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Russian Stocks Volatility: Effect of Sanctions in 2014 and 2022

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RUSSIAN STOCKS VOLATILITY:
EFFECT OF SANCTIONS IN 2014 AND 2022

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Abstract

Sanctions are an important factor that might have significant influence on the economics of the country. This paper examines stock return volatility of the two Russian companies – Petropavlovsk PLC and Amur Minerals Corporation, considering the effect of sanctions imposed on the country in 2014 and 2022. GARCH(1,1) models are compared with GARCH-X, where X – is a dummy variable, reflecting the sanctions' pressure. Various specifications of models were examined. Sanctions' pressure appeared to have positive influence on Amur Mineral company's stock returns, and negative - on Petropavlovsk PLC.

Keywords: GARCH-X, Russian Stock Market, Volatility Forecasting, Sanctions Impact

I. INTRODUCTION

Return volatility is the degree of variability - deviation of an asset's return from its average value over a certain period. There are various factors that affect volatility: politics (Schwert, 1989), economics (Schwert, 1989; Beltratti & Morana, 2006), news (Baker et al., 2019), market manipulations (Nishimura et al., 2021), etc.

Because of the events of February 20, 2014, various economic sanctions were imposed on Russia. After the events of February 24, 2022, the package of sanctions was inflicted on the country, again. Because the Russian Federation is deeply integrated into world economics (Jithendranathan & Kravchenko, 2002), the stock market was affected by sanctions in both years, changing the volatility of securities.

Volatility is a measure of risk that reflects the market situation; it is used for calculating assets' prices, forming investment portfolios. Therefore, it is important for investors and governments to forecast it. Although volatility cannot be calculated directly, there are various methods for estimating it.

In his study, Engle (1982) introduced the autoregressive conditional heteroscedasticity (ARCH) model that uses a function to describe the error variance given by the AR model. In the case of variances to which the ARMA models are applicable, GARCH modeling is used (Bollerslev, 1986).

Noticed by Mandelbrot (1963), repeatedly confirmed and explained later (Granger & Ding, 1995; Crouhy & Rockinger, 1997; Lux & Marchesi, 1998), the effect of volatility clustering, characteristic of financial markets, was poorly predicted by standard models. ARCH and GARCH models described the phenomenon more accurately, remaining the most popular approaches for a long time.

However, GARCH models require quite complex calculations and perform poorly at intraday frequencies (Andersen et al., 2001). In this regard, in recent years, researchers have given preference to a non-parametric approach - realized volatility models (Andersen & Bollerslev, 1998) - based on high-frequency data, which increases the accuracy of the forecast. Realized volatility is a consistent estimate of unobserved volatility, as it converges to unobserved volatility at high data frequency. The model valuation is the sum of the squares of intraday returns.

Used by many researchers (Wang, 2009; Craioveanu and Hillebrand, 2012; Ceylan, 2014; Pyrlik & Leonova, 2021), RV models turned out to outperform ARCH family models regardless of index and time horizon (Mastro, 2014; Аганин, 2017). The analysis confirms that the realized volatility model is much more accurate measure of volatility than the conditional variance.

Realized volatility modeling seems to be the most attractive, nevertheless, during the data search it appeared to be impossible to find quotes of frequency higher than daily. Therefore, despite all the restrictions, it was decided to apply GARCH-modeling.

In the paper, the effect of the sanctions in 2014 and 2022 pressure on the commodity sector of economics is studied, considering quotes on the London Stock Exchange. Amur Minerals Corporation, and Petropavlovsk PLC, the two large mining companies of Russia, are examined. Two types of models are compared – GARCH-X (where X reflects sanctions pressure), and a benchmark GARCH(1,1) model. GARCH-X showed negative influence of the sanctions on the volatility for Petropavlovsk PLC, and positive for Amur Minerals.

