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IES Working Paper: 33/2018



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Residual Shape Risk on Czech Natural Gas Market

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Abstract:

This paper introduces residual shape risk as a new subclass of energy commodity risk. Residual shape risk is caused by insufficient liquidity of energy forward market when retail energy supplier has to hedge his short sales by a non-exible standard baseload product available on wholesale market. Because of this inflexibility energy supplier is left with residual unhedged position which has to be closed at spot market. The residual shape risk is defined as a difference between spot and forward prices weighted by residual unhedged position which size depends on the shape of customers' portfolio of a given retail energy supplier. For empirical evaluation of residual shape risk we use a real portfolio of a leading natural gas retail supplier in the Czech Republic over the period 2016-2017. The size of residual shape risk in our example corresponds approximately to 1 percent of profit margin of natural gas retail supplier.

JEL Classification: C51, C58, Q41, Q47

Keywords: natural gas markets, spot prices, forward prices, residual shape risk

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those of the authors and not necessarily those of our institutions. All remaining errors are solely our responsibility.

1 Introduction

A liberalization of the European gas markets under the Directive 2003/55/EC (EC 2003) led to a fragmentation of natural gas supply chain. One of many consequences of this “unbundling” process (Stern & Rogers 2017) is a current move towards the situation when company supplying the retail customers is not able to purchase natural gas directly from its parent company, but it has to purchase gas on the open market. However the granularity of monthly baseloads available on the open market does not allow for perfect hedging of daily deliveries of natural gas to final consumers. This introduces a new source of commodity risk into natural gas markets. In this paper we therefore conceptualize this new subclass of commodity risk, which we call residual shape risk (RSR), and we empirically evaluate it on a real portfolio of a leading natural gas retail supplier in the Czech Republic.

The evaluation of RSR requires modelling of prices of evaluated commodity, in our application natural gas. The literature (Baum *et al.* 2018; Benth *et al.* 2008; Borovkova & Mahakena 2015; Brix *et al.* 2018; Cao *et al.* 2018; Gomez-Valle *et al.* 2017a;b; Hsu *et al.* 2017; Mason & Wilmot 2014; Mishra & Smyth 2016; Safarov & Atkinson 2017) shows that the gas prices and energy commodities in general have quite complex price distribution as compared to financial assets. Gas prices commonly depart from normality by exhibiting heavy tails and a leptokurtic shape (Benth *et al.* 2008). They also exhibit jumps (Cao *et al.* 2018; Mason & Wilmot 2014), a time-varying volatility (Baum *et al.* 2018; Brix *et al.* 2018), and a mean reversion (Brix *et al.* 2018; Hsu *et al.* 2017). Moreover, they are affected by many other factors like storage, weather, seasonality and political events and decisions (Gomez-Valle *et al.* 2018).

As our financial risk metrics we use Value-at-Risk (VaR) and Expected Shortfall (ES). VaR is the financial loss that is not exceeded with probability $1 - \alpha$, where α is the confidence level. For discussion of VaR in the energy markets risk management see Andriosopoulos & Nomikos (2015). While VaR is a standard financial measure used by Basel II and Basel III financial regulatory framework, its limitation is that it does not

provide any indication of how much may be lost if extreme tail events happen. Therefore it is usually complemented by a computation of Expected Shortfall, which is also alternatively known as Conditional Value at Risk (CVaR). ES (CVaR) measures the average of worst losses. The ES at level α is the expected return of a portfolio in α percent of worst cases (Baum *et al.* 2018). Obviously, for the computation of VaR and ES the selection of appropriate distribution is crucial (Hung *et al.* 2008; Khindanova & Atakhanova 2002).

In the rest of this paper we firstly define RSR and explain its calculation in the section 2. Then we continue with description of data and empirical evaluation of RSR on Czech natural gas market in the section 3. In the section 4 we summarize our results and conclude.

2 Conceptualization of Residual Shape Risk

2.1 Definition of Residual Shape Risk

As already mentioned before, the residual shape risk stems from insufficient liquidity of wholesale products for hedging shaped sales. Thus, it can be represented for natural gas markets as a weighted difference between forward and spot price of natural gas where the weight is the deviation of the daily volume around the volume hedged at the forward market. In the empirical section of this paper, we use volumetric hedging. It means that the volume purchased at forward market is an average volume in the period which corresponds to a length of standard future product. In the Czech market, which we use in the empirical section, the shortest standard product, which can be traded on forward market, is one month. Thus, we evaluate the RSR against a deviation of daily volumes from average volumes in particular months. Hence we define the RSR as

$$RSR^p = \frac{\sum_{t=1}^N (V_t - \bar{V}_t)(S_t - F_t)}{\sum_{t=1}^N V_t}, \quad (1)$$

where index p denotes particular profile with a length of N . V_t is forecasted consump-

tion volume in a day t . \bar{V}_t is the average volume bought on monthly forward product, i.e monthly baseload. The second part of the product is a difference of spot price at delivery S_t and forward price F_t . We divide the expression by the total volume of the profile in order to obtain profit or loss per MWh of an energy commodity. The forward price F_t is a weighted price of standard products consequently purchased and sold on forward market when shaping the profile. We shape the profile successively as individual products become liquid. Thus, we start by a purchase of year baseload, followed by a sale of summer and purchase of winter baseload. Since we are dealing with a retail supply of an energy commodity, we always want to have an average volume in the corresponding period, i.e. we hedge the profile volume neutral. The sum of residual positions is zero. We repeat this algorithm as individual blocks become liquid until we hedge profile by monthly baseloads. Hence, we obtain a forward price for every day t which is a weighted price of these successive purchases and sales on the forward market.

We determine the RSR as a profit and loss distribution. This means that positive value of the RSR is actually loss. Whenever additional volume has to be purchased on the spot market and the spot price is higher then the forward price was, loss occurs. This means that in formula (1) $V_t > \bar{V}_t$ and $S_t > F_t$. Similarly, when both inequalities are opposite, i.e. when there is a long position in the particular gas day and the weighted forward price is higher than the spot price, the loss occurs again. Loosely speaking, given the higher realized spot price, higher volume was purchased on the forward market than it should have been. Contrary, whenever these two differences have opposite sign a gain is incurred. For example, the residual position was purchased for the spot price that was lower than the forward price.

We derive forward prices as expected spot prices at delivery. Hence, we expect the difference between them to be zero. Nevertheless, the RSR will not be zero in general. One would have to hedge the profile value neutral against expected spot prices. As we will use volumetric hedge, we do not expect the loss distribution to have exactly zero mean. Lastly, to determine the size of this risk we use Monte Carlo simulation of spot prices. In this way the hedge strategy described above is realized on simulated price paths

to obtain the RSR loss distribution. We employ conventional five percent Value at Risk measure along with the Expected Shortfall, which captures the tail distribution better.

2.2 Calculation of Residual Shape Risk

First step of the RSR estimation is to model spot prices of an evaluated commodity, in our case natural gas. We follow approach suggested in Benth *et al.* (2008). We model the spot price dynamics with Ornstein-Uhlenbeck process using a sum of Gaussian and two compound Poisson processes to create a more complex jump mixed diffusion process. This induces desired leptokurtic shape for price innovations. As a second step, forward prices are then derived as expected spot prices at delivery using characteristics of spot price processes. In the third step we choose an appropriate risk evaluation metrics and apply it to particular consumer profile.

