believe that there are also bank-specific differences and time-specific factors that can affect NIM. Certain banks may have uncontrollable characteristics such as a strong deposit franchise or brand recognition that affect their profitability. Given that we have panel data, we can added bank entity fixed effects in order to control for these potential implicit differences.

We also expect that there are time dependent macroeconomic effects that impact all banks during a given financial quarter (e.g, Fed Funds Rate, geopolitical factors, COVID-19) and affect their NIM or deposit flight value during that time. As a result, we decided to fit a time fixed effect to this model following [1]. This would give us a model as follows:

$$\begin{aligned} Y_{i,t} &= \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_p x_{p,i,t} + \text{Bank Effects} + \text{Time Fixed Effects} + \epsilon_{it} \\ &= \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_p x_{p,i,t} + \sum_k \gamma_k B_k + \sum_s \delta_s T_s + \epsilon_{it}, \end{aligned}$$

where γ_k represents the entity fixed effect for bank k, B_k is a dummy variable indicating whether an observation is for the k^{th} bank in a dataset, δ_s represents the time fixed effect at time s, and T_s is a dummy variable indicating whether an observation is for the s^{th} quarter present in the dataset.

We choose to run a fixed effects model over a mixed/random effects model for the following reasons: First, since we have the full dataset of banks over time and we do not need to generalize beyond the groups in our data, random effects that allow for better generalization to new groups in the data may not actually be useful. Fixed effects are also simpler, do not engage in the assumption that the random effect is uncorrelated with other predictors (which is likely not true in our data as a bank id may be correlated with the bank's asset strategy and composition), and are more frequently used in economics contexts. We did attempt a mixed-effects model for our profitability analysis out of curiosity, and results are described in the Appendix.

Model Selection Criteria

In our analysis, we constructed several regression models for each research question. To compare model performance, we used the Akaike Information Criterion (AIC), which is computed according to:

$$AIC = -2l(\hat{\theta}_{MLE}) + 2d,$$

where $l(\hat{\theta}_{MLE})$ is the maximized log-likelihood of the data computed under assumption that linear regression errors are normally distributed with constant variance and d is the number of parameters in the model. As a result, this statistical criterion rewards goodness of fit (captured by the negative log likelihood term) while penalizing complexity (captured by the d term) of the model. Across the various models we fit, we seek to identify the best explanatory model by minimizing AIC to balance the tradeoff between overfitting and strong model performance. AIC calculation was implemented in `R` using the default `AIC` function.

As a complementary model selection criterion, we also assessed some models by their adjusted R-squared values (R^2_{adj}). Adjusted R-squared values for regressions fit on n data points $Y_1 \dots Y_n$ were computed according to:

$$R^2_{adj} = 1 - \frac{\frac{1}{n-p-1}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\frac{1}{n-1}\sum_{i=1}^{n}(Y_i - \bar{Y})^2},$$

where $p+1$ is the number of parameter estimates (p slope parameter estimates and 1 intercept parameter estimate), $\hat{Y}_i$ is the model's fitted value for the ith observation, and $\bar{Y}$ is the sample mean of the response variable. R^2_{adj} is similar to standard R^2 calculations in that it captures the amount of variance in the data that is accounted for by the model regression. However, it adjusts for the degrees of freedom spent in parameter estimates, penalizing models that include parameters that don't significantly improve the explanatory power of the model. Through model selection, we seek to find models with higher R^2_{adj} values.

Results

Bank Profitability

Baseline OLS Model

After removing outliers with NIM values less than -10 and greater than 10, we fit a baseline OLS model including all the predictors described in Table 1 according to the methods described in the previous section.

Slope parameter estimates and other summary statistics can be found in Table 3. This model had $R^2_{adj} = 0.416$ and $AIC = 77,883.22$.

To assess whether our linear regression assumptions are valid for this dataset, we assessed diagnostic plots (Figure 3). From the Residuals vs. Fitted Values plot, we confirmed the validity of our assumption of the linearity of the systematic component of our model, as there does not appear to be a non-linear trend in the residuals. Further, the plot supports the assumption of homogeneity of variance, as the residuals appear to be uniform in magnitude across the range of fitted values. From the Normal QQ plot, we noted that our Normality assumption approximately holds. It does appear that the data has heavier tails in both directions than a theoretical Normal distribution. However, given that we are working in the limit of large sample size ($n = 35,363$), we have that Normality approximately holds under the Central Limit Theorem.

Table 3: Profitability Baseline OLS Model

Variable	Coefficient	Std. Error	p-value
Securities	0.019***	0.001	<0.01
Securities 3mo	−0.016***	0.002	<0.01
Securities 3-12mo	−0.025***	0.003	<0.01
Securities 1-3 Yr	−0.018***	0.002	<0.01
Securities 3-5 Yr	−0.008***	0.002	<0.01
Securities 5-15 Yr	−0.002**	0.001	0.015
Securities 15 Yr	−0.009***	0.001	<0.01
Demand Dep	−0.003***	0.0004	<0.01
Dep	0.006***	0.001	<0.01
Nonint. Dep	0.015***	0.0005	<0.01
Uninsured Dep	−0.007***	0.0003	<0.01
Liabilities	−0.069***	0.001	<0.01
Loan Total	−0.067***	0.003	<0.01
RE Loan	0.010***	0.001	<0.01
CRE Loan	0.006***	0.001	<0.01
C&I Loan	0.013***	0.001	<0.01
Personal Loan	0.044***	0.001	<0.01
Other Loans	−0.017***	0.002	<0.01
Loans 3mo	0.087***	0.003	<0.01
Loans 3-12mo	0.109***	0.003	<0.01
Loans 1-3 Yr	0.089***	0.003	<0.01
Loans 3-5 Yr	0.069***	0.003	<0.01
Loans 5-15 Yr	0.078***	0.003	<0.01
Loans 15 Yr	0.084***	0.003	<0.01
Ln(Assets)	−0.073***	0.004	<0.01
Constant	7.906***	0.123	<0.01
Observations		35,363	
R^2		0.416	
Adjusted R^2		0.416	
Residual Std. Error		0.728 (df = 35337)	
F Statistic		1,007.327*** (df = 25; 35337)	

