Forecasting Bank Loan Portfolio Credit Quality

Abstract

Bank failures are a result of the bank's financial condition. A bank's financial condition is impacted heavily by the performance of its loan portfolio. Asset quality is an important determinant of portfolio performance and improved forecasts of portfolio credit quality provide banks, their regulators, and policy makers enhanced surveillance capabilities. In this Research Note, we characterize the relationship between the WAIN Street Business Default Index (BDX) and the credit quality of loan portfolios at US banks. Our analysis shows that incorporating BDX data into regression models improves prediction accuracy of portfolio delinquency rates and charge-offs. In a majority of instances, a causality between the BDX and portfolio credit quality can be established, providing a stronger basis for forecasting. The analysis shows that there is a strong relationship between BDX data concerning very small businesses and bank loan portfolio credit quality.

Data

We use the WAIN Street Business Default Index (BDX) and its business-size based sub-indices as the predictor (independent) variable. The BDX is a monthly gauge of nationwide business defaults derived from the credit performance of nearly 18 million US businesses across all industries, geographies, and business size. The index is quoted as a seasonally adjusted annualized rate. The index inception date is December 2009. The monthly series is aggregated into a quarterly series and seasonally adjusted to remove residual seasonality for this analysis.
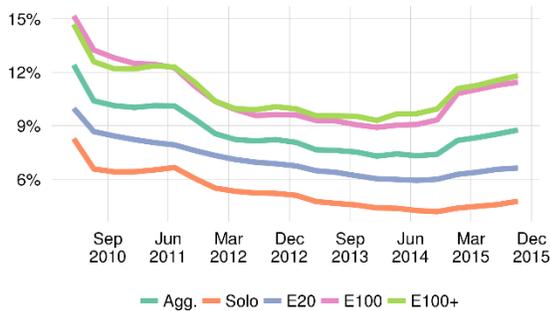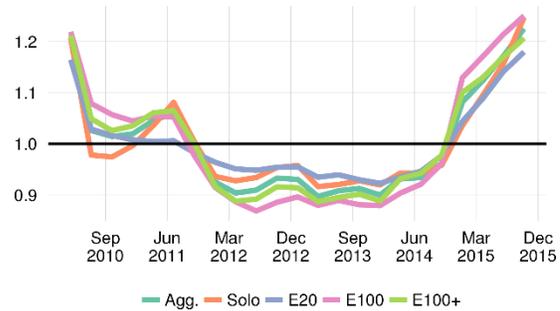

Figure 1 Quarterly BDX

Figure 2 Ratio-detrended quarterly BDX

Business Default Index	Definition
Aggregate	All businesses
Solo	Businesses without paid employees
E20	Businesses with 1 to 19 employees
E100	Businesses with 20 to 99 employees
E100+	Businesses with 100 or more employees

For the dependent variable, we use the delinquency rate and net charge-offs of loan portfolios of bank peer groups based on asset size. We get the non-seasonally adjusted, quarterly data starting from Q1 1991 from the Federal Reserve. The data is seasonally adjusted for this analysis. Table 5 describes the 28 dependent series.

Our final data set covers twenty-two quarters from Q1 2010 to Q2 2015.

Seasonal Adjustment

We use the Census Bureau's X-13ARIMA-SEATS program for seasonal adjustment. We set the sensitivity for outlier detection to low[1] since our analysis encompasses a brief and extraordinary period.

Data Detrending

Both the BDX and portfolio credit quality data exhibit a strong time trend. We use the Hodrick–Prescott filter[2] to identify the trend component. We de-trend each value by taking the ratio of the observed value and the trend. Hence, for the final series, values greater than/less than one indicate that the observed value is above/below trend. The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test confirms that all final series are trend stationary.

Methodology

As a compromise between managerial and academic perspectives, we fix the time horizon for this analysis at six quarters. Thus, our analysis incorporates at most six lags of any variable. We perform a pairwise analysis of each BDX predictor and portfolio credit quality dependent variable. We identify predictors for each portfolio credit quality series that improve prediction accuracy and Granger cause. All models that are not significant at the 0.05 level are discarded.

