Australian National University

Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Understanding the US Natural Gas Market: A Markov Switching VAR Approach

CAMA Working Paper 14/2018
April 2018

Chenghan Hou
Center for Economics, Finance and Management Studies, Hunan University, China

Bao H. Nguyen
School of Economics, University of Economics Ho Chi Minh City (UEH), Vietnam
Development Policy Centre, Crawford School of Public Policy, ANU
Centre for Applied Macroeconomic Analysis, ANU

Abstract

Over the past three decades, the US natural gas market has witnessed significant changes. Utilizing a standard Bayesian model comparison method, this paper formally determines four regimes existing in the market. It then employs a Markov switching vector autoregressive model to investigate the regime-dependent responses of the market to its fundamental shocks. The results reveal that the US natural gas market tends to be much more sensitive to shocks occurring in regimes existing after the Decontrol Act 1989 than the other regimes. The paper also finds that shocks to the natural gas demand and price have negligible effects on natural gas production while the price of natural gas is mainly driven by specific demand shocks. Augmenting the model by incorporating the price of crude oil, the results show that the impacts of oil price shocks on natural gas prices are relatively small and regime-dependent.

Electronic copy available at: https://ssrn.com/abstract=3156000

Keywords

Natural gas market, Bayesian model comparison, Markov Switching VAR model.

JEL Classification

C32,E32,Q4

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Electronic copy available at: https://ssrn.com/abstract=3156000

Understanding the U.S. Natural Gas Market: A Markov Switching VAR Approach

Chenghan Hou* Bao H. Nguyen†

March 27, 2018

Abstract

Over the past three decades, the US natural gas market has witnessed significant changes. Utilizing a standard Bayesian model comparison method, this paper formally determines four regimes existing in the market. It then employs a Markov switching vector autoregressive model to investigate the regime-dependent responses of the market to its fundamental shocks. The results reveal that the US natural gas market tends to be much more sensitive to shocks occurring in regimes existing after the Decontrol Act 1989 than the other regimes. The paper also finds that shocks to the natural gas demand and price have negligible effects on natural gas production while the price of natural gas is mainly driven by specific demand shocks. Augmenting the model by incorporating the price of crude oil, the results show that the impacts of oil price shocks on natural gas prices are relatively small and regime-dependent.

JEL-codes: C32,E32,Q4

Keywords: Natural gas market, Bayesian model comparison, Markov Switching VAR model.

*Center for Economics, Finance and Management Studies, Hunan University, China. Email: chenghan.hou@hotmail.com

†Development Policy Centre, Crawford School of Public Policy, Australian National University, Australia and School of Economics, University of Economics Ho Chi Minh City (UEH), Vietnam. Email: bao.nguyen@anu.edu.au

Electronic copy available at: https://ssrn.com/abstract=3156000

1 Introduction

Over the past three decades, the United States (US) has witnessed significant changes in the structure of the natural gas market. Table 1 provides a clear picture of the changes. With regard to the supply side, in the past natural gas was mainly extracted from gas wells and this conventional form accounted for 79 percent of total supplies. However, in recent years, natural gas production has been replaced by unconventional forms. In particular, products found in shale gas and coalbed wells have gradually became the major source of the gas market. By 2016, 48 percent of total natural gas production was supplied the unconventional forms. These changes would not have been realized without a period of deregulation introduced to the market, such as the Natural Gas Wellhead Decontrol Act of 1989. Although such deregulation has often focused on price mechanisms and the supply side of the natural gas market, significant changes have also taken place on the demand side. As can be seen from the table, while commercial and residential users have remained as major users, with more than 50 percent of the market share, expenditure from electric generators has increased dramatically, accounting for more than one third of total natural gas consumption.

A common approach in empirical work on natural gas markets, or natural gas prices in particular, is often based on the investigation of the relationship between the price of natural gas and the price of crude oil, rather than exploring how the natural gas market actually works. This approach, therefore, ignores the possibility of structure changes, which is likely to exist in the US natural gas market as we just discussed. More importantly, it also ignores the structural interactions between underlying market fundamental factors, e.g supply and demand shocks. Consequently, previous studies tend to provide conflicting evidence. Some studies, for example, Pindyck (2004), Brown and Yücel (2008), Brigida (2014) Zamani (2016), and Jadidzadeh and Serletis (2017) find that movements in crude oil prices have played a key role in shaping natural gas prices. In contrast, other studies conclude that there is a very weak or no connection between the crude oil prices and natural gas prices (Serletis and Rangel-Ruiz, 2004; Bachmeier and Griffin, 2006; Ramberg and Parsons, 2012). The common feature of these investigations is that they do not capture the possible regime shifts in the natural gas market or allow for changes in natural gas demand and production as endogenous. Brigida (2014), for example, relying on an error correction model, finds that regime-switching exists in the relationship between oil and natural gas prices but does not further investigate the underlying sources of the shift. Jadidzadeh and Serletis (2017) study the reactions of natural gas prices to shocks stemming from the global crude oil market based on a linear VAR model, which implicitly assumes that reactions of the natural gas price are time-invariant.

This paper departs from the traditional literature by explicitly allowing structural changes in the US natural gas market and treating market fundamental disturbances as endogenous shocks. To that end, we first utilize a standard Bayesian model comparison to determine the number of regime existing in the market. It then makes use the advantage of the Markov switching vector autoregressive model (MS-VAR) to capture possible structural shifts. The novelty in applying this econometric framework lies in the two main important features of the MS-VAR model. First, the MS-VAR model does not restrict the size of the change when a structural break occurs, but it often assumes a small number of in-sample breaks. Hence, if the data does not favour a large number of regimes, the MS-VAR model seems to be a natural choice (Sims et al., 2008). In addition, the Markov switching models allow for regime recurrence. This feature is not assumed in the traditional structural break models. Allowing the regime recurrence does not only tend to improve the estimation accuracy but also helps us to understand more about the interrelationship among the detected regimes. Finally, following the seminal work of Kilian (2009), our benchmark specification includes three market fundamentals: natural gas production, a proxy for the demand for natural gas, and the price of natural gas. This specification allows us to disentangle three different types of structural shocks that would result from: (1) supply shocks caused by exogenous disruptions in US natural gas production; (2) demand shocks driven by unpredicted changes in US economic activity; and (3) specific demand shocks that could be associated with speculative or precautionary motives.

We contribute to the literature in the following ways. First, this is the first paper conducting a formal Bayesian model comparison exercise to determine whether there are regime changes in the US natural gas market and how many regimes we should select to improve the model in-sample fit. Second, we investigate whether regime recurrence occurs in the US natural gas market by employing a heat-map plot. Third, we further investigate and compare the transmission mechanism of the regime-dependent responses of natural gas market to fundamental shocks. Finally, this paper also extends the analysis by examining how the US natural gas market reacts to the disturbances of oil prices in the context of regime shifts.

The main findings of the paper are as follows. First, our Bayesian model comparison exercise provides strong empirical evidence supporting the existence of four regimes in the US natural gas market over the last three decades. Second, the paper finds that the US natural gas market tends to be much more sensitive to shocks occurring in the regimes existing after the Decontrol Act 1989 than those in the other regimes. Third, the paper also finds that shocks to the natural gas demand and price have negligible effects on natural gas production while the price of natural gas is mainly driven by specific demand shocks. Finally, augmenting the model by incorporating the price of crude oil, the results show that the impacts of oil price shocks on natural gas prices are relatively small and regime-dependent.

The remainder of the paper is organized as follows. Section 2 outlines the econometric methodology, including the model specification and discussion of the identification. Next, Section 3 provides a brief overview of the regulation changes and the pricing of the U.S. natural gas market. Section 4 discusses the data used in the paper. Sections 5 then presents the results, including model comparisons, regime characteristics and impulse response functions. Finally, Section 6 concludes the paper.

2 Empirical methodology

As highlighted in the introduction, the MS-VAR modelling framework has important features that can capture well the typical properties of the natural gas market as compared to its competitors. In general, there are three common methods that can be applied to detect the regime switching. The first method is that we can simply split the sample estimation into different subsamples and test whether there is a structural break. For example, to study the volatility of oil price shocks and the effectiveness of monetary policy, Blanchard and Gali (2008) and Nakov and Pescatori (2010) set a particular point in time (1984) as a break point. With this traditional method, we have to accept the assumption that all model parameters change at the same time, which is not necessarily the case. More importantly, prior knowledge is often required for determining the break date, which is likely to incur an issue of model misspecification (Boivin, 2006).

Another method often used to study the strcutrual instability in the literature is the threshold models. This class of models allows for discrete shifts in the model parameters, like the MS-VAR model, but the researcher has to specify a threshold value or transition variable.[1] Recent examples of this approach in the energy literature include Rahman and Serletis (2010) and Nguyen and Okimoto (2017). Unlike threshold models, the number of regime changes detected by the MS-VAR model is based on a latent Markov process which is directly estimated from data. In other words, the main advantage of the MS-VAR model over threshold models is that the researcher needs not to predetermine the threshold value or transition variable before estimation.

The third popular approach in the literature is the time-varying parameter model. This class of non-linear models has been widely used in studying the relationship be-

[1] Recent surveys of this literature can be found in Hubrich and Teräsvirta (2013) and Teräsvirta et al. (2014).

tween macroeconomic variables (Primiceri, 2005; Cogley and Sargent, 2005; Clark and Ravazzolo, 2015; Chan and Eisenstat, 2018) and recently found to perform well in studying energy market (Baumeister and Peersman, 2013; Cross and Nguyen, 2017; Nguyen and Cross, 2017). The time-varying parameter model possesses many nice features that allows it to suited well for modelling gradually changing relationship among the variables of interest. However, the changes in economic structure, like those in the US natural gas market, may not always shift gradually. For example, regulations and technology constraints on production and transmission in the natural gas market are likely to change drastically. In this case, we believe that the MS-VAR model serves as an appropriate tool for modelling the structural instability.

