**Graph Theory-Based Network Analysis of Regional Uncertainties of the US Economy[[1]](#footnote-1)#**

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**Abstract**

We study the transmission mechanism of time-varying macroeconomic uncertainty across the US states. We analyse the contemporaneous and temporal causal relationships of uncertainty at the state level by utilising the Bayesian graphical VAR (BGVAR) model. Our results show that the current uncertainty of each state strongly depends on the previous level of uncertainty in its own state. We find evidence of strong contemporaneous and lagged dependence among US states. The analysis of this paper has important policy implications.

**JEL Codes:** C32

**Keywords:** Uncertainty Spillover, Macroeconomic Uncertainty, US States, Bayesian Graphical Structural VAR

**1. Introduction**

The effect of uncertainty on macroeconomy and financial markets has attracted great attention of financial academics and practitioners in the wake of the 2008 global financial crisis (e.g., Antonakakis, Balcilar, Gupta, and Kyei, 2017; Bloom, 2009, Chuliá, Gupta, Uribe, and Wohar, 2017, Gupta, Hammoudeh, Modise, and Nguyen, 2014; among others). A number of recent studies (e.g., Angelini et al., 2018; Carriero et al., 2016; Jurado et al., 2015; Mumtaz, 2018; among others) find evidence that macroeconomic uncertainty is a driver of economic fluctuations and it plays an important role in affecting real economic activity and asset pricing. While there is a growing interest in understanding uncertainty and its impact on macroeconomic and financial variables, the transmission mechanism of uncertainty across borders remains an underexplored area. The research on uncertainty interconnectedness has important implications for policy responses to the global financial crisis. If uncertainty spills over across borders, then even there is no change of uncertainty in the domestic market, the negative impact of uncertainty can still present itself through trade and financial linkages among economies (Klößner and Sekkel, 2014; Balli, Uddin, Mudassar, and Yoon, 2017). Furthermore, uncertainty spillover effects can magnify the adverse influence when domestic uncertainty does rise (Bernal, Gnabo, and Guilmin, 2016). [[3]](#footnote-3) The few existing studies focus mainly on international uncertainty linkages at the country level and provide some evidence that uncertainty transmits across national borders (e.g., Antonakakis, Gabauer, and Gupta, 2018; Antonakakis, Gabauer, Gupta, Plakandaras, 2018; Christou, Gozgor, Gupta, and Lau, 2019; Gabauer and Gupta, 2018; Gupta, Pierdzioch, and Risse 2016; Gupta, Lau, and Wohar, 2016; Huang, Tong, Qiu, and Shen, 2018; Klößner and Sekkel, 2014; Yin and Han, 2014;). Our contribution to this emerging stream of literature is to examine the behaviour of macroeconomic uncertainty dependence among US states using the state-level data. If there is a linkage of uncertainty across state economies, the changes of macroeconomic uncertainty in one state can have an impact on economic and financial variables of other states even there are no changes in their domestic levels of uncertainty of these states. This paper contributes to economic policy-making decisions of state governors. It is of great value for policy makers to understand the transmission channel of uncertainty spillovers given the important role of uncertainty in affecting macroeconomy (Balcilar et al., 2016). In the US, states have sufficiently autonomy in polices they adopted and state governors bear responsibility for the performance of the state economy (Brown, 2010).

The state-level uncertainty data used in this paper is based on the h-step-ahead forecast of a factor-augmented vector autoregression (FAVAR) system estimated by Mumtaz (2018) using the uncertainty measure proposed by Jurado et al. (2015). The new measure provides direct econometric estimates of time-varying uncertainty under a data-rich environment, which is free from both the restriction of specific theoretical models and the dependence of any individual macroeconomic variables.[[4]](#footnote-4) The Bayesian Graphical Structural VAR (BGVAR) model of Ahelegbey et al. (2016) is employed to examine the contemporaneous and dynamic causal structures of macroeconomic uncertainty across the 50 US states. This newly developed model is superior to the standard Structural VAR (SVAR) model that is often criticised for imposing implausible structural restrictions based on a specific economic theory. The BGVAR model allows for the investigation of causal relationships between variables without the restriction of economic models.[[5]](#footnote-5) Moreover, it provides a framework to represent and estimate an unambiguous direction of causations by means of the directed edges. [[6]](#footnote-6) This model adapts an approach where important variables can be identified with a causal interpretation. Ahelegbey et al. (2016) confirm that the BGVAR methodology is more parsimonious and offers a better representation of the causal relations among variables than the Granger causality approach.[[7]](#footnote-7)

The remainder of this paper is organised as follow. Section 2 describes the data and methodology. Section 3 presents the results and analysis. Section 4 provides a summary of findings and concluding remarks.

**2. Data and Methodology**

The US state-level uncertainty data used in this paper is based on the h-step-ahead (h =1, 2, 3, 4) forecast of a factor-augmented vector autoregression (FAVAR) system estimated by Mumtaz (2018). The dataset consists of quarterly macroeconomic uncertainty measures for the 50 US states at four different forecast horizons (i.e. in 3, 6, 9, and 12 months) over the period from 1977:Q2 to 2015:Q3. The state-level macroeconomic uncertainty measures are calculated using the real per-capita growth rates of personal income, benefit income, dividend income, social insurance contributions, other income, the seasonally adjusted employment growth rate, unemployment rate, and house price growth rate. These time series are obtained from the Federal Reserve Bank of St Louis database. The uncertainty measures for each state are constructed following the procedures proposed by Jurado et al. (2015).[[8]](#footnote-8)

In order to examine the contemporaneous and lagged causal relationships of macroeconomic uncertainty across US states, this paper utilises the Bayesian graphical VAR (BGVAR) model of Ahelegbey et al. (2016). The Dynamic Bayesian Network is applied to the following standard structural VAR (SVAR) model presented in equation (1).[[9]](#footnote-9)

$Y\_{t}=B\_{0}Y\_{t}+\sum\_{i=1}^{p}B\_{i}Y\_{t-i}+ε\_{t}$ (1)

where $Y\_{t } $is a vector of response variables. *p* is the lag order. $ε\_{t}\~ N (0, I\_{p})$. $ B\_{0}$ is a $(n\_{y}×n\_{y})$ matrix of structural parameters with zeros on the diagonal.