Assessing improvement in prediction accuracy

To gauge the improvement in prediction accuracy we fit two separate regression models[3]. The *restricted* model consists solely of lags of the dependent variable. The *unrestricted* model includes lags of both the dependent and independent variables. We gauge improvement in prediction accuracy by comparing model standard errors. We calculate the ratio of the standard errors of the unrestricted and restricted models and consider values less than one to be an improvement since that indicates the unrestricted model has a lower standard error. Similarly, we calculate the ratio of the adjusted R-squared values of the unrestricted and restricted models and consider values greater than one to be an improvement since that indicates increased explanatory power of the unrestricted model.

Establishing causality

Granger causality determines whether a predictor time series is useful in forecasting a dependent time series based on the presence of a statistically significant relationship between the dependent variable and lagged values of the predictor variable. In other words, a variable X Granger causes variable Y if variable Y can be better predicted using the histories of both X and Y than it can be predicted using the history of Y alone. A challenge in testing for Granger causality is identifying the amount of history to incorporate – the lag order. We take a pragmatic approach and search for the smallest lag order less than or equal to six quarters at which the BDX Granger causes portfolio credit quality at the 0.05 significance level.

Results

We report both the improvement in prediction accuracy and Granger causality results in Table 4. The BDX based on very small businesses, E20 and Solo, is a good predictor of bank loan portfolio credit quality for a majority of cases. We report the best predictor for each portfolio credit quality measure and whenever

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[1] We set the value to which the absolute values of the outlier t-statistics are compared to as 4.

[2] We use a smoothing parameter, lambda, value of 25,600 for the quarterly data which is higher than the "standard" 1,600 and in line with recent suggestions of using larger values for lambda.

[3] The models are selected by a simple search that eliminates variables which are not significant at the 0.05 level.

the best predictor is not a very small business predictor, we additionally report the very small business predictor.

Identifying best predictors

Our goal is to forecast and hence, we use standard error rather than adjusted R-squared to choose amongst predictors. We define the best predictor to be the one that provides the greatest improvement in standard error and prefer predictors that also Granger cause. We break ties by using the p-value of the Granger causality test.

Commercial loans

The E20 BDX substantially improves prediction accuracy and Granger causes commercial loan portfolio delinquencies and charge-offs for all banks as a group and also for the largest banks – banks with assets in excess of 20B. Consistent with practitioner experience, our analysis demonstrates that very small businesses foretell what happens in bank loan portfolios.
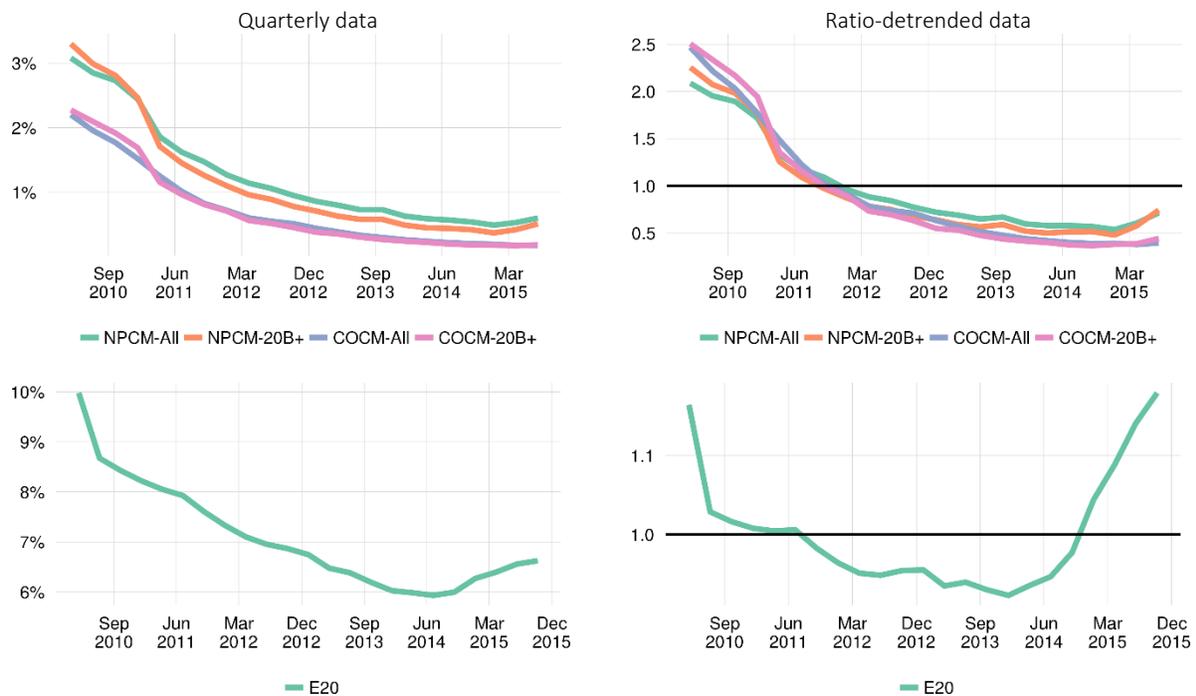