Note: *p<0.1; **p<0.05; ***p<0.01

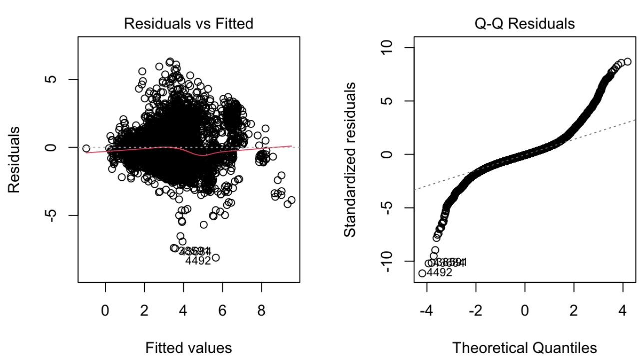

Figure 3: Profitability Baseline Model Diagnostics

Ridge and LASSO Regularization

Given that the linearity assumption of linear regression appears to hold, as described above, our model appears to be generally well-specified. However, to verify that we do not have unnecessary predictors that don't greatly improve the explanatory power of the model, we implement Ridge and LASSO regularization to potentially identify predictors to remove from the model and give us a rough sense of feature importance.

Cross validation runs for Ridge regression (Figure A.1) identified an optimal shrinkage parameter value of $\lambda_{\text{ridge}} = 0.037$. This small shrinkage value means that the parameter estimates for our baseline model are not greatly shrunk, suggesting that this set of parameters is providing significant explanatory power without unneeded complexity. As expected, the shrunk Ridge parameter estimates (Table A.3) are similar to the baseline regression model's estimates. Finally, we had $AIC = 78,523.23$, which suggests that Ridge regularization doesn't improve model fit above the baseline regression.

Cross validation runs for LASSO regularization identified an optimal shrinkage parameter of $\lambda_{\text{LASSO}} = 0.0000649$ (Figure A.2). Again, this low value for the shrinkage parameter suggests that our selected set of parameters is not overly complex. Indeed, inspecting the coefficient estimates for this LASSO regularization shows that none of our parameter estimates are shrunk to 0 (Table A.4). Finally, for the LASSO regularized model, we had $AIC = 77,885.46$, which suggests that LASSO regularization doesn't improve model fit above the baseline regression.

In sum, these regularized models suggest that we have a specified model that does not include unnecessary predictors.

Time and Entity Fixed Effect Model

In addition to variability across banks, there are likely time dependent macroeconomic effects that impact all banks during a given financial quarter and affect their NIM value during that time. As a result, we decided to fit a time and entity fixed effects model that controlled for both unobserved variables that vary across time but equally impact all banks at that time (time effects) as well as variables that vary across banks but are constant across time (e.g., bank-specific policies). Note that there are 1989 unique banks represented in the dataset and 70 financial quarters, so our time and fixed effects model contributes a total of 2058 additional parameters (as there is no constant intercept term).

Fitting this regression using the standard `lm` function but now controlling for the financial quarter and bank ID gave a model with $R^2_{adj} = 0.9879$ and $AIC = 37,295.19$ (Table 4). This is by far the best model fit, suggesting that we have correctly controlled for the time and entity fixed effects described above.

To verify that the high R^2 value does indeed indicate a good fit, we verified that the assumptions of linear regression still hold by checking diagnostic plots (Figure 4). The residuals vs. fitted values plot confirms that the assumptions of linearity and homogeneity of variance still hold, while the QQ plot suggests that approximate Normality remains a valid assumption under the limit of large n. Further, the fact that the time and entity fixed effects model had a lower AIC than the baseline suggests that its additional variables provide additional explanatory power without introducing unnecessary complexity or overfitting to the training data.

Table 4: Profitability OLS Model with Fixed Effects

Variable	Coefficient	Std. Error	p-value
Securities	0.013***	0.001	<0.01
Securities 3mo	−0.009***	0.001	<0.01
Securities 3-12mo	−0.006***	0.002	<0.01
Securities 1-3 Yr	−0.021***	0.001	<0.01
Securities 3-5 Yr	−0.016***	0.002	<0.01
Securities 5-15 Yr	−0.007***	0.001	<0.01
Securities 15 Yr	−0.008***	0.001	<0.01
Demand Dep	0.002***	0.0004	<0.01
Dep	0.007***	0.001	<0.01
Nonint. Dep	0.004***	0.001	<0.01
Uninsured Dep	−0.0002	0.0004	0.672
Liabilities	−0.062***	0.001	<0.01
Loan Total	−0.058***	0.003	<0.01
RE Loan	0.014***	0.001	<0.01
CRE Loan	0.006***	0.001	<0.01
C&I Loan	0.019***	0.002	<0.01
Personal Loan	0.031***	0.002	<0.01
Other Loans	0.013***	0.002	<0.01
Loans 3mo	0.074***	0.002	<0.01
Loans 3-12mo	0.083***	0.003	<0.01
Loans 1-3 Yr	0.073***	0.003	<0.01
Loans 3-5 Yr	0.073***	0.002	<0.01
Loans 5-15 Yr	0.069***	0.003	<0.01
Loans 15 Yr	0.077***	0.003	<0.01
Ln(Assets)	−0.125***	0.010	<0.01
Observations	35,363		
R^2	0.989		
Adjusted R^2	0.988		
Residual Std. Error	0.398 (df = 33280)		
F Statistic	1,383.293*** (df = 2083; 33280)		

Note: *p<0.1; **p<0.05; ***p<0.01

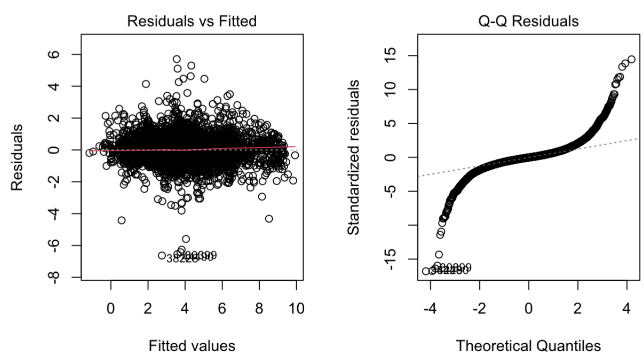

Figure 4: Profitability Time and Entity Fixed Effects Model Diagnostics

Interpreting Model Coefficients

Looking at the systematic (non entity or time specific) parameter estimates from our best model (Table 4), we can make some rough qualitative conclusions about how our predictor variables impact a bank's predicted profit. We focus on the time and entity fixed effects model since this is the model that controls for the most confounders and appears best able to model the associations between our predictors and response. Predictors with a positive slope estimate can be interpreted as saying that increasing a bank's investment in that asset is associated with an increase in their expected profitability, as measured by NIM. A negative slope parameter estimate can be interpreted as saying holding more of that asset is predictive of reduced bank profitability. Obviously, we cannot assume any causal relationships here. Instead, we focus on the interesting associations suggested by this model.

