Estimating U.S. Housing Price Network Connectedness: Evidence from Dynamic Elastic Net, Lasso, and Ridge Vector Autoregressive Models*

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Abstract

This paper investigates the dynamic connectedness of random shocks to housing prices between the 50 U.S. states and the District of Columbia. The paper implements a standard vector autoregressive (VAR) model as well as three VAR models with shrinkage effects – Elastic Net, Lasso, and Ridge VAR models. The transmission of real housing return shocks on a regional basis flows from Southern states to the other three regions, whereas the Northeast receives those shocks. The West receives shocks from the South and transmits shocks to the Midwest and the Northeast. Finally, the Midwest transmits shocks to the Northeast and receives shocks from the South and the West. Our results have important implications for policymakers and investors. To the extent that the housing market affects the business cycle, the Federal Reserve can monitor housing market movements in the net transmitter states to gather information about the beginnings of the housing market cycle. Moreover, the determination of which states or regions function as the main transmitter of shocks provides information to investors on acquiring housing assets in these markets rather than the ones that are more susceptible to such shocks as net receivers.

Keywords: Dynamic Connectedness, Elastic Net VAR, Lasso VAR, Ridge VAR, U.S. Housing.

JEL codes: C32, C52, R31.

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1 Introduction

The housing markets play a critical role in the macroeconomy, affecting both the business cycle and the financial system. The important role of housing markets in the business cycle became dramatically clear during the sub-prime mortgage market collapse in late 2006 and the resulting Great Recession and financial crisis of 2007-2009, the worst recession since World War II until the COVID-19 recession of 2020. Shiller (2012), for example, argues that the housing bubble provided the major, if not the only, cause of the sub-prime mortgage crisis and the worldwide Great Recession and financial crisis of 2007–2009. Leamer et al. (2007) more provocatively asserts that "housing is the business cycle" in the United States or, more precisely, that house prices drive the U.S. business cycle.

One can argue that the recent Great Recession and financial crisis, more than any other macroeconomic event, makes a strong case for examining the dynamics of house prices, and, in particular, the role of persistence and the effect of shocks on house price dynamics. This paper considers the "connectedness" of housing markets across the 50 U.S. states and the District of Columbia. The basis of connectedness comes from the estimation of a vector autoregressive (VAR) model, where we examine how exogenous shocks to house prices in one state affect the exogenous shocks to house prices in another state, or vice versa. That is, connectedness measures cross-state relationships between exogenous shocks to house prices and not the cross-state relationships between the movements in the house prices themselves.

Given that the housing market leads the business cycles of the United States (Balcilar et al., 2014; Leamer, 2015; Nyakabawo et al., 2015; Emirmahmutoglu et al., 2016), analysis of regional housing market connectedness is an important question for policymakers. That is, determining which states and/or regions drive the overall housing market allows policy authorities to undertake policy decisions that target specific states or regions before implementing nationwide policies, which might not work, due to the heterogeneity of the housing market (Fairchild et al., 2015). Moreover, the determination of which states or regions act as the main transmitter of shocks provides information to investors on acquiring housing assets in these markets rather than the ones that are more susceptible to such shocks as net receivers.

Dividing the United States into four Census regions (Northeast, South, Midwest, and West), we find that shocks in the South affect shocks in the Northeast, Midwest, and West. Shocks in the West affect shocks in the Midwest and the Northeast. Shocks in the Midwest affect shocks in the Northeast. Finally, shocks in the Northeast do not affect shocks in the other regions.

The remainder of this paper is organized as follows. Section 2 presents the relevant literature review and Section 3 describes the empirical methodologies applied in the study. Furthermore, Section 4 provides a short overview of the employed dataset whereas Section 5 illustrates the findings of the study and discusses the relevant arguments, with Section 6 comparing our findings with the existing literature on this topic. Finally, Section 7 summarises the key elements, provides a framework for policy implications, and concludes the study.

2 Literature Review

A significant literature exists that considers the "ripple effect" in house prices in the United Kingdom and the United States. This literature begins with theorizing and empirical analysis in the United Kingdom. The ripple effect refers to the observation that house price increases in Southeastern United Kingdom generally led with some time lag to house price increases in Northwest United Kingdom (Meen, 1999). More recent work on the ripple effect in the United Kingdom includes Cook (2003, 2005), Holmes and Grimes (2008), and Tsai (2015). Cook (2003, 2005) tests for convergence and cointegration in house prices, introducing asymmetric responses to house price increases and decreases. Holmes and Grimes (2008) apply unit-root tests to the first principal component of the set of regional to national house price differentials. Tsai (2015) examines regional and national housing market spillover effects in the United Kingdom.

In the United States, Gupta and Miller (2012b,a) consider the cointegration and Granger causality in three metro areas (Los Angeles, Las Vegas, and Phoenix) in three different states (California, Nevada, and Arizona) and between house prices in Southern California counties. Chiang and Tsai (2016) examine regional and interregional ripple effects in the United States for eight metropolitan areas – Los Angeles, San Diego, San

Francisco, Chicago, Boston, New York, Miami, and Tampa – and three regions – East, South, and West. Tsai (2018) considers the ripple effect for the four Census regions (South, West, Midwest, and Northeast) in the United States. Tsai (2019) considers the interrelationships between house prices in 10 U.S. metropolitan areas – Boston, Chicago, Denver, Las Vegas, Los Angeles, Miami, New York, San Diego, San Francisco, and Washington DC – at three price tiers – low, medium, and high price tiers.

The ripple effect literature relies on the concept of the Law of One Price (LOOP), which proposes that a homogeneous good that sells in two different markets should sell for the same price, after the incorporation of transaction and transportation costs. Fundamentally, the LOOP uses the arbitrage of goods prices between markets to generate the convergence of prices across regional markets. That is, for example, if one can transport the good between markets at a relatively low cost, one can buy in the low-price market and sell it in the high-price market after transporting the good from the low-price market to the high-price market. Clearly, housing goods fail in, at least, two important areas (i) lack of homogeneity in housing goods and (ii) lack of transportability between markets. In addition, rather than comparing house prices, we compare house price indexes. Thus, comparing house price indexes, rather than individual home prices, across geographic regions, activates the idea of Purchasing Power Parity (PPP). PPP extends the LOOP to price indexes, implying that trade between geographic regions of goods leads to a convergence of the regions' price indexes for goods. Once again, the successful operation of PPP requires the arbitrage of goods between regions.

Housing economists address the issue of non-homogeneous housing goods by considering their characteristics. That is, hedonic housing good models allow the comparison of house prices based on the characteristics embedded into the housing good, such as the number of bedrooms, the number of baths, the square footage, and so on. In addition, researchers want to ensure that the house price index can accommodate the quality of the house. A "repeat-sales" index based on multiple sales of the same home attempts to address this last issue. To do so successfully requires that repeat sales include information on renovations and depreciation. A "constant quality" index can compare housing good prices across time and space. Typically, the geographic reach of the housing market reflects the commuting shed for the metropolitan area. That is, houses compete with each other within the same metropolitan area. Original work on this hypothesis was done by Tirtiroğlu (1992) and Clapp and Tirtiroglu (1994) examining housing market efficiency in the Hartford, Connecticut spatial market.

Since moving houses from one metropolitan market to another proves too costly, does this necessarily imply that the housing markets in different MSAs do not exhibit linkages? Trade theory provides an answer. The factor price equalization theorem (Samuelson, 1948) shows that although capital and labor frequently do not flow freely between countries, goods, and services do flow and can proxy for capital and labor flows. The flows of goods and services between countries cause the prices of labor and capital to equalize, albeit absent any flow of capital and labor between countries. Since housing goods cannot easily flow between markets, do other flows exist that can cause LOOP or PPP to hold? First, the migration of home buyers can link the housing markets to different metropolitan areas. Second, large home builders operate in multiple metropolitan areas, allowing them to move operations in repose to shifts in metropolitan demands and differential returns on home building activity. In sum, the movement of home buyers and home builders' operations between regions in response to price differences can arbitrage the prices of homes, even though the homes themselves do not move between regions.

Home builders face two basic components to their cost of supplying new housing – construction (replacement) costs and land value. If the demand for housing rises in one region, that will draw resources, including construction labor, from other regions. As a result, construction costs in both regions will rise. It rises first in the market where the demand for housing rises to attract more resources and construction workers. And as a consequence, as the supply of resources and construction workers in the other region fall, their costs and wages will rise. The equalizing of construction costs tends to equilibrate house prices across regions.

Just as we cannot transport housing between regions, we cannot transport land as well. Thus, if a region faces a fixed, or extremely inelastic, supply of land, then that region's house prices and land values will rise. That is since house prices include construction (replacement) costs and land prices, higher land prices will drive up house prices even though construction (replacement) costs may equilibrate between regions.

Antonakakis et al. (2018) analyzed the U.K. regional housing markets and Antonakakis et al. (2021) examined the four aggregated U.S. regional housing markets, using the connectedness approach. Connectedness examines the relationships between the random shocks in a vector autoregressive (VAR) system, identifying the pattern of transmission of shocks across housing markets in this case. Antonakakis et al. (2018) used quarterly data on 13 regions in the United Kingdom (North, North West, West Midlands, Outer South East, London, Wales, Northern Ireland, Yorkshire and Humberside, East Midlands, East Anglia, Outer Metropolitan, South West, and Scotland), examining the VAR model of annual nominal housing returns. Antonakakis et al. (2021) used monthly data on four U.S. regions (Midwest, Northeast, South, and West), examining the VAR model of annual housing returns and the growth rate of housing volumes.

Since our paper comes closest to the analysis of Antonakakis et al. (2021), we offer comments on how our paper adds to this work. First, Antonakakis et al. (2021) employ four aggregated U.S. regional housing prices and, thus, mask the interconnectedness and spillovers across the states within a region. As we use 51 U.S. state-level housing prices, we can model those intraregional interrelationships. This extension proves of major importance as the analysis of Antonakakis et al. (2021) indirectly argues that each state within a region behaves identically. As our analyses demonstrate, this is not the case. Thus, by using U.S. regional housing prices, the analysis omits relevant spillovers and can produce biased estimates, as housing prices behave heterogeneously within regions. Thus, assuming a constant relation between regions – which indirectly implies that the spillover of all states in region A exerts the same effect on all states in region B. We provide numerous results in our paper where this is not the case. Thus, our study extends and refines the analysis and findings of Antonakakis et al. (2021).

Furthermore, using a measure of real returns on housing that emerge from real housing prices conforms to how the housing market operates and how it affects the business cycle. As noted above, the housing markets play a critical role in the macroeconomy, affecting both the business cycle and the financial system. The business cycle examines the cyclical movement in macroeconomic variables in the real sector, including housing. Thus, from this point of view, examining real house prices makes economic sense. Moreover, housing, as a real asset, provides an inflation hedge, at least in the medium to long term, to investors. Asset allocation decisions should use the real return, which we approximate by the growth rate of the real house price.