Table 1: Commercial loan portfolio relationship with BDX

Commercial loan portfolio[1]	BDX	Prediction accuracy[2]		Granger causality[5]	
		Standard error ratio[3]	Adj. R-squared ratio[4]	Lag order[6]	p-value[7]
Non-performing commercial loans					
All banks (NPCM-All)	E20	0.29	1.02	3	0.00001
Banks with assets greater than 20B (NPCM-20B+)	E20	0.20	1.02	3	0.00001
Net commercial loan charge-offs					
All banks (COCM-All)	E20	0.66	1.00	2	0.00074
Banks with assets greater than 20B (COCM-20B+)	E20	0.43	1.02	3	0.00010

Excerpted from Table 4. See Table 4 for footnotes.

Commercial real estate

The E20 and Solo BDX improve forecasts of commercial real estate (CRE) portfolio delinquencies and charge-offs. The result is intuitive. As business finances weaken, businesses falter in meeting their CRE obligations. Smaller banks are impacted later than the largest banks likely because of the local knowledge and relationships that smaller banks have with their customers.
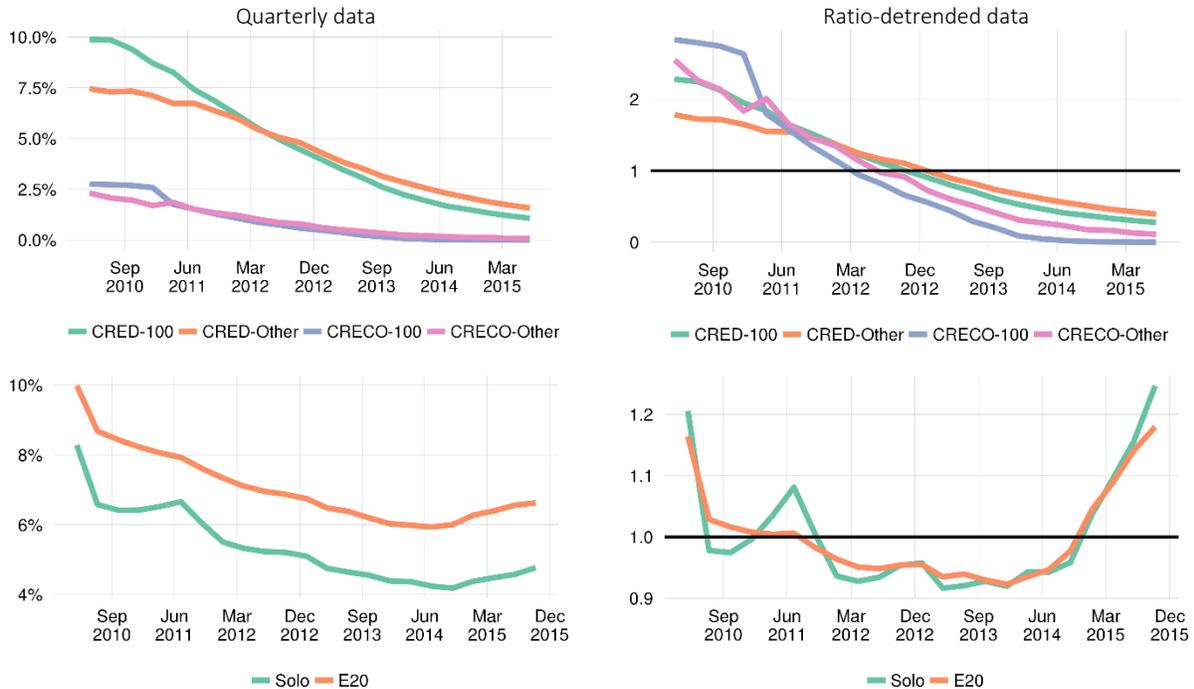

