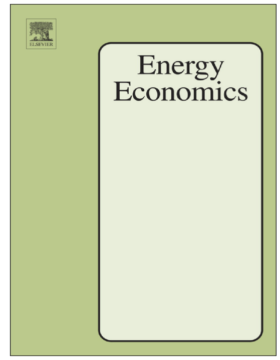
Ren, X., Lu, Z., Cheng, C., Shi, Y. and Shen, J. (2019) On dynamic linkages of the state natural gas markets in the USA: evidence from an empirical spatio-temporal network quantile analysis. *Energy Economics*, 80, pp. 234-252. (doi: 10.1016/j.eneco.2019.01.001)



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PII: S0140-9883(19)30007-6
DOI: https://doi.org/10.1016/j.eneco.2019.01.001
Reference: ENEECO 4273

To appear in: *Energy Economics*

Received date: 15 July 2018
Revised date: 26 December 2018
Accepted date: 1 January 2019

On dynamic linkages of the state natural gas markets in the USA: Evidence from an empirical spatio-temporal network quantile analysis

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Abstract

We empirically investigate the dynamic linkages of the state-level natural gas markets in the USA. By introducing a novel spatio-temporal network quantile econometric model, we can estimate the dynamic cross-state dependency or market integration of the state-level natural gas markets and the dependence of the state natural gas markets on the national crude oil market at different quantile levels. We find that significant local dynamic neighbouring market integrations exist in the natural gas markets not only in the eastern and central states as evidenced in the literature but also in some western and southwest states. Our results also show that there are significant linkages of the state-level natural gas markets to the national crude oil market through the lagged price shocks and the long-run price equilibrium with the national gas markets under varying price shock propagations. The results can help local government and energy users to mitigate the negative impacts from the expected or unexpected fluctuations in the oil and the neighbouring natural gas markets, which will enact appropriate state-level price discovery and energy policy and investment decision makings.

Keywords: Spatio-temporal model, natural gas markets, quantile regression, oil

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market, cross-market integration

JEL: C31 C33 Q41

1. Introduction

As an indicator of the market that is highly influenced by local policy and market competition, the extent of integration or segregation among different local energy markets has received increasing attention in the energy economics literature (c.f., Cuddington and Wang, 2006; Holmes et al., 2013; Apergis et al., 2015; Ghoddusi, 2016, and the references therein). In particular, for the natural gas markets in the USA, since the policy of deregulation in the natural gas industry, the integration or segregation of the markets has become of wide interest not only by academics but also for investment decision-making by enterprises and energy policy-making by governments (Park et al., 2008; Apergis et al., 2015). The natural gas industry was, in fact, historically one of the most highly regulated sectors in the economy of the USA. On one hand, the deregulation has segregated regional natural gas markets in some regions because of the significant differences in transportation, resource volumes and energy consumptions among different states (De Vany and Walls, 1993; Cuddington and Wang, 2006). On the other hand, a well-developed pipeline system for regional natural gas supplies and the "law of one price" among markets have contributed to the price interactions across different natural gas spot markets (c.f., Cuddington and Wang, 2006; Park et al., 2008). Therefore, how a regional natural gas market is either strongly or weakly correlated to the nearby natural gas markets is of fundamental interest. In this paper, our objective is to empirically investigate the dynamic integrations or linkages of the natural gas markets at the state level in the USA.

Credibly identifying and quantifying the dynamic linkages among the regional or state-level natural gas markets is a key issue for our objective. It however poses significant empirical challenges. In particular, in empirical analysis, some key characters of the regional natural gas markets, e.g., features of the underground pipeline network, may not all be available to be considered, and empirical challenges hence arise as these unconsidered features are likely to be spatially correlated (c.f., Cuddington and Wang, 2006; Park et al., 2008; Arano and Velikova, 2009). Vector time series analysis and the pair-wise approach have often been adopted in analysing the integrations of regional energy markets in the literature (c.f., De Vany and Walls, 1993; Pesaran, 2007; Holmes et al., 2013). For example, De Vany and Walls (1993) used cointegration method to investigate the integrations by considering one hundred and ninety market pairs among twenty spatially separated natural gas markets in the U.S.. Park et al. (2008) considered the relationships in mean among a relatively small number of eight North American natural gas spot markets by combining the advances in causal flow analysis with vector time series analysis. Holmes et al. (2013) applied the pair-wise approach to analyse the spatial market integrations in the US regional gasoline markets. Note, however, that although these methods are helpful in studying the pair-wise linkages, they also suffer from some drawbacks. For instance, the vector time series analysis may lead to over-parametrisation when considering the natural gas markets at the state level in the USA, where we are considering the 48 main states, excluding the isolated Hawaii and Alaska and the small District of Columbia, in this paper. This makes it difficult for the vector time series approach to be implemented for analysis. Also, like the cointegration method used in De Vany and Walls (1993), the pair-wise approach only considers the spatial dependence between the regional markets in pairs, ignoring the impacts from other (nearby) states, which can not be used to credibly identify and quantify the dynamic linkages of the state-level natural gas markets from a holistic perspective. Moreover, these analyses are based on the relationship in mean or average by applying the usual mean regression analysis, which cannot characterise the relationship in the tail of the price or return distribution that is important in risk analysis.

Differently from the existing literature, in this paper, we will empirically investigate the dynamic linkages of the USA's natural gas markets at the state level in a more holistic manner by proposing a spatio-temporal network quantile analysis. A significant advantage associated with the method lies in that it combines dynamic spatial (cross-sectional) linkage analysis with quantile regression to model the price shock propagation and cross-market dependency of the natural gas markets not only for the normal market situations (e.g., at a median level) but also for the extreme market scenarios (e.g., at a low or high quantile level). First, the novel spatial weight matrix model structure (Anselin, 1988) used in our analysis will allow us to avoid the over-parametrisation issue and overcome the drawback of the pair-wise analysis in estimating the dynamic impacts of all the (nearby) neighbouring state markets on, or their dynamic linkages to, the natural gas market at a concerned state at different quantile levels. Second, differently from the mean (regression) analysis, the quantile analysis is also more popular in the energy risk management analysis (c.f., Yu et al., 2003). Correctly estimating the tail behavior of the price change distribution is crucially important for energy portfolio risk management and has significant policy implications (c.f., Aloui et al., 2014; Fan et al., 2008; Hung et al., 2008; Lahiani et al., 2017; Shahbaz et al., 2018). Third, as two of the most important sources of energy (Petroleum, 2017), natural gas and crude oil are well known to mutually substitute and complement each other on both the demand and the supply sides in the energy markets (Brown and Yücel, 2008; Hartley et al., 2008; Villar and Joutz, 2006; Wolfe and Rosenman, 2014). Due to these characteristics, there was, historically, co-movement or causality relationship between the natural gas and the crude oil markets (c.f., Aloui et al., 2014; Batten et al., 2017; Serletis and Rangel-Ruiz, 2004; Wolfe and Rosenman, 2014, and the references therein). By using the monthly natural gas commercial prices and the spot prices of the West Texas Intermediate (WTI) crude oil and the

Henry Hub natural gas, our introduced model can be fully used to investigate the dynamic relationship of the USA 48 states' natural gas markets as well as their dynamic linkages to the national crude oil market at different quantile levels.

The main contributions of this paper to the existing literature are highlighted in the following aspects. Firstly, the dynamic relationship of the state-level natural gas markets as well as their dynamic linkages to the national crude oil market for the 48 main states in the USA will be more holistically investigated. Specifically, by our suggested spatio-temporal quantile network econometric model, we can overcome the over-parametrisation issue of vector time series analysis and the drawbacks of pair-wise analysis in modelling the dynamic integrations or linkages for the 48 states in the USA as a whole at different quantile levels. Secondly, our empirical findings (c.f., Section 4) show that positive spatial neighbouring effects significantly exist among the natural gas markets not only in the eastern and middle states but also in some western and southwest states, while so do the dynamic linkages to the national crude oil market for the state-level natural gas markets in the southern and eastern states, which are heterogeneous at different quantile levels. Thirdly, by discovering the heterogeneous dynamic integrations of the natural gas markets across different states, our results help to uncover the risk transmission mechanisms of the local neighbour state natural gas markets and the national oil market in the model with a broader perspective on decision-making for management of energy risks. The recognised tail behaviour in price shocks from the quantile analysis will help investors to hedge against the energy price risks in maximizing their profits. Last but not the least, our empirical findings may also help local industry or government to mitigate the negative impacts from the expected or unexpected fluctuations in the national oil and the neighbouring natural gas markets, which will enact appropriate state-level price discovery, investment decision-making and energy policy-making.

This paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes the data used in this study with the methodology of spatio-temporal network quantile model introduced. Section 4 presents and discusses the corresponding estimation results and findings. Section 5 concludes.

2. Literature review

In this section, we review the studies that analyse the energy market integration, in particular those focusing on the relationship between the crude oil and the natural gas markets, and summarize the theoretical and empirical literatures which consider the spatial econometrics models and quantile methods.

Some previous literature has analysed the energy markets, either at a theoretical or at an empirical level. For example, focusing on the integration of regional retail fuel markets, Holmes et al. (2013) considered the pair-wise approach (Pesaran, 2007) to test the regional integration in the US gasoline market, which verifies the law of one price in the regional gasoline markets in the US. This approach was also applied by Cárdenas et al. (2017) on the diesel market integration in France. Blair et al. (2017) used an error-correction model to investigate the regional differences in the price pass-through in the US gasoline markets. However, on the natural gas markets in the USA concerned about in this paper, the literature appears not that extensive with regard to the market integration. See, for example, De Vany and Walls (1993), Cuddington and Wang (2006), Park et al. (2008), Apergis et al. (2015) and Ghoddusi (2016) who considered the integration and liberalization of the North American natural gas market, while Neumann et al. (2006), Renou-Maissant (2012) and Kuper and Mulder (2016) examined the natural gas market integration in the European countries, by using time-series analysis. Another strand of the literature has examined the equilibrium relationship between the natural gas and the crude oil markets. Most of these studies adopted time series modelling methods; see, e.g., Vücel and Guo (1994), Serletis and Rangel-Ruiz (2004), Bachmeier and Griffin (2006), Panagiotidis and Rutledge

(2007), Brown and Yücel (2008), Wolfe and Rosenman (2014). The existing literature has rarely investigated the relationship between the state-level natural gas markets and the national crude oil market in the U.S., and also typically neglected the spatial neighbouring linkages or dynamic market integrations and the tail behaviour of the extreme price changes in the state-level natural gas markets. Differently, we will propose a spatio-temporal network quantile econometric model, which combines the spatial econometrics and quantile regression, to explore the issues above in a more holistic manner.

The spatial neighbouring effects are mostly neglected in the previous studies on the natural gas markets. These studies, either based on a national perspective or ignoring the geographical heterogeneity in different states, may get a biased estimate of the market relationship. A spatial econometric model can help to measure the horizontal (multi-state) transmission effect or dynamic market integration. The methodology has been applied in other research fields. For example, in urban economics field, Fingleton (2008) developed a spatial GMM estimator for a house price model with moving average errors. Holly et al. (2010) constructed a spatio-temporal model to investigate the US house prices at the state level and identify a significant spatial dependence. In environmental sciences, Auffhammer and Carson (2008) used province-level data to construct a spatial econometrics model to forecast China's emissions. Yu (2012) analyzed the influential factors of China's regional energy intensity considering spatial dependence. Some empirical literatures that use station-level data to analyze the gasoline price dispersion can be found in e.g., Clemenz and Gugler (2006) and Yilmazkuday and Yilmazkuday (2016).

In addition, the tail behaviour in extreme price changes of the natural gas was also often neglected. Most of the existing literatures examine the linkage in conditional mean between energy markets. See, e.g., Alquist and Gervais (2013), Hamilton (2009), Lee et al. (2012), Li et al. (2012). For example, a large number of studies use the time series regression or vector autoregressive (VAR) model in conditional mean to test the causal relationship between the oil price and other variables (c.f., Hamilton, 1983; Jones and Kaul, 1996; Masih and Masih, 1997; Kling, 1985; Papapetrou, 2001; Cong et al., 2008). The classical conditional mean regression is a widely used statistical method in data analysis. In particular, if the error is normally distributed, the results of mean regression method are unbiased and efficient. However, from a risk management perspective, risk managers often focus on the tail behavior of distributions, and the energy price returns do not comply with the normal distribution, having an obvious peak and fat tails. In this case, the classic conditional mean regression will yield less informed results. Moreover, the outliers in energy prices may also affect the estimation accuracy of the classical mean regression. Therefore, the quantile regression method proposed by Koenker and Bassett Jr (1978) has many advantages in comparison with conditional mean regression (c.f., Bera et al., 2016; Sherwood et al., 2016; Xu and Lin, 2016, for a review). An increasing number of researchers have used quantile regression to analyse energy data. For example, Sim and Zhou (2015) and Reboredo and Ugolini (2016) applied quantile approach to examine the effect of oil price shocks on stock returns at different quantile levels, Fan et al. (2008) and Hung et al. (2008) estimated the value at risk for energy prices by using GARCH models, and Aloui et al. (2014) examined the dependence relationship between the WTI crude oil and the Henry Hub natural gas markets in extreme levels of quantiles.

