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Supply and demand determinants of natural gas price volatility in the U.K.: A vector autoregression approach

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ABSTRACT

Since 2008, the U.K. natural gas market has witnessed a marked drop in volatility. This fall has coincided with specific events in oil and gas sector such as the onset of the U.S. "shale gas revolution" and the subsequent rerouting of liquefied natural gas (LNG) shipments from the U.S. to other markets such as Asia and Europe. LNG cargoes, along with other sources of flexibility such as underground storages and interconnector import, can potentially reduce volatility. On the other hand, demand shocks can increase volatility. To examine the dynamics relationship between daily shocks in U.K. gas demand and supply, and the gas spot price volatility, we use a vector autoregressive (VAR) model. While we find evidence that daily deviations in aggregated gas demand significantly impacts volatility, we are unable to find direct evidence for an impact from shocks in disaggregated demand or supply. In fact, one important contribution of the paper is to suggest that flexible sources of supply such as LNG, storage and interconnector flows react to shocks in retail demand, dampening their potential effects on volatility.

1. Introduction

Since 2008, the global natural gas markets have experienced a substantial change in market conditions. For instance, the financial crisis of 2008 had a large impact on U.S. natural gas prices, resulting in a large fall in gas prices from a high of around 14 USD/mmbtu[1] to below 2 USD/mmbtu. In the subsequent years, U.S. gas production experienced a game change with the onset of shale gas production from around 2009 [7,55]. Before the Shale gas revolution, the U.S. was a net importer of LNG. Due to increased domestic production from unconventional plays from 2009 onwards, LNG imports to the U.S. dropped dramatically, resulting in LNG cargoes having to find their port of call in other markets, such as Europe and Asia. The U.S. shale gas revolution in the U.S. thus impacted European gas markets through a shift in the LNG destination. LNG shipments introduce flexibility into global and regional gas markets through two ways. First, LNG cargoes can be rerouted between regional markets in order to take advantage of preferable price spreads. Second, LNG cargoes also possess timing flexibility, and can be rerouted to markets experiencing peaking prices. In fact, LNG regasification capacity is often marketed as a peak shaving service. Hence, this flexibility provides LNG with the possibility to influence volatility. In fact [4], attributes the fall in volatility to increased LNG imports. This inherent flexibility combined with increased LNG imports to the U.K. since 2008 might be one possible explanatory factor behind the decreased volatility in gas spot prices.

However, the U.K. gas system contains overcapacity, representing sources of flexibility. For instance, interconnecting pipelines link the U.K. market to Ireland, Belgium and the Netherlands, and the flows through these interconnectors can be adjusted or even reversed within a short period of time. In addition, underground gas storage facilities are able to switch between injection and withdrawal promptly, sometimes within hours. Therefore, several competing sources of flexible gas supply have the potential to react to shocks in prices (volatility), making the total picture quite complex. In fact, shocks in demand may be met by flexible sources, and may not result in increased volatility. We therefore find it appropriate to use a vector autoregression to capture the dynamics in the system. Since reactions to shocks in the system might take hours or even days, we find it appropriate to use lagged variables as explanatory factors.

To control for the impact of other external factors on gas volatility we also include the OVX crude oil volatility index. The literature suggests a hierarchy of volatility influence from oil to gas to

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[1] mmbtu = million british thermal units.

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electricity markets [29].

There have been several studies addressing the impact of LNG on energy markets, especially on market integration (e.g. Refs. [8,16,54,55]. Nevertheless, to the best of our knowledge, no study has addressed the impact of disaggregated supply or demand on volatility. Relevant studies tend to focus on the impact of aggregate demand and supply shocks on energy or stock market volatility [25,73].

We use a data sample for 2007–2014, which includes daily demand, supply and price data. We have collected disaggregated supply sources and demand uses. The supply sources include production from oil and gas field production, from LNG imports, imports through interconnectors, and withdrawals from underground gas storages. The uses of demand include demand from the industrial sector, the power sector and residential demand, in addition to demand from injection into underground gas storages and exports through interconnectors. To reduce the dimensions we use net storage withdrawals (daily storage withdrawals less daily storage injections) and net interconnector imports (daily interconnector imports minus daily interconnector exports).

Volatility is modelled using an autoregressive moving average generalized autoregressive conditional heteroskedasticity (ARMA-GARCH) model. We examine the effects of seasonal and trend adjusted demand and supply shocks on volatility in an eight-dimensional vector autoregressive (VAR) model.

Consistent with previous research we find that deviations in aggregate demand has a significant impact on the spot price volatility in the U.K. Contrary to expectations, we are unable to find robust evidence of the impact of deviations in disaggregated demand and supply on gas volatility. In fact, it seems that the deviations in some subcomponents are mitigated by opposite deviations in other supply/demand elements. This indicates that there is substantial flexibility in the U.K. gas system, which acts in a way to reduce the impact of individual shocks to the system on volatility. Only when there is a shock to the aggregated demand is volatility significantly affected. Moreover, we find that the long-term gas volatility is associated with trends in demand and crude oil volatility.

We make four contributions to the literature. First we examine the impact of deviations in disaggregated demand and supply on volatility. Similar studies apply aggregated demand or supply data (see e.g. Ref. [73]). However, sources of supply and demand vary in terms of flexibility and possible impact on volatility. Some sources are quite flexible and can respond to situations with increased volatility. Secondly, we look at daily data, which might uncover a different set of dynamic relationships compared to for instance monthly data. Third, we examine the claim that LNG is a major contributor to the reduction in volatility in the U.K. since 2010 and do not find direct evidence of a strong link between LNG and volatility. Fourth, our research suggests that flexibility in the gas system may explain why we are not able to find statistically significant relationships between disaggregated supply and demand shocks, and volatility.

The remainder of the paper is organized as follows: Chapter 2 reviews the literature, chapter 3 addresses the U.K. gas market and the reasons why the gas price volatility can be affected by shocks in different supply and demand elements. Chapter 4 develops the methodology and chapter 5 presents the data. In chapter 6 we present and discuss the results and chapter 7 concludes.

2. Background and literature

2.1. The U.K. Natural gas wholesale market

Unlike oil, which is sold globally, gas markets are regional markets. With the arrival of liquefied natural gas (LNG), gas markets have become more interconnected [8,16,54,55]. Nevertheless, complete global gas market integration will still be limited by LNG specific constraints such as liquefaction capacities (converting gas in gaseous form to liquid form), regasification capacities (converting gas in liquid form to gaseous form) and the availability of specialized LNG transport vessels and freight rates [56].

The U.K. natural gas wholesale market is the most liquid of all regional gas markets in Europe. Although it is a regional market for the United Kingdom, it is also connected to other markets in Europe through interconnectors and short-distance LNG vessels, making it part of a larger European market. The market place in the U.K., the National Balancing Point (NBP), is a pipeline grid, with several entry and exit points throughout the grid. Unlike many stock or commodity exchanges, the market place is not limited to a specific geographical point, but rather a notional market place comprising the entire grid.

