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A Choice Model for Correspondent Banking Relationships

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A Choice Model for

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Abstract

Employing a granular hand-collected dataset, this paper studies the formation of local financial networks as a consequence of one of the largest bank failures during the Great Depression. The collapse of the National Bank of Kentucky caused ripples throughout the interbank network as 233 banks were faced with the decision to form new connections to reallocate reserves. Tracing over 1600 institutional linkages between 1929 and 1934, I evaluate the decision-making process of commercial banks under a nested logit framework. I find that peer effects and other regional metrics, contrary to national connectivity measures, act as principal determinants in network formation. Further, I show how the connections selected influenced bank survivorship.

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1 Introduction

Our current financial system, with the forces of supply and demand establishing a configuration of linkages, is characterized by its high degree of interdependence. The Global Financial Crisis (GFC) stressed the significance of studying the intricacies of financial networks to assess the spread of contagion (Bekaert, Ehrmann, Fratzscher and Mehl, 2014; Glasserman and Young, 2016; Duffie 2019). Economists have focused on understanding the various characteristics that make financial systems vulnerable to risk and evaluating how macroeconomic environments respond when "systemically significant" financial institutions suspend or fail.[1]

Existing research has examined the topology of financial networks (Das, Mitchener and Vossmeyer, 2020), liquidity in financial networks (Brunetti, Harris, Mankad and Michailidis, 2019), susceptibility to financial contagion (Elliott et.al, 2014; Glasserman and Young, 2016), density and stability of financial networks, (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2015) and the network measures of systemic risk (Brownless, Chabot, Ghysels and Kurz, 2015). As such, the study of financial systems has led to extensive research on *network effects* rather than *network formation*, that is how financial institutions form relationships with other financial institutions. Motivated by this gap, I evaluate the various determinants of connectivity. This paper analyzes how banks form connections with other financial institutions and the features that influence their decision.

To answer this question, I investigate the restructuring of the U.S. commercial banking system as a consequence of the Great Depression. While the GFC has played a large role in determining the financial networks that exist today, the historical network provides a transparent structure to understand connection decisions in specific regulatory environments. Further, evaluating the shaping of the network enables us to understand and identify the sources of susceptibility in later recessions. During the Great Depression, national and state banking laws required commercial banks to hold a fraction of reserves in the reserve and central reserve cities of the Federal Reserve. This mandatory requirement led banks across the nation to form connections with other financial institutions which led to the development of the inter-bank network. The Great Depression, with the prevalence of correlation networks and physical networks, provides a unique setting to study this question. Correlation networks are described as those where links are formed indirectly, for example through return correlations (Billio et al., 2012; Diebold and Yilmaz, 2014). On the other hand, physical networks arise from direct links as a result of agent choices (Brunetti et al., 2019). This paper addresses the evolution of the latter with the reallocation of reserves being the immediate stimulus. In the 1900s, the

[1] The Dodd Frank Act (2010) defines a systemically important financial institution (SIFI) as one that is large, complex, linked to other financial institutions and "critical," providing services that may have few close substitutes

national banking landscape was shaped from explicit contractual relationships and the failure of an influential, financial institution faced the banks it was connected to with a definitive choice.

The formation of interbank relationships is an integral concept to understand the causes of bank failures during the Panic. The correlation between suspensions of country banks due to the closure of principal banks was particularly pronounced during the initial banking depression.[2] When compared to the latter, on average, banks that cleared via larger financial institutions possessed less capital, lower deposits, and fewer assets; operated in more rural areas; invested more in agriculture; diversified investments less across industries; and employed smaller staff with less experience (Richardson 2007). These factors contributed to the domino-like collapse of commercial banks when a large institution it was connected to, went under water.

This phenomenon was observed in July of 1929 as a fruit fly epidemic caused the suspension of several principal banks in central Florida by posing a threat to the state's citrus industry. Subsequently, within a two-week period, more than 120 banks suspended operations (Carlson, Mitchener and Richardson, 2011). In the South, a similar situation occurred when the National Bank of Kentucky in Louisville, KY suspended operations because of heavy withdrawals and its association with the Caldwell Chain (Fugate, 1976). This closure also forced the suspension of its affiliate, the Louisville Trust Company (another principal correspondent), to suspend operations on the same day. During the next week 15 respondents of the national banks were discontinued, four of which were respondents of the trust company.[3]

To understand these correlations, I study a particular consequence of the Great Depression. The financial meltdown of 1929 resulted in the failure of one of the earliest and largest banks in the 1930s, the National Bank of Kentucky in Louisville, KY. The magnitude of its collapse is reflected in its 0.65% contribution to systemic risk during the panic (Das, Mitchener and Vossmeyer 2020). To meet their state's reserve requirements, many banks across Kentucky and other neighboring states held deposits with the National Bank of Kentucky. When this bank failed, the numerous banks that it was associated with had to initiate financial connections with other banks in Louisville to reapportion their reserves. Studying the failure of the National Bank of Kentucky as one of the several turning points in the shaping of financial networks, I collect data on its connected banks from 1929 to 1934 and model their decision-making process under a multinomial choice setting. Further, I extend the

[2] Country banks are those that are located in the hinterlands.

[3] NARA National Archives and Record Administration, Record Group 82, Federal Reserve Central Subject File, file number, 434.-1, Bank Changes 1921-1954 Districts 1929-1954 - Consolidations, Suspensions and Organizations 6386 a,b,c, (By States) 1930-1933. NARA Bank Changes, American Mutual Savings Bank, Louisville, KY, 17 November 1930; First Standard Bank, Louisville, KY, 18 November 1930

implications of these decisions by analyzing how each new linkage made by a bank affected its probability of surviving the Depression. The binary outcome of failure in 1934 is modeled using a probit regression.

Employing micro-level hand-collected data detailing balance-sheet information and other metrics on each bank connected to the National Bank of Kentucky (NBK), I evaluate how bureaucratic features, regulatory environments and local network measures act as key determinants in the process of institutional and regional interbank reconnection. Evaluating over 1600 institutional linkages, I find that a significant determinant of connectivity is peer effects. Namely, if a particular bank's neighboring bank connects to a specific institution in Louisville, with the failure of NBK, the bank of interest will initiate a financial relationship with its neighbor's bank. Moreover, banks connect to larger banks, relative to their own size. I also find strong evidence that liquid banks are very conservative with their connections and are most likely to not form a new connection. Instead, they tend to increase deposit funds with existing connections. This aligns with liquidity hoarding behaviors exhibited by financial institutions during times of uncertainty. However, in studying how a bank's selection impacted its probability of survival, I find that the decision to form multiple linkages lowered a bank's probability of failure by almost ~21 percentage points. This result is relative to a bank that chose to increase its fraction of reserves with existing institutions, or form a new linkage with a bank outside Kentucky. Further, forming a single new connection decreased a bank's probability of failure by ~10 percentage points compared to a bank that formed no new connections. In this manner, liquidity hoarding behaviors were negatively correlated with bank survival.

The turbulence experienced by financial markets in 2007 stressed the importance of studying financial networks as the effects of the meltdown were felt around the globe. Given the central role of commercial banks in providing liquidity to markets, the interbank network plays an important role in our economy. Although financial networks that exist today are relatively concentrated, understanding their formation has a variety of policy implications. This paper demonstrates how network positioning and relationships within localized financial systems influence the formation of interbank linkages, and in turn, structure networks.

There has been a growing interest as to how different network structures respond to the breakdown of a single financial institution in order to trace risk (Allen and Gale, 2000). Research has also focused on whether interbank markets are able to anticipate contagion (Dasgupta 2004; Caballero and Simsek 2013). In parallel, this paper contributes to the dynamic, complementary literature studying financial networks in previous periods, regarding the interbank network during the national banking era (Carlson 2010; Mitchener and Richardson, 2013; Dupont, 2017) financial contagion during crises (Calomiris and Carlson, 2016; Das, Mitchener and Vossmeyer, 2020; Summer, 2013) and the formation of financial networks (Aymanns and Georg, 2014; Babus 2016). My paper is the first to study the reformation of a financial system after a crisis by assessing the decision-making of local networks. Although previous research has studied risk inherent in networks built through institutional linkages, this study gains ground by focusing on the failure of a particular institution to understand how network measures interact with the shaping of local financial systems.

