The Spatial Transmission of U.S. Banking Panics: Evidence from 1870-1929

Marc Dordal i Carreras* Seung Joo Lee‡

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Abstract

We study the propagation of localized banking panics across the United States, employing digitized state-level balance sheet data on the National Banks for the 1870-1929 period. Geographically localized panics result in the robust spillover outside the state borders where they originate, leading to moderately persistent credit contractions and the accumulation of liquid assets. We provide a tractable model illustrating a key trade-off: while interbank markets, e.g., the pyramidal reserve structure of the banking system during the National Banking Era, allow banks to access cheaper funding, they spread the effects of panics throughout the country as observed in the data.

Keywords: Interbank Markets, Spatial Propagation, Panics

JEL Codes: E32, G21, N11, N21

*Hong Kong University of Science and Technology, email: marcdordal@ust.hk.

†Saïd Business School, University of Oxford, email: seung.lee@sbs.ox.ac.uk.

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1 Introduction

The United States features a prominent history of banking panics dating back to the eighteenth century, experiencing a minimum of fifteen panic waves between 1865 and 1930 (Jalil, 2015), many of them to have had a profoundly negative imprint on the overall economy. In this paper, we investigate how a banking panic stemming from one state can be transmitted to different states, based on the historical bank balance sheet data from 1870 to 1929.[1]

The relative instability of the U.S. banking system at that time is traced to its specific institutional structure, in particular to the lack of a central bank (or equivalent) until 1913 (i.e., National Banking Era) and to the unit banking regulations that severely limited the capacity of National Banks to branch and diversify risks: see Calomiris and Haber (2014). Thus, banks at that time formed an interbank market with a pyramidal structure of reserves, with central reserve cities (especially New York) on top and reserve cities playing an important role as liquidity providers at the regional and national levels.[2]

The interbank lending market creates an interesting trade-off, however: while it allows banks to access cheaper funding sources and sustain, on average, higher levels of credit, on the other hand it exposes them to risks of runs and panics outside their state borders, from

[1] As the Great Crash of 1929 and the Great Depression, which affected the entire country quite severely in a simultaneous manner, started in year 1929, we cut our data's time period there.

[2] During the National Banking Era, banks in the central reserve cities were required to hold reserves of 25% of their deposits, all of which needed to be held as cash. Banks in the reserve cities were required to hold reserves of 25% of deposits as well, but they were allowed to hold half of reserves in the form of deposits at their correspondent banks in the central reserve cities. Finally, other national banks were required to hold 15% of deposits, and up to three-fifths of the reserve could be held as interbank deposits at correspondent banks in either reserve cities or central reserve cities.

which they would have otherwise been insulated by the unit banking system, and allows the spatial propagation of panics outside their origin states. We provide a tractable model of the interbank relationship consistent with the overlapping inter-state financial network, capturing this key trade-off, and estimate the degree of spatial transmission of panics across states[3] based on the digitized state-level bank balance sheet data extracted from the Abstract of Reports in the Annual Report of the Office of the Comptroller of the Currency, and the historical banking panic series of Jalil (2015). We explain our data sources more in depth in Section 2.

We find the spatial transmission of a regionally localized banking panic strong enough. To be specific, our empirical analysis uncovers that regional panics have a moderate impact on banking sector activities across different states, with deposits and lending declining by between 2% and 4% and those banks accumulating additional liquid reserves as a liquidity buffer on their aftermath. However, these negative effects of panics are largely transitory, with the bank balance sheet strength across states returning to their pre-crisis trends within two years. More importantly, we find a lagged but robust response of the entire banking system outside the state borders in which the panics originated, which we attribute to inter-state financial linkages among banks.

Literature Kemmerer (1910) provides an early documentation of historical panic episodes based on historical newspaper reports. More recently, DeLong and Summers (1986), Gor-

[3]The literature has long argued that distresses in the upper layers of the pyramid, either through temporary suspensions of deposit convertibility or squeezes in interbank lending, are main drivers of panic propagation across states and amplification. Calomiris and Carlson (2017), focusing on the 1893 panic that stemmed from New York, find that a bank operating in the interior that depended on deposits that it had placed with city correspondents became illiquid due to the suspension of convertibility by its correspondent banks in New York. Banks with a higher exposure to New York were more likely to suspend activity or even close.

ton (1988),[4] Wicker (2006), Reinhart and Rogoff (2009), and Jalil (2015) provide the alternative classifications based on different criteria and varying regional details. Jalil (2015) especially provides quantitative impacts of a banking panic based on the empirical estimation of the impact of major, nationwide panics on industrial production and prices, with results suggesting large and persistent negative effects on the economic levels. Due to the comprehensive list of each panic's geographical coverage and dating, we use the historical banking panic series constructed by Jalil (2015). Mitchener and Richardson (2019) similarly find roles of interbank lending markets in amplifying reduction in lending during the Great Depression,[5] while we focus on regional panics before the Great Depression era.

Layout Section 2 presents the detailed explanation of our data sources, especially the state-level bank balance sheet data and the banking panic series. Section 3 introduces a tractable model of interbank markets, where we derive the equilibrium relation between balance sheet levels in different states. Section 4 develops an estimation strategy consistent with the model and presents the main quantitative results. Section 5 concludes. Section 6 presents figures, and Section 7 presents tables.

Online Appendix A. The Model Derivation provides missing proofs and derivations for Section 3, Online Appendix B. Are Panics Exogenous or Correlated with Business Cycles? studies whether a panic can be regarded exogenous, based on the Granger causality test, and Online Appendix C. Robustness Check presents additional robustness results for the

[4] Gorton (1988) in particular documents that panics in the earlier periods can be mostly explained not by self-fulfilling prophecy, but by depositors changing their perception of fundamental risks based on the arrival of new information. Recently, Correia et al. (2024) document that few individual bank failures in US history were purely liquidity driven, and failures are highly predictable based on bank fundamentals.

[5] Mitchener and Richardson (2019) find that between the peak in the summer of 1929 and the banking holiday in the winter of 1933, interbank amplification reduced aggregate commercial bank lending by 15%.

estimation of the degree of propagation of a panic.

2 Data

Banking Panic Series We rely on the historical banking panic series of Jalil (2015), who provides a detailed list of panics' geographical coverage and dating. Table 2 presents a quarterly reproduction of Jalil (2015)'s series for our sample period, from 1870 to 1929. It also documents each panic's state of origin and other affected states where panics directly occurred.

Jalil (2015) narrowly defines a banking panic as a "widespread run by private agents in financial markets. . . [in order to] convert deposits into currency"[6] and categorizes panics into major and minor ones. The minor panics are geographically localized and generally thought of as less severe, while the major panics are characterized as those rapidly engulfing most of the United States and accompanied by serious distresses across the country.[7] Given the focus on the spatial propagation of a panic, we will mostly focus on the minor panics.[8]

State-level Bank Balance Sheets During the National Banking Era (from 1864 to 1912), national banks (i.e., those chartered by the federal government) were subject to the same set of rules and regulations regardless of where they were located, and all the banks were unit, or single-office banks. These banks were required to report to the Office of the Comptroller of the Currency, their primary regulator. One way was through the *call reports* that contain

[6]This narrow definition allows for a homogeneous set of events across the sample period.

[7]In Table 2, there are only three major panics in our sample period: the 1873 panic that started in Europe, the 1893 panic that Calomiris and Carlson (2017) focus, and the 1907 panic that started in New York.

[8]In Online Appendix B. Are Panics Exogenous or Correlated with Business Cycles?, we test whether each panic can be regarded exogenous (and thus not related to the business cycle), and show that only minor panics pass this exogeneity test.

information on banks' balance sheets and were filed about four or five times a year.[9] which we rely on as these reports provide the state-level bank balance sheet information.

To be specific, we collect the data on state-level bank balance sheet aggregates from the Abstract of Reports contained within the Annual Report of the Office of the Comptroller of the Currency. Leveraging the fact that Weber (2000) already digitized the series for the 1880-1910 period, we extend the timespan to 1870-1929 by digitizing the data for 1870-1879 and 1911-1929 periods ourselves. The data basically consist of self-reported balance sheets of all existing banks with a national charter, aggregated by the Comptroller of the Currency at the reserve city and state level.[10] See Table 1 for an overview of the contained categories, and Figure 8 presents an actual Abstract of Reports for banks in Alabama from October 1913 to September 1914 as an example. The District of Columbia is included in our sample and treated as a state. We exclude Alaska and Hawaii due to their long distance to the contiguous United States, and convert the reporting frequency to quarterly, as some years feature five reports.

The Abstract of Reports contains many different categories (e.g., "Overdrafts", "Other bonds for deposits", "Capital stock"), which vary across years typically due to the subdivision of big categories into smaller ones in later years.[11] Thus, we group different categories

[9] Another method was the filing of *examination reports* by examiners who actually visited each bank once or twice a year. For example, to be included in the sample of Calomiris and Carlson (2017), a bank needs to have provided information for the September 1892 call report and to have had at least one examination report completed prior to May 1893 (the onset of the 1893 major panic).

[10] For states with a reserve city, for each macroeconomic variable, we aggregate the statewide level with the level of the respective reserves cities, which allows us to obtain the total aggregate composition of state-level balance sheets.

[11] For example, the category "Loans and discounts" in Table 1 (and Figure 8) contains "Overdrafts" in the initial years, and then "Overdrafts" eventually becomes a category of its own in later years in our sample.

in the reports into the following ones: for resource sides, (i) loans and discounts; (ii) bonds and securities; (iii) real estates; and (iv) cash and short-term assets; (v) other assets. For liability sides: (i) bank capital; (ii) deposits; and (iii) other liabilities.[12]

Figure 2 shows the time-series of US aggregate log-deposits and deposits in New York from 1870 to 1945, with the minor and major panics from Jalil (2015). We observe the procyclicality of the digitized deposits in New York and the overall United States. Note that minor panics that originated in New York (e.g., the 1884 panic) have a huge negative impact on deposit levels in the entire United States.

3 Model

This section presents a simple partial equilibrium model that theoretically establishes the link between deposit fluctuations and the spatial transmission of panics across different states.[13] All the detailed derivations are provided in Online Appendix A. The Model Derivation. There are N states in the economy, each one containing a representative bank (or infinitely many banks in perfect competition).

For expositional purposes we assume that each bank is divided into two separate divisions: deposit division and loan division. The deposit division raises deposits from their own state while the loan division provides loans to firms in the same state. To handle mismatch between deposits amount and the loan demand in each state, banks form an interbank (or interstate) loan market, where each state bank supplies loanable funds to banks in other

[12]For example, in Figure 8, categories “Bonds for circulation” and “Bonds for deposits” belong to “bonds and securities” under our grouping. “Dividends unpaid” and “Reserved for taxes” in the liability side belong to “bank capital”.

[13]In terms of the modeling techniques with extreme value distributions, we borrow insights from Dordal i Carreras et al. (2024) and Lee and Dordal i Carreras (2024).

states.

Time is discrete and quarters are indexed by t. Each quarter is comprised of a continuum $[0,\ 1]$ of moments indexed by τ in which loan contracts are signed between distinct banks or with private borrowers. The model structure is illustrated in Figure 1.

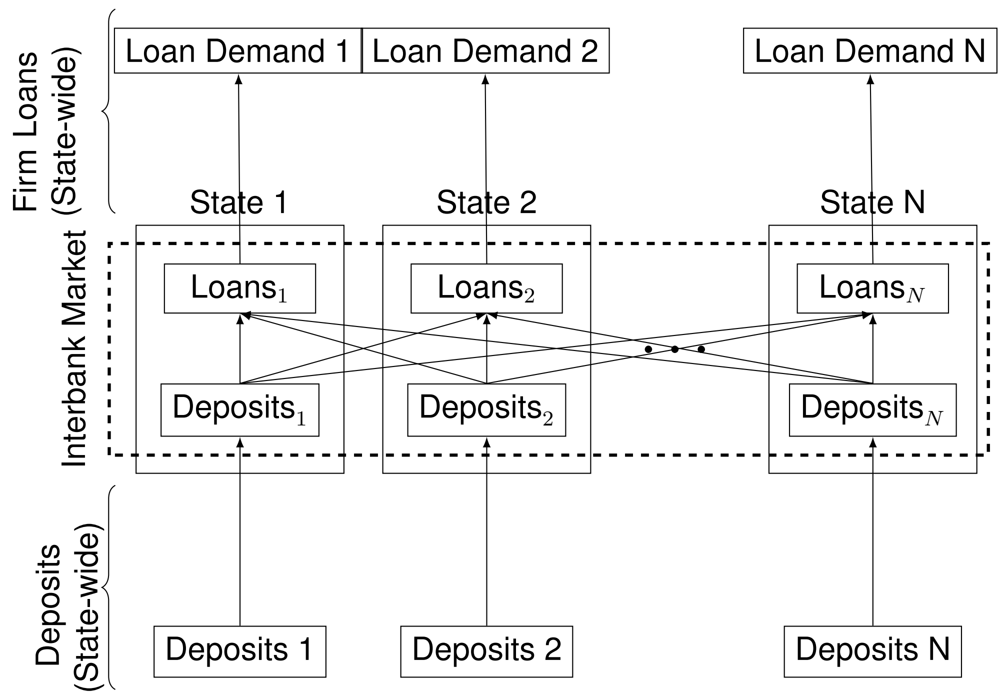


Figure 1: Model structure: Households in each state allocate savings across banks in the same state in the form of deposits. Banks lend these funds to firms in the same state. Banks in different states form an interbank market where they borrow and lend loanable funds.

Loan Division We assume the loan division of bank i (i.e., a representative bank in state i) supplies credit to the regional economy. Loan supply of bank i is subject to the following constraints:

$$L^S_{i,t}(\tau) \geqslant 0 \ , \tag{1}$$

$$L^S_{i,t}(\tau) \leqslant M_{i,t}(\tau) \ , \tag{2}$$

where $L^S_{i,t}(\tau)$ is the amount of loan supplied by bank i at period t and moment τ, which is repaid at the start of next period $t+1$. $M_{i,t}(\tau)$ is bank i's total funding available for loans, raised from local depositors or through the interbank market. In equilibrium, equation (2) should hold with equality. In each period t, the loan division i solves the following profit maximization problem:

$$\max_{\{L^S_{i,t}(\tau)\}} \int_0^1 \left[R^F_{i,t}(\tau)L^S_{i,t}(\tau) - R^I_{i,t}(\tau)M_{i,t}(\tau)\right] \mathrm{d}\tau \ , \tag{3}$$

where $R^I_{i,t}(\tau)$ represent the effective interest rate charged on funds obtained from the own deposit division or banks in other states through the interbank market. Its dependence on τ implies that a loan made in period t at moment τ is due at the start of period $t+1$. Likewise, $R^F_{i,t}(\tau)$ is the interest rate charged on loans made in period t at moment τ in state i.