Finally, as we also discussed above, the ripple effect relies on the arbitrage of prices across markets. Two components of that arbitrage process for housing include home buyers migrating across different housing markets geographically and home builders operating in different housing markets geographically. Thus, home buyers and home builders (suppliers) make decisions based on real values, not getting fooled, for example, by inflation-induced changes in construction costs.

3 Empirical Methodology

3.1 Lasso, Ridge & Elastic Vector Autoregressions

Sims (1980) introduced one of the most popular and still widely used multivariate time-series models in applied econometrics, namely the vector autoregressive (VAR) model. This framework not only forecasts the future of multiple time series in a dynamic way but also comes with a sophisticated toolbox, including impulse response analysis and forecast error variance decomposition. The toolbox provides further information about the spillovers of shocks. Mathematically, a VAR(p) with a lag length of p can be formulated as follows:

$$\boldsymbol{y}_t = \boldsymbol{\beta}_0 + \sum_{i=1}^{p} \boldsymbol{\beta}_i \boldsymbol{y}_{t-i} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{\Sigma}) \tag{1}$$

where $\boldsymbol{y}_t$, $t = 1, ..., T-p$, is an $k \times 1$ dimensional vector of the endogenous variables, $\boldsymbol{\beta}_0$ is an $k \times 1$ dimensional vector of all intercepts, and $\boldsymbol{\beta}_i$ represents the $k \times k$ dimensional VAR coefficient matrix of the ith lag. The $k \times 1$ dimensional error vector, $\boldsymbol{u}_t$, $t = 1, ..., T-p$ is multivariate normally distributed with means equal to zero and a variance-covariance matrix equals to $\boldsymbol{\Sigma}$. $\boldsymbol{\Sigma}$ is a diagonal matrix as $var(u_i) = \sigma_i^2$, $i = 1, ..., k$ and $cov(\boldsymbol{u}_i, \boldsymbol{u}_j) = 0$, $i, j = 1, ..., k$ and $i \neq j$.[1] Those characteristics allow estimating the VAR model

[1] One can argue that the assumption of a diagonal variance-covariance matrix is restrictive. This assumption, however, is used in all connectedness modeling and, more generally, in most VAR modeling.

equation-by-equation often by the ordinary least squares method. This is good news as we are estimating the U.S. real estate return dynamics of all states, meaning that $k = 51$ and, hence, a joint estimation with a lag length of one[2] would mean that $k + k^2 p = 2,652$ parameters need to be estimated, but we only have $T = 418$ observations ($2,652 >> 418$), which would mean that this model cannot be estimated. Using the equation-by-equation estimation procedure makes this feasible as it just estimates, $k + 1 = 52$ parameters ($52 < 418$). Additionally, as we deal with this high-dimensional network, we employ different regularization methods that shrink and select parameters and compare the results with the standard equation-by-equation VAR model.

Hereby, the Elastic net (Zou and Hastie, 2005) can be seen as the generalization of the OLS, Ridge, and Lasso (Tibshirani, 1996) estimation methods, that shrink and select parameters. The Elastic net can be outlined for each variable j, $j = 1, ..., k$, as follows:[3]

$$\underset{\boldsymbol{\beta}}{\text{argmin}} \left(\overbrace{\left[T^{-1} ||y_{jt} - \beta_{j0} - \sum_{i=1}^{p} \sum_{j=1}^{k} \beta_{ji} y_{jt-i}||_2 \right]}^{MSE} + \lambda \overbrace{\left[(1-\alpha) \underbrace{||\beta_{j0} + \sum_{i=1}^{p} \sum_{j=1}^{k} \beta_{ij}||_2}_{\text{Ridge Penalty}} + \alpha \underbrace{||\beta_{j0} + \sum_{i=1}^{p} \sum_{j=1}^{k} \beta_{ij}||_1}_{\text{Lasso Penalty}} \right]}^{P_\alpha} \right)$$

For example, Antonakakis et al. (2021) adopted this assumption in a similar context. Moreover, Tsai (2015) as well as Miao et al. (2011) used this assumption (see, Equation (2) in Miao et al. (2011)). One way to relax this assumption is to implement an SVAR model. But such models require credible orderings of the error shocks and arbitrarily ordered variable structure will lead to incorrect results. With 8.065817e+67 different combinations of 51 states, choosing the incorrect one seems quite probable. Hence, we follow Wiesen et al. (2018) who recommend using generalized forecast-error variance decompositions when theoretical support of a structural representation is missing. Alternatively, one can use a spatial modeling approach (see, for example, Beenstock et al. (2019)). This requires, however, adding spatial lags, which in turn, could make the VAR coefficients less stable due to the added burden of estimating spatial lag coefficients. Furthermore, a large literature exists that details how to specify the connectivity matrix. Therefore, estimating a spatial model in line with the pursued research question is simply not feasible.

[2] The Bayesian information criterion suggests using a lag length of one.

[3] We use a grid-search algorithm [0, 0.1., 0.2, ..., 1.0] to find the 'optimal' α parameter for the Elastic net approach. Furthermore, λ is set equal to unity, which is the default option in most machine learning settings as it penalizes the Elastic net approach by the value of the estimated VAR coefficients. If λ is within zero and unity, it indicates that the penalization term increases by less than the values of the VAR coefficients, while a λ parameter larger than unity implies that the penalization term increases by more than the values of the estimated VAR coefficients. In case λ becomes extremely large, all VAR coefficients would be close to zero.

where the first part represents a loss function, which is in our case the mean squared error (MSE), and the second part is the Elastic net penalty (P_α), which equals a weighted average of the Ridge penalty and the Lasso penalty. Whereas Lasso uses an ℓ^1-norm penalty to achieve a sparse solution, Ridge uses an ℓ^2-norm penalty. This means that the Lasso penalty term proves more effective than the Ridge penalty term if parameters lie between 0 and 1 whereas the Ridge penalty proves stronger than the Lasso penalty for parameters > 1. As VAR coefficients usually lie in the range between 0 and $|1|$, the Lasso regression will shrink parameters more strongly than the Ridge regression. In general, the ℓ^p-norm is defined by: $||\beta||_p = (\sum_{i=1}^{p}\sum_{j=1}^{k}|\beta_{ij}|^p)^{1/p}$.

The regression coefficients as well as the penalty parameter α for each U.S. state j, $j = 1, ..., k$ are chosen based upon a 10-fold cross-validation.[4] The cross-validation method is often used in machine learning and selects penalty parameters that improve a model's forecasting performance.

Besides estimating the full Elastic net regression model, we also estimate restricted submodels, namely OLS ($\lambda = 0$), Ridge ($\alpha = 0$), and Lasso ($\alpha = 1$). This approach has merits given the role of Ridge and/or Lasso penalties compared to the OLS model. Demirer et al. (2018) showed that using standard OLS equation-by-equation VAR models with high-dimensions leads to poor out-of-sample performance and inaccurate estimation of spillovers. Thus, shrinkage techniques should be used with high-dimensional multivariate time-series frameworks. Lasso and Ridge regression minimize prediction contributions of redundant variables by shrinking the coefficients to zero. The noise in the coefficients of redundant variables helps to explain why the OLS-based dynamic total connectedness could differ from the others. In the empirical results section, we find further support for the usefulness of our proposed approach.

To the best of our knowledge and excepting, Demirer et al. (2018), who employed a Lasso-VAR model to estimate the connectedness measures of daily bank stock return volatilities, this is the first paper that uses regularization methods to shrink and select

[4]Cross-validation is a statistical technique used to assess the performance and generalizability of machine learning models. It divides a dataset into k equally sized folds. The model is trained k times, each time using a different fold as the test set, and the remaining folds as the training set. Finally, the performance of the model is evaluated on each test set and the results are averaged to produce a single performance estimate.

VAR parameters to compute connectedness measures.

3.2 Connectedness Measures

The starting point for the connectedness approach of Diebold and Yilmaz (2012) transforms the VAR(p) in (1) into its vector moving average representation using the Wold theorem: $\boldsymbol{y}_t = \sum_{j=0}^{\infty} \boldsymbol{\theta}_j \boldsymbol{u}_{t-i}$ where $\boldsymbol{\theta}_0 = \boldsymbol{I}_k$ and $\boldsymbol{\theta}_j = \boldsymbol{\beta}_1 \boldsymbol{\theta}_{j-1} + ... + \boldsymbol{\beta}_p \boldsymbol{\theta}_{j-p}$.

In the next step, the Generalized Forecast Error Variance Decomposition (GFEVD)[5] of Koop et al. (1996) and Pesaran and Shin (1998), which is invariant to the ordering of the variables in the VAR. The GFEVD ($\tilde{\phi}_{ij}^g(H)$) can be interpreted as the variable j's contribution to variable i's H-step ahead forecast error variance. It is also called pairwise directional connectedness and can be mathematically formulated by,

$$\phi_{ij}^g(H) = \frac{\sigma_{ii}^{-1} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i' \boldsymbol{\theta} \boldsymbol{\Sigma} \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{\theta} \boldsymbol{\Sigma} \boldsymbol{\theta}' \boldsymbol{\iota}_i)} \qquad \tilde{\phi}_{ij}^g(H) = \frac{\phi_{ij}^g(H)}{\sum_{j=1}^{k} \phi_{ij}^g(H)},$$

where $\sum_{j=1}^{k} \tilde{\phi}_{ij}^g(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}_{ij,t}^g(H) = k$. and $\boldsymbol{\iota}_j$ is a zero vector with unity on the jth position.

Based upon the bilateral pairwise directional connectedness, aggregated connectedness measures are derived that provide an overview of the network spillover dynamics:

$$TO_j = \sum_{i=1, i \neq j}^{k} \tilde{\phi}_{ij}^g(H) \tag{2}$$

$$FROM_j = \sum_{j=1, i \neq j}^{k} \tilde{\phi}_{ij}^g(H) \tag{3}$$

$$NET_j = TO_j - FROM_j \tag{4}$$

$$TCI = k^{-1} \sum_{j=1}^{k} TO_j \equiv k^{-1} \sum_{j=1}^{k} FROM_j. \tag{5}$$

$$NPDC_{ij} = \tilde{\phi}_{ij}(H) - \tilde{\phi}_{ji}(H). \tag{6}$$

Equation (2) represents the aggregated impact a shock in variable j exerts on all other

[5] As to the best of our knowledge, no economic theory exists that explains and justifies the variable ordering in case of real estate return dynamics, we have chosen the GFEVD instead of its orthogonalized counterpart. Hereby, we follow the study of Wiesen et al. (2018), which emphasizes that without a proper economic theory, the GFEVD should be the model of choice.

variables, which is defined as the total directional connectedness to others. Furthermore, Equation (3) formulates the aggregated influence that shocks to all other variables exert on variable j, which is the so-called total directional connectedness from others. Subtracting the impact others exert on variable j from the impact variable j exerts on others generates the net total directional connectedness (4). This metric reveals whether a variable is a net transmitter or a net receiver of shocks. If $NET_j > 0$ ($NET_j < 0$), the effect of a shock in variable j on all others is larger (smaller). Thus, variable j is considered a net transmitter (receiver) of shocks. Finally, the total connectedness index (TCI) (5), which measures the average effect state exerts on all other states or the average effect of all other states on a given state, is often considered the systemwide connectedness and, hence, the market risk. A large (small) TCI means that the average propagation of a shock in one variable to all others is high (low) and, thus, the market risk is high (low). Finally, equation (6), which is the net pairwise directional connectedness ($NPDC_{ij}$), identifies whether variable i drives or is driven by variable j. A positive (negative) $NPDC_{ij}$ implies that variable j dominates (is dominated by) variable i.

