Déjà Vu All Over Again:
The Causes of U.S. Commercial Bank Failures *This* Time Around

by
Rebel A. Cole and Lawrence J. White

2010 FDIC Bank Research Conference
Arlington, VA
Oct. 28, 2010

Summary

- We analyze the determinants of bank failures occurring during calendar year 2009 (and first nine months of 2010).
- We find that traditional proxies for the CAMELS components, do an excellent job in explaining the failures of banks that were closed during 2009, just as they did in the previous banking crisis of 1985 – 1992.

Summary

- C-A-E-L proxies include:
  - C: Ratio of Total Equity to Total Assets
  - A: Ratio of Nonperforming Assets to Total Assets
    - NPA =PD30-89 + PD90 + Nonaccrual + REO
  - E: Ratio of Net Income to Total Assets
  - L: Ratio of Liquid Assets to Total Assets
    - Liquid Assets = Cash + Securities

Summary

- We also find that Construction & Development lending and reliance upon Brokered Deposits for funding are associated with higher failure rates.
- Surprisingly, we do not find that residential mortgages played a significant role in determining which banks failed and which banks survived.

Summary

- Also, surprisingly, these results are remarkably robust going back in time as far as five years prior to 2009.
- Out-of-Sample Forecasts are incredibly accurate as shown by the tradeoff in Type 1 versus Type 2 Errors.

Introduction

- Why did the number of U.S. bank failures spike upwards in 2008 and 2009?
- During 2000 – 2007, only 31 U.S. commercial banks failed.
- During 2008 and 2009, the number of failures rose to 30 and 119, respectively.
- Through Sep. 30, 107 commercial banks have failed during 2010.

Introduction

- The obvious (and incorrect) answer would be to attribute these failures to bad investments in “toxic” subprime and other residential mortgages, as well as the securities backed by such mortgages.

Introduction

- To the contrary, we find that banks investing in residential mortgages and securities were *less* likely, rather than more likely, to fail.
- Instead, we find that banks investing in commercial real estate, esp. C&D loans were more likely to fail.
- Banks relying upon brokered deposits for funding also were more likely to fail.

Introduction

- Moreover, we find that these factors were apparent as far back as 2004—five years before the failures we analyze.

Introduction

- Why is this important?
- Going back to Bagehot (1873) and Schumpeter (1912), economists have recognized the critical role of banks in determining economic growth.
- More recently, King and Levine (1994) and Levine and Zervos (1998) have empirically linked financial intermediation to long-run growth in an economy.

Literature on U.S. Bank Failures

- Meyer and Pifer (JF 1970)
- Martin (JBF 1977)
- Pettway and Sinkey (JF 1980)
- Thomson (JFSR 1992)
- Whalen (ER of FRB-Cleveland 1992)
- Tam and Kiang (MS 1992)
- Cole and Gunther (JBF 1995, JFSR 1998)
- Wheelock and Wilson (RESTAT 2005)
- Cole and Wu (mimeo 2010)

Literature on Recent U.S. Bank Failures

- Torma (SSRN 2010)
- Cole and White (Stern NYU 2010)
- . . . . Pretty sparse . . . .

Data

- Failure data from FDIC's website
- Quarterly Bank Call Report data from FRB-Chicago's website for 2004 - 2010
  - Going away at end of 2010!
  - Thank the greedy FFIEC for this loss of access
  - FFIEC provides vastly inferior product
- Structure data also from FRB-Chicago's website.
  - Not available from FFIEC
  - Thanks again FFIEC!

Methodology

- Simple Logistic Regression Model in SAS
- Alternative measures of “failure:”
  - Closed by FDIC
  - Closed by FDIC or “technically insolvent”
  - Technically Insolvent:
    - (TE + LLR < .5 * NPA)
    - (TE + LLR <
      .2*PD3089 + .5*PD90 + 1.0*(NA + REO)
      (substandard, doubtful, loss write-downs)

Methodology

- 117 Commercial Bank Closures
- 147 technical insolvencies

Model

- Simple model specification that follows the existing literature:
  - Proxies for CAMEL components
  - Loan portfolio allocation
    - Res RE
    - Comm RE: NFNR, MF and C&D
    - C&I
    - Consumer