The main supply sources of gas in the U.K. are 1) pipelines directly from fields or via processing plants on the U.K. Continental shelf or the Norwegian Continental shelf, 2) imports through interconnecting pipelines to Ireland (Moffat), the Netherlands (BBL) and Belgium (IUK), 3) LNG imports via LNG regasification facilities, and 4) withdrawals from underground storages (both seasonal and fast-response (so-called fast cycle) storages). The main uses of gas in the U.K. are 1) demand from the residential sector (LDZ[2] demand), 2) demand from industry (excluding power sector), 3) demand from the power sector,[3] 4) interconnector exports and 5) injection of gas into underground storage.

The different supply and demand elements are characterized by different elasticities.[4] Residential demand is very much affected by temperature since a substantial portion of gas is used for heating. Gas is a minor part of the cost for industrial sector. The opposite is the case for the power sector where gas is the major input factor. Pipeline imports from fields can be fairly inflexible since the flows are governed by geological characteristics and production permits.[5]

However, some of the supply and demand elements are more elastic. For instance, as a response to increased demand, underground storages can switch from injection of gas to withdrawal of gas, interconnectors can switch from export to imports and LNG shippers can reroute LNG cargoes to the U.K. Some of these assets are able to respond to changing demand quite quickly (such as fast cycle storages which are able to switch flow direction in a matter of hours) and interconnectors. Others flexible assets respond more slowly, such as LNG. Hence, these flexible assets contribute to peak shaving. In summary, shocks to different sources and uses of gas can have different impact on spot price volatility due to differing price elasticities of supply.

Ref. [4] attribute the drop in volatility to increased LNG imports and a fall in gas demand. Since 2009, supply from LNG to the U.K. has increased rapidly (Fig. 1). However, as Fig. 1 shows, the supply peaked around 2011. This increase between 2009 and subsequent decrease from 2011 can be related to two defining events for natural gas. The year 2009 is by many commentators considered as the start of the "Shale gas revolution" in U.S. [7,55]. Around the same time (~2009), due to technology advancements in the field, the U.S. experienced an increase in domestic tight gas (also called shale gas)

[2] LDZ = local distribution zones.

[3] Gas used to generate electricity in gas-fired power plants (e.g. CCGT), representing a substantial portion of total gas demand. During the 1990s "the dash for gas" resulted in replacement of coal fired power plants with gas fired power plants.

[4] [73] uncover several supply functions for the U.K gas market.

[5] However, some fields are flexible and can respond to changing demand. For instance, the Troll and Oseberg oil and gas fields on the Norwegian Continental shelf have flexible production rates.

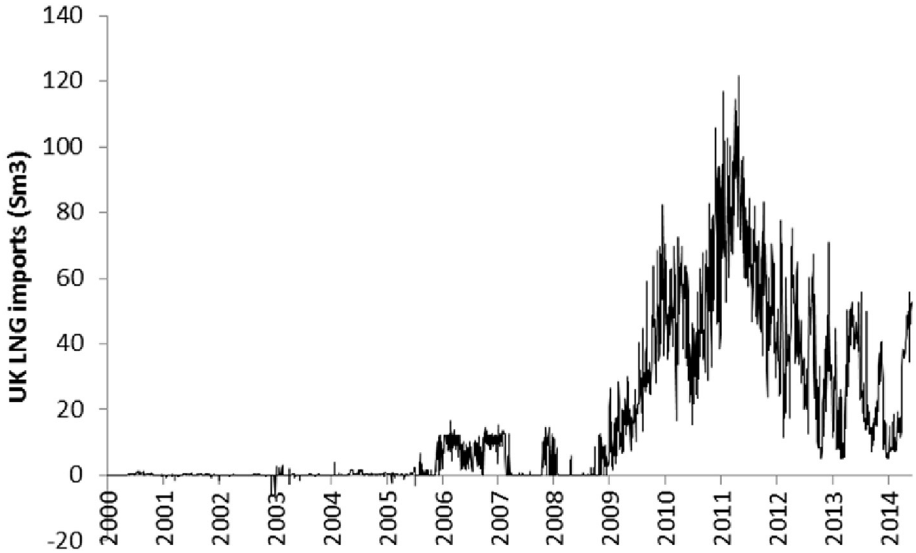


Fig. 1. Daily LNG imports to the U.K. (in million standard cubic meters, mSm^3).
Source: U.K. National Grid.

production. This has put a dampening effect on U.S. natural gas prices, effectively making it one of the lowest priced gas markets in the world. This structural shift resulted in a reduction in U.S. LNG imports. Consequently, the LNG had to be rerouted elsewhere, e.g. Europe and the U.K. A few years later in 2011, the Fukushima nuclear power plant disaster in Japan resulted in a shutdown of nuclear power generation, leading to an increase in natural gas demand, met by a growth in LNG imports. Subsequently LNG cargoes were diverted towards Asia, resulting in the fall in LNG imports in the U.K. from 2011 onwards. At the same time, since 2010, the U.K. has witnessed a substantial drop in gas price volatility. However, LNG importations have fallen since 2011, while volatility has remained at historical lows. The relationship between LNG and volatility is therefore not straightforward. It seems that the patterns in LNG imports can be explained by price differences between regional markets [61,70]. As a consequence of the shale gas revolution around 2008, U.S. gas prices dropped, resulting in rerouting of LNG cargoes to the U.K. After the Fukushima incident in early 2011, there was a tightening of the global flexible LNG market resulting in a progressive re-direction of LNG away from Europe and towards Asia [61]. Moreover, the impact of LNG on volatility might also be affected by type of LNG purchase contract.[6] Spot contracts are more likely to be used for peak shaving than long-term contracts, and we therefore expect the former to be stronger linked to volatility than the latter type of contract.

2.2. Literature

Since the seminal works of [64,65]; a vast body of literature on volatility has emerged. Substantial advances have been made on theoretical stochastic volatility modelling. Examples include the models of [19] and [41]; local volatility models [23,24,27,28], SABR [36] and the (G)ARCH family[7] [12,30] to name a few. Especially the development of conditional volatility models has facilitated empirical analyses on the drivers of volatility, both in equity, fixed income, and commodity markets. A substantial part of the literature on equity volatility has focused on the association between volatility and news arrival, trading activity and price changes [5,43]. Similar studies can also be found for energy commodities. Ref. [40] studies the impact of trading volume and maturity on volatility in natural gas markets.

Another important thread of research addresses the transmission of volatility across markets, including both spillover effects between commodity and equity markets as well as between different commodity markets (see Ref. [68] for a review). Several studies have uncovered volatility spillover effects between oil and equity markets [3,20,42,49,51,52,57,69,77], and between oil and gas markets [31]. A recent study shows that there is a bidirectional spillover effect between natural gas and crude oil and between natural gas and heating oil markets [45]. These findings indicate that natural gas volatility is affected by and can impact several other commodity and financial markets.

