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Do Bank Failures Affect Real Economic Activity? State-Level Evidence from the Pre-Depression Era

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Abstract

This paper provides empirical evidence documenting the existence of a credit channel during the pre-Depression era using a newly constructed, state-level quarterly time series from 1900Q1 through 1931Q2 for the 48 contiguous states. It also investigates the source and size of the credit channel, and it examines the dynamic effects of bank failures on business failures. Granger-causality tests find evidence that bank failures cause commercial failures at the aggregate U.S. level and over half of the 48 states. The cross-sectional variation allows us to test two explanations of the credit channel discussed in the literature: (i) a reduction in consumption spending from the slow liquidation of failed-bank deposits, and (ii) a decrease in investment spending from a disruption of credit to bank-dependent firms. Our results support both theories, but the evidence in favor of the first is stronger statistically. Branch banking restrictions, state-sponsored deposit insurance, and differences in the agricultural-manufacturing share of commerce do not affect the empirical importance of an independent credit channel. Using aggregate U.S. level data, our structural model indicates that bank failures account for about 25% of commercial failures, and that bank failures have only minor subsequent effects within the banking sector.

Key words: Credit channel, Bank runs, Deposit insurance, Granger causality
JEL classifications: E32, E51, G21
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1 Introduction

Does the failure rate in the banking system have an independent effect on real economic activity? This question has attracted considerable attention since Friedman and Schwartz (1963) and Bernanke (1983) hypothesized the existence of a so-called credit channel, which links stability in the banking sector to the growth rate in the real sector. Although it is well known that bank failures and commercial failures both increase as economic conditions deteriorate, the existence of a credit channel in which bank failures are an independent factor that amplifies the severity of commercial failures remains an open issue.

The main contribution of this paper is to exploit a newly constructed state-level quarterly time series of bank failures and commercial failures from the first quarter of 1900 through the second quarter of 1931 to examine four important issues that previous research into the credit channel has not been able to address. First, using tests for Granger causality, we find evidence that bank failures cause commercial failures at the aggregate U.S. level and in over half of the 48 contiguous states. We do not find significant evidence that commercial failures cause bank failures. Based on these results, we conclude that the aggregate U.S. and over half of the states had an operative credit channel during this period.

Second, we exploit the variation across states in the credit channel evidence to evaluate two propagation theories of the credit channel advanced in the literature. Bernanke (1983), Calomiris and Mason (2003), Anari, Kolari, and Mason (forthcoming), and others hypothesize that bank failures are an independent source of commercial failures due to (i) a disruption of funds to consumers from the slow liquidation of failed-bank deposits; and, (ii) a disruption of credit to bank-dependent firms which curtails commercial investment, restricts demand, and forces commercial-firm liquidations. We find evidence in favor of both propagation theories, but our results suggest that the consumer liquidity-based explanation is stronger statistically. Third, we evaluate whether controls for regulatory and economic differences across states affect the likelihood of having an operative credit channel. We find that controls for differences in branch banking, state-sponsored deposit insurance, and differences in the agricultural-manufacturing share of commerce have an insignificant impact on the likelihood of having a credit channel.

Lastly, we measure the size and dynamic effect of bank failures and commercial failures at the aggregate U.S. level. Using a structural moving-average model, we find that bank failures account for about 25% of commercial failures at all forecast horizons, and that bank failures have only a short-lived impact in the banking sector. These results provide additional evidence to a long-standing debate as to whether financial panics amplify recessions. For example, De Long and Summers (1986) argue that the effect of financial panics on the real side of the economy may have been small because their impact on variables such as interest rates was short-lived. Calomiris and Hubbard (1989), on the other hand, argue that financial panics may have had large recessionary effects because of the inevitable contraction in the supply of credit during periods of financial distress. The evidence that bank failures account for as much as 25% of commercial failures, despite the evidence that episodes of bank failures appear to be short lived, is compelling evidence that a credit channel existed at the turn of the 20th century, and not just during the Depression years. Moreover, the effect may be large enough to help explain why the variability of the business cycle was higher in the Pre-World War II period than afterwards.[1]

Previous research that evaluates the impact of bank failures on real economic activity has focused on analyses of either Depression era or post-Depression era data.[2] Friedman and Schwartz (1963), Bernanke (1983), Calomiris and Mason (2003)

[1]See Romer (1999) for a detailed discussion on how the variability of short-run economic fluctuations has decreased in the U.S. since the turn of the century.

[2]To our knowledge, Grossman (1993) is the only study that directly examines the role of bank failures in the propagation of business cycles using pre-Depression data. His data consist of a monthly series of U.S. bank failures for national banks from 1865 through 1914. He finds that small-bank failures can lead to a 2% decline in real economic activity, and large-bank failures can lead to as

and Anari, Kolari, and Mason (forthcoming) find evidence of a credit channel in Depression-era data.[3] Studies of the credit channel that use post-Depression-era data have not yielded a consensus, however. Using data from the late 1980s and early 1990s, Ashcraft (2003) finds evidence of a credit channel, whereas Gilbert and Kochin (1989) and Clair and O'Driscoll (1994) do not.[4]

Our state-level pre-Depression-era data have several advantages for evaluating hypotheses about the credit-channel relative to the data used in previous studies. First, pre-Depression-era data are free from the effects of the New Deal financial reforms. The regulatory structure imposed on the financial industry during the 1930s was in part designed to attenuate any effects of the credit channel that may have existed. For example, the introduction of deposit insurance at the national level in 1935 most likely reduced the importance of credit channel effects caused by liquidity-constrained consumers. Hence, more recent data are unlikely to yield answers that are as informative as those we obtain here. Second, our pre-Depression data include several episodes of bank runs and bank failures that occurred over several business cycles. In contrast, the Depression era had many bank failures compressed into a relatively short period of time that was characterized by unusual economic distress. Consequently, results from studies that use Depression-era data are more likely to

much as a 20% decline. However, his sample includes only national banks, and most banks at the time were chartered at the state level. Miron, Romer, and Weil (1993) look at the role of the lending channel from an historical perspective, but they do not examine the role of bank failures.