The theory and practice of the MS-VAR model were laid out by Krolzig (1997) who generalized the univariate MS model proposed by Hamilton (1989). Since then, many types of the MS-VAR model have been developed and refined by Rubio-Ramirez et al. (2005); Sims and Zha (2006); Sims et al. (2008); Hubrich and Tetlow (2015), Hou (2017) and Chang et al. (2017). As with these studies, we adopt a sufficiently rich set of the MS-VAR model to capture the number of regime changes in the US natural gas market and use its structural form to investigate the responses of the market to its market fundamental shocks.

2.1 Model

In the spirit of the global crude oil model proposed by Kilian (2009), the US natural gas market is modelled by employing a three-variable MS-VAR model.[2] These variables include the percentage change in the US natural gas production $\Delta prod$, the percentage change in US real economic activity Δip, and the percentage change in the real price of US natural gas Δrpg. Let $\mathbf{y}_t = (\Delta prod_t, \Delta ip_t, \Delta rpg_t)\prime$ be a 3×1 vector of observation at time t. To be specific, the structural representation of the M-states MS-VAR can be expressed as

$$\mathbf{B}_{0,s_t}\mathbf{y}_t = \mathbf{b}_{s_t} + \mathbf{B}_{1,s_t}\mathbf{y}_{t-1} + \cdots + \mathbf{B}_{p,s_t}\mathbf{y}_{t-p} + \boldsymbol{e}_t, \quad \boldsymbol{e}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}_{s_t}), \tag{1}$$

[2] Kilian (2009) employs a three-variable recursive VAR model consisting of global crude oil production, real global economic activity and real price of crude oil to investigate the effects of demand and supply shocks in the crude oil market. We also note that, while Kilian (2009) use real global economic activity to proxy the movements of global demand for crude oil, we use real US industrial production to capture the fluctuations of demand for the US market. This reflects the fact that, different from oil markets, natural gas markets are not global. Natural gas prices are mainly determined by regional supply and demand.

where $\boldsymbol{e}_t$ is the structural error term which follows a Gaussian distribution with diagonal covariance matrix $\boldsymbol{\Omega}_{s_t}$ at time t. The reduced form of the model can be obtained by premultiplying $\mathbf{B}_{0,s_t}^{-1}$ to both side of (1):

$$\mathbf{y}_t = \mathbf{c}_{s_t} + \mathbf{A}_{1,s_t}\mathbf{y}_{t-1} + \cdots + \mathbf{A}_{p,s_t}\mathbf{y}_{t-p} + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{s_t}), \tag{2}$$

where $\mathbf{c}_{s_t} = \mathbf{B}_{0,s_t}^{-1}\mathbf{b}_{s_t}$ is an 3×1 time-varying intercepts, $\mathbf{A}_{i,s_t} = \mathbf{B}_{0,s_t}^{-1}\mathbf{B}_{i,s_t}, i = 1, \ldots, p$, are 3×3 VAR coefficient matrices at time t. The covariance matrix for reduce-form error $\boldsymbol{\epsilon}_t = \mathbf{B}_{0,s_t}^{-1}\boldsymbol{e}_t$ can be decomposed as $\boldsymbol{\Sigma}_{s_t} = \mathbf{B}_{0,s_t}^{-1}\boldsymbol{\Omega}_{s_t}\mathbf{B}_{0,s_t}^{-1\prime}$. We postpone a more detailed discussion about the matrix $\mathbf{B}_{0,s_t}$ in Section 2.2. The regime indicator variable s_t is assumed to follow a M-state Markov process with transition probabilities $Pr(s_t = j|s_{t-1} = i) = p_{ij}$, $i, j = 1, \ldots, M$. Compactly, we can rewrite equation (2) as:

$$\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\beta}_{s_t} + \boldsymbol{\epsilon}_t \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_{s_t}),$$

where $\boldsymbol{\beta}_{s_t} = \mathrm{vec}\left((\mathbf{c}_{s_t}, \mathbf{A}_{1,s_t}, \ldots, \mathbf{A}_{p,s_t})'\right)$ is $k_\beta \times 1$ a $k_\beta = 3(3p+1)$ vector of VAR coefficients and $\mathbf{X}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, \ldots, \mathbf{y}'_{t-p})$. The VAR coefficients, $\boldsymbol{\beta}_{s_t}$, and covariance, $\boldsymbol{\Sigma}_{s_t}$, are allowed to be changing over time and the dynamics of these time-varying parameters are governed by the regime indicator variable $s_t \in \{1, \ldots, M\}$.

To complete the model specification, we assume the following independent prior for the model parameters:

$$\boldsymbol{\beta}_i \sim \mathcal{N}(\boldsymbol{\beta}_0, \mathbf{V}_0), \quad \boldsymbol{\Sigma}_i \sim \mathcal{IW}(\mathbf{S}_0, \nu_0), \quad \text{for } i = 1, \ldots, M,$$

where $\mathcal{IW}(\mathbf{S}, \nu)$ denotes the Inverse Wishart distribution with scale matrix $\mathbf{S}$ and the degree of freedom ν. For the regime transition probability, we assume

$$(p_{i1}, \ldots, p_{iM}) \sim \mathcal{D}(\alpha_{i1}, \ldots, \alpha_{iM}), \quad \text{for } i = 1, \ldots, M,$$

where $\mathcal{D}(a_1, \ldots, a_M)$ denotes the Dirichlet distribution with concentration parameters $(a_1, \ldots, a_M)$ which implies the prior mean $\mathbb{E}(p_{i1}, \ldots, p_{iM}) = (\frac{\alpha_{i1}}{\sum_{j=1}^M \alpha_{j1}}, \ldots, \frac{\alpha_{iM}}{\sum_{j=1}^M \alpha_{j1}})$. As many time series data have been evolving with high persistence, frequently switching among regimes over time is empirical implausible. We incorporate this feature by imposing an informative prior on the regime transition probability. In particular, we assume

$$\begin{pmatrix} \alpha_{11} & \alpha_{12} & \ldots & \alpha_{1M} \\ \alpha_{21} & \alpha_{22} & \ldots & \alpha_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{M1} & \alpha_{M2} & \ldots & \alpha_{MM} \end{pmatrix} = \mathbf{1}_M + \rho\mathbf{I}_M,$$

where $\mathbf{1}_M$ is a $M \times M$ matrix with its entries all equal to one.

The $\rho > 0$ is the parameter that control the degree of the regime persistence. To see this, it can be verified that the expected value of probability for two subsequent periods belonging in the same regime is $\mathbb{E}(p_{ii}) = \frac{1+\rho}{\rho+M}$, which implies that a higher value of ρ indicates a high regime persistence. We follow Nguyen and Okimoto (2017) by setting $p = 6$ as the lag length of the model. The regime persistence parameter ρ and the number of regime M are of particular interest in our empirical study. To this end, we select the values for these two parameters through a formal Bayesian model comparison exercise in Section 5.1. More details about the priors are provided in the Appendix B.

2.2 Identification

The structural shocks can be recovered from the reduced-form shocks through the relation $\boldsymbol{\epsilon}_t = \mathbf{B}_{0,s_t}^{-1}\mathbf{e}_t$. In this paper, we identify the structural shocks by assuming a recursive ordering on $\mathbf{B}_{0,s_t}^{-1}$. To be specific, the relationship between the reduced-form error, $\boldsymbol{\epsilon}_t$, and the structure shock, $\boldsymbol{e}_t$, or the natural gas market fundamental shocks, at time t can be decomposed as follows:

$$\boldsymbol{\epsilon}_t = \begin{pmatrix} \epsilon_{\Delta prod,t} \\ \epsilon_{\Delta ip,t} \\ \epsilon_{\Delta rpg,t} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ b_{21,s_t} & 1 & 0 \\ b_{31,s_t} & b_{32,s_t} & 1 \end{pmatrix} \times \begin{pmatrix} e_{\Delta prod,t} \\ e_{\Delta ip,t} \\ e_{\Delta rpg,t} \end{pmatrix} = \mathbf{B}_{0,s_t}^{-1}\mathbf{e}_t. \tag{3}$$

Recalls that $\mathbf{e}_t = (e_{\Delta prod,t}, e_{\Delta ip,t}, e_{\Delta rpg,t})' \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Omega}_{s_t})$, where $\boldsymbol{\Omega}_{s_t}$ is a diagonal covariance matrix. Similar to Kilian (2009), the recursive identification scheme based on equation (3) postulates a vertical short-run supply curve of natural gas, which is plausible with monthly data. This assumption implies that shifts in the demand curve, either driven by US economic activity, $e_{\Delta ip}$, or specific factors related to the real price of natural gas, $e_{\Delta rpg}$, do not have a contemporaneous effect on the level of natural gas production but unexpected changes in the natural gas production can immediately impact on the economic activity and the price of natural gas. It also assumes that the reaction of US economic activity to natural gas price shocks is delayed after a month.

The impulse responses to the supply and demand shocks are constructed in a given regime, therefore we ignore any feedback from changes in s_t into the dynamics of the natural gas market variables. By doing that, we assume the system can stay for a long time in a regime. Having said that, the estimated time-varying coefficients and variance shocks support our assumption. Our results show that almost all regimes span a considerable length of time and hence impulse response functions in different regimes have their own economic history and can be comparable among them.

In this paper, we adopt the Bayesian approach and use the Markov chain Monte Carlo method to obtain draws from the posterior distribution of the model parameters. The details of the posterior sampler are presented in Appendix of this paper. To allow for convergence of the Markov chain to a stationary distribution, all our empirical estimates are based on $55,000$ posterior draws with discarding the first $5,000$ draws as a burn-in period.