The impact of news arrivals related to inventory announcements on volatility has been a popular topic in recent years [10,18,33,37,47,48,53]. These generally find a substantial increase in volatility around the time of the release of natural gas storage reports, especially related to inventory surprises. Ref. [10] find that large volatility days are often associated with substantial jump components, which are in turn associated with inventory announcement dates. Similar results are found in other energy markets as well, such as oil markets [17,74].[8] Furthermore, research also indicates that weather, along with storage news impacts natural gas volatility. Ref. [18] find that the jump portion of volatility is a function of unanticipated low temperatures and inventory surprises. Similarly [53], finds that extreme weather conditions and low inventories affect natural gas volatility. Recently Ref. [47], find that regime shifts in the natural gas market correlate well with major events affecting supply and demand. Hence, the literature seems to suggest a link between information about the supply (inventories) and demand (e.g. the impact of extreme weather), and volatility. These results are consistent with key theories for commodity prices such as the Theory of Storage [15,44,72,76]. This theory, which equates the difference between forward and spot

[6] We thank an anonymous review for highlighting this issue.

[7] Numerous variants of ARCH and GARCH models exist (see Ref. [12] for an extensive list).

[8] [74] find that crude oil futures volatility increases preceding OPEC announcements and [17] studies the impact of crude oil inventory on crude oil volatility.

prices to the cost of carry and a convenience yield, predicts a negative relationship between inventory levels and spot price volatility. In the spirit of the theory of storage [35], study the association between volatility and inventory levels in oil and gas and markets. While they find a negative relation between volatility and inventory levels in the oil market, this association only prevails during periods of scarcity defined by inventory levels being below historical averages in natural gas markets, especially during the cold winter months. Hence, studies on natural gas market volatilities need to take into account strong seasonality in the relationship between the demand and supply situation, and volatility.

The limit of the studies described above is that they focus either on the total supply and demand picture, or limited to inventories. Ref. [59] investigate the relationship between inventories, spot and futures gas prices and volatility. A recent study by Ref. [73] find that different supply curve assumptions result in different U.K. natural gas volatility characteristics. Moreover [25], find that aggregate demand and supply shocks impacts crude oil volatility. These studies address the relation between aggregate demand and supply, and volatility. However, both demand and supply can be disaggregated into subcomponents, each with a potentially different impact on volatility. Our main contribution is to try to fill this void in the literature. Furthermore, disaggregating allows us to also examine the impact of a key supply element in recent years, such as LNG. This is important since the literature suggests that LNG is believed to have furthered market integration globally [8,16,54]. However, information on how LNG impacts volatility is missing.

3. Methodology

Since volatility is not directly observable, it has to be estimated. The simplest approach is to calculate the standard deviation of returns for historical asset prices. However, this approach has its limitations as it puts equal weight on all historical observations. Hence, weighting schemes are used in order to make sure that recent innovations to volatility are weighted more than older observations, resulting in better estimation of current volatility than simple averaging.

A popular model for volatility modelling, which takes into account long run volatility, is the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model [11]. Let $r_t = \mu_t + \sigma_t \varepsilon_t$ be the return process of a price series, where ε_t is a strong white noise process and μ_t a conditional mean process. The GARCH (p,q) model for the conditional variance σ_t^2 is given as:

$$a_t = \sigma_t \varepsilon_t, \tag{1}$$

where

$$\sigma_t^2 = \gamma V_L + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2. \tag{2}$$

where σ_t is the conditional standard deviation, α_i are coefficients on ARCH terms, β_i are coefficients on GARCH terms, V_L is the long run volatility with weight γ. Similar studies on the relationship between volatility and energy demand and supply shocks also use conditional volatility estimates [25,73]. Ref. [25] repeat their analysis using realized volatility and implied volatility and find similar results across the three different volatility measures. We therefore find that using conditional volatility appropriate for our study.

The next step is to model the impact on volatility of demand and supply shocks (in the form of deviations from seasonal normal). First, we disaggregate the aggregate supply and demand into subcomponents. Supply is divided into 1) pipeline gas into U.K. from the North Sea (from oil and gas fields situated on the U.K. continental shelf and the Norwegian continental shelf ($PIPE_t$), 2) importations from Ireland and mainland Europe through interconnectors, 3) LNG imports (LNG_t) and 4) withdrawal from underground natural gas storages. Demand is divided into 1) residential demand (LDZ_t), 2) demand from industry (not including the power sector) (IND_t), 3) demand from gas-fired power plants ($POWER_t$), 4) exports to Ireland and Mainland Europe through Interconnectors, and 5) injections into underground natural gas storages. In order to reduce the number of dimensions in the VAR system we create a net storage withdrawal variable ($STORAGE_t$) by subtracting storage injections from storage withdrawals. Likewise, net interconnector imports ($INTER_t$) are calculated as interconnector imports less exports.

To capture shocks in demand or supply, we calculate deviations from seasonal normal demand or supply subcomponents. The latter variables are denoted using lower case letters, while the upper case variables refer to the unadjusted demand and supply subcomponents. It is crucial to adjust for seasonality which is an important factor in natural gas markets. We apply a seasonal and trend decomposition procedure based on loess, STL [21] on all demand and supply subcomponents. STL is a filtering procedure which allows us to decompose the time series' into seasonal, trend and residual components. The resulting variable is then used as our measure of deviation from seasonal normal, and subsequently applied in our VAR model. We also apply the STL procedure for both gas and oil volatility to remove trends and seasonality. This is appropriate for two reasons. First, the data demonstrates a downward trend in both gas and oil volatility. Second, gas volatility exhibits seasonality [71]. For ease of comparing the coefficients we also normalize the adjusted demand and supply variables by subtracting the mean and dividing by the standard deviations.

The relationship between volatility and supply and demand deviations are empirically estimated using a vector autoregressive model (VAR). The VAR model is a time series model that describes the dynamics of the data in terms of linear functions of lagged variables. For instance, with two variables, y_t and x_t, the first order VAR model, a VAR(1), models the dynamics of the data as

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_0 \\ \alpha_1 \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix},$$

where α_0 and α_1 are constant intercept parameters, and α_{11},α_{12},α_{21} and α_{22} are parameters that determines the effect of the one period lagged data on the current data. The last term $[\varepsilon_{1,t},\varepsilon_{2,t}]'$ are possibly correlated error terms. The model can be extended with more lags and to higher dimensional data. The model is primarily used for forecasting or structural data analysis, and because of its simple structure has enjoyed great popularity in applied economic analysis. For instance [66,67], pioneered the use of VAR models in the analysis of macroeconomics time-series data. The parameters of the model can be estimated using either multivariate least squares estimation, or, assuming the probability distribution of the error term is known, maximum likelihood estimation. For a detailed description of the VAR model see for instance [38] or [50].

We apply the VAR model to estimate the relationship between supply and demand deviations and volatility. There are several benefits to applying this methodology. First, we are able to estimate empirically the relationship between the supply and demand deviations and volatility in a time-series model. Second, the VAR model allows us to capture the dynamics between the explanatory variables. For instance, we are able to assess how LNG deviations are affected by other supply and demand deviations, as well as volatility.