2.3 Spot Model

A general form of geometric stochastic process for spot prices $S(t)$ (Benth *et al.* 2008) is

$$\ln S(t) = \ln \Lambda(t) + \sum_{i=1}^m X_i(t) + \sum_{j=1}^n Y_j(t), \quad (2)$$

where, for $i = 1, \dots, m$,

$$dX_i(t) = (\mu_i(t) - \alpha_i(t)X_i(t))dt + \sum_{k=1}^p \sigma_{ik}(t)dB_k(t), \quad (3)$$

and, for $j = 1, \dots, n$,

$$dY_j(t) = (\delta_j(t) - \beta_j(t)Y_j(t))dt + \eta_j(t)dI_j(t). \quad (4)$$

$$I_j(t) = \gamma_j(t) + \int_0^t \int_{|z|<1} z \tilde{N}_j(dz, du) + \int_0^t \int_{|z|\geq 1} z N_j(dz, du) \quad (5)$$

The term $\Lambda(t)$ in the first equation represents continuously differentiable deterministic seasonal function. The coefficients $\mu_i, \alpha_i, \sigma_{ik}, \delta_j, \beta_j$ and η_j are all continuous functions.

μ_i and δ_j are means to which Ornstein-Uhlenbeck (OU) processes $X_i(t)$ and $Y_j(t)$ revert. Equations 3 and 4 represent normal and jump part of the price process, respectively. The model further assumes that $B_k(t)$ are p independent Brownian motions. $I_j(t)$ is a pure jump semimartingale independent increment (II) process. As the model contains n $I_j(t)$ processes, it is again assumed that theses processes are independent of each other. Each process can be represented by its associated random jump measure $N_j(dt, dz)$ by the Lévy-Kintchine representation (5).

For the subsequent analysis we assume $m = n = p = 1$, i.e. we have one normal and one jump OU process with one Brownian motion. Further we assume to have constant speeds of mean reversion common for the diffusion $B(t)$ and the jump $I(t)$ part. This is an extension to the Schwartz one-factor model (Schwartz 1997) by including jumps. Hence, the model reduces to

$$\ln S(t) = \ln \Lambda(t) + X(t) + Y(t), \quad (6)$$

with OU processes $X(t)$ and $Y(t)$ following dynamics

$$dX(t) = -\alpha X(t)dt + \sigma dB(t), \quad (7)$$

and

$$dY(t) = -\alpha Y(t)dt + dI(t). \quad (8)$$

The process of logarithmic prices (6) has dynamics

$$d \ln S(t) = d \ln \Lambda(t) - (\ln S(t) - \ln \Lambda(t))dt + \sigma dB(t) + dI(t). \quad (9)$$

2.4 Forward Model

A price of gas futures settled during the delivery period is

$$F(t, \tau_1, \tau_2) = \mathbb{E}_Q \left[\int_{\tau_1}^{\tau_2} \frac{r e^{-ru}}{e^{-r\tau_1} - e^{-r\tau_2}} S(u) du \mid \mathcal{F}_t \right]. \quad (10)$$

The price of a contract settled in the end of the delivery period is

$$F(t, \tau_1, \tau_2) = \mathbb{E}_Q \left[\int_{\tau_1}^{\tau_2} \frac{1}{\tau_2 - \tau_1} S(u) du \mid \mathcal{F}_t \right]. \quad (11)$$

Simple weight function can be introduced to describe both options. Consider weight function $\widehat{w}(u)$, which is equal to one when the futures contract is settled in the end of the delivery and to $\exp(-ru)$ when the contract is settled continuously. In our case we use daily granularity. Further, let define function

$$w(u, s, t) = \frac{\widehat{w}(u)}{\int_s^t \widehat{w}(v) dv}, \quad (12)$$

where $0 \leq u \leq s < t$. The function $w(u, s, t) = 1/(t - s)$ when $\widehat{w}(u) = 1$. In the continuous settlement case

$$w(u, s, t) = \frac{re^{-ru}}{e^{-rs} - e^{-rt}}.$$

Such defined function integrates to unity and hence, we can describe the general relation between spot and futures price as

$$F(t, \tau_1, \tau_2) = \mathbb{E}_Q \left[\int_{\tau_1}^{\tau_2} w(u, \tau_1, \tau_2) S(u) du \mid \mathcal{F}_t \right]. \quad (13)$$

Benth *et al.* (2008) show that the forward price is given as

$$f(t, \tau) = \Lambda(\tau) \Theta(t, \tau, 0) \exp(e^{-\alpha(\tau-t)} X(t) + e^{-\alpha(\tau-t)} Y(t)) \quad (14)$$

where $\Theta(t, \tau, 0)$ is given as

$$\ln \Theta(t, \tau, 0) = \psi(t, \tau, -ie^{-\alpha(\tau-t)}) + \frac{1}{2} \sigma^2 \int_t^\tau (e^{-\alpha(\tau-u)})^2 du, \quad (15)$$

with $\psi(-ic)$ being the logarithm of the moment generating function of increment processes $Y(t)$, also called a cumulant function. The integral in the second part of the expresion represents cumulant function for Brownian motion though. The zero in the

function $\Theta(t, \tau, 0)$ means we are deriving expectation with market price of risk equal to zero, thus under equivalent measure \mathbb{P} . The expression in (14) can be rewritten then as

$$f(t, \tau) = \Lambda(\tau)\Theta(t, \tau, 0) \left(\frac{S(t)}{\Lambda(t)} \right)^{e^{-\alpha(\tau-t)}}. \quad (16)$$

Let assume now for simplicity that $n = 0$ in the spot model specification (2), thus the dynamics in spot prices are completely driven by the Wiener process. Then under the assumption of zero market price of risk, the dynamics of forward price is

$$\frac{df(t, \tau)}{f(t, \tau)} = e^{-\alpha(\tau-t)} \sigma dB(t). \quad (17)$$

3 Empirical Evaluation

3.1 Data

For the purpose of our empirical analysis we choose the Czech OTE price index. It is a daily index, which represents country-wide price of natural gas at a particular gas day and we treat it as a spot price index as the gas day is the lowest granularity of the Czech natural gas market. The OTE index is derived as a weighted average of trades executed on the Intra-Day Gas market, where weights are volumes of particular trades.

The time series ranges between 1.1.2016 and 31.12.2017. It consists of 731 daily observations. The data were downloaded from the web page of the market operator the OTE. These data are published every day and they are publicly available¹. Summary statistics of observed natural gas prices are presented in the Table 1.

Further, we employ data about consumers portfolio of a leading Czech gas retail supplier for a period between 1.1.2016 and 31.12.2017. It is used as a consumption profile for the purpose of our analysis. The profile consists of initial forecasts of consumption for households and small entrepreneurs. These forecasts are made using so-called standardized load profiles (SLP). SLP represents typical shape of annual consumption for

¹Data available at OTE web page <http://www.ote-cr.cz/statistika/rocni-zprava>.

particular group of customers. It predicts customers consumption based on expected temperatures and days in a week. These diagrams are thoroughly described in Novak *et al.* (2017). Our profile consists of mixture of different types of SLPs.

Table 1: Data Summary - Index OTE

Statistic	N	Mean	St. Dev.	Min	Max
S	731	15.930	2.580	11.180	23.030

In order not to disclose a size of the portfolio we scale the volume to unity according to (18):

$$c_d = \frac{V_d}{\sum_{d=1}^N V_d}. \quad (18)$$

We do this for both years. Thus, for each day we obtain a value that represents percentage of total year consumption on that day.