3 Regulation changes in the US natural gas market

Before estimating the model, it is useful to acknowledge the periods of important regulatory reforms in the US natural gas market. Indeed, the market received major reforms moving from a highly regulated to a highly competitive industry (Mohammadi, 2011; Joskow, 2013). In general, over the sample period from 1980 to 2016, a major deregulation, the Natural Gas Wellhead Decontrol Act of 1989 (NGWDA), is introduced in 1989. Therefore, the behaviour of the natural gas market can be different between periods before and after 1989.

Prior to 1989, natural gas wellhead prices were regulated by the Natural Gas Policy Act of 1978 (NGPA). The NGPA established price ceilings for wellhead first sales of natural gas that vary with the applicable gas category and gradually increase over time. It also established a three-stage elimination of price ceilings for certain categories. Right after the NGPA was passed, the global crude oil market experienced a deep crisis in 1979/80, when the price of West Texas Intermediate crude oil rose from less than \$15 per barrel in September 1978 to almost \$40 in April 1980 (Baumeister and Kilian, 2016). The jump in oil prices initially exacerbated shortages of natural gas because major customers, such as industrial and electrical users, switched from oil to natural gas. However, the price of crude oil peaked only in 1981 and fell back to about \$15 per barrel in July 1988, making natural gas less economical compared to crude oil. As a consequence, customers began to switch from natural gas to other forms of energy. The high volatility in oil prices and hence the large fluctuations in the demand of the natural gas market required a newly adequate price system rather than the NGPA celling price scheme introduced in 1978. As a consequence, in 1989 Congress passed the Natural Gas Wellhead Decontrol Act of 1989 (NGWDA) in an effort to bring natural gas prices up to market-clearing levels by removing all price ceilings dictated by NGPA. The US system of natural gas price regulation came to an end in 1992 with Federal Energy Regulatory Commission Order 636, further allowing more efficient use of the interstate natural gas transmission system by fundamentally changing the way pipeline companies conduct business.

4 Data

There are different types of natural gas prices that are observed in different markets; therefore, the behavior of these prices may vary across suppliers and users and the responses to exogenous shocks are also different. In this section, we begin by briefly reviewing the pricing of natural gas in U.S. markets and then describe the data used in this paper.

As highlighted by Nguyen and Okimoto (2017), the price of gas travels from wellheads (upstream markets) where natural gas is produced to the end users (downstream markets). According to Brown and Yucel (1993) and Mohammadi (2011), there are six separate segments, including wellhead, city gate, and four end-use nodes (e.g., commercial, industrial, residential, and electrical customers). It begins with *wellhead price*. The price of gas is first determined at the wellhead by independent brokers and pipeline companies. Therefore, the wellhead price often refers to the price of the upstream market. Pipeline companies and brokers then sell their natural gas to local distribution companies (LDCs) and some end users. The prices observed in this market refer to *city gate prices*. Generally, because industrial and electrical end users can switch easily between natural gas and other forms of energy to minimize their costs, these end users tend to purchase their natural gas directly from pipeline companies and brokers with competitive spot prices. For this reason, prices paid by industrial and electrical users refer to *industrial prices* and *electric power prices*. In contrast, commercial and residential users normally cannot switch between different fuel forms; their energy expenditure is linked with a single fuel type. As a consequence, both commercial customers and residential customers purchase their natural gas from LCDs, and they are offered *commercial prices* and *residential prices*, respectively.

The above overview suggests that, in nature, the wellhead price serves as a benchmark reference for downstream markets, including physical and spot markets.[3] Therefore, this paper utilizes the wellhead price as the benchmark price for the U.S. market. Similar to Jadidzadeh and Serletis (2017), we divide the nominal price series sourced from the U.S. Department of Energy (EIA) by the U.S. CPI to obtain the real price of natural gas. The natural gas price series is in percent changes by taking the first difference of the monthly logarithm of the variable. We also note that the set of available data the wellhead price is only from January 1980 to December 2012. Thus, we extend the data to the latest date by using natural gas import prices from January 2013 onward. That being said, because the domestic natural gas market is a competitive market, the movements of the wellhead price and the import price (in log levels) are almost identical, as can be seen

[3] An examination of the relationship between upstream and downstream prices can be found in Mohammadi (2011).

from Figure 1. Regarding natural gas production, we use monthly U.S. natural gas gross withdrawals, also compiled by the EIA, as a proxy for natural gas supply. The variable is seasonally adjusted and then enters the model by taking the first difference of the natural logarithm. To capture the U.S. economic activity, that drives demand for natural gas in the U.S. market, we utilize the U.S. monthly industrial production index, seasonally adjusted, retrieved from the Federal Reserve Bank of St. Louis and then transform the index to a growth rate by taking the first difference of the natural logarithm. Finally, we use the US refiners' acquisition cost for imported crude oil (IRAC), published by the EIA, to compute the real price of crude oil with the same method used to calculate for the real natural gas price.[4]

5 Empirical results

We begin our analysis with a discussion of the Bayesian comparison exercise. This formal exercise is applied to determine the best model by which the number of optimal regime changes detected. Having identified the number of regimes, we then analyse the dynamic impulse responses of the natural gas to different natural gas supply and demand shocks. The role of oil prices is also examined in this section as a sensitivity analysis.

5.1 Model comparison

In this subsection, we conduct a formal model comparison exercise using the marginal likelihood as a selection criterion. To be specific, given model M_i, the marginal likelihood is defined as

$$p(\mathbf{y}^o|M_i) = \int p(\mathbf{y}^o|\theta_i, M_i)p(\theta_i|M_i)d\theta_i,$$

where $\mathbf{y}^o = (\mathbf{y}_1^o, \ldots, \mathbf{y}_T^o)$ is the observed data with sample size T and θ_i is a vector of parameters for model M_i. In addition, the marginal likelihood of model M_i can be rewritten as a product of one step ahead predictive likelihoods evaluated at the observed data. Specifically, the marginal likelihood of model M_i can be factored as $p(\mathbf{y^o}|M_i) = p(\mathbf{y}_1^o|M_i)\prod_{t=2}^{T} p(\mathbf{y}_t^o|\mathbf{y}_1^o, \ldots, \mathbf{y}_{t-1}^o, M_i)$. We will use this expression to compute the marginal

[4] A discussion on whether or not we should consistently use the price of oil and natural gas in percent change (first differences of the natural logs of the variables), along with other variables, can be found, for example, in Kilian (2009), Kilian and Park (2009), Kilian and Murphy (2014), Lütkepohl and Netšunajev (2014), and Jadidzadeh and Serletis (2017). According to these empirical works, it is not clear whether the real price of crude oil, and hence the natural gas price in this paper, should be modelled in log levels or log differences. The level specification is preferred because it produces consistent impulse response estimates, regardless of the assumption of unit root.

likelihood and use it as a criteria determining the best candidate specification. The marginal likelihood is often used in model selection or model averaging in Bayesian data analysis (Hoeting et al., 1999). Intuitively speaking, the marginal likelihood can be interpreted as the predictive probability of the observed data. Thus, a larger value of marginal likelihood implies a better in-sample fit of the model given the observed data. More discussion and details about the marginal likelihood can be found in Kass and Raftery (1995).

To determine the number of regime M, and the persistence parameter ρ, we compare the marginal likelihoods of the MS-VAR with different combination of $M = 1, 2, 3, 4, 5$ and $\rho = 0, 10, 50, 100, 500, 1000$. To facilitate the comparison, we report the difference of log marginal likelihood of the MS-VAR models to the constant VAR model. Hence, the model with a positive value indicates a better in-sample fit as compared with the constant VAR model. The estimated relative log marginal likelihoods are presented in Table 2. It is immediately obvious that the model with $M = 4$ and $\rho = 50$ is the preferred one. In other words, the empirical results evidence that regime switching exists within the US natural gas market. In the next subsection, we discuss the economic characterization of these regimes by examining the estimated coefficients and covariance shocks over time.

5.2 Regime characteristics

Having discovered that the 4-regime model provides the best in-sample fit for the US natural gas market, we now examine the economic characterization of these regimes. The time-varying estimated coefficients and the standard deviations of the structural socks are shown in Figure 2 and Figure 3 respectively. To improve the readability of the plots, we only present some selected β_i and σ_i. Several interesting observations arise with regard to the interpretation of these results. First, we find evidence that regime switches in the US natural gas market driven by not only the variances of shocks but also its market fundamental changes (switching in model coefficients). Therefore, the transmission of shocks is certainly different among regimes, as discussed in the following section.

Second, based on the magnitude of of the estimated time-varying coefficients, β_i, and covariance matrix, σ_i, the results also reveal clearly that four regimes exist over the sample period from 1980M1 to 2016M11. Accordingly, there were likely two regimes existing during the period before 1989, namely R1 and R2 for short. This period is associated with the phase that the US natural gas market was regulated by the NGPA. From 1989 onward, another two different regimes are evidently detected and we call them R3 and R4. It is worth mentioning that the MS-VAR model allows for regime recurrence, which is distinguished from other non-linear VAR models, and hence the four regimes are frequently observed over the sample period.[5] Figure 4 illustrates this feature. The figure displays a heat map for the latent states s_t, which further provides a more nuanced picture of regime clustering over the last three decades. Following Song (2014); Hou (2017), we plot the estimation of $P(s_i = s_j|y_{1:T})$ and report in a table in which colour differences denote different probabilities over the range of $i = 1, \ldots, T$ and $j = 1, \ldots, T$. More precisely, the clustering of the regimes is presented through a $T \times T$ matrix; therefore the figure is symmetric against the 45^0 line. For interpretation purposes, the light color on the main diagonal of the figure indicates a new regime that occurs in the period $i = j$ are unique and light color off the main diagonal indicates regime recurrences. Presented in this manner, we clearly observe periods of unique regime, which confirms structure changes in the US natural gas market. At the same time, the figure also shows recurrences in regime (regime switching) existing in some periods in the market.