We carry out the analysis in two steps. First, we investigate the impact on gas volatility of deviations in aggregate demand and crude oil volatility. Second, we repeat the first analysis using deviations in disaggregated supply and demand to try to isolate the effect of LNG deviations. In addition, we examine the regression parameter stability using split samples and empirical fluctuation processes.

In the first step, we model the system as a 2-dimensional VAR. Let v_t be the natural logarithm of σ_t and let $\boldsymbol{x_t} = (v_t, demand_t)'$ denote the (2×1) vector of time series variables. We model the relationship between demand deviation and volatility a the 2-dimensional VAR(p) model. In addition, we include the lagged natural logarithm of crude oil volatility as an exogenous variable. The VAR system becomes

$$\boldsymbol{x_t} = \boldsymbol{A}_0 + \sum_{i=1}^{p} \boldsymbol{A_i x_{t-i}} + \theta ovx_t + \boldsymbol{\varepsilon_t^1} \tag{3}$$

where $\boldsymbol{A}_0$ is a (2×1) vector of constants, $\boldsymbol{A_i}$ are (2×2) coefficient matrices and $\boldsymbol{\varepsilon_t}$ is an (2×1) unobservable zero mean white noise vector process, serially uncorrelated or independent, with time invariant covariance matrix $\boldsymbol{\Sigma}$, and p is the number of lags. Crude oil volatility is represented by the natural logarithm of the (trend and seasonally adjusted) OVX crude oil volatility index, and is denoted by ovx_t.

In the second step, we disaggregate total gas supply and demand into subcomponents. The de-trended and de-seasonalized subcomponents are then included in the VAR model, where $\boldsymbol{y_t} = (v_t, lng_t, storage_t, inter_t, pipe_t, ldz_t, industry_t, power_t)'$. The resulting system of disaggregated demand and supply deviations and volatility is the following 8-dimensional VAR (p) model:

$$\boldsymbol{y_t} = \boldsymbol{B}_0 + \sum_{i=1}^{p} \boldsymbol{B_i y_{t-i}} + \theta ovx_t + \boldsymbol{\varepsilon_t^2} \tag{4}$$

where $\boldsymbol{B}_0$ is a (8×1) vector of constants, $\boldsymbol{B_i}$ are (8×8) coefficient matrices and $\boldsymbol{\varepsilon_t^2}$ is an (8×1) unobservable zero mean white noise vector process, serially uncorrelated or independent, with time invariant covariance matrix $\boldsymbol{\Sigma}$, and p is the number of lags.

3.1. *Hypotheses on the impact of shocks in aggregate demand on volatility*

In line with previous research, we expect deviations in aggregate demand to be positively and significantly associated with changes in volatility.

H1. significant and positive coefficient on deviations in daily aggregate demand.

3.2. *Hypotheses on the impact of shocks in elastic supply variables on volatility*

We expect positive deviations in net storage withdrawals, LNG imports and interconnector imports to have a negative impact on volatility. These three elements are flexible and have the capability for responding quickly to increases in prices. A sudden increase in gas prices are therefore likely to be met by increased LNG imports, storage withdrawals and Interconnector imports, which will lead to a subsequent decrease in prices. Hence, lagged variables for shocks in LNG, storage and Interconnector supplies should therefore lead to a reduction in volatility, and therefore a negative relationship between volatility and lagged explanatory variables. On alternative form the relevant hypotheses are:

H2. significant and negative coefficient on deviations in daily LNG imports.

H3. significant and negative coefficient on deviations in daily net storage withdrawals.

H4. significant and negative coefficient on deviations in daily net Interconnector imports.

3.3. *Hypotheses on the impact of shocks in inelastic supply/demand elements on gas price volatility*

A priori, we expect a positive effect of inelastic demand shocks on volatility, and a negative effect of inelastic supply shocks. Deviations in the gas demand from the residential or industry sectors should lead to increased volatility. Positive deviation from seasonal normal gas supplies from oil and gas field production should lead to decreased volatility. The resulting hypotheses are:

H5. significant and negative coefficient on deviations in daily shocks in pipeline imports.

H6. significant and positive coefficient on deviations in daily shocks in LDZ demand.

H7. significant and positive coefficient on daily deviations in demand from the industry sector.

The impact of shocks in the power demand is a bit more unclear. In the UK a large proportion of the electricity generation capacity is from gas fired power plants (effect of the “dash for gas” in the 1990s). Gas fired power plants are typically quite flexible (e.g. Combined Cycle Gas Turbines, CCGTs) and can readily respond to peaks in the electricity markets. Therefore, there is a strong link between the gas markets and power markets in the U.K. However the direction of the link is not straightforward. In isolation, we would expect that a positive shock in power demand will result in increased volatility. However, there might be more complex dynamics in place. A positive shock in the demand for gas from the power market might be due to a rapid fall in gas prices (i.e. increased volatility). A negative shock in the demand for power might be caused by a sudden increase in gas prices which (i.e. also increased volatility). If the interaction effects are dominant, then the significance of this variable will not be significant. Nevertheless, we expect that the effect that power demand shocks lead gas price volatility dominates. The hypothesis therefore becomes

H8. significant and positive coefficient on daily deviations in demand from the power sector.

4. Data

4.1. *Data source*

We use daily observations of the Day ahead forward contract from Heren (www.heren.com) as a proxy for spot prices. Daily observations of disaggregated daily U.K. natural gas demand and supply at the U.K. National Balancing Point (NBP) system are collected from National Grid. On the demand side the variables include i) residential demand which is an aggregate from 12 local distribution zones (LDZ), ii) industrial demand (excluding industrial demand from the power sector), iii) demand from the power sector, iv) injections into underground natural gas storage facilities and v) exports through three interconnectors to Belgium (Interconnector UK, IUK), Netherlands (Balgzand to Bacton Line, BBL) and Ireland (Moffat to Ireland). The supply components include vi) field production from the U.K. continental shelf (UKCS) and the

Norwegian continental shelf (NCS) brought into the National Balancing Point at subterminals, vii) liquefied natural gas (LNG) imports into terminals with subsequent regasification before entering the NBP (or NTS) system, viii) withdrawals from underground natural gas storage facilities and ix) imports through three interconnectors to Belgium, Netherlands and Ireland.

Moreover, to control for impact of exogenous factors we also include oil volatility. The literature suggests that crude oil volatility has predictive power for natural gas volatility [58], and that there exist a hierarchy of volatility influence from oil to gas to electricity markets [29]. In line with [49] we use the OVX index (www.cboe.com) as a proxy for crude oil volatility.

