Liquidity from Two Lending Facilities

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Abstract

During financial crises, the Lender of Last Resort (LOLR) uses lending facilities to inject critical funding into the banking sector. An important obstacle for policymakers is designing the facility so that banks are not reluctant to approach due to stigma, and attracting banks with liquidity concerns rather than those prone to risk-taking and moral hazard incentives. We use an unexpected disclosure that introduced stigma at one of two similar LOLRs during the Great Depression to evaluate whether or not banks used LOLR assistance to improve their liquidity needs using a novel trivariate model with recursive endogeneity. We find evidence that banks that approached the facility with stigma were less liquid and reduced their position of safe assets in comparison with banks that approached the facility with no stigma. Thus, stigma forced the pool of LOLR borrowers to separate into different groups of banks that ex-post revealed their liquidity preferences to policymakers. This finding informs policymakers' ex-ante decision of designing a facility that only attracts banks with liquidity concerns.

1 Introduction

During the recent financial crisis, the Federal Reserve (Fed) acted as the Lender of Last Resort (LOLR) to inject critical liquidity into the banking sector through its main emergency lending facility, the discount window (Armantier et al., 2015). The discount window was designed to alleviate funding stresses in the banking sector, thereby lessening a "credit crunch" to the real economy. However, banks were reluctant to borrow from the Federal Reserve's discount window because, if it somehow became known, would lead market participants to infer weakness – the so-called stigma problem (Bernanke, 2009). The implications of this problem are that banks contract

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their lending and experience deposit withdrawals after their LOLR loans are revealed to the public (Anbil, 2017; Vossmeyer, 2017).

When designing LOLR lending facilities policymakers prefer to lend to banks that are solvent but illiquid, rather than to banks that increased their risk-taking because of the presence of a LOLR (Madigan, 2009). Traditional LOLR theory suggests that banks should borrow from their LOLR to stop runs and the monetary authority should lend unsparingly at a penalty rate (Bagehot, 1873). Then, the LOLR could ease funding constraints during a financial crisis, limiting its transmission to the real economy. However, the very presence of the LOLR may create moral hazard incentives for banks where they increase their risk-taking (Carpinelli and Crosignani, 2017). In this scenario, LOLR lending facilities may increase overall systemic risk in the financial system, rather than ease funding constraints. It is difficult for policymakers to ex-ante determine each bank's liquidity preferences when they pool together at a LOLR.

In this paper, we examine which banks borrow from the LOLR and when they do so. We shed light on how policymakers can design lending facilities that achieve three objectives: 1) ease funding constraints; 2) are least subject to a stigma problem; and 3) attract banks with liquidity concerns. However, since a bank's decision to borrow from the LOLR is also a function of these three objectives, it is especially difficult to empirically disentangle each component of the bank's decision. In typical identification settings, we cannot isolate a bank's risk-taking from its funding needs because its decision to borrow from the LOLR is impacted by both objectives. Motivated by this difficulty, we use an unexpected event from the Great Depression that allows us to cleanly analyze why banks approach their LOLR.

The Great Depression was the worst financial crisis in U.S. history where LOLR lending was considerable (Bernanke, 1983). We use a unique setting where there existed two LOLRs: the Reconstruction Finance Corporation (RFC) and the Federal Reserve's Discount Window (DW). Beginning February 2, 1932, each LOLR had a nearly identical lending facility that provided loans confidentially to banks. However, on August 22, 1932, the Clerk of the House of Representatives took it upon himself to publish several partial lists of banks that had secretly borrowed from the RFC, which unexpectedly introduced a stigma problem at the RFC (Anbil, 2017; Vossmeyer, 2017). Using a unique hand-collected data set of balance sheet, DW, and RFC loan information for banks in the Federal Reserve 6th District from January 1931 to September 1933, we develop a novel trivariate model with recursive endogeneity to estimate the effect of the Clerk's publication on banks' choice of LOLR and their subsequent liquidity seeking behavior. We find that the pool of LOLR borrowers ex-post separated into specific groups after the publication of the list: those banks that continued borrowing from the RFC ("RFC banks"), those banks that switched away from the RFC ("switched banks"), and banks that only borrowed from the DW ("DW banks"). This separation of banks ex-post revealed information about their liquidity preferences to policymakers after the publication of the list. This information was unavailable prior since all LOLR borrowers pooled together. To the best of our knowledge, the combination of DW and RFC loan information make our paper the first to study the entirety of LOLR lending to financial intermediaries during a crisis.

Next, for clarity, we study how the publication of the lists affected the balance sheet composition of banks based on their choice of LOLR using a linear panel data model. Our identification strategy, based on the unexpected introduction of stigma at the RFC, allows us to analyze the balance sheets of banks that approached the LOLR with stigma (RFC) in comparison with banks that approached the LOLR with no obvious stigma (DW).

Our trivariate model allows us to jointly model a bank's choice of LOLR and its performance. The publication of the lists adds a useful dimension to our model by allowing us to endogenously accommodate how the timing and which facility each bank approached revealed information about their liquidity preferences to policymakers, because the LOLR choice equation drastically changed after the revelation. Furthermore, the joint model allows us to estimate the covariance (and implied correlation) between the determinants of each LOLR choice and bank liquidity, giving insights as to how the unobservables are related. This is important because we also examine the performance of the three groups that banks separated into based on their LOLR choice using a simple reduced form approach.

From our trivariate model, we have three significant findings. First, RFC banks decreased their position of safe assets (as a ratio of total assets) by 9 percentage points, while switched and DW banks maintained their position of government securities. The unexpected introduction of stigma at the RFC ex-post revealed that those banks that remained borrowing from the RFC (RFC banks) were less concerned with liquid assets on their balance sheets than banks that switched or stayed at the DW.

Second, our model allows us to take advantage of a fourth category of banks: banks that did not apply to a LOLR ("non-applicant banks") because comparing banks that approached a LOLR to banks that did not approach introduces a sample selection bias into a reduced form approach (Vossmeyer, 2016). Further, with the non-applicant category, we are able to capture the entire banking population eligible for support from these LOLRs. We find that non-applicant banks increased their position of safe assets (as a ratio of total assets) by 7 percentage points. Since we expect non-applicant banks to be the most well-capitalized in this economy because these banks did not seek LOLR assistance, switched and DW banks have the most similar balance sheets to non-applicant banks. The DW attracted banks that sought higher liquid assets than the RFC after stigma was unexpectedly introduced at the RFC. These banks valued the anonymity of the DW. However, banks with higher funding stress and plausibly less liquid securities on their balance sheet approached the RFC after the publication of the list.

Third, banks that borrowed from the DW in 1931 were likely to approach the RFC in 1932. Specifically, borrowing from the DW prior to the RFC's establishment, increased the probability that a bank approached the RFC by 14.6 percentage points. This result suggests that banks' choice of approaching the DW and RFC were similar, reinforcing the validity of our reduced form approach when we compare the balance sheets of banks that chose one facility over the other.

From our linear panel data model, we have three significant findings. First, those banks that switched away from the RFC (switched banks) maintained similar levels of their loans-and-discount portfolios to DW banks. This result suggests that switched and DW banks were not forced to either write down their loans-and-discounts portfolios, or contract their lending any differently. However, switched banks did experience a 4.1 percentage point drop in their bonds-and-securities portfolio, but the magnitude of the drop was quite small suggesting only slightly higher funding stress to that of DW banks. The identities of both switched and DW banks remained confidential throughout this period.

Second, banks that were unexpectedly revealed on a list ("revealed banks") were 52% more likely to borrow from the RFC after the publication of the lists despite the expectation that subsequent lists of bank identities would be published. Revealed banks experienced a 9.8 percentage point drop in their bonds-and-securities portfolio relative to DW banks. In addition, revealed banks reduced their loans-and-discounts portfolio by 15.3 percentage points. These results suggest that revealed banks either wrote down their loan-and-discounts portfolios, or contracted their lending in comparison with DW banks. Furthermore, their lower bonds-and-securities portfolios also suggests that revealed banks were experiencing higher funding stresses perhaps leading to the sale of assets in comparison with DW banks.

Third, RFC banks also experienced a 5.2 and 5.5 percentage point drop in their bonds-and-securities and loans-and-discounts portfolios, respectively, in comparison with DW banks, but the magnitudes of these drops were far smaller than that of revealed banks. RFC banks also either wrote down their loans-and-discounts portfolios and reduced their bonds-and-securities portfolios in comparison with DW banks, but by not as much as revealed banks. Anbil (2017) and Vossmeyer (2017) find that the publication of the lists caused deposit withdrawals at the revealed banks which forced them to contract their lending and sell assets off their balance sheet, which is likely driving the larger drops. Overall, the results suggest that although not all RFC banks were revealed to the public, there was enough desperation for funds to risk their identity being revealed. This desperation is not evident for switched or DW banks.

Altogether, our results imply that a lending facility that guarantees anonymity (and does not have a stigma problem) might attract banks that have legitimate funding concerns. We find that the DW attracted banks that purchased more government securities onto their balance sheet. Moreover, these banks did not contract their lending in comparison with RFC banks. Since policymakers are concerned with designing a lending facility that attracts solvent yet illiquid banks that would continue lending to the real economy during a financial crisis, designing a lending facility that guarantees anonymity may achieve these goals. Designing a lending facility with no stigma reduces policymakers' ex-ante concern that LOLR assistance goes to less liquid banks.