4 Dataset

The seasonally adjusted monthly nominal house price data for the 50 states and the District of Columbia come from Freddie Mac, with the indices based on an ever-expanding database of loans purchased by either Freddie Mac or Fannie Mae. The data are available for download from http://www.freddiemac.com/research/indices/house-price-index.page. We generate corresponding real values by deflating the nominal house price indexes with the seasonally adjusted consumer price index (CPI) that comes from the FRED database of the Federal Reserve Bank of St. Louis. The data cover the period from January 1976 through November 2019. We work with the annual growth rates of real house prices. That is, we examine an approximation of real housing returns.[6]

The rationale for using state-level house price data is the dimension of geography, a feature unique to housing markets. Studies find that housing markets for many countries in the world have strong spatial linkages. This is the case in the United States too as

[6]Complete details of the unit-root tests are available upon request from the authors.

the geographical proximity of adjacent states/regions is an important factor driving state housing prices. For example, Miao et al. (2011) find that the strongest correlation in the housing returns generally appears in geographically adjacent regions. Hence, we have decided to include all 51 U.S. states in our analysis as it is suggested by a broad strand of literature (see, Del Negro and Otrok, 2007; Holmes and Grimes, 2008; Miao et al., 2011; Barros et al., 2012, 2014; Apergis and Payne, 2012; Marfatia, 2021; Sheng et al., 2021; Gupta et al., 2021).

5 Empirical results

We employ a rolling-window estimation with a 120-month (10-year) window and a 10-month forecast horizon, with repeated 10-fold cross-validation in each window. When reporting findings, we use the Net Effect method calculations, unless the exhibit clearly shows the reporting of all four methods (see Figure 1).

5.1 State-Specific Connectedness Results

We begin by examining total connectedness or the average effect a state exerts on all other states (equivalently, the average effect of all other states on a given state). The risk in the housing market, as measured by total connectedness, steadily increased since 1995, reaching its peak in 2007 and remaining at that level until it slowly began decreasing from 2015 onwards (see Figure 1). The three methods that penalized parameter estimates using the Lasso, Ridge, and Net Elastic methods of penalization trended generally together, not differing by too much. The standard OLS results, however, produced higher total connectedness than the Lasso, Ridge, and Net Elastic methods during the beginning of the sample period through 2007. Then, dynamic total connectedness did not differ much across the four models for the high volatility period followed by the Great Recession and Financial Crisis of 2007-2009.[7]

[7]Heightened connection during the global financial crisis suggests that the housing market across the U.S. states and regions despite its heterogeneities comovement strongly during periods of a slowdown in the market. We investigated this issue further, by estimating a Bayesian dynamic factor model (DFM) to deduce the importance of the common component in the house price movements relative to state-specific shocks as in Del Negro and Otrok (2007). Once we recovered this national component from our year-on-year growth rate of real house prices and computed the correlation with the total connectedness measures derived from the four models, we found a statistically significant negative correlation in all

[Insert Figure 1 around here]

Figure 2 provides an overview of the total U.S. housing market spillover. That is, for each state, we calculate the total directional connectedness to other states minus the total directional connectedness from other states. Thus, a positive (negative) number means that the shocks from the state in question exert a larger (smaller) effect on all other states than the effect of all other states' shocks on this state. Further, Figure 2 uses lighter colors for more of a transmitter of shocks to other states and darker colors for more of a receiver of shocks from other states.

We can see that the main transmitters of shocks include Arkansas (AR), Colorado (CO), Ohio (OH), and Washington (WA) whereas the main receivers of shocks include Hawaii (HI), New York (NY), North Carolina (NC), West Virginia (WV), and Maine (ME). Even though this map provides a good overview of the spillovers, it will be interesting to see how the spillovers behave on a regional level, which we show below.

[Insert Figure 2 around here]

To see whether a state, on average, significantly transmits or receives shocks, we calculated t-tests for each state and determined the 99% confidence interval (see Figure 3). Figure 3 shows that the VAR approach based on the OLS and Ridge regressions sometimes differs significantly from the VAR approach based on the Lasso and Elastic Net regressions. We can see this for SD, HI, and NE. This outcome occurs because the OLS does not penalize the parameter estimates at all and the Ridge regression squared parameters penalized parameter estimates by a squared factor. We know that the parameters in a VAR model usually vary between zero and one. Hence, the penalization of the Ridge regression does not exert much of a penalty unless the parameter estimate is close to one. The Lasso regression, however, penalizes parameters between zero and one more severely as the absolute value and not its squared value is penalized. The fact that the Elastic Net-based VAR model closely approximates the Lasso-based VAR results indicates that the Elastic Net parameter gives the Lasso penalization term more weight than the Ridge regression

cases. Complete details of these results are available upon request from the authors. It must be noted that similar to our finding, Ngene et al. (2017) found support for the hypothesis that herding effects at the state-level U.S. housing returns are more prominent during the recession periods.

parameter. Thus, the results of the Elastic Net approach should provide the most reliable findings as the estimation process allows in every step to decide whether the Elastic Net should weigh the results of the Lasso or the Ridge regression more. This illustrates that the Lasso regression should be preferred over the Ridge regression in applied time-series econometrics that use the VAR model or other time-series modeling techniques, where the parameter estimates should lie between zero and one. This theoretical consideration is supported by the data as the Ridge regression results differ the most from all others and are valuable information for researchers and practitioners.[8]

[Insert Figure 3 around here]

5.2 Regional-Specific Connectedness Results

We aggregate the state spillovers to the regional level to get an overview of the interdependencies across regions Figure 4 illustrates the dynamic total connectedness for each region without considering the interregional spillovers. The findings suggest that the Northeastern and Southern regions appear highly connected throughout the period of analysis whereas the Midwestern and Western regions appear less interconnected and, hence, exhibit a lower housing market risk. This has important implications for portfolios and risk management as the risk of Mortgage-Backed Securities (MBSs) and Collateralized Debt Obligations (CDOs) can be reduced by investing more into Western and Midwestern regional mortgages as the markets are not as highly synchronized as the markets in the Northeastern and Southern regions. Notably, this relates to the subprime market crisis of 2006 that led to the Great Recession and the Financial Crisis of 2008-2009. It appears that the subprime market crisis started in the Northeastern and Southern regions and fueled over time the risk in the Midwestern region. Moreover, for the Western region, the sharp increase could indicate that its risk was mainly caused by the contagion effect of the other three regions. Further, the Western region lived through another increase in market risk in 2012, which could mark the further deterioration of the U.S. housing market via defaulted loans. Finally, after 2015, all regions start decreasing together until

[8] Hence, from here onwards, we will disregard the Ridge regression results and mainly focus on the findings of the Elastic Net model. Empirical results of the other models are available upon request.

the end of the sample period, whereby the level of risk concerning the Midwestern and Western regions still substantially exceeds the pre-crisis period.

[Insert Figure 4 around here]

In addition to intraregional connectedness, spillovers across regions are also of major interest. Figure 5 illustrates interregional dynamic total connectedness, which shows a substantial increase in 2008 due to the U.S. subprime market crisis. This sudden increase in the U.S. housing interrelatedness shows the contagious effect the crisis had nationwide.

[Insert Figure 5 around here]

Table 1 reports the average connectedness measures on a regional level – Northeast, Midwest, South, and West. We find that the Northeastern region is the main receiver of shocks whereas the South is the main transmitter of shocks followed by the Western and Midwestern regions.

[Insert Table 1 around here]

The OLS, Lasso, and Elastic Net results confirm that the South is the net pairwise transmitter to all others followed by the West and Midwestern regions, leaving the Northeastern region as the sole receiver of all net pairwise spillover shocks. This behavior is visualized in Figure 6.

[Insert Figure 6 around here]

5.3 Northeastern, Southern, Midwestern, and Western Regional Spillovers

Finally, to complete the picture, we isolate each region and identify the spillover effects within each region by itself. Figures 7, 8, 9 and 10 show the spillovers from the Northeastern, Southern, Midwestern, and Western regions, respectively, on a state-by-state basis. In the Northeast region, New Hampshire (NH) is the largest net transmitter of shocks whereas New York (NY) is the largest net receiver of housing price shocks. Comparing our findings to all states (Figure 1) and regional (Figure 6) spillover effects, we note that

New York State is the one constant as a net receiver of spillover effects from all states and all regions.

In the Southern region, Arkansas (AR) is the largest transmitter of shocks whereas North Carolina (NC) and West Virginia (WV) are the largest receivers of shocks. Comparing our findings to all states (Figure 1) and regional (Figure 6) spillover effects, we note that Arkansas is the one constant as a net transmitter of spillover effects from all states and all regions, although when we consider all states Arkansas trails behind Ohio as a net transmitter.

In the Midwestern region, Ohio (OH) is the largest transmitter of shocks whereas Iowa (IA) and Minnesota (MN) are the largest receivers of shocks. Comparing our findings to all states (Figure 1) and regional (Figure 6) spillover effects, we note that Ohio is a net transmitter of spillover effects from all states but a net receiver from the South and the West and a net transmitter to the Northeast when we consider the regions.

In the Western region, Colorado (CO) and Washington (WA) are the largest transmitters of shocks whereas Oregon (OR) is the largest receiver of shocks. Comparing our findings to all states (Figure 1) and regional (Figure 6) spillover effects, we note that Colorado and Washington are net transmitters of spillover effects and Oregon is a net receiver of spillover effects from all states and all regions. In this case, however, the net transmitter status of Colorado and Washington and the net receiver status of Oregon strengthen when we examine the isolated region of the West.

[Insert Figure 7, 8, 9 and 10 around here]

In sum, returning to Figure 2 and the description of the largest senders and receives of shocks for all 50 states and the District of Columbia simultaneously, we see a large overlap with the regional findings.

6 Discussions

We gain several insights from comparing and contrasting our findings with existing research on the comovement of U.S. state housing markets. The following remarks, however, are worth noting before that. First, the focus of the existing literature considers a narrower geographical definition of housing markets. For example, Gupta and Miller (2012a,b) studied the housing markets of Los Angeles, Las Vegas, and Phoenix as well as the southern California housing market, respectively. Chiang and Tsai (2016) considered eight metropolitan areas housing markets, while Tsai (2019) examined 10 metropolitan areas' housing markets. Gao et al. (2009) studied housing market dynamics of 19 major cities.[9] Further, apart from the differences in the sample periods across all studies, the methodological contribution of our paper also merits attention. Hence, any comparisons should be in the context of these differences.

