Analysis of Stigma and Bank Behavior

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Topic

Stigma can arise when the identities of banks receiving assistance from a financial rescue program are revealed to the public.

Stigma can manifest itself in 2 ways:

1) Stigmatized rescue program

   • Loan authorizations become public knowledge → banks may become reluctant to seek assistance.

   • Less banks seeking assistance → rescue program cannot achieve its objectives.

2) Stigmatized recipient bank

   • Being revealed may impede a bank’s ability to function as a financial intermediary.

   • Less banking services being offered/utilized ⇒ less economic activity.
Motivation

Concerns of stigma have existed since the Great Depression and remain an active topic in academic and policy circles.

Despite its awareness, few empirical studies examining the presence and magnitude of stigma exist.

Methodological and data difficulties:

- *methodological* – several non-random selection mechanisms qualifying banks for emergency assistance.
- *data* – necessity to have high frequency, bank-level observations.
Motivation

Actions taken to minimize stigma during the recent crisis render it impractical to study (Geithner 2014, Gorton 2015).

Reconstruction Finance Corporation (RFC):

- February, 1932: Program started (public had knowledge of the program but not loan authorizations).
- July, 1932: House of Representatives mandated the RFC report the names of banks receiving assistance and the amounts lent.

This paper exploits these events to investigate stigma and examine the effect it has on banks’ desire to seek assistance from the RFC and banks’ ability to operate as financial intermediaries.
Contributions


This paper contributes to the literature by:

1. Did banks become reluctant to seek assistance from the RFC after the names were public knowledge?
   - Time series model of daily inquires submitted to the RFC.
   - Provides insights as to the magnitude of the change in the application rate and economic consequences of such actions.

2. Did stigma affect revealed banks’ ability to facilitate credit channels?
   - Multivariate model of bank-level application decisions, approval decisions, and lending.
   - Computation of treatment effects of stigma on banking lending and the probability of bank failure.

3. Extensive Bayesian model comparison study.
Outline

1. Relation to 2007-2008 crisis
2. Time Series Analysis (stigmatized rescue program)
   • Data and methodology
   • Results
3. Multivariate Analysis (stigmatized recipient bank)
   • Data and methodology
   • Treatment effect of stigma
   • Treatment effect of reluctance
4. Model comparison, sensitivity analyses
5. Concluding remarks
Relation to today

2007-2008 Crisis:

- Special lending programs were developed to assist banks
- Initially did not reveal identities
- Bloomberg L.P. later filed requests under the Freedom of Information Act
- Federal Reserve took many actions to reduce the effect of stigma

Armantier et al. (2015):

- Look at discount window stigma
- Demonstrate banks' willingness to pay to avoid stigma (44 bps)

Current study complements these findings by quantifying the consequences of realized stigma at the bank level (incurred historically), as opposed to the cost of avoiding stigma today.
Stigmatized Rescue Program

“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
Inquires submitted to the RFC

To address the concerns of a stigmatized rescue program, a daily time series of RFC application requests is constructed.

- *RFC Card Index to Loans Made to Banks and Railroads, 1932-1957*
- *Paid Loan Files and Declined Loan Files*

The current analysis focuses on the following states: Alabama, Arkansas, Michigan, Mississippi, and Tennessee.

**Figure:** Number of inquires submitted to the RFC each day.
New bank inquiries submitted to the RFC

**Figure:** Number of inquiries submitted to the RFC each day from new applicants.

Following the *NYT* publication, there is a major drop in new applications.

Evidence of a stigmatized rescue program.
### Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Daily Mean</th>
<th>St. Dev.</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Before revealing: All Inquires</td>
<td>4.71</td>
<td>4.3</td>
<td>953</td>
</tr>
<tr>
<td>Before revealing: New Applicants</td>
<td>3.45</td>
<td>4.2</td>
<td>696</td>
</tr>
<tr>
<td>After revealing, before FDIC: All Inquires</td>
<td>4.03</td>
<td>3.7</td>
<td>1858</td>
</tr>
<tr>
<td>After revealing, before FDIC: New Applicants</td>
<td>0.60</td>
<td>1.0</td>
<td>278</td>
</tr>
<tr>
<td>After FDIC: All Inquires</td>
<td>4.65</td>
<td>5.8</td>
<td>1860</td>
</tr>
<tr>
<td>After FDIC: New Applicants</td>
<td>1.23</td>
<td>3.4</td>
<td>491</td>
</tr>
</tbody>
</table>