4.2. Gas price volatility estimation

To estimate contemporaneous volatility we use a ARMA(1,1) - GARCH(1,1) model.

$$r_t = \mu + \theta_1 r_{t-1} + \theta_2 a_{t-1} + a_t \tag{5}$$

$$a_t = \sigma_t \varepsilon_t, \tag{6}$$

$$\sigma_t^2 = \gamma V_L + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \tag{7}$$

where r_t is natural gas returns, modeled as an autoregressive moving average process. The parameters of the resulting model is shown in Table 1. The significance of the coefficients and the diagnostics tests indicate a good fit to the data and we use an ARMA (1,1) – GARCH (1,1) to estimate the volatility of U.K. spot gas prices used in this paper. Fig. 2 presents the estimated time series of gas volatility between October 2007 and June 2014. The graph suggests that volatility has fallen, due to decreases in both the number and magnitude of "spikes".[9]

Table 2 presents the descriptive statistics for the disaggregated supply and demand data, both unadjusted and decomposed into season, trend and a residual. The supply side is dominated by pipeline production both from indigenous UKCS production and imports from the NCS. The three flexible supply elements, interconnector import, LNG import and storage withdrawals are approximately of the same magnitude. On the demand side, the residential sector is by far the largest component, followed by demand from electricity producers. Average interconnector imports are lower than exports resulting in a net export during 2007–2014. Likewise, the data suggest a net storage withdrawal over the same time period, indicating a fall in working volume[10] for gas storage facilities.

In order to ease the comparison of the coefficients from the regressions, the residuals for the variables in Table 3 are normalized to give mean 0 and standard deviation 1. All variables are stationary (Table 3).

5. Results and discussion

In order to determine the number of lags in our VAR model in Eqs. (3) and (4) we use three of the most common information criteria: Akaike information criterion (AIC: Ref. [1], Schwarz Bayesian information Criterion (SIC: Ref. [63], Hannan-Quinn (HQ: Ref. [39] and final prediction error (FPE: Ref. [2]. The number of lags varies between 1 and 2. We therefore choose to use one lag and apply a VAR(1) model with OVX volatility as an exogenous variables and contemporaneous UK gas price volatilities and supply/demand shocks as endogenous variables.[11] Results are presented with White Ref. [75] corrected standard errors.

In the first step we examine the empirical model with deviation in aggregate demand (Table 4). In line with prior research we find a significant and positive effect of deviation in demand on gas price volatility. However, we do not find evidence of a feedback effect from volatility on aggregate demand deviation.

Next, we include disaggregated demand deviations in the VAR system. The results are presented in Table 5.

Contrary to expectations, we do not find evidence that any of the disaggregate demand or supply deviations affect U.K. gas price volatility. We therefore reject hypotheses H_2 to H_8. Moreover, we cannot find evidence of a volatility spillover between oil and gas markets.

An explanation for why the disaggregated demand and supply variables do not have a significant impact on gas volatility can be

Table 1
Daily spot price volatility is estimated using ARMA(1,1) - GARCH(1,1).

ARMA-GARCH	Coef	p-value
μ	<-0.0001	0.8830
θ_1	0.8340	<0.0001
θ_2	−0.8997	<0.0001
γV_L	<0.0001	<0.0001
α	0.1867	<0.0001
β	0.8649	<0.0001
Diagnostics	Statistic	p-value
Jarque-Bera	58045.08	<0.0001
Shapiro-Wilk	0.8942	<0.0001
Ljung-Box Q(10)	11.0007	0.3575
Ljung-Box Q(15)	16.8270	0.3293
Ljung-Box Q(20)	18.2938	0.5681
LM Arch test	4.0069	0.9833

Note: Tests for normality, i.e. null hypotheses of normal distributed residuals: Jarque-Bera and Shapiro-Wilk tests. Tests for independence in the residuals (null hypothesis of no autocorrelation): Ljung-Box Q tests, where Q denotes the number of lags. Test for ARCH effects in the residuals: LM ARCH test.

Table 2
Descriptive statistics for aggregate demand and disaggregated supplies and demand.

Variable	Unadjusted		Season		Trend		Residual	
	Mean	St.dev.	Mean	St.dev.	Mean	St.dev.	Mean	St.dev
Volatility								
v_t	4.20	0.61	<0.01	0.19	4.19	0.40	<0.01	0.41
ovx_t	3.54	0.36	<0.01	0.05	3.54	0.31	0.01	0.13
Supplies								
$pipe_t$	194.60	50.44	2.30	35.84	192.05	30.70	0.32	16.64
lng_t	33.02	25.86	0.19	6.45	32.83	21.23	−0.01	11.04
$storage_t$	4.78	28.96	0.88	21.14	3.83	2.77	0.07	19.80
$inter_t$	−9.87	26.23	0.94	17.65	−10.94	10.90	0.13	14.68
Demand								
ldz_t	153.90	75.23	4.37	70.99	149.40	12.02	0.43	25.14
$power_t$	58.06	15.48	0.05	2.57	57.96	13.18	0.05	6.65
ind_t	10.96	1.55	0.01	0.39	10.95	0.95	0.01	1.09
$demand_t$	265.78	70.09	3.94	61.48	261.38	25.41	0.46	25.25

Note: All supply and demand variables are volumes measured in million standard cubic meters (mSm^3). The volatility variables are calculated as the natural logarithms of annualized (seasonal and trend adjusted) U.K. gas volatility (v_t), and the (seasonal and trend adjusted) Chicago Board of Options Exchange (CBOE) OVX crude oil volatility index (ovx_t), respectively.

[9] By a "spike" we mean a short-lived and reversed extreme price movement.

[10] The storage capacity of a gas storage facility consists of two volumes, the cushion gas which pressurizes the reservoir or cavern, and the working gas volumes which can be withdrawn or injected during normal operations.

[11] The results are similar with a VAR(1) model.

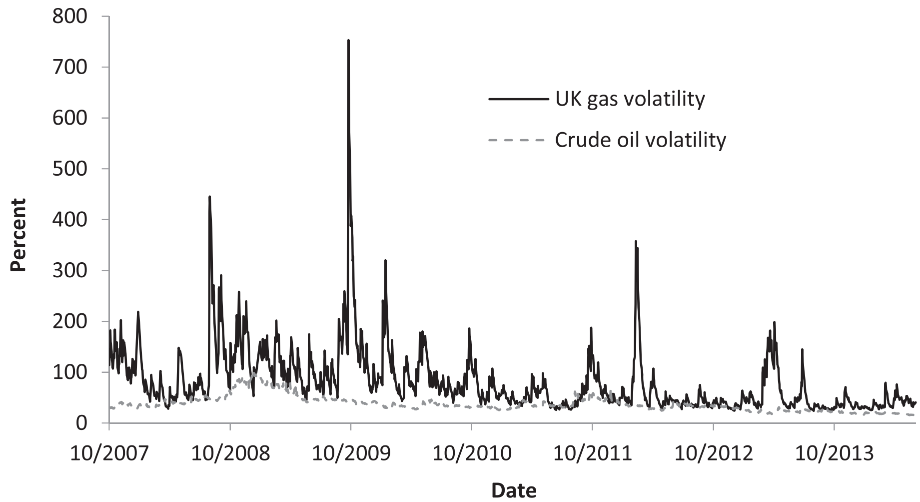


Fig. 2. UK natural gas spot price volatility estimated using an ARMA(1,1) - GARCH(1,1) model and OVX crude oil volatility 2007–2014.