We find significant variation in total connectedness across time with peak connectedness in 2007. This corroborates the dynamic nature of the ripple and contagion effects in the U.S. regional housing markets (Barros et al., 2014; Kallberg et al., 2014; Chiang and Tsai, 2016; Marfatia, 2021). One reason for the time-varying nature of connectedness could be the disposition effects observed in the housing markets. Housing price co-movements appear relatively stronger in up than down markets (Chiang and Tsai, 2016).

We also find that the housing markets of Arkansas, Colorado, Ohio, and Washington are net transmitters of shocks, whereas Hawaii, New York, North Carolina, West Virginia, and Maine are net receivers of shocks. These results support the findings of Marfatia (2021). Moreover, Marfatia (2021) estimates the role of national-, regional-, and state-specific factors in driving housing prices in all U.S. states and finds that the unique state-specific factor explains more than one-third of the variation in house prices in Arkansas, Colorado, and Washington.

Barros et al. (2014) also find that the housing markets of Colorado, Ohio, and Washington exhibit evidence against the convergence hypothesis, thus, indicating that state-specific economic and demographic factors greatly influence the movement of housing prices in these states. This makes them candidate markets for playing the role of net transmitters of shocks across markets. Interestingly, Hawaii, West Virginia, and Maine also display mean reversion in Barros et al. (2014).

Our state-level results, however, partly contrast with Chiang and Tsai (2016). Focusing on eight metropolitan areas, Chiang and Tsai (2016) find that Los Angeles, New York, and Miami are the sources of shocks in their respective regions. The potential reasons for

[9] A few exceptions include Barros et al. (2014), Marfatia (2021), and Gupta et al. (2021).

contrasting results could reflect their adopted geographical definition and limited eight metropolitan areas' analysis. Further, the dynamic spillover and connectedness in the U.S. housing market highlighted in the literature could magnify the effects of differences in the sample periods under consideration.

The regional level analysis shows that the Midwest transmits shocks on the net to the Northeast and receives shocks on the net from the South and the West. This partly corroborates Tsai (2018) findings, which suggest that the regions most and least affected by regional housing prices are the Midwest and Northeast regions, respectively. Fadiga and Wang (2009) also find that house prices in the Northeast and West share the source of variability in the long run, whereas housing markets in the South and Midwest appear to possess their own dynamics.

The findings of this study carry significant implications for portfolio and risk management. The interconnectedness results shed light on regions with higher connectivity as well as those acting as primary net transmitters and net receivers of shocks. Given that the primary purpose of creating MBSs and CDOs is to reduce interdependencies among regional housing markets, our analysis becomes a valuable tool for enhancing the diversification of MBSs and CDOs. This, in turn, can lead to more effective risk mitigation strategies and better overall performance in the market.

7 Conclusions

We examine the connectedness between real housing return shocks across the 50 U.S. states and the District of Columbia as well as four regions (Midwest, Northeast, South, and West), using a VAR modeling approach that selects parameter estimates using Lasso, Ridge, and Elastic Net methods.

Total connectedness steadily increased since 1995, peaking in 2007, and remained at that level until 2005 when it slowly began decreasing. The Lasso, Ridge, and Net Elastic methods of penalization trended generally together, not differing by too much. The standard OLS results, however, produced higher total connectedness than the other three methods during the beginning of the sample period through 2007. Then, dynamic total connectedness did not differ much across the four models for the high volatility period followed by the Great Recession and Financial Crisis of 2007-2009.

On a state basis, the main transmitters of shocks include Arkansas, Colorado, Ohio, and Washington whereas the main receivers of shocks include Hawaii, New York, North Carolina, West Virginia, and Maine. At the regional level, we find that the South transmits real housing return shocks to the other three regions, whereas the Northeast receives those shocks. The West receives shocks from the South and transmits shocks to the Midwest and the Northeast. Finally, the Midwest transmits shocks to the Northeast and receives shocks from the South and the West.

From the perspective of policy decisions, policymakers need to monitor the behavior of housing market movements in states like Arkansas, Colorado, Ohio, Washington, and the South region closely, as these markets serve as transmitters of shocks. To the extent that "housing really is the business cycle" (Leamer, 2015), the Federal Reserve can monitor housing market movements in the net transmitter states to gather information about the beginnings of the housing market cycle. At the same time, these markets also provide investment opportunities for housing market investors. In this regard, note that with overall market connectedness being high during periods of crises, diversification opportunities for investors across regional markets diminish.

Future research could examine the national and regional factors that drive connectedness. Clearly, this information will help policymakers to design sector-specific policies. Preliminary analysis using national-level variables indicates that measures of economic (Jurado et al., 2015) and real estate uncertainties (Nguyen Thanh et al., 2020) are more important in (positively) driving connectedness than macroeconomic variables such as output growth, inflation, and interest rates.[10] At the same time, as in He and Hamori (2021), one could conduct analyses of spillovers and connectedness of higher moments of real housing returns, namely, volatility and skewness, given the importance of these metrics in portfolio allocation decisions of real estate investors.[11] With our focus being

[10] These results are available upon request from the authors.

[11] Diebold and Yilmaz (2012) used the differences between the maximum and minimum price of a series as a proxy for volatility. Thus, the number of observations does not change when using returns or volatility. In our case, we deal with housing prices and do not have the information on the minimum or maximum price for each month. Another option calculates the standard deviation based on a pre-specified rolling-window in the first stage while using the rolling-window VAR methodology in the second stage. This approach makes the most sense when using daily data. For our monthly data, a range of three years (36 months) may produce reasonable estimates of volatility but severely restricts our time-series sample.

real housing returns in this paper and in light of the contribution we aim to make to the ripple and contagion effects literature, we leave such questions for future research.[12]

As suggested by a referee, the connectedness approach used in this article could be related to recent articles such as Balcilar et al. (2021) and Lastrapes and Wiesen (2021). Lastrapes and Wiesen (2021), however, only provide joint connectedness measures on the aggregated level (TO, FROM, and NET) and, therefore, the spillovers between states could not be calculated, which is one of our contributions compared to studies that consider aggregated regional housing prices such as Antonakakis et al. (2021). Further, the connectedness framework proposed by Balcilar et al. (2021) uses a TVP-VAR model, which would estimate in each step 51x51x2 (variance-covariances + VAR coefficients) and (51x51)x(51x51) coefficient variance-covariances for a total of 6,770,403 parameter estimates at each point in time. We ran this procedure but consistently received errors as the matrices were not invertible or the procedure did not converge.

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[12]Initial results based on the total connectedness of volatility and skewness depicted a positive correlation with the TCI of housing returns. Granger causality tests involving the TCIs detected a strong causal influence of volatility and skewness on returns, with feedback more likely on skewness than volatility. With TCIs of volatility and skewness measuring the co-movement of uncertainty and in line with the importance of aggregate real estate uncertainty driving TCI of housing returns, the causality results should not come as a surprise. Complete details of these results are available upon request from the authors.

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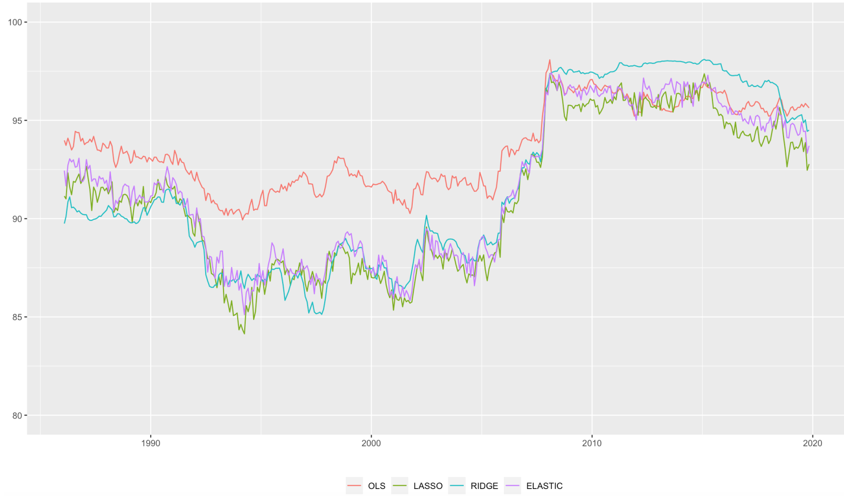
Table 1: Aggregated Regional Connectedness Table

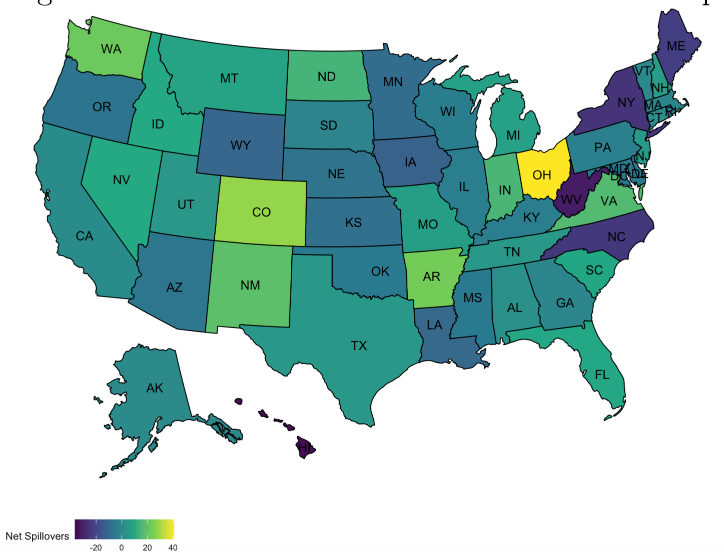
	Northeast	South	Midwest	West	FROM
Northeast	62.4	12.2	12.3	13.1	37.6
South	7.3	72.5	9.9	10.3	27.5
Midwest	6.9	11.6	70.5	11.0	29.5
West	6.7	11.1	10.6	71.6	28.4
TO	20.9	34.9	32.7	34.4	122.9
Net Spillovers	-16.7	7.5	3.2	6.0	TCI
Net Pairwise Transmission	0	3	1	2	41.0

