Uncovering Heterogeneity in the Resolution of Bank Failures

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Abstract

This article studies the FDIC's problem of resolving failed banks over the period 1984-1992 as an amalgam of two distinct decision rules. The results show that bank failures that were accompanied by regional economic distress were administered by a decision rule that favored less severe resolution methods such as the provision of financial assistance. This decision rule showed greater sensitivity to bank fundamentals than the rule applied to banks that failed in normal economic conditions. These results are based on an efficient collapsed Gibbs sampler developed in this paper to estimate Bayesian latent class models to detect unobserved heterogeneity in bank resolution.

JEL Classification: C11, C38, G21, G33, G38

Key words: Bank failures, Bayesian inference, Discrete data analysis, Savings and Loans Crisis, Markov Chain Monte Carlo (MCMC), Federal Deposit Insurance Corporation (FDIC).

1 Introduction

Public policy response to widespread bank failures in the midst of a banking crisis has consistently entailed a transfer of resources from the taxpayer to either the depositor or the

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bank shareholder. The Savings and Loans (S&L) Crisis of the 1980's resulted in $132 billion in direct costs to the taxpayer (FDIC, 1998) and the Financial Crisis of 2008 resulted in Congress authorizing $475 billion under the Dodd Frank Act of 2010 for TARP [1]. These policy responses were structured and implemented in the backdrop of experiences from the Great Depression and banking crises abroad, which exposed the deleterious effects of bank crises on economic activity as established in Bernanke (1983), Calomiris and Mason (2003) and Dell'Ariccia et al. (2008).

Ashcraft (2005) isolated the real effects of bank failures from the underlying economic conditions that engender such failures by studying closures of healthy banks. The study also found evidence of bank resolution methods associated with more permanent dissolution of banking relationships with a greater decline in economic activity. Consequently, the manner in which failed banks are resolved during a banking crisis has bearing on its larger economic repercussions. I study the FDIC's decision rule in resolving failed banks during the period 1984-1992, when the US experienced the largest number of bank failures since the Great Depression. The bank failures in this period occurred against the backdrop of regional and sector-specific crises, salient among which were the recession following the collapse of energy prices in Texas, Louisiana and Oklahoma, agricultural recession in Kansas, Iowa and Nebraska and the real-estate downturns in California, the Southeast and the Northwest (Hanc, 1997). Did the FDIC resolve bank failures differently when they occurred in the midst of regional economic distress? The answer to this question sheds light on the whether policy responses took cognizance of the indirect costs of bank failures on economic activity in addition to following statutory guidelines on controlling the direct costs of resolutions. This line of enquiry also allows the comparison of regulatory responses to bank failures with predictions from theories of optimal bank resolution.

The identification of separate decision rules applied by the FDIC in regions that vary by economic conditions involves initially categorizing banks on the basis of observed measures of economic performance in their region of operation. The a priori grouping of banks by economic indicators can be arbitrary and the choice of inappropriate thresholds to achieve this grouping can distort resulting inferences. I address the problem of arbitrary catego-

[1](source: `https://www.treasury.gov/initiatives/financial-stability/TARP-Programs`)

rizations by using latent class models, an econometric technique that identifies statistically distinct clusters on the basis of observables and estimates separate parametric relationships within each cluster. I develop an efficient Bayesian algorithm based on a Collapsed Gibbs Sampler (Liu, 1994) to estimate latent class models with ordinal outcomes. The hierarchical structure of the Bayesian latent class model reflects the hierarchical decision structure attributed to the FDIC, which consists of first assessing regional economic health followed by the evaluation of bank-level characteristics. The use of a Bayesian estimation method provides a coherent framework for performing inference on all estimated quantities of interest, including the change in the probability of alternative resolution methods in response to changes in bank characteristics.

The broad categories of resolution methods available to the FDIC during the period of interest can be summarized as 1) Type I: Assistance 2) Type II: Facilitated mergers and 3) Type III: Liquidation with payout to depositors, which is studied as an ordinal outcome with increasing severity in the disruption of banking relationships associated with each successive category. I find that banks that failed in unfavorable local economic conditions faced a higher median probability of receiving Type I resolution, a category that involved the provision of financial assistance to restore failing banks to solvency, compared to banks that failed in a relatively more favorable economic climate (20% for the former against 3% for the latter). Conversely, banks that failed in regions of low economic distress were eight times more likely to be liquidated than similar banks that failed in regions of high distress (8% and 1% respectively). These findings are in line with the optimal bailout policy developed in Cordella and Yeyati (2003), which recommends that the regulator provide ex-ante commitments to bailouts when banks fail in a climate of macroeconomic distress.

The study of heterogeneity in decision rules based on the condition of the banking industry in addition to economic indicators provides additional rationale for the use of more than one decision rule by the FDIC in resolving bank failures. Type I resolutions involving financial assistance to failed banks were used more extensively in regions that experienced adverse economic conditions and in which the banking industry was also distressed. This finding corroborates both the too-many-to-fail (Acharya and Yorulmazer, 2007b) and cash-in-the-market (Acharya and Yorulmazer, 2007a) hypotheses that bailing out failed banks is optimal in the face of widespread bank failures in order to limit the acquisition of banking assets by inefficient users from outside the industry. An additional specification of the model that incorporates Congressional voting data on bills pertaining to bank regulation results in distinct latent classes and marginally higher marginal likelihood relative to the baseline model based on regional distress. This finding highlights the potential role of political economy factors in securing Open Bank Assistance or Purchase and Assumptions for failed banks in lieu of their liquidation under Type III resolutions.

The presence of two distinct decision rules based on regional distress is validated when banks are aggregated by bank holding company and when Insured Deposit Transfers (IDTs), a sub-category of Type II resolutions are treated as Type III resolutions. A comparison of the FDIC's resolution decisions with that of the FSLIC shows that the latter's resolution policies deviated from theory-based recommendations for optimal resolution policies in Cordella and Yeyati (2003). The FSLIC resolved a higher percentage of failures using assistance transactions than the FDIC and bank-level financial characteristics were not statistically important in determining the probability of receiving such assistance in regions of high economic distress.

The FDIC was authorized to provide Open Bank Assistance until 1992 as regulation under FDICIA (Federal Deposit Insurance Corporation Improvement Act) inhibited the use of this method subsequently. The period 1984-1992 lends itself to the examination of theories of bank resolution in two important ways. Firstly, a large number of these theoretical models focus on the regulator's decision underlying bank bailouts versus facilitating mergers and liquidations. Open Bank Assistance under Type I resolution is closest to the 'bailout' option described in theoretical models as it was not merely restricted to systemically important institutions (under too-big-to-fail provisions). Secondly, interstate banking restrictions ensured that regional banking crises were geographically contained, thus creating conditions in which bank failures that were crisis-driven and idiosyncratic occurred contemporaneously. These conditions permit the study of bank resolutions in crisis and non-crisis conditions from the same time period, thus ensuring that systemic considerations such as macroeconomic factors remained constant across the two sub-groups.

Previous theoretical and empirical studies have investigated the effects of widespread bank failures and contrasted them with failures that occur routinely due to idiosyncratic factors. Brown and Dinç (2011) find empirical support for this theory in their evaluation of the competing risk hazard of government takeover and private-sector acquisitions of failed banks among the 10 largest banks in 21 emerging markets. Hoggarth et al. (2004) provide an overview of the resolution mechanisms available to regulators in a banking crisis and conclude that unlike with individual bank failures that entail unaided resolutions within private sector, system-wide bank failures elicit liquidity support and government guarantees. While there is agreement among the aforementioned theoretical and empirical studies regarding dissimilarities in the resolution of failed banks when such failures occur sporadically as against when they are pervasive across the industry, such distinctions have not been empirically validated in comprehensive bank-level studies. This paper addresses this open question by studying FDIC responses to all failures that occurred in the US among banks insured by the corporation during 1984-1992.

Bennett and Unal (2014) and Balla et al. (2015) are important bank-level studies that provide insights into the FDIC's bank resolution process during the S&L crisis. Bennett and Unal (2014) model the losses resulting to the FDIC and focus on Type II and Type III resolutions since their outcome of interest is the loss resulting to the FDIC from receiverships and Type I resolutions do not involve the establishment of a receivership by the FDIC. Balla et al. (2015) assess the impact of recent banking legislation on bank failures and the FDIC's losses across the banking crisis of the 1980's and the great recession and the type of bank resolution is not of primary interest in their study. This paper provides a comprehensive study of the FDIC's resolution policy by analyzing all resolution categories that were at the FDIC's disposal in the period of interest.

The article is organized as follows: Section 2 provides a background to the role of the FDIC as a receiver of failed banks, the resolution methods at its disposal during the period of study as well as details of legislations pertaining to bank resolution. Section 3 develops the empirical specification by building from the random utility framework for latent class model and establishing the relationship between a possible hierarchical decision structure of the FDIC and the econometric model. This section also includes an efficient MCMC sampling algorithm to estimate latent class models for ordinal outcomes. Section 4 details the various datasets used in this study, their source and a set of descriptive statistics. Section 5 provides the results of the model, Section 6 contains results of an extensive model comparison exercise that tests alternative specifications of the model. Section 7 considers results under aggregation by Bank Holding Company, adjusts for Insured Deposit Transactions and evaluates the decisions of the FSLIC in the resolution of failed thrifts. Section 8 provides the results of prior sensitivity exercises and Section 9 provides concluding remarks.

2 Background

This study considers bank failures during 1984-1992, a period marked by over 1200 bank failures, the largest number of bank failures in US history. Several regions of the US faced economic downturns during this period due to distress in specific sectors such as energy, real-estate and agriculture. The high interest and inflation rates that followed the oil shocks of the 1970's and the deregulation of interest rates exposed banks to significant interest rate risk during this period. The surge in the cost of funding and the increased competition from thrifts and foreign banks, contributed toward deterioration in bank fundamentals and eventual failure. (Hanc, 1998).

The FDIC played a crucial role during the large-scale bank failures of this period since, apart from its primary role as a deposit insurer, it is also the receiver of banks that are closed by their chartering agencies. The resolution mechanisms at the disposal of the FDIC evolved since its inception in 1933 up until the present through various legislative measures. During the period of study, 1984-1992, once a bank failed and entered the resolution process, the FDIC could apply one of the three possible actions:

- Type I: Open Bank Assistance (OBA) - This category comprises of assistance transactions (A/A) to acquirers toward the purchase of a failing bank as a whole institution, assistance to restore a failing bank to solvency (OBA) and reprivatization (REP). The bank charter survives and therefore does not result in the severing of banking relationships when resolved under this category. There are no cases of reprivatization in the data sample considered in this study and 'Open Bank Assistance (OBA)' is used to denote the remaining two types of transactions.

- Type II: Purchase and Assumption (P&A) - This resolution method involves the transfer of insured deposits as well as some other assets and liabilities to an acquiring institution. The banking charter of the failing institution is terminated. This resolution category includes sub-categories of acquisition methods that differ from each other in the components of the failed bank being acquired. In the following discussion Purchase and Assumption (P&A) refers to all sub-categories of Type II resolution.

- Type III: Deposit Payout (PO) - This action involves paying out the insured depositors and liquidating the institution.

2.1 Regulatory Landscape

The legislation governing bank resolution has undergone changes over the period from 1980-1992. The most significant changes affected the circumstances under which the FDIC was permitted to provide open bank assistance. The FDIC was first authorized to provide assistance to failed banks in 1950 under the Federal Deposit Insurance Act. Under this law, the FDIC was limited to providing assistance to failed banks if the institution's continued existence was deemed to be essential to the community in which it operated. The FDIC developed a cost test in 1951 to identify whether payouts or assumption transactions would result in the lower cost.

The Garn-St. Germain Depository Institutions Act of 1982 dropped the essentiality test and permitted the FDIC to provide Open Bank Assistance conditional on this resolution method being less expensive than a deposit payoff. The Act formalized the cost test that had been previously implemented by the FDIC to ensure that an assumption transaction did not cost the FDIC more than a liquidation (FDIC, 1984).

The Competitive Equality Banking Act (CEBA) of 1987 authorized the FDIC to create bridge banks to resolve failed banks (FDIC, 1998). A bridge bank is a temporary full-service controlled by the FDIC, which permitted the deposit insurer to act as an acquiring institution in an assumptions transaction. These temporary institutions were allowed to operate for two years with a one-year extension and could subsequently be resolved through a purchase and assumption, a merger or a stock sale. The Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA) of 1989 amended the CEBA to provide three one-year extensions.

In 1991, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) mandated the least cost test, which required the FDIC to undertake the resolution method that imposed the lowest cost to the FDIC. The Resolution Trust Corporation Completion Act of 1993 prohibited the FDIC from using its funds to provide assistance to failing institutions, particularly if such assistance resulted in benefits to the troubled institution's shareholders (Walter, 2004). Consequently, the FDIC has not provided Open Bank Assistance since 1993.

2.2 Open Bank Assistance

The FDIC retained the authority to decide on the provision of period of Open Bank Assistance during the period under study 1984-1992. These transactions were completed upon agreement from shareholders and subordinated debt-holders (Bovenzi and Muldoon, 1990). The types of transactions covered under OBA are listed in Subsection 10.1. OBA transactions were historically provided to large banks and the largest bank failure handled by the FDIC until then, Continental Illinois in 1984, was resolved with FDIC assistance that resulted in the term "too-big-to-fail"[2]. Isaac (2010) qualified this decision as being "too-big-to-liquidate" as Continental Illinois was a money-center bank with an estimated $6 billion of deposits from around 2300 small banks. In other cases, such as with First City Bancorporation of Texas in 1987, the constraints imposed by the bank holding company structure resulted in a Type I resolution being optimal to the FDIC (Bovenzi and Muldoon, 1990). The impending failure of the lead bank First City National Bank, Houston entailed that the FDIC would have to risk financial instability in the case of liquidation or bear large losses in a P&A transaction as the holding company structure did not allow for loss-sharing with the subsidiary banks.