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

The daily time series data is modeled using an autoregressive Poisson.

\[ y_t = \text{number of assistance requests submitted to the RFC on day } t \text{ from new applicant banks.} \]

The model is as follows

\[ y_t \sim Po(\lambda_t), \quad \lambda_t = \exp(x_t' \beta + \rho \log(y_{t-1} + 1)), \]

where \( x_t \) 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.
### Time Series Results

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.38 (0.04)</td>
<td>0.17 (0.06)</td>
<td>0.24 (0.06)</td>
<td>0.25 (0.05)</td>
</tr>
<tr>
<td>$\rho$, $y_{t-1}$</td>
<td>0.86 (0.02)</td>
<td>0.73 (0.02)</td>
<td>0.69 (0.03)</td>
<td>0.68 (0.02)</td>
</tr>
<tr>
<td>$1{t \geq July \ 21, \ 1932}$</td>
<td>-0.62 (0.05)</td>
<td>-0.09 (0.09)</td>
<td>-0.04 (0.08)</td>
<td></td>
</tr>
<tr>
<td>$1{t \geq August \ 22, \ 1932}$</td>
<td>(July 21-31, 1932)</td>
<td>-0.62 (0.10)</td>
<td>-0.41 (0.16)</td>
<td></td>
</tr>
<tr>
<td>$1{t \geq October \ 7, \ 1932}$</td>
<td>(August, 1932)</td>
<td>-0.48 (0.16)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1{t \geq October \ 22, \ 1932}$</td>
<td>(September, 1932)</td>
<td>-0.30 (0.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1{t \geq November \ 28, \ 1932}$</td>
<td>(October, 1932)</td>
<td>-0.13 (0.20)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1{t \geq December \ 22, \ 1932}$</td>
<td>(November, 1932)</td>
<td>-0.10 (0.20)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$1{t \geq January \ 26, \ 1933}$</td>
<td>(Loans over 100K Feb-July, and December 1932)</td>
<td>0.33 (0.27)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log-Marginal Lik.</td>
<td>-611.7</td>
<td>-557.0</td>
<td>-547.2</td>
<td>-551.5</td>
</tr>
</tbody>
</table>

- The third specification supports indicators for the July announcement and August New York Times publication.
- Model 3 best represents the data, temporal changes in the series, and the dates in which the series shifts.
Time Series Results

The results show a negative effect stemming from the *New York Times* initial announcement.

In order to gauge magnitude, estimated covariate effects are considered:

\[
\{\text{Pr}(y_t = j | x_t) - \text{Pr}(y_t = j | x_t^\dagger)\} = \\
\int \{\text{Pr}(y_t = j | x_t, y_{t-1}, \theta) - \text{Pr}(y_t = j | x_t^\dagger, y_{t-1}, \theta)\} \pi(y_{t-1}) \pi(\theta | y) dy_{t-1} d\theta.
\]

where \( x_t^\dagger \) represents the case when no loan authorizations are revealed and \( x_t \) is the original case.
Time Series Results

The goal is to obtain a sample of draws and evaluate the mean of the predictive distribution \( \{ \Pr(y_t = j|\mathbf{x}_t) - \Pr(y_t = j|\mathbf{x}^\dagger_t) \} \).

<table>
<thead>
<tr>
<th></th>
<th>Revealing – No Revealing</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta \Pr(y_t = 0) )</td>
<td>0.233</td>
</tr>
<tr>
<td>( \Delta \Pr(y_t = 2) )</td>
<td>-0.082</td>
</tr>
<tr>
<td>( \Delta \Pr(y_t = 3) )</td>
<td>-0.084</td>
</tr>
<tr>
<td>( \Delta \Pr(y_t = 4) )</td>
<td>-0.052</td>
</tr>
</tbody>
</table>

**Table:** Estimated covariate effects.

- Revealing the loan authorizations increases the probability of the RFC receiving 0 applications a day by 23.3 percentage points.
- Negative stigma effect from the revealing, where banks became reluctant to seek assistance from the RFC.
Time Series Results

The time series analysis answers the first question of interest: Did announcing the RFC’s loan authorizations deter banks from participating in the rescue program? YES.