The SVAR model of Eq (1) can be written into the reduced form of VAR as follows:

$Y\_{t}= \sum\_{i=1}^{p}A\_{i}Y\_{t-i} +u\_{t}$ (2)

where $A\_{i}=A\_{0}^{-1}B\_{i}^{\*}$,$ 1\leq i\leq p$. $A\_{0}=(I-B\_{0})$. $u\_{t}=A\_{0}^{-1}ε\_{t}$.

It is noteworthy that $A\_{0}$ are not identified, which require some identification restrictions to perform structural analysis. The SVAR model is thus widely criticised for imposing implausible assumptions or, at least, assumptions that are only as creditable as the underlying economic models (Ahelegbey et al., 2016). This critique motivates the use of the Bayesian graphical VAR (BGVAR) model of Ahelegbey et al. (2016) in this paper, in light of the lack of underlying economic theory for the emerging macroeconomic uncertainty spillovers literature. The BGVAR model has two distinctive advantages over the SVAR model. First, it is not necessary to impose restrictions from an economic theory in the BGVAR model to identify the causal order of structural models. Second, the BGSVAR model offers insight into the contemporaneous and dynamic (temporal) dependence of response variables with a causal interpretation, and it provides a simple framework to represent and estimate an unambiguous direction of causation among the variables by means of the directed edges. There is a one-to-one relationship between the regression matrices of the SVAR model and a directed acyclic graph (DAG), given as:

$X\_{t-s}^{j}⟶X\_{t}^{i}⟺B\_{s,ij}^{\*}\ne 0, 0\leq s\leq p $ (3)

where $X\_{t}^{i}$ represents the realisation value of the *i*-th variable at time t. The relationship $X\_{t-s}^{j}⟶X\_{t}^{i}$ means that $X\_{t-s}^{j}$ causes $X\_{t}^{i}$. It can be referred to as contemporaneous causal relationships for $s=0$, and as lagged dependence for $1\leq s\leq p$.

Define $B\_{s}^{\*}=(G\_{s}∘Φ\_{s})$ , $0\leq s\leq p$ (4)

where $G\_{s}$ is a binary connectivity matrix that indicates dependence, and $Φ\_{s}$ is a coefficient matrix. The operator $∘$ is the Hadamard product. G0 represents the connectivity matrix of contemporaneous dependence. Gs (1≤s≤p) denotes the connectivity matrix of the temporal dependence.

There is a one-to-one correspondence between regression matrices and the directed acyclic graphs such that.

 $B\_{s,ij}^{\*}=\left(\begin{matrix}ϕ\_{s,ij} &if B\_{s,ij}^{\*}=1\\0&if B\_{s,ij}^{\*}=0\end{matrix}\right)$ (5)

Based on the SVAR in Eq (1), the DAG can be represented as follows

 $Y\_{t}=\left(G\_{0}∘Φ\_{0}\right)Y\_{t}+\sum\_{i=1}^{p}\left(G\_{i}∘Φ\_{i}\right) Y\_{t-i}+ ε\_{t}$ (6)

where $(G\_{i}∘Φ\_{i})$ are the graphical model structural coefficient matrices whose non-zero elements describe the value associates with the instantaneous and lagged dependences.

The estimation of the model requires the choice of the optimal lag order, a set of parameters, $\{Β\_{0}^{\*},Β\_{1}^{\*},…,Β\_{p}^{\*},∑\_{ε}\}$, and the inference of causal structure $G =\left(G\_{0},G\_{1}, …,G\_{p}\right)$.[[10]](#footnote-10) The model produces the posterior probabilities of edges for both temporal and contemporaneous relationships, namely multivariate autoregressive (MAR) and multivariate instantaneous (MIN) structures.

**3. Results and Analysis**

Tables 1-2 summarise the results of edge probabilities for 50 US states of both MAR and MIN structures. Tables 1 reports the dynamic (lagged) dependence of the MAR structure (for h =1), and Tables 2 presents the contemporaneous relationship of the MIN structure (for h =1).[[11]](#footnote-11) Tables 3-4 show the number of cases that US states are the origination of directed edges for the MAR and MIN structures based on macroeconomic uncertainty measures at four different forecast horizons. The results reveal the following causality patterns based on the posterior probability of 0.50 or above.

In the case of MAR structure, we find that the current uncertainty of each state strongly depends on the previous level of uncertainty in its own state. In Table 1, we find that Arizona, California, Iowa, Idaho, Kansas, Louisiana, Missouri, North Carolina, New Hampshire, New York, and Ohio are important transmitters of uncertainty to other states.[[12]](#footnote-12) For example, the lagged uncertainty level in California is more likely to explain current uncertainty in nine states, i.e., Californiat-1 → (Californiat, Georgiat, Marylandt, Minnesotat, Ohiot, Oklahomat, Pennsylvaniat, South Carolinat, and Vermontt), with a probability higher than 0.50. In contrast, the current level of uncertainty in California only strongly depends on the previous level of uncertainty in its own state and in Arizona i.e., (Californiat-1 Arizonat-1) → Californiat. The results at horizons h1 to h4 are consistent to some extent. For example, Table 3 shows strong evidence of directed edges originating from California, Iowa, Kansas, Louisiana, and New Hampshire to at least nine states at all four horizons. Moreover, we find that preceding uncertainty in Alabama, District of Columbia, Delaware, Hawaii, Michigan, North Dakota, and Oregon also provides important information in explaining the structural dynamics of uncertainty in a relatively large number of states. There are at least nine cases that these states show strong evidence of directed edges from explanatory to response states. The results show that the dynamic spillover effect (temporal dependence) of uncertainty among US states is strong at all four forecast horizons.

Tables 2 report results of the contemporaneous interconnectedness among US states for the MIN structure. The results show that the origination of a large number of direct edges concentrates on a relatively small number of states. In Table 2, there is strong evidence of the contemporaneous causality from Massachusetts to fifteen states (i.e., Arizona, California, Florida, Kentucky, Maine, North Carolina, North Dakota, Nebraska, New Mexico, Nevada, New York, Pennsylvania, Utah, Wisconsin, West Virginia) at horizon h1, i.e., current uncertainty of these states strongly depends on the current level of uncertainty in Tennessee at the h1 horizon. Table 4 presents the number of cases that US states are the origination of directed edges for the MIN structure. MIN reveals strong contemporaneous causations originated from Alaska, Kansas, Kentucky, Idaho, Maryland, Massachusetts, Montana, Nevada, North Carolina, Texas, and Vermont at horizon h1. There are at least nine cases that these states are the origination of directed edges with a probability higher than 0.50. The results show evidence of strong contemporaneous dependence across all four forecast horizons.

