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Abstract

During banking crises, regulators must decide between bailouts or liquidations, neither of which are publicly popular. A comprehensive assessment of regulators, however, requires examining all their decisions against regulators' objectives of preserving financial stability while discouraging moral hazard. I develop a Bayesian latent class model to assess regulators on these competing objectives and evaluate banking and savings and loan (S&L) regulators during the 1980's crises. I find the banking authority (FDIC) conformed to these objectives whereas the S&L regulator (FSLIC), which subsequently became insolvent, deviated from them. Timely interventions based on this evaluation could have redressed the FSLIC's decision structure and prevented losses to taxpayers.

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

Key words: Bank failures, Bank resolution, Bailout, Liquidation, Savings and Loans Crisis, Markov chain Monte Carlo (MCMC), Federal Deposit Insurance Corporation (FDIC), Federal Savings and Loans Insurance Corporation (FSLIC), Bayesian inference, Discrete data analysis, Latent class models.

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1 Introduction

The global financial crisis of 2008 led to widespread bank failures, reviving debate over how financial regulators might preserve immediate financial stability while also safeguarding against future moral hazard. Regulators bail out banks when they place greater emphasis on preserving financial stability and liquidate institutions when they are more attentive to the curtailment of moral hazard incentives. Critical assessments of these actions are essential to ensuring regulators balance the competing concerns in a manner that serves the public interest. During banking crises, regulators typically oversee a large number of troubled banks. However, the public typically scrutinizes decisions related to specific banks instead of evaluating whether the decision rule applied to all banks serves the public interest. Individuals disfavor bailouts because they represent transfers from taxpayers to shareholders.[1] The public also criticizes bank liquidations because they are costly for disintermediated depositors and loan customers.[2] How can the public and their representatives in Congress comprehensively assess the actions of regulators against their competing objectives of preserving financial stability and restraining moral hazard?

In this paper, I assess resolution agencies against these two objectives by evaluating the extent to which their decisions align with optimal theoretical rules. Resolution agencies are financial regulators that determine and administer the bailout, sale or liquidation of failed banks. To address the trade-off between financial stability and moral hazard, theoretical studies recommend resolution strategies that vary with the state of the economy and of the banking industry extant at the time of bank failures. I test whether resolution agencies applied state-dependent rules in line with theoretical models by developing a Bayesian latent class model. This method uncovers distinct decision rules for resolving bank failures in disparate states such as recessions and expansions if regulators had indeed applied resolution rules that varied by economic conditions.

I assess resolution agencies from two sub-sectors of the U.S. banking industry, commercial banks and Savings and Loans (S&L), [3] during their simultaneous crises of the 1980's, which was marked by the highest number of bank and S&L failures since the Great Depression. Notably, the resolution authorities of the two sub-sectors underwent contrasting trajectories following the crises. The resolution authority for banks, the

[1] "The firms we rescued were usually not gracious about the terms of their rescues, while the overwhelming sentiment among the public was that they shouldn't have been rescued at all." (Bernanke et al., 2019)

[2] When Penn Square Bank was liquidated in 1982, in the first instance of a bank failure where uninsured depositors went uncompensated, (Isaac, 2010) noted, "The public chose not to blame the management that created the Penn Square debacle. Instead, it focused its anger on the agency that came in under extraordinarily difficult circumstances to get the depositors their money"

[3] " A Savings and Loans institution is a financial institution that ordinarily possesses the same depository, credit, financial intermediary, and account transactional functions as a bank, but that is chiefly organized and primarily operates to promote savings and home mortgage lending rather than commercial lending. Also known as a savings bank, a savings association, a savings and loan association, or an S&L." FDIC (1998)

Federal Deposit Insurance Corporation (FDIC) survived the crisis, albeit with depleted insurance funds whereas the S&L counterpart, the Federal Savings and Loans Insurance Corporation (FSLIC) faced insolvency by the end of the crisis and was closed at a cost of $132 billion to the taxpayer (FDIC, 1998). The two types of depository institutions and their regulators are comparable on account of the fundamental similarities across banks and S&L's in that both offer loans and deposits, undertake maturity transformation, monitor information and offer liquidity and payments services (Freixas and Rochet, 2008). Accordingly, I compare the resolution decisions of the two agencies in addition to assessing each regulator against theoretical optimal rules. The results expose specific weaknesses in the FSLIC's decision structure and the FDIC's relative strengths that are likely to have contributed to the former's failure and the latter's survival.

Overall, the FSLIC assigned assistance with a higher probability than the FDIC. The FSLIC assigned these resolutions on a case-by-case basis instead of adhering to a data-driven, state-dependent rule that the FDIC adopted. The FDIC aligned with the optimal decision rules from theoretical studies by distinguishing across banks that failed in the presence of disparate levels of macroeconomic and industry-wide distress. The agency primarily provided assistance to relatively healthier banks that failed amid adverse economic or banking industry conditions. The FSLIC did not assign different decision rules to S&L's based on economic or industry distress. Instead, the agency's decision rules varied by whether failed S&L's belonged to regions where elected representatives provided political support to the industry.

First, I evaluate whether the agencies adhered to the optimal bailout rule in Cordella and Yeyati (2003) by providing bailouts to banks or S&L's that failed amid macroeconomic distress and withholding such assistance for failures in normal economic conditions. This state-dependent rule is designed to counter the moral hazard effects of bailouts by deterring banks from undertaking excessive risks that may result in idiosyncratic failures during economic expansions. I find that the FSLIC deviated from and the FDIC adhered to this optimal rule. Banks that failed amid high economic distress received financial assistance, or bailouts from the FDIC with an average probability of 25% compared to 3% for banks that failed amid low distress. The FSLIC separated S&L institutions into two classes that did not statistically differ across measures of regional distress and assigned assistance with a probability of 68% and 70% within the groups. Furthermore, the FDIC targeted assistance to institutions with relatively stronger balance sheets within the class of banks that failed in high economic distress whereas the FSLIC did not statistically distinguish across healthy and weak S&L's in providing such assistance.

Second, this study examines whether resolution agencies experienced a too-many-to-fail problem and responded to it in the form of a greater reliance on bailouts and financial assistance to acquiring institutions as described in theoretical models in Acharya and Yorulmazer (2007) and Acharya and Yorulmazer (2008). The results show that the FDIC's decision rules qualitatively aligned with the theoretical rules as the agency provided assistance with a probability of 27% for failures amid economic and banking industry distress and a statistically lower probability of 4% for failures amid low levels of such distress. The FDIC, however, relied on measures of regional distress to a greater extent than on measures of banking industry distress in partitioning banks into classes. The FSLIC assigned assistance with probabilities of 76% and 70% among groups of institutions that did not statistically differ by industry and economic distress.

Third, this study examines the extent to which political pressures influenced the resolution decisions of the two agencies. Whereas the previous two hypotheses examined the extent to which regulators followed optimal theoretical rules, this assessment examines potential institutional weaknesses. This line of inquiry is motivated by the literature on the regulatory capture of agencies (Stigler, 1971) and theoretical study by DeYoung et al. (2013) that showed that agencies prone to political pressures were more likely to provide bailouts at a cost of inducing moral hazard. I find that political support for the banking industry played a limited role in the FDIC's decisions as the average probability of assistance to banks changed marginally upon adding measures of political support to measures of economic distress. The average probability of assistance was 27% in the presence of high levels of political support and economic distress and 3% in low levels of political support and economic distress. Political economy factors played a more prominent role in the decisions of the FSLIC. Notably, the FSLIC assigned assistance to S&L's that likely received a higher degree of political support and failed amid lower economic distress at a statistically higher probability of 92% relative to 59% for S&L's that failed amid low political support and in a climate of higher economic distress. The FSLIC, accordingly, deviated from the optimal decision rules that would have curtailed moral hazard and protected financial stability. The FDIC aligned with optimal rules to a greater extent by incorporating economic and banking distress in its decision rules and limiting the influence of political pressure on its decisions.

The institutional setting for the crises of the 1980's renders it particularly suitable for comparing regulatory decisions with state-dependent decision rules resulting from theoretical studies. Two features of the period under study generated regional variation in the state of the economy and the banking industry, thereby providing the conditions for potentially applying heterogeneous decision rules as recommended by theoretical models. First, bank and S&L failures in this period occurred against the backdrop of shocks in specific sectors, namely, agriculture, real-estate and energy that resulted in regional crises (FDIC, 1998). Second, banks were subject to varying levels of branching restrictions and operated either within state borders or across states that had entered into reciprocal arrangements (Kroszner and Strahan, 1999). The combination of sectoral crises that were regionally contained and branching restrictions that limited the geographic scope of banking markets entailed that certain bank failures occurred amid economic and financial distress, and others, in relatively normal economic conditions. In addition, the period under study, 1984-1992 spans the regulatory regime when the FDIC had the authority to autonomously provide assistance to troubled banks. The agency's authority to provide assistance is salient as theoretical studies focus on the trade-off between liquidating failed banks and assisting them. Comparisons with theoretical models that concern the dispensation of assistance become incongruent beyond the sample period, post-1992, when new legislation placed restrictions on this authority. [4] Therefore, the 1980's provided an institutional setting in which regulators had access to the full set of resolution methods described in theoretical studies, as well as variation in economic and industry conditions in which bank failures occurred.

This paper provides a new methodology to evaluate regulators in the form of a Bayesian latent class model for ordered outcomes. Assessing regulators requires evaluating whether the entirety of their decisions can be categorized into two separate rules that are applied conditional on the presence or absence of economic distress, adverse banking industry conditions or political support respectively. Even though economic and banking industry conditions, as well as certain measures of political support are observable, the thresholds based on these measures used by regulators to categorize banks is unobservable. For example, it is not apparent whether a bank that failed in a state with an unemployment rate of 5% in 1985 would have been categorized in the class of high or low economic distress. Latent class models incorporate such uncertainty by assigning banks into distinct decision rules or classes with probability, rather than certainty. In model comparison exercises, I show that this method dominates alternatives such as a standard ordinal probit model with interaction terms in explaining regulators' decisions. The Bayesian method developed in this paper enables a statistical comparison of parameters across latent classes and thereby a comparison across alternative rules, which previous likelihood-based methods do not address. This method additionally allows for inferences on all estimated quantities of interest, including marginal effects and the probability of class membership without reliance on asymptotic approximations.

This article contributes to the empirical literature examining bank resolution decisions in two ways. First, this study comprehensively evaluates how regulators' decisions align with optimal rules from alternative theoretical models, as well as the extent to which political economy factors interfere with optimal decisions. Second, this is the first article to compare between the decision rules of the FDIC and FSLIC during the simultaneous crises in the banking and S&L industries. Brown and Dinç (2011) found support for the too-many-to-fail hypothesis in a cross-country study of large banks in emerging markets.

[4]The FDIC Improvement Act (1991) required the FDIC to adopt the least costly resolution method, thereby limiting its use of open bank assistance. Prior to the FDICIA, the FDIC could implement any resolution method as long as it was less costly than a deposit payoff. The Resolution Trust Corporation Completion Act (1993) prohibited the FDIC from providing assistance, particularly if shareholders of the troubled bank stood to benefit from such assistance (Walter, 2004)

The current study examines the role of this hypothesis in the U.S., across both, banking and S&L industries during a period of widespread distress across both sectors. Bennett and Unal (2014) and Balla et al. (2015) are bank-level studies that examine the FDIC's resolutions during the period studied in this paper. The primary focus within these papers was on examining the costs that accrued to the agency from enabling acquisitions and liquidations and excluded the effects of assistance transactions. Both studies also consider selection effects related to the assignment of resolution method, and the occurrence of failures respectively. This article uses the insights on determinants of failures and resolution methods from both studies in constructing explanatory variables, but considers all three resolution methods to evaluate the optimality of the decision rules of the FDIC and the FSLIC.

The findings from this paper show that regular assessments of resolution authorities by lawmakers and the public can uncover gaps between observed and optimal resolution rules and provide guidelines for corrective actions. Timely assessments of the FSLIC could have revealed the excessive assistance provided to institutions that did not experience systemic shocks to the local economy and to institutions that received political support. Interventions based on these assessments could have potentially prevented both, the failure of the agency and the ensuing costs to the taxpayer. Conversely, the decision structure of the FDIC identified in this paper can provide a road-map for newer resolution authorities that face widespread failures from systemic shocks.

2 Resolution Methods

The FDIC and FSLIC served as both, deposit insurers and resolution authorities for the banking and S&L industries respectively during the period under study. When banks and S&L institutions were closed by their chartering agencies,[5] the FDIC and FSLIC applied one of the following resolution mechanisms (Walter, 2004).

1. Type I: Open Bank Assistance (OBA) - Under this resolution method, the resolution authority provides financial assistance to acquirers toward the purchase of a failing bank or grants direct assistance to the failing bank. The bank's charter survives and banking relationships are preserved when this resolution category is used.

2. Type II: Purchase and Assumption (P & A) - Resolutions under this category consist of the assumption of a part of the assets and liabilities of a failed bank by an acquiring institution. The banking charter of the failed institution is terminated.

[5]Federal banks and S&L's were chartered by the Office of Comptroller of Currency (OCC) and the Federal Home Loan Bank Board (FHLBB) respectively. State banking departments provided state-level charters to banks and S&L's.

3. Type III: Deposit Payout (PO) - Under this resolution category, the resolution authority liquidates the failed institution and pays out its insured depositors from the insurance fund. Accordingly, the banking charter of the failed institution is terminated.

Resolutions under the Type I category correspond to bailouts since they represent transfers from the regulator to the failing bank to restore the latter to solvency. A large theoretical literature places greater focus on the decision to provide bailouts to failed banks relative to the remaining two resolution methods. The period under study is particularly suited to evaluate the decisions of the FDIC against such theoretical models since the agency was subject to restrictions in applying Type I resolutions before 1982 and after 1993.

Prior to 1982, the FDIC was restricted to providing assistance to a bank only when the institution's continued existence was deemed to be essential to the community in which it operated. The Garn-St.Germain Depository Institutions Act of 1982 dropped this essentiality test. After 1993, new legislation 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 was authorized to autonomously provide assistance under Type I resolutions during 1984-1992, the time period considered in this study. The FSLIC retained this authority from the start of the sample period until its closure in 1989.

3 Testable Hypotheses from Theoretical Studies

This section examines the optimal decision rules recommended by the branches of theoretical literature that consider alternative constraints and institutional factors associated with the resolution of failed banks. This section identifies the specific testable hypotheses obtained from each of these studies.

Economic Distress and Bank Resolutions

Cordella and Yeyati (2003) determined an optimal bailout strategy in which the regulator commits ex-ante to providing bailouts to banks if their failure occurred due to macroeconomic distress and liquidating them otherwise. This result is obtained by identifying the rule that results in the franchise value effect of bailouts dominating over their moral hazard effect. Bailouts generate moral hazard incentives in this model by diluting the effect of the portfolio risk chosen by the bank on its present discounted value, thereby providing incentives to incur excessive risk. On the other hand, bailouts generate franchise value effects through their function as a pure subsidy, which increases firm value and reduces incentives for risk-taking (Keeley, 1990). If the resolution authority provides bailouts independently of the level of the macroeconomic shock instead of adopting the optimal state-dependent strategy, the moral hazard effect outweighs the value effect and results in incentives for risk-taking beyond the level incurred in the absence of bailouts, which is already at least as high as the socially optimal level of risk. Accordingly, this model recommends the provision of bailouts under macroeconomic distress, when bank failures are less likely to have arisen due to their unsound portfolio decisions and more likely to have arisen due to exogenous factors.

Hypothesis H_1: In testing for the adherence to this optimal strategy, the primary empirical consideration is to identify whether the FDIC and FSLIC applied different decision rules for banks that failed in normal economic conditions and those that failed amid macroeconomic distress. Conditional on the presence of two distinct rules, the subsequent econometric inference centers on testing the hypothesis that the probability of receiving a Type I resolution was higher for banks that failed amid high economic distress relative to those that failed amid low distress.

Banking Industry Distress and Bank Resolutions

On account of the historically large number of failures that the FDIC and FSLIC were required to resolve during the period studied in this paper, the effects of industry-wide distress on optimal resolution rules are pertinent in evaluating their decisions. Acharya and Yorulmazer (2007) developed state-contingent optimal strategies that considered the simultaneous failure of many banks and the concomitant issue of the herding of risks by banks endogenously, also succinctly referred to as the "too-many-to-fail" problem. The ex-post optimal resolution rule consisted of facilitating acquisitions of failed banks when such failures were small in number but providing bailouts when there were a large number of failures, and when banks retained a sufficiently elevated level of "specialness" i.e., the ability to use banking assets more efficiently than outside firms. This rule is inherently time-inconsistent as it provides incentives for banks to engage in common risks that increase the probability of failures occurring jointly rather than idiosyncratically, whereas from an ex-ante standpoint, the optimal resolution strategy seeks to generate no correlation in risks across banks.