Two natural follow up questions are:

1. Once the names were released, what happened to the revealed banks and their ability to facilitate credit channels?
2. How did this drop in participation affect economic activity?
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.

Employ a multivariate treatment effect model in the presence of sample selection to properly control for the several selection mechanisms that qualify banks for emergency assistance.
The model stemming from the figure contains a system of 5 equations with 1 selection mechanism, 1 selected treatment, and 3 treatment response equations.

**Model**

**Application Stage**

\[ y_{i1}^* = x_{i1}'\beta_1 + \varepsilon_{i1} \]  \hspace{1cm} (1)

(Always observed)

**Approval Stage**

\[ y_{i2}^* = x_{i2}'\beta_2 + \varepsilon_{i2} \]  \hspace{1cm} (2)

(Observed for applicant sample)

**Potential Outcomes**

- **Applied-declined sample**
  \[ y_{i3}^* = (x_{i3}' y_{i1})\beta_3 + \varepsilon_{i3} \]  \hspace{1cm} (3)

- **Applied-approved sample**
  \[ y_{i4}^* = (x_{i4}' y_{i1} y_{i2} (y_{i2} \times Stig_i))\beta_4 + \varepsilon_{i4} \]  \hspace{1cm} (4)

- **Non-applicant sample**
  \[ y_{i5}^* = x_{i5}'\beta_5 + \varepsilon_{i5} \]  \hspace{1cm} (5)
Model

Data missingness restricts the model to systems of 2 or 3 equations

Non-applicant sample, \( i \in N_1 \)

\[
\begin{align*}
\mathbf{y}_{iC}^* & = \left( \begin{array}{c} y_{i1}^* \\ y_{i5}^* \end{array} \right), \\
\mathbf{x}_{iC} & = \left( \begin{array}{cc} x_{i1}' & 0 \\ 0 & x_{i5}' \end{array} \right), \\
\Omega_C & = \left( \begin{array}{cc} \Omega_{11} & \Omega_{15} \\ \Omega_{51} & \Omega_{55} \end{array} \right)
\end{align*}
\]

Applied-declined sample, \( i \in N_2 \)

\[
\begin{align*}
\mathbf{y}_{iD}^* & = \left( \begin{array}{c} y_{i1}^* \\ y_{i2}^* \\ y_{i3}^* \end{array} \right), \\
\mathbf{x}_{iD} & = \left( \begin{array}{ccc} x_{i1}' & 0 & 0 \\ 0 & x_{i2}' & 0 \\ 0 & 0 & (x_{i3}' y_{i1}) \end{array} \right), \\
\Omega_D & = \left( \begin{array}{ccc} \Omega_{11} & \Omega_{12} & \Omega_{13} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} \end{array} \right)
\end{align*}
\]

Applied-approved sample, \( i \in N_3 \)

\[
\begin{align*}
\mathbf{y}_{iA}^* & = \left( \begin{array}{c} y_{i1}^* \\ y_{i2}^* \\ y_{i4}^* \end{array} \right), \\
\mathbf{x}_{iA} & = \left( \begin{array}{ccc} x_{i1}' & 0 & 0 \\ 0 & x_{i2}' & 0 \\ 0 & 0 & (x_{i4}' y_{i1} y_{i2} (y_{i2} \times \text{Stig}_i)) \end{array} \right), \\
\Omega_A & = \left( \begin{array}{ccc} \Omega_{11} & \Omega_{12} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{24} \\ \Omega_{41} & \Omega_{42} & \Omega_{44} \end{array} \right)
\end{align*}
\]
Estimation

The likelihood is given by $f(y|\theta) = \int f(y, y^*|\theta) dy^*$ where $\theta$ is all model parameters, and $f(y, y^*|\theta) =$

$$\prod_{i \in N_1} f_N(y^*_i|\mu_C, \Omega_C) \times \prod_{i \in N_2} f_N(y^*_i|\mu_D, \Omega_D) \times \prod_{i \in N_3} f_N(y^*_i|\mu_A, \Omega_A).$$

- Discreteness of multiple outcome variables renders this likelihood analytically intractable.
- A collapsed Gibbs sampler with data augmentation is employed.
- These estimation techniques improve the mixing properties of the Markov chain and have low storage costs.
Why Bayes?

- Discreteness of the outcome variables, in conjunction with endogeneity, render most 2-stage estimators inapplicable.