Assuming perfect competition on the credit supply market, the solution of the problem (3) brings the following first order condition:

$$R^F_{i,t}(\tau) = R^I_{i,t}(\tau) \ . \tag{4}$$

Interbank funds $M_{i,t}(\tau)$ are an homogeneous, fungible good (i.e., money), and loan division n borrows them from the cheapest source at each moment τ, formally

$$\begin{aligned} R^I_{i,t}(\tau) &= \min_n \left\{R^I_{ni,t}(\tau)\right\} \ , \\ M_{i,t}(\tau) &= M_{ni,t}(\tau), \quad n = \arg\min_j \left\{R^I_{ji,t}(\tau)\right\} \ . \end{aligned} \tag{5}$$

where $R^I_{ni,t}(\tau)$ represents the rate charged by bank n for bank i, and $M_{ni,t}(\tau)$ is the amount of loan actually made by bank n to bank i in period t at moment τ.

Deposit Division The deposit division n receives deposits $D_{n,t}$ from the inhabitants of state n at the beginning of each quarter t, and distributes them to its own loan division or to banks in other states through the interbank market. The production of interbank (loanable) funds from deposits entails a cost, which is given by

$$\sum_{i=1}^{N} \int_0^1 T_{ni} \cdot z_{ni,t}(\tau) \cdot M_{ni,t}(\tau) \, \mathrm{d}\tau = (D_{n,t})^{\alpha} \,, \qquad \alpha > 1 \,, \tag{6}$$

where $M_{ni,t}(\tau)$ are loan amounts made by deposit division n to loan division i, and $D_{n,t}$ are local deposits in state n. The parameter $\alpha > 1$ captures the economies of scale in allocating and/or storing a large supply of deposits.

The parameter $T_{ni} \geqslant 1$ represents a cost associated to trading with different regions. It can capture different types of costs of transferring loanable funds, e.g., direct trade costs, agency problems, imperfect information about trading partners. Without loss of generality, we normalize the cost of trading with its own loan division to one for banks in all states, i.e., $T_{nn} = 1, \ \forall n$. Variable $z_{ni,t}(\tau)$ is an exogenous technology shock that follows a Weibull distribution, i.e.,

$$z_{ni,t}(\tau) \sim \text{Weibull}\,(1, \kappa) \ ,$$

with unit scale parameter and shape parameter κ that captures within-quarter varying difficulty to create loans.[14]

The representative deposit division n faces a upward-sloping (inverse) deposit supply curve $\rho_n^S(\cdot)$, i.e., it faces $\rho_n^S(D_{n,t})$ as the rate on deposits when demanding $D_{n,t}$ as deposit

[14]It can be understood as un-modelled seasonal fluctuations in demand and supply for loanable funds.

amounts.[15] The profit maximization problem of deposit division n is therefore given by

$$\max_{\{M_{ni,t}(\tau)\},D_{n,t}} \sum_{i=1}^{N} \int_0^1 R^I_{ni,t}(\tau) M_{ni,t}(\tau) \mathrm{d}\tau - \rho^S_n(D_{n,t}) \cdot D_{n,t} \ , \tag{7}$$

subject to the loan provision constraint (6).[16] The first order condition pins down the interbank loan rate $R^I_{ni,t}(\tau)$ charged on any bilateral transaction between banks in two different states n and i at each moment τ as follows:

$$R^I_{ni,t}(\tau) = T_{ni} \cdot z_{ni,t}(\tau) \cdot \left(\frac{1}{\alpha}\right) \underbrace{\rho^S_n(D_{n,t}) \left(1 + \frac{1}{\varepsilon^S_{n,t,D,\rho}}\right)}_{\equiv \rho_{n,t}} \cdot (D_{n,t})^{-(\alpha-1)} \ . \tag{8}$$

where

$$\varepsilon^S_{n,t,D,\rho} \equiv \left[\frac{\rho^{S'}_n(D_{n,t}) D_{n,t}}{\rho^S_n(D_{n,t})}\right]^{-1} > 0.$$

represents an elasticity of deposit supply in state n in quarter t.

From equation (8), we see that an increase in $D_{n,t}$ leads to lower interest rate $R^I_{ni,t}(\tau)$ charged by bank n, due to assumed economies of scale in producing loanable funds, i.e., $\alpha > 1$. When deposit supply is less elastic, i.e., $\varepsilon^S_{n,t,D,\rho}$ is lower, an interbank rate $R^I_{ni,t}(\tau)$ becomes higher.[17] Finally, a higher trading cost T_{ni} generates higher equilibrium interbank rate offered by bank n to bank i. For simplicity, the heterogeneity of deposit rates and the deposit supply elasticity across different states is abstracted away in our analysis, and we

[15] We assume that $\rho^S_n(D_{n,t})$ is convex enough in $D_{n,t}$ that guarantees the existence and uniqueness of the solution of optimization (7) subject to (6). For this issue, see Online Appendix A. The Model Derivation.

[16] We can microfound the inverse deposit supply curve $\rho^S_n(\cdot)$ by relating the compensation of deposits to the prevailing risk-free rate on government bonds and the cash with zero return, as in Drechsler et al. (2017).

[17] Under less elastic deposit supply, the marginal cost of attaining additional one dollar amount of deposit for bank n is higher, leading to higher interest rates on interbank lending at the optimum, ceteris paribus.

thus assume that $\rho_{n,t} \equiv \rho_t$, $\forall n$.[18]

Equilibrium When the loan division of bank i supplies credit to the regional economy, it faces an exogenous loan demand throughout the quarter t, which is given by

$$L^D_{i,t}(\tau) \equiv \left(R^F_{i,t}(\tau)\right)^{-\beta} \cdot \varepsilon_{i,t} \ , \qquad \forall i \ , \tag{9}$$

where $R^F_{i,t}(\tau)$ is the interest rate on private loans and $\varepsilon_{i,t}$ a regional loan demand shock in state i in quarter t. In equilibrium, the final loan rate $R^F_{i,t}(\tau)$ is connected to the interbank interest rate $R^I_{i,t}(\tau)$ by (4), and $R^I_{i,t}(\tau)$ is in turn a minimum of $R^I_{ni,t}(\tau)$ over n, as explained in (5). Finally, $R^I_{ni,t}(\tau)$ is given in (8), and the loan market is equilibrated, i.e., $L^D_{i,t}(\tau) = L^S_{i,t}(\tau)$ for $\forall i, t, \tau$.

Equation (8), together with the properties of the Weibull distribution, makes the interbank rate $R^I_{i,t}(\tau)$ follow the Weibull distribution itself, i.e.,

$$R^F_{i,t}(\tau) = R^I_{i,t}(\tau) \sim \text{Weibull}\left(\Phi_{i,t}, \kappa\right) \ , \tag{10}$$

where

$$\Phi_{i,t} = \left(\frac{\rho_t}{\alpha}\right) \cdot \left[\sum_{n=1}^{N} \left(T_{ni}\right)^{-\kappa} \left(D_{n,t}\right)^{\kappa(\alpha-1)}\right]^{-\frac{1}{\kappa}} \ . \tag{11}$$

The total lending demand in quarter t is then

$$L^D_{i,t} = \int_0^1 L^D_{i,t}(\tau)\mathrm{d}\tau = \left[\int_0^1 R^F_{i,t}(\tau)^{-\beta}\mathrm{d}\tau\right] \cdot \varepsilon_{i,t} \qquad \forall i \tag{12}$$

[18]Since $R^I_{ni,t}(\tau)$ is proportional to $T_{ni} \cdot z_{ni,t}(\tau)$ at optimum, deposit division n is indifferent in forming loanable funds to different states, i.e., the destination state i does not matter for the profit of deposit division n. Therefore, optimization (7) is consistent with the fact that interbank funds are fungible, and loan division i borrows from the cheapest source at each moment τ.

where due to the law of large numbers (LLN), we can employ

$$\int_0^1 R^F_{i,t}(\tau)^{-\beta}\mathrm{d}\tau = \mathbb{E}\left[R^F_{i,t}(\tau)^{-\beta}\right] .$$

From equations (10), (11), and (12), the credit in state i can be written as

$$L^D_{i,t} = \left[\sum_{n=1}^{N} (T_{ni})^{-\kappa} (D_{n,t})^{\kappa(\alpha-1)}\right]^{\frac{\beta}{\kappa}} \left(\frac{\alpha}{\rho_t}\right)^{\beta} \Gamma\left(1-\frac{\beta}{\kappa}\right) \varepsilon_{i,t} \qquad \forall i . \tag{13}$$

Note that the extended credit $L^D_{i,t}$ in state i (i) is increasing in deposits in all other states n; (ii) is decreasing in transport cost T_{ni} from other states n to state i; (iii) is decreasing in ρ_t, the uniform deposit rate. From (13), we infer that a drop in $D_{n,t}$ in state n can lead to collapses in lending $L_{i,t}$ in different states i. This will be a basis of our empirical analysis of the transmission of banking panics across states in Section 4.

Key Trade-off To better understand the model implications, we consider a case where deposits in different states are equal, i.e., $D_{n,t} = \bar{D}_t, \ \forall n$, and the transaction costs between different regions are infinite, i.e., $T_{ni} \to \infty, \ i \neq n$ with $T_{ii} = 1$ for $\forall i$. Then, equation (13) becomes

$$L^D_{i,t} = \left(\frac{\alpha}{\rho_t}\right)^{\beta} \cdot \left(\bar{D}_t\right)^{\beta(\alpha-1)} \Gamma\left(1-\frac{\beta}{\kappa}\right) \cdot \varepsilon_{i,t} , \qquad \forall n , \tag{14}$$

and banks are forced to entirely rely on their domestic depositors to fund their lending activity. In this case, no matter what happens to other states in terms of deposit amounts, it does not affect state i's loan amounts in equilibrium.

The opposite case with no transaction costs $T_{ni} = 1 \ , \ \forall n, i$ yields the following expression:

$$L_{i,t}^{D}=\underbrace{N^{\frac{\beta}{\kappa}}}_{>1}\cdot\left(\frac{\alpha}{\rho_t}\right)^{\beta}\cdot\left(\bar{D}_t\right)^{\beta(\alpha-1)}\Gamma\left(1-\frac{\beta}{\kappa}\right)\cdot\varepsilon_{i,t}\ ,\qquad\forall n\ , \tag{15}$$

where banks in any state are able to supply $N^{\frac{\sigma}{\kappa}}>1$ times more credit,[19] given the homogeneous deposit amount $\bar{D}_t$. However, we can observe that the loan amount $L_{i,t}^{D}$ becomes $N^{\frac{\sigma}{\kappa}}>1$ times more volatile given the volatility of $\bar{D}_t$, creating a potential instability. Thus, we can observe that the interbank lending system creates an interesting risk-return trade-off for the aggregate funding.

An interesting observation emerges from these exercises: interbank transactions improve the allocation of funding across the banking sector and allow the economy to sustain higher (on average) levels of credit. But on the other hand, as illustrated by equation (13), credit supply becomes linked to deposit fluctuations outside its regional borders, setting the theoretical foundations for the spatial spread of panics, which we empirically analyze using the historical data of the National Banking Era in Section 4.

4 Empirical Estimation

4.1 Methodology

A log-linear approximation of equation (13) leads to[20]

$$\log\left(L_{i,t}\right)=\mu_i+s_t+\sum_{n=1}^{N}\tilde{T}_{ni}\cdot\log\left(D_{n,t}\right)+\epsilon_{i,t}\ ,\qquad\forall n\ , \tag{16}$$

[19]Of course, the gains from a market with realistic transaction costs are likely to be lower than (15).

[20]The derivation of equarion (16) is provided in Online Appendix A. The Model Derivation.

where μ_i and s_t represent state and seasonal (time) fixed effects, respectively, and coefficient $\tilde{T}_{ni}$ captures the intensity of responses of loans in state i to deposit fluctuations in state n. For example, a higher trading cost (T_{ni}) between states n and i makes harder for bank n to lend to bank i in interbank markets, thus lowering the intensity of responses of state i loans to fluctuations in state n deposits, i.e., lower $\tilde{T}_{ni}$.

In order to study the spatial propagation of panics throughtout states, we assume the following particular functional specification for $\tilde{T}_{in}$:

$$\tilde{T}_{ni} = \lambda_1 + \lambda_2 \log\left(Distance_{ni}\right) + \lambda_3 Neighbor_{ni} + \lambda_4 Own_{ni} \ , \tag{17}$$

where $Distance_{ni}$ is measured as the Euclidean distance between the most populated city of state n and that of state i (in geographical centroids), $Neighbor_{ni}$ is a binary variable equal to one if the states pair n and i are neighbors (i.e., share a border) and Own_{ni} is a binary variable equal to one if $n = i$. Basically, we assume the sensitivity of loans in state i to fluctuations in deposits in state n only depends on the geometric distance (and whether they are neighbors) between the two states.[21]

Also, we assume that in the data a linear relationship between deposits and panic events holds, for example,

$$\log\left(D_{n,t}\right) = c_n + \log\left(D_{n,t-1}\right) + \phi Panic_{n,t} + \upsilon_{n,t} \ , \tag{18}$$

where $Panic_{n,t}$ is a binary variable equal to one if state n experiences a panic in banking sector in quarter t.[22]

[21] $\lambda_4 \neq 0$ can be attributed to the "home bias" in interbank lending markets.

[22] For example, for the (minor) panic of 1884, we have

$$Panic_{NY,1884Q2} = Panic_{PA,1884Q2} = Panic_{NJ,1884Q2} = 1$$

With equations (16), (17), and (18), which are based upon the simple partial-equilibrium model presented in Section 3, we can evaluate the spatial and dynamic propagation of panics by estimating the following set of Jordà Local Projections (Jordà, 2005):

$$y_{i,t+h} = \eta^y_{i,h} + s^y_{t,h} + \sum_{j=1}^{4} \theta^y_{j,h} F^j_{i,t} + \sum_{l=1}^{L} \beta^y_{l,h} \mathbf{X_{i,t-1}} + \epsilon_{i,t+h}, \quad h = 1, \ldots, H \ , \tag{19}$$

where

$$F^1_{i,t} = \sum_{n=1}^{N} Panic_{n,t} \qquad\qquad F^3_{i,t} = \sum_{n=1}^{N} Neighbor_{ni} \cdot Panic_{n,t}$$

$$F^2_{i,t} = \sum_{n=1}^{N} \log\left(Distance_{ni}\right) \cdot Panic_{n,t} \qquad F^4_{i,t} = \sum_{n=1}^{N} Own_{ni} \cdot Panic_{n,t} \ ,$$

and $\eta^y_{i,h}$ and $s^y_{t,h}$ are state and seasonal fixed effects, and $X_{i,t-l}$ is a set of control variables that includes four lags of variables $\{F^j_{i,t}\}^4_{j=1}$ and those of the left hand side variable $y_{i,t}$. For dependent variables $y_{i,t}$, we consider (i) (log) deposits; (ii) (log) loans; and (iii) liquidity ratio, which is defined as the ratio of cash, species and short-term assets to total assets of state i; (iv) (log) average bank capital; (v) (log) the number of active banks.

Are Banking Panics Exogenous? In order for our regression equation (19) to be identified, our panic variable $Panic_{n,t}$ must be exogenous, i.e., uncorrelated with the error term $\epsilon_{i,t+h}$. Then the coefficients $\left\{\theta^y_{j,h}\right\}$ in (19) would capture the causal and spatial dynamic transmission of panics.

Jalil (2015) provides some narrative evidence that backs this assumption, with individual episodes of fraud, foreign shocks or even weather, acting as the trigger of panics.[23] Our

where $1884Q2$ means the second quarter of year 1884.

