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Perceiving Uncertainty on Financial Markets During the COVID-19 Pandemic

Bachelor's thesis

Author: Matej Balažovič
Study program: Bakalářský program Ekonomie a Finance
Supervisor: PhDr. František Čech Ph.D.
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Declaration of Authorship

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Matej Balazovic

Abstract

This thesis examines the effects of the COVID-19 pandemic on forward rate agreements (FRA) spreads in the Czech Republic. Since FRA serves as a useful instrument to hedge against possible risk associated with interest rate movements, it is a relevant indicator of a consensus view and perceived uncertainty about the future financial situation. We measure the effects by employing ARMA-GJR-GARCH modeling. Several COVID-19 indices, representing the government response to the pandemic, are included as explanatory variables. The results show a significant drop in FRA spreads as the pandemic began, as well as a strong increase in the FRA spreads volatility, which doubled during that period. Our main findings suggest that the COVID-19 affected the decrease of FRA spreads. However, we were not able to explain the volatility increase by the COVID-19 data.

JEL Classification F12, C52, C58, E44, G10
Keywords perceived uncertainty, FRA spreads, ARMA, GARCH, COVID-19 pandemic

Title Perceiving Uncertainty on Financial Markets During the COVID-19 Pandemic
Author's e-mail mato.balazovic@gmail.com
Supervisor's e-mail frantisek.cech@fsv.cuni.cz

Abstrakt

Táto práca skúma vplyv pandémie COVID-19 na FRA spready v Českej republike. Keďže FRA slúži ako užitočný nástroj na zabezpečenie proti možnému riziku spojenom s pohybom úrokových sadzieb, je to relevantný indikátor konsenzuálneho názoru a vnímanej neistoty ohľadom budúcej finančnej situácie. Účinky meriame pomocou ARMA-GJR-GARCH modelovania. Ako vysvetľujúce premenné sú zahrnuté viaceré indexy COVID-19, ktoré predstavujú reakciu vlády na pandémiu. Výsledky ukazujú pád FRA spreadov pri začiatku pandémie a taktiež zvýšenie volatility FRA spreadov, ktorá sa počas daného obdobia zdvojnásobila. Naše hlavné zistenia naznačujú, že COVID-19 ovplyvnil pokles FRA spreadov. Zvýšenie volatility sme však dátami o COVID-19 nedokázali vysvetliť.

Klasifikace JEL	F12, C52, C58, E44, G10
Klíčová slova	Vnímanie neistoty, FRA spready, ARMA, GARCH, pandémia COVID-19

Název práce	Vnímanie neistoty na finančných trhoch počas pandémie COVID-19

E-mail autora	`mato.balazovic@gmail.com`
E-mail vedoucího práce	`frantisek.cech@fsv.cuni.cz`

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Acronyms

ACF Autocorrelation Function

ADCC Asymmetric Dynamic Conditional Correlation

ADF Augmented Dickey-Fuller

AIC Akaike Information Criterion

AR Autoregressive

ARCH Autoregressive Conditional Heteroscedasticity

ARMA Autoregressive Moving-Average

BIC Bayesian Information Criterion

BPS Basis Points

CBOE Chicago Board Options Exchange

CSAD Cross-Sectional Absolute Deviation

CSSD Cross-Sectional Standard Deviation

FRA Forward Rate Agreement

GARCH Generalized Autoregressive Conditional Heteroscedasticity

iid independent and identically distributed

KPSS Kwiatowski, Phillips, Schmidt and Shin

LIBOR London Interbank Offered Rate

MA Moving-Average

OTC Over-the-Counter

PACF Partial Autocorrelation Function

RND Risk-Neutral Density

WHO World Health Organization

Chapter 1

Introduction

Investors and the whole finance community will remember the beginning of March 2020 for a long time. We were witnesses of frozen trading activity for 15 minutes on New York Stock Exchange 3 times in 8 days. The Nasdaq experienced its largest percentage loss ever recorded, following the Dow industrials and the S&P 500 with the second-highest percentage loss since WWII. Even though the COVID-19 pandemic started by the end of 2019 in China, with positive cases growing around the world, there was no substantial importance attributed to it. Nevertheless, the shock that happened once the prices started dropping was sudden and strong.

Behavioral Finance, a branch of Behavioral Economics, helps us explain the decision-making process of investors during such turbulent periods, where traditional theories often fail to do so. There is a significant amount of literature documenting how cognitive biases and heuristics affect the behavior of investors and financial professionals. An unexpected shock, such as the COVID-19 pandemic, triggers significant financial instability and poses fear to financial markets. This often leads to investors mirroring the behavior of others, causing even higher uncertainty. As John Maynard Keynes argued in his General Theory of Employment, Interest and Money, “animal spirits”- representing a “spontaneous urge to action instead of inaction”- are drivers of the economy (Shiller (2020)).