[3]Calomiris and Mason (2003) use county-level data from 1930 through 1932 and find that a one-standard-deviation decrease in loan-supply growth results in a decline of 7% to 9% in local income. Anari, Kolari, and Mason (forthcoming) extend Bernanke's (1983) work by explicitly testing the role of deposit liquidation in explaining the persistence of the Great Depression. Using a vector autoregression model, they find that the stock of deposits in failed banks is as important as the money stock in explaining output changes during the Depression.

[4]Ashcraft (2003) examines FDIC-induced closures of 38 subsidiaries of First RepublicBank Corporation in 1988 and 18 subsidiaries of First City Bank Corporation in 1992 and finds that real income declines by about 3% at the county level. Gilbert and Kochin (1989) use county-level data from Kansas, Nebraska, and Oklahoma between 1981 and 1986 and do not find any significant relationship between bank failures and local economic activity, as measured by sales and employment. Clair and O'Driscoll (1994) use Gilbert and Kochin's (1989) methodology to examine the impact of bank failures on local economic activity in several Texas counties between 1981 and 1991. Like Gilbert and Kochin (1989), they are unable to find a significant relationship between bank failures and local economic activity.

be biased in favor of finding a credit channel due to the overwhelming weakness in aggregate demand during the Depression. The post-Depression era has had several business cycles but few bank failures, with the exception of the thrift crisis in the late 1980s. Thus, results from studies that use post-Depression-era data are bound to be dominated by this single event. Third, the states were much less integrated then than now. The impact of the federal government on the nation was much less far-reaching and influential, financial markets were much less developed, and, while there was the possibility of communication and transportation, states were still relatively isolated. Thus, it is not inappropriate to study each of the 48 states as separate "countries" during this period.

The remainder of this paper is organized as follows: Section 2 describes the data, Section 3 tests for the existence of a credit channel, Section 4 investigates explanations of the credit channel, Section 5 determines the size and dynamic effect of bank failures and commercial failures, and Section 6 concludes.

2 Data

The primary data are the liabilities of firms that failed in the banking, manufacturing, trade, and other sectors obtained from *Dun's Review.* These data include over 24,000 quarterly observations for the 48 contiguous United States from the first quarter of 1900 through the second quarter of 1931. There are a variety of errors in the original data, such as misaligned entries, typographical errors, additions, etc. After cleaning the original data, we construct two time series for each state and the aggregate United States: (i) the liabilities of failed banks normalized by bank deposits, and (ii) the liabilities of failed commercial enterprises normalized by net bank loans. We define commercial failures as the sum of manufacturing failures, trade failures, and other failures. Net bank loans are total bank loans less real estate loans, which we use to proxy for loans to the commercial sector. Bank loans, real estate loans, and bank

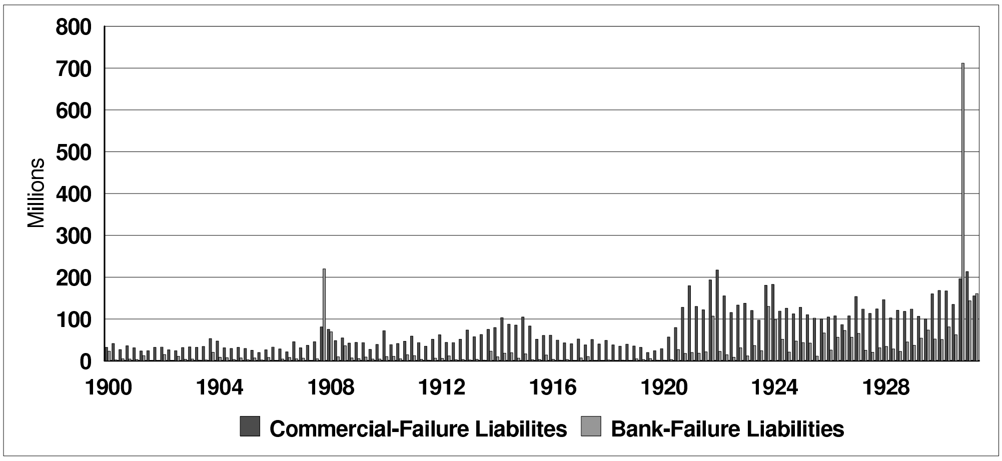

Figure 1: Liabilities of bank failures and liabilities of commercial failures at the aggregate U.S. level.