Acharya and Yorulmazer (2008) recognized this time-inconsistency and proposed the provision of liquidity to surviving banks in a systemic crisis as both, an alternative to bailouts and as a measure against the purchase of banks by inefficient outsiders. This resolution method, while ex-post equivalent to bailouts, addressed their ex-ante sub-optimality by mitigating the incentive to correlate risks. The fundamental inefficiency that the authors addressed in this paper is the cash-in-the-market pricing or acquisitions of failed banks by surviving banks that can potentially occur at fire-sale prices in a systemic crisis.

Hypothesis H_2: The first testable hypothesis from the two studies is that regulators applied distinct rules in the presence and absence of industry distress. Second, the resolution rule employed in the presence of industry distress designated a higher proportion of resolutions as Type I compared to the rule applied in its absence.

This paper examines the de facto resolution decisions that were ultimately taken by regulatory agencies and consequently, the decisions that the agencies determined to be ex-post optimal. Since the provision of assistance to failed banks as well as to acquiring banks are considered to be Type I resolutions as detailed in Section 2, the resulting testable hypotheses from both studies (Acharya and Yorulmazer, 2007, 2008) are equivalent.

Political Economy Factors and Bank Resolutions

A separate branch of literature has studied the regulatory capture of agencies (Stigler, 1971), which subsequent empirical studies (Duchin and Sosyura, 2012; Igan et al., 2012) have revealed, were directly relevant to the banking industry owing to evidence of political influence on regulatory outcomes within the sector. DeYoung et al. (2013) studied the effects of limits on resolution technology and other political or economic pressures on resolution decisions, and ultimately, on incentives among banks to maintain complex operational structures that generate large externalities upon closure. In the theoretical model, political pressures on regulatory authorities are manifested in the form of a steeper discount associated with future outcomes relative to present conditions. A salient finding of the paper was that when a resolution authority experiences pressure to place greater emphasis on maintaining current liquidity, the latter will provide more bailouts than when the authority prioritizes the prevention of future moral hazard.

Hypothesis H_3: The primary hypothesis is that the presence of political influence induces a separate decision rule that is distinct from the rule applied in its absence. Subsequently, inferences center on whether the decision rule utilized under political influence resulted in a higher probability of receiving a Type I resolution relative to the rule applied in the absence of political influence.

4 Empirical Specification

In this section, I propose a latent class model for ordinal outcomes to represent the decision rules of resolution agencies and to evaluate these decision rules against optimal rules from theoretical studies. I develop an efficient Bayesian method to estimate this model and provide the results from simulation exercises.

4.1 Ordering of Resolution Decisions

The primary outcome of interest, the resolution decision made by the FDIC and FSLIC, is modeled as an ordered variable by specifying the resolution methods available to the agencies as ordered categories. Previous studies showed that the three methods resulted in progressively more severe effects on economic outcomes (Ashcraft, 2005) and on the level of liquidity (DeYoung et al., 2013). The role of banks as producers of information on borrowers and relationship lenders (Diamond, 1984; Leland and Pyle, 1977) results in the effects of the resolution methods intensifying from Type I through Type III. In particular, 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 Type I assistance allows a bank to continue functioning in its present form. A Type II assumptions transaction results in certain loan and deposit relationships continuing within the acquiring bank's books. A Type III liquidation and deposit payout results in the termination of all banking relationships.

In the following discussion, a bank's franchise value is its present discounted value and incorporates the value of its customer relationships and resulting informational advantages. The specification of resolution methods as an ordered outcome variable allows for a decision structure in which the agencies order institutions by franchise value and assign Type I resolutions to the most valuable and Type III resolutions to the least valuable institutions.

The ordering of institutions by franchise value is consistent with a cost-minimization objective, which was relevant to both agencies since they were required to preserve their insurance funds by controlling their costs of resolution(FDIC, 2007). The FDIC was in fact statutorily restricted from providing any resolution that cost more than a Type III resolution under the cost test in the Garn - St.Germain Depository Institutions Act of 1982. Therefore, a Type III resolution was pursued as a last resort if the FDIC received no other bids for a less costly Type II resolution (FDIC, 1998).[6] Finally, cost considerations also favored the provision of Type I resolutions to institutions that retained sufficient franchise value to ultimately recover to solvency. The provision of assistance to weak institutions that were unlikely to survive would have imposed future costs on the FDIC.

In the following discussion, bank i refers to a representative bank or S&L without loss of generality. Let y_i denote the resolution method applied on bank i. y_i takes values $1, 2$ and 3 to denote resolution types I, II and III respectively.

[6] " 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.

4.2 Latent Class Model for Ordinal Outcomes

I use a latent class model to represent state-contingent rules in the two agencies' decision structure. The latent class model consists of a hierarchical structure in which the first layer is a class-membership model that assigns units into classes with probability. The second layer specifies relationships between the outcome of interest and covariates that are homogeneous within and heterogeneous across classes. Relatedly, the optimal decision rules from theoretical models described in Section 3 consisted of state-contingent rules, which entailed heterogeneity in relationships between the outcome and covariates across sub-groups of banks that failed in different states of nature. Each distinct rule in a theoretical model represents a distinct latent class in the empirical model. Therefore, the latent class structure permits a direct comparison between theoretical decision rules and the observed decisions of the FDIC and FSLIC.

Figure 1 depicts the structure of the latent class model. The class indicator s is introduced into the model to denote assignment of banks into one of the two classes. The classes correspond to the two distinct states of nature, such as high or low underlying economic distress, described previously in the theoretical models. Within each latent class, the agency applies a class-specific decision rule on failed banks to assign them one of the three available resolution methods.

The distinguishing feature of the latent class model is that classes are determined with probability and not deterministically. This feature is relevant to the current problem since the true assignment of banks into distinct classes by agencies is not observable as the data record the final decision made by the agencies but not the rationale that motivated each decision. Specifically, y is observed but s is not. As a result, the probabilistic assignment of banks into classes addresses the researcher's uncertainty on class assignments by agencies.

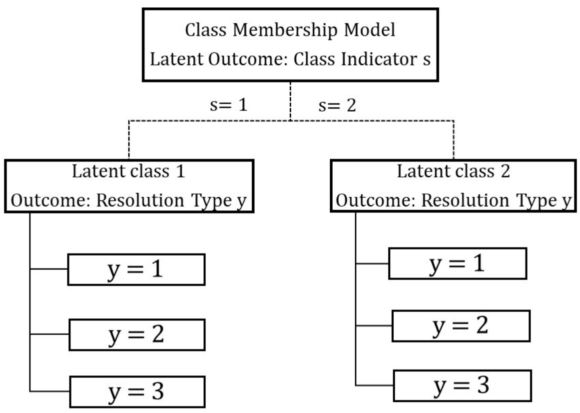

Figure 1: Structure and components of the latent class model for bank resolutions.

The proposed empirical specification is a latent class model for ordered outcomes. This specification, as described in the foregoing discussion, arises from the requirement to address the inherent ordering in resolution methods and the unobserved heterogeneity in decision rules.

4.3 Bayesian Estimation Approach

This study provides two main contributions to the literature on latent class estimation. First, I address an open question in the literature by developing a Bayesian estimation algorithm for a latent class model with ordered outcomes. Second, I introduce an efficient sampling method to generate faster convergence to the posterior distribution relative to standard approaches by developing a Collapsed Gibbs sampler (Liu, 1994) within the MCMC algorithm. Greene and Hensher (2010) developed a classical method to estimate latent class models with ordered outcomes by way of an Expectation-Maximization algorithm. The Bayesian method developed in this paper supports key inferences by providing a statistical framework to compare parameters across latent classes, which the likelihood-based EM method does not address. This estimation method additionally allows for inferences on all estimated quantities of interest, including marginal effects and the probability of class membership without reliance on asymptotic approximations.

Heckman and Singer (1984) proposed latent class models as a nonparametric alternative to random coefficients models in addressing unobserved heterogeneity without the problems of "over-parameterization" and excessive sensitivity to distributional assumptions associated with the latter method. Latent class models have since been developed for a range of outcomes including multinomial (Burda et al., 2008; Greene and Hensher, 2003), count (Deb and Trivedi, 1997; Nagin and Land, 1993; Wang et al., 1998; Wedel et al., 1993) and ordered (Greene et al., 2014) responses. These studies apply latent class models to study heterogeneity in fields ranging across healthcare, marketing and transportation. The following discussion develops a new interpretation of latent class models as a tool to assess banking regulators.

4.4 Random Utility Framework

The decision structure of the resolution agency is hierarchical as shown in Figure 1. When bank i fails, the agency first determines the decision rule through which bank i is parsed, or equivalently, the latent class s_i into which it is assigned. Subsequently, the agency determines the specific resolution method y_i to apply on the bank. The random utility representation of this model is based on the framework developed by Marschak (1974).

The resolution agency's problem of assigning bank i to one of the two decision rules or latent classes is modeled as a binary choice problem with a latent outcome s_i. The outcome s is latent as the regulatory agency's assignment of banks to classes is not observed by the researcher. To apply the random utility representation to this discrete choice problem, I introduce the continuous latent variable l_i, which represents the difference in utilities or value to the resolution agency from assigning bank i to latent class 2 relative to latent class 1. I introduce a set of covariates W_i, parameters α and the error term ν_i to express l_i as,

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

The covariates W in this model are determined by the theoretical study underlying the hypothesis of interest. In testing hypothesis I, the covariates consist of economic indicators, for hypothesis II, they contain measures of the banking industry's health and for hypothesis III, the covariates include measures of political support for the banking industry.

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

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

Within latent class s_i, the resolution agency's utility function z_{i,s_i} determines the final resolution method applied on bank 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 the resolution agency derives from preserving bank $i's$ franchise value as discussed in Subsection 4.1. The covariates X consist of the bank's characteristics that are representative of its franchise value, salient among which are its size, the quality of its assets and composition of risky asset classes. $X_i'\beta_{s_i}$ and ϵ_{i,s_i} represent the observable and unobservable components of utility respectively (Train, 2009). The relationship between the observed outcome y_i and the latent utility z_{i,s_i} is represented using the threshold-crossing framework,

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

The agency selects a resolution method that preserves more of the bank's franchise value as z_{i,s_i} crosses a progressively larger threshold. When z_{i,s_i} is below the lowest threshold, γ_{1,s_i}, bank i loses all its franchise value as the agency's utility level corresponds to liquidation under a Type III resolution.

4.5 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,

$$P_{ij} = \sum_{s=1}^{2} P_{ij|s} Q_{is}. \tag{3}$$

$P_{ij|s}$ 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,

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

The likelihood function is obtained as,

$$\mathcal{L} = \prod_{i=1}^{n} P_{ij},$$

where P_{ij} is defined in 3 and its components in equations 4 and 5.

4.6 Augmented Posterior

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 is obtained by augmenting the likelihood with the latent variables z and s using the method of Albert and Chib (1993). The resulting expression for the augmented posterior is,

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

$f(y_i|z_{is})$ 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, $f_{\mathcal{N}}(z|x_i'\beta_s, \sigma_s)$ for $s = 1, 2$.

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 thereby, their joint density is,

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

Finally, I assign a multivariate normal prior to α so that,

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

In the following discussion, S is the full vector of class membership indicators s_i and z is the full vector of latent variables z_{i,s_i} for the n observations.

4.7 MCMC Algorithm

This MCMC algorithm is designed to generate faster convergence to the posterior distribution relative to standard sampling approaches by reducing autocorrelations across successive draws. This improvement arises from a Collapsed Gibbs sampler (Liu, 1994) developed in this section. A standard approach to developing an MCMC algorithm results in a Gibbs sampler that draws from the full conditionals of all parameters as well as the two latent variables S and z. In the Collapsed Gibbs sampler developed below, the discrete latent variable S is marginalized out of the conditional for α. This novel approach to marginalization results in a sharper decline in autocorrelations across successive lags of sample draws. Consequently, the draws from this algorithm are close to independent and identically distributed early in the chain.

Figures 10 and 11 display the autocorrelations of α under a full Gibbs sampler and the proposed Collapsed Gibbs sampler respectively. The figures show that the reduction in autocorrelations gained from the latter method is striking. The autocorrelations from the full Gibbs sampler are close to 1 at lower lags and decay slowly whereas the autocorrelations from the Collpsed Gibbs sampler are negligible even at lower lags and taper to zero within 5 lags.

Algorithm: Collapsed Gibbs Sampler

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 $i = 1, 2, ..., n$.

The details underlying each step in the Collapsed Gibbs sampler are provided in Subsection 10.2 in the Appendix. The steps in the standard full Gibbs sampler are summarized in Subsection 10.3 in the Appendix. Simulation results based on a sample size of 1200 are provided in Subsection 10.4 and results based on larger sample sizes are provided in Appendix 10.5 in the Appendix. An extended algorithm that includes steps for estimating cut-points is described in Subsection 10.6.

4.8 Model Comparison

Subsequent to estimating the model, the empirical objective is to then identify the specification of the model that is corroborated by the data most decisively. Accordingly, this section develops the procedure for the comparison of posterior probabilities of estimated models. This is a method of model comparison that conforms to the Bayesian principle of representing uncertainty in the form of probability statements. Specifically, in comparing models $\mathcal{M}_i$ and $\mathcal{M}_j$, the posterior odds ratio, $\mathcal{P}_{ij}$, is evaluated to select between the pair of models, where,

$$\mathcal{P}_{ij} = \frac{P(\mathcal{M}_i|y)}{P(\mathcal{M}_j|y)} = \frac{m(y|\mathcal{M}_i)}{m(y|\mathcal{M}_j)} \frac{P(\mathcal{M}_i)}{P(\mathcal{M}_j)}.$$

The first term on the right hand side of the second equality 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 following standard convention in which the *a priori* probability of each model occurring is equal, this quantity singularly determines the evidence in favor of one model against the other. Therefore, Bayesian model selection among L models, $\{\mathcal{M}_1, \mathcal{M}_2, ..., \mathcal{M}_L\}$, proceeds by comparing the marginal likelihood across these models.

The *basic marginal likelihood identity* recognized by Chib (1995) allows for the exact evaluation of the marginal likelihood by MCMC methods. This identity expresses the marginal likelihood of model l as

$$m(y|\mathcal{M}_l) = \frac{f(y|\mathcal{M}_l, \theta_l)\pi(\theta_l|\mathcal{M}_l)}{\pi(\theta_l|y, \mathcal{M}_l)},$$

where θ_l is a parameter vector specific to model l. The computation of the marginal likelihood simply requires the evaluation of this ratio for a given θ_l^*, typically the posterior mean or mode. The likelihood and prior ordinates at θ_l^* can be evaluated analytically for the latent class model with ordered outcomes. The posterior ordinate is estimated to obtain $\hat{\pi}(\theta_l^*|y, \mathcal{M}_l)$ using methods outlined in Chib and Jeliazkov (2001) and Chib (1995). The algorithm for the computation of the marginal likelihood is provided in Appendix 10.8.

5 Data

This study examines bank resolutions by the FDIC between 1984 and 1992 and S&L resolutions by the FSLIC from 1984 until the agency's closure in 1989. This period encompasses coincident crises in both industries and excludes the first wave of distress in the early 1980's that was specific to the S&L industry as shown in Figure 12. Data on resolution methods applied to failed banks and S&L's are obtained from the Historical Statistics on Banking (HSoB) maintained by the FDIC.

Failed banks from the HSoB are matched with call report data from the Federal Reserve of Chicago to obtain information from the financial statements of each institution. I aggregate the call reports by certificate number, which the FDIC uniquely assigns to each head office depository institution, and use this identifier to merge the two datasets. To allow for the duration of 90 to 100 days (FDIC, 1998) between the FDIC receiving notification of an institution that is in danger of failing and determining the resolution method, call reports from two quarters prior to the date of failure are used in the study. County-level statistics on the banking industry are obtained by aggregating bank-level data from the Research Information System (RIS) of the FDIC, which is available starting from 1984. The sample consists of 1385 banks, of which there are 118, 1175 and 92 institutions resolved under resolution types I, II and III respectively.

The failed S&L institutions in the sample are matched with Thrift Financial Reports as of six months prior to failure from the Research Information System (RIS) of the FDIC. There are 389 S&L institutions in the sample of which 270, 104 and 15 institutions underwent resolution methods I, II and III respectively. The data on S&L institutions is less extensive than the corresponding bank-level data due to differences in the reporting requirements for banks and S&L's. Specifically, data on Agricultural loans, Nonperforming loans and Core Deposits are not available for S&L institutions for the period under study.

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 continuum codes from the US Department of Agriculture. Information on branching deregulation laws was collated using the table in Strahan et al. (2003). Congressional voting data were obtained from the website of GovTrack [7] and converted into state-level percentages of representatives who voted in favor of each bill evaluated in this study.

All variables have been normalized prior to estimation in order to preempt any nu-

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

merical issues.

6 Bank Resolution by the FDIC

This section provides an assessment of the FDIC's resolution decisions over the period 1984-1992 by evaluating the agency's decision rules against theoretical optimal rules. I perform this assessment by interpreting the results from the latent class model developed in Section 4 to test the three hypotheses derived from theoretical studies as summarized in Section 3.