3.2 Model Estimation

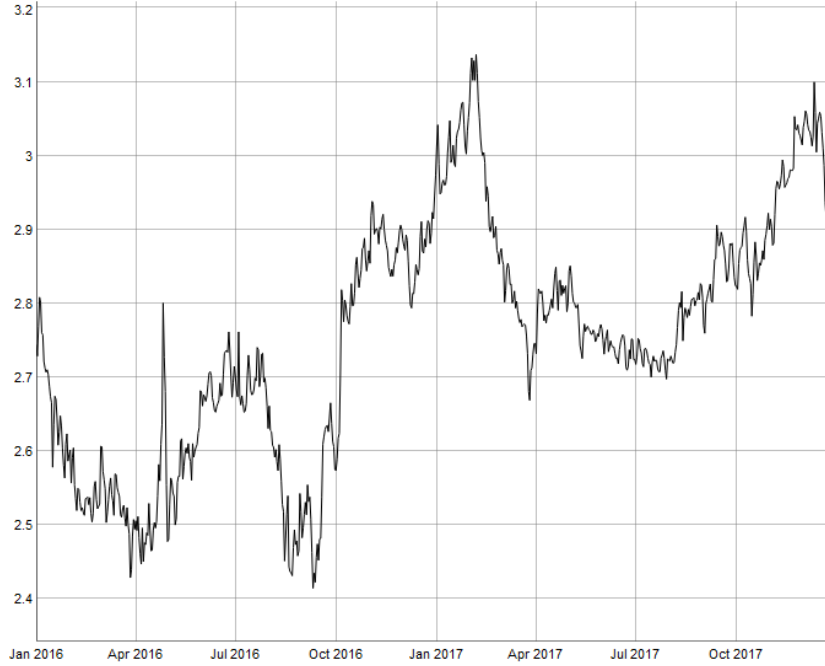
This section describes consecutive steps we take in order to appropriately estimate our model. We start with an analysis of an observed gas spot prices, where we obtain their distributional properties. Based on the analysis we fit a jump mixed diffusion process, which we use for the Monte Carlo (MC) simulation of spot and forward prices afterwards. Lastly, we use these simulations for an evaluation of the RSR over customer portfolio of a real company.

3.2.1 Spot Price Analysis

First, we look at a development of logarithmic spot prices. As there are no negative prices in our sample, we can take logarithm of every price. Logarithmic prices are chosen deliberately in order to impose geometric nature of the model, which restricts simulation to generate non-negative prices. The development of logarithmic spot prices is presented in the Figure 1. From the visual inspection of the plot, we expect the price to follow

some kind of seasonality and trend. It is a common feature of energy prices to exhibit some periodicity, natural gas in particular. As it is plentifully used for heating it tends to be more expensive in the winter when a demand increases.

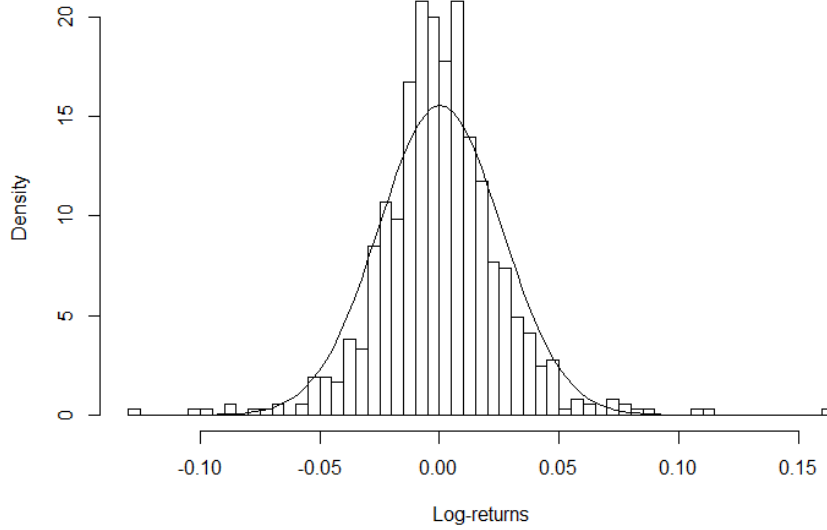
Figure 1: Time series of logarithmic spot price.



We also check for outliers as they would affect fitted cyclical and mean function. To detect possible outliers we look at the differenced time series. In our case such series becomes series of log returns. The Figure 2 shows histogram of this series along with a fitted normal density curve. It is visually clear that the data are non-normal. The Shapiro-Wilk test confirms this by rejecting null hypothesis of normal distribution with p-value zero. The histogram shows leptokurtic shape, i.e. higher probability of observation close to mean and heavier tails than normal distribution. This is a common feature of energy prices (Dukhanina *et al.* 2018; Hsu *et al.* 2017).

In order to determine whether the observation is an outlier we adopt approach described in Benth *et al.* (2008). An observation is deemed to be outlying when it is lower than $Q_1 - 3 \times IQR$, or greater than $Q_3 + 3 \times IQR$, where Q_1 and Q_3 are lower and upper quartile, respectively. The IQR is interquartile range, defined as difference between the upper and the lower quartile. Following this rule six observation were found to be out-

Figure 2: Histogram of log-returns with a fitted normal density curve.



lying. Hence, we replaced them with an average of preceding and following observation. The mean function is then estimated on this new trimmed time series.

There are few evident cycles to search for in the energy sector. As mentioned above we expect to find some form of yearly cycle, which represents an inclination of gas wholesale prices to grow in the winter and stay lower in the summer. However, we make use of the Fourier transform to precisely determine all possible cycles in the data. Following this approach, two signals were found. Firstly, the most important cycle was determined to be yearly as expected. Secondly, we found cycle with half year periodicity. The second cycle could be attributed to injecting of natural gas into underground storages during summer. Storage companies incur some additional costs when they have to turn over the flow in storage, i.e. to switch between injecting and withdrawing. Such situation can happen during high temperature days when there is a high demand for electricity to power air-conditioners and gas fired power plants have to be switched on. Hence, it can cause temporal increase in spot prices. We use relationship defined in the equation (19) for modelling trend and seasonal components of spot prices.

$$\ln\Lambda(t) = a_0 + a_1t + a_2\cos(2\pi t/365) + a_3\cos(2\pi t/182.5) \quad (19)$$

The linear time trend is often added to energy price series as measure of inflation in price level. The cosines of year and half year component coincide in winter making the yearly cycle approximately 3 times stronger than the other one. The coefficients in the mean level function were estimated by running an OLS regression of the logarithmic spot prices on transformed time variables as specified in the seasonal function $\ln\Lambda(t)$ described by equation (19). The results are presented in the Table 2. All estimates have p-value zero to several decimals, i.e. all are highly significant. We also estimated the effect of quarterly and weekly cycles, however they appeared to be insignificant. The fit of mean level function on logarithmic spot price is shown in the Figure 3.

Table 2: Estimated coefficients of the mean level function

	Estimate	Std. Error	t value	Pr(> t)
\hat{a}_0	2.566	0.006	412.289	0
\hat{a}_1	0.001	0.00001	35.167	0
\hat{a}_2	0.105	0.004	23.928	0
\hat{a}_3	0.056	0.004	12.666	0

By subtracting the mean level function from the original time series of logarithmic spot prices we obtain detrended and deseasonalized prices, which are ready for subsequent analysis. The resulting series is presented in the Figure 4.

Further, when we look at the histogram of returns of this “detrended” series in the Figure 5, we see that it still departs from normality in a leptokurtic way. The Shapiro-Wilk normality test rejects the null hypothesis of normal distribution at one percent significance level. If we assume that the spot prices follow the geometric Brownian motion, then any test should reject null hypothesis of stationarity as the discrete time approximation of the Brownian motion is the AR(1) process with coefficient equal to unity, i.e. a random walk. Hence, we apply the Dickey-Fuller test to deseasonalized log prices which tests null hypothesis of unit root. The test yields statistic of -3.898 . It corresponds to rejection

Figure 3: Fitted mean level function on logarithmic prices.



Figure 4: Detrended and deseasonalized logarithmic spot prices.