The empirical literature on why banks approach their LOLR is limited most likely due to researchers facing major challenges in identification. Drechsler et al. (2016) show that weakly capitalized banks took out more LOLR loans and used riskier collateral than strongly capitalized banks. We are able to shed light on the lending facility that would attract more strongly capitalized banks during a financial crisis. Our results align with theirs in that we find weak banks borrowed to buy less-safe assets. Carpinelli and Crosignani (2017) find that banks that experienced a wholesale funding dry-up before the European Central Bank's (ECB) Long Term Refinancing Operation (LTRO) used their funding to restore credit supply, while banks that did not receive as much funding used it to increase their holdings of high-yield government bonds. We shed light on the type of lending facility where a bank "reaching for yield" may not occur. Finally, Acharya et al. (2016) find that the ECB temporarily reduced funding pressure for banks but did not address solvency concerns via LTROs, suggesting it was difficult for the ECB to separate solvent but illiquid banks from those prone to risk-taking.

Second, our paper directly relates to a growing macroeconomic theory literature on how adverse selection affects markets. Bajaj (2017) studies the transition of a no-information revelation regime (pooling equilibrium) to information revelation (separating equilbrium). She shows that a negative shock to the quality of the regime implies a switch from no information to information revelation. Our paper presents a no-information revelation regime where there are two similar LOLRs and policymakers cannot determine information about the quality of banks that approach either facility. However, the revelation of banks that borrowed from the RFC in the *New York Times* caused a negative shock to the design of the RFC which led banks to separate into distinct groups that ex-post revealed information about their liquidity preferences to policymakers. To the best of our knowledge, our paper is one of the first to provide purely empirical evidence of these macroeconomic theories.

Finally, our paper is also related to the literature of how banks use their LOLR loans. Benmelech et al. (2017) find that had LOLR interventions been effective in preventing the collapse of the asset-backed commercial paper market, then the interventions might have contained the real effects of the crisis. We find that DW and switched banks maintained their loans-and-discounts portfolios which suggests there was not as much of a contraction of lending at those banks which can be interpreted as a success of the DW. Sumit et al. (2015) find that banks are less likely to lend to borrowers that most need the funding during the financial crisis. This may limit the effectiveness of LOLR lending facilities. However, Alves et al. (2016) find that when Portuguese banks were prevented from going to repo markets during the European sovereign debt crisis, it was the virtually unlimited access to central bank funding that helped banks continue to provide funding to the real economy. Our paper suggests that an anonymous lending facility (with no stigma problem) will attract banks that will maintain their lending and that are concerned with the liquidity of their balance sheet.

The remainder of the paper is organized as follows. Section 2 describes the RFC and DW as LOLRs to the U.S. banking system during the Great Depression, and details the publication of lists beginning on August 22, 1932. Section 3 describes the data, the development of our trivariate model with recursive endogeneity, and our linear panel data model. Section 4 presents the results of the trivariate model and our reduced form approach. Finally, Section 5 discusses the implications for future LOLR facilities and concludes.

2 Historical Background

2.1 The Reconstruction Finance Corporation and the Discount Window

In response to an acceleration of bank suspensions after Britain left the gold standard in 1931, President Hoover created the RFC (Olson, 1977). The RFC began privately authorizing loans on February 2, 1932 to several types of institutions including commercial banks, insurance companies, and building and loan associations.[1]

We assume that the RFC and the DW served as simultaneous LOLRs to the U.S. banking system during the Great Depression. At the end of 1931, only 39% of banks were eligible to borrow from the discount window at the Fed (henceforth referred to as member banks). There were 18,734 banks operating in the US as of June 30, 1932. Of these banks, 7,246 were Federal Reserve member banks (FRB, 1959, 1932). Mitchener and Richardson (2016) show that the withdrawal pressures of non-member banks on member banks magnified liquidity risk during the Great Depression. If all banks had been member banks, systemic withdrawal pressures would have been substantially lower (Calomiris and Mason, 2003; FRB, 1932).[2] As a result, President Hoover argued that another LOLR was needed to provide emergency liquidity assistance to the remaining non-member banks (Olson, 1977). The RFC Act was submitted to Congress on December 7, 1931, and it was passed into law on January 22, 1932. 44% of all banks received loans from the RFC by June 30, 1933.[3]

We acknowledge that considering the RFC as a LOLR may be controversial. However, we merely use the terminology because during the period we are finding that the RFC's operations were similar to the DW, and it was *acting* in a manner that aligns with role of an LOLR. Furthermore, anecdotal evidence from DW and RFC loan applications suggest that many banks simultaneously applied

[1]Of the total amount of bank loans requested from the RFC, 80% were granted. According to RFC (1932), the amount of bank loan applications received in 1932 was $1,188,957,193. The amount authorized was $949,858,000. In contrast, member banks borrowed $518 million on average from the DW every month in 1932 (FRB, 1932).

[2]National banks were Fed members, as well as some state banks. See Calomiris et al. (2015) for more discussion on the decision to become a member bank.

[3]In fact, Rose (2016) shows that the RFC lent to a systemically important insurance company in 1933 acting as a LOLR.

to both the RFC and the DW, and offered similar reasoning as to why they needed assistance. Additionally, RFC loan applications cite DW examiner notes before authorizing a loan and vice versa, which suggests that RFC and DW loan officers worked very closely together. Finally, Eugene Meyer was both the Chairman of the Fed and RFC when the RFC began authorizing loans.

There were three differences between the RFC and the Fed's discount window. First, the RFC interest rate was 1.5-2 percentage points higher than the Fed's. The discount rate averaged 3.5% across Fed Districts (FRB, 1932). Second, discount window loans were offered for shorter durations than RFC loans. This inconvenience likely directed member banks to the RFC which was offering longer maturity loans (FRB, 1932). RFC loans were given with maturities up to three years but banks could roll over their loans for an additional two years (RFC, 1932). Third, the RFC had more discretion with their collateral requirements than the Fed but both accepted the same types of collateral which included gold, Treasury securities, and commercial, industrial, and agricultural paper (FRB, 1932; Olson, 1977). By the end of 1932, 6,865 eligible institutions (banks and nonfinancial firms) had been authorized over $1.6 billion in loans by the RFC (RFC, 1932). At the DW, over $6 billion in loans were authorized in 1932.[4] These facts highlight the significance of the RFC and DW's effect on the financial system and their functions as LOLRs.

For a thorough review of the RFC, see Butkiewicz (1995, 1999), Mason (2001, 2003, 2009), and Calomiris et al. (2013). For more information about the DW during the Great Depression, see Richardson and Troost (2009) and Wheelock (1990).

2.2 Revelation of the First List

The main event in this paper is the unexpected publication of banks that confidentially borrowed from the RFC beginning on August 22, 1932. We model banks' choice of LOLR and subsequent liquidity seeking behavior using a trivariate model with recursive endogeneity. We also analyze the performance of eligible banks in the Federal Reserve 6th District after the publication of the first list in a reduced form setting.[5]

Initially, the identities of all RFC borrowers (banks and non-banks) were kept secret from the

[4] We are unaware of how many eligible banks received DW loans beyond those in the Federal Reserve 6th District. By the end of 1932, there were 6,816 eligible DW member banks (FRB, 1932). The majority of DW member banks were National Banks and therefore were much larger than the country banks that were located in more rural areas. These country banks were the banks that the RFC was intended to support (Calomiris et al., 2015).

[5] Our paper is limited to studying banks in the Federal Reserve 6th District because DW data is only available from this District. In addition, we only study banks that were eligible to approach both the DW and RFC.

public. Since its establishment, the RFC had used elaborate secret codes to transmit messages to its loan agencies and individual banks (Olson, 1977). However, on July 21, 1932, the Emergency Relief and Construction Act of 1932 (ERCA) amended the original RFC Act to expand the RFC's authority into state and local relief, public works construction, slum clearance, and so on. In this act, Section 201 (b) required that monthly reports of new borrower names be made known to Congress only (RFC, 1932). President Hoover initially planned to veto the bill because of the addition of the last-minute clause but was assured by the Senate Majority Leader that RFC loans would not be revealed to the public without congressional approval (CFC, 1932). It was decided that the monthly reports of new borrower names would be confidential and held by the Clerks of the Senate and the House of Representatives until Congress resumed session in December (RFC, 1932). Despite this decision, on August 22, 1932, South Trimble, the Clerk of the House of Representatives, took it upon himself to release a partial list of the identities of banks that accepted new loans from the RFC to inform the U.S. public. The list was first published in the *New York Times* and the *Commercial & Financial Chronicle* and coverage of this list was widespread. It was likely that the publication of the list was unexpected given the assurances that no borrower list would be released without congressional approval.