Summarizing above, combining spatio-temporal and quantile regression methods can make it more comprehensive to investigate the complex relationships between regional natural gas markets and the national oil market. We therefore apply a spatio-temporal network quantile econometric model to investigate the dynamic relationships or market integration among the these markets.

3. Data and methodology

3.1. Data

Our data consist of monthly natural gas commercial prices of 48 states (excluding Alaska, Hawaii and the District of Columbia) in the US and monthly West Texas Intermediate WTI crude oil, and Henry hub natural gas, spot prices[1]. As there are missing data after Dec 2016 in some states, we choose the time interval from Jan 1997 to Dec 2016 as our sample period. Commodity prices are expressed in US dollars.

[Figure 1 about here.]

[Table 1 about here.]

Table 1 displays summary statistics for monthly natural gas prices, where ADF is for the *p*-value of augmented Dickey-Fuller test for unit root, with alternative hypothesis of being a stationary series. The result of unit root test shows that the prices series are not stationary (except for California). Jarque-Bera test indicates the non-normality of most natural gas price series. The time series plots of the monthly WTI crude oil price and its return series as well as the density plot are displayed in Figure 1, which shows that the WTI price series is nonstationary while its return series appears stationary and non-normal. Therefore, we will consider the returns of the natural gas commercial prices and the WTI crude oil price by taking the difference in the logarithm of two consecutive monthly prices.

In addition, we consider the effects of the long-run price equilibrium of the WTI crude oil and the Henry Hub natural gas markets on the state-level natural gas markets in our model. Although the WTI crude oil and the Henry hub natural

[1]Refer to the EIA Energy Glossary: https://www.eia.gov/tools/glossary/

gas prices are non-stationary, they share a common long-run trend (Hartley et al., 2008; Villar and Joutz, 2006). Therefore, a cointegrating relationship between them may exist and have significant impact on the regional natural gas markets in the U.S.. Ramberg and Parsons (2012) found a structural break in February 2009 by using the cointegration test based on the augmented Dickey-Fuller test statistic (c.f., Gregory and Hansen, 1996). Therefore, we estimate the following equation:

$$lnZ_t = \phi_0 + \phi_1 lnX_t + \phi_2 D_t + \epsilon_t, \tag{3.1}$$

and do the cointegration test by the approach of Gregory and Hansen (1996), where Z_t denotes the Henry hub natural gas price at time t, X_t is the WTI crude oil price at time t, and D_t is a dummy variable used to account for the structure change ($D_t = 0$ if time is between Jan 1997 and Feb 2009, and $= 1$ otherwise). Here ϵ_t is the stochastic error term, used to describe the long-run price disequilibrium between the WTI crude oil and Henry Hub natural gas markets, which will be shown to have important effect on the state-level natural gas markets.

3.2. Methodology

In order to comprehensively identify the market linkages among different state natural gas markets and uncover the underlying impacts of the national crude oil market on the state-level natural gas markets, we incorporate quantile regression method into spatio-temporal autoregressive model. We, therefore, construct a spatio-temporal network τ-th quantile econometric model as follows:

$$\begin{aligned} &Q_\tau(\Delta \ln Y_t(s_i)|\Delta \ln X_{t-1}, Y^{\mathrm{sl}}_{t-1}(s_i), ..., Y^{\mathrm{sl}}_{t-p}(s_i), \Delta \ln Y_{t-1}(s_i), ..., \Delta \ln Y_{t-q}(s_i)) \\ =&\alpha_{0,\tau}(s_i) + \sum_{j=1}^{p} \lambda_{\tau,j}(s_i) Y^{\mathrm{sl}}_{t-j}(s_i) + \sum_{l=1}^{q} \beta_{\tau,l}(s_i)\Delta \ln Y_{t-l}(s_i) + \alpha_{1,\tau}(s_i)\Delta \ln X_{t-1} \\ &+ \gamma_\tau(s_i)\widehat{\epsilon}_{t-1}, \end{aligned} \tag{3.2}$$

$$Y_t^{sl}(s_i) = \sum_{k=1}^{N} W_{ik} \Delta \ln Y_t(s_k), \quad i = 1, ..., N, t = 1, ..., T.$$

Here $\Delta \ln Y_t(s_i) = \ln Y_t(s_i) - \ln Y_{t-1}(s_i)$ denotes the return of natural gas price in state i at time t and $\Delta \ln X_t$ is the return of oil price at time t. The parameter $\lambda_{\tau,j}(s_i)$ accounts for the spatial autoregressive effect of j-order lag in state i at τ quantile. The time autoregressive coefficient $\beta_{\tau,l}(s_i)$ denotes the time l-order lag coefficient of $\Delta \ln Y_t(s_i)$ in state i at τ quantile. Note $\widehat{\epsilon}_{t-1} = \ln Z_{t-1} - \hat{\phi}_0 - \hat{\phi}_1 \ln X_{t-1} - \hat{\phi}_2 D_{t-1}$ represents the estimated residuals for the shocks in the long-run equilibrium relationship between the WTI crude oil and Henry Hub natural gas prices as given in (3.1) and $\gamma_\tau(s_i)$ represents the effect of this disequilibrium on the state i's natural gas price return. Here p and q stand for the orders of the spatial neighbouring and the concerned state autoregressive temporal lags, respectively.

The spatially lagged response variable $Y_t^{sl}(s_i)$ denotes spatial neighbouring effects of the dependent variable, where w_{ik} is a spatial weight for the (i, k)-th element ($1 \leq i, k \leq N$) of a pre-specified nonnegative spatial weighting matrix $W = [w_{jk}]_{j,k=1}^N$. This matrix reflects the geographic relationship between natural gas markets among different states. There are different kinds of weighting matrices used in the literature, among which distance function matrix and binary contiguity matrix are the most commonly used specifications (LeSage and Pace, 2009). In this study, considering the fact that natural gas is mainly transported by pipeline together with the common practice in econometrics, we choose the binary contiguity matrix for the spatial weight matrix. Let $\mathcal{A}(s_i)$ be a set of the states that connect with state i by natural gas pipelines. Then the element w_{ij} between states i and j in the spatial weight matirx W is defined by

$$w_{ij} = \begin{cases} 1 & if \quad j \in \mathcal{A}(s_i), \\ 0 & otherwise. \end{cases}$$

Moreover, as usual, $w_{ii} = 0$, and we normalize the spatial weights by row such that the summation of the row elements is equal to 1. Besides, the orders p and q for spatial neighbouring autoregressive lags and the temporal lags, respectively, will be decided by Akaike information criterion (AIC).

Then the unknown parameters in the model can be estimated in two steps. First, we use OLS regression to estimate the model $\ln Z_t = \phi_0 + \phi_1 \ln X_t + \phi_2 D_t + \epsilon_t$ and the predicted residuals $\widehat{\epsilon}_t = lnZ_t - \hat{\phi}_0 - \hat{\phi}_1 lnX_t - \hat{\phi}_2 D$ from this regression are saved. The second step is to estimate the model (3.2) by:

$$\begin{aligned}
&(\widehat{\alpha}(s_i), \widehat{\lambda}(s_i), \widehat{\beta}(s_i), \widehat{\gamma}(s_i)) \\
&= \arg \min_{(\alpha(s_i),\lambda(s_i),\beta(s_i),\gamma(s_i))} \sum_{t=1}^{T} \rho_\tau \Big\{ \Delta \ln Y_t(s_i) - \alpha_0(s_i) - \sum_{j=1}^{p} \lambda_j(s_i) Y^{sl}_{t-j}(s_i) \\
&\quad - \sum_{l=1}^{q} \beta_l(s_i) \Delta \ln Y_{t-l}(s_i) - \alpha_1(s_i) \Delta \ln X_{t-1} - \gamma(s_i) \widehat{\epsilon}_{t-1} \Big\}, \qquad (3.3) \\
&Y^{sl}_t(s_i) = \sum_{k=1}^{N} W_{ik} \Delta \ln Y_t(s_k), \quad i = 1, ..., N, \ t = 1, ..., T,
\end{aligned}$$

where $\rho_\tau(y) = y(\tau - \mathbf{1}_{y<0})$ is the quantile check function, and $\mathbf{1}_A$ is the indicator function of set A which equals 1 if A is true and 0 otherwise.

This equation can be solved by linear programming. In order to have comprehensive information on the dynamic neighbouring linkages among the state-level natural gas markets and the linkages of the natural gas markets in 48 states to the crude oil market, we set five representative quantiles (i.e., 10th, 25th, 50th, 75th and 90th). In addition, we also use nine quantiles (i.e., 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th) to display the varying characteristics of different coefficients of interest (c.f., Section 4). A bootstrap method (He and Hu, 2002) is used to obtain the confidence intervals of the estimate parameters in above model. Specific discussion about quantile regression method is referred to Koenker (2005).

4. Empirical findings

4.1. Global spatial autocorrelation analysis

First, we want to recognize whether the average and the standard deviation of natural gas prices have spatial affinities with corresponding state dispersions (Figure 2). From Figure 2(a), we can clearly observe that the eastern states in the U.S. (such as Alabama, Delaware and Rhode.Island) have relatively higher natural gas prices than the states in western and central USA (such as Nebraska, Idaho and Wyoming) over our sample period. It also shows that the mean natural gas price in one state tends to be close to those of neighbouring states in the same region, indicating that there can be dynamic linkages between natural gas markets across states. Moreover, the dispersion of state-level natural gas prices (Figure 2(b)) have a similar pattern. For example, states in the eastern America (such as Delaware, Georgia, Maine and West Virginia) have higher dispersions and fluctuations in natural gas prices, whereas the western states, such as California, Nebraska and Utah present a low volatility in natural gas prices. Taking together the results of Figure 2, we can find the 'spatial herding behaviour' in the state-level natural gas markets. This spatial clustering phenomenon is also supported by Moran's I test.

[Figure 2 about here.]

The Moran's I test (Moran, 1950) defined as follows:

$$I_t = \frac{\sum_i^N \sum_j^N w_{ij}(x_{it} - \bar{x}_t)(x_{jt} - \bar{x}_t)}{\sum_i^N (x_{it} - \bar{x}_t)^2}, \tag{4.1}$$

where x_{it} is the natural gas price return for state i at time t, $\bar{x}_t$ is the mean of x_{it} over the states i's, w_{ij} is the row-standardised spatial weights matrix element defined in Section 3.2. The results of Moran's I over twenty years, given in Table 2, confirm that positive spatial autocorrelation is significant at the 5% significance level overall in most of the considered time periods.

[Table 2 about here.]

The Moran's I test only assesses the overall pattern and the time trend of the spatial autocorrelation (Anselin, 1993). To further examine the clustering effects of spatial neighbours of the natural gas price returns in different states, we plot a scatter diagram of spatial neighbouring effects for year 2016, displayed in Figure 3. The vertical axis represents the natural gas price returns x_{it} at time t for state i for 48 states, and the horizontal axis shows the corresponding states' temporal lag 1 spatial neighbouring natural gas price returns, $\sum_{j=1}^{48} w_{ij} x_{j,t-1}$, in these states. It clearly indicates that there appears a significant linear relationship between the two variables. Therefore, spatial neighbouring effect or local market integration seems to be an important factor that influences the state-level natural gas markets, and dynamic spatial models incorporating both spatial neighbouring effect and dynamic effect are then incorporated in the analysis of the state-level returns of the natural gas prices in the U.S. states in this paper.

[Figure 3 about here.]

4.2. Empirical results of spatio-temporal network quantile econometric modelling

To comprehensively investigate the effects of the crude oil market on state-level natural gas markets and the neighbour state effects on the monthly natural gas price returns , we choose five representative quantile levels (i.e., 10th, 25th, 50th, 75th and 90th) for implementing the quantile regression. Before proceeding to the rigorous empirical investigation, we first decide the orders of spatial neighbouring autoregressive lags and the temporal lags, p and q, in our model (3.2), by quantile regression Akaike information criterion (AIC), calculated by the function 'AIC.rq' of the R package "quantreg" (Koenker et al., 2018). The details of the AIC values for different orders of (p, q) for the 48 states are provided in Table 3. The result given in Table 3 shows that the chosen orders p and q by the AIC are only slightly different for each state. To ensure consistency, in our models, similarly to that in Blair et al. (2017), we use the same lag lengths for all states with $(p, q) = (1, 1)$ selected based on the AIC values for most of the states.