Figure 1: Dynamic Total Connectedness



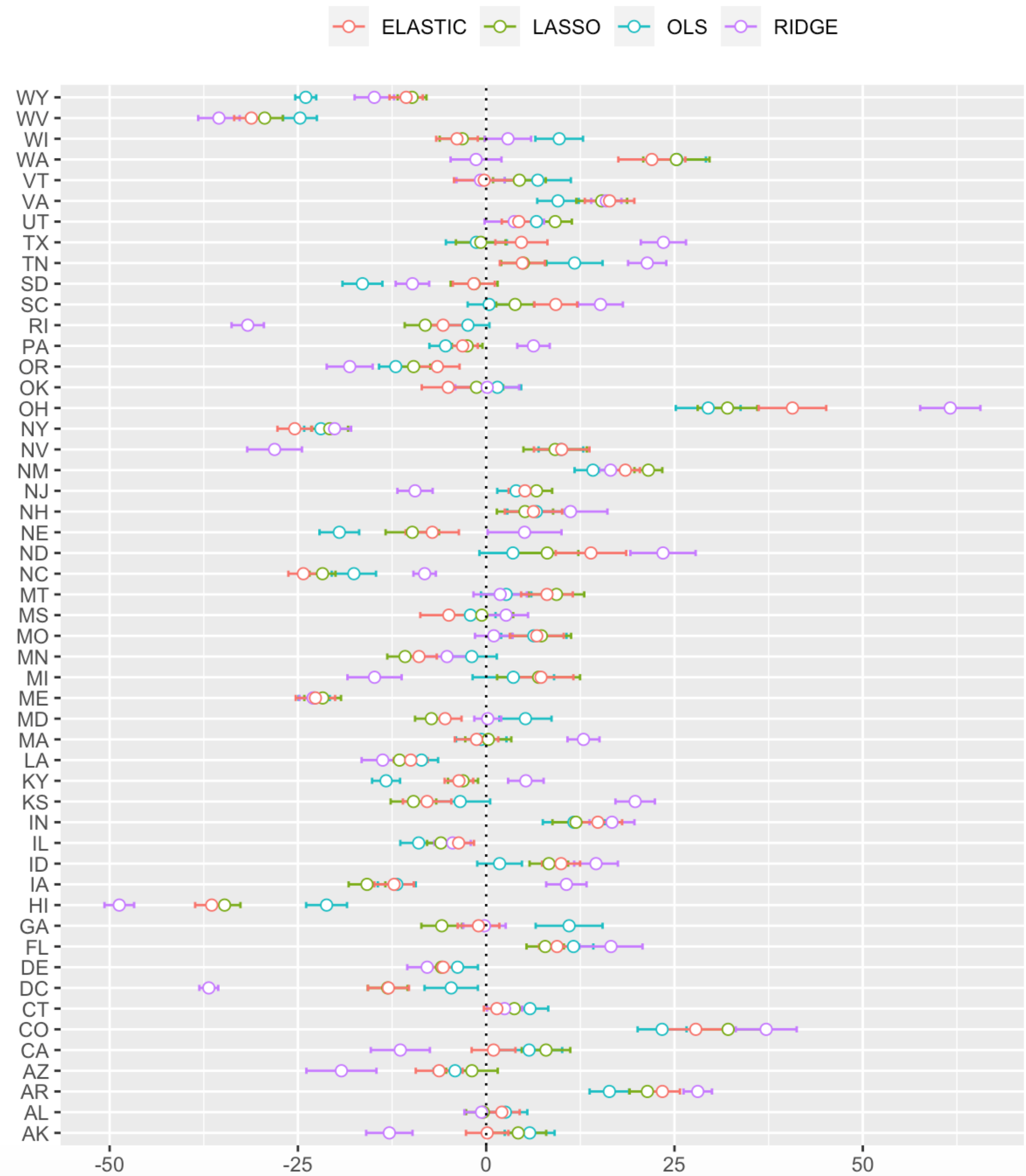
Notes: Results are based on all 120-month rolling-window models with a 10-step-ahead forecast horizon.

Figure 2: Net Total Directional Connectedness Map



Notes: Results are based on all 120-month rolling-window models with a 10-step-ahead forecast horizon.

Figure 3: Average Net Total Directional Connectedness



Notes: Results are based on all 120-month rolling-window models with a 10-step-ahead forecast horizon. The means and their corresponding 95% confidence intervals are shown.

Figure 4: Intraregional Dynamic Total Connectedness

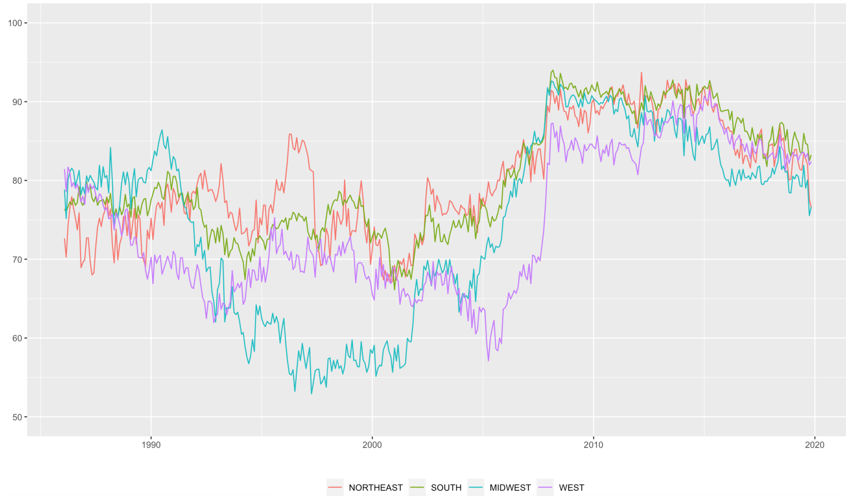


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Figure 5: Interregional Dynamic Total Connectedness

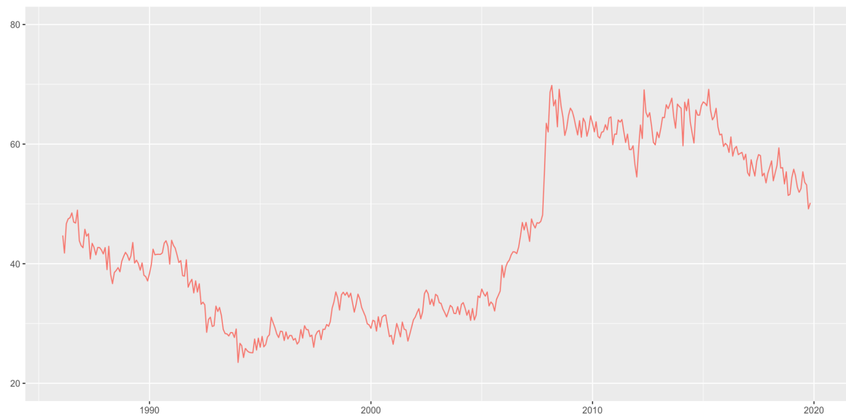

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Figure 6: Regional Dynamic Total Connectedness

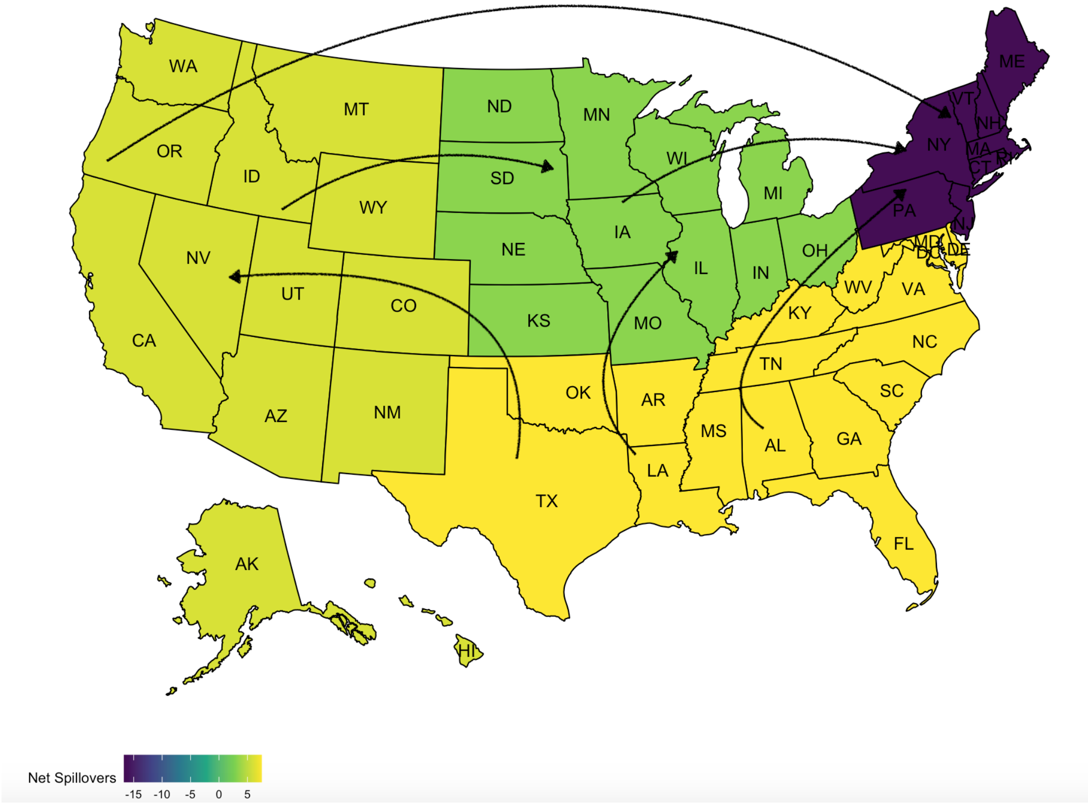

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Figure 7: Northeastern Net Total Dynamic Connectedness

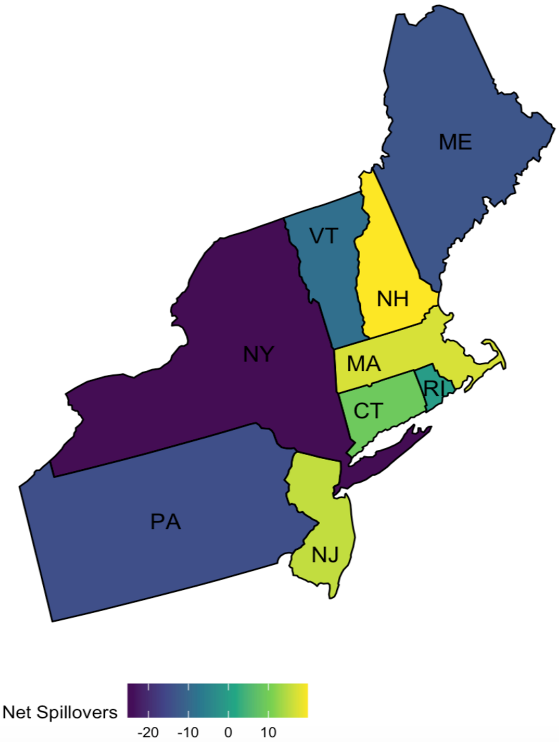

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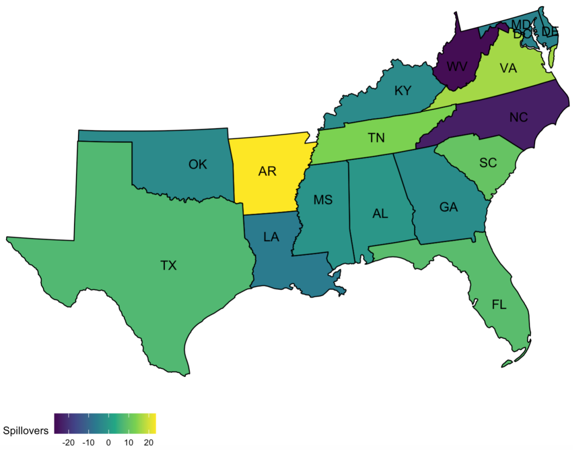
Figure 8: Southern Net Total Dynamic Connectedness



Notes: Results are based on all 120-month rolling-window models with a 10-step-ahead forecast horizon.