[23] About 1884 panic originated from New York, Jalil (2015) documents that "On May 14, the Metropolitan Bank closed its doors following a serious run. *Rumors had been circulating that its president had misappro-*

result in Online Appendix B. Are Panics Exogenous or Correlated with Business Cycles? independently test whether a panic is independent of the business cycle conditions in the state it originates from, based on Granger causality and find that the minor panics of the series of Jalil (2015) are an independent source of variation. Therefore, we consider only the minor panics in Table 2 for our regression (19).

Note that even if this assumption is violated within the states where the panics originated, the estimates $\left\{\theta^{y}_{j,h}\right\}$ of the spatial transmission are still likely to remain causal as long as the regional economy of non-origin regions is uncorrelated with the causes of the panic in the origin states. The plausibility of this hypothesis is reinforced by the unit banking system and the restrictions on interstate branching throughout our sample period, leaving the interbank market as the most obvious and significant source of spatial transmission of panics.

4.2 Spatial Transmission: Results

Based on the above discussion about panic exogeneity, we run regression (19) focusing on Jalil (2015)'s minor (regional) panics: in this regression, if state n experiences a minor panic in quarter t, regardless of where it originates, we assign $Panic_{n,t} = 1$.

priated funds for speculative purposes. The suspension of the Metropolitan Bank, an institution holding reserves from banks throughout the nation, led to the intervention of the New York Clearing House." About 1907 major panic originated from New York as well, Jalil (2015) documents "The actions of a group of New York City financiers, with controlling interests over several banks, triggered the panic of 1907. The group misappropriated bank funds to speculate on rising copper prices. The gamble proved to be a mistake. Copper prices collapsed and news of these events triggered runs on the banks implicated in the speculation. Rumors that other banks and trust companies might be connected to the speculators unsettled public confidence and a panic quickly spread throughout the city."

Figures 3, 4, 6, 5, and 7 of Section 6 provide a graphical overview of the results of the regression. The figures are constructed specifically as follows:

Step 1 Estimate equation (19) for all h, obtain $\left\{\hat{\theta}^{y}_{j,h}\right\}_{j=1}^{4}$.

Step 2 Assume a sudden panic in the state of New York, i.e., $Panic_{NY,t} = 1$, and then report $\sum_{j=1}^{4} \hat{\theta}^{y}_{j,h} F^{j}_{i,t}$ for each variable y.

P-values are constructed using Driscoll-Kraay standard errors in order to provide consistent estimates to spatial correlation, heteroskedasticy and auto-correlated error terms.

Figure 3 reports the evolution of deposits following a panic. We observe that the impact of panics ranges from -4% in the simulated origin state to around -3% in other states even far to the west, suggesting the rapid spatial propagation across the entire United States. The effect of the panic after one year features a lagged negative response of deposits outside the origin state, though the result is not quite statistically significant. After two years, we observe that deposits have returned to their pre-panic trend everywhere. This result is consistent with the literature, e.g., Calomiris and Carlson (2017) and can be understood as sequential deposit runs outside the origin state.[24]

Figure 4 depicts a similar pattern for bank lending (loans), with an initial 4% drop in the origin state, and mild but significant reductions of bank lending throughout the country. Throughout the first year after a panic, lending decreases by 3%-4% across different states. Eventually, it returns to the pre-crisis level everywhere except in the origin and neighbor states, though the results are no longer statistically significant.

[24] Gorton (1988) finds that banking panics during the National Banking Era can mostly be explained not by self-fulfilling prophecy, but by depositors changing their perception of the fundamental risk based on the arrival of new information about fundamentals. Sequential deposit runs across different states after a local panic can be understood from that perspective.

Figure 5 shows the evolution of the liquidity ratio, defined as the ratio of cash, species, and short-term assets to total assets that banks hold. It increases on impact on the origin state and persistently rises above its pre-crisis level by 4-8% across the country thereafter, but the result becomes significant for many states after 6-7 quarters. It is consistent with the stronger negative response of bank lending vis-à-vis deposits in Figures 3 and 4, which suggests that banks reallocate their portfolio towards safer assets like bonds following panics.

Figures 6 and 7 show the evolution of (average) bank capital and the number of banks, respectively. While there is no discernible effect on impact, bank capital diminishes by up to 1.5% after two years across many states including the neighbor states and those further out in the west, where the point estimates become significant after 3 quarters. Similarly, the number of active banks drops by 1.5-1.8% after two years, though only the origin state and some neighboring states are affected.

The overall picture that emerges from these results is broadly consistent with the results found by the literature on financial crisis. In specific, our results that bank lending is significantly negatively affected throughout states is consistent with the Vector Autoregression (VAR) analysis of Jalil (2015), in which both price levels and output are negatively affected by a panic in a similar time period.

In sum, in our sample periods, (minor) panics have a moderate impact on the banking sector across several dimensions, even if their effects largely vanish after two years. More surprisingly, panics display a robust spatial transmission outside their initial state boundaries, reaching even states that are geographically far from the origin state, depending on the initial structure of interbank loan markets formed among states.

4.2.1 Robustness

Panic Dummies for Origin States Only In the above regression (19), we assigned $Panic_{i,t} = 1$ if state i experiences a panic in quarter t, regardless of where it originates.[25] For robustness checks, we re-run regression (19) assuming $Panic_{i,t} = 1$ only for the origin state i of each panic.[26] The results are provided in Online Appendix C.1. Panic Dummies for Origin States Only and very close to the above original results (Figures 3, 4, 6, 5, 7). We conclude that our results of the spatial propagation of panic shocks across states are robust under these different regression specifications.

Deposit Size Effects In the above regression (19), we abstract from a potential channel in which a panic in states with a larger financial market will have bigger impacts on other states across the United States. To account for this so-called size effects, we slightly modify the regression (19) by controlling lagged deposit shares as follows:

$$y_{i,t+h} = \eta^y_{i,h} + s^y_{t,h} + \sum_{j=1}^{5} \theta^y_{j,h} F^j_{i,t} + \sum_{l=1}^{L} \beta^y_{l,h} \mathbf{X_{i,t-1}} + \epsilon_{i,t+h}, \;\; h = 1, \ldots, H \;, \qquad (20)$$

[25]For example, for the panic of 1884 in Table 2,

$$Panic_{NY,1884Q2} = Panic_{PA,1884Q2} = Panic_{NJ,1884Q2} = 1,$$

where $1884Q2$ means the second quarter of year 1884.

[26]Jalil (2015) provides a list of the origin states of panics, based on anecdotal sources, e.g., the Commercial and Financial Chronicle. See Table 2 for the list of origin states.

where

$$F^1_{i,t} = \sum_{n=1}^{N} Panic_{n,t} \qquad F^3_{i,t} = \sum_{n=1}^{N} Neighbor_{ni} \cdot Panic_{n,t}$$

$$F^2_{i,t} = \sum_{n=1}^{N} \log\left(Distance_{ni}\right) \cdot Panic_{n,t} \qquad F^4_{i,t} = \sum_{n=1}^{N} Own_{ni} \cdot Panic_{n,t}$$

$$F^5_{i,t} = \underbrace{\sum_{n=1}^{N} \log\left(\frac{D_{n,t-1}}{D_{t-1}}\right) \cdot Panic_{n,t}}_{\text{New control}}$$

and $D_{t-1} = \sum_n D_{n,t-1}$ and $\eta^y_{i,h}$ and $s^y_{t,h}$ are state and seasonal fixed effects. $X_{i,t-l}$ is a set of control variables that includes four lags of variables $\{F^j_{i,t}\}^5_{j=1}$ and those of the left hand side variable $y_{i,t}$. In Online Appendix C.2. Deposit Size Effects, we follow the same steps in Section 4.2 with the initial log deposit share of New York at its average across the sample periods.

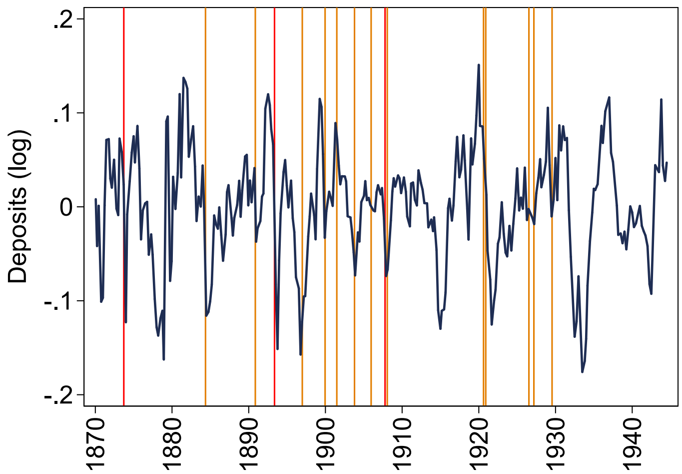
The results are surprisingly similar to our original results, which suggests the size effect of the spatial propagation of panics is not too big.

5 Conclusions

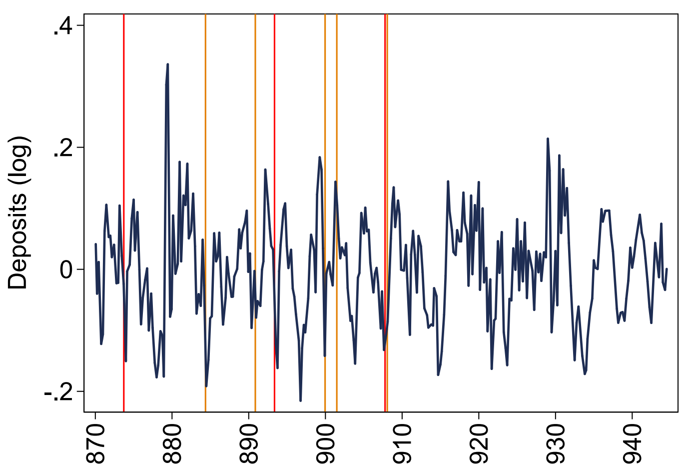
This paper provides a quantitative analysis of the impacts and geographical propagation of historical banking panics in the United States. Our tractable model formalizes a key trade-off stemming from the interbank relation that was prevalent during the National Banking Era: the interbank loan networks allow banks to access cheaper funding sources and raise the level of credit supply, while exposing them to risks of runs and panics outside their state borders, thereby allowing a minor panic in one state to be transmitted to other states.

We find that during 1870-1929, a panic in one state was accompanied by moderate and temporary drops in deposits and lending, increased liquidity holdings, and a small negative impact on bank capital and the number of active banks, in many other states, with the results being statistically significant up to two years from the onset of a panic.

6 Figures



(a) Filtered US aggregate (log)-deposits from 1870 to 1945: the red vertical lines represent major panics according to Jalil (2015), while yellow lines represent the dates of minor panics documented by Jalil (2015) as well.



(b) Filtered (log)-deposits in the state of New York from 1870 to 1945: the red vertical lines represent major panics according to Jalil (2015), while yellow lines represent the dates of minor panics that affected New York, documented by Jalil (2015) as well.

Figure 2: Time-series deposits of the United States as a whole and the state of New York.

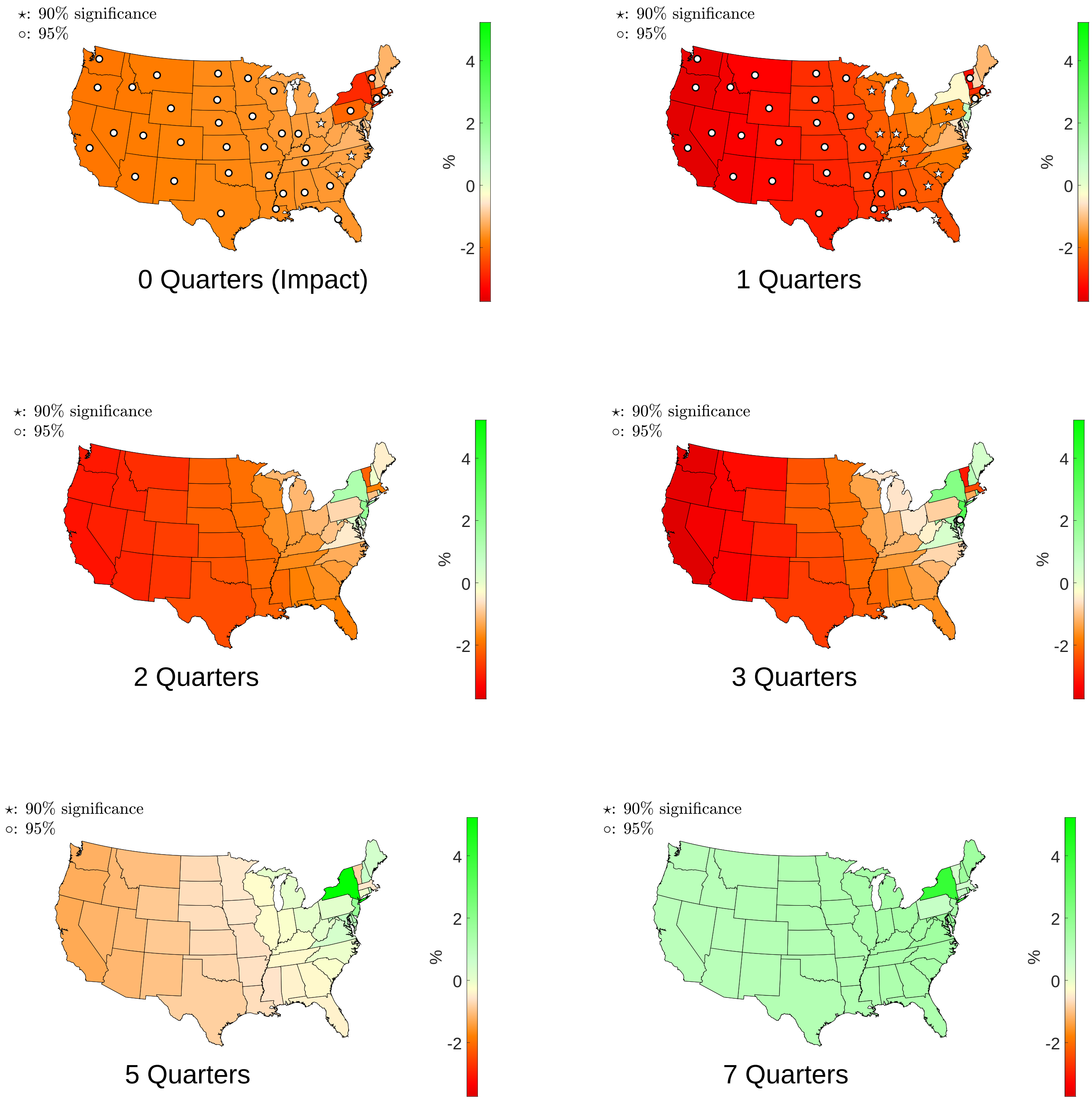


Figure 3: Impulse-response of bank deposits to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors.