Bank size did not solely determine the FDIC's decision to provide assistance to failed banks. The presence of large contingent liabilities and potential for claims arising from fraud and negligence of bank management preclude the possibility of obtaining assistance or the arrangement for a merger. The FDIC decided on liquidating and paying out depositors

[2](source: `https://www.federalreservehistory.org/essays/failure_of_continental_illinois`)

of Penn Square in in 1982, which had been originating and servicing loans that financed a speculative oil boom in Oklahoma to several larger banks. The risks of contagion were countered by the likely claims that could arise from purchasers of the bad loans against the FDIC if the bank had been permitted to continue to operate or if had been merged with another institution (Isaac, 2010). In the sample period considered in this study, 90% of banks that received assistance had assets of less than $500 million six months prior to their failure. Furthermore, a policy statement by the FDIC in 1986 stated that proposals for Open Bank Assistance had to provide for capital infusion from sources other than the FDIC, indicating that the institution was required to demonstrate sufficient continuation value to investors if it was provided with the opportunity to retain its charter. The decision to provide assistance was therefore determined by a combination of bank size, contagion risks as well as the quality of bank assets and management.

2.3 Ordering of Outcomes

Ashcraft (2005) points out that each of the three resolution categories entail a progressively more severe breakdown of relationships between the bank and its customers. The provision of assistance allows a bank to continue functioning in its present form. An assumptions transaction results in certain loan and deposit relationships continuing within the acquiring bank's books. A liquidation and deposit payout results in the termination of all banking relationships.

While the three resolution methods involve a natural progression of severity of impact on banking relationships, the FDIC viewed the decision to adopt each resolution method from the perspective of the cost to the deposit insurance fund and broader implications for financial stability.

The decision process of the FDIC could therefore be summarized as follows:

- The cost test would determine whether the FDIC would liquidate the bank and payout insured depositors or choose a Type I or Type II resolution.
- Banks whose failure would result in financial instability with no evidence of fraud or smaller banks that retained sufficient value to demonstrate their ability to continue

functioning as a going concern if provided with assistance were resolved under a Type I transaction.

- Banks with sufficient franchise value to elicit bids from acquirers but not significant enough to be offered OBA were resolved under Type II methods.
- A Deposit Payout was pursued as a last resort if the FDIC received no other bids that were less costly than this resolution method (FDIC, 1998). Banks that failed to invite any bids that were less expensive than liquidation after paying off depositors were subject to a Type III resolution.[3]

This ranking of banks resulting from the legislative constraints on the FDIC provides the motivation to model bank resolution type as an ordinal outcome in the following section. This specification will subsequently be tested empirically by comparing models in which the FDIC's decision is considered to be an ordinal outcome with one in which the decision is treated as multinomial.

3 Empirical Specification

In this section, I discuss the choice of the latent class model for ordinal outcomes to model the FDIC's decisions on resolving failed banks and develop an efficient Bayesian method to estimate this model.

3.1 Modeling the FDIC's Decisions Using A Latent Class Model for Ordinal Outcomes

Heckman and Singer (1984) presented duration models with latent classes as a nonparametric alternative to random coefficients models to model unobserved heterogeneity. Latent class models have since been developed for different outcome types and applied in a wide range of fields including transportation (Greene and Hensher, 2003), healthcare (Deb and Trivedi, 2002) and marketing (Swait, 1994). The use of latent class models is suitable in studies where

[3] "The FDIC used deposit payoffs in the worst situations, those where no one really wanted the failed bank franchise in a P&A transaction." Source: Managing the Crisis: The FDIC and RTC Experience, Volume 1, pp. 100-101.

1) there is a well-founded theoretical motivation to expect heterogeneity in the relationship between covariates and the response, 2) the researcher expects the presence of a *finite* number of heterogeneous classes in the data and 3) while the true class affiliations of observations is known to the decision-maker and unobserved by the researcher, the probability of belonging to a class can be estimated using observable covariates.

The study of FDIC's resolution of bank failures meets each of these requirements and lends itself to estimation using this method. Acharya and Yorulmazer (2007b) provide an important theoretical rationale for the hypothesis of heterogeneity in FDIC's treatment of bank failures. The authors find that the ex-post optimal response of the regulator when a large number of banks fail is different from the optimal response to a few failures.This result motivates the specification of two latent classes in the ordinal outcome model. The equilibrium outcome in their two-bank model involves the purchase of the failed bank by the healthy bank when only one bank fails and a time-inconsistent ex-post strategy of bailout of both banks when they both fail. As a result, banks find it optimal to herd or choose portfolios of loans in similar industries and are, in turn, likely to fail simultaneously. In interpreting the conclusions of their study within the context of the banking crisis of the 1980's, I consider failures of banks due to idiosyncratic and systemic factors as the two different outcomes requiring distinct decision-rules. Identifying the occurrence of "too many" failures is challenging as this threshold varies by the size of the banking sector in each market across the country. It is, however, plausible that banks that fail concurrently with distress in the local economy in which they operate are more likely to be exposed to market or systemic risk and for a correlation to exist among the assets of all such banks. Banks that fail when there is no significant regional economic distress are likely to have failed due to problems in their own portfolio or practices and therefore likely to fail when there are other bank failures in the same market. The FDIC would have identified the class into which each failed bank belonged at the time of their failure based on a range of bank-specific and economic indicators and undertaken the optimal strategy relevant to that class. As the econometrician to whom true classes are unobservable, I estimate the probability of each bank belonging to one of two classes using a latent class model with local economic outcomes as covariates that predict class membership.

3.1.1 Random Utility Framework

The latent classes in the context of bank resolutions represent two different decision protocols (Gopinath, 1997) of the FDIC in arriving at the type of resolution method. The FDIC first identifies the decision protocol (the latent class) s_i to be applied to a bank i and then decides on the type of resolution method y_i conditional on the decision protocol. The random utility representation of this model is based on the framework developed by Marschak (1974) and involves representing the choice of the decision rule and the ultimate decision on resolution type conditional on the decision rule using this framework.

The choice among the two decision protocols is modeled as a binary discrete choice problem with outcome s, a set of covariates W and parameters α. It is important to note that s is unobserved and is therefore a discrete latent variable. The random utility representation is then applied to this discrete choice problem with the introduction of an additional error term ν_i and the definition of the latent variable l_i, the difference in utilities or value to the FDIC from deciding on bank i using decision protocols 1 and 2 (Jeliazkov and Rahman, 2012)

$$l_i = W_i'\alpha + \nu_i. \tag{1}$$

The relationship between the discrete variable s_i and the continuous variable l_i can be expressed in the following threshold crossing framework

$$s_i = \begin{cases} 1 & \text{if } l_i \leq 0 \\ 2 & \text{otherwise} \end{cases}.$$

Subsequent to the determination of the decision protocol to be used, consider the FDIC's utility function z_{i,s_i} from resolving bank i under latent class s_i, where,

$$z_{i,s_i} = X_i'\beta_{s_i} + \epsilon_{i,s_i}, \quad s = 1, 2. \tag{2}$$

z_{i,s_i} is the utility to the FDIC of keeping bank i open under decision protocol s_i. This utility can be considered to represent the overall assessment of the bank's social value by the FDIC based on its financial health and other factors such as size. $X_i'\beta_{s_i}$ represents the part of utility that involves criteria that the researcher can observe and ϵ_{i,s_i} represents the part of the utility that the researcher cannot observe Train (2009). Let y_i denote the resolution type assigned to bank i, which is observed in the data. When banks show the potential to recover to solvency with the provision of financial support or are systemically important enough that the termination of their charter is to be prevented, they are provided with Open Bank Assistance (Type I resolution). When banks are unlikely to recover to financial health but retain sufficient franchise value so that their assets draw bids from surviving banks, they are resolved with a Purchase and Assumptions transaction (Type II resolution). Banks that show no prospect of recovery and whose assets do not invite viable bids from other banks are liquidated under a Deposit Payout (Type III resolution). The FDIC selects each of these options depending on whether the value it attributes to the bank crosses a threshold $\gamma_{k,s}$. This relationship between the observed outcome y_i and the latent utility z_{i,s_i} can be represented as,

$$y_i = \begin{cases} 3 & \text{if } -\infty < z_{i,s_i} \leq \gamma_{1,s_i} \\ 2 & \text{if } \gamma_{1,s_i} < z_{i,s_i} \leq \gamma_{2,s_i} \\ 1 & \text{if } \gamma_{2,s_i} < z_{i,s_i} \leq \infty \end{cases} .$$

3.1.2 Likelihood Function

The likelihood contribution P_{ij} of bank i receiving resolution treatment j is the sum of the likelihood contribution based on each latent class weighted by the probability of belonging to each of the two latent classes,

$$P_{ij} = \sum_{s=1}^{S} P_{ij|s} Q_{is}. \tag{3}$$

$P_{ij|s}$ is the probability of y_i taking a particular value j conditional on belonging to class s. Q_{is} is the probability of observation i belonging to class s. On specifying a $\nu_i \sim \mathcal{N}(0, 1)$, we obtain the following binary probit representation of the class membership model.

$$Q_{is} = \Phi(w_i'\alpha)^{s'} [1 - \Phi(w_i'\alpha)]^{1-s'}, s' = s - 1, \quad s = 1, 2. \tag{4}$$

In estimating the ordinal outcome model conditional on class membership, I use the identification scheme in which the cut-points $\gamma_{1,1}$ and $\gamma_{1,2}$ are restricted to 0 and the penultimate cut-points in both classes, $\gamma_{2,1}$ and $\gamma_{2,2}$ are restricted to 1 (Jeliazkov and Rahman, 2012). This identification restriction eliminates the need for estimating cut-points and allows the scale parameter to be estimated as a free parameter. On specifying a $\mathcal{N}(0, \sigma^2)$ distribution for the unobserved component ϵ_i, the probability of y_i taking a particular value j conditional on class s is,

$$P_{ij|s} = \Phi(\frac{\gamma_{j,s} - x_i'\beta_s}{\sigma_s}) - \Phi(\frac{\gamma_{j-1,s} - x_i'\beta_s}{\sigma_s}) \quad s = 1, 2. \tag{5}$$

3.2 Augmented Posterior

On augmenting the likelihood with the latent variables z and s defined above, the augmented posterior for the parameters and latent variables $\theta = \{\beta_1, \beta_2, \sigma_1^2, \sigma_2^2, \alpha, z, s\}$ in this model with two classes can be represented as follows,

$$f(\theta|y) \propto \prod_{i=1}^{n} \sum_{s=1}^{2} \{\mathbf{1}(s_i = s) f_{y_i|z_{i,s}} f_{z_{i,s}|\beta_s \sigma_s} Q_{is}\} f(\beta_1, \sigma_1^2) f(\beta_2, \sigma_2^2) f(\alpha).$$

$f(y_i|z_{is})$ is the indicator function $\mathbf{1}(\gamma_{y_i-1,s} < z_{is} \leq \gamma_{y_i,s})$. $f(z_{i,s}|\beta_s, \sigma_s)$ is the normal density, $f_{\mathcal{N}}(z|x_i'\beta_s, \sigma_s), \quad s = 1, 2.$

I assign a multivariate normal prior to β_s and an Inverse Gamma prior to σ_s^2 for $s = 1, 2$. The priors are independent and the joint density is given by,

$$f(\beta_s, \sigma_s^2) = f_{\mathcal{N}}(\beta_s|\beta_{0,s}, B_{0,s}) f_{\mathcal{IG}}\Big(\sigma_s^2|\frac{\nu}{2}, \frac{d}{2}\Big).$$

The prior for α is a multivariate normal, so that,

$$f(\alpha) = f_{\mathcal{N}}(\alpha|\alpha_0, A_0).$$

3.3 MCMC Algorithm

The MCMC algorithm to estimate this model involves augmentation using two latent variables, the discrete class indicator, s_i and the continuous variable z_{i,s_i} that underlies the ordinal outcome y_i. The standard approach to constructing the MCMC algorithm for this model involves drawing from full conditionals for each of the parameters and the two latent variables within a Gibbs sampler. This algorithm improves upon the standard method by constructing a Collapsed Gibbs sampler (Liu, 1994) in which the discrete latent variable s has been marginalized out of the conditional for α. This novel approach to marginalization significantly improves mixing and reduces autocorrelations among successive MCMC draws. The improvement afforded by this method is established in Figures 15 and 16 in the Appendix, which provide the autocorrelation plots of α under a full Gibbs sampler and the proposed collapsed Gibbs sampler respectively. In the following discussion, S is the full vector of class membership indicators s_i for the n observations, where each s_i can take values $s = 1, 2$.

Algorithm 1

1. Sample β_s from the distribution $\beta_s|z, S, \sigma_s^2$ for $s = 1, 2$.

2. Sample σ_s^2 from $\sigma_s^2|\beta_s, z, S$ for $s = 1, 2$.

3. Sample α from $\alpha|\beta, \sigma^2, y$ for where $\sigma^2 = \{\sigma_1^2, \sigma_2^2\}$ and $\beta = \{\beta_1, \beta_2\}$.