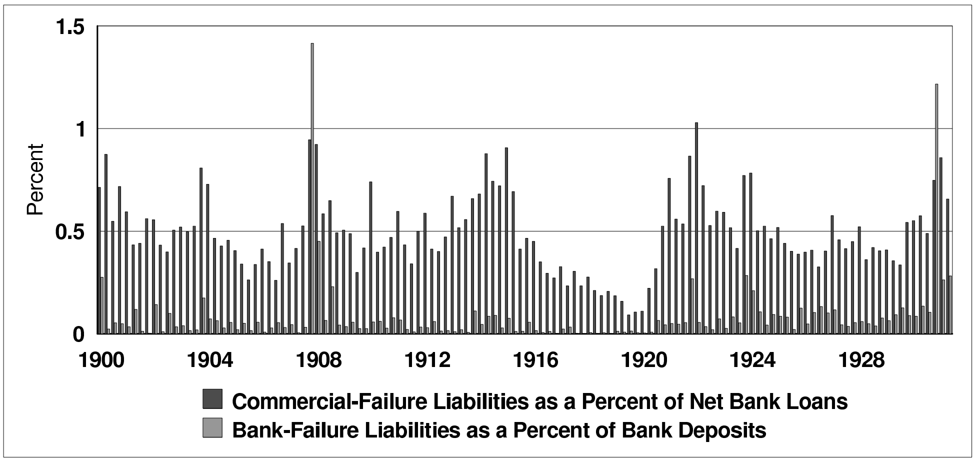

Figure 2: Bank failures normalized by bank deposits and commercial failures normalized by net bank loans at the aggregate U.S. level, with both series expressed as percentages.

deposits are obtained annually at the state level from *All Bank Statistics*, as reported by Flood (1998). We linearly interpolate bank deposits and net bank loans to obtain quarterly estimates.[5]

[5] *Dun's Review* does not clarify whether bank suspensions are included in bank failures. To get an idea of whether suspensions are included, we compared our number of aggregate U.S. bank failures with the total number reported by Goldenweiser (1933, Table 1) which excludes suspensions before 1921, at least for national banks. We find that our number is marginally higher than Goldenweiser's before 1920, but substantially smaller thereafter. This suggests that our data may include a few suspensions, but it is unlikely that they would make any significant difference to our results since the largest proportion of bank suspensions occurred after 1931.

Our time period is limited to 1900 through 1931. *Dun's Review* did not report consistent failure data by state until the late 1890s, and it stopped reporting failure data after the second quarter of 1931. While we cannot replicate results from studies that use Depression- and post-Depression-era data, our pre-Depression-era period is rich enough to capture several well-known periods of financial distress, such as the financial panics of 1901, 1903, 1907.

Figure 1 shows the aggregate U.S. liabilities of failed bank and commercial enterprises. Figure 2 shows the aggregate liabilities of failed banks as a percentage of bank deposits and the liabilities of failed commercial enterprises as a percentage of net bank loans. The two figures show that the liabilities of failed banks are much more volatile than the liabilities of failed commercial enterprises, and that bank failures tend to lead commercial failures. Tables 1 and 2 list state-level summary statistics for the liabilities of failed banks as a percentage of bank deposits and the liabilities of commercial enterprises as a percentage of net bank loans, respectively. The tables show several interesting features of the state-level data. First, bank failures are much more volatile than commercial failures. Second, there is considerable variation in commercial failures and bank failures across states. Third, the median value of bank failures is zero in 38 of the 48 states, which shows that many of the observations are zero and indicates the heteroskedastic nature of the bank-failure series - extended periods of relative tranquility followed by periods of sharp activity. This is a pattern consistent with episodes of bank runs. Fourth, the median value of bank failures is always substantially larger than the mean, as one would expect given the variability of the bank-failure series. In contrast, the mean of commercial failures is always larger than, but relatively close to, the median value.

Table 1
Summary Statistics:
Bank Failures as a Percentage of Bank Deposits
Quarterly Data by State from 1900Q1 through 1931Q2

State	Minimum	Maximum	Mean	Median	Std Dev
Alabama	0.000%	2.375%	0.150%	0.000%	0.363%
Arizona	0.000	7.331	0.273	0.000	1.032
Arkansas	0.000	27.255	0.488	0.007	2.474
California	0.000	1.337	0.021	0.000	0.123
Colorado	0.000	5.121	0.153	0.000	0.515
Connecticut	0.000	1.098	0.024	0.000	0.124
Delaware	0.000	1.815	0.018	0.000	0.165
Florida	0.000	17.299	0.614	0.000	2.147
Georgia	0.000	4.868	0.336	0.014	0.848
Idaho	0.000	15.095	0.396	0.000	1.520
Illinois	0.000	2.225	0.060	0.006	0.217
Indiana	0.000	3.298	0.118	0.000	0.421
Iowa	0.000	2.788	0.174	0.015	0.388
Kansas	0.000	1.315	0.111	0.000	0.221
Kentucky	0.000	23.121	0.254	0.000	2.062
Louisiana	0.000	1.280	0.037	0.000	0.145
Maine	0.000	0.960	0.027	0.000	0.138
Maryland	0.000	3.988	0.080	0.000	0.386
Massachusetts	0.000	1.010	0.025	0.000	0.112
Michigan	0.000	1.782	0.032	0.000	0.167
Minnesota	0.000	1.208	0.106	0.014	0.209
Mississippi	0.000	12.955	0.280	0.000	1.290
Missouri	0.000	4.098	0.086	0.009	0.375
Montana	0.000	16.956	0.532	0.000	2.024
Nebraska	0.000	4.354	0.201	0.000	0.568
Nevada	0.000	16.412	0.344	0.000	1.954
New Hampshire	0.000	4.106	0.036	0.000	0.368
New Jersey	0.000	0.422	0.013	0.000	0.052
New Mexico	0.000	41.164	0.651	0.000	3.909
New York	0.000	2.629	0.078	0.001	0.302
North Carolina	0.000	15.150	0.238	0.000	1.357
North Dakota	0.000	18.156	0.491	0.000	1.864
Ohio	0.000	0.924	0.062	0.006	0.144
Oklahoma	0.000	4.475	0.181	0.000	0.516
Oregon	0.000	9.514	0.186	0.000	0.913
Pennsylvania	0.000	0.930	0.046	0.001	0.123
Rhode Island	0.000	14.845	0.123	0.000	1.322
South Carolina	0.000	2.435	0.232	0.000	0.459
South Dakota	0.000	12.129	0.578	0.000	1.603
Tennessee	0.000	11.468	0.222	0.000	1.061
Texas	0.000	3.074	0.137	0.010	0.360
Utah	0.000	0.898	0.059	0.000	0.169
Vermont	0.000	0.382	0.004	0.000	0.036
Virginia	0.000	0.619	0.034	0.000	0.107
Washington	0.000	3.611	0.121	0.000	0.404
West Virginia	0.000	2.761	0.074	0.000	0.294
Wisconsin	0.000	0.673	0.040	0.000	0.106
Wyoming	0.000	11.857	0.234	0.000	1.146