The rest of the paper is organized as follows. Section II (i) describes the data. Section II (ii) shows methodology and models used. Section III presents results. Section IV contains conclusions and discussion. The last section includes references and appendix.

II. DATA AND METHODOLOGY

i) Data

Due to the impossibility of finding intraday stock quotes, there was made a decision to take daily quotes for the period from February 20, 2013 - to May 6, 2022 (2326 observations after the data preprocessing). The start date is chosen because it is necessary to consider the period before the first packet of sanctions; the end date is the last available date at the time of writing this article.

The data source is London Stock Exchange[I]. The choice stems from the fact that in February 2022 trading on the Moscow Exchange was suspended. Thus, it would be impossible to trace the impact of the sanctions. American Stock Exchanges either stopped trading Russian shares after the events of 2022 or did not have enough data for the period of 2014.

The two companies of the mining sector of economics are considered - Amur Minerals Corporation (that mines copper and gold), and Petropavlovsk PLC (that mines gold and iron ore concentrate). At the beginning, more companies were supposed to be studied but it appeared to be impossible to find the data for other companies. It ain’t much but it’s honest work.

ii) Empirical analysis

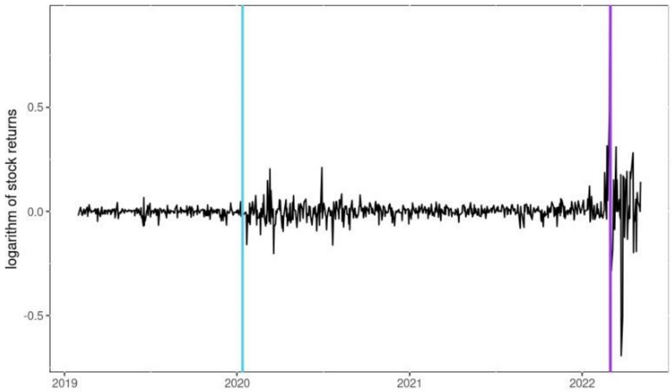
To distinguish the effect of the sanctions and obtain the best model, for each company there were compared the two types of models: GARCH(1,1) and various specifications of GARCH-X.

GARCH(1,1) is the most popular benchmark model because it captures the underlying variability of volatility (Hansen & Lunde, 2005). To construct the optimal GARCH(1,1) with ARMA(p,q) in means we went through the coefficients of *p* and *q* from 0 to 5, model types of sGARCH, eGARCH and gjrGARCH, and distributions of normal and Student. 216 models were constructed for both enterprises. Among those there were chosen the ones without autocorrelation in residuals (p-value in Ljung Box test > 0.05), and with the lowest BIC (Bayesian information criteria) values.

[I] The data was downloaded from the website investing.com.

For Amur Minerals gjrGARCH(1,1) with ARMA(0,1) in means, normal distribution and BIC = -2.8460 appeared to be the best model. Petropavlovsk PLC models' highest p-value in Ljung-Box test though was 0.000000002[II]. The data was divided into 8 parts – 300 observations in 7, and 226 in the last – to figure if the correlation stays within all the time.

number	period	maximum p-value in Ljung-Box test during the period	minimum p-value in Ljung-Box test during the period
1	February 20, 2013 – April 29, 2014	0.7557	0.0062
2	April 30, 2014 – July 7, 2015	0.4257	0.0001
3	July 8, 2015 – September 12, 2016	0.8160	0.0136
4	September 13, 2016 – November 16, 2017	0.9251	0.0014
5	November 17, 2017 – January 28, 2019	0.9721	0.0038
6	**January 29, 2019 – April 2, 2020**	**0.0426**	**0.0000**
7	April 3, 2020 – June 14, 2021	0.9100	0.0006
8	**June 15, 2021 – May 5, 2022**	**0.0650**	**0.0000**



There is a noticeable increase in volatility of stock return after January 13, 2020 (blue intercept) – the first case of covid-19 outside of China. The last period is also characterized with the extension of volatility values (violet intercept) – imposition of sanctions (March 2, 2022).

