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Modes of Contagion in the Banking Panic of 1930

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Abstract

Throughout the 1930s bank failures were highly clustered in time and space. This suggests that financial linkages between banks and/or systematic shocks that affected many banks simultaneously played important roles in depression era banking panics. This paper uses a Bayesian hazard rate model of bank suspensions with spatial and network effects to explore modes of contagion during the banking panic of 1930 in Tennessee, Mississippi, and Alabama.

1 Introduction

During financial crises, optimal policies depend upon the nature of events. If contagion transmits illiquidity from one institution to the next, then injecting liquidity into the system can yield benefits far in excess of costs (Bernanke (1983), Diamond and Dybvig (1983), Diamond and Rajan (2005), Diamond and Rajan (2006)). In contrast, if falling asset values force institutions into insolvency, pumping liquidity into the financial system may sustain zombie banks and amplify problems. Determining whether contagion occurs is, therefore, a key for determining optimal policies and understanding historical events.

Economists studying financial crises, however, disagree about the existence and nature of contagion, even for events that have been observed by experts and studied extensively, such as the financial crisis of 2008 and the banking turmoil of the Great Depression. The Depressions initial crisis occurred during the fall of 1930, when the United States economy appeared to be recovering from the short, sharp recession following the stock market crash. It marked the point when macroeconomic time series, such as the money stock, price level, industrial production, and retail sales, began plunging toward the nadir reached two years later.

Conclusions concerning the banking crisis in the fall of 1930 fall into three schools of thought. One, the crisis occurred because the real economy contracted. Asset prices fell. Loan default rates rose. Insolvency forced banks out of business. Contagion played little or no role in event (Temin (1976), White (1984)). Two, the crisis occurred because depositors panicked. Heavy withdrawals forced banks into receivership. The Federal Reserve could have eased the crisis by acting as a lender of last resort (Friedman and Schwartz (1963), Richardson and Troost (2010)). Three, the crisis began with the failure of Caldwell and Company, the largest bank holding company in the South. The crisis initially spread through interbank networks extending from the Caldwell conglomerate. Later, runs on banks radiated from the vicinity of counterparty cascades (McFerrin (1939), Richardson (2007), Wicker (1980)).

The debate remains unresolved for several reasons. Scholars lack data about paths of contagion, such as interbank relationships and proximity to panics, and data from the balance sheets of most of the banks caught up in the crisis. Scholars have yet to employ methods that nest the various hypotheses in a single empirical framework, which can be used to see which best fits the data. Given current data and techniques, predictions of pertinent theories appear observationally equivalent, preventing scholars from distinguishing fact from fiction.

This essay relaxes those constraints. New data describe the balance sheets of all banks in three states near the center of the crisis. The data indicate where each bank operated and correspondent relationships among banks (i.e. ongoing financial interactions facilitated by deposits of funds). Documents from the archives of the Federal Reserve describe what happened to each bank during the crisis (liquidation, temporary suspension, run by depositors, etcetera) and all other changes of

status (e.g. merger, voluntary liquidation) that the banks experienced during the depression. A hazard model of bank suspensions incorporating that information enables the estimation of network and spatial effects. Network effects illuminate contagion via interbank relationships. Spatial effects illuminate contagion when depositors panic in the vicinity of banks that failed. Data on bank balance sheets and the environments in which banks operated enables us to distinguish, as far as possible, between liquidity and asset shocks.

Our econometric results indicate that contagion occurred during the initial banking crisis of the Great Depression. Contagion flowed through interbank channels, but quickly became geographic, as depositors panicked in the vicinity of institutions that failed. These shocks, on average, forced weaker banks out of business, generating a correlation between outcomes and balance-sheet characteristics such as leverage, liquidity, and net worth. Contagion explains some, but not necessarily all, of the tight clustering of failures in time and space.

Our results suggest that simple dichotomies that attribute bank failures primarily to *either* liquidity shocks *or* asset shocks are insufficiently nuanced to explain why banks failed, and why failures tended to be clustered together. Banks that were less well capitalized and/or held less liquid assets prior to the crisis did fail in larger numbers, but so did banks that were geographically proximate or had counterparty relationships to those banks. Liquidity and asset shocks interact. Panics force banks to convert assets to cash quickly and at some loss. Runs target banks that depositors believe have lost or anticipate will lose resources due to declining asset values. Depositors also act strategically, and withdraw funds from institutions when it appears that other depositors are doing so. Statistical analysis rules out some, but not all, possible scenarios. In sum, statistical evidence indicates contagion played a prominent role during the initial banking panic of the Great Depression, but given current capabilities, interpretation of the event still depends, in part, on the prior beliefs of researchers.

2 Data

2.1 Data Sources

The data examined in this analysis come from array of sources. The Rand McNally Bankers Directory describes bank balance sheets, correspondent relationships, and characteristics. Observations drawn from the July issue provide a panel of annual observations on state and national banks at their spring calls. The United States censuses of agriculture, manufacturing, and population describe the characteristics of counties. This data can be downloaded from the Inter-university Consortium for Political and Social Research (ICPSR) Study number 3. Duns Review and the Federal Reserve Bulletin time-series data on the aggregate economy.

The archives of the Federal Reserve Board provide documents describing changes in bank status. Form St. 6386b from the Division of Bank Operations reports the incidence and cause of each bank suspension. The reports distinguish between temporary and permanent suspensions. A temporary suspension occurred when a bank closed its doors to depositors for at least one business day and later resumed operations. Permanent suspensions, which we refer to as liquidations, were the subset of suspensions in which banks ceased operations, surrendered charters, and repaid creditors under the auspices of a court-appointed receiver. Form St. 6386a reports changes in bank status including voluntary liquidations and reopenings of suspended banks. Form St. 6386c reports consolidations of banks.[1]

These sources provide a panel of data consisting of all banks that operated in Alabama, Mississippi, and Tennessee between July 1929 and July 1933. The panel contains information which other scholars have used, such as bank characteristics and economic conditions, and information which scholars have not analyzed, such as potentials paths of contagion (including correspondent linkages and proximity to failed banks) and multiple measures of financial distress.

Numerous independent sources enable us to determine the dates and the nature of the banking crisis that occurred during the fall of 1930. These can be classified in three categories. The first is the Federal Reserves St. 6386 database, which indicates the dates and causes of bank suspensions. The

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[1]These records reside in Record Group 82, Central Subject File of the Federal Reserve Board of Governors, 1913-1954, National Archives and Records Administration, College Park, Maryland. For detailed descriptions of this data, see Richardson (2006, 2007a, 2007b, and 2008).

second is narrative descriptions of events reported by state banking departments in their annual reports. The third is articles in an array of publications including the four newspapers with the largest circulation in Tennessee, the Chattanooga Times, Knoxville Journal, Memphis Commercial Appeal, and Nashville Banner; the three newspapers with the largest circulation in Mississippi, the Meridian Star, Vicksburg Herald, and Vicksburg Sunday Post-Herald; leading papers from the headquarters cities of the 6th and 8th Federal Reserve Districts, the Atlanta Journal, St. Louis Globe-Democrat, and St. Louis Post-Dispatch; and national newspapers that reported on these events, including the New York Times and Wall Street Journal. We also consulted Duns Review, Bradstreets Weekly, Bankers Magazine, and the Commercial and Financial Chronicle. We accessed these periodicals and newspapers through Proquest Online, interlibrary loan, or the microfilm reading room of the Library of Congress.

2.2 The location and timing of bank suspensions

Our analysis of the banking panic of 1930 focuses on the performance of banks operating in Tennessee, Mississippi, and Alabama. We chose three states for two reasons. First, the vast majority of banks that failed in 1930 and 1931 were located in the south. Historians (Wicker (1996),White (1984)) have identified the onset of the banking panic with the failure of Caldwell and Company, an investment house based in Nashville that had extensive business relationships with banks in a number of southern states. Our study region contains many – but by no means all – banks that had did business with Caldwell and Company. Second, the three states in our study region provide a unique opportunity to examine the effects of monetary policy during the crisis. As shown in Figure 1, the study region is divided between the 6th and the 8th Federal Reserve districts. Because the district boundary cuts across both Tennessee and Mississippi, it is possible to separate the effects of differences in reserve bank policies from other state-level factors.

1086 banks were operating in our study area as of September 1, 1930. Of these, 211 had been forced to suspend operations by July 1, 1931. Figure 2 shows the number of bank suspensions in our study region per week in 1930 and 1931. Bank suspensions were highly clustered in time. Two-thirds of the suspensions observed in our sample occurred in the three-month span from November 1, 1930 to January 30, 1931.

Figure 3 suggests that bank suspensions were also geographically correlated. In Tennessee, several banks in and around Union City in the northwest and Kingsport in northeast suspended operations early in the crisis. These suspensions were followed by a wave of bank closings in Nashville and the northwest. In Mississippi, early suspensions were clustered around McComb in the south and Oxford and Tupullo in the north. Later suspensions were spread across the Gulf Coast and the northern quarter of the state. Alabama saw fewer suspensions overall, with the majority of suspensions clustered around Bermingham.

2.3 Network topology

Our analysis exploits several features of the Depression-era banking system. The first was prohibitions on branch banking, which existed in all of the states that we analyze. This rule restricted a banks operations to a single building, which in turn, limited banks clientele to a local community, usually within fifteen miles of the bank that they patronized. Most of a banks borrowers and deposits lived within this radius.