Consider the set of securities predictors. Imagine that a bank increases the amount of its assets invested in securities by one percent. First, let's consider the case in which that entirety of that one percent increase comes from increasing the bank's holdings in 3 month securities. The expected increase in NIM associated with this change is $\hat{\beta}_{\text{Securities}} + \hat{\beta}_{\text{Securities 3 mo}} \approx 0.013 - 0.009 \approx 0.004$ if all of our other predictors are held constant. Therefore, we can interpret this as saying that an increase in the amount of bank assets allocated to 3 month securities is associated with an increase in profitability. By similar reasoning, we see that increasing holdings in 3-12 month, 5-15 year, and 15+ year securities is predictive of an increase in bank profitability. Long-term securities appear to be associated with a slightly higher profitability than short-term securities but holding 3-12mo securities is most profitable. In contrast, holding more midterm securities (1-5 years) is associated with a decrease in bank profitability. This suggests that the low risk associated with short-term securities outweighs the low return from these securities while the high risk associated with long-term securities is outweighed by their higher return. In contrast, medium-term securities may be in a range where the risk-reward trade-off is not beneficial on average for the bank. These results cast doubt on our hypothesis that banks which hold more of their assets in high duration assets are less profitable on average.

Next, consider the set of loans predictors. Each loan has two identifiers: type (e.g., RE, CRE, Personal, etc.) and duration (e.g., 3 months, 3-12 months, etc.). Therefore, the total expected effect of a one percent increase in a bank's allocation of assets to a certain type of loan is given by $\hat{\beta}_{\text{Loan Total}} + \hat{\beta}_{\text{Loan Type}} + \hat{\beta}_{\text{Loan Duration}}$. For example, the expected increase in NIM associated with a one percent increase in assets allocated to 3 month personal loans, holding other predictors constant, is given by: $-0.058 + 0.031 + 0.074 \approx 0.047$.

Following this calculation through for all loan predictors in the regression, we see that increasing any kind of loan as a percent of assets is associated with an expected increase in bank profitability. This result suggests that loans are generally mutually beneficial for both banks and their clients all else equal.

Breaking down loans by type, we see that offering more C&I and personal loans as a percent of assets is expected to bring in the most profit for banks. Breaking down loans by duration, we see that short term (3-12 months) and long-term (15+ years) loans are expected to bring in the most profit for banks. These results are reasonable based on our preexisting knowledge of the industry. The real estate and commercial real estate sectors are most susceptible to significant industry downturns and have had lackluster performance over the past decade, especially over the past few years. It again also appears that the risk-return trade-off for long-term loans leads to profitability on average unlike we hypothesized.

Predicting Bank Failure

Baseline Model

After limiting our response variable range to [-100,100] to better represent Deposit Flight in the average bank, we fit a baseline OLS model including the predictors described in Table 2.

Slope parameters estimates can be found in table 5. We find the AIC and the R^2_{adj} scores to be $AIC = 228,296$ and $R^2_{adj} = 0.018$ respectively as well. These statistical criteria suggest that the baseline model is not a good fit for the data and only explains a very small amount of the variance in deposit flight present in the dataset. There may be many other factors not captured by our model that explain bank failure. We will explore this issue further throughout the model selection process.

In terms of the assumptions made for linear regression, looking at the diagnostic plot for this model (Figure 5), we see that our assumptions of linearity and homogeneity of variance appear to hold based on the residuals vs. fitted values plot. The Normal QQ plot reveals that the distribution of our deposit flight response variable has heavier tails in both directions than a Normal distribution. However, under the limit of large $n = 33,532$, we have that this approximate Normality holds under the Central Limit Theorem.

Table 5: Bank Stability Baseline OLS Model

Variable	Coefficient	Std. Error	p-value
Ln(Assets)	-0.102^{***}	0.036	<0.01
Uninsured Ratio	0.017^{***}	0.003	<0.01
Non-Interest Deposit	-0.056^{***}	0.008	<0.01
Interest Deposit	-0.066^{***}	0.007	<0.01
Brokered Deposit	0.029^{**}	0.012	0.014
Insured Broker Deposit	-0.002	0.012	0.793
Cash	-0.051^{***}	0.007	<0.01
HTM to Total Securities Ratio	-0.022^{***}	0.007	<0.01
Fair Value of AFS Treasuries	1.973^{***}	0.343	<0.01
Amortized Cost of AFC Treasuries	-1.939^{***}	0.335	<0.01
Securities 5-15 Yr	0.001	0.009	0.885
Securities 15 Yr	0.019^{*}	0.010	0.066
Net Interest Margin	0.095^{***}	0.027	<0.01
Deposit Rate	-0.454^{***}	0.053	<0.01
Total Net Loans	0.041^{***}	0.005	<0.01
Commercial Real Estate Loans	-0.014^{***}	0.005	<0.01
C&I Loans	0.013^{**}	0.005	0.013
Loans 5-15 Yr	0.020^{***}	0.006	<0.01
Loans 15 Yr	-0.017^{***}	0.007	<0.01
Constant	7.034^{***}	1.091	<0.01
Observations	33,532		
R^2	0.018		
Adjusted R^2	0.018		
Residual Std. Error	7.278 (df = 33,512)		
F Statistic	32.566^{***} (df = 19; 33,512)		