Finally, switching in shock variances is substantially different, as can be seen from Table 3. The table shows the normalized standard deviations from regime to regime. More precisely, we normalize the standard deviations such that the volatilities of R1 are unity and compare to that of other regimes. Presented in this manner, it is immediately clear that the variances of the shocks of the natural gas price stand out for all regimes with an upward trend. This finding clearly suggests that shocks to the price of natural gas play a more important role in driving market dynamics than shocks to natural gas production and US economic activity.

5.3 Regime-dependent reactions of the US natural gas market

In this subsection, we investigate the responses of the US natural gas market to its fundamental shocks and compare these responses across regimes. The market fundamental shocks include a natural gas supply shock, a demand shock, and a specific demand shock. We again note that, in our structural model, the supply shock presents an exogenous disruption of US natural gas production that may be caused, for example, by bad weather. Therefore, this shock is normalized as a negative shock in the model, while the demand and specific demand shock are positive shocks. It is important to distinguish the difference between the demand and specific demand shock. This is, while the demand shock arises from the fact that increases in real US economic activity, the specific demand shock is associated with specific factors, which are not directly related to the changes in real demand for gas or gas production, causing higher natural gas prices. These factors could be associated with changes in expectation about the future price of natural gas.

The estimated impulse responses to one standard deviation shocks are presented in

[5]To axamine the charaterictics of these regimes and the corresponding impulse responses, we therefore select four periods over the sample as regime presentatives.

Figure 5-7. As expected, the empirical results reveal that the US natural gas market is much more sensitive to its fundamental shocks occurring after the Decontrol Act 1989 when price ceilings were abolished. Along with this feature, the results also show that US natural gas production does no respond significantly to the fluctuation of US economic activity but the economy is quite sensitive to changes in the natural gas supply. We also observe that both shifts in demand and supply play equal role in driving the natural gas price. In what follows, we examine these responses in detail.

Figure 5 presents the dynamic responses of natural gas production to shocks across three regimes. The results show that the responses of natural gas production to the demand shock is not much different among the four regimes. As we just mentioned, an unexpected change in US economic activity has no impact on the development of the supply of natural gas. Changes in the supply of the natural gas are mainly driven by its own shocks in natural. However, the natural gas production is found to be more sensitive to unexpected changes in the specific demand shock in recent years. We find that a sudden increase in the price of gas, which is not related to changes in natural gas production or US economic activity, has slightly positive effects on natural gas production but the impact is very short-lived and turns out to be heterogeneous after just about two months. These characteristics did not exist in the regimes before 1989, meaning that the natural gas supply elasticity was about inelastic under the NGPA ceiling price scheme.

Turning to the responses of US economic activity to the natural gas supply and price shock, we find that the impact of a sudden disruption of natural gas production on the economy tends to be persistent across regimes. This is, the results show that a fall in the natural supply leads to a slightly fall in US economic activity, as can be seen in Figure 6. In contrast, with R3 and R4 an unexpected increase in the natural gas price has a positive impact on the economy, although the impact is quite small. With R1 and R2, those impacts are insignificant.

The final variable in our analysis is the price of natural gas, for which the associated responses are presented in Figure 7. Sharing the same features with the responses of natural gas supply and the US economy, we also observe that the dynamic responses of the price of natural gas are different across regimes. Before the Control Act, as the price of natural gas was controlled under ceiling prices, fundamental shocks such as the supply and demand shock had no impact on the price. Since the price ceilings were removed in 1989 the natural gas price is found to react strongly to the shocks. A negative supply shock leads to about 1 percent increase in the price. A similar impacts is also found for the demand shock. A one standard deviation increase in US economic activity also leads to increasing in the price of gas with the same level. While the shocks to natural gas production and US economic activity are found to have moderate effects driving the movements of natural gas prices, we observe that the price of natural gas strongly responds to the specific demand shock. This shock produces a consistent impact on the price in R3 and R4, which increases the price about 10 percent in recent periods.

5.4 The role of oil prices

To examine whether the movements of crude oil prices have an impact on the US natural gas market, we augment our benchmark model by incorporating the global price of crude oil. Following Nguyen and Okimoto (2017), shocks to the price of crude oil are allowed to have a contemporaneous effect on the natural gas market. Figure 8 shows the estimated impulse response functions across three regimes.[6] The results show that oil price shocks have a considerable role in influencing the natural gas price and natural gas production but impact patterns depend on regimes. More precisely, while the natural gas supply responds negatively to the oil price shock, the reactions of the price of natural gas price are found to be mixed across regimes. The price tends to increase with R1 and R4 but decrease with the other regimes. The results further evidence that the connection between natural gas market and oil price movements are regime dependent. The results are consistent with recent findings in Nguyen and Okimoto (2017) and Caporin and Fontini (2017). The dynamic impulse responses also show that the price of oil reacts to shocks to the price of natural gas but the reaction is very small and mixed.

6 Conclusion

In this paper, we investigated whether regime switching exists in the US natural gas market and analysed the reactions of the market to its fundamental shocks across various regimes. To this end, we applied a formal Bayesian model comparison to detect efficiently the number of regime switches in the market and then we utilized a Bayesian class of MS-VAR models that allows for time-variation in model coefficients and shock variances.

The paper has three major findings. First, the results support regime switching in the US natural gas market. In particularly, formal Bayesian model comparison techniques revealed the model with four regimes is the best in-sample fit. There were two regimes prevailed prior to the introduction of the NGWDA in 1989. The second and fourth regime have existed since the NGWDA was implemented, which corresponds to the period that US natural gas prices freely fluctuate in response to supply and demand shocks. Second, the paper finds that the US natural gas market tends to be much more sensitive to

[6] To improve the readability of the plot, we do not present the error bands, but they are available upon request.

shocks occurring in regimes existing after the Decontrol Act 1989 than the other regimes. Third, the paper also finds that shocks to the natural gas demand and price have negligible effects on natural gas production while the price of natural gas is mainly driven by specific demand shocks. Finally, augmenting the model by incorporating the price of crude oil, the results reveal that the impacts of oil price shocks on natural gas prices are relatively small and regime-dependent, which is likely to contrary to common perceptions.

References

Bachmeier, L. J. and Griffin, J. M. (2006). Testing for market integration crude oil, coal, and natural gas. *The Energy Journal*, 27(2):55–71.

Baumeister, C. and Kilian, L. (2016). Forty years of oil price fluctuations: why the price of oil may still surprise us. *Journal of Economic Perspectives*, 30(1):139–60.

Baumeister, C. and Peersman, G. (2013). Time-varying effects of oil supply shocks on the US economy. *American Economic Journal: Macroeconomics*, 5(4):1–28.

Blanchard, O. J. and Gali, J. (2008). *The macroeconomc effects of oil shocks: why are the 2000s so different from the 1970s?* Centre for Economic Policy Research.

Boivin, J. (2006). Has US monetary policy changed? Evidence from drifting coefficients and real-time data. Technical report.

Brigida, M. (2014). The switching relationship between natural gas and crude oil prices. *Energy Economics*, 43:48–55.

Brown, S. P. and Yucel, M. K. (1993). The pricing of natural gas in US markets. *Economic Review-Federal Reserve Bank of Dallas*, page 41.

Brown, S. P. and Yücel, M. K. (2008). What drives natural gas prices? *The Energy Journal*, 29(2):45–60.

Caporin, M. and Fontini, F. (2017). The long-run oil–natural gas price relationship and the shale gas revolution. *Energy Economics*, 64:511–519.

Chan, J. C. and Eisenstat, E. (2018). Bayesian model comparison for time-varying parameter VARs with stochastic volatility. *Journal of Applied Econometrics*, Forethcoming.

Chang, Y., Choi, Y., and Park, J. Y. (2017). A new approach to model regime switching. *Journal of Econometrics*, 196(1):127–143.

Chib, S. (1996). Calculating posterior distributions and modal estimates in Markov mixture models. *Journal of Econometrics*, 75(1):79–97.

Clark, T. E. and Ravazzolo, F. (2015). Macroeconomic forecasting performance under alternative specifications of time-varying volatility. *Journal of Applied Econometrics*, 30(4):551–575.

Cogley, T. and Sargent, T. J. (2005). Drifts and volatilities: monetary policies and outcomes in the post WWII US. *Review of Economic dynamics*, 8(2):262–302.

Cross, J. and Nguyen, B. H. (2017). The relationship between global oil price shocks and China's output: a time-varying analysis. *Energy Economics*, 62:79–91.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, pages 357–384.

Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999). Bayesian model averaging: a tutorial. *Statistical science*, pages 382–401.

Hou, C. (2017). Infinite hidden markov switching VARs with application to macroeconomic forecast. *International Journal of Forecasting*, 33(4):1025–1043.

Hubrich, K. and Teräsvirta, T. (2013). Thresholds and smooth transitions in vector autoregressive models. In *VAR Models in Macroeconomics–New Developments and Applications: Essays in Honor of Christopher A. Sims*, pages 273–326. Emerald Group Publishing Limited.

Hubrich, K. and Tetlow, R. J. (2015). Financial stress and economic dynamics: the transmission of crises. *Journal of Monetary Economics*, 70:100–115.

Jadidzadeh, A. and Serletis, A. (2017). How does the US natural gas market react to demand and supply shocks in the crude oil Market? *Energy Economics*.

