



Appendix

Summary of key technical features of the four baseline models

We summarize the key features of the four baseline models in this appendix. We then provide data on the performance of the models. Per the body of the paper, we chose simple models to provide baseline estimates of future consolidation based on historical patterns. Observers can then compare current consolidation against these historical trends. The models were not selected because they necessarily provide the most accurate forecast of the future number of banks.

Additional technical specifications are available from the authors.

Model 1: Simple, Constant Extrapolation of Consolidation Trend

The first baseline model is a naïve autoregressive process on the number of banks. It captures the trend in the number of banks:

$$y_t = \beta y_{t-1} + \varepsilon$$

The series are not stationary; therefore, the β captures the trend. States, the Ninth District and the nation are modeled independently.

Model 2: Simple Trend Model Accounting for Rate of Change

The second model is an ARIMA (0,2,1) model; a moving average of the second difference model was applied to each of the states, the Ninth District and the nation independently.

$$\Delta y_t - \Delta y_{t-1} = \mu + \varepsilon_t - \beta \varepsilon_{t-1}$$

Each model was fit using an automated stepwise ARIMA fit procedure employing the Akaike Information Criterion. In almost all cases, the (0,2,1) model best fit the criterion, consistent with previous findings of Jones and Critchfield (2005).

The second modeling approach is consistent with the periods of accelerated consolidation and periods of slowing consolidation found in the data.

Model 3: Size-Dependent Consolidation Baseline

The third approach calculates a historic transition matrix of the form

$$y_t = \sum_{j=1}^n \sum_{i=1}^n \beta_{i,j} y_{i,t-1} + \beta_{entry} y_{t-1}$$

There are i asset size groups with $y_{i,t}$ banks. The coefficient $\beta_{i,j}$ is the share of banks in group i that transition to group j . We chose the asset size groups as follows:

- The largest asset size group is banks larger than \$10 billion, a standard definition of a “large bank” in the bank analytical literature.
- The remaining asset groups were chosen so that they contained the same number of banks in the final observation before we make our forecast. Each asset group contains about 900 banks in 2013. In 2000, there were more banks in low asset categories and a smaller share of banks in high asset categories. The number of entrants is scaled at the number of current banks in the states, the Ninth District and the nation. The transition matrix $[\beta_{i,j}]$ is calculated from national data at a quarterly frequency.
- Given that the estimation of the model is done on a national basis, forecasts for each region (the states, the Ninth District and the nation) are differentiated only by the initial distribution of banks across asset groups. Other parameters are the same for each region.

This modeling approach will eventually provide a stable distribution of banks. None of the state’s current banking sector asset distributions are close to that stable distribution. As a result, this modeling approach will forecast declining bank population. Janicki and Prescott (2006) observed changing transition matrices from decade to decade, so this model uses data from the last decade for calculating the transition matrix.

The transition matrix takes the following form. Each column represents the expected size of a bank next period or probability of exit given its current size.

	Starting size of banks							
	< \$37 m	< \$58 m	< \$79 m	< \$114 m	< \$174 m	< \$316 m	< \$10 b	> \$10 b
< \$37 m	74.61%	7.01%	0.53%	0.08%	0.04%	0.03%	0.02%	0.01%
< \$58 m	17.87%	63.48%	10.43%	0.59%	0.05%	0.03%	0.02%	0.00%
< \$79 m	2.73%	20.88%	55.31%	7.55%	0.47%	0.02%	0.04%	0.00%
< \$114 m	0.44%	4.51%	25.91%	63.59%	9.19%	0.39%	0.02%	0.00%
< \$174 m	0.09%	0.54%	4.08%	21.42%	65.50%	6.45%	0.15%	0.00%
< \$316 m	0.06%	0.10%	0.45%	2.86%	19.53%	76.73%	3.72%	0.08%
< \$10 b	0.07%	0.07%	0.17%	0.22%	1.44%	12.16%	90.24%	4.98%
> \$10 b	0.01%	0.00%	0.00%	0.00%	0.00%	0.03%	0.60%	88.73%
Exit	4.12%	3.41%	3.12%	3.68%	3.78%	4.16%	5.18%	6.19%

Model 4: Bank Survival Baseline

Model 4 combines a logit model of bank survival and a Poisson model for the arrival of new banks within each state. Forecasts are made calculating the average survival of banks in each state and the expected number of new banks. We estimate the following equation:

$$y_t = \sum_{i=1}^N \frac{Prob(x_i, x_{region})}{N} y_{t-1} + F(y_{new,t-1}, \overline{y_{new}})$$

The first part of the equation is the individual projected outcome for banks estimated using a logit regression. The independent variables are bank specific and state dependent. The second portion is the expected number of new banks estimated with a Poisson regression on a state's average number of entries, last period entries and an interaction term.