The second is the hierarchical nature of the correspondent banking system. Depositors and borrowers did most of their business with banks in their communities. Financiers referred to these institutions as country banks, metaphorically because the banks served many rural clients and technically to distinguish them from reserve banks which operated in federally-designated reserve cities. Country banks deposited a portion of their reserves in banks in reserve cities, which in turn deposited funds in banks in the central reserve cities of New York and Chicago. These interbank deposits counted as a portion, usually half, of country banks legally-required reserves. Interbank deposits also enabled country banks to access services offered by their money center correspondents. Correspondents offered an array of services such as the clearing of checks, processing international payments, access to money and equity markets, and offering investment advice. Correspondents extended lines of credit, which respondents could draw upon when circumstances required access to cash, and discounted commercial paper, which respondents would do when they needed additional

resources, perhaps to handle seasonal flows of funds or to pay panicked depositors. By rediscounting commercial paper that they acquired from their clients, correspondents linked country banks to central-bank credit.

We have compiled data on the correspondence relationships of all banks operating in Tennessee, Mississippi and Alabama in 1930. In cases where one or more banks within the study region had a correspondence relationship with a bank outside the study region, we include the outside bank in our analysis of network topology, but we do not model its performance during the banking crisis.[2] We do not consider correspondence relationships between pairs of outside banks in our analysis of network topology. Of the 1086 banks in our analysis, only 20 reported no correspondence relationships.

Bank i is said to be a correspondent of bank j if bank i reported that it had placed deposits in bank j. The set of all banks and directional correspondence relationships among banks defines a directed graph. Figure 4 shows correspondence relationships among banks on our study region. Note that because more than one bank may be present in the same city or town, some vertexes or edges on the map represent more than one bank or relationship.

The importance of a single bank within the correspondence network can be assessed by measuring its centrality. The *degree centrality* of a bank is defined as the average number of other banks with whom it has a correspondence relationship in either direction. This measure can be decomposed into the *indegree centrality* – the average number of other banks in the network whose deposits the bank holds – and *outdegree centrality* – the average number of other banks within the network with whom the bank has placed deposits. Figure 5 shows the indegree and outdegree centrality of all banks in our sample, sorted by degree centrality. Taken together, Figures 4 and 5 clearly show the hierarchical nature of depression-era bank correspondence relationships. Most rural banks placed deposits in one or two larger banks. Larger city banks typically held deposits from dozens of smaller rural banks while placing their own deposits in a much smaller number of money center banks. City banks have very high indegree centrality even though their outdegree centrality is not much higher than that of rural banks.

3   The frailty weibull specification

The focus of this paper is on identifying sources of spatial and temporal correlations in bank failures during the banking crisis of 1930. To accomplish this, we estimate a Weibull hazard model of bank suspension times that incorporates three broad types of exogenous information: observable bank balance sheet and other characteristics recorded prior to the crisis, bank locations, and bank correspondence relationships.

Let i index all banks in our study area that were operating as of September 1, 1930. If a bank did not suspend operations by June 30, 1931, it is treated as a right-censored observation in our analysis. Denote the censoring time in business days from September 1, 1930 by T and let t_i be the minimum of the time to suspension or T for bank i. The independent variable t_i has a censored Weibull distribution given by

$$f\left(t; \alpha, \lambda\right) = \left[\alpha t^{\alpha-1} \exp\left(\lambda\right)\right]^{1\{t<T\}} \exp\left(-t^{\alpha} \exp\left(\lambda\right)\right). \tag{1}$$

For simplicity we assume that all banks share the same strictly positive hazard shape parameter α. Bank characteristics enter the model through the bank-specific intensity parameter

$$\lambda_i = \beta_0 + \left[\sum_{k=1}^{K} x_{ik}\beta_k\right] + W_i + V_i.$$

The term in brackets is a linear combination of observable, exogenous bank characteristics. The slope coefficients on exogenous variables have the usual interpretation; a positive value of β_k implies that a higher value of x_{ik} is associated with a higher hazard for bank i. W_i and V_i are frailty terms included to capture cross-bank dependence in suspension times associated with geographic proximity and correspondence network relationships.

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[2]All of the out-of-area correspondent banks in our study survived the initial banking panics of the Depression and remained in operation without interruption until the banking holiday of March 1933.

3.1 Modeling spatial dependence

Let r index R regions that partition the two-dimensional plane on which observations are situated and let S_r be the set of banks that lie in region r. The definition of regions is somewhat arbitrary. Researchers usually either use political boundaries, such as counties, or impose a regular tessellation on the plane. We use the latter approach because it is both more convenient and more flexible. In this analysis, the study region is divided into a regular grid in which each grid-square is 30 miles on a side.[3]

Let w_r denote the frailty term for region r All observations within region r share the same frailty, so the spatial frailty associated with observation i is defined as

$$W_i = \sum_{r=1}^{R} 1\{i \in S_r\} w_r.$$

This specification implies dependence in realized suspension times for banks within a region. Following Banerjee, Wall and Carlin (2003), we allow for spatial dependence across regions using the conditionally autoregressive model proposed by Besag (1974) and refined by Sun, Tsutakawa and Speckman (1999). Let A_r be the set of regions adjacent to region r, let $\#(A_r)$ be the number of elements in A_r, and let $\mathbf{w}_{-r}$ be the $R-1$ dimensional vector of all region-specific frailty terms except w_r. We assume that w_r is normally distributed conditional on $\mathbf{w}_{-r}$ with PDF

$$g(w_r|\mathbf{w}_{-r}; \sigma, \rho) = \frac{1}{\sigma} \phi \left(\frac{w_r - \rho \bar{w}_r}{\sigma} \right)$$

where, $\phi(\cdot)$ is the standard normal PDF and $\bar{w}_{-r} = \frac{1}{\#(A_r)} \sum_{s \in A_r} w_s$ is the average frailty term for regions adjacent to region r. The parameters σ and ρ describe the overall volatility and dependence of the region-specific frailties. Sun et al. (1999) show that, as long as ρ lies on the open interval (-1,1) this conditional specification implies that the vector of region frailties is normal with mean zero a well defined, non-singular covariance matrix.

3.2 Modeling financial network relationships

A number of approaches were considered for modeling common network frailties. In principle, a conditional autoregressive framework similar to the one used for modeling spatial dependence could be used, but this approach is not well suited to a dissassortive network such as the one studied here.[4] An important practical consideration is that simulation speed and convergence rates are greatly improved if the number of parameters characterizing network linkages is kept reasonably small.

The analysis of correspondence network topology presented in Section 2.3 indicates that most banks in our study region are linked to a very small number of highly interconnected city banks. To capture this feature of the interbank correspondence network we identified M banks in our sample with indegree centrality of greater than four percent and defined fixed effects associated each.[5] Let $d(i,j)$ denote the degrees of separation between banks i and j within the correspondence network and let J be the set of all highly-interconnected banks. Define the subset J_i of J as the set of all highly-interconnected banks that are closest to bank i:

$$J_i = \{j \in J \mid d(i,j) \leq d(i,h) \forall h \in J\}$$

The network effect associated with observation i is defined as

$$V_i = \sum_{m=1}^{M} \frac{1\{j_m \in J_i\}}{\max\{\#(J_i), 1\}} \nu_m$$

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[3]Alternative specifications with finer grids were also considered, but did not produce notably different results.

[4]When a small number of network nodes have a large number of connections while most nodes have few connections, one must either impose very strong restrictions on the CAR correlation parameter or allow for very large differences in the marginal variances of bank-specific frailties in order to ensure a positive definite correlation matrix. Neither of these approaches proved practical in this application.

[5]Specifications with higher and lower thresholds were also considered. This cutoff provided a reasonable balance between parsimony and model flexibility.

where j_m is the mth element of J. Each indicator variable in the sum describes a set of banks that are closest (in terms of network distance) to one of the M highly interconnected banks in the correspondence network. In cases where an observation is equally close to more than one highly-interconnected bank, it is assigned to more than one group but is given a lower weight in each. The small number of banks that reported no correspondence relationships are assigned a network effect of zero. The parameter vector $\nu = (\nu_1, \ldots, \nu_M)$ determines the within-group frailty of each subset of closely-linked banks.

3.3 Bayesian estimation approach

Estimating duration models with complex dependence structures is notoriously difficult tn a classical setting, but relatively straightforward under a Bayesian framework. Our objective is to estimate the posterior distribution of the $K+M+3$ vector of model parameters $\theta = (\alpha, \beta_0, \ldots \beta_K, \rho, \sigma, \nu_1, \ldots, \nu_M)$. For simplicity, we impose independent priors for each parameter. We use normal priors for each β_k and ν_m, gamma priors for α and σ, and uniform priors for ρ. All priors are made vague (but proper) by using very large values for those hyperperameters that characterize the dispersions of the prior distributions.