The increased uncertainty due to the pandemic could be seen in financial markets around the world. Further, the response of the major central banks was aggressive, hoping to ease the fear and bring stability back to the markets. This allowed analyzing various financial instruments and examining their relationship with the COVID-19 pandemic.

The objective of this thesis is to examine the effects of COVID-19 on the forward rate agreements (FRA). This interest rate derivative is defined as a contract "between two parties wishing to protect themselves against a future movement in interest rates" (Association (1989)). It can also be used for speculative purposes, to take a position on movements in interest rates (Chippindale & Nishimura (2002)). Hence, it contains the perceived uncertainty of economic agents and describes their consensus opinion about the future financial situation in a specific country. We analyze FRA data in the Czech Republic, and we work with two different samples to capture the change due to the pandemic. Moreover, FRA spreads, representing the "yield curve" at different maturities, are created to capture the perceived uncertainty about the foreseeable future. We anticipate finding a negative relationship between the COVID-19 and FRA spreads, as the pandemic should have intensified the fear, thus harming the economy and FRA spreads. To measure the possible effects, we implement standard statistical and time-series techniques, including estimation of GARCH models.

This thesis is structured in the following way. Chapter 2 provides a literature review of existing research relevant for our analysis and presents the hypotheses of this thesis. Chapter 3 covers the necessary methodology for the estimation of conditional heteroscedastic models. Chapter 4 provides an overview of the examined data. Chapter 5 shows the empirical results of our analysis, and Chapter 6 summarizes our findings and proposes further extensions of this work.

Chapter 2

Literature Review

Throughout this chapter, we explore studies that are related to the topic of this thesis. First, we will examine the effects of COVID-19 on stock markets. Second, we will discuss the effects of COVID-19 on derivatives markets. Furthermore, we will look at the factors affecting investors' behavior during the pandemic. Finally, we will review the term structure of interest rates and cover the purpose and usage of forward rate agreements (FRA).

2.1 Effects of COVID-19 on Stock Markets

Since the outbreak of the coronavirus disease in the city of Wuhan in December 2019, various studies have examined the impacts on many stock markets around the world using several approaches and looking at numerous parameters. Besides the direct impact on numerous high traded assets such as the S&P 500, which lost 34% as of August 2020, a significant amount of research has focused on measuring fear, stress, and uncertainty on stock markets.

Baker *et al.* (2020) examined the relationship between news related to COVID-19 and stock market volatility using textual analysis. They found an unprecedented impact that no other infectious disease has made in recent history. They concluded that even with a significantly lower excess mortality rate from COVID-19, being 1/14th in comparison to Spanish flu as of June 2020, government responses worldwide, including lockdowns, closure of non-essential businesses, and bans of public gatherings attributed to "fear" represented in stock market jumps.

Grima *et al.* (2021) investigated the effect of the COVID-19 new daily cases and deaths on the CBOE volatility index (VIX). VIX is derived from the price of

S&P 500 index options and is considered one of the best measures to capture stress on equity markets. The authors use the fully modified least-squares (FMOLS) estimates to determine the long-term relationship between the VIX and the new daily cases and deaths. The analysis results show that a 1% increase in new cases positively affected the VIX index by 32.54%. Interestingly, there was a more significant impact of new cases on VIX than deaths. This may be due to several reasons. Since deaths are delayed new cases, the shock had already been incorporated into the price. Moreover, the government response and restrictions are more sensitive to new daily cases as they threaten the healthcare system, creating uncertainty about restricted economic activity.

Another approach to measuring market stress was documented by Zhang *et al.* (2020) who calculated the standard deviation of daily returns in the top 10 countries with the highest number of positive cases. The results confirmed a substantial increase in risk levels in all selected countries.

2.2 Effects of COVID-19 on Derivatives Markets

Since the derivatives market includes financial instruments through which investors can often express their views on the foreseeable future, there is no doubt this segment of financial markets is essential to understand better the views and behavior of economic agents around the world. Derivative can be any financial transaction whose value depends on the underlying asset (Hunt & Kennedy (2004)). There is a vast number of them, and it might sometimes be peculiar to interpret them because of their complexity. However, there has been some research on the impact of the current pandemic on the derivatives market, more specifically on options and futures markets.