4. Sample s_i' from $s_i'|\alpha, \beta, \sigma^2, y$ for $i = 1, 2, ..., n$.

5. Sample z_{i,s_i} from $z_{i,s_i}|\beta, \sigma^2, y, S$ for $i = 1, 2, ..., n$.

Sampling coefficients of the Ordinal Model: β

The coefficients of the ordinal model β_s, are sampled for the two latent classes, i.e., for $s = 1, 2$ from their respective conditional posterior distributions, $\beta_s \sim \mathcal{N}\big(\hat{\beta}_s, \hat{B}_s\big)$, where $\hat{B}_s = \big(B_{0,s}^{-1} + X_s' X_s/\sigma_s^2\big)^{-1}$ and $\hat{\beta}_s = \hat{B}_s\big(B_{0,s}^{-1}\beta_{0,s} + X_s' z_s/\sigma_s^2\big)$. The matrices X_s and z_s are rows of X and z that correspond to class s and can be obtained using $X_s = \big\{X_i : s_i = s\big\}$ and $z_s = \big\{z_i : s_i = s\big\}$. This computation is efficient as it involves working with matrices of reduced dimensions n_1 and n_2, without having to preserve the full length n of the matrices X and z.

Sampling the variance of the Ordinal Model: σ^2

The variances are sampled using the conditionals $\sigma_s^2|z, S, \beta \sim IG(\hat{\nu_s}, \hat{d_s})$ for s = 1,2, where $\hat{\nu} = (\nu + n_s)/2$ and $\hat{d} = \big(d + (z_s - X_s\beta_s)'(z_s - X_s\beta_s)\big)/2$. X_s and z_s are the matrices retained from the previous step. n_s is the number of observations in class s and is updated in every MCMC iteration.

Sampling coefficients of the Class Membership Model: α

The coefficients of the class membership model α are sampled from $\alpha|\beta, \sigma^2, y$ marginally of S by using a Metropolis Hastings step with tailored proposal $\alpha^\dagger \sim q(\alpha|\beta, \sigma^2, y)$. The proposed draw $\alpha^\dagger$ from this proposal is accepted with probability,

$$\Upsilon_{MH}(\alpha, \alpha^\dagger) = \min\left\{1, \frac{f(\alpha^\dagger|\beta, \sigma^2, y)q(\alpha|\beta, \sigma^2, y)}{f(\alpha|\beta, \sigma^2, y)q(\alpha^\dagger|\beta, \sigma^2, y)}\right\},$$

where $q(\alpha|\beta, \sigma^2, y) = f_T(\hat{\alpha}, V, \nu)$, $\hat{\alpha} = \arg\max f(y|\alpha, \beta, \sigma^2)f(\alpha)$, V is the inverse of the negative Hessian of $\ln\big\{f(y|\alpha, \beta, \sigma^2)f(\alpha)\big\}$ evaluated at $\hat{\alpha}$ and ν is the degree of freedom parameter.

The expression $f(\alpha|\beta, \sigma^2, y)$ is proportional to the product of $f(y|\alpha, \beta, \sigma^2)$ and $f(\alpha)$ where,

$$f(y|\alpha, \beta, \sigma^2) = \prod_{i=1}^{n}(1 - \Phi(W_i'\alpha))P_{y_i|1} + \Phi(W_i'\alpha)P_{y_i|2}.$$

The expressions for $P_{y_i|s}$, $s = 1, 2$ are obtained by replacing the indicator j in Equation 5 with the outcome y_i to obtain,

$$P_{y_i|s} = \Phi(\frac{\gamma_{y_i,s} - x_i'\beta_s}{\sigma_s}) - \Phi(\frac{\gamma_{y_i-1,s} - x_i'\beta_s}{\sigma_s}), \;\; s = 1, 2. \tag{6}$$

This MH step enhances the efficiency of the overall algorithm by circumventing the need for additional data augmentation through the latent variable l_i from Equation 1.

Sampling the class membership indicator: S

The vector S of class membership indicators s_i identifies the latent class $s = 1, 2$ to which each observation i belongs. These indicators are sampled from a Bernoulli distribution by introducing the binary variable $s_i' = s_i - 1$, where $s_i'|\alpha, \beta, \sigma^2, y \sim Bern(K_i)$ for i = 1,2,....,n and,

$$K_i = \frac{\Phi(W_i'\alpha)P_{y_i|2}}{\Phi(W_i'\alpha)P_{y_i|2} + (1 - \Phi(W_i'\alpha))P_{y_i|1}}.$$

The values $P_{y_i|2}$ and $P_{y_i|2}$ are retained from the previous step and are computed using 6.

Sampling the latent variable: z

The sampling of continuous latent variables z_{i,s_i} is based on the data augmentation step from Albert and Chib (1993), resulting in $z_{i,s_i}|\beta, \gamma, \alpha, \sigma^2, y \sim TN_{(\gamma_{y_i-1}, \gamma_{y_i})}(x_i'\beta_{s_i}, \sigma^2_{s_i})$ for i = 1,2,...n. The second subscript s_i is added to establish that the sampling scheme augments just the continuous outcomes associated with the class s to which each observation belongs and does not require the augmentation based on the counterfactual latent class. This approach minimizes storage requirements and permits the sampling of the entire vector z in one step.

3.4 Simulation Study

The simulation study based on Algorithm 2 was performed on two sets of parameter specifications, the first of which considered latent classes whose means are distinct from each other and the other, in which the means overlap. The simulation exercise has been performed on a sample of 1200 observations under both studies. Table 1 provides the 1 standard deviation credibility intervals in the estimation of parameters under the two specifications. The priors in this estimation are $\alpha \sim \mathcal{N}(0, 3 \times I), \beta_s \sim \mathcal{N}(0, I)$ and $\sigma^2_s \sim (4.3, 2.8)$ for $s = 1, 2$. The credibility intervals under specification 1 all contain the true values of parameters within the except for β_{21}, which marginally falls short of the true value. Under specification 2, the true values of parameters marginally lie beyond credibility intervals for α_2, β_{21}, β_{12} and σ^2_2. The credibility intervals are also narrower under specification 1 relative to specification 2. These results show that estimates are more precise when there is a greater separation across latent classes.

Table 1: Credibility intervals based on two parameter specifications

	Param. Spec. 1		Param. Spec. 2	
	True Values	Cred. Int.	True Values	Cred. Int.
Class Membership				
α_1	-0.3	[-0.42,-0.26]	-0.3	[-0.5,-0.22]
α_2	1.5	[1.29,1.53]	1.5	[1.14,1.48]
Latent class 1				
β_{11}	0.6	[0.57,0.64]	0.6	[0.59,0.67]
β_{21}	-0.7	[-0.69,-0.61]	-0.6	[-0.67,-0.57]
β_{31}	-0.6	[-0.62,-0.53]	-0.6	[-0.69,-0.6]
β_{41}	0.5	[0.48,0.58]	0.5	[0.48,0.57]
σ_1^2	0.25	[0.2,0.27]	0.25	[0.22,0.29]
Latent class 2				
β_{12}	0.1	[0.06,0.17]	0.1	[-0.03,0.08]
β_{22}	0.6	[0.56,0.66]	-0.1	[-0.12,-0.04]
β_{32}	0.2	[0.18,0.26]	-0.1	[-0.11,-0.02]
β_{42}	0.8	[0.79,0.94]	0.8	[0.79,0.92]
σ_2^2	0.25	[0.21,0.29]	0.25	[0.17,0.24]

4 Data

This study considers bank failures between 1984 and 1992 using data from Historical Statistics on Banking maintained by the FDIC. These institutions have been matched with call reports from the Federal Reserve of Chicago using the certificate number issued by the FDIC. These reports have been aggregated up by certificate number, which is uniquely assigned to each head office depository institution. This results in 1385 banks, of which there are 118, 1175 and 92 institutions resolved under resolution types 1, 2 and 3 respectively in the time period of interest. Information on branching deregulation laws was collated using the table in Strahan et al. (2003).

Data on quarterly housing starts at the state level have been obtained from IHS Global Insight. Data on annual unemployment at the state level were obtained from the Iowa Community Indicators Program of Iowa State University. The quarterly share of employment across sectors at the county level has been collated from the Bureau of Economic Analysis. Classification of cities into metro and non-metro status was performed based on the Rural-Urban continuuum codes from the US Department of Agriculture. HHI was computed based on the historical Statistics on Depository Institutions data from the FDIC. Congressional voting data was obtained from the website of GovTrack [4].

All variables have been normalized prior to estimation in order to preempt any numerical issues.

Table 2: Descriptive statistics of bank, county and state-level characteristics

	OBA		P&A		Dep. Payoff	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Bank-level characteristics						
C&I Loan Ratio	27%	13%	28%	13%	28%	13%
CLD Loan Ratio	6%	8%	5%	8%	4%	8%
Agricultural Loan Ratio	4%	10%	9%	10%	18%	10%
Consumer Loan Ratio	24%	18%	19%	18%	20%	18%
Real Estate Loan Ratio	39%	17%	42%	17%	31%	17%
Loan Loss Reserves Ratio	6%	6%	4%	6%	5%	6%
Nonperforming loans Ratio	6%	6%	8%	6%	8%	6%
Interest Receivable Ratio	1%	1%	1%	1%	2%	1%
Securities Ratio	12%	12%	13%	12%	14%	12%
Core Deposits Ratio	63%	18%	73%	18%	74%	18%
Earnings	-3%	6%	-3%	6%	-4%	6%
Size(Assets mlns.)	212	654	170	890	47	96
County/ state characteristics						
Herfindahl Index (HHI)	0.15	0.13	0.26	0.21	0.26	0.20
Unemployment	8.07	1.45	7.17	1.61	6.38	1.38
Housing starts	13.46	7.04	11.17	12.91	15.68	17.50
Metro/Non-metro	0.78	0.41	0.64	0.48	0.49	0.50
Per capita income growth rate	2.60	2.68	4.54	4.99	5.84	6.55
Farm, Agri and Mining	8%	8%	11%	11%	16%	14%
Manufacturing	11%	5%	11%	7%	8%	5%
Construction	6%	1%	5%	2%	5%	2%
Fin Serv and Transport	39%	7%	36%	9%	36%	11%
Government	15%	6%	16%	7%	16%	6%
% Republicans	35%	14%	40%	18%	47%	19%
vote for enhancing reg. agencies powers	83%	14%	80%	21%	83%	18%
vote for restoring civil penalties for fin. inst.	93%	20%	88%	23%	82%	28%
vote for recommitting S&L restructuring bill	97%	2%	98%	3%	98%	3%
vote for CEBA	99%	3%	98%	5%	98%	4%
vote for disclosure of CRA ratings	33%	17%	37%	23%	33%	26%
Count	118	-	1175	-	92	-

5 Results

In this section, I present results from two benchmark models that differ from each other in the characteristics used to define the latent classes. The first model identifies latent classes based on regional economic indicators whereas the latter model incorporates data on Congressional voting patterns to explain the mechanisms through which the FDIC could

[4] https://www.govtrack.us

have followed alternative decision rules. These results are based on 10000 iterations of the collapsed Gibbs sampler from Section 3.3 collected after a burn-in of 1000 iterations.

5.1 Regional Distress and Bank Resolutions

This specification uses regional distress to identify variations in the FDIC's decision rules on bank resolutions in response to broader economic conditions within which the failures occurred. Cordella and Yeyati (2003), in their model of bank bailouts, concluded that an optimal resolution policy that reduces risk-taking among banks requires ex-ante commitments to bailouts when banks fail in a climate of macroeconomic distress. I utilize the latent class approach to identify alternative decision rules applied by the FDIC under high and low regional economic distress and use bank-level characteristics in the ordinal model for the probability of each resolution category.

The covariates in the class membership model and the model for resolution type together constitute the types of information that bank examiners are instructed to review per the OCC's guidelines (U.S. Department of the Treasury, 2011). Walter (2004) summarizes these guidelines and lists data from bank financial statements, information on local economic conditions, the health of industries serviced by the bank, and market indicators of the banks well-being as important considerations in bank examinations.

5.1.1 Class Membership

This model postulates that the alternative decision rules adopted by the FDIC were based on the economic characteristics of regions in which failed banks were located. The class membership model incorporates state-level unemployment rate and housing starts as well as county-level per capita income growth and employment share of agriculture as covariates. These regional economic indicators are based on the year prior to failure. State-level unemployment and housing starts as well as county-level income growth encompass systemic fluctuations at the regional level and represent factors considered by bank examiners while evaluating alternative resolution methods. The share of employment in agriculture at the county level identifies areas that were more likely to be affected by the agricultural recession of the mid-80's detailed in Hanc (1998). The results in table 1 show that the unemployment rate and number of housing starts are statistically important in determining class membership. Per capita income growth and the share of agricultural employment are of moderate importance in determining latent classes. The negative sign associated with the coefficient of unemployment and the positive sign for housing starts and per capita income growth imply that banks that failed during periods of high unemployment or periods of regional economic stress belong to latent class 1. As a result latent class 1 will be labeled as the class of failures under "High Regional Distress (HRD)" and latent class 2, as the class of failures under "Low Regional Distress (LRD)".

5.1.2 Resolution Type

The covariates considered in the model for resolution type are primarily drawn from Balla et al. (2015). The various ratios are based on balance sheet and income statement information from quarterly call reports. Each of these ratios are calculated 6 months prior to the date of failure as this is intended to replicate the duration between the regulators' final examination and decision on the type of resolution procedure to be applied on the failed bank. This subsection provides an overview of the relative magnitudes and signs of coefficients in the two latent classes. A more detailed analysis of the impact of each covariate on the probability of receiving each of the three resolution types is discussed in detail in Section 5.2, which describes covariate effects. Since all continuous explanatory variables have been standardized, direct comparisons across posterior means of covariates can be made to draw inferences about relative magnitudes. Positive signs of coefficients are indicative of an increase in the probability of resolutions involving the closure of a bank charter (Type II and III resolutions) for a one standard deviation change in the covariate and negative signs are indicative of an increase in the probability of a Type I resolution.