[Table 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

[Figure 7 about here.]

[Table 4 about here.]

The estimation results for testing the cointegration between the WTI crude oil and the Henry hub natural gas market prices by using the approach of Gregory and Hansen (1996) under model (3.1) are provided in Table 4, and the results of the spatio-temporal network quantile econometric regression under model (3.2) in the Tables 5-9 (in the Appendix). In Figures 4-7, we depict, over states in maps, the results of estimating the coefficients $\alpha_1(s_i)$, $\lambda(s_i)$, $\beta(s_i)$ and $\gamma(s_i)$ at different quantile levels, respectively, where the null hypothesis of the coefficients being zero is rejected at 5% significance level. In Figure 4, it clearly shows that the large and significantly positive coefficients of the spatial neighbouring effects usually appear at the states in the middle of the USA. Further, Figure 5 shows the autoregressive effects of the natural gas price returns that are heterogeneous and more significant at the 50th quantile. Figure 6 illustrates the effects of the oil market on the state-level natural gas markets that are more significant in the south and southeast of the United States at different quantiles. Figure 7 displays the effects of the adjustment toward the long-run equilibrium relationship between the WTI crude oil and the Henry Hub natural gas markets. These results clearly show that the tails of the price return distribution contain important information that the conditional mean regression cannot fully reveal. This suggests that the method of using spatial-temporal network quantile econometric regression model is appropriate and reasonable for this empirical analysis.

4.3. Discussions

The spatial-temporal network quantile regression can visually reveal the spatial neighbouring effects of natural gas markets in the states of the USA and the effects of the oil market on state-level natural gas markets at different quantiles. The results for some typical states[2] are presented in Figures 9–10 on the spatial

[2]Here we choose Connecticut, Pennsylvania and West Virginia from the northeast region, Alabama and Tennessee from the southeast region, Ohio from the mideast region, Colorado

neighbouring effects, autoregressive effects, the spillover effects of crude oil market and the effects of the shocks in the long-run price equilibrium between the WTI crude oil and the Henry Hub natural gas markets. From these figures, we can clearly see the dynamic linkages with significant heterogeneity on these effects[3].

First, we analyze the impacts of the neighbouring states' natural gas markets or market integrations. From Figure 4, we can clearly observe that the linkages of local natural gas market to the neighbour natural gas markets are heterogeneous. In particular, there exist significant positive spatial neighbouring effects, indicating the strong linkage with the neighbour states, in the natural gas markets in most of the border states at the 5% significance level, as identified by comparing Figure 4 and Figure 8. For example, some eastern states of the USA, such as Connecticut, Ohio, Pennsylvania, Tennessee and West Virginia, have a significantly positive basin-shaped or U-shaped curve spatial neighbouring effect, respectively (Figure 9(c), Figure 9(e), Figure 10(b), Figure 10(c) , and Figure 10(e)), which indicates the stronger integration of natural gas market at higher and lower quantiles. In some middle states, such as Colorado and Wyoming in the central region, the curve of the coefficients for the spatial neighbouring effects seems like a trigonometric function, with the values between 0.2 and 0.6 (Figure 9(b) and Figure 10(f)). And for New Mexico, we can observe an inverted U-shaped spatial neighbouring effect in Figure 9(d). In Figure 9(f), a decreasing trend of the spatial neighbouring

and Wyoming from the central region, New Mexico, Oklahoma and Texas from the southwest region, and Oregon from the western region (c.f., Figure 8). Figure 8 shows the information on the transportation capacity (in Million cubic feet per day) between the six geographical regions, international borders, and offshore Gulf of Mexico in 2016.

[3]To verify the asymmetry of the coefficients, we considered the Wald test for quantile regression coefficients. Due to the space limit, we only show the results of the Wald tests for the equality of slope coefficients (at the quantile levels of 0.1 against 0.5 and 0.9, and 0.5 against 0.9) for some typical states, provided in Table 10 in the Appendix. Complete results are available upon request. We found that there are significant differences between the coefficients under different quantile levels for some states, which largely support the heterogeneity of these effects.

effect implies that the lower the price changes in the natural gas markets of the neighbour states, the higher the influence on natural gas market in Oklahoma. Similar to Oklahoma, Oregon in the western region also has a decreasing trend of the spatial neighbouring effect (Figure 10(a)).

These significantly high degrees of linkages between state-level natural gas markets are also evident, implying that spatial arbitrage could enforce the law of one price and promote integration of the natural gas markets in the central and eastern states of the U.S. at different quantile levels, which is similar to the results of Cuddington and Wang (2006). Moreover, unlike Cuddington and Wang (2006), we find that the natural gas markets in southern states are under integration at upper quantiles while some western state-level natural gas markets are under integration at lower quantiles. There are two main reasons for the integration of the natural gas markets. The first one is owing to geographical locations. The transported volumes of the cross-state natural gas are large through the well-developed pipeline system in these border states (see Figure 8), and hence the transactions are more frequent in the border states. Therefore, the natural gas markets are more likely to be influenced by the nearby states in these areas. The second reason is the productions and consumptions of the natural gas, which also contribute to the spatial neighbouring effects. Specifically, for some states with production below consumption, such as Alabama, Connecticut, Missouri, Montana, Oregon and Wyoming, there are a high natural gas import from the nearby states to meet its own consumption requirement, which makes their natural gas markets significantly affected by the natural gas markets in the neighbour states. In contrast, in Colorado, Kansas, New Mexico, Ohio, Oklahoma, Pennsylvania and West Virginia, there exist vast resources of natural gas, where the status of the natural gas resources also makes their natural gas markets significantly influenced by the neighbour states.

Second, we examine the dynamic linkage between the future and the past of one state natural gas market. From Figure 5, there appear more states with significant dynamic linkage of the price changes (at the 5% significance level) in the natural gas markets around at 50th quantile than at other quantiles. This indicates that at the median level, the price changes in state-level natural gas markets in the future may be more easily influenced by its past. The results may attribute to the characteristics of the natural gas prices such as time-dependent and mean-reverting dynamics (Ramberg and Parsons, 2012; Thompson et al., 2009). In addition, there exist some states, e.g. Florida, Nevada, Vermont and Wisconsin, where significantly autoregressive effects are present in their natural gas markets, while spatial neighbouring or oil spillover effects on the natural gas markets are insignificant. Also, this finding may imply that the natural gas markets of these states are more segregated.

Third, the impacts of the national crude oil market are investigated. We can observe in Figure 6 that the effects of the national crude oil market on the natural gas markets exist significantly in the southern and eastern states, which are clearly heterogeneous. In particular, these effects in the northeast region, such as Maryland, Pennsylvania, Ohio, Rhode Island and Virginia are significant and positive at the lower quantile levels. This indicates that the natural gas markets in these states are vulnerable to the impact of price falling in crude oil market. However, the effect of price changes in the crude oil market on the natural gas market in Connecticut is statistically significant at almost all quantiles. The curve of the coefficient seems like a trigonometric function, with the values between 0.1 and 0.4 (Figure 9(c)). Moreover, for the southern states, such as Alabama, Connecticut, Georgia, Kentucky, New Mexico, Tennessee and Texas, the effects from the crude oil market are statistically significant and positive at most quantile levels. More specifically, Alabama and Texas have a U-shaped curve for the impacts of the price changes in crude oil market on the natural gas markets at different quantile levels. As shown in Figure 9(a) and Figure

10(d), a U-shaped curve illustrates the higher (either positive or negative) price fluctuations (corresponding to higher or lower quantile levels) in the natural gas markets in Alabama and Texas are more susceptible to the impact of the crude oil price shocks. For New Mexico and Tennessee, the effects of price changes in the crude oil market are significantly positive and have an inverted U-shaped curve from the 30th to the 80th quantiles (Figure 9(d) and Figure 10(c)).

The main reason for the significant impacts of the national crude oil market on the state-level natural gas markets is owing to the relatively large-scale inflow-outflow capacity of the natural gas and the high proportion of the natural gas and oil consumptions in these states. This situation causes a strong substitutional relationship between the natural gas and the crude oil, implying that the price changes in the crude oil market have a significantly positive impact on the natural gas markets. In addition, in some border states (i.e. the states located on the boards of the six regions in Figure 8, such as Arkansas, Kansas, Missouri, etc.), although there exist no significant oil price effects, the natural gas markets in these states are still indirectly influenced by the price changes in the crude oil market. In other words, the natural gas markets in these states are affected, through the significantly spatial neighbouring effects, by the natural gas markets in the nearby states, which are influenced by the price changes in the crude oil market. Clearly, the impacts of the price changes in the crude oil market are transmitted through the spatial effects from the neighbour states' natural gas markets.

[Figure 8 about here.]

[Figure 9 about here.]

[Figure 10 about here.]

Finally, this paper studies the effects of the long-run equilibrium shocks from the national crude oil and natural gas markets. As shown in Figure 7, the effects of the long-run relationship of the WTI crude oil and Henry Hub natural gas markets on the state-level natural gas markets are statistically significant at the 5% significance level, but they are heterogeneous in the western and eastern states of the USA. Averaging across all states, the adjustment process tends to be faster at higher or lower quantiles for deviations from the long run equilibrium level. In addition, for California, it only has significant long-run equilibrium shock effect. Specifically, there is statistically significant and positive effect of the long-run relationship of the WTI crude oil and Henry Hub natural gas markets around the middle quantile levels, while the adjustment effect is not statistically significant when the price has larger fluctuation in the natural gas market of California.

In summary, compared with the papers using mean regression analysis, our spatio-temporal network quantile model provides a more comprehensive picture of the dynamic linkages of the state-level natural gas markets, as indicated above on the spatial neighbouring effects, the autoregressive effects, the oil spillover effects and the effects of the long-run equilibrium shocks from the WTI crude oil and Henry Hub natural gas markets, for the natural gas markets of the 48 states in the USA. These findings can help us to better understand the heterogeneous effects of those dynamic linkages among different markets.

5. Conclusions

This study aims at exploring the dynamic linkages or market integrations of the state-level natural gas markets with the neighbouring states and the national crude oil market in terms of the spatial effects from the neighbour state natural gas markets as well as the oil price spillover effects from the WTI oil market. We introduce a spatio-temporal network quantile econometric model in this study. It can help to reveal the significant individual (state) and distributional (quantile) heterogeneities in the effects of the neighbouring state natural gas markets and the oil market price shocks among the 48 states in the USA. Compared with traditional mean regression, our model can provide us with comprehensive understanding of the spatial neighbouring or market integrations and the oil market price shock effects that impact the state-level natural gas prices.

This study uses the monthly data covering a period from Jan. 1997 to Dec. 2016 for the 48 states (excluding Alaska, Hawaii and the District of Columbia) in the USA. The empirical results indicate that the degree of the dynamic impacts owing to price shocks from both the local neighbouring natural gas markets and the national crude oil market, on the natural gas prices at a concerned state, varies by state. We find that significant local dynamic neighbouring market integrations exist in the natural gas markets not only in the eastern and central states as evidenced in the literature (Cuddington and Wang, 2006; Park et al., 2008) but also in some western and southwest states at different quantile levels. Our results also show that there are significant linkages of the state-level natural gas markets to the national crude oil market through its lagged price shock and its long-run price equilibrium with the national gas market with varying price shock propagations at different quantile levels. The effects of the crude oil market price shocks on the state-level natural gas markets are heterogeneous and statistically significant in the southern states of the USA at different quantile levels. The impacts on the state-level natural gas markets may also come from the shocks or deviations from the long-run equilibrium of the WTI crude oil and Henry Hub natural gas markets, which are statistically significant in some western and eastern states and heterogeneous over states in the USA.

The results obtained can help local government and energy users to mitigate the negative impacts from the expected or unexpected fluctuations in the oil and the neighbouring natural gas markets. In particular, as a clean and cheap energy, natural gas can be used as a substitute to oil in many cases. An in-depth understanding of the relationship between the crude oil and the natural gas markets can help them better managing energy risk. Also, energy users in the border of the six geographical regions can pay more attention to the natural gas markets in the neighbour states to reduce their risk transmission from the neighbour states. Moreover, local state governments may formulate relevant energy policies on the basis of their geographical location and natural resource endowment. Quantile regression methods can help to discover the full relationship between different variables, especially those which have fat tails in distributions and are important for energy risk management and policy decision-making. In short, the findings from our study can enact appropriate state-level price discovery, investment decisions and energy policies.