Table 2: Commercial real estate portfolio relationship with BDX

Commercial real estate portfolio[1]	BDX	Prediction accuracy[2]		Granger causality[5]	
		Standard error ratio[3]	Adj. R-squared ratio[4]	Lag order[6]	p-value[7]
Delinquency rate					
100 largest banks (CRED-100)	E100	0.62	1.00	1	0.00695
100 largest banks (CRED-100)	E20	0.65	1.00	1	0.00053
Non 100 largest banks (CRED-Other)	Solo	0.70	1.00	5	0.01840
Charge-off rate					
100 largest banks (CRECO-100)	E20	0.10	1.03	3	0.00005
Non 100 largest banks (CRECO-Other)	E100+	0.43	1.00	4	0.02261
Non 100 largest banks (CRECO-Other)	E20	0.45	1.01	4	0.00036

Excerpted from Table 4. See Table 4 for footnotes.

Consumer loans

The Solo BDX Granger causes and improves prediction accuracy by over 25% for consumer loan portfolios. For the smallest banks, the E20 BDX is a net improvement as it provides new predictive power. Although, the BDX is a gauge of business credit performance, the Solo and E20 sub-indices having predictive power for consumer loan portfolios is intuitive. It reflects the real life interaction between the finances of the business and its principals.   The Solo BDX tracks the credit performance of the self-employed and sole proprietors whose business and personal lives are intricately intertwined. Challenges on the business front quickly translate into personal financial challenges. Similarly, the E20 tracks the smallest of the small businesses. These businesses lack capital and often a personal guarantee is the only way to get capital. When the business suffers, the principal/guarantor suffers and a consumer default event occurs.
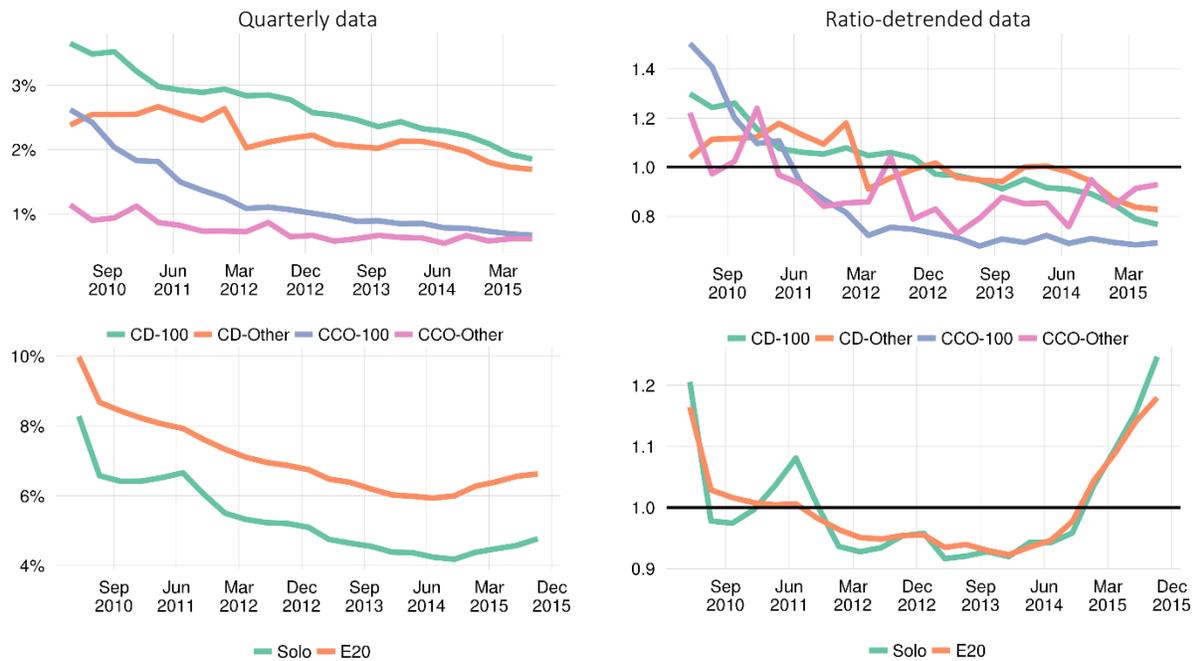