Overall, the magnitudes of coefficients and covariate effects are larger for banks in HRD compared to those in LRD. This indicates that bank-specific characteristics played an important role in the type of resolution outcome for banks that failed during a period of regional economic stress. For banks that failed due to institution-specific factors, the relationship between resolution type and financial characteristics is tenuous as observed in Table 4.

A comparison of the two sets of posterior means reveals that the Real Estate Loan Ratio, Loan Loss Reserves Ratio and Nonperforming Loans Ratio show the greatest separation in magnitudes of posterior means across the two latent classes. On account of the risk posed by real estate bubbles across the country, a higher concentration of real estate loans would be associated with greater risk of failure and consequently, with a more severe form of resolution. This relationship is noticed in the coefficient within the HRD class but is absent in LRD, where the coefficient is negative and of small magnitude. Loan loss reserves, on account of being negatively associated with bank failure (Balla et al., 2015), are likely to entail a lower probability of liquidation. This is reflected in the negative coefficient associated with this variable within HRD but not in the small positive coefficient within LRD. Nonperforming loans should be unambiguously associated with weak asset quality and hence a higher probability of bank closure by the regulators. While the coefficient for HRD provides evidence of such a relationship, the coefficient within LRD is both weak and negative.

Balla et al. (2015) found the Interest Receivable Ratio to be highly predictive of both bank failure and loss subsequent to failure in their study. Bennett and Unal (2014) also found increasing values of an equivalent variable, Earned Income to be reflective of asset quality as this variable is indicative of distressed assets that have not yet been written off. This ratio is seen to be important in the FDIC's evaluation of bank health as it results in a positive posterior mean in both latent classes, with a significantly larger effect within HRD. Bank size measured as the log of assets is found to be negatively associated with the probability of being subjected to a Type III resolution across both latent classes. The prevailing importance of bank size after controlling for other aspects of banks' financial health sheds light on the possible emphasis on the "too-big-to-fail" doctrine by authorities during the crisis of the 1980's.

The coefficient of Commercial and Industrial (C&I) loan ratio indicates higher levels of risk attributed to increases in this ratio by the FDIC (FDIC, 1998) and consequently, higher probability of a Type III resolution. Concentrations of these loans (27.5%) are higher than those of Construction and land development (CLD) loans (4.6%) in the sample period considered and this is commensurate with the larger impact of this ratio on resolution outcomes compared to the latter. These ratios help control for balance sheet composition in order to permit comparisons across measures of asset quality such as Nonperforming Loans Ratio and Interest Receivable Ratio.

Interstate is an indicator variable that takes the value 1 if interstate banking was legal in the state in which a bank is located in the year of failure. Interstate banking laws are likely to affect resolution outcomes as they determine the breadth of demand for assets of failed banks. In the theoretical model by Acharya and Yorulmazer (2007a), the occurrence of a large number of bank failures reduces the total liquidity among surviving banks and induces the requirement for regulatory intervention in the form of assistance or provision of liquidity in order to prevent acquisition of banks by inefficient outsiders. The liquidity provision facility described in their model is akin to assistance under Type I resolutions. This model suggests that interstate banking, by expanding the set of available acquiring banks, should be associated with an increase in the probability of a Type II resolution and an equivalent decline in the probability of a Type I resolution. The positive sign associated with this coefficient in both latent classes confirms the Cash-in-market hypothesis.

A higher ratio of securities to assets is an indicator of greater liquidity in the balance sheet of the bank. A greater proportion of core deposits improves the franchise value of the bank and makes it more attractive to potential acquirers. These two characteristics, in addition to the earnings ratio are expected to result in a lower probability of liquidation under Type III resolutions. I find, however, that the sign of the coefficient is counter to what we would expect for Securities and Core Deposits Ratios. The covariate effects for these three variables are not strong and this indicates that on controlling for other balance sheet items such as Nonperforming Loans and Interest Receivable Ratios, the role of these variables in determining the resolution type is diminished. The differences across the two latent classes

Table 3: Posterior estimates for the class membership model.

Class membership model		
	Post. Mean	Post. SD
Intercept	2.070	0.420
State level Unemployment	-3.874	0.925
Housing starts	1.076	0.633
Per capita income growth	0.395	0.450
Farm, Agri and Mining	0.781	0.484

can be summarized by the estimated probability of each resolution type for the HRD and

Table 4: Posterior Estimates for the two latent classes of the ordinal probit model with FDIC's resolution category as the outcome

	Latent Class 1 (High Reg. Distress)		Latent Class 2 (Low Reg. Distress)	
	Post. Mean	Post. SD	Post. Mean	Post. SD
Intercept	0.168	0.071	0.617	0.034
C&I Loan Ratio	0.057	0.030	0.008	0.017
CLD Ratio	-0.062	0.030	0.023	0.017
Real Estate Loan Ratio	0.162	0.036	-0.011	0.021
Loan Loss Reserves Ratio	-0.124	0.029	0.023	0.017
Nonperforming Loans Ratio	0.123	0.028	-0.008	0.018
Interest Receivable Ratio	0.092	0.038	0.048	0.018
Securities Ratio	0.042	0.027	-0.026	0.016
Core Deposits Ratio	0.005	0.030	0.004	0.017
Earnings	-0.014	0.028	-0.018	0.017
Size	-0.085	0.036	-0.041	0.018
InterState	0.142	0.077	-0.053	0.041
Sigma	0.087	0.015	0.088	0.006

LRD failures. The results in Table 5 provide the conditional and marginal probabilities of each resolution type. The columns "HRD" and "LRD" provide the probability,

$$\text{Avg. Prob}(Y = j|s) = \frac{1}{nG}\sum_{i=1}^{n}\sum_{g=1}^{G} P_{ij|s}^{(g)}, \quad j = 1, 2, 3, \tag{7}$$

where $s = 1$ and $s = 2$ correspond to the results for the class of HRD and LRD failures respectively and g is the index for the G post burn-in MCMC draws. The values $P_{ij|s}^{(g)}$ are computed for each MCMC iteration using 5. The values in the column "Overall" are similarly obtained by averaging $P_{ij}^{(g)}$ from 3 over the n observations and G MCMC iterations.

These results demonstrate that the latent class algorithm results in two distinct classes, with the average probability of a Type I resolution in the HRD class of 22.7%, about eight times the equivalent probability in the LRD class of failures. The average probability of a Type III resolution in the LRD class, at 8.9%, is more than twice the average probability of this resolution type in the HRD class.

Table 5: Average estimated probability of each resolution type under the latent classes for failures in High Regional Distress (HRD) and Low Regional Distress (LRD) classes

	HRD	LRD	Overall
Type I	0.227	0.035	0.093
Type II	0.741	0.876	0.832
Type III	0.032	0.089	0.075

5.2 Covariate Effects

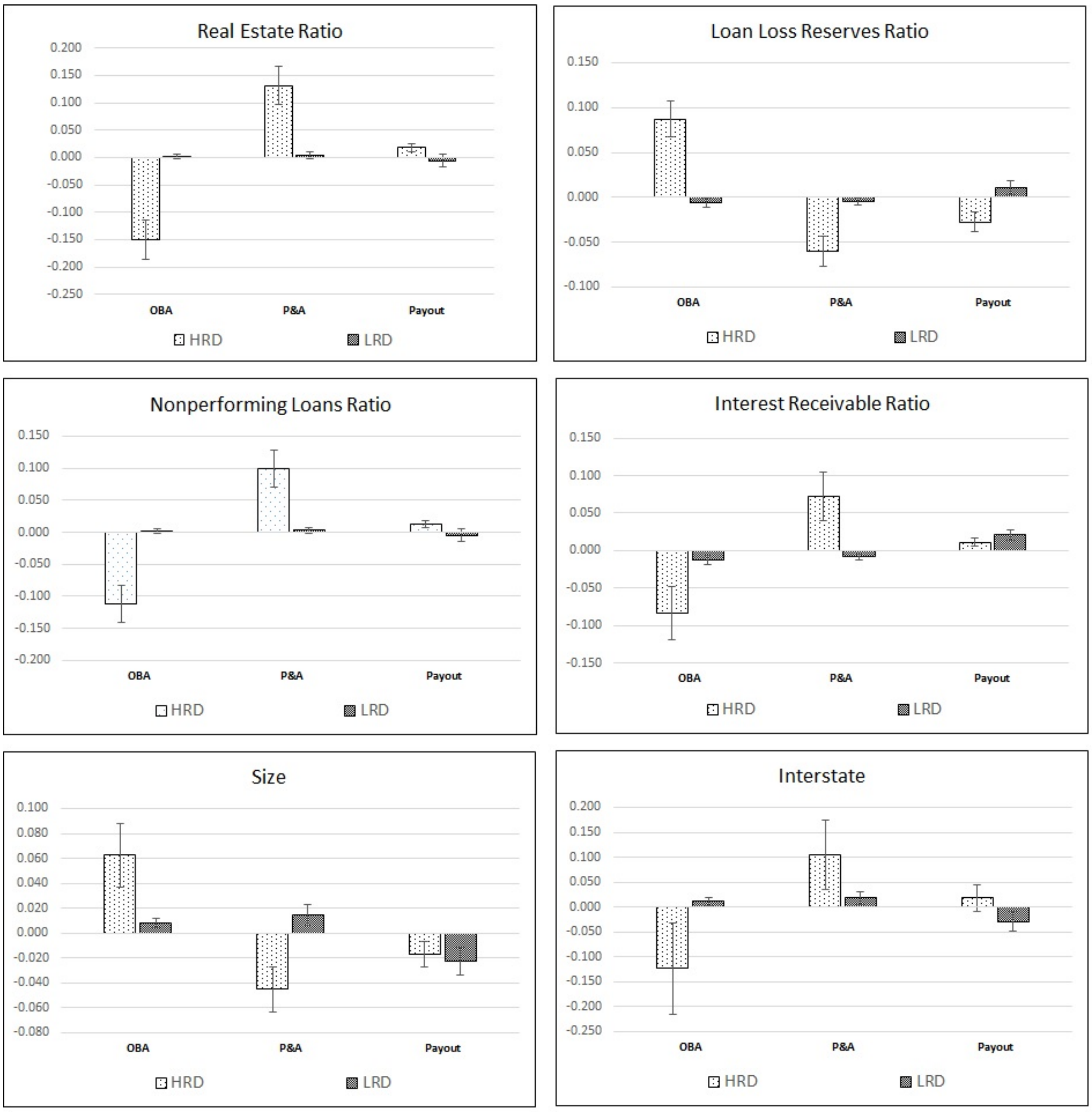

Figure 1: Covariate effects across High Regional Distress (HRD) and Low Regional Distress (LRD) latent classes.

Figure 1 summarizes the results of the model by providing the covariate effects for the two latent classes defined by the extent of regional distress. The bar on the left represents the average change in probability of the resolution type occurring for a one standard deviation change in the covariate of interest in the latent class comprising of failures in the HRD class. The bar on the right represents the equivalent quantities for the latent classes comprising of LRD failures. The credible interval of these effects based on a 1 posterior standard deviation interval around the mean is represented by the error bars. The six largest covariate effects from the ordered response model have been reported in this section. The covariate effects of the remaining variables are provided in Figure 12 of the Appendix.

The magnitudes of the covariate effects are distinctly larger in the HRD latent class relative to the LRD failures. The majority of banks in the HRD class are seen to arise from a small group of states, namely, Texas, Louisiana, Colorado and Massachusetts and are banks that failed in 1987 and 1988. Banks in the class of LRD failures originate from a wide group of states and there are approximately an equal number of banks by each year of failure in this group. The results suggest that the decision protocol of the FDIC involving systemic failures was applied to banks from a limited set of states and was mainly in use during 1987 and 1988. The stronger covariate effects for banks in this class is also indicative of a more clearly defined ordering of banks by the FDIC based on their financial characteristics for this group of banks compared to those whose failures were largely idiosyncratic. These differences in covariate effects across the latent classes are also indicative of failures that did ot occur within the context of broader regional distress being evaluated on a case-by-case basis, which potentially included the assessment of unobservable individual circumstances by the FDIC in addition to the evaluation of financial statement information.

A unit standard deviation change in Real Estate Ratio and Nonperforming Loans Ratio results in a reduced probability of obtaining Open Bank Assistance among HRD failures and increases the probability of such banks undergoing a Purchase and Assumptions resolution or even a Deposit Payout under both models. The LRD failures do not experience such a sharp change in their probability of receiving alternative resolution types and even undergo a marginally decreased prospect of being liquidated by the use of a Deposit Payout for an equivalent change in these ratios.

Changes in Interest Receivable Ratio elicits contrasting responses from the FDIC across the two latent classes for the same magnitude of change in these two covariates. An increase in Interest Receivable Ratio among HRD failures results in a reduction in the probability of Open Bank Assistance and a corresponding increase in the probability of Purchase and Assumptions. Banks that failed due to factors specific to their own institutions were more likely to have received the most severe form of resolution, a Deposit Payout as the probability of the other two resolution types decreases for these institutions. A one standard deviation increase in log of assets among banks that failed in economically distressed regions increases the probability of an Open Bank Assistance and decreases the probability of the remaining two resolution types among systemic failures. LRD failures experience a moderate increase in the probability of Open Bank Assistance and Purchase and Assumptions and a decrease in the probability of a Deposit Payout.