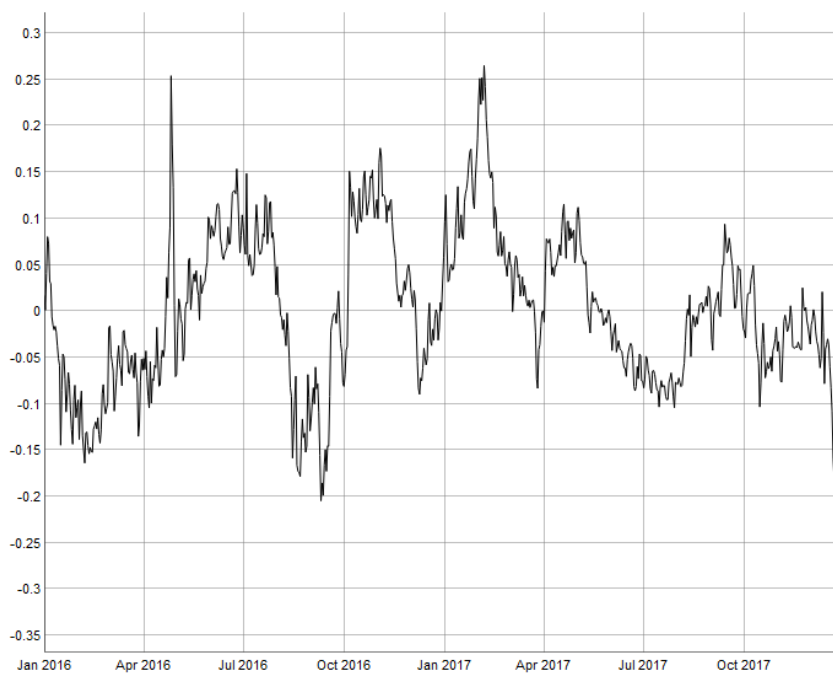
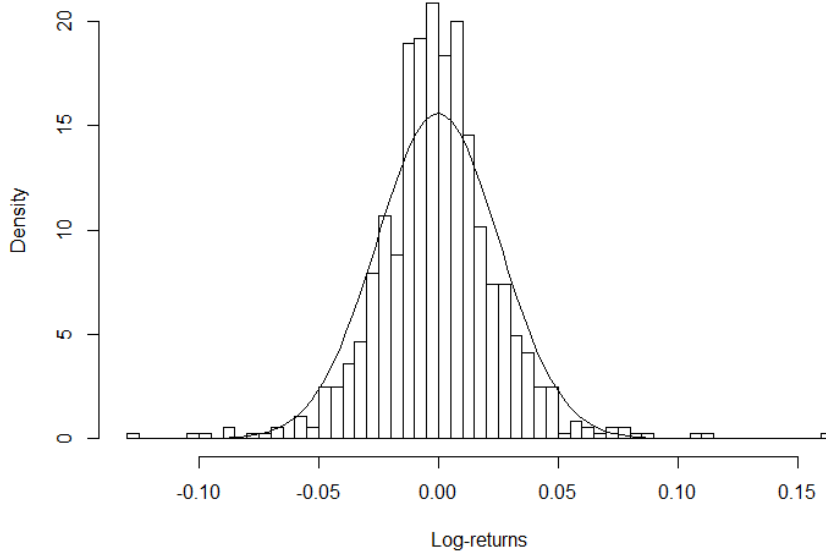


Figure 5: Histogram of log returns from detrended spot prices.



of the null at roughly one percent confidence level. Also, the result of the test suggests that the autoregression coefficient is less than one. This behaviour is expected from the mean-reverting process. Therefore, we continue with an analysis of the autocorrelation function (ACF) and the partial autocorrelation function (PACF).

Clearly, the ACF of deseasonalized logarithmic spot prices reveals that the underlying process has long memory. The ACF is plotted in the Figure 6. Further, the PACF indicates that the prices follow AR(1) process as one can see in the Figure 7. Thus, we continue with model defined as

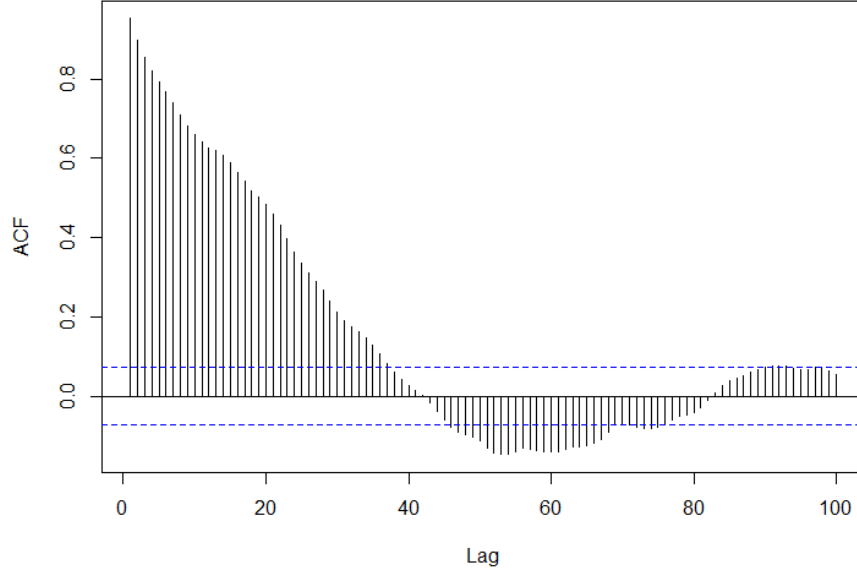
$$z_t = \rho z_{t-1} + e_t \quad (20)$$

where the e_t is assumed to be an i.i.d. process.

The data have daily granularity, thus we shift from a continuous to a discrete time. Then we let $Z(t) = X(t) + Y(t)$. Therefore $Z(t) = \ln S(t) - \ln \Lambda(t)$. From the dynamics of OU processes $X(t)$ and $Y(t)$ defined in equations 7 and 8 we have

$$dZ(t) = -\alpha Z(t)dt + \sigma dB(t) + dI(t). \quad (21)$$

Figure 6: The ACF of deseasonalized logarithmic spot prices with 95 % confidence bounds.



To achieve discrete approximation we add $Z(t)$ to both side of the equation and we get daily increments as

$$Z(t) \approx (1 - \alpha)Z(t - 1) + \sigma\Delta B(t) + \Delta I(t). \quad (22)$$

Note that $\Delta B(t)$ is a daily increment of Brownian motion i.e. $B(t) - B(t - 1)$. Similarly, $\Delta I(t)$ is an increment of the jump process $I(t) - I(t - 1)$. Both increments of Brownian motion and general Lévy process are i.i.d. sequences of random variable. Hence, their sum $\sigma\Delta B(t) + \Delta I(t)$ is also an i.i.d. Then we see that our discrete approximation corresponds to the AR process in (20) with $\rho = 1 - \alpha$ and $e_t = \sigma\Delta B(t) + \Delta I(t)$.

Hence, we continue by fitting AR(1) model on deseasonalized logarithmic spot prices $Z(t)$, defined in the equation (22), to determine speed of mean reversion. Thus, the estimated speed of mean reversion is

$$\hat{\alpha} = 1 - \hat{\rho} = 1 - 0.955 = 0.045.$$

Figure 7: The PACF of deseasonalized logarithmic spot prices with 95 % confidence bounds.