Joskow, P. L. (2013). Natural gas: from shortages to abundance in the United States. *The American Economic Review*, 103(3):338–343.

Kass, R. E. and Raftery, A. E. (1995). Bayes factors. *Journal of the american statistical association*, 90(430):773–795.

Kilian, L. (2009). Not all oil price shocks are alike: disentangling demand and supply shocks in the crude oil market. *The American Economic Review*, 99(3):1053–1069.

Kilian, L. and Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, 29(3):454–478.

Kilian, L. and Park, C. (2009). The impact of oil price shocks on the US stock market. *International Economic Review*, 50(4):1267–1287.

Krolzig, H.-M. (1997). *Markov-switching vector autoregressions: modelling, statistical inference, and application to business cycle analysis*. Springer Science & Verlag, Berlin.

Lütkepohl, H. and Netšunajev, A. (2014). Disentangling demand and supply shocks in the crude oil market: how to check sign restrictions in structural VARs. *Journal of Applied Econometrics*, 29(3):479–496.

Mohammadi, H. (2011). Market integration and price transmission in the US natural gas market: from the wellhead to end use markets. *Energy Economics*, 33(2):227–235.

Nakov, A. and Pescatori, A. (2010). Oil and the great moderation. *The Economic Journal*, 120(543):131–156.

Nguyen, B. H. and Cross, J. (2017). Time-varying macroeconomic effects of energy price shocks: a new measure for China. *CAMA Working paper*.

Nguyen, B. H. and Okimoto, T. (2017). Asymmetric reactions of the U.S. natural gas market and economic activity. *CAMA Working paper*.

Pindyck, R. S. (2004). Volatility in natural gas and oil markets. *The Journal of Energy and Development*, 30(1):1–19.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies*, 72(3):821–852.

Rahman, S. and Serletis, A. (2010). The asymmetric effects of oil price and monetary policy shocks: a nonlinear VAR approach. *Energy Economics*, 32(6):1460–1466.

Ramberg, D. J. and Parsons, J. E. (2012). The weak tie between natural gas and oil prices. *The Energy Journal*, 33(2):13–35.

Rubio-Ramirez, J. F., Waggoner, D. F., and Zha, T. A. (2005). Markov-switching structural vector autoregressions: theory and application. working paper, Federal Reserve Bank of Atlanta.

Serletis, A. and Rangel-Ruiz, R. (2004). Testing for common features in North American energy markets. *Energy Economics*, 26(3):401–414.

Sims, C. A., Waggoner, D. F., and Zha, T. (2008). Methods for inference in large multiple-equation Markov-switching models. *Journal of Econometrics*, 146(2):255–274.

Sims, C. A. and Zha, T. (2006). Were there regime switches in US monetary policy? *The American Economic Review*, 96(1):54–81.

Song, Y. (2014). Modelling regime switching and structural breaks with an infinite hidden Markov model. *Journal of Applied Econometrics*, 29(5):825–842.

Teräsvirta, T., Yang, Y., et al. (2014). Specification, estimation and evaluation of vector smooth transition autoregressive models with applications. *Research Paper*, 8.

Zamani, N. (2016). How the crude oil market affects the natural gas market? Demand and supply shocks. *International Journal of Energy Economics and Policy*, 6(2):217–221.

Appendix A Estimation

In this appendix we provide the details of the posterior sampler for the MS-VAR. Let $\boldsymbol{\Theta} = \{\boldsymbol{\beta}_i, \boldsymbol{\Sigma}_i\}_{i=1}^M$ be the collection of the parameters in the M regimes, and $\mathbf{P}$ be the $M \times M$ Markov transition matrix, i.e., $\mathbf{P}_{ij} = p_{ij}$. To simplify the notation, we adopt the following convention $x_{t_1:t_2} = (x_{t_1}, \ldots, x_{t_2})$.

The posterior draws can be obtained by sequentially sampling from:

1. $p(s_{1:T}|\boldsymbol{\Theta}, \mathbf{y}_{1:T})$;
2. $p(\boldsymbol{\Theta}|s_{1:T}, \mathbf{y}_{1:T})$;
3. $p(\mathbf{P}|s_{1:T})$.

To implement Step 1: We apply the forward-backward algorithm of Chib (1996). To be specific, given $p(s_{t-1}|\mathbf{y}_{1:t-1}, \theta)$ we compute $p(s_t|\mathbf{y}_{1:t})$ by

$$\begin{aligned}
p(s_t|\mathbf{y}_{1:t}, \theta) &= \frac{p(y_t|s_t, \boldsymbol{\Theta})p(s_t|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})}{\sum_{s_t} p(y_t|s_t, \boldsymbol{\Theta})p(s_t|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})} \\
&= \frac{p(y_t|s_t, \boldsymbol{\Theta}) \sum_{s_{t-1}} p(s_t, s_{t-1}|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})}{\sum_{s_t} p(y_t|s_t, \boldsymbol{\Theta})p(s_t|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})} \\
&= \frac{p(y_t|s_t, \boldsymbol{\Theta}) \sum_{s_{t-1}} p(s_t|s_{t-1})p(s_{t-1}|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})}{\sum_{s_t} p(y_t|s_t, \boldsymbol{\Theta})p(s_t|\mathbf{y}_{1:t-1}, \boldsymbol{\Theta})}
\end{aligned}$$

until we get $p(s_T|\mathbf{y}_{1:T}, \boldsymbol{\Theta})$. Then we implement the backward sampling by first sample s_T from $p(s_T|\mathbf{y}_{1:T}, \boldsymbol{\Theta})$, then we sample s_t given s_{t+1} from

$$p(s_t|s_{t+1:T}, \mathbf{y}_{1:T}, \boldsymbol{\Theta}) = \frac{p(s_t|\mathbf{y}_{1:t}, \boldsymbol{\Theta})p(s_{t+1}|s_t)}{\sum_{s_t} p(s_t|\mathbf{y}_{1:t}, \boldsymbol{\Theta})p(s_{t+1}|s_t)}.$$

To implement Step 2: Note that conditional $s_{1:T}$, we can regroup data into M distinct regimes. For $i = 1, \ldots, M$, the model in a regime i can be written as

$$\mathbf{y}^i = \mathbf{X}^i\boldsymbol{\beta}_i + \epsilon^i \quad \epsilon^i \sim \mathcal{N}(\mathbf{0}, \mathbf{I}_{T_i} \otimes \boldsymbol{\Sigma}_i),$$

where $\mathbf{y}^i$ and $\mathbf{X}^i$ collect the observations belonging to regime i and T_i is the number of observations in regime i. Following the standard results for the linear regression model, we have

$$\boldsymbol{\beta}_i \sim \mathcal{N}(\widehat{\boldsymbol{\beta}}_i, \widehat{\mathbf{K}}_i^{-1}), \quad \boldsymbol{\Sigma}_i \sim \mathcal{IW}(\widehat{\mathbf{S}}_i, \widehat{\nu}_i),$$

where $\widehat{\mathbf{K}}_i = \mathbf{X}^{i'} (\mathbf{I}_{T_i} \otimes \boldsymbol{\Sigma}_i)^{-1} \mathbf{X}^i + \mathbf{V}_0^{-1}$, $\widehat{\boldsymbol{\beta}}_i = \widehat{\mathbf{K}}_i^{-1} \left(\mathbf{X}^{i'} (\mathbf{I}_{T_i} \otimes \boldsymbol{\Sigma}_i)^{-1} \mathbf{y}^i + \mathbf{V}_0^{-1}\boldsymbol{\beta}_0\right)$, $\widehat{\nu}_i = T_i + \nu_0$ and $\widehat{\mathbf{S}}_i = (\mathbf{y}^i - \mathbf{X}^i)(\mathbf{y}^i - \mathbf{X}^i)' + \mathbf{S}_0$.

To implement Step 3: Given $s_{1:T}$, we draw the jth row of $\mathbf{P}$ for $j = 1, \ldots, M$

$$(p_{j1}, \ldots, p_{jM}) \sim \mathcal{D}(\alpha_{j1} + n_{j1}, \ldots, \alpha_{jM} + n_{jM}),$$

where $n_{kl} = \sum_{j=1}^{T-1} \mathbb{1}(s_j = l, s_{j+1} = k)$ and $\mathbb{1}(A)$ is the indicator function that is equal to one if statement A is true and zero otherwise.

Appendix B Priors

We outline the hyperparameters of the prior for fitting the MS-VAR model. We assume the conditional mean coefficients to follow a Minnesota prior. For the prior mean, we set $\boldsymbol{\beta}_0 = \mathbf{0}$. For the variance, we assume that $\mathbf{V}_0 = \text{diag}(v_1, \ldots, v_k)$, where $k = n(np+1)$. If we write $(v_1, \ldots, v_k) = \text{vec}((\mathbf{c}_0, \mathbf{A}_{10}, , \ldots, \mathbf{A}_{p0})')$, then we set $\mathbf{c}_0$ to be a vector with 10 in all its entries, i,e, the prior variance of the intercepts of the VAR model is equal to 10. For the variance of the VAR coefficient, we set

$$\mathbf{A}_l^{ij} = \begin{cases} \frac{\lambda_1^2 \lambda_2}{l^{\lambda_3}} \frac{\sigma_i}{\sigma_j} & \text{for } l = 1, \ldots, p \text{ and } i \neq j, \\ \frac{\lambda_1^2}{l^{\lambda_3}} & \text{for } l = 1, \ldots, p \text{ and } i = j. \end{cases}$$

where $\mathbf{A}_l^{ij}$ denotes the (i, j) th element of the matrix $\mathbf{A}_l$ and σ_r is set equal to the standard deviation of the residual from AR(p) model for the variable r. For the hyperparameters, we set $\lambda_1 = 0.05$, $\lambda_2 = 0.5$, $\lambda_3 = 2$. For the covariance matrix, we set $\nu_0 = n+4$ and $\mathbf{S}_0 = (\nu_0 - n - 1) \times \mathbf{I}_n$.