2 Historical Background

At the beginning of the 20th century, the national financial network consisted of an extensive interbank system which was responsible for the clearing of payments and movement of capital. This structure had evolved out of the Civil War and in turn, the establishment of nationally chartered banks. The National Banking Act of 1864 brought along with it an increased circulation of bank drafts as a national payments mechanism (James and Weiman 2010). Due to legal restrictions on branch banking, the network was composed largely of small, single office banks. Commercial banks were classified into central reserve city banks (located in New York, Chicago, or St. Louis), reserve city banks (located in selected large cities such as Philadelphia, or San Francisco) and country banks (located elsewhere). These cities were selected due to their concentrations of financial activity. Besides, the regulatory environment at the time ensured that the institutional linkages in place were self-perpetuating. The National Banking Acts of the 1860s required country banks with national bank charters to meet legal reserve requirements by depositing a portion of their reserves as cash in their vaults and the remainder (originally up to 80%) in banks in reserve or central reserve cities (White, 1983). This was supplemented by State laws which required state-chartered banks to portion their reserves between vault cash and interbank balances kept in larger city banks. Hence, the linkages of financial institutions led to the development of the correspondent banking network.

To facilitate the interregional movement of capital as well as meet mandatory reserve requirements, country banks were encouraged to form relationships with reserve and central reserve banks. Accordingly, a "respondent" bank is defined as one that initiates a business relationship with another bank for its customers or itself for the purpose of depositing interbank balances. A "correspondent" bank is the recipient of these deposits and was typically a bank located in a reserve or central reserve city. Correspondent-respondent bank linkages resulted in the cumulation of financial activity in these cities, assembling a pyramid-like structure. These directional relationships are illustrated in Figure 1. Citizens Bank in Albany, KY lists two correspondents in 1929: National Bank of Kentucky and Lincoln Bank & Trust Company. In turn, the correspondent bank National Bank of Kentucky lists three correspondents: Philadelphia National Bank (Philadelphia, PA), Continental Illinois Bank and Trust (Chicago, IL) and Guaranty Trust (New York, NY). Similarly, Lincoln Bank & Trust

Co. lists two correspondents: Guaranty Trust and Chase National Bank in New York, NY. Following suit, Philadelphia National Bank, Continental Illinois Bank and Trust, Guaranty Trust and Chase National Bank list other correspondents and so on, forming the interbank network.

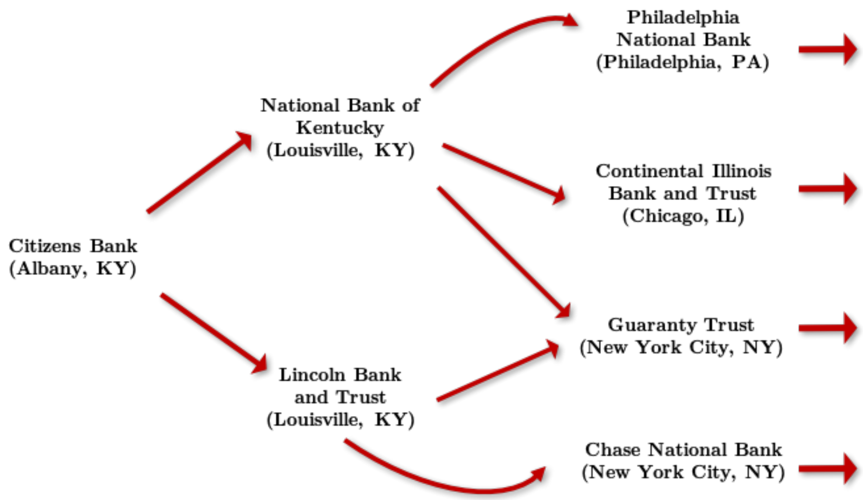

Figure 1: Correspondent-respondent linkages

With the banking panics of 1893 and 1907, came the need for a regulatory, financial institution. Consequently, the 1913 Federal Reserve Act led to the establishment of the Federal Reserve System. With this came the mandate of member banks to hold reserves with Reserve banks. Unlike our financial system today, where all commercial banks are part of the Federal Reserve System, the interbank network, especially country banks, were obligated to only follow state mandates rather than a national mandate. However, all national banks were required to join the Federal Reserve System, and hence could no longer satisfy a portion of their reserve requirements by holding balances with institutions in reserve or central reserve cities. The framers of the central bank intended to reduce the nation's reliance on the interbank system by consolidating deposits in the Federal Reserve's 12 regional reserve banks as opposed to having them sprawled amongst hundreds of banks across the nation. Acknowledging the interbank network's susceptibility to banking panics, they sought to minimize the importance of interbank linkages. The Act was then amended in 1917 and demanded for national and state-member banks to hold deposits at their regional Federal Reserve Bank to meet reserve requirements. However, by 1929, only 10% of state-chartered commercial banks had joined the Federal Reserve System, leaving much of the pyramid-like inter-banking structure in place.

The ill-fated day of September 4, 1929 brought with it the stock market crash that catalyzed one of most severe economic depressions. The Great Depression led to the suspension and failure of commercial banks across the country, and consequently remodeled the entire banking network. Apart from being one of the worst financial meltdowns in history, it had a massive impact on the real economy and brought along with it a staggering unemployment rate and damaging policies which set the course of its lengthy and fragile recovery. With the Great Depression, we saw that the "core-periphery" structure of the U.S. interbank system was most vulnerable for contagion via correspondent-respondent bank connections (Hojman and Sziedl, 2008). As such, the failure of a major correspondent bank sent waves across the entire network. Following the restructuring of the U.S. interbank network as a result of the Great Depression, this paper studies the failure of the National Bank of Kentucky to understand the process of financial network formation.

Following the stock market crash, the banking crisis can be traced to the failure of the Bank of Tennessee, a subsidiary of Caldwell and Company, in November 1930 (Richardson, 2007). Caldwell and Company was an investment banking firm located in Tennessee. To expand its sources of additional funds, Caldwell extended its activities into areas of commercial banking and insurance. The firm controlled the largest chain of banks in the South with assets north of $200 million and also the largest insurance group in the region with assets estimated around $230 million (Wicker 1996). The fundamental cause of the failure of Caldwell was its weak and precarious financial state on the eve of the depression. The firm's balance sheet for June 30, 1929 showed Caldwell's vulnerability to even the slightest jolt in depositor confidence. Often compared to the Lehman Brothers of the 1930s, the collapse of Caldwell set up a chain reaction of bank failures. By this time, 55% of its total assets were illiquid and outside sources provided 90% of the Company's total funds. Its affiliation with the firm led the National Bank of Kentucky to shut its doors on November 17, 1930.

The National Bank of Kentucky was a venerable institution established in 1834. Initially it had been a state bank known as the Bank of Kentucky till it received its charter in 1900 under the National Banking Act and was renamed. The institution had survived the Civil War and several other banking panics. It was the trusted institution of several Kentuckians from urban and rural areas, and a correspondent for numerous state banks, cities and counties across Kentucky, Illinois, Indiana and Tennessee. With resources estimated to be over $50 million the national bank became the largest south of the Ohio River (Fugate, 1976). On July 20, 1929 the National Bank of Kentucky and the Louisville Trust Company merged into a holding company known as BancoKentucky Company. Under the aggressive and colorful leadership of James Brown, the company believed a merger with Caldwell and Co. would put an to end its deteriorating financial situation. However, once the merger was publicly disclosed in June 1930, Caldwell provided Brown with the financial truth that the investment bank was already insolvent. Not long after did BancoKentucky experience the repercussions of the failure of Caldwell. Of the 143 banks that failed in November 1930, 129 can be traced to the collapse of Caldwell (Fugate, 1976). Moreover, of the 233 respondent banks that were linked to the National Bank of Kentucky, 52 failed.

Before the financial downturn, the period of the 1920s saw growth, consolidation and new charters across the nation. With the passing of the national banking acts, the First National Bank of Louisville became Louisville's first bank to receive its national charter in 1863. Accordingly, at the end of June 1929, the National Bank of Kentucky, Citizens Union National Bank and the First National Bank were Louisville's only three national banks. Thus, along with the fateful failure of the National Bank of Kentucky on November 17, 1930, the Louisville Trust Company also shut its doors on the same day. However, after undergoing a restructuring, it reopened in July 1931 and Louisville continued to remain an active reserve city (Kleber 2001). In 1929, Liberty Bank and Trust was the largest state bank in Kentucky and was a member of the Federal Reserve System. Lincoln Bank and Trust Company was a fully equipped commercial bank and was also a member of the central banking system. Moreover, in 1932, the Bank of Commerce, another state mandated bank was established and held a significant portion of Louisville's deposits. These six banks gained status as appealing prospects in Louisville. In this manner, the failure of NBK left its respondents with the decision to either initiate a relationship with one of the correspondents or select a different alternative entirely.