The loan authorization date for a bank determined whether the bank identity was revealed. The first monthly report that was submitted by the RFC to Congress revealed banks that had loans authorized between July 21 and July 31, 1932. Since ERCA was passed on July 21, this first monthly report was the only one Mr. Trimble had access to. Banks not revealed had a loan authorized on or before July 20, 1932. Since Mr. Trimble published all names available to him on the monthly lists, this suggests he did not choose which banks to reveal in a way that is systematic with bank characteristics. Because Congress was not in session, Mr. Trimble published four additional lists of borrower names following the August 22, 1932 list, finishing on January 26, 1933. The lists included all banks with loans authorized between July 21 and December 31, 1932, and loans over $100,000 authorized between February 2 and July 20, 1932.

2.3 Choice of LOLR

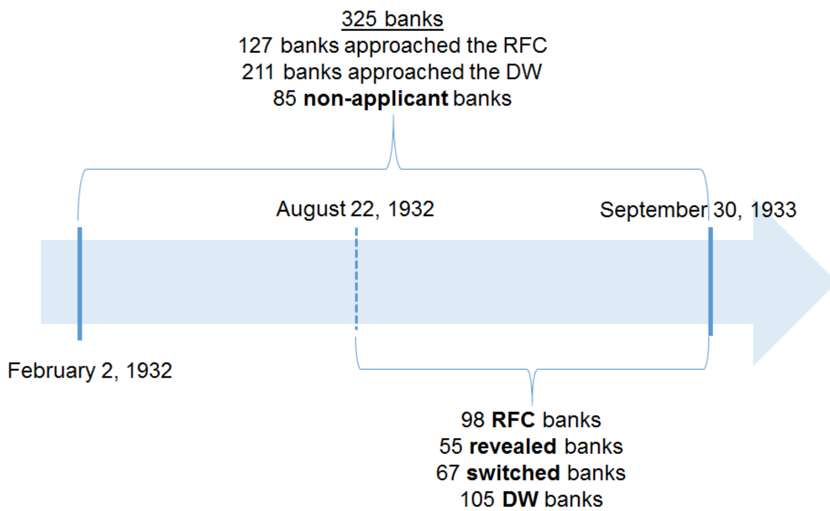
Prior to the publication of the first list on August 22, 1932, banks approached the RFC and DW interchangeably. The interest rate, collateral requirements, and duration of the loan were known at both LOLR facilities which would have affected banks' choice of LOLR. However, after August 22, a stigma problem was unexpectedly introduced at the RFC because loan confidentiality could no longer be guaranteed at the RFC because of the renegade Clerk. We find that the pool of LOLR borrowers ex-post separated into specific groups after the publication of the first list: banks that continued borrowing from the RFC (RFC banks), banks that switched away from the RFC (switched banks), and banks that remained only at the DW (DW banks). The separation of banks ex-post revealed information about their liquidity preferences to policymakers. In our linear model, we examine the performance of these bank groups based on their choice of LOLR lending facility.

We also introduce two additional bank groups into our trivariate model. We include a fourth category of banks that never applied to either the RFC or DW for a loan (non-applicant banks). Finally, we also include a fifth category of banks that were revealed on a list in the *New York Times*. We expect this final group of banks to endure the largest cost of stigma at the RFC since the public viewed the news that a bank borrowed from its LOLR as a sign of financial weakness (Anbil, 2017; Vossmeyer, 2017).

Figure 1 shows that there are 325 eligible banks in the Federal Reserve 6th District, where 127 borrowed from the RFC, 211 borrowed from the DW, and 85 non-applicants that did not borrow from any LOLR (as of September 30, 1933). There were 98 RFC banks that borrowed from the RFC after August 22, 1932. During the same period, there were 105 DW banks that borrowed solely from the DW. There were 55 revealed banks on a list in the *New York Times* that had a loan authorized between February 2, 1932 and December 31, 1932. Finally, there were 67 switched banks that borrowed from the RFC prior to August 22, 1932, but either stopped borrowing from a LOLR or borrowed from the DW.

We expect non-applicant banks to be the highest capitalized banks in the 6th District because the Atlanta Federal Reserve Bank was accommodative with LOLR policy in the United States (Richardson and Troost, 2009). The findings in Richardson and Troost (2009) support our case in that the DW was not stigmatized in this district. The President of the Atlanta Federal Reserve Bank did not adhere to the Real Bills Doctrine where the LOLR would only lend to banks against "real" loans as collateral, such as trade contracts with merchants. Accordingly, we assume non-applicant banks did not apply for LOLR loans because they were well-capitalized. Since we can model the choice selection mechanism, we compare switched, RFC, DW, and revealed banks to

Figure 1: RFC vs. DW Banks



This figure displays the timeline illustrating how many eligible banks were in the Federal Reserve 6th District between February 2, 1932 and September 30, 1933. Non-applicant banks were banks that never approached a LOLR during this time period. RFC banks borrowed from the RFC after August 22, 1932. DW banks borrowed from the DW after August 22, 1932. Revealed banks were revealed on a list in the *New York Times* on or after August 22, 1932. Finally, switched banks borrowed from the RFC prior to August 22, but then either switched to the DW or stopped borrowing from the LOLR afterwards.

non-applicant banks. Since stigma is costly and present at the RFC (Anbil, 2017; Vossmeyer, 2017), we expect the performance of switched and DW banks to be the most like non-applicant banks. These banks were unwilling to bear the cost of stigma and not as desperate for funds to remain at the RFC. Next, since revealed banks faced withdrawals and possible fire sales due to the publication of the list, we expect these banks to be the most desperate for liquid securities, and their performance to be unlike non-applicant banks. Finally, we expect the performance of RFC banks that continued to borrow from the RFC to be worse than DW banks because these banks were willing to risk their identities becoming revealed at the RFC, suggesting they were desperate for funds.[6]

[6] We do not observe if banks were rejected from the DW since these data do not exist. Vossmeyer (2016) highlights the importance of modeling declined applications. However, in this case, we observe three banks that approached the RFC that were rejected for loans but then subsequently borrowed from the DW. This suggests that the RFC did not receive all the banks that the DW may have rejected.

Table 1 describes summary statistics of RFC, DW, switched, revealed, and non-applicant banks as of December 31, 1931, prior to the publication of the list. The balance sheets of RFC, DW, switched, and revealed banks, which make up the pool of LOLR borrowers, appear remarkably alike. However, non-applicant banks have a considerably smaller loans-and-discounts (scaled by total assets) portfolio to that of RFC, DW, switched, or revealed banks. Furthermore, their cash-due-to-banks and bond-and-securities portfolio levels are much higher compared to the other bank groups suggesting that non-applicant banks exhibited some hoarding of cash during the Great Depression, and were likely the highest capitalized banks in the 6th District. Interestingly, many non-applicant banks would approach the RFC by the end of the Depression, particularly after the RFC experienced a regime change and could purchase preferred stock in banks. Finally, Table 1 also confirms the sample selection issues of comparing banks that approached the LOLR to banks that did not, which we are able to control for in our trivariate model.

Why would a bank want to borrow from the RFC given the existence of the DW if it was a member bank? First, we can see from RFC loan applications that many banks were encouraged to borrow from the RFC to increase its validity as a LOLR. Second, RFC loans were of longer duration than DW loans so rollover risk for RFC loans would be less. Therefore, the RFC might have attracted banks more concerned with rollover risk despite the higher interest rate on the loan. Third, anecdotal evidence suggests that RFC examiners were more lenient with the collateral requirements for a loan. If a bank had a much weaker balance sheet, the bank may prefer approaching the RFC first. We are able to control for many of these observable characteristics in the choice framework. However, some of these preferences are latent or unobservable for individual banks. Hence, the joint model will estimate the covariance between the errors of LOLR choice and bank liquidity, so we can better understand the relationship.

After stigma was unexpectedly introduced at the RFC, what might cause a bank to switch to the DW? If the bank was more concerned with its depositors discovering that it received LOLR assistance than rollover risk, the bank would seek assistance from the DW. However, if the bank did not have the collateral required to receive a loan at the DW, it might decide to remain at the RFC. Those banks that switched to the DW (switched banks) were more concerned about stigma than rollover risk, and had the necessary collateral to borrow from the DW. However, those banks that stayed at the RFC were more concerned about rollover risk, or did not have the necessary collateral to borrow from the DW. The introduction of stigma and banks' subsequent choice ex-post revealed their liquidity seeking preferences to policymakers. This information about their preferences was unavailable to policymakers before the publication of the list since banks were pooling and borrowing from both LOLR facilities. These liquidity preferences are difficult, if not impossible, to disentangle in a setting where there is a single lending facility.

Table 1: Summary Statistics of RFC and DW Banks

Variable	**RFC**	**DW**	**Switched**	**Revealed**	**Non-Applicant**
No. Banks	98	105	67	55	85
Financial Ratios (averages)					
Cash / Assets	0.13	0.16	0.13	0.12	0.21
Loans / Assets	0.62	0.55	0.64	0.60	0.42
Bonds / Assets	0.19	0.22	0.16	0.20	0.31
Deposits / Liabilities	0.70	0.69	0.67	0.65	0.74
Paid Up Capital / Liabilities	0.10	0.13	0.10	0.10	0.10
County Characteristics (averages)					
Population ($\times$1000)	42.7	58.5	37.8	48.6	54.0
No. Manufact. Est.	51	81	46	56	65
Cropland ($\times$1000 acres)	94.0	87.7	96.8	83.9	81.1
Unemp. Rate	0.043	0.047	0.041	0.046	0.048

This table provides summary statistics for RFC, DW, switched, and revealed banks. RFC banks are those that approached the RFC after August 22, 1932. DW banks are those that approached the DW after August 22, 1932. Switched banks are those that borrowed from the RFC prior to August 22, 1932, and then switched to the DW or stopped borrowing from a LOLR altogether afterwards. Revealed banks are those that were revealed on a list published in the *New York Times*. Non-applicant banks are those that did not approach a LOLR before September 1933. Characteristics of the banks in each subgroup include the cash-due-to-banks, loans-and-discounts, bonds-and-securities, deposits, and paid-up capital, all scaled by total assets. All bank data are as of December 31, 1931 and from the *Rand McNally Bankers' Directory*. All county data are from the 1930 census.