Figure 9: Midwestern Net Total Dynamic Connectedness

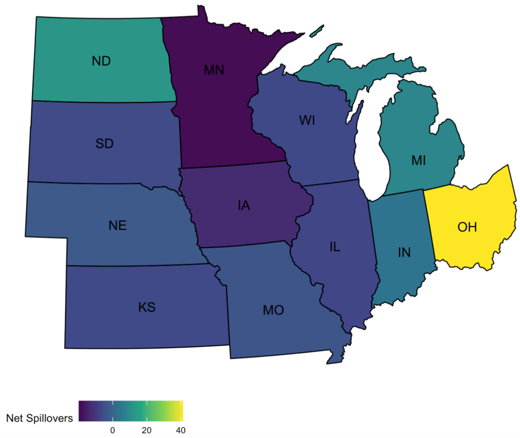


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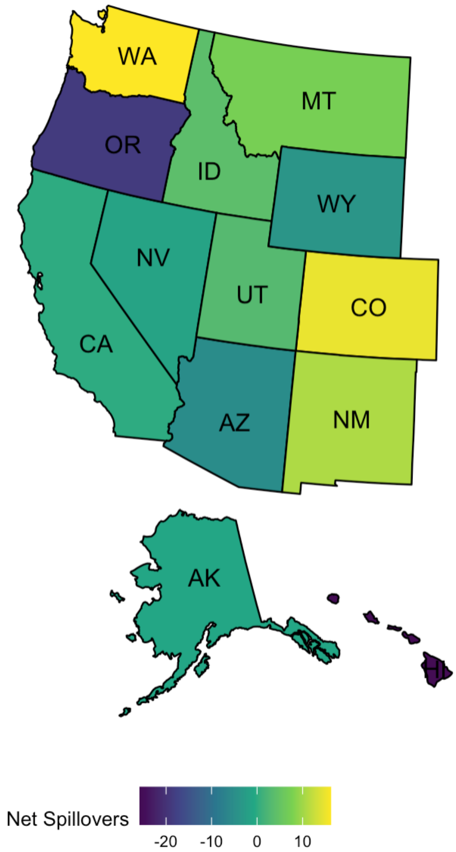
Figure 10: Western Net Total Dynamic Connectedness



Notes: Results are based on all 120-month rolling-window models with a 10-step-ahead forecast horizon.

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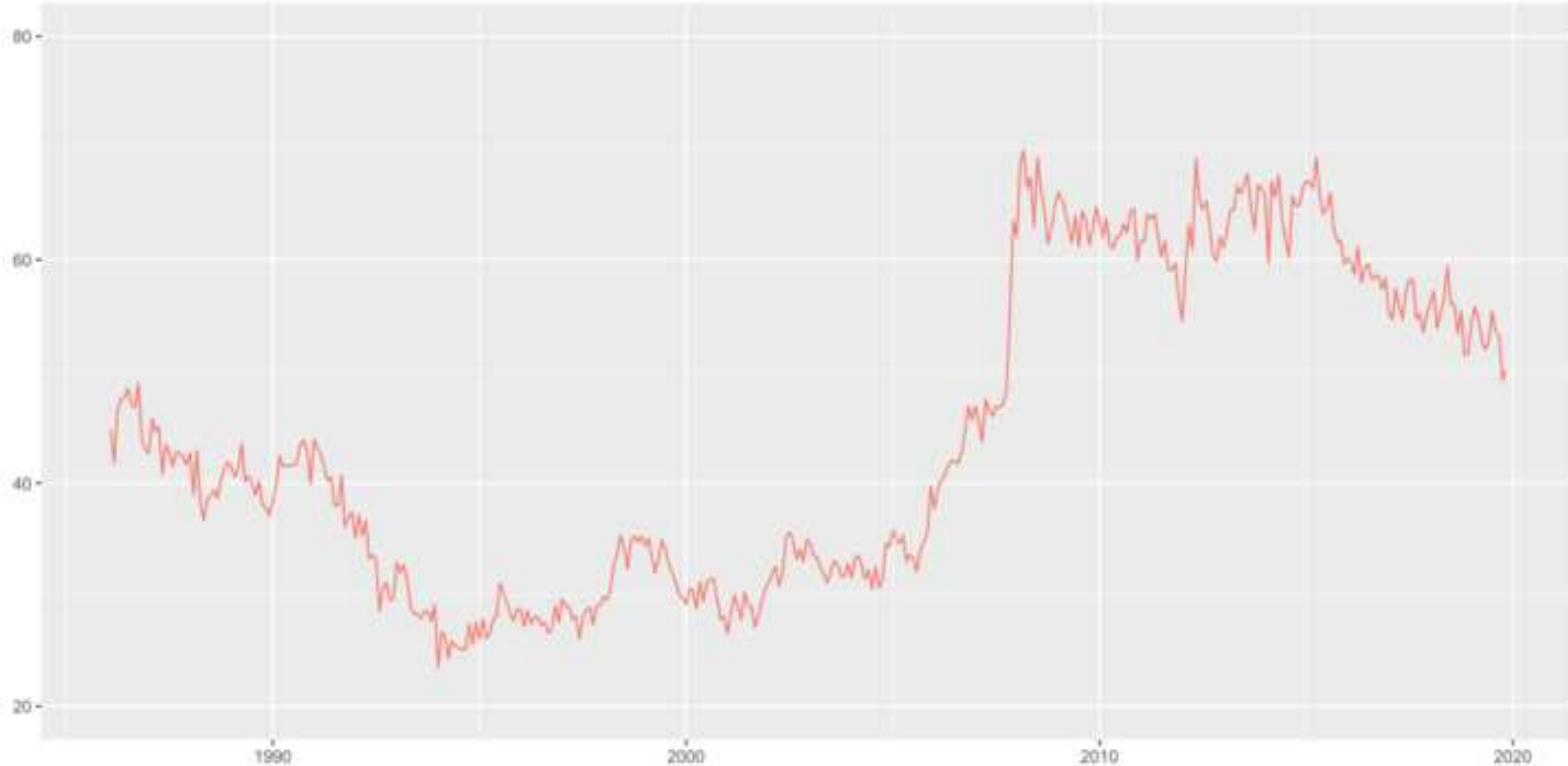

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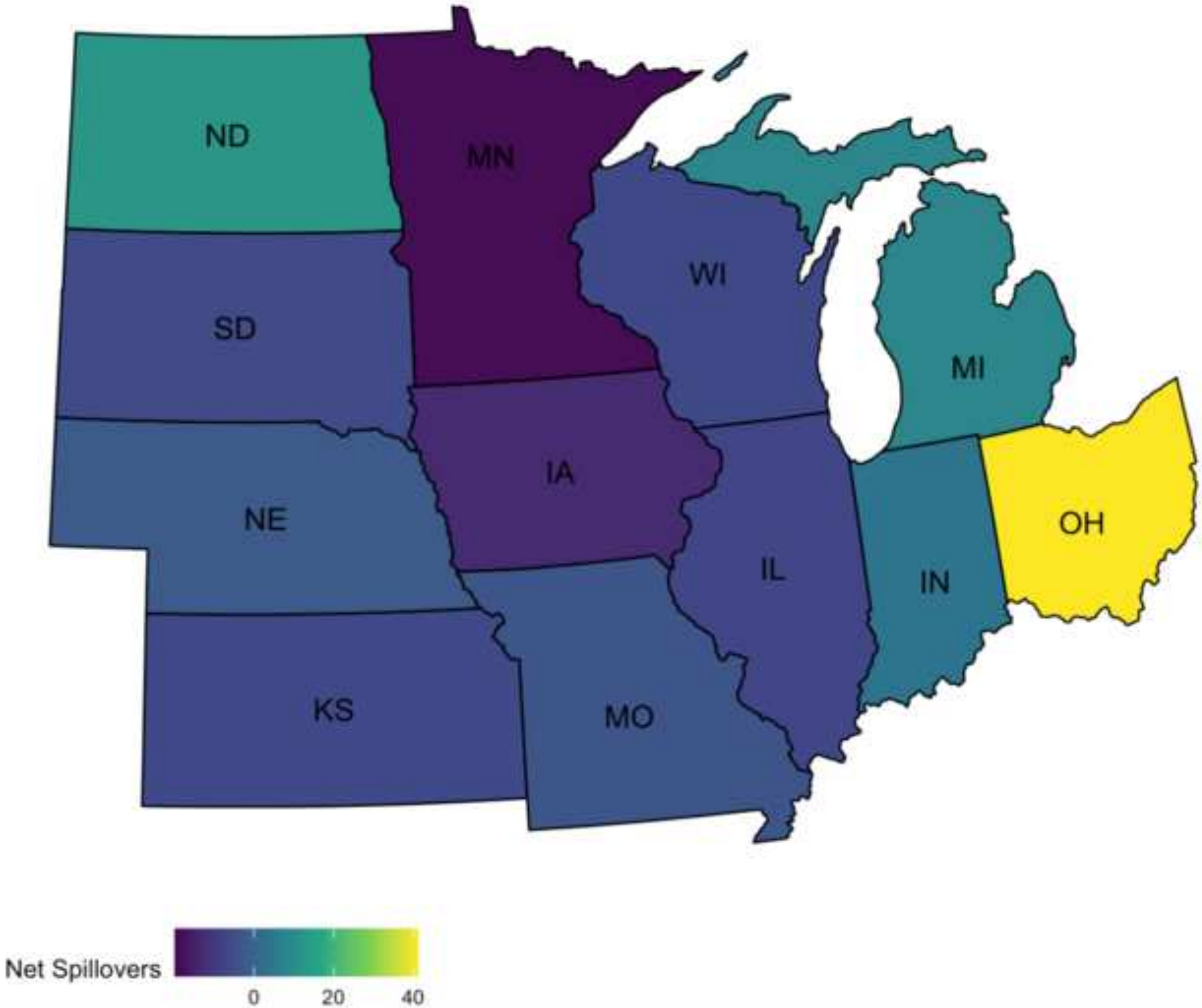