Table 2
Summary Statistics:
Commercial Failures as a Percentage of Net Bank Loans
Quarterly Data by State from 1900Q1 through 1931Q2

State	Minimum	Maximum	Mean	Median	Std Dev
Alabama	0.005%	11.500%	1.094%	0.723%	1.499%
Arizona	0.000	13.176	0.490	0.239	1.274
Arkansas	0.056	6.908	1.109	0.885	0.969
California	0.077	1.353	0.414	0.374	0.196
Colorado	0.016	3.327	0.484	0.397	0.440
Connecticut	0.113	7.328	0.817	0.573	0.897
Delaware	0.000	4.456	0.482	0.240	0.675
Florida	0.038	8.354	1.548	1.185	1.452
Georgia	0.076	2.778	0.844	0.706	0.570
Idaho	0.024	4.331	0.634	0.422	0.739
Illinois	0.049	1.625	0.449	0.361	0.281
Indiana	0.083	8.077	0.793	0.577	0.827
Iowa	0.009	0.874	0.200	0.182	0.123
Kansas	0.008	1.365	0.266	0.214	0.213
Kentucky	0.018	2.177	0.411	0.352	0.291
Louisiana	0.001	4.936	0.525	0.338	0.628
Maine	0.079	2.982	0.613	0.504	0.406
Maryland	0.065	4.854	0.689	0.505	0.671
Massachusetts	0.096	2.192	0.493	0.429	0.316
Michigan	0.044	1.149	0.377	0.335	0.217
Minnesota	0.017	5.477	0.425	0.329	0.534
Mississippi	0.005	3.600	0.857	0.624	0.733
Missouri	0.049	2.596	0.359	0.273	0.320
Montana	0.035	3.403	0.414	0.286	0.472
Nebraska	0.003	1.905	0.240	0.158	0.283
Nevada	0.000	1.295	0.214	0.146	0.260
New Hampshire	0.013	2.204	0.323	0.253	0.304
New Jersey	0.067	2.650	0.638	0.596	0.362
New Mexico	0.000	13.087	0.501	0.247	1.324
New York	0.078	1.908	0.505	0.402	0.333
North Carolina	0.010	2.824	0.664	0.516	0.505
North Dakota	0.000	1.272	0.242	0.192	0.210
Ohio	0.080	1.822	0.562	0.481	0.310
Oklahoma	0.006	4.091	0.591	0.503	0.513
Oregon	0.071	6.500	1.026	0.842	0.909
Pennsylvania	0.098	1.408	0.400	0.350	0.213
Rhode Island	0.012	2.651	0.358	0.261	0.397
South Carolina	0.000	3.459	0.664	0.533	0.577
South Dakota	0.000	1.582	0.190	0.158	0.213
Tennessee	0.046	8.362	0.740	0.525	0.892
Texas	0.032	1.988	0.518	0.415	0.362
Utah	0.049	3.887	0.552	0.313	0.653
Vermont	0.005	6.287	0.411	0.225	0.678
Virginia	0.039	11.152	0.552	0.389	1.011
Washington	0.112	3.815	1.008	0.901	0.630
West Virginia	0.018	2.146	0.423	0.373	0.345
Wisconsin	0.020	2.103	0.417	0.348	0.283
Wyoming	0.000	1.015	0.208	0.128	0.222

3 The Existence of a Credit Channel

We perform Granger-causality tests to evaluate the relationship between bank failures and commercial failures. The model used to determine whether bank failures Granger cause commercial failures is

$$c_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i c_{t-i} + \sum_{i=1}^{k} \beta_i b_{t-i} + \epsilon_t \tag{1}$$

and the model used to determine whether commercial failures Granger cause bank failures is

$$b_t = \alpha_0 + \sum_{i=1}^{k} \alpha_i b_{t-i} + \sum_{i=1}^{k} \beta_i c_{t-i} + \epsilon_t \tag{2}$$

where b_t represents the liabilities of bank failures normalized by bank deposits at time t, and c_t the liabilities of commercial failures normalized by net bank loans. α_0 is a constant, the α_i are autoregressive parameters, the β_i are the parameters of interest in our Granger causality tests. The model is estimated with $k = 4$ lags to capture annual variation in quarterly data. Because the bank-failure and commercial-failure series exhibit periods of high volatility, we estimate the regressions with robust standard errors using White (1980)'s correction for heteroskedasticity.

