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Covid-19 and the Russian invasion: The effect on McDonald's stock returns volatility

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Abstract. This paper investigates the effects of the COVID-19 pandemic and the Russian invasion of Ukraine on the conditional volatility of returns on the stock of McDonald's Corporation. For this purpose, TARCH and GARCH models on the daily price data since the start of 2010 were utilized. The analyses showed that both events have a significant and positive influence on the volatility. Additionally, a significant asymmetric effect of positive and negative returns on volatility was uncovered.

Contents

1 Introduction

McDonald's Corporation (MCD) is by revenue the largest fast-food restaurant chain globally (Forbes 2017), utilizing the franchise-based business model (Purdy 2017). As of March 2020, similarly as nearly all other global firms, it had to cope with various measures and restrictions connected to the COVID-19 pandemic (MCD 2020). Additionally, on 8th March 2022 the company announced a temporary cease of all its operation in Russia, as a reaction to the Russian aggression on Ukraine (MCD 2022b). We suspect that these two factors may have a potential to increase uncertainty in the markets and thus to increase the volatility of returns on McDonald's Corp. stock.

This paper aims to investigate the effect of these two conditions imposed on McDonald's Corporation on the volatility of their stock returns. An approach to modelling conditional volatility that is widely accepted in literature as well as by practitioners is to use a member of the autoregressive conditionally heteroskedastic models (ARCH) family (Engle & Patton 2007). Especially useful for our work proved to be the TARCH model (Zakoian 1994), which is able to capture the asymmetric effect of positive and negative news, represented by the sign of a return. With its use, we test two alternative hypotheses that under the duration of (a) COVID-19 pandemic and (b) McDonald's departure from Russia, the volatility of their stock returns is systematically higher. The opposing null hypotheses state that the first and the second conditions respectively do not affect the volatility.

The remainder of the paper is structured as follows: Section 2 summarizes the data used for the analysis, Section 3 details the econometric methods that were employed, Section 4 comments on the results derived from the models, and Section 5 concludes.

2 Data Description

For the purpose of our analysis, we utilize the daily closing stock prices[1] of McDonald's Corporation downloaded from Yahoo! Finance (MCD 2022a). The time series ranges from the 1st January 2010 to the 30th April 2022.[2] In Table 1 we present the summary statistics of the raw prices as well as the calculated logarithmic returns. The latter is a common transformation in volatility modelling since it ensures that the underlying series is stationary. Based on Figure 1 we expect the series of raw prices to be non-stationary since it follows an obvious increasing trend.[3] On the other hand, the log-returns appear to be mean-stationary. We can observe some variance clustering, however, the unit root test devised by Dickey & Fuller (1979) rejects the null hypothesis in favor of stationarity at any conventional significance level. Therefore, we will use the log-returns to model the volatility.

As can be seen, the log-returns have a mean equal to approximately zero which supports the assumption that returns should not on average be positive or negative. The value of daily standard deviation implies the average annualized volatility of approximately 0.19%. Moreover, the skewness coefficient suggests that the distribution is negatively skewed. If we also consider the very high kurtosis, the assumption that the log-returns follow a Gaussian distribution is likely violated.[4] This is further illustrated in Figure 2 which presents the histogram of the log-returns. The distribution is very heavy-tailed and most of the values are densely concentrated around zero. As a result, we will assume the Student's t-distribution for the innovations of the mean model throughout our analysis.[5]

Table 1: Summary statistics

	Raw prices	Log-returns
n	3103	3102
Mean	137.26	0.00
St. Dev.	55.44	0.01
Skewness	0.64	-1.67
Kurtosis	2.08	36.52

[1] The prices are adjusted for stock splits.

[2] We utilized the code provided by the lecturer to extend the range of the supplied data.

[3] The unit root test proposed by Dickey & Fuller (1979) generates a p-value of 0.29 which suggests that we cannot reject the null hypothesis of a presence of a unit root.

[4] A test proposed by Jarque & Bera (1987) yields a statistic of 145 198 which results in the rejection of the null hypothesis of normality at any conventional significance level

[5] We perform a formal test of innovations normality in Section 4.