Combining the spatial econometrics and quantile regression method can help to better investigate the complex relationships between oil price and regional natural gas prices. The parametric models applied in this paper may have some shortcoming in uncovering the underlying relationship for some states. A non-parametric quantile approach may be developed in the further research to study the dynamic energy market relationships (c.f., Al-Sulami et al., 2017; Gao et al., 2006; Hallin et al., 2004; Lu et al., 2007, 2009, based on conditional means).

Acknowledgements

The authors are grateful to the editor and both referees for their helpful comments and suggestions which have improved the present version of this paper. This work was partially supported by the European Research Agency's Marie Curie Career Integration Grant [grant numbers PCIG14-GA-2013-631692], which is also acknowledged.

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Appendix

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

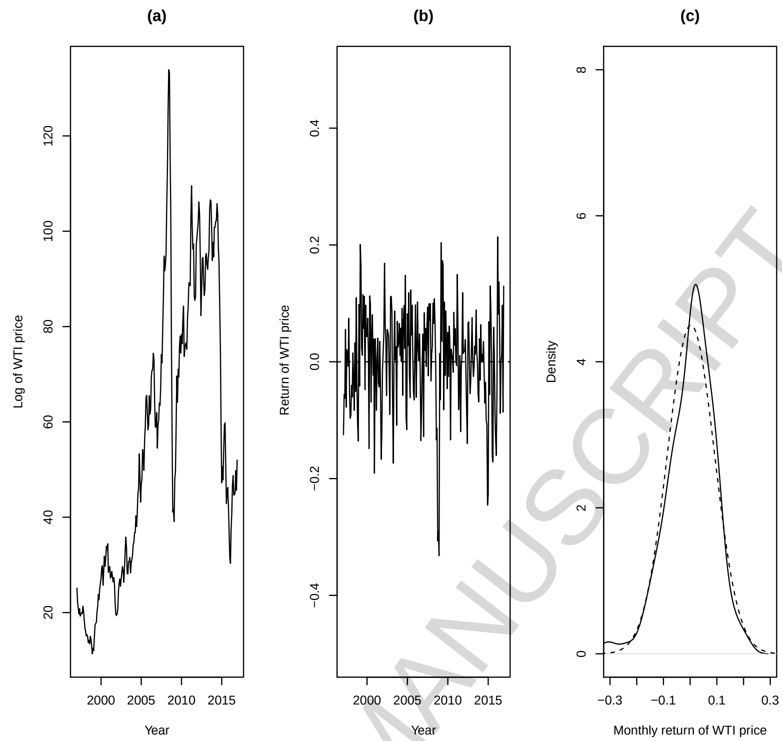
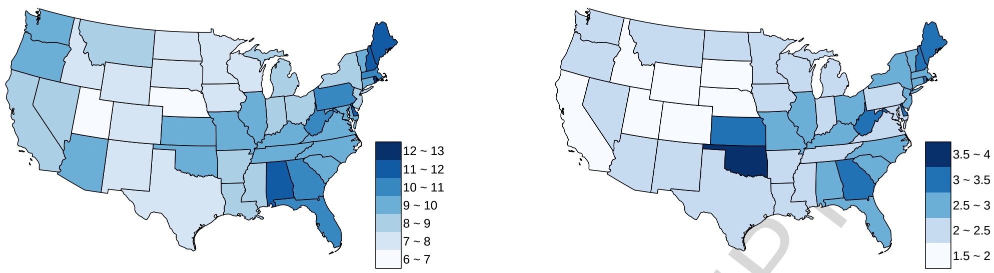


Figure 1: *The time-series plots of the monthly WTI price data from Jan 1997 to Dec 2016 (left) and its monthly return data (middle) and the density plot (the kernel density estimate in solid line and the normal density estimate in dashed line) of the monthly return data (right).*



(a) Mean (b) Standard Deviation

Figure 2: *Spatial Distributions of Natural Gas Prices: Mean and Standard Deviation*

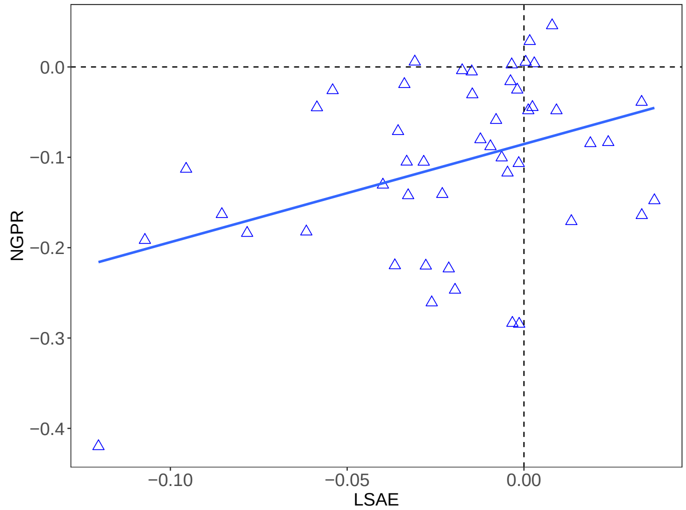
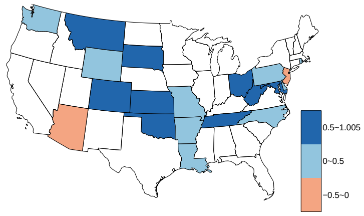
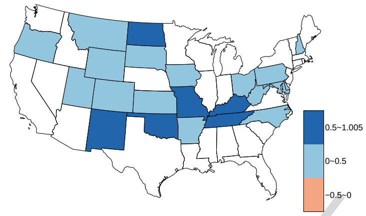


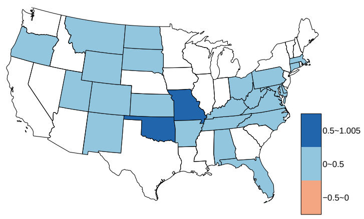
Figure 3: *Scatter plot of spatial neighbouring effects of 48 states in the U.S. (2016).* ***Note****: The vertical axis represents the natural gas price returns in 48 states, and the horizontal axis shows the time lag 1 spatial neighbouring natural gas price returns in these states*



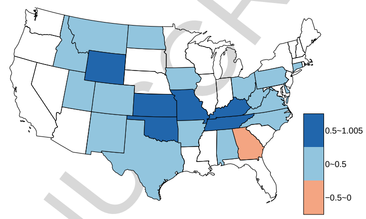
(a) $\tau = 0.1$



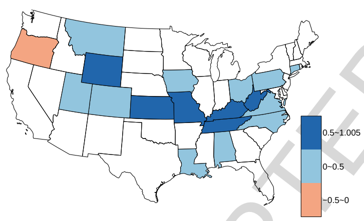
(b) $\tau = 0.25$



(c) $\tau = 0.5$

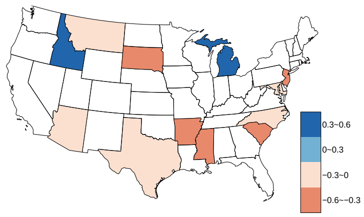


(d) $\tau = 0.75$



(e) $\tau = 0.9$

Figure 4: *Maps of influence coefficients of spatial neighbouring effects.* ***Notes:*** *The insignificant areas (the p-value of the coefficient is larger than 0.05) have been represented in white.*



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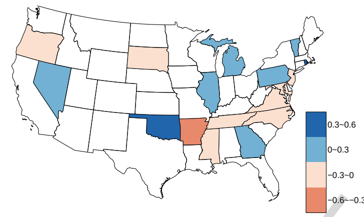
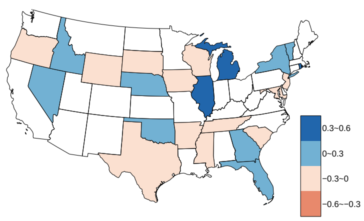


(b) $\tau = 0.25$



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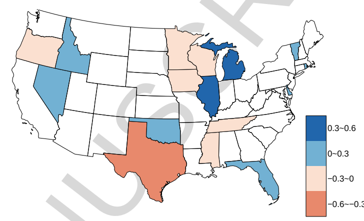

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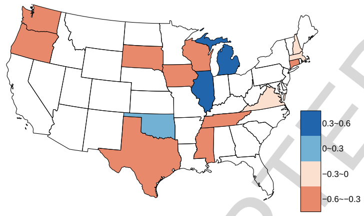
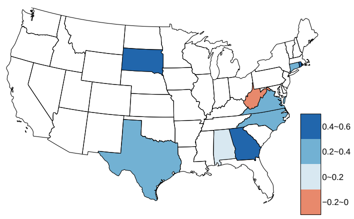


(e) $\tau = 0.9$

Figure 5: *Maps of influence coefficients of autoregressive effects.* ***Notes:*** *The insignificant areas (the p-value of the coefficient is larger than 0.05) have been represented in white.*



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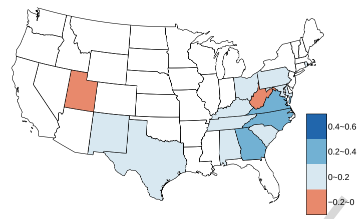

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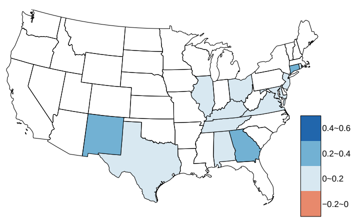

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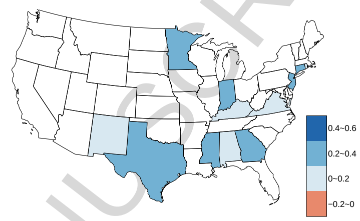
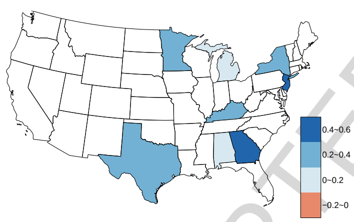
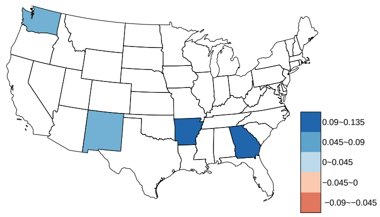


(d) $\tau = 0.75$



(e) $\tau = 0.9$

Figure 6: *Maps of influence coefficients of oil price effects.* ***Notes:*** *The insignificant areas (the p-value of the coefficient is larger than 0.05) have been represented in white.*



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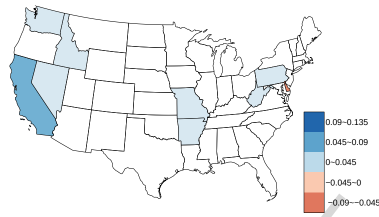
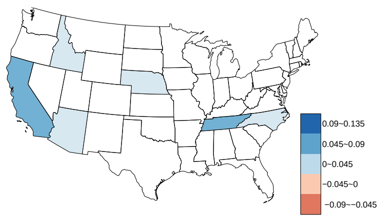
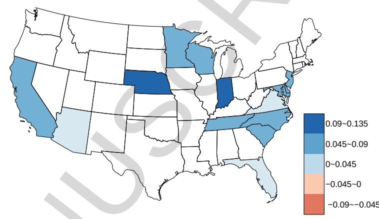


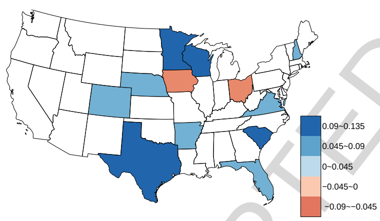
(b) $\tau = 0.25$



(c) $\tau = 0.5$



(d) $\tau = 0.75$



(e) $\tau = 0.9$

Figure 7: *Maps of the effects of the long-run relationship of the WTI crude oil and Henry Hub natural gas prices on the state-level natural gas price returns.* ***Notes:*** *The insignificant areas (the p-value of the coefficient is larger than 0.05) have been represented in white.*