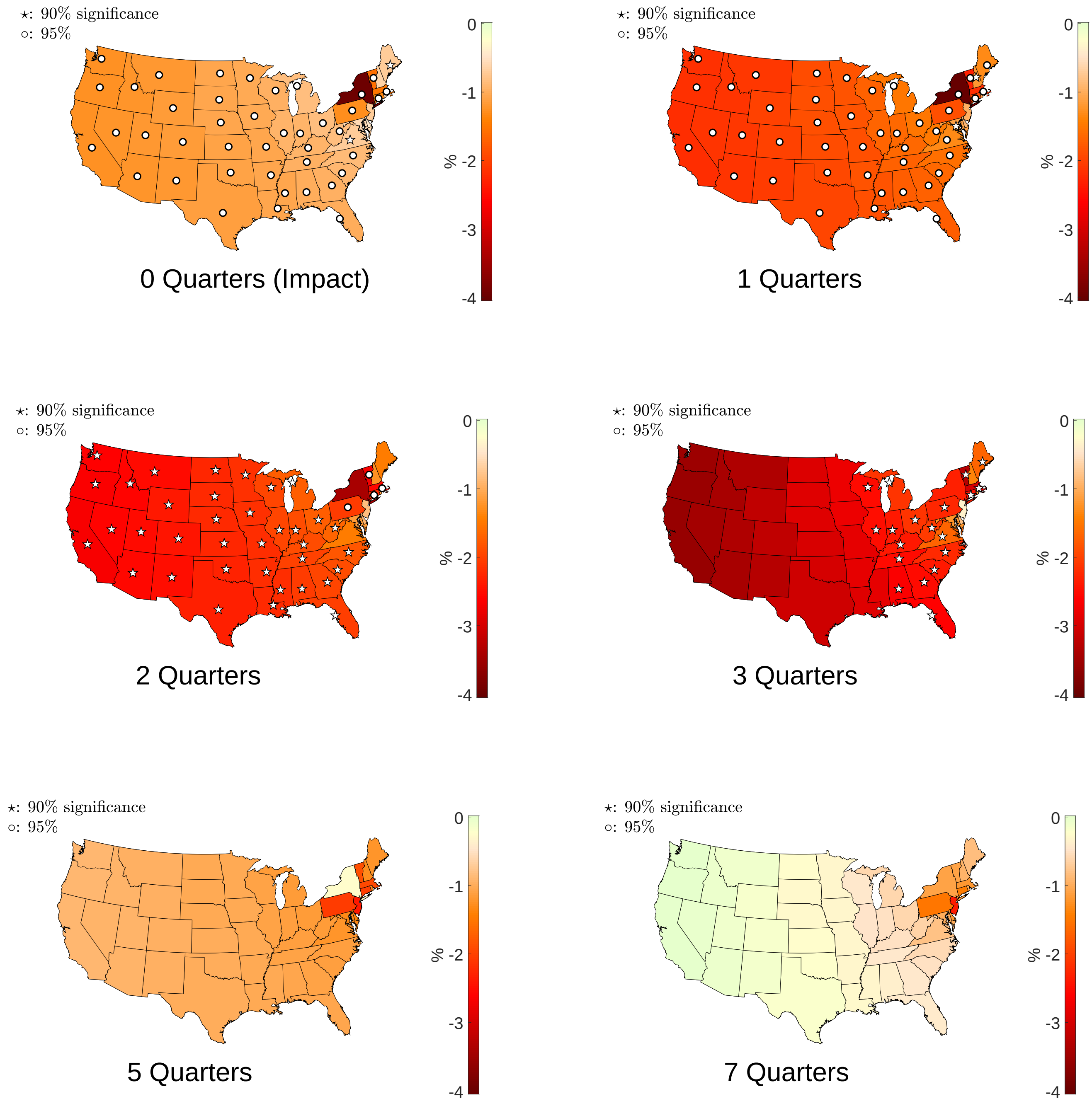


Figure 4: Impulse-response of bank loans across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$

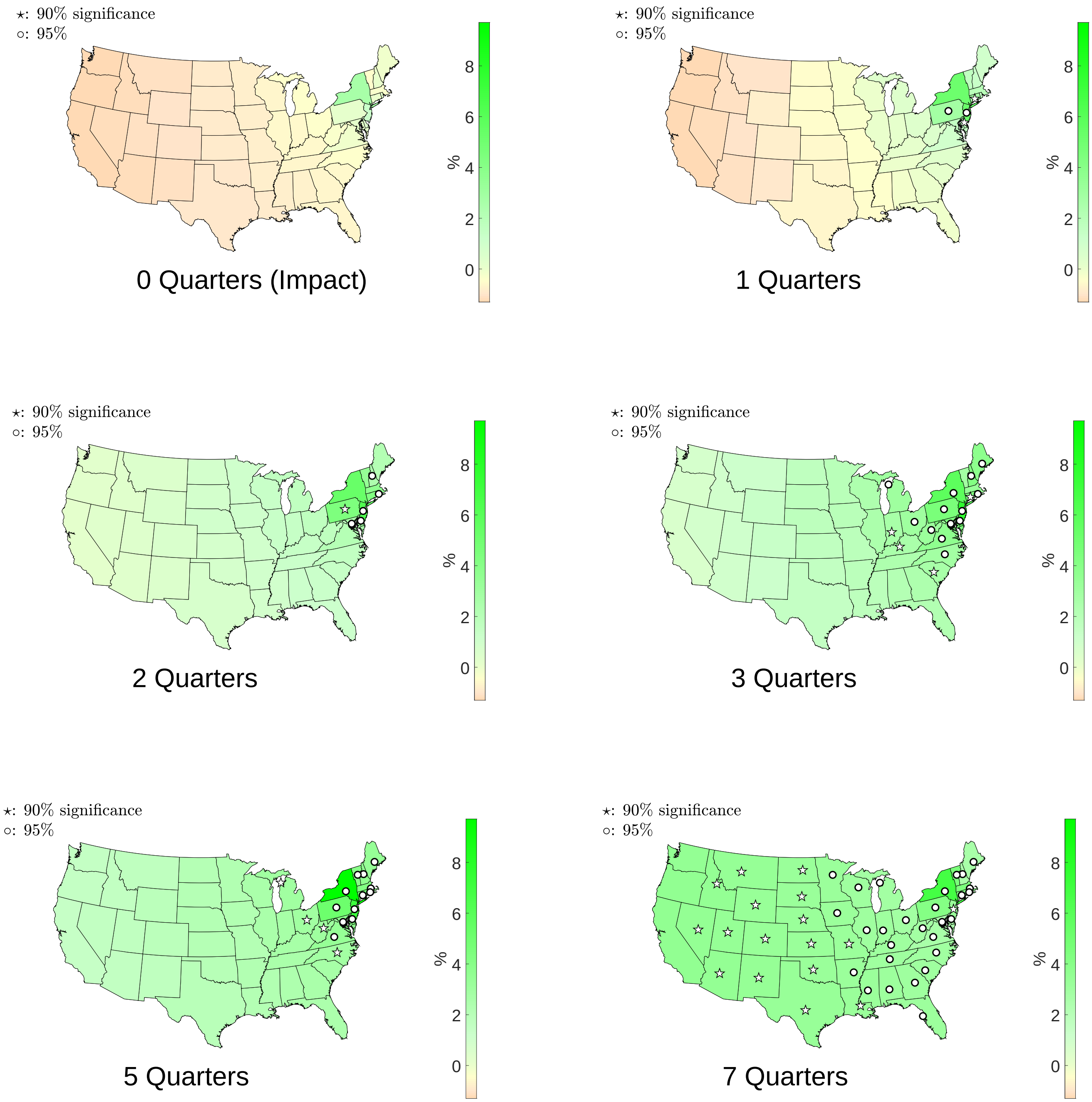


Figure 5: Impulse-response of liquidity ratios across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$

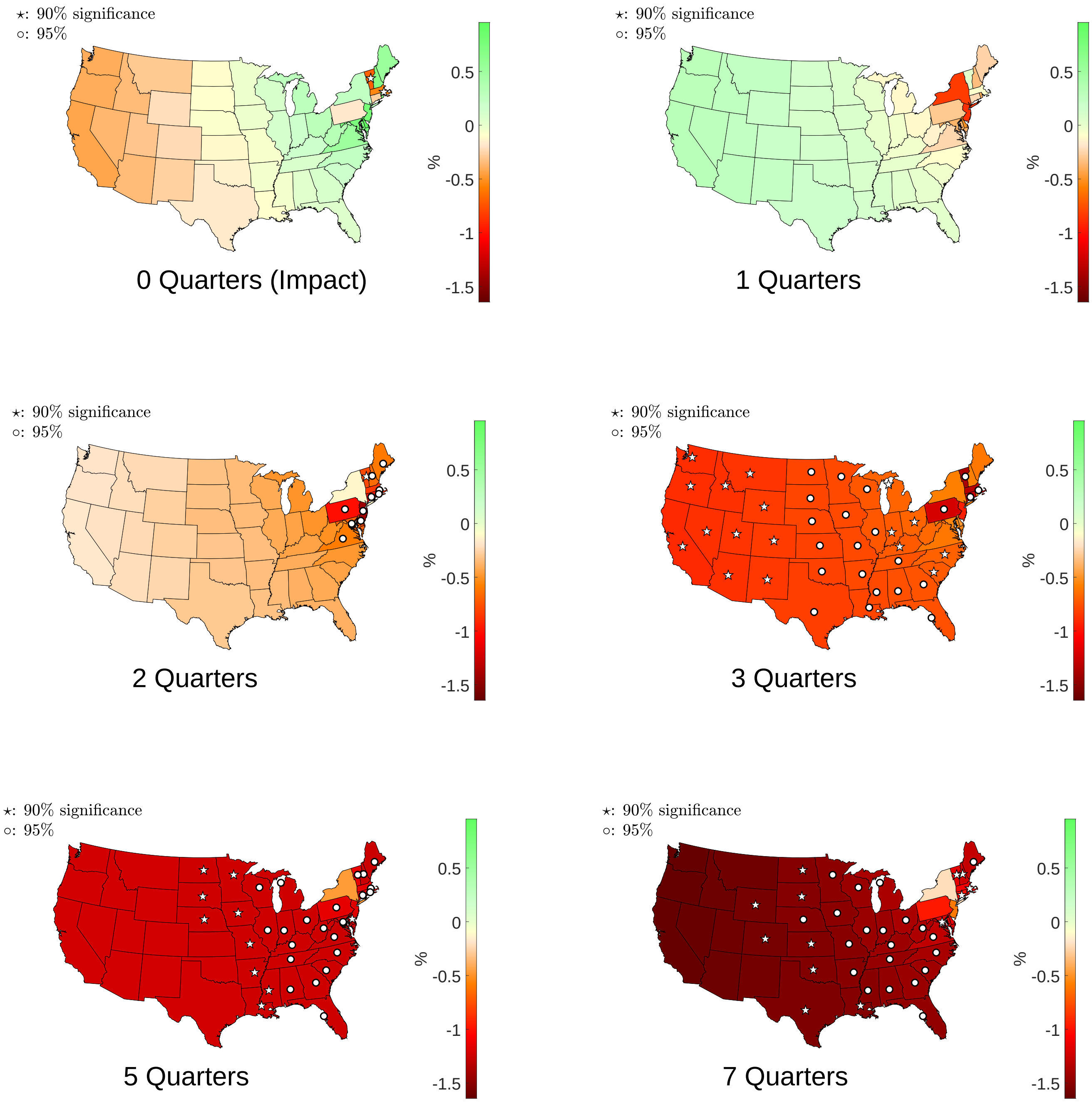


Figure 6: Impulse-response of bank capital across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$

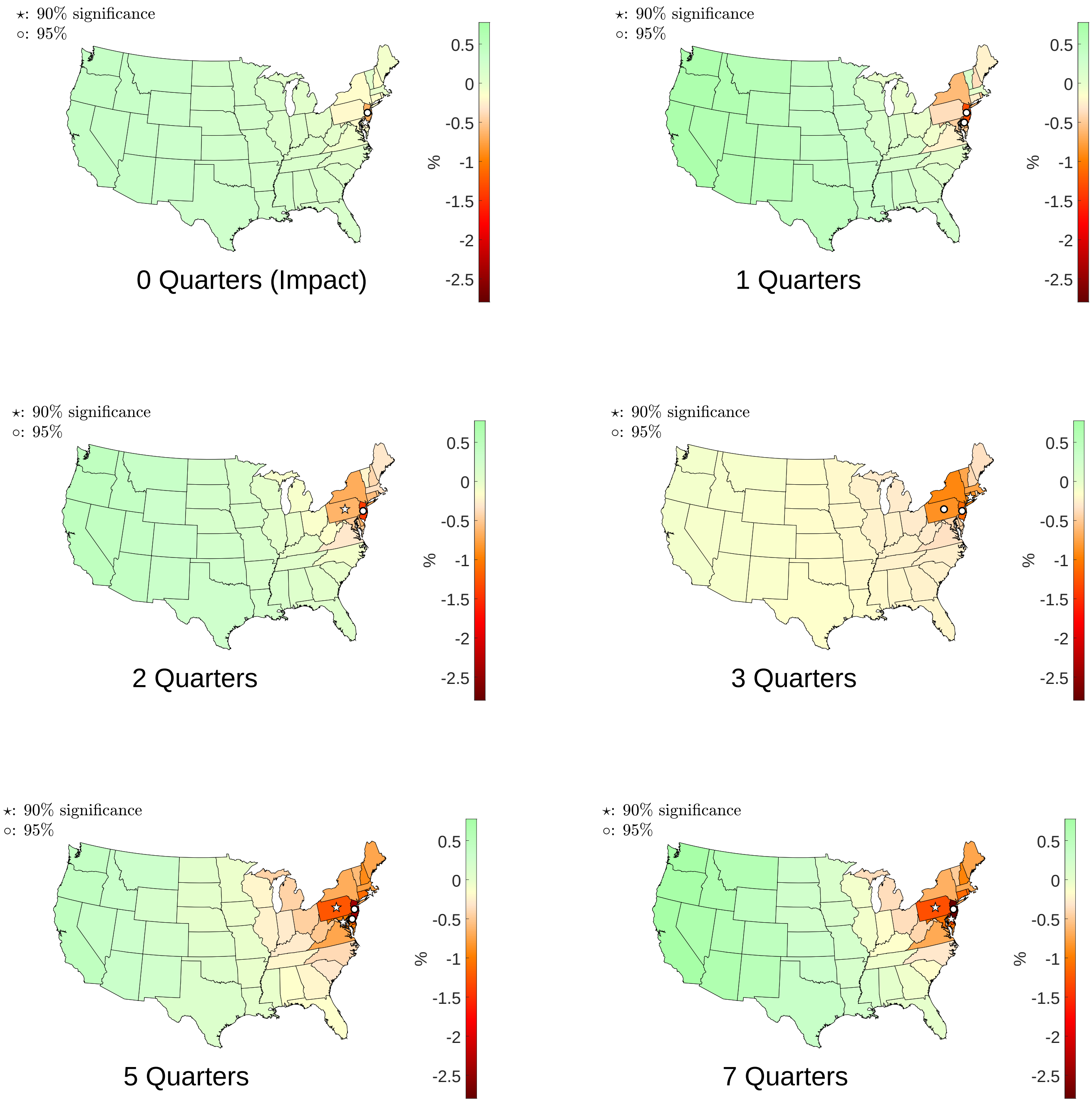


Figure 7: Impulse-response of the number of banks across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$

7 Tables

Resources	Liabilities
Loans and discounts	Capital stock
Overdrafts	Surplus fund
Bonds for circulation	Undivided profits
Bonds for deposits	National bank circulation
Other bonds for deposits	State bank circulation
U.S. Bonds on hand	Due to national banks
Premium on bonds	Due to State banks
Bonds, securities, etc	Due to trust companies, etc
Banking house, furniture, etc	Due to reserve agents
Real state, etc	Dividends unpaid
Current expenses	Individual deposits
Due from national banks	Certified checks
Due from State banks	U.S. deposits
Due from reserve agents	Deposits U.S. disbursing officers
Internal revenue stamps	Bonds borrowed
Cash items	Notes rediscounted
Clearing-house exchanges	Bills payable
Bills of other banks	Clearing-house certificates
Fractional currency	Other liabilities
Trade dollars	Specie
Legal-tender notes	
U.S. certificates of deposit	
Three per cent certificates	
5% fund with Treasury	
Clearing-house certificates	
Due from U.S. Treasury	
Total	Total

Table 1: Balance sheet original categories of the Abstract of Reports. The Abstract of Reports, contained in the Annual Report of the Comptroller of the Currency, provides regional aggregates of the categories that we list in Table 1. The categories reported tend to vary slightly across time, typically due to the subdivision of big categories into smaller ones on the latest reports. For example, the category "Loans and discounts" contained "Overdrafts" in the initial years, and overdrafts eventually became a category on its own.