Covid-19 and the subsequent crisis, as well as the actions of the Russian authorities in Ukraine in 2022, are probably the reason for this significant change in the company's stock returns and the presence of autocorrelation in all the models. For Petropavlovsk PLC eGARCH(1,1) with ARMA(0,0) in means, Student's t-distribution and BIC = -4.1295 is the best benchmark model.

After defining optimal GARCH(1,1), GARCH-X models were constructed. GARCH-X is a GARCH model with an additional explanatory variable (X). For both enterprises there was created

[II] Characteristics of the top5 constructed GARCH(1,1) models for both companies are in the appendix: tables №1 and №2.

a dummy-variable that reflects the dates of declaring the significant (by this article's author opinion) sanctions, which are[III]:

March 6, 2014. Since that date, the US President gave the US administration the right to impose property and visa sanctions against individuals and legal entities that «assume power in the Crimean region without the permission of the government of Ukraine».

May 12, 2014. The EU Foreign Affairs Council, among others, included 13 people in the list of EU sanctions against those responsible, in its opinion, for destabilizing the situation in Ukraine. The EU also decided to freeze the assets of two companies from Sevastopol and Crimea - Feodosia and Chernomorneftegaz.

September 12, 2014. The European Union included Rosneft, Transneft, Gazprom Neft in the sanctions list. The EU banned the supply of dual-use goods to nine companies in the defense sector of the Russian Federation and also tightened access to loans from a number of state-owned banks of the Russian Federation and reduced the term of loans.

March 2, 2022. The European Union began disconnecting seven Russian banks from SWIFT: VTB, Rossiya, Otkritie, Novikombank, Promsvyazbank, Sovcombank and VEB.RF. He also banned the sale, supply, transfer, and export of euro banknotes to Russia. The prohibition applies to individuals or legal entities, organizations, and bodies in Russia, including the Russian Government and the Central Bank of Russia, or for use in Russia. The US announced blocking sanctions against 22 Russian defense-related companies, as well as export controls on oil and gas equipment.

In GARCH-X modeling, X – is the dummy variable that reflects the imposition of sanctions. There were considered the following GARCH-X specifications:

1) with different coefficients order: from GARCH-X(1,1) to GARCH-X(3,3);
2) of different GARCH model types: sGARCH-X, eGARCH-X, and gjrGARCH-X;
3) with different periods of «1»-s in dummy variables: a day, a week, a month, 3 months, a year, 3 years, 5 years and the period including all the days after the declaration of sanctions.

Effect of the sanctions through the external variable was added into the GARCH part of the equation. The best model for Amur Minerals corporation turned out to be eGARCH-X(3,3) with ARMA(0,1) in means, normal distribution, with the one-year effect of sanctions and BIC = -2.8706.

[III] The descriptions of the imposed sanctions were taken from TASS and Wikipedia.

Petropavlovsk PLC models', again, showed the highest result in Ljung-Box text of p-value = 0.000000002[IV].

number	period	maximum p-value in Ljung-Box test during the period	minimum p-value in Ljung-Box test during the period
1	February 20, 2013 – April 29, 2014	0.7551	0.0431
2	April 30, 2014 – July 7, 2015	0.4649	0.0001
3	July 8, 2015 – September 12, 2016	0.2494	0.0001
4	September 13, 2016 – November 16, 2017	0.9842	0.0023
5	November 17, 2017 – January 28, 2019	0.9721	0.0022
6	**January 29, 2019 – April 2, 2020**	**0.0552**	**0.0000**
7	April 3, 2020 – June 14, 2021	0.9208	0.0151
8	June 15, 2021 – May 5, 2022	0.4859	0.0000

Again, the sixth period is predicted the worst, leaving the autocorrelation unfixed, which is probably happening due to the corona-crisis. The last period, though, is forecasted well now, because of the inclusion of sanctions into the model. EGARCH-X(1,3) with ARMA(0,0) in means, Student's t-distribution, with the 5-year effect of sanctions and BIC = -4.1320 appears to be the most optimal GARCH-X model for Petropavlovsk PLC.