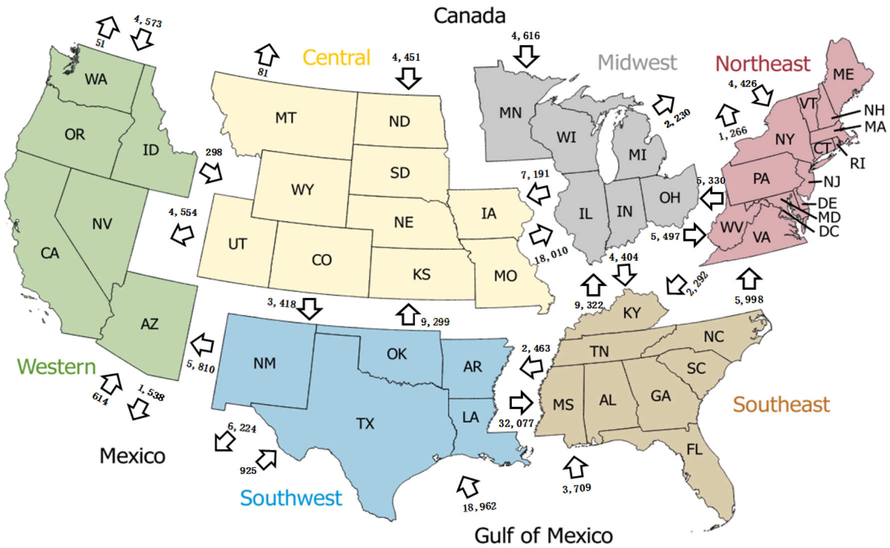
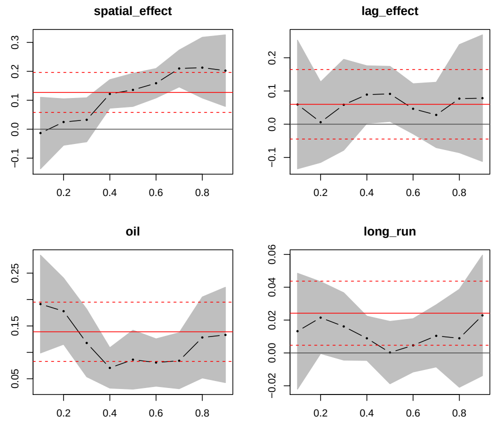
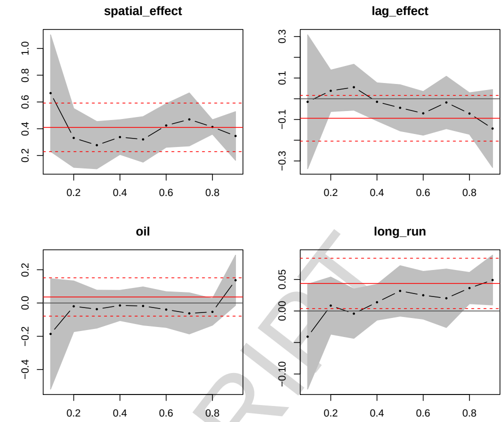


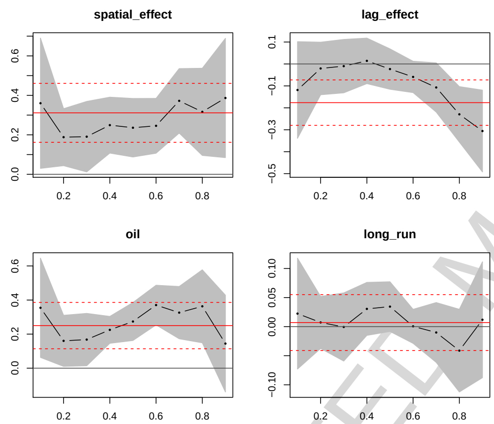
Figure 8: *Region to region capacity map of natural gas in the U.S. in 2016. Source from: U.S. Energy Information Administration (https://www.eia.gov/naturalgas)*



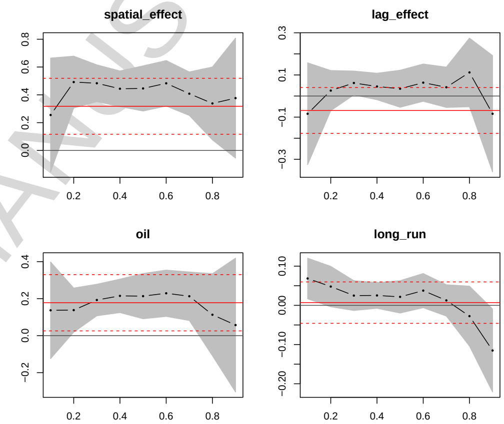
(a) Alabama



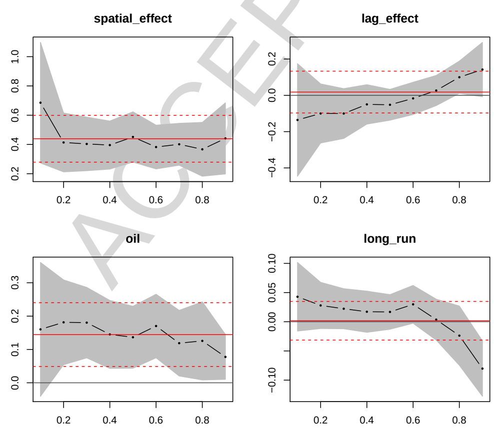
(b) Colorado



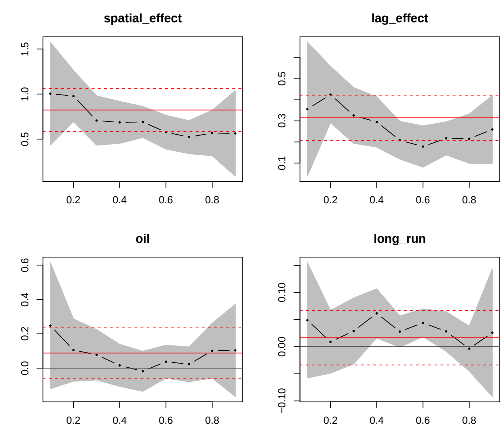
(c) Connecticut



(d) New Mexico

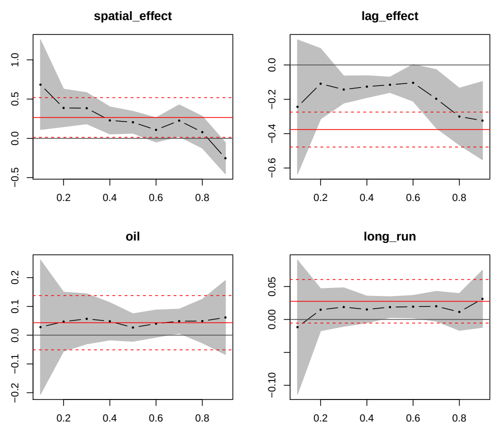


(e) Ohio

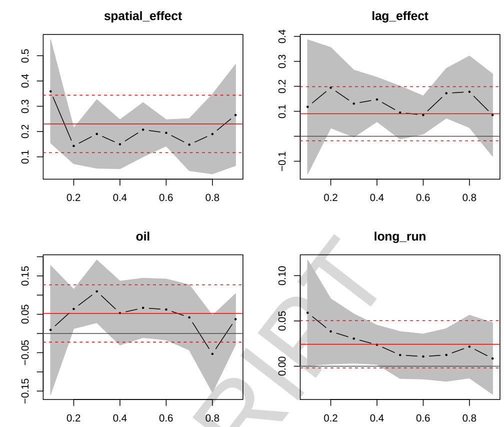


(f) Oklahoma

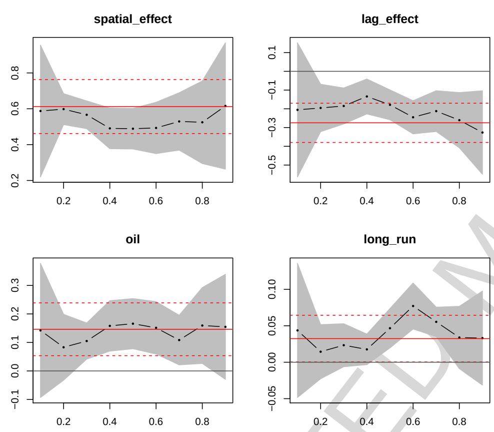
Figure 9: *Quantile estimate: The effects of driving forces on natural gas price returns in six typical states.* ***Notes:*** *Shaded areas correspond to 95% confidence intervals of quantile estimation. The vertical axis indicates the elasticities of the explanatory variables. The red horizontal lines represent confidence intervals of OLS estimation.*



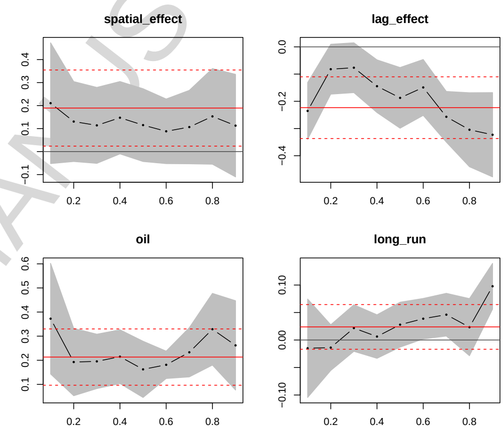
(a) Oregon



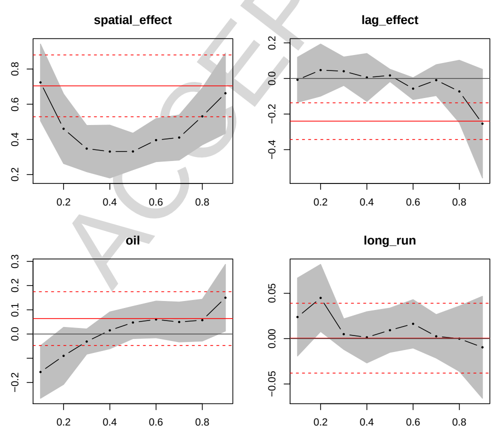
(b) Pennsylvania



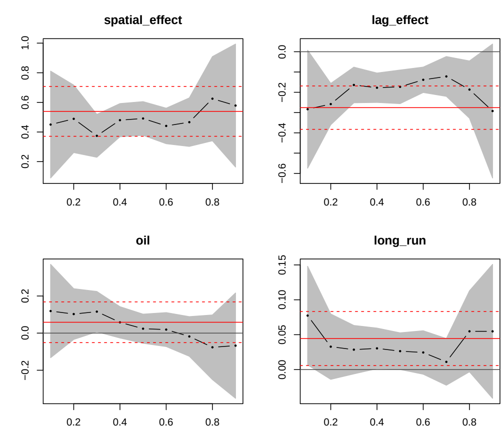
(c) Tennessee



(d) Texas



(e) West Virginia



(f) Wyoming

Figure 10: *Quantile estimate: The effects of driving forces on natural gas price returns in other typical states.* ***Notes:*** *Shaded areas correspond to 95% confidence intervals of quantile estimation. The vertical axis indicates the elasticities of the explanatory variables. The red horizontal lines represent confidence intervals of OLS estimation.*

States	Mean	SD	Skewness	Kurtosis	ADF test	JB test
Alabama	11.6074	2.9750	-0.0786	-0.7172	0.9131	0.0772
Arizona	9.3186	2.2816	0.0462	-0.9040	0.9572	0.0188
Arkansas	8.3656	2.1349	0.0732	-0.7149	0.5801	0.0798
California	8.2555	1.9519	1.0402	1.5343	0.0129	0.0000
Colorado	7.2736	1.9036	-0.0573	-0.6283	0.0936	0.1470
Connecticut	9.5747	2.7300	0.4323	-0.0812	0.5545	0.0224
Delaware	11.8462	3.2957	0.0511	-0.9752	0.5384	0.0096
Florida	10.4675	2.5040	0.3223	0.5142	0.3764	0.0278
Georgia	10.4266	3.2944	0.3391	0.4676	0.4628	0.0284
Idaho	7.8770	1.9996	0.0666	-0.6123	0.8148	0.1583
Illinois	9.1169	2.7531	0.5212	0.2457	0.0530	0.0028
Indiana	8.6208	2.4740	0.6741	0.2860	0.3163	0.0001
Iowa	7.8189	2.1043	0.4594	0.0766	0.2515	0.0132
Kansas	9.7164	3.0846	0.1800	-0.5514	0.4945	0.1268
Kentucky	9.4930	2.8306	0.5177	0.3213	0.6603	0.0024
Louisiana	8.9126	2.3330	0.6042	0.3792	0.4237	0.0003
Maine	11.3884	3.1338	-0.0559	-0.4548	0.3503	0.3669
Maryland	9.8669	2.2163	0.2447	-0.3374	0.3665	0.1810
Massachusetts	10.9304	2.8829	0.3619	-0.1418	0.4318	0.0658
Michigan	8.0125	2.0820	0.0676	-0.7671	0.6232	0.0554
Minnesota	7.4144	2.1506	0.6331	0.5210	0.2534	0.0001
Mississippi	8.1578	2.4531	0.8789	0.9666	0.5164	0.0000
Missouri	9.6955	2.5701	-0.2070	-0.7709	0.8377	0.0248
Montana	8.3928	2.3152	0.4045	0.2445	0.4313	0.0251
Nebraska	6.7468	1.9187	0.7023	0.6353	0.3979	0.0000
Nevada	8.4107	2.1253	0.3641	-0.9356	0.9419	0.0010
New.Hampshire	11.8781	3.0855	-0.3047	-0.7467	0.5305	0.0108
New.Jersey	8.8214	2.9931	0.0786	0.1579	0.5115	0.7444
New.Mexico	7.1075	2.2800	0.6887	0.7913	0.5347	0.0000
New.York	8.6009	2.5356	0.4684	-0.2703	0.5850	0.0087
North.Carolina	9.7717	2.5928	0.6687	0.2148	0.6466	0.0001
North.Dakota	7.1034	2.1173	0.7244	0.7176	0.1484	0.0000
Ohio	8.6724	2.5085	0.7273	-0.0567	0.6225	0.0000
Oklahoma	9.9751	3.6791	0.3814	-0.8651	0.3400	0.0015
Oregon	9.1020	2.3823	-0.2184	-0.7224	0.8142	0.0321
Pennsylvania	10.4781	2.3870	0.5686	0.1351	0.5426	0.0013
Rhode.Island	12.9184	3.3067	0.1784	-0.9566	0.5411	0.0064
South.Carolina	9.7501	2.6529	1.0066	1.6956	0.6091	0.0000
South.Dakota	7.1755	1.9217	0.6424	0.4048	0.2954	0.0001
Tennessee	9.2335	2.4284	0.7813	1.0006	0.5430	0.0000
Texas	7.4864	2.2243	0.7079	0.9450	0.5005	0.0000
Utah	6.6864	1.5946	-0.2660	-0.4041	0.2351	0.1149
Vermont	9.2151	2.9309	0.3067	-1.0177	0.9419	0.0010
Virginia	9.2561	2.1775	0.4439	0.0814	0.5617	0.0175
Washington	9.1160	2.4832	-0.3625	-0.7373	0.8007	0.0053
West.Virginia	10.0850	3.0457	0.6492	-0.3199	0.9087	0.0001
Wisconsin	7.5983	2.1887	0.5796	0.0519	0.4879	0.0011
Wyoming	7.0640	1.8871	0.1295	-0.2241	0.0685	0.5819
Henry hub	4.4812	2.2589	1.3342	2.0411	0.2177	0.0000