We use an F(k, n-2k-1) test of the null hypothesis that $\beta_1 = \cdots = \beta_k = 0$ in equation (1) and equation (2). Rejection of the restriction $\beta_1 = \cdots = \beta_k = 0$ in equation (1) indicates that bank failures Granger cause commercial failures, and rejection of the restriction $\beta_1 = \cdots = \beta_k = 0$ in equation (2) indicates that commercial failures Granger cause bank failures. We use the p-values from these two tests to evaluate whether a state has an operative credit channel. Specifically, we conclude that a credit channel exists if bank failures Granger cause commercial failures with a p-value at or below 0.10 and commercial failures do not Granger cause bank failures with a p-value greater than 0.10.

Table 3 lists test statistics and p-values from the F test for Granger causality, as well as a column indicating whether the evidence supports an operative credit

Table 3
F Test for Granger Causality:
Aggregate U.S. and by State from 1900Q1 through 1931Q2

	Bank Failures Granger cause Commercial Failures		Commercial Failures Granger cause Bank Failures		Evidence in Favor of a Credit Channel?
State	Test Statistic	P-Value	Test Statistic	P-Value	Y/N
United States	9.06	0.000	0.85	0.497	Y
Alabama	0.16	0.960	0.32	0.863	N
Arizona	0.81	0.524	1.56	0.189	N
Arkansas	4.14	0.004	1.40	0.238	Y
California	30.08	0.000	0.52	0.722	Y
Colorado	1.13	0.344	0.68	0.604	N
Connecticut	1.71	0.152	1.00	0.408	N
Delaware	89.68	0.000	0.43	0.790	Y
Florida	1.43	0.229	1.16	0.334	N
Georgia	0.67	0.612	0.42	0.795	N
Idaho	3.76	0.007	0.70	0.591	Y
Illinois	2.27	0.066	0.65	0.631	Y
Indiana	11.21	0.000	0.43	0.789	Y
Iowa	1.49	0.210	0.19	0.945	N
Kansas	0.33	0.855	0.74	0.564	N
Kentucky	1.38	0.246	0.32	0.866	N
Louisiana	0.39	0.818	0.60	0.666	N
Maine	3.23	0.015	0.58	0.674	Y
Maryland	319.96	0.000	0.42	0.796	Y
Massachusetts	2.98	0.022	0.80	0.527	Y
Michigan	5.15	0.001	0.48	0.750	Y
Minnesota	4.18	0.003	0.57	0.687	Y
Mississippi	1.96	0.106	0.74	0.566	N
Missouri	0.87	0.484	1.85	0.123	N
Montana	1.90	0.115	2.20	0.074	N
Nebraska	7.19	0.000	0.67	0.617	Y
Nevada	1.94	0.108	0.47	0.758	N
New Hampshire	411.56	0.000	0.38	0.823	Y
New Jersey	1.99	0.100	1.08	0.372	Y
New Mexico	0.34	0.847	0.55	0.703	N
New York	1.51	0.203	0.91	0.460	N
North Carolina	6.99	0.000	0.46	0.766	Y
North Dakota	5.89	0.000	0.57	0.684	Y
Ohio	0.38	0.819	0.82	0.514	N
Oklahoma	0.51	0.731	5.67	0.003	N
Oregon	3.41	0.011	0.29	0.885	Y
Pennsylvania	3.89	0.005	0.94	0.446	Y
Rhode Island	145.16	0.000	0.24	0.913	Y
South Carolina	0.99	0.417	1.28	0.282	N
South Dakota	2.54	0.043	1.36	0.254	Y
Tennessee	1.99	0.101	1.30	0.275	N
Texas	4.39	0.003	2.04	0.093	N
Utah	1.64	0.169	1.28	0.282	N
Vermont	28.67	0.000	0.39	0.817	Y
Virginia	0.95	0.439	0.95	0.439	N
Washington	2.14	0.080	0.60	0.667	Y
West Virgina	1.26	0.292	1.23	0.302	N
Wisconsin	2.38	0.056	0.97	0.425	Y
Wyoming	21.79	0.000	0.68	0.609	Y

channel. The test finds significant evidence that bank failures Granger cause commercial failures at the aggregate U.S. level with a p-value of 0.000. At the state level, the test finds significant evidence that bank failures Granger cause commercial failures in 25 (20) of the 48 states at the 0.10 (0.05) level, and another 4 states show weaker evidence of Granger causality with p-values ranging from 0.101 to 0.115. In contrast, the test finds no evidence that commercial failures Granger cause bank failures at the aggregate U.S. level with a p-value of 0.497. Moreover, only 3 (1) states show evidence that commercial failures Granger cause bank failures at the 0.10 (0.05) level.[6]

The evidence that bank failures Granger cause commercial failures in 25 (20) of the 48 states at the 0.10 (0.05) level is much stronger than would obtain by pure statistical chance. Assuming that each state is an independent observation, a type I error would generate 5 (2.5) significant states at the 0.10 (0.05) level. Furthermore, the state-level evidence that bank failures cause commercial failures is strong enough to show up at the aggregate level. In contrast, the evidence that commercial failures Granger cause bank failures in only 3 (1) states at the 0.10 (0.05) level is within the margin of a type I error. Therefore, we conclude that there not is a channel from commercial failures to bank failures. This raises the question of what causes bank failures. Calomiris and Gorton (1991) document the pervasiveness of bank runs during this period due to problems of asymmetric information between depositors and banks. The fact that the autoregressive component in equation (2) captures much of the variation in bank failures is consistent with this observation. Thus, the evidence is consistent with the hypothesis that bank failures are caused by the inherently unstable nature of the financial system due to the severe information gaps between depositors and banks. In such an environment, bank runs quickly translate to banking panics, financial crises, and ultimately, bank failures.

[6]Although we do not report the results here, we test for seasonality effects. The results change only marginally and in a direction that is more favorable to the credit channel.