An increase in Loan Loss Reserves ratio among systemic failures is associated with a higher probability of receiving Open Bank Assistance in the class of HRD failures. However, an equivalent increase in this financial statement item among idiosyncratic failures is associated with an increase in their probability of being liquidated. A possible explanation for this disparity in response from the FDIC is that among systemic failures, bank regulators can benchmark the changes in reserve ratios to deterioration in asset quality resulting from market-wide fluctuations. The FDIC is likely to have considered the greater extent of asymmetric information inherent in the increase in Loan Loss Reserve Ratio among idiosyncratic failures, and viewed the increase in this ratio as a signal of progressively deteriorating asset quality.

5.3 Demand-Side Factors

In addition to considerations of regional economic factors, the state of the banking industry in the region in which the bank operates is important in determining resolution outcomes. Shleifer and Vishny (2011, 1992) establish that liquidation values of a firm's assets are lower than the values associated with their best use when its industry faces financial distress and the highest potential bidders do not bid on the assets. Bennett and Unal (2014) developed an "industry distress" hypothesis based on this theoretical model and found that periods of banking crises resulted in impediments to liquidations, which in turn led to the FDIC choosing private sector reorganizations at a higher cost than the potential cost of liquidation. Acharya and Yorulmazer (2007a,b) in their theoretical model, concluded that when a large number of banks fail and their liquidation entails acquisition of banking assets by inefficient users, it is optimal for the regulator to bail out failed banks. The authors also found that it is ex-post equivalent to providing liquidity to surviving banks to facilitate their acquisition of assets of failed banks. This literature points to alternative decision rules for bank resolution depending on the health of the banking industry. The models predict that the FDIC is likely to have engaged in Type I and Type II resolutions when the industry was distressed, and that Type III resolutions would have occurred when the banking industry was sufficiently healthy to afford the absorption of the liquidated assets.

The predictions from the literature on cash-in-the-market hypothesis are tested by considering latent classes on the basis of the health of the banking industry. Bank closures within a county six months prior to failure and the proportion of assets in banks with Texas ratio greater than 100% are considered as indicators of the extent of distress in the banking industry.

The Texas Ratio for a bank is defined as,

$$\text{Texas Ratio} = \frac{\text{Non-performing Assets}}{\text{Tangible Equity} + \text{Loan Loss Reserves}}$$

and the bank is considered to be distressed when this ratio exceeds a threshold of 1 (Cooke et al., 2015; Siems et al., 2012). The posterior moments for four different specifications

Table 6: Posterior estimates for class membership models that consider indicators for regional economic distress and distress in the banking industry. Posterior standard deviations are reported in parentheses.

	M1	M2	M3	M4
Intercept	2.07 (0.42)	2.25 (0.46)	2.16 (0.38)	1.98 (0.35)
State level Unemployment	-3.87 (0.92)	-3.30 (0.87)	-2.83 (0.58)	-2.79 (0.59)
Housing starts	1.08 (0.63)	0.77 (0.66)	-	-
Per capita income growth	0.40 (0.45)	0.48 (0.47)	-	-
Farm, Agri and Mining	0.78 (0.48)	0.46 (0.52)	-	-
Previous Closures	-	-0.24 (0.17)	-0.22 (0.12)	-
% Assets in Banks with Texas Ratio > 100%	-	-0.35 (0.20)	-0.38 (0.15)	-0.40 (0.17)

incorporating the two measures of banking distress are reported in Table 6. In order to evaluate qualitative differences in results across the specifications, I compare the covariate effects of Interest Rate Receivable Ratio, which is a measure of asset quality and of Size and report the findings in Figures 2 and 3. The latent classes resulting from these models are labeled as "High Regional and Banking Distress (HRBD)" and "Low Regional and Banking Distress (LRBD)" failures on account of the presence of indicators of banking sector distress in the class membership model. These results show that a unit standard deviation change in Interest Rate Receivable Ratio results in nearly identical changes in the probability of each resolution type conditional on class membership. A unit standard deviation increase in Size broadly results in changes in the probability of each resolution type that are qualitatively similar across the four model specifications. Model specifications 3 and 4, which comprise of State level Unemployment and characteristics pertaining to distress in the banking sector, result in larger changes in the probability of OBA in the class of HRBD failures and greater reduction in the probability of a Payout in the class of LRBD failures.

The entire distribution of the probability of each resolution category conditional on class membership is provided in Figure 4. This distribution represents the post burn-in draws of the mean probability,

$$\text{Mean Prob}(Y = j|s)^{(g)} = \frac{1}{n}\sum_{i=1}^{n} P_{ij|s}^{(g)}, \quad j = 1, 2, 3, \tag{8}$$

for $g = 1, 2, ..., G$. Model specifications 3 and 4 result in greater separation across the two latent classes in the distribution of the probability of OBA and Purchase and Assumptions relative to specification 1 and 2. The state of the banking industry provides additional sources of heterogeneity in the FDIC's decision rules beyond that provided by indicators of regional economic distress. These results align with the predictions from Shleifer and Vishny (1992) and Acharya and Yorulmazer (2007a), particularly in the greater reliance on public financial assistance in the form of OBA when the local banking industry has experienced failures and deterioration in asset quality.

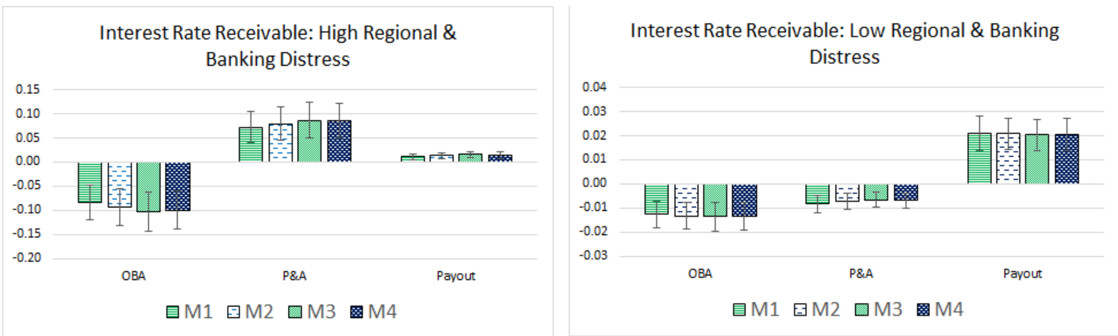

Figure 2: Covariate effects of Interest Rate Receivable Ratio across the four model specifications for latent classes based on regional and banking sector distress.

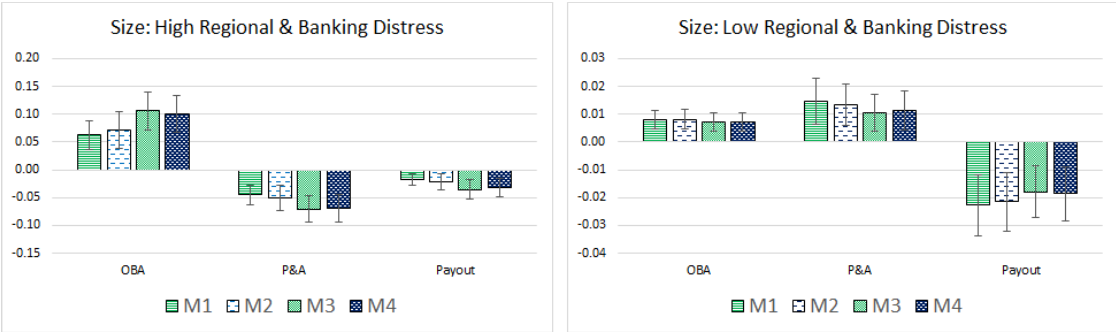

Figure 3: Covariate effects of Size across the four model specifications for latent classes based on regional and banking sector distress.

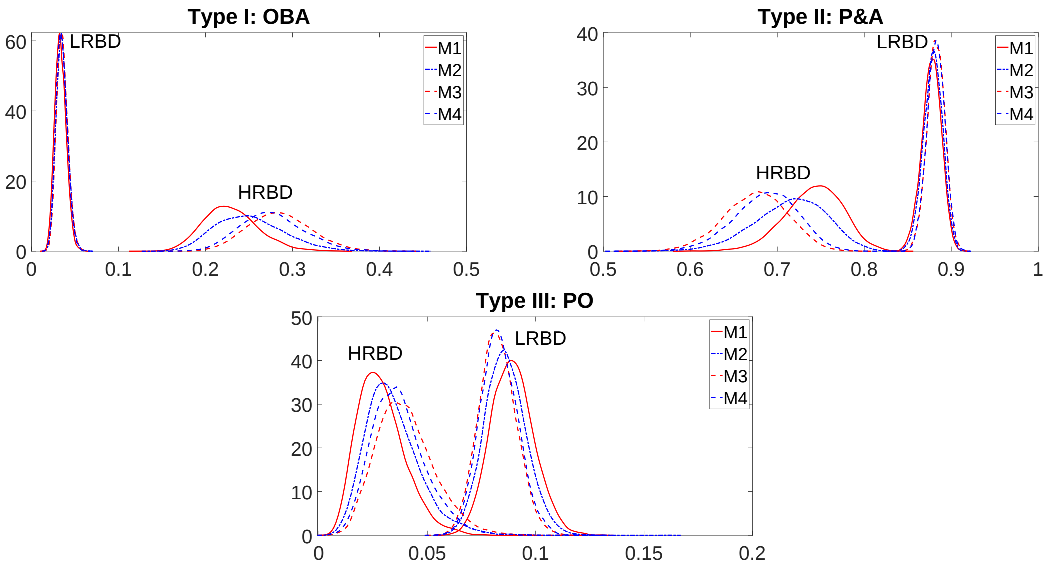

Figure 4: Distributions of Average estimated probability of each resolution type conditional on membership in the High Regional and Banking Distress (HRBD) and Low Regional and Banking Distress (LRBD) latent classes across the four model specifications.

5.4 Political Economy Factors

A growing branch of the literature has studied the effects of political economy factors on bank failure resolutions and enforcement actions. Lambert (2018) found that regulators initiated enforcement actions with a lower probability against lobbying banks. Igan et al. (2012) found that being a lobbying lender was associated with receiving a higher share of bailout funds during the Financial Crisis of 2008. Theoretical models of lobbying and regulation provide a framework for understanding the incentives of lobbying among interest groups and the resultant impact on the framing of relevant policies. Stigler (1971) developed a theory of regulatory capture in which regulations are acquired and developed for the benefit of the industry that they are designed to administer. Becker (1983) considered competition among opposing political pressure groups and identified an equilibrium in which the provision of political subsidies to interest groups is countered by the organization of the taxpayers.

I consider factors related to the political economy of bank regulation and resolution as potential sources of heterogeneity in the FDIC's decision rule on bank resolution. This model includes Congressional voting data on bills pertaining to banks and financial intermediation in the class membership model in addition to the local economic factors considered earlier. I study the votes of members of Congress in the vote to adopt the Competitive Equality Bank Act (CEBA) of 1987 in specification 5. While the major provisions of the Act pertained to resolving the insolvency of the Federal Savings and Loan Insurance Corporation, the insurer of S&L institutions, and in closing the "non-bank bank loophole", additional provisions directly pertained to the resolution of failed banks and a loan-loss amortization program for agricultural banks (Hanc, 1997). The CEBA provided the FDIC with the option to establish a temporary national bank or a bridge bank for a maximum period of three years. This option provided an alternative to liquidation when acquirers were not forthcoming for a failed bank in the period immediately following its failure (Huber, 1988). Representatives from constituencies in which bank failures and weaknesses in the industry posed a significant risk to stability would be expected to vote in favor of the Act. The votes in favor of the Act potentially also represent the strength of the banking lobby in districts represented by members of Congress.

The bills considered in specifications 6,7 and 8 are all components of the Financial Institutions Reform, Recovery and Enforcement Act(FIRREA) of 1989. I considered the vote on restoring civil penalties as a candidate covariate since votes against the bill are likely to represent a positive bias in favor of the banking industry, resulting either from lobbying or from concerns for the banking sector within a constituency. The bills proposing the restoration of civil penalties for criminal offenses involving financial institutions and those requiring the disclosure of ratings assigned to banks and thrifts under the Community Reinvestment Act (CRA) would have elicited positive votes from members of Congress who were in favor of introducing additional checks on the banking industry.

I consider the percent of representatives from each state who voted in favor of each of the four bills as a covariate in the class membership model while excluding representatives who did not vote. Additionally, I include the percentage of Republicans in each state to ascertain that voting was not determined entirely by party affiliation. These covariates are based on the study of the political economy of branching restrictions and deposit insurance by Economides et al. (1996).

The models summarized in Table 7 identify latent classes based on regional economic distress and political support of elected representatives for legislation in favor of the banking industry in specifications 5 and 6 and in favor of the introduction of additional checks and balances on the industry in specifications 7 and 8. The consideration of voting behavior enables us to recognize political action motivated by either bank lobbying or adverse conditions faced by constituents as a potential mechanism that results in alternative decision rules followed by the FDIC. The results show that the unemployment rate is statistically important in determining class membership in all four specifications. The variables denoting votes in favor of banking legislation are statistically important in specifications 5, 6 and 8. The negative signs associated with the coefficient of unemployment and the share of state-level congressional votes for CEBA and the S&L restructuring bill and the positive sign associated with the vote for civil penalties and ratings disclosure imply that banks that failed in regions of high unemployment or regions in which Congress members favor bank relief measures belong to latent class 1. Banks belonging to latent class 2 belong to regions that are less distressed and represented by members of Congress less motivated by bank relief legislation, relative to latent class 1. As a result latent class 1 will be labeled as the class of failures under "High Regional Distress and/or Poltical Support (HRDP)" and latent class 2, as the class of failures under "Low Regional Distress and Poltical Support (LRDP)".