Finally, it is important for our identification in our panel linear model that the list of revealed banks be chosen by Mr. Trimble in a way that is uncorrelated with the outcome variables used in the estimation. There should be nothing systematically important about the dates of loan authorizations that he chose to publish implying that the decision of when a bank chose to borrow from the RFC also needs to be uncorrelated with all outcome variables. Otherwise, the revealed, switched, DW and RFC groups may differ along a number of observable dimensions, thereby biasing the results of the estimation. Since Mr. Trimble published all names available to him on the monthly lists, this suggests he did not choose which banks to reveal in a way that is associated with bank characteristics. Mr. Trimble would have been unable to choose which banks to reveal since it was the RFC that provided the names to the Clerks' Office (Anbil, 2017).

3 Data and Methodology

3.1 Data

RFC loan information and borrower names are from the *RFC Card Index to Loans Made to Banks and Railroads 1932-1957* acquired from the National Archives. The cards report the name and address of the borrower, date, request and amount of the loan, whether the loan was approved or declined, and loan renewals. The names of banks revealed to the public are from the *New York Times* and verified in the *Commercial & Financial Chronicle.* These announcements included the loan amounts and interest rates. All data are hand-collected.

The DW data are proprietary, have never been seen before, and are from the Federal Reserve Bank of Atlanta Archives. Therefore, our DW data only include banks from the 6th District which are the states of Alabama, Florida, Georgia, and portions of Tennessee.[7] The data are from daily ledgers containing loan and collateral amounts outstanding from January 1, 1931 through September 30, 1933. The ledgers report the name and address of the borrower, date, the loan amount outstanding, and the collateral amount outstanding.[8]

Our data include National and State Member banks that were eligible to borrow from both the RFC and DW. Since the RFC only began authorizing loans on February 2, 1932, we include only those DW loans made after this date in the linear analysis. After February 2, all banks in the sample were eligible to borrow from either LOLR. We end the loan sample at September 30, 1933 since that is when our DW data end.

Bank balance sheet data are from *Rand McNally Bankers' Directory,* which was published every six months. We collect the amounts of paid-up capital, surplus and profits, deposits, other liabilities, loans and discounts, bonds and securities, miscellaneous, cash due from other banks, and

[7]We do not have data on banks from Mississippi or Louisiana because we think those banks went to the New Orleans Federal Reserve Branch.

[8]Since we do not observe discount window flows, we assume large increases in the loan amount outstanding is a new loan.

the name of the president for each bank. The data are hand-collected from eight books beginning December 31, 1930 and continuing to September 30, 1934, resulting in eight observations per bank. We also collect bank balance sheet data from the Office of the Comptroller of the Currency. These yearly data include the amount of U.S. Treasury government securities versus other securities on each bank's balance sheet for December 1931, December 1932, and December 1933. Other securities do not include government securities and are likely corporate bonds. For failed banks, we assume total assets and liabilities are zero. We filter out observations where the balance sheet data are identical from period to period, approximately 11% of the data. We observe if the bank failed from the *Rand McNally Bankers' Directory* and verify the failure in the *Moody's Directory*.

To account for differing macroeconomic trends and business environments across each county, we include several additional control variables as of December 30, 1930 in the estimation. These variables also capture the broader health of the banking system. We use the dollar amount of total deposits and the total number of banks in each state to account for the size, organization, and resources of the banking system. Next, we use the dollar amount of suspended deposits and the total number of suspended banks in each state to account for the health of the banking system. Suspended banks include both banks that closed their doors to depositors for at least one business day and later resumed operations, and banks that ceased operations, surrendered their charters, and repaid creditors under a court-appointed receiver (Heitfield et al., 2017). The data are from the FDIC Bank Deposit Data, 1920-1936 (Inter-university Consortium for Political and Social Research). Finally, we also include data from the 1930 census of population, manufacturing, and agriculture at the county level to capture cross-sectional changes in a bank's business environment.

3.2 Methodology

We employ two methodological approaches in this paper: a trivariate analysis and a reduced form approach. The trivariate framework employs a cross-sectional sample, which includes all National banks operating in the 6th Federal Reserve District. This is a total of 270 banks that faced an LOLR choice: receive both DW and RFC assistance, receive DW assistance, receive RFC assistance, or receive no assistance. The analysis jointly models this choice set along with bank performance. In our reduced form approach, the main source of identification is the unexpected publication of banks that confidentially borrowed from the RFC beginning on August 22, 1932. We analyze the performance of eligible banks in the Federal Reserve 6th District after the publication of the first list in a panel data set from December 31, 1930 to September 30, 1934, where these panel data do not include non-applicant banks.

The combination of these methodological approaches and unique data allows us to answer the following questions: did the publishing of bank names that borrowed from the RFC shift more banks to the discount window and away from the RFC? How did banks that continued borrowing from the RFC after August 22, 1932 use their loans in comparison to banks that shifted to the discount window? Did the revealing of bank names make the discount window a more effective LOLR facility than the RFC? With the results, we can cleanly identify whether liquidity seeking behavior after receiving an LOLR loan should be an important consideration for policymakers when designing future LOLR lending facilities.

3.2.1 Trivariate Model

As discussed in Section 2.1, the RFC and DW were similar in many aspects, with slight differences in interest rates, maturity, and collateral requirements. These differences, along with other unobservables (e.g., bank management, encouragement to borrow from the RFC over the DW, financial contagion, fundamentals), may lead to different decision-making processes for each program. Furthermore, as the DW was established before the RFC, participation in the RFC program could be driven by previous access to the DW. To accommodate these concerns, we employ a trivariate model with recursive endogeneity and jointly examine the determinants of LOLR choice and bank liquidity after the disbursements. The model is as follows:

$$z_{i1} = \boldsymbol{x}'_{i1}\boldsymbol{\beta}_1 + \varepsilon_{i1} \tag{1}$$

$$z_{i2} = \boldsymbol{x}'_{i2}\boldsymbol{\beta}_{21} + +x_{i2,endog}\beta_{22} + \varepsilon_{i2} \tag{2}$$

$$z_{i3} = \boldsymbol{x}'_{i3}\boldsymbol{\beta}_{31} + \boldsymbol{x}'_{i3,endog}\boldsymbol{\beta}_{32} + \varepsilon_{i3} \tag{3}$$

for banks $i = 1, \ldots, n$ and $\varepsilon_i \equiv (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}) \sim N_3(0, \boldsymbol{\Omega})$, where

$$\boldsymbol{\Omega} = \begin{pmatrix} 1 & \omega_{12} & \omega_{13} \\ \omega_{21} & 1 & \omega_{23} \\ \omega_{31} & \omega_{32} & \omega_{33} \end{pmatrix}. \tag{4}$$

The observed choices $\{y_{i1}, y_{i2}\}'$ are related to the latent data through

$$y_{ij} = \begin{cases} 1 & \text{if } z_{ij} > 0 \\ 0 & \text{if } z_{ij} \leq 0 \end{cases} \tag{5}$$

for $j = 1, 2$, i.e., equations (1) and (2). For equation (3), the latent data are the observed data $y_{i3} = z_{i3}$. The first observed outcome y_{i1} takes the value 1 if the bank received assistance from the DW and 0 otherwise. The second outcome y_{i2} takes the value 1 if the bank received assistance from the RFC and 0 otherwise. Thus, the set of all possible outcomes for equations (1) and (2) (LOLR choice) is:

$$y_i = \begin{cases} (1,1)' & \text{if the bank received both DW and RFC assistance} \\ (1,0)' & \text{if the bank received DW assistance and no RFC assistance} \\ (0,1)' & \text{if the bank received RFC assistance and no DW assistance} \\ (0,0)' & \text{if the bank received no assistance.} \end{cases} \tag{6}$$

Equation (3), bank liquidity, is jointly modeled with LOLR choice. The bank liquidity outcome is measured in 1933 and is calculated as the amount of U.S. securities held as a ratio of total assets. The covariates that enter $\boldsymbol{x}_{i1}$ include 1931 balance sheet information and correspondent information. The covariates that enter $\boldsymbol{x}_{i2}$ include 1932 balance sheet information and county information. Also included is $x_{i2,endog}$ which is an indicator if the bank borrowed from the DW prior to the establishment of the RFC. This is endogenous because it is a function of y_{i1}. The covariates that enter $\boldsymbol{x}_{i3}$ include county information and lagged balance sheet information. The covariates selected for each equation follow the findings in Vossmeyer (2016), where the exclusion restrictions are based on information excluded from the RFC applications. The RFC applications do no include information on correspondents and bank age, so this information is excluded from the RFC equation. These characteristics, however, affect bank performance, so they are included in the other equations. Apparent from the RFC *Paid Loan Files* and *Declined Loan Files*, the RFC examiners often commented on the county in which the bank operated, which is why this information enters the RFC equation. This variable selection framework is formally tested via model comparison in Vossmeyer (2016).