Note: *p<0.1; **p<0.05; ***p<0.01

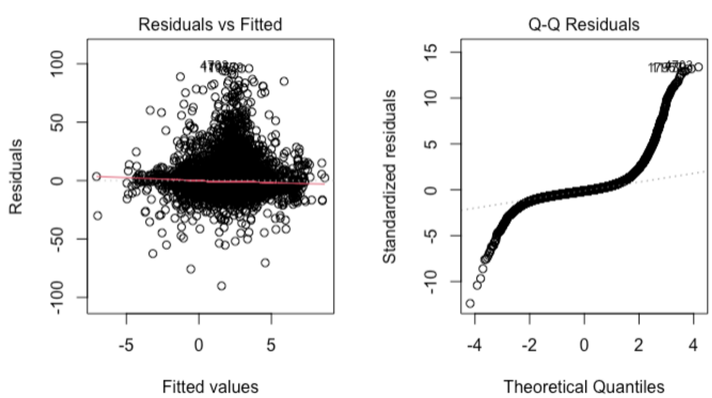

Figure 5: Bank Failure Baseline Model Diagnostics

Ridge and LASSO Regularization

We then decided to do feature selection via Ridge and LASSO regression to see if we could simplify our models. We ran cross-validation and fit models according to the optimal lambda values.

The Ridge regularized model had an optimal shrinkage parameter of $\lambda_{\text{ridge}} = 0.0578$. This low value for λ suggests that the parameter estimates are only slightly shrunk relative to the baseline model. (Table A.5). This ridge regularized model has $AIC = 228,324$.

The LASSO regularized model had a small optimal shrinkage parameter value of $\lambda_{\text{LASSO}} = 0.0000578$. Looking at the regularized coefficient estimates, we see that none are shrunk to 0 (Table A.6). This LASSO regularized model has $AIC = 228,296$.

These regularization results suggest that our chosen set of predictors do not contain unnecessary variables that add to model complexity without improving explanatory power.

Fixed Time and Entity Model

To try to assuage the issue of low variance explained by our model, we separately tried a model with interaction terms using a stepwise algorithm based on AIC. We find an increase of only 0.02 in adjusted R^2 telling us there are not significant interactions that explain our low variance. The specific analysis for these interaction terms is found in the Appendix (Table A.7). As such, we find it necessary to see whether controlling for time and entity effects increases the predictive power of our model. We expect that certain time period dummies can likely explain deposit flight (e.g. a financial crisis) and certain banks may also be more or less susceptible to deposit flight based on unobserved characteristics such as brand name (e.g. Banks with high brand recognition who are considered "too big to fail" such as Bank of America may be less susceptible to deposit flight all else equal).

Staying consistent with the models we fit previously, we fit a time and entity fixed effect model. This gave us $R^2_{adj} = 0.110$ and $AIC = 226937.9$. We see that this model has the lowest AIC out of our previous models as well as the highest R^2_{adj} of our models. This tells us that controlling for time and entity fixed effects does increase the explanatory power of our model which is as expected.

Our specific coefficients are shown in Table 6. Figure 6 illustrates that our model appears to generally fulfill linearity. There may be a slight violation of homoskedasticity, but we believe it is generally inconsequential to our results. Though normality is violated, our large sample size makes this violation non-consequential according to the Central Limit Theorem.

Table 6: Bank Stability OLS Model with Fixed Effects

Variable	Coefficient	Std. Error	p-value
Ln(Assets)	-4.127^{***}	0.180	<0.01
Uninsured Ratio	-0.004	0.006	0.548
Non-Interest Deposit	-0.076^{***}	0.019	<0.01
Interest Deposit	-0.108^{***}	0.017	<0.01
Brokered Deposit	-0.010	0.016	0.515
Insured Broker Deposit	0.045^{***}	0.017	<0.01
Cash	-0.148^{***}	0.011	<0.01
HTM to Total Securities Ratio	-0.001	0.011	0.928
Fair Value of AFS Treasuries	-0.573	0.411	0.161
Amortized Cost of AFC Treasuries	0.606	0.402	0.130
Securities 5-15 Yr	0.046^{***}	0.015	<0.01
Securities 15 Yr	0.042^{**}	0.016	0.009
Net Interest Margin	0.043	0.080	0.586
Deposit Rate	0.187	0.157	0.237
Total Net Loans	0.093^{***}	0.011	<0.01
Commercial Real Estate Loans	0.005	0.015	0.748
C&I Loans	0.023^{*}	0.013	0.074
Loan 5-15 Yr	0.037^{***}	0.012	<0.01
Loan 15 Yr	-0.015	0.015	0.321
Constant	60.275^{***}	7.640	<0.01
Observations		33,532	
R^2		0.164	
Adjusted R^2		0.110	
Residual Std. Error		6.927 (df = 31,489)	
F Statistic		3.031^{***} (df = 2,042; 31,489)	

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

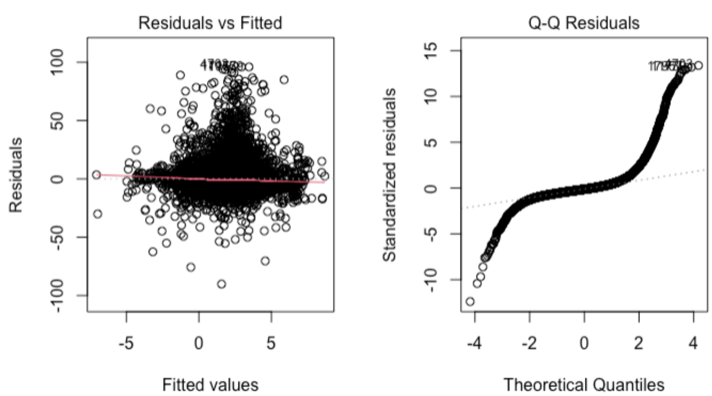

Figure 6: Bank Failure with Time and Entity Fixed Effects Model Diagnostics

Coefficient Interpretation

We decide to use the fixed effects model as model which we interpret because this model performs the best and is the most intuitive.

The coefficients from this model are quite different from what we hypothesized and may suggest that our regression is not capturing the relationships we would like it to because of potential confounding variables, reverse causality, or other endogeneity problems. Recall that a negative coefficient tells us that a 1 p.p. increase in this variable at time $t-1$ is associated with a deposit flight at time t. A positive coefficient tells us that a 1 p.p. increase in this variable at time $t-1$ is associated with a deposit inflow at time t.

