Forecasting conditional volatility on the RIN market using MS GARCH model

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Introduction

In the recent years the topic about pollution of environment is quite popular. Many countries organize the government policy taking into account environmentally friendly policy. Dealing with pollution problems is one of the wide-spread sphere of using Pigovian tax. It is considered that this tax allows decreasing level of emissions with the least public costs.

According to the idea which was offered by A. Pigou, appearance of externalities means the difference in estimations economical situation from two points of view. On the one hand, it is private which includes only interests of participants of a concrete business. On the other hand, it is social or public which allow for interests of all economic units including third party.

So both types of externalities lead to market inconsistence in effective distribution of resources. For going back to effective stage it is necessary to implement internalization or change externalities to internal effects. So if this method is created and difference between private and public estimations disappears, all economic units will include externalities in their estimation. There are two ways to solve problems of externalities, the first one is using possibilities of private sector and the second way is using government possibilities.

From the government side it is possible to use different cash payments (taxes) or regulation. In the first case necessity to make payment, which was established by the state, corrects private costs and benefits regarding to public ones and parties make effective decisions. In the second case government can influence economic units strongly through system of administrative and legal methods.

However, the combination of these two cases is possible too, and an example of it can be the world emission market which is closely linked to the Kyoto Protocol. The market based emissions trading schemes and carbon taxes. The emission trading is market-based approach used to control pollution by providing economic incentives for achieving reductions in the emissions of pollutants [1.37]. The key differences in the emissions market, compared with other commodities markets, are that it is a politically-generated and managed market and that the underlying is a dematerialised allowance certificate, as opposed to a physical commodity [1.16]. A broad range of countries have introduced this market such as China, Japan, European countries and the USA.

According to statistics presented by Department of the Environment of Australian government [2.2], the USA has 18.3% of Global Emissions including residential and commercial buildings. It is the second place in the world rating of counties' pollution. Only three countries have percentage which is higher than 10%. The first place is China and the third one is the European Union which have 19.1% and 13.4% respectively.

Maybe because of big share of the world pollution the USA organized not only the emission market, but also the RIN market. The RIN market plays a critical role in successfully implementing the RFS2 (Renewable Fuel Standard) which was introduced after enactment of Energy Policy Act of 2005 [1.29].

The emergence of this market is connected with partial transition from traditional fossil fuels to a more environment fuels as renewable ones or ethanol, which is obtained by processing of corn, cereals, cellulose or others. So drivers used not clear gasoline, but mixture of gasoline and ethanol in some proportion.

Moreover, the RIN market has the trading system too, actors can trade securities as RINs. There are several limitations, firstly, each blender should have concrete number of RINs at the reporting period at the end of year, and secondly, after two years of RIN existence the security loses all functions.

Besides that, many researches drew attention to the RIN market after the huge increase of price of one RIN at the end of 2012. At the same time there was change of trend. It was one of the popular issue under discussion, in the other words, scientists and workers tried to understand what happened and what influenced RIN prices. Nowadays there is a less developed set of risk management tools, compared to other markets, for firms active even in the emissions markets, primarily due to the relatively short track record of pricing and trading history

[1.16]. It influences not only investigation of the emission market, but also the RIN market, since they are similar.

To address these problems we need to find process which explained price behavior and forecast conditional volatility and returns.

This paper consists of four sections. Section 1 describes the RIN market, defines RIN, specifies key actors and their functions as well as functions of EPA, which controls the market performance, and the last changes on the market. Section 2 includes information about some possible models to estimate RIN prices. Section 3 illustrates all results which were achieved. The last section is conclusion, which repeats main characteristics of the market and all results of estimation and forecast.

1. The market description

1.1. What does RIN mean?

Regarding RFS, which is standard set based Energy Independence and Security Act of 2007, every gallon of renewable fuel has to be identified in the system of accounting units of renewable fuels and to have unique renewable identification number (RIN). Additionally, RIN has to be given not only to every gallon of ethanol which was produced in the USA, but also to every gallon of imported ethanol. So this way the government stimulates blenders to add ethanol to gasoline before selling it to the service stations.

According to Security Act of 2007, US Environmental Protection Agency (EPA) establishes requirements for the production, transportation and export of renewable fuels. Due to the predominance of ethanol obtained from corn (conventional ethanol), the most common RIN is for this kind of biofuel (conventional RIN). Moreover, EPA establishes mandate for every blender, it means that each of them must have more than the concrete number of RINs at the reporting period at the end of year. If blender has deficit or surplus of RINs, they can buy or sell RINs separately from ethanol. Blenders communicate with each other strongly or through special agencies, because nowadays RIN is not traded on the Exchange. [1.19]

RIN is a 38-digit serial number had unique code of biomass gallon, number of consignment, producer and type of biofuel (conventional, advanced or others). Depending on the type of biofuel RIN is called conventional, cellulosic, biodiesel or others (Fig. 1). In addition to that, RIN is security, because it is a financial instrument that represents an ownership position in a publicly-traded corporation, and tax, because every blender has to pay it and control level of pollution.

Also RIN is investment as emissions. “A key aspect of EU scheme [trading scheme of emissions] is that it allows companies to use credits from Kyoto’s project-based mechanism, joint implementation and the clean-development mechanism to help them comply with their obligations under the scheme. This means the system not only provides a cost-effective means for EU-based industries to cut their emissions but also creates additional incentives for businesses to invest in emissions-reduction projects in developing nations as China and India, and in South America and Africa.” [1.17] So RIN is instrument which reallocates cash flows from blenders of one state to blenders of other states.

38-character code:
KYYYYCCCCFFFFFBBBBBRRDSSSSSSSSEEEEEEEE

K	RIN assignment code (1=Assigned; 2=Separated)
YYYY	Year batch is produced/imported
CCCC	Company registration ID
FFFFF	Facility registration ID
BBBBB	Producer-assigned batch number
RR	Equivalence value for the renewable fuel
D	Renewable type code[1]
SSSSSSSS	RIN block starting number
EEEEEEEE	RIN block ending number

[1]Five separate RIN categories: D=3 for cellulosic biofuel; D=4 for biomass-based diesel; D=5 for advanced biofuel; D=6 for other renewable fuel; and D =7 for cellulosic diesel.
Source: U.S. Environmental Protection Agency.

Figure 1. Renewable Identification Number code definitions [1.28]

1.2. The main actors of the market

All actors of the RIN market can be divided into following groups (Fig.2):

1. Farmers;

Farmers are entrepreneurs who grow raw materials for ethanol. As it was mentioned before, it may be corn, grain crops or other agricultures. This group is also included entrepreneurs who prepare wood for processing (ethanol production).

2. Refiners;

Refiners are manufactures who produce ethanol. The number of refiners is about 211 in 28 states, common productivity is approximately 14.7 bln gallons of ethanol. For recent 10 years output has increased, only in 2012 it was a little decrease. In 2005 production surged because of imposition of RFS. This increase was not only because of production rise in old plants, but also because of building new ones. For 10 years the number of plants becomes fourfold and the number of states has already increased by 40%. [2.7]

3. Blenders;

Blenders are manufactures who mix ethanol with gasoline. It must be mentioned that blenders are located not in the same places as refiners. Blenders are concentrated in the Northern or North-Western parts of the USA, but refiners are generally placed on coasts. The latter can be explainable by necessity to import or export gasoline and ethanol.

4. Owners of fuel stations;

This group includes entrepreneurs who sell fuel to ultimate consumers. Their number depends on fuels what they sell. For example, E85 were sold by 3000 fueling stations. It was because of the number of vehicles which fuel was for.