Results:
Differences in Means: 2004 Data

	Survivors	Failures			
Variable	Mean	Mean	Difference	t-Difference	
TE	0.114	0.118	-0.004	-0.51	
LLR	0.009	0.009	0.000	-1.26	
ROA	0.011	0.007	0.003	3.15	***
NPA	0.014	0.014	0.000	0.17	
SEC	0.240	0.140	0.099	14.34	***
BD	0.019	0.065	-0.045	-6.54	***
LNSIZE	11.696	12.079	-0.383	-4.54	***
CASHDUE	0.049	0.036	0.013	5.51	***
GOODWILL	0.004	0.003	0.001	1.86	*
RER14	0.146	0.109	0.037	5.75	***
REMUL	0.012	0.029	-0.017	-4.63	***
RECON	0.052	0.171	-0.118	-13.60	***
RECOM	0.144	0.221	-0.077	-9.71	***
CI	0.099	0.109	-0.009	-1.64	
CONS	0.059	0.031	0.028	8.57	***
Obs.	7,397	232			

Results:
Differences in Means of 2009 Survivors and Failures

Variable		2008	2007	2006	2005	2004
TE		+	+			
LLR		-	-	-	-	
ROA		+	+	+	+	+
NPA		-	-	-		
SEC		+	+	+	+	+
BD		-	-	-	-	-
LNSIZE		-	-	-	-	-
CASHDUE		+	+	+	+	+
GOODWILL		+			+	+
RER14		+	+	+	+	+
REMUL		-	-	-	-	-
RECON		-	-	-	-	-
RECOM		-	-	-	-	-
CI		+				
CONS		+	+	+	+	+

Results:
Logistic Regression:
2009 Failure = 1, 2009 Survivor = 0

Variable		2008	2007	2006	2005	2004
TE		-	-			+
LLR				-	-	-
ROA		-	-	-	-	-
NPA		+	+	+	+	+
SEC		-			-	-
BD		+	+	+		+
LNSIZE				+	+	
CASHDUE		-			-	-
GOODWILL		+	+		-	-
RER14		-				
REMUL			+	+	+	+
RECON		+	+	+	+	+
RECOM			+	+	+	+
CI		-				
CONS			-	-	-	