3 Data

3.1 Data Sources and Collection

I collected data on the U.S. correspondent banking network for all commercial banks connected to the National Bank of Kentucky. To study interlinkages, I recorded information detailing the respondent banks' list of correspondents between 1929 and 1934. I only used the respondent banks that were alive when the National Bank of Kentucky crashed so as to estimate network measures as a consequence of its failure. These data, as well as information on each bank's balance sheet and other characteristics (location, population of city or town, date of first charter, age since establishment, Federal Reserve membership, etc.), were hand-collected from Rand McNally *Bankers Directory*.[4]

The bank-level balance sheet and income data is used to derive bank-specific measures of risk and also define and compute key financial metrics. In this paper, assets refer to the sum of loans and discounts, miscellaneous assets, bonds and securities, and cash and exchanges

[4] In particular, I used the July 1929, July 1930, July 1932, July 1933 and July 1934 issues from Rand McNally's *Bankers Directory*.

(due from banks); equity is the sum of paid-up capital plus surplus and profits. The directory categorizes liabilities into paid-up capital, surplus and profits, deposits, and other liabilities.

3.2 Choice Set

Alternatives 1-6

As a consequence of its failure, NBK's respondents had the choice of selecting a new correspondent to form a financial linkage with. By the end of 1930, the Louisville banking community was left with two federally chartered banks with assets totaling ~$60 million and thirteen state-chartered banks with assets of ~$90 million (Kleber 2001). The Federal Reserve Bank of St. Louis Louisville Branch was established in 1917 as a branch of the Federal Reserve Bank of St. Louis. Legal regulations imposed by the central bank required deposits of member banks to be held with them. As such, using federal reserve membership as one of my several criteria, I constructed my choice set. The two national banks were Citizens Union National Bank and the First National Bank. Citizens Union National bank was born out of a merger between Union National Bank and Citizens National Bank in 1919. In 1930, excluding the deposits of NBK, Citizens Union National had a market share of ~26%, calculated as a percentage of Louisville's deposits. Around the same time, First National Bank roughly had a ~15% market share. Since both banks were nationally chartered and operated under the Fed's mandate, the correspondents were appealing alternatives for respondent banks.

Liberty Bank and Trust was the largest state bank in Kentucky. It was also a member bank of the Federal Reserve System. In 1930, excluding the deposits of NBK, it held a 20% share of Louisville's deposits. Although its assets shrunk from $33.6 million to $22.2 million from 1929 to 1934, it was on the path of recovery and its incorporation to the Federal Reserve network and historical performance record made it an inviting option for respondent banks looking to form correspondent linkages. Similarly, the Lincoln Bank and Trust Company was a popular state commercial bank that was also a member of the Federal Reserve system. It had an 8% market share in 1930, excluding NBK's deposits. Its path to recovery was strong as its deposits expanded from ~$9.6 million to ~$11 million from 1929 to 1933. Although Liberty Bank & Trust, and Lincoln Bank & Trust were not under a national mandate, they were Federal Reserve members which had the effect of stamping a seal of security for respondent banks looking to form potential correspondent connections.

In July 1929, the National Bank of Kentucky merged with Louisville Trust Company to form the BancoKentucky holding company. However, its failure in November 1930 forced the Louisville Trust Company to suspend operations. Through the receiver of Louisville Trust Co, the First National Bank of Louisville acquired the successful installment loan business that had been developed by Louisville National Bank & Trust which merged to form Louisville

Trust Co. in May 1929 (Kleber, 2001). With time, the bank was able to successfully restructure and reopen in July 1931. The Louisville Trust Company was also a part of the Federal Reserve System. Moreover, many important community and financial leaders supported the reorganization verbally and financially to restore the public's confidence in the institution (Kleber, 2001). The Bank of Commerce, established in 1932, gained a lot of public support and became a viable contender as an attractive alternative for respondent banks. Considering these factors, I construct the choice set of six Louisville alternatives and populate each bank's data into my choice model. However, instead of selecting a single new correspondent, respondent banks also had the option of selecting many new correspondents to appropriately diversify the location of their interbank deposits.

Alternative 7

The Many Alternative is the choice selected when a respondent bank adds more than one new correspondent to its list of existing correspondents between November, 1930 and July, 1934. Balance-sheet and income data for this choice is populated by taking a weighted average by market share of the correspondent banks chosen. For example, Brownsville Deposit Bank located in Brownsville, KY chooses Citizens Union National and Lincoln Bank and Trust. These two correspondent banks have approximately a 16% and 4.7% market share, respectively.[5] The balance-sheet items are then calculated by taking an average weighted against market share. Accordingly, I multiply Citizens Union National's data by 16% and divide by the two banks' combined market share to standardize the metric. Similarly, I calculate the line items for Lincoln Bank and Trust and add the two sums. For the variable indicating whether the correspondent bank is a federal reserve member, I put a 1. This is because from the list of 6 correspondents, only the Bank of Commerce is a non-federal reserve member. For the independent variable quantifying eigencentrality and the year of establishment, a simple average is taken. Likewise, market share is calculated by taking a sum of the market share of the banks chosen.

For banks that have chosen an alternative other than Many, a weighted average by market share is taken for all six Louisville correspondents. Eigencentrality and the correspondent's age is calculated by taking a simple average. Market share is calculated by summing the market share of the six Louisville correspondents. While connections were to form in reserve cities like Louisville, after NBK failed, a respondent bank may have not wanted to connect with another bank in Louisville and instead chosen to meet reserve requirements

[5] Since market share information was populated using 1929 data, deposits of NBK were included due to the correspondent's active operational status. Hence, these market share metrics differ from those listed in the previous sub-section.

by forming a linkage with a bank outside Kentucky, or increase the proportion of its deposits with existing correspondents.

Alternative 8

This alternative is chosen when respondent banks choose to add none of the six Louisville banks to their existing list of correspondents. Accordingly, if a respondent chooses to connect with a correspondent in New York, its choice will still be none. However, less than a fourth of the respondents selected a correspondent other than the aforementioned Louisville alternatives in our choice set.[6] For banks that make this decision, I populate the balance-sheet data and other general characteristics of its geographically nearest correspondent bank in 1934. For most respondents, the nearest correspondent is usually one of the 6 Louisville correspondents. This indicates that a respondent was already linked to one of the correspondents from the choice set prior to NBK's failure. However, in some cases, the nearest correspondent can be a bank in a different state. For example, the respondent Citizens National Bank in Bowling Green, KY had the National Bank of Kentucky, KY; Citizens Union National, KY; Chemical Bank, NY; Guaranty Trust, NY; and Fifth Third Union, OH listed as correspondents in 1929. In 1934, it had Guaranty Trust, NY; Chemical Bank, NY, and Continental Illinois Bank and Trust, IL listed as correspondents and hence, it selected alternative 8. Geographically, Continental Illinois Bank and Trust is closest to the respondent, and thus, its information is populated in the None alternative.

Similarly, I fill in the data for the None alternative for respondent banks who have selected an alternative between 1 and 7 with the information of its nearest correspondent. For example, Union National Bank in Providence, KY added Citizens Union National to its list of existing correspondents in 1934, thereby choosing the first alternative in our choice set. Its list of correspondents in 1929 were the National Bank of Kentucky, KY and Old National Bank, IN. Whereas in 1934, its list of correspondents were Citizens Union National, KY; Old National Bank, IN; and National City Bank, IN. Accordingly, to fill in the data for the None alternative, I populate the information of Union National Bank's geographically closest correspondent which is Old National Bank in Evansville, IN.

Illustrated below in Figure 2 is the choice set for each respondent bank. If a respondent makes the decision to select a single new correspondent, it will be placed in Nest I. From there, it further decides which specific correspondent it wants to link with and selects an alternative from 1 to 6. If a respondent chooses to initiate multiple financial linkages, it is placed in Nest

[6] The remainder of the respondent banks that selected this alternative chose to initiate no new connection, and thus, increased reserves with existing correspondents.

II.[7] Similarly, if it chooses to form no new connections with our Louisville correspondents, it is placed in Nest III. These alternatives are mutually exclusive and exhaustive.