Resources.	Oct. 21, 1913.	Jan. 13, 1914.	Mar. 4, 1914.	June 30, 1914.	Sept. 12, 1914.
ALABAMA.	90 banks.	90 banks.	90 banks.	90 banks.	90 banks.
Loans and discounts	$45,513,715.05	$42,849,992.35	$42,905,637.89	$43,582,574.87	$41,812,117.43
Overdrafts	396,119.39	288,816.63	238,160.73	104,561.68	111,129.33
Bonds for circulation	8,747,750.00	8,935,750.00	8,934,750.00	9,101,750.00	9,103,749.95
Misc. securities	...	...	...	...	4,861,281.14
Bonds for deposits	411,000.00	485,000.00	505,713.00	410,000.00	397,000.00
Other b'ds for deposits	496,153.75	500,655.64	476,900.75	274,500.00	418,500.00
U. S. bonds on hand	9,000.00	9,000.00	9,000.00	9,000.00	10,000.00
Premiums on bonds	91,245.71	78,576.04	77,412.29	70,094.79	63,521.91
Bonds, securities, etc.	3,348,927.54	3,358,970.02	3,308,569.78	3,363,852.16	2,321,201.77
Stocks	...	...	...	143,858.49	179,144.71
Banking house, etc.	2,173,798.88	2,169,921.91	2,169,114.21	2,190,582.18	2,196,334.97
Real estate, etc	322,342.75	311,914.19	322,095.64	333,964.56	333,918.44
Due from nat'l banks	4,195,515.45	4,300,854.48	3,666,789.64	2,169,436.13	1,727,789.62
Due from State banks	1,714,335.10	1,660,222.11	1,303,238.00	976,877.10	845,832.72
Due from res've agts	6,959,955.73	7,374,465.51	6,348,607.03	,403,111.15	3,215,822.55
Cash items	308,028.93	262,611.25	239,394.00	187,521.17	238,991.11
Clear'g-house exch'gs	324,608.67	250,191.01	311,139.61	270,994.99	179,617.99
Bills of other banks	889,950.00	1,124,469.00	978,233.00	964,975.00	1,535,034.00
Fractional currency	29,160.00	41,041.08	45,683.69	45,333.69	42,625.33
Specie	2,852,883.16	3,248,435.06	3,002,017.36	3,043,383.10	2,852,801.47
Legal-tender notes	662,485.00	709,896.00	531,574.00	459,927.00	341,739.00
5% fund with Treas	424,287.50	429,037.50	413,137.50	434,437.50	561,766.50
Due from U. S. Treas	33,700.00	39,750.00	14,902.00	21,625.00	5,350.00
Total	79,904,962.61	78,429,569.78	75,802,070.12	72,563,370.56	73,355,269.94

(a) An example of balance sheets: asset side of banks in the state of Alabama from October 1913 to September 1914.

Liabilities.	Oct. 21, 1913.	Jan. 13, 1914.	Mar. 4, 1914.	June 30, 1914.	Sept. 12, 1914.
ALABAMA.	90 banks.	90 banks.	90 banks.	90 banks.	90 banks.
Capital stock	$10,180,290.00	$10,320,100.00	$10,375,500.00	$10,405,000.00	$10,405,000.00
Surplus fund	5,851,293.59	6,042,995.00	6,013,995.00	6,052,170.00	6,119,925.00
Undivided profits	1,452,249.96	1,345,635.01	1,623,606.48	1,662,905.41	1,599,714.20
Nat'l-bank circulation	8,694,175.00	8,885,470.00	8,803,060.00	8,984,400.00	11,008,827.50
State-bank circulation	...	...	...	...	...
Due to national banks	2,280,617.15	2,191,660.20	1,784,251.77	1,184,974.72	1,014,920.21
Due to State banks	2,549,617.27	2,500,465.48	1,927,496.87	1,073,390.53	890,665.68
Due to trust co.'s, etc.	224,690.83	367,524.10	297,992.96	148,529.49	107,222.35
Due to reserve agents	114,311.60	116,283.51	44,660.72	99,095.45	123,588.71
Dividends unpaid	35,842.00	65,113.41	9,985.42	209,618.42	39,996.50
Individual deposits	43,555,062.18	44,766,048.83	43,484,032.59	39,135,391.86	55,916,560.84
United States deposits	1,526,438.50	1,209,730.53	579,288.80	393,796.17	608,724.64
Postal savings deposits	47,602.83	48,465.95	53,074.55	52,905.32	56,663.19
Dep'ts U.S.dis. officers	31,631.18	124,907.27	164,556.38	...	...
Bonds borrowed	390,800.00	47,800.00	47,800.00	...	...
U. S. bonds borrowed	...	...	...	8,000.00	15,000.00
Other bonds borrowed	...	...	...	21,800.00	181,800.00
Notes rediscounted	726,613.10	183,648.36	9,000.00	146,602.99	765,222.31
Bills payable	2,199,018.25	183,000.00	635,000.00	2,919,054.89	4,440,750.00
Reserved for taxes	35,931.62	14,235.03	32,280.09	54,521.26	45,394.45
Other liabilities	8,777.55	16,487.10	6,488.49	11,204.05	15,294.36
Total	79,904,962.61	78,429,569.78	75,802,070.12	72,563,370.56	73,355,269.94

(b) An example of balance sheets: liability side of banks in the state of Alabama from October 1913 to September 1914.

Figure 8: Balance sheet original categories of the Abstract of Reports: banks in the state of Alabama from October 1913 to September 1914.

States	Panic, start	Panic, end	Reporting date	Time to start (days)
All (Major) - from **Europe**	18sep1873	30sep1873	26dec1873	99
NY, PA, NJ	13may1884	31may1884	20jun1884	38
NY	10nov1890	22nov1890	19dec1890	39
All (Major)	13may1893	19aug1893	12jul1893	60
IL, MN, WI	26dec1896	26dec1896	09mar1897	73
MA, NY	16dec1899	31dec1899	13feb1900	59
NY	27jun1901	06jul1901	15jul1901	18
PA, **MD**	18oct1903	24oct1903	17nov1903	30
All (Major) - from **NY**	12oct1907	30nov1907	03dec1907	52
NY	25jan1908	01feb1908	14feb1908	20
MA	12aug1920	02oct1920	08sep1920	27
ND	27nov1920	19feb1921	29dec1920	32
FL, **GA**	14jul1926	21aug1926	31dec1926	170
FL	08mar1927	26mar1927	23mar1927	15
FL	20jul1929	07sep1929	04oct1929	76
			Median	38.5

Table 2: Banking panics chronology (in the sample period). The series is extracted from Jalil (2015). The first column reports the states in which the panic initially originated (**bold** font) and other "affected" states (normal font) where panics arose. The start and end dates of panics are obtained from the classification appendix of Jalil (2015) when possible or by reading the original sources listed in Jalil (2015). The fifth column reports the number of days elapsed between the start of a crisis and the first Abstract of Reports from the Comptroller of the Currency observed after the crisis.[27]

[27] There was a relatively minor panic in 1905 that stemmed in Chicago, Illinois. Starting on December 18, 1905 by the collapse of three banks (the Chicago National Bank, the Home Savings Bank and the Equitable Trust Company), these failures produced only mild consequence in Chicago and the United States due to the actions of the Chicago Clearing House Association. We omit the 1905 panic in Table 2 since the first reporting after this crisis occurred in the first quarter of the next year. See the classification appendix of Jalil (2015) for more details.

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<u>Online Appendices</u> for

The Spatial Transmission of U.S. Banking Panics: Evidence from 1870-1929

MARC DORDAL I CARRERAS SEUNG JOO LEE

Online Appendix A. The Model Derivation

Problem of Loanable Fund Allocation Deposit division of a bank in state n solves

$$\max_{\{M_{ni,t}(\tau)\},D_{n,t}} \sum_{i=1}^{N} \int_0^1 R^I_{ni,t}(\tau) M_{ni,t}(\tau) d\tau - \underbrace{\rho^S_n(D_{n,t}) D_{n,t}}_{\text{Cost of loanable funds}} \tag{A.1}$$

subject to

$$\sum_{i=1}^{N} \int_0^1 T_{ni} z_{ni,t}(\tau) M_{ni,t}(\tau) d\tau = (D_{n,t})^\alpha . \tag{A.2}$$

The maximization problem thus becomes

$$\max_{\{M_{ni,t}(\tau)\}} \sum_{i=1}^{N} \int_0^1 R^I_{ni,t}(\tau) M_{ni,t}(\tau) d\tau - \rho^S_n \left(\underbrace{\left(\sum_{i=1}^{N} \int_0^1 T_{ni} z_{ni,t}(\tau) M_{ni,t}(\tau) d\tau \right)^{\frac{1}{\alpha}}}_{=D_{n,t}} \right) \cdot \left(\sum_{i=1}^{N} \int_0^1 T_{ni} z_{ni,t}(\tau) M_{ni,t}(\tau) d\tau \right)^{\frac{1}{\alpha}} . \tag{A.3}$$

We observe that if $\rho^S_n(\cdot)$ is convex enough, even with $\alpha > 1$, the assumed economies of scale in in allocating a large supply of deposits, the objective function in (A.3) becomes strictly concave in $\{M_{ni,t}(\tau)\}$, which guarantees the existence and uniqueness of the solution of optimization (A.3). The first order condition yields

$$R^I_{ni,t}(\tau) = T_{ni} \cdot z_{ni,t}(\tau) \cdot \left(\frac{1}{\alpha}\right) \underbrace{\rho^S_n(D_{n,t}) \left(1 + \underbrace{\frac{\rho^{S'}_n(D_{n,t})D_{n,t}}{\rho^S_n(D_{n,t})}}_{\equiv\left(\varepsilon^S_{n,t,D,\rho}\right)^{-1}}\right)}_{\equiv\rho_{n,t}} \cdot (D_{n,t})^{-(\alpha-1)}, \tag{A.4}$$

where

$$\varepsilon^S_{n,t,D,\rho} \equiv \left[\frac{\rho^{S'}_n(D_{n,t})D_{n,t}}{\rho^S_n(D_{n,t})}\right]^{-1} > 0.$$

represents the elasticity of deposit supply, proving (8).

Aggregation We use the following properties of the Weibull distribution. When $\{X_i\}_{i=1}^N$ are mutually independent, and X_i follows the Weibull distribution with λ_i as the scale parameter and κ as the shape paramete, i.e., $X_i \sim W(\lambda_i, \kappa)$:

Property A.1 (Scalar Multiplication)**.** $cX_i \sim W(c\lambda_i, \kappa)$ for some scalar c.

Property A.2 (Moments)**.** $\mathbb{E}((X_i)^n) = (\lambda_i)^n \,\Gamma\left(1 + \frac{n}{\kappa}\right)$ for $n \in \mathbb{R}$.

Property A.3 (Minimum of $\{X_i\}$)**.**

$$\min_i\{X_i\} \sim W\left(\left(\sum_{i=1}^N (\lambda_i)^{-\kappa}\right)^{-\frac{1}{\kappa}}, \kappa\right).$$

From (8) and using $z_{ni,t}(\tau) \sim W(1, \kappa)$, we obtain from Property A.1 that

$$R^I_{ni,t}(\tau) = T_{ni} \cdot z_{ni,t}(\tau) \cdot \left(\frac{\rho_t}{\alpha}\right) \cdot (D_{n,t})^{-(\alpha-1)} \sim W\left(T_{ni}\left(\frac{\rho_t}{\alpha}\right) \cdot (D_{n,t})^{-(\alpha-1)}, \kappa\right),$$

which, with Property A.3, leads to

$$R^I_{i,t}(\tau) = \min_n \left\{ R^I_{ni,t}(\tau) \right\} \sim W\left(\Phi_{i,t}, \kappa\right),$$

where

$$\Phi_{i,t} = \left(\frac{\rho_t}{\alpha}\right) \cdot \left[\sum_{n=1}^{N} \left(T_{ni}\right)^{-\kappa} \left(D_{n,t}\right)^{\kappa(\alpha-1)}\right]^{-\frac{1}{\kappa}}, \tag{A.5}$$

thus proving equations (10) and (11).

Finally, with the help of Property A.2, and the fact that $R^F_{i,t}(\tau) = R^I_{i,t}(\tau)$,

$$\begin{aligned} \mathbb{E}\left[R^F_{i,t}(\tau)^{-\beta}\right] &= \mathbb{E}\left[R^I_{i,t}(\tau)^{-\beta}\right] = \left(\Phi_{i,t}\right)^{-\beta} \Gamma\left(1 - \frac{\beta}{\kappa}\right) \\ &= \left(\frac{\rho_t}{\alpha}\right)^{-\beta} \cdot \left[\sum_{n=1}^{N} \left(T_{ni}\right)^{-\kappa} \left(D_{n,t}\right)^{\kappa(\alpha-1)}\right]^{\frac{\beta}{\kappa}} \cdot \Gamma\left(1 - \frac{\beta}{\kappa}\right), \end{aligned} \tag{A.6}$$

from which we can obtain the expression for equilibrium loan amounts in state i as follows:

$$L^D_{i,t} = \mathbb{E}\left[R^F_{i,t}(\tau)^{-\beta}\right] \cdot \varepsilon_{i,t} = \left[\sum_{n=1}^{N} \left(T_{ni}\right)^{-\kappa} \left(D_{n,t}\right)^{\kappa(\alpha-1)}\right]^{\frac{\beta}{\kappa}} \left(\frac{\alpha}{\rho_t}\right)^{\beta} \Gamma\left(1 - \frac{\beta}{\kappa}\right) \varepsilon_{i,t} \qquad \forall i,$$

proving equation (13).