The posterior distribution of θ cannot be expressed in closed form. More importantly, it cannot be easily computed analytically because it depends on high-dimensional integrals. Fortunately, the Gibbs sampler (with Metropolis-Hastings steps) provides a computationally efficient means of sampling from the posterior distribution. We find that the Markov Chain Monte Carlo algorithm converges after a burn-in period of about 100,000 iterations. In each model specification presented in this paper we use one million simulated draws from the posterior distribution of θ.[6]

4 Results

4.1 Model diagnostics

Four model specifications are considered: a baseline model that includes bank characteristics but no spatial or network frailties, a model with bank characteristics and spatial frailties, a model with bank characteristics and network frailties, and a full model that includes both spatial frailties and network frailties. To compare these specifications we use three penalized information criteria. Each of the three statistics are structurally similar in that they are expressed as the sum of a likelihood-based measure of goodness-of-fit and a penalty measure of model complexity. In each case the scale of the statistic is arbitrary, but lower values imply preferred models. Under the *Akaike information criteria* (AIC), the model fit measure is derived from the log-likelihood of the data evaluated at posterior mean model parameters and the complexity measure is set proportional to the number of model parameters.

$$C_{AIC} = -2\left(L(\bar{\theta})\right) + 2H$$

where $L(\theta) = \sum_i \ln f(t_i|\theta)$ is the log-likelihood of the data, $\bar{\theta}$ is the posterior mean of θ, and H is the dimension of θ. The AIC tends to favor more complex models because it imposes little penalty for high-dimensional parameter vectors. The *Bayesian information criteria* (BIC) uses the same fit measure as the AIC, but rescales the penalty function to grow with the sample size.

$$C_{BIC} = -2\left(L(\bar{\theta})\right) + 2\ln(N)H$$

where N is the number of observations. The BIC has some theoretical appeal since choosing among a set of models using the criteria can sometimes be shown to be equivalent to choosing the model with the highest posterior probability. Both the AIC and the BIC can be criticized on the grounds that they are not sensitive to dispersion in the distribution of θ but may be highly sensitive to immaterial differences in the way models are parametrised. The *deviance information criteria* (DIC) addresses these defects by deriving fit and complexity measures from expectations of the log-likelihood.

$$C_{DIC} = -2E_\theta\left[L(\theta)\right] - 2\left(E_\theta\left[L(\theta)\right] - L(\bar{\theta})\right)$$

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[6]The full model specification took about six hours to run using Matlab on a mid-range desktop computer.

where expectations are taken with respect to the posterior distribution of θ. The first term is a fit measure that tends to be worse when the posterior distribution of θ is more dispersed. The second term is a measure of model complexity that, under certain conditions, can be shown to be invariant to the way a model is parametrised.

The last column of Table 1 reports the three penalized information criteria for each of our four model specifications. The full model performs best under the DIC, while the specification that includes only spatial frailties performs best under the AIC and the BIC. Under all three criteria the model with spatial frailties alone performs better than the model with network frailties alone. Decomposing the information criteria into goodness-of-fit and penalty terms shows why. Adding network effects provides only a modest improvement in model fit relative to adding spatial frailties but significantly increases model complexity. Table 2 reports the posterior means of estimated model parameters under each specification. Mean parameter values do not appear to be particularly sensitive to whether or not spatial and network effects are included. For the remainder of this analysis we will focus on the posterior distribution of parameters under the full model specification.

Figure 6 compares the predicted suspension probabilities for banks that did and did not suspend operations during the study period.[7] As one would hope, on average our empirical model assigns higher suspension probabilities to banks that actually did suspend operations. The 211 banks that suspended operations during the study period had an average predicted suspension probability of 21.1 percent, while the 875 banks that did not suspend operations during the study period had a predicted suspension probability of 14.4 percent. Nonetheless, as Figure 6 makes clear, idiosyncratic factors not captured in our model clearly also played a role in determining which banks survived the crisis and which did not.

4.2 Bank characteristics, spatial and network frailties

Figure 7 and the first block of rows in Table 3 describe the posterior distribution of the Weibull shape parameter and slope coefficients that capture the effects of observable bank characteristics on bank suspension hazard rates. The distribution of α indicates a baseline hazard function that rises to a single peak before declining steadily thereafter. This baseline hazard function may be shifted upward or downward depending on bank characteristics and spatial and network effects. In interpreting the slope coefficients, note that a positive coefficient implies a positive relationship between the corresponding exogenous variable a bank's hazard of suspending operations during the crisis.

"National bank" and "reserve district" describe the regulatory environment faced by a bank. "National bank" is a dummy variable that is equal to one if the bank was regulated under a national charter or zero if it was regulated under a state charter. National and state banks do not appear to have performed differently during the crisis, The posterior distribution of this slope coefficient is centered near zero, with significant mass on both sides of the origin. "Reserve district" is a dummy variable that is equal to one if the bank was part of the 8th Federal Reserve district and zero if it was part of the 6th district. Though a 95th percentile credible region for the district slope coefficient does cover zero, most of the mass of this parameter lies on the positive half-line suggesting that banks in the 6th district performed worse than banks in the 8th district after controlling for other factors. The posterior mean of this coefficient (0.46) implies that the baseline suspension hazard function for banks in the 8th district can be expected to be 50 percent higher than that for banks in the 6th district.

To capture the effects of bank size, banks are grouped into three broad buckets based on reported balance sheet assets. The reference group of "small" banks have than one-million dollars in assets, mid-sized banks have between one- and ten-million dollars in assets, and large banks have greater than ten million in assets. Of the 1086 banks studied, 186 are mid-sized, 17 are large, and the remainder are small. As one might expect, bank size is very highly correlated with bank centrality, so we cannot separately identify the effects of a bank's balance sheet size from those of its position within the interbank correspondence network. The coefficient on the "mid-size" dummy variable is centered around zero, indicating that all banks with less than ten million in assets performed similarly. On the other hand, the coefficient on the "large" dummy variable is significantly positive,

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[7]Bank i's predicted suspension probability was computed as $p_i = F(T; \bar{\alpha}, \bar{\lambda}_i)$ where $F(\cdot)$ is the Weibull CDF and $\bar{\alpha}$ and $\bar{\lambda}_i$ are the posterior means of α and λ_i respectively. This approach does not reflect parameter uncertainty. In a future revision of this paper we intend to address this limitation.

indicating that the largest, most central banks performed much worse after controlling for other factors. The posterior mean of this coefficient (1.18) implies a baseline hazard function for these banks that is three times higher than that of other banks.

The final three variables "Capital/Assets", "Securities/Assets", and "Cash/Deposits" describe characteristics of bank balance sheets that previous research has shown to be important in predicting bank suspensions. Most of the mass of the posterior distribution of the coefficient for "Capital/Assets" lies on the negative half-line indicating, rather intuitively, that banks that were better capitalized before the crisis were less likely to suspend operations during the crisis. Similarly, the largely negative range of the "Cash/Deposits" coefficient implies that banks with better liquidity provisioning were more likely to remain open for business. Banks that were more heavily invested in marketable securities also appear to have fared better, as indicated by the largely negative range of the posterior distribution of the coefficient on "Securities/Assets".

Figure 8 shows how bank characteristics affected the distribution of bank suspension hazard rates in our study area. Each dot in the figure represents a single bank, and the color of each dot identifies the quartile of the component of that bank's posterior mean hazard intensity parameter $\bar{\lambda}_i$ associated with that bank's observable characteristics ($\sum_k x_{ik} \bar{\beta}_k$) The tendency for the largest city banks to suspend operations at higher rates shows up clearly in this figure, as does the elevated hazard of banks in the 8th reserve district.

Figure 9 and the second block of rows in Table 3 describe the marginal posterior distributions of the spatial frailty dispersion parameter (σ) and conditional autoregressive parameter (ρ). All else equal, a higher value of σ implies that spatial frailties are more important in determining bank suspension rates, but it is difficult to interpret the magnitude of σ independently of other model parameters. Though an agnostic prior was specified for ρ, nearly all of the mass of its posterior distribution lies on the positive unit interval, indicating strong positive correlation between region-specific frailties.

Under our model specification, each 30-mile square region in the study area has an associated latent frailty, resulting in 168 unique frailty parameters that can be roughly interpreted as region-specific residuals. The MCMC algorithm used to draw from the posterior distribution of the model parameter vector θ also provides the joint posterior distribution of these frailties. Figure 10 shows how the posterior means of the region-specific frailties are distributed in the study area. Each dot represents a single bank location and the color of a dot identifies the quartile of that location's spatial frailty. Large positive frailties (red dots) show regions where bank suspension hazard rates were elevated relative to those that would be predicted from observable bank characteristics and network frailties. Large negative frailties (blue dots) show regions where bank suspension hazard rates were particularly low. Suspension rates were highly elevated in central Tennessee, central Mississippi, and southeastern Alabama. Suspension rates were lower than predicted in and around Memphis, east of Chattanooga, near Jackson, and along Alabama's gulf coast. The largest positive mean frailty, 1.71, was located near the gulf coast of Mississippi while the largest negative frailty, -1.91, was located about 50 miles north of Memphis, Tennessee.

Rather than imposing a specific correlation structure on network frailties, as was done with spatial frailties, network frailties were estimated under a fixed-effects specification that allows for arbitrary correlation among elements of the network frailty parameter vector ν. The fourth column of Table 2 describes the posterior mean of each of the network frailty parameters. All elements on ν were positively correlated with one-another, with pairwise posterior correlations ranging from 0.45 to 0.90. In most cases, the posterior means of the network parameters were positive, implying that banks with correspondence relationships typically had higher hazard rates than the 20 sample banks that reported no correspondence relationships. Figure 11 shows how the posterior means of network frailties were distributed among banks. Broadly, Alabama banks linked to city banks in Birmingham and Tennessee banks with links to city banks in Nashville had network frailties in the lowest quartile while banks in all three states with links to city banks in Memphis and Chattanooga tended to have particularly high network frailties.