The covariate effects for Interest Receivable Ratio and Size and the posterior distribution of the probability of each resolution type conditional on class membership are provided in Figures 17, 18 and 19 in the Appendix. Specifications 6, 7 and 8 are qualitatively similar with respect to the covariate effects of Interest Rate Receivable and Size and the posterior distribution of conditional probabilities of resolution types. Specification 5, which involves the vote for CEBA results in a larger effect of bank size and results in wider differences in the probability distribution for Type I and Type II resolutions across the two latent classes. This specification, however, results in a greater overlap in the probability distributions for

Type III resolution across the two latent classes. Overall, political economy factors are seen to capture additional dimensions of information beyond that represented by indicators of regional economic distress.

Table 7: Posterior estimates for class membership models that consider indicators for regional economic distress and political support for the banking industry. Posterior standard deviations are reported in parentheses.

	M5	M6	M7	M8
Intercept	3.21 (0.54)	2.06 (0.43)	2.50 (0.50)	2.85 (0.62)
State level Unemployment	-2.64 (0.46)	-3.53 (0.69)	-3.65 (0.73)	-3.29 (0.71)
Farm, Agri and Mining	0.73 (0.35)	0.98 (0.57)	0.47 (0.34)	0.61 (0.36)
% vote for CEBA	-2.49 (0.95)	-	-	-
% vote for Recommitting S&L restructuring bill	-	-1.32 (0.43)	-	-
% vote for restoring civil penalties for criminal offenses involving financial institutions	-	-	-0.58 (0.83)	-
% vote for requiring reg. agencies to disclose ratings given to banks and thrifts	-	-	-	1.35 (0.78)
% Republicans	0.61 (0.46)	0.76 (0.51)	0.06 (0.65)	0.61 (0.62)

6 Model Comparison

In this section, I provide an empirical motivation for considering latent class models over estimating a simple ordinal probit model with additional covariates. I also compare alternative specifications of the model based on different combinations of covariates with the benchmark models described in Section 5.

Model comparison in the following analysis is based on the log Marginal Likelihood. The principle behind the use of this quantity arises from the use of the posterior odds ratio, described below to compare models i and j.

$$\frac{P(M_i|y)}{P(M_j|y)} = \frac{P(y|M_i)}{P(y|M_j)}\frac{P(M_i)}{P(M_j)}$$

The first term on the right hand side of the equation above is the Bayes factor and the second term is the prior odds. The Bayes factor is the ratio of marginal likelihoods of models i and j and is the decisive factor in determining the evidence in favor of one model against the other. Therefore, model comparisons involve computing marginal likelihoods and directly comparing these magnitudes with each other. I have used the methodology outlined in Chib and Jeliazkov (2001) to compute the marginal likelihood for the latent class models and the methodology from Chib (1995) to obtain the marginal likelihood for the simple ordinal probit model.

Table 8: Log marginal likelihood for the benchmark model (M1) and the ordinal and multinomial probit models with covariates from M1

Model	LML
Model Spec. 1 (M1)	-701.11
Ordinal probit model (one class) (a)	-731.88
Ordinal probit model (one class) + class membership covariates from M1 (b)	-730.35
Multinomial probit model (one class) (c)	-1283.99
Multinomial probit model (one class) + class membership covariates from M1 (d)	-796.94

The results from Table 8 demonstrate that the benchmark ordinal model with latent classes, M1, performs better than the standard ordinal probit and multinomial probit models in explaining the FDIC's decision process. Model (a) is an ordinal probit model and Model (c) is a multinomial probit in which the covariates are obtained from the ordinal model of M1. In models (b) and (d), model (a) is augmented with covariates from the class membership models of M1. The results from this model comparison analysis provide further evidence in favor of the presence of unobserved heterogeneity in the resolution of failed banks as well as the ordering inherent in the FDIC's resolution decisions.

Table 9: Log marginal likelihood for the benchmark model (M1) and models based on banking industry distress and political economy factors

Model	Covariates	LML
1	Regional Economic Indicators	-701.11
	Regional Economic and Banking Industry Distress	
2	Regional Economic Indicators, Previous closures + % Distressed Assets	-697.99
3	Unemployment, Previous closures + % Distressed Assets	-697.04
4	Unemployment + % Distressed Assets	-698.18
	Regional Economic Distress and Political Economy Factors	
5	Unemployment, Farm, Agri & Mining + % vote for CEBA	-696.71
6	Unemployment, Farm, Agri & Mining + % vote for Recommitting S&L restructuring bill	-697.02
7	Unemployment, Farm, Agri & Mining + % vote for restoring Civil penalties for criminal offenses involving Fin. Inst.	-705.12
8	Unemployment, Farm, Agri & Mining + % vote for requiring reg. agencies to disclose ratings given to banks and thrifts	-701.64

The results in Table 9 provide a coherent framework for comparing models that were studied in Sections 5.3 and 5.4. A comparison of the values of log Marginal Likelihood establishes that indicators of the health of the banking industry as well as voting on bills that involved measures to resolve the weaknesses in the banking and S&L sector marginally improve upon the model comprising solely of indicators of regional economic distress in explaining the FDIC's decision rule.

Table 10: Comparison of alternative specifications of the class membership and ordinal outcome models with benchmark model M1

Model Num.	Incl. relative to M1	Excl. relative to M1	LML
		Ordinal model	
9	Agri. loan ratio	-	-712.48
10	Cons. loan ratio	CI Ratio	-707.21
11	Past due loans	Non-perf loans	-710.33
12	Non-accrual loans	Non-perf loans	-703.57
		Class membership model	
13	Composition of sectors	-	-719.58
14	Metro/ Non-Metro indicator	-	-702.90
15	HHI	-	-756.47
16	Size	-	-700.91
17	Size‡	Per capita income growth	-701.36
18	-	Per capita income growth, Farm agri mining	-718.73
	Benchmark M1		-701.11

‡ Size is excluded from the ordinal outcome model while it is included in the class membership model

The results based on the inclusion of additional covariates in the ordinal and class membership equations are summarized in Table 10. Models 9 through 12 retain the same covariates as M1 in the class membership model and consist of alternative specifications for the ordinal model conditional on class membership. The consideration of additional loan categories relative to M1 in specifications 9 and 10 results in a decline in the log marginal likelihood. Finally, the models that consider the components of the Non performing loans ratio (Nonperforming loans ratio = Non-accrual ratio + Past due ratio) are rejected in favor of M1 on account of their lower log marginal likelihood.

Models 13 through 18 of Table 10 retain the same covariates as M1 in the ordinal model conditional on class membership and consist of alternative specifications for the class membership model. The inclusion of the share of all sectors apart from agriculture in specification

13 or the HHI in specification 15 result in a decline in the marginal likelihood. The inclusion of a Metro/Non-Metro indicator in Specification 14 also provides estimates that are supported by the data almost as much as M1. Models 16 and 17, in which bank size is used a covariate in the class membership provide log marginal likelihoods that are close to and marginally lower than that of M1. This result indicates that bank size was potentially considered as a criterion to distinguish among banks to which two distinct sets of rules would be applied by the FDIC and lends credence to the "too-big-to-fail" doctrine discussed in Section 2.2. The exclusion of per capita income growth and the share of farming, agriculture and mining in model 18 results in a decline in the marginal likelihood, indicating the relevance of these county-level indicators in determining the FDIC's decision on bank resolution.

7 Additional Institutional Factors

7.1 Insured Deposit Transfers

Underlying the FDIC's three categories of bank resolution are certain sub-categories of methods that share characteristics in common across two broad resolution types. In particular, Type II resolutions consist of a range of Purchases and Assumptions transactions as well as Insured Deposit Transfers (IDT). An IDT involves the transfer of insured and secured deposits, cash and other assets of a failed bank to an agent institution, which in turn pays customers the amount of their insured deposits or permits them to open a new account in the agent institution (FDIC, 2007). Since these transactions involve the transfer of assets and deposits like other Type II resolutions but are primarily intended to result in payouts in the manner of Type III resolutions, I have estimated the benchmark model, M1 by considering all IDT resolutions as Type III instead of Type II transactions. Figure 5 shows a leftward shift in the distributions of the average probability of Type II transactions for the two classes in the adjusted model relative to M1 and an equivalent rightward shift in the probability of Type III transactions as expected from the nature of the adjustment of outcome categories. The separation in the distributions of the two classes continues to hold, hence corroborating the relevance of the indicators of regional distress in identifying two distinct groups of banks that were subjected to alternative decision rules even under the alternative categorization of resolutions.

Table 11: Distribution of failures by resolution types under two alternative categorizations

	Baseline	IDT Adjusted
Type I: OBA	118	118
Type II: P&A	1175	1014
Type III: PO	92	253

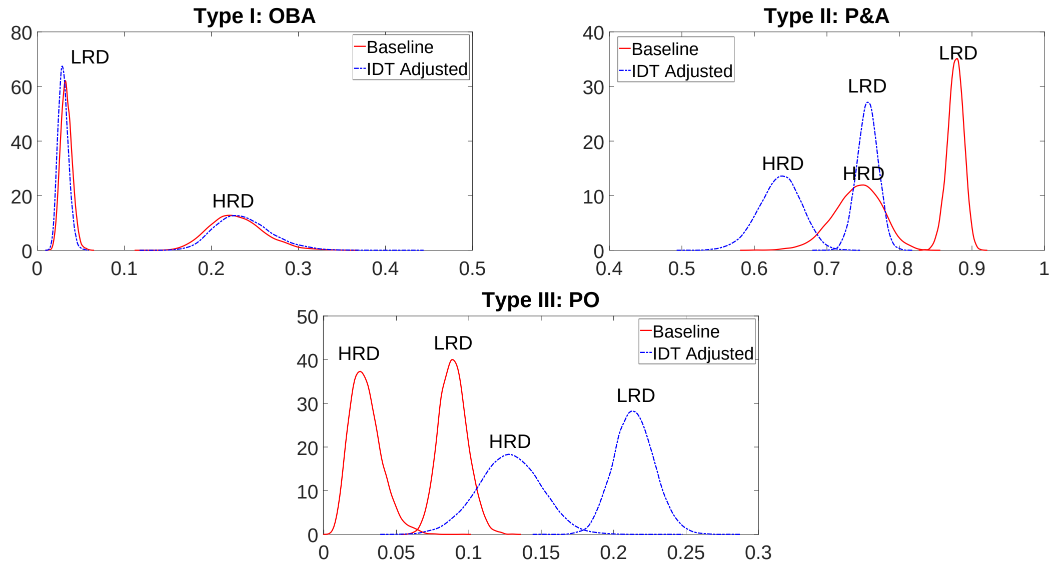

Figure 5: Distributions of Average estimated probability of each resolution type conditional on membership in the High Regional Distress (HRD) and Low Regional (LRD) latent classes across the Baseline model and model with outcome adjusted for IDT transactions.

Figures 6 and 7 show that the probability of a Payout increases by a greater extent in response to a unit standard deviation change in Interest Receivable Ratio under the adjusted model relative to the baseline model. The probability of a Payout decreases by a greater magnitude in response to a unit standard deviation increase in bank size. These figures illustrate the preservation of the ordering of outcomes despite the change in their categorization. If IDT's had been assigned at random to banks, their reassignment into the Type III group would have weakened the estimates of coefficients of financial variables and consequently resulted in smaller covariate effects. This would also have been the case if banks that received IDT's had better financial characteristics than the average bank that received a Type II resolution. The preservation of the statistical importance of the covariate effects despite the adjustment to the outcome categories shows that IDT transactions represent an intermediate category that are at the lower end of the distribution of Type II resolutions and at the high end of Type III resolutions. The log marginal likelihood from this model is -1028, which is more than 300 points lower on the log scale than that resulting from the benchmark model. This comparison shows that the data favors the inclusion of IDT's within Type II resolutions rather than with Deposit Payout transactions in Type III.

Figure 6: Covariate effects of Interest Rate Receivable Ratio across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

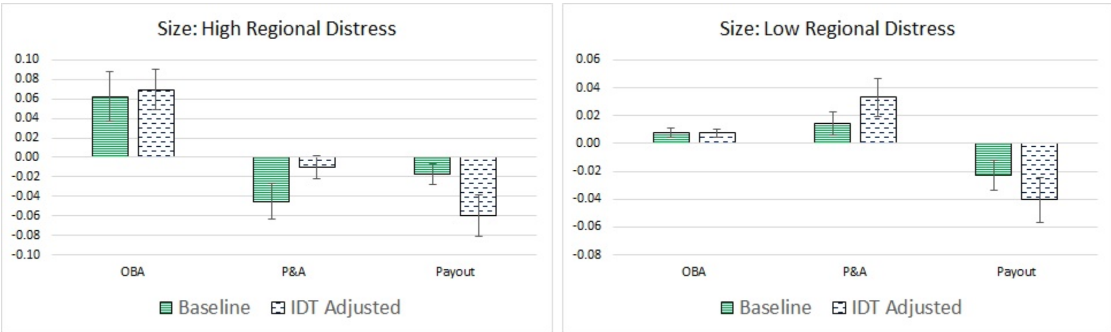

Figure 7: Covariate effects of Size across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

7.2 Bank Holding Companies

A bank holding company(BHC) is an organization that owns and/or controls one or more U.S. banks[5]. The Federal Reserve maintained that bank holding companies were to function as a source of strength to their banking subsidiaries by providing capital and resources to safeguard against failure in times of financial distress. FIRREA (1989) introduced cross-guarantee provisions, thereby permitting the FDIC to recover some of its costs of resolving bank failures from the capital of the solvent institutions within the bank holding company. Ashcraft (2008) found that banks within a multi-bank holding company benefited from the resources of the parent organization, both in terms of experiencing lower probability

[5](source: https://www.ffiec.gov/nicpubweb/content/help/institution%20type%20description.htm)

of default and higher likelihood of obtaining capital, particularly after the cross-guarantee provisions passed under FIRREA(1989). Prior to this regulation, the FDIC found that bank holding companies retained their strong banks while allowing weaker banks to fail, eventually transferring the costs of failure to the FDIC. M Corp, a bank holding company from Texas with several insolvent banks among its 25 subsidiaries, won the right to retain its healthy banks through litigation and passed on a cost of $2 billion from its failed bank subsidiaries to the FDIC (Seidman, 2000). Since the cross guarantee provision was introduced toward the end of the analysis sample and to ensure consistency in the unit of analysis in the sample, results in Section 5 are at the individual bank-level. The results in this subsection have been computed by aggregating entities that were affected by the cross-guarantee provision to the bank-holding company level. The list of the 11 bank holding companies impacted by the legislation have been obtained from Bennett and Unal (2015).