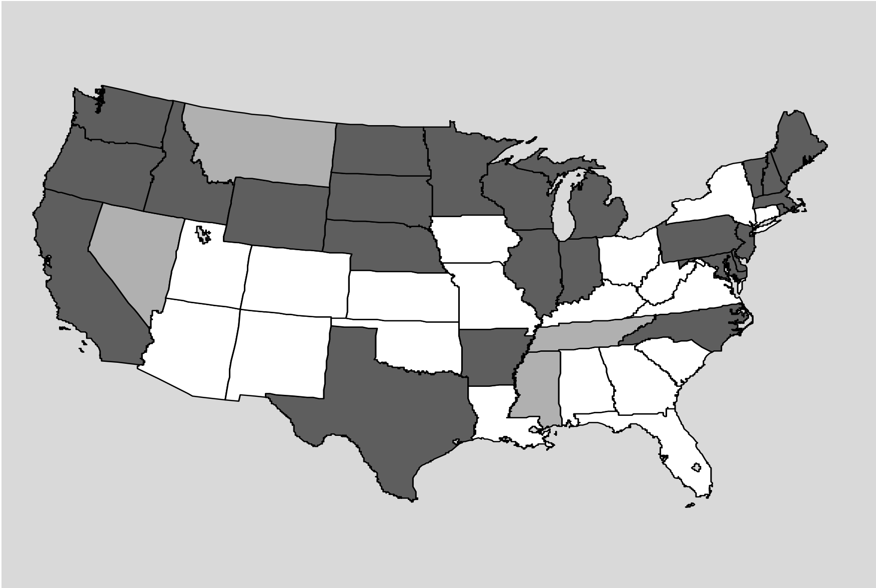

Figure 3: The 24 states with a credit channel significant at the 0.10 level are shaded in black, the 5 states with p-values from 0.101 to 0.115 are shaded in gray, and the remaining states are unshaded.

The power of the joint test of the hypothesis that there is a credit channel is, by design, related to the strength of our ability to simultaneously conclude that bank failures Granger cause commercial failures and commercial failures do not Granger cause bank failures. The power increases with lower p-values from the first test and higher p-values from the second test. It is evident from Table 3 that there is a high correlation between concluding that bank failures Granger cause commercial failures and concluding that there is an operative credit channel. In 24 of the 25 states that show significant evidence in favor of a bank to commercial failure channel, we also conclude that there is a credit channel. The only exception is Texas, which also shows evidence that commercial failures cause bank failures.

There is no obvious geographic pattern of states that show evidence of a credit channel. To see this, Figure 3 identifies the 25 states which show significant evidence that bank failures Granger cause commercial failures with p-values at or below the 0.10 level by black shading, the 4 states with p-values from 0.101 to 0.115 by gray shading, and the remaining states left unshaded. Although more states in the north exhibit evidence in favor of a credit channel than the south, there is no clear interpretation of this evidence. One advantage of identifying whether a state has an operative credit channel is to exploit the cross-sectional variation in testing different explanations. We perform these tests in the following section.

4 Explanations of the Credit Channel

Recent research has advanced two theories that explain how the credit channel propagates: a consumption-based explanation and a commercial investment-based explanation. The intuition behind the consumption-based explanation is straightforward. According to Bernanke (1983) and Anari, Kolari, and Mason (forthcoming), deposits at failed banks become illiquid assets for depositors until the bank is liquidated, or reopened in case of a suspension. Consumption spending therefore declines as bank failures cause consumers to become liquidity constrained. The decline in consumer spending reduces aggregate demand, thereby increasing commercial failures. The commercial-investment explanation, advanced by Bernanke (1983), Calomiris (1993a), and Calomiris and Mason (2003), is the essence of the traditional credit-channel literature. In a world where financial markets are incomplete, a disruption in financial intermediation due to bank failures increases the cost of borrowing for information-intensive borrowers. This increase effectively tightens credit, which reduces investment demand and amplifies an economic downturn. DeLong (1991), Carrosso (1970) and Lamoreaux (1994) argue that this explanation is particularly important in the pre-Depression era when financial markets were much less sophisticated and long-lasting bank relationships were common for medium and large firms, as well as smaller bank-dependent firms.

We use the variation of the evidence of a credit channel across states to determine the importance of the two explanations. We hypothesize that the credit channel is

Table 4
Sources of the Credit Channel

Independent Variable	Dependent Variable: Does the state have a credit channel? (a)	(b)	(c)	(d)	(e)	(f)	(g)
Log (Per Capita Bank Deposits)	0.650						
	(0.038)						
Log (Per Capita Net Bank Loans)		0.803					
		(0.045)					
Log (Bank Deposits/ Net Bank Loans)			1.641				2.197
			(0.096)				(0.071)
Branch Banking				-0.174			-0.081
				(0.768)			(0.903)
Deposit Insurance					-1.526		-1.551
					(0.188)		(0.209)
Agricultural States						0.167	1.144
						(0.773)	(0.143)
Chi Sq.	4.91	4.56	3.08	0.09	2.14	0.08	6.72
	(0.027)	(0.033)	(0.079)	(0.768)	(0.144)	(0.773)	(0.151)
Pseudo R^2	0.074	0.069	0.046	0.001	0.032	0.001	0.101