First, we see that higher assets in the previous period predicts a significant deposit flight in the next period. We expected that banks with higher assets are considered to be a “safer” place to place one’s money all else equal. We would not have expected there to be a deposit outflow predicted for bigger banks in a next period. This could be because there may be some degree of mean reversion in assets. In other words, a bank with high assets (and thus high deposits) may have a value that reverts closer to the mean in the next period. It also could be because a bank with higher assets may deliberately try to reduce reliance on deposits to diversify funding sources. We also may be facing an issue of reverse causality where a bank expecting future deposit outflows holds greater assets in the previous period. Regardless of how we explain this coefficient, this is a non-intuitive outcome that goes against our preexisting knowledge. This suggests there may be other factors at play in this regression that muddle the relationship between holding these specific assets and bank deposit flight. We see a similar relationship for cash which we think can be explained in the same way as the assets coefficient.

For deposit types, we find that the coefficient for brokered deposits is positive. This is also the opposite direction from what we expected, but we believe there is a reasonable explanation for this coefficient. Banks that increase their reliance on brokered deposits are usually banks that are trying to stem an outflow of deposits by basically "buying" more expensive deposits. As such, we expected an increase in brokered deposit use to coincide with deposit outflows, but the opposite is true in this regression. This may indicate that the average bank who is picking up brokered deposits is buying enough deposits to make up for lost deposits meaning the use of brokered deposits is associated with deposit inflow.

Other deposit types have negative coefficients probably because they are deposit types that can easily leave the bank unlike brokered deposits. This theory appears to be true especially given that interest-bearing deposits have a more negative coefficient since they are more sensitive to bank-specific rates and actions.

Lastly, we see that having a higher amount of securities, even long-term securities, is associated with a deposit inflow in the next period. Again, this is the opposite of what we expected considering how much of the March 2023 banking crisis was driven by banks reaching for yield with long-term securities. It is unclear why securities would be associated with greater deposits in the next period unless these asset allocations are endogenously chosen by the bank based on their expectations. In other words, we might be capturing the effect of bank increasing their securities portfolio and taking on more risk in a previous quarter precisely *because* they expect their deposits to increase in the next periods.

A similar argument follows for loans. A higher loan total and medium-to-long-term loans are associated with deposit inflows which could reflect the same bank decision-making discussed in the securities case.

Lastly, we find it surprising that the uninsured ratio variable was insignificant. Many of the biggest bank runs have occurred on banks with higher uninsured deposit ratios precisely because individual depositors were scared of losing their money if the bank failed. However, we can rationalize this result by looking at two competing effects. First is the "bank-run" effect where depositors are more weakly attached to the bank if their deposits are uninsured, leading to significant outflows in the event of any crisis. The second is the fact that uninsured deposits are also volatile in the positive direction (deposit inflows). Uninsured deposits typically come from big businesses and high net worth individuals rather than mom and pops who park their money in the bank for the long-term. This means that banks with high uninsured deposit ratios likely also have quarters of strong deposit inflows that may cancel out the occasional outflow on average. Silicon Valley Bank (SVB), an institution with a high percent of uninsured deposits, is a great example of both sides of this effect. Since SVB's clients were primarily businesses in Silicon Valley, they saw huge deposit inflows when these businesses started doing quite well and huge outflows in the event of their risk management failures as a result of their high uninsured deposit percentage.

Ultimately, what we find from the results of this regression is that it is 1) extremely difficult to predict bank stability just using balance sheet and income statement variables and 2) there are likely many other confounding factors and problems of endogeneity that muddle the relationship between holding any specific asset or liability and the stability of a bank. In this case, exogenous changes in these assets may be required to try to understand the true relationships between these assets/liabilities and bank stability.

Discussion

Summary and Implications

For the profitability component of this study, we found that a time and entity fixed effects model that regressed bank NIM against its various assets was a reasonable fit for our dataset. The adjusted R-squared value of 0.99 and minimized AIC value suggest that this regression successfully accounts for much of the variability in bank profitability observed in the dataset. Given that our AIC value is low and the number of predictors compared to observations is reasonable, we have reason to believe that this model is not overfit.

In this work with bank profitability, we sought to balance the model's goodness of fit with its complexity. Our initial baseline model was the most simple with the fewest parameters, but it lacked explanatory power. Introducing time and entity fixed effects increased model complexity but dramatically improved explanatory power. These results suggest that there are indeed real effects on bank profitability that depend on temporal factors (e.g., macroeconomic trends) and are specific to each bank (e.g., bank investment strategy). In this specific case, increasing complexity was necessary for producing an accurate, intuitive model.

Interpreting the final model provided interesting insights on the predictors of bank profitability. We found that holding more short- and long-term securities is expected to increase bank profitability, while holding more medium-term securities is expected to decrease bank profitability. A similar time and category dependence was apparent for a bank's loan holdings as well. Strikingly, offering more loans of any type was expected to increase bank profitability. That said, personal and commercial & industrial loans were expected to have the greatest positive contribution to profitability. Time-wise, our regression suggested that short- and long-term loans were expected to bring in the most profit. Similar to the duration dependence seen with securities, mid-term loans contributed the least to bank profitability.

The policy implications of this result are that 1) encouraging bank lending appears to be both profitable for a bank and, as we already know, useful in greasing the wheels of the financial system. In other words, these results appear to confirm that lending is a good thing that should be encouraged despite increasing findings of lending friction in banking literature! 2) Bank profitability does appear to increase when holding longer-term securities and loans which can suggest that the risk introduced by duration is outweighed by the outsized returns these assets generate. In other words, reaching for yield has appeared to be a successful strategy for banks on average which may suggest to policymakers that this bank risk-taking is not as detrimental as initially thought. However, both of these propositions come from a non-causal, correlation analysis and should be further explored to establish causality before any action is taken on these results.