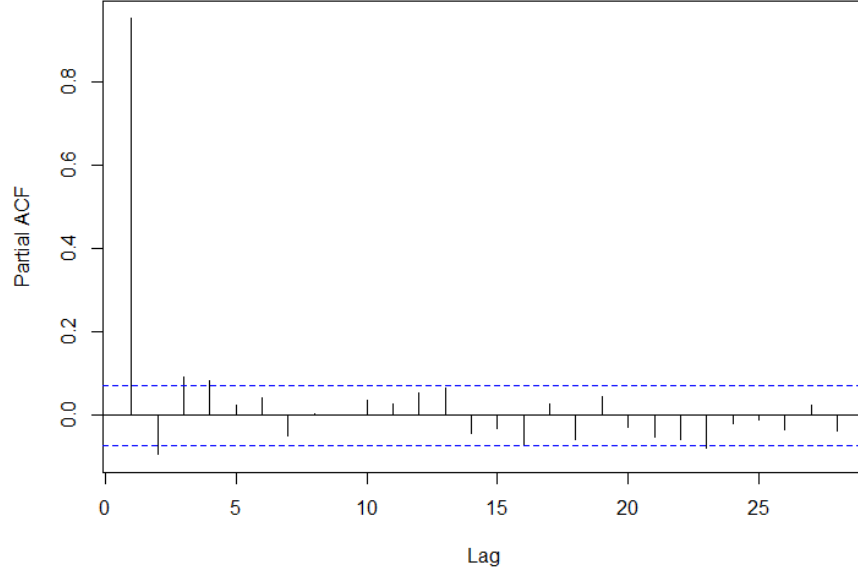
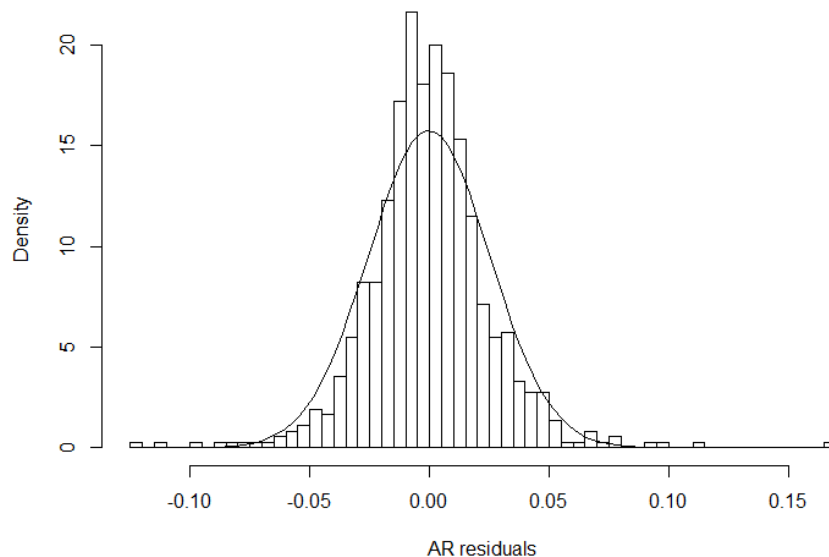


Table 3: Fitted AR(1) model.

<i>Dependent variable:</i>	
$\hat{\rho}$	0.955*** (0.011)
Log Likelihood	1,647.015
σ^2	0.001
Akaike Inf. Crit.	-3,290.029
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	

Hence, the spot prices revert rather slowly towards the seasonal level. The fitted AR(1) model is presented in the Table 3. Finally we look at the distribution of obtained residuals. Their histogram is depicted in the Figure 8 along with fitted normal distribution density curve. We see that the increment process indeed reveals leptokurtic shape. The Shapiro-Wilk test rejects the null hypothesis of normally distributed errors with p -value equal to zero to several decimals. Therefore, we try to account for non-normal features of residuals by decomposing them into a mixed diffusion process.

Figure 8: The histogram of obtained residuals from AR(1) model fit with normal density curve.

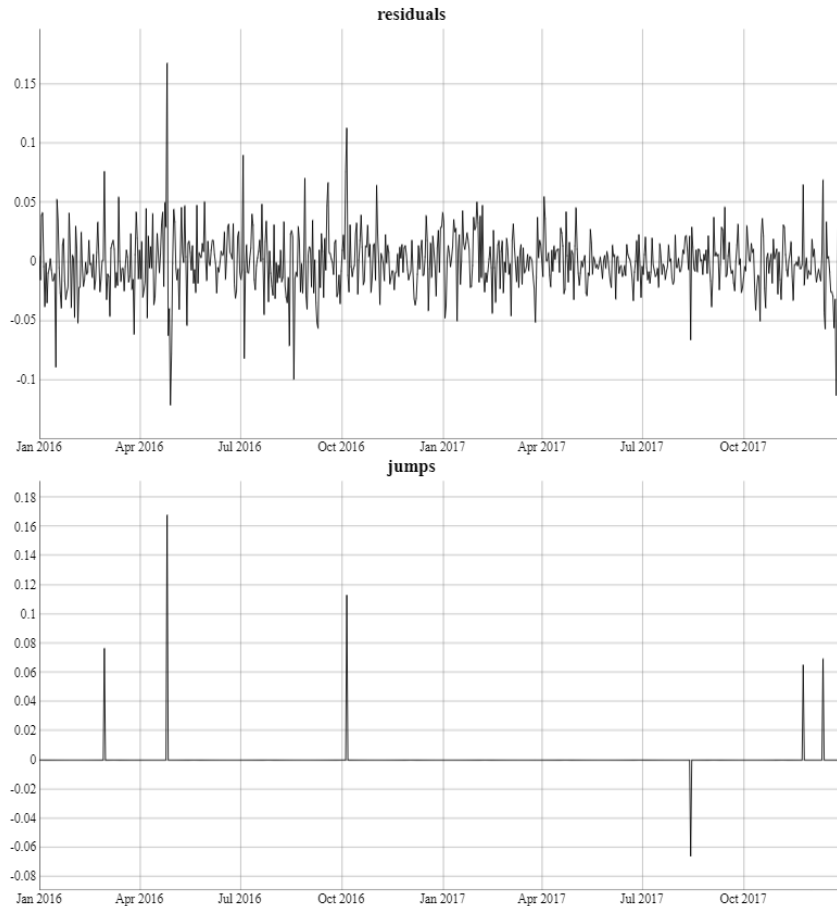


3.2.2 Residuals as a Jump Mixed Diffusion Process

Now we decompose residuals into two separate processes: a Gaussian process and a jump process. We choose the window size of 16 days for estimating instantaneous volatility as recommended in Lee & Mykland (2007). The test indicates six jumps at five percent significance level. The comparison of jumps with series of residuals is presented in the Figure 9. Indeed we estimated jumps at places where one would expect them. However, when we look at the series of residuals, there are observations which look more like jumps

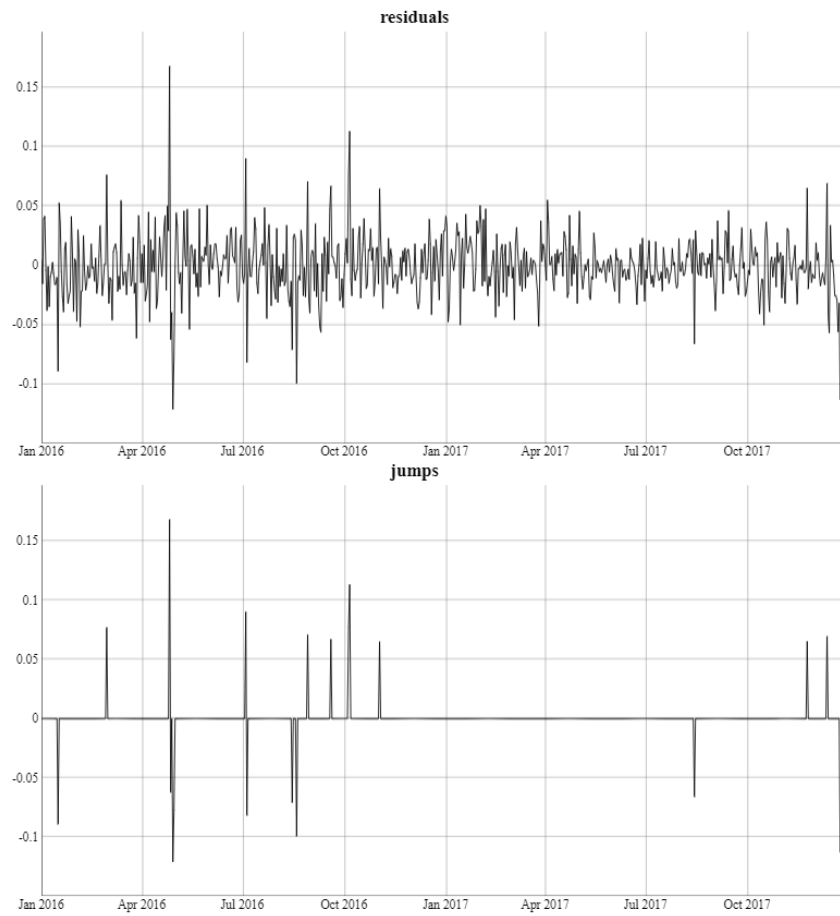
than like normal innovations. For instance, the second estimated jump is followed by a return of approximately the same negative size. It is not determined to be jump at any choice of K not even at ten percent significance level, though.