3 Methodology

As was already established, our goal is to estimate the conditional volatility of MCD stock returns. A widely used in this area are the generalized autoregressive conditional heteroskedasticity (GARCH) models introduced by Bollerslev (1986) who futher extended the work of Engle (1982). In addition, the literature suggests that the effect of returns on volatility may be asymmetric.[6] Negative returns usually have a greater impact on volatility than positive returns of the same magnitude. Therefore, we will utilize the TARCH model proposed by Zakoian (1994). Generally, in a TARCH(p,q) model, the following two equations are jointly estimated by the Maximum Likelihood estimator (MLE):

$$r_t = \mu_t + u_t, \tag{1}$$

where r_t denotes the log-returns, μ_t represents an appropriate autoregressive moving average model (ARMA), and $u_t = \epsilon_t \sigma_t$, where σ_t^2 is the conditional variance and ϵ_t is white noise. In addition,

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \gamma_1 I_{t-1} u_{t-1}^2, \tag{2}$$

where

$$I_{t-1} = \begin{cases} 1 & \text{if } u_{t-1} < 0 \\ 0 & \text{if } u_{t-1} \geq 0 \end{cases} \tag{3}$$

In equation (2), γ_1 captures the asymmetry effect. As indicated by the literature, the coefficient is expected to be positive since a negative return should increase the conditional variance more than a positive return of the same magnitude.

We will decide the orders p and q of the TARCH model such that the standardized residuals (ϵ_t) are a white noise without any lag dependencies. For this purpose, we will utilize the test proposed by Ljung & Box (1978) which examines the null hypothesis of independence of a given time series. In addition, we will investigate the autocorrelation function (ACF) and partial-autocorrelation function (PACF) which capture the unconditional and conditional lag dependence, respectively. Lastly, to assess the normality of the residuals, we will use the test devised by Jarque & Bera (1987).

Moreover, since our main aim is to investigate the effect of two major events in the last two years on the volatility of MCD's stock returns, we will extend the equation for the conditional variance by two additional terms:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \gamma_1 I_{t-1} u_{t-1}^2 + \delta_1 I_t^{Covid-19} + \delta_2 I_t^{Withdrawal}, \tag{4}$$

where $I_t^{Covid-19}$ is a dummy variable representing the Covid-19 pandemic. It attains the value 0 up until the 20th January 2020 when it becomes 1. During this day a first case of Covid-19 was registered in the USA. The withdrawal

[6]See, for example, Christie (1982); Engle & Patton (2007); Nelson (1991)

from the Russian market is captured by $I_t^{Withdrawal}$ which is 0 up until the 8th March 2022 when it becomes 1. On this date the McDonald's Corporation announced its departure from Russia. Our hypothesis is that both coefficients are statistically significant and positive. We expect these two events to increase the conditional variance since they bring a substantial level of uncertainty.

In addition to the inspection introduced in the previous paragraph, we will investigate some of the stylized facts about asset returns volatility as outlined in Engle & Patton (2007). In this way we can verify that our model satisfies the requirements generally imposed on a volatility model. These facts include the persistence of volatility, mean reverting, asymmetric impact of innovations, and the influence of exogenous variables. We cover the last two stylized facts by utilizing the TARCH model and including the event dummy variables, respectively.

While defining our TARCH model, we assumed that the log-returns can be characterized by an ARMA model. In order to find the best one fitting our data, we will once again perform the test proposed by Ljung & Box (1978) and inspect the ACF and PACF. We will also rely on information criteria during the model selection. To avoid overfitting, we will prefer a parsimonious model with weak dependencies in the residuals which we will subsequently hope to model using TARCH. Moreover, we will verify the need for modelling volatility in our data using the Engle's ARCH test described in Engle (1982). The ultimate goal is then for ϵ_t to not have any lag dependencies.[7]