4.3 Putting it all together

Since all banks share the same hazard shape parameter α, any cross-bank differences in suspension hazard rates flow through the bank-specific intensity parameters λ_i which reflect the sum of the effects of bank characteristics, geographic location and network relationships. Figure 12 compares

the cross sectional distribution of the posterior means of the three broad components of λ_i. To make comparisons easier, each factor is centered at its grand mean. The factors are not orthogonal to one another, so there is no unambiguous way of decomposing the variation in λ_i. However, Figure 12 suggests that all three components were important, with network frailties playing a somewhat smaller role than bank characteristics and geographic frailties. This is conclusion is consistent with the information criteria diagnostics discussed earlier.

Figure 13 shows how bank-specific hazard intensity parameters were distributed within our study area. Bank suspension hazard rates were particularly elevated in all major cities except Memphis, in eastern and northwestern Tennessee, and in the northern half and southern coast of Mississippi. Comparing Figures 8, 10, 11 and 13 suggests that different factors led to clustered suspensions in different regions. High suspension hazard rates in northwestern Tennessee and northern Mississippi can be attributed to the combined effects of adverse bank characteristics and network factors associated with Memphis city banks. At the same time, the negative influences of these factors on banks in southwestern Tennessee near Memphis were more than offset by positive local geographic factors. Banks in central Tennessee appear to have had higher hazard rates because of adverse observable bank characteristics and geographic factors, not because of adverse network factors associated with Nashville city banks. The elevated hazard rates of banks in southern Mississippi can be linked to negative network and geographic factors, but not to observable bank characteristics. The elevated hazard rate of banks in eastern Tennessee appear to reflect a combination of all three types of factors.

5   Conclusions

Depression-era bank suspensions were highly correlated in both time and space. Three broad hypotheses can explain why bank failures tend to be clustered together: correlated liquidity shocks, correlated asset shocks, and financial linkages between banks. If depositors believe that asset values are likely to be correlated across banks, bad news about the condition of one institution could cause depositors to revise their beliefs about other institutions, leading to contemporaneous liquidity draws on many banks at once. Spatially correlated shocks can also occur on the asset side of bank balance sheets, since banks that are nearer to one-another are more likely to invest in similar assets that share common exposure to local factors such as weather and regional business conditions. Finally, financial relationships between banks might cause weakness in one institution to spread to other counterparties. Depression-era banks subject to branch banking restrictions operated through networks of correspondence relationships, so liquidity and asset shocks to one bank could directly affect the balance sheets of its counterparties.

This empirical analysis of bank suspensions during the banking panic of 1930 shows that banks that were more liquid and had less leverage prior to the crisis were more likely to survive, as were banks in the 6th Federal Reserve District where the Federal Reserve Bank of Atlanta pursued a more accomodative liquidity policy. Importantly, however, we also find strong evidence that bank failures were clustered in ways that cannot be explained by observable bank characteristics. Geographic proximity to other failed institutions was an important source of contagion in bank failures, while interbank credit relationships appear to have played a somewhat smaller role.

Our findings suggest two productive avenues for future research. First, it would be useful to better understand *why* geographic and network effects mattered. For example, did spatial contagion arise from correlated local asset shocks or localized depositor runs? Similarly, did interbank relationships matter because distressed rural banks withdrew reserve deposits from money center banks, or because insolvent city banks imposed credit losses on rural banks. New data from the National Archives on the disposition of closed banks' balance sheets may shed light on these questions in the near future.

Second, insofar as we have shown that spatial and network effects led to correlated bank suspensions, one might reasonably hope to assess the real-side implications of such contagion. Bernanke (1983) and others have argued that widespread bank failures at the onset of the Great Depression meant that banks were not able to adequately fulfill their roles as financial intermediaries. A critical implication of this line of reasoning is that bank failures that are clustered together are likely to have a disproportionate effect on the broader economy. When large numbers of financial intermediaries fail together, borrowers and lenders who do business with failed institutions have fewer opportunities to substitute away to still-functioning intermediaries. As a result, the marginal effect of an additional bank failure will be greater during a banking panic than during more normal times when

failures are geographically and temporally dispersed.

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Table 1: Information criteria for selected model specifications

	Information Measure	Complexity Measure	Penalized Information
Model Specification			
Akaike Information Criteria			
Baseline	3091.1	18.0	3109.1
Spatial Frailties	2875.3	22.0	2897.3
Network Effects	3059.0	56.0	3115.0
Spatial and Network	2850.1	60.0	2910.1
Bayesian Information Criteria			
Baseline	3091.1	125.8	3216.9
Spatial Frailties	2875.3	153.8	3029.1
Network Effects	3059.0	391.5	3450.5
Spatial and Network	2850.1	419.4	3269.6
Deviance Information Criteria			
Baseline	3109.7	18.6	3128.2
Spatial Frailties	2910.8	35.5	2946.2
Network Effects	3085.6	26.6	3112.2
Spatial and Network	2889.4	39.3	2928.7

Table 2: Posterior means of model parameters under various specifications

	Baseline	Spatial Frailties	Network Effects	Spatial and Network
Shape Parameter (α)	1.14	1.22	1.15	1.24
Constant	-6.76	-7.47	-7.42	-8.12
National Bank	-0.15	0.01	-0.08	0.07
Reserve District	0.65	0.75	0.46	0.46
Mid-Size	0.11	0.01	0.08	0.04
Large	1.08	1.37	0.90	1.18
Capital/Assets	-3.18	-3.47	-2.87	-3.36
Securities/Assets	-1.78	-2.30	-2.19	-2.35
Cash/Deposits	-1.66	-1.21	-1.70	-1.23
Spatial Dispersion (σ)		1.42		1.53
Spatial Corr. (ρ)		0.73		0.67
Network Effect 1			0.53	0.59
Network Effect 2			0.80	1.04
Network Effect 3			1.14	1.28
Network Effect 4			0.82	1.31
Network Effect 5			0.94	1.17
Network Effect 6			0.60	0.55
Network Effect 7			0.87	0.79
Network Effect 8			0.37	-0.07
Network Effect 9			0.45	0.44
Network Effect 10			-0.38	-0.42
Network Effect 11			0.43	0.39
Network Effect 12			0.67	0.40
Network Effect 13			1.11	1.43
Network Effect 14			-0.16	-0.29
Network Effect 15			1.16	0.91
Network Effect 16			1.65	1.18
Network Effect 17			1.12	0.92
Network Effect 18			-1.23	-1.44
Network Effect 19			0.92	0.69