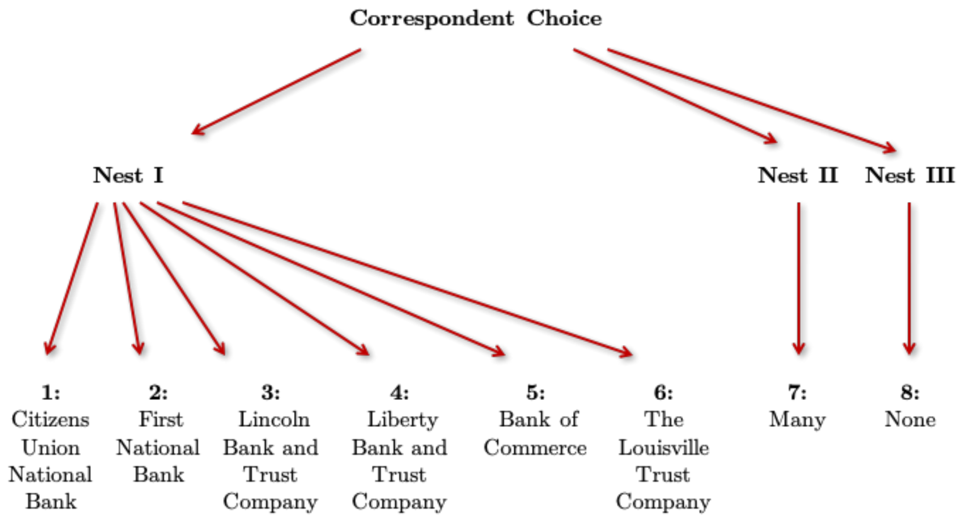

Figure 2: Choice Set of respondent bank

3.3 Network Statistics

3.3.1 Correspondent Features

Using balance sheet data, I computed several financial ratios. The loan ratio is calculated by dividing the loans and discounts by total assets. Similarly, the equity ratio is the sum of paid-up capital and surplus profits divided by total assets. The deposit ratio is calculated by estimating total deposits as a percentage of total assets. The table below describes the balance sheet particulars of the six correspondents in our choice set.

Table 1: Financial Metrics on Correspondent Choice Set

Bank Names	Total Assets	Loan Ratio	Equity Ratio	Deposit Ratio
Citizens Union National	34,652,840	0.67	0.09	0.76
First National Bank	20,228,640	0.47	0.10	0.80
Lincoln Bank and Trust	9,642,570	0.71	0.13	0.78
Liberty Bank and Trust	33,562,840	0.57	0.10	0.64
Bank of Commerce	1,199,440	0.54	0.13	0.82
Louisville Trust	25,995,610	0.64	0.13	0.74

[7] Respondents that selected the Many alternative chose several combinations of the six Louisville correspondents. Hence, I did not branch this nest out further.

Moreover, I computed financial metrics of the 233 respondents chosen in our sample set. Bank size is approximated using a respondent's total assets. The other ratios are computed as a percentage of assets. For each alternative, the average of these metrics is computed and shown in Table 2. It summarizes these averages based on the choice a respondent bank selected into.

Table 2: Descriptive Statistics of Respondent Banks Grouped by Alternative

Alternative	1	2	3	4	5	6	7	8
Number of Banks	58	25	23	5	2	1	26	92
Bank Size	13.36	13.56	13.21	12.96	11.92	16.38	13.00	13.31
Bank Age	40	40	32	45	26	69	35	17
Total Assets *(in '000s)*	1,184	1,047	680	514	172	12,972	735	1,193
Loan Ratio	0.64	0.66	0.68	0.74	0.79	0.73	0.66	0.61
Equity Ratio	0.16	0.16	0.15	0.19	0.21	0.17	0.16	0.17
Cash Ratio	0.15	0.15	0.14	0.13	0.14	0.08	0.14	0.17

As illustrated, we see that respondents that choose alternative eight, that is no new correspondents have higher cash ratios compared to respondents selecting into other alternatives. Since liquidity can be captured by cash ratios, this implies that respondents selecting into alternative 8 enjoyed thicker liquidity cushions relative to others.

3.3.2 Respondents Features

The National Bank of Kentucky's respondent relationships spanned not just Kentucky but also stretched across Indiana (31), Tennessee (9) and Illinois (1).[8] The average respondent size is 13.3 and generally hovers between 11 and 16. The average age of respondents in our dataset is 37 years with the youngest bank being 6 years and the oldest, a 100 years. Regarding financial ratios, the average respondent loan ratio is around 0.64, at times it was as low as 0.08 and as high as 0.95, suggesting large constraints on liquidity. The average cash ratio was 0.15 and hovered between 0.09 and 0.2 with the lowest being negligible and the highest up to 0.55. Similarly, bond ratios floated around 0.16, going up to 0.25 in some instances. From our sample size of 233 respondents, 65 were national banks and 3 were state banks that were a part of the Federal Reserve System, indicating a membership rate of ~30%. Figure 3 illustrates the respondents in our sample size according to the alternative that each bank selected.

[8] The numbers in parentheses refer to the number of NBK's linkages in each respective state.

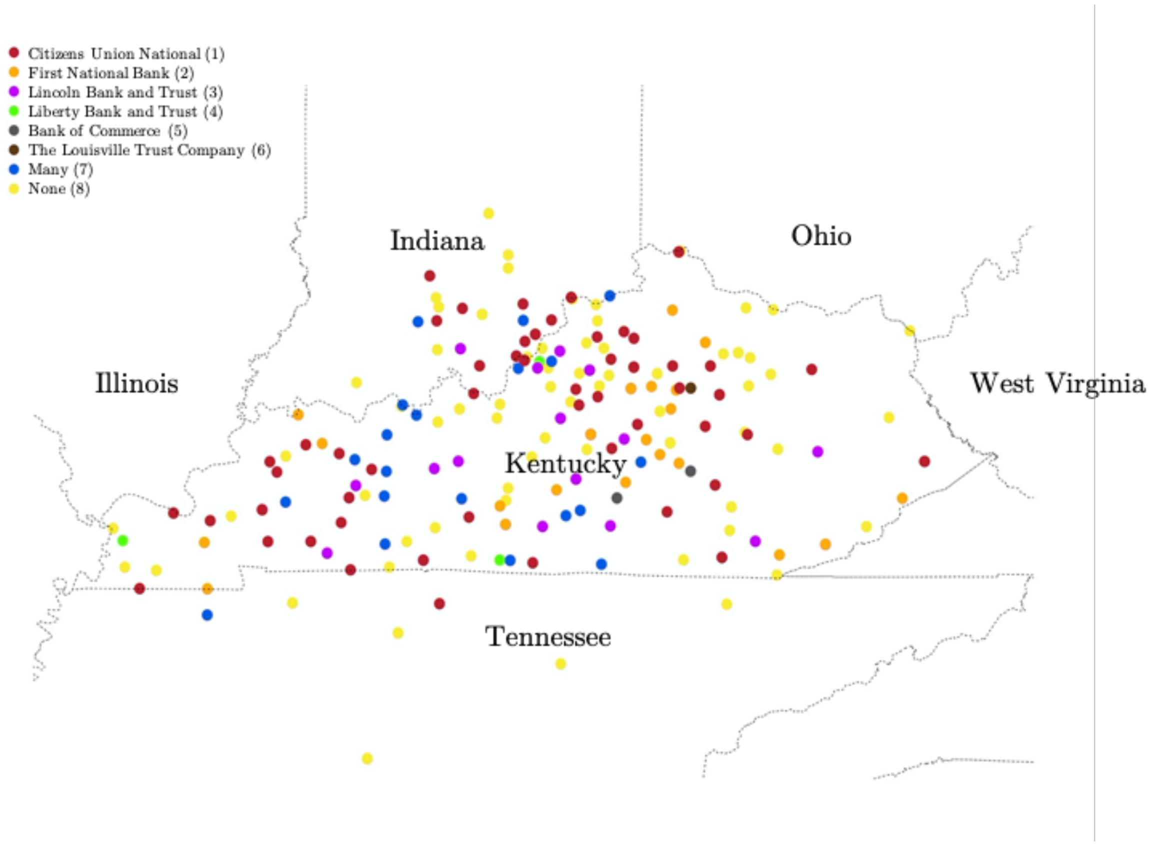

Figure 3: Respondent Network Density based on Alternative Selected

3.3.3 Peer Network Features

To quantify local network measures, I looked at the choices made by respondents' neighboring banks. This allows us to understand if peer effects have a role in determining respondent choices. To measure these effects, I look at the correspondents of banks from 1929 to 1934 and constructed a fraction variable to reflect the percentage of banks in a respondent's town selecting into a specific choice. However, if there are no other banks in the same town then the input is 0 for all choices 1-8. For example, Citizens Union Bank is located in Central City, KY. There is only one other bank in Central City and it lists Lincoln Bank as a correspondent in 1934. Accordingly, I would input a 1 into Choice 3 (Lincoln Bank) to reflect this information. If there is more than one bank in the respondent's town, fractions are used to indicate the proportion of banks selecting into an alternative. For example, People's Liberty Bank and Trust in Covington, KY has five other neighboring banks located in the same town. Out of these five, two listed Citizens Union National as their sole correspondent bank in Louisville, and three listed no bank in Louisville in 1934. Accordingly, I input a 0.4 (⅖) into Choice 1 (Citizens Union National) and a 0.6 (⅗) into Choice 8 (None). Thus, the sum across all alternatives for this variable is equal to 1. These fractions provide helpful magnitudes which enable me to analyze the proportions of neighboring banks selecting into an alternative.