- Likelihood
  - analytically unavailable
  - $\Omega$ has missing elements - guarantee positive definiteness?
    - MCMC methods reparameterize to avoid this issue
  - dimensionality issues

- Not of the Bayesian persuasion
  - maximum simulated likelihood - very slow
  - Bernstein-von Mises theorem - posterior mean and the MLE have the same asymptotic distribution
Data

1. RFC Card Index – RFC applications and approvals.
3. 1930 Census – Location characteristics.
4. New York Times – Stig variable indicates if a bank’s name was revealed in the initial New York Times select lists.

The sample includes all banks operating in 1932 in:
- Alabama
- Arkansas
- Mississippi
- Michigan
- Tennessee

The sample consists of 1,794 banks:
- 908 banks applied for assistance (about 50%)
- 800 of those were approved (about 88%)
  - 192 revealed (24%)
- 108 of those were declined
## Data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-Applicant</th>
<th>Declined</th>
<th>Non-revealed</th>
<th>Revealed</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Banks</td>
<td>886</td>
<td>108</td>
<td>609</td>
<td>192</td>
</tr>
<tr>
<td>Average Age</td>
<td>25</td>
<td>25</td>
<td>29</td>
<td>35</td>
</tr>
<tr>
<td><strong>Financial Ratios (averages)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cash / Assets</td>
<td>0.17</td>
<td>0.11</td>
<td>0.14</td>
<td>0.13</td>
</tr>
<tr>
<td>Deposits / Liabilities</td>
<td>0.71</td>
<td>0.70</td>
<td>0.72</td>
<td>0.70</td>
</tr>
<tr>
<td>Cash / Deposits</td>
<td>0.29</td>
<td>0.17</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td><strong>Charters and Memberships (counts)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>State Bank</td>
<td>609</td>
<td>73</td>
<td>510</td>
<td>150</td>
</tr>
<tr>
<td>National Bank</td>
<td>198</td>
<td>23</td>
<td>81</td>
<td>35</td>
</tr>
<tr>
<td><strong>Correspondents (averages)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Corr.</td>
<td>2.5</td>
<td>2.7</td>
<td>2.5</td>
<td>3.3</td>
</tr>
<tr>
<td>Out of State Corr.</td>
<td>1.4</td>
<td>1.6</td>
<td>1.4</td>
<td>2.0</td>
</tr>
<tr>
<td><strong>Market Shares (averages)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Liab. / County Liab.</td>
<td>0.21</td>
<td>0.20</td>
<td>0.22</td>
<td>0.25</td>
</tr>
<tr>
<td>Liab. / Town Liab.</td>
<td>0.71</td>
<td>0.66</td>
<td>0.76</td>
<td>0.68</td>
</tr>
<tr>
<td><strong>County Characteristics (averages)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No. Wholesale Retailers</td>
<td>27</td>
<td>33</td>
<td>28</td>
<td>28</td>
</tr>
<tr>
<td>No. Manufact. Est.</td>
<td>34</td>
<td>44</td>
<td>36</td>
<td>39</td>
</tr>
<tr>
<td>Cropland (×1000 acres)</td>
<td>100</td>
<td>116</td>
<td>100</td>
<td>107</td>
</tr>
</tbody>
</table>
Data

Outcomes for each equation:

- \( y_{i1} \): total amount of RFC assistance requested by each bank by December 1933.
- \( y_{i2} \): total amount of RFC assistance approved.
- \( y_{i3} - y_{i5} \): the amount of “loans and discounts” (hereafter, LD) for each bank taken from its January 1935 balance sheet.
  - captures a bank’s long-run financial intermediary function.

Covariates: balance sheet characteristics, charters, memberships, departments, correspondent networks, market shares, county characteristics, political variables.
Analysis of the resulting parameter estimates is complicated by the discreteness of the outcome variables.

- Interpretation is afforded with covariate and treatment effect calculations.

In general terms, the covariate effect on lending:

\[
\delta_j = \int \frac{\partial E(y_i|x, \theta)}{\partial x_j} f(x) \pi(\theta|y) dx d\theta
\]

\[
\approx \frac{1}{nG} \sum_{i=n}^{n} \sum_{g=1}^{G} \frac{\partial E(y_i|x_i, \theta^{(g)})}{\partial x_j}
\]

for \( g = 1, \ldots, G \) draws from the posterior distribution.
Covariate Effect

$\delta_{RFC}$ is the covariate effect of the endogenous covariate $y_{i2}$ in equation 4.