Table 3: Posterior distribution of model parameters

	Mean	St. Dev.	2.5th Pct.	Median	97.5th Pct.
Shape Parameter (α)	1.24	0.08	1.09	1.24	1.39
Constant	-8.12	1.02	-10.41	-8.06	-6.35
National Bank	0.07	0.23	-0.38	0.07	0.51
Reserve District	0.46	0.35	-0.21	0.46	1.16
Mid-Size	0.04	0.23	-0.41	0.04	0.47
Large	1.18	0.47	0.23	1.20	2.07
Capital/Assets	-3.36	1.06	-5.44	-3.36	-1.26
Securities/Assets	-2.35	0.81	-3.98	-2.34	-0.81
Cash/Deposits	-1.23	0.60	-2.43	-1.22	-0.08
Spatial Dispersion (σ)	1.53	0.08	1.05	1.52	2.08
Spatial Correlation (ρ)	0.67	0.08	0.07	0.72	0.96
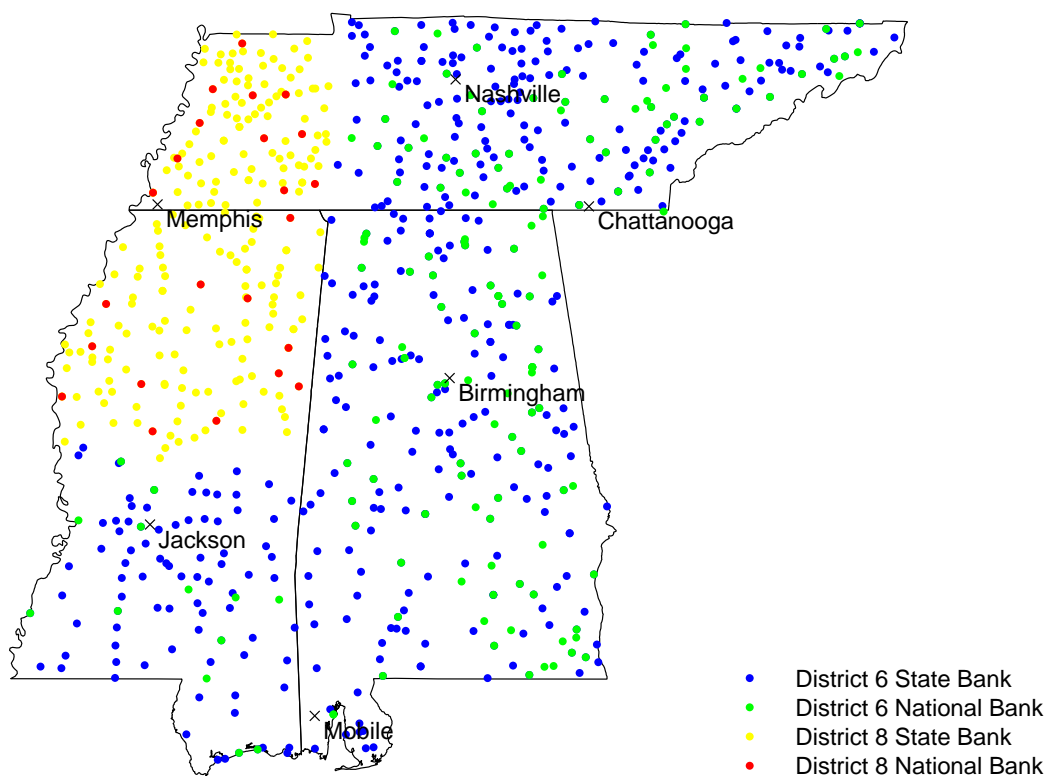
Figure 1: Location and regulatory jurisdiction of banks in Tennessee, Mississippi and Alabama.
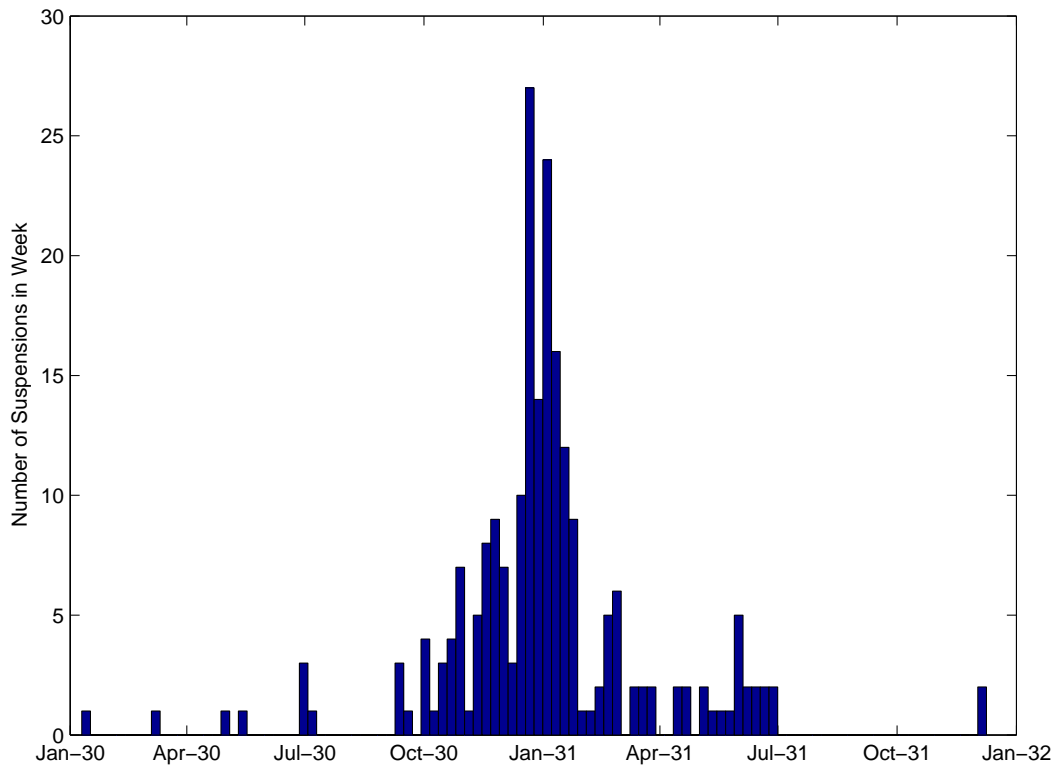
Figure 2: Bank suspensions per week in Tennessee, Mississippi and Alabama.
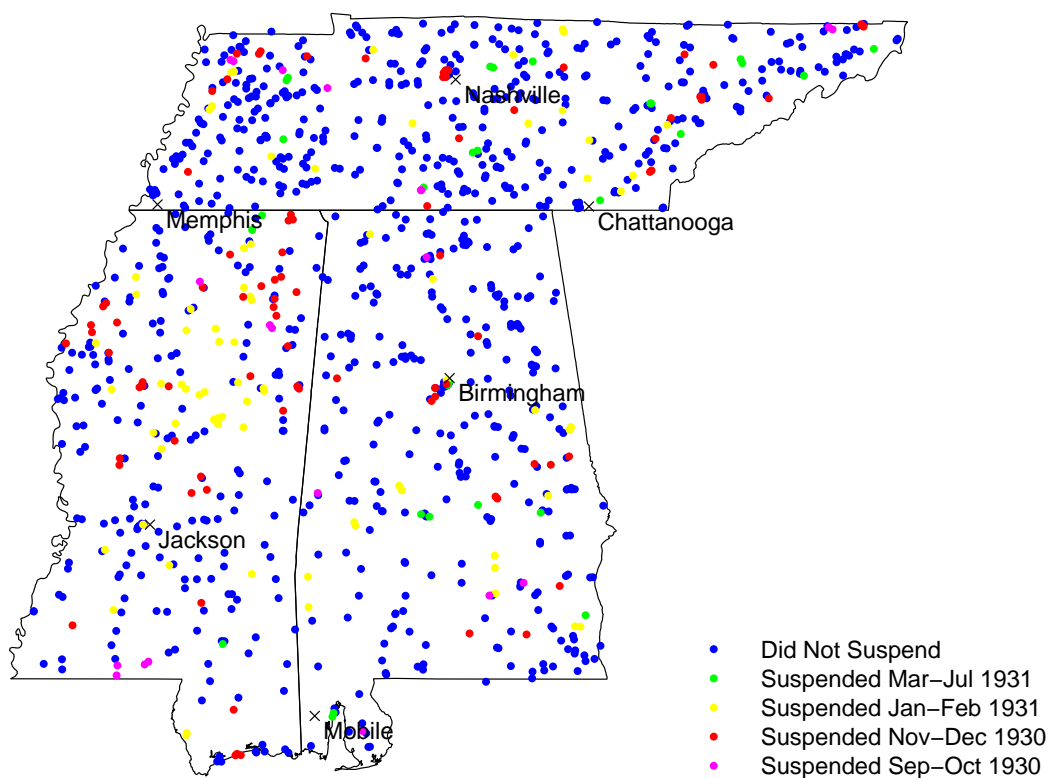
Figure 3: Location of banks suspended operations during the banking crisis of 1930
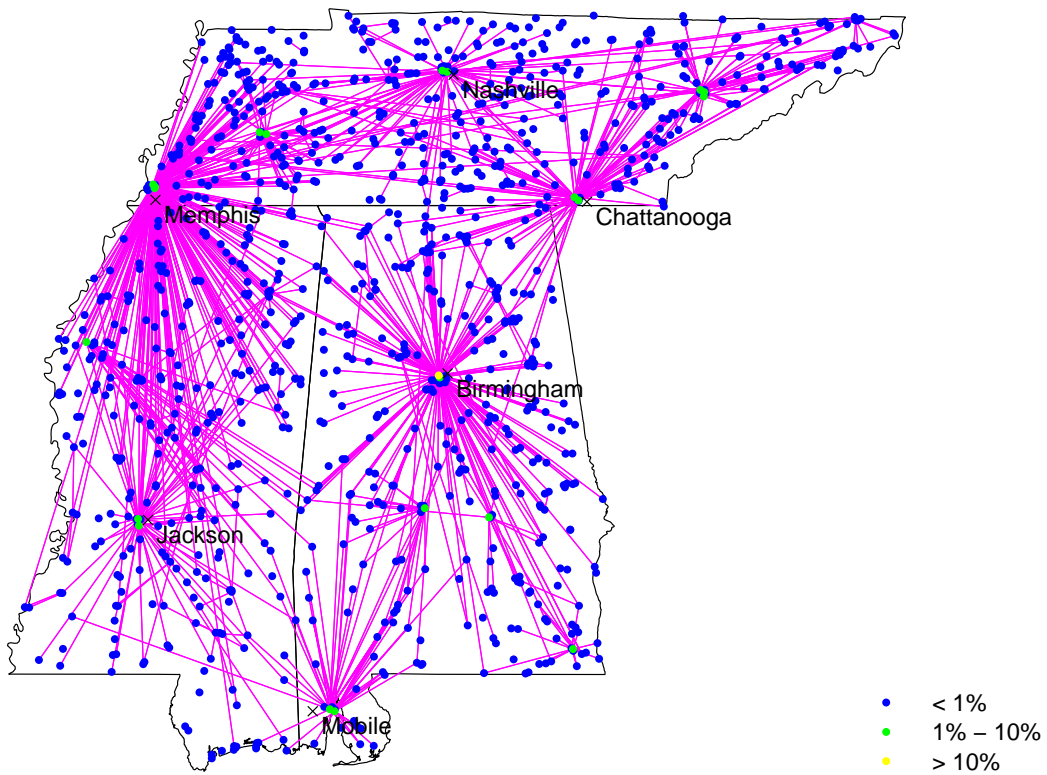
Figure 4: Network of bank correspondence relationships as of July 1930 (Dot colors indicate a bank's degree centrality)
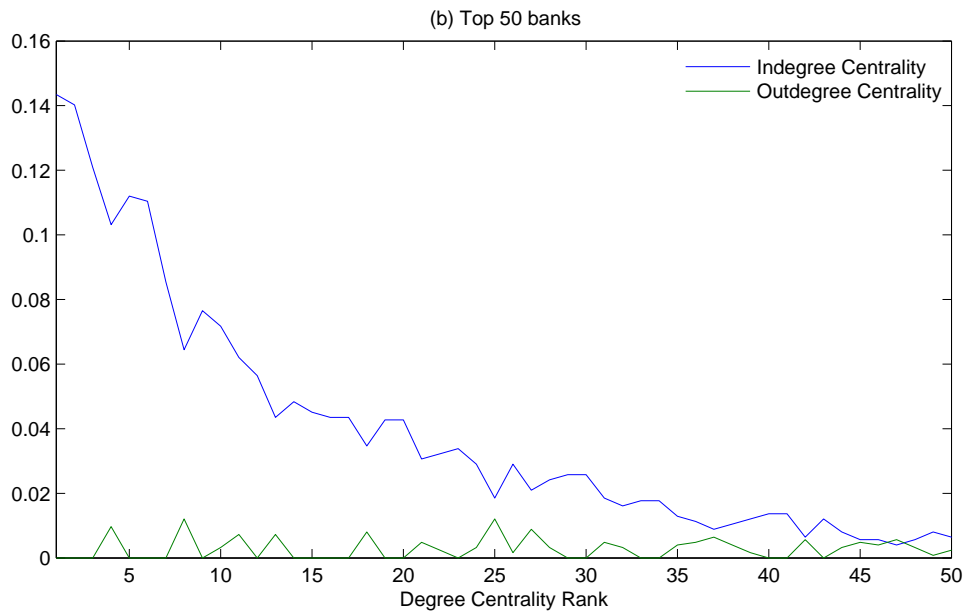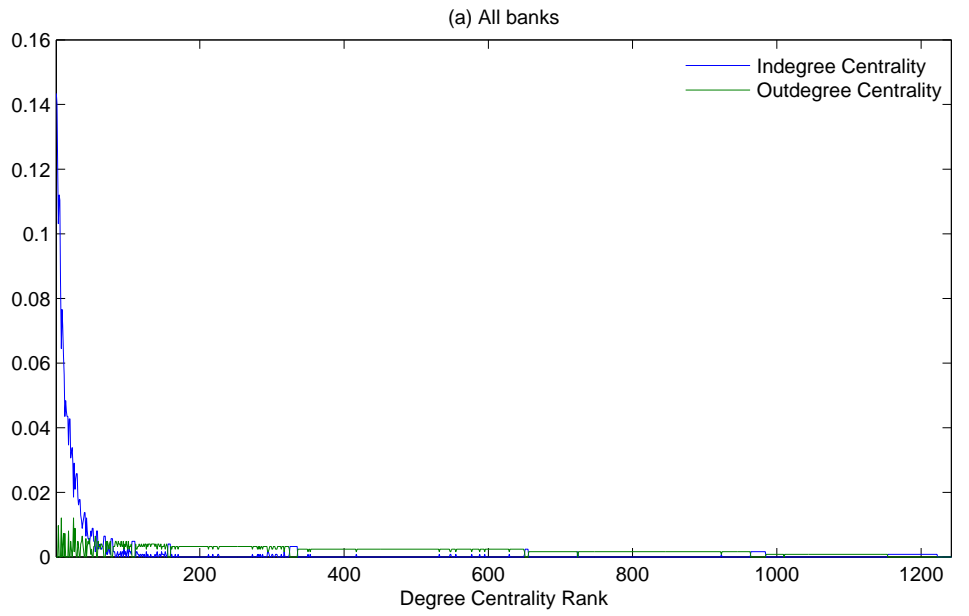
Figure 5: Indegree and outdegree centrality for each bank, sorted by degree centrality.
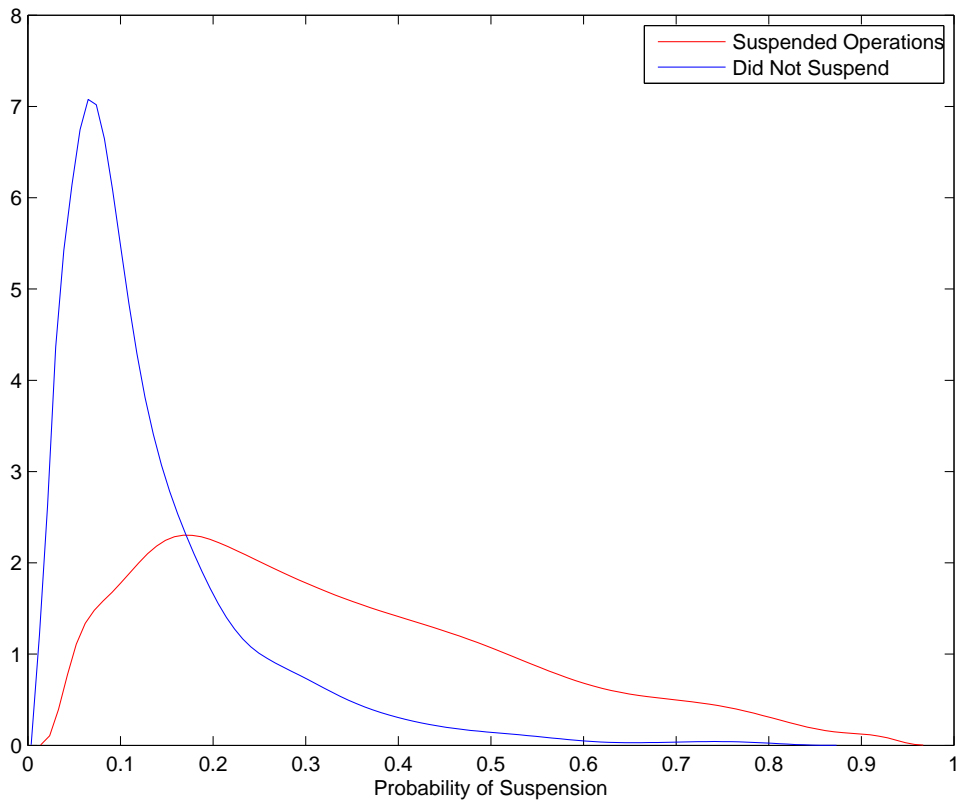
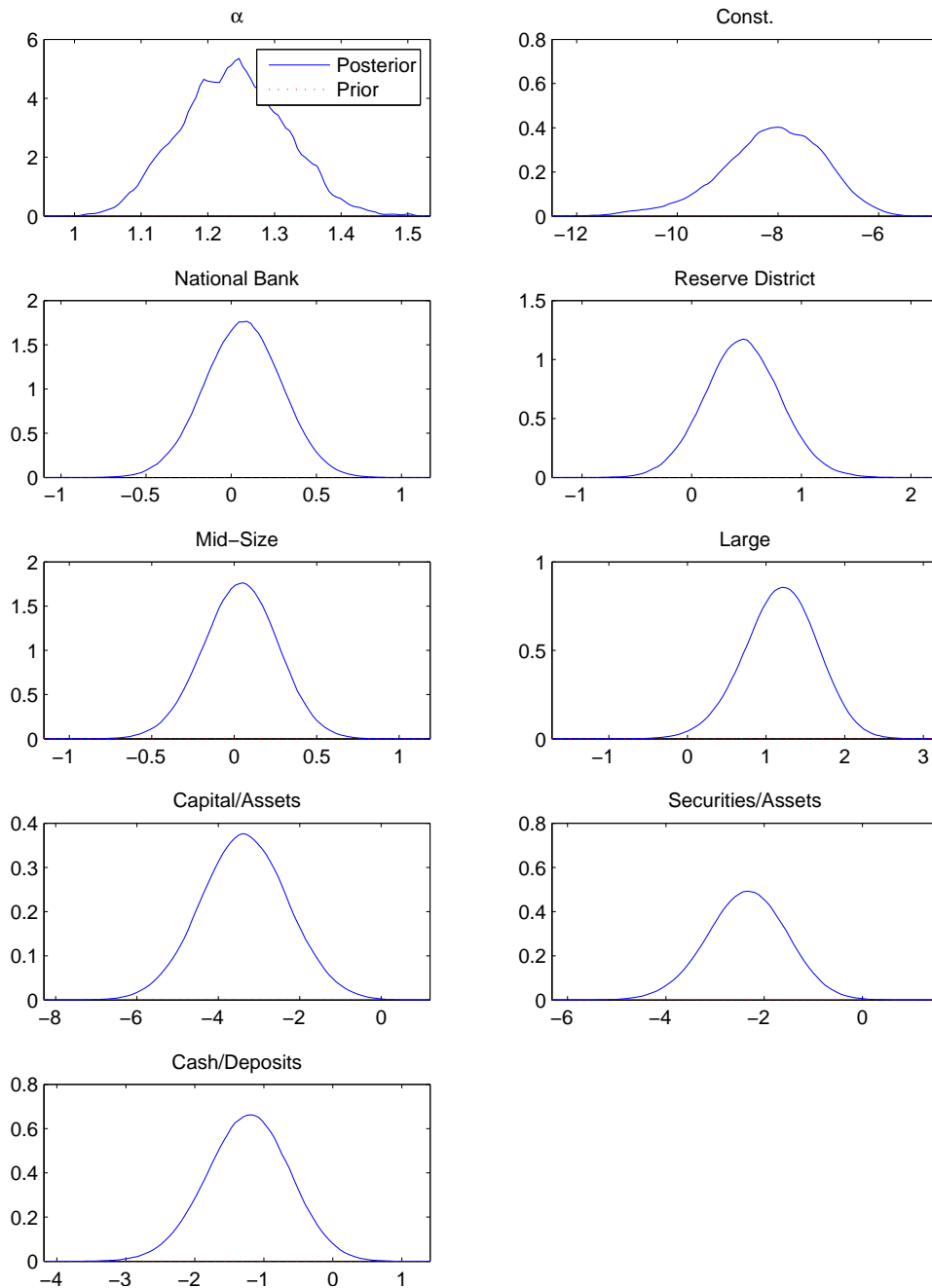Figure 6: Distribution of predicted suspension probabilities of banks that did and did not suspend operations during the study period