6.1 Regional Distress

In this subsection, I find that the FDIC's responses supported Hypothesis H_1 derived from Cordella and Yeyati (2003) as the agency provided assistance to banks that failed amid economic distress with a higher probability than to institutions that failed in low economic distress. Furthermore, I find that within the class of high regional distress, the FDIC targeted assistance to institutions with relatively healthy balance sheets and arranged for the sale or liquidation of the remaining institutions. Finally, on performing Bayesian model comparison, I find that the latent class model dominates standard ordinal probit specifications in explaining the FDIC's resolution decisions.

The period of this study, 1984-1992, presents a unique set of economic and banking conditions that facilitate the test for the presence of the strategy from Cordella and Yeyati (2003) in the FDIC's decisions. By virtue of the combination of regionally-contained sectoral crises and branching restrictions during this period, the FDIC simultaneously administered both, bank failures that occurred amid high and low economic distress. The major sectoral crises that occurred during this period were the recessions following the collapse of energy prices in Texas, Louisiana and Oklahoma, the agricultural recession in Kansas, Iowa and Nebraska and the real-estate-led downturns in California, the Southwest and the Northeast (FDIC, 1997). Moreover, this period predates the elimination of the interstate branching restrictions mandated by the 1994 Riegle-Neal Interstate Banking and Branching Efficiency Act. As a result, banks operated either within state borders or across states that had entered into reciprocal arrangements that permitted interstate acquisitions (Kroszner and Strahan, 1999).

6.1.1 Class-membership Model

I perform a Bayesian model comparison to select the specification of the class-membership model that is most decisively supported by the data. The class membership model is represented in the first level of the decision structure in Figure 1. The covariates in

Table 1: Descriptive statistics of bank, county and state-level characteristics in the data sample for FDIC resolution decisions

	Type I		Type II		Type III	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Bank-level characteristics						
C&I Loan Ratio	27%	13%	27%	16%	28%	16%
CLD Loan Ratio	6%	8%	5%	7%	4%	8%
Real Estate Loan Ratio	39%	17%	42%	21%	31%	20%
Loan Loss Reserves Ratio	6%	6%	4%	3%	5%	7%
Nonperforming loans Ratio	6%	6%	8%	5%	8%	6%
Interest Receivable Ratio	1%	1%	1%	1%	2%	1%
Securities Ratio	12%	12%	13%	10%	14%	11%
Core Deposits Ratio	63%	18%	73%	13%	74%	15%
Earnings	-3%	6%	-3%	4%	-4%	4%
Size(Assets mlns.)	212	654	171	893	47	96
State charter Fed member	4%	20%	7%	26%	14%	35%
State charter non-Fed member	50%	50%	53%	50%	48%	50%
Insurer characteristic						
Dep. Ins. Fund/ Total Deposits	14%	11%	16%	23%	10%	20%
State characteristics						
Interstate branching	0.86	0.34	0.77	0.42	0.51	0.50
Unemployment	8%	1%	7%	2%	6%	1%
Housing starts	13%	7%	11%	13%	16%	17%
Regional crisis indicator	71%	45%	39%	49%	34%	47%
County characteristics						
Per capita income growth rate	3%	3%	5%	5%	6%	7%
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%
County-level characteristics of bank distress						
% Assets in Banks with Texas Ratio > 100%	13%	16%	5%	11%	7%	15%
% Deposits in Banks with Texas Ratio > 100%	12%	13%	5%	11%	7%	15%
% banks with Texas Ratio > 100%	8%	8%	6%	9%	7%	11%
Previous Closures	4.00	6.27	2.62	6.15	1.54	4.72
Count	118	-	1175	-	92	-
State-level political economy characteristics						
% Republicans in 1987	41%	12%	43%	17%	52%	22%
% Republicans in 1989	35%	14%	40%	18%	47%	19%
% vote for for recapitalizing federal deposit insurance and 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	-	1170	-	92	-

Table 2: Descriptive statistics of S&L, county and state-level characteristics in the data sample for FSLIC resolution decisions

	Type I		Type II		Type III	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
S&L-level characteristics						
C&I Loan Ratio	3%	5%	4%	6%	5%	9%
CLD Loan Ratio	14%	20%	27%	25%	20%	25%
Real Estate Loan Ratio	93%	11%	96%	17%	103%	20%
Loan Loss Reserves Ratio	5%	8%	9%	11%	4%	5%
Interest Receivable Ratio	1%	1%	2%	3%	2%	1%
Securities Ratio	20%	15%	13%	9%	12%	10%
Size(Assets mlns.)	471	1961	316	484	201	243
Insurer characteristic						
Dep. Ins. Fund/ Total Deposits	-1%	18%	0%	22%	7%	22%
State characteristics						
Interstate branching	0.69	0.46	0.54	0.50	0.33	0.47
Unemployment	8%	2%	8%	2%	8%	2%
Housing starts	16%	17%	19%	22%	23%	25%
County characteristics						
Per capita income growth rate	4%	4%	4%	4%	6%	3%
Farm, Agri and Mining	7%	8%	8%	8%	9%	7%
Manufacturing	14%	8%	13%	7%	14%	7%
Construction	5%	3%	5%	2%	5%	1%
Fin Serv and Transport	37%	8%	37%	9%	34%	10%
Government	15%	6%	16%	7%	20%	15%
Count	270	-	104	-	15	-
County-level characteristics of S&L distress						
% Assets in Banks with Texas Ratio > 100%	3%	8%	2%	5%	3%	6%
% Deposits in Banks with Texas Ratio > 100%	3%	8%	2%	5%	3%	6%
% banks with Texas Ratio > 100%	4%	8%	3%	7%	3%	5%
Previous Closures	0.24	0.29	0.27	0.56	0.76	0.77
Count	270	-	102	-	15	-
State-level political economy characteristics						
% Republicans in 1987	41%	11%	41%	15%	43%	10%
% Republicans in 1989	35%	14%	40%	18%	47%	19%
% vote for recapitalizing federal deposit insurance and 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	97%	5%	97%	6%	94%	6%
% vote for disclosure of CRA ratings	33%	17%	37%	23%	33%	26%
Count	267	-	103	-	15	-

the second level of the hierarchy, the resolution type model are constant across all the specifications considered and are discussed in Subsection 6.1.3.

Table 3 summarizes the covariate effects from the class membership model for four specifications that include indicators of state and county-level economic performance along with controls for institutional features underlying the resolution decision. The values of log marginal likelihood reported in the last row of Table 3 point to specification (3) as the selected model as it has the highest posterior odds among the four candidate specifications. This selected specification highlights a statistically important role for state-level unemployment in assigning banks into two different decision rules. The other covariates that inform the assignment of banks to latent classes are county-level indicators of economic performance along with a control variable for the amount of insurance fund available per dollar of insured deposit in the banking system.

Among alternative specifications considered in Table 3, specifications (1) and (2) of the model entirely consist of state and county-level indicators of economic performance and controls for county-level shares of employment by sector where the latter is a more parsimonious setting that is nested within the former. Specification (4) augments specification (2) with indicators for the charter status of failed banks since chartering agencies, namely, the OCC for federally chartered banks and state banking departments for state-chartered banks, retain the final authority to enforce closure. The timing of the decision to close banks varied across agencies.[8] The reference group in this class membership model consists of nationally chartered banks that are supervised by the OCC.

In the following discussion, latent class 1 is labeled as the class of failures under "High Regional Distress (HRD)" and latent class 2, as "Low Regional Distress (LRD)". In the model for class membership in Equation 4, the event of success in the binary probit model (where the latent binary indicator s_i equals 1) is represented by a bank belonging to latent class 2. Therefore, the negative signs associated with unemployment in specification (3) and the positive signs for covariate effects of GDP growth rate and housing starts in 3 show that latent class 2 contains banks that failed during periods of low unemployment or periods of relatively low regional economic stress whereas banks that failed amid high regional distress belong to latent class 1. These findings support the first element of hypothesis H_1 by confirming that the FDIC distinguished across banks based on economic distress in applying its resolution decisions.

[8] "In the states that had the most closings and the most late closings, the state authorities closed problem banks more quickly than the OCC did...Part of the difference was due to the fact that state banking authorities had greater flexibility under applicable law...the OCC had to wait until the bank was insolvent before being able to close it."(FDIC, 1998)

Table 3: Covariate effects from class-membership models for specifications of latent classes based on regional distress

	(1)	(2)	**(3)**	(4)
State-level characteristics				
Unemployment	-0.12 (0.06)	-0.11 (0.05)	**-0.10 (0.04)**	-0.15 (0.08)
County-level characteristics				
Housing starts	0.11 (0.05)	0.09 (0.05)	**0.05 (0.05)**	0.1 (0.05)
Per capita GDP growth	0.04 (0.05)	0.05 (0.05)	**0.04 (0.05)**	0.04 (0.05)
Farm, agri, mining	0.11 (0.09)	0.07 (0.05)	**0.06 (0.04)**	0.07 (0.05)
Manufacturing	0.03 (0.05)	-	-	-
Construction	0.02 (0.04)	-	-	-
Fin Serv Transport	0 (0.07)	-	-	-
Government	0.04 (0.05)	-	-	-
Insurer characteristics				
Dep. Ins. Fund/ Total Deposits	-	-	**-0.05 (0.03)**	-
Bank-level characteristics				
State charter Fed member	-	-	-	0.03 (0.07)
State charter non-Fed member	-	-	-	-0.06 (0.05)
log Marginal Likelihood	-703.35	-701.10	**-699.79**	-700.19

Note: The reported values are posterior means of the covariate effects. Posterior standard deviations are in parantheses.

6.1.2 Heterogeneity in Decision Rules

The results from the second level of the decision structure in Figure 1 show that the average probability of the FDIC assigning a Type I resolution was statistically higher among HRD banks than among LRD banks. These findings confirm that the FDIC's decisions fully aligned with hypothesis H_1 in that the agency was more likely to provide assistance to banks when their failure was accompanied by regional distress.

The average probability of each resolution type for the HRD and LRD failures is computed as follows.

$$\text{Avg. Prob}(Y = j|s) = \frac{1}{nG} \sum_{i=1}^{n} \sum_{g=1}^{G} P_{ij|s}^{(g)}, \quad j = 1, 2, 3, \tag{6}$$

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.

Figure 2 provides the full posterior density of the average probability of receiving each resolution method across the two latent classes. The average probability of receiving a Type I resolution among HRD banks was 24.6% compared to 3.3% for LRD banks. The fully disjoint posterior densities of the average probability of receiving a Type I resolution for the HRD and LRD classes shows that the difference between their averages is statistically important. This observation continues to hold for Type II resolutions with statistically important differences in average resolution probabilities across HRD

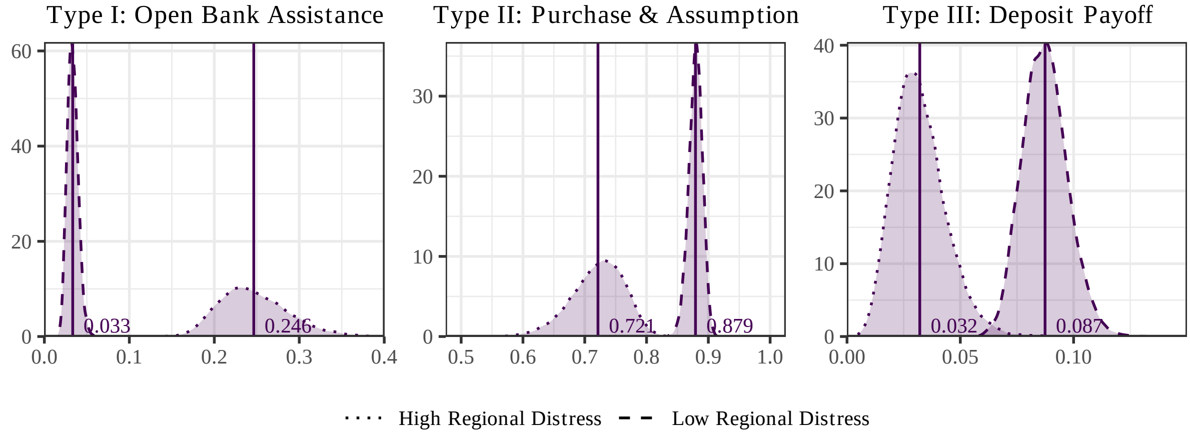

Figure 2: Probability of the FDIC assigning each resolution method within classes based on regional distress.

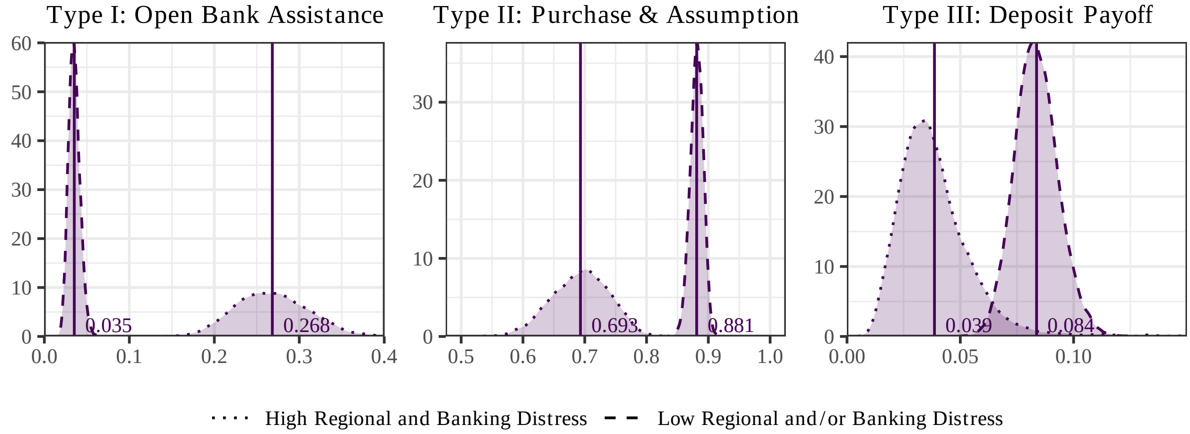

Figure 3: Probability of the FDIC assigning each resolution method within classes based on regional and banking distress.

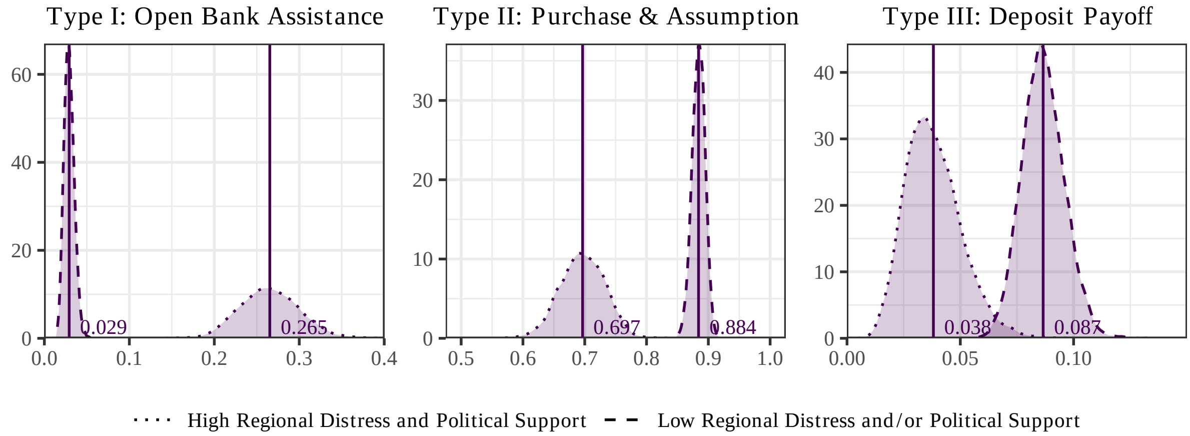

Figure 4: Probability of the FDIC assigning each resolution method within classes based on regional distress and political economy factors. NOTE: In all three figures, the horizontal axis represents the probability of assigning a resolution method and the vertical axis represents the posterior density associated with that probability based on a kernel density estimate.

and LRD classes at 72.1% and 87.9% respectively. The theoretical benchmark does not explicitly address the decision to facilitate partial or whole acquisitions of failed banks and the findings from the estimation provide new insights into the differences in the probabilities of implementing this resolution method under varying varying levels of economic distress. Finally, in a further confirmation of the predictions of the theoretical model, the average probability of being liquidated under a Type III resolution was 8.7% for LRD banks compared to 3.2% for HRD banks. This difference is also statistically important, as evidenced by the minimal overlap in posterior densities of the two classes.

6.1.3 Resolution Type

The next stage of the empirical analysis centers on the results from the ordinal probit models represented in 5 and depicted in the second level of the decision structure in Figure 1. These models estimate separate relationships between the resolution method y_i and bank-level financial indicators X_i in the LRD and HRD classes. If the FDIC responded differently to LRD and HRD failures for the same change in bank financial characteristics, this would manifest in different magnitudes of covariates across the two classes and provide conclusive evidence of the presence of two different decision rules implemented by the agency.