Our bank stability analysis was less successful than the profitability analysis. Like the profitability model, we balance the model's goodness of fit with its complexity. We again find that the model controlling for time and entity fixed effects performed the best in terms of both AIC and R^2_{adj} metrics which suggests that temporal factors and bank-specific factors are related to deposit flight outcomes. However, compared to the profitability model, significantly less variance in deposit flight was explained by our model. In addition, many of the variables had coefficients with counterintuitive interpretations. What this analysis seems to suggest is that our regression likely did not pick up the actual effect of holding a certain asset on bank stability. Instead, problems of confounding variables, reverse causality, and endogeneity likely muddled the relationship between our predictor and response variables. As a result, however, it appears that trying to predict forms of bank stability using the balance sheet and income statement of a bank from the previous period is quite difficult.

The implication of this result is that policymakers need to go beyond simple balance sheet predictive models when they engage in stress-testing. The raw financials of a company typically does not tell us nearly enough to predict a bank's stability and qualitative analysis is likely required to fully understand how stable a bank is.

Challenges, Limitations, and Future Work

A major challenge we encountered in this study was identifying the best set of predictors to include in our regressions that would make for not only well-formulated but also interpretable models. For example, after some initial model-building, we decided to scale our predictor variables for the profitability regression as percent of a bank's total assets. For one, this put our coefficient parameter estimates on a reasonable scale. Secondly, this transformation was important for the interpretability of our coefficients. Our investigation into profitability was not concerned with the raw amount of certain assets, as this variability is largely determined by variability in bank size as measured by total assets. Instead, the more meaningful question was how the *distribution* of a bank's holdings across its available assets was predictive of its profitability, for which it made sense to express our predictors relative to each bank's total assets.

In the bank stability analysis, we also had to redo our analysis after recognizing that a bank's deposit flight is determined primarily not by its assets in the present by its assets in the past. This realization led us to identify one-period time-lagged predictors as our best bet.

Our study may be limited by external variables not controlled for in our model. For example, bank reputation at a certain point in time and socioeconomic disruptions like COVID-19 can have profound impacts on the financial system, while not explicitly showing up in any of the predictors we had access to in this dataset. Although we sought to account for these variables' effects through time and entity fixed effects modeling, this is a less precise approach than if we were able to explicitly control for these factors. In addition, specific changes in policy over time may have changed the relationships between our predictor and response variables. For example, after the Dodd-Frank Wall Street Reform Act, certain assets may have been less profitable than before due to new capital restrictions which could affect our parameter estimates. As such, future research may benefit from focusing on the past few years (although the landscape may be temporarily different due to COVID-19).

Further, in our analysis of bank stability and failure, our regression models may have been hindered by reverse causality in the actual dynamics of the financial system. Our analysis assumed that assets held in the prior financial quarter would be predictive of deposit flight. In practice, however, banks may anticipate periods of deposit flight and respond by holding assets in the present. In this way, our response variable of (predicted) deposit flight may actually be impacting our predictor variables. The same problem may be present in our profitability analysis. For example, it is possible that banks expecting greater profitability just hold more loans and that the mechanism is not that loans are associated with greater profitability. This issue of reverse causality plus the earlier issue of omitted variables tells us that causal inference may be the best next step to confirm our findings.

Another consideration specific to our work with bank stability is the timescale of the dynamics of the financial system. In this paper, we assumed that predictors related to a bank's assets one financial quarter in the past would be predictive of deposit flight banks experience in the present. This lag time, however, may be different from the actual timescale on which deposit flight reacts to a bank's standings. A future direction for this project includes screening a range of lag times for our regression and identifying which leads to the best-performing model.

As mentioned earlier, we believe that the best next step for our analysis is to try to engage in some causal inference. This would likely require us trying to use exogenous variation in the composition of assets held by banks to try to establish a causal relationship between our predictors and response. One way we could do this is by examining policy changes and possible exogenous variation in their effects. The Dodd-Frank Wall Street Reform of 2020 and the Basel II (and later Basel III) regulations affected banks of different sizes and geographies differently and thus may provide us with the exogenous variation needed to establish causal relationships. This will require significant research to fully implement, but a correct implementation could have true, undoubted implications for policymakers.

References

[1] Alexander Gerber and Martin Christoph Hanck Schmelzer, Martin Arnold. *10.4 Regression with Time Fixed Effects | Introduction to Econometrics with R.*

Appendix

Supplementary Analysis: Mixed Model Regression for Profitability

In our analysis, we also tried implementing mixed models that would allow for random effects that vary across banks. The intuition behind this approach is that the baseline model assumes that the systematic component of the model holds generally and applies equally to all banks included in the dataset. In reality, however, banks employ different strategies and policies that likely vary widely within the dataset. These bank-specific differences, in some part, likely explain why some banks are quite profitable as measured by NIM, while other banks struggle. Controlling for these bank-specific differences using random effects promised to improve the explanatory power of our baseline model. This may have the advantage over our fixed effects model of better estimating variability across groups and increasing the generalizability/fit of the model.

First, we fit a mixed model with a random intercept, indexed by bank ID. The subject-specific formalism for this model is:

$$Y_{i,t} = \alpha_i + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_{20} x_{20,i,t} + \epsilon_{it},$$

where the notation is identical as before, except that α_i is a random intercept that varies for each each bank i. Under the assumptions of mixed linear regression models, we have that $\alpha_i \overset{iid}{\sim} N(\mu_\alpha, \sigma_\alpha^2)$, where the mean and variance parameters are constant. Implementing this mixed model gives $AIC = 61,177.54$ (Table A.1).

Table A.1: Profitability Mixed Model with Random Intercept

Variable	Coefficient	Std. Error	p-value
Securities	0.012***	0.001	<0.01
Securities 3mo	−0.017***	0.002	<0.01
Securities 3-12mo	−0.001	0.003	0.536
Securities 1-3 Yr	−0.019***	0.002	<0.01
Securities 3-5 Yr	−0.018***	0.002	<0.01
Securities 5-15 Yr	−0.007***	0.001	<0.01
Securities 15 Yr	−0.013***	0.001	<0.01
Demand Dep	0.002***	0.0005	<0.01
Deposit	0.002**	0.001	<0.05
Noninterest Deposit	0.001	0.001	0.265
Uninsured Deposit	−0.005***	0.0004	<0.01
Liabilities	−0.048***	0.001	<0.01
Loan Total Net	−0.054***	0.003	<0.01
Real Estate Loan	0.016***	0.002	<0.01
CRE Loan	0.008***	0.001	<0.01
C&I Loan	0.017***	0.002	<0.01
Personal Loan	0.050***	0.002	<0.01
Other Loans	0.005**	0.003	<0.05
Loan 3mo	0.072***	0.003	<0.01
Loan 3-12mo	0.069***	0.003	<0.01
Loan 1-3 Yr	0.065***	0.003	<0.01
Loan 3-5 Yr	0.061***	0.003	<0.01
Loan 5-15 Yr	0.056***	0.003	<0.01
Loan 15 Yr	0.067***	0.003	<0.01
Log Assets	−0.260***	0.009	<0.01
Constant	9.419***	0.185	<0.01
Observations		35,666	
Log Likelihood		−30,560.770	
Akaike Inf. Crit.		61,177.540	
Bayesian Inf. Crit.		61,415.030	

