Graph Theory-Based Network Analysis of Regional Uncertainties of the US Economy[#]

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Highlights

- The dependence of macroeconomic uncertainty across US states was examined.
- The Bayesian graphical VAR (BGVAR) model was used to study uncertainty spillovers.
- Evidence of strong contemporaneous and lagged dependence among US states was found.

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.

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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).[1] 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;

[1]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.

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.[2] 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

[2] 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.

allows for the investigation of causal relationships between variables without the restriction of economic models.[3] Moreover, it provides a framework to represent and estimate an unambiguous direction of causations by means of the directed edges.[4] 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.[5]

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.

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[3] 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

[4] 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).

[5] 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.

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).[6]

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).[7]

$$Y_t = B_0 Y_t + \sum_{i=1}^{p} B_i Y_{t-i} + \varepsilon_t \tag{1}$$

where Y_t is a vector of response variables. p is the lag order. $\varepsilon_t \sim N\ (0, I_p)$. B_0 is a $(n_y \times n_y)$ 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:

[6] See online technical appendix of Mumtaz (2018) for details of the uncertainty construction procedures.

[7] See Dagum et al. (1992) for details of the Dynamic Bayesian Network technique.

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + u_t \tag{2}$$

where $A_i = A_0^{-1} B_i^*$, $1 \leq i \leq p$. $A_0 = (I - B_0)$. $u_t = A_0^{-1} \varepsilon_t$.

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:

$$X_{t-s}^{j} \longrightarrow X_t^{i} \Leftrightarrow B_{s,ij}^{*} \neq 0, \quad 0 \leq s \leq p \tag{3}$$

where X_t^i represents the realisation value of the *i*-th variable at time t. The relationship $X_{t-s}^{j} \longrightarrow X_t^i$ 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 $B_s^* = (G_s \circ \Phi_s)$, $\quad 0 \leq s \leq p$ (4)

where G_s is a binary connectivity matrix that indicates dependence, and Φ_s is a coefficient matrix. The operator $\circ$ is the Hadamard product. G_0 represents the connectivity matrix of contemporaneous dependence. G_s ($1 \leq s \leq p$) 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.

$$B^*_{s,ij} = \begin{pmatrix} \phi_{s,ij} & \text{if } B^*_{s,ij} = 1 \\ 0 & \text{if } B^*_{s,ij} = 0 \end{pmatrix} \tag{5}$$

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

$$Y_t = (G_0 \circ \Phi_0) Y_t + \sum_{i=1}^{p} (G_i \circ \Phi_i)\, Y_{t-i} + \varepsilon_t \tag{6}$$

where $(G_i \circ \Phi_i)$ 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, $\{B^*_0, B^*_1, \ldots, B^*_p, \sum_\varepsilon\}$, and the inference of causal structure $G = (G_0, G_1, \ldots, G_p)$.[8] The model produces the posterior probabilities of edges for both temporal and contemporaneous

[8] 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.

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).[9] 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.[10] For example, the lagged uncertainty level in California is more likely to explain current uncertainty in nine states, i.e., $\text{California}_{t-1} \rightarrow$ (California_t, Georgia_t, Maryland_t, Minnesota_t, Ohio_t, Oklahoma_t, Pennsylvania_t, South Carolina_t, and Vermont_t), 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., (California_{t-1} Arizona_{t-1}) $\rightarrow \text{California}_t$. 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

[9] The results of edge probabilities for 50 US states of both MAR and MIN structures (for h =2, 3, 4) are available upon request.

[10] These states are highlighted in bold in the tables.

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	Massachusett s	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	Washingto n

	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							

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		

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