In Figure 5, it is clear that the magnitudes of the covariate effects from the selected model, specification (3), described in the preceding subsection, are larger for banks that belong to the latent class "High Regional Distress (HRD)" relative to banks in the class labeled "Low Regional Distress (LRD)". This pronounced difference in the effects of each covariate on the FDIC's decisions across the two classes confirms the presence of two distinct decision rules in the agency's resolution procedure. The larger covariate effects for banks in the class of HRD failures indicate that within the group of banks that failed amid regional economic distress, the FDIC ordered banks based on their financial characteristics and provided Type I resolutions to relatively healthier banks and Type II and III resolutions to relatively weaker banks. The smaller covariate effects in the LRD class suggest that the FDIC evaluated banks that failed in low economic distress on a case-by-case basis rather than appraising their relative financial strength. This approach potentially included evaluating unobservable individual circumstances, which are captured by the error term in Equation 4.4. These results reveal a smaller role for observed financial statement information in determining resolution methods within the LRD class relative to the HRD class of banks and further support the hypothesis that banks in the former group are likely to failed due to largely idiosyncratic factors.

The financial variables, Real Estate Loan Ratio and Nonperforming Loans Ratio, both exhibit qualitatively similar covariate effects. A unit standard deviation increase in Real Estate Ratio and Nonperforming Loans Ratio is associated with a reduced probability of obtaining assistance under a Type I resolution among HRD failures and an increased probability of such banks undergoing Type II and III resolutions. Since nonperforming loans provide a succinct measure of the quality of the failed bank's assets, these results reveal that the FDIC provided assistance under Type I to banks that had relatively healthier balance sheets even among those banks that failed amid economic distress, which is consistent with the theoretical rule developed in Cordella and Yeyati (2003). Cole and Gunther (1995) and Balla et al. (2019) identified concentration in real estate ratios as an important driver of failures in their study of the causes of bank failures during this period. Balla et al. (2019) explain that states that underwent recessions during this period, particularly, states on the East Coast and in oil-producing regions, also experienced significant declines in real estate prices. As a result, the FDIC is more likely to have associated a concentration of real estate loans in states in the HRD category with more adverse portfolio quality, and in turn, to have adopted a more severe response in the resolution method. The effects of these covariates on banks within the class of LRD failures, on the other hand, are not statistically important.

The Interest Receivable Ratio is seen to be important in the FDIC's evaluation of bank health, with elevated levels of this ratio eliciting more stringent resolution methods from the FDIC. Balla et al. (2015) originally identified 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 an equivalent variable, Earned Income, to be reflective of asset quality as this variable is emblematic of income reported from distressed assets on the bank's books that have not yet been written off. Accordingly, an increase in Interest Receivable Ratio among HRD failures resulted in a reduction in the probability of Type I resolution and a corresponding increase in the probability of a Type II resolution, entailing partial or whole acquisitions of the failed institutions. Banks that belonged to the LRD class of failures experienced a more severe response in the form of an increased probability of a Type III resolution and hence, complete liquidation, along with a decreased probability of the other two resolution methods.

Larger banks were less likely to be liquidated under a Type III resolution across both latent classes. Among HRD failures, a standard deviation increase in log of assets was also associated with a decreased probability of a Type II resolution and a compensatory increase in the probability of assistance under Type I resolution. LRD failures experienced an increase in the probability of both, Type I and II resolutions concomitantly with a decrease in the probability of a Type III resolution. The increased probability of Type I resolutions associated with a larger bank reveals that the "too-big-to-fail" doctrine was present in the decisions of resolution authorities during the crisis of the 1980's.

The estimation results provide new insights into the role of Loan Loss Reserve Ratio, an accounting variable that records the amount of reserves set aside to meet expected losses. An increase in Loan Loss Reserves ratio was associated with a higher probability of receiving Type I resolution in the class of HRD failures. Contrarily, among LRD failures, an equivalent increase in this measure was associated with an increase in their probability of receiving a Type III resolution and being liquidated. A possible explanation for this disparity is that in the HRD class of banks, where failures are more likely to have occurred due to systemic factors, changes in reserve ratios can be attributed to the deterioration in asset quality resulting from market-wide fluctuations. However, among LRD failures, the FDIC is likely to have viewed the increase in this ratio as a signal of deterioration in asset quality arising from issues idiosyncratic to the failed bank.

Interstate is an indicator variable that identifies whether interstate banking was legal in the state in which a bank is located in the year of failure and is derived from summary tables in Strahan et al. (2003). Intuitively, interstate banking laws are likely to affect resolution outcomes as they determine the breadth of demand for assets of failed banks. In the cash-in-the-market model developed by Acharya and Yorulmazer (2008), 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, akin to Type I resolutions. This model predicts that interstate banking, by expanding the set of available acquiring banks in the event of a failure, 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 increased probability of Type II resolutions is observed among both, HRD and LRD classes, even though the LRD class of failures also underwent a modest increase in the probability of Type I resolutions.

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 13 of the Appendix.

6.1.4 Rationale for Latent Classes

I examine whether the FDIC's decisions require an empirical specification based on latent classes instead of a standard ordinal probit model. Model comparison exercises offer statistical evidence in favor of the presence of two distinct decision rules for latent classes of banks that failed in high and low economic distress as opposed to a single rule for all banks that can be represented by a simple ordinal probit model. The values of log marginal likelihood in Table 4 decisively support the latent class model with a Bayes Factor that exceeds 1000 (Kass and Raftery, 1995) relative to the standard ordinal probit specifications. The latent class model similarly dominates a specification in which the ordinal probit model for bank resolution includes the covariates from the class membership model of specification (3).

Moreover, the latent class model, which allows for modeling the researcher's uncertainty with respect to the FDIC's classification of banks into the two groups, is decisively

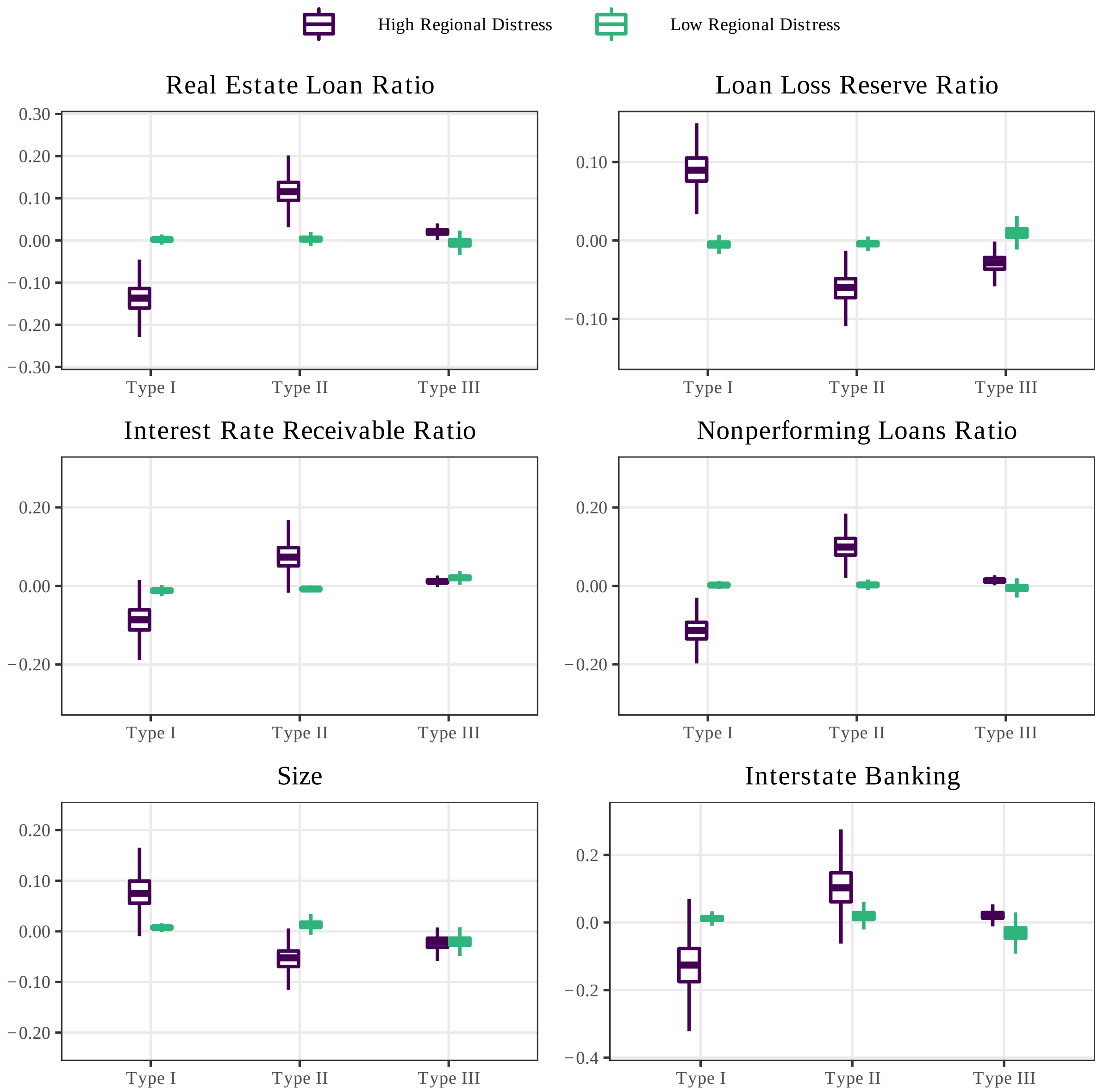

Figure 5: Covariate effects from the models for resolution type for banks in the class of High Regional Distress (HRD) and Low Regional Distress (LRD).

supported by the data relative to a specification that classifies failures into classes in a deterministic manner. The latter specification consists of the standard ordinal probit model with interaction terms between bank-level financial indicators and an indicator for a regional recession obtained from FDIC (1998). This specification with interaction terms implicitly assumes knowledge of the FDIC's criterion for parsing banks through distinct decision rules.

Table 4: Log marginal likelihood from standard ordinal probit and latent class specifications of the FDIC's resolution decision.

Model	log Marginal Likelihood
Ordinal probit model	-729.66
Ordinal probit model + class membership covariates from (3)	-722.55
Ordinal probit model with interactions	-729.52
Selected latent class model (spec. 3)	-699.79

6.2 Banking Industry Distress

In this subsection, I examine whether the FDIC's responses supported Hypothesis H_2 derived from Acharya and Yorulmazer (2007) and Acharya and Yorulmazer (2008), i.e., whether the agency provided assistance with higher probability to banks that failed amid distress within the banking industry. The results show that the agency's decision rules qualitatively aligned with this hypothesis as it provided Type I resolutions with a marginally higher probability when the local banking industry experienced failures. However, measures of regional distress remained the most important determinants of membership into classes that received statistically different levels of Type I resolution.

Table 5 summarizes the covariate effects and log marginal likelihood from model specifications (5) through (7) that are based purely on banking industry distress and specifications (8) through (10) that incorporate a combination of banking industry and economic distress. The data favor the latter three specifications over the former three as evidenced by their higher marginal likelihood. Specifically, the Bayesian model selection procedure based on posterior odds selects specification (8), which defines distress in the banking industry using previous closures and the percent of assets in distressed banks within a county. On account of the negative covariate effect of unemployment, previous closures and percent of assets in distressed banks and the positive signs for housing starts and per capita income growth, latent class 2 contains banks that failed amid relatively low regional or banking distress and banks that failed amid high regional and banking distress belong to latent class 1. As a result, in the following discussion, latent class 1 will be labeled as the class of failures under "High Regional and Banking Distress (HRBD)" and latent class 2, as the class of failures under "Low Regional and / or Banking Distress (LRBD)".

In the model specifications in Table 5, distressed banks are defined as those institutions whose Texas ratio exceeded 100% based on previous literature that utilize this measure (Cooke et al., 2015; Siems et al., 2012). The Texas Ratio for a bank is defined as,

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

This measure of distress identifies institutions whose capital would be insufficient to absorb losses that could emanate from nonperforming assets.

Figure 3 provides the entire posterior distribution of the probability of the FDIC assigning each resolution category under the selected model, specification (8). These results qualitatively align with the predictions from Shleifer and Vishny (1992) and Acharya and Yorulmazer (2008) represented by Hypothesis H_2, which posited a greater reliance on public financial assistance in the form of Type I resolutions when the local banking industry experienced distress. The figure shows that the average probability of a Type I resolution was 26.8% under banking and regional distress and 3.5% under low regional and banking distress. These probabilities are marginally higher than the probability of Type I resolution of 24.6% and 3.3% under high and low regional distress respectively, depicted in Figure 2. Correspondingly, the average probability of Type II resolutions under banking and regional distress was 69.3%, which was lower than the equivalent probability under regional distress at 72.1%. Liquidations under Type III resolutions remained largely unchanged with probabilities of 3.9% and 3.2% respectively under classes based on high regional and banking distress and solely regional distress. The inclusion of measures of banking distress to indicators of regional distress from Section 6.1.1 primarily resulted in substitutions between Type I and II resolutions. Overall, the densities based on the two models show that measures of regional distress continue to be the most important determinants of heterogeneity in the FDIC's decision rules and that measures of bank

Table 5: Covariate effects from class-membership models for specifications of latent classes based on regional and banking industry distress.

	(5)	(6)	(7)	**(8)**	(9)	(10)
State-level characteristics						
Unemployment	-	-	-	**-0.07 (0.04)**	-0.08 (0.04)	-0.1 (0.05)
County-level characteristics						
Housing starts	-	-	-	**0.03 (0.05)**	0.04 (0.05)	0.06 (0.06)
Per capita GDP growth	-	-	-	**0.04 (0.05)**	0.04 (0.05)	0.07 (0.06)
Farm, agri, mining	-	-	-	**0.03 (0.04)**	0.04 (0.04)	0.06 (0.05)
Banking industry characteristics						
Previous closures	-0.08 (0.08)	-0.07 (0.06)	-0.08 (0.07)	**-0.02 (0.01)**	-0.02 (0.01)	-0.01 (0.02)
% Assets in distressed banks	-0.03 (0.04)	-	-	**-0.03 (0.02)**	-	-
% Dep. in distressed banks	-	-0.03 (0.02)	-	-	-0.03 (0.02)	-
% distressed banks	-	-	-0.01 (0.01)	-	-	-0.02 (0.03)
Insurer characteristics						
Dep. Ins. Fund/ Total Dep.	-	-	-	**-0.05 (0.03)**	-0.05 (0.03)	-0.05 (0.04)
log Marginal Likelihood	-719.29	-705.30	-719.14	**-697.22**	-697.78	-701.21

Note: The reported values are posterior means of the covariate effects. Posterior standard deviations are in parantheses.

distress marginally augment the separation across the two classes.

The current results provide new insights into the resolution decisions of the FDIC in the presence of regional and banking industry distress. In a previous study by Bennett and Unal (2014), the authors also found empirical support for an "industry distress" hypothesis based on the theoretical models in Shleifer and Vishny (2011, 1992). Their results showed that periods of banking crises resulted in impediments to liquidations, which in turn led to the FDIC choosing private sector reorganizations (Type II resolutions) over liquidations (Type III resolutions) even if the former entailed a higher cost. The authors did not consider the decision to provide Type I resolutions as these transactions did not result in a receivership, which provided measures of the primary outcome of interest in their study, FDIC losses. I find that, additionally, in the presence of banking crises along with regional distress, the FDIC marginally shifted the mix of resolutions away from Type II resolutions toward Type I resolutions. These findings show that banking industry distress in addition to regional distress likely contributed to a "too-many-to-fail" response from the FDIC in line with predictions from the theoretical literature (Acharya and Yorulmazer, 2007).

6.3 Political Economy Factors

This subsection addresses constraints to the FDIC's decision-making in the form of political pressures to provide Type I resolutions represented by Hypothesis H_3. The following model specifications thereby examine this hypothesis, which is based on theoretical studies of regulatory capture (Stigler, 1971) and political pressures on resolution decisions (DeYoung et al., 2013) as well as empirical studies pertaining to political factors underlying the 2008 crisis and bailouts (Duchin and Sosyura, 2012; Igan et al., 2012). I find that political factors played a limited role in the FDIC's decisions as the average probability of Type I assistance to banks increased marginally from 24.6% amid economic distress to 26.5% in the presence of political support and economic distress.