As literature already suggests, the futures market incorporates new macroeconomic information into the prices faster than the spot market, and thus it is a better and more accurate representation of investors' beliefs (Banerjee *et al.* (2020)). Banerjee (2021) used the bivariate asymmetric dynamic conditional correlation ADCC GARCH framework to unveil evidence of financial contagion during COVID-19 in the futures market in 17 main trading partners of China. *Financial contagion* has been defined by Forbes & Rigobon (2002) "*as a significant increase in cross-market linkages after a shock to one country.*" By investigating the consistency of dynamic correlation of the index futures markets before the pandemic and comparing it to the pandemic period, they found a significant sudden surge in correlation in all included countries as the pandemic started. Moreover, they found that the negative shocks had a higher impact than the positive ones and that both developed and developing countries suffered equally from the financial contagion effect.

Emm *et al.* (2021) examined the derivatives market during the pandemic in-depth by looking at trade-related activity on global futures and options exchanges. Since the market consists of both hedgers as well as speculators, there are different incentives for these participants to react to the increased volatility of the derivatives market. Hedgers had to manage higher risks, and speculators could spot an opportunity to profit from an information asymmetry. Hence, the authors investigated the trade volume, as it was expected to increase due to these incentives. The analysis shows a substantial increase of 60.7% in global futures and options trade volume during the start of the pandemic. By looking at the changes across different asset groups, they found the most significant jump of 66% in equity futures, which is the largest part of the Financials, for both absolute and percentage-wise amounts.

To capture the change of uncertainty on derivates market by another approach, Agarwalla *et al.* (2021) explored the impact on the tail risk, which represents the small probability of an extreme event occurrence. They used Indian Nifty index options and futures contracts to measure risk-neutral density (RND) changes and the first four statistical moments. RND can help us analyze traders' reactions to a shock in financial markets as well as their attitudes toward the potential ones (Souissi (2017)). In their study, the authors extracted risk-neutral probability density from option prices and documented a dramatic change in the left tail being more than 100 times fatter than the right tail after declaring a global pandemic by WHO. The probability of the index declining by at least 25% increased from less than 10^{-8} to 1,5% and by the end of March to 13%. Moreover, both tails became eight times fatter, meaning there had been an increase of uncertainties in both directions. By using data from options markets, the authors were able to work with forward-looking measures to interpret the change of uncertainty.

Another study by Hanke *et al.* (2020) also used information about options prices. They extracted RNDs from six different markets, confirmed the increased width of RNDs from the previous authors, and contributed by finding increases in implied volatilities across all options maturities. Furthermore, they found that the mortality ratio, as well as the number of cases, had an impact on the markets. Countries with lower mortality seem to be viewed more optimistically, whereas countries with higher mortality show lower potential for optimistic scenarios.

2.3 Factors Affecting Investors Behavior During COVID-19

There has been a growing literature that shows how psychological biases and mental shortcuts affect human behavior. To present these in the context of finance, a subfield of Behavioral Economics called Behavioral Finance evolved. This branch tries to present and explain why people often make irrational investment decisions using insights from psychology. Even though it might be sometimes hard to measure precisely the impact of psychological biases on financial decisions, one might look at the consequences of such effects.

During financial distress and instability that can be generated by a shock such as the COVID-19 pandemic, investors are more prone to mirror the decisions of others as a result of experiencing a higher uncertainty (Kurz & Kurz-Kim (2013)). This phenomenon is called herding behavior, and it drives trading activities in the same direction and thus disrupts the financial markets to function efficiently (Kizys *et al.* (2021)). In a recent study, Kizys *et al.* (2021) examined the presence of herding behavior during this pandemic by looking at cross-sectional absolute deviation (CSAD) and cross-sectional standard deviation (CSSD). These measures can determine whether an investor's decisions feature herding based on the average distance between an individual stock return and the market return. In their study, the authors confirmed their hypothesis about herding behavior being present during the start of the pandemic. Moreover, they found that government responses and the degree of stringency can affect the perceived uncertainty on financial markets and the investors' confidence in them. Governments with more strict responses resulted in a decrease in CSSD and CSAD indicators, implying lower herding behavior of investors. Another study Espinosa-Méndez & Arias (2021) confirms the occurrence of herding behavior in 5 major European capital markets. The authors found robust evidence of herding behavior triggered by the COVID-19 pandemic in all of the five markets and concluded that fear and uncertainty of less-informed investors could lead to abandoning their beliefs and adopting the beliefs of others.