Notes: The dependent variable equals 1 if the state has a credit channel as reported in the last column of Table III. It is equal to 0 otherwise. The independent variables are: "Log (Per Capita Bank Deposits)" is defined as logarithm of total deposits divided by the state population. "Log(Per Capita Net Bank Loans)" is defined as the logarithm of total loans minus real estate loans divided by the state's population. "Log(Bank Deposits/Net Bank Loans)" is defined as the logarithm of bank deposits relative to net bank loans. The loans and deposits figures are for 1896. The state population figures are for 1900. "Branch Banking" - an indicator variable which equals 1 if the state permitted branch banking, 0 otherwise. "Deposit Insurance" is an indicator variable which equals 1 if the state had some form of deposit insurance. "Agricultural State?" - an indicator variable which equals 1 if at least 55 percent of the state's income was derived from agriculture. Constant term included in all regressions but not reported. P-values are reported in parentheses.

more likely to operate through consumer-spending disruptions in states with higher per capita bank deposits, since higher per capita bank deposits imply greater exposure to consumer-spending disruptions. Similarly, we hypothesize that the credit channel is more likely to operate through commercial-investment disruptions in states with higher per capita net bank loans.[7] In order to avoid endogeneity problems with our sample period, we use per capita bank deposits and per capita net bank loans in 1896.[8]

[7]We use net bank loans as our proxy for commercial and industrial (C & I) loans, which may not be entirely correct. To the extent that our measure does not include C & I loans, its inclusion should work against our hypothesis, not in favor of it.

[8]Population figures are from Flood (1998).

We test the two theories by fitting a logistic regression in which the dependent variable is 1 if the evidence summarized in the last column of Table 3 indicates that the state has a credit channel and 0 otherwise. The independent variables are the log of per capita bank deposits and the log of per capita net bank loans.[9] Columns (a) and (b) in Table 4 report the impact of per capita bank deposits and per capita net bank loans have on the likelihood of a credit channel. We fit separate regressions first in order to isolate the impact of each variable independently. The coefficients are both positive and statistically significant at the 0.05 level, indicating that the likelihood of a credit channel increases as per capita bank deposits and per capita net bank loans increase. Therefore, these regression results support both the consumption-based and commercial investment-based explanations. To determine whether one of the two explanations has a larger impact on the likelihood of a credit channel, we replace the independent variables with the log of the ratio of bank deposits to net bank loans. The results, reported Column (c), indicate that the coefficient is positive and statistically significant at the 0.10 level, which indicates that the likelihood of having a credit channel increases with the log of bank deposits relative to net bank loans. Consequently, we argue that the consumption-based explanation is stronger empirically.

A natural extension of this analysis is to determine whether other state-level regulatory or economic characteristics explain the likelihood of having an operative credit channel. Previous research indicates that branch-banking regulations, state-sponsored deposit insurance, and an agricultural-manufacturing partition of states may be important factors.[10] To evaluate whether these factors influence the like-

[9]We use the log transformation of these variables in order to reduce the influence of states with extremely high or low values of deposits or net loans per capita.

[10]White (1982), Calomiris (1993b, 2000), Mitchener (2004), and Ramirez (2003) find evidence that branch banking influences bank failures; White (1994), Wheelock (1992, 1993), Wheelock and Wilson (1994), and Calomiris (2000) find that state-sponsored deposit insurance increases the likelihood of bank failures; and Calomiris (1992) and Alston, Grove, and Wheelock (1994) find that bank failures were higher in highly agricultural states.

lihood of having an operative credit channel, we include as independent variables: (i) a branch-banking indicator,[11] (ii) a deposit-insurance indicator,[12] and (iii) an agricultural-state indicator,[13] all of which are set to 1 if the state possesses the characteristic and 0 otherwise. The logistic regression results in Table 4 Columns (d), (e), and (f) show that none of these state-level characteristics is significant in explaining the likelihood of having an operative credit channel.[14]

As a robustness check, we include the log of the ratio of bank deposits to net bank loans in the regression as well as the three characteristic indicator variables. The results in Table 4 Column (g) show that branch banking, state-sponsored deposit insurance, and the agricultural-manufacturing split remain insignificant, whereas the ratio of the log of bank deposits to net bank loans remains significant at the 10% level.

5 The Size and Dynamic Effect of Bank Failures and Commercial Failures

This section presents forecast-error variance decompositions and impulse response functions from a structural moving-average model in order to show the size and dynamic effect of bank failures and commercial failures at the aggregate U.S. level. There are two main findings. First, regarding the credit channel, bank failures ac-

[11]Branch-banking states are from White (1983), Table 4. There are 10 states with state-wide branching: Arizona, California, Delaware, Georgia, Maryland, North Carolina, Rhode Island, South Carolina, Tennessee, and Virginia; and 9 states with limited branch banking: Louisiana, Maine, Massachusetts, New York, Ohio, Mississippi, Pennsylvania, Kentucky, and Michigan.

[12]States with deposit insurance are from the FDIC Annual Report of 1955: Kansas (1909-1929), Mississippi (1914-1930), Nebraska (1911-1930), North Dakota (1917-1929), Oklahoma (1908-1923), South Dakota (1916-1927), Texas (1910-1927), and Washington (1917-1921).

[13]Agricultural states are from Calomiris and Ramirez (2004). They are identified as states for which at least 55% of their income is derived from agriculture: Alabama, Arkansas, Georgia, Idaho, Indiana, Iowa, Kansas, Minnesota, Mississippi, Montana, Nebraska, New Mexico, North Carolina, Oklahoma, Oregon, South Carolina, South Dakota, Tennessee, Texas, Vermont, Wisconsin, and Wyoming.