The endogenous covariate vector $\boldsymbol{x}_{i3,endog}$ is a set of indicator variables defined by y_{i1} and y_{i2} and the timing of the loan authorization. The indicator groups follow along with Section 3.2.2 which allow for a comparison of the multivariate and linear model results. The groups are: (i) *RFC Bank*, (ii) *DW Bank*, (iii) *Switched*, (iv) *Revealed*, and (v) *Non-Applicant*. The first four groups are the same as the linear model section and group (v) is introduced for the trivariate model to capture the population of national banks.

Estimation of the trivariate model relies on simulation techniques due to the discrete outcomes in the first two equations, endogenous covariates, and restricted covariance matrix, where the restrictions are normalizations for identificaiton. This paper implements a Bayesian framework for the model described by equations (1)-(5). The model is completed by specifying the prior distributions for the parameters. It is assumed that $\boldsymbol{\beta}$ has a joint normal distribution with mean $\boldsymbol{b}_0$ and variance $\boldsymbol{B}_0$ and (independently) and $\boldsymbol{\omega} \sim N(\boldsymbol{\rho}_0, \boldsymbol{R}_0)1\{\boldsymbol{\omega} \in S\}$, where S is the set of parameters that produce the positive definite matrix $\boldsymbol{\Omega}$. The complete-data posterior is given by:

$$\pi(\boldsymbol{\beta}, \boldsymbol{\Omega}, \boldsymbol{z}|\boldsymbol{y}) \propto \left(\prod_{i=1}^{n} \left[\prod_{j=1}^{2} 1\{z_{ij} > 0\} \right] N(\boldsymbol{z}_i|\boldsymbol{X}_i\boldsymbol{\beta}, \boldsymbol{\Omega}) \right) \times N(\boldsymbol{\beta}|\boldsymbol{b}_0, \boldsymbol{B}_0) N(\boldsymbol{\omega}|\boldsymbol{\rho}_0, \boldsymbol{R}_0) 1\{\boldsymbol{\Omega} \in S\}.$$

The above posterior gives rise to a Markov chain Monte Carlo (MCMC) estimation algorithm. The novel algorithm is designed particularly for this application and is inspired by other work on multivariate discrete data models (Jeliazkov et al., 2008) and models with restricted covariance matrices (Chan and Jeliazkov, 2009). Furthermore, the algorithm features data augmentation for the sampling of z, which follows from Tanner and Wong (1987) and Albert and Chib (1993). Details on the sampler are below, where as a matter of notation, we use "$\backslash k$" to represent all elements in a set except the kth one. Details on the sampler are as follows:

Algorithm 1 *MCMC Estimation Algorithm*

1. *Sample* $[\boldsymbol{\beta}|\boldsymbol{z}, \boldsymbol{\Omega}] \sim N\left(\hat{\boldsymbol{b}}, \hat{\boldsymbol{B}}\right)$, *where* $\hat{\boldsymbol{b}}$ *and* $\hat{\boldsymbol{B}}$ *are given by*

$$\hat{\boldsymbol{b}} = \hat{\boldsymbol{B}} \left(\boldsymbol{B}_0^{-1}\boldsymbol{b}_0 + \sum_{i=1}^{n} \boldsymbol{X}_i'\boldsymbol{\Omega}^{-1}\mathbf{z}_i \right) \quad \textit{and} \quad \hat{\boldsymbol{B}} = \left(\boldsymbol{B}_0^{-1} + \sum_{i=1}^{n} \boldsymbol{X}_i'\boldsymbol{\Omega}^{-1}\boldsymbol{X}_i \right)^{-1}.$$

2. *Sample* $\boldsymbol{\Omega}|\mathbf{y}, \boldsymbol{\beta}, \mathbf{z}$ *using the Metropolis-Hastings algorithm (use* $\boldsymbol{\omega}$ *to produce* $\boldsymbol{\Omega}$*)*

3. *For equations* $k = 1, 2$, *sample* $\mathbf{z}_{ik}|\mathbf{y}, \boldsymbol{\beta}, \boldsymbol{\Omega}, \mathbf{z}_{\backslash k} \sim \mathcal{TN}_{\mathcal{A}_i}(\mu_{k|\backslash k}, V_{k|\backslash k})$ *where* $\mu_{k|\backslash k}$ *and* $V_{k|\backslash k}$ *are the usual conditional mean and conditional variance, respectively. If* $y_{ik} = 0$, $\mathcal{A}_i$ *is* $(-\infty, 0)$, *and if* $y_{ik} = 1$, $\mathcal{A}_i$ *is* $(0, \infty)$.

The sample for the multivariate model is slightly different than that of Section 3.2.2, which will be discussed shortly. The sample includes *all* national banks in Alabama, Florida, Georgia, and Tennessee operating in the 6th district in 1931. This is a total of 270 banks. The difference between this sample and that of the next Section is that these data only include National banks.

Section 3.2.2 has the additional group of State banks that are Federal Reserve member banks. The purpose of using only National banks is to better assess bank liquidity. If we narrow the sample to National banks, we can gather balance sheet data from the OCC's Individual Statements of Condition of National Banks. These data are more detailed and provide more balance sheet categories. Much of Mason's work on the RFC (Mason, 2001; Calomiris et al., 2013) utilized the National bank sample for the reason of better balance sheet information, and has been successful in assessing the RFC's effectiveness. For our purposes, the OCC data separately measures U.S. government securities from other bonds and securities, which allow us to better understand bank liquidity. Furthermore, this sample is different from Section 3.2.2 because it also includes non-applicant banks, which is 85 banks of the 270. Thus, with these data, we can model the two choice equations and control for the endogenous treatment in the liquidity behavior equation.

3.2.2 Reduced Form Specification

We run the following bank-level ordinary least squares regression (OLS) from December 31, 1930 through September 30, 1934:

$$Y_{i,t} = \alpha + \beta_1 RFCBank_i \times 1\{t \geq List\} + \boldsymbol{\gamma} X_i \times 1\{t \geq List\} + \eta_t + \delta_i + \epsilon_{i,t} \tag{7}$$

where $Y_{i,t}$ is the outcome of interest measured every six months t for bank i. $RFCBank$ is a dummy equal to 1 if the banks borrowed from the RFC after August 22, 1932 (RFC banks). $1\{t \geq List\}$ is a dummy equal to 1 following the start of list publications on August 22, 1932. The coefficient of interest is β_1, which measures the change in Y_i following the publication of the lists for RFC banks in comparison with DW banks.[9] We use three main outcome variables of interest: bonds-and-securities at time t divided by total assets from *t-1*; loans-and-discounts at time t divided by total assets from *t-1*; and cash-due-from-banks at time t divided by total assets from *t-1*. We use these outcome variables as proxies for the performance of each bank. For failed banks, we record zero for these ratios. We scale bonds-and-securities, loans-and-discounts, and cash-and-exchanges by total assets from *t-1* to account for the bank's size, and to ensure the size of the balance sheet is not confounding Y_i contemporaneously. Finally, we run two additional versions of equation (7) to examine the performance of Switched banks in comparison with DW banks, and Revealed banks

[9] Note that we do not include a $1\{t \geq List\}$ dummy nor a $RFCBank$ dummy since they are not identified once we include half-year and bank fixed effects.

in comparison with DW banks.

A key issue that prevents both specifications from identifying the effect of the revelation on $Y_{i,t}$ is that $Y_{i,t}$ may be correlated with unexplained macroeconomic conditions and/or bank borrower characteristics in the error term $\epsilon_{i,t}$. Therefore, we include controls, $X_i \times 1\{t \geq List\}$ to mitigate this bias where the controls only enter into the specification after the first list is published on August 22, 1932 to ensure the covariates do not confound $Y_{i,t}$ (Barrot, 2016).

X_i is a vector of controls measured at December 31, 1930 and includes the following covariates at the state level: employment rate, per capita income, total deposits, total deposits at suspended banks, the number of banks, the number of suspended banks. X_i also includes the following covariates at the county level: the total population, the number of manufacturing establishments, the total $ sales of wholesale establishments, the total $ sales of retail establishments, the amount of crop land, the number of unemployed persons, and the unemployment rate. These covariates are intended to capture observable proxies for macroeconomic conditions and bank characteristics that might explain $Y_{i,t}$, and only enter the specification after $1\{t \geq List\}$ equals 1. This feature is to ensure that the controls do not confound $Y_{i,t}$ prior to the publication of the list. However, the specification may still be biased if some bank characteristics are unobservable. Therefore, we rely on bank fixed effects, δ_i to exclude biases that could result from time-invariant bank characteristics and to capture the extent to which each bank affects $Y_{i,t}$. Additionally, we include half-year fixed effects, η_t to account for time trends in $Y_{i,t}$ eliminating the concern that aggregate changes in $Y_{i,t}$ and the publication of the lists occurred together.