The role of political economy considerations in the FDIC's resolution decisions during the 1980's has not been examined in detail in previous studies. The immediate reason for the sparse attention to this question in previous periods is that data on lobbying did not become available until after the Lobbying Disclosure Act of 1995. I address the paucity of data on direct measures of lobbying in two ways. First, I measure political support for financial institutions by way of the percentage of Congressional representatives from each state who voted for a bill that is favorable to the banking or S&L industry. This approach recognizes votes in favor of legislation that benefits the banking industry as indicative of lobbying efforts by the industry, which is consistent with the theoretical model of Becker (1983) in which pressure groups compete for political favors. This approach also follows from Kroszner and Strahan (1999) and Economides et al. (1996), who provide evidence of private interest groups influencing the voting behavior of elected representatives on legislation pertaining to the banking industry. Second, I include the measures of congressional voting in the class membership model that classifies banks into groups that are subject to different decision rules rather than in the model for resolution types. Consequently, instead of associating political support with the resolution method applied on specific banks, this specification suggests that such support is likely to have influenced the FDIC to adopt an overall stance that is more likely to result in assistance.

Since votes in favor of the banking industry are also likely to represent the special concerns that the elected representatives may have for the banking industry in their constituency if it is particularly distressed, measures of voting behavior potentially provide information on the condition of the industry in each state. Therefore, the classes arising from the specifications in this section represent distinct levels of "political support" instead of construing them to purely represent "regulatory capture".

The model specifications in Table 6 consist of voting measures on bills that pertain to the regulation of the banking and S&L industry and in some cases, directly concern specific issues relating to the resolution of failed banks. The variables that measure percentage of votes in favor of a bill are based on the definition in Economides et al. (1996) and exclude representatives who did not vote. Moreover, in keeping with their specification, I also include the percentage of Republicans in each state as a covariate to ascertain that voting was not determined entirely by party affiliation. The comparison of values of log marginal likelihood reveals that the data favor specifications that include measures of regional distress over those that only generate latent classes based on political economy factors. In particular, specification (17), which has the largest marginal likelihood and thereby, the highest posterior odds relative to the remaining specifications records statistically important negative covariate effects for both state-level unemployment and the percentage of votes for the S&L restructuring bill. The bill to restructure the S&L industry recommended that the FDIC insure deposits held at S&L institutions in addition to commercial banks following the failure of the FSLIC. Literature on voting suggests that this bill would have elicited votes from representatives who were potentially lobbied by the beneficiaries of these bills. Institutions at risk of failure in the S&L industries would have likely benefited from and lobbied for this bill as the expanded role of the FDIC would have increased their ability to obtain assistance and function as going concerns. As a result latent class 1 will be labeled as the class of failures under "High Regional Distress and Political Support (HRDP)" and latent class 2, as the class of failures under "Low Regional Distress and / or Political Support (LRDP)".

Table 6: Covariate effects from class-membership models for specifications of latent classes based on regional distress and political support.

	(11)	(12)	(13)	(14)	(15)	(16)	**(17)**	(18)	(19)	(20)
State-level characteristics										
Unemployment	-	-	-	-	-	-0.04 (0.02)	**-0.13 (0.04)**	-0.09 (0.05)	-0.1 (0.05)	-0.06 (0.03)
County-level characteristics										
Housing starts	-	-	-	-	-	-0.06 (0.03)	**-0.05 (0.04)**	0.07 (0.08)	0.03 (0.09)	-0.04 (0.08)
Per capita GDP growth	-	-	-	-	-	-0.01 (0.03)	**0.00 (0.04)**	0.04 (0.05)	0.02 (0.05)	0.03 (0.05)
Farm, agri, mining	-	-	-	-	-	0.07 (0.04)	**0.09 (0.05)**	0.05 (0.05)	0.06 (0.04)	0.08 (0.06)
Insurer characteristics										
Dep. Ins. Fund/ Total Deposits	-	-	-	-	-	-0.03 (0.03)	**-0.05 (0.03)**	-0.04 (0.04)	-0.05 (0.04)	-0.02 (0.03)
Political economy characteristics										
% vote for CEBA	-0.01 (0.01)	-	-	-	-	-0.09 (0.02)	-	-	-	-
% vote for recommitting S&L restructuring bill	-	-0.02 (0.01)	-	-	-	-	**-0.14 (0.03)**	-	-	-
% vote for restoring civil penalties for criminal offenses involving financial institutions	-	-	0.01 (0.01)	-	-	-	-	-0.03 (0.04)	-	-
% vote for recapitalizing federal deposit insurance and enhancing powers of federal regulatory agencies	-	-	-	0.01 (0.01)	-	-	-	-	-0.05 (0.06)	-
% vote for requiring reg. agencies to disclose CRA ratings given to banks and thrifts	-	-	-	-	0.01 (0.02)	-	-	-	-	0.21 (0.11)
% Republicans	0.01 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.00)	-0.01 (0.01)	0.05 (0.09)	**0.12 (0.05)**	0.03 (0.06)	0 (0.08)	0.2 (0.11)
log Marginal Likelihood	-714.54	-701.29	-706.70	-716.31	-699.83	-698.29	**-693.68**	-705.50	-700.32	-704.52

Note: The reported values are posterior means of the covariate effects. Posterior standard deviations are in parantheses.

Figure 4 plots the posterior distribution of the probability of the FDIC assigning each resolution method to banks in the two latent classes defined by regional distress and political economy factors in specification (17). The distributions reveal that in the presence of political support to the banking industry and high regional distress, the average probability of a Type I, Type II and Type III resolution is 26.5%, 69.7% and 3.8% respectively. On comparing these average probabilities with the equivalent values of 24.6%, 72.1% and 3.2% among bank failures that occurred amid high regional distress represented in Figure 2, we find that political support for the banking industry resulted in marginally higher probability of the FDIC assigning a Type I resolution during economic distress.

The details underlying the bills in the remaining specifications are provided in Appendix 10.11.

7 Savings and Loans Resolution by FSLIC

The S&L industry underwent a more severe crisis than the banking industry in the period leading up to 1989. At the peak of the crisis in 1989, 8.9% of operating S&L institutions that held 9.5% of industry deposits failed. This compares with 2.1% of banks that failed at the peak of the banking crisis in 1988, comprising 1.7% of total bank deposits.[9] S&L institutions were comparable to commercial banks in terms of the products they offered during this period. Deregulation in the early 1980's had permitted S&L's to diversify beyond their traditional business of providing fixed rate mortgages and foray into commercial and real-estate loans that had been routinely serviced by commercial banks. The legislation also specified weaker standards for S&L's to offer these loans relative to those that applied to banks.[10] When real estate and oil prices dropped precipitously in 1984-85, a wave of failures took place among S&L institutions that had accumulated large shares of these nontraditional loans. The period under study in this paper covers the failures that occurred over 1984-1989. The industry had also undergone an earlier wave of failures in the early 1980's. The rising interest rates preceding that period led to sharp increases in costs of deposit funds but substantially lower revenue increases on their assets that predominantly comprised of 30-year fixed-rate mortgage loans. Indeed, the deregulation and regulatory forbearance that followed in the industry was a direct policy response to these earlier failures. Section 10.12 provides an overview of the history

[9] Computations based on Historical Bank Data on https://banks.data.fdic.gov/

[10] The Depository Institutions Deregulation and Monetary Control Act of 1980 (DIDMCA) and the Garn-St Germain Depository Institutions Act of 1982 allowed S&L's to diversify their portfolio by permitting federally chartered institutions to lend acquisition, development, and construction (ADC) loans and also authorized these institutions to offer Adjustable Rate Mortgages (ARM's). The legislation also included provisions for regulatory relief in the form of lowered net worth standards and capital requirements including even the elimination of loan-to-value restrictions on ADC loans.

of the crisis in the S&L industry and distinguishes between the two waves of S&L failures.

The Federal Savings and Loans Insurance Corporation (FSLIC) insured S&L's and served as a receiver for failed institutions, both of which were functions the FDIC performed within the banking industry. The FSLIC, however, was ultimately dissolved following unsustainable resolution losses that resulted in its insolvency in 1989. This section compares the decision rules of the FSLIC against theoretical rules summarized in Section 3.To compare the FDIC with the FSLIC, I analyze their decisions through the same empirical lens. Accordingly, in this Section, I estimate the specifications in Section 6 for FDIC decisions.

7.1 Regional Distress

The FSLIC's designation of S&L institutions into classes based on regional distress is found to be ambiguous and does not support Hypothesis H_1. Table 7 summarizes the covariate effects from estimating the specifications reported in Section 6.1, on S&L resolutions by the FSLIC.

Specification ($3^{\dagger}$) is determined to be the model selected by the data by virtue of its marginal likelihood being the largest among candidate models. The covariate effects for unemployment, per capita income and housing starts in this specification are, however, not statistically important. Accordingly, the latent classes generated by this model cannot be distinguished as representing "high" or "low" regional distress and are labeled as "Regional Distress Class 1" and "Regional Distress Class 2".

Figure 6 shows the posterior densities for the probability of the FSLIC assigning each resolution method to S&L's in the two latent classes. These densities offer two main insights into the decisions of the FSLIC. First, on comparing with Figure 2, it is clear that the FSLIC relied more heavily on Type I resolutions relative to the FDIC. The average probabilities of the FSLIC assigning a Type I resolution were 67.5 % and 69.6% in class 1 and 2 compared with probabilities of 24.6 % and 3.3% of the FDIC assisting banks that failed in high and low regional distress respectively. Second, the FSLIC recognizably deviated from the optimal resolution strategy developed in Cordella and Yeyati (2003) since the posterior densities for the two classes overlap across all three resolution methods. Accordingly, the average probabilities of receiving a Type I resolution are not statistically different across the two classes. This finding signifies that the FSLIC did not distinguish between institutions that failed amid high and low economic distress in assigning Type I assistance.

The box plots for covariate effects from specification ($3^{\dagger}$) in Figure 9 show that the FSLIC adopted a common decision rule in resolving institutions in the two classes. The covariate effects of S&L financial characteristics are homogeneous across the two latent classes. This contrasts with the covariate effects on the FDIC's responses in Figure 5, which are statistically different across the classes of banks that failed amid high and low regional distress. In both latent classes in the FSLIC's decision structure, a standard deviation increase in Real Estate Loan Ratio is seen to result in an average decline of around 7% in the probability of receiving a Type I resolution and a corresponding increase in the probability of receiving the other two resolution methods. Since S&L's were primarily engaged in providing retail mortgages, which were a sub-category of real estate loans, the latter asset class featured prominently in the books of all S&L's and on average represented 95% of the assets of these institutions. It is notable that the covariate effect of this loan category is statistically important despite high concentrations in real estate being typical of the industry. This finding suggests that the FSLIC likely viewed institutions with excessive concentrations of real estate loans as ineligible to operate as going concerns since the market value of these assets would have been adversely affected by the collapse in real estate prices during this period.

Overall, the FSLIC's decision rules do not demonstrate explicit reliance on covariates that represent the financial strength of S&L's. This suggests that the agency undertook resolution decisions on a case-by-case basis rather than by adopting a consistent data-driven rule. Loan Loss Reserve Ratio and Interstate branching are the other two covariates with statistically important effects on the FSLIC's choice of resolution method relative to the remaining covariates in the model. The FSLIC facilitated the acquisition or liquidated institutions with larger loan loss reserves with a greater probability than it provided Type I assistance to such institutions. This response is similar to the FDIC's response to larger loss reserves in the class of banks that failed amid low regional distress. This suggests that the FSLIC, like the FDIC in this class of banks, viewed larger loss reserves as a signal of greater deterioration in the asset quality of the failed institution. The FSLIC also assigned Type I assistance to a greater extent in states where interstate branching was permitted for S&L's in class 1. Interstate branching during the period under study pertains only to the deregulation within the banking industry as the S&L industry was not subject to interstate branching restrictions (Roster, 1985). The deregulation of interstate branching for banks entailed increased competition in local markets for S&L's operating in these regions. The FSLIC's assistance to S&L's in regions where branching was deregulated potentially reflected liquidity support to overcome the greater competition from the banking industry.

The FSLIC's decisions deviated from the decision structure implied by Hypothesis H_1 in two ways. First, the agency did not develop distinct decision rules to resolve failures that occurred amid high and low regional distress and is observed to have adopted a common decision rule for both groups of S&L's. Second, the decision rule that the FSLIC implemented did not unambiguously select financially healthier institutions for the provision of Type I resolutions. The theory underlying this hypothesis suggests that by not fully disentangling economic and idiosyncratic factors while providing assistance, the FSLIC potentially fostered moral hazard among S&L institutions.

Table 7: Covariate effects from class-membership models of S&L's for specifications of latent classes based on regional distress.

	(1†)	(2†)	(3†)	(4†)
State-level characteristics				
Unemployment	-0.08 (0.06)	-0.71 (0.14)	**-0.17 (0.48)**	-0.72 (0.11)
County-level characteristics				
Housing starts	-0.21 (0.1)	-0.01 (0.04)	**-0.03 (0.09)**	-0.02 (0.04)
Per capita GDP growth	-0.13 (0.09)	0.02 (0.06)	**0.00 (0.09)**	0.01 (0.05)
Farm, agri, mining	-0.09 (0.08)	0.04 (0.04)	**-0.01 (0.09)**	0.04 (0.03)
Manufacturing	0 (0.07)	-	-	-
Construction	0.09 (0.05)	-	-	-
Fin Serv Transport	-0.11 (0.12)	-	-	-
Government	-0.16 (0.1)	-	-	-
Insurer characteristics				
Dep. Ins. Fund/Total Dep.	-	-	**0.01 (0.08)**	-
S&L-level characteristics				
State charter	-	-	-	-0.07 (0.15)
log Marginal Likelihood	-302.32	-305.40	**-302.02**	-305.44

Note: The reported values are posterior means of the covariate effects. Posterior standard deviations are in parantheses.

7.2 S&L Industry Distress

The FSLIC's resolution decisions do not support Hypothesis H_2. This hypothesis entails assigning the preponderance of Type I resolutions to S&L institutions that failed in the presence of distress in the S&L industry. The FSLIC did not distinguish between institutions that failed amid elevated levels of distress in the industry from those that failed in more benign industry conditions in assigning resolution decisions. As a result, the probability of the FSLIC assigning a Type I resolution was not statistically different across the two groups of S&L's.

Table 8 reports the covariate effects and log marginal likelihood from specifications ($5^\dagger$) through ($7^\dagger$) that are exclusively based on measures of distress in the S&L industry as well as from ($8^\dagger$) through ($10^\dagger$), which augment the specifications based on industry distress with measures of regional distress. The definition of a distressed S&L in the specifications reported in the table is an institution whose Texas ratio exceeded 100% and is consistent with the definition of distressed banks in Section 6.2.

Bayesian model comparison identifies specification ($8^\dagger$) as the selected model since it exhibits the highest marginal likelihood, and consequently the largest posterior odds relative to other specifications. However, neither the covariates pertaining to industry distress, namely, previous closures and the percentage of assets in distressed institutions, nor the measures of regional economic performance such as unemployment, housing starts and per capita income growth are statistically important in this specification. The two

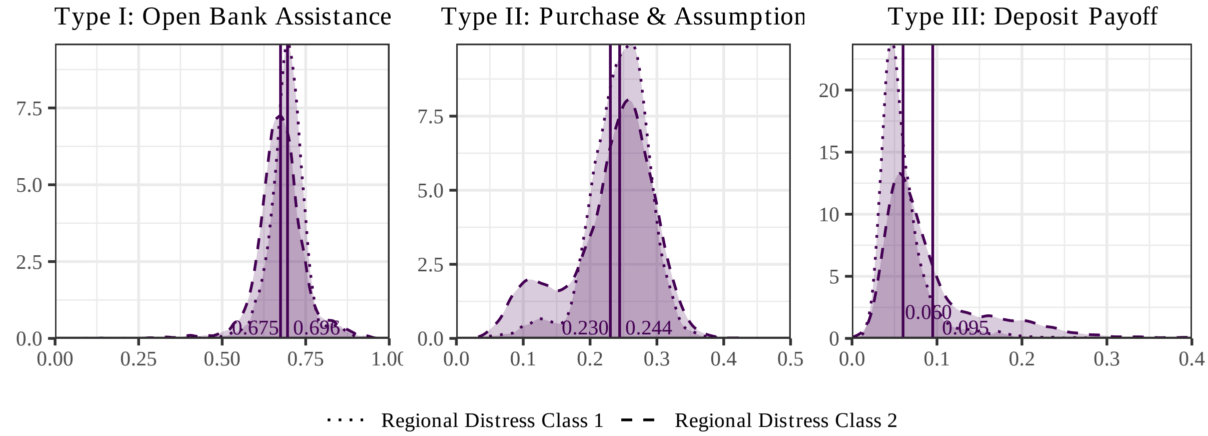

Figure 6: Probability of the FSLIC assigning each resolution method within classes based on regional distress.