- Lending in each state is linked to deposits in all other states. Especially with $\alpha > 1$, a decrease in $D_{n,t}$ leads to a drop in $L^D_{i,t}$.

Log-linearization From equation (13),

$$\log L^D_{i,t} = \frac{\beta}{\kappa} \cdot \log\left(\sum_{n=1}^{N} \left(T_{ni}\right)^{-\kappa} D_{n,t}^{\kappa(\alpha-1)}\right) + \beta \log \frac{\alpha}{\rho_t} + \log \Gamma\left(1 - \frac{\beta}{\kappa}\right) + \epsilon_{i,t},$$

which leads to

$$
\begin{aligned}
\check{L}^{D}_{i,t} &= \frac{\beta}{\kappa}\left(\sum_{n=1}^{N} T_{ni}^{-\kappa} D_{n,t}^{\kappa(\alpha-1)}\right) \underbrace{-\beta\check{\rho}_t}_{\equiv s_t} + \epsilon_{i,t} \\
&= \frac{\beta}{\kappa}\sum_{n=1}^{N}\left(\underbrace{\frac{\left(T_{ni}\right)^{-\kappa} D_n^{\kappa(\alpha-1)}}{\sum_{n=1}^{N}\left(T_{ni}\right)^{-\kappa} D_n^{\kappa(\alpha-1)}}}_{\equiv \xi_{ni}}\right)\left(-\kappa\check{T}_{ni} + \kappa(\alpha-1)\check{D}_{n,t}\right) + s_t + \epsilon_{i,t} \\
&= \left(\underbrace{-\beta\sum_{n=1}^{N}\xi_{ni}\check{T}_{ni}}_{=\mu_i}\right) + \sum_{n=1}^{N}\left(\underbrace{\beta(\alpha-1)\xi_{ni}}_{\equiv \tilde{T}_{ni}}\right)\check{D}_{n,t} + s_t + \epsilon_{i,t} \\
&= \mu_i + s_t + \sum_{n=1}^{N}\tilde{T}_{ni}\check{D}_{n,t} + \epsilon_{i,t},
\end{aligned}
$$

deriving equation (16).

Online Appendix B. Are Panics Exogenous or Correlated with Business Cycles?

Here, we test whether panics listed in Table 2 of Section 7 (or Jalil (2015)) can be regarded exogenous, which is crucial for our estimation in Section 4.1. In that purpose, we run the following regression based on Granger causality, in order to check whether a panic is an exogenous source of disturbance or correlated with the business cycle conditions:

$$Panic_{i,t} = \mu_i + \mu_t + \sum_{l=1}^{4} \left[\beta_l^D \Delta \log\left(D_{i,t-l}\right) + \beta_l^L \Delta \log\left(L_{i,t-l}\right) + \beta_l^B \Delta \log\left(Bank_{i,t-l}\right)\right] + \varepsilon_{i,t} \ ,$$

where $Panic_{i,t}$ is defined as a binary variable equal to one if state i experiences a panic in banking sector in quarter t, and we control for 4 lags of growth rates of deposits, loans, and the number of banks in the same sate i as the relevant business cycle variables. Finally, μ_i and μ_t account for the state and quarter fixed effects, respectively.

	1	**2**	**3**	**4**
Joint F-test, p-value	***	***	H_0	H_0
R-squared	0.37%	1.96%	0.07%	0.104%
All panics	X	X		
Minor panics			X	X
Individual fixed effects		X		X
Seasonal dummies		X		X

Table B.1: Granger causality test. We regress panic episodes on four lagged changes of deposits, loans, and number of banks according to

$$Panic_{i,t} = \mu_i + \mu_t + \sum_{l=1}^{4} \left[\beta_l^D \Delta \log\left(D_{i,t-l}\right) + \beta_l^L \Delta \log\left(L_{i,t-l}\right) + \beta_l^B \Delta \log\left(Bank_{i,t-l}\right)\right] + \varepsilon_{i,t}.$$

The table reports results for the null hypothesis H_0: $\beta_l^D = \beta_l^L = \beta_l^B = 0, \ \forall l$. Types of panics and controls included in each specification are indicated with an X. Significance levels are: *** for $p < 0.01$, ** for $p < 0.05$, * for $p < 0.1$, and H_0: $p \geqslant 0.1$.

Table B.1 contains the results of the above Granger causality test. It reports results on the joint null hypothesis $H_0: \ \beta_l^D = \beta_l^L = \beta_l^B = 0, \ \forall l = 1 \sim 4$. Columns 1 and 2 report the results only using nationwide *major* panics of Jalil (2015), while columns 3 and 4 report the result based on regional *minor* panics of Jalil (2015). As we can see, the null is rejected for both specifications (with or without the fixed effects) based on the major panics as the dependent variable, but we are not able to reject it at 10% when focusing on the regional (minor) series.

As major panics do not contribute much to the identification of spatial transmission due to their nationwide nature anyway, we exclude them from the sample as explained in Section 2. Therefore, in Sections 4.1 and 4.2, we regard the minor panics of Jalil (2015) as an exogenous variation.

Online Appendix C. Robustness Check

C.1. Panic Dummies for Origin States Only

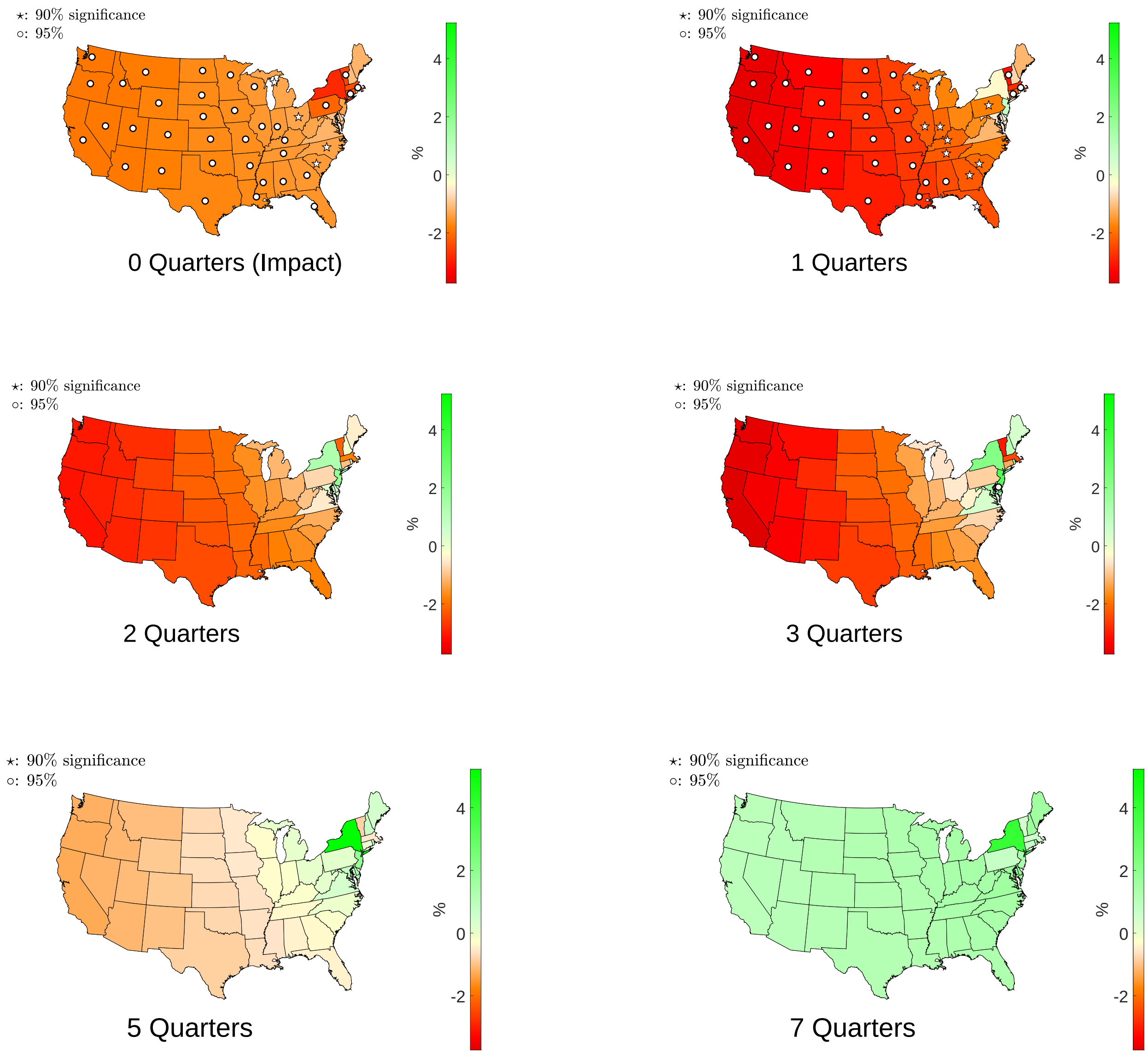

Figure C.1: Impulse-response of bank deposits to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. ○ $p < 0.05$, ⋆ $p < 0.1$. Here, we assume $Panic_{i,t} = 1$ only for the origin state i where each panic listed in Table 2 (Jalil, 2015) is known to have originated.

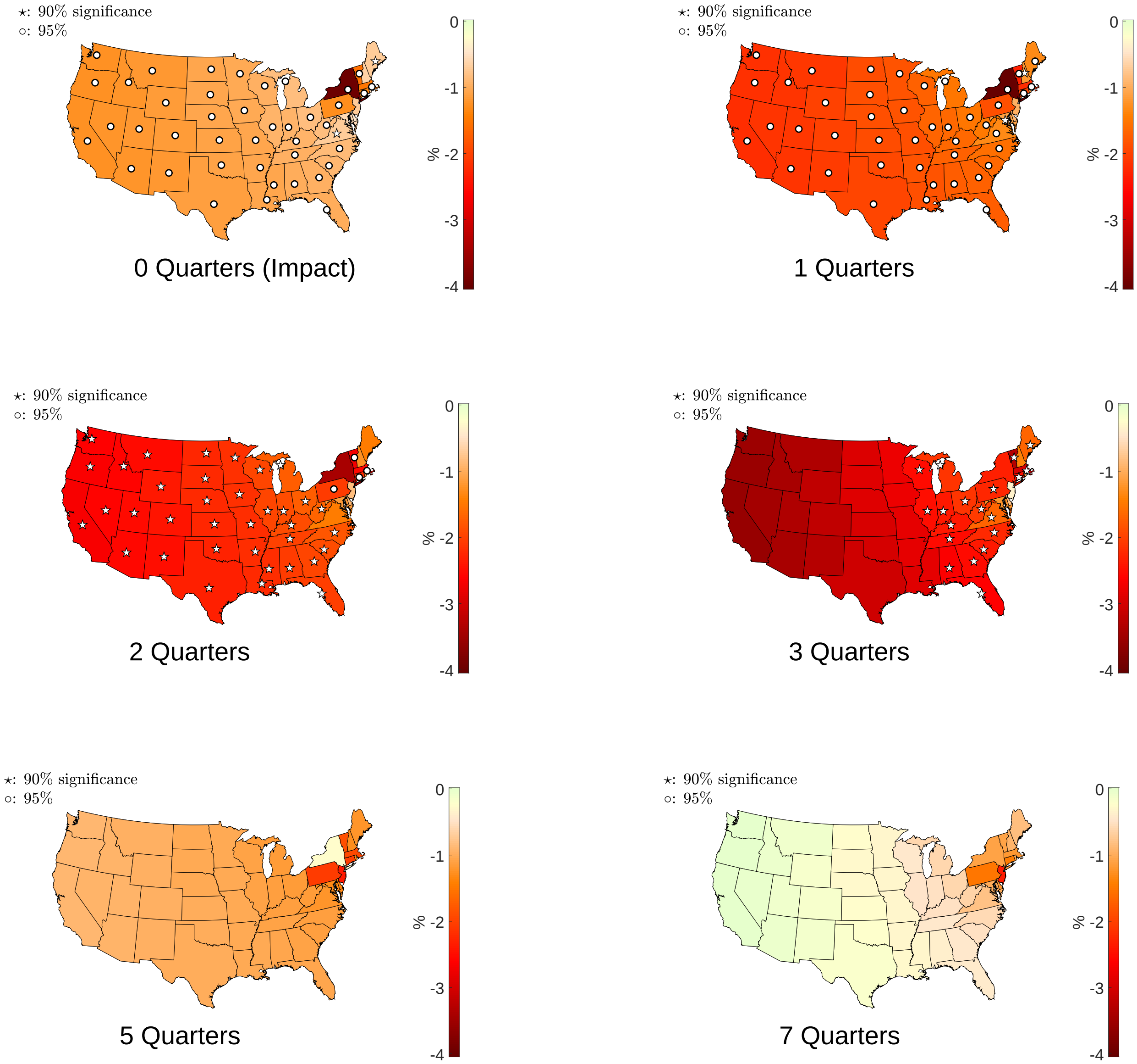

Figure C.2: Impulse-response of bank loans across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$. Here, we assume $Panic_{i,t} = 1$ only for the origin state i where each panic listed in Table 2 (Jalil, 2015) is known to have originated.

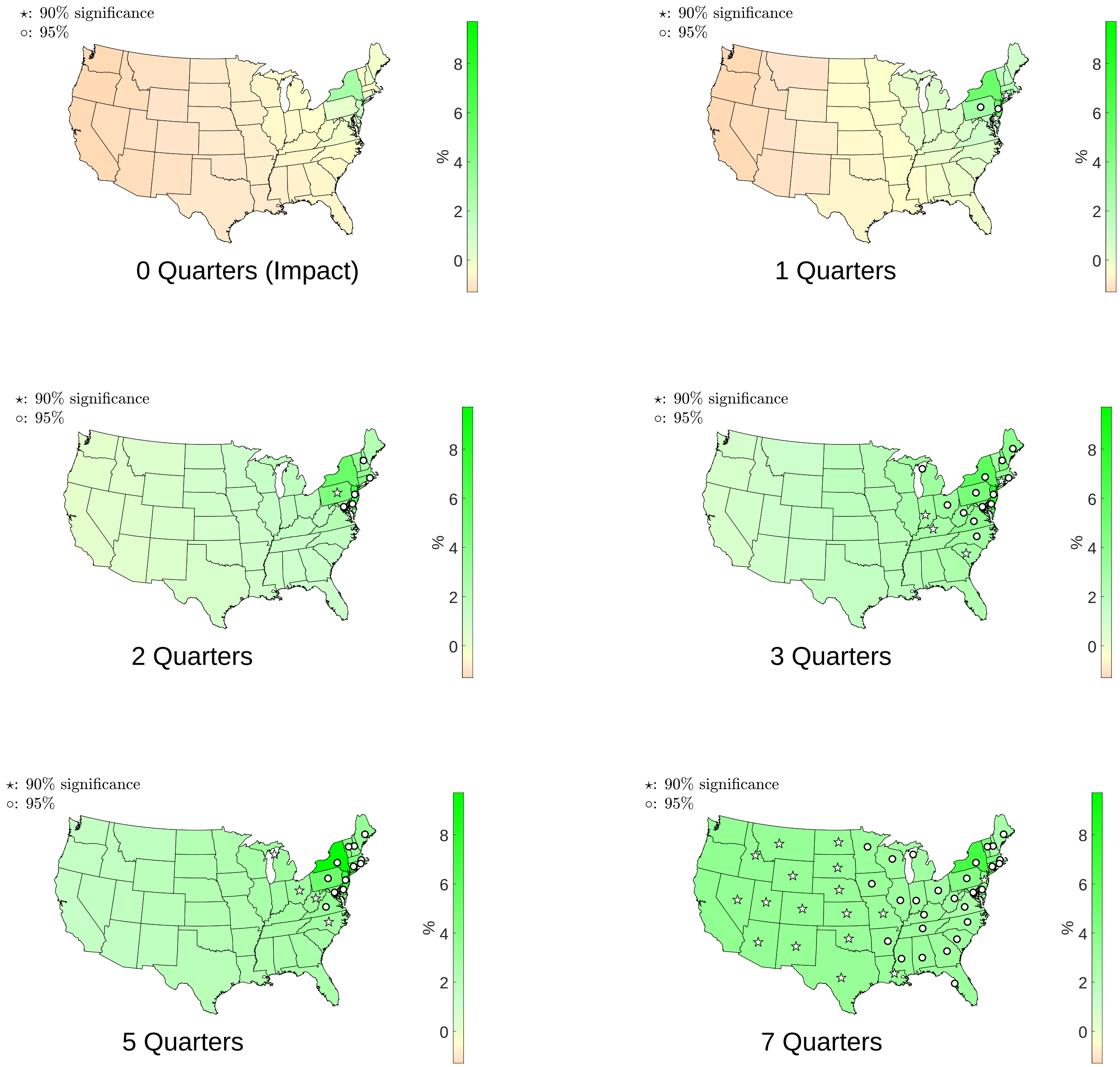

Figure C.3: Impulse-response of liquidity ratios across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ$ $p < 0.05$, $\star$ $p < 0.1$. Here, we assume $Panic_{i,t} = 1$ only for the origin state i where each panic listed in Table 2 (Jalil, 2015) is known to have originated.