Tables

Table 1: Structural changes in the US natural gas market

	1982	2006	2016
		Percent	
Production	**100**	**100**	**100**
Gas well	79	73	33
Oil well	21	27	19
Shale gas and Coalbed well	0	0	48
Consumption	**100**	**100**	**100**
Residential	26	24	17
Commercial	15	15	12
Industrial	38	46	33
Transportation	3	3	3
Electric power	18	12	35

Source: Calculation based on data from U.S. Energy Information Administration (EIA), *Monthly Energy Review*, various volumes.

Table 2: Relative log marginal likelihoods.

	$\rho = 0$	$\rho = 10$	$\rho = 50$	$\rho = 100$	$\rho = 500$	$\rho = 1000$
$M = 2$	-4.91	17.93	16.83	16.59	23.19	22.81
$M = 3$	3.88	37.61	42.28	40.24	21.49	21.97
$M = 4$	-0.78	39.47	**49.14**	45.60	29.72	20.73
$M = 5$	-7.81	34.00	45.43	47.53	28.91	19.88

Note: The table presents the relative log marginal likelihoods of MS-VAR model with different combination of (M, ρ) to the constant VAR model. Our results indicate that the MS-VAR with $(M, \rho) = (4, 50)$ performs the best.

Table 3: Relative standard deviations of structural shocks by regime

	$\Delta prod$	Δip	Δrpg
R1	1	1	1
R2	0.36	0.39	3.79
R3	2.67	1.29	113.58
R4	0.16	0.27	123.36

Note: Entries are normalized such that the volatility of each variable is unity for the first regime (R1).

Figures

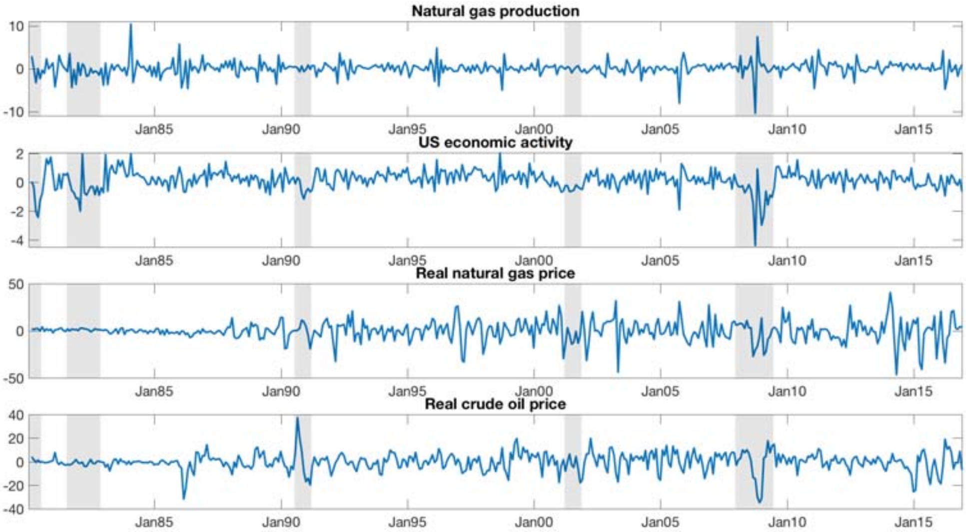

Figure 1: Historical evolution of the series (1980M2-2016M11).

Note: The monthly raw data of crude oil prices, natural gas prices and production collected from EIA. U.S. monthly industrial production index (US economic activity) is sourced from Fed of St. Louis. All series are express in percent change. The shaded region shows recessions as defined by the NBER.

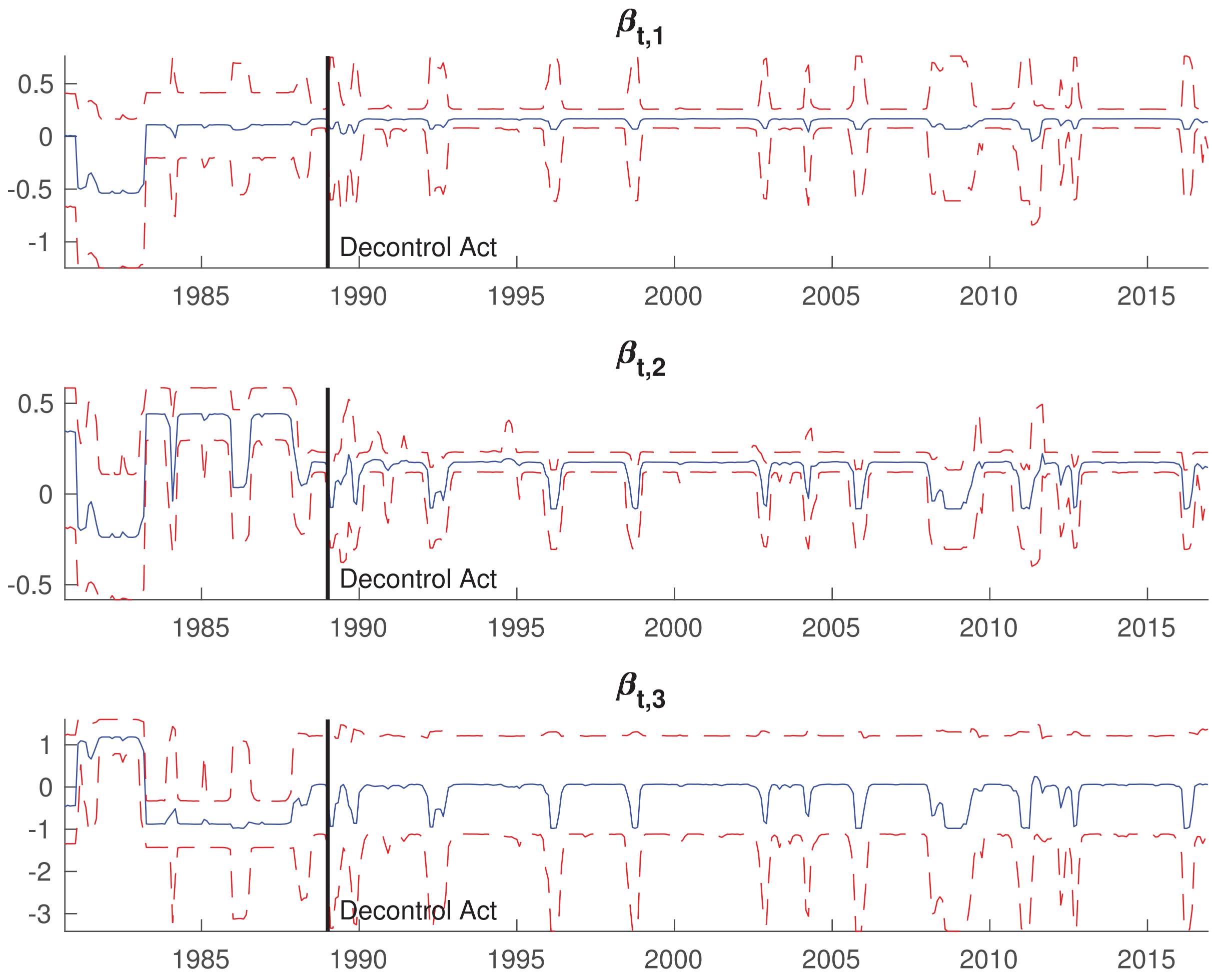

Figure 2: Time-varying intercept coefficients.

Note: The figure shows the (selected) estimated time-varying VAR coefficients β_i of MS-VAR together with the 95 percent probability bands.