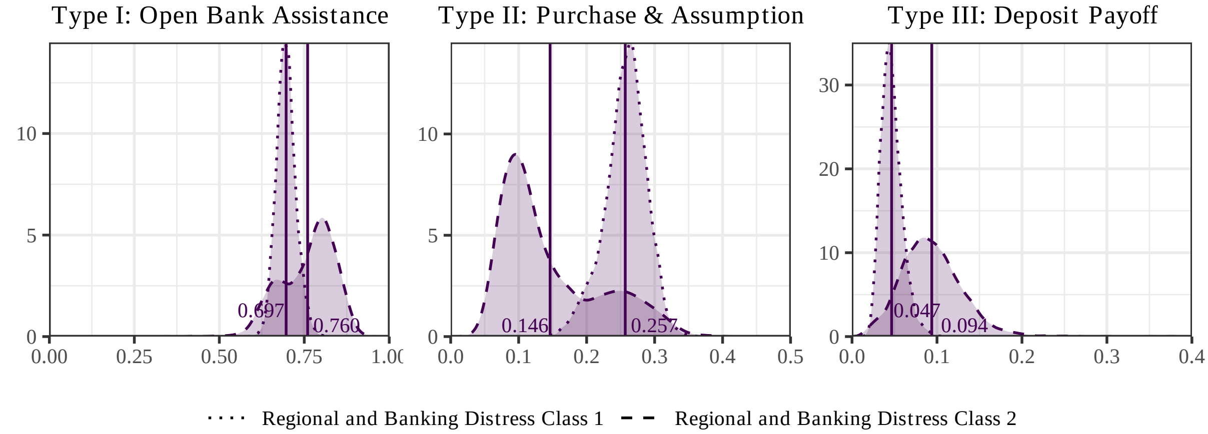

Figure 7: Probability of the FSLIC assigning each resolution method within classes based on regional and S&L industry distress.

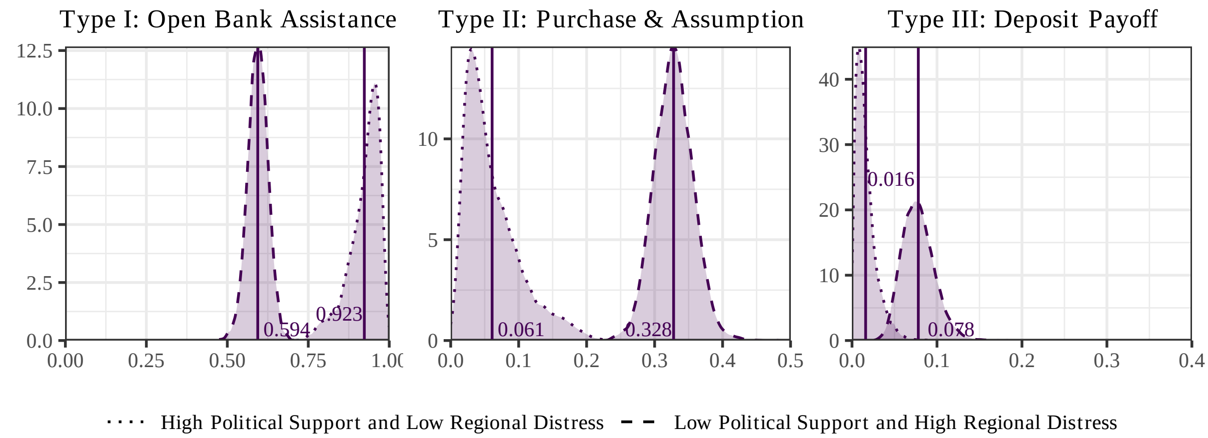

Figure 8: Probability of the FSLIC assigning each resolution method within classes based on regional distress and political economy factors. NOTE: In all three figures, the horizontal axis represents the probability of assigning a resolution method and the vertical axis represents the posterior density associated with that probability based on a kernel density estimate.

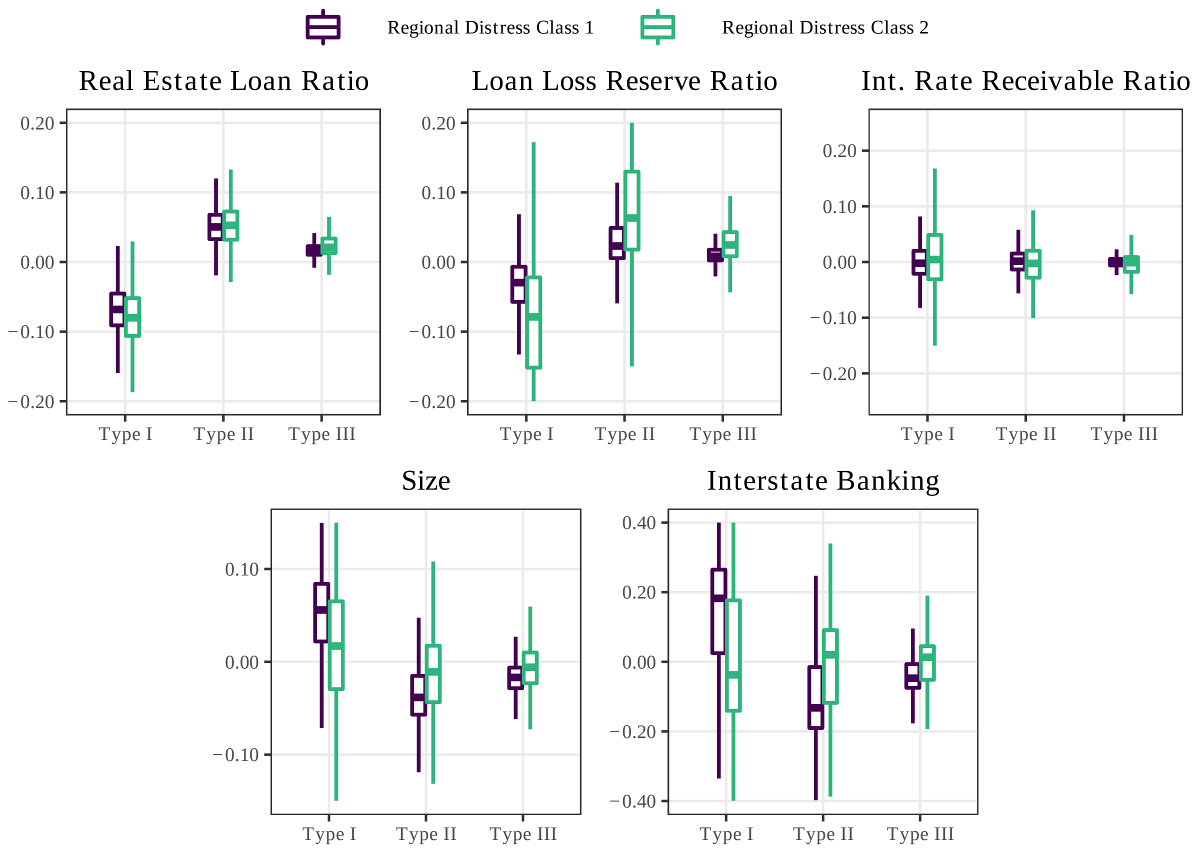

Figure 9: Covariate effects from the models for resolution type for S&L's in the classes based on regional distress.

latent classes do not necessarily represent differences based on local economic or S&L industry characteristics. Accordingly, the two classes are labeled as "Regional and Banking Distress Class 1" and "Regional and Banking Distress Class 2".

In Figure 7, we find that the average probability of the FSLIC assigning a Type I resolution are 69% and 76% in latent classes 1 and 2 respectively. However, the average probabilities of a Type I resolution are not statistically different across the two classes. The posterior densities of the probability of the FSLIC selecting a Type I resolution across the two classes are observed to overlap. The average probability of a Type II resolution is 25.7% in class 1 and 14.6% in class 2. Despite lesser overlap across the two densities for Type II resolutions relative to Type I resolutions, the average probabilities of the FSLIC assigning a Type II resolution are not statistically different across the two classes of S&L's. Finally, the posterior densities of the probability of a Type III resolution entirely overlap in classes 1 and 2 with averages of 4.7% and 9.4% respectively and are thereby not statistically different from each other.

One of the implications of the theory from (Acharya and Yorulmazer, 2007) on which Hypothesis H_2 is based is that the probability of Type II resolutions are likely to be statistically different across classes of institutions that failed in high and low industry distress. According to this theoretical model, widespread distress in the S&L industry stymies the demand for failed S&L's, which results in fewer Type II resolutions and thereby creates the necessity for assistance in the form of Type I resolutions. Since the two latent classes are not explicitly based on industry distress, the FSLIC's resolution decisions are not consistent with this effect of S&L industry distress and thereby do not support any of the implications of Hypothesis H_2.

7.3 Political Economy Factors

The FSLIC's resolution decisions support Hypothesis H_3, which states that the agency was more likely to assign Type I assistance to institutions that received political support. The previous sub-sections showed that the FSLIC's probability of assigning each resolution method did not statistically differ across groups of institutions that failed in varying levels of regional or industry distress. Among institutions that failed in the presence of political support, however, the probability of receiving a Type I resolution was statistically higher relative to institutions that failed in the absence of such support.

The specifications relating to H_3 include measures of congressional voting on bills relating to the banking and S&L industry in line with the specifications developed in Section 6.3. The estimation of latent class models for S&L resolutions is constrained by the presence of only 16 Type III resolutions as depicted in the data summaries in Section 5 and therefore a subset of specifications are estimable. The measures of voting in the evaluated this section are interpreted to represent both, lobbying by the two industries as well as the elected representatives' concern for the health of financial institutions in their constituencies. A range of studies pertaining to the Savings and Loans crisis (Lowy, 1991; Mason, 2004) detailed the widespread lobbying efforts of both, the trade association of S&L's viz., the U.S. League as well as individual institutions, toward influencing elected representatives on legislation that affected the regulation of the industry. However, the extent to which the FSLIC's decisions were persuaded by such lobbying ventures has not been evaluated.[11] I find that political economy factors played a prominent role in the decisions of the FSLIC to provide not only Type I assistance but also facilitate acquisitions and liquidate institutions under resolution Types II and III respectively.

In Table 9, the selected model is specification ($18^{\dagger}$) by virtue of its larger marginal likelihood relative to all other specifications. This model determines latent classes based on the percent of votes in favor of a bill to reform the federal deposit insurance sys-

[11] A particularly well-known instance of lobbying by an S&L institution that was undertaken with the specific intent to influence regulatory actions is the case of the Keating Five, named after Charles Keating, the owner of the California-based Lincoln S&L Association. In 1987, Keating had enlisted five senators to whose campaigns he had contributed to advocate for the relaxation of the FHLBB's rules on direct investment in real estate and the suspension of the examination of his organization. However, the regulators from the San Francisco office of the FHLBB who had met with the five senators upheld their position and recommended strong action against the S&L. This incident illustrates a broader theme pertaining to the S&L industry - while there was evidence of the presence of political influence in S&L regulation, the effects of such influence were indeterminate.

tem and to restore civil penalties for criminal offenses involving financial institutions.[12] Accordingly, votes against the bill represent political support for the S&L industry as the legislation provided for alternative mechanisms to penalize fraudulent practices by financial institutions. The covariate effects for per capita income growth, the percent vote in favor of the bill restoring civil penalties and the control for the share of Republican representatives are statistically important in the selected model. Since latent class 2 consists of institutions that failed in counties with a high per capita income growth and a low share of votes in favor of the bill, this class is labeled as "High Political Support and Low Regional Distress" and latent class 1 is the class of "Low Political Support and High Regional Distress".

Figure 8 plots the posterior density of the probability of receiving each resolution method under specifications ($18^{\dagger}$). Where previously, the densities in Figures 6 and 7 overlapped considerably, the inclusion of measures of political support notably generates distinct latent classes with minimal overlap. This shows that the difference between the classes of S&L's that failed in the presence of high regional distress and low political support, and those that failed in a climate of low regional distress but high degree of political support is statistically important. The FSLIC assigned Type I resolutions to institutions that failed in regions with high political support but low regional distress with average probability of 92.3% and to institutions that failed in high regional distress and low political support with a probability of 59.4%. This finding suggests that political support outweighed the effects of economic forces in determining the eligibility of failed S&L's for assistance. The probabilities of Types II and III resolution for S&L's that failed in the presence of political support and low levels of regional distress was 6.1% and 1.6% respectively. In the presence of regional distress and low level of political support, the FSLIC assigned Type II and III resolutions with a probability of 32.8% and 7.8% respectively. Overall, the FSLIC not only favored the assignment of assistance to institutions in regions with political support, the agency was also less likely to liquidate such institutions under Type III resolutions.

The FSLIC's resolution decisions were more likely to have been driven by political factors as predicted by Hypothesis H_3 rather than by the extent of economic or industry distress accompanying the failure of S&L's. Political support is measured by the share of votes in favor of legislation that affected the banking and S&L industries. Previous literature (Becker, 1983; Economides et al., 1996; Kroszner and Strahan, 1999) suggests that voting measures reveal underlying lobbying by interest groups and the potential for regulatory capture. However, in the absence of lobbying data from this period, vote

[12] This provision of FIRREA was used to force settlements against large financial institutions during the Global Financial Crisis of 2008-90. See https://scholarship.law.upenn.edu/cgi/viewcontent.cgi?article=1502&context=jbl

Table 8: Covariate effects from class-membership models for specifications of latent classes based on regional and S&L industry distress

	($5^{\dagger}$)	($6^{\dagger}$)	($7^{\dagger}$)	($8^{\dagger}$)	**($9^{\dagger}$)**	($10^{\dagger}$)
State-level characteristics						
Unemployment	-	-	-	**-0.19 (0.23)**	0.06 (0.05)	0.03 (0.09)
County-level characteristics						
Housing starts	-	-	-	**-0.08 (0.08)**	0.10 (0.07)	0.07 (0.1)
Per capita GDP growth	-	-	-	**-0.10 (0.09)**	0.13 (0.07)	0.17 (0.1)
Farm, agri, mining	-	-	-	**-0.05 (0.07)**	0.06 (0.05)	0.04 (0.05)
S&L industry characteristics						
Previous closures	0.12 (0.18)	0.11 (0.18)	0.07 (0.12)	**-0.03 (0.07)**	0.03 (0.08)	0.03 (0.05)
% Assets in distressed S&L's	-0.01 (0.1)	-	-	**0.02 (0.07)**	-	-
% Dep. in distressed S&L's	-	-0.02 (0.09)	-	-	-0.05 (0.02)	-
% distressed S&L's	-	-	-0.02 (0.08)	-	-	-0.09 (0.08)
Insurer characteristics						
Dep. Ins. Fund/ Total Dep.	-	-	-	**0.03 (0.05)**	**-0.03 (0.02)**	-0.01 (0.06)
log Marginal Likelihood	-301.40	-300.83	-300.95	**-297.15**	-300.69	-300.33

Note: The reported values are posterior means of the covariate effects. Posterior standard deviations are in parantheses.

Table 9: Covariate effects from class-membership models of S&L's for specifications of latent classes based on regional distress and political support

	($12^{\dagger}$)	($13^{\dagger}$)	**($14^{\dagger}$)**	($16^{\dagger}$)	($17^{\dagger}$)	($18^{\dagger}$)	($19^{\dagger}$)	($20^{\dagger}$)
State-level characteristics								
Unemployment	-	-	-	-0.16 (0.13)	-0.12 (0.07)	**-0.03 (0.06)**	-0.02 (0.06)	-0.2 (0.14)
County-level characteristics								
Housing starts	-	-	-	-0.03 (0.09)	0.04 (0.07)	**0.03 (0.07)**	0.03 (0.07)	0.01 (0.08)
Per capita GDP growth	-	-	-	0.13 (0.12)	0.06 (0.06)	**0.21 (0.10)**	0.08 (0.1)	0.07 (0.09)
Farm, agri, mining	-	-	-	0.03 (0.07)	-0.02 (0.04)	**-0.04 (0.05)**	-0.02 (0.06)	0.01 (0.05)
Insurer characteristics								
Dep. Ins. Fund/ Total Deposits	-	-	-	0.00 (0.07)	-0.09 (0.06)	**-0.04 (0.06)**	0.03 (0.05)	0.09 (0.07)
% vote for CEBA	-	-	-	-0.22 (0.12)	-	-	-	-
% vote for Recommitting S&L restructuring bill	0.36 (0.22)	-	-	-	0.36 (0.11)	-	-	-
% vote for restoring civil penalties for criminal offenses involving financial institutions	-	-0.25 (0.1)	-	-	-	**-0.14 (0.05)**	-	-
% vote for recapitalizing federal deposit insurance and enhancing powers of federal regulatory agencies	-	-	-0.36 (0.09)	-	-	-	-0.25 (0.1)	-
% vote for requiring reg. agencies to disclose CRA ratings given to banks and thrifts	-	-	-	-	-	-	-	0.25 (0.08)
% Republicans	0.08 (0.15)	0.24 (0.13)	0.3 (0.09)	0.18 (0.11)	0.16 (0.04)	**0.26 (0.08)**	0.2 (0.09)	0.05 (0.08)
log Marginal Likelihood	-299.08	-294.01	-300.04	-301.15	-297.52	**-288.06**	-299.10	-300.40

shares for legislation favoring banks and S&L's are broadly interpreted to represent the support of political representatives for these industries either due to lobbying or concerns for the health of institutions. Under either interpretation, the FSLIC deviated from hypotheses H_1 and H_2 that address moral hazard and financial stability concerns respectively and was likely influenced by motivations outside of these objectives.