The analysis has important policy implications in that it highlights the transmission channel of regional uncertainty of the US Economy. A major implication is that policymakers should not neglect uncertainty spillovers from other states when making policy decisions. The changes of macroeconomic uncertainty of one state can transmit across state borders and affect economic and financial variables (such as, personal income, dividend income, employment growth rate, unemployment rate, house price growth rate, and so on) of other states.

**4. Conclusions**

The Bayesian graphical VAR (BGVAR) model is employed in this paper to study the contemporaneous and dynamic lagged dependence of macroeconomic uncertainty across 50 US states. This study examines the behaviour of macroeconomic uncertainty interconnectedness using the state-level data and finds evidence of strong contemporaneous and temporal causal relationships among US states. The results show that the current uncertainty of each state strongly depends on the previous level of uncertainty in its own state. Moreover, the results of the contemporaneous interconnectedness show that the origination of direct edges concentrates on a few states, i.e., current uncertainty in a large number of states strongly depends on the current level of uncertainty in a relatively small number of states. The findings of this paper has important implications for policy-making decisions.

As part of future research, it might be interesting to conduct rolling estimation analysis to examine the behaviour of dependence over time, especially during the recent crisis period. It might also be worthwhile to explore the potential determinants of cross-state uncertainty spillovers and to provide theoretical and economic explanations of the observed transmission channels.

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Table 1 Results of the MAR structure at the h1 horizon