Table 3
Stationarity tests.

	ADF
v_t	−8.559
ovx_t	−5.972
$pipe_t$	−7.863
lng_t	−8.380
$storage_t$	−12.574
$inter_t$	−8.918
ldz_t	−11.577
$power_t$	−8.588
ind_t	−8.805
$demand_t$	−12.744

Note: The values are the test statistics from the augmented Dickey-Fuller test [26,62] with maximum 10 lags. The number of lags selected according to Akaike Information Criterion [1]. We use ADF tests for both stationarity and trend stationarity. The critical statistics for this test are 10% = −1.62, 5% = −1.95 and 1% = −2.58.

Table 4
Results from a VAR model using aggregate demand and crude oil volatility.

	v_t	$demand_t$
v_{t-1}	0.9223***	−0.0295
ovx_{t-1}	−0.0344	0.1055
$demand_{t-1}$	0.0102***	0.8276***
intercept	0.0004	0.0008

Note: Significance levels denoted by asterisks, *: p < 0.10, **: p < 0.05, and ***: p < 0.01.

found by examining the dynamics between the demand and supply deviations. For instance, positive deviations in LDZ demand on time *t−1* is positively associated with positive and significant deviations in pipeline imports, LNG imports, and storage withdrawals at time *t*. Likewise, positive deviations in power demand at time *t−1* is associated with positive and significant deviations in storage withdrawals and pipeline imports at time *t*. On the supply side we can observe that oversupply through pipelines at time *t−1* seems to be compensated by storage injections and interconnector exports at time *t*. To conclude, the U.K. gas system seems quite flexible, such that deviations in one or more of the supply or demand elements is compensated by opposite deviations in the other elements. Hence, shocks in single demand or supply elements are likely to be mitigated by the optimization of flexible assets such as storage or interconnectors. In fact, theory also suggests a strong link between volatility and natural gas storages. Storage capacity can be modelled using option theory [9,13,14,22,32,34]. Moreover, flexibility in natural gas pipelines can also be valued as a storage facility [6]. There might also be flexibility related to production from oil and gas fields which resembles embedded options. For instance, shale gas reservoirs can shut in production for short periods of time, a flexibility which represents a type of gas storage [46].

In summary, we can only find evidence of a link between demand/supply deviation and gas volatility on an aggregate level. At the disaggregate level, there seems to be a complicated dynamic between the gas assets mitigating any effects on volatility.

Table 5
Results from a VAR model using disaggregate demand and supply, and crude oil volatility.

	Volatility	Demand	Supply					
	v_t	ldz_t	$power_t$	ind_t	$pipe_t$	lng_t	$storage_t$	$inter_t$
v_{t-1}	0.9216***	−0.0536	0.0156	0.0025	−0.0256	0.0492	0.0085	−0.0838
ovx_{t-1}	−0.0247	0.0505	−0.0136	−0.0014	0.5480***	−0.0642	−0.0403	−0.2895***
ldz_{t-1}	0.0014	0.8716***	0.1842***	−0.0441	0.3232***	0.0971**	0.4991***	0.0673
$power_{t-1}$	0.0072	0.0065	0.8173***	−0.0193	0.0553**	0.0344	0.0975***	0.0060
ind_{t-1}	0.0047	−0.0258*	0.0445***	0.8993***	0.0044	−0.0023	0.0401**	0.0175
$pipe_{t-1}$	0.0007	−0.0071	−0.0789**	0.0275	0.4611***	−0.0109	−0.1892***	−0.0889***
lng_{t-1}	0.0003	−0.0340	−0.0636**	0.0287	−0.1798***	0.7690***	−0.1508***	−0.0856***
$storage_{t-1}$	−0.0022	−0.0441	−0.1433***	0.0152	−0.1337**	−0.1305***	0.3542***	−0.0047
$inter_{t-1}$	0.0013	0.0217	−0.0529*	0.0357*	−0.1765***	−0.0386	−0.2008***	0.7666***
Intercept	0.0003	0.0009	0.0004	0.0001	−0.0030	0.0014	0.0003	0.0019

Note: Significance levels denoted by asterisks, *: p < 0.10, **: p < 0.05, and ***: p < 0.01.

Table 6
Correlations between trends in the variables.

	v_t
ovx_t	0.842
$pipe_t$	0.917
lng_t	−0.276
$storage_t$	−0.393
$inter_t$	−0.155
ldz_t	0.691
$power_t$	0.879
ind_t	0.638
$demand_t$	0.783

Table 7
Results from a VAR model using aggregate demand and crude oil volatility 2007–2010.

	v_t	$demand_t$
v_{t-1}	0.9068***	−0.0803
ovx_{t-1}	−0.0147	0.2496*
$demand_{t-1}$	0.0018	0.8133***
intercept	0.0011	0.0119

Note: Significance levels denoted by asterisks, *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 8
Results from a VAR model using aggregate demand and crude oil volatility 2011–2014.

	v_t	$demand_t$
v_{t-1}	0.9305***	0.0004
ovx_{t-1}	−0.0494	−0.0393
$demand_{t-1}$	0.0167***	0.8371***
intercept	0.0011	−0.0085

Note: Significance levels denoted by asterisks, *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

The observation that gas price volatility has fallen during the period is still unexplained. However, there is a strong correlation between the trends for variables such as gas volatility, oil volatility, LDZ, power, industrial and aggregate demand (Table 6). Hence, the decreased U.K. gas price volatility is associated with a fall in demand from the residential, power and industrial sector, as well as a decrease in the crude oil price volatility. While the correlations do not provide evidence on the causal relationship between the trends, they do suggest that the long term trend in volatility is governed by trends in demand and impulses from other commodity and financial markets. Our results also suggest that daily deviations in aggregated demand affect the volatility in the short-term.

5.1. Robustness tests: parameter stability

Fig. 1 suggests contrasting developments in U.K. LNG imports before and after the Fukushima incident. During 2009 to 2010, there were increasing LNG imports, followed by falling LNG importations after 2010 when Asia became the premium priced market as a consequence of nuclear power station shutdown in Japan. A possible consequence of the divergent trends in LNG imports before and after the Fukushima event are unstable model coefficients, changing from one period to the next. To examine the parameter stability, and implicitly also the robustness of the methodology we apply, additional tests are performed. First, we create two separate data sets, one for 2007 to 2010 and one with data from 2011 to 2014, and re-run the VAR estimation on the two data sets (Equations (3) and (4)). Tables 7–10 show the results from the VAR estimation on these two datasets.

Second, we carry out an empirical fluctuation test to uncover the existence of structural breaks in the data, which may have occurred as a consequence of the Fukushima disaster, or due to

Table 9
Results from a VAR model using disaggregate demand and supply, and crude oil volatility 2007–2010.