Tables 11 and 12 reveal that IDT's, like Deposit Payoffs, were primarily applied to banks that were not part of BHC's or those that were not under the cross-guarantee program. As a result, IDT resolutions are similar to a Type III resolution rather than a Type II resolution when analyzed at the BHC level. Furthermore, the ordinal nature of the three resolution categories is statistically supported under the categorization that groups IDT's with Deposit Payoffs rather than with P&A transactions in the covariate effects reported in Figures 8 and 9. These covariate effects are obtained by estimating Model Specification 1 on failures aggregated at the BHC level and the effects are qualitatively similar to those obtained in Section 5 under the specification adjusted for IDT's.

Table 12: Distribution of failures aggregated by Bank Holding Company by resolution types under two alternative categorizations

	BHC Baseline	BHC IDT Adjusted
Type I: OBA	61	61
Type II: P&A	1082	919
Type III: PO	92	255

7.3 Resolution of Savings and Loans Institutions by FSLIC

The bank failures of the 1980's occurred in the backdrop of a more severe crisis within the Savings and Loans industry. Savings and Loans (S&L) or Thrift institutions can be

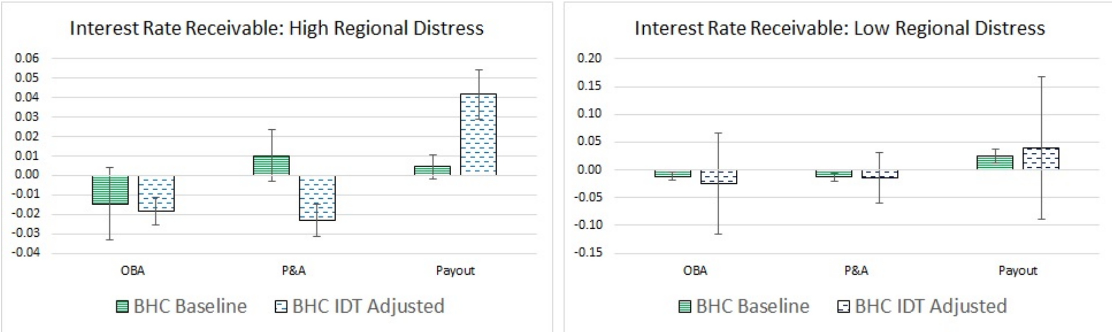

Figure 8: Covariate effects of Interest Rate Receivable Ratio aggregated by Bank Holding Company across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

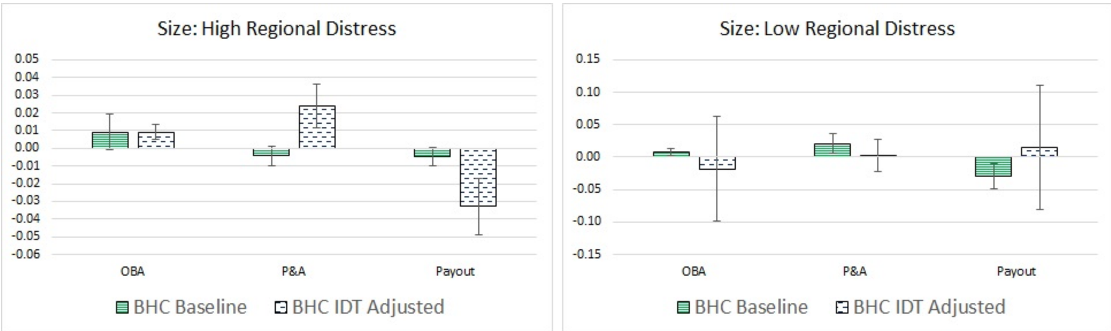

Figure 9: Covariate effects of Size aggregated by Bank Holding Company across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

considered to be banks that are mainly instituted to promote savings and home mortgage rather than commercial lending (FDIC, 2007). Prior to 1989, the Federal Savings and Loans Insurance Corporation (FSLIC) insured these institutions and served as a receiver for failed thrifts. In 1980, the FSLIC insured about 4,000 S&L institutions and 1,295 of these institutions failed between 1980 and 1994. The FSLIC itself was declared insolvent in 1987 but operated until its dissolution in 1989. The Resolutions Trust Corporation (RTC) was instituted in place of the FSLIC in 1989 under FIRREA as a temporary agency under the purview of the FDIC. The failure of the FSLIC and subsequent federal funding required to finance the resolution of failed thrifts cost the taxpayer $132 billion (FDIC, 1998).

Since the FDIC and the FSLIC were both insurers faced with the task of resolving failed depository institutions in their respective industries, it is instructive to analyze the decisions made by the FSLIC through the same empirical lens used to study the FDIC's decisions. From Table 13, it is clear that that the FSLIC relied on Open Bank Assistance more heavily than the FDIC as they constitute the majority of all failure resolutions. The covariate effects of Thrift Size in Figure 11 show that the FSLIC was more likely to provide

Open Bank Assistance to larger thrifts, particularly when they belonged to regions with high economic distress. Thrifts that failed in regions of low regional distress faced a lower probability of receiving Open Bank Assistance and instead were more likely to receive an IDT or a Deposit Payout. The covariate effect of Interest Rate Receivable Ratio reported in Figure 10 illustrates a point of deviation between the the FSLIC and the FDIC in their approach to bank asset quality. While the FDIC's decisions revealed statistically important covariate effects of this variable in the High Regional Distress latent class, this is not the case for the FSLIC resolutions. On the contrary, the covariate effects are stronger in the class of failures in thrifts from regions with low economic distress and under the categorization that groups IDT's with Deposit Payoffs. The relatively weaker effects of asset quality on the FSLIC's decisions in regions of high economic distress is in line with the documented evidence of the FSLIC entering into long term assistance agreements to facilitate the acquisition of a failing thrift by a healthy thrift (FDIC, 1998). The resolution of failed thrifts by the FSLIC deviates from the FDIC's approach to resolving failed banks in the former's limited response to asset quality in determining the assignment of Open Bank Assistance in distressed regions. This approach to resolution deviates from the optimal bailout policy described in Cordella and Yeyati (2003), who recommend a commitment to bailout in the face of macroeconomic shocks rather than allowing for financial assistance to counter an institution's idiosyncratic distress resulting from its portfolio choice.

Table 13: Distribution of thrift failures by resolution types under two alternative categorizations

	Thrift Baseline	Thrift IDT Adjusted
Type I: OBA	284	284
Type II: P&A	112	38
Type III: PO	16	90

8 Prior Sensitivity

The results from model specification 1 have been generated by considering alternative prior distributions for the coefficients of the ordinal model. The prior distributions for the remaining parameters are diffuse with $\alpha \sim \mathcal{N}(0, 3 \times I)$ and $\sigma_s^2 \sim (4.3, 2.8)$ for $s = 1, 2$. Table 14 summarizes the estimation results for the coefficients of the Interest Receivable Ratio and

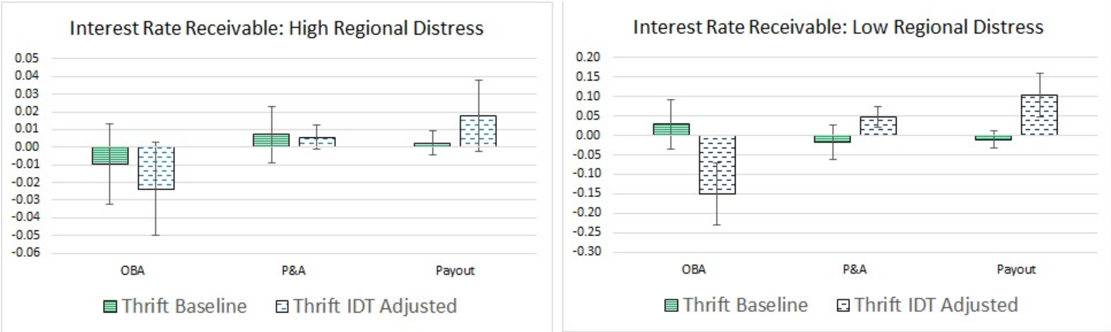

Figure 10: Covariate effects of Interest Rate Receivable Ratio for Thrifts across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

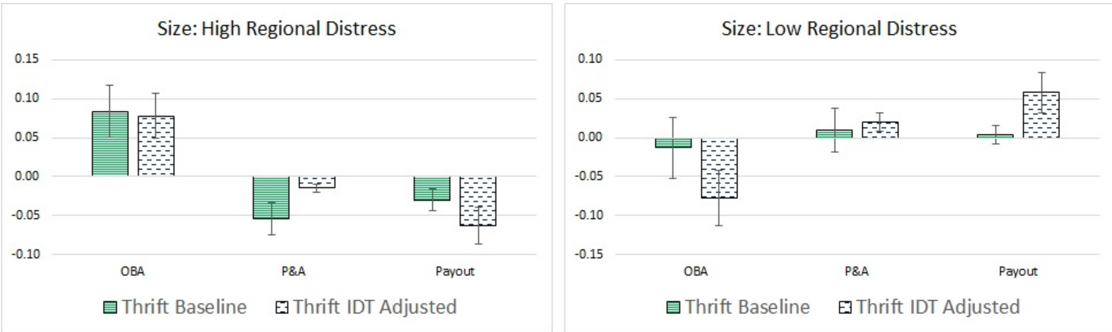

Figure 11: Covariate effects of Size for Thrifts across the Baseline model and model with outcome adjusted for IDT transactions for latent classes based on regional distress.

Bank Size as they represent asset quality and franchise value, two important dimensions of a bank's value. The posterior means are robust to the prior specifications and this result holds for all of the remaining estimated parameters across model specifications. The reported results and covariate effects in the previous sections are conclusively driven by the data rather than by the choice of priors.

Table 14: Prior and posterior means and standard deviations of β_{IRR} and β_{Size} under alternative prior specifications

	Baseline		Informative		Diffuse	
	Prior	Posterior	Prior	Posterior	Prior	Posterior
$\beta_{IRR,1}$	0.00 (1.00)	0.092 (0.04)	0.10 (0.80)	0.092 (0.04)	0.00 (3.16)	0.091 (0.038)
$\beta_{IRR,2}$	0.00 (1.00)	0.048 (0.02)	0.10 (0.80)	0.047 (0.02)	0.00 (3.16)	0.048 (0.017)
$\beta_{Size,1}$	0.00 (1.00)	-0.085 (0.04)	-0.10 (0.80)	-0.084 (0.03)	0.00 (3.16)	-0.085 (0.035)
$\beta_{Size,2}$	0.00 (1.00)	-0.041 (0.02)	-0.10 (0.80)	-0.041 (0.02)	0.00 (3.16)	-0.041 (0.018)

9 Conclusion

The findings from the paper provide an insight into the FDIC's problem of assigning failed banks into appropriate resolution categories during the banking crisis of the 1980's. The results point to the presence of two distinct decision rules followed by the deposit insurer, one for banks that failed amidst distress in the regional economy and another for banks that failed in relatively normal economic conditions. Bank failures accompanied by regional economic distress and political support were provided with financial assistance by the FDIC and consequently offered an opportunity to recover to solvency with higher probability than banks that failed under normal economic conditions and did not receive political support. Bank liquidations, which entailed permanent cessation of banking relationships, were more common in the latter group compared to the former. These results continue to hold even when poltical economy considerations are replaced by indicators of the health of the banking industry. The specification that combines political economy and regional economic climate is favored by model comparison exercises over the specification that only addresses regional economic performance. Model comparison exercises also provide greater evidence in favor of the presence of two decision protocols, as implied by a latent class model over a single decision rule as suggested by a standard ordinal probit model.

A notable finding in this analysis is that covariate effects in the model for resolution type are stronger in the class of systemic failures compared to idiosyncratic failures in both benchmark models. This points to the likelihood that the FDIC undertook more detailed investigation of bank characteristics when faced with the possibility of widespread bank failures due to increased resources being made available to the institution [6]. The legislation that followed the Savings and Loans crisis (prominent among which was the Federal Deposit Insurance Act of 1992) revoked the FDIC's ability to provide Open Bank Assistance due to concerns that the prolific use of this resolution method resulted in transfers from taxpayers to bank shareholders. The detailed assessment of the FDIC's decisions in this paper shows that while systemic and regional considerations were important in determining outcomes,

[6] The FDIC's annual report for the year 1988 states the following with respect to open bank assistance, "In response to the increasing volume of requests from banks for financial assistance, in June 1988 the Assisted Acquisitions and Transactions Section was formed within the Legal Division to handle assistance transactions. The section drafts and negotiates agreements for open bank assistance and provides legal support for related financial transactions, such as the sale of securities acquired in assistance transactions."

the FDIC placed greater and not lesser emphasis on the financial health of banks that failed during economic distress in order to qualify them for financial assistance and mergers over liquidation.