|  |  |
| --- | --- |
| Response States\_ t |  Explanatory States\_ t-1 |
| Alaska | Alaska | Nebraska | Pennsylvania | West Virginia |  |  |  |  |  |  |  |
|  | 1.00 | 0.50 | 0.52 | 0.68 |  |  |  |  |  |  |  |
| Alabama | Alabama | **Arizona** | **Missouri** | **North Carolina** | South Carolina | South Dakota |  |  |  |  |  |
|  | 1.00 | 0.56 | 0.79 | 0.57 | 0.73 | 0.50 |  |  |  |  |  |
| Arkansas | Arkansas | Colorado | Massachusetts | **New Hampshire** |  |  |  |  |  |  |  |
|  | 0.97 | 0.81 | 0.51 | 0.58 |  |  |  |  |  |  |  |
| Arizona | Alabama | **Arizona** | **North Carolina** | **Ohio** | South Dakota |  |  |  |  |  |  |
|  | 0.51 | 0.98 | 0.78 | 0.55 | 0.58 |  |  |  |  |  |  |
| California | **Arizona** | **California** |  |  |  |  |  |  |  |  |  |
|  | 0.53 | 1.00 |  |  |  |  |  |  |  |  |  |
| Colorado | Colorado | District of Columbia | **Kansas** | Nebraska | New Mexico |  |  |  |  |  |  |
|  | 1.00 | 0.54 | 0.57 | 0.60 | 0.51 |  |  |  |  |  |  |
| Connecticut | Connecticut | Illinois | **Kansas** | Kentucky | Massachusetts | North Dacota | New Mexico | Nevada | Rhode Island | Vermont | Washington |
|  | 1.00 | 0.60 | 0.55 | 0.53 | 0.60 | 0.58 | 0.85 | 0.56 | 0.54 | 0.50 | 0.59 |
| District of Columbia | District of Columbia | Hawaii | Idaho | Nevada |  |  |  |  |  |  |  |
|  | 1.00 | 0.50 | 0.51 | 0.51 |  |  |  |  |  |  |  |
| Delaware | Arkansas | Colorado | Delaware | **North Carolina** | North Dacota | **New York** |  |  |  |  |  |
|  | 0.52 | 0.53 | 1.00 | 0.59 | 0.50 | 0.66 |  |  |  |  |  |
| Florida | Alabama | Florida | Iowa | **Louisiana** | Maine | **Missouri** | **New Hampshire** | **Ohio** | South Dakota |  |  |
|  | 0.57 | 0.81 | 0.52 | 0.54 | 0.76 | 0.52 | 0.57 | 0.79 | 0.52 |  |  |
| Response States\_ t | Explanatory States\_ t-1 |
| Georgia | **California** | District of Columbia | Georgia | **Missouri** | **New Hampshire** | **Ohio** | Washington |  |  |  |  |
|  | 0.50 | 0.59 | 0.98 | 0.94 | 0.50 | 0.60 | 0.96 |  |  |  |  |
| Hawaii | Colorado | District of Columbia | Hawaii | **Idaho** | **New Hampshire** | **Ohio** |  |  |  |  |  |
|  | 0.50 | 0.56 | 1.00 | 0.78 | 0.56 | 0.51 |  |  |  |  |  |
| Iowa | **Iowa** | **Idaho** | Illinois | Michigan | New Mexico | Utah |  |  |  |  |  |
|  | 0.99 | 0.62 | 0.64 | 0.55 | 0.56 | 0.56 |  |  |  |  |  |
| Idaho | **Idaho** | Illinois | **Louisiana** |  |  |  |  |  |  |  |  |
|  | 1.00 | 0.55 | 0.79 |  |  |  |  |  |  |  |  |
| Illinois | Connecticut | **Idaho** | Illinois | Mississippi | Nevada | **New York** | Virginia |  |  |  |  |
|  | 0.55 | 0.53 | 1.00 | 0.55 | 0.63 | 0.89 | 0.51 |  |  |  |  |
| Indiana | **Iowa** | Illinois | Indiana | **Kansas** | **New Hampshire** | Utah |  |  |  |  |  |
|  | 0.82 | 0.53 | 1.00 | 0.50 | 0.51 | 0.53 |  |  |  |  |  |
| Kansas | **Iowa** | **Kansas** | Montana | **New York** | Oregon |  |  |  |  |  |  |
|  | 0.69 | 1.00 | 0.50 | 0.51 | 0.68 |  |  |  |  |  |  |
| Kentucky | Alabama | Kentucky | Maine | **North Carolina** | New Jersey | **New York** | **Ohio** | Wisconsin |  |  |  |
|  | 0.51 | 0.96 | 0.60 | 0.51 | 0.51 | 0.63 | 0.60 | 0.60 |  |  |  |
| Louisiana | **Idaho** | **Louisiana** | Maine | North Carolina | Rhode Island |  |  |  |  |  |  |
|  | 0.82 | 1.00 | 0.63 | 0.59 | 0.68 |  |  |  |  |  |  |
| Massachusetts | Alaska | Connecticut | Massachusetts | Maine | **North Carolina** | **Ohio** | Rhode Island | Virginia | Wisconsin |  |  |
|  | 0.55 | 0.59 | 1.00 | 0.64 | 0.53 | 0.51 | 0.52 | 0.59 | 0.83 |  |  |
| Maryland | **California** | **Idaho** | **Louisiana** | Maryland | **New Hampshire** | New Mexico | Washington | Wisconsin |  |  |  |
|  | 0.53 | 0.55 | 0.83 | 0.99 | 0.54 | 0.50 | 0.60 | 0.59 |  |  |  |
| Maine | **Idaho** | **Louisiana** | Maine | **North Carolina** | North Dacota | Rhode Island |  |  |  |  |  |
|  | 0.57 | 0.78 | 1.00 | 0.85 | 0.52 | 0.55 |  |  |  |  |  |
| Response States\_ t | Explanatory States\_ t-1 |
| Michigan | District of Columbia | **Kansas** | Michigan | Mississippi | **North Carolina** | **New York** | Rhode Island |  |  |  |  |
|  | 0.54 | 0.55 | 1.00 | 0.52 | 0.62 | 0.54 | 0.56 |  |  |  |  |
| Minnesota | **California** | **Idaho** | Illinois | **Louisiana** | Minnesota | **New Hampshire** | New Jersey |  |  |  |  |
|  | 0.60 | 0.51 | 0.65 | 0.63 | 1.00 | 0.63 | 0.57 |  |  |  |  |
| Missouri | **Iowa** | **Missouri** |  |  |  |  |  |  |  |  |  |