Differences in investors' reactions to a crisis can be found across countries. National culture affects the perception through which the individual agents react to a period of financial instability. Existing literature proves that cultural differences shape risk avoidance and the preferences of investors (Anderson *et al.* (2011)). Fernandez-Perez *et al.* (2021) investigated the cultural effect on stock market responses during the current pandemic. The analysis provided evidence of a significant effect of national culture on both the magnitude and volatility of returns. Surprisingly, the country's cultural values affected the magnitude of the response. Democracy, political corruption, and trade openness affected the stock returns. Furthermore, highly individualistic countries experienced a smaller stock market decline, and countries with higher uncertainty avoidance suffered a larger decrease of 5,40% compared to countries with lower uncertainty avoidance. This discovery is in hand with previous findings that suggest that conservative investors are slower in updating their views and models with incoming information (Edwards (1968)).

2.4 Term Structure of Interest Rates and Forward Rate Agreements

The term structure of interest rates represents the relationship of interest rates at different maturities. According to Expectation theory, the term structure depicts the market expectation of short-term interest rates, meaning that the long-term interest rates may indicate the future short-term rates (Shiller & McCulloch (1990)). Term structure can be depicted graphically on a yield curve, which is a helpful indicator for investors as it depicts the current state of the economy as well as the future trajectory of rates. During normal times of a healthy economy, the yield curve is upward sloping, meaning that rational investors would require a higher risk premium (yield) for longer maturities according to liquidity theory. However, a negative yield curve, also called inverted, is downward sloping and indicates an economic slowdown. It implies that investors are willing to accept higher interest rates in the short term because there might be significant uncertainty about the future development of the economy or negative predictions about future growth. Furthermore, the literature suggests that the spread between long-term and short-term rates becomes negative before economic recessions. Findings from the Euro area about sovereign bonds revealed that all sovereign bond yields dropped significantly as of the start of the COVID-19 pandemic and that the term spread became more narrow and volatile (Papavassiliou (2021)).

A forward rate agreement (FRA) is defined as "*an agreement to borrow or lend a notional cash sum for a period of time lasting up to twelve months, starting at any point over the next twelve months, at an agreed rate of interest (the FRA rate)*" (Teasdale (2012)). The only thing exchanged is the difference in interest rates, not the notional amount. The settlement value can be represented by the following equation:

$$Settlement = \frac{(r_{ref} - r_{FRA}) * NP * \frac{n}{B}}{1 + (r_{ref} * \frac{n}{B})}, \tag{2.1}$$

where r_{ref} is the reference interest rate, r_{FRA} stands for the FRA rate, NP is the notional principal, n represents the number of days in the contract period, and B is the day-count base.

This interest rate derivative is widely used to hedge against the risk associated with future movements in interest rates. When a company would like to take a loan in the near future but is afraid that interest rates will increase, it can protect itself by entering the FRA and locking the interest rate based on the FRA rate. Hence it might be considered a representative of a consensus opinion about the future trajectory of the economy in a country.

2.5 Hypotheses

The literature on FRA is unusually scarce. Compared with other interest rate derivatives, such as futures that are regulated and traded on a futures exchange, FRAs are an OTC agreement and are not regulated; hence, it is a more complex component to work with. However, as already described, there is some evidence of the COVID-19 pandemic's effect on the Derivatives Market. Examining the effects on FRA is rather challenging, as the rates are based on LIBOR, which represents the average interest rate at which major global banks borrow from one another. LIBOR is determined each day by asking a panel of contributor banks for a rate at which they would be willing to borrow funds for different maturities. Since it is calculated using a trimmed mean, which means removing the lowest and highest quartile, we are losing some information about extreme reactions to a current situation.

However, we still believe in finding some relationship between the COVID-related data and FRA spreads. More specifically, we expect to detect a negative effect of COVID-19 data on FRA spreads, as the negative news and government restrictions could strengthen the fear and perceived uncertainty, harming the state of the economy and deteriorating FRA spreads. We also assume that examining different maturities will bring a better understanding of how investors perceived the threat of COVID-19 with respect to time.

Moreover, we anticipate finding a significant increase in the volatility of the FRA spreads included in our analysis during the pandemic. We believe this possible volatility increase might be partially explained by our COVID-19 data.

Chapter 3

Methodology

The main purpose of this chapter is to provide sufficient theoretical background and introduce the core concepts used in this thesis. As for this section, we covered the necessary theory primarily from Kočenda & Černỳ (2015) and Tsay (2005).

3.1 Stationarity

Stationarity is the foundation of time series analysis. A stationary time series data have statistical properties that do not vary in time and are essential for numerous models to be valid. Moreover, by relaxing the stationarity assumption, we could run into so-called spurious regression, which means finding a relationship between non-stationary trending variables where there is none.