Note: *p<0.1; **p<0.05; ***p<0.01

Second, we decided to fit a model that included both a random intercept and a random slope parameter, indexed by bank ID. We chose to allow random slope estimates for the log-transformed assets predictor. The reasoning behind this selection is that in the previously described regressions, this predictor variable consistently had a high estimate value and high level of statistical significance, as measured by a t-based hypothesis test. Intuitively, we expect that bank-specific random effects correlate with its size (i.e., the total amount of assets) as different-sized banks likely have contrasting strategies, clientele, and assets distributions. This model can be formalized as:

$$Y_{i,t} = \alpha_i + \beta_{\ln(\text{assets}),i} \cdot \ln(\text{assets})_{i,t} + \beta_1 x_{1,i,t} + \beta_2 x_{2,i,t} + ... + \beta_{29} x_{29,i,t} + \epsilon_{it},$$

with the same parametrization as before, except that $\beta_{\ln(\text{assets}),i} \overset{iid}{\sim} N(\mu_\beta, \sigma^2_\beta)$ is a random slope parameter fit for the log-transformed assets predictor. Fitting this model gives $AIC = 54474.43$ (Table A.2).

Ultimately, these methods performed worse (as measured by AIC) than our time and entity fixed effects model, so we chose to omit them from our final analysis.

Table A.2: Profitability Mixed Model with Random Intercept and Slope

Variable	Coefficient	Std. Error	p-value
Securities	0.014***	0.001	<0.01
Securities 3mo	−0.007***	0.002	<0.01
Securities 3-12mo	−0.005**	0.003	<0.05
Securities 1-3 Yr	−0.019***	0.002	<0.01
Securities 3-5 Yr	−0.018***	0.002	<0.01
Securities 5-15 Yr	−0.007***	0.001	<0.01
Securities 15 Yr	−0.010***	0.001	<0.01
Demand Dep	0.004***	0.0005	<0.01
Deposit	−0.0001	0.001	0.926
Noninterest Deposit	−0.0002	0.001	0.710
Uninsured Deposit	−0.003***	0.0004	<0.01
Liabilities	−0.048***	0.002	<0.01
Loan Total Net	−0.042***	0.003	<0.01
Real Estate Loan	0.014***	0.002	<0.01
CRE Loan	0.015***	0.001	<0.01
C&I Loan	0.013***	0.002	<0.01
Personal Loan	0.053***	0.002	<0.01
Other Loans	−0.003	0.003	0.297
Loan 3mo	0.063***	0.003	<0.01
Loan 3-12mo	0.063***	0.003	<0.01
Loan 1-3 Yr	0.054***	0.003	<0.01
Loan 3-5 Yr	0.052***	0.003	<0.01
Loan 5-15 Yr	0.047***	0.003	<0.01
Loan 15 Yr	0.058***	0.003	<0.01
Log Assets	−0.280***	0.024	<0.01
Constant	9.510***	0.393	<0.01
Observations	35,666		
Log Likelihood	−27,207.220		
Akaike Inf. Crit.	54,474.430		
Bayesian Inf. Crit.	54,728.890		

Note: *p<0.1; **p<0.05; ***p<0.01

Other Tables

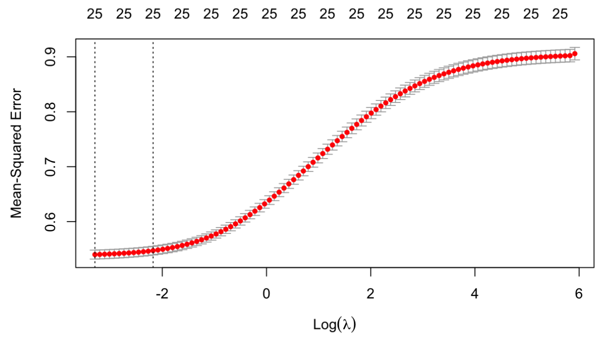

Figure A.1: Ridge Regression Cross Validation Run

Variable	Coefficient
Securities	0.0134
Securities 3mo	-0.0095
Securities 3-12mo	-0.0208
Securities 1-3yr	-0.0125
Securities 3-5yr	-0.0038
Securities 5-15yr	0.0027
Securities 15yr	-0.0039
Demand Deposit	-0.0031
Deposit	0.0050
Noninterest Deposit	0.0147
Uninsured Deposit	-0.0056
Liabilities	-0.0668
Loan Total Net	0.0113
Real Estate Loan	0.0013
CRE Loan	0.0068
CI Loan	0.0054
Personal Loan	0.0359
Other Loans	-0.0253
Loan 3mo	0.0155
Loan 3-12mo	0.0338
Loan 1-3yr	0.0184
Loan 3-5yr	0.0006
Loan 5-15yr	0.0080
Loan 15yr	0.0123
Log Assets	-0.0677