4 Empirical analysis

4.1 ARMA model

Before proceeding to modelling volatility, we will first select an appropriate mean model from the ARMA family. As can be seen from Figure 3, both ACF and PACF show many significant autocorrelations. This is confirmed by the Ljung-Box test which rejects the null hypothesis of no autocorrelation at all conventional significance levels.[8] The best model based on minimizing the Schwarz Information Criterion is a simple ARMA(1,0). An inspection shows that it is not entirely successful in removing all the dependencies in the residuals. However, as noted in the previous section, we may be able to remove these dependencies by modelling the second moment. In addition, we do not want to overfit the model and thus we opt for parsimony. Nevertheless, since the minimization of the Akaike Information Criterion results in an ARMA model of higher order, we will use it as a robustness check. Lastly, as discussed in Section 2 the log-returns do not appear to follow normal distribution. This is confirmed for the innovations of the mean model as well since the Jarque-Bera test yields a test statistic of 119 054 resulting in a rejection of the null hypoth-

[7]We can inspect ϵ_t by standardizing the residuals u_t from the mean equation using the estimated volatility σ_t. From (1) follows that $\epsilon_t = \frac{u_t}{\sigma_t}$.

[8]The null hypothesis is rejected for lag orders 4, 8, and 12.

esis of normality. Consequently, we will assume the Student's t-distribution to account for the heavy tails.

4.2 TARCH estimation

Following the extant literature and the common practice, we will estimate a TARCH(1,1) model. We will then assess whether the results pass the obligatory specification tests. The estimated model has the following form:

$$r_t = \mu + \theta_1 r_{t-1} + u_t,\ u_t = \sigma_t \epsilon_t, \tag{5}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1}^{Sign} u_{t-1}^2 + \delta_1 I_t^{Covid-19} + \delta_2 I_t^{Withdrawal} \tag{6}$$

The estimation results are available in Table 2. As can be seen, all the coefficients are highly statistically significant apart from δ_2. Therefore, we do not find any evidence to support our hypothesis that the withdrawal from the Russian market had a significant effect on volatility. This issue could possibly be caused by an insufficient amount of data since a quite short period of time elapsed since the departure from the Russian market. On the other hand, the results suggest that the Covid-19 pandemic had a positive and significant impact on the volatility of MCD's stock returns. The magnitude of the coefficient is quite small[9] but as we show later, it has a non-negligible impact on volatility estimates. We can also observe that the TARCH term is statistically significant and positive implying that there indeed appears to be an asymmetric effect of returns on volatility. Therefore, we confirmed one of the stylized facts specified in Section 3. In addition, the volatility appears to be moderately persistent since the estimates of β_1 and α_1 are both highly statistically significant and sum up to approximately 0.87.[10] In order to confirm that the volatility is mean-reverting, we verify the stability condition $\alpha_1 + \beta_1 < 1$. We perform a likelihood ratio test. Our baseline model is the unrestricted model in this case and the restricted model is an iGARCH model which imposes the restriction that $\alpha_1 + \beta_1 = 1$. The test strongly rejects the null hypothesis that the restriction holds. Therefore, our model should be correctly specified in this regard. The last stylized fact is the effect of exogenous variables. In our analysis we concern ourselves only with the two major events already discussed above.

It is important to mention that the shape parameter estimating the degrees of freedom of the Student's t-distribution is highly statistically significant. Its magnitude suggests that the density of the innovations is far from normal distribution, especially due to its heavy tails. Consequently, our decision of utilizing the Student's t-distribution appears to be justified.

Our model also passes all the necessary specification tests. The standardized residuals do not seem to have any dependencies even in the 20th lag. Similarly, there seem to be no significant ARCH effects left. A brief glance at Figure 4

[9] The value is approximately $8 * 10^{-6}$

[10] This value implies a volatility half-life of about 5 days.

reveals that there are still some dependencies in the standardized residuals in distant lags, however, we did not manage to remove these by increasing the order of the TARCH model nor the ARMA model. Stock returns do not behave very well in general and therefore, we deem the results produced by the baseline model satisfactory.

Lastly, we present the estimated volatility in Figure 5. As can be seen, the estimation fits the data fairly well. The influence of Covid-19 can be observed from the large variance cluster of the returns occurring after the start of the pandemic. Our model seems to capture it adequately. For illustration purposes, we also include the volatility estimated by a TARCH(1,1) model excluding the event dummy variables. The results show that not recognizing the Covid-19 pandemic causes the model to underestimate the volatility in the post-covid period.