|  | 0.54 | 1.00 |  |  |  |  |  |  |  |  |  |
| Mississippi | District of Columbia | Illinois | Mississippi | Nebraska | Nevada |  |  |  |  |  |  |
|  | 0.78 | 0.88 | 0.84 | 0.67 | 0.52 |  |  |  |  |  |  |
| Montana | **Idaho** | **Kansas** | Montana | **New York** | Oklahoma |  |  |  |  |  |  |
|  | 0.55 | 0.53 | 1.00 | 0.88 | 0.50 |  |  |  |  |  |  |
| North Carolina | **Arizona** | **Louisiana** | Maine | **Missouri** | **North Carolina** | Rhode Island | South Dakota |  |  |  |  |
|  | 0.54 | 0.50 | 0.71 | 0.50 | 1.00 | 0.80 | 0.69 |  |  |  |  |
| North Dacota | **Arizona** | Delaware | **Iowa** | **Missouri** | **North Carolina** | North Dacota | **Ohio** | South Dakota |  |  |  |
|  | 0.53 | 0.69 | 0.50 | 0.60 | 0.69 | 0.99 | 0.54 | 0.54 |  |  |  |
| Nebraska | Alabama | Nebraska | **New Hampshire** | Oregon |  |  |  |  |  |  |  |
|  | 0.59 | 1.00 | 0.70 | 0.52 |  |  |  |  |  |  |  |
| New Hampshire | **New Hampshire** | **Ohio** | Oklahoma |  |  |  |  |  |  |  |  |
|  | 1.00 | 0.52 | 0.52 |  |  |  |  |  |  |  |  |
| New Jersey | Illinois | New Jersey | **New York** | Washington |  |  |  |  |  |  |  |
|  | 0.56 | 1.00 | 0.56 | 0.50 |  |  |  |  |  |  |  |
| New Mexico | Connecticut | **Kansas** | New Mexico | **New York** | Rhode Island | South Carolina | Washington |  |  |  |  |
|  | 0.52 | 0.87 | 1.00 | 0.51 | 0.50 | 0.52 | 0.53 |  |  |  |  |
| Nevada | Alabama | **Arizona** | Mississippi | **North Carolina** | **New Hampshire** | Nevada | Utah | Washington |  |  |  |
|  | 0.53 | 0.56 | 0.50 | 0.56 | 0.59 | 0.99 | 0.54 | 0.92 |  |  |  |
| Response States\_ t | Explanatory States\_ t-1 |
| New York | **Kansas** | **Missouri** | **New York** | West Virginia |  |  |  |  |  |  |  |
|  | 0.64 | 0.50 | 1.00 | 0.53 |  |  |  |  |  |  |  |
| Ohio | **California** | District of Columbia | **Idaho** | **Kansas** | **Louisiana** | **New Hampshire** | **Ohio** | Utah |  |  |  |
|  | 0.54 | 0.52 | 0.51 | 0.53 | 0.63 | 0.57 | 1.00 | 0.50 |  |  |  |
| Oklahoma | **California** | **Iowa** | Montana | **New** York | Oklahoma |  |  |  |  |  |  |
|  | 0.56 | 0.51 | 0.59 | 0.81 | 1.00 |  |  |  |  |  |  |
| Oregon | Hawaii | **Iowa** | **Idaho** | **Kansas** | Massachusetts | **New Hampshire** | Oregon |  |  |  |  |
|  | 0.53 | 0.77 | 0.55 | 0.70 | 0.52 | 0.52 | 1.00 |  |  |  |  |
| Pennsylvania | Alaska | **Arizona** | **California** | Connecticut | **Kansas** | **Ohio** | Pennsylvania | South Dakota | West Virginia |  |  |
|  | 0.55 | 0.52 | 0.60 | 0.51 | 0.72 | 0.53 | 0.94 | 0.60 | 0.85 |  |  |
| Rhode Island | **Kansas** | Maine | **Missouri** | **North Carolina** | Oklahoma | Rhode Island |  |  |  |  |  |
|  | 0.67 | 0.52 | 0.70 | 0.91 | 0.54 | 1.00 |  |  |  |  |  |
| South Carolina | **Arizona** | **California** | **Idaho** | **Louisiana** | **New Hampshire** | South Carolina | Utah |  |  |  |  |
|  | 0.57 | 0.57 | 0.50 | 0.50 | 0.51 | 0.92 | 0.59 |  |  |  |  |
| South Dakota | District of Columbia | Georgia | **Kansas** | **Missouri** | **North Carolina** | **Ohio** | South Dakota | Tennessee | Washington |  |  |
|  | 0.57 | 0.57 | 0.51 | 0.63 | 0.62 | 0.55 | 0.90 | 0.52 | 0.70 |  |  |
| Tennessee | **Arizona** | **Iowa** | Mississippi | **New Hampshire** | New Jersey |  |  |  |  |  |  |
|  | 0.51 | 0.61 | 0.53 | 0.59 | 0.51 |  |  |  |  |  |  |
| Texas | Alabama | **Kansas** | Texas |  |  |  |  |  |  |  |  |
|  | 0.50 | 0.75 | 0.99 |  |  |  |  |  |  |  |  |
| Utah | **Iowa** | New Mexico | Utah |  |  |  |  |  |  |  |  |
|  | 0.88 | 0.67 | 1.00 |  |  |  |  |  |  |  |  |
| Virginia | **Louisiana** | Massachusetts | Maine | Oklahoma | South Carolina | Utah | Virginia |  |  |  |  |
|  | 0.52 | 0.80 | 0.69 | 0.50 | 0.56 | 0.54 | 1.00 |  |  |  |  |
| Response States\_ t | Explanatory States\_ t-1 |
| Vermont | **California** | **Iowa** | Illinois | Mississippi | **New Hampshire** | Oregon | Vermont |  |  |  |  |
|  | 0.64 | 0.67 | 0.50 | 0.59 | 0.66 | 0.57 | 0.81 |  |  |  |  |
| Washington | Maryland | Nevada | Washington |  |  |  |  |  |  |  |  |
|  | 0.50 | 0.89 | 1.00 |  |  |  |  |  |  |  |  |
| Wisconsin | Alaska | Alabama | Kentucky | Oklahoma | South Dakota | Wisconsin |  |  |  |  |  |
|  | 0.63 | 0.63 | 0.59 | 0.51 | 0.50 | 1.00 |  |  |  |  |  |
| West Virginia | Alaska | **Kansas** | **New York** | **Ohio** | Pennsylvania | South Dakota | West Virginia |  |  |  |  |
|  | 0.61 | 0.56 | 0.56 | 0.51 | 0.55 | 0.57 | 0.99 |  |  |  |  |