Finally, standard errors are clustered at the bank level according to Bertrand et al. (2004). The results are robust to including $Y_{i,t-1}$ as a control variable to account for autocorrelation in the dependent variable (Petersen, 2009). Furthermore, all continuous variables are winsorized at the 1% level to avoid outliers driving the estimation results.

4 Results

4.1 Trivariate Model

Table 2 displays the results for the trivariate model with recursive endogeneity. Columns 2-4 display the results for the DW selection, RFC selection, and bank liquidity, respectively. The results are based on 11,000 MCMC draws with a burn in of 1,000. Inefficiency factors were computed for the estimated parameters and all are low, implying excellent mixing of the Markov chain. The priors are centered at 0 with a variance of 25.

Table 2: Results for the trivariate model with recursive endogeneity.

	DW	RFC	Bank Liquidity
Intercept	0.883 (0.672)	-0.436 (0.687)	0.112 (0.034)
	[-0.44, 2.15]	[-1.82, 0.90]	[0.05, 0.18]
Loans / Assets	2.868 (0.675)	3.233 (0.633)	
	[1.57, 4.21]	[2.03, 4.49]	
Other Securities / Assets	0.880 (1.10)	3.398 (1.152)	0.199 (0.095)
	[-1.31, 3.01]	[1.20, 5.72]	[0.01, 0.38]
Deposits / Liabilities	-3.046 (0.710)	-3.868 (0.681)	
	[-4.43, 1.63]	[-5.23, 2.60]	
No. Correspondents	0.025 (0.044)		
	[-0.05, 0.11]		
Bank Age			-0.105 (0.055)
			[-0.21, -0.00]
County Population		0.513 (0.249)	
		[0.019, 0.99]	
Manufact. Est.		-0.005 (0.002)	
		[-0.01, -0.00]	
Cropland		-0.336 (0.140)	
		[-0.59, -0.06]	
Unemployment rate			1.430 (0.521)
			[0.40, 2.43]
Endog: DW, Pre-RFC		0.593 (0.234)	
		[0.00, 1.18]	
Endog: RFC Bank			-0.085 (0.029)
			[-0.14, -0.03]
Endog: Non-Applicant			0.069 (0.026)
			[0.02, 0.12]
Endog: Switched			-0.073 (0.061)
			[-0.19, 0.05]
Endog: Revealed			-0.122 (0.029)
			[-0.18, -0.07]

Posterior means, standard deviations (in parentheses), and 95% credibility intervals (in brackets, calculated using quantiles) are based on 11,000 MCMC draws with a burn-in of 1,000.

The first purpose to the multivariate modeling is to understand the determinants of LOLR choice. The coefficients in the DW and RFC columns demonstrate that the loans-and-discounts portfolio has a positive impact on receiving both DW and RFC assistance. Interestingly, the other securities to assets ratio is not statistically different from 0 for DW assistance, and positively associated with RFC assistance. The RFC mainly took bonds and securities as collateral and had more discretion with regard to collateral than the DW, so this is possibly being reflected in that result.

Column 3 also displays the results for the county information. As discussed in Section 3.2.1, the RFC *Paid Loan Files* and *Declined Loan Files* provide the examiners' reports on each application decision. The examiners often discussed information about the applicant's county and business environment, which is why these are being controlled for in the RFC assistance equation. The results demonstrate that county population has a positive effect on RFC assistance, and cropland and manufacturing have a negative effect. The results align with Calomiris and Mason (2003) and Richardson (2007) who find that bank distress is a continuation of agricultural distress.

The endogenous covaraite in the RFC equation is "DW, Pre-RFC". The variable is an indicator that takes the value 1 if the bank accessed the DW prior to the RFC's establishment in 1932. The result is positive and statistically different from 0. Thus, accessing the DW in 1931 has a positive effect on accessing the RFC. Interest remains in the change in the probability of receiving RFC assistance, between cases when banks did and did not receive DW assistance prior to 1932. Thus, the probability difference is described below, where the two vectors $\boldsymbol{X}_i^{\dagger}$ and $\boldsymbol{X}_i^{\ddagger}$ differ only in the value of $\boldsymbol{X}_{i,DW\ Pre-RFC}$ and $\boldsymbol{\theta}$ is all model parameters. To understand the magnitude of this result, the covariate effect is averaged over the sample and MCMC draws and is calculated as follows:

$$\delta_{DW,Pre-RFC} = \int [\Pr\left(\boldsymbol{y}_i = 1 | \boldsymbol{X}_i^{\dagger}, \boldsymbol{\theta}\right) - \Pr\left(\boldsymbol{y}_i = 1 | \boldsymbol{X}_i^{\ddagger}, \boldsymbol{\theta}\right)] f\left(\boldsymbol{X}\right) \pi\left(\boldsymbol{\theta} | \boldsymbol{y}\right) d\boldsymbol{X} d\boldsymbol{\theta}.$$

The covariate effect is 0.146. The histogram of the probability distribution is displayed in Figure 2. Thus, after controlling for a banks health, balance sheet, and business environment, receiving DW assistance increases the probability of receiving RFC assistance by 14.6 percentage points. The result implies banks are viewing the LOLRs similarly and the choice is entering the banks' random utility function as they maximize.[10]

Focusing now on the bank liquidity equation, the results show that the unemployment rate in a county has a positive impact on the U.S. government securities held at banks. Thus, banks in

[10]This is per McFadden's (1974) initial discussion of the latent utility specification for discrete choice models. See Train (2003) for a review.

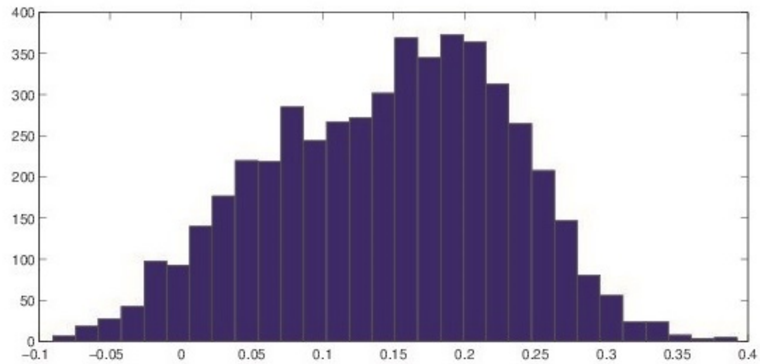


Figure 2: Covariate effect of DW assistance on RFC assistance.

areas with higher unemployment rates will increase their holdings of safe assets. The results for the endogenous covariates show that relative to *DW Banks*, (i) banks that stayed at the RFC decreased their holdings of U.S. government securities, (iii) banks that switched are not statistically different in U.S. government securities, (iv) revealed banks decreased their holdings of U.S. government securities, and (v) non-applicant banks increased their holdings of U.S. government securities. Therefore, revealed and RFC banks reduced their positions of safe assets during a financial crisis, inconsistent with liquidity seeking behavior. Because the publication of the list forced pooled banks to separate, by reducing their positions of safe assets RFC banks revealed their liquidity preferences to policymakers by continued borrowing from the RFC. This information would have been impossible to determine prior to the publication of the list when banks were pooling by borrowing from both LOLR facilities.

Table 3 presents the posterior means, standard deviations, and implied correlation form for $\mathbf{\Omega}$. The results show a positive correlation between applying for DW and RFC funding, however, the 95% credibility interval overlaps zero. This implies that unobservables are not driving the results of the relationship between the DW and RFC (recall that the endogenous covariate was positive and statistically different from 0). Variables controlled for in the equation, which include balance sheet characteristics, county characteristics, and borrowing from the DW before the RFC, adequately represent the joint determinants for LOLR choice. Also note that there is a positive correlation between LOLR assistance and holdings of U.S. securities. The correlations are of similar size and sign for both ω_{13} and ω_{23}, implying the unobservables are analogous for both LOLR choice options.

Table 3: Results for $\mathbf{\Omega}$ in the trivariate model.

$\mathbf{\Omega}$	ω_{11}	ω_{12}	ω_{22}	ω_{13}	ω_{23}	ω_{33}
Mean	1	0.159	1	0.031	0.033	0.021
Standard Deviation	.	0.236	.	0.011	0.010	0.004
Implied Correlation	1	0.159	1	0.214	0.228	1

Posterior means, standard deviations, and implied correlation form for $\mathbf{\Omega}$. Posterior means and standard deviations are based on 11,000 MCMC draws with a burn-in of 1,000.

4.2 Reduced Form

For clarity and simplicity, we use a linear panel data model to examine the response of banks to the publication of the list on August 22, 1932 where all banks in our sample were eligible to approach both the DW and the RFC. Using our trivariate model, we are able to effectively model banks' choice of LOLR and find that banks separate their LOLR choice into several groups: DW banks, RFC banks, Switched banks, and non-applicant banks. Based on this choice, we analyze the performance and balance sheet composition of banks in these groups after the publication of the list. A benefit of this approach is that we can utilize the panel structure of the data and capture the time dimension of the revelation.