- $\delta_{RFC} = 0.574.$ ($\beta_{RFC} = 1.45 (0.19)$)
- $10,000$ of RFC assistance translates to $5,740$ of “loans and discounts” in 1935.
- This result accords well with the loan-to-deposit ratios during the 1930s and during banking panics, in general.
Covariate Effect

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- $\delta_{RFC} = 0.574$. ($\beta_{RFC} = 1.45 (0.19)$)

- $10,000$ of RFC assistance translates to $5,740$ of “loans and discounts” in 1935.

- This result accords well with the loan-to-deposit ratios during the 1930s and during banking panics, in general.

$\delta_{RFC \times Stig}$ is the covariate effect of the interaction term between the endogenous covariate $y_{i2}$ and the $Stig_i$ variable in equation 4.

- $\delta_{RFC \times Stig} = -0.0319$. ($\beta_{RFC \times Stig} = -0.08 (0.02)$)

- Publishing a bank’s name in the *New York Times* reduces the conversion of RFC lending to bank lending by $319$ for every $10,000$.

- Weakened credit channels, sluggish recovery, offsets a bank’s function as a financial intermediary.
Treatment Effect

Consider the difference in the probability of bank failure if the loan authorizations were not released.

Two probabilities need to be computed:

- \( \Pr(y_{i4} = 0|w_i^\dagger, z_i, \theta) \) where \( w_i^\dagger \) authorizations revealed.
- \( \Pr(y_{i4} = 0|w_i^{\ddagger}, z_i, \theta) \) where \( w_i^{\ddagger} \) authorizations not revealed.

The objective is to obtain the predictive distribution:

\[
\{\Pr(y_{i4} = 0|w_i^\dagger) - \Pr(y_{i4} = 0|w_i^{\ddagger})\}
\]

\[
= \int \{\Pr(y_{i4} = 0|w_i^\dagger, z_i, \theta) - \Pr(y_{i4} = 0|w_i^{\ddagger}, z_i, \theta)\} \pi(z_i) \pi(\theta|y) dz_i d\theta.
\]

The mean result gives the expected difference in the computed pointwise probabilities as \( w_i^\dagger \) is changed to \( w_i^{\ddagger} \).
Treatment Effect

The mean of the predictive distribution 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.

While stigma has moderate negative effects on bank lending, it is not severe enough to actually cause bank failure.
Treatment Effect of Reluctance

The time series analysis addressed:

- whether and how much the revealing reduced bank participation in the rescue program.
- interest remains in how this drop in participation affected economic activity.

The Multivariate Analysis framework offers a unique platform to answer this question.

- Focus on the non-applicant sample (886 banks).
- Reasons for not seeking assistance: stable bank health, insolvency, or stigma.
- Tease out the latter group and see what happens if they requested assistance.
Treatment Effect of Reluctance

Non-applicant sample are carefully matched with banks in the approved bank sample.

- Not so unhealthy that they would not have qualified for assistance.
- Not too healthy in which they did not need assistance.
- Subsequent characteristics were considered for more borderline cases.
- 218 banks appear very similar to the approved bank subsample, and thus are the potential “stigma non-applicants”.

Granted RFC assistance is matched based on similar banks in the approved pool as a ratio of total assets.
Treatment Effect of Reluctance

Interest centers upon a scenario in which these banks actually applied for assistance and the difference in the probability of failure between this scenario and the original case where they did not apply.

Using the CRT simulation method and the predictive distribution approach for the 218 sample:

- The mean of the distribution is $-0.016$.
- If the stigma non-applicants actually applied for assistance, the probability of failure for those banks decreases by 1.6 percentage points.
- Small effect – possibly spared a few banks from failure, but not many.
Treatment Effect of Reluctance

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.

Using draws from the posterior and the covariate effect approach on lending for the 218 banks (stigma non-applicants):

- The covariate effect of RFC lending on bank lending is $\delta_{RFC} = 0.664$.
- 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.
Treatment Effect of Reluctance

Story seems to be:

- RFC program became stigmatized and saw a massive drop in bank participation.
- 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.
Model Comparison

Bayesian model comparison useful:

1. Time Series Analysis: determining which model with RFC revealing dates is best supported by the data and best represents shifts in the series.