This paper also provides a novel, efficient Bayesian method to estimate latent class models with ordinal outcomes. These models uncover heterogeneity in the relationship between outcomes and covariates and can be applied to study a broad range of economic questions involving ordinal outcomes such as educational attainment and sovereign bond ratings.

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10 Appendix

10.1 Types of Open Bank Assistance

- Loans, contributions, deposits, asset purchases, or the assumption of liabilities.
- A cash contribution to restore capital to a positive level.
- An FDIC note or loan to cover the deficit was common in larger OBA transactions.
- Losses were covered for a specified amount on a pool of assets over a specified period of time in certain cases.
- Required new management, sought the dilution of ownership interest to a nominal amount, and called for a private sector infusion of capital.
- OBA also used by the FDIC to facilitate the acquisition of a failing bank or thrift by a healthy institution.

10.2 Regional Distress and Bank Resolutions

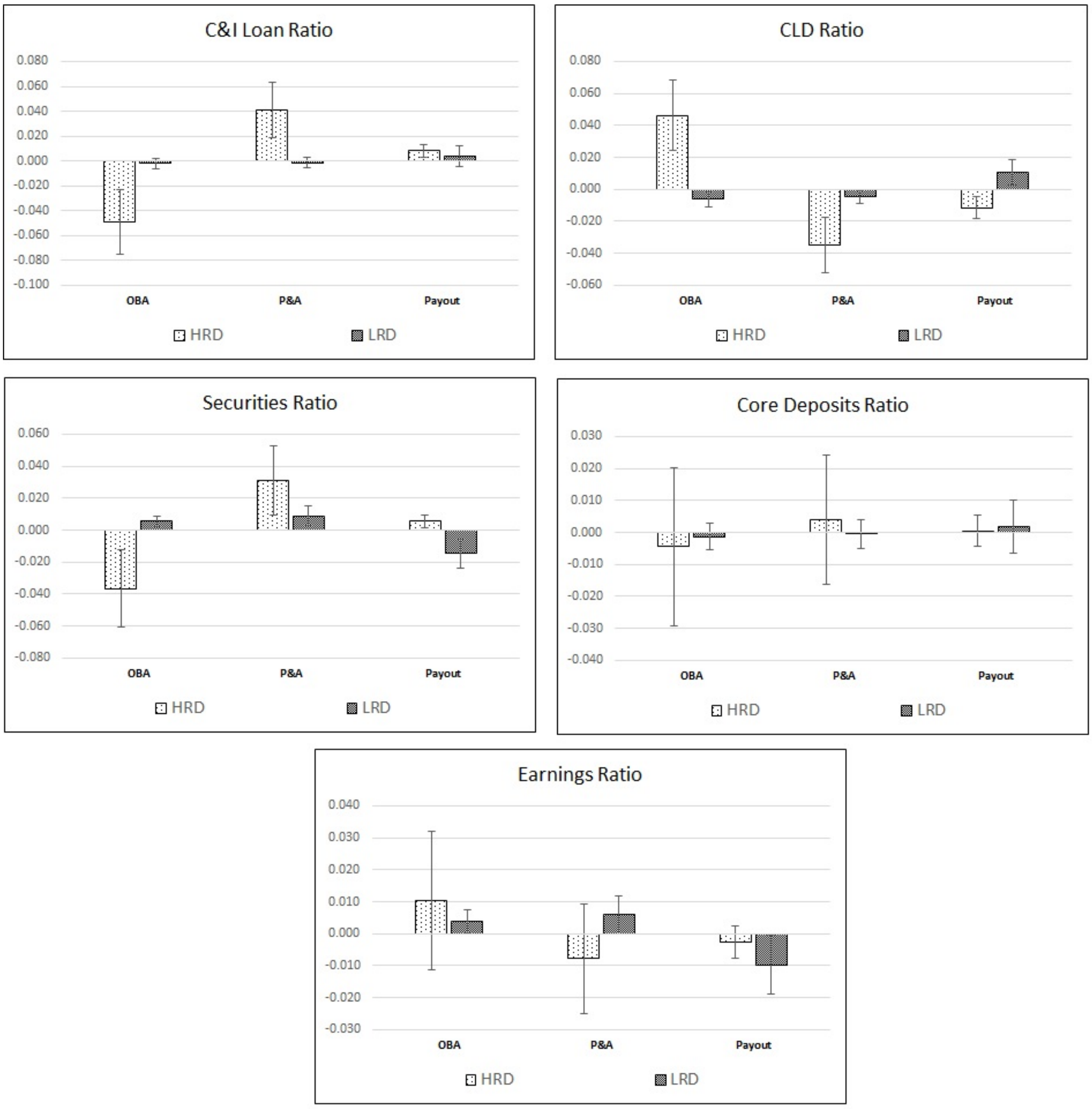

Figure 12: Covariate effects across latent classes for the model with class membership defined by regional economic factors and the model with membership defined by regional economic and political factors.

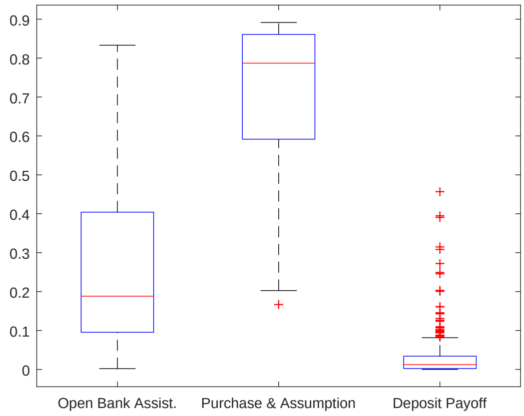

Figure 13: Box plots of probability of each resolution category given a bank belongs to latent class 1 (systemic)

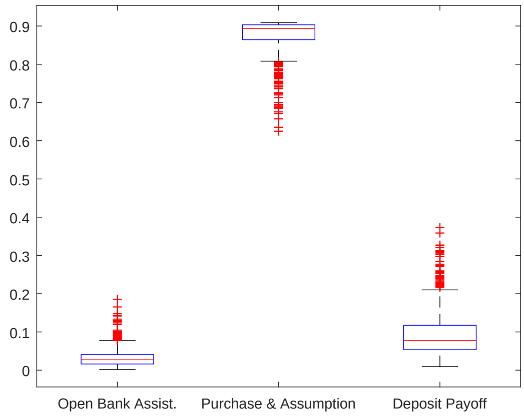

Figure 14: Box plots of probability of each resolution category given a bank belongs to latent class 2 (idiosyncratic)

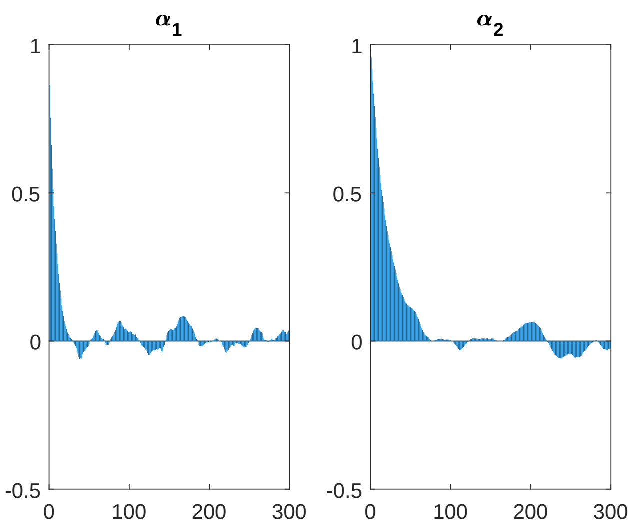

Figure 15: Autocorrelation in the posterior sample of α from a full Gibbs sampler in a simulation exercise based on a sample of 1200 observations.

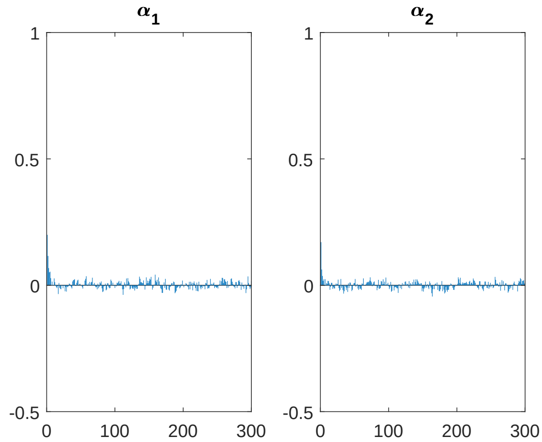

Figure 16: Autocorrelation in the posterior sample of α from the collapsed Gibbs sampler in a simulation exercise based on a sample of 1200 observations. (α_1 is the intercept and α_2 is the coefficient of the unique continuous covariate within the class membership model considered in the simulation exercise)

10.3 Political Economy Factors

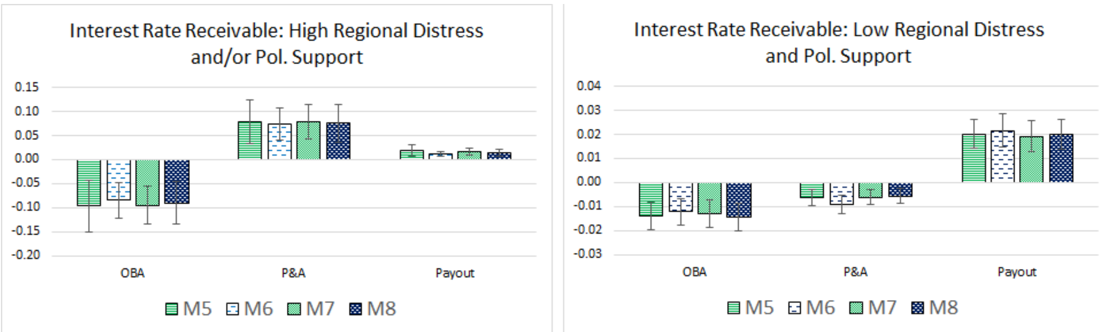

Figure 17: Covariate effects of Interest Rate Receivable Ratio across the four model specifications for latent classes based on regional distress and political support.

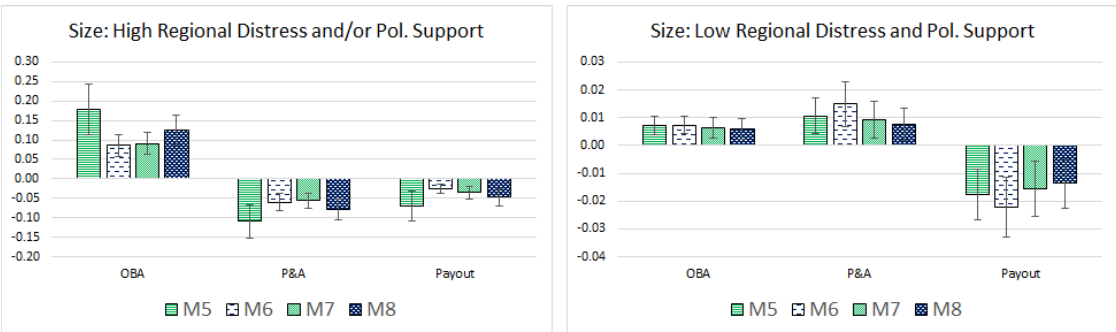

Figure 18: Covariate effects of Size across the four model specifications for latent classes based on regional distress and political support.

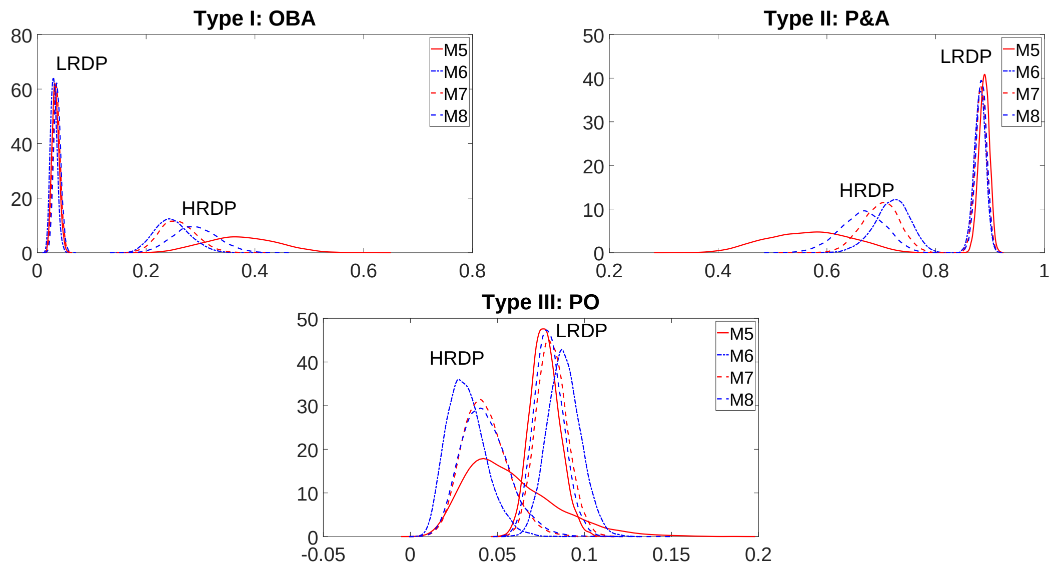

Figure 19: Distributions of Average estimated probability of each resolution type conditional on membership in the High Regional Distress and/or Poltical Support (HRDP) and Low Regional Distress and Political Support (LRDP) latent classes across the four model specifications.