Figure 7: Marginal posterior distributions of the Weibull shape parameter and bank characteristic coefficients
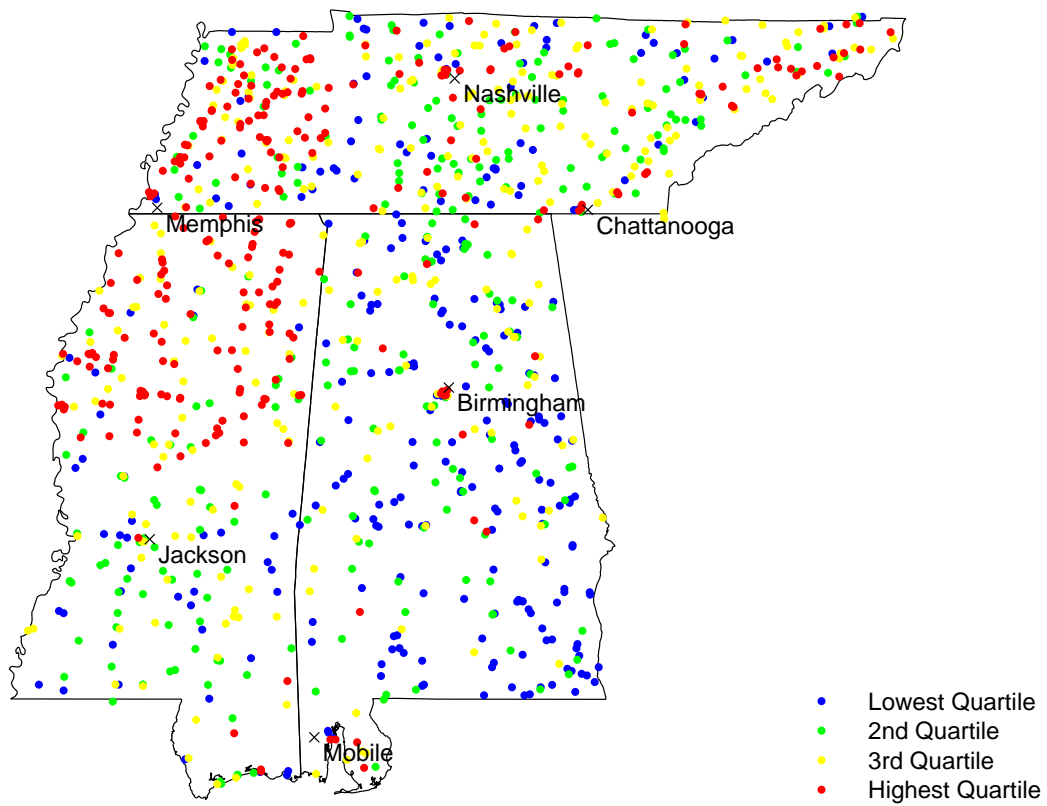
Figure 8: Posterior mean of bank characteristics effects $(X_i\beta)$, by quartile
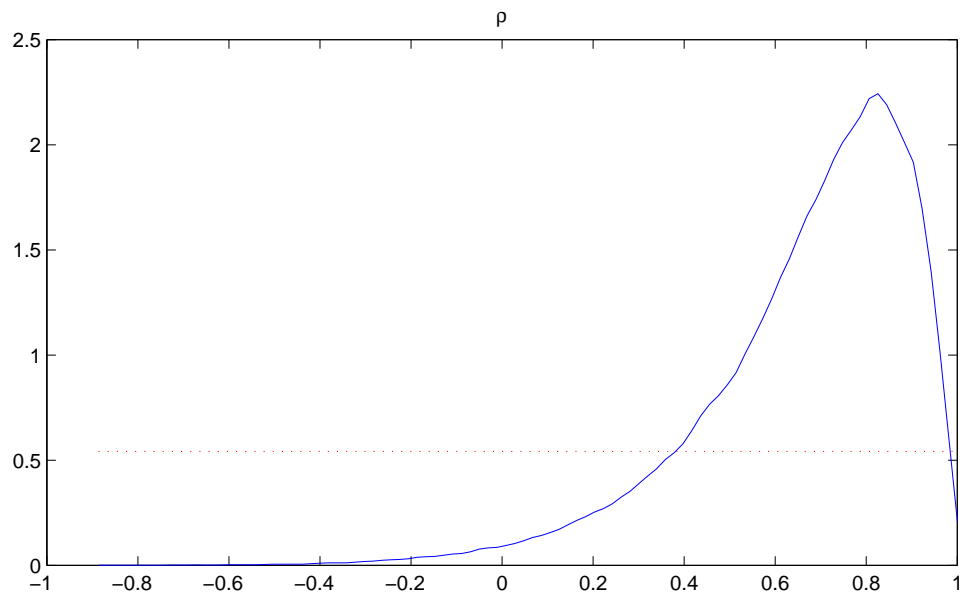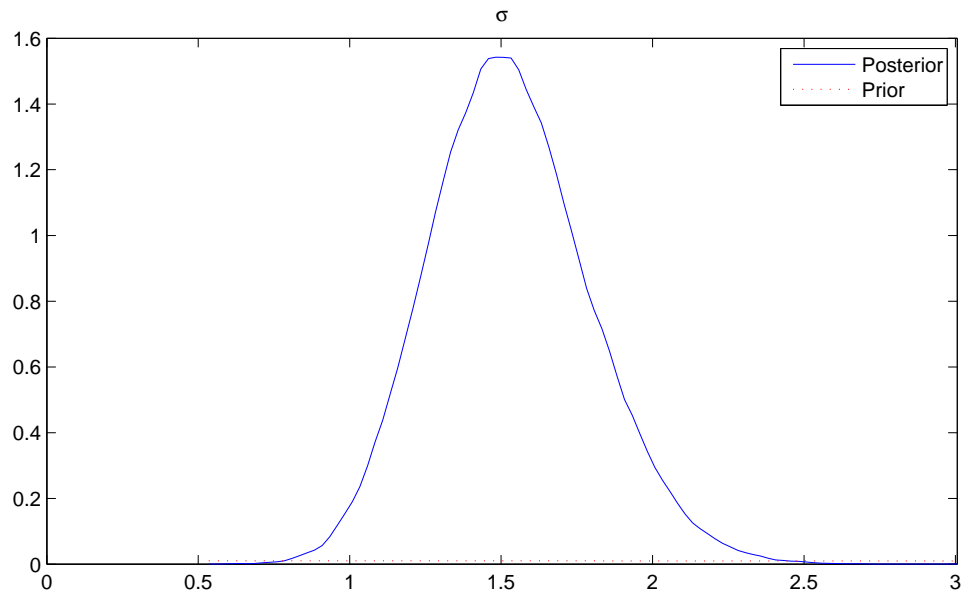
Figure 9: Marginal posterior distributions for conditional autoregressive parameters describing spatial frailties
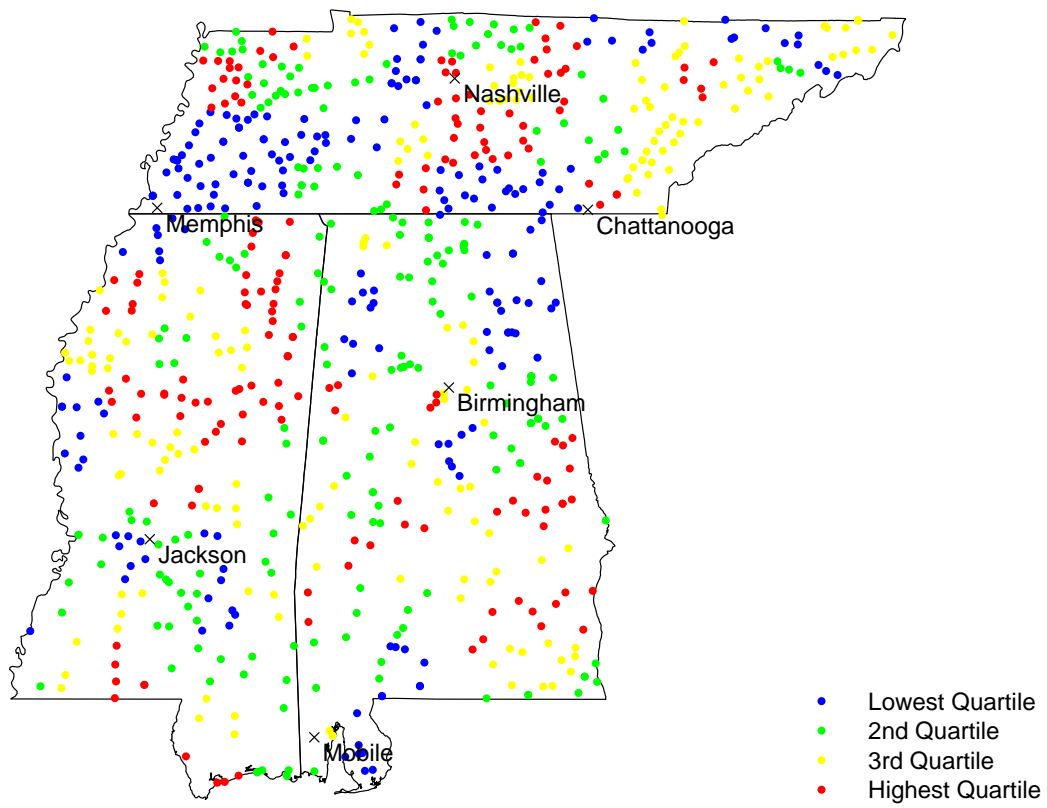
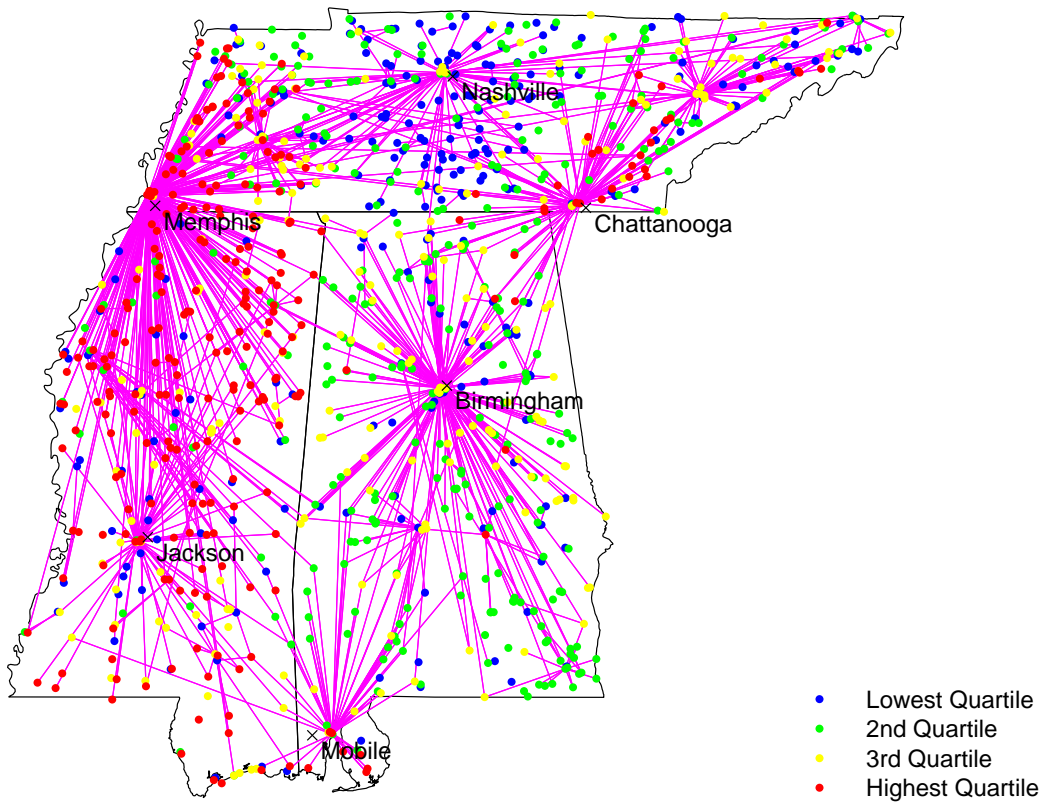Figure 10: Posterior mean spatial frailties (W_i), by quartile