The model employs a number of independent variables that attempt to capture three phenomena: poor bank performance that could lead to failure or distressed consolidation, features of banks that may lead one bank to acquire another and state trends that could affect the speed of consolidation. We consider a wide variety of variables for inclusion in the model. We include variables that meet baseline measures of economic and statistical significance. All included variables are significant at the 1 percent confidence level and individually improve the Akaike Information Criterion.

The model is estimated on national data.

Variables in the analysis include:

- *Supervisory CAMELS rating*: Federal bank supervisors rate commercial banks on a 1 to 5 “CAMELS” rating scale with “1” rated banks in the strongest condition and “5” rated banks in the weakest. We include dummy variables for the 1 to 5 supervisory rating. We include a one-year lag. We also interact the rating with capital and bank share of state deposits. Lower CAMELS ratings mean a greater likelihood of survival. Higher ratings and low capital ratios are associated with higher chances of failure. Higher state deposit ratios tend to indicate expanding state where consolidation is likely. Banks with weak ratings in state with more deposits are less likely to merge or fail.
- *Share of loans in nonaccrual*: The percentage of loans classified as not accruing interest measures the quality of the bank's loan portfolio. A higher share of nonaccrual loans as a share of total assets is associated with a decreasing probability of survival.
- *Deposit asset ratio*: Banks with more deposit fundings are more likely to consolidate. An interaction term between deposit asset ratio and capital ratio is positively correlated with the probability of merger. Well-capitalized banks with high deposit ratios have a higher probability of consolidating through mergers, all else equal.
- *Capital ratio*: The simple common-equity-to-total-assets ratio measures bank condition. The interaction with the capital ratio and deposit asset ratio is discussed above. As noted, we also interact capital with supervisory ratings. More capital decreases the likelihood of failure in low-rated banks, but banks with average or better ratings are more likely to consolidate when they have higher capital ratios. Lagged capital ratios are included to capture changes in the ratio: Declines in the ratio increase the chance of consolidation.

- *Loan-to-asset ratio*: Banks with higher loan-to-asset ratios are more likely to consolidate.
- *State deposit ratio*: The average deposit-to-asset ratio of banks in a state is negatively correlated with consolidation. As mentioned above, this ratio interacts with the supervisory CAMELS rating in a significant way.
- *Previous year, state survival rate*: Recent consolidation increases the likelihood of further consolidation. The state consolidation rate from the previous year remains highly significant even in the presence of additional variables.
- *Rural/urban type*: Dummy variables for five MSA classifications are included. Banks in urban areas (metros of at least 50,000) are more likely to consolidate. Banks in smaller towns and rural areas are less likely to consolidate.
- *Charter type*: National banks are more likely to survive; nonmember banks are slightly more likely to consolidate or fail; state member banks are most likely to consolidate.
- *Federal Reserve district*: A dummy variable for each of the 12 Federal Reserve districts.

Performance

The following tables describe the root mean square error of the models' quarterly forecast since 1985 and the distribution of the errors over the same horizon. In terms of root mean square error, the data suggest that deviations from the model forecast are consistent with historical performance. There is negative skew in the first three models; in other words, there are occasional large overestimates of the number of banks. The bank survival model has a positive skew biased upward for Ninth District banks; that is, the model underestimates the number of banks.

Root mean squared error of quarter ahead projections from 1985 to 2013 for 9 th District states				
RMSE	Trend	Rate of Change	Asset Size	Bank Survival
Minnesota	4.2	4.1	4.2	9.8
Montana	2.3	2.3	2.3	1.8
North Dakota	1.5	1.4	1.5	2.0
South Dakota	1.2	1.2	1.2	1.3
NW Wisconsin	1.2	1.2	1.2	-
UP Michigan	1.0	1.0	1.0	-

Distribution of errors of quarter ahead projections from 1985 to 2013 for 9 th District states								
Residual Distribution	Trend		Rate of Change		Asset Size		Bank Survival	
	5%	95%	5%	95%	5%	95%	5%	95%
Minnesota	-7.7	4.7	-7.9	6.6	-7.9	4.5	2.9	15.8
Montana	-4.2	1.9	-3.2	2.3	-4.5	1.8	-0.4	3.2
North Dakota	-2.5	1.6	-2.0	1.4	-2.5	1.6	0.3	3.9
South Dakota	-2.4	1.6	-2.3	1.7	-2.4	1.6	-0.8	2.2
NW Wisconsin	-2.4	1.5	-2.3	1.5	-2.5	1.4	-	-
UP Michigan	-1.7	1.1	-1.6	1.2	-1.9	1.1	-	-