There are two types of stationarity processes. The first one is called strict stationarity, and the second one is called weak or covariance stationarity. Since strict stationarity is an extreme assumption to achieve in reality, and it is hard to verify it empirically, for the purpose of this thesis, we will work only with a weak stationarity assumption as it is sufficient for the models used. Hence, when mentioning stationarity, we mean weak stationarity.

A time-series $\{r_t\}$ is said to be weakly stationary if the mean of r_t and the covariance between r_t and $r_{t-\ell}$, where ℓ is an arbitrary integer, are time-invariant and thus constant. This implies that if we plot weakly stationary data, we would observe that the values fluctuate with a constant variation around a fixed level. Consequently, this enables us to make predictions about future values.

3.1.1 ADF Test

We employ a test known as the Augmented Dickey-Fuller (ADF) test to determine the stationarity of our data. (Dickey & Fuller (1979)). It is an extension of the Dickey-Fuller test that requires data to be generated with an AR(1) process. In this extended version, we include p lags and have the following equations that describe the procedure of the test:

$$\Delta y_t = \alpha_0 + \theta y_{t-1} + \gamma_1 \Delta y_{t-1} + ... + \gamma_p \Delta y_{t-p} + \varepsilon_t \tag{3.1}$$

$$H_0 : \theta = 0, H_1 : \theta < 0, \tag{3.2}$$

where α_0 is a constant term, ε_t is the error term, Δy_{t-p} is the first difference at lag p, and θ is the coefficient of our interest, based on which we test the null hypothesis that the time series follows a unit root. Conclusively, we want to reject the null hypothesis and accept the alternative and thus confirm that our data is stationary. However, according to (Kočenda & Černý (2015)), the drawback of this test is its low power not to reject a false H_0.

3.2 Estimation of ARMA Process

Since we are working with financial time series, we can expect some level of dependency in our dataset. In other words, there might be a relationship between past and future values of the financial data. To account for this relationship, we employ a widely used ARMA modeling, which is a combination of Autoregressive methods AR(p) and Moving-Average methods MA(q). The autoregressive moving average process ARMA(p,q), where p and q are the orders of the autoregressive and moving-average parts, respectively, can be decomposed in the following way:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t \tag{3.3}$$

$$y_t = \mu + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{3.4}$$

The Equation 3.3 represents the AR(p) model, where y_t is the actual value at time t, constant c, error term ε_t and ϕ_i being the model parameters. This model predicts the future value of a time series based on the previous observations and random error.

The Equation 3.4 represents the second part of ARMA(p,q), the MA(q) model, that uses past errors as explanatory variables. It also consists of the average of the time series μ, model parameters θ_j, and a white noise ε_t.

Once we combine these equations, we can define the ARMA(p,q) as follows:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t, \tag{3.5}$$

where c is a constant, p and q are the orders for respective parts, and ε_t are white noise residuals.

In order to build the ARMA model, we will use the Box-Jenkins methodology (Box *et al.* (2015)), where we are interested in finding the most parsimonious model of the data generating process. What is meant by that is that we are trying to balance the model's goodness of fit with the number of parameters used. To implement the Box-Jenkins methodology, we begin with finding the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) that are essential tools to determine the parameters p and q in our ARMA(p,q) specification.

3.2.1 Autocorrelation Function (ACF)

When having a stationary time series, the Autocorrelation Function (ACF) is vital in identifying the appropriate order of the moving-average (MA) part of the Autoregressive Moving-Average (ARMA) model. ACF describes the partial correlation between a time series and its lags. To determine the correlation coefficient between y_t and y_{t-l}, the Autocorrelation Function is defined as follows:

$$\rho_\ell = \frac{Cov(y_t, y_{t-\ell})}{\sqrt{Var(y_t)Var(y_{t-\ell})}} = \frac{Cov(y_t, y_{t-\ell})}{Var(y_t)} = \frac{\gamma_\ell}{\gamma_0},$$

where ρ_ℓ describes the ℓ-th lag autocorrelation of y_t. We also used the weak stationarity property of y_t under which it holds that $Var(y_t) = Var(y_{t-\ell})$.