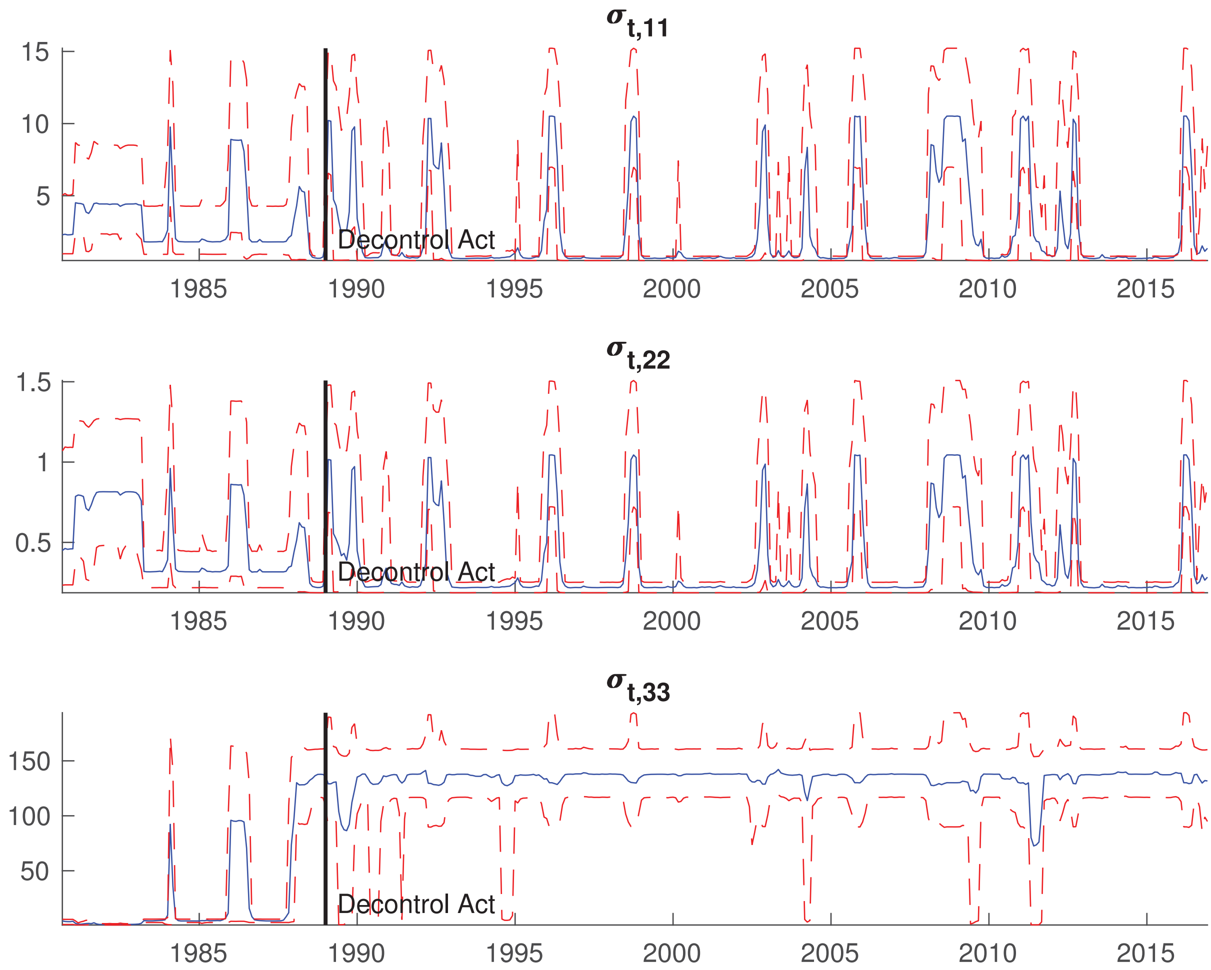

Figure 3: Time varying variance - covariances.

Note: The figure shows the (selected) estimated time-varying covariance matrices σ_i of the MS-VAR together with the 95 percent probability bands.

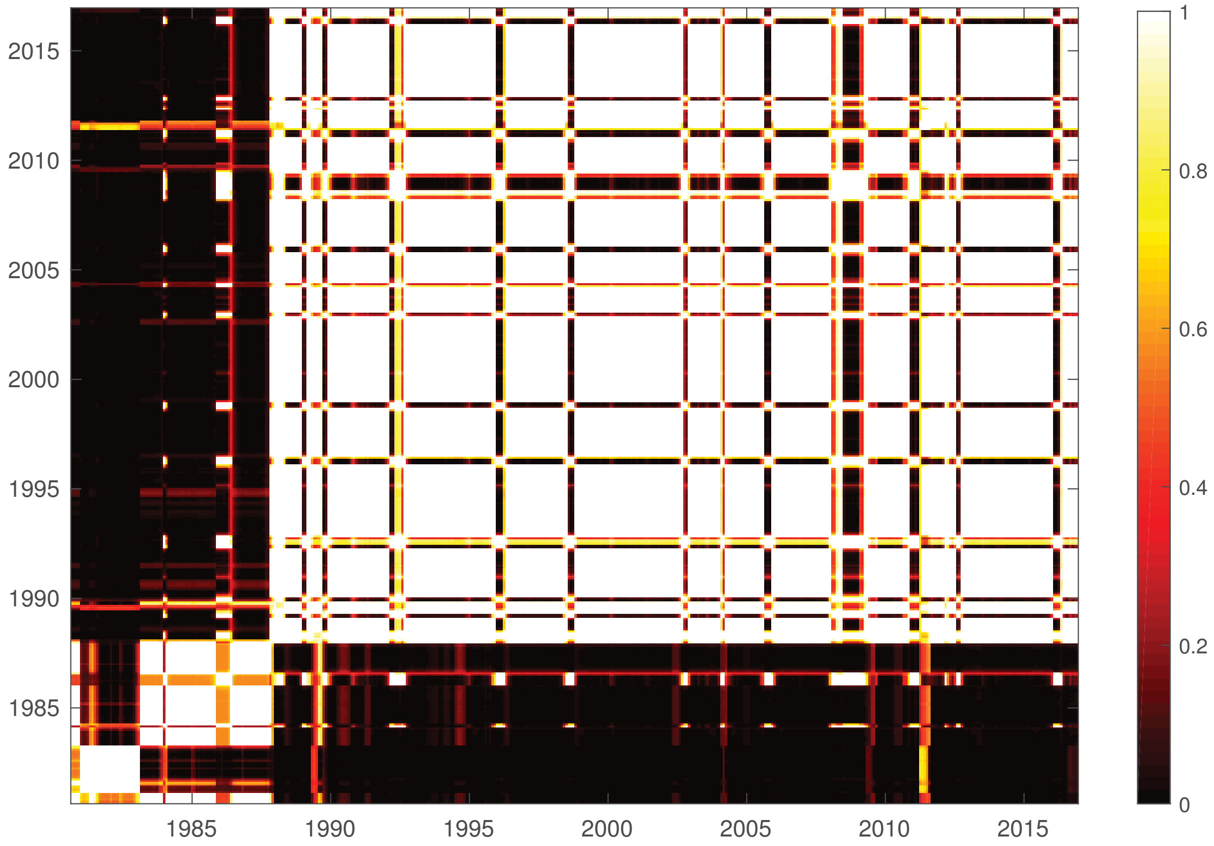

Figure 4: The estimated heat map for regime clustering.

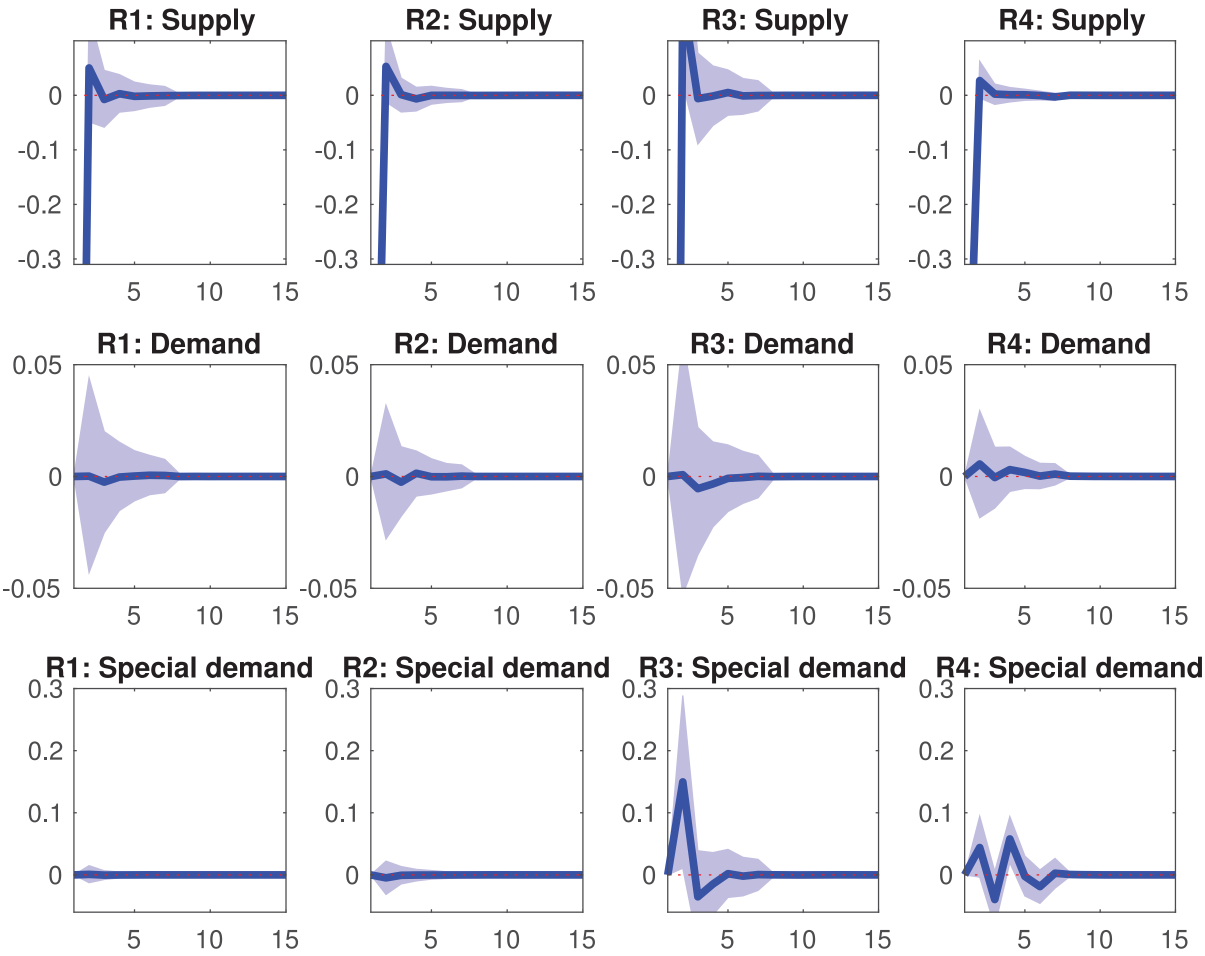

Figure 5: Natural gas production responses.

Note: The figure shows impulse responses base on the MS-VAR model of the four regimes (R1, R2, R3 and R4). The shaded areas indicate 68% posterior credible sets.