3.4 Connectivity Measures

3.4.1 Correspondent Centrality

To understand if a correspondent's degree of centrality played a role in determining a respondent bank's decision to initiate a relationship, I decided to test a its measure of centrality. The concept of centrality can be described as the number of connections a correspondent bank has, also referred to as a node. However, this kind of degree centrality ignores those nodes that may have few connections but still exert a large influence on the correspondent network. Hence, by adjusting for the degree of depth, we can estimate a correspondent's influence on the network using eigencentrality. Using the method outlined in their paper, Table 3 shows eigencentrality values for each alternative in the choice set (Das, Mitchener and Vossmeyer, 2020). This metric stresses the importance of a correspondent bank's positioning in the interbank network spread across the nation.

Table 3: Centrality of Correspondent Choice Set

Bank Names	EigenCentrality
Citizens Union National	0.039
First National Bank	0.012
Lincoln Bank and Trust	0.028
Liberty Bank and Trust	0.022
Bank of Commerce	0.006
Louisville Trust	0.032

3.4.2 Respondent Centrality and Market Share

To understand the importance of local network effects, I used market share to capture the significance of regional demand. As such, it is calculated as the percentage of a correspondent's deposits over deposits across Louisville. To contrast the effects of correspondent centrality, I also estimated respondent centrality by recording each respondent bank's number of connections in 1929. This is approximated to act as a *degree of connectedness.*

3.5 Bank Survivorship

The failure rate of respondents in my dataset of 233 banks was ~22.1%.[9] These commercial banks failed in the period between November 30, 1930 and July 30, 1934. To account for the

[9] This failure rate was much smaller than the national average where almost 40% of banks suspended operations or failed.

case of failed banks, I populate the respondent's data from the year immediately prior to failure. As such, the data would be from either 1930, 1931, 1932, or 1933. Analyzing the decisions of banks that survived and those that failed would in turn let us infer how choices made by the respondent played a role in determining its outcome. Table 4 exhibits the rate of failure of respondent banks classified by the alternatives they chose into.

Table 4: Failure Rates Grouped by Alternative

Choice Set	Failure (%)
Citizens Union National	22
First National Bank	16
Lincoln Bank and Trust	22
Liberty Bank and Trust	0
Bank of Commerce	0
Louisville Trust	0
Many	12
None	28

I consider failed banks to be those that underwent a merger or acquisition, were liquidated, or discontinued operations. Each of these three alternatives result in a significant restructuring or elimination of the initial financial institution in the pre-crisis years and thus, fall under the generic terminology of a failed bank. Specific respondent characteristics categorized by bank survival is shown in Table 5.

Table 5: Respondent Bank Statistics according to Survivorship

Metric	Survived	Failed
Nest I	92	22
Nest II	23	3
Nest III	66	26
Bank Size	13.35	13.13
Bank Age	38	35
Total Assets	1,260,619	937,268
Bond Ratio	0.17	0.12
Loan Ratio	0.64	0.64
Equity Ratio	0.17	0.15
Cash Ratio	0.15	0.18

While this paper studies how the failed respondents made a certain choice, I also conduct a preliminary analysis to evaluate the implications of selecting an alternative to a bank's probability of survival. We see that almost 40% of banks that selected into Nest III failed, as compared to 23% and 13% failure rates for Nests I and II, respectively.

3.6 Choice Framework Construction

From the National Bank of Kentucky's 233 linkages, 52 banks failed after the correspondent's collapse. I carefully constructed my choice set after considering various factors such as Federal Reserve membership, centrality measures, age, market share and other financial metrics. The six Louisville correspondents had a combined market share of 57.2% in total and thus, represent a considerable portion of commercial banking in the city. I looked at each surviving bank's correspondents in 1929 and 1934, and 1929 and year immediately prior to failure for failed banks to determine the choice made.[10] If a respondent bank belongs to the first nest, this implies that it chose a single new correspondent. Similarly, if a respondent bank belongs to the second nest, this implies that it chose multiple new correspondents. Lastly, if a respondent bank belongs to the third nest, this implies that it chose no correspondents.

4 Methodology

4.1 Multinomial Logit

Each respondent had the optionality of several alternatives when faced with the decision of institutional linkages following the failure of one of their primary correspondents, the National Bank of Kentucky. Accordingly, our choice set is mutually exclusive, exhaustive, and has a finite number of alternatives j. However, since $j \neq 2$, the multinomial logit setting must be used. Substitution patterns within the multinomial choice setting state that when the attributes of a certain alternative improve, the probability of it being chosen rises. In the context of this paper, the statement implies that some respondents who would have chosen other alternatives under the original attributes, will now have an increased probability of selecting this alternative instead. For a multinomial logit setting to work, the assumption of independence of irrelevant alternatives must hold. The assumption states that any item added to the set of choices will decrease all other items' likelihood by an equal fraction. Since probabilities sum to one over all alternatives, the increased probability of a certain alternative will translate into a necessary decrease in the probability of other alternatives. This substitution pattern implies the independence of irrelevant alternatives. However, this is not the case for our choice set.

[10] Banks are matched according in 1929 and 1934 based on their name, location, and routing number. Routing numbers take into account name or charter changes and thus, are a reliable matching tool.

For example, consider the case where a respondent bank is going to choose alternative 1, that is adding Citizens Union National to their existing list of correspondents. Assume that this alternative is suddenly made unavailable (in a hypothetical situation in which Citizens Union National fails). If IIA were to hold, this would imply that the probability of choosing alternatives two to eight increase by the same ratio. However, this assumption is likely to fail. The probability of choosing alternatives two to six, that is adding a single correspondent, will increase by the same ratio but it is unlikely that the probability of selecting the many or the none alternative will also increase by the same proportion. Thus, I resort to a variation of the multinomial logit setting, the nested logit model.

4.2 Nested Logit Framework

Generalized Extreme Value (GEV) models allow substitution iterations among alternatives present in the model. When all the correlations in a GEV model are 0, the model reduces to a product of independent extreme value distributions and assumes the form of a standard logit model (Prashker and Shlomo, 2008; Train, 2009). Nested logit models are a common type of GEV model.

In this section, I employ a nested logit model to analyze the correspondent choice structure. This model was appropriate as the set of alternatives faced by the respondent bank, who is the decision-maker, can be partitioned into subsets, called "nests." The outcome variable, y_n, thus equals 1 depending on the nest bank n belongs to. This framework allows for the independence of irrelevant properties to hold which is imperative for subsequent analysis. This condition in the context of nests states that for any two alternatives that are in the same nest, the ratio of probabilities is independent of the attributes or existence of all other alternatives. The nested logit relaxes the assumption of independently distributed errors and the independence of irrelevant alternatives that are inherent in conditional and multinomial logit models by clustering similar alternatives into nests.

4.2.1 Construction of Nests

Nest I is the choice of selecting a single correspondent bank. It contains the six Louisville correspondents - Citizens Union National, First National Bank, Lincoln Bank and Trust, Bank of Commerce, and Louisville Trust. After selecting Nest I, a respondent must then select into one of the six alternatives. Nest II and Nest III are degenerative nests. Nest II is the choice of selecting many Louisville correspondent banks. Nest III is the choice of selecting no Louisville correspondent banks.

In the context of my study, this translates into the notion that once a respondent bank has selected Nest I, they have an equal probability of choosing any of the six Louisville correspondents and these probabilities are independent of the other alternatives of Nest I and Nest III. In other words, if the choice of selecting First National Bank, one of the six Louisville correspondents, is removed, the probability of choosing many Louisville correspondents (Nest II) or no Louisville correspondents (Nest III) will increase by the same proportion. Similarly, the probability of choosing any of the six Louisville correspondents if Nest III is removed will rise by the same proportion. IIA holds between these six alternatives and thus, they are placed into the same nest. Consequently, the independence of irrelevant alternatives holds within each nest.

Another implication of the property is that for any two alternatives in different nests, the ratio of probabilities can depend on the attributes of other alternatives in the two nests. This corresponds to the idea that for a respondent bank n making a choice to select either Citizens Union National Bank (Nest I), or no Louisville correspondent bank (Nest III), the ratio of probabilities of making either of these decisions will depend on the other alternatives comprising Nest I and Nest III. For example, if the choice to select First National Bank is removed, the probabilities to choose another single correspondent from Nest I (Citizens Union National, Lincoln National Bank, Louisville Trust etc.) rises proportionately more than the probability to choose the Many (Nest II) or None (Nest III) alternatives. As such, the independence of irrelevant alternatives does not hold for alternatives in different nests.

The nested logit can be pictured using a tree diagram to represent the substitution patterns. At the bottom of the tree are the six Louisville alternatives. Above the six alternatives are the three types of decisions a respondent bank can make. In this tree, each branch denotes a subset of alternatives which represents a nest and thus, the independence of irrelevant alternatives holds within each nest. In the diagram illustrated in Figure 2 we see each branch representing one of the three nests. The first branch contains six twigs for each of the six Louisville correspondents which represent the different alternatives from which a respondent bank can choose. The second and third branches are degenerative nests as they do not further break down into twigs. Namely, there is proportional substitution across twigs within the same branch but not across branches.