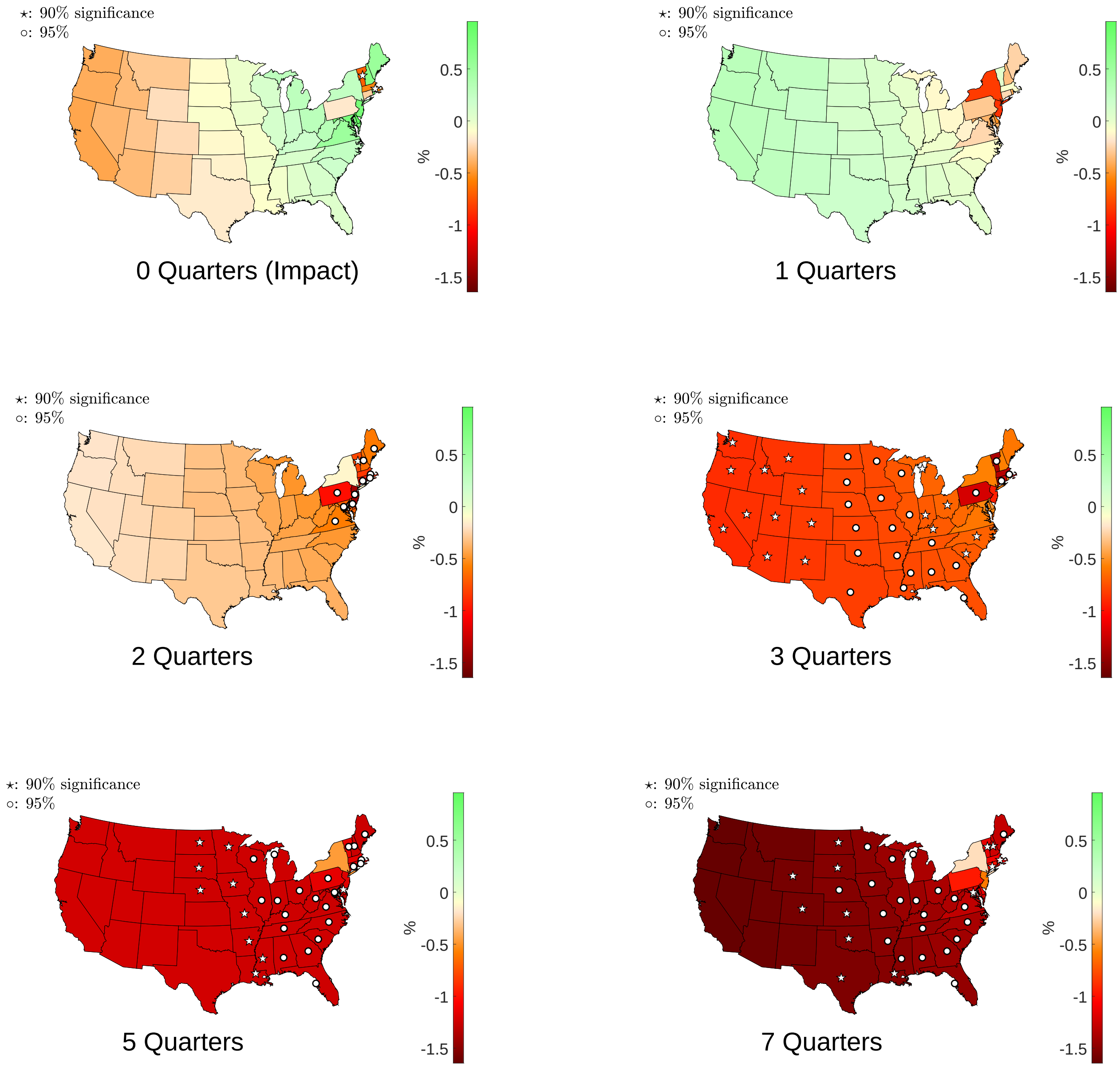

Figure C.4: Impulse-response of bank capital across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ\ p < 0.05$, $\star\ p < 0.1$. Here, we assume $Panic_{i,t} = 1$ only for the origin state i where each panic listed in Table 2 (Jalil, 2015) is known to have originated.

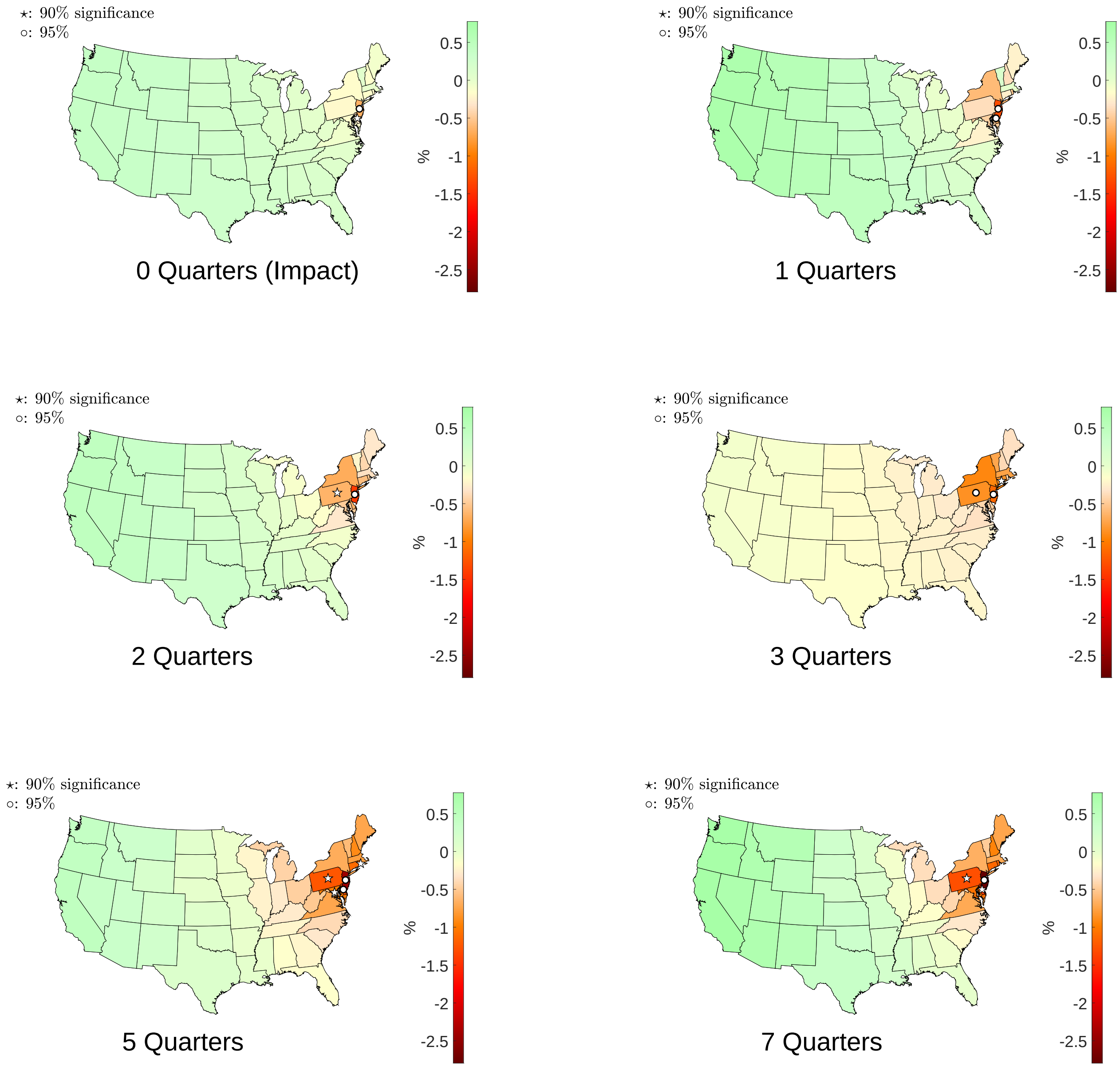

Figure C.5: Impulse-response of the number of banks across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ$ $p < 0.05$, $\star$ $p < 0.1$. Here, we assume $Panic_{i,t} = 1$ only for the origin state i where each panic listed in Table 2 (Jalil, 2015) is known to have originated.

C.2. Deposit Size Effects

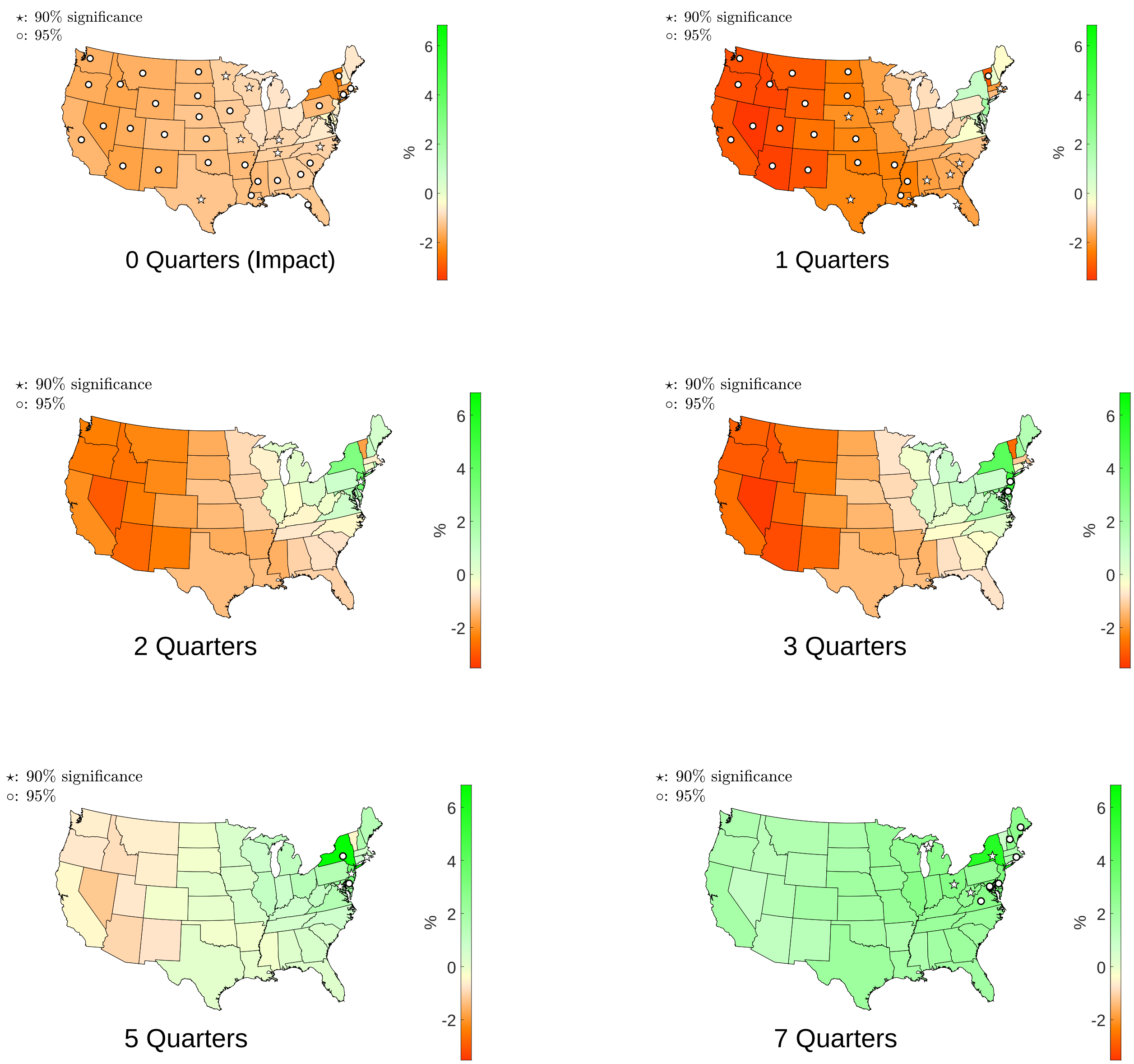

Figure C.6: Impulse-response of bank deposits to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. Here, we control the relative size of deposits in the previous quarter interacted with panic dummies. See Section 4.2.1.