Table A.3: Profitability Ridge Regression Coefficients

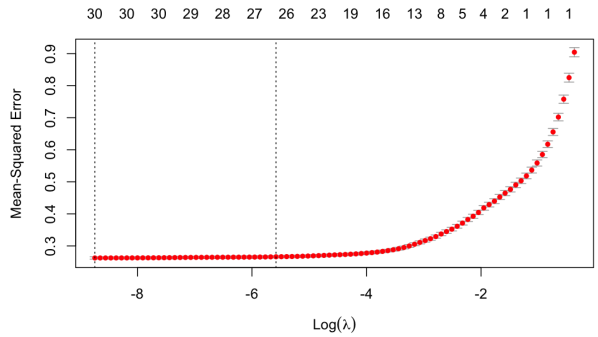

Figure A.2: Profitability Ridge Regression Cross Validation Run

Variable	Coefficient
Securities	0.0188
Securities 3mo	-0.0152
Securities 3-12mo	-0.0246
Securities 1-3yr	-0.0177
Securities 3-5yr	-0.0077
Securities 5-15yr	-0.0021
Securities 15yr	-0.0084
Demand Deposit	-0.0034
Deposit	0.0060
Noninterest Deposit	0.0149
Uninsured Deposit	-0.0068
Liabilities	-0.0693
Loan Total Net	-0.0599
Real Estate Loan	0.0094
CRE Loan	0.0065
CI Loan	0.0130
Personal Loan	0.0434
Other Loans	-0.0176
Loan 3mo	0.0807
Loan 3-12mo	0.1025
Loan 1-3yr	0.0830
Loan 3-5yr	0.0631
Loan 5-15yr	0.0715
Loan 15yr	0.0775
Log Assets	-0.0727

Table A.4: Profitability Lasso Regression Coefficients

Variable	Coefficient
Log Assets Lagged	-0.0867
Uninsured Ratio Lagged	0.0167
Noninterest Deposit Std Lagged	-0.0511
Interest Deposit Std Lagged	-0.0603
Brokered Deposit Std Lagged	0.0261
Insured Brokered Deposit Std Lagged	0.0011
Cash Std Lagged	-0.0500
HTM to Total Ratio Lagged	-0.0205
Treasuries AFS FV Std Lagged	0.1149
Treasuries AFS AC Std Lagged	-0.1241
Securities 5-15 Year Std Lagged	-0.0013
Securities 15 Year Std Lagged	0.0145
Net Interest Margin Lagged	0.0922
Deposit Rate Lagged	-0.4602
Loan Total Net Std Lagged	0.0385
CRE Loan Std Lagged	-0.0145
CI Loan Std Lagged	0.0130
Loan 5-15 Year Std Lagged	0.0192
Loan 15 Year Std Lagged	-0.0176

Table A.5: Stability Ridge Regression Coefficients

Variable	Coefficient
Log Assets Lagged	-0.1004
Uninsured Ratio Lagged	0.0170
Noninterest Deposit Std Lagged	-0.0566
Interest Deposit Std Lagged	-0.0660
Brokered Deposit Std Lagged	0.0296
Insured Brokered Deposit Std Lagged	-0.0023
Cash Std Lagged	-0.0514
HTM to Total Ratio Lagged	-0.0218
Treasuries AFS FV Std Lagged	1.4142
Treasuries AFS AC Std Lagged	-1.3937
Securities 5-15 Year Std Lagged	0.0008
Securities 15 Year Std Lagged	0.0176
Net Interest Margin Lagged	0.0944
Deposit Rate Lagged	-0.4598
Loan Total Net Std Lagged	0.0405
CRE Loan Std Lagged	-0.0143
CI Loan Std Lagged	0.0128
Loan 5-15 Year Std Lagged	0.0197
Loan 15 Year Std Lagged	-0.0174

Table A.6: Bank Stability Lasso Regression Coefficients

Table A.7: Bank Failure: Interaction Effects Regression with Stepwise Selection

Variable	Coefficient	Std. Error	p-value
Uninsured Ratio	−0.081***	0.017	<0.01
Noninterest Deposit Std	0.027***	0.006	<0.01
Domestic Deposit Std	−0.076***	0.010	<0.01
Brokered Deposit Std	0.077***	0.005	<0.01
Cash Std	−0.075***	0.015	<0.01
HTM to Total Ratio	0.026	0.018	0.110
Securities 15 Year Std	0.110***	0.031	<0.01
Net Interest Margin	0.230*	0.134	0.072
Deposit Rate	−0.536***	0.090	<0.01
Loan Total Net Std	0.036***	0.008	<0.01
CRE Loan Std	−0.052***	0.007	<0.01
CI Loan Std	−0.153***	0.032	<0.01
Loan 5-15 Year Std	−0.208***	0.041	<0.01
Uninsured Ratio:Noninterest Deposit Std	−0.001***	0.0002	<0.01
Uninsured Ratio:Domestic Deposit Std	0.001***	0.0002	<0.01
Uninsured Ratio:Cash Std	0.001***	0.0002	<0.01
Uninsured Ratio:HTM to Total Ratio	−0.002***	0.0004	<0.01
Uninsured Ratio:Loan 5-15 Year Std	−0.0005**	0.0002	0.032
Uninsured Ratio:CRE Loan Std	0.001***	0.0002	<0.01
Uninsured Ratio:Securities 15 Year Std	0.0001	0.0005	0.788
Uninsured Ratio:Net Interest Margin	−0.005***	0.001	<0.01
Uninsured Ratio:Deposit Rate	0.004	0.002	0.103
Uninsured Ratio:Loan Total Net Std	0.0001	0.0002	0.620
Uninsured Ratio:CI Loan Std	0.0005**	0.0002	0.048
Domestic Deposit Std:Cash Std	0.002***	0.0002	<0.01
Domestic Deposit Std:Loan 5-15 Year Std	0.003***	0.0005	<0.01
Domestic Deposit Std:CI Loan Std	0.002***	0.0003	<0.01
Domestic Deposit Std:Net Interest Margin	−0.002	0.001	0.152
Brokered Deposit Std:Deposit Rate	−0.009***	0.002	<0.01
Securities 15 Year Std:Net Interest Margin	−0.034***	0.008	<0.01
Net Interest Margin:Loan Total Net Std	−0.003**	0.002	0.044
HTM to Total Ratio:Net Interest Margin	0.001	0.001	0.576
Loan Total Net Std:CI Loan Std	0.0001	0.0003	0.865
Constant	5.484***	0.945	<0.01
Observations		35,472	
R^2		0.040	
Adjusted R^2		0.039	
Residual Std. Error		5.821 (df = 35,438)	
F Statistic		44.526*** (df = 33; 35,438)	

Note: *p<0.1; **p<0.05; ***p<0.01