[14]Deposit insurance was not in effect over the full sample period for any of the eight states with deposit insurance. However, p-values over the subperiods for which deposit insurance was in effect are only marginally different from the p-values using the entire sample.

count for approximately 25% of commercial failures; and second, bank failures have a large, but short-lived impact in the banking sector. This last finding is consistent with the hypothesis that bank failures were caused primarily by bank runs, which were typically short-lived events as well.[15]

Let $x_t = (c_t, b_t)'$ where c_t and b_t are defined above, then the vector autoregression (VAR) under consideration is

$$x_t = \delta + \sum_{i=1}^{k} \phi_i x_{t-i} + \epsilon_t \tag{3}$$

where δ is a (2 x 1) vector of constants, k is the number of VAR lags, ϕ_i is a (2 x 2) parameter matrix, and ϵ_t is a mean zero vector of innovations with covariance structure Σ. Equation (3) can be rewritten as

$$\Phi(L)x_t = \epsilon_t \tag{4}$$

and inverted to an infinite-order moving-average model

$$x_t = C(L)\epsilon_t \tag{5}$$

where $C(L) = \Phi(L)^{-1}$ and the contemporaneous effect of ϵ_t on x_t is the identity matrix. Equation (5) is a reduced-form model since the innovations ϵ are contemporaneously correlated with covariance structure Σ. We need a structural model with orthogonal innovations in order to draw inference about the size and dynamic effect of bank failures and commercial failures.

Our structural model is

$$x_t = A(L)\eta_t \tag{6}$$

where η_t is a mean zero vector of orthogonal innovations with a covariance structure normalized to the identity matrix. We identify the structural model by comparing Equations (5) and (6) and observing that $\epsilon_t = A(0)\eta_t$ and $A(k) = C(k)A(0)$, where

[15] There are several papers that document and analyze the nature of bank runs in the U.S. at the turn of the 20th century. See, for example, Calomiris and Gorton (1991) and Canova (1994).

$A(0)$ is the contemporaneous effect of η_t on x_t. Therefore the four elements of $A(0)$ just identify the structural model. We use two types of restrictions to identify the structural model: covariance restrictions and a contemporaneous restriction on one of the two structural innovations. Covariance restrictions establish three of the four restrictions necessary to identify $A(0)$, since $\Sigma = A(0)A(0)'$. The fourth restriction is an assumption that the contemporaneous response of bank failures to commercial failures is zero.

We estimate the structural model at the aggregate U.S. level, where we find that bank failures Granger cause commercial failures and commercial failures do not Granger cause bank failures. Consequently, we impose this triangular restriction on the reduced-form matrices $C(k)$. In conjunction with the contemporaneous triangular restriction on the matrix $A(0)$, the structural matrices $A(k) = C(k)A(0)$ are also triangular and the credit channel flows through from the reduced-form VAR to the structural model.[16]

The model is estimated with 4 VAR lags, a choice that captures annual variation in quarterly data and is supported by a likelihood ratio test that finds that the reduced-form VAR residuals are consistent with white noise. The forecast-error variance decompositions are normalized such that the variances of the two structural innovations sum to 100%. Table 5 presents forecast-error variance decompositions, and Figure 4 presents impulse response functions, from the structural model at the aggregate U.S. level. They include one-standard-error confidence intervals, which are bootstrapped using 1,000 repetitions of the model.

There are four combinations of bank failures and commercial failures to consider. First, the credit channel in which bank failures affect commercial failures. The forecast-error variance decompositions in Table 5 show that bank failures account for

[16]We estimated the structural model without imposing the triangular credit-channel restriction on the reduced-form matrices $C(k)$ and find that the results change very little. The forecast-error variance decompositions from the unrestricted model are within 1.6 percentage points of the restricted model at all forecast horizons, and the impulse response functions are nearly identical.

Table 5
Forecast-Error Variance Decompositions
for U.S. Bank Failures and Commercial Failures

Forecast	Percentage Due to Bank Failures:		Percentage Due to Commercial Failures:	
Horizon	Commercial	Bank	Commercial	Bank
(Quarters)	Failures	Failures	Failures	Failures
1	22.4%	100.0%	77.6%	0.0%
	(9.5%)	(0.0%)	(9.5%)	(0.0%)
2	30.2	100.0	69.8	0.0
	(12.9)	(0.0)	(12.9)	(0.0)
3	29.4	100.0	70.8	0.0
	(12.3)	(0.0)	(12.3)	(0.0)
4	29.8	100.0	70.2	0.0
	(12.3)	(0.0)	(12.3)	(0.0)
8	26.6	100.0	73.4	0.0
	(11.7)	(0.0)	(12.3)	(0.0)
12	26.3	100.0	73.7	0.0
	(11.7)	(0.0)	(11.7)	(0.0)
16	26.3	100.0	73.7	0.0
	(11.7)	(0.0)	(11.7)	(0.0)
24	26.2	100.0	73.8	0.0
	(11.7)	(0.0)	(11.7)	(0.0)
40	26.2	100.0	73.8	0.0
	(11.7)	(0.0)	(11.7)	(0.0)

Standard errors are listed in parentheses. They are bootstrapped using
1,000 repetitions of the model.

approximately 25% of commercial failures across all forecast horizons, with a small hump at short-run and medium-run horizons. The impulse response functions in Figure 4 show that bank failures have a relatively large impact on commercial failures in the first two quarters, but fall quickly and then diminish slowly over time. Second, bank failures account for 100% of bank failures at all forecast horizons, by construction, and the impulse response is very short-lived. Third, commercial failures do not have any impact on bank failures by construction. And fourth, commercial failures account for approximately 75% of commercial failures across all forecast horizons, with a small dip at short-run and medium-run horizons, and the impulse response diminishes fairly consistently over time.