Figure 9: Residuals (top) and estimated jumps (bottom) following Lee & Mykland (2007).



Therefore we apply different jump detection approach suggested by Clewlow & Strickland (2000). Under this alternative approach 20 jumps are detected. The recursive filtering algorithm determines observation to be a jump when it deviates more than three standard deviations from the mean and replaces it with a median of the sample then. The procedure is repeated until no new jumps are found. In our case the algorithm converges after five iterations. The estimated jumps are presented in the Figure 10. Using this (Clewlow & Strickland 2000) approach we are able to eliminate large jumps that follow one after another. It is primarily appreciable in the beginning of the series.

Figure 10: Residuals (top) and estimated jumps (bottom) following Clewlow & Strickland (2000).



We estimate standard deviation of filtered residuals after every iteration. The estimates are presented in the Table 4 along with number of detected jumps. After last iteration the estimated standard deviation becomes estimate of the σ from the normal part of the stochastic process. The $\hat{\sigma}$ is 0.0204. Our estimate is approximately five times lower than estimated value of 0.1 for the National Balancing Point (NBP) day ahead prices in Steele (2010).

Hence, the Czech market appears to be calmer. It may be due to the fact that the UK has relatively limited gas storage capacity compared to the Czech Republic. The Czech storage capacity ranks among the highest in Europe. Total storage capacity represents approximately 40 percent of total annual gas consumption in the Czech Republic. Moreover, withdrawal capacity of Czech gas storages should cover higher demand during days with low temperatures (Zaplatilek 2015). Therefore the lack of extreme price movements at the Czech market may be given by this high gas storage capacity.

Table 4: Summary of the jump filtering algorithm.

Iteration	Detected jumps	Std. deviation
1	11	0.0218
2	17	0.0208
3	19	0.0205
4	20	0.0204
5	20	0.0204

The arrival of a new information which causes price to jump is usually modelled as a compound Poisson process. Before we define such process, it is convenient to look at the distribution of jump sizes. In literature they are often assumed to come from the normal distribution. However, when we look at the histogram of estimated jump sizes depicted in the Figure 11, it looks that the normal distribution might not be a good choice in our case. Benth *et al.* (2008) propose to look at positive and negative jumps separately. Their histograms are presented in the Figure 12. Indeed, the histograms suggest that the exponential distribution may fit the data better. Therefore, we define Lévy process $I(t)$ rather as a sum of two jump process as

$$I(t) = I^+(t) + I^-(t). \quad (23)$$

Hence, we have two compound Poisson processes defined as

$$I^\pm(t) = \sum_{k=1}^{N^\pm(t)} J_k^\pm, \quad (24)$$

where $N^\pm(t)$ are Poisson processes with intensities λ^\pm . The sequences J_k^\pm are assumed to be exponentially distributed i.i.d. random variables which represent jump sizes with average size m_J^\pm . Thus, $J_k^\pm \sim \text{Exp}(\frac{1}{m_J^\pm})$.

Table 5: Estimated jump sizes and intensities.

Estimate	Positive jumps	Negative jumps
$\hat{\lambda}$	0.0151	0.0123
$\widehat{m_J}$	0.087	0.0865

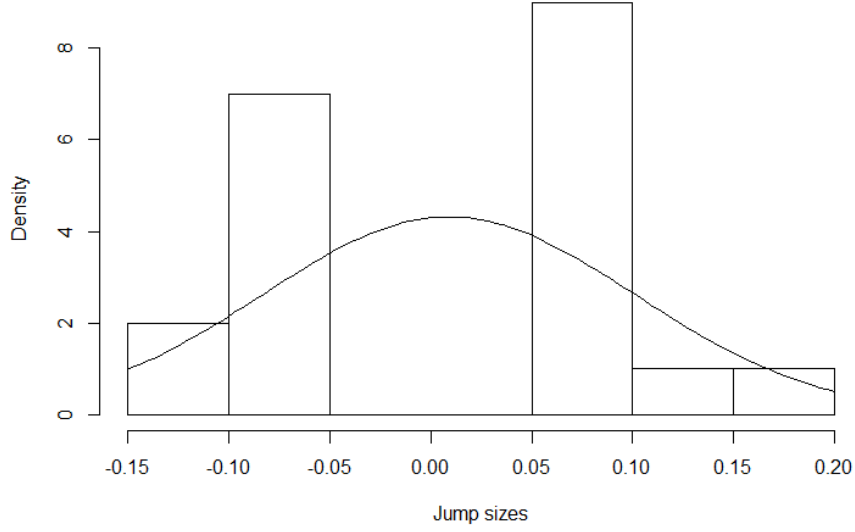
The estimated parameters of the Lévy process defined in the equation 24 are summarized in the Table 5. Out of 20 jumps, 11 turned out to be positive, thus the estimated intensity of the positive jump arrival is slightly higher than the negative one. Still, the intensities are almost the same and imply that approximately five negative and positive jumps arrive during the year. The parameters of assumed exponential distributions for jump sizes were estimated with use of maximum likelihood approach. We have to multiply negative jumps by -1 as the exponential distribution is defined only on positive numbers. Estimated average jump size is slightly higher for positive jumps.

Further, we derive a cumulant function of the jump process. This is convenient for pricing forwards. Let have a Poisson process $N(t)$ with intensity λ . Then general compound Poisson process is defined as

$$L(t) = \sum_{i=1}^{N(t)} X_i,$$

where X_i is a sequence of i.i.d. random variables independent of $N(t)$. Such process

Figure 11: Histogram of estimated jump sizes.



is a Lévy process with cumulant function given as

$$\psi(\theta) = \lambda(e^{\psi_X(\theta)} - 1), \quad (25)$$

where $\psi_X(\theta)$ is a cumulant function of X_i (Benth *et al.* 2008). Hence, we have to find cumulant function of the process which describes jump sizes first. The cumulant function $\psi_X(\theta)$ evaluated at $-i$ becomes the natural logarithm of the moment generating function of random variable X_i . Let X_i be exponentially distributed with parameter κ ². The moment generating function of X_i is given as

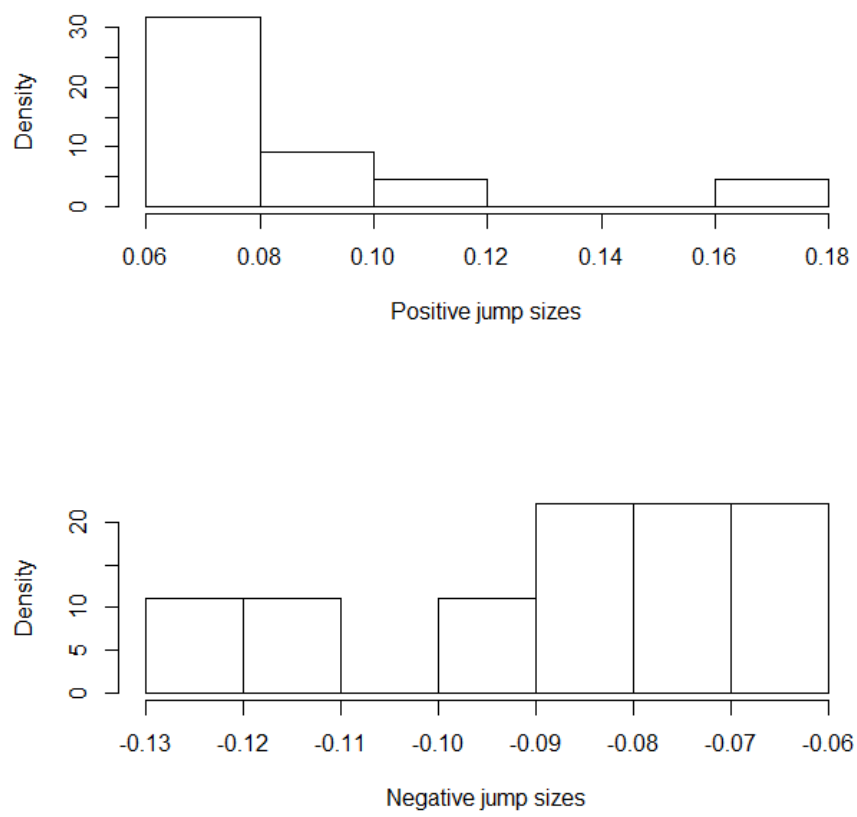
$$M_X(t) = \frac{\kappa}{\kappa - t}, t < \kappa. \quad (26)$$