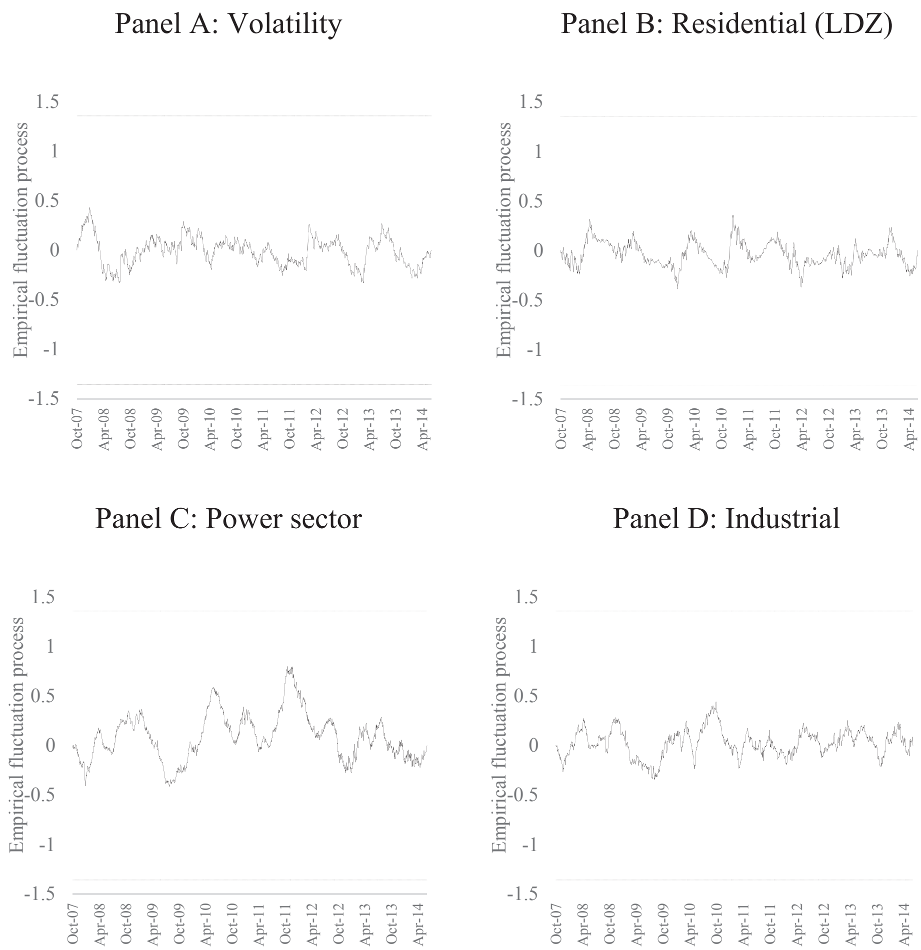
	Volatility	Demand	Supply					
	v_t	ldz_t	$power_t$	ind_t	$pipe_t$	lng_t	$storage_t$	$inter_t$
v_{t-1}	0.8993***	−0.1001*	−0.0477	−0.0080	−0.0757	0.0952*	−0.0527	−0.1415***
ovx_{t-1}	−0.0359	0.1555	−0.0581	0.1381	0.4857***	−0.0439	0.0729	−0.2587*
ldz_{t-1}	−0.0066	0.8213***	0.0834*	−0.0559	0.0923*	0.0335	0.7041***	0.0316
$power_{t-1}$	<0.0001	0.0136	0.8548***	0.0077	0.0098	0.0460*	0.1819***	−0.0052
ind_{t-1}	0.0027	−0.0294	0.0223	0.9161***	0.0055	−0.0109	0.0172	0.0058
$pipe_{t-1}$	0.0040	0.0197	−0.0223	0.0163	0.6722***	0.0016	−0.3672***	−0.0669*
lng_{t-1}	0.0029	−0.0178	−0.0237	0.0042	−0.0889*	0.7776***	−0.2229***	−0.0527*
$storage_{t-1}$	0.0028	−0.0130	−0.1099***	0.0289	0.0498	−0.0821**	0.1962***	0.0104
$inter_{t-1}$	−0.0085	0.0298	−0.0189	0.0174	−0.0577	0.0186	−0.3649***	0.7768***
Intercept	0.0017	0.0063	0.0072	−0.0030	0.0074	−0.0194	0.0118	0.0056

Note: Significance levels denoted by asterisks, *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.

Table 10
Results from a VAR model using disaggregate demand and supply, and crude oil volatility 2011–2014.

	Volatility	Demand	Supply					
	v_t	ldz_t	$power_t$	ind_t	$pipe_t$	lng_t	$storage_t$	$inter_t$
v_{t-1}	0.9312***	−0.0216	0.0764	0.0092	0.0445	0.0231	0.0327	−0.0400
ovx_{t-1}	−0.0202	−0.0695	0.1855	−0.2485*	0.5285**	0.0422	−0.0615	−0.3129*
ldz_{t-1}	0.0160**	0.9231***	0.2990***	−0.0410	0.5608***	0.1726**	0.2830***	0.1194**
$power_{t-1}$	0.0126	0.0062	0.7894***	−0.0342	0.1061***	0.0351	0.0180	0.0140
ind_{t-1}	0.0061	−0.0250	0.0826***	0.8636***	0.0094	0.0261	0.0500	0.0323
$pipe_{t-1}$	−0.0073	−0.0373	−0.1292**	0.0303	0.2608***	−0.0305	−0.0350	−0.1171***
lng_{t-1}	−0.0024	−0.0447*	−0.0976**	0.0492**	−0.2617***	0.7469***	−0.0714*	−0.1158***
$storage_{t-1}$	−0.0134	−0.0816**	−0.2013***	0.0155	−0.3443***	−0.1786***	0.5272***	−0.0391
$inter_{t-1}$	0.0028	0.0094	−0.0956**	0.0578**	−0.2873***	−0.0867**	−0.0658	0.7377***
Intercept	0.0001	−0.0051	−0.0095	0.0020	−0.0222	0.0148	−0.0060	0.0030

Note: Significance levels denoted by asterisks, *: $p < 0.10$, **: $p < 0.05$, and ***: $p < 0.01$.



Note: The black line represents the estimated fluctuation process, while the dashed lines represent the 5% significance level boundaries. If the fluctuation process exceeds the critical value boundaries, then the null hypothesis of no structural breaks is rejected at the 5% significance level.

Fig. 3. Empirical fluctuation tests (OLS-CUSUM) for the volatility and demand equations.

other circumstances. Specifically, we apply the OLS-CUSUM[12] test [60]. This test estimates an empirical process which captures the fluctuation in regression residuals. The CUSUM process uses cumulative sums of standardized residuals. Since the limiting processes for the said empirical process is known, boundaries associated with certain significance levels can be computed. The null hypothesis is that there are no structural breaks in the estimated regression model. If the empirical fluctuating process crosses the boundaries, the null hypothesis can be rejected and we are able to conclude that there are structural breaks in the estimated model. The results from the empirical fluctuation test is presented in Figs. 3 and 4.