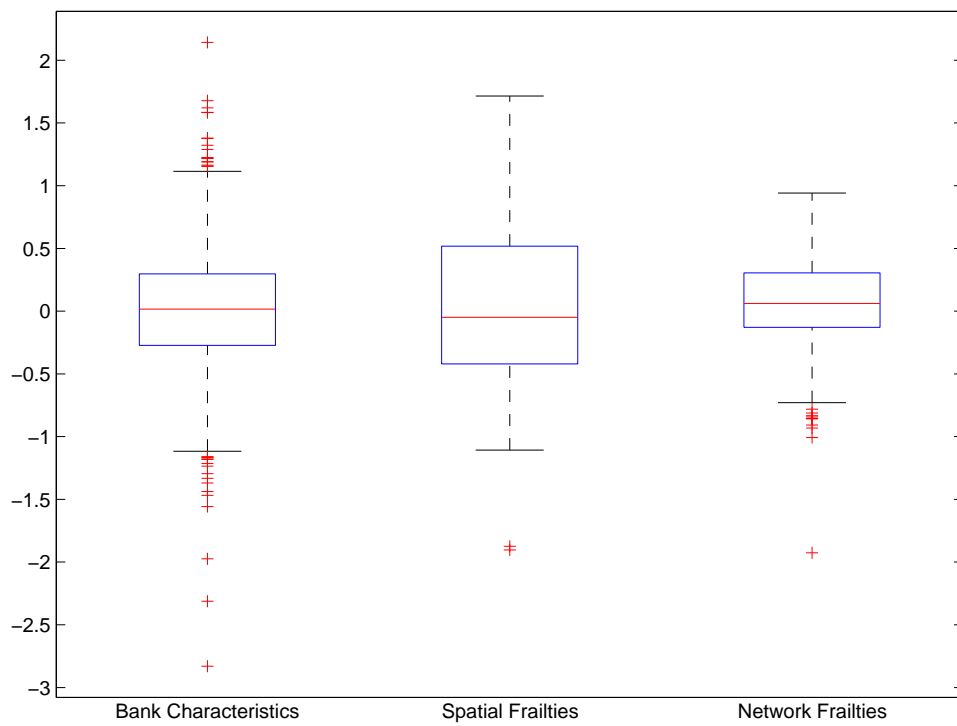Figure 11: Posterior mean network frailties (V_i), by quartile