4.2.2 Choice Probabilities

To investigate the respondents' choices to form a new linkage, I employ the nested logit framework. The set of alternatives, j, are partitioned into $K(=3)$ non-overlapping subsets denoted B_1,B_2 and B_3. Thus, utility a respondent bank n gains from a specific alternative j

in nest B_k can be observed through the utility equation. Further, we can decompose the equation into the observed fraction of utility being captured by two parts:
i. W which is the portion of utility that is constant for all alternatives within a nest
ii. V which is the portion of utility that varies over alternatives within a nest

Accordingly, the utility equation can be expressed as:

$$Unj \ = Wnk \ + \ Vnj \ + \epsilon nj \tag{1}$$

for $j \ \epsilon \ B_k$, where

- Wnk depends only on variables that describe nest k. They refer to respondent-specific characteristics such as bank size, financial metrics, network measures capturing peer effects and respondent centrality, federal reserve membership etc. Thus, these variables do not vary over alternatives within each nest.
- Vnj depends on variables that describe alternative j. They refer to correspondent-specific characteristics such as institutional affiliations, correspondent centrality, balance-sheet measures etc., and in turn, correspondent-respondent ratios.[11] Thus, these variables differ over alternatives within the nest k.

Further, assume that the vector of unobserved utility, $\epsilon_{nj} = \langle \epsilon_{n1}, \epsilon_{n2} \cdot \cdot, \epsilon_{nj} \rangle$ follows a generalized extreme value under a nested logit. The joint cumulative distribution function of error terms is:

$$\exp \left(- \sum_{k=1}^{K} \left(\sum_{j \epsilon B_k} e^{-\epsilon_{nj}/\lambda_k} \right)^{\lambda_k} \right) \tag{2}$$

In this choice model, the ϵ_{nj}'s are correlated within each nest. For example, for two alternatives j and m in nest B_k, ϵ_{nj} is correlated with ϵ_{nm}. However, for $j \ \epsilon \ B_k$ and $m \ \epsilon \ B_i$, the fraction of unobserved is uncorrelated since the alternatives belong to different nests. That is $\text{cov}(\epsilon_{nj}, \epsilon_{nm}) = 0$ where $k \neq i$.

The parameter λ_k denotes the degree of independence in unobserved utility among alternatives in a particular nest, B_k. It is also referred to as a dissimilarity parameter. Accordingly, a high value of λ_k implies greater independence and less correlation. In other words, the alternatives in B_k are less similar for unobserved reasons. Thus, $1 - \lambda_k$ is often considered to be a measure of correlation. If this value is high, it indicates high correlation. As such, a value of $\lambda_k = 1$ implies complete independence in the nest. If $\lambda_k = 1$ for all nests, the nested logit can be

[11] These include respondent-correspondent size, respondent-correspondent equity and bond ratios and so on.

reduced to its standard form. The probability from this distribution where the respondent bank n chooses alternative i from the choice set is expressed as:

$$P_{ni} = \frac{e^{V_{ni}/\lambda_k}(\sum_{j\,\epsilon\,B_k} e^{V_{nj}/\,\lambda_k})^{\lambda_k-1}}{\sum_{i=1}^{K}\left(\sum_{j\,\epsilon\,B_i} e^{V_{nj}/\,\lambda_i}\right)^{\lambda_i}} \tag{3}$$

Through this equation, it is proven that IIA holds within each nest but not across nests. Considering alternatives $i \epsilon B_k$ and $m \epsilon B_i$, we see that the denominator is the same for all alternatives, so the ratio of probabilities for these alternatives is:

$$\frac{P_{ni}}{P_{nm}} = \frac{e^{V_{ni}/\lambda_k}(\sum_{j\,\epsilon\,B_k} e^{V_{nj}/\,\lambda_k})^{\lambda_k-1}}{e^{V_{nm}/\lambda_i}(\sum_{j\,\epsilon\,B_i} e^{V_{nj}/\,\lambda_i})^{\lambda_i-1}} \tag{4}$$

Further, if alternatives i and m belong to the same nest, then the equation above reduces to:

$$\frac{P_{ni}}{P_{nm}} = \frac{e^{V_{ni}/\lambda_k}}{e^{V_{nm}/\lambda_i}} \tag{5}$$

From this equation we see that the ratio is independent of all other alternatives, thus IIA holds within nests. But if i and m belong to different nests, then the portion of the equation in parentheses does not cancel so the ratio of probabilities depends on the attributes of all alternatives in the nests containing i and m, this is also known as the independence from irrelevant nests. Also, it is important to note that the dissimilarity parameter λ_k can differ over nests.

With the decomposition of the observed utility in this manner, we can write the nested logit probability as the product of two standard logit probabilities. This translates into letting the probability of choosing alternative $i \epsilon B_k$ equal the probability of choosing nest B_k multiplied by the probability that alternative i is selected given that the nest B_k is chosen be expressed as:

$$P_{ni} = P_{nB_k} \times P_{ni|B_k} \tag{6}$$

where P_{nB_k} is the marginal probability of selecting an alternative if nest B_k is chosen, and $P_{ni|B_k}$ is the conditional probability of choosing i given that an alternative in nest B_k is selected. The marginal and conditional probabilities assume the form of logits and thus, can be expressed as:

$$P_{nb_k} = \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{i=1}^{K} e^{W_{ni}+\lambda_i I_{ni}}} \tag{7}$$

$$P_{ni|b_k} = \frac{e^{V_{ni}/\lambda_k}}{\sum_{j\epsilon B_k} e^{V_{nj}/\lambda_k}} \tag{8}$$

where

$$I_{nk} = ln \sum_{j\epsilon B_k} e^{V_{nj}/\lambda_k} \tag{9}$$

In the equation above, I_{nk} is the value of inclusive utility for alternative k in the first level. It is calculated as the log of the denominator of the second level. This value links the two levels of the nested logit by bringing information from the bottom level to the top level. In this manner, $\lambda_k I_{nk}$ reflects the expected value of utility to respondent n from alternatives available in nest B_k. Accordingly, correspondent features vary across all alternatives whereas respondent features remain constant.

Thus, multiplying the marginal and conditional probabilities we have:

$$P_{ni} = \frac{e^{W_{nk}+\lambda_k I_{nk}}}{\sum_{i=1}^{K} e^{W_{ni}+\lambda_i I_{ni}}} \times \frac{e^{V_i/\lambda_k}}{\sum_{j\epsilon B_k} e^{V_{nj}/\lambda_k}} \tag{10}$$

Accordingly, P_{ni} gives us the probability of choosing a specific alternative. We can then add these probabilities of all alternatives belonging to B_k to find the probability of choosing a specific nest. So, to express the probability of a respondent bank, n, choosing Nest I, we can sum the following equations:

$$P_{n1} = P_{nB_I} \times P_{n1|B_I} \tag{11}$$

$$P_{n2} = P_{nB_I} \times P_{n2|B_I} \tag{12}$$

$$P_{n3} = P_{nB_I} \times P_{n3|B_I} \tag{13}$$

$$P_{n4} = P_{nB_I} \times P_{n4|B_I} \tag{14}$$

$$P_{n5} = P_{nB_I} \times P_{n5|B_I} \tag{15}$$

$$P_{n6} = P_{nB_I} \times P_{n6|B_I} \tag{16}$$

Thus, the probability of respondent n choosing B_I is

$$P_{nI} = P_{n1} + P_{n2} + P_{n3} + P_{n4} + P_{n5} + P_{n6} \tag{17}$$

This calculation is much simpler for Nests II and III since they are degenerative.

4.2.3 Estimation

The nested logit model's parameters are estimated using the full information maximum likelihood model (FIML) as it maximizes the likelihood function. This method is the most efficient, statistical approach as the different nests are estimated simultaneously rather than sequentially which occurs in the multi-step maximum likelihood approach and this parametrization is consistent with random utility maximization.

5 Results

5.1 Covariate Effects

The dissimilarity parameter for Nest I, $\lambda_k = 0.45$, is consistent with the condition that $0 < \lambda_k < 1 \forall k$ and hence, agrees with a random utility model setup.[12] After constraining Nests II and III, the likelihood ratio test for IIA indicates that the null stating all log-sum coefficients are 1 can be rejected at the 99% level (p=0.054). Thus, the test confirms that a nested logit framework should be used. Using maximum likelihood measures, my nested logit regression output is displayed in Table 6.