8 Discussion and Contemporary Relevance

When the banking and S&L industries simultaneously experienced failures over 1984 - 1992 in large numbers that were unprecedented since the Great Depression, the results from Sections 6 and 7 showed that resolution authorities of each of the two industries responded in notably disparate ways. The FDIC adopted a distinct decision rule for banks that failed in regions of high distress and another for banks that failed in expansionary conditions or amid low economic distress and favored the provision of assistance transactions to healthy banks in regions of high distress, in accordance with the optimal strategy in Cordella and Yeyati (2003). The FSLIC, on the other hand, did not distinguish across failures by the extent of their exposure to regional distress, and thereby deviated from this optimal strategy. These deviations acquire heightened significance since the agency subsequently failed at a cost of $ 132 billion to the taxpayers.

Were there structural differences between the FDIC and FSLIC that contributed to these distinct resolution strategies? First, diluted standards for closing S&L institutions implied that the financial position of S&L's was more critical than that of banks at the time of failure. The FHLBB, which chartered S&L's, had less political independence than banking agencies and was required to allow institutions to operate with minimal capital (FDIC, 1998). Second, deregulation and forbearance resulted in a deeper crisis in the S&L industry than in the banking industry (9% S&L failures relative to 2% bank failures). Following deregulation in the mid-1980's, S&L's that previously operated purely within the retail loan and deposit market were permitted entry into the commercial loan market. Despite their entry into a line of business that was historically serviced by banks, capital requirements were lower for S&L's than they were for banks. This forbearance resulted in the rapid expansion of the S&L industry accompanied by augmented risk-taking, which ultimately led to widespread failures.

A regular assessment of resolution authorities by lawmakers and the public can uncover gaps between observed and optimal resolution rules and also point out the source of such gaps. Assessments of the FSLIC could have revealed the issues arising from deregulation of the S&L industry and prompted a review of the structure of the agency, preventing both, the failure of the agency and the ensuing costs to the taxpayer.

The findings on the resolution decisions of the FDIC and FSLIC point to ingrained differences in the policies and procedures of the two agencies that are relevant to the events that occurred during and after the financial crisis of 2008. Following the closure of the FHLBB and the FSLIC in the aftermath of the S&L crisis, the FDIC was entrusted with the insurance of S&L deposits and the supervision of S&L's was assigned to the newly incorporated Office of Thrift Supervision (OTS). However, the creation of a new regulatory agency did not fundamentally improve the efficiency of S&L supervision. The OTS was widely regarded as a weak regulator, particularly following the failure of Washington Mutual and Countrywide (Granja and Leuz, 2017) and was ultimately abolished under Title III of the Dodd Frank Act. The FDIC, on the other hand, survived the financial crisis of 2008 and underwent an expansion of its authority under the Orderly Liquidation Authority of the Dodd Frank Act. The agency is presently responsible for the resolution of not only banks and S&L's but any systemically important financial institution. The expanded authority of the FDIC is consistent with its institutional strengths recognized by the assessment framework developed in this paper.

9 Conclusion

During banking crises, financial regulators intervene to bail out certain failed institutions and liquidate others. Regulators are expected to meet the dual objectives of preserving financial stability and discouraging moral hazard in the process of reaching such decisions. However, they can be susceptible to principal-agent problems (Demirgüç-Kunt, 1991) and may deviate from socially optimal resolution decisions. Furthermore, as bailouts typically entail transfers from taxpayers to bank depositors and equity holders, these actions evoke public disapproval even when they are carried out in the public interest. The risk of regulatory transgressions creates a need for the public to regularly evaluate regulators' actions. Additionally, in order to mitigate biases in assessments from unduly strong subjective beliefs against public assistance, an objective framework of assessment is essential. This paper provides an empirical framework to assess agencies that resolve failed banks and to systematically determine if the agencies acted in the public interest.

An important line of inquiry in assessing the optimality of resolution decisions consists of evaluating whether regulatory agencies applied two different decision rules for bank failures amid economic distress and under normal economic conditions. Since the true classification of banks into distinct decision protocols is unobservable, I have developed a Bayesian latent class estimation framework to detect unobserved heterogeneity in the resolution outcomes of banks based on underlying economic conditions. This flexible estimation approach permits inferences on whether the decision rules across the latent classes are statistically different. Bayesian model comparison exercises predicated on posterior odds inform the selection of models that best explain the decision rules of regulatory agencies.

I utilize this modeling framework to assess the responses of the FDIC and the FSLIC to bank and S&L failures respectively during the crises of the 1980's in the two industries. This study shows that the decision rules of the FSLIC, which subsequently faced insolvency at a significant cost to taxpayers were inconsistent with optimal decision rules identified by theoretical studies. The FDIC, which survived the earlier crisis as well as the financial crisis of 2008 was found to have undertaken decisions that were consistent with optimal rules. These findings consequently validate the applicability of this approach to assess regulators. The insights from this study can potentially guide the development of resolution strategies among newer resolution agencies such as the the Single Resolution Board under the European Central Bank.

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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 Collapsed Gibbs Sampler

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 $\ln\{f(y|\alpha, \beta, \sigma^2)f(\alpha)\}$ 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,

$$P_{y_i|s} = \Phi(\frac{\gamma_{y_i,s} - x_i'\beta_s}{\sigma_s}) - \Phi(\frac{\gamma_{y_i-1,s} - x_i'\beta_s}{\sigma_s}), \quad s = 1, 2. \tag{7}$$

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 7.

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.

10.3 Full Gibbs Sampler

Algorithm: Full Gibbs Sampler

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. (a) Sample α from $\alpha|s, \beta, \sigma^2, y$.
   (b) Sample $l_i|\alpha, s$, where for $i = 1, 2, ..., n$.
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 $i = 1, 2, ..., n$.

Steps 1, 2, 4 and 5 are identical to the algorithm described in Section 4.7. Step 3 of this algorithm is described below.

Sampling coefficients of the Class Membership Model: α

(a) The coefficients of the class membership model α are sampled from the full conditional $\mathcal{N}(\hat{\alpha}, \hat{A})$ where $\hat{A} = (A_0 + W'W)^{-1}$ and $\hat{\alpha} = \hat{A}(A_0^{-1}\alpha_0 + W'l)$.

(b) The latent variable l is sampled using the data augmentation approach in Albert and Chib (1993) and drawing from the full conditional distribution, $\mathcal{TN}_{\mathcal{B}_i}(W_i'\alpha, 1)$, where

$$\mathcal{B}_i = \begin{cases} (0, \infty), & \text{if } s_i = 2 \\ (-\infty, 0] & \text{if } s_i = 1 \end{cases}$$

10.4 Simulation Study

The simulation study is based on the Collapsed Gibbs sampler and uses two parameter specifications, the first of which contains latent classes with disparate means and the other, means that overlap. The simulation exercise has been performed on a sample of 1200 observations under both specifications. These results show that estimates are more precise when there is a greater separation across latent classes.The priors in this estimation are $\alpha \sim \mathcal{N}(0, 3 \times I), \beta_s \sim \mathcal{N}(0, I)$ and $\sigma_s^2 \sim (4.3, 2.8)$ for $s = 1, 2$. Table 10 summarizes the one-standard deviation credibility intervals from the estimation of all parameters under the two specifications. The two-standard deviation credibility intervals, not shown here, contain the true values for all parameters under both specifications.

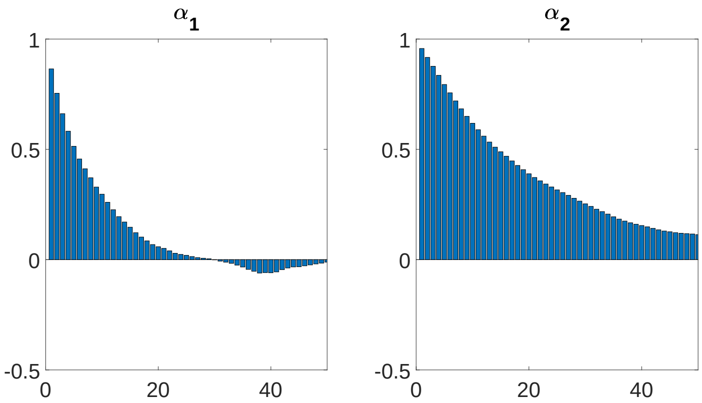

Figure 10: Autocorrelation in the posterior sample of α from a full Gibbs sampler in a simulation exercise based on a sample of 1200 observations.

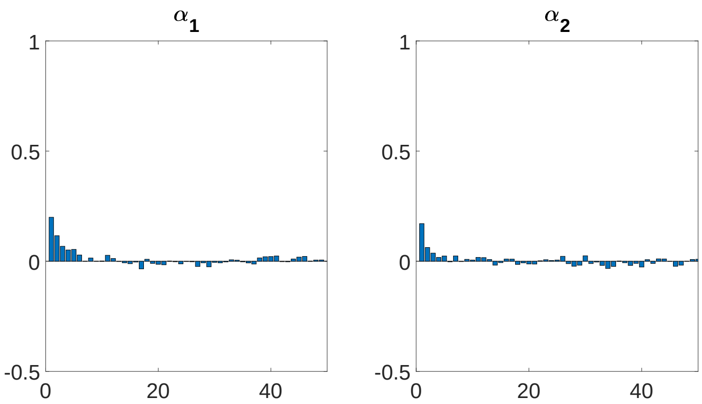

Figure 11: Autocorrelation in the posterior sample of α from the collapsed Gibbs sampler in a simulation exercise based on a sample of 1200 observations. (α_1 is the intercept and α_2 is the coefficient of the continuous covariate within the class membership model considered in the simulation exercise)

Table 10: Credibility intervals from simulation studies based on two parameter specifications

	Spec. 1: Disparate Means		Spec. 2: Common Means	
	True Values	Cred. Int.	True Values	Cred. Int.
	Class Membership			
α_1	-0.3	[-0.42,-0.26]	-0.3	[-0.50,-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,-0.60]
β_{41}	0.5	[0.48,0.58]	0.5	[0.48,0.57]
σ_1^2	0.25	[0.20,0.27]	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]

The more conservative one-standard deviation credibility intervals under specification 1 contain the true values of parameters with the exception of β_{21}, for which the credibility interval lies marginally above the true value. Under specification 2, the true values of parameters lie marginally beyond credibility intervals for α_2, β_{12} and σ_2^2. The credibility intervals are also narrower under specification 1 relative to specification 2, further demonstrating the enhanced precision of estimates under more separated classes.

The results from the simulation exercise have been corrected for label-switching using Papastamoulis (2016). This issue affects MCMC algorithms constructed for the estimation of finite mixture models and results in switching of class labels in the course of the chain. The class labels have been reassigned post-estimation using an ordering constraint on the intercept in both classes.

Simulation results based on larger sample sizes provided in Appendix 10.5 demonstrate the consistency of this estimation method.

The derivations of expressions to evaluate covariate effects are provided in Appendix 10.7.

10.5 Additional Simulation Results

Table 11: Simulation exercises for larger sample sizes demonstrate the consistency of the estimation method

	True Values	$n = 5000$	$n = 10000$	$n = 15000$	$n = 20000$	$n = 50000$
			Class Membership			
α_1	-0.4	-0.38 (0.05)	-0.43 (0.04)	-0.46 (0.03)	-0.39 (0.03)	-0.4 (0.01)
α_2	1.5	1.39 (0.07)	1.59 (0.06)	1.61 (0.05)	1.53 (0.04)	1.51 (0.02)
			Latent class 1			
β_{01}	-0.4	-0.48 (0.06)	-0.44 (0.04)	-0.38 (0.02)	-0.43 (0.03)	-0.4 (0.02)
β_{11}	-0.8	-0.77 (0.08)	-0.82 (0.05)	-0.77 (0.03)	-0.84 (0.04)	-0.78 (0.02)
β_{21}	-0.4	-0.4 (0.06)	-0.42 (0.04)	-0.33 (0.03)	-0.45 (0.04)	-0.4 (0.02)
β_{31}	0.6	0.68 (0.1)	0.62 (0.06)	0.55 (0.05)	0.63 (0.05)	0.59 (0.03)
σ_1^2	0.25	0.24 (0.04)	0.31 (0.03)	0.25 (0.02)	0.29 (0.02)	0.23 (0.01)
			Latent class 2			
β_{02}	-0.2	-0.2 (0.04)	-0.19 (0.03)	-0.21 (0.02)	-0.22 (0.02)	-0.2 (0.01)
β_{12}	0.8	0.8 (0.03)	0.82 (0.02)	0.84 (0.02)	0.8 (0.02)	0.8 (0.01)
β_{22}	-0.3	-0.26 (0.04)	-0.31 (0.02)	-0.33 (0.02)	-0.28 (0.02)	-0.31 (0.01)
β_{32}	0.9	0.89 (0.07)	0.86 (0.05)	0.89 (0.04)	0.94 (0.03)	0.89 (0.02)
σ_2^2	0.25	0.25 (0.02)	0.25 (0.01)	0.25 (0.01)	0.25 (0.01)	0.26 (0.01)

Note: The reported values are posterior means of the parameters. Posterior standard deviations are in parantheses.

10.6 Estimation of Model with cut-points

The following algorithm is based on the identification scheme used previously, viz., $\gamma_{1,s} = 0$ and $\gamma_{J-1,s} = 1$ for $s = 1, 2$. In order to ensure that the ordering of the cut-points is preserved without having to resort to the introduction of computationally intensive constraints into the estimation procedure, the following transformation proposed in **?** is used.

$$\delta_{j,s} = ln\frac{(\gamma_{j,s} - \gamma_{j-1,s})}{(1 - \gamma_{j-1,s})}, 2 \leq j \leq J-2, s = 1, 2$$

This algorithm uses an MH step to sample δ and β in one block along the lines of the examples provided in Chib and Jeliazkov (2001). A normal prior is assigned to δ_s, denoted by $f_{\mathcal{N}}(\delta|\delta_{0,s}, D_{0,s})$ for $s = 1, 2$.

10.6.1 MCMC Algorithm

Algorithm: Collapsed Gibbs Sampler for Model with cut-points

1. Sample β_s and δ_s jointly from $(\beta_s, \delta_s)|y, s, \sigma$ 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 $i = 1, 2, ..., n$.

Steps 2–5 are identical to the algorithm described in Section 4.7. Step 1 of this algorithm is described below.

Sampling coefficients and cut-points of the Ordinal Model: β and δ

Sample $(\beta_s, \delta_s)|y, s, \sigma$ by drawing $(\beta_s^\dagger, \delta_s^\dagger) \sim q(\beta_s, \delta_s|y, s, \sigma^2)$, with $q(\beta_s, \delta_s|y, s, \sigma)$ is the proposal density $f_{\mathcal{T}}(\beta_s, \delta_s|m, V, \nu)$. $m = \arg\max f(y|\beta, \delta, \sigma^2, s) f_{\mathcal{N}}(\beta_s|\beta_{0,s}, B_{0,s}) f_{\mathcal{N}}(\delta_s|\delta_{0,s}, D_{0,s})$, V is the inverse of the negative of the hessian of the logarithm of the maximand evaluated at m and ν is the degrees of freedom. The proposed draw $\theta_s^\dagger = (\beta_s^\dagger, \delta_s^\dagger)$ is accepted with probability $\Upsilon_{MH}(\theta_s, \theta_s^\dagger)$,

$$= min\Big\{1, \frac{f(y|\beta^\dagger, \delta^\dagger, \sigma^2, y) f_{\mathcal{N}}(\beta_s^\dagger|\beta_{0,s}, B_{0,s}) f_{\mathcal{N}}(\delta^\dagger|\delta_{0,s}, D_{0,s}) q(\beta_s, \delta_s|y, s, \sigma^2)}{f(y|\beta, \delta, \sigma^2, y) f_{\mathcal{N}}(\beta_s|\beta_{0,s}, B_{0,s}) f_{\mathcal{N}}(\delta|\delta_{0,s}, D_{0,s}) q(\beta_s^\dagger, \delta_s^\dagger|y, s, \sigma^2)}\Big\}.$$

10.7 Covariate Effects

An intuitive interpretation of the relationship between covariates and outcomes is provided by covariate effects in models with discrete dependent variables. Consider any covariate, $x_k \in X$, whose effects on the outcome y marginally of the other variables in X is of interest. The covariate effect measures the change in the probability of observing each category $j = 1, 2, 3$ of y for a given change in x_k, averaged over the entire sample.