Figure 12: Distributions of posterior means of bank characteristic, spatial frailty and network frailty components of bank hazard intensity parameters (centered at grand means)
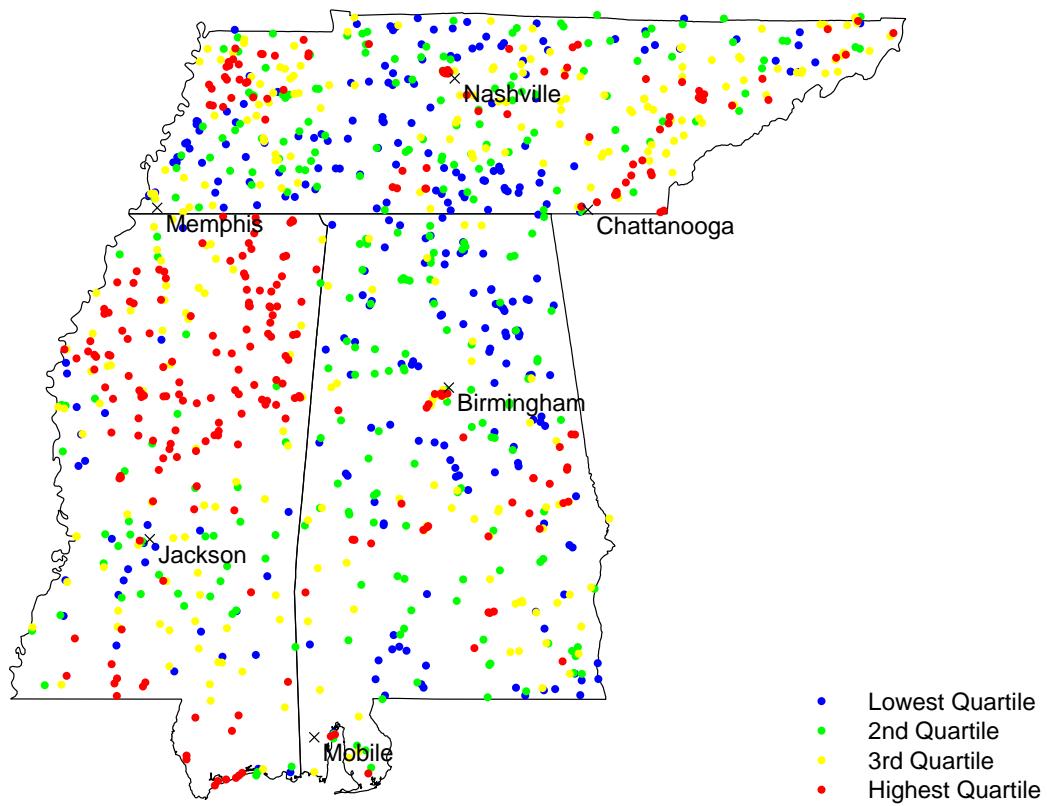
Figure 13: Posterior mean of bank hazard intensity parameter (λ_i), by quartile.