III. RESULTS

The influence of sanctions on Amur Minerals Corporation in the GARCH-X model is estimated as 0.2735 and appears to be statistically significant (p-value = 0.0148). Petropavlovsk PLC, though, showed unexpected impact of sanctions – the estimate of X is equal to -0.0485, and p-value = 0.0323[V].

After the 2022 sanctions, Petropavlovsk PLC company suffered significant losses, turning out to be on the verge of liquidation. Gazprombank, the main creditor and client of Petropavlovsk, was included into the sanctions list on March 24, so Petropavlovsk was not able to sell their products to the bank anymore[VI]. Considering that, sanctions were expected to have a major influence on the company's quotes. Nevertheless, according to the models, the opposite happened. The unexpected results might have been obtained because of the few observations in 2022. Perhaps, if one applies the models used in this paper in several years, the results will be more intuitive.

[IV] Characteristics of the top5 constructed GARCH-X models for both companies are in the appendix: tables №3 and №4.
[V] All the parameters of the optimal GARCH-X models for both enterprises are in the appendix: tables №5 and №6.
[VI] Forbes.ru.

Amur Minerals Corporation, in turn, officially declared that the impact of the 2022 sanctions on the company is minimal[VII]. Whether this was done to eliminate the panic of shareholders or whether the sanctions actually did not affect the company, the model shows a pretty considerable sanctions' influence on the volatility.

IV. COUNCLUSIONS AND DISCUSSION

In this article, we explored the impact of sanctions on the volatility of the stock returns of the two Russian companies. Two types of models were considered - GARCH(1,1) and GARCH-X.

For both companies the optimal GARCH-X models showed a slightly smaller BIC value, than GARCH(1,1) specifications. The additional regressor for the enterprises is statistically significant, reflecting positive impact of sanctions on Amur Minerals stock exchange volatility, and negative - on Petropavlovsk. This states that models with an external variable (sanctions) are more effective that benchmark models.

The article is relevant in the light of recent events. The obtained results reflect specifics of the companies, which can be studied in more detail. Methods used in the work can be useful to investors, owners, managers of companies, as they show how different political situations lead to changes in important market indicators. For more accurate results, other important market events can be included in the analysis (e.g., pandemic). Intraday data with realized volatility approach could upgrade the results as well.

[VII] Russian Sanctions Update (amurminerals.com).

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Appendix

II. The characteristics of top5 (out of 216[VIII]) GARCH(1,1) with ARMA(p,q) in means models

Table №1. Amur Minerals Corporation: GARCH(1,1) models

type of the model	distribution	ARMA(p, q)	p-value in Ljung-Box test	Bayesian information criteria (BIC)
gjrGARCH	normal	ARMA(0,1)	0.0672	-2.8460
gjrGARCH	normal	ARMA(2,0)	0.0692	-2.8459
sGARCH	normal	ARMA(1,0)	0.0573	-2.8446
gjrGARCH	normal	ARMA(1,0)	0.0736	-2.8444
eGARCH	normal	ARMA(2,0)	0.0573	-2.8426

Table №2. Petropavlovsk PLC: GARCH(1,1) models

type of the model	distribution	ARMA(p, q)	p-value in Ljung-Box test	Bayesian information criteria (BIC)
eGARCH	Student's	ARMA(0,0)	2.45e-09	-4.1295
eGARCH	Student's	ARMA(1,0)	2.22e-16	-4.1284
eGARCH	Student's	ARMA(0,1)	2.22e-16	-4.1284
sGARCH	Student's	ARMA(0,0)	2.45e-09	-4.1260
eGARCH	Student's	ARMA(1,1)	6.66e-16	-4.1252