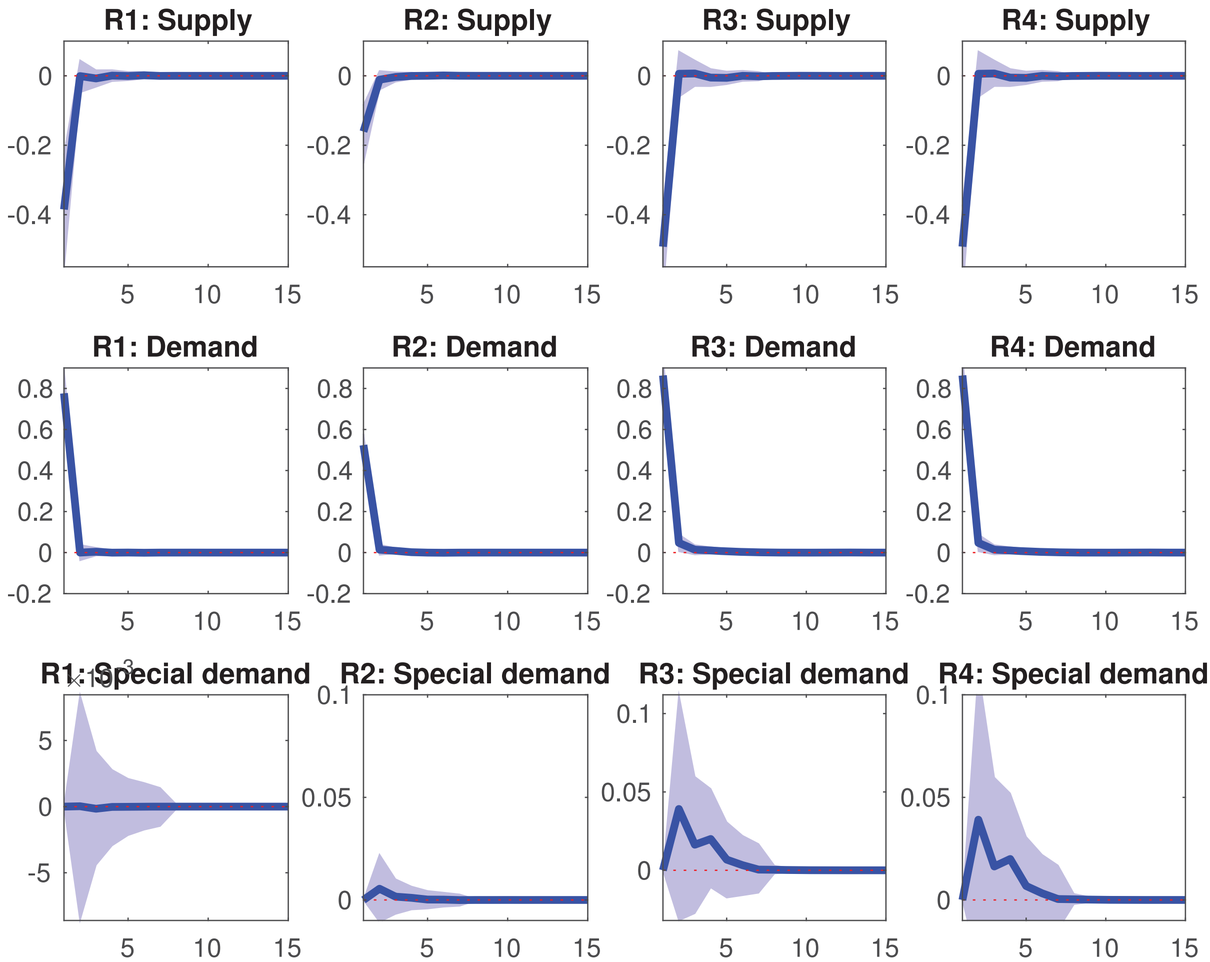

Figure 6: US economic activity responses.

Note: See Figure 5

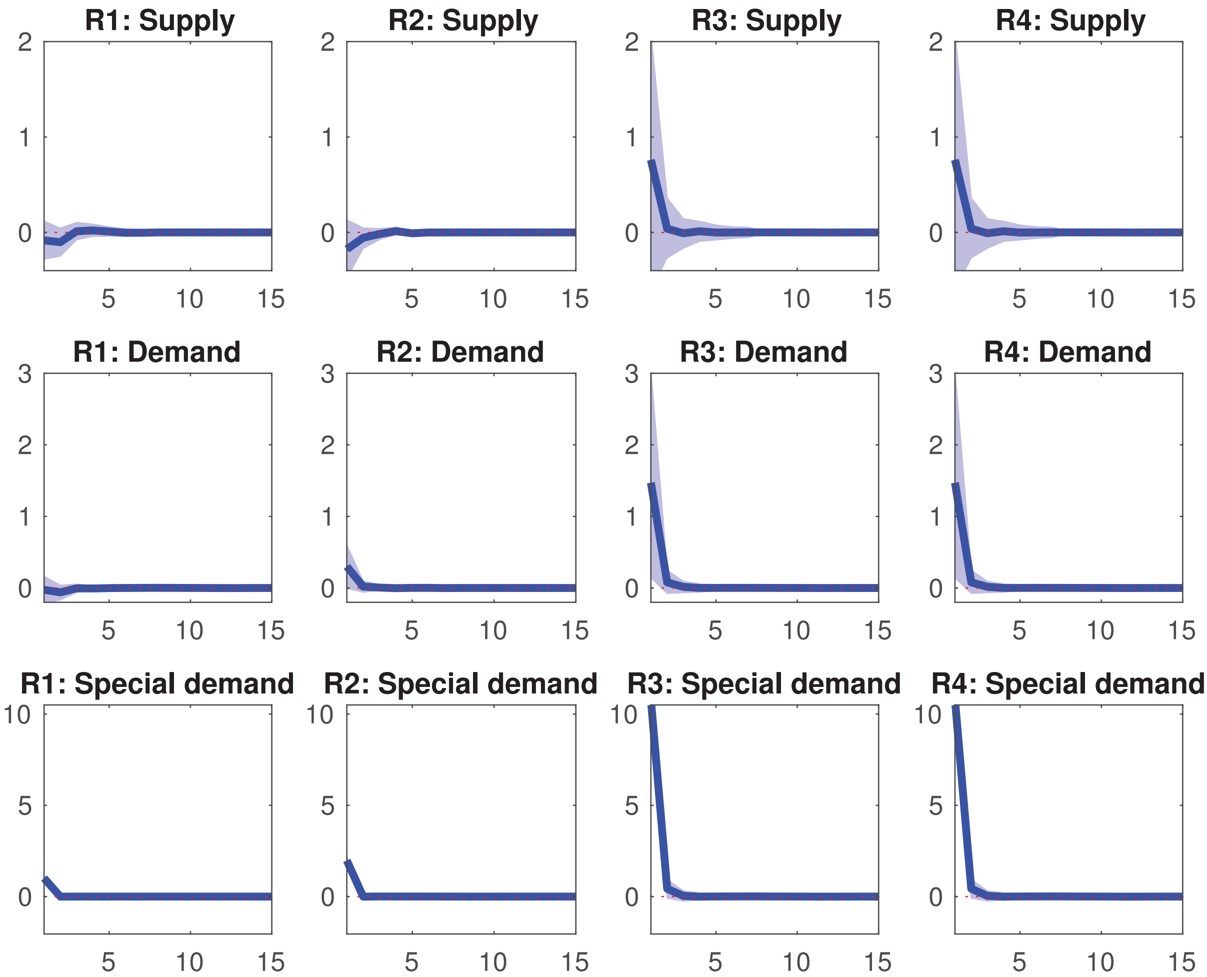

Figure 7: Natural gas price responses.

Notes: See Figure 5

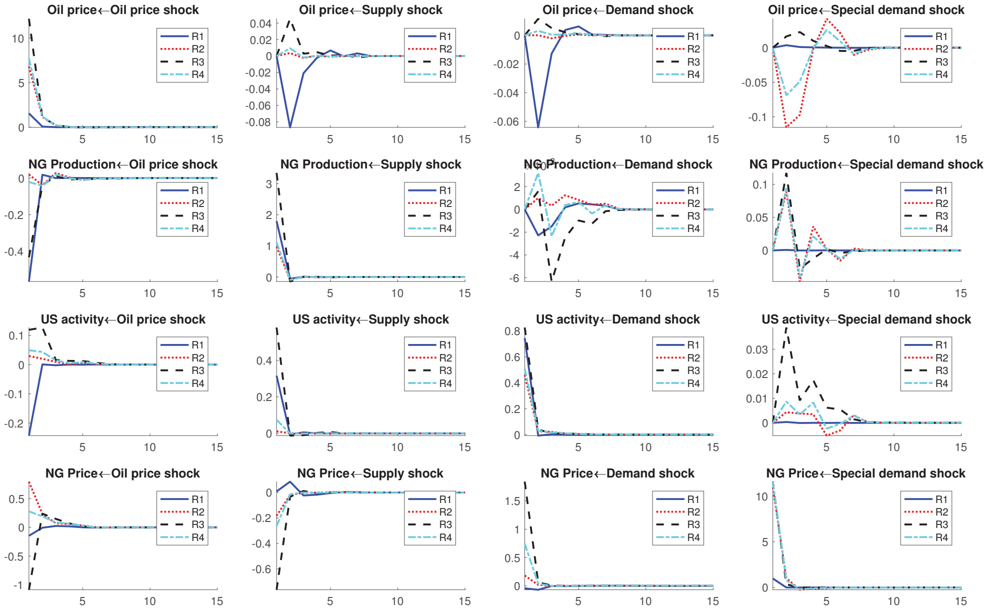

Figure 8: IRFs of the augmented model.

Notes: The Figures show impulse responses base on the augmented MS-VAR model of the four regimes (R1, R2, R3 and R4)