Tables 7 and 8 show that the empirical model coefficients change between the two periods. The change only to a small degree for the autocorrelation terms, and more for the lagged demand in the volatility equation. The coefficient on the latter variable was only significant post 2011 (Table 8), and not in the pre-2011 model (Table 7). However, the number of observations are smaller when splitting the initial dataset in two, potentially affecting parameter significance.

Tables 9 and 10 paint the same picture, the autoregression coefficients are in general only mildly affected, while the other coefficients change more, but not to a very large extent. The general impression is that the coefficients in the VAR model fluctuate, but to a limited extent. The overall results seem to be consistent across the two time periods. The significance of some of the parameters also change, some being significant in the first period and not in the second, and vice versa. However, a reduction in the number of observations may be one of the reasons for a change in parameter significance. For this reason we have also applied a second type of methodology for assessing parameter stability, the OLS-CUSUM approach, on the entire dataset.

The OLS-CUSUM results in Figs. 3 and 4 support the general impression from the analysis of the split dataset. The coefficients are not stable, and fluctuate over time. Especially the empirical fluctuation process for the pipeline and LNG equations exhibit substantial variations (Fig. 4, panels C and D, respectively). Despite

[12] OLS-CUSUM: Ordinary least-squares cumulative sum (of residuals).

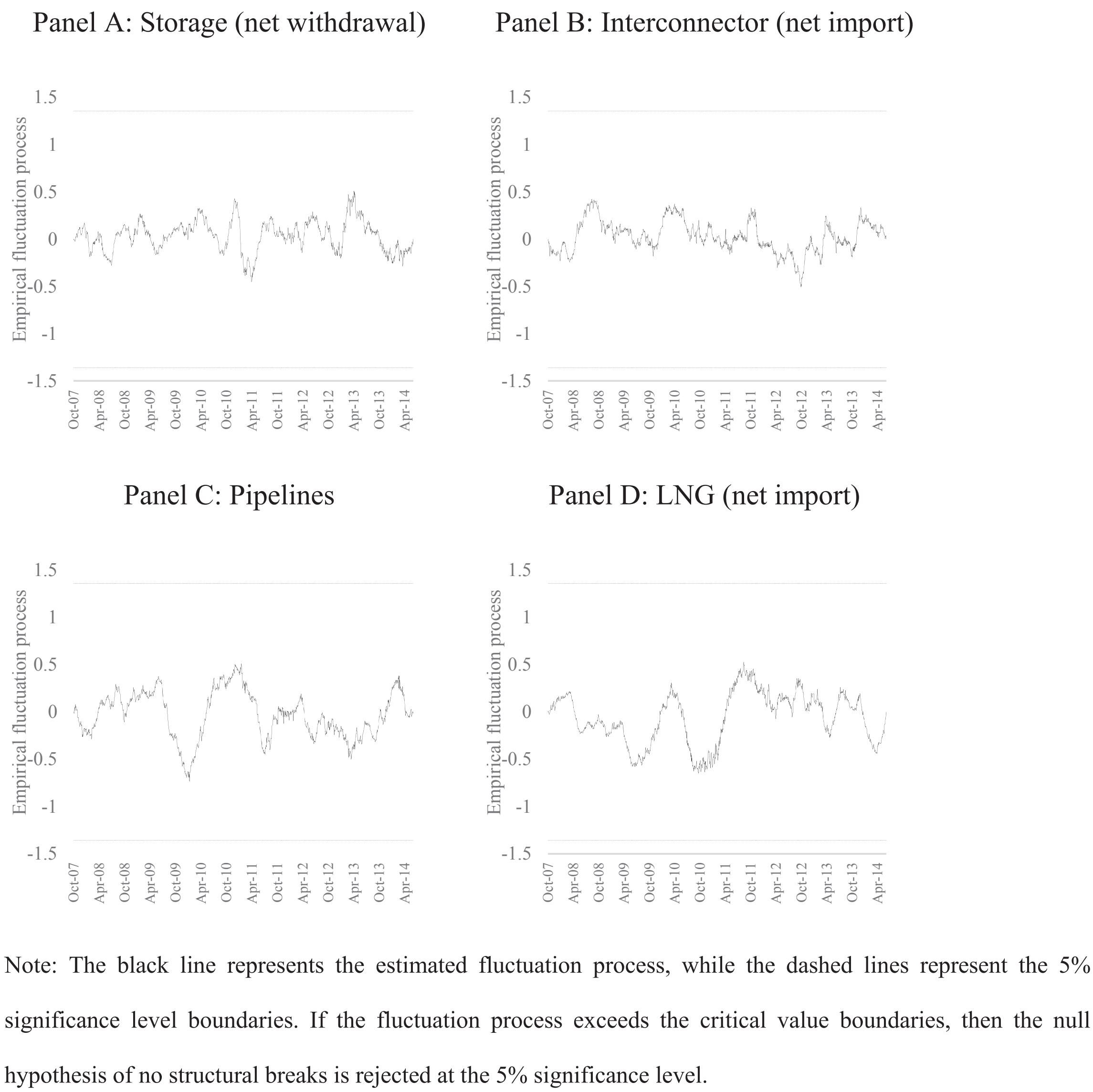


Fig. 4. Empirical fluctuation tests (OLS-CUSUM) for the supply equations.

time-varying nature of the coefficients are time-varying, it is within certain limits. We are unable to reject the null hypothesis of no structural shifts, and we can keep the original model as presented in Table 5.

6. Conclusions

This study seeks to examine the impact of LNG import deviations on the U.K. natural gas spot price volatility. The flexibility in LNG supplies suggests that it might have a role in peak-shaving and therefore have an impact on volatility. Increased volatility might also attract LNG cargoes and therefore lead to shocks in LNG imports. In addition, LNG might compete with other sources of flexibility making the dynamics complex. We therefore find it appropriate to apply a VAR model to capture the dynamics in the system.

We find evidence that deviations in demand affect gas volatility on an aggregate level. However, we are unable to uncover any relationship between deviations in disaggregated demand or supply variables, such as LNG, and volatility. Our results suggest that there are complex interactions in the U.K. gas system mitigating the effect that a deviation in a single demand or supply variable might have on volatility. Only when the total system is shocked is there an effect on volatility. A possible avenue of further study is to use high-frequency data to try to uncover the effect of disaggregated demand and supply on gas volatility. There is likely to be some delay in the response time for the flexible assets, such that the intraday volatility might be affected by deviations in for instance residential demand. This effect might not be uncovered using daily data, but effects might materialize using data with higher granularity.

Moreover, a possible explanation for the poor relationship between LNG deviations and volatility might also be explained by LNG cargoes being sold on different types of contracts. Spot contracts are more likely to influence volatility than long-term supply contracts. A topic for further study is whether splitting the LNG supply by type of contract might better capture a potential LNG-volatility relationship.

Finally, we find that the fall in volatility is associated with decreased demand and a drop in crude oil volatility. While we find that the decreased gas volatility coincides with decreased crude oil volatility and gas demand, we have not examined the causal relationship. This is a topic for further study.

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