This table summarises results of the selected edges for the MAR structure based on posterior probabilities greater than 0.5. The states highlighted indicate strong evidence of directed edges originating from explanatory to response states. There are at least nine cases that explanatory states have strong evidence of directed edges to response states.

Table 2 Results of the MIN structure at the h1 horizon

|  |  |
| --- | --- |
| Response States\_ t | Explanatory States\_ t |
|  |
| Alaska | Null |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Alabama | Kentucky | Maine | **Montana** |  |  |  |  |  |  |
|  | 0.90 | 0.77 | 0.58 |  |  |  |  |  |  |
| Arkansas | **Maryland** | **Vermont** |  |  |  |  |  |  |  |
|  | 0.52 | 0.50 |  |  |  |  |  |  |  |
| Arizona | **Alaska** | Colorado | Kentucky | Mississippi | **North Carolina** | **Nevada** | South Carolina | **Vermont** |  |
|  | 0.53 | 0.51 | 0.55 | 0.66 | 0.97 | 0.80 | 0.50 | 0.56 |  |
| California | **Alaska** | **Massachusetts** | **Maryland** | Minnesota | **North Carolina** |  |  |  |  |
|  | 0.99 | 0.56 | 0.86 | 0.65 | 0.50 |  |  |  |  |
| Colorado | Arkansas | **Kansas** | Maine | Minnesota | **Nevada** | Tennessee | **Texas** |  |  |
|  | 0.61 | 0.63 | 0.58 | 0.71 | 0.53 | 0.57 | 0.89 |  |  |
| Connecticut | **Idaho** | Illinois | **Massachusetts** | **North Carolina** | New Mexico |  |  |  |
|  | 0.60 | 0.76 | 0.96 | 0.67 | 0.75 |  |  |  |  |
| District of Columbia | Colorado | Mississippi | **Nevada** | Ohio |  |  |  |  |  |
|  | 0.58 | 0.72 | 0.92 | 0.53 |  |  |  |  |  |
| Delaware | Arkansas | Colorado | Indiana | **Kansas** | Michigan | New Mexico | New York | Rhode Island | Wisconsin |
|  | 0.75 | 0.58 | 0.80 | 0.56 | 0.50 | 0.58 | 0.53 | 0.68 | 0.63 |
| Florida | **Alaska** | Alabama | Indiana | Kentucky | Maine | **Nevada** | Ohio | West Virginia |
|  | 0.87 | 0.58 | 0.63 | 0.55 | 0.82 | 0.54 | 0.57 | 0.58 |  |
| Georgia | **Nevada** | **Texas** | **Vermont** | Washington |  |  |  |  |
|  | 0.79 | 0.51 | 0.91 | 0.51 |  |  |  |  |  |
| Hawaii | Colorado | **Idaho** | **Maryland** | **North Carolina** | Ohio | **Vermont** |  |  |  |
|  | 1.00 | 0.94 | 0.55 | 0.55 | 0.77 | 0.56 |  |  |  |
| Response States\_ t | Explanatory States\_ t |
| Iowa | **Idaho** | Illinois | Indiana | **Kansas** | Minnesota | Mississippi | **Montana** | **Vermont** |  |
|  | 0.62 | 0.65 | 0.58 | 0.73 | 0.57 | 0.54 | 0.64 | 0.67 |  |
| Idaho | **Massachusetts** | **Maryland** | **Montana** |  |  |  |  |  |  |
|  | 0.51 | 0.58 | 0.73 |  |  |  |  |  |  |
| Illinois | **Maryland** | **Montana** |  |  |  |  |  |  |  |
|  | 0.52 | 0.60 |  |  |  |  |  |  |  |
| Indiana | **Idaho** | Illinois | **Kansas** | **Massachusetts** | **North Carolina** | Tennessee | **Texas** | **Vermont** |  |
|  | 0.52 | 0.54 | 0.87 | 0.66 | 0.65 | 0.60 | 0.68 | 0.55 |  |
| Kansas | **Montana** | **Texas** |  |  |  |  |  |  |  |
|  | 0.62 | 0.61 |  |  |  |  |  |  |  |
| Kentucky | Alaska |  |  |  |  |  |  |  |  |
|  | 0.66 |  |  |  |  |  |  |  |  |
| Louisiana | Connecticut | **Idaho** | **Maryland** | Maine | Rhode Island | Washington |  |  |
|  | 0.70 | 0.97 | 0.76 | 0.74 | 0.58 | 0.51 |  |  |  |
| Massachusetts | Null |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| Maryland | **Massachusetts** |  |  |  |  |  |  |  |  |
|  | 0.55 |  |  |  |  |  |  |  |  |
| Maine | **Alaska** | **Idaho** | Kentucky | **Massachusetts** | **Texas** |  |  |  |  |
|  | 0.75 | 0.73 | 0.74 | 0.80 | 0.50 |  |  |  |  |
| Michigan | **Idaho** | **Massachusetts** | Mississippi | **Montana** | New Mexico | **Texas** |  |  |  |
|  | 0.58 | 1.00 | 0.58 | 0.73 | 0.81 | 0.77 |  |  |  |
| Minnesota | **Idaho** | **Maryland** |  |  |  |  |  |  |  |
|  | 0.55 | 0.57 |  |  |  |  |  |  |  |
| Missouri | Alabama | Georgia | Iowa | Louisiana | Mississippi | New Mexico | **Vermont** | Washington |
|  | 0.69 | 0.54 | 0.54 | 0.74 | 0.85 | 0.94 | 0.51 | 0.70 |  |
| Mississippi | Illinois | **Massachusetts** | **Maryland** | **Vermont** |  |  |  |  |  |
|  | 0.70 | 0.77 | 0.79 | 0.74 |  |  |  |  |  |
| Response States\_ t | Explanatory States\_ t |
| Montana | Null |  |  |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |
| North Carolina | **Alaska** | Kentucky | **Massachusetts** | Maine | **Montana** |  |  |  |  |
|  | 0.60 | 0.53 | 0.86 | 0.53 | 0.90 |  |  |  |  |
| North Dacota | **Alaska** | Connecticut | **Idaho** | Kentucky | Maine | **North Carolina** |  |  |  |
|  | 0.60 | 0.60 | 0.52 | 0.53 | 0.63 | 0.62 |  |  |  |
| Nebraska | **Alaska** | Alabama | **Kansas** | Mississippi | **North Carolina** | **Vermont** |  |  |  |
|  | 0.53 | 0.71 | 0.60 | 0.79 | 0.74 | 0.62 |  |  |  |
| New Hampshire | Colorado | Indiana | **Kansas** | **Massachusetts** | **Maryland** | Minnesota | **Montana** | Nebraska |
|  | 0.68 | 0.59 | 0.89 | 0.61 | 0.86 | 0.77 | 0.71 | 0.56 |  |
| New Jersey | Arkansas | Colorado | Illinois | Indiana | Minnesota | **Nevada** | Tennessee |  |
|  | 0.70 | 0.81 | 0.80 | 0.51 | 0.93 | 0.63 | 0.76 |  |  |
| New Mexico | **Alaska** | **Kansas** | **Massachusetts** | **Maryland** |  |  |  |  |  |
|  | 0.75 | 0.63 | 0.94 | 0.69 |  |  |  |  |  |
| Nevada | **Alaska** | Illinois | Kentucky | Mississippi | Tennessee |  |  |  |
|  | 0.53 | 0.62 | 0.57 | 0.50 | 0.51 |  |  |  |  |
| New York | **Alaska** | Alabama | Illinois | Kentucky | **Montana** | **Nevada** | West Virginia |  |
|  | 0.55 | 0.63 | 0.65 | 0.54 | 0.92 | 0.50 | 0.85 |  |  |
| Ohio | **Idaho** | **Kansas** | Kentucky | **Montana** | Texas |  |  |  |  |
|  | 0.82 | 0.73 | 0.64 | 0.54 | 0.80 |  |  |  |  |
| Oklahoma | California | **Kansas** | Kentucky | Minnesota | **Montana** | Tennessee | **Texas** | **Vermont** | Wisconsin |
|  | 0.50 | 0.50 | 0.63 | 0.54 | 0.95 | 0.55 | 0.68 | 0.55 | 0.60 |
| Oregon | Connecticut | Iowa | **Idaho** | **Kansas** | **Massachusetts** | **North Carolina** | **Vermont** |  |  |
|  | 0.71 | 0.58 | 0.52 | 0.95 | 0.67 | 0.54 | 0.78 |  |  |
| Pennsylvania | **Alaska** | Kentucky | **Massachusetts** | **Montana** | **Texas** |  |  |  |  |
|  | 1.00 | 0.55 | 0.83 | 0.58 | 0.64 |  |  |  |  |
| Rhode Island | Connecticut | **Massachusetts** | **Maryland** | Maine | **North** **Carolina** | New Mexico | **Nevada** |  |  |
|  | 0.57 | 0.68 | 0.69 | 0.51 | 0.85 | 0.65 | 0.50 |  |  |
| Response States\_ t | Explanatory States\_ t |
| South Carolina | Arkansas | **Idaho** | **Kansas** | **Massachusetts** | **Maryland** | Minnesota | **Texas** | **Vermont** |  |
|  | 0.73 | 0.53 | 0.53 | 0.59 | 0.72 | 0.62 | 0.73 | 0.60 |  |
| South Dakota | Colorado | Kentucky | Montana | North Carolina | Nevada | Washington | West Virginia |  |
|  | 0.56 | 0.61 | 0.83 | 0.56 | 0.54 | 0.62 | 0.66 |  |  |
| Tennessee | **Montana** | **Texas** |  |  |  |  |  |  |  |
|  | 0.53 | 0.73 |  |  |  |  |  |  |  |
| Texas | Vermont |  |  |  |  |  |  |  |  |
|  | 0.59 |  |  |  |  |  |  |  |  |
| Utah | Alaska | Arkansas | Iowa | Indiana | **Kansas** | Kentucky | **Montana** | New Mexico | **Nevada** |
|  | 0.51 | 0.50 | 0.50 | 0.50 | 0.68 | 0.53 | 0.54 | 0.57 | 0.83 |
| Virginia | Connecticut | **Massachusetts** | **Maryland** | Maine | New Mexico | **Vermont** |  |  |  |
|  | 0.80 | 1.00 | 0.73 | 0.80 | 0.51 | 0.51 |  |  |  |
| Vermont | **Kansas** | **Maryland** | Minnesota | Tennessee |  |  |  |  |
|  | 0.50 | 0.57 | 0.54 | 0.55 |  |  |  |  |  |
| Washington | **Massachusetts** | **Maryland** | **North Carolina** | **Nevada** |  |  |  |  |  |
|  | 0.60 | 0.63 | 0.74 | 0.83 |  |  |  |  |  |
| Wisconsin | **Alaska** | Alabama | Kentucky | **Massachusetts** | **Maryland** |  |  |  |  |
|  | 0.70 | 0.77 | 0.99 | 0.61 | 0.58 |  |  |  |  |
| West Virginia | **Alaska** | Kentucky | **Montana** | Ohio | Pennsylvania |  |  |  |
|  | 0.99 | 0.87 | 0.50 | 0.52 | 0.56 |  |  |  |  |