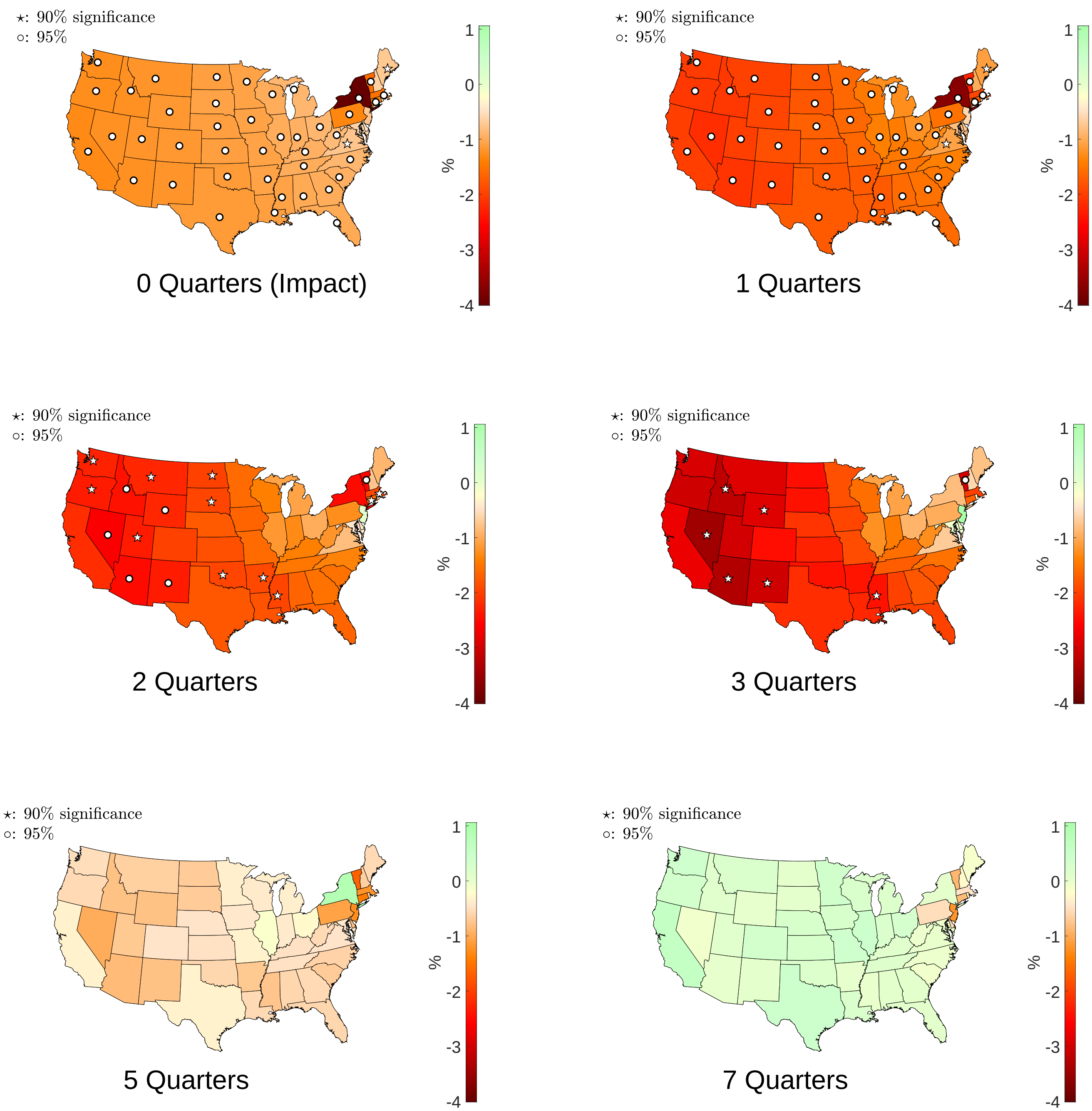

Figure C.7: Impulse-response of bank loans across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ p < 0.05, \star p < 0.1$. Here, we control the relative size of deposits in the previous quarter interacted with panic dummies. See Section 4.2.1.

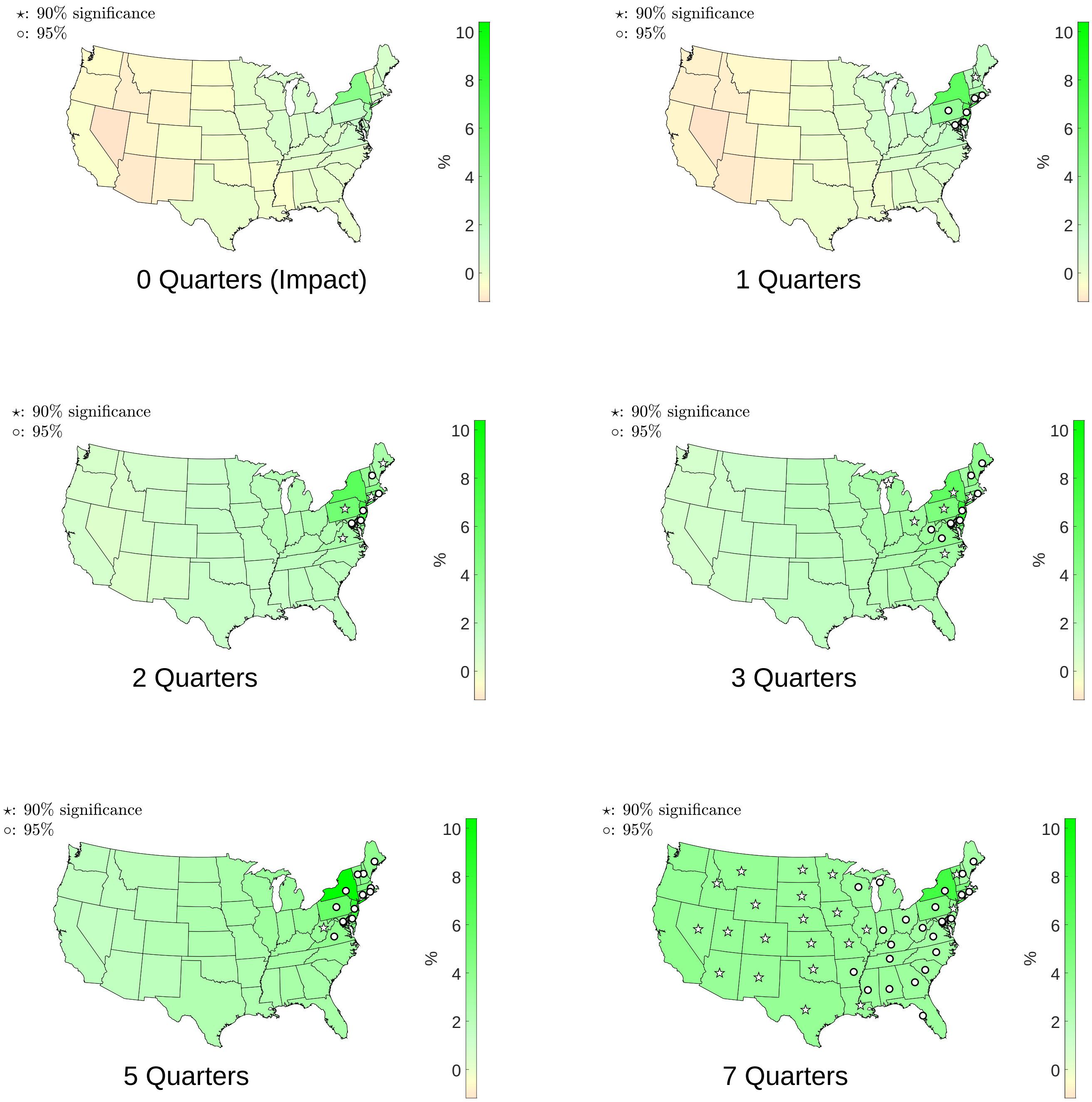

Figure C.8: Impulse-response of liquidity ratios across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ p < 0.05, \star p < 0.1$. Here, we control the relative size of deposits in the previous quarter interacted with panic dummies. See Section 4.2.1.

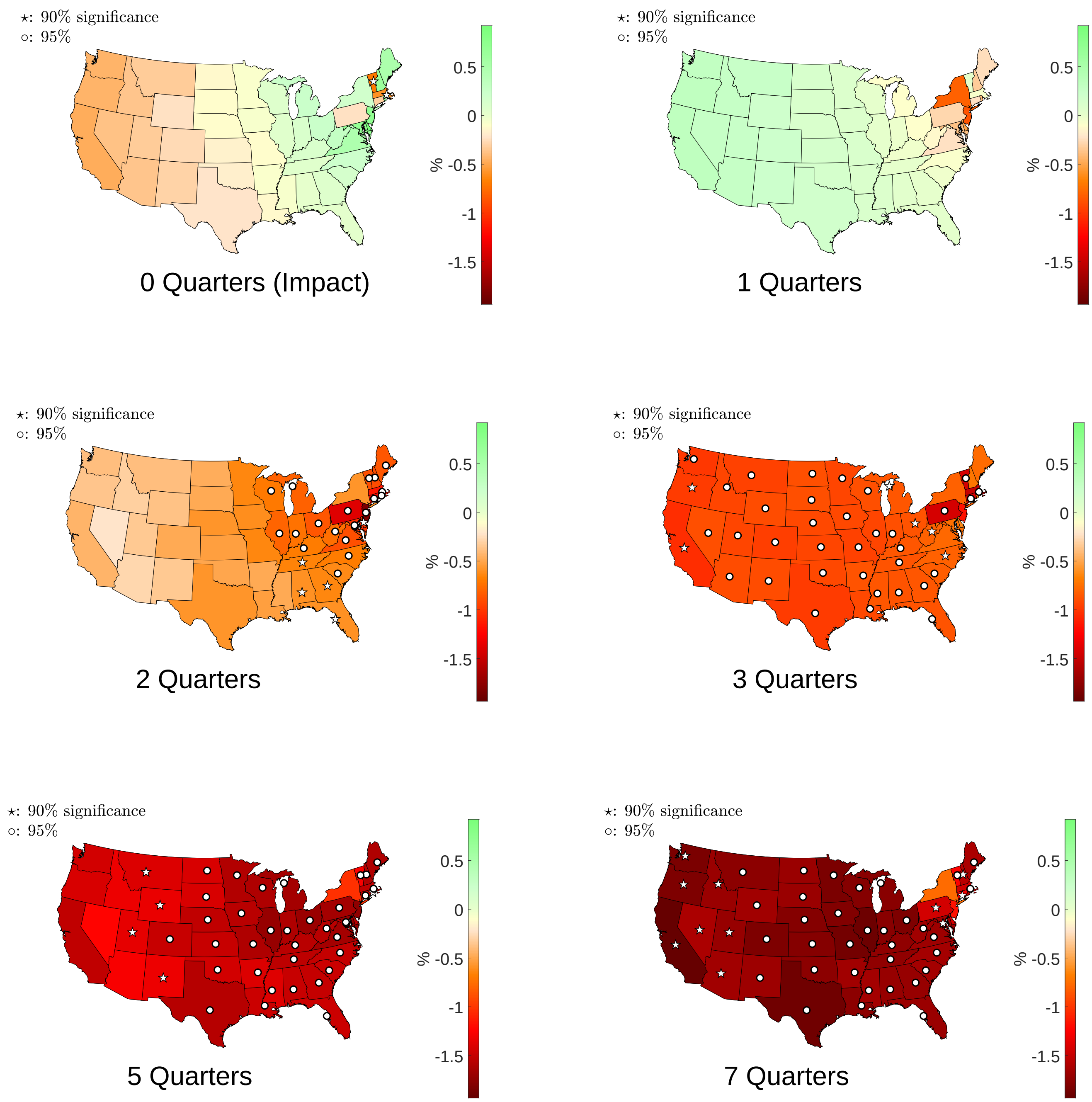

Figure C.9: Impulse-response of bank capital across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ p < 0.05, \star p < 0.1$. Here, we control the relative size of deposits in the previous quarter interacted with panic dummies. See Section 4.2.1.

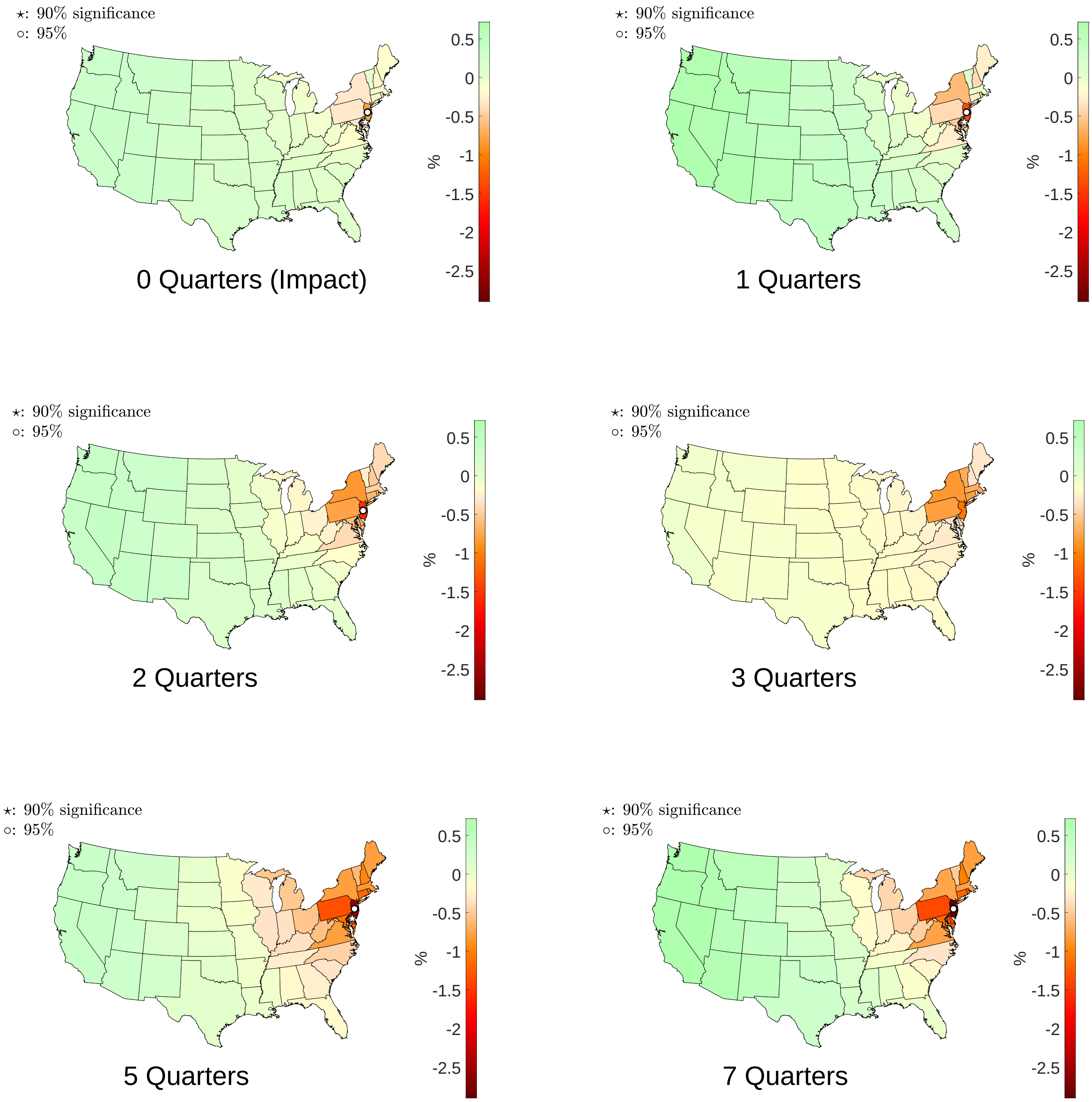

Figure C.10: Impulse-response of the number of banks across states to a panic from New York. Right bar reports graph estimates color scale. P-values constructed using Driscoll-Kraay standard errors. $\circ$p < 0.05, $\star$p < 0.1. Here, we control the relative size of deposits in the previous quarter interacted with panic dummies. See Section 4.2.1.