Hence, the cumulant function of X_i for $\theta \in \mathbb{R}$ is

$$\psi_X(\theta) = \ln\left(\frac{\kappa}{\kappa - i\theta}\right). \quad (27)$$

²We use here κ as the parameter of the exponential distribution instead of a common λ in order not to confuse it with the Poisson process.

Figure 12: Histogram of estimated jump sizes.



Let make a connection to the jump process assumed by our model. The jump sizes J_k^\pm are exponentially distributed with parameters $\frac{1}{m_J^\pm}$. For calculation of forward prices we evaluate cumulant function at $-iz$ for $z \in \mathbb{R}$. Therefore, we derive $\psi(-iz)$ which becomes the logarithm of the moment generating function. Hence,

$$\psi_{J^\pm}(-iz) = \ln\left(\frac{\frac{1}{m_J^\pm}}{\frac{1}{m_J^\pm} - z}\right) = -\ln(1 - m_J^\pm z). \quad (28)$$

Then we input this expression into the formula (25) to derive cumulant function of the jump process

$$\psi_{I^\pm}(-iz) = \lambda^\pm(e^{-\ln(1-m_J^\pm z)} - 1) = \lambda^\pm\left(\frac{1}{1 - m_J^\pm z} - 1\right), \quad (29)$$

where λ^\pm is intensity of the compound Poisson process assumed for new information arrival.

3.2.3 Forwards Price

Forward contracts can be priced given expected spot price at delivery adjusted by price of risk by taking expectation in equation (10). To derive prices of corresponding futures contracts that deliver energy over a specified period, averages of forwards with delivery within this period have to be calculated. Having estimated all desired coefficients of the spot dynamics, we are able to price yearly, quarterly, and monthly gas futures contracts now.

We derive forward prices for errors represented as the mixed jump diffusion process. The futures contracts are assumed to be settled at the end of the delivery period, i.e. we let $\tilde{w}(u) = 1$ in 12. Then with price of market risk equal to zero the price of futures contracts becomes

$$F(t, \tau_1, \tau_2) = \frac{1}{\tau_2 - \tau_1} \int_{\tau_1}^{\tau_2} f(t, u) du. \quad (30)$$

The forward price $f(t, \tau)$ is given as

$$f(t, \tau) = \Lambda(\tau)\Theta(t, \tau, 0) \left(\frac{S(t)}{\Lambda(t)} \right)^{e^{-\alpha(\tau-t)}}. \quad (31)$$

For the mixed jump diffusion process the $\ln \Theta(t, \tau, 0)$ function is defined as

$$\ln \Theta(t, \tau, 0) = \int_t^\tau \frac{1}{2} \sigma^2 z^2 + \lambda^+ \left(\frac{1}{1 - m_J^+ z} - 1 \right) + \lambda^- \left(\frac{1}{1 - m_J^- z} - 1 \right) du \quad (32)$$

where $z = e^{-\alpha(\tau-u)}$.

We are able to derive futures contract price with any finite delivery period in any time t now.

3.2.4 Consumption Profiles

Finally, as we constructed a model for forward and spot prices, we are able to evaluate the RSR. Obviously, we need some consumption profile from which the residual position can be derived because the RSR depends on the shape of the profile. Hence, the real shape of Czech leading natural gas selling firm portfolio is used here. The portfolio consists of forecasted households consumption between years 2016 and 2017. We scale the shape of the portfolio to unity in order not to reveal its size as this information is confidential. It is not a problem because we evaluate the RSR per MWh, so just the shape is crucial for our calculations. We will refer to this portfolio as a profile from now on.

We hedge the profile with standard baseload products. Prices of these products were referred to as futures prices in the previous sections. The Table 6 presents all relevant gas futures contracts available at the Power Exchange Central Europe (PXE) throughout years 2016 and 2017. It provides the start and the end of the delivery, a length, and a liquidity for every product. We also present the first day when the product can be traded, i.e. becomes liquid. The time ranges between 0 and 731. When a product is liquid in time 0 it means it became liquid before the beginning point of our time horizon (January 1, 2016). We relate the time notation with respect to start of the hedging strategy. Thus, we start to hedge one day before the first delivery day. We do this for simplicity of the algorithm. However, one can start earlier. For instance, when the yearly

baseloads become liquid as these products are traded longest time before the delivery. Our strategy is to re-hedge in the first day when shorter product becomes liquid. These days correspond to days in the column `adj_first_day`. The residual position derived from the consumption profile is depicted in the Figure 13.

Figure 13: The residual position derived from consumption profile.

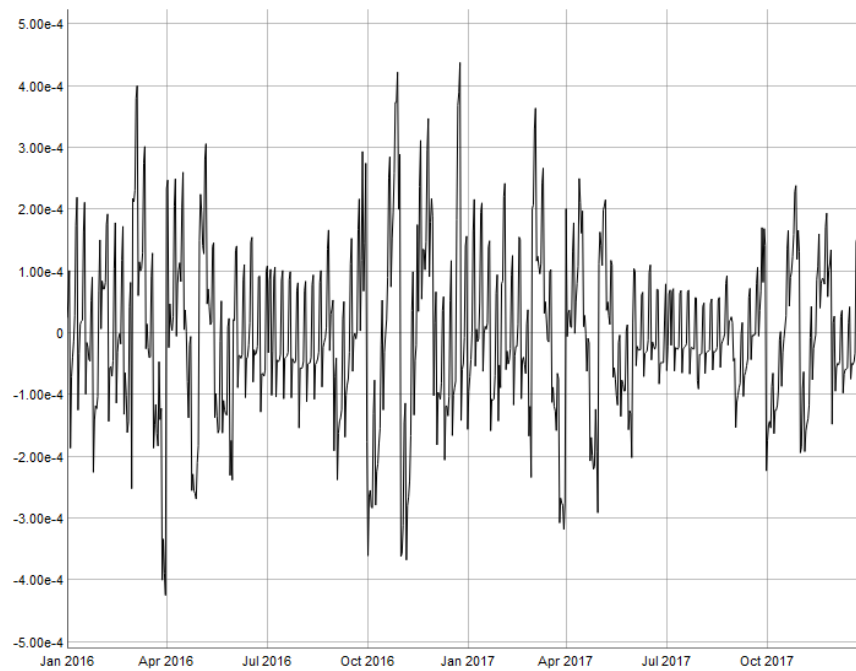


Table 6: Summary of liquid wholesale standard products - futures.