In the end of 2010 EPA allowed to use E15, but only for vehicles which were produced after 2001. In spite of better properties than E10, E15 were less popular. In 2011 only 10 fueling stations sold it. However, in 2013 there were about 24 fueling stations selling E15 out of 180,000 stations across the U.S. [2.3] According to information presented by Department of Energy, there are 10 mln of FFVs[1] in the USA and only 500 thousand of them are filled up E85. One of reasons is that owners do not know about characteristics of their cars [2.4].

5. EPA;

This actor regulates the market. In other words, every year it checks that every gallon of ethanol, which is produced in the USA or imported to the country, has RIN and every blender has enough RIN, not more that 20% are transited to next year and there are other violations. Also it analyzes current situation to forecast the value of mandate for next year. Forecast is really responsible thing, because, as it will be mentioned below, some researchers argue that it can influence RIN prices.

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[1] Flexible Fuel Vehicle

All work of this agency is addressed to reducing carbon pollution and other greenhouse gas emissions from the transportation and energy sectors. In collaboration with other agencies which work, EPA will build strong partnerships with states, tribes, and local communities to enhance the resiliency of local infrastructure as part of EPA's Sustainable Communities initiative. [2.5]

6. Private agencies

Private agencies provide information about RIN prices, the market review. Examples of them are RINAlliance[2] and EcoEngineers[3].

Renewable fuel blenders across the country utilize the experience of regulatory professionals as private agencies for consulting, compliance, RIN management and RIN marketing services as well as other services in the renewable fuel sector including plant design review, compliance advisory, on-site verification and certification and regulatory consulting under national and international renewable fuel standards.[2.9]

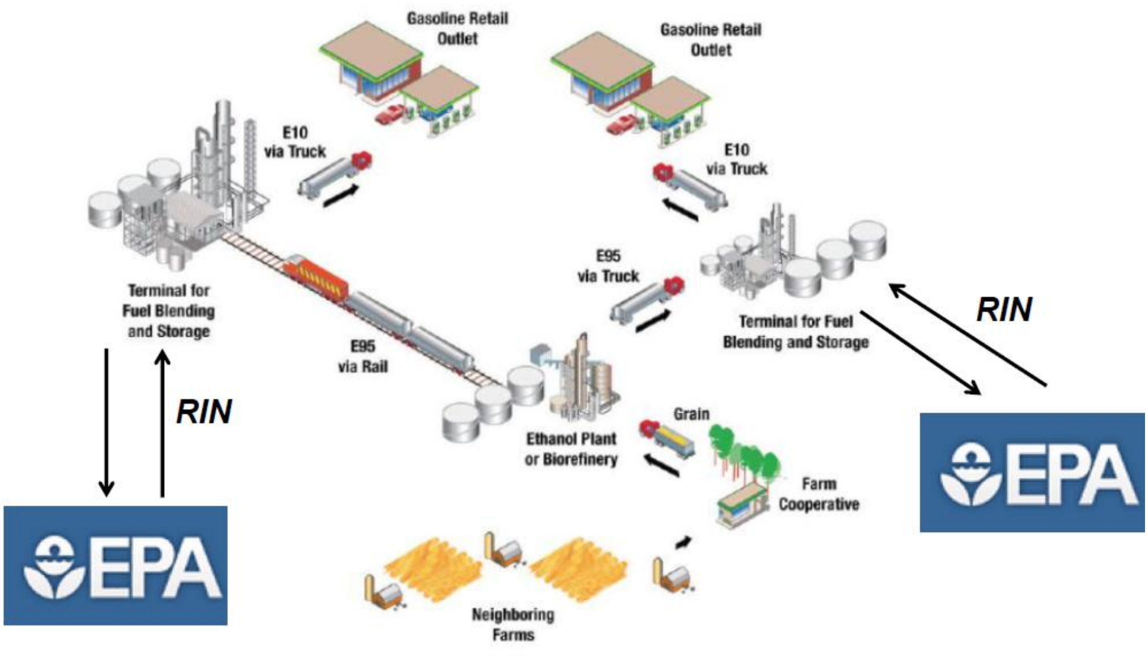

Figure 2. Scheme of the RIN market**write mandate, move RIN and arrows

Nowadays RINAlliance is one of the biggest private agencies in the USA which serves 130 blenders with EPA reporting and RIN marketing. They currently

[2] http://rinalliance.com/
[3] http://www.ecoengineers.us/

manage more than 2 million RINs per day while aggregating and marketing RINs that have been separated within the RINAlliance system. Because of 140 million fraudulent RINs circulating within the RFS RIN system RINAlliance and other agencies had to design a new system of due diligence that was capable of re-establishing the relationships between RIN buyers and sellers.

Since 2011 RINAlliance has been partnering with EcoEngineers to design a third party assurance plan that provided on-site audits and continual monitoring of feedstock, production, fuel quality, and overall mass-balance of facilities. EPA is currently drafting rules that promote a similar process (RIN Quality Assurance Program) for the identical reason of making the RIN market stable. [1.17]

1.3. The last market tendency

Since the end of 2013 researchers have started to have interests in behavior of RIN prices and efficiency of the market. For example, an analysis by Iowa State University economists B. Babcock and S. Pouliot of the EPA's ethanol market system finds that it works effectively and as intended in tracking compliance with RFS. The authors conclude that rather than volatility and high prices which were at the end of 2012 being a sign that something was wrong with RIN markets or RFS, RIN prices did their job by signaling that higher ethanol mandates were coming and would be costly to achieve. [2.8] This huge 'jump" of the price can be because of reducing the size of the corn crop and that led to record-high prices and the idling of ethanol plants in late 2012 and early 2013, as market prices for ethanol were not sufficient to allow producers to offset higher production costs and sustain significantly positive margins. [2.1]

Some scientists researched the dependence between mandate and price level. For example, R. Miao and et al. [1.30] develop a two-period conceptual model. They find that the investment impact of mandates depends on investors' marginal costs and the distribution of the price of cellulosic biofuels in the second period.

In the summer of 2013 there was significant price increase of three assets at the same time. Firstly, gasoline and RIN prices grew, and then gas prices went up. Some experts conjectured that the financial crisis would repeat. However, the Renewable Fuels Association concluded that it was seasonal driving and influence of rising of crude oil price as well as that, according to results of Granger causality analysis, there is no causality between gasoline and RIN prices. [2.1]

At the end of 2013 EPA determined biofuel mandate levels for 2014 which became hither. Babcock and Pouliot argue this increase will lead to fall of RIN prices dramatically. Because high RIN prices imply high compliance costs, this mandate would create a large incentive to lower compliance costs. [1.2]

All these factors influence RIN prices, but now it is impossible to understand all impacts. As executive director of media relations for Valero Bill Day mentioned, “it is difficult to analyze the RIN market <…> because the RINs market is so opaque. It’s not a regulated market like gasoline or crude oil or other commodities that trade on the New York exchange or CBOT. It’s mostly private transactions.” [2.6]

This paper is just an attempt to understand behavior of RIN prices and forecast their value. It does not present other factors which can influence RIN price; partly it was not done because of lack of necessary information.

2. Theoretical background

2.1. Description of models which are useful for forecast

In this section we describe models which are useful for forecast when a researcher has only one series without any other factors which can explain behavior of given variable. These models are ARMA, ARMA-GARCH, GARCH-M and MS ARMA-GARCH.

ARMA

One of the key moments in Econometrician history was in 1951 when Peter Whittle published his thesis which described autoregressive–moving-average (ARMA) model. [1.39] Since this year many of authors used the model to analyze time series and forecast future values of series. For example, using ARMA model it is possible to forecast births as J. McDonald do. [1.28] Additionally, N. Muler and et. al deal with inward movement of residential telephone extensions in a fixed geographic area. [1.31]

The model consists of only equation:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

where X_t a given time series, c is a constant, $\varphi_1, \dots, \varphi_p$ are parameters of the autoregressive part, $\theta_1, \dots, \theta_q$ are parameters of the moving average part and $\varepsilon_t, \dots, \varepsilon_{t-q}$ are white noise error terms. Because of the number of parameters, it is usually called ARMA(p,q).