Table 2: TARCH(1,1) estimation results

μ	0.0007^{***}
	(5.23)
r_{t-1}	-0.0581^{***}
	(-3.27)
α_0	0.0000^{***}
	(4.9)
u_{t-1}^2	0.0184^{***}
	(4.2)
σ_{t-1}^2	0.8535^{***}
	(47.44)
$I_{t-1}^{Sign} u_{t-1}^2$	0.1241^{***}
	(8.07)
$I_t^{Covid-19}$	0.0000^{***}
	(16.39)
$I_t^{Withdrawal}$	0.0000
	(0.7)
shape (*t-distr. df*)	4.5074^{***}
	(12.9)
Observations	3102
Ljung-Box (ϵ_t)	0.83
Ljung-Box (ϵ_t^2)	0.97
ARCH test	0.97

*p<0.1; **p<0.05; ***p<0.01
Robust t-statistics in parentheses.
For all tests we display the p-values.
The lag order used in the tests is 20

4.3 Short-term estimation

Since we did not find any significant evidence for our hypothesis regarding the withdrawal from the Russian market, we will attempt to shorten the estimation period. In this way, we might be able to capture the short-term effect by disregarding possibly irrelevant past information. In order to have a sufficient number of observations, we consider a time series of log returns starting in December 2021. This leaves us with 104 observations.

The estimation results are available in Table 3. For the mean model we selected ARMA(0,0) since there did not appear to be any significant dependencies in the shortened period and it was also the output of the automatic model selection process based on information criteria.[11] In addition, we estimated a GARCH(1,1) model since there did not appear to be any sign bias.[12] Moreover, the shape parameter was statistically insignificant when t-distribution was assumed and therefore, we assume that the residuals from the mean model follow normal distribution. Finally, our model passes all the required specification tests and therefore, the results should be reliable.

As can be seen, the coefficient of our interest is positive and statistically significant. Therefore, we can support our hypothesis that the withdrawal from the Russian market may have increased the volatility of MCD's stock returns. We treat the results with caution since more data may be needed to further support our hypothesis.

4.4 Robustness analysis

In the current subsection we provide a verification of the robustness of our results. While selecting the orders of the ARMA and TARCH models, the simplicity was preferred over complicated structures to avoid overfitting. However, while modelling mean, the other candidate next to the used ARMA(1,1) model was ARMA(4,5). In case of volatility estimated based on such mean model, the risk of overfitting is high, nonetheless we include the comparison of the two volatility estimates as a robustness check (see Figure 6). The estimated coefficients of the ARMA(4,5)-TARCH(1,1) model are very similar to the ARMA(1,1)-TARCH(1,1), suggesting the results are robust.

Moreover, we verified that the assumption regarding the distribution of mean model residuals does not dramatically influence our results. We estimated an identical baseline model with the assumption that the residuals follow normal distribution. The results were not substantially affected.[13]

[11] ARMA(0,0) was chosen based on both AIC and BIC

[12] The Negative Sign Bias test yielded a p-value of 0.19

[13] We do not present the results explicitly for the sake of brevity, however, they are available upon request.

5 Conclusion

The aim of this paper was to asses whether the unique conditions induced by the COVID-19 pandemic and the 2022 Russian invasion of Ukraine affected the volatility of returns on the McDonald's Corporation's stock. For this purpose, the TARCH(1,1) and GARCH(1,1) models were utilized, with the addition of dummy variables representing the considered events. Our findings suggest that there is a positive and significant effect of the Covid-19 pandemic on the returns volatility in the analyzed period from January 2010 to April 2022. We found no significant evidence of an influence of the Russian invasion in this period. Nevertheless, while utilizing a shorter time span from December 2021 to April 2022, we found the effect to be positive and statistically significant. Moreover, the TARCH estimation revealed a significant asymmetric effect of past returns on MCD's stock volatility. The results were shown to be robust to changes in model specifications. Since the Russian invasion of Ukraine is still a recent event, its more profound inspection is an opportunity for future research.