Bold entries represent the selected edges for the MAR structure based on posterior probabilities greater than 0.5. The states highlighted indicate strong evidence of directed edges originating from explanatory to response states. There are at least nine cases that explanatory states have strong evidence of directed edges to response states.

Table 3 Number of cases that US states are the origination of directed edges (the MAR structure)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Explanatory States | # of being the origination with p>0.5, h=1 | # of being the origination with p>0.5, h=2 | # of being the origination with p>0.5, h=3 | # of being the origination with p>0.5, h=4 |
| Alaska | 5 | 8 | 2 | 1 |
| Alabama | 8 | 4 | 9 | 9 |
| Arkansas | 2 | 3 | 6 | 8 |
| Arizona | 9 | 2 | 2 | 2 |
| California | 9 | 15 | 16 | 16 |
| Colorado | 4 | 8 | 2 | 3 |
| Connecticut | 5 | 4 | 6 | 4 |
| District of Columbia | 8 | 13 | 13 | 13 |
| Delaware | 2 | 9 | 11 | 13 |
| Florida | 1 | 5 | 6 | 7 |
| Georgia | 2 | 5 | 3 | 1 |
| Hawaii | 3 | 5 | 8 | 11 |
| Iowa | 11 | 9 | 14 | 13 |
| Idaho | 13 | 4 | 2 | 5 |
| Illinois | 9 | 7 | 6 | 3 |
| Indiana | 1 | 6 | 4 | 8 |
| Kansas | 15 | 19 | 21 | 28 |
| Kentucky | 3 | 2 | 2 | 3 |
| Louisiana | 10 | 14 | 14 | 11 |
| Massachusetts | 5 | 6 | 1 | 1 |
| Maryland | 2 | 2 | 1 | 6 |
| Maine | 8 | 2 | 3 | 1 |
| Michigan | 2 | 11 | 17 | 14 |
| Minnesota | 1 | 1 | 2 | 1 |
| Missouri | 9 | 15 | 16 | 14 |
| Mississippi | 6 | 2 | 3 | 3 |
| Montana | 3 | 3 | 7 | 4 |
| North Carolina | 13 | 12 | 4 | 3 |
| North Dacota | 4 | 9 | 8 | 7 |
| Nebraska | 4 | 3 | 3 | 3 |
| New Hampshire | 15 | 10 | 12 | 14 |
| New Jersey | 4 | 3 | 1 | 2 |
| New Mexico | 6 | 3 | 3 | 2 |
| Nevada | 6 | 2 | 0 | 0 |
| New York | 11 | 7 | 10 | 9 |
| Ohio | 12 | 3 | 1 | 3 |
| Oklahoma | 6 | 5 | 3 | 2 |
| Oregon | 4 | 7 | 12 | 4 |
| Pennsylvania | 3 | 2 | 1 | 1 |
| Rhode Island | 8 | 5 | 1 | 0 |
| South Carolina | 4 | 4 | 3 | 3 |
| South Dakota | 9 | 0 | 0 | 3 |
| Tennessee | 1 | 1 | 1 | 1 |
| Explanatory States | # of being the origination with p>0.5, h=1 | # of being the origination with p>0.5, h=2 | # of being the origination with p>0.5, h=3 | # of being the origination with p>0.5, h=4 |
| Texas | 1 | 2 | 3 | 3 |
| Utah | 7 | 3 | 4 | 4 |
| Virginia | 3 | 1 | 2 | 4 |
| Vermont | 2 | 1 | 1 | 1 |
| Washington | 8 | 3 | 1 | 1 |
| Wisconsin | 4 | 7 | 8 | 8 |
| West Virginia | 4 | 4 | 2 | 2 |

Table 4 Number of cases that US states are the origination of directed edges (the MIN structure)