This model is useful, but it works only with stationary time series whereas many of them have integrability of order one or two. In other words, if author analyzes price dynamics which is non-stationary and has time series integrability of order one then returns will be stationary, but it will ARIMA(p,1,q) model.

Besides existence of unit roots, conditions of statinarity for AR should be fulfilled. In other words, all roots of the equation $1 - \varphi_1 z - \varphi_2 z^2 - \dots - \varphi_p z^p$

should be more than one in absolute value. In the case of AR(1), it is -1<φ_1<1. MA is always stationary.

ARMA-GARCH

Financial data usually estimated using ARMA-GARCH models which have not only ARMA equation, but additional one described behavior of volatility. For example, A. Carvalhal and B. Mendes estimated usual ARMA-GARCH model working with emerging market stock returns. 1.6] Also there are some modifications such as FIGARCH, which was estimated by K. Choi and S. Hammoudeh [1.5] who deal with the spot and futures prices of crude oil and of two refined products such as the gasoline and heating oil, or ARMA-EGARCH, which was estimated by M. Karanasos and J. Kim who research four East Asia Stock Indices. [1.20]

ARMA(p,q)-GARCH(k,m) model has the following structure:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \, \varepsilon_{t-i}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2$$

$$\varepsilon_t = \sigma_t u_t$$

where X_t a given time series, c and α_0 are constants, $\varphi_1, \dots, \varphi_p$ are parameters of the autoregressive part, $\theta_1, \dots, \theta_q$ are parameters of the moving average part, $\varepsilon_t, \dots, \varepsilon_{t-q}$ are residuals; $\alpha_1, \dots, \alpha_k$ and $\beta_1, \dots, \beta_m$ are parameters of GARCH model, σ_t^2 is conditional heteroskedasticity as well as u_t is white noise with standard normal distribution.

This model was described by Bollerslev (1986) [1.29]. If heteroskedasticity depends on only errors, it is ARCH model which was offered by Engle (1982) [1.9].

As ARMA model, GARCH also has some restrictions. First of all, the unconditional variance $E(\sigma_t^2) = \frac{\alpha_0}{1-\alpha_1-\cdots\alpha_k-\beta_1-\cdots-\beta_m}$ is not negative, so $\sum_{i=1}^{l}(\alpha_i + \beta_i) < 1$, where $l = \max(k, m)$. Secondly, for (weakly) covariance stationary of the process the roots of the equation $1-(\alpha_1+\beta_1)z-(\alpha_2+\beta_2)z^2-\cdots-(\alpha_l+\beta_l)z^l$ have to be outside unit circle. Lastly, α_0 should be positive, but α_i and β_j should be not negative for all i and j.

GARCH-M

The return of the asset can depends not only on previous returns of different periods (AR model) and residuals of previous periods (MA model), but also on its volatility (GARCH-M or GARCH in Mean). In other words, the ARMA(p,q)-GARCH-M(k,m) model has the following structure:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \,\varepsilon_{t-i} + \mu\,\sigma_t^2$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{k} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{m} \beta_j \sigma_{t-j}^2$$

$$\varepsilon_t = \sigma_t u_t$$

The parameter μ does not any limitations, but the sign of this parameters shows that the return is positively or negatively related to volatility.

MS GARCH

In recent years researchers of financial assets have started to work with MS GARCH which was suggested by Hamilton (1989) [1.13]. The idea of this model is that parameters dependent from two or more regimes.

There are two types of this model. The first one is path-dependent MS GARCH model, the conditional density of X_t depends on all previous values of s_t. It complicates the model estimation, because of the number of parameters which increases period by period, so authors use Monte Carlo method. For instance, L. Bauwens and et al. illustrate the model on Standard & Poor 500 (S&P500) [1.3] and J.Henneke estimated MS-ARMA-GARCH model using the stock price series which is the value-weighted portfolio of stocks traded on the NYSE [1.15].

The second type is non- path-dependent MS GARCH model of Klassen [1.23], the conditional density of X_t depends only on the current regime s_t. The number of parameters is the same for all periods, so authors use maximum likelihood method. For example, S. Blazsek and A. Downarowicz estimated hedge fund indices and forecast volatility [1.4], J. Marcucci analyzes closing price index from the S&P100 stock market [1.26].

According to results of White's Reality Check test [1.41] and Hansen's test [1.14] for Superior Predictive Ability which were compared by Marcucci [1.26], the MS GARCH model with normal innovations does outperform all standard GARCH models in forecasting volatility at shorter horizons. At longer horizon, standard GARCH models outperform the MS GARCH.

MS GARCH model also has three equations as GARCH:

$$X_t = c(s_t) + \varepsilon_t(s_t) + \sum_{i=1}^{p} \varphi_i(s_t) X_{t-i} + \sum_{i=1}^{q} \theta_i(s_t)\varepsilon_{t-i}(s_t)$$

$$\sigma_t^2(s_t) = \alpha_0(s_t) + \sum_{i=1}^{k} \alpha_i(s_t)\varepsilon_{t-i}^2(s_t) + \sum_{j=1}^{m} \beta_j(s_t)\sigma_{t-j}^2(s_t)$$

$$\varepsilon_t(s_t) = \sigma_t(s_t) u_t$$

where s_t is a regime which forms a Markov process.

2.2. Description of the chosen model

In this paper we illustrate non-path-dependent MS AR(1)-GARCH-M(1,1) model with two regimes for normal and Student-t distributions. The main idea of using MS GARCH is to forecast zero returns which can't be forecasted by GARCH model and, on the other hand, it is not correct to exclude them as some authors did, for example, in a paper where O. Sabbaghi and N. Sabbaghi research returns of Carbon Financial Instruments [1.35]. Later excluding of zeros is discussed in the paper by M. Paolella and L. Taschini [1.32] and authors suggest two ways. The first way is to do only the unconditional analysis of the tails of the data, in other words, to avoid the zeros-problem, because the zeros are in the centre. The second one is a conditional analysis using mixed-normal and mixed-stable GARCH models. In this paper we don't compare results of estimation using MS ARMA-GARCH-M and mixed GARCH model. We just consider results of regime switching GARCH model and a model from the previous paper [1.19] where we excluded zeros and estimated ARMA-t-GARCH model as O. Sabbaghi and N. Sabbaghi [1.35].

So MS AR(1)-GARCH-M(1,1) model has the following structure:

$$X_t = c(s_t) + \varepsilon_t(s_t) + \varphi_1(s_t)X_{t-1} + \mu(s_t)\sigma_t^2(s_t)$$

$$\sigma_t^2(s_t) = \alpha_0(s_t) + \alpha_1(s_t)\varepsilon_{t-1}^2(s_t) + \beta_1(s_t)\sigma_{t-1}^2(s_t)$$

$$\varepsilon_t(s_t) = \sigma_t(s_t)u_t$$

This structure is for standard normal distributed residuals. If model has Student-t distributed residuals then the degree of freedom also depends on the regime.

If model has only two regimes, then transition probability matrix $P = \{\eta_{ij}\}$ will be 2x2. The transition probability matrix of s_t is given by the four parameters:

$$\Pr[s_t = 1|s_{t-1} = 1] = \eta_{11}$$

$$\Pr[s_t = 2|s_{t-1} = 1] = \eta_{21}$$

$$\Pr[s_t = 1|s_{t-1} = 2] = \eta_{12}$$

$$\Pr[s_t = 2|s_{t-1} = 1] = \eta_{22}$$

where $\eta_{11} + \eta_{21} = 1$ and $\eta_{22} + \eta_{12} = 1$.