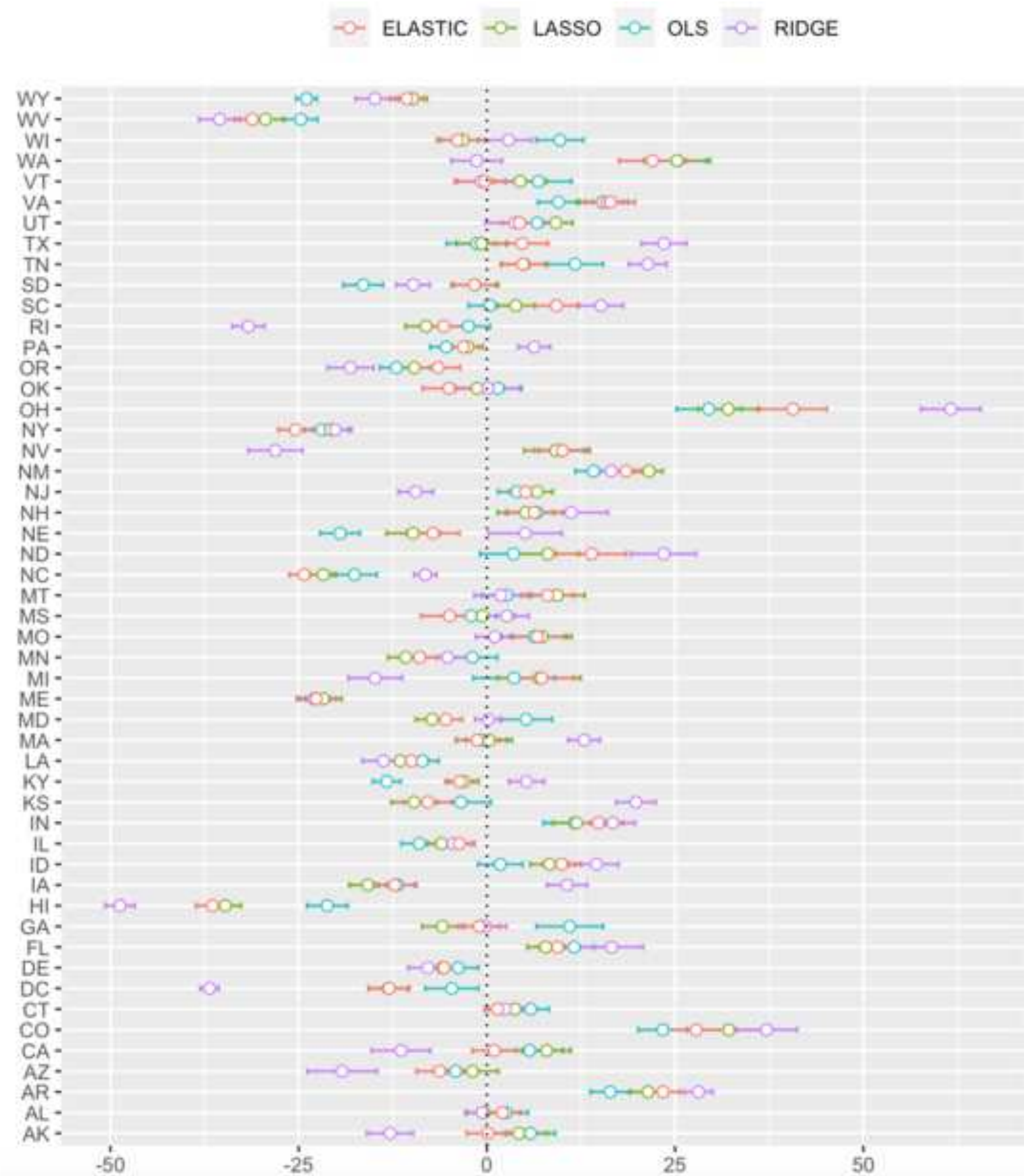
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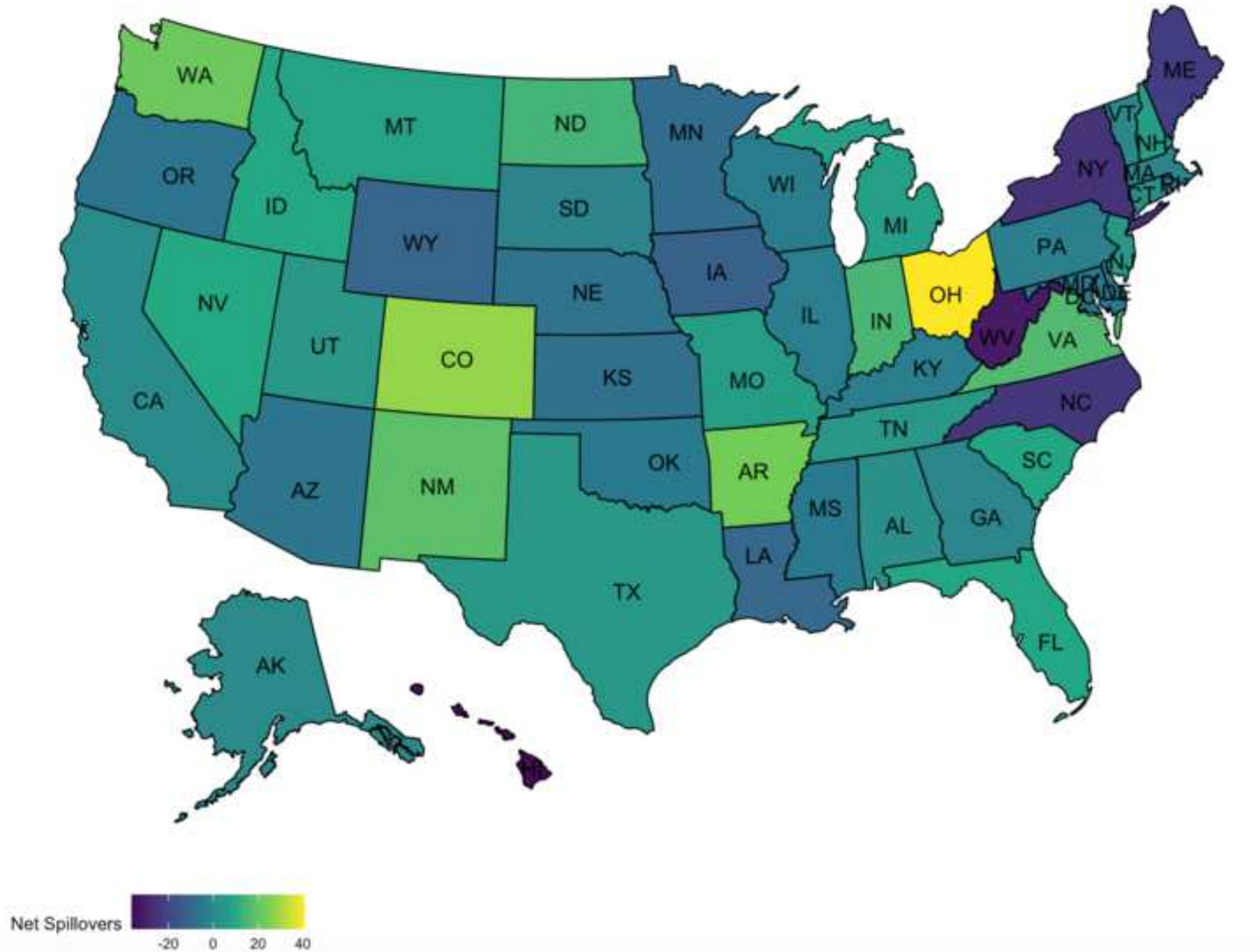

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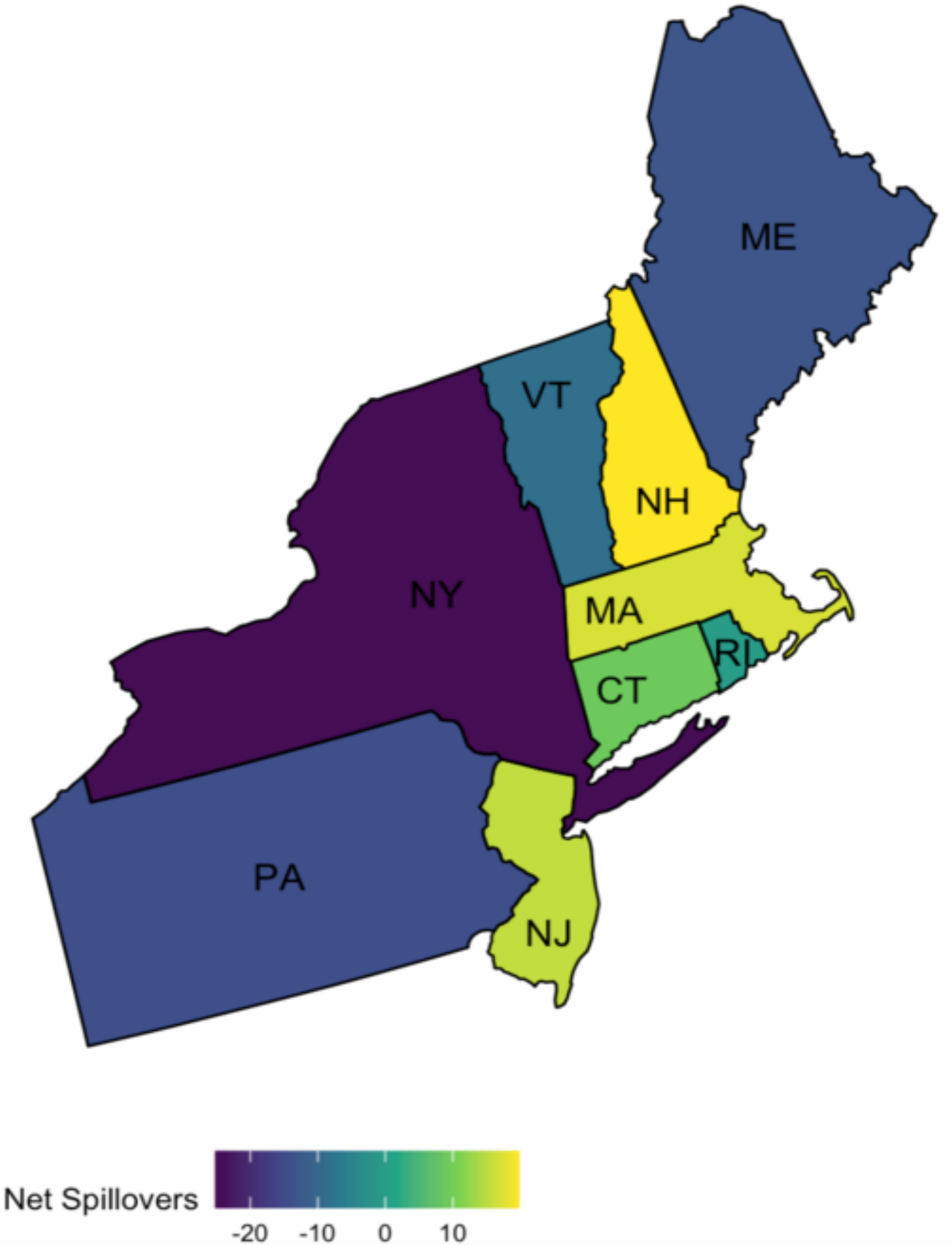