3.2.2 Partial Autocorrelation Function (PACF)

On the other hand, the Partial Autocorrelation Function helps us to determine the appropriate order of the autoregressive (AR) part of the ARMA model. In contrast with ACF, the Partial Autocorrelation Function controls for any correlation among all shorter lags, whereas the ACF does not control for other lags. Hence, both ACF and PACF give us the same value at the first lag but different values for lags of higher order. The theoretical PACF can be defined as follows:

$$\phi_{1,1} = \rho_1,$$
$$\phi_{2,2} = (\rho_2 - \rho_1^2)/(1 - \rho_1^2),$$
$$\vdots$$
$$\phi_{s,s} = \frac{\rho_s - \sum_{j=1}^{s-1} \phi_{s-1j}\rho_{s-j}}{1 - \sum_{j=1}^{s-1} \phi_{s-1j}\rho_j} \text{ for s>2},$$

where $\phi_{s,j} = \phi_{s-1,j} - \phi_{s,s}\phi_{s-1,s-j}$.

3.2.3 Box-Pierce Test and Ljung-Box Test

In time series analysis, there are two well-known tests to use to find out whether there is any group of autocorrelations ρ_s different from zero. In the first test introduced by Box & Pierce (1970), the null hypothesis states that any group of the series residuals is independent white noise against the alternative that suggests dependence in residuals. It is defined as follows:

$$Q(k) = T \sum_{\ell=1}^{k} \hat{\rho_\ell}^2, \tag{3.6}$$

where the *Q(k)* is assymptotically χ^2 distributed with k degrees of freedom. T stands for the number of observations and lastly $\hat{p_\ell}$ stand for the elements of sample ACF.

The second test proposed by Ljung & Box (1978) is an adjusted version of the previous one that is better suited for analysis with smaller samples. The Ljung-Box test is defined followingly:

$$Q(k) = T(T+2) \sum_{\ell=1}^{k} \frac{\hat{\rho_\ell}^2}{T - \ell} \tag{3.7}$$

For the purpose of our analysis, we will perform the Ljung-Box test as it is a more preferred one.

3.2.4 Information Criteria

When looking for the right ARMA(p,q) model specification, we can have several different models that seem like a good fit for our data. However, to avoid overspecified models, we should rely on information criteria that estimate the quality of each model.

The most common one is called the Akaike information criterion (Akaike (1998)), defined as:

$$AIC = -2ln(\hat{L}) + 2k, \tag{3.8}$$

where $\hat{L}$ is the maximum value of the likelihood function for the model, and k stands for the number of estimated parameters. From the construction of the criterion, there can be seen that the AIC tries to balance the goodness of fit with the number of parameters to achieve efficiency. We prefer the model with the lowest AIC value. However, since this information criterion is biased towards selecting models with more explanatory variables, it is vital to include another information criterion in our analysis in order to obtain more robust results. Hence, we include the Bayesian information criterion (BIC), defined as

$$BIC = -2ln(\hat{L}) + kln(T), \tag{3.9}$$

where T is the number of observations.

3.3 Conditional Heteroscedastic Models

The drawback of working with financial time series is that usually, they do not satisfy the homoscedasticity assumption. In other words, the variance is not constant across time. In the ARMA(p,q) model specified in Section 3.2, we assumed that the variance is constant for all the values, which means we are losing essential information about the behavior of the time series.

We would like to inspect the behavior of the volatility across time. To do so, we will relax the assumption that the conditional variance of the error term is equal to the unconditional variance, and we will try to model the conditional variance by the autoregressive process. Suppose we have a time series y_t and the conditional mean and conditional variance of y_t given F_{t-1}:

$$\mu_t = E(r_t|F_{t-1}), \quad \sigma^2 = Var(r_t|F_{t-1}) = E[(r_t - \mu_t)^2|F_{t-1}], \tag{3.10}$$

where F_{t-1} describes the information that is available at time $t-1$. Moreover, we will still model the conditional mean μ_t based on our ARMA(p,q) model as the series y_t is assumed to be serially independent. However, since the variance in ARMA(p,q) model is constant, as we mentioned above, we will model it using conditional heteroscedasticity models. Consider the following equations:

$$y_t = \mu_t + a_t, \quad \mu_t = \phi_0 + \sum_{i=1}^{k} \beta_i x_{it} + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{i=1}^{q} \theta_i a_{t-i} \tag{3.11}$$

After we combine Equation 3.10 and Equation 3.11 we end up with:

$$\sigma^2 = Var(r_t|F_{t-1}) = Var(a_t|F_{t-1}). \tag{3.12}$$

Next, we introduce the models that are concerned with and can help us forecast the change of σ^2 in time.