To study local network formation, I looked at the effects of several network measures that could influence a respondent bank's decision. The choice set selected had correspondent banks varying significantly on the spectrum of size. The largest correspondent, Citizens Union National, was 17 times the size of the smallest correspondent, Bank of Commerce.[13] However, instead of considering the correspondent's size in absolute terms, I wanted to capture the respondent's size relative to the correspondent. In accordance with existing literature, size was estimated using a bank's total assets (Berrospide, 2013; Das et al., 2020). To standardize the metric, I employed the natural logarithm:

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[12] For Nests II and III, $\lambda_k = 1$ due to their degenerate nature.

[13] In Section 3, Table 1 exhibits the respective market shares of the correspondents in the selected choice set.

$$Size\ Ratio = \frac{ln\ (1 + Respondent's\ Total\ Assets)}{ln\ (1 +\ Correspondent's\ Total\ Assets)} \tag{18}$$

My findings demonstrated that a respondent bank was more likely to choose a correspondent bank larger than itself. This result was significant at the 1% level. Research on the commercial banking sector finds that bank size is positively related to service use due to greater administrative capacity in conducting financial transactions, and other security reasons (Lawrence and Lougee, 1970). This aligns with my results.

Table 6: Nested Logit Regression Output[14]

Alternative		
Size Ratio		-2.246***
		(0.882)
Correspondent Market Share		-1.612**
		(0.833)
Bank in Town Connection		0.643***
		(0.243)
Correspondent EigenCentrality		-0.857
		(1.678)
Nest Equations		
1	Equity Ratio	0.555
		(0.476)
	Federal Reserve Membership	1.490**
		(0.670)
	Degree Centrality	-0.256
		(0.320)
2	Base	
3	Equity Ratio	0.794*
		(0.475)
	Federal Reserve Membership	0.934
		(0.687)
	Degree Centrality	0.174
		(0.216)

Following the positive correlation between bank size and the probability of selecting a correspondent, it seemed natural for this relationship to be reflected between a correspondent's market share and probability of its selection since a large market share implies substantial financial activity. In this case, market share was calculated as a correspondent's deposits as a percentage of Louisville's deposits to gauge its influence in the city's banking community.

[14] Maximum likelihood estimates are shown and standard errors are shown in parentheses. *** implies significance at the 1% level, ** implies significance at the 5% level, * implies significance at the 10% level.

However, I found that a correspondent's market share was negatively correlated with a respondent bank's decision of choosing it.

This result has interesting implications as it demonstrates deviations from the norm of a respondent bank's decision in environments of financial instability. During the crisis, a respondent bank was less likely to choose a correspondent that held a greater portion of deposits. This follows from the notion that market share captures regional demand for a particular correspondent, and thus, a large market share signals numerous depositors. So in a panic situation, a bank responsible for a large number of depositors can be run on from individuals in the town, and by other respondent banks. Historically, a loss of depositor confidence has been seen and attributed to the exacerbation of several crises (Iyer and Puri, 2012; Wadhwani 2011). Further, a correspondent's market share is positive correlated with centrality. As such, a correspondent bank that is highly sought after in its community must cater to its several respondent linkages. Thus, a respondent might be wary of initiating a relationship as if it is unable to contribute a significant portion of reserves (dependent on the respondent's size), its relationship will be of low importance to the correspondent. This is corroborated by the understanding that in interbank markets, business partners trade privately, which often leads to a relationship with preferential treatment and repeated transactions (Davidovic, 2018). Contextualized in a crisis situation, if the correspondent goes under, the respondent bank will be near the end of a lengthy list as to the recovery of its reserves. Moreover, since this correspondent was responsible for numerous respondents, runs could commence elsewhere and adversely affect the correspondent, and in turn the respondent. This is widely consistent with literature on local contagion where local bank failures raise the probability that another local bank will also fail (Calomiris and Mason, 2003).

To understand how local networks influence outcomes, I estimated the effect of a neighboring bank's institutional linkages on a respondent's decision. A neighboring bank was a bank in the same town, and if there were multiple present, the variable was recorded as the geographically nearest bank by distance. The neighboring bank's ties to NBK were disregarded as its inclusion would still capture peer effects for a particular respondent.[15] I found that a respondent bank was more likely to initiate a relationship with its neighboring bank's correspondent. For example, consider Citizens Bank in Bloomfield that was previously a respondent of the National Bank of Kentucky. Citizens Bank has only one neighboring bank Muir, Wilson & Muir which is also in Bloomfield. Muir, Wilson & Muir is a respondent of Citizens Union National, that is alternative one. This implies that Citizens Bank has an increased probability of selecting the first alternative. Moreover, this result is significant at the 1% level. Existing literature on banking panics finds that during a financial crisis, banks

[15] A small portion of the banks that were considered for fractional variable were also respondents in the sample set.

are more likely to act conservatively and quickly based on information they receive from their local environment (Davidovic and Kothiyal, 2018; Aymanns and Georg, 2014). As such, peer effects play an influential role in determining how local networks form and further, in identifying the determinants of connectivity.

To trace systemic risk and in turn, the paths of financial contagion, researchers have focused on looking at centrality measures of financial institutions. Eigencentrality captures national demand. I looked at correspondent eigencentrality to understand if this measure for *connectedness* affected a respondent bank's decision in linking with them. Interestingly, I found that its measure was not significant in the respondent's decision-making process. This result suggests that a respondent bank did not take into consideration a correspondent bank's influence in the interbank network, a short-sight is reflective of the technology at the time. Outside of listing the principal correspondents, without digitizing the network, banks were unaware of the number of respondent banks linked to a financial institution. Consequently, local financial networks exert a greater influence on a respondent's decision than correspondents' positioning in the interbank system. As found in existing literature, this result suggests that heightened uncertainty about a situation, in this case the Great Depression, promotes synchronized behavior amongst banks. When financial networks are fragmented and social measures are strong, banks tend to follow peers' actions to make decisions (Aymanns and Georg, 2014). As such, the insignificance of the parameter emphasizes the effect of regional connectivity on network formation rather than centrality measures capturing the structure of the countrywide inter-banking system.

5.2 Nest Equations

Using the nested logit model to analyze the decision-making process, I estimated the variability of respondent-specific features across nests. The omitted group is Nest II, and hence all results are relative to this nest. The regression output is shown in Table 6. Evaluating the parameters for direction and significance, I analyzed the nest equations which demonstrate characteristics of the respondents that selected into a specific nest. This enables us to categorize features of respondents based on the specific nest selected by them. I configured my dataset relative to Nest II to ease the interpretation of selecting a single correspondent, or no correspondent, compared to selecting multiple. First, I looked at how Federal Reserve membership affected a respondent's decision. The evidence suggested that respondent banks that were part of the Federal Reserve system were more likely to choose a single Louisville correspondent as opposed to many Louisville correspondents. However, this relationship exhibited weak significance for respondent banks that selected no new Louisville correspondents.

Looking at balance-sheet measures, I found that respondent banks with healthy equity ratios, tended to select a single new correspondent or no new correspondents. Again, equity ratios were calculated by looking at capital and surplus profits as a percentage of total assets. These results tend to suggest that financially healthy respondents demonstrated cautious behavior. Instead of forming multiple new institutional linkages, banks selected either a single new correspondent or no new correspondents. These patterns point to liquidity hoarding behaviour as is often seen by banks in times of crises (Berrospide, 2013; Krishnamurthy 2011). Although selecting many Louisville correspondents suggests rational behavior in terms of receiving a diversification discount, healthy banks tended to select other alternatives. Existing literature on commercial banking operations insinuates that diversification of assets is always a safer alternative (Bell, 1932; Klein and Saidenberg, 2010). However, due to the surrounding financial uncertainty respondent banks inferred that the costs of initiating many connections exceeded the benefits of such diversification. Evidently, this behavior was furthered by the panic of going underwater.

Motivated by my findings on correspondent centrality, I tested an approximate for respondent centrality to understand whether a respondent bank's positioning in the interbank network affected its decision of selecting an alternative. A respondent's number of linkages is synonymous to its degree of connections. Thus, respondent centrality is expressed by the equation below:

$$Respondent\ Centrality = \sqrt{Degree\ of\ Connections} \tag{19}$$

From my sample size, around a third had three linkages, a quarter had two and a fourth of respondents had 4 linkages. According to the above findings, respondent centrality should be positively correlated with an increased probability of bank survivorship. Instead, the results pointed to the insignificance of the measure. This finding is supported by existing literature regarding the limitations of centrality of local networks (Dequiedt and Zenou, 2017). These measures are considered to be inefficient estimators as a majority of respondent banks in our sample size are not central nodes in the interbank network.