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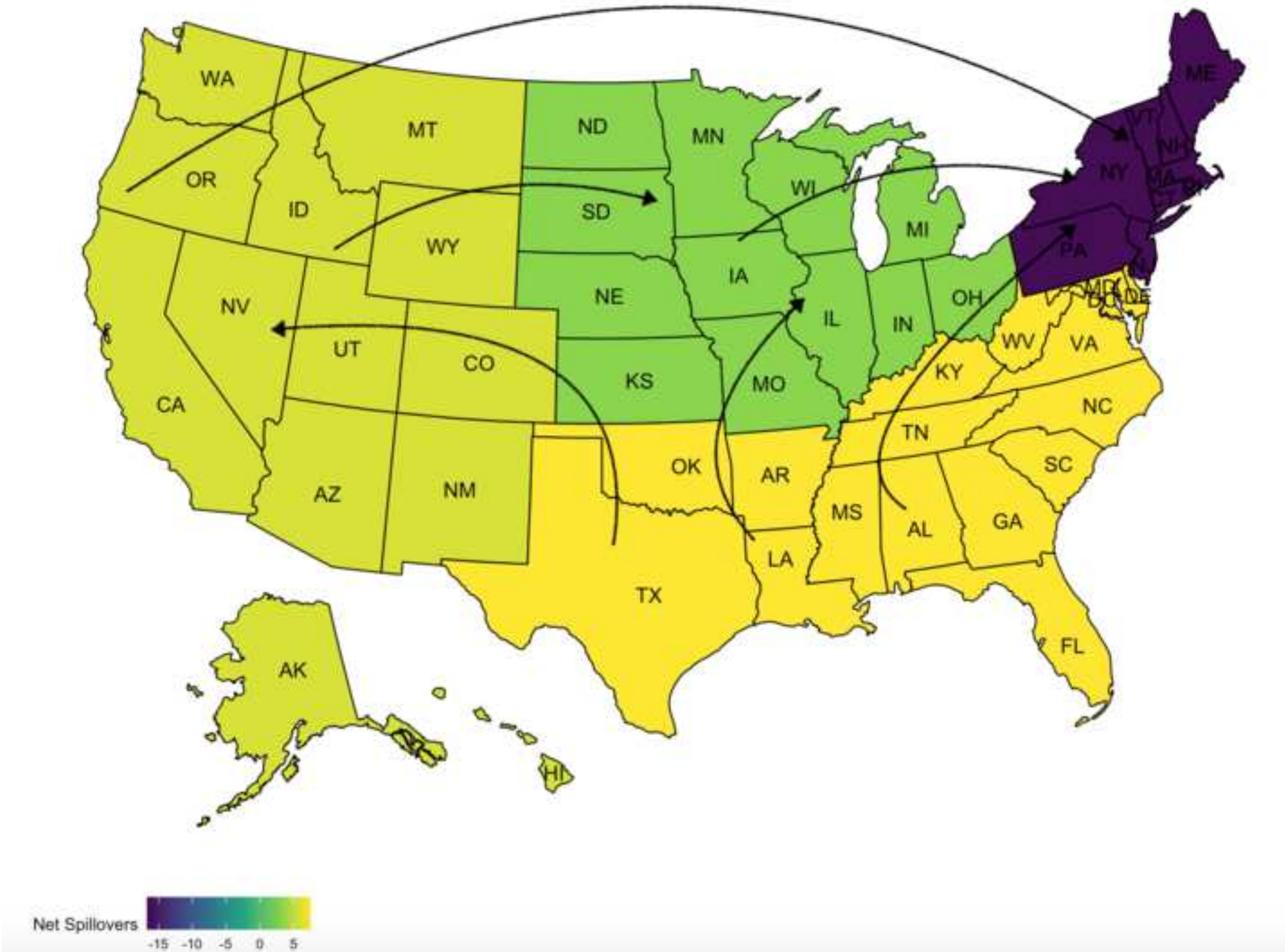
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Net Spillovers
-15
-10
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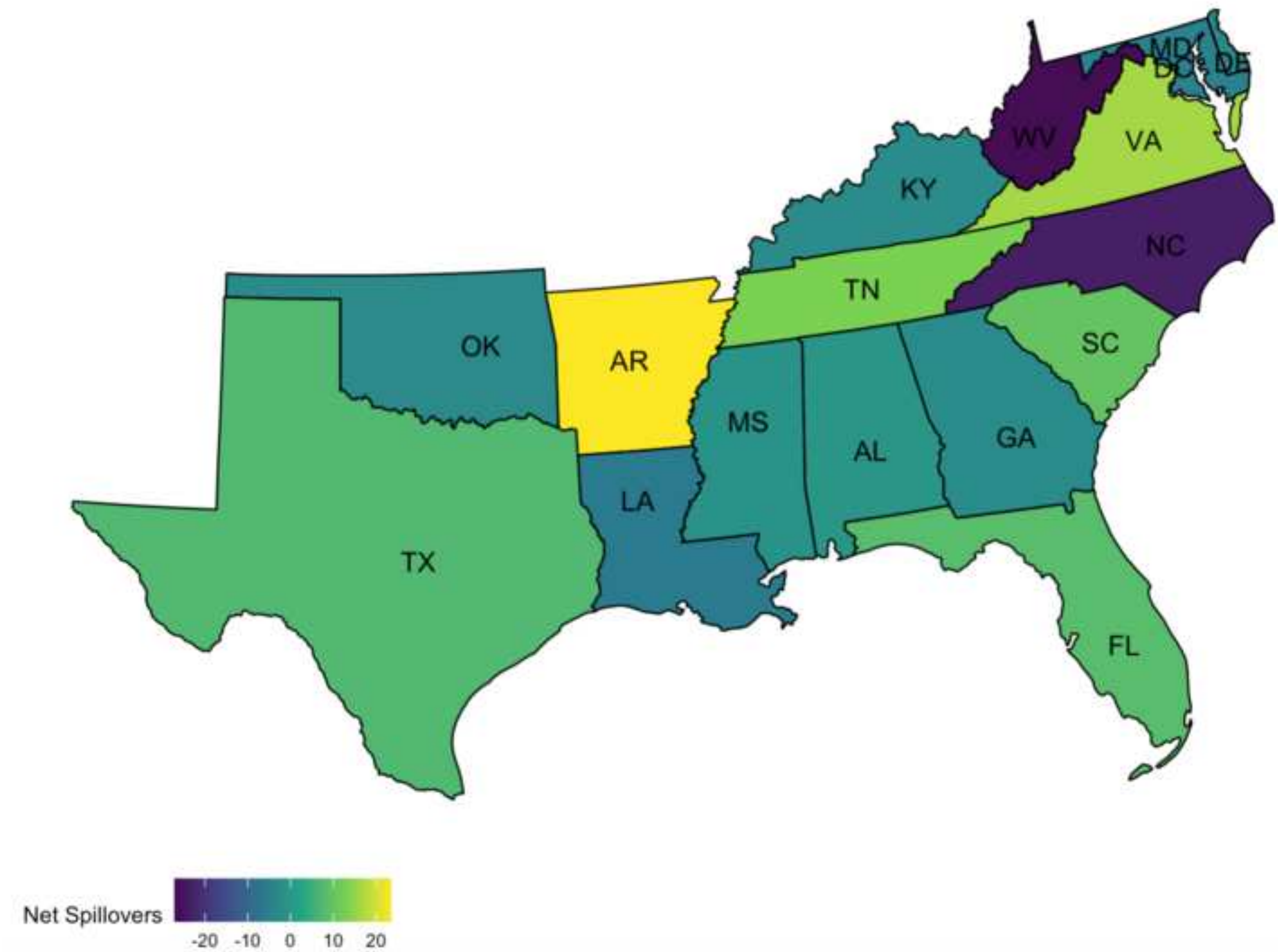
5

Figure

Click here to access/download;Figure;south.png



Figure

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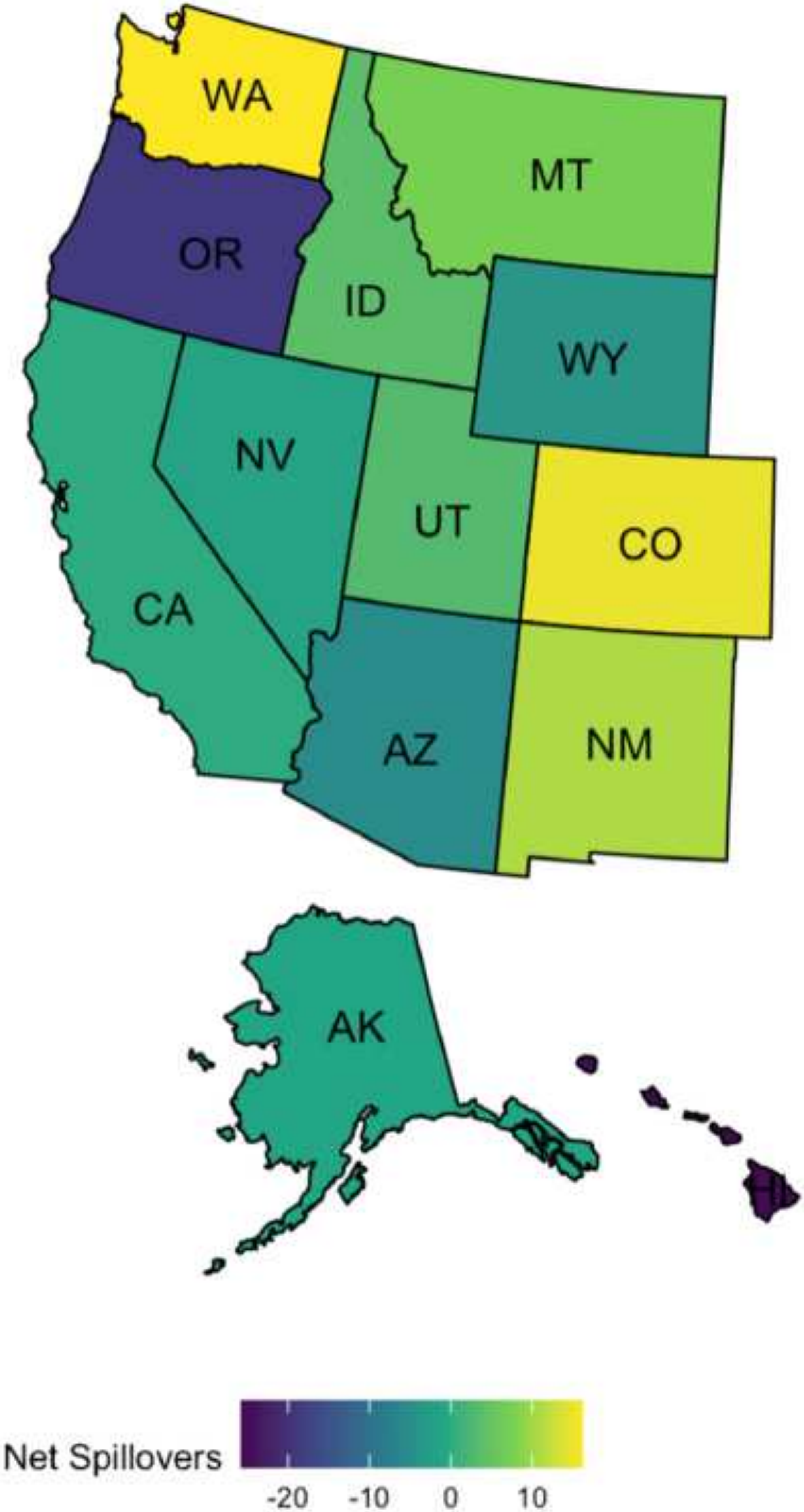
WA
MT
OR
ID
WY
NV
UT
CO
CA
AZ
NM
AK
Net Spillovers
-20
-10
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