2. Multivariate Analysis: examining the issue regarding the link between the size of a bank’s network, age, and name publication.

Consider 2 models – $\{M_{Stig}, M_{NoStig}\}$ –

- If the stigma variable is actually just picking up elements of the bank’s correspondent network and age, marginal likelihood for $M_{Stig}$ should be lower than that of $M_{NoStig}$.

- 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.
Model Comparison

Marginal likelihood (Chib, 1995) for model $\mathcal{M}_{Stig}$ is expressed as

$$m(y|\mathcal{M}_{Stig}) = \frac{f(y|\mathcal{M}_{Stig}, \theta_{Stig})\pi(\theta_{Stig}|\mathcal{M}_{Stig})}{\pi(\theta_{Stig}|y, \mathcal{M}_{Stig})}.$$
Model Comparison

Marginal likelihood (Chib, 1995) for model $\mathcal{M}_{\text{Stig}}$ is expressed as

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

<table>
<thead>
<tr>
<th></th>
<th>Stigma</th>
<th>No Stigma</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log-Marginal Lik.</td>
<td>-7952.0</td>
<td>-7978.6</td>
</tr>
<tr>
<td>Numerical S.E.</td>
<td>(0.423)</td>
<td>(0.445)</td>
</tr>
<tr>
<td>$\Pr(\mathcal{M}_k</td>
<td>\mathbf{y})$</td>
<td>0.999</td>
</tr>
</tbody>
</table>

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

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 coefficient reported $\beta_{RFC \times Stig} = 0.080$

<table>
<thead>
<tr>
<th>Mean($\beta_{RFC \times Stig}$)</th>
<th>SD($\beta_{RFC \times Stig}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1.5</td>
</tr>
<tr>
<td>-1</td>
<td>-0.079</td>
</tr>
<tr>
<td>0</td>
<td>-0.076</td>
</tr>
<tr>
<td>1</td>
<td>-0.074</td>
</tr>
</tbody>
</table>

Table: $\beta_{RFC \times Stig}$ as a function of the hyperparameters.
Concluding Remarks

1) Stigmatized rescue program
   • Applications drop drastically and the probability of no applications submitted on a given day increases by 23.3 percentage points.
   • Consequences of this drop in participation manifests itself in credit channels, with lending potentially reaching a higher capacity.

2) Stigmatized bank
   • Moderately reduced the conversion of RFC lending to bank lending at the revealed banks.
   • Impedes a bank’s function as a financial intermediary.
Concluding Remarks

Overall:

• stigma mitigates the rescue program’s objective of restoring confidence in the financial system

• contraction in bank lending prolongs the resuscitation of the financial system

• not drastic enough to cause bank failures – shock to banking system is limited

Contributes to studies on the recent crisis because these historical events describe the implications of realized stigma, instead of avoided stigma, and thus explain why banks today incur costs to evade stigma.
Thank You

Feel free to contact me with any questions or comments.

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### Reconstruction Finance Loans of $100,000 or More From Feb. 2 to July 21, 1932

**Summary by States of loans authorized from Feb. 2, 1932, to July 29, 1932, inclusive, and changes in such loans from July 21, 1932, to Jan. 6, 1933.** (Inclusive loans are omitted.)

<table>
<thead>
<tr>
<th>State</th>
<th>Loans Approved</th>
<th>Loans Outstanding</th>
<th>Loans Decreased</th>
<th>Loans Increased</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>New York</strong></td>
<td><strong>Total</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>New Jersey</strong></td>
<td></td>
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<tr>
<td><strong>Connecticut</strong></td>
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<tr>
<td><strong>Illinois</strong></td>
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<tr>
<td><strong>Delaware</strong></td>
<td></td>
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<tr>
<td><strong>Washington, D.C.</strong></td>
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<td></td>
</tr>
<tr>
<td><strong>Florida</strong></td>
<td></td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

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**Reconstruction Finance Corporation Loans Up to July 21, 1932.**

- The balances outstanding for principal and current disbursements and returns are indicated in the schedules of loans. The total amount of all disbursements is $3,909,905,000.

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**BANKS AND TRUST COMPANIES.**

- Loans and advances of banks and trust companies, as reported by the Reconstruction Finance Corporation.

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**New York Times**