Table 3: Consumer loan portfolio relationship with BDX

Consumer loan portfolio[1]	BDX	Prediction accuracy[2]		Granger causality[5]	
		Standard error ratio[3]	Adj. R-squared ratio[4]	Lag order[6]	p-value[7]
Delinquency rate					
100 largest banks (CD-100)	Solo	0.66	1.01	2	0.03767
Non 100 largest banks (CD-Other)	Solo	0.74	1.19	4	0.01039
Charge-off rate					
100 largest banks (CCO-100)	Solo	0.41	1.06	4	0.00111
Non 100 largest banks (CCO-Other)	E20			3	0.00375

Excerpted from Table 4. See Table 4 for footnotes.

Limitations

For this Research Note, we evaluated 28 portfolio credit quality series (dependent variables) against five business default rate series (independent variables). At various points in each evaluation, we employ heuristics to automate decisions concerning model selection and other model inputs. Each technique suffers from well-known challenges. Granger causality testing is highly sensitive to the choice of lag order and tends to overfit. Lagged regression models can always benefit from additional diagnostics and tuning for outliers. We are confident of our results and happy to acknowledge that specific models could always benefit from a more robust analysis.

Conclusion

This Research Note establishes that the WAIN Street Business Default Index (BDX) has explanatory power for the credit quality of loan portfolios at US banks. We find a strong causal relationship between credit performance as gauged by the BDX and actual bank portfolio experience. A methodology incorporating BDX data improves portfolio surveillance capabilities and by leveraging monthly BDX data, early warning of forthcoming quarterly results can be obtained. As the BDX reflects macroeconomic trends, it's inclusion into a stress testing framework can be valuable. Finally, this Research Note adds to the knowledge base of very small businesses foretelling macroeconomic trends.