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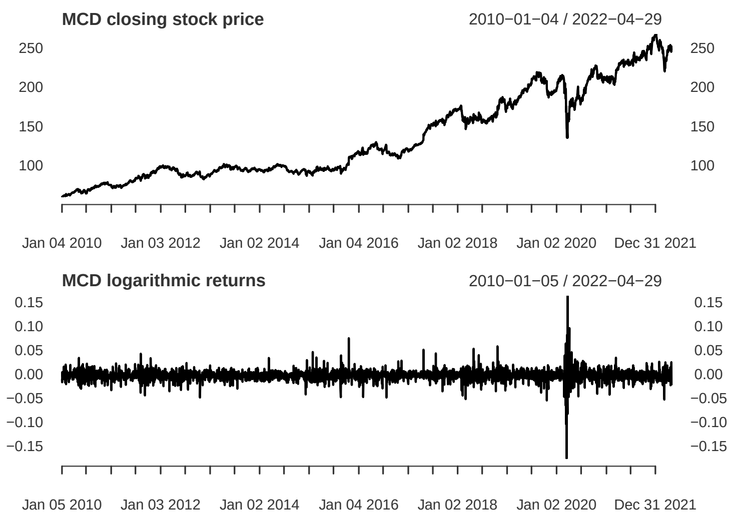
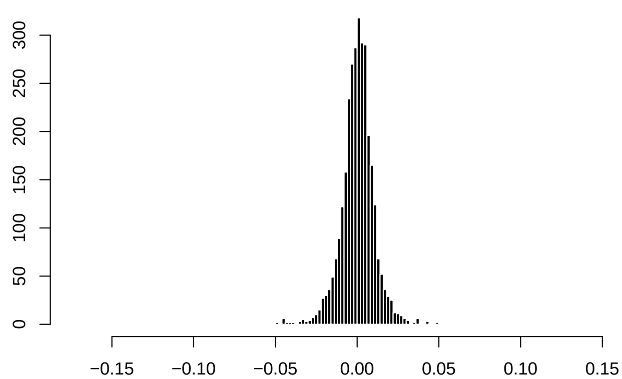
Appendix

Figure 1: Time series of MCD closing prices and log-returns



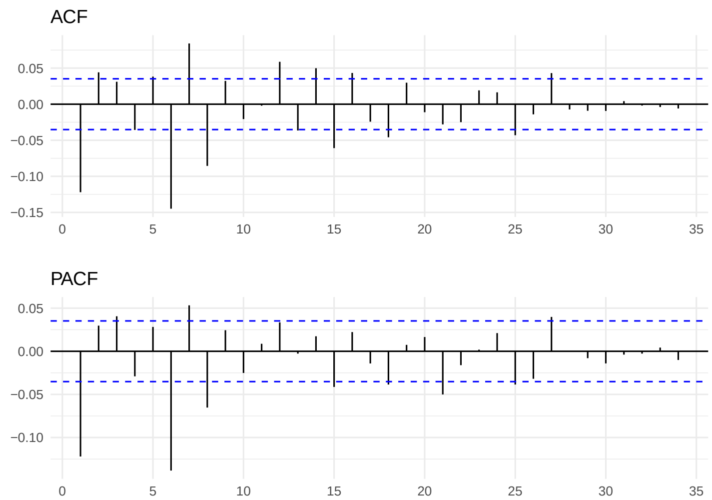
Source: Authors' computations based on the data from MCD (2022a)

Figure 2: Histogram of MCD log-returns



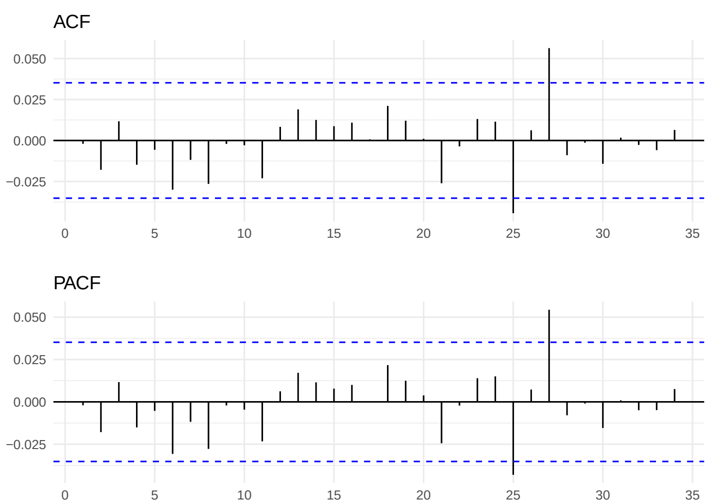
Source: Authors' computations based on the data from MCD (2022a)