First, we determine the probability that a revealed bank continued borrowing from the RFC after its identity was revealed in the *New York Times*. Table 4 presents the results. From the OLS regression in Column (1), revealed banks were 52% more likely to continue borrowing from the RFC. This result suggests that revealed banks may have continued borrowing from the RFC because their identities were already revealed and they needn't worry about "additional" stigma. Furthermore, since deposit withdrawals followed after the publication of the list, they likely needed more funds (Anbil, 2017).

Next, we compare the performance of switched banks to DW banks after the publication of the list. Since stigma is costly and remaining at the RFC increases the probability that the loan would be revealed, the performance of switched and DW banks should be similar. Table 5 presents the results. Switched banks experienced a small drop in their bonds-and-securities portfolio of 4.1% percentage points in comparison with DW banks. This result is possibly by construction because switchers had to pledge collateral to the RFC and then possibly more collateral to the DW.

Table 4: Probability of RFC Bank Given Revealed Identity

	(1) OLS	(2) Logit	(3) Probit
main			
Revealed Bank	0.518***	2.455***	1.488***
	(6.98)	(4.72)	(5.02)
Controls	Yes	Yes	Yes
Observations	230	230	230
R^2	0.3316		

This table presents the results of OLS, logit, and probit cross-sectional regressions on the probability of being an RFC bank. A RFC bank is a bank that borrowed from the RFC after August 22, 1932, the publication of the first list. A Revealed Bank is a bank that was revealed on a list on or after August 22. Controls is a vector of bank-level, state-level and county-level controls. Bank-level controls include the average log of total assets. State-level controls include per capita income, total dollar deposits, total dollar deposits at suspended banks, the number of banks, and the number of suspended banks. County-level controls include the total population, the number of manufacturing establishments, the dollar amount of wholesale sales, the dollar amount of retail sales, the amount of crop land, the number of unemployed persons, and the unemployment rate. Standard errors are calculated robustly and presented in parentheses. All continuous variables are winsorized at the 1% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Next, from Columns (2) and (3), we observe no differences in the estimates of the loan-and-discounts and cash-due-from-banks portfolios between switched and DW banks after the publication of the list. This result confirms our earlier conjecture that switched and DW banks would have similar balance sheet trends after the publication of the list because both groups of banks wanted to avoid stigma, and were less concerned with rollover risk. Because the publication of the list forced pooled banks to separate, switched and DW banks revealed their liquidity seeking preferences to policymakers by borrowing only from the DW. This information would have been impossible to determine prior to the publication of the list when banks were pooling by borrowing from both LOLR facilities.

Next, we compare the performance of revealed banks to DW banks after the publication of the list. Table 6 presents the results. Revealed banks experienced a large 9.8 and 15.3 percentage point drop in their bonds-and-securities and loans-and-discounts portfolio, respectively, in comparison with DW banks.

Table 5: Switched to DW vs DW Borrowing After

	(1) bonds/assets(t-1)	(2) loans/assets(t-1)	(3) cash/assets(t-1)
$SwitchedBank_i \times 1\{t = List - 1\}$	-0.008	-0.022	0.007
	(-0.46)	(-0.93)	(0.61)
$SwitchedBank_i \times 1\{t \geq List\}$	-0.042**	-0.052	-0.018
	(-2.29)	(-1.58)	(-1.29)
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
$Controls_i \times 1\{t \geq List\}$	Yes	Yes	Yes
Observations	822	832	832
R^2	0.8265	0.6852	0.6374

This table presents the reduced form estimates of the effect of list publications of RFC borrowers beginning on August 22, 1932 on bonds-and-securities, loans-and-discounts, and cash-due-from-banks. Switched Bank is a dummy that equals 1 if the bank borrowed from the RFC prior to August 22, and then borrowed from the DW or not at all afterwards. $SwitchedBank_i \times 1\{t \geq List\}$ equals 1 if the bank switched to the DW on or after August 22. $SwitchedBank_i \times 1\{t = List - 1\}$ equals 1 if the bank switched to the DW before the first list was published. $Controls_i \times 1\{t \geq List\}$ is a vector of bank-level, state-level, and county-level controls that turn on when $1\{t \geq List\}$ equals 1, and are measured as of December 31, 1930. Bank-level controls include the log of total assets. State-level controls include per capita income, total dollar deposits, total dollar deposits at suspended banks, the number of banks, and the number of suspended banks. County-level controls include the total population, the number of manufacturing establishments, the dollar amount of wholesale sales, the dollar amount of retail sales, the amount of crop land, the number of unemployed persons, and the unemployment rate. Standard errors are clustered at the bank level and presented in parentheses. All continuous variables are winsorized at the 1% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Although the revelation was costly to these banks, they were far more likely to approach the RFC suggesting they were desperate for funds.[11] The performance of these banks was much worse than switched and DW banks because they were unable to maintain the same trends of their bond-and-securities and loans-and-discounts portfolios. Overall, these results imply that the RFC attracted more desperate banks after the publication of the lists. It is also likely that these banks

[11] We do not observe which banks were rejected from the DW. However, from our trivariate model, we find that borrowing from the DW in 1931 increased the probability that a bank received RFC assistance by 14.6 percentage points.

Table 6: Revealed vs DW Borrowing After

	(1) bonds/assets(t-1)	(2) loans/assets(t-1)	(3) cash/assets(t-1)
$Revealed_i \times 1\{t = List - 1\}$	-0.026	-0.060	-0.001
	(-0.80)	(-1.58)	(-0.05)
$Revealed_i \times 1\{t \geq List\}$	-0.098***	-0.153***	-0.024
	(-2.94)	(-3.04)	(-1.37)
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
$Controls_i \times 1\{t \geq List\}$	Yes	Yes	Yes
Observations	728	734	734
R^2	0.8391	0.6568	0.6263

This table presents the reduced form estimates of the effect of list publications of RFC borrowers beginning on August 22, 1932 on bonds-and-securities, loans-and-discounts, and cash-due-from-banks. $Revealed_i \times 1\{t \geq List\}$ equals 1 if the bank was published on a list on or after August 22. $Revealed_i \times 1\{t = List - 1\}$ equals 1 for revealed banks prior to the publication of the lists. $Controls_i \times 1\{t \geq List\}$ is a vector of bank-level, state-level, and county-level controls that turn on when $1\{t \geq List\}$ equals 1, and are measured as of December 31, 1930. Bank-level controls include the log of total assets. State-level controls include per capita income, total dollar deposits, total dollar deposits at suspended banks, the number of banks, and the number of suspended banks. County-level controls include the total population, the number of manufacturing establishments, the dollar amount of wholesale sales, the dollar amount of retail sales, the amount of crop land, the number of unemployed persons, and the unemployment rate. Standard errors are clustered at the bank level and presented in parentheses. All continuous variables are winsorized at the 1% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

were more concerned with rollover risk due to their shrinking bond-and-securities portfolios, and preferred the longer-duration loans of the RFC over their fear of stigma. Prior to the publication of the list, policymakers would have been unable to determine these distinct liquidity preferences from switched or DW banks. The publication forced banks to separate into groups that ex-post revealed their liquidity preferences.

Finally, we compare the performance of RFC banks to DW banks after the publication of the list. Table 7 presents the results. RFC banks experienced a 5.2 and 5.8 percentage point drop in their bonds-and-securities and loans-and-discounts portfolio (albeit at the 10% level), respectively, in comparison with DW banks. These banks were willing to approach the RFC despite the chance their identities would be revealed on a subsequent list. This behavior suggests that RFC banks were also desperate for LOLR funds, and they preferred longer-duration loans over the cost of being revealed to the public (the stigma problem). The drop in their bonds-and-securities and loans-and-discounts portfolio was far less than revealed banks, reflecting this cost. Given that RFC and revealed banks continued to borrow from the RFC despite its stigma problem, this suggests that banks that approached the RFC preferred longer-duration loans despite the cost of stigma. This information about their liquidity preferences was revealed to policymakers only after the publication of the list.

Table 7: RFC Borrowing After vs DW Borrowing After

	(1) bonds/assets(t-1)	(2) loans/assets(t-1)	(3) cash/assets(t-1)
$RFCBank_i \times 1\{t = List - 1\}$	-0.023	-0.036	0.001
	(-1.22)	(-1.33)	(0.13)
$RFCBank_i \times 1\{t \geq List\}$	-0.052***	-0.055*	-0.016
	(-2.92)	(-1.83)	(-1.32)
Time FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
$Controls_i \times 1\{t \geq List\}$	Yes	Yes	Yes
Observations	937	947	947
R^2	0.8453	0.6714	0.6287

This table presents the reduced form estimates of the effect of list publications of RFC borrowers beginning on August 22, 1932 on bonds-and-securities, loans-and-discounts, and cash-due-from-banks. $RFCBank_i \times 1\{t \geq List\}$ equals 1 if the bank borrowed from the RFC after the first list was published on August 22, 1932. $RFCBank_i \times 1\{t = List - 1\}$ equals 1 for RFC banks prior to the publication of the lists. $Controls_i \times 1\{t \geq List\}$ is a vector of bank-level, state-level, and county-level controls that turn on when $1\{t \geq List\}$ equals 1, and are measured as of December 31, 1930. Bank-level controls include the log of total assets. State-level controls include per capita income, total dollar deposits, total dollar deposits at suspended banks, the number of banks, and the number of suspended banks. County-level controls include the total population, the number of manufacturing establishments, the dollar amount of wholesale sales, the dollar amount of retail sales, the amount of crop land, the number of unemployed persons, and the unemployment rate. Standard errors are clustered at the bank level and presented in parentheses. All continuous variables are winsorized at the 1% level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels respectively.

Furthermore, interestingly, RFC banks experienced no drop in the cash-due-to-banks portfolio. This might suggest that RFC banks continued to support their correspondent network, although qualitatively less than DW banks.

5 Implications for LOLR Facilities

In this paper, we examine which banks borrow from the LOLR and when they do so. We shed light on how policymakers can design lending facilities that achieve three objectives: 1) ease funding constraints; 2) are least subject to a stigma problem; and 3) attract banks with liquidity concerns.

We use a unique setting of an unexpected disclosure of partial bank lists that introduced stigma at one of two nearly identical LOLRs during the Great Depression: the RFC and the DW. Using a unique hand-collected data set of balance sheet, DW, and RFC loan information for banks in the Federal Reserve 6th District, we implement a novel trivariate model with recursive endogeneity to model each banks' choice of LOLR and their subsequent liquidity preferences. We find that the pool of LOLR borrowers ex-post separated into specific groups of banks that revealed information about the liquidity preferences to policymakers. Prior to the publication of the list, this information would have been unavailable because banks were pooling by borrowing from both LOLR facilities. After the separation, for clarity, we also use a linear panel data model to highlight the differences in balance sheet composition across the groups.

Altogether, our results imply that a facility that guarantees anonymity might attract banks that value a more liquid balance sheet. We find that the DW attracted banks that purchased more government securities onto their balance sheet. These banks were more concerned with stigma over rollover risk, and this information was revealed to policymakers only after banks separated. Moreover, these banks did not contract their lending in comparison with RFC banks. Since policymakers are concerned with designing a lending facility that is least subject to stigma and attracts banks that are simply illiquid rather than riskier, it seems that designing a facility that guarantees anonymity will reduce moral hazard concerns, continue bank lending to the real economy, and reduce policymakers' ex-ante concern of lending to riskier banks.

References

Acharya, V., Pierret, D., and Steffen, S. (2016), "Lender of Last Resort versus Buyer of Last Resort: Evidence from the European Sovereign Debt Crisis," *Working Paper*.

Albert, J. and Chib, S. (1993), "Bayesian Analysis of Binary and Polychotomous Response Data," *Journal of the American Statistical Association*, 88, 669–679.

Alves, N., Bonfim, D., and Soares, C. (2016), "Surviving the perfect storm: the role of the lender of last resort," *Working Paper*.

Anbil, S. (2017), "Managing Stigma During a Financial Crisis," *Journal of Financial Economics*, forthcoming.

Armantier, O., Ghysels, E., Sarkar, A., and Shrader, J. (2015), "Discount Window Stigma During the 2007-2008 Finanial Crisis," *Journal of Financial Economics*, 118, 317–335.

Bagehot, W. (1873), *Lombard Street: A Description of the Money Market*, London, NY: H.S. King.

Bajaj, A. (2017), "Adverse Selection and Liquidity in Asset Markets," *working paper*.

Barrot, J.-N. (2016), "Trade Credit and Industry Dynamics: Evidence from Trucking Firms," *Journal of Finance*, 71, 1975–2016.

Benmelech, E., Meisenzahl, R. R., and Ramcharan, R. (2017), "The Real Effects of Liquidity During the Financial Crisis: Evidence from Automobiles*," *The Quarterly Journal of Economics*, 132, 317.

Bernanke, B. (2009), "The Federal Reserve's Balance Sheet: An Update," in *Speech at the Federal Reserve Board Conference on Key Developments in Monetary Policy*.

Bernanke, B. S. (1983), "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression," *American Economic Review*, 73, 257–276.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004), "How Much Should We Trust Differences-In-Differences Estimates?" *The Quarterly Journal of Economics*, 119, 249–275.

Butkiewicz, J. (1995), "The Impact of Lender of Last Resort during the Great Depression: The Case of the Reconstruction Finance Corporation," *Explorations in Economic History*, 32, 197–216.

Butkiewicz, J. (1999), "The Reconstruction Finance Corporation, the Gold Standard, and the Banking Panic of 1933," *Southern Economic Journal*, 66, 271–293.

Calomiris, C. and Mason, J. (2003), "Fundamentals, Panics, and Bank Distress during the Depression," *American Economic Review*, 93, 1615–1645.

Calomiris, C. W., Mason, J. R., Weidenmier, M., and Bobroff, K. (2013), "The Effects of the Reconstruction Finance Corporation Assistance on Michigan's Banks' Survival in the 1930s," *Explorations in Economic History*, 50, 525–547.

Calomiris, C. W., Jaremski, M., Park, H., and Richard, G. (2015), "Liquidity Risk Bank Networks and Value of Joining Fed," *NBER Working Paper*.

Carpinelli, L. and Crosignani, M. (2017), "The Effect of Central Bank Liquidity Injections on Bank Credit Supply," *Working Paper*.

CFC (1932), "Publicity to be given to loans made by RFC," *Commercial & Financial Chronicle*, August 20, 1932.

Chan, J. and Jeliazkov, I. (2009), "MCMC Estimation of Restricted Covariance Matrices," *Journal of Computational and Graphical Statistics*, 18, 457–480.

Drechsler, I., Drechsel, T., Marques-Ibanez, D., and Schnabl, P. (2016), “Who Borrows from the Lender of Last Resort?” *The Journal of Finance*, 71, 1933–1974.

FRB (1932), *Nineteenth Annual Report of the Federal Reserve Board.*

FRB (1959), *All-Bank Statistics United States 1896-1955.*

Heitfield, E., Richardson, G., and Wang, S. (2017), “Contagion During the Initial Banking Panic of the Great Depression,” *Working Paper.*

Jeliazkov, I., Graves, J., and Kutzbach, M. (2008), “Fitting and Comparison of Models for Multivariate Ordinal Outcomes,” *Advances in Econometrics*, 23, 115–156.

Madigan, B. F. (2009), “Bagehot’s Dictum in Practice: Forumating and Implementing Policies to Combat the Financial Crisis,” in *Speech for Federal Reserve Bank of Kansas City’s Annual Economic Symposium*, Jackson Hole, Wyoming.

Mason, J. R. (2001), “Do Lender of Last Resort Policies Matter? The Effects of Reconstruction Finance Corporation Assistance to Banks During the Great Depression,” *Journal of Financial Services Research*, 20, 77–95.

Mason, J. R. (2003), “The Political Economy of Reconstruction Finance Corporation Assistance During the Great Depression,” *Explorations in Economic History*, 40, 101–121.

Mason, J. R. (2009), *The Evolution of the Reconstruction Finance Corporation as a Lender of Last Resort in the Great Depression.*, In Bailouts: Public Money, Private Profit.

McFadden, D. (1974), “Conditional Logit Analysis of Qualitative Choice Behavior,” *Frontiers in Econometrics*, pp. 105–142.

Mitchener, K. J. and Richardson, G. (2016), “Network Contagion and Interbank Amplification during the Great Depression,” *NBER Working Paper.*

Olson, J. S. (1977), *Herbert Hoover and the Reconstruction Finance Corporation 1931-1933*, The Iowa State University Press.

Petersen, M. (2009), “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches,” *Review of Financial Studies*, 22, 435–480.

RFC (1932), *Reconstruction Finance Corporation Act as amended and Provisions of the Emergency Relief and Construction Act of 1932.*

Richardson, G. (2007), “Categories and Causes of Bank Distress During the Great Depression, 1929-1933: The illiquidity Versus Insolvency Debate Revisited,” *Explorations in Economic History*, 44, 588–607.

Richardson, G. and Troost, W. (2009), “Monetary Intervention Mitigated Banking Panics During the Great Depression: Quasi-Experimental Evidence from a Federal Reserve District Border 1929-1933,” *Journal of Political Economy*, 117, 1031–1073.

Rose, J. (2016), "The Resolution of a Systemically Important Insurance Company during the Great Depression," *Finance and Economics Discussion Series*, 5.

Sumit, A., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2015), "Do Banks Pass Through Credit Expansions? The Marginal Profitability of Consumer Lending During the Great Recession," *Working Paper*.

Tanner, M. A. and Wong, W. H. (1987), "The Calculation of Posterior Distributions by Data Augmentation," *Journal of the American Statistical Association*, 82, 528–549.

Train, K. E. (2003), *Discrete Choice Methods with Simulation*, Cambridge University Press, Cambridge.

Vossmeyer, A. (2016), "Sample Selection and Treatment Effect Estimation of Lender of Last Resort Policies," *Journal of Business and Economic Statistics*, 34, 197–212.

Vossmeyer, A. (2017), "Analysis of Stigma and Bank Behavior," *Working Paper*.

Wheelock, D. (1990), "Member Bank Borrowing and the Fed's Contractionary Monetary Policy during the Great Depression," *Journal of Money, Credit, and Banking*, 22, 409–426.