Table 4: Relationship between BDX and portfolio credit quality

Portfolio credit quality data[1]	BDX	Prediction accuracy[2]		Granger causality[5]	
		Standard error ratio[3]	Adj. R-squared ratio[4]	Lag order[6]	p-value[7]
Non-performing commercial loans					
All banks (NPCM-All)	E20	0.29	1.02	3	0.00001
Banks with assets under 300M (NPCM-300M)	Solo	0.53	1.00		
Banks with assets between 300M and 1B (NPCM-1B)	E20	0.91	1.01	1	0.03816
Banks with assets between 1B and 10B (NPCM-10B)	Solo	0.60	1.01		
Banks with assets between 10B and 20B (NPCM-20B)	E100	0.18	1.10	4	0.00017
Banks with assets between 10B and 20B (NPCM-20B)	Solo	0.34	1.09	4	0.00741
Banks with assets greater than 20B (NPCM-20B+)	E20	0.20	1.02	3	0.00001
Net commercial loan charge-offs					
All banks (COCM-All)	E20	0.66	1.00	2	0.00074
Banks with assets under 300M (COCM-300M)	Solo	0.89	0.97		
Banks with assets between 300M and 1B (COCM-1B)	E100	0.62	1.01		
Banks with assets between 300M and 1B (COCM-1B)	Solo	0.81	0.97		
Banks with assets between 1B and 10B (COCM-10B)	E20	0.64	1.00	1	0.03812
Banks with assets between 10B and 20B (COCM-20B)	E100+	0.86	0.91		
Banks with assets greater than 20B (COCM-20B+)	E20	0.43	1.02	3	0.00010
Lease Delinquency rate					
100 largest banks (LD-100)	E100+	0.58	0.94	4	0.02283
100 largest banks (LD-100)	E20	0.72	0.80		
Non 100 largest banks (LD-Other)	E100	0.46	1.04	4	0.02038
Non 100 largest banks (LD-Other)	E20	0.50	0.99	4	0.02677
Lease Charge-off rate					
100 largest banks (LCO-100)	E20			1	0.02296
Non 100 largest banks (LCO-Other)	E100+	0.80	1.02		
Non 100 largest banks (LCO-Other)	Solo	0.97	0.64		
CRE Delinquency rate					
100 largest banks (CRED-100)	E100	0.62	1.00	1	0.00695
100 largest banks (CRED-100)	E20	0.65	1.00	1	0.00053
Non 100 largest banks (CRED-Other)	Solo	0.70	1.00	5	0.01840
CRE Charge-off rate					
100 largest banks (CRECO-100)	E20	0.10	1.03	3	0.00005
Non 100 largest banks (CRECO-Other)	E100+	0.43	1.00	4	0.02261
Non 100 largest banks (CRECO-Other)	E20	0.45	1.01	4	0.00036
Credit card Delinquency rate					
100 largest banks (CCD-100)	E100+	0.32	1.01	4	0.00001
100 largest banks (CCD-100)	Solo	0.49	1.00	4	0.00363

Non 100 largest banks (CCD-Other)	E20	0.36	1.11	5	0.03588
Credit Card Charge-off rate					
100 largest banks (CCCO-100)	E20	0.38	1.20	1	0.01501
Non 100 largest banks (CCCO-Other)	E100	0.61	1.53		
Non 100 largest banks (CCCO-Other)	E20	0.69	1.44		
Consumer Delinquency rate					
100 largest banks (CD-100)	Solo	0.66	1.01	2	0.03767
Non 100 largest banks (CD-Other)	Solo	0.74	1.19	4	0.01039
Consumer Charge-off rate					
100 largest banks (CCO-100)	Solo	0.41	1.06	4	0.00111
Non 100 largest banks (CCO-Other)	E20			3	0.00375

1. Table 5 describes the data.
2. Prediction accuracy is evaluated by comparing two models. The restricted model consists solely of lags of the dependent variable. The unrestricted model includes lags of both the dependent and independent variables. When blank, only an unrestricted model could be fitted and hence, the improvement is unbounded.
3. The ratio of the standard error of unrestricted model and restricted model. Values less than one indicate unrestricted model has a lower standard error.
4. The ratio of adjusted R-squared of the unrestricted model and restricted model. Values greater than one indicate unrestricted model has greater explanatory power.
5. The results are for Granger causality from the BDX to portfolio credit quality. When blank, there was no Granger causality at the 0.05 significance level.
6. Lag order at which Granger causality was tested.
7. The significance level of the Granger causality test.