Note: SD represents the standard deviation. ADF is for the p-value of augmented Dickey-Fuller test for unit root, with alternative hypothesis of being a stationary series. JB is for the p-value of empirical statistic of the Jarque-Bera test for normality, with null hypothesis of being normal.

Table 2: *The Moran's I test result*

Date	Moran's I statistic	p-value
1997	0.0651	0.3726
1998	-0.0757	0.5559
1999	0.0395	0.5410
2000	0.1094	0.1643
2001	0.2738	0.0039
2002	0.2165	0.0214
2003	0.0691	0.3921
2004	0.2318	0.0165
2005	-0.0561	0.7460
2006	0.1593	0.0797
2007	0.2578	0.0087
2008	0.4587	0.0000
2009	0.2762	0.0054
2010	0.3010	0.0023
2011	0.2120	0.0298
2012	0.3551	0.0003
2013	0.3587	0.0004
2014	0.1776	0.0291
2015	0.3353	0.0008
2016	0.2823	0.0043

Note: This table displays Moran's I test results (Moran, 1950) for the spatial autocorrelation of regional natural gas price return of 48 states in the U.S. from 1997 to 2016.

Table 3: *The AIC values for different pairs of orders for the 48 states*

States	$p = q = 1$	$p = 1, q = 2$	$p = 2, q = 1$	$p = q = 2$
Alabama	-816.01	-812.88	-812.64	-811.09
Arizona	-895.42	-891.33	-893.46	-892.46
Arkansas	-524.64	-520.24	-526.02	-524.13
California	-472.52	-473.34	-469.58	-472.94
Colorado	-490.51	-488.34	-485.88	-487.22
Connecticut	-381.52	-382.56	-377.49	-380.80
Delaware	-488.04	-484.72	-490.36	-488.82
Florida	-801.50	-794.61	-794.57	-792.65
Georgia	-339.60	-344.10	-337.27	-342.21
Idaho	-958.52	-952.14	-952.89	-951.15
Illinois	-368.80	-366.12	-366.21	-364.22
Indiana	-307.95	-303.72	-312.52	-313.24
Iowa	-319.87	-316.17	-316.36	-320.40
Kansas	-440.02	-440.50	-441.05	-441.38
Kentucky	-543.71	-542.23	-561.66	-560.14
Louisiana	-573.12	-575.06	-571.32	-573.23
Maine	-366.91	-362.39	-363.10	-362.41
Maryland	-509.32	-509.04	-508.98	-508.88
Massachusetts	-396.49	-391.85	-395.65	-393.69
Michigan	-688.56	-681.71	-681.72	-679.74
Minnesota	-407.24	-415.90	-409.97	-414.07
Mississippi	-448.37	-451.81	-446.25	-450.19
Missouri	-683.83	-688.17	-690.54	-694.28
Montana	-528.90	-529.32	-529.27	-529.40
Nebraska	-462.39	-474.38	-462.43	-473.10
Nevada	-889.10	-886.07	-882.76	-884.19
New.Hampshire	-470.02	-472.30	-466.72	-471.46
New.Jersey	-310.45	-306.10	-305.42	-304.36
New.Mexico	-387.23	-399.91	-387.09	-402.98
New.York	-467.26	-466.70	-466.13	-469.95
North.Carolina	-577.54	-572.88	-574.06	-572.41
North.Dakota	-380.49	-377.06	-377.12	-375.35
Ohio	-572.81	-570.39	-570.42	-568.51
Oklahoma	-375.93	-374.50	-372.29	-374.80
Oregon	-682.83	-678.04	-678.01	-678.53
Pennsylvania	-672.05	-669.37	-669.55	-669.78
Rhode.Island	-545.84	-540.61	-539.77	-538.61
South.Carolina	-540.97	-536.36	-536.42	-534.53
South.Dakota	-382.68	-379.56	-379.36	-379.89
Tennessee	-572.07	-568.77	-570.95	-576.09
Texas	-468.81	-468.32	-468.70	-468.35
Utah	-636.50	-638.50	-631.13	-638.36
Vermont	-764.46	-757.86	-757.80	-755.98
Virginia	-635.56	-633.18	-633.52	-631.56
Washington	-764.25	-757.29	-759.43	-757.72
West.Virginia	-578.57	-575.79	-572.34	-575.92
Wisconsin	-348.33	-349.77	-348.38	-349.78
Wyoming	-521.61	-516.29	-524.60	-525.46

Table 4: *The estimation result for cointergration test*

	Estimate	Std. Error	t statistic	p-value
ϕ_0	-1.1322	0.1183	-9.5740	0.000
ϕ_1	0.7375	0.0327	22.5606	0.000
ϕ_2	-0.7987	0.0411	-19.4164	0.000

Note: This table displays the results of the estimation for the cointegration test by the method of Gregory and Hansen (1996), for the WTI crude oil and the Henry hub natural gas prices, in model (3.1).

Table 5: *The estimation results for the 0.1-level quantile*

States	$\alpha_1(s_i)$		$\lambda(s_i)$		$\beta(s_i)$		$\gamma(s_i)$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Alabama	0.1914	0.0008	-0.0133	0.8599	0.0593	0.6149	0.0132	0.5380
Arizona	-0.0329	0.3376	-0.0830	0.0008	-0.2458	0.0002	0.0177	0.3714
Arkansas	-0.1665	0.0951	0.4794	0.0142	-0.5564	0.0146	0.0949	0.0029
California	0.1413	0.3274	-0.1988	0.5083	0.1564	0.2517	0.0614	0.1971
Colorado	-0.1859	0.3577	0.6659	0.0126	-0.0148	0.9401	-0.0408	0.4211
Connecticut	0.3544	0.0465	0.3601	0.0741	-0.1187	0.3768	0.0224	0.6994
Delaware	-0.0665	0.4447	0.4796	0.0118	-0.0048	0.9786	-0.0330	0.4114
Florida	0.0991	0.0869	-0.0342	0.6430	-0.0121	0.8919	-0.0170	0.2575
Georgia	0.5325	0.0000	-0.2774	0.1200	0.0752	0.2845	0.0993	0.0143
Idaho	0.1145	0.0660	0.2008	0.1779	0.3982	0.0070	0.0166	0.2986
Illinois	0.1370	0.3476	0.3914	0.1080	0.1478	0.2631	0.0236	0.6623
Indiana	0.0721	0.7104	0.4953	0.0836	0.0315	0.8300	0.0469	0.4138
Iowa	0.1954	0.3817	0.0674	0.8232	-0.1023	0.6142	0.1137	0.0599
Kansas	0.0684	0.6699	0.5474	0.0254	0.3125	0.0590	-0.0226	0.7429
Kentucky	0.1123	0.2388	0.3324	0.1806	0.0839	0.6087	0.0544	0.0723
Louisiana	-0.0892	0.4094	0.4658	0.0355	-0.1621	0.3942	0.0283	0.5810
Maine	-0.1711	0.3877	0.1380	0.5984	0.0729	0.1327	0.0690	0.4768
Maryland	0.1533	0.1410	0.5032	0.0062	-0.2715	0.0307	0.0461	0.1010
Massachusetts	0.1191	0.4821	0.3839	0.1281	0.0757	0.5429	0.0483	0.3172
Michigan	0.0086	0.8989	0.1562	0.1946	0.3689	0.0037	-0.0090	0.7069
Minnesota	0.3219	0.0576	0.2803	0.1894	-0.2922	0.0640	-0.0302	0.5916
Mississippi	0.1193	0.4076	-0.1693	0.5260	-0.3215	0.0117	-0.0423	0.4090
Missouri	0.1766	0.1117	0.4208	0.0004	0.1781	0.2604	0.0333	0.2302
Montana	0.1047	0.2154	0.5221	0.0002	-0.2779	0.0026	0.0667	0.0524
Nebraska	0.2106	0.1766	-0.0646	0.7755	0.1558	0.3680	0.0502	0.3520
Nevada	0.0022	0.9502	0.0099	0.9445	0.1364	0.2809	0.0278	0.0890
New.Hampshire	-0.1064	0.2269	0.1205	0.3143	0.0299	0.8095	0.0792	0.0653
New.Jersey	0.2805	0.2323	-0.4261	0.0016	-0.3317	0.0000	-0.0620	0.3692
New.Mexico	0.1371	0.3886	0.2551	0.3067	-0.0840	0.5681	0.0685	0.0309
New.York	-0.0647	0.4655	0.1499	0.2910	0.0759	0.5197	0.0356	0.3146
North.Carolina	0.2135	0.0084	0.2924	0.0474	-0.2206	0.0343	-0.0059	0.8391
North.Dakota	0.1741	0.3531	0.6636	0.0521	-0.2428	0.3200	0.0317	0.5463
Ohio	0.1603	0.1905	0.6854	0.0067	-0.1356	0.4727	0.0429	0.2318
Oklahoma	0.2480	0.2680	1.0044	0.0042	0.3557	0.0671	0.0488	0.4510
Oregon	0.0279	0.8439	0.6836	0.0501	-0.2438	0.3050	-0.0117	0.8504
Pennsylvania	0.0094	0.9265	0.3589	0.0042	0.1179	0.4706	0.0590	0.0958
Rhode.Island	0.4488	0.0022	0.3276	0.0080	0.0470	0.7211	0.0068	0.8620
South.Carolina	0.0795	0.3834	-0.0040	0.9656	-0.3441	0.0004	-0.0245	0.4064
South.Dakota	0.5004	0.0015	0.6474	0.0055	-0.4369	0.0049	0.0373	0.4426
Tennessee	0.1421	0.3216	0.5875	0.0092	-0.2055	0.3458	0.0436	0.4362
Texas	0.3726	0.0082	0.2104	0.1891	-0.2353	0.0003	-0.0149	0.7840
Utah	-0.1413	0.1825	0.1954	0.3160	0.0664	0.6351	0.0207	0.6122
Vermont	-0.0315	0.7790	-0.0279	0.8280	0.2238	0.2688	0.0382	0.4272
Virginia	0.3624	0.0027	0.0933	0.6765	-0.1899	0.2643	0.0010	0.9812
Washington	0.1107	0.1084	0.3099	0.0336	-0.1949	0.0792	0.0798	0.0028
West.Virginia	-0.1568	0.0185	0.7239	0.0000	-0.0074	0.9237	0.0238	0.3633
Wisconsin	0.1098	0.6712	0.0232	0.9405	-0.1081	0.5886	0.0648	0.4867
Wyoming	0.1190	0.4375	0.4503	0.0413	-0.2835	0.1103	0.0774	0.0733