In this manner, bank size, peer effects and liquidity hoarding integrated with fears of high regional demand captured through a correspondent's market share, seemed to be driving forces in a respondent bank's decision. As discussed earlier, respondent banks perceive larger banks as more secure prospects to initiate relationships with, however, this relationship is somewhat weakened by the correspondent's appeal in the local community as supported by the evidence on market share. Moreover, I found that respondent banks placed a high degree of importance on the actions of their surrounding banks. Accordingly, the onset of financial uncertainty brought about by the Great Depression coerced banks into exhibiting complementary patterns. In response to this fear, banks began to accumulate liquidity.

During the Great Depression, one of the primary issues that respondent banks faced was the immobilization of reserves due to correspondent linkages. The pyramid-like structure of the interbank network limited country banks' access to reserves during times of crisis. With a surge of loss in depositor confidence and liquidity withdrawals being the norm, the bank had to rely on its correspondent, who may have been in a similar situation. The correspondent bank also might not have the funds on hand because its reserves consisted of checks in the mail, rather than cash in its vault (Richardson, 2007). If so, the correspondent would, in turn, have to request reserves from another correspondent bank, and in turn delay the process of retrieving liquidity for the original respondent. As such, respondents were motivated to accumulate liquidity instead of initiate correspondent relationships. This notion is corroborated by the finding of a negative correlation between market share and a respondent's decision. Hence, to further understand the merits and demerits of selecting an alternative, I evaluated bank failure in the period between 1930 and 1934.

6 Bank Survivorship based on Choice Selection

6.1 Model Estimation and Results

Since the underlying evaluation is based on firm-level data, we can also study the effects of a respondent's decision on its survivorship through the Depression. This section provides a preliminary analysis to study the implications of selecting into a specific nest on a bank's status following the failure of the National Bank of Kentucky. I use the original sample of NBK's respondents in 1929 to predict survivorship in 1934. However, linkages in 1929 that failed prior to the correspondent's collapse are excluded to correctly estimate the impact of the event. Thus, the outcome variable y_n equals 1 if bank n fails and does not appear in 1934, otherwise it equals 0. (i.e., 0 is encoded as bank survivorship). This is estimated through the following expression:

$$y_n^* = x_n' \beta + \varepsilon_n \tag{20}$$

The mapping from the latent to observed data is $y_n = 1 \{y_n^* > 0\}$ and $\varepsilon_n \sim N(0,1)$ as it takes on the form of a probit model. This specification is deliberately parsimonious to convenience the interpretations of respondent choice selection and understand the configuration of networks. Accordingly, the covariates in vector x_n include respondent-specific characteristics such as institutional membership, balance-sheet data, and other network measures. The model is estimated using maximum likelihood methods. The coefficients of the nests are assessed relative to the third nest to ease interpretation of results. Further, nest-wise specification allows us to draw a parallel to the results from the nested logit model. Table 7 presents the regression results with failure as the outcome variable.[16]

Table 7: Probit Model Regression

Failure	Coefficient
Nest 1	-0.363*
	(0.203)
Nest 2	-0.756**
	(0.368)
Federal Reserve Membership	0.310
	(0.252)
Bond Ratio	-2.385***
	(0.829)
Equity Ratio	-4.116**
	(1.946)
Degree Centrality	0.060
	(0.128)
Size	-0.229**
	(0.129)
_cons	3.317
	(1.714)

Relative to banks that selected no new correspondents, banks that chose a single new correspondent or multiple new correspondents had an increased probability of surviving the depression following the collapse of NBK. This result suggests the merits of diversification as opposed to increasing reserves with existing correspondents.[17] In this context, diversification implies expansion of a respondent's institutional linkages. To elaborate, the respondent bank would be diversifying its reserve holdings across several banks in order to minimize its risk as opposed to concentrating its reserves into a single institution.

6.2 Marginal Effects

Corroborating these results that studied sign and significance, I calculated the marginal effects for the selected discrete variables as seen in Table 8. Thus, effects are calculated for each of the 233 observations and then averaged. Relative to banks that selected no new

[16] Maximum likelihood estimates are shown and standard errors are shown in parentheses. *** implies significance at the 1% level, ** implies significance at the 5% level, * implies significance at the 10% level.

[17] From the sample of respondent banks that chose Nest III, that is no new Louisville correspondent, less than a third chose a new correspondent outside the choice set and from a state other than Kentucky. These banks were primarily based in Indiana and Tennessee. The remaining two-thirds added no new correspondents from any state to their existing list.

correspondents, respondents that selected one new correspondent, holding all else constant, had a lower probability of failure by 9.8 percentage points. Moreover, if banks formed multiple connections with correspondents, it lowered their probability of failure by an impressive 20.6 percentage points. The result strongly suggests that banks that had apportioned their reserves across institutions had a lower likelihood of failure relative to banks that had chosen to form no new linkages.

Table 8: Probit Model Marginal Effects[18]

Variable	dy/dx
Nest 1	-0.099*
	(0.054)
Nest 2	-0.206**
	(0.098)
Federal Reserve Membership	0.085
	(0.068)
Bond Ratio	-0.650***
	(0.217)
Equity Ratio	-1.123**
	(0.516)
Centrality	0.016
	(0.035)
Size	-0.062*
	(0.035)

As seen previously, respondent centrality was not a determining factor in a bank's probability of failure. The insignificance of respondent centrality emerges from a fragmented interbank network where none of the respondent banks acted as central nodes. Federal reserve membership was included to investigate whether institutional linkage would have an effect on a respondent's probability of failure but I found a weak, positive correlation between bank failure and reserve membership. This result in unsurprising since only ~30% of the respondent banks in our sample set were part of the Federal Reserve system.

The specification also includes standard financial ratios such as respondents' bond and equity ratios. Generally, existing literature asserts that banks with healthier financial ratios were more likely to survive the depression and my results strongly aligned with this perspective. Further, results indicate that a respondent's size is negatively correlated with its probability of failure where size is determined by taking the natural log of a respondent's total

[18] Maximum likelihood estimates are shown and standard errors are shown in parentheses. *** implies significance at the 1% level, ** implies significance at the 5% level, * implies significance at the 10% level.

assets. On that account, marginal effects indicated strong, positive correlations between large, financially robust banks and the probability of their survivorship in the depression. Moreover, these results emphasize the merits of connecting with many correspondents to meet reserve requirements as this decision was negatively correlated with bank failure.

7 Conclusion

Using a rich, hand-collected dataset, I trace the network of interbank linkages to study the effects of one of the largest failures during the Great Depression, the National Bank of Kentucky. Its failure is treated as a turning point to analyze network formation under crisis situations. Due to the failure of their principal correspondent, NBK, respondent banks needed to reallocate their reserves in accordance with legal mandates. I draw on various firm-specific variables as well as nation-wide network measures to estimate their effects on the alternative chosen. Under a multinomial choice setting, I categorize a respondent bank's decisions into forming a single, new institutional linkage, forming multiple linkages or no new linkages. The first choice of selecting a single new correspondent is further broken down into six alternatives consisting of Louisville banks, and hence necessitating the employment of a nested logit framework.

Spanning the decisions of 233 respondents, I found strong evidence demonstrating the influential role played by peer effects in a respondent's selection of an alternative. In times of financial uncertainty, commercial banks place an increased importance on information procured from their immediate surroundings. Instead of considering their national positioning and the implications of their decision in the context of the interbank network, respondents tend to follow the actions of their neighboring banks. Further, due to the surrounding financial uncertainty, banks tended to exhibit liquidity hoarding behaviors. This disincentivized respondents from forming new linkages. My sample set of respondents included all commercial banks tied to the National Bank of Kentucky at the onset of the depression. By 1934, their institutional linkages were re-evaluated and about a fifth of the respondents had failed. Using a bank's failure status as my outcome of interest, I found that banks that formed multiple correspondent relationships, were less likely to fail as opposed to banks that selected to increase their reserves with existing correspondents.

This paper investigates how banks initiate institutional linkages when the financial system is exposed to contagion risk. While results in this paper are limited to the context of the Great Depression, the findings emphasize the importance of understanding the *structure* of financial flows to in turn, assess the functioning of a financial system and its inherent stability. The sinuous structure of linkages between financial institutions and infrastructures, among sectors of the economy and across entire financial systems, can be captured through network structures. Previous research has contributed to the existence and importance of institutional linkages but there is limited literature on the specific determinants that initiate and advance them. Accordingly, the assessment of how networks form along with evidence of how their decisions relate to performance gives us insight on how choices made in a network setting impact bank behavior, and at large, the national economy. Employing this information in policy construction can help minimize the effect of external shocks. A holistic understanding of a respondent's concerns at a time of financial instability can help allay fears not just for the bank itself, but also everyone in its network by devising pointed strategies. This paper demonstrates that having an intricate understanding of the decision-making process behind network formation is of great regulatory consequence. Although the face of financial crises may change over the years, appearing as a mortgage meltdown or even a global pandemic, network analysis will serve to dampen future repercussions.

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