3.3.1 Autoregressive Conditional Heteroscedasticity (ARCH) Model

The Autoregressive Conditional Heteroscedasticity model approach proposed by Engle (1982) is the first model that is able to differentiate between conditional and unconditional variance and thus systematically capture the behavior of the time series variance across time. The general ARCH(m) can be defined in a following way:

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \ldots + \alpha_m a_{t-m}^2, \tag{3.13}$$

where $\{\epsilon_t\}$ denotes an iid random variable, that has a zero mean and variance of 1, and σ_t is the conditional variance of a_t.

After examining the ARCH equation, we can see that shocks directly affect the conditional variance. In financial time series, this might be described by a phenomenon called "volatility clustering", which refers to a situation where a period with high volatility is followed by another high volatility period and vice versa.

In the literature about ARCH models, there is often mentioned a term called ARCH effect, which is present if a time series exhibits conditional heteroscedasticity. To determine whether our series has an ARCH effect, we perform the ARCH test that uses the Lagrange multiplier test to determine the significance of the autocorrelation in the squared series.

However, since the ARCH model is the first to deal with conditional heteroscedasticity, it has several drawbacks. Probably the major weakness is that we do not have any information about the source of variations since the conditional variance is defined mathematically only. Moreover, positive and negative shocks are weighted equally and have the same impact on the volatility. In reality, financial time series react differently to positive and negative shocks. Hence, more generalized models have been developed to address the weaknesses of the ARCH models.

3.3.2 Generalised Autoregressive Conditional Heteroscedasticity (GARCH) Model

The generalized autoregressive conditional heteroscedasticity (GARCH) model was developed by Bollerslev (1986). Thanks to its structure, it is a handy extension of the ARCH model that found application mainly in the field of finance. The GARCH(m,s) can be written as:

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \omega + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2, \tag{3.14}$$

where $\{\epsilon_t\}$ denotes an iid random variable with zero mean and variance of 1, ω is the long-term variance that is higher than zero, α_i represents the actual variance at time t, β_j stands for the predicted variance for time t, and as a stability condition, it has to hold that $\sum_{i=1}^{max(m,s)}(\alpha_i + \beta_i) < 1$. This further indicates that the unconditional variance of a_t is finite, whereas the conditional variance of σ^2 fluctuates over time and is positively correlated to its own lags. From the GARCH equation, we can see that predicted future variance is a result of a weighted average of the long-term average variance, from which we can conclude that GARCH captures the volatility clustering.

3.3.3 GJR-GARCH

GJR (Glosten-Jagannathan-Runkle) belongs to the GARCH family, and we will employ it in this thesis. The reason for that is that this extension of the standard sGARCH model captures the leverage effect, which refers to a situation, whereas volatility of financial or macro variables is asymmetrically affected by past positive or negative shocks, which is often observed in the markets. The GJR-GARCH(1,1) is richer than the standard one, and thus it should fit the sample data better. The model can be described in the following equation:

$$\sigma_t^2 = \omega + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma a_{t-1}^2 S_{t-1}, \tag{3.15}$$

where S_t represents a dummy variable which is equal to 1 if $a_t < 0$ (bad news) and equals 0 if $a_t > 1$(good news). The γ coefficient predicts the volatility in the following period. If it is positive (negative), the volatility is more likely to increase (decrease) as well.

Chapter 4

Data

This chapter will provide necessary information about the data used in the analysis. We use both financial and non-financial data from various time frames to capture and understand changes in behavior in response to the COVID-19 pandemic.