Table 6: *The estimation results for the 0.25-level quantile*

States	$\alpha_1(s_i)$		$\lambda(s_i)$		$\beta(s_i)$		$\gamma(s_i)$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Alabama	0.1237	0.0017	0.0402	0.3906	0.0323	0.6716	0.0184	0.1702
Arizona	0.0238	0.3079	-0.0394	0.2078	-0.0454	0.5112	0.0190	0.0609
Arkansas	-0.0488	0.3366	0.3957	0.0000	-0.3393	0.0000	0.0393	0.0176
California	0.0374	0.6677	-0.2523	0.2107	0.0740	0.4232	0.0784	0.0103
Colorado	-0.0391	0.6245	0.3033	0.0193	0.0880	0.2780	-0.0135	0.6081
Connecticut	0.1145	0.3260	0.1837	0.1239	0.0677	0.4441	0.0049	0.9019
Delaware	0.0740	0.2321	0.4757	0.0000	0.0545	0.4715	-0.0568	0.0173
Florida	0.0524	0.1972	0.0252	0.7111	0.1484	0.1329	-0.0142	0.3756
Georgia	0.2826	0.0102	-0.1757	0.3153	0.1306	0.0409	0.0491	0.0783
Idaho	0.0332	0.2921	0.1015	0.1511	0.0616	0.3238	0.0225	0.0279
Illinois	0.1422	0.1168	0.1902	0.2019	0.2941	0.0004	0.0517	0.1057
Indiana	0.0483	0.6694	0.1919	0.2488	-0.0670	0.4896	0.0552	0.1053
Iowa	0.1592	0.1489	0.3632	0.0458	-0.1197	0.2656	0.0280	0.3765
Kansas	0.1044	0.2864	0.3860	0.0014	0.1219	0.1421	0.0486	0.0703
Kentucky	0.1858	0.0096	0.5575	0.0001	-0.1480	0.1382	0.0490	0.0644
Louisiana	0.0185	0.8041	0.1010	0.3547	0.0433	0.6804	0.0025	0.9211
Maine	0.0459	0.4500	-0.0332	0.7148	0.0487	0.5385	0.0370	0.2969
Maryland	0.1512	0.0168	0.3365	0.0010	-0.1859	0.0116	0.0393	0.0680
Massachusetts	0.0262	0.7396	0.2439	0.0762	-0.0047	0.9463	0.0267	0.3775
Michigan	0.0232	0.6970	0.1358	0.1679	0.2352	0.0093	-0.0018	0.9272
Minnesota	0.0319	0.7561	0.0619	0.6337	-0.0437	0.6232	-0.0360	0.2441
Mississippi	0.0441	0.5881	-0.1657	0.2695	-0.1694	0.0170	-0.0250	0.3938
Missouri	0.0319	0.4912	0.5128	0.0000	0.0869	0.2006	0.0312	0.0131
Montana	0.0268	0.7291	0.4615	0.0000	-0.1241	0.2862	0.0519	0.0636
Nebraska	0.1040	0.1579	-0.0257	0.7405	0.0849	0.1278	0.0106	0.5132
Nevada	0.0342	0.4300	0.0384	0.7333	0.2144	0.0110	0.0297	0.0432
New.Hampshire	0.0728	0.4577	0.0617	0.0416	0.0625	0.5292	0.0433	0.1635
New.Jersey	0.0778	0.4742	-0.0209	0.9002	-0.1505	0.0124	0.0254	0.5133
New.Mexico	0.1624	0.0043	0.5294	0.0000	0.0557	0.3521	0.0278	0.3118
New.York	-0.0101	0.8911	0.0135	0.8589	0.1373	0.0504	0.0270	0.2603
North.Carolina	0.2067	0.0011	0.2572	0.0118	-0.2030	0.0162	0.0203	0.2995
North.Dakota	0.1971	0.0531	0.6120	0.0013	-0.2408	0.0963	0.0492	0.1595
Ohio	0.1850	0.0037	0.4187	0.0001	-0.1333	0.1000	0.0154	0.4491
Oklahoma	0.0665	0.5026	0.7923	0.0000	0.4135	0.0000	0.0183	0.5996
Oregon	0.0810	0.2010	0.4017	0.0065	-0.1404	0.0000	0.0256	0.2186
Pennsylvania	0.0958	0.0456	0.1812	0.0200	0.2006	0.0044	0.0348	0.0327
Rhode.Island	0.1926	0.0273	0.0474	0.4900	0.3996	0.0001	0.0123	0.6188
South.Carolina	0.1585	0.0210	-0.0375	0.3069	-0.0956	0.3443	-0.0046	0.8298
South.Dakota	0.0637	0.5151	0.4412	0.0089	-0.2811	0.0092	0.0395	0.1755
Tennessee	0.1202	0.0153	0.5782	0.0000	-0.2231	0.0015	0.0108	0.5639
Texas	0.1912	0.0106	0.1311	0.1909	-0.0508	0.4124	0.0176	0.4881
Utah	-0.1262	0.0116	0.2945	0.0010	-0.0475	0.5178	0.0166	0.3166
Vermont	0.0108	0.8208	0.0265	0.6929	0.1773	0.0110	0.0055	0.7259
Virginia	0.2691	0.0000	0.2030	0.0607	-0.1741	0.0389	0.0214	0.2821
Washington	0.0133	0.7725	0.1237	0.1335	-0.0539	0.4179	0.0333	0.0013
West.Virginia	-0.0532	0.0175	0.4900	0.0000	0.0693	0.0768	0.0350	0.0486
Wisconsin	0.1577	0.1011	0.1770	0.1259	-0.1057	0.1187	0.0468	0.1455
Wyoming	0.0831	0.3025	0.3477	0.0130	-0.1350	0.1610	0.0190	0.5160

Table 7: *The estimation results for the 0.5-level quantile*

States	$\alpha_1(s_i)$		$\lambda(s_i)$		$\beta(s_i)$		$\gamma(s_i)$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Alabama	0.0861	0.0118	0.1358	0.0001	0.0912	0.0718	0.0002	0.9856
Arizona	0.0085	0.7156	-0.0311	0.1919	-0.0237	0.5310	0.0204	0.0107
Arkansas	-0.0012	0.9824	0.2669	0.0026	-0.1268	0.0131	0.0283	0.1052
California	0.0948	0.2455	-0.3009	0.0897	-0.0503	0.5392	0.0761	0.0053
Colorado	-0.0179	0.7976	0.3204	0.0022	-0.0436	0.5203	0.0318	0.1931
Connecticut	0.2739	0.0001	0.2360	0.0094	-0.0232	0.6787	0.0344	0.1861
Delaware	0.0087	0.8884	0.3761	0.0000	0.1099	0.1450	0.0069	0.7067
Florida	0.0260	0.4388	0.0334	0.0175	0.2123	0.0016	0.0036	0.6683
Georgia	0.2406	0.0069	-0.0812	0.5097	0.0621	0.0020	0.0362	0.2023
Idaho	0.0089	0.5420	0.0491	0.0799	0.1377	0.0000	0.0087	0.0256
Illinois	0.1827	0.0337	0.1413	0.3306	0.3551	0.0000	0.0390	0.1783
Indiana	0.0225	0.8250	0.0117	0.9399	0.0309	0.7410	0.0678	0.0510
Iowa	0.1014	0.3454	0.3178	0.0692	-0.2146	0.0106	0.0480	0.1793
Kansas	0.0989	0.1918	0.2416	0.0479	0.1597	0.0760	0.0123	0.6150
Kentucky	0.1281	0.0357	0.4667	0.0000	0.0179	0.8022	0.0189	0.3713
Louisiana	0.0223	0.6666	0.0296	0.6881	0.1327	0.0523	-0.0057	0.7474
Maine	0.0442	0.3907	0.0100	0.8208	0.0313	0.5310	0.0055	0.7158
Maryland	0.1713	0.0187	0.4282	0.0007	-0.1852	0.0251	0.0249	0.3076
Massachusetts	0.0542	0.4830	0.2778	0.0241	-0.0817	0.1299	0.0263	0.3351
Michigan	0.0322	0.3634	0.0771	0.2619	0.3994	0.0000	0.0121	0.4269
Minnesota	0.0649	0.2863	0.0259	0.7957	-0.0175	0.7652	0.0145	0.4801
Mississippi	0.1080	0.0703	-0.1619	0.1989	-0.1881	0.0016	0.0190	0.4433
Missouri	0.0674	0.1374	0.6063	0.0000	-0.0194	0.7373	0.0078	0.5717
Montana	0.0558	0.2777	0.3216	0.0000	-0.0310	0.4706	0.0014	0.9396
Nebraska	0.0269	0.7205	-0.0024	0.9778	0.1229	0.0369	0.0403	0.0142
Nevada	-0.0053	0.7830	0.0662	0.2021	0.1353	0.0015	0.0074	0.2312
New.Hampshire	0.0718	0.1621	0.0257	0.7090	-0.0364	0.5567	0.0196	0.3839
New.Jersey	0.1533	0.0000	0.0248	0.7653	-0.1322	0.0014	0.0098	0.6718
New.Mexico	0.2136	0.0044	0.4460	0.0000	0.0346	0.5178	0.0217	0.3890
New.York	0.0420	0.5158	0.0247	0.7518	0.1883	0.0061	0.0141	0.5431
North.Carolina	0.0944	0.1185	0.3188	0.0003	-0.1323	0.0734	0.0398	0.0288
North.Dakota	0.0797	0.3421	0.3720	0.0048	-0.1434	0.1128	0.0492	0.0716
Ohio	0.1366	0.0165	0.4512	0.0000	-0.0519	0.3163	0.0168	0.3517
Oklahoma	-0.0180	0.8006	0.6902	0.0000	0.2081	0.0002	0.0278	0.1140
Oregon	0.0266	0.3633	0.2048	0.0168	-0.1154	0.0000	0.0188	0.0519
Pennsylvania	0.0667	0.1564	0.2074	0.0016	0.0949	0.1411	0.0124	0.4310
Rhode.Island	0.1108	0.0000	-0.0083	0.8401	0.3379	0.0000	-0.0001	0.9958
South.Carolina	0.0267	0.6078	-0.0275	0.2156	-0.1358	0.0067	0.0288	0.0906
South.Dakota	0.0746	0.3574	0.3300	0.0262	-0.2408	0.0165	-0.0067	0.8230
Tennessee	0.1658	0.0022	0.4888	0.0000	-0.1787	0.0003	0.0467	0.0048
Texas	0.1621	0.0233	0.1151	0.2331	-0.1874	0.0062	0.0279	0.2620
Utah	-0.0234	0.5618	0.2007	0.0015	-0.0795	0.1071	0.0245	0.0913
Vermont	-0.0014	0.9442	0.0216	0.3702	0.2085	0.0000	0.0042	0.5464
Virginia	0.1246	0.0204	0.2747	0.0026	-0.0825	0.2312	0.0148	0.4183
Washington	0.0064	0.7741	0.0520	0.1471	0.0061	0.8707	0.0070	0.3621
West.Virginia	0.0475	0.2413	0.3314	0.0000	0.0171	0.4178	0.0093	0.5314
Wisconsin	0.0422	0.6520	0.0313	0.7947	-0.2231	0.0002	0.0152	0.6023
Wyoming	0.0238	0.6181	0.4913	0.0000	-0.1731	0.0007	0.0264	0.0998