The framework for computing covariate effects while addressing both data variability and parameter uncertainty described in Jeliazkov and Vossmeyer (2018) has been adapted to the latent class model for ordinal outcomes. Each of these issues is overcome by averaging over the sample and the posterior distribution of parameters respectively. Equation 8 details how the output from the MCMC algorithm developed in Subsection 4.7, which consists of G draws from the posterior distribution of parameters, is used in evaluating covariate effects for each of the two latent classes. The probabilities in the parentheses in the final step of this equation are obtained by using the expression in Equation 5. The parameter vector θ_s consists of the coefficients α, β_s and the error variance σ_s^2.

$$\begin{aligned}\Big\{Pr(y=j|x_k^{\dagger},s)-Pr(y=j|x_k^{\ddagger},s)\Big\} &= \int\Big\{Pr(y=j|x_k^{\dagger},X_{\backslash k},\theta_s)\\ &\quad -Pr(y=j|x_k^{\ddagger},X_{\backslash k},\theta_s)\Big\}f(X_{\backslash k})f(\theta_s|y)\mathrm{d}X_{\backslash k}\mathrm{d}\theta_s\\ &\approx\frac{1}{nG}\sum_{i=1}^{n}\sum_{g=1}^{G}\Big\{Pr\left(y_i=j|x_k^{\dagger},X_{i,\backslash k},\theta_s^{(g)}\right)\\ &\quad -Pr\left(y_i=j|x_k^{\ddagger},X_{i,\backslash k},\theta_s^{(g)}\right)\Big\},\ \ s=1,2.\end{aligned} \tag{8}$$

10.8 Evaluating the Marginal Likelihood

The algorithm to evaluate the estimated posterior ordinate $\hat{\pi}(\theta^*|y,\mathcal{M}_l)$ referenced in 4.8 is described below. In latent class model with ordered outcomes, the parameter vector θ, excluding any latent variables, consists of the coefficients α, β and the error variance σ^2. The objective of this exercise is to evaluate the posterior ordinate at the posterior mean, $\theta^* = \{\alpha^*, \beta^*, \sigma^{2*}\}$. The law of total probability is used to decompose the posterior ordinate at θ^* as,

$$\pi(\alpha^*, \beta^*, \sigma^{2*}|y) = \pi(\alpha^*|y)\pi(\beta^*|\alpha^*, y)\pi(\sigma^{2*}|\alpha^*, \beta^*, y)$$

The order of this decomposition has been chosen to minimize computational time and effort. The first component, $\pi(\alpha^*|y)$ is estimated using the method introduced in Chib and Jeliazkov (2001). By conditioning the other two densities on α^*, these ordinates can be estimated using reduced Gibbs samplers described in Chib (1995).

The following reduced Gibbs sampler provides the estimated ordinate $\hat{\pi}(\beta^*|\alpha^*, y)$.

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

The ordinate $\hat{\pi}(\sigma^{2*}|\alpha^*, \beta^*, y)$ is obtained by iterating over the following reduced Gibbs sampler

1. Sample σ_s^2 from $\sigma_s^2|\beta_s^*, z, S$ for $s = 1, 2$.
2. Sample s_i' from $s_i'|\alpha^*, \beta^*, \sigma^2, y$ for $i = 1, 2, ..., n$.
3. Sample z_{i,s_i} from $z_{i,s_i}|\beta^*, \sigma^2, y, S$ for $i = 1, 2, ..., n$.

10.9 Historical Bank and S&L Failures

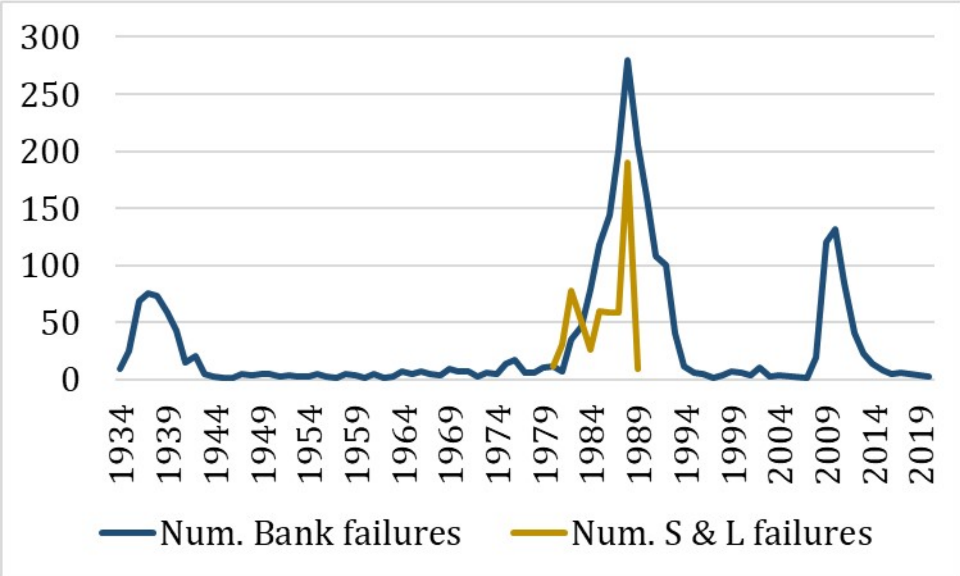

Figure 12: Number of failed banks resolved by the FDIC and number of failed S&L's resolved by the FSLIC from 1934 to 2019

10.10 Regional Distress and Bank Resolutions

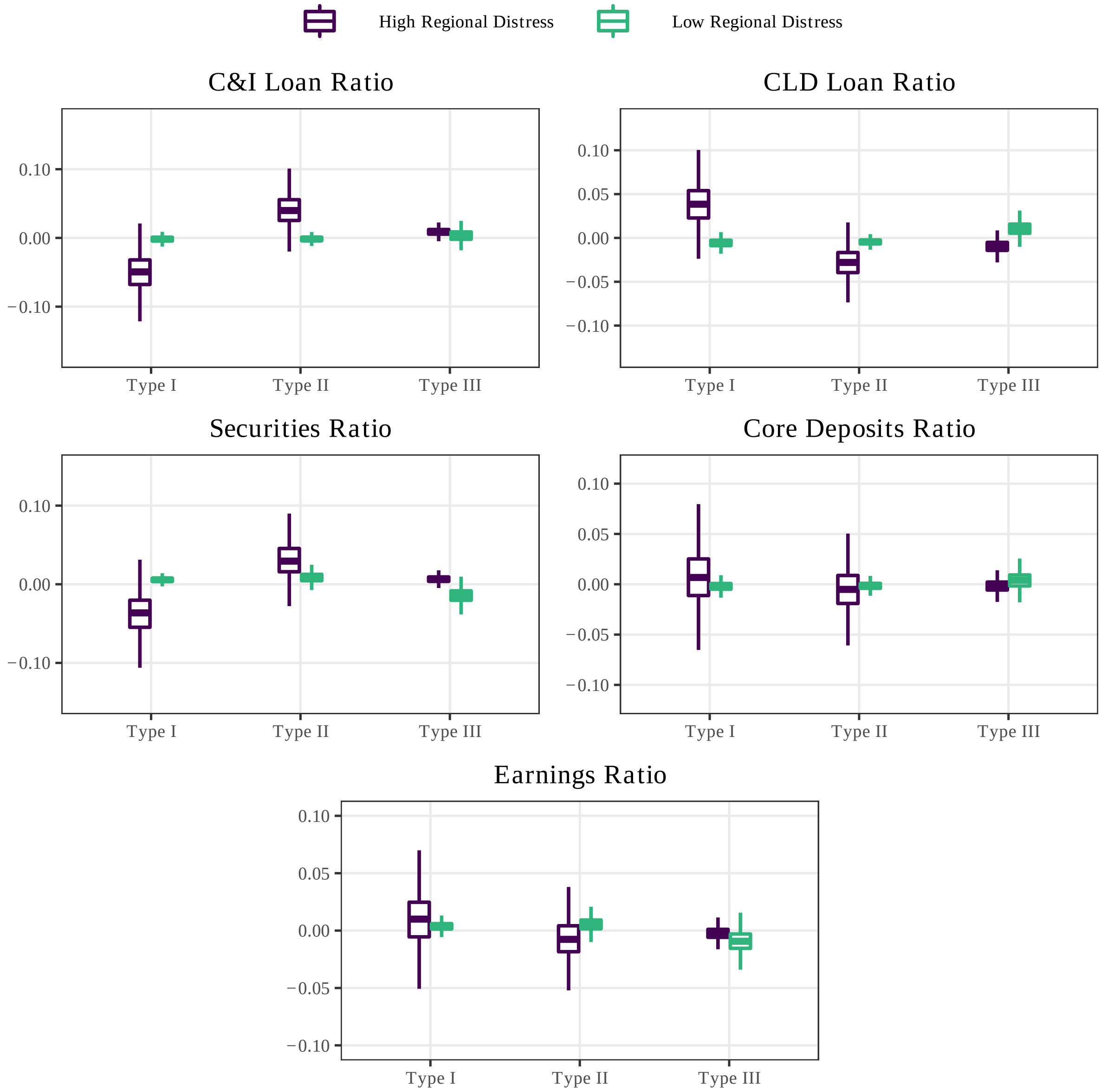

Figure 13: Additional covariate effects from the models for resolution type for banks in the class of High Regional Distress (HRD) and Low Regional Distress (LRD).

In Figure 13, a standard deviation increase in Commercial and Industrial (C&I) loan ratio is associated with an increased probability of Type II and Type III resolutions and a corresponding decline in the probability of a Type I resolution among HRD failures. These findings are consistent with the higher levels of risk attributed to increases in this ratio by the FDIC (FDIC, 1998). A standard deviation increase in Construction and Land Development Loans (CLD) is associated with an increased probability of Type I resolutions among HRD failures and of Type III resolutions among LRD failures. In the period under study, C&I loans constitute a higher concentration of bank balance sheets (27.5% of assets) than CLD loans (4.6% of assets). Accordingly, an increase in C &

I loans represents a more acute concentration in that loan category and elicits a more stringent response than an equivalent increase in CLD loans.

The remaining covariates, securities ratio, core deposits ratio and earnings ratio did not result in statistically important effects on resolution decisions upon controlling for other balance sheet items pertaining to size, asset quality and interstate branching restrictions. An increase in each of these characteristics is associated with an increase in the bank's franchise value and is accordingly expected to result in a lower probability of liquidation under Type III resolutions.

10.11 Political Economy Factors and Bank Resolutions

The Competitive Equality Bank Act (CEBA) of 1987 considered in specifications (11) and (16) 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 served as an alternative to liquidation when acquirers were not forthcoming for purchasing a bank in the period immediately following its failure (Huber, 1988)[13]. The bills considered in specifications (12) through (15) and (17) through (20) are all components of the Financial Institutions Reform, Recovery and Enforcement Act(FIRREA) of 1989. The bill to restructure the S&L industry, considered in specfications (12) and (17) recommended that the FDIC insure deposits held at S&L institutions in addition to commercial banks following the failure of the FSLIC. This bill also authorized the establishment of the Resolution Trust Corporation (RTC) to resolve failed S&L institutions that had been within the purview of the FSLIC and any additional failures that arose within the next three years. Specifications (14) and (19) include voting measures on a bill to reform, recapitalize and consolidate the federal deposit insurance system as well as to enhance the powers of federal regulatory agencies. The remaining two bills introduced additional checks on the banking industry by proposing the restoration of civil penalties for criminal offenses involving financial institutions and the disclosure of ratings assigned to banks and thrifts under the Community Reinvestment Act (CRA).

10.12 Two Waves of Failures in the Savings and Loans Industry

The origin of distress in the S&L industry in the period of study can be traced back to events from the early 1980's. The high interest rate regime of the late 1970's and early 1980's in the U.S., when the federal funds rate was set to targets as high as 20%, exposed the S&L industry to particularly severe interest rate risk owing to the regulatory constraints on these institutions. S&L institutions experienced more acute maturity

[13]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, closing the "non-bank bank loophole", and a loan-loss amortization program for agricultural banks (FDIC, 1997).

mismatches than commercial banks since their liabilities, like those of commercial banks, primarily consisted of retail deposits whereas their assets were restricted to 30 year fixed rate mortgages. The rising interest expenses on deposits and the stagnated revenues from their fixed-rate mortgages led to 35.5% of S&L institutions becoming unprofitable by year-end 1980 (White, 1991).

The legislative response to distress in the S&L industry was to deregulate and provide forbearance to weak S&L's in the form of the Depository Institutions Deregulation and Monetary Control Act of 1980 (DIDMCA) and the Garn-St Germain Depository Institutions Act of 1982. These enactments allowed S&L's to diversify their portfolio by permitting federally chartered institutions to lend acquisition, development, and construction (ADC) loans and also authorized these institutions to offer Adjustable Rate Mortgages (ARM's). However, these measures to ease asset-side constraints were supplemented with provisions for regulatory relief in the form of lowered net worth standards and capital requirements including even the elimination of loan-to-value restrictions on ADC loans. Effectively, these new provisions authorized S&L's to offer a category of high-risk loans that they had no previous experience in servicing, while being required to adhere to fewer restrictions than their banking counterparts who had a longer history of offering these loans. The opportunity for high returns with lax regulatory norms resulted in an extraordinary expansion of the industry at a growth rate of 56% between 1982 and 1985(FDIC, 1998). White (1991) noted the changing composition of S&L balance sheets following these regulatory changes with traditional mortgages declining to 53% of industry assets in 1985 from their previous values of 65% in 1982 along with a material shift toward non-traditional assets such as commercial mortgage loans, land loans and direct equity investments. A second wave of failures took over the S&L industry, particularly in the Southwest and among institutions that had accumulated large shares of these non-traditional assets starting from the period 1984-1985, when both oil and real estate prices dropped precipitously and directly contributed to the deterioration of the value of projects financed by S&L institutions.

The two waves of failures in the S&L industry and the resulting regulatory response had direct implications on the the operation of the FSLIC and eventually resulted in its insolvency and dissolution in 1989. The DIDMCA increased federal deposit insurance from $40,000 to $100,000 per account (Kaufman et al., 1981), consequentially raising the FSLIC's liabilities in the event of an S&L failure. Subsequently, the elevated levels of failure in the S&L industry depleted the resources of the FSLIC to such a dire extent that it was declared insolvent by the U.S. General Accounting Office in 1986. The Competitive Equality Banking Act of 1987 attempted to recapitalize the FSLIC by allowing it to borrow up to $10.825 billion with a cap of $3.75 billion that could be borrowed in any 12 month period. As these additional funds proved to be inadequate to resolve failed institutions, the FSLIC pursued a strategy of conducting resolutions of 222 S % L's in

1988 with minimal cash outlays by relying on promissory notes and tax reductions for acquirers. Despite these resourceful responses, the agency was faced with 250 insolvent S&L's with $80.8 billion in assets by the end of 1988. On February 6, 1989, President George H. W. Bush announced proposals for legislation governing the S&L industry and its regulating agencies that ultimately resulted in the Financial Institutions Reform, Recovery, and Enforcement Act (FIRREA). The proposals called for the dissolution of the Federal Savings and Loan Insurance Corporation (FSLIC) and its subsequent merger with the FDIC. The creation of the Resolution Trust Corporation (RTC) was proposed to resolve the pending cases of insolvent S&L's. Finally, the new legislation abolished the lead agency within which the FSLIC was instituted, the Federal Home Loan Bank Board (FHLBB) that also chartered and regulated S&L's. The Office of Thrift Supervision subsequently replaced the FHLBB in examining and supervising S&L institutions.

10.13 Regional Distress and S&L Resolutions

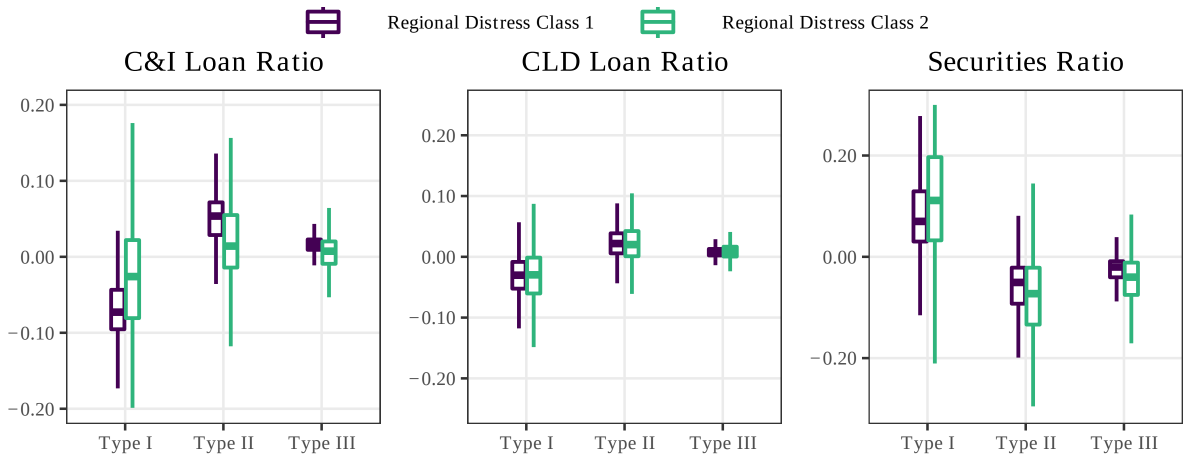

Figure 14: Additional covariate effects from the models for resolution type for S&L's in the class of High Regional Distress (HRD) and Low Regional Distress (LRD).