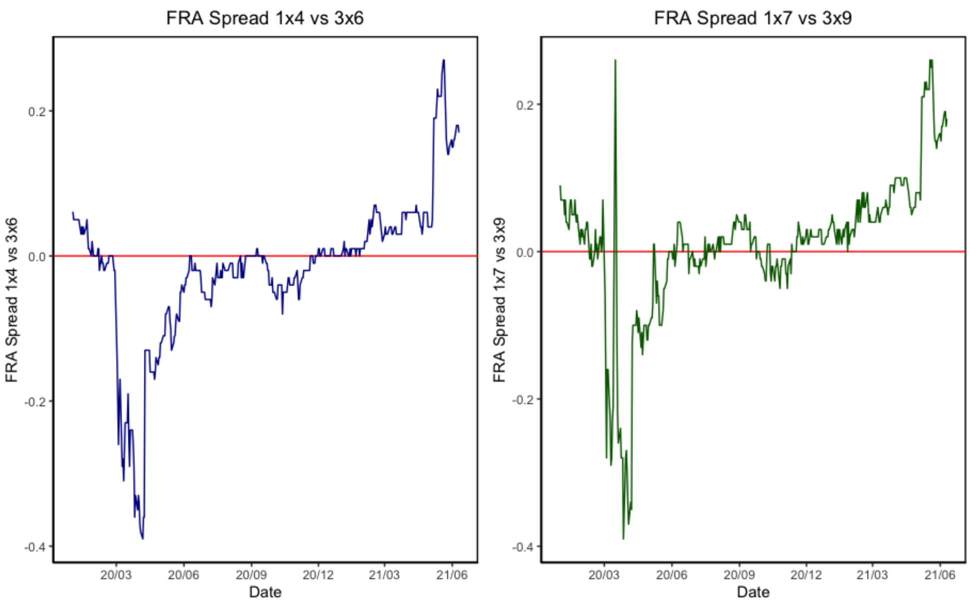
4.1 Forward Rate Agreement Spread

Forward Rate Agreement Spread represents the response variable in our analysis, as it captures the uncertainty about the foreseeable future. There are various FRA types that depend on the borrowing period and the date at which FRA becomes effective. For example, FRA 1x4 refers to a three-month loan that will begin in one month. Buying FRA means borrowing a notional amount of money. Buyers of FRA want to protect themselves against a rise in interest rates. When such a rise happens between the traded date of FRA and the maturity date, the buyer will be protected. Sellers of the FRA would have to pay the difference between the traded and the actual rate. As already mentioned, the notional amount is not actually being exchanged. It is used only for the calculation of the interest payment. However, we do not analyze the FRA rates directly. Instead, we create FRA spreads that will represent the "yield curve" at different maturities. Thus, a negative spread value means that investors feel substantial uncertainty about the future and are willing to accept higher interest rates in the short term. A zero value of a spread represents a scenario, whereas investors see no difference between short and long investments. FRA spreads are created by subtracting the shorter FRA rate from the longer maturity FRA rate. For example, FRA spread 1x4 vs. 6x9 is created as follows:

$$FRA_{1x4vs6x9} = FRA_{6X9} - FRA_{1x4} \tag{4.1}$$

We include FRA spreads 1x4 vs. 3x6 and 1x7 vs. 3x9 in our analysis, as we assume these will react significantly with COVID-19 data. We will focus on FRA spreads in the Czech Republic, as including other regions would be beyond the scope of this thesis. The data were downloaded from the Thomson Reuters database. To capture the changes in behavior before and during the pandemic, we will be working with two sample sizes, the pre-COVID sample starting at 01.04.2014 and lasting up to 31.12.2019, and the second one as the COVID-19 sample size, starting at 01.01.2020 and finishing at 10.06.2021. In Figure 4.1, the FRA spreads are displayed for the COVID-19 period.

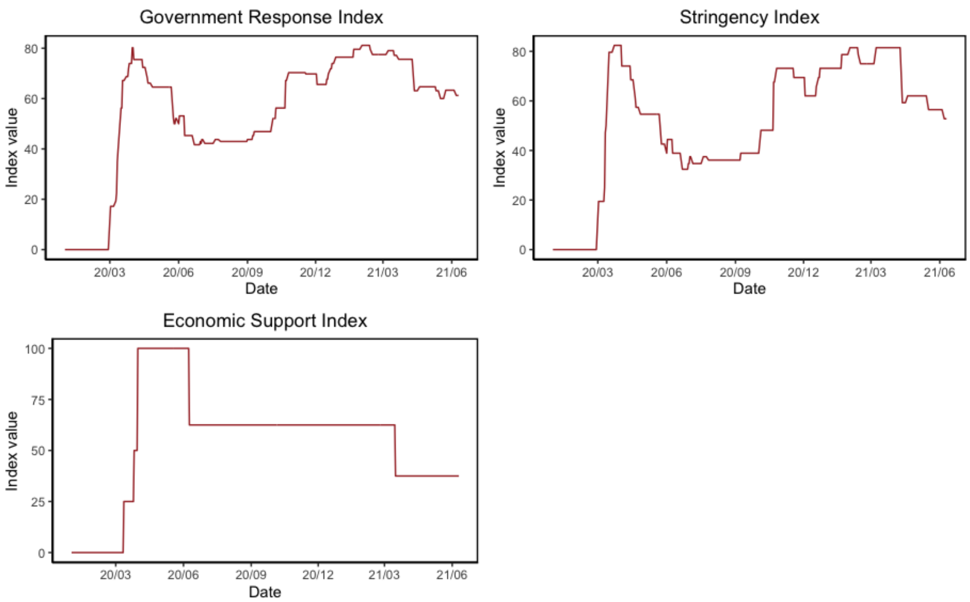
Figure 4.1: FRