Analysis of Stigma and Bank Behavior

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Abstract

During financial downturns, rescue programs are designed to provide assistance to weak banks to alleviate the crisis and restore confidence in the financial system. A complicating factor is that participating banks are often stigmatized by accepting assistance from the administration, which then, in turn, stigmatizes the rescue program itself. This paper investigates stigma in two ways: (i) it examines how stigma changes a bank's participation in the rescue program and decision to seek assistance, (ii) it analyzes how stigma affects a bank's ability to operate as a financial intermediary, using a novel data set from the Reconstruction Finance Corporation (RFC) during the Great Depression. To answer the former point, a daily time series of RFC assistance requests is constructed and modeled using an auto-regressive Poisson to provide insights as to the magnitude of the change in the application rate and the economic consequences of such actions. To address the latter point, a joint model for bank-level application decisions, approval decisions, and lending is developed, in which treatment effects for stigmatized bank performance are computed. The results indicate that stigma mitigates the objectives of the rescue program and moderately reduces the effectiveness of banks as financial intermediaries. Additionally, extensive model comparison exercises are conducted, which demonstrate support from the data for the stigma model specification.

Keywords: Bayesian inference; Financial crises; Great Depression; Marginal likelihood; Reconstruction Finance Corporation.

1 Introduction

Emergency lending policies are utilized by banks during times of economic hardship. The objective of the central bank is to provide assistance or liquidity to weak banks and prevent solvent, illiquid institutions from falling victim to runs and undue failure. When the identities of banks receiving assistance are revealed, stigma arises, thereby reducing market participants' confidence in the

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corresponding financial institutions. The concerns of stigma have existed since the Great Depression and remain a topic of active discourse in academic and policy circles. Despite its awareness, few empirical studies examining the presence and magnitude of stigma exist. Methodological and data limitations have hindered research in this area, where methodological difficulties stem from the several non-random selection mechanisms qualifying banks for emergency assistance and data difficulties arise from the necessity to have high frequency observations and variation in the timing or publication of the names of banks receiving assistance.

The actions taken to minimize stigma during the recent financial crisis render it impractical to study. For a review, see Geithner (2014) and Gorton (2015). However, the Great Depression offers a unique program and event to examine. The program of interest is the Reconstruction Finance Corporation (RFC). The RFC was established in early 1932 as a government-sponsored rescue program created to reduce the incidence of bank failure. By July 1932, the House of Representatives mandated the RFC to report the names of all banks receiving assistance and amounts lent. Prior to this date, the public did not know which banks were receiving assistance, although they did have knowledge of the program itself. This paper exploits these events to investigate stigma.

Previous studies on the RFC include Butkiewicz (1995), Mason (2001, 2003), Calomiris et al. (2013), and Vossmeyer (2014, 2016). While stigma is not the main focus of any of these papers, Butkiewicz (1995) and Mason (2001) address it in their analyses. Butkiewicz (1995) employs a time series of RFC lending and finds that the publication of the RFC loan recipients offsets the RFC's initial effectiveness. Mason (2001), on the other hand, uses a micro-level data set of Federal Reserve member banks and finds positive effects from the publication. Additionally, a working paper by Anbil (2015) finds that the presence of stigma imposed a 5-7% loss in the deposits-to-assets ratio at the RFC revealed banks.

The current study contributes to the literature in several ways. First, the paper examines the banks' perspective, as opposed to investigating depositors' withdrawal decisions. The banks' perspective of stigma addresses two important questions that are yet to be addressed in the literature: (i) Did banks become reluctant to seek assistance from the RFC after the names were public knowledge? (ii) Once the recipient names were released, did stigma affect the revealed banks' ability to operate as financial intermediaries and facilitate credit channels? The second contribution of this paper is in the novel micro-level data and methodological (time series and multivariate) approaches used to answer the aforementioned questions. Specifically, to address (i), a daily time series of inquires submitted to the RFC from financial institutions is constructed and modeled using an autoregressive Poisson. This element not only provides insights as to the magnitude of the change in the application rate, but also the economic consequences of such actions. To address (ii), the paper presents a multivariate model for a banks' application decisions, the RFC's approval decisions, and bank lending following the disbursements. By employing a multiple selection framework, the treatment effects of stigma on bank lending and the probability of bank failure are computed. The third contribution of this paper is in the Bayesian framework, which permits extensive model comparison studies. This element aids in disentangling stigma from time dynamics and other forms of financial restructuring.

The results of the paper demonstrate a major drop in bank participation rates with the RFC following the publication of the RFC's loan authorizations. The drop in participation stunted the recovery with many banks not applying for needed support and dampening their lending. For the banks that were revealed, the conversion of RFC lending to bank lending contracts, thereby impeding a bank's function as a financial intermediary. Overall, the findings in this paper demonstrate that stigma hinders the objectives of an emergency rescue program and prolongs the resuscitation of the economy. The results offer broad implications for lender of last resort policies and interventions in financial markets.

The rest of the paper is organized as follows: Section 2 describes the historical background and relation to the 2007-2008 crisis, Section 3 presents the times series data and methods used to examine stigma's effect on banks' desire to seek assistance from the RFC. The multivariate approach to analyzing how stigma affects banks' financial intermediary functions is discussed in Section 4. Section 5 contains additional considerations, including model comparison and sensitivity analysis, and finally, Section 6 offers concluding remarks.

2 Historical Background

As stress on the financial system increased and bank health deteriorated in the early 1930s, it was apparent that additional assistance was necessary to resuscitate financial markets. President Hoover did not believe a government credit institution would be successful and turned to voluntary action. Hoover enacted the National Credit Corporation (NCC) in 1931 in which bankers formed a temporary credit pool, and major banks were to lend money to smaller banks experiencing difficulty. However, the NCC was not successful because banks were reluctant to lend and the program failed to provide the necessary relief funds (Nash, 1959). Eugene Meyer, then Governor of the Federal Reserve Board, convinced President Hoover that a public agency was needed to make loans to troubled banks. On December 7, 1931, a bill was introduced to establish the Reconstruction Finance Corporation. The legislation was approved and the RFC opened for business on February 2, 1932.

The RFC was a government-sponsored agency of the Executive Branch of the United States government and was not accountable to Congress. It was funded by the United States Treasury and was granted an initial capital stock of $500 million (Mason, 2003). Although upon its completion, the RFC had borrowed $51.3 billion from the Treasury (Jones, 1951). Activities of the RFC did not change the monetary base as the RFC had no power to print or create money. In its first year of operation, the RFC made short maturity loans at high rates collateralized by banks' best quality, most liquid assets. After the 1933 Emergency Banking Act, the RFC could purchase preferred stock and recapitalize banks. The RFC's operations were straightforward. Any struggling bank could apply for assistance, which made the RFC much broader than the Federal Reserve's discount lending because member institutions comprised less than one quarter of the banks in operation at this time. The RFC reviewed the submitted applications in a reasonable amount of time and determined whether or not the bank was fit to receive assistance.

From February - July 1932, the public had knowledge of the RFC, however, the RFC did not reveal the names of banks receiving assistance. After July, the House of Representatives amended an act which required that lists of RFC loan recipients be made available and select parts were eventually published in the *New York Times*. The first *New York Times* list became available in late August and revealed loan authorizations that occurred between July 21 – July 31, 1932. Subsequent lists were published in the *New York Times* during the fall of 1932 and early 1933, which detailed loans over $100,000 from February - July and all loans between August - December. Note that the names of banks being declined assistance were never published, although the RFC was rejecting many banks (details on declined applications appear in Section 4.2.1).

During the 2007-2008 financial crisis, events surrounding emergency lending programs unfolded very similar to that of the 1930s. Special lending facilities were developed to assist banks in need and initially did not reveal the identities of banks receiving assistance. Bloomberg L.P. later filed requests for the identities of borrowing banks under the Freedom of Information Act to the Board of Governors of the Federal Reserve System (Gorton, 2015). The Federal Reserve was unsuccessful at withholding the names of the borrowers, however, it took many actions to reduce the consequences of stigma (see Geithner (2014) for a discussion). In a recent paper, Armantier et al. (2015) look at discount window stigma during the 2007-2008 crisis. Their results demonstrate banks' willingness to pay to avoid stigma, which is around 44 basis points. The current study complements these findings by quantifying the consequences of *realized* stigma at the bank level (incurred historically), as opposed to costs of *avoiding* stigma today. The historical findings in this paper help explain why banks were willing to pay such costs to avoid stigma during the most recent crisis. The parallels between the Great Depression and Great Recession with regard to stigma are uncanny and make the current study a relevant topic of interest.

While policy-makers today were concerned about signaling weak banks to market participants, they often highlighted even more concern for a stigmatized rescue program, where the revealing would prompt banks to not seek assistance or participate in the rescue programs despite needing support. Specifically, in discussing how he made large institutions' participation in TARP inevitable, Geithner states, "our hope was that smaller institutions would then feel free to apply for TARP funding without stigma." Geithner then states, "I warned the bankers that if they all didn't accept the capital, TARP would become stigmatized, the system would remain undercapitalized, and they all would remain at risk" (Geithner, 2014). The quantitative evaluation of the repercussions of a stigmatized rescue program is addressed in the next section, as well as Section 4.3.1.

3 Time Series Analysis

3.1 Data and Methodology

To address the concerns of a stigmatized rescue program in the context of the RFC, a daily time series of RFC application and renewal requests is constructed from the *RFC Card Index to Loans Made to Banks and Railroads, 1932-1957.* These cards were collected from the National Archives in College Park, Maryland, and 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. Further information is obtained from the *Paid Loan Files* and *Declined Loan Files*, also obtained from the National

Archives, which include the exact information regulators had on the banks from the applications and the original examiners' reports on the decisions. Because the data need to be hand-coded from the cards, the current analysis focuses on the following states: Alabama, Arkansas, Michigan, Mississippi, and Tennessee. The 5 states were selected for reasons mainly pertaining to the multivariate analysis, which are outlined in Section 4.2.1.

Figure 1 presents a bar graph that details the number of inquires submitted to the RFC from banks each day from early 1932 - early 1934. The first red line marks July 21, 1932 – the date that the House of Representatives amended an act which required that lists of RFC loan recipients be made available to the public. The second red line marks August 22, 1932 – the date that the *New York Times* published the first list of RFC loan authorizations. It is easy to see from Figure 1 that there is a small dip in the requests submitted to the RFC following the *New York Times* publication date. This is suggestive of the program being stigmatized and banks becoming reluctant to seek assistance, however, it does not appear to be lasting.

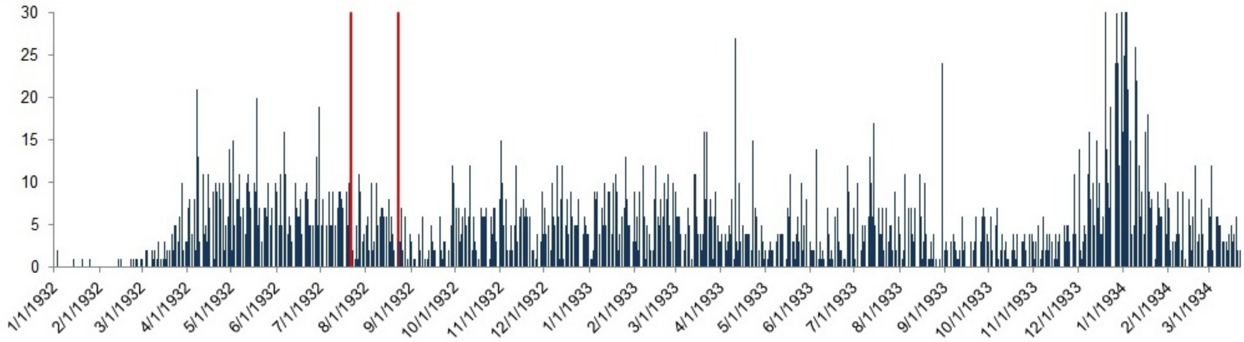

Figure 1: Number of inquires (applications and renewals) submitted to the RFC from banks each day.

In examining Figure 1, it is important to note that banks could submit multiple applications and renewal inquires to the RFC. Thus, Figure 1 shows all inquires, including repeat applications from banks already receiving assistance. In terms of understanding stigma, it would be worth examining an image that only displays inquires submitted from new applicant banks, not repeats. If the program itself is stigmatized, reluctance of seeking assistance will likely stem from new applicants, rather than banks already receiving assistance, as they may have already been revealed. Figure 2 displays a similar image to the previous one, but now only counts the inquires from new-applicant banks each day.

Figure 2 tells quite a different stigma story. Following the *New York Times* publication (second red line), there is a major drop in new applications submitted to the RFC and the drop lasts for over a year. The applications we see in Figure 1 after the revealing date are mostly from repeat applicants. Many of these banks have been revealed to the public and are likely requesting more assistance from the RFC to combat the deposit withdrawals noted in Anbil (2015). However, new applicants became reluctant to seek assistance, which is why the counts are so low through the end of 1932 and all of 1933. This is evidence of one form of the "stigma effect" – stigmatized rescue program. It is worth noting that the rejection rates were consistent through these periods, thus the notion that banks stopped applying because of the costs associated with being declined is not supported.

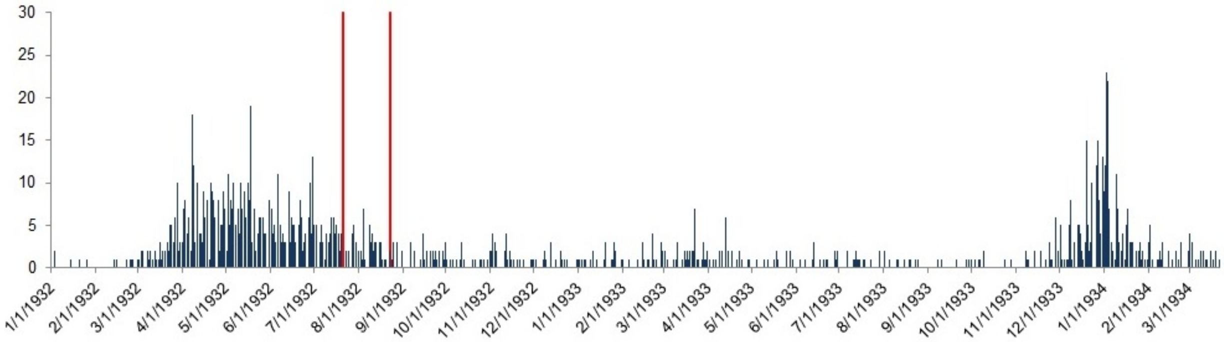

Figure 2: Number of inquires submitted to the RFC from new-applicant banks each day.

Common to both figures is the increase in applications in early 1934. This increase is due to the introduction of the Federal Deposit Insurance Corporation (FDIC). The FDIC and RFC worked closely in this period to help banks in need of assistance. Both agencies shared their examination reports of each bank and influenced decisions for support. The *Paid Loan Files* and *Declined Loan Files* collected for the study reflect collaboration between the RFC and FDIC. Apparent from Figure 2 is not only stigma's lengthy effect, but the overcoming of stigma through an extra support unit, the FDIC. With deposit insurance protection, banks were willing to deal with the stigma associated with the RFC and receive the liquidity or capital they needed. Table 1 offers simple summary statistics, detailing daily averages, standard deviations, and totals for the three periods of interest. Before the revealing, the average number of applications submitted to the RFC from new applicant banks was 3.45 applications a day and after it was 0.60 applications, demonstrating a large drop in participation.

	Daily Mean	St. Dev.	Total
Before revealing: All Inquires	4.71	4.3	953
Before revealing: New Applicants	3.45	4.2	696
After revealing, before FDIC: All Inquires	4.03	3.7	1858
After revealing, before FDIC: New Applicants	0.60	1.0	278
After FDIC: All Inquires	4.65	5.8	1860
After FDIC: New Applicants	1.23	3.4	491

Table 1: Summary statistics for inquires submitted to the RFC from financial institutions.

The daily time series data is modeled using an autoregressive Poisson. Let y_t be the number of assistance requests submitted to the RFC on day t from new applicant banks. The model is as follows,

$$y_t \sim Po(\lambda_t), \quad \lambda_t = \exp(\boldsymbol{x}_t'\boldsymbol{\beta} + \rho \log(y_{t-1} + 1)),$$

where $\boldsymbol{x}_t$ includes indicators for the amended act and newspaper publication dates. The model is estimated using Markov chain Monte Carlo (MCMC) simulation techniques, specifically the Accept-Reject Metropolis-Hastings (ARMH) algorithm (Tierney, 1994). For a review of this algorithm, see Chib and Greenberg (1995) and Chib and Jeliazkov (2005). The Bayesian methods implemented in this paper are attractive for several reasons, in particular for marginal likelihood and model comparison purposes. With Bayesian methods, interest lies in the posterior density as the target density

$$\pi(\boldsymbol{\theta}|\boldsymbol{y}) \propto f(\boldsymbol{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}),$$

where $f(\boldsymbol{y}|\boldsymbol{\theta})$ is the likelihood obtained from the Markov transition matrix and $\boldsymbol{\theta}$ is all model parameters. Here, a description of the general ARMH algorithm is offered. Let $h(\boldsymbol{y}|\boldsymbol{\theta})$ denote a source density and $\mathcal{D} = \{\theta : f(\boldsymbol{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta}) \leq ch(\boldsymbol{\theta}|\boldsymbol{y})\}$, where c is a constant and $\mathcal{D}^c$ is the complement of $\mathcal{D}$. Then the ARMH algorithm is defined as follows.

Algorithm 1 *ARMH*

1. A-R Step: Generate a draw $\boldsymbol{\theta}' \sim h(\boldsymbol{\theta}|\boldsymbol{y})$. Accept the draw with probability

$$\alpha_{AR}(\boldsymbol{\theta}'|\boldsymbol{y}) = min\left\{1, \frac{f(\boldsymbol{y}|\boldsymbol{\theta}')\pi(\boldsymbol{\theta}')}{ch(\boldsymbol{\theta}'|\boldsymbol{y})}\right\}$$

   and repeat the process until the draw is accepted.

2. M-H step: Given the current value $\boldsymbol{\theta}$ and the proposed value $\boldsymbol{\theta'}$

   (a) If $\boldsymbol{\theta} \in \mathcal{D}$, set $\alpha_{MH}(\boldsymbol{\theta}, \boldsymbol{\theta'}|\boldsymbol{y}) = 1$

   (b) If $\boldsymbol{\theta} \in \mathcal{D}^c$ and $\boldsymbol{\theta'} \in \mathcal{D}$, set $\alpha_{MH}(\boldsymbol{\theta}, \boldsymbol{\theta'}|\boldsymbol{y}) = \frac{ch(\boldsymbol{\theta}|\boldsymbol{y})}{f(\boldsymbol{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})}$

   (c) If $\boldsymbol{\theta} \in \mathcal{D}^c$ and $\boldsymbol{\theta'} \in \mathcal{D}^c$, set $\alpha_{MH}(\boldsymbol{\theta}, \boldsymbol{\theta'}|\boldsymbol{y}) = min\left\{1, \frac{ch(\boldsymbol{\theta}|\boldsymbol{y})}{f(\boldsymbol{y}|\boldsymbol{\theta})\pi(\boldsymbol{\theta})}\right\}$

   Return $\boldsymbol{\theta'}$ with probability $\alpha_{MH}(\boldsymbol{\theta}, \boldsymbol{\theta'}|y)$, otherwise return $\boldsymbol{\theta}$.

3.2 Time Series Results

The results for the autoregressive Poisson model are displayed in Table 2, and are based on 11,000 MCMC draws (burn-in of 1,000) with the priors centered at 0 and a variance of 25. Table 2 also displays the marginal likelihood associated with each model specification. A discussion about marginal likelihood computations and prior sensitivity is offered in Section 5. Evidenced in the table is the support from the data for the third specification, which contains the highest marginal likelihood (on the log scale). The third specification supports indicators for the July announcement and August *New York Times* publication. Model (4) includes additional indicators for later *New York Times* publications in which they released more RFC loan authorizations, however, this specification is less supported by the data (although other dates are statistically different from zero). Thus, one can conclude that the model with the first two date indicators best represent the data, temporal changes in the series, and the dates in which the series shifts.

	(1)	(2)	(3)	(4)
Intercept	-0.38 (0.04)	0.17 (0.06)	0.24 (0.06)	0.25 (0.05)
$\rho,\ y_{t-1}$	0.86 (0.02)	0.73 (0.02)	0.69 (0.03)	0.68 (0.02)
$1\{t \geq July\ 21,\ 1932\}$		-0.62 (0.05)	-0.09 (0.09)	-0.04 (0.08)
$1\{t \geq August\ 22,\ 1932\}$			-0.62 (0.10)	-0.41 (0.16)
$1\{t \geq October\ 7,\ 1932\}$				-0.48 (0.16)
$1\{t \geq October\ 22,\ 1932\}$				-0.30 (0.17)
$1\{t \geq November\ 28,\ 1932\}$				-0.13 (0.20)
$1\{t \geq December\ 22,\ 1932\}$				-0.10 (0.20)
$1\{t \geq January\ 26,\ 1933\}$				0.33 (0.27)
Log-Marginal Lik.	-611.7	-557.0	-547.2	-551.5

Table 2: Posterior means and standard deviations are based on 11,000 MCMC draws with a burn-in of 1,000. Marginal likelihood computations are discussed in Section 5.1. The priors are centered at 0 with a variance of 25. Prior sensitivity is presented in Section 5.2.

Focusing on Model (3), the results show a large negative effect stemming from the *New York Times* initial announcement (August 22, 1932). In order to gauge the magnitude, estimated covariate effects for the parameters are considered. Let $\boldsymbol{x}_t^\dagger$ represent the case when no loan authorizations are revealed and $\boldsymbol{x}_t$ is the original case with the announcement and *New York Times* publication. Thus, interest lies in the average difference in the implied probabilities $\{\Pr(y_t = j|\boldsymbol{x}_t) - \Pr(y_t = j|\boldsymbol{x}_t^\dagger)\}$, where j represents a particular number of applications submitted that day and the probabilities are those from the Poisson distribution. As discussed in Jeliazkov et al. (2008), a practical procedure is to marginalize out the remaining covariates using their empirical distribution, while the parameters are integrated out with respect to their posterior distribution. The goal is to obtain a sample of draws and find the mean of the following predictive distribution:

$$\{\Pr(y_t = j|\boldsymbol{x}_t) - \Pr(y_t = j|\boldsymbol{x}_t^\dagger)\} = \int \{\Pr(y_t = j|\boldsymbol{x}_t, y_{t-1}, \boldsymbol{\theta}) - \Pr(y_t = j|\boldsymbol{x}_t^\dagger, y_{t-1}, \boldsymbol{\theta})\}\pi(y_{t-1})\pi(\boldsymbol{\theta}|y)dy_{t-1}d\boldsymbol{\theta}.$$

In order to examine the magnitude of the stigma effect in terms of banks' reluctance to seek assistance from the RFC, the probabilities are calculated with the number of daily applications submitted to the RFC, j, set to values surrounding the pre-revealing and post-revealing averages.

Table 3 presents the results for the estimated covariate effects. The results demonstrate that revealing the loan authorizations reduces the probability of the RFC receiving 3 applications a day (near the pre-revealing average) by 8.4 percentage points. Revealing the loan authorizations actually increases the probability of the RFC receiving 0 applications a day by 23.3 percentage points, relative to no revealing. Thus, in agreement with the raw data, the model finds a significant negative stigma effect from the revealing, where banks became reluctant to seek assistance from the RFC. This effect has several harmful implications, including the RFC being unable to achieve its objective of restoring confidence in the financial system and the lengthening of the Depression since banks are unwilling to apply for the support they need.

	Revealing – No Revealing
$\triangle\Pr(y_t = 0)$	0.233
$\triangle\Pr(y_t = 2)$	-0.082
$\triangle\Pr(y_t = 3)$	-0.084
$\triangle\Pr(y_t = 4)$	-0.052

Table 3: Estimated covariate effects. $\triangle\Pr(\cdot)$ expresses the difference in the probability of a particular count if the names were not revealed.

The time series analysis offered in this section answers the first question of interest: Did announcing the RFC's loan authorizations deter bank participation in the rescue program? Yes, there is a major drop in participation with the probability of the RFC receiving no applications a day increasing by 23.3 percentage points. The two natural follow up questions are: (a) Once the names were released, what happened to those banks and their ability to facilitate credit channels? (b) How did this drop in participation affect economic activity? These two questions are addressed in Section 4 and Section 4.3.1, respectively.

4 Multivariate Analysis

4.1 Model and Estimation

The purpose of the multivariate analysis is to examine how the publication of the RFC's loan authorizations affected the revealed banks' ability to operate as financial intermediaries. This section is methodologically intensive in order to properly control for the several selection mechanisms that qualify banks for rescue assistance. Hence, a multivariate treatment effect model in the presence of sample selection is employed, which was developed in Vossmeyer (2016). The methodology deals with several important issues prevalent in policy and program evaluation, including application and approval stages, non-random treatment assignment, endogeneity, and discrete outcomes. It is applicable in the case of the RFC because banks had to apply for assistance from the RFC. Following the application stage, the RFC reviewed the submitted material and determined whether or not the bank was fit to receive assistance. After these 2 selection stages, the resulting set of treatment response or potential outcomes are for banks that do not apply for assistance, banks that apply and are declined assistance, and banks that apply and are approved assistance, thereby capturing the entire banking population. The model differs dramatically from conventional treatment models which only consider the treated and untreated groups. The conventional structure ignores the initial selection mechanism in which banks choose to apply for assistance. Overlooking the application stage erroneously groups banks that do not apply for assistance with those that are declined assistance. Thus, the untreated group comprises the most and least healthy banks, leading to a fundamental misspecification. Motivated by these difficulties, this article does not use the conventional methods and instead utilizes the multivariate model in the presence of sample selection, which is graphically presented in Figure 3.

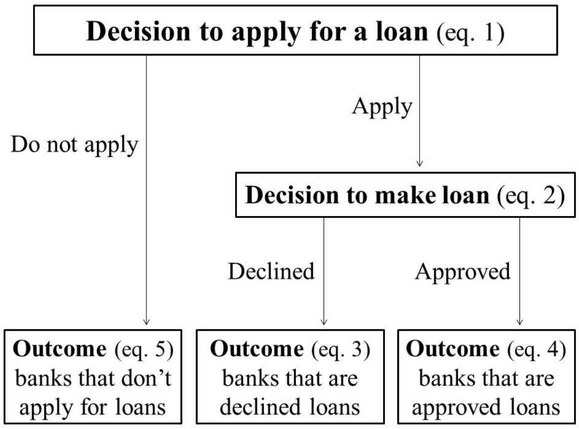

Figure 3: Multivariate treatment effect model in the presence of sample selection.

The model is a system of 5 equations with 2 selection mechanisms and 3 treatment response outcomes given by:

$$\begin{array}{rcll}
\textit{Application Selection Mechanism} & : & y_{i1}^* = \mathbf{x}_{i1}'\boldsymbol{\beta}_1 + \varepsilon_{i1} \quad (\textit{always observed}) & (1) \\
\textit{Approval Selected Treatment} & : & y_{i2}^* = \mathbf{x}_{i2}'\boldsymbol{\beta}_2 + \varepsilon_{i2} \quad (\textit{observed for applicants}) & (2) \\
\textit{Potential Outcomes} & - & \text{Treatment Responses } (\textit{only one is observed}) & \\
\text{Applied-declined sample} & : & y_{i3}^* = (\mathbf{x}_{i3}' \; y_{i1})\boldsymbol{\beta}_3 + \varepsilon_{i3} & (3) \\
\text{Applied-approved sample} & : & y_{i4}^* = (\mathbf{x}_{i4}' \; y_{i1} \; y_{i2} \; (y_{i2} \times Stig_i))\boldsymbol{\beta}_4 + \varepsilon_{i4} & (4) \\
\text{Non-applicant sample} & : & y_{i5}^* = \mathbf{x}_{i5}'\boldsymbol{\beta}_5 + \varepsilon_{i5} & (5)
\end{array}$$

It is further characterized by 5 dependent variables of interest where $\mathbf{y}_i^* \equiv (y_{i1}^*, y_{i2}^*, y_{i3}^*, y_{i4}^*, y_{i5}^*)'$ are the continuous latent data and $\mathbf{y}_i \equiv (y_{i1}, y_{i2}, y_{i3}, y_{i4}, y_{i5})'$ are the corresponding observed censored data. The latent variables relate to the observed censored outcomes by $y_{ij} = y_{ij}^* \cdot 1\{y_{ij}^* > 0\}$ for equations $j = 1, \ldots, 5$, (Tobin, 1958). A discussion about the censoring appears in Section 4.2. The outcome for equation (1), y_{i1}, is the total amount of RFC assistance requested by bank i. The outcome for equation (2), y_{i2}, is the total amount of RFC assistance approved for bank i. This equation is only observed for the selected sample of applicant banks. The outcome for equations (3)-(5) represent bank performance for the respective subsamples of banks that do not apply, banks that apply and are declined, and banks that apply and are approved. Only one of these equations is ever observed, the other two are the counterfactuals. Note that y_{i1} and y_{i2} enter potential outcome equations (3) and (4) as endogenous covariates for the applicant sample. This can be understood as the requested and approved treatments entering the performance equations. Additionally, an interaction term enters equation (4). This term interacts the endogenous approved RFC funds with an indicator variable that takes the value "1" if a bank's name was revealed as an RFC recipient. This is the key covariate of interest. Detailed descriptions of this variable appear in Section 4.2 and treatment effect calculations are presented in Section 4.3.

Data missingness restricts the model to systems of 2 or 3 equations depending on the subsample to which the bank belongs. If $y_{i1} = 0$, the bank did not apply for assistance – y_{i1} and y_{i5} are observed, and y_{i2}, y_{i3}, and y_{i4} are not observed. If $y_{i1} > 0$ and $y_{i2} = 0$, the bank applied for assistance and was declined – y_{i1}, y_{i2} and y_{i3} are observed, and y_{i4} and y_{i5} are not observed. If $y_{i1} > 0$ and $y_{i2} > 0$, the bank applied for assistance and was approved – y_{i1}, y_{i2} and y_{i4} are observed, and y_{i3} and y_{i5} are not observed. The exogenous covariates $\mathbf{x}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{x}_{i3}, \mathbf{x}_{i4}, \mathbf{x}_{i5})$ are needed only when their corresponding equations are observed. For identification reasons, assume that the covariates in $\mathbf{x}_{i2}$ contain at least one more variable than those included in the other equations. This variable is regarded as the instrumental variable used in treatment models that is correlated with the treatment and not the errors (Chib, 2007; Greenberg, 2008). Although identification in models with incidental truncation does not require exclusions, they are typically empolyed so the resulting inference does not solely depend on distributional assumptions. Finally, the model assumes that the errors $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3}, \varepsilon_{i4}, \varepsilon_{i5})'$ have a multivariate normal distribution $\mathcal{N}_5(0, \boldsymbol{\Omega})$, where $\boldsymbol{\Omega}$ is an unrestricted symmetric positive definite matrix. It is possible to explore other distributional forms for this joint model, but the normality assumption provides the groundwork for more flexible distributions, including finite mixtures, dirichlet processes, and scale mixtures.

For the i-th bank, define the following vectors and matrices,

$$\mathbf{y}^*_{iC} = (y^*_{i1}, y^*_{i5})', \quad \mathbf{y}^*_{iD} = (y^*_{i1}, y^*_{i2}, y^*_{i3})', \quad \mathbf{y}^*_{iA} = (y^*_{i1}, y^*_{i2}, y^*_{i4})',$$

$$\mathbf{X}_{iC} = \begin{pmatrix} \mathbf{x}'_{i1} & 0 \\ 0 & \mathbf{x}'_{i5} \end{pmatrix}, \quad \mathbf{X}_{iD} = \begin{pmatrix} \mathbf{x}'_{i1} & 0 & 0 \\ 0 & \mathbf{x}'_{i2} & 0 \\ 0 & 0 & (\mathbf{x}'_{i3}\ y_{i1}) \end{pmatrix},$$

$$\mathbf{X}_{iA} = \begin{pmatrix} \mathbf{x}'_{i1} & 0 & 0 \\ 0 & \mathbf{x}'_{i2} & 0 \\ 0 & 0 & (\mathbf{x}'_{i4}\ y_{i1}\ y_{i2}\ (y_{i2} \times Stig_i)) \end{pmatrix}.$$

Let $N_1 = \{i : y_{i1} = 0\}$ be the n_1 banks that do not apply for assistance and $N_2 = \{i : y_{i1} > 0 \textit{ and } y_{i2} = 0\}$ be the n_2 banks that apply and are declined assistance. Set $N_3 = \{i : y_{i1} >$

0 *and* $y_{i2} > 0\}$ to be the n_3 banks that apply and are approved assistance. Upon defining $\boldsymbol{\beta} = (\boldsymbol{\beta}_1', \boldsymbol{\beta}_2', \boldsymbol{\beta}_3', \boldsymbol{\beta}_4', \boldsymbol{\beta}_5')'$ and $\boldsymbol{\Omega}$, note that in $\boldsymbol{\Omega}$ the elements Ω_{25}, Ω_{35}, Ω_{45}, and Ω_{34} are not identified because their corresponding equations cannot be observed at the same time. Thus, there are 11 unique estimable elements in $\boldsymbol{\Omega}$, whereas the remaining ones are non-identified parameters due to the missing outcomes. The variance-covariance matrix of interest is,

$$\boldsymbol{\Omega} = \begin{pmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14} & \Omega_{15} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24} & \cdot \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \cdot & \cdot \\ \Omega_{41} & \Omega_{42} & \cdot & \Omega_{44} & \cdot \\ \Omega_{51} & \cdot & \cdot & \cdot & \Omega_{55} \end{pmatrix}.$$

The variance-covariance matrices for the three subsamples are as follows

$$\boldsymbol{\Omega}_C = \begin{pmatrix} \Omega_{11} & \Omega_{15} \\ \Omega_{51} & \Omega_{55} \end{pmatrix}, \quad \boldsymbol{\Omega}_D = \begin{pmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{pmatrix}, \quad \boldsymbol{\Omega}_A = \begin{pmatrix} \Omega_{11} & \Omega_{12} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{24} \\ \Omega_{41} & \Omega_{42} & \Omega_{44} \end{pmatrix}. \tag{6}$$

Let $\boldsymbol{\mu}_j$ define the mean in equations $j = 1, \ldots, 5$. The likelihood is $f(\mathbf{y}|\boldsymbol{\theta}) = \int f(\mathbf{y}, \mathbf{y}^*|\boldsymbol{\theta}) d\mathbf{y}^*$, where $\boldsymbol{\theta}$ is all model parameters and $f(\mathbf{y}, \mathbf{y}^*|\boldsymbol{\theta})$ is the complete-data likelihood given by

$$f(\mathbf{y}, \mathbf{y}^*|\boldsymbol{\theta}) = \prod_{i \in N_1} f_N(\mathbf{y}_{iC}^*|\boldsymbol{\mu}_C, \boldsymbol{\Omega}_C) \times \prod_{i \in N_2} f_N(\mathbf{y}_{iD}^*|\boldsymbol{\mu}_D, \boldsymbol{\Omega}_D) \times \prod_{i \in N_3} f_N(\mathbf{y}_{iA}^*|\boldsymbol{\mu}_A, \boldsymbol{\Omega}_A).$$

The likelihood is defined in terms of the 3 subsets of the sample, without components for the non-identified parameters, which follows from Chib (2007) and Chib et al. (2009). The censoring of multiple outcome variables renders this likelihood analytically intractable and hence estimation relies on simulation-based techniques. A Bayesian framework is implemented, thus standard semi-conjugate priors are applied where $\boldsymbol{\beta}$ has a joint normal distribution and (independently) $\boldsymbol{\Omega}$ has an inverted Wishart distribution. The prior on $\boldsymbol{\Omega}$ implies a distribution on functions of the elements in $\boldsymbol{\Omega}$ that correspond to the subsamples of interest. Combining the likelihood and priors leads to a posterior distribution, which is simulated by MCMC methods. For computational efficiency, a collapsed Gibbs sampler with data augmentation is employed which follows from Chib et al. (2009) and Li (2011). The particular algorithm that is utilized was developed in Vossmeyer (2016). The algorithm is attractive because of its excellent mixing properties, low storage costs, and computational speed. The sampler does not simulate the outcomes that are missing due to the application selection mechanism and does not require the joint distribution for the potential outcomes, which result in an efficient sampler that maintains tractability in the sampling densities. A summary of algorithm is offered below, however, the full derivation and details of the updating formulas are provided in Vossmeyer (2016).[1]

Algorithm 2 *Gibbs Sampler*

1. Sample $\boldsymbol{\beta}$ from the distribution $\boldsymbol{\beta}\ |\mathbf{y}, \mathbf{y}^*, \boldsymbol{\theta} \setminus \boldsymbol{\beta}$.
2. Sample $\boldsymbol{\Omega}$ from the distribution $\boldsymbol{\Omega}|\mathbf{y}, \mathbf{y}^*, \boldsymbol{\theta} \setminus \boldsymbol{\Omega}$ in a 1-block, multi-step procedure.
3. For $i \in N_1,$ sample y^*_{i1} from the distribution $y^*_{i1}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{y}^* \setminus \mathbf{y}^*_1$.
4. For $i \in N_2,$ sample y^*_{i2} from the distribution $y^*_{i2}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{y}^* \setminus \mathbf{y}^*_2$.
5. For $i : y_{i3} = 0$, sample y^*_{i3} from the distribution $y^*_{i3}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{y}^* \setminus \mathbf{y}^*_3$.
6. For $i : y_{i4} = 0$, sample y^*_{i4} from the distribution $y^*_{i4}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{y}^* \setminus \mathbf{y}^*_4$.
7. For $i : y_{i5} = 0$, sample y^*_{i5} from the distribution $y^*_{i5}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{y}^* \setminus \mathbf{y}^*_5$.

Bayesian estimation techniques are necessary here for several reasons. First, the censoring of the outcome variables, in conjunction with endogeneity, render most two-stage estimators inapplicable. Second, the missing elements in $\boldsymbol{\Omega}$ make it unclear how to guarantee positive-definiteness and the Bayesian approach reparameterizes the model to avoid the issue. Finally, maximum simulated likelihood is applicable, however, it is very slow. The availability of a full-set of conditionals makes Gibbs sampling the most attractive option.

4.2 Data

Examining the RFC presents limitations because data are not readily available and need to be hand-coded from record books. As a result, many of the previous papers either look at a time series of RFC lending (Butkiewicz, 1995) or bank-level data restricted to Federal Reserve member banks (Mason, 2001; Calomiris et al., 2013). In addition, dealing with sample selection is difficult because neither the *New York Times* nor the quarterly and monthly *Reports of Activities of the Reconstruction Finance Corporation* report applied or declined assistance. This paper overcomes these limitations and contributes to this literature by employing a comprehensive, bank-level data set built from the original applications submitted to the RFC. With these more detailed data, the multivariate treatment effect model can be employed to control for the selection mechanisms

[1]The notation "\" represents "except", e.g., $\mathbf{y}^* \setminus \mathbf{y}^*_1$ says all elements in $\mathbf{y}^*$ except $\mathbf{y}^*_1$:

qualifying banks for assistance, thereby implementing a more complete framework to examine the publication of the RFC's authorizations and stigma.

The RFC cards employed in Section 3.1 are used to define the RFC application and approved amounts (y_{i1} and y_{i2}). These data are merged with a separate data set constructed from the *Rand McNally Bankers' Directory*. The directory describes balance sheets, charters, correspondent relationships, and other characteristics for all banks (Federal Reserve members and nonmembers) in a given state for a given year. Additional data are gathered from the 1930 U.S. census of agriculture, manufacturing and population, describing the characteristics of the county and a bank's business environment. Census covariates include the number of wholesale retailers, number of manufacturing facilities, acres of cropland, and percent of votes which were Democratic.

The data are applied to the 5 equation model as follows: the outcome variable for equation (1), y_{i1}, is the total amount of RFC assistance requested by each bank by December 1933. This outcome is censored with point mass at zero for banks that do not apply for assistance and a continuous distribution for the different loan requests. The outcome variable for equation (2), y_{i2}, is the total amount of RFC assistance approved. This outcome is also censored with point mass at zero for banks that are declined assistance and a continuous distribution for the different loan approvals. The RFC's decision to lend was based on the solvency of the banks. However, after going through the examiners' reports, it is apparent that the RFC also considered banks' importance to their local market and features of that market (e.g., agriculture and town size). Finally, the outcome variable for equations (3)–(5) is the total amount of "loans and discounts" (hereafter, referred to as LD) for each bank taken from its January 1935 balance sheet. The outcome for the treatment responses is again censored with point mass at zero for banks that failed since the time of the loan application period and a continuous distribution with LD representing a bank's health and the state of the local economy. LD is chosen to measure a bank's performance following the literature on the credit crunch and its relation to economic activity (Bernanke, 1983; Calomiris and Mason, 2003). This particular element of the paper is unique because it captures a bank's financial intermediary function. Changes to lending, which can occur either by bank supply or consumer demand of loans, is an important quantity with respect to recovery. Furthermore, this quantity represents a more long-run outcome. While short-run responses are interesting in their own respect, these outcomes are not available because the balance sheet data are only available every 6 months. Thus, this paper focuses on stigma's long term effect on lending to offer board implications for the duration of the recovery and resuscitation of the financial system.

Finally, the *Stig* variable in equation (4) is constructed from historical issues of the *New York Times*. While eventually all RFC authorizations were available through congressional reports, the select lists revealed through the newspaper during the second half of 1932 and early 1933 are the events of interest because the newspaper is the most accessible form of the information. Additionally, upon the initial release of information, the public did not know how extensive the RFC program was and that significant numbers of banks were receiving assistance. Therefore, it is reasonable to believe that those in the initial revealing were the most stigmatized because people had yet to realize how far the program reached. The *Stig* variable takes the value "1" if a bank's name was revealed in the *New York Times* and "0" otherwise.[2] Further details on the group of revealed banks are provided in the next section.

4.2.1 Descriptive Statistics

The data set includes all banks operating in 1932 in Alabama, Arkansas, Michigan, Mississippi, and Tennessee. Unlike previous studies on the RFC, this includes non-Federal Reserve member banks, as well as member institutions. Solely looking at members may misrepresent the banking population because these institutions were often healthier and had additional outlets for relief funds through the discount window. Furthermore, banks that solely received assistance through the discount window were safe from being publicly announced. The sample consists of 1,794 banks, of which 908 banks applied for RFC assistance and 800 of those were approved while 108 were declined assistance. Roughly half of the banks in each state applied for assistance from the RFC. From the applicant pool, about 88% of the submitted applications were approved. In this sample, of the 800 banks approved RFC assistance, 192 bank names were published in the initial *New York Times* reports. Note that there are some small discrepancies between the RFC cards and the *New York Times*. It appears in some cases that certain names were skipped over, which can seemingly be attributed to newspaper typing mistakes as the missed names are in alphabetical order.

These 5 states are studied because many relief efforts were focused in these areas, and they provide variation across bank and county characteristics, sizes, and Federal Reserve districts. Federal

[2]Other specifications of the *Stig* variable were considered, where it was defined by particular lists. However, these specifications achieved a lower posterior model probability than the presented case.

Reserve district variation is necessary because RFC lending was concurrent with lending through the discount window. Federal Reserve policies differed across districts and hence impacted the rate at which banks failed (Richardson and Troost, 2009). Richardson and Troost (2009) find that the loose lending policies in the 6th district reduced bank failures, relative to the strict policies in the 8th district. The lending capabilities of the RFC were larger than that of the Federal Reserve's discount lending because the RFC could assist nonmember banks, which is 81% of this sample.

			Approved	
Variable	**Non-Applicant**	**Declined**	**Non-revealed**	**Revealed**
No. Banks	886	108	609	192
Average Age	25	25	29	35
Financial Ratios (averages)				
Cash / Assets	0.17	0.11	0.14	0.13
Deposits / Liabilities	0.71	0.70	0.72	0.70
Cash / Deposits	0.29	0.17	0.19	0.19
Equity	0.21	0.18	0.20	0.19
Charters and Memberships (counts)				
State Bank	609	73	510	150
National Bank	198	23	81	35
ABA Member	487	63	364	154
Correspondents (averages)				
Total Correspondents	2.5	2.7	2.5	3.3
Out of State Corres.	1.4	1.6	1.4	2.0
Market Shares (averages)				
Liab. / County Liab.	0.21	0.20	0.22	0.25
Liab. / Town Liab.	0.71	0.66	0.76	0.68
County Characteristics (averages)				
No. Wholesale Retailers	27	33	28	28
% Vote Democratic	67	65	69	65
No. Manufact. Est.	34	44	36	39
Cropland ($\times$1000 acres)	100	116	100	107

Table 4: Characteristics of the banks in each subgroup in 1932 and county characteristics.

Table 4 presents descriptive statistics, separated by four subgroups: non-applicants, declined banks, approved non-revealed banks, and approved revealed banks. The table some differences between these groups of banks. Banks that apply for assistance hold less cash, with the declined sample holding the lowest amount, relative to banks that do not apply for assistance. Approved banks tend to be more important to their local market, coinciding with information in the examiners' files. Additionally, declined banks appear to operate in areas with more manufacturing and agriculture, relative to the other subsamples. Before the fall of 1930, the decrease in agricultural prices concentrated bank failures in farming areas, explaining the harsh economic condition of these regions (Richardson, 2007). These fundamental differences across the banks' balance sheets and locations motivate the joint model employed in this paper.

With respect to the revealed and non-revealed, the banks look relatively similar in terms of financial ratios, charters, market shares, and county characteristics. The main differences lie in bank age and correspondent network. Correspondent banks were designated in reserve cities of the Federal Reserve system and often provided smaller, local banks with liquidity (Richardson and Troost, 2009). Correspondent relationships represented a bank's importance to the national network of banking (Calomiris et al., 2013), so more correspondents generally represented a bigger bank. Table 4 displays that revealed banks had a larger correspondent network. This is consistent with the fact that part of the published names included loans over $100,000 from February - July. Also, Table 4 demonstrates revealed banks had been operating longer. This complication – a relationship between bank network size, age, and the *New York Times* list – is addressed via model comparison in Section 5.1. The model selection exercise tests whether the stigma variable is simply picking up an effect of bank age/network size or if it is actually adding information to the specification.

4.3 Multivariate Results

Table 5 displays the results for the multivariate treatment effect model with sample selection. The results are based on 11,000 MCMC draws with a burn in of 1,000. The priors on $\boldsymbol{\beta}$ are centered at 0 with a variance of 5, and the priors on $\boldsymbol{\Omega}$ imply that $E(\boldsymbol{\Omega}) = .4 \times I$ and $SD(\text{diag}(\boldsymbol{\Omega})) = 0.57 \times I$. Section 5.2 reports the sensitivity of the results to the prior specification.

While there are many results presented, the discussion will be focused on stigma and its effect on bank lending. Interpretation of the resulting parameter estimates presented in Table 5 is complicated by the censoring of the outcome variables. The basic result for $(y_{i2} \times Stig)$ is that it is negative with a 95% credibility interval (calculated using quantiles) that does not include zero. Further interpretation is afforded using covariate and treatment effect calculations, which are important for understanding the model and for determining the impact of a change in one or more of the covariates. This section considers the magnitude of the parameter estimate and discusses methods for treatment effects.

The key estimate of interest is $\beta_{RFC \times Stig}$, which is the coefficient on the interaction term of the

Variable	1) Application	2) RFC Decision	3) Declined	4) Approved	5) Non-applicant
Intercept	-0.787 (0.170)	-0.740 (0.207)	-0.951 (0.667)	0.381 (0.218)	-0.207 (0.084)
Bank Age	0.002 (0.001)		-0.002 (0.007)	-0.001 (0.001)	-0.001 (0.001)
Financial Characteristics					
Paid-Up Capital	1.377 (0.162)	1.317 (0.187)	8.515 (2.136)	3.470 (0.184)	1.694 (0.169)
Loans & Discounts	0.281 (0.021)	0.346 (0.024)	-0.765 (0.184)	-0.102 (0.130)	0.060 (0.020)
Bonds & Securities	-0.508 (0.043)	-0.563 (0.051)			
Cash / Assets	-1.715 (0.290)	-1.577 (0.345)	-0.207 (1.048)	0.944 (0.296)	-0.119 (0.111)
Deposit / Liab.	0.263 (0.070)	0.185 (0.074)			
Total Assets			0.234 (0.150)	0.183 (0.007)	0.261 (0.011)
Correspondents					
No. Corres.			-0.105 (0.107)	0.062 (0.021)	0.023 (0.016)
Corres. Out State			0.151 (0.116)	0.014 (0.021)	0.009 (0.016)
Charters, Memberships, and Depts.					
Bond Dept.	0.116 (0.034)				
Savings Dept.	-0.046 (0.026)				
Trust Dept.	0.042 (0.029)				
ABA Member		-0.028 (0.026)			
National Bank		-0.050 (0.038)	0.701 (0.361)	-0.078 (0.075)	-0.046 (0.049)
State Bank			0.433 (0.325)	-0.035 (0.070)	-0.009 (0.043)
County Characteristics					
Wholesale Retail			0.005 (0.003)	0.001 (0.000)	0.000 (0.000)
% Vote Demo.		0.000 (0.000)			
Manufact. Est.		0.000 (0.000)	-0.004 (0.002)	-0.001 (0.000)	0.000 (0.000)
Acres Cropland		-0.307 (0.196)	-0.288 (1.130)	0.554 (0.280)	0.283 (0.190)
Town Pop. 1932	-0.964 (0.179)	-1.511 (0.201)			
Town Pop. 1935			-0.463 (0.145)	-4.029 (0.702)	-5.420 (0.625)
Market Shares					
Liab./County Liab.		0.107 (0.056)			
Liab./Town Liab.	0.172 (0.071)		0.452 (0.274)	-0.007 (0.056)	-0.018 (0.038)
Dummies					
Fed Dist. 6	0.137 (0.168)	0.070 (0.207)	0.224 (0.456)	-0.059 (0.196)	0.155 (0.060)
Fed Dist. 7	0.344 (0.167)	0.249 (0.206)	0.258 (0.438)	-0.290 (0.198)	0.003 (0.061)
Fed Dist. 8	0.336 (0.170)	0.332 (0.211)	0.103 (0.471)	-0.297 (0.201)	0.157 (0.061)
RFC Request (y_1)			1.166 (0.369)	-0.906 (0.215)	
RFC Approve (y_2)				1.446 (0.189)	
$y_2 \times Stig$				-0.080 (0.029)	

Table 5: Posterior means and standard deviations are based on 11,000 MCMC draws with a burn-in of 1,000. Columns 2-6 display the results for equations 1-5, respectively.

endogenous approved RFC loan amount and the stigma indicator in equation (4). After controlling for a bank's health, business environment, and contagion channels, $\beta_{RFC\times Stig}$ reflects how the conversion of RFC lending to bank lending is impacted by the *New York Times* reporting the loan authorizations. Before discussing the covariate effect of stigma, details of the results of the endogenous covariate y_{i2} are necessary. To calculate how a change in RFC lending transfers to bank lending, the covariate effect is averaged over both observations and MCMC draws from the posterior distribution to deal with both data variability and parameter uncertainty. In general terms, the covariate effect calculation for the jth covariate is as follows:

$$\begin{aligned}\delta_j &= \int \frac{\partial E(y_i|\mathbf{x},\boldsymbol{\theta})}{\partial x_j} f(\mathbf{x})\pi(\boldsymbol{\theta}|\mathbf{y})d\mathbf{x}d\boldsymbol{\theta} \\ &\approx \frac{1}{nG}\sum_{i=n}^{n}\sum_{g=1}^{G}\frac{\partial E(y_i|x_i,\boldsymbol{\theta}^{(g)})}{\partial x_j} \qquad (7)\end{aligned}$$

for $g = 1,\ldots,G$ draws from the posterior distribution.

The covariate effect of the RFC (the endogenous y_{i2} in equation (4)) is $\delta_{RFC} = 0.574$. This can be interpreted as \$10,000 of RFC assistance translates to \$5,740 of LD in 1935, which is a strong, positive result. RFC assistance is effectively pushed beyond banks, trickling into local economies through lending, thus promoting and restoring confidence in the financial system. Now that the effectiveness of the RFC is understood, attention can be focused on stigma. Implementing the techniques in equation 7, the covariate effect of the RFC-stigma interaction term is $\delta_{RFC\times Stig} = -0.0319$. Thus, publishing a bank's name in the *New York Times* reduces the conversion of RFC lending to bank lending by \$319 for every \$10,000. The result displays moderate negative effects of stigma. Once revealed as a bailout recipient, a bank's lending is contracted. It is unclear if the contraction is coming from the bank's supply of loans, consumers' demand for loans, or both. However, it does show that the publication of the RFC authorizations reduced lending, stigmatized banks, and weakened credit channels. With less credit available in local markets, recovery becomes sluggish. Therefore, the effects of stigma include mitigating the RFC's objective of encouraging lending and offsetting a bank's function as a financial intermediary.

Another aspect to consider, in addition to a bank's lending function, is how stigma affects a bank's probability of failure. Interest lies in the average difference in the implied probabilities between the cases when a bank is revealed as a recipient of RFC assistance and when a bank is not revealed. Let $\mathbf{z}_i$ reflect all covariates other than the interaction term of interest, $w_i^\dagger$ be the case when a bank's name is not published, $w_i^{\ddagger}$ be the case when a bank's name is published in the *New York Times*, and set $y_{i4} = 0$ to represent bank failure. As conducted in Section 3.2, a predictive distribution can be constructed by evaluating

$$\{\Pr(y_{i4} = 0|w_i^{\dagger}) - \Pr(y_{i4} = 0|w_i^{\ddagger})\} = \int \{\Pr(y_{i4} = 0|w_i^{\dagger}, \mathbf{z}_i, \boldsymbol{\theta}) - \Pr(y_{i4} = 0|w_i^{\ddagger}, \mathbf{z}_i, \boldsymbol{\theta})\}\pi(\mathbf{z}_i)\pi(\boldsymbol{\theta}|\boldsymbol{y})d\mathbf{z}_i d\boldsymbol{\theta}. \tag{8}$$

Note that this distribution is marginalized over $\{\mathbf{z}_i\}$ and $\boldsymbol{\theta}$, so there is no residual uncertainty coming from the sample or estimation procedure. The mean of the predictive distribution gives the expected difference in computed pointwise probabilities as being revealed changes to not revealed (Jeliazkov et al., 2008). Computing the probabilities is not straightforward and requires additional simulation techniques. The Chib-Ritter-Tanner (CRT) method is employed to evaluate the likelihood function, which was developed in Jeliazkov and Lee (2010).

Specifically, the question of interest is – in the sample of approved-revealed banks, what is the difference in the probability of bank failure if the bank names were never published? The mean of the predictive distribution $\{\Pr(y_{i4} = 0|w_i^{\dagger}) - \Pr(y_{i4} = 0|w_i^{\ddagger})\}$ is -0.0048. In other words, if the *New York Times* did not publish the list of banks receiving assistance, the probability of failure for those banks decreases by 0.48 of a percentage point.[3] This is a rather small effect and it sheds some light on the broader picture of stigma. While stigma has moderate negative effects on bank lending, it is not severe enough to actually cause bank failure. These findings offer policy-makers some perspective about how the stigma problem manifests itself in bank lending, as well as the magnitude of the issue. While it may not be large enough to shock the financial system with a failure, its effect on lending mitigates relief efforts and prolongs recovery.

4.3.1 Treatment Effect of Reluctance

The time series analysis in Section 3 addressed the question as to whether and how much the revealing deterred bank participation in the rescue program. However, interest remains in how this drop in participation affected economic activity. Because the program became stigmatized, many banks did not seek assistance, who perhaps needed additional support during the Depression, thus what was the effect of this reduction in support? The data and methodological framework developed in the Multivariate Analysis offer a unique platform to answer this question.

[3]The opposite computation was done for the subsample of non-revealed banks (i.e., what happens if they were revealed) and the results again show a minimal effect.

With the entire population of banks in the 5 states, one can focus on the non-applicant sample (886 banks). These are banks that did not seek assistance from the RFC. Their particular reasons for not seeking assistance are unclear, however likely fall into the classes of: stable bank health, insolvency, or fear of having their name revealed as a recipient of emergency help – stigma. In order to tease out the latter group, the banks in the non-applicant sample are carefully matched based on balance sheet characteristics with banks in the approved bank sample. Generally speaking, they were selected on the basis that they were not so unhealthy that they would not have qualified for a loan (i.e., they don't look like the declined bank subsample) and not too healthy in which they did not need assistance. Subsequent characteristics, such as network and county characteristics were considered for more borderline cases. After carefully examining each bank in the 886 non-applicant sample, 218 banks appear very similar to the approved bank subsample, and thus are the potential "stigma non-applicants".[4]

Interest centers upon a scenario in which these banks actually applied for assistance and the difference in economic outcomes between this scenario and the original case in which they did not apply. These quantities are available using the simulation methods described by (8). The predictive distribution is described by the probability difference characterized by the probability of failure conditional on RFC assistance and the probability of failure conditional on no assistance for the sample of 218 stigma non-applicants. The granted RFC amount for each of these banks is matched based on similar banks in the approved pool as a ratio of total assets. Evaluating the likelihood function in each case and computing the probability is done using the Chib-Ritter-Tanner simulation method. The mean of the predictive distribution is -0.016. In other words, if the stigma non-applicants actually applied for assistance, the probability of failure for those banks decreases by 1.6 percentage points. This is a small effect, indicating that in the sample of stigma non-applicants, being granted RFC assistance would have possibly spared a few banks from failure, but not many. In the raw data, 37 banks in this sample failed.

The next aspect to consider is lending. While not applying does not have major implications for bank survival in the sample of stigma non-applicants, perhaps the stigma effect manifests itself in lending as it did for the revealed-approved banks. To answer this question, the methods described in (7) are employed for the 218 banks. In this sample, the covariate effect of RFC lending is

[4]A more selective approach was also used and narrowed the sample to 71 banks, however, the results do not vary much from 218 sample and hence are not presented.

$\delta_{RFC} = 0.664$. Thus, \$10,000 dollars of RFC assistance would translate to \$6,640 of LD. This result is positive and actually represents a higher conversion than that of the approved bank subsample. With these banks not applying for assistance because the RFC was stigmatized, lending could have reached a higher capacity, thereby improving credit channels.

Notably, the analysis in this section rests on the selection of banks and simulated RFC support. While these procedures add uncertainty to the results, the findings corroborate with that of the actual approved-revealed sample. The story seems to be that, because the RFC program became stigmatized and saw a massive drop in bank participation (as pictured in Figure 2), many banks did not reach out for the support they needed. Had they reached out and received the support, it would have converted to more bank lending and economic activity. The results provide insights into the economic consequences and implications of the drop in participation, which was otherwise unexplored.

5 Additional Considerations

5.1 Model Comparison

Model comparison is an important aspect with regard to stigma. In the time series analysis, Section 3, marginal likelihood computations are useful in determining which model with RFC revealing dates is best supported by the data and best represents shifts in the series. Those results are presented in Table 2. In the multivariate analysis, model comparison is necessary to examine the potential relationship between the size of a bank's network and being revealed, which is shown in Table 4. The correlations in bank characteristics, time of the loan application, and publication in the *New York Times* are worth investigating in a thorough model comparison exercise, which is the focus of this section.

An issue in the multivariate analysis of stigma is model formulation since the appropriate specification of the 5 equations is subject to uncertainty. In particular, it is of interest to know if adding the stigma interaction variable in equation (4) leads to overfitting and a lower posterior model probability. While the existing research on stigma often presents significant point estimates to provide evidence for their results, model comparison is lacking in the literature. It is unclear with the existing work whether models with stigma measures actually provide a better fit. It could be the case that stigma measures actually have very little explanatory power when it comes to overall bank performance. Ignoring model comparison may lead a researcher to exacerbate a result from a specification that is not actually supported by the data. To fill this gap, that paper employs Bayesian model comparison techniques to discover whether the stigma specification is best supported by the data.

Model selection is also useful to examine the aforementioned issue regarding the link between the size of a bank's network, age, and name publication, which is discussed in detail in Section 4.2.1. If the stigma variable is actually just picking up elements of the bank's age and correspondent network, then the marginal likelihood should fall in the stigma specification. Variables for the correspondent network and age are already included in the bank performance equation, so adding stigma would result in overfitting of the model.

For model comparison, given the data $\mathbf{y}$, interest centers upon two models $\{\mathcal{M}_{Stig}, \mathcal{M}_{NoStig}\}$, each characterized by a model-specific parameter vector $\boldsymbol{\theta}_{Stig}$ and $\boldsymbol{\theta}_{NoStig}$ and sampling density $f(\mathbf{y}|\mathcal{M}_{Stig}, \boldsymbol{\theta}_{Stig})$, $f(\mathbf{y}|\mathcal{M}_{NoStig}, \boldsymbol{\theta}_{NoStig})$. Bayesian model selection proceeds by comparing the models through their posterior odds ratio which is written as,

$$\frac{\Pr(\mathcal{M}_{Stig}|\mathbf{y})}{\Pr(\mathcal{M}_{NoStig}|\mathbf{y})} = \frac{\Pr(\mathcal{M}_{Stig})}{\Pr(\mathcal{M}_{NoStig})} \times \frac{m(\mathbf{y}|\mathcal{M}_{Stig})}{m(\mathbf{y}|\mathcal{M}_{NoStig})}.$$

Chib (1995) recognized the *basic marginal likelihood identity (BMI)* in which the marginal likelihood for model $\mathcal{M}_{Stig}$ can be expressed as

$$m(\mathbf{y}|\mathcal{M}_{Stig}) = \frac{f(\mathbf{y}|\mathcal{M}_{Stig}, \boldsymbol{\theta}_{Stig})\pi(\boldsymbol{\theta}_{Stig}|\mathcal{M}_{Stig})}{\pi(\boldsymbol{\theta}_{Stig}|\mathbf{y}, \mathcal{M}_{Stig})}.$$

Calculation of the marginal likelihood is then reduced to finding an estimate of the posterior ordinate, typically taken as the posterior mean or mode. Evaluation of the likelihood is done by employing the Chib-Ritter-Tanner (CRT) method from Jeliazkov and Lee (2010). Note that the prior on $\boldsymbol{\Omega}$ implies a distribution on functions of the elements in $\boldsymbol{\Omega}$ that are used in marginal likelihood computations, which only involve the identified components.

The results of the model comparison are presented in Table 6. The table displays the log-marginal likelihood estimate, numerical standard error, and posterior model probability. The marginal likelihood is 26 points higher on the log scale in favor of the stigma specification, giving it a posterior model probability of nearly 1. The specification without the stigma measures is not supported by the data. The information brought forth by a single covariate, the interaction between name publication and RFC assistance, is immense. This result has two important implications.

First, in addition to the credible point estimate for $\beta_{RFC\times Stig}$, it is clear that the data heavily support this variable entering the model. Second, the complication with the stigma indicator and network size/age is not an issue, as there is no evidence of overfitting.

	Stigma	**No Stigma**
Log-Marginal Lik.	-7952.0	-7978.6
Numerical S.E.	(0.423)	(0.445)
$\Pr(\mathcal{M}_k\|y)$	0.999	2.8×10^{-12}

Table 6: Log-marginal likelihood estimates, numerical standard errors, and posterior model probabilities.

The model comparison results strengthen the previous finding of negative stigma effects. While the stigma effect is not excessive, it contracted credit channels and harmed recovery. It is important to note that stigma did not reverse the effectiveness of the RFC. The RFC program remained successful through the publication of the authorizations. There were indeed drawbacks to the revealing, however, they were manifested in lending not failure.

5.2 Sensitivity Analysis

The priors for the multivariate model appear at the beginning of Section 4.3. Prior selection generally involves some degree of uncertainty and this section evaluates how sensitive the results are to the assumptions about the prior distribution.

The key coefficient of interest, $\beta_{RFC\times Stig}$, is the estimate on the endogenous interaction variable $y_{i2} \times Stig$ in equation (4). The coefficient reported in Table 5 shows $\beta_{RFC\times Stig} = 0.080$, which implies that stigma has a negative impact on bank lending. To check the sensitivity of this result to the prior specification, Table 7 reports the coefficient $\beta_{RFC\times Stig}$ for different hyperparameters.

	SD($\beta_{RFC\times Stig}$)		
Mean($\beta_{RFC\times Stig}$)	1.5	4.4	14.14
-1	-0.079	-0.086	-0.087
0	-0.076	-0.085	-0.087
1	-0.074	-0.085	-0.087

Table 7: $\beta_{RFC\times Stig}$ as a function of the hyperparameters. The priors for $\boldsymbol{\beta}$ in the benchmark model are centered at zero with a variance of 5.

The results indicate nearly no sensitivity around the benchmark result of 0.08. This finding holds true for all of the parameter estimates. Skeptics of stigma who would place strong negative priors on its existence would be overridden by the data. The data speak loudly for the multivariate results of stigma and the overall findings. Note that the model rankings in Section 5.1 are also not sensitive to the different prior specifications. Furthermore, the priors on the time series model (presented in Table 2) are not sensitive to varying hyperparameters.

6 Concluding Remarks

This paper considers the stigma effect that arises when banks receive assistance from an emergency lending program during a financial crisis. The effect is examined by looking at the change in bank participation rates in the rescue program and by looking at banks' ability to operate as financial intermediaries. The particular program of interest is the Reconstruction Finance Corporation and the event that is explored is the publication of the names of banks receiving assistance in the *New York Times.*

The results indicate that the publication of the RFC loan authorizations severely stigmatized the program, with bank applications dropping drastically and the probability of no applications submitted on a given day increasing by 23.3 percentage points. The consequences of this drop in participation manifests itself in credit channels, with lending not reaching its full capacity. The results also indicate that stigma moderately reduced the conversion of RFC lending to bank lending at the revealed banks. Thus, stigma mitigates the rescue program's objective of restoring confidence in the financial system and impedes a bank's function as a financial intermediary. Furthermore, a contraction in bank lending prolongs the resuscitation of the financial system. The stigma effect, however, is not drastic enough to cause bank failures, hence its shock to the overall banking system is limited. The findings in this paper contribute to the results in Armantier et al. (2015), which show that banks paid a premium to avoid discount window stigma during the 2007-2008 crisis. These historical events describe the implications of *realized* stigma, instead of *avoided* stigma, and thus explain why banks today incur costs to evade stigma.

This paper further contributes to the existing work on stigma by implementing a complete Bayesian methodological framework. The framework and model selection exercises disentangle the confounding factors that occur during financial restructuring and demonstrate support for the stigma model specification. Overall, the findings in the paper provide useful insights for policy-makers looking to combat the many obstacles involved in crises and corresponding market interventions.

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