Out-of-Sample Forecasting Accuracy
Type 1 vs. Type 2 Error Rates

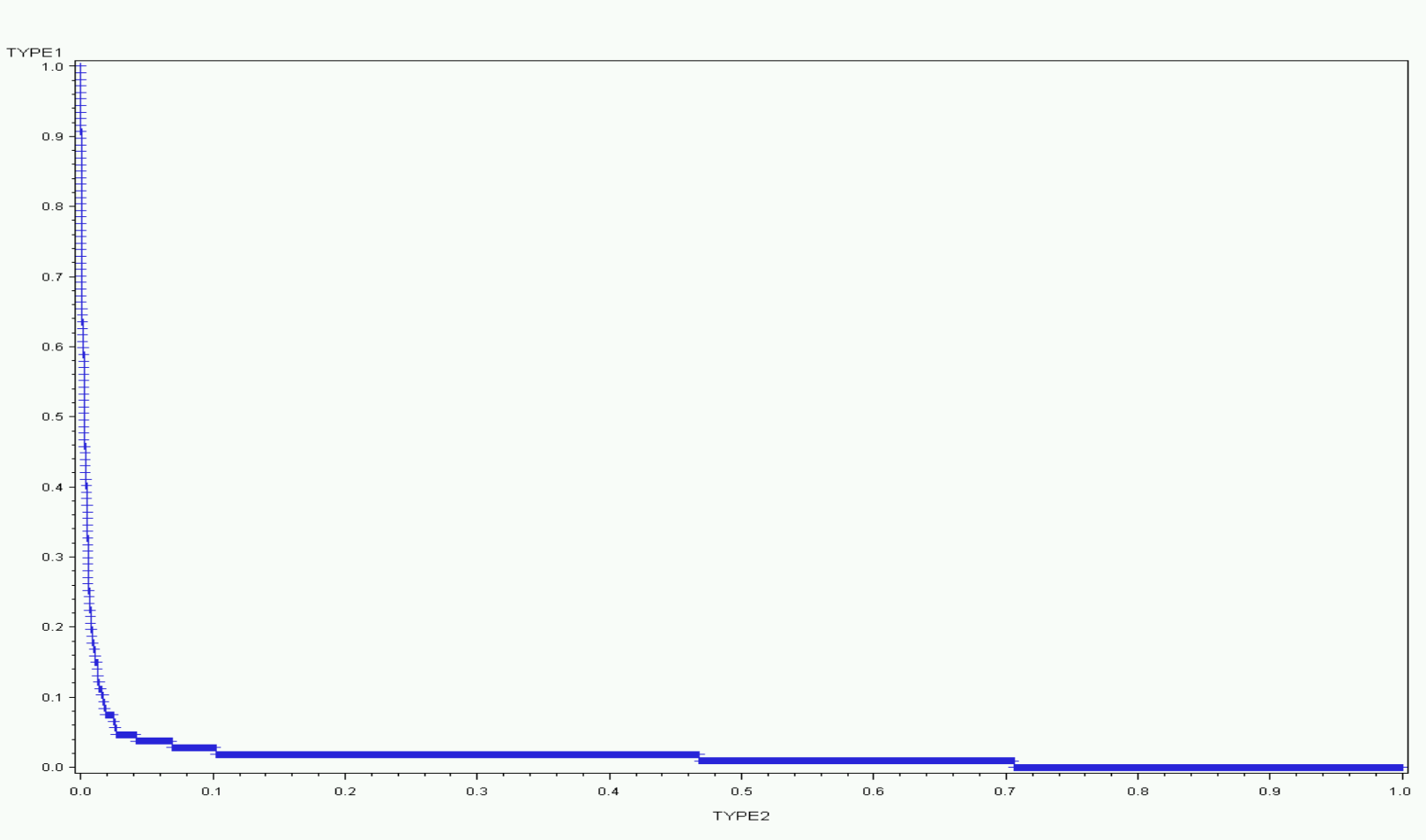
- How well does the model do in forecasting future “out-of-sample” failures?
- We examine trade-off of Type 1 vs. Type 2 error rates
- Type 1 Error: Failure misclassified as Survivor
- Type 2 Error: Survivor misclassified as Failure

Out-of-Sample Forecasting Accuracy
Type 1 vs. Type 2 Error Rates

- For each Type 2 Error Rate, what percentage of Failures do we misclassify (Type 1 Error Rate)?

- From a banking supervision perspective, think of this as examining X% of all banks and identifying Y% of all banks that will fail within next 9 months.