For non-path-dependent case likelihood function will be:

$$L = \prod_{t=1}^{k} \sum_{i=1,2} f(X_t|s_t = i, I_{t-1}) \Pr\,[s_t = i|I_{t-1}]$$

where $I_{t-1} = (X_1, \ldots, X_{t-1})$ denotes excess data observed until period t-1 and f is a density function. Regarding Kim and Nelson's paper [1.21], the conditional probability equals:

$$\Pr[s_t = j|I_{t-1}] = \sum_{i=1,2} \Pr[s_t = j|s_{t-1} = i] \Pr[s_{t-1} = i|I_{t-1}]$$

where

$$\Pr[s_t = i|I_{t-1}] = \frac{f(X_{t-1}|s_{t-1} = i, I_{t-2}) \Pr[s_{t-1} = i|I_{t-2}]}{\sum_{i=1,2} f(X_{t-1}|s_{t-1} = i, I_{t-2}) \Pr[s_{t-1} = i|I_{t-2}]}$$

and the initial values of the conditional probability are:

$$Pr[s_0 = 1|I_0] = \frac{1 - \eta_{22}}{2 - \eta_{11} - \eta_{22}}$$

$$Pr[s_0 = 2|I_0] = \frac{1 - \eta_{11}}{2 - \eta_{11} - \eta_{22}}$$

For normal distribution and regime $s_t = i$ the density function is:

$$f(X_t|s_t = i, I_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_t^2(s_t = i)}} \exp\left\{-\frac{[X_t - \varphi_1(s_t = i)X_{t-1} - c(s_t = i)]^2}{2\sigma_t^2(s_t = i)}\right\}$$

And for Student-t distribution it will be [1.26]:

$$f(X_t|s_t = i, I_{t-1}) =$$

$$= \frac{\Gamma\left(\frac{n+1}{2}\right)}{\sqrt{(n-2)\pi h_t}\Gamma\left(\frac{n}{2}\right)} * \left(1 + \frac{[X_t - \varphi_1(s_t = i)X_{t-1} - c(s_t = i)]^2}{(n-2)h_t}\right)^{-\frac{n+1}{2}}$$

Moreover, there are two stationary conditions. The first one is for ARMA part [1.12]:

$$\sum_{i=1,2} Pr[s_0 = i|I_0] \ln(|\varphi_i|) < 0$$

and the second condition is for GARCH part which says that the all eigenvalues of matrix V must be inside the unit circle [1.1], where V is:

$$V = \begin{bmatrix} \frac{(\alpha_1 + \beta_1)\eta_{11} Pr[s_0 = 1|I_0]}{Pr[s_0 = 1|I_0]} & \frac{(\alpha_1 + \beta_1)\eta_{12} Pr[s_0 = 2|I_0]}{Pr[s_0 = 1|I_0]} \\ \frac{(\alpha_2 + \beta_2)\eta_{21} Pr[s_0 = 1|I_0]}{Pr[s_0 = 2|I_0]} & \frac{(\alpha_2 + \beta_2)\eta_{22} Pr[s_0 = 2|I_0]}{Pr[s_0 = 2|I_0]} \end{bmatrix}$$

2.3. Preparation tests

As it was mentioned before, firstly we should check that the series has unit roots or not. There are several tests such as Dickey-Fuller test [1.8], Phillips-Perron test [1.34], Perron test [1.33] and Zivot-Andrews test [1.40]. Both the first test and the second one work with data which is without breaks or changing trend, for example. Perron test solves this problem, however, an author should assume when a break was. In our case it is not obviously, so we use the last test, Zivot-Andrews test.

Zivot and Andrews transform Perron test which is conditional on structural change at a known point in time into conditional unit-root test. The null hypothesis argues that there is no exogenous structural break. In other words, the process has the following structure:

$$y_t = \mu + y_{t-1} + e_t$$

where y_t is a given series, μ is a constant and e_t is a vector of residuals. The alternative hypothesis is that y_t represented by a trend-stationary process with a one-time break in the trend occurring at an unknown point in time. The process has unit root if the absolute value of minimum t-statistic is more than the critical value.

Additionally, Zivot and Andrews find that some of series for which they reject the unit-root null hypothesis have thicker tails than the normal distribution. They do test again using Student-t distribution, but the results are the same as for the normal distribution.

Secondly, it is necessary to test the series on the ARCH affect. A time series has autoregressive conditional heteroscedastic (ARCH) effects if it exhibits conditional heteroscedasticity or autocorrelation in the squared series. If model doesn't have the ARCH affect, a model doesn't have a GARCH part, only an ARMA one.

There are two tests, ARCH test [1.9] and Ljung-Box test [1.25]. Engle's ARCH test is a Lagrange multiplier test to assess the significance of ARCH effects. The null hypothesis is

$$H_0: a_0 = a_1 = a_2 = \cdots = a_m = 0$$

in an equation

$$e_t^2 = a_0 + a_1 e_{t-1}^2 + \cdots + a_m e_{t-m}^2 + u_t$$

where $\mathrm{e_t}$ is the residual series and $\mathrm{u_t}$ is a white noise error process. The test statistic for Engle's ARCH test is the usual F statistic for the regression on the squared residuals. Under the null hypothesis, the F statistic follows a χ^2distribution with m degrees of freedom. A large critical value indicates rejection of the null hypothesis in favor of the alternative.

The second test is Ljung-Box test checked that the first m lags of the sample autocorrelation function of the e_t series are zeros, so the null hypothesis is

$$H_0: p_0 = p_1 = p_2 = \cdots = p_m = 0$$

Under the null hypothesis,

$$Q(m) = N(N+2) \sum_{h-1}^{m} \frac{p_h^2}{N-h}$$

follows to the χ^2distribution with m-g degrees of freedom, where N is the length of the observed time series, g is a number of parameters in a model. Also Ljung-Box test is possible to use for checking autocorrelation of the residuals, so the researcher can understand if a model has ARMA part.

2.4. One-sample Kolmogorov-Smirnov test

Not all financial series is correctly to estimate with the normal distribution, because for some of them residuals have a leptokurtic distribution. This fact was found by Mandelbrot [1.27] and Fama [1.10,1.11]. The leptokurtic distribution has a more acute peak and thicker tails than the normal distribution, for example, Student-t, lognormal or exponential distributions.

The estimation of MS GARCH model depends on chosen distribution, because likelihood has the density function. So we estimate MS AR GARCH model, and after that we check distribution using Kolmogorov - Smirov test [1.24, 1.36].

This test can be used to reject of not reject hypothesis that a sample has a chosen distribution. It is possible to compare with all known distributions.

The empirical distribution function F_n for n independent and identically distributed (iid) observations X_i is defined as

$$F_n(x) = \frac{1}{n}\sum_{i=1}^{n} I_{X_i \le x}$$

where I is an indicator function which shows that X_i is in the area $\{-\infty, x]$ or not, in other words,

$$I_{X_i \le x} = \begin{cases} 1, & X_i \le x \\ 0, & X_i > x \end{cases}$$

The Kolmogorov – Smirnov statistic for a given cumulative distribution function $F(x)$ is

$$D_n = sup_x|F_n(x) - F(x)|$$

where sup is the supremum of the set of distances and $F(x)$ is the checked distribution function of the given sample.

This test uses the critical values of the Kolmogorov distribution (K_α). The null hypothesis, which agrues that the sample has the distribution with the function $F(x)$, is rejected at level α if

$$\sqrt{n}D_n > K_\alpha$$

This test is used for checking the distribution in the normal case, because the residuals should have exactly standard normal distribution regarding the structure of the GARCH model. In the case with Student-t distribution we don't have to do it, because a degree of freedom is one of the parameters which are estimated by the model.