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Explanatory States | # of being the origination with p>0.5, h=1 | # of being the origination with p>0.5, h=2 | # of being the origination with p>0.5, h=3 | # of being the origination with p>0.5, h=4 |
| Alaska | 15 | 1 | 17 | 0 |
| Alabama | 5 | 2 | 0 | 2 |
| Arkansas | 5 | 0 | 0 | 0 |
| Arizona | 0 | 0 | 0 | 0 |
| California | 1 | 0 | 0 | 3 |
| Colorado | 7 | 3 | 2 | 2 |
| Connecticut | 5 | 3 | 0 | 0 |
| District of Columbia | 0 | 0 | 4 | 1 |
| Delaware | 0 | 1 | 4 | 0 |
| Florida | 0 | 3 | 3 | 6 |
| Georgia | 1 | 1 | 2 | 7 |
| Hawaii | 0 | 3 | 10 | 5 |
| Iowa | 3 | 1 | 3 | 1 |
| Idaho | 12 | 0 | 1 | 17 |
| Illinois | 7 | 4 | 0 | 12 |
| Indiana | 6 | 0 | 0 | 3 |
| Kansas | 13 | 12 | 9 | 5 |
| Kentucky | 15 | 1 | 0 | 0 |
| Louisiana | 1 | 5 | 3 | 6 |
| Massachusetts | 18 | 3 | 9 | 1 |
| Maryland | 16 | 0 | 0 | 3 |
| Maine | 8 | 17 | 14 | 13 |
| Michigan | 1 | 4 | 1 | 0 |
| Minnesota | 8 | 15 | 0 | 0 |
| Missouri | 0 | 0 | 6 | 8 |
| Mississippi | 7 | 18 | 0 | 0 |
| Montana | 16 | 22 | 8 | 3 |
| North Carolina | 11 | 11 | 0 | 0 |
| North Dacota | 0 | 0 | 2 | 1 |
| Nebraska | 1 | 0 | 6 | 3 |
| New Hampshire | 0 | 17 | 15 | 9 |
| New Jersey | 0 | 6 | 6 | 0 |
| New Mexico | 7 | 0 | 4 | 0 |
| Nevada | 11 | 15 | 8 | 1 |
| New York | 1 | 1 | 3 | 5 |
| Ohio | 4 | 2 | 15 | 20 |
| Oklahoma | 0 | 3 | 1 | 0 |
| Oregon | 0 | 1 | 2 | 0 |
| Pennsylvania | 1 | 8 | 8 | 8 |
| Rhode Island | 2 | 8 | 0 | 0 |
| South Carolina | 1 | 0 | 0 | 15 |
| South Dakota | 0 | 24 | 17 | 15 |
| Tennessee | 6 | 0 | 25 | 4 |
| Explanatory States | # of being the origination with p>0.5, h=1 | # of being the origination with p>0.5, h=2 | # of being the origination with p>0.5, h=3 | # of being the origination with p>0.5, h=4 |
| Texas | 11 | 2 | 2 | 5 |
| Utah | 0 | 1 | 0 | 3 |
| Virginia | 0 | 2 | 0 | 0 |
| Vermont | 14 | 0 | 0 | 0 |
| Washington | 4 | 8 | 5 | 0 |
| Wisconsin | 2 | 5 | 4 | 8 |
| West Virginia | 3 | 0 | 0 | 0 |

1. # We would like to thank four anonymous referee for many helpful comments. However, any remaining errors are solely ours. [↑](#footnote-ref-1)
2. \* Corresponding author. [↑](#footnote-ref-2)
3. Klößner and Sekkel (2014) and Balli et al. (2017) provide some economic explanations about the transmission channels through which uncertainty spillovers take place from the perspectives of the trade and financial linkages and the negative impact of economic policy uncertainty on macroeconomic fundamentals. For example, the effect of increasing policy uncertainty in one economy may affect economic fundamentals (such as capital flows, bond risk premia, etc.) of other economies, with the potential effect of rising economic policy uncertainty in these economies. Baker, Bloom and Davis (2016) find evidence of adverse effects of economic policy uncertainty on investment and employment on the firm and macroeconomic levels. Bernal et al. (2016) and Bai, Zhang, Liu, Wang (2019) find empirical evidence that uncertainty leads to high degrees of risk spillovers and negatively affects real economy activities and financial markets in other economies. [↑](#footnote-ref-3)
4. Existing studies (e.g., Zhang, Lei, Ji, and Kutan, 2019; Gabauer and Gupta, 2018; among others) mainly use news-based measures of economic policy uncertainty (EPU) to quantify measures of uncertainty. This paper uses the uncertainty measure of Jurado et al. (2015) to reflect the comprehensive uncertainty of macroeconomic fundamentals of state economies. [↑](#footnote-ref-4)
5. This is an appealing feature of the model employed in this paper due to the lack of underlying economic theory for the emerging macroeconomic uncertainty interconnectedness literature. A number of studies (e.g., Ji, Bouri, Roubaud, and Kristoufek, 2019; Ji, Bouri, Lau, and Roubaud, 2019; Luo and Ji, 2018; Zhang, Lei, Ji, and Kutan, 2019; among others) employ the total spillover index of Diebold and Yılmaz (2014) to measure interconnectedness. However, as pointed out by Antonakakis, Gabauer, Gupta, and Plakandaras (2018), the methodology arbitrarily sets the rolling window-size and there is a loss of observations/information in the process [↑](#footnote-ref-5)
6. Ahelegbey et al. (2016) show that one of the appealing features of the BGVAR model is the possibility of giving a graphical representation of the logical impactions of models. A directed acyclic graph (DAG) (i.e., the edges of DAG are directed and connected without circles so that these edges can only flow forward and the graph is not cyclic) is used in this approach to represent an unambiguous direction of causal relationship between variables. For example, the relationship A⟶B means that the variable A causes the variable B. The node A (ancestor) from which a directed edge originates is the explanatory variable, and the node B (descendant) to which the directed edge ends is the response variable. If A⟶B⟶C, A and C would be probabilistically dependent in the absence of B. The edge probabilities (i.e., the posterior probabilities of the presence of edges) are produced by the model under the MAR structure (i.e., the multivariate autoregression structure, which captures the dynamic causal relationship between variables and detects edges that are persistent over time) and the MIN structure (i.e., multivariate instantaneous structure, which presents the contemporaneous dependence among variables). [↑](#footnote-ref-6)
7. Ahelegbey et al. (2016) suggest that the BGVAR model offers a more accurate representation of the linkages among variables than the Granger causality approach. The traditional pairwise Granger causality test (P-GC) only deals with bivariate time series and does not consider the conditioning on relevant covariates, and the modified conditional Granger causality test (C-PC) has a problem of over-parametrisation which leads to inefficiency in accurately gauging the causal relationships. [↑](#footnote-ref-7)
8. See online technical appendix of Mumtaz (2018) for details of the uncertainty construction procedures. [↑](#footnote-ref-8)
9. See Dagum et al. (1992) for details of the Dynamic Bayesian Network technique. [↑](#footnote-ref-9)
10. See Ahelegbey et al. (2016) for details of the statistical inference and estimation procedures. The optimal lag order is set to 1 based on the Bayesian Information Criterion (BIC), and 50,000 draws are used. [↑](#footnote-ref-10)
11. The results of edge probabilities for 50 US states of both MAR and MIN structures (for h =2, 3, 4) are available upon request. [↑](#footnote-ref-11)
12. These states are highlighted in bold in the tables. [↑](#footnote-ref-12)