Product	Type	Length	Start	End	liquid_Ahead	adj_first_day
M1-16	M	31	1	31	92	0
M2-16	M	29	32	60	92	0
M3-16	M	31	61	91	90	0
M4-16	M	30	92	121	91	1
M5-16	M	31	122	152	90	32
M6-16	M	30	153	182	92	61
M7-16	M	31	183	213	91	92
M8-16	M	31	214	244	92	122
M9-16	M	30	245	274	92	153
M10-16	M	31	275	305	92	183
M11-16	M	30	306	335	92	214
M12-16	M	31	336	366	91	245
M1-17	M	31	367	397	92	275
M2-17	M	28	398	425	92	306
M3-17	M	31	426	456	90	336
M4-17	M	30	457	486	90	367
M5-17	M	31	487	517	89	398
M6-17	M	30	518	547	92	426
M7-17	M	31	548	578	91	457
M8-17	M	31	579	609	92	487
M9-17	M	30	610	639	92	518
M10-17	M	31	640	670	92	548
M11-17	M	30	671	700	92	579
M12-17	M	31	701	731	91	610
Q1-16	Q	91	1	91	365	0
Q2-16	Q	91	92	182	366	0
Q3-16	Q	92	183	274	366	0
Q4-16	Q	92	275	366	366	0
Q1-17	Q	90	367	456	366	1
Q2-17	Q	91	457	547	365	92
Q3-17	Q	92	548	639	365	183
Q4-17	Q	92	640	731	365	275
Sum-16	S	183	91	273	548	0
Win-16	S	182	274	455	548	0
Sum-17	S	183	456	638	548	0
Cal-16	Y	366	1	366	730	0
Cal-17	Y	365	367	731	731	0

3.2.5 RSR Results

As a final step, we evaluate the RSR by Monte Carlo simulation. We derive 25,000 simulations of spot price paths defined by discrete version of formula 2:

$$S(t) = \Lambda(t) \exp(Z(t)) \quad (33)$$

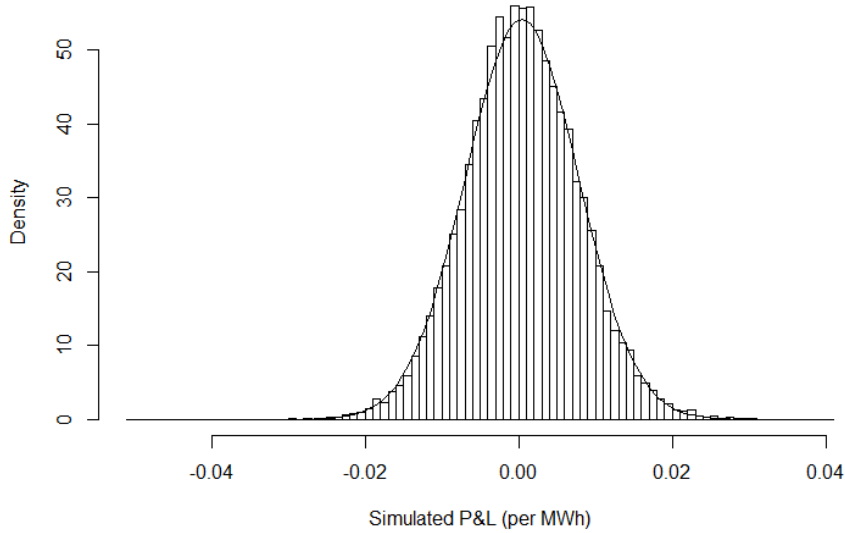
where

$$Z(t) = (1 - \alpha)Z(t - 1) + \sigma\Delta B(t) + \Delta I^+(t) + \Delta I^-(t) \quad (34)$$

and $\Lambda(t)$ is exponential of function defined in equation 19.

The calculations were made in the R Studio with seed 1. Once realizations of spot prices are derived, the algorithm “walks” through the hedge strategy path 25,000 times while storing a result of the RSR costs after every path calculated by expression 1. The calculation takes about one hour of computer processing unit time. The simulated RSR profit and loss per MWh distribution is presented in Figure 14.

Figure 14: The simulated RSR profit and loss per MWh with jump mix-diffusion errors.



The Table 7 shows descriptive statistics of simulated RSR profit and loss distributions.

The VaR and the ES are 0.013 and 0.016 EUR/MWh respectively. The ES for mixed-diffusion process is approximately 0.1 percent of average spot prices in our sample, which is 15.93 EUR/MWh. However the important benchmark for retail energy supplier is not a price but his profit margin. Under an assumption of 10 percent profit margin, we obtain the RSR for ES on the level of approximately 1 percent of profit margin.

Table 7: Statistics of simulated RSR distributions.

Statistic	mixed diffusion process
mean	0.000
st. dev.	0.007
$VaR_{0.05}$	0.013
$ES_{0.05}$	0.016

We should take into account that an energy supply is extremely competitive business everywhere, including Czech Republic. Almost every half a year some Czech gas supply company is going bankrupt. The Czech market operator OTE a.s. registered 69 natural gas suppliers by the end of May 2018 ³. It appears that margins are low and probably a lot of companies operate close to zero economic profit. In such environment the supplier should be aware even about relatively low risk like the RSR, as we estimated. Nevertheless, a trading activity on energy markets grows every year and energy markets become more linked up. For instance, during hot summer when people switch on air conditioners and there is low water levels in hydro power pumped plants additional capacity has to be added into the system. This capacity is usually covered by gas fired power plants, which can be dispatched quickly. Hence, a higher demand for an electricity may cause higher demand for a natural gas and affect prices accordingly. Moreover, the power sector shifts towards more volatile, decentralized, renewable power sources. Naturally, it affects electricity prices, but it may also affect natural gas prices. Usually extreme energy prices are positively correlated with extreme weather conditions. With the climate change, natural gas spot prices may become more volatile. Hence, the RSR may become more relevant

³Suppliers with more then 100 points of delivery - <http://www.ote-cr.cz/statistika/mesicni-zpravaplyn/pocty-opm-dodavatelu>

in the near future.

4 Conclusions

As a result of European energy sector liberalization activities at the energy supplier business, the last unit in energy supply chain, became close to activities of portfolio managers and traders on the financial markets. Moreover, as the market introduces more standard products including financial futures, wholesale energy markets become attractive for speculative traders. In a such environment, the energy managers had to adopt risk measuring metrics usually used in the financial sector. With a growing use of flat baseload products used for hedging of prices of short sales to final consumers the difference of forward and spot prices weighted by volume the residual position, which we term residual shape risk (RSR), appeared as a new concept which was missing in the previous more integrated gas markets. While we introduce, motivate and illustrate the RSR on the natural gas market, this concept may be applied for similar energy commodities too.

In order to evaluate RSR, first the dynamics of natural gas spot prices is estimated and subsequently forward prices are derived as expected spot prices at delivery using characteristics of the underlying spot price process. The RSR is then evaluated on an appropriate shape (profile) of retail energy supplier portfolio. Using volumetric hedge by hedging the profile with standard products that are liquid in a given time, the profit and loss distribution caused by the RSR is obtained. This distribution is derived by Monte Carlo simulation of spot price paths and by applying the volumetric hedging strategy on them. As a last step five percent VaR and ES financial risk metrics for these distributions are obtained.

In our illustrative example of RSR for leading Czech natural gas retail supplier we obtained VaR and ES values of 0.013 and 0.016 EUR/ MWh, respectively. This means that even when looking at the tail of the distribution, we do not predict loss higher than 2 Euro cents per MWh in extreme cases. This risk approximately corresponds to 1 percent

of profit margin of natural gas retail supplier. This means that while it is not negligible risk, it is definitely not of a first order of importance for natural gas supplier and it does not call for a need to change current business policies and practices.

Since the Czech natural gas spot prices have lower volatility than British National Balancing Point (NBP) prices our empirical results are conservative in the sense of leading to a low value of RSR. In the environment with more volatile energy spot prices RSR would be higher and therefore more important for business decision making, possibly leading to changes in hedging practices. In particular with the increased RSR, the value neutral hedging, leading to zero expected value of RSR, could be more attractive to energy suppliers than currently used volumetric hedging.

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