2.5. Forecast volatility and returns

According to Klassen's paper [1.23], a recursive formula for the n-step ahead variance forecast for a GARCH(1,1) process is:

$$\hat{\sigma}^2_{t+n} = \sum_{i=1,2} \hat{\sigma}^2_{t+n}\,(s_{t+n} = i)\Pr\,[s_{t+n} = i|I_{t-1}]$$

where

$$\hat{\sigma}^2_{t+n}(s_{t+n}) = E[\sigma^2_{t+n}(s_{t+n})|I_{t-1}] =$$
$$= \alpha_0(s_{t+n}) + [\alpha_1(s_{t+n}) + \beta_1(s_{t+n})E[\sigma^2_{t+n-1}(s_{t+n-1})|s_{t+n}, I_{t-1}]$$

A recursive formula for the n-step ahead observation forecast is calculated the similar way:

$$\hat{X}_{t+n} = \sum_{i=1,2} \hat{X}_{t+n}\,(s_{t+n} = i)\Pr\,[s_{t+n} = i|I_{t-1}]$$

As it was mentioned above, we estimate MS GARCH model using normal and student destitutions. The model for forecasting is chosen according to results of a test for superior predictive ability. This test was illustrated by White [1.41] who suggests choosing the best model according to an expected loss. In other words, the forecast which has less the expected loss is better. This loss is calculated the following way:

$$EL = \sum_{i=t+1}^{t+n} (\hat{X}_i - X_i)^2$$

where n is a length of forecasted period, $\hat{X}_i$ is forecasted observations and X_i is real value of these observations for forecasted period which is presented by EcoEngineers company.

Additionally, the forecast using the estimation of MS GARCH model will be called "better forecast" than the forecast of GARCH model if it can forecast zero returns. In other case, this model will be impossible to compare, because they work with different initial sample (MS GARCH estimates the whole sample while GARCH estimates a sample without zero returns).

Moreover, the MS GARCH forecast of observations is compared with the forecast of bid and ask prices which are presented by EcoEngineers company (more information about it is in the next section). It is unknown what model EcoEngineers uses, but we compare our results with their ones using White's test again.

3. Results of estimation

3.1.1. Data description

The data set analyzed in this paper is RIN price. As it was mentioned in Section 1 there are two types of RINs conventional and advanced. The last group includes RINs such as biomass-based diesel (D4), advanced biofuels (D5) and cellulose (D6). Data is provided by the EcoEngineers company, but it gives information only about prices of advanced RINs, so we analyze these three series.

The sample period is from January 3, 2011 to April 30, 2014 for a total of 836 observations for each series. As forecasted period is two weeks or 10 days, bid and ask prices as well as real value of RIN prices were taken only from May 1, 2014 to May 14, 2014.

The RIN prices were unstable for the whole analyzed period (Fig. 3). The first peaks were in the beginning of September in 2011. The D4 RIN peak was 198.5 and it is absolute maximum as of today. The D5 RIN peak constitutes 126.25 and it was on the next day after the D4 RIN peak (September,15). The D6 RIN series had a little increase on 14 of September, but because of small value of price it was not so dramatic.

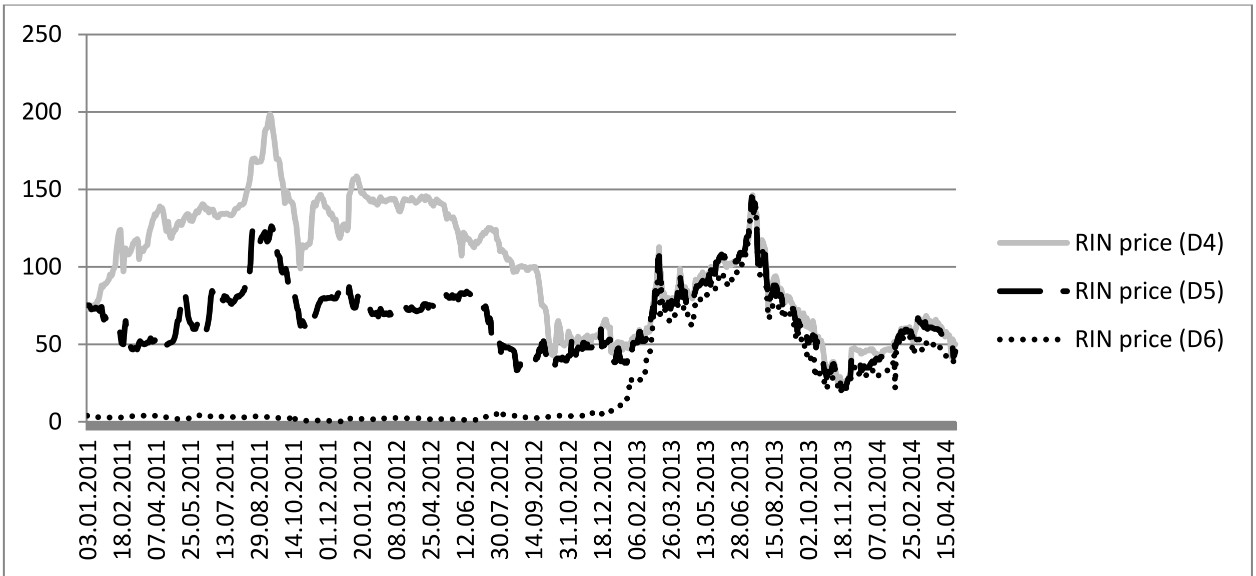

Figure 3. The dynamics of the RIN prices (in cents)

In one year, in October of 2012 the D4 RIN price and the D5 RIN price became too close; the difference was less than 20 cents and in the beginning of

2013 prices differed only by several cents. At the same time the D6 RIN price started to surge and in the first days of March in 2013 all three prices had similar values. The reasons of this "jump" are mentioned in Section 1.

The second peak was on July, 17 of 2013. The value of all prices was about 145 cents. This point was the absolute maximum for the D5RIN price and the D6 RIN price. The next peak was achieved in February-March of 2014. At this time the peak of cellulose RIN price happened earlier.

In the previous paper [1.19] it was found out that these three RIN series really have positive correlations which have increased since "jump" period. Although reasons of the RINs behavior are a timely topic, they are not researched in this paper.

Table 1 shows some descriptive statistics of the RIN prices. The means differ dramatically, because only after the end of 2013 prices have much the same value. Also because of this "joining" all series have a high value of standard deviation. Additionally, maximum and minimum prices confirm that it was "price jump".

Table 1. Descriptive Statistics of RIN prices

	D4	D5	D6
Mean	99,711	67,405	23,901
Standard Deviation	38,604	22,490	31,837
Min	20,954	21	0,32
Max	198,5	145	145,219

3.2. Test results

As it was mentioned above in Section 2, before the estimation of the model we should do Zivot-Andrews test, Ljung-Box test and ARCH test.

Zivot-Andrews test

The figure 4 illustrates dynamics of t-statistic for all cases. The first column has statistics for the prices while the second one has for the returns. Each line corresponds to the returns of the RIN D4, the RIN D5 and the RIN D6, respectively. The returns are calculated as the difference between the logarithm of current price and the logarithm of price in the previous time moment.