IV. The characteristics of top5 (out of 702 before the preprocessing[IX]) GARCH-X(r,s) with ARMA(p,q) in means models

Table №3. Amur Minerals Corporation: GARCH-X models

type of the model	period of the sanctions' influence	distribution	GARCH(r,s)	ARMA(p, q)	p-value in Ljung-Box test	BIC
eGARCH	1 year	normal	GARCH(3,3)	ARMA(0,1)	0.0902	-2.8706
eGARCH	1 year	normal	GARCH(3,3)	ARMA(2,0)	0.0619	-2.8697
eGARCH	1 year	normal	GARCH(3,3)	ARMA(1,0)	0.0643	-2.8694
eGARCH	1 year	normal	GARCH(2,3)	ARMA(0,1)	0.1298	-2.8683
gjrGARCH	1 year	normal	GARCH(2,3)	ARMA(0,1)	0.1252	-2.8680

[VIII] You can find all of them, as well as the code, on Github (just click here). The tables are named: «GARCH(1,1) Amur» and «GARCH(1,1) Petro».

[IX] You can also find all of them on Github. The tables are named: «X-GARCH Amur» and «X-GARCH Petro».

Table №4. Petropavlovsk PLC: GARCH-X models

type of the model	**period of the sanctions' influence**	**distribution**	**GARCH(r,s)**	**ARMA(p, q)**	**p-value in Ljung-Box test**	**BIC**
eGARCH	5 years	Student's	GARCH(1,3)	ARMA(0,0)	2.45e-09	-4.1320
eGARCH	3 years	Student's	GARCH(1,3)	ARMA(0,0)	2.45e-09	-4.1303
eGARCH	5 years	Student's	GARCH(2,1)	ARMA(0,0)	2.45e-09	-4.1297
eGARCH	5 years	Student's	GARCH(1,2)	ARMA(0,0)	2.45e-09	-4.1285
eGARCH	3 years	Student's	GARCH(2,1)	ARMA(0,0)	2.45e-09	-4.1285

V. Parameters of the optimal GARCH-X specifications (robust standard errors)

Table №5. Amur Minerals Corporation: eGARCH-X(3,3) + ARMA(0,1)

	Estimate	**Std. Error**	**t value**	**Pr (> | t |)**
mu	0.0009	0.0006	1.3541	0.1756
ma1	-0.1290	0.0584	-2.2077	0.0272
omega	-1.8509	0.4782	-3.8702	0.0001
alpha1	-0.1259	0.0631	-1.9942	0.0461
alpha2	0.0200	0.0339	0.5912	0.5543
alpha3	-0.0572	0.0540	-1.0595	0.2893
beta1	0.4169	0.0662	6.2937	0.0000
beta2	-0.5238	0.0816	-6.4181	0.0000
beta3	0.7789	0.0832	9.3567	0.0000
gamma1	0.3525	0.1227	2.8721	0.0040
gamma2	0.2520	0.0943	2.6713	0.0075
gamma3	0.2639	0.1776	1.4851	0.1375
vxreg1	0.2735	0.1122	2.4361	0.0148

Table №6. Petropavlovsk PLC: eGARCH-X(1,3) + ARMA(0,0)

	Estimate	**Std. Error**	**t value**	**Pr (> | t |)**
mu	0.0009	0.0004	2.1005	0.0356
omega	-0.1732	0.0633	-2.7372	0.0061
alpha1	0.0416	0.0278	1.4967	0.1344
beta1	0.4563	0.1036	4.4031	0.0000
beta2	-0.0495	0.0646	-0.7654	0.4439
beta3	0.5605	0.1282	4.3712	0.0000
gamma1	0.4390	0.0536	8.1823	0.0000
vxreg1	-0.0485	0.0226	-2.1406	0.0323
shape	3.2367	0.2611	12.3951	0.0000