Table 8: *The estimation results for the 0.75-level quantile*

States	$\alpha_1(s_i)$		$\lambda(s_i)$		$\beta(s_i)$		$\gamma(s_i)$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Alabama	0.1063	0.0041	0.2007	0.0000	0.0504	0.3989	0.0059	0.6460
Arizona	-0.0169	0.5139	-0.0290	0.2327	-0.0127	0.8332	0.0259	0.0032
Arkansas	0.0330	0.5879	0.2323	0.0270	-0.0946	0.1448	0.0405	0.0746
California	0.0915	0.2334	-0.1539	0.3484	-0.0567	0.4586	0.0539	0.0292
Colorado	-0.0848	0.1471	0.4092	0.0000	-0.0426	0.5093	0.0216	0.2204
Connecticut	0.3543	0.0015	0.3865	0.0007	-0.1497	0.0671	-0.0222	0.5104
Delaware	0.0386	0.5299	0.1889	0.0000	0.1017	0.0148	0.0495	0.0007
Florida	0.0570	0.0611	0.0023	0.9115	0.2252	0.0012	0.0293	0.0321
Georgia	0.3489	0.0000	-0.3363	0.0322	0.0685	0.3717	0.0400	0.1891
Idaho	0.0242	0.3942	0.0738	0.0280	0.1767	0.0037	0.0069	0.5077
Illinois	0.0746	0.4769	0.1230	0.4851	0.4018	0.0000	0.0342	0.2864
Indiana	0.2114	0.0082	0.2057	0.2126	-0.0908	0.3060	0.0979	0.0002
Iowa	0.0553	0.5948	0.4489	0.0076	-0.2497	0.0021	-0.0306	0.3284
Kansas	0.1603	0.1194	0.5083	0.0006	-0.0841	0.4815	0.0364	0.2953
Kentucky	0.1526	0.0193	0.6530	0.0000	-0.0809	0.3256	0.0422	0.0666
Louisiana	0.0115	0.8547	0.1686	0.0827	0.0432	0.6342	0.0048	0.8350
Maine	-0.0589	0.4764	-0.0908	0.2208	-0.0013	0.9874	-0.0159	0.5789
Maryland	0.1006	0.2672	0.1396	0.3613	-0.1605	0.1068	0.0655	0.0295
Massachusetts	0.0402	0.7114	0.2737	0.0565	-0.0766	0.2195	0.0622	0.0710
Michigan	0.0586	0.2959	0.1563	0.1052	0.4035	0.0000	0.0335	0.0926
Minnesota	0.3112	0.0006	0.1559	0.1301	-0.1695	0.0205	0.0528	0.0018
Mississippi	0.2064	0.0028	0.0140	0.9324	-0.2165	0.0000	0.0029	0.8802
Missouri	0.0563	0.1922	0.6197	0.0000	-0.0130	0.7958	-0.0093	0.4964
Montana	0.0429	0.4328	0.3857	0.0000	-0.1406	0.1253	0.0389	0.0585
Nebraska	0.0279	0.7736	0.0119	0.9248	0.0120	0.8842	0.0966	0.0028
Nevada	-0.0233	0.4236	-0.0054	0.9425	0.1299	0.0452	0.0039	0.6962
New.Hampshire	0.1007	0.2590	-0.0255	0.5261	-0.0690	0.3277	0.0194	0.4793
New.Jersey	0.2910	0.0025	0.0158	0.9095	-0.1055	0.3249	0.0766	0.0490
New.Mexico	0.1791	0.0131	0.4190	0.0000	0.0768	0.1886	0.0168	0.3559
New.York	0.0108	0.8744	0.1429	0.1828	0.0556	0.4526	-0.0341	0.1721
North.Carolina	-0.0023	0.9724	0.2137	0.0284	-0.1291	0.1343	0.0580	0.0120
North.Dakota	0.1446	0.2026	0.3753	0.0408	-0.2215	0.0752	0.0294	0.4353
Ohio	0.0898	0.1851	0.4524	0.0000	0.0650	0.2426	-0.0013	0.9286
Oklahoma	0.0822	0.2953	0.6077	0.0000	0.2282	0.0006	0.0025	0.9258
Oregon	0.0353	0.4096	0.2684	0.0987	-0.2121	0.0422	0.0167	0.3483
Pennsylvania	0.0072	0.8820	0.1586	0.0348	0.1273	0.0840	0.0202	0.2583
Rhode.Island	0.1673	0.0050	-0.0508	0.4962	0.2137	0.0029	0.0376	0.0921
South.Carolina	0.0142	0.8331	-0.0232	0.5143	-0.0764	0.4855	0.0570	0.0309
South.Dakota	-0.0723	0.5165	0.3000	0.1113	-0.2082	0.0681	-0.0119	0.7405
Tennessee	0.1070	0.1455	0.5604	0.0000	-0.1977	0.0155	0.0571	0.0090
Texas	0.3316	0.0000	0.2153	0.0434	-0.3340	0.0001	0.0487	0.1016
Utah	-0.0106	0.8489	0.2698	0.0007	0.0552	0.4812	0.0321	0.1630
Vermont	-0.0140	0.8078	0.0163	0.8023	0.2820	0.0000	0.0143	0.3965
Virginia	0.1063	0.0256	0.3506	0.0009	-0.1003	0.0768	0.0383	0.0183
Washington	-0.0064	0.8865	0.1478	0.2473	-0.0346	0.6630	0.0128	0.3980
West.Virginia	0.0364	0.4311	0.4244	0.0000	-0.0089	0.9221	-0.0033	0.8454
Wisconsin	0.0938	0.3436	-0.0347	0.7386	-0.2889	0.0000	0.0495	0.0250
Wyoming	-0.0530	0.5286	0.5072	0.0001	-0.1243	0.1116	0.0403	0.1657

Table 9: *The estimation results for the 0.9-level quantile*

States	$\alpha_1(s_i)$		$\lambda(s_i)$		$\beta(s_i)$		$\gamma(s_i)$	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
Alabama	0.1330	0.0162	0.2023	0.0077	0.0784	0.4995	0.0228	0.3069
Arizona	-0.1222	0.1628	0.0046	0.9598	-0.1131	0.6131	0.0522	0.1434
Arkansas	0.0385	0.7385	0.2089	0.0819	-0.1323	0.0953	0.0728	0.0054
California	-0.0268	0.8540	-0.0436	0.8974	-0.2262	0.1312	0.0895	0.0828
Colorado	0.1369	0.1371	0.3460	0.0020	-0.1436	0.2104	0.0491	0.0422
Connecticut	0.1445	0.4037	0.3867	0.0364	-0.3058	0.0075	0.0119	0.8448
Delaware	0.1662	0.0903	0.2877	0.1374	-0.2237	0.2560	0.0764	0.1048
Florida	0.0980	0.1239	-0.0195	0.7964	0.2950	0.1368	0.0554	0.0327
Georgia	0.5685	0.0005	-0.5558	0.1772	-0.0669	0.6576	0.0495	0.5025
Idaho	0.0912	0.1004	0.1914	0.1137	0.1870	0.2078	0.0047	0.7933
Illinois	-0.0854	0.7364	-0.0740	0.8655	0.5816	0.0224	0.0528	0.5615
Indiana	0.2482	0.1989	0.2118	0.4316	-0.1484	0.2938	0.0373	0.4344
Iowa	-0.1904	0.2013	0.4494	0.0129	-0.3016	0.0021	-0.0885	0.0175
Kansas	0.1240	0.1530	0.6569	0.0000	-0.1688	0.1309	0.0129	0.3678
Kentucky	0.2501	0.0122	0.8734	0.0000	-0.1907	0.1754	0.0337	0.3823
Louisiana	-0.0811	0.4858	0.3712	0.0065	0.0749	0.5212	0.0117	0.7215
Maine	-0.0963	0.7614	-0.2578	0.2433	-0.0376	0.6921	0.0556	0.4640
Maryland	0.0917	0.4723	0.1695	0.4102	-0.1702	0.2196	0.0440	0.3188
Massachusetts	0.1637	0.2512	-0.0609	0.8065	-0.2320	0.0320	0.0892	0.1019
Michigan	0.1058	0.0443	0.1248	0.1952	0.4270	0.0000	0.0199	0.3071
Minnesota	0.3022	0.0388	0.0978	0.6410	-0.2612	0.0864	0.1236	0.0165
Mississippi	0.2070	0.2204	0.4144	0.0861	-0.5015	0.0003	0.0979	0.0755
Missouri	0.0057	0.9621	0.5989	0.0004	-0.0896	0.6572	-0.0350	0.2927
Montana	0.1018	0.2886	0.4829	0.0000	-0.3116	0.0991	0.0316	0.1745
Nebraska	-0.0252	0.7484	-0.1518	0.2672	0.0533	0.4038	0.0789	0.0040
Nevada	-0.0164	0.8613	0.1852	0.4354	0.1201	0.4375	0.0008	0.9815
New.Hampshire	0.0600	0.4660	-0.1226	0.2916	-0.2844	0.0133	0.0638	0.0340
New.Jersey	0.4243	0.0000	0.1962	0.5790	-0.2113	0.4189	0.0411	0.6741
New.Mexico	0.0573	0.7944	0.3765	0.1529	-0.0840	0.6172	-0.1151	0.0749
New.York	0.2479	0.0076	0.0220	0.9048	0.1372	0.4533	-0.0436	0.1982
North.Carolina	-0.0438	0.6703	0.3619	0.0199	-0.1193	0.3907	0.0609	0.0963
North.Dakota	0.1380	0.5196	0.1611	0.6417	-0.2048	0.3537	-0.0062	0.9300
Ohio	0.0776	0.0590	0.4413	0.0031	0.1422	0.1195	-0.0802	0.0059
Oklahoma	0.1037	0.5261	0.5630	0.0522	0.2593	0.0087	0.0258	0.7184
Oregon	0.0615	0.4317	-0.2528	0.0376	-0.3240	0.0200	0.0312	0.2368
Pennsylvania	0.0372	0.3538	0.2652	0.0300	0.0851	0.3955	0.0086	0.7204
Rhode.Island	0.1337	0.3651	-0.0306	0.8288	0.1794	0.1239	0.0135	0.7326
South.Carolina	-0.1071	0.5250	-0.0613	0.2600	0.0180	0.9231	0.1283	0.0304
South.Dakota	-0.1342	0.4623	0.2513	0.2709	-0.3430	0.0044	-0.0164	0.7326
Tennessee	0.1547	0.1689	0.6158	0.0044	-0.3265	0.0167	0.0331	0.3992
Texas	0.2617	0.0211	0.1128	0.4063	-0.3229	0.0007	0.0978	0.0001
Utah	0.0268	0.7962	0.3861	0.0141	-0.0486	0.6833	0.0393	0.3298
Vermont	-0.1869	0.1080	-0.0233	0.7716	-0.0609	0.5245	0.0005	0.9885
Virginia	0.1377	0.0769	0.3175	0.0079	-0.2448	0.0397	0.0602	0.0164
Washington	-0.0566	0.6226	0.3516	0.0695	-0.3005	0.0277	0.0081	0.8024
West.Virginia	0.1499	0.0751	0.6623	0.0000	-0.2540	0.1725	-0.0096	0.7802
Wisconsin	0.0373	0.8258	0.0487	0.8145	-0.4502	0.0016	0.1215	0.0398
Wyoming	-0.0674	0.6965	0.5786	0.0228	-0.2924	0.1468	0.0548	0.3489

Table 10: *The Wald tests for the equality of slopes*

State		$\lambda(s_i)$			$\beta(s_i)$			$\alpha_1(s_i)$			$\gamma(s_i)$	
	0.1 vs 0.5	0.1 vs 0.9	0.5 vs 0.9	0.1 vs 0.5	0.1 vs 0.9	0.5 vs 0.9	0.1 vs 0.5	0.1 vs 0.9	0.5 vs 0.9	0.1 vs 0.5	0.1 vs 0.9	0.5 vs 0.9
Alabama	0.041	0.033	0.371	0.779	0.903	0.909	0.058	0.434	0.396	0.531	0.743	0.297
Colorado	0.173	0.246	0.840	0.876	0.552	0.378	0.381	0.132	0.107	0.135	0.094	0.541
Connecticut	0.515	0.918	0.393	0.452	0.261	0.010	0.632	0.369	0.434	0.827	0.894	0.695
Georgia	0.278	0.518	0.222	0.843	0.372	0.377	0.015	0.849	0.038	0.132	0.536	0.849
New.Mexico	0.428	0.724	0.780	0.394	1.000	0.456	0.616	0.757	0.451	0.208	0.009	0.025
Ohio	0.325	0.378	0.948	0.645	0.167	0.031	0.839	0.510	0.337	0.451	0.005	0.001
Oklahoma	0.343	0.301	0.645	0.420	0.644	0.603	0.209	0.583	0.434	0.735	0.801	0.976
Oregon	0.147	0.009	0.000	0.576	0.759	0.115	0.992	0.828	0.636	0.609	0.507	0.616
Pennsylvania	0.210	0.569	0.623	0.882	0.857	0.922	0.555	0.794	0.595	0.167	0.213	0.873
Tennessee	0.643	0.923	0.533	0.898	0.620	0.251	0.861	0.942	0.917	0.954	0.871	0.719
Texas	0.546	0.623	0.987	0.585	0.429	0.161	0.119	0.515	0.373	0.411	0.053	0.019
West.Virginia	0.003	0.739	0.013	0.742	0.203	0.134	0.002	0.003	0.203	0.573	0.413	0.563
Wyoming	0.844	0.686	0.715	0.513	0.972	0.533	0.512	0.393	0.577	0.213	0.743	0.609

Note: This table displays the results of the Wald tests (p-value) for the equality of slopes (0.1 against 0.5 and 0.9 quantiles) in some typical states.

Highlights

1. We analyze market integration of the state-level natural gas markets in the USA.
2. A novel spatio-temporal quantile model is used to examine spatial dynamic linkages.
3. The effects of crude oil market exhibit significant differences across quantiles.
4. Significantly heterogeneous spatial neighbouring effects exist in the USA.