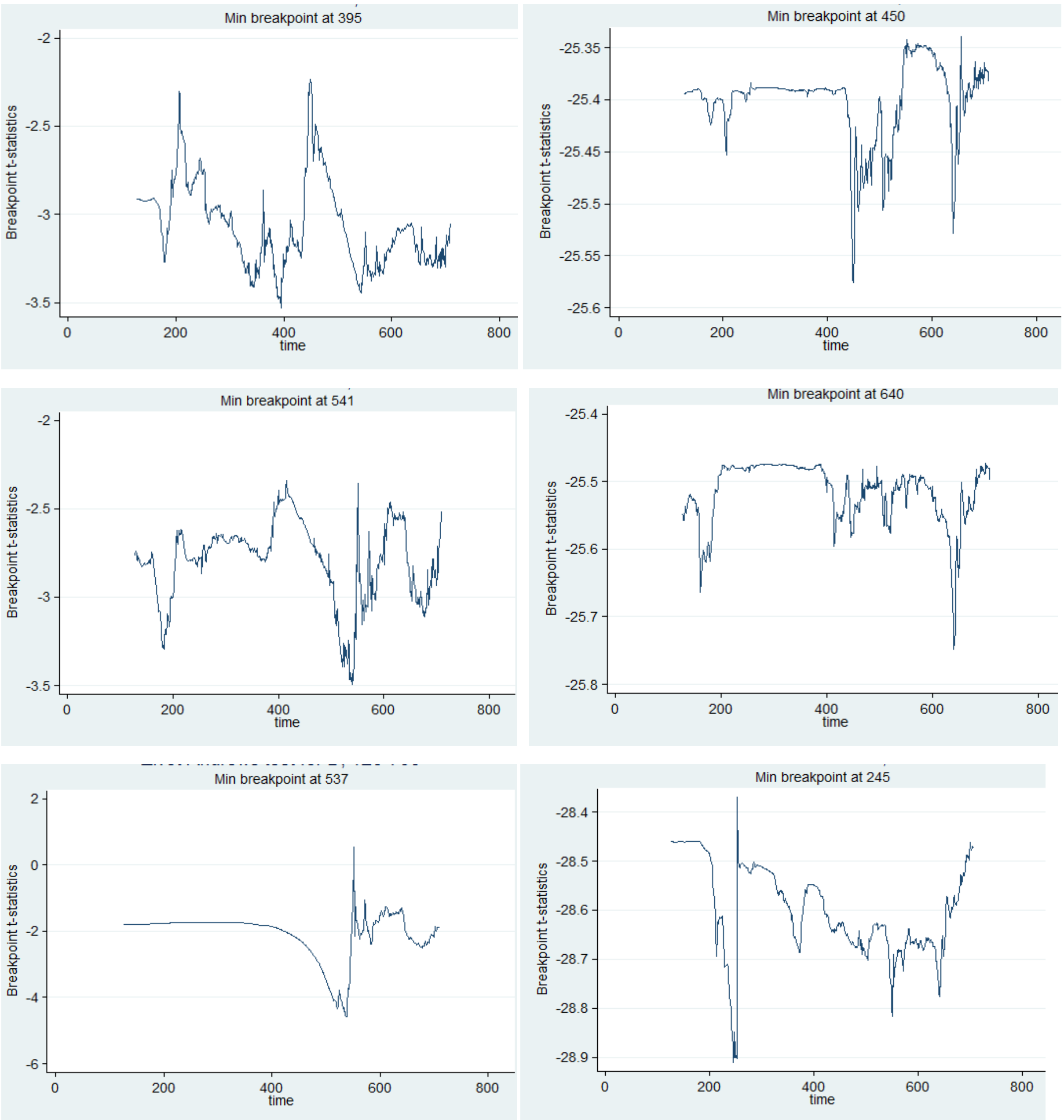

Figure 4. T-statistics for Zivot-Andrews test.

The dynamics of t-statistic helps to find the minimum and compare with the critical value. All minimum t-statistics are presented in table 2. The critical values are the same for all cases, in other words, at the 1% level it is -5.57, at the 5% it is -5.08 and at the 10% level it is -4.82.

Table 2. Results of Zivot-Andrews test for RIN prices and RIN returns.

	prices		returns	
	Minimum t-statistic	The number of observation	Minimum t-statistic	The number of observation
D4 RIN	-3.529	395	-25.576	450
D5 RIN	-3.494	541	-25.748	640
D6 RIN	-4.577	537	-28.911	245

As it was said in Section 2, the hypothesis about the lack of the unit root is rejected if value of t-statistic is higher than the critical value absolutely. So minimum t-statistics for price processes are not high enough to reject the hypothesis whereas values for the returns case are high significantly. Therefore, processes of RIN returns are stationary and all models will estimate parameters for them.

Ljung-Box and ARCH tests

As it was described in Section 2, the null hypothesis, that a process does not have ARCH effect, is rejected if test statistic is higher than the critical value. Both tests showed that all series have ARCH effect (Appendix 1), so the type of the model which should be estimated is MS ARMA-GARCH-M.

3.3. Returns description

For all three series Zivot-Andrews test does not reject the hypothesis that price process has at least one unit root whereas the test rejects the same hypothesis for the return process. So we estimate all models using RIN returns.

All returns change in the gap [-0.5; 0.5] except several points of D6 RIN series (Fig. 5). There are four outliers on 3rd January 2012, 12th March 2013 as well as 3rd and 4th February 2014. These outliers are excluded from the analyzed sample.

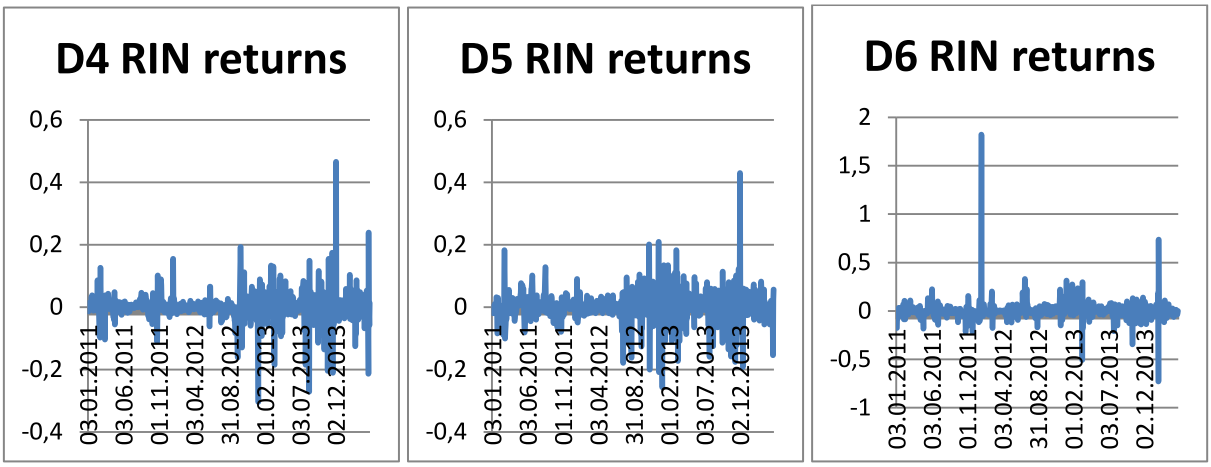

Figure 5. RIN returns

We observe almost zero mean and small standard deviation for all return series (Table 3, where the D6 RIN sample does not have outliers). Minimum points are much the same, but maximum points differ from each other dramatically. Additionally, each series has positive skewness and a usual excess kurtosis for this type of data and sample size.

Table 3. Descriptive Statistics of RIN returns

	D4 RIN returns	D5 RIN returns	D6 RIN returns
Mean	0,000	-0,001	0,001
Standard Deviation	0,047	0,048	0,060
Min	-0,304	-0,257	-0,344
Max	0,466	0,429	0,329
Skewness	0,479	0,364	0,476
Kurtosis	18,349	11,989	6,058

3.4. Results of estimation

First of all, we estimate MS GARCH with normal distribution. All results are presented in Table 4. Regardless of chosen RIN return sample, residuals do not have standard normal distribution, according to Kolmogorov-Smirnov test. This test definitely rejects the hypothesis that the distribution is standard normal, because probability is too small, it approximately equals 0. Also we can calculate that the residuals probable have distribution with high parameter than 0 and 1.

Since the definition of GARCH model with normal distribution presupposes that it has to be standard normal one, so we reestimate model adding additional restrictions for parameters of distribution. Thus, the model is estimated a way that residuals have to have zero mean and unit standard deviation. The new values of parameters are represented in the last three columns of Table 4.