Table 5: Definition of portfolio credit quality data variables

Portfolio credit quality data	Series ID	Description[1,2]
Non-performing commercial loans	NPCM-All	Percentage of commercial loans that are classified as non-performing. Non-performing commercial loans are those commercial loans that bank managers classify as 90-days or more past due or nonaccrual in the call report. This series includes data for all banks.
Non-performing commercial loans - 300M	NPCM-300M	Non-performing commercial loans at banks with total assets up to $300M.
Non-performing commercial loans - 1B	NPCM-1B	Non-performing commercial loans at banks with total assets from $300M to $1B.
Non-performing commercial loans - 10B	NPCM-10B	Non-performing commercial loans at banks with total assets from $1B to $10B.
Non-performing commercial loans - 20B	NPCM-20B	Non-performing commercial loans at banks with total assets from $10B to $20B.
Non-performing commercial loans - 20B+	NPCM-20B+	Non-performing commercial loans at banks with total assets above $20B.
Net commercial loan charge-offs	COCM-All	Percentage of commercial loans charged off as losses minus recoveries on loans previously charged-off. This series includes data for all banks.
Net commercial loan charge-offs - 300M	COCM-300M	Net commercial loan charge-offs at banks with total assets up to $300M.
Net commercial loan charge-offs - 1B	COCM-1B	Net commercial loan charge-offs at banks with total assets from $300M to $1B.
Net commercial loan charge-offs - 10B	COCM-10B	Net commercial loan charge-offs at banks with total assets from $1B to $10B.
Net commercial loan charge-offs - 20B	COCM-20B	Net commercial loan charge-offs at banks with total assets from $10B to $20B.
Net commercial loan charge-offs - 20B+	COCM-20B+	Net commercial loan charge-offs at banks with total assets above $20B.
Lease Delinquency rate - 100 largest banks	LD-100	Delinquency rate on lease financing receivables at banks ranked 100 largest by asset size.
Lease Delinquency rate - Non 100 largest banks	LD-Other	Delinquency rate on lease financing receivables at banks not among the 100 largest by asset size.
Lease Charge-off rate - 100 largest banks	LCO-100	Charge-off rate on lease financing receivables at banks ranked 100 largest by asset size.
Lease Charge-off rate - Non 100 largest banks	LCO-Other	Charge-off rate on lease financing receivables at banks not among the 100 largest by asset size.
CRE Delinquency rate - 100 largest banks	CRED-100	Delinquency rate on commercial real estate loans (excluding farmland) at banks ranked 100 largest by asset size.

CRE Delinquency rate - Non 100 largest banks	CRED-Other	Delinquency rate on commercial real estate loans (excluding farmland) at banks not among the 100 largest by asset size.
CRE Charge-off rate -100 largest banks	CRECO-100	Charge-off rate on commercial real estate loans (excluding farmland) at banks ranked 100 largest by asset size.
CRE Charge-off rate - Non 100 largest banks	CRECO-Other	Charge-off rate on commercial real estate loans (excluding farmland) at banks not among the 100 largest by asset size.
Credit card Delinquency rate - 100 largest banks	CCD-100	Delinquency rate on credit card loans at banks ranked 100 largest by asset size.
Credit card Delinquency rate - Non 100 largest banks	CCD-Other	Delinquency rate on credit card loans at banks not among the 100 largest by asset size.
Credit Card Charge-off rate - 100 largest banks	CCCO-100	Charge-off rate on credit card loans at banks ranked 100 largest by asset size.
Credit Card Charge-off rate - Non 100 largest banks	CCCO-Other	Charge-off rate on credit card loans at banks not among the 100 largest by asset size.
Consumer Delinquency rate - 100 largest banks	CD-100	Delinquency rate on other consumer loans at banks ranked 100 largest by asset size.
Consumer Delinquency rate - Non 100 largest banks	CD-Other	Delinquency rate on other consumer loans at banks not among the 100 largest by asset size.
Consumer Charge-off rate - 100 largest banks	CCO-100	Charge-off rate on other consumer loans at banks ranked 100 largest by asset size.
Consumer Charge-off rate - Non 100 largest banks	CC0-Other	Charge-off rate on other consumer loans at banks not among the 100 largest by asset size.

1. Delinquent loans and leases are those past due thirty days or more and still accruing interest as well as those in nonaccrual status.
2. Charge-offs are the value of loans and leases removed from the books and charged against loss reserves. Charge-off rates are annualized, net of recoveries.

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