Figure 3: ACF and PACF of log-returns



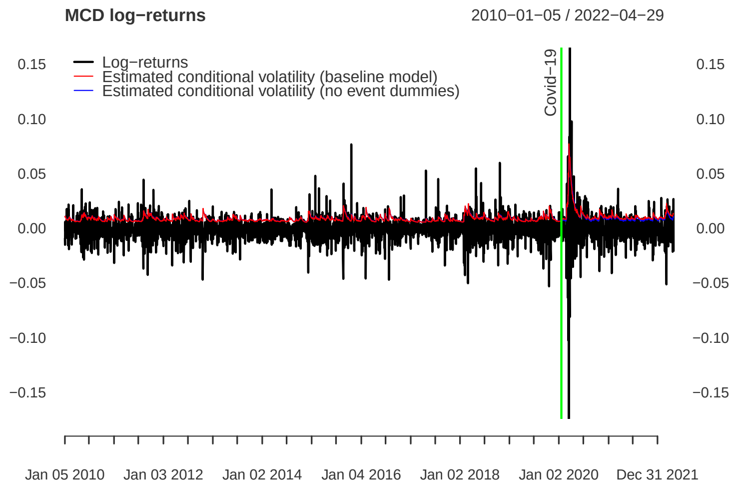
Source: Authors' computations based on the data from MCD (2022a)

Figure 4: ACF and PACF of stadardized residuals of the baseline model



Source: Authors' computations based on the data from MCD (2022a)

Figure 5: MCD log-returns and estimated conditional volatility



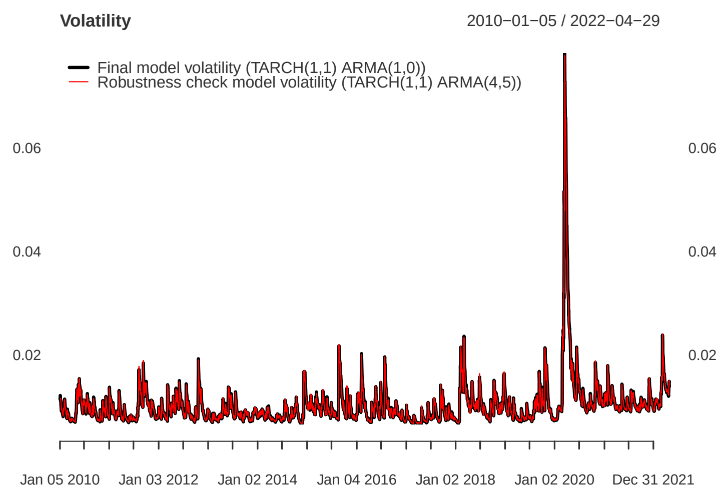
Source: Authors' computations based on the data from MCD (2022a)

Table 3: GARCH(1,1) estimation results (short-term)

μ	0.00
	(0.3)
α_0	0.00
	(1.53)
u_{t-1}^2	0.16***
	(2.78)
σ_{t-1}^2	0.76***
	(4.88)
$I_t^{Withdrawal}$	0.00***
	(23.83)
Observations	104
Ljung-Box (ϵ_t)	0.3
Ljung-Box (ϵ_t^2)	0.92
ARCH test	0.92

*p<0.1; **p<0.05; ***p<0.01
Robust t-statistics in parentheses.
For all tests we display the p-values.
The lag order used in the tests is 10

Figure 6: Comparison of ARMA(1,0) and ARMA(4,5) estimated volatility



Source: Authors' computations based on the data from MCD (2022a)