Also we estimate MS GARCH model with two Student-t distributions. If we ignore the fact that financial assets usually has leptokurtic distribution and estimate the model using standard normal distribution, then estimators will be consistent and asymptotically normal, but not efficient.

For the D4 RIN returns changing model from normal distribution to standard normal one does not influence significantly the parameters, it is a little change of parameter which reflects the dependence between returns and volatility in a return equation and conditional probabilities. Moreover, this revision does not impact the value of likelihood, probably it is because of small lack between -0.0042 and 0 as well as 1.0303 and 1, in spite of the rejection by Kolmogorov-Smirnov test.

Besides that, for the D4 RIN return choosing of a distribution effect results and values of parameters dramatically. Also the model with Student-t distribution has two regimes with similar degree of freedom whereas the model with standard normal distribution has only one regime, in other words, it is usual AR(1)-GARCH-M(1,1) model.

In the D5 RIN returns case, making exact standard normal distribution effect seriously. It does not influence parameters of the second regime, but impact parameters of the first one, for instance, two parameters become zeros. In addition, the value of likelihood decreased twofold. Despite of appearance both regimes, the estimation with standard normal distribution can lead to big mistakes in forecast.

Table 4. Values of estimated parameters

parameter	Student-t distribution			Normal distribution			Standard normal distribution		
	D4 RIN	D5 RIN	D6 RIN	D4 RIN	D5 RIN	D6 RIN	D4 RIN	D5 RIN	D6 RIN
$c(s_t = 1)$	-0.475	3.7262	0.0001	0.0005	0.0003	0.0059	0.0005	-0.0006	0.0059
$c(s_t = 2)$	-0.573	0.0003	-0.001	0.0005	0.0003	0.0059	0.0005	0.003	0.0059
$\varphi_1(s_t = 1)$	0.1570	0.1275	0.2896	0.2292	0.2914	0.2154	0.2292	0.119	0.2154
$\varphi_1(s_t = 2)$	0.1571	0.2563	0.2785	0.2292	0.2914	0.2154	0.2292	0.2914	0.2154
$\mu(s_t = 1)$	2.0784	-1.995	-0.142	0.1967	-1.81	-0.345	0.1971	0.7519	-0.345
$\mu(s_t = 2)$	2.9597	-0.299	-0.062	0.1969	-1.81	-0.345	0.1967	-1.81	-0.345
$\alpha_0(s_t = 1)$	0.0031	0.9509	0.0021	0.0001	0.0001	0.0072	0.0001	0.0001	0.0072
$\alpha_0(s_t = 2)$	0.0025	0.0002	0.001	0.0001	0.0001	0.0072	0.0001	0.0001	0.0072
$\alpha_1(s_t = 1)$	0.0004	0.005	0.9977	0.2732	0.2164	0.305	0.2732	0	0.3050
$\alpha_1(s_t = 2)$	0.0003	0.5263	0.7182	0.2732	0.2164	0.305	0.2732	0.2164	0.3050
$\beta_1(s_t = 1)$	0.9865	0.4911	0	0.7092	0.7618	0	0.7092	0	0
$\beta_1(s_t = 2)$	0.987	0.4463	0.2645	0.7092	0.7618	0	0.7092	0.7618	0
η_{11}	0.5678	0.4998	0.5	0.5185	0.1887	0.5047	0.5260	0.5	0.3070
η_{22}	0.5684	0.4999	0.5	0.5185	0.1887	0.5047	0.5260	0.4965	0.3070
mean				-0.042	0.0058	-0.0101	0	0	0
std[4]				1.0303	1.0183	1.0030	1	1	1
$n(s_t = 1)$[5]	2	2	2.599						
$n(s_t = 2)$	2	3.028	2.796						
EL	0.0042	0.0051	0.0051				0.0035	0.0128	0.0039
likelihood	2217.2	2064	1599.6	2049.9	1849.1	486.9	2049.9	1051.1	486.9

[4] Standard deviation
[5] degree of freedom

The model with Student-t distribution for the D5 RIN returns also has both regimes and, in contrast to results of estimation of the model for the D4 RIN returns, parameters of regimes differ from each other sufficiently. In this case we receive two distributions with different degrees of freedom.

For the D6 RIN returns the change of normal distribution to standard normal one impacts only conditional probability, all other parameters are the same. In spite of the very little difference between parameters of normal distribution with 0 and 1, Kolmogorov-Smirnov test rejects the hypothesis that it is standard normal distribution again.

In the previous cases with Student-t distribution conditional probability is approximately 0.5, but for the D6 RIN return it is exactly 0.5. Moreover, changing distribution significantly has affect on the value of the likelihood, it is less threefold.

3.5. Results of forecast

Using White's test, which was described above, we choose the MS GARCH model with standard normal distribution for all cases as a "better" model, because value of EL is less than for Student-t distribution (Table 4). Moreover, MS AR(1)-GARCH-M(1,1) does not forecast zero returns, so we cannot say that this model is "better" than AR(1)-GARCH(1,1) with excluding zero returns in advance.

The Figure 6 represents return and volatility forecast for D5 RIN return, it is the case when we have both regimes. The forecasted returns do not fluctuate the way which the real data changes, probably it happens because the forecast of volatility is stable after the fourth step.

Additionally, because of probability which is close to 0.5, the forecasted volatility is similar as average between high and low volitilities which equals approximately 0.0051 and 0.0001, respectively.

Moreover, it is seen that that the first four steps are forecasted almost right, because the forecasted returns are not so far from the real returns. It means that maybe it is better to reestimate model every four or five days and do new forecast.

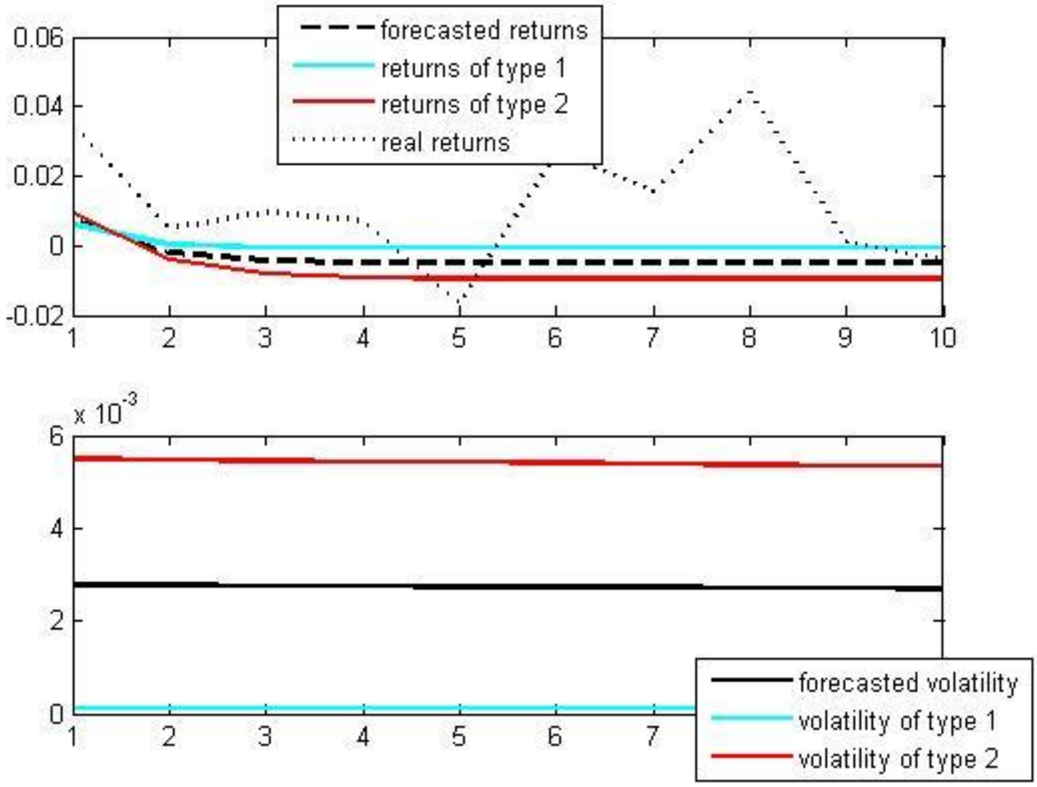

Figure 6. The forecast of returns and volatility for the D5 RIN

3.6. Comparing the price forecast with the forecast doing by EPA

Except prices of RINs, every day EPA reports its forecast for this day. It includes bid and ask prices. Bid price is the price at which a participant is prepared to buy commodity and ask price is the price at which a participant is prepared to sell commodity. [1.22]

Using received forecast and data which are reported by EPA, we forecast prices and analyze what forecast is “better”. As it was mentioned in Section 2, “better” means that average between bid and ask prices has less EL than our forecast.