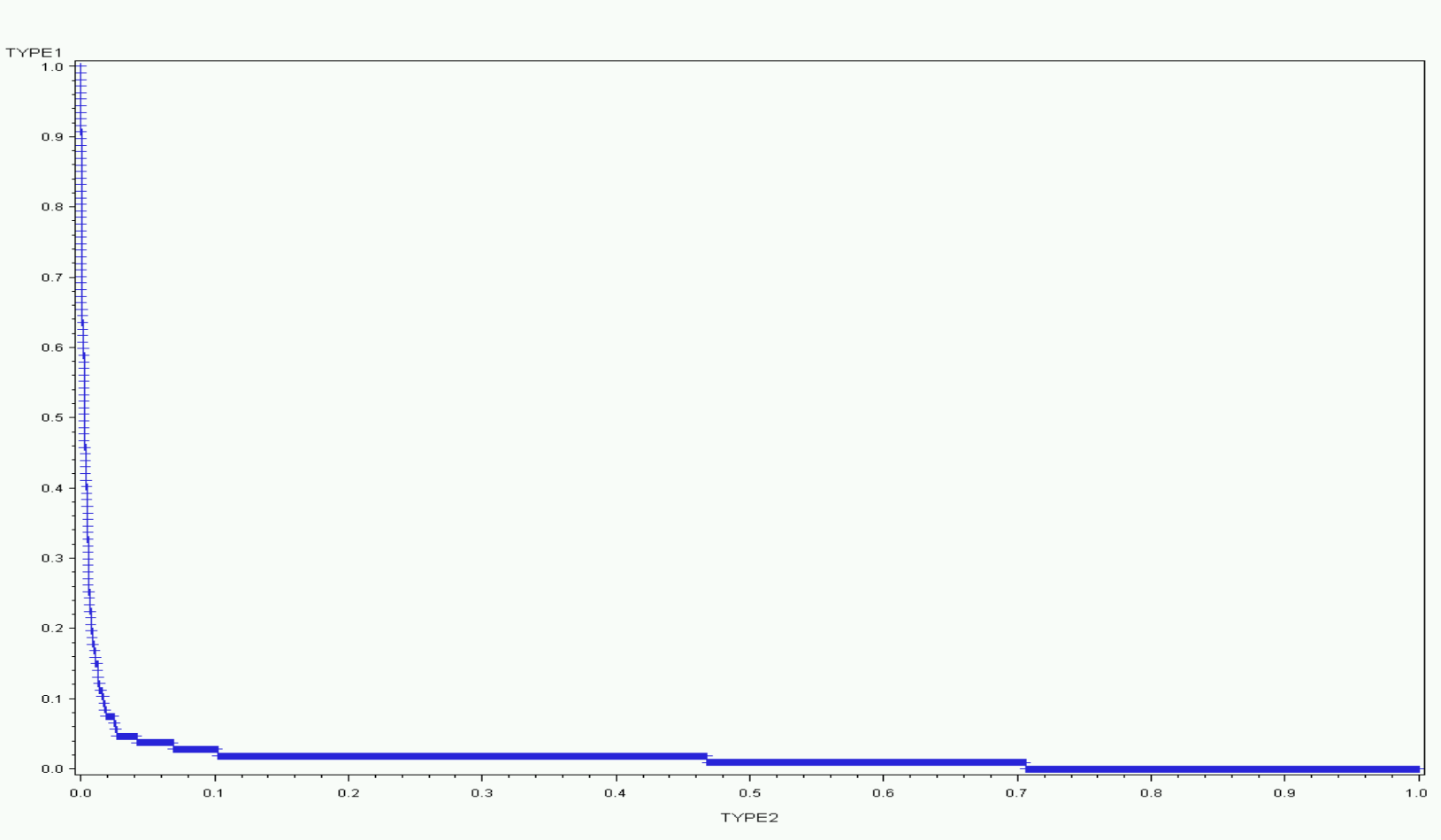
2010 Out-of-Sample Accuracy: Type 1 vs. Type 2 Error Rates 2008 Data, 2009 Closures Only



2010 Out-of-Sample Accuracy: Type 1 vs. Type 2 Error Rates 2008 Data, 2009 Closures Only

Type 2 Error Rate	Type 1 Error Rate
10%	2.8%
680 of 6,793	104 of 107
5%	3.7%
340 of 6,793	103 of 107
1%	17.8%
68 of 6,793	88 of 107

2010 Out-of-Sample Accuracy: Type 1 vs. Type 2 Error Rates 2008 Data, 2009 Closures and Insolvencies



Robustness Checks

- Exclude technical failures
- Exclude actual failures
- Exclude 40 largest banks
- Divide sample into small banks and large banks at $300 M in assets

Robustness Checks

- Add State dummies: AZ, CA, FL, GA, IL, NV
- FHLB Advances (thanks to Scott Frame)
- Mortgage and Govt. Agency Securities
- Asset Growth
- Anything else I could think of on the bank balance sheet.

- Nothing else seems to matter.

Conclusions

- In this study, we analyzed the determinants of bank failures occurring during calendar year 2009 (and first nine months of 2010).
- We find that traditional proxies for the CAMELS components, do an excellent job in explaining the failures of banks that were closed during 2009, just as they did in the previous banking crisis of 1985 – 1992.

Conclusions

- We also find that Construction & Development lending and reliance upon Brokered Deposits for funding are associated with higher failure rates.
- Surprisingly, we do not find that residential mortgages or RMBS played a significant role in determining which banks failed and which banks survived.

Conclusions

- Finally, we find that this model is extremely accurate in out-of-sample forecasting tests, at least for 2010 closures.

- Plus ça change, plus c'est la même chose…