Our forecast is not the best way to predict future prices, for example, the D6 RIN prices (Figure 7). Starting the second period our forecast differ dramatically from the real price whereas the bid and ask prices increase the similar rates. It means that we do not include a significant factor in our estimation which can influence the rise of RIN price in this case. Blazsek and Downarowicz [1.3] in their paper put an additional factor in the return equation. This factor has high correlation with their data. So probably significant factors enable to forecast RIN volatility and RIN prices better.

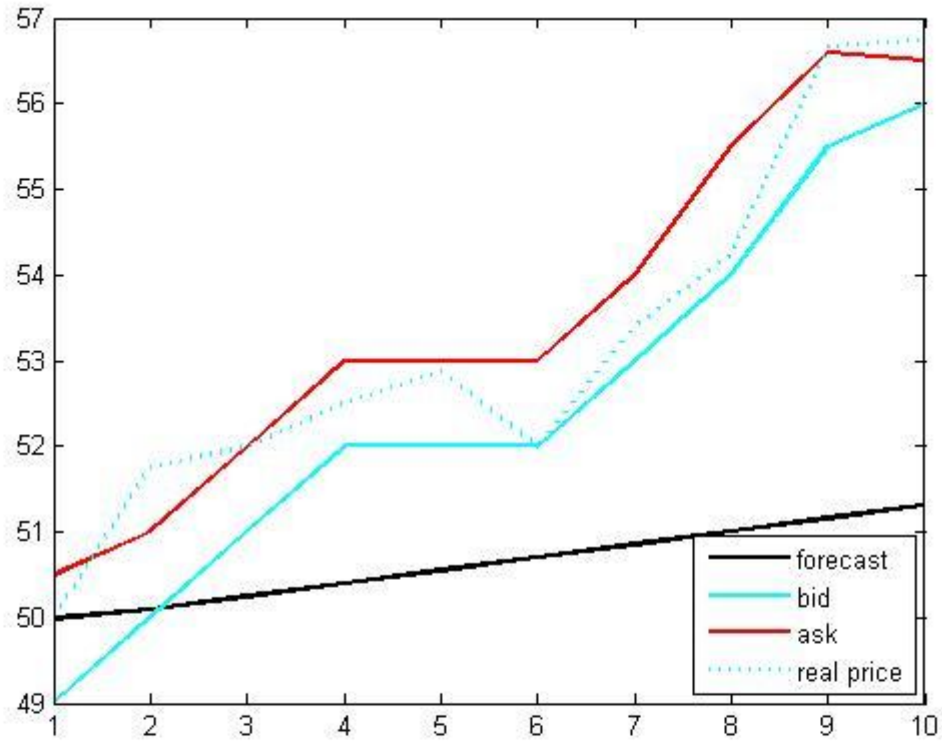

Figure 7. The price forecast for D6 RIN

Conclusion

The RIN market is a young market, it has big potential for development as environmentally friendly structure as well as financial one. For nine years of existence this market has change significantly, for example, EPA which is regulator of this market understands that it is possible to influence RIN prices changing level of mandates.

The main actors of financial side of this market are refiners who produce ethanol and received RINs from EPA for each gallon of ethanol as well as blenders who buy this ethanol with RINs. Each blender decides how much ethanol is mixed with gasoline, because there are several types of combination, for example, E10 (10% ethanol and 90% gasoline, E15, E85 and etc.). A blender do not have to buy all necessary RINs from refiners, it is possible to buy from another blender who has excess of this financial asset. At the report period blenders should have the concrete number of RINs which was reported them by EPA. Only 20% of RIN excess can be kept for the next year, others become invalid.

In this paper we define what RIN means, describe the market structure and all its actors including refiners, blenders and EPA. Also it has short part about the last tendency on the market and what is researched now. Besides that, we specify possible ways to estimate dynamics of a financial asset and forecast returns and volatility as well as some necessary tests such as Zivot-Andrews, ARCH and Ljung-Box tests.

According to the main target of this paper to identify MS GARCH model cannot forecast better than GARCH model, because it cannot forecast zero returns. Additionally, according to White's test we identify than standard normal distribution is better.

At the same time our forecast of volatility using MS GARCH with standard normal distribution does not work the right way. In other words, forecasted volatility and returns are not fluctuated and also forecasted returns differ significantly from the real returns, especially, after the fourth period.

Futhermore, we compare our price forecast with data which are presented by EPA. Every day it reports bid and ask prices. Using White test again, we measure the difference between our forecasted prices and real ones as well as the difference between the average of bid and ask prices and real prices too. The value of calculated parameter is less in our case. In addition, the price does not change the way it should do, in other words, maybe we do not include a significant factor in our analysis.

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Appendix

Appendix 1. Results of ARCH and Ljung-Box tests

RIN	m		ARCH test	*Ljung-Box (e)*	*Ljung-Box (e^2)*
D4	5	H	1	1	1
		p-value	0.0032	0.0041	0.0010
		ARCHstat/Qstat	17.7774	17.2176	20.5222
		Critical Value	11.0705	11.0705	11.0705
	10	H	1	1	1
		p-value	0.0000	0.0049	0.0000
		ARCHstat/Qstat	40.2538	25.2620	53.5790
		Critical Value	18.3070	18.3070	18.3070
	15	H	1	1	1
		p-value	0.0000	0.0000	0.0000
		ARCHstat/Qstat	52.8802	51.0660	79.4077
		Critical Value	24.9958	24.9958	24.9958
D5	5	H	1	1	1
		p-value	0.0813	0.0012	0.0449
		ARCHstat/Qstat	11.7937	20.1625	11.3460
		Critical Value	11.0705	11.0705	11.0705
	10	H	1	1	1
		p-value	0.0000	0.0012	0.0000
		ARCHstat/Qstat	48.7915	29.0264	57.1199
		Critical Value	18.3070	18.3070	18.3070
	15	H	1	1	1
		p-value	0.0000	0.0017	0.0000
		ARCHstat/Qstat	54.2107	36.0569	67.2264
		Critical Value	24.9958	24.9958	24.9958
D6	5	H	1	1	1

		p-value	0.0032	0.0041	0.0010
		ARCHstat/Qstat	17.7774	17.2176	20.5222
		Critical Value	11.0705	11.0705	11.0705
	10	H	1	1	1
		p-value	0.0000	0.0049	0.0000
		ARCHstat/Qstat	40.2538	25.2620	53.5790
		Critical Value	18.3070	18.3070	18.3070
	15	H	1	1	1
		p-value	0.0000	0.0000	0.0000
		ARCHstat/Qstat	52.8802	51.0660	79.4077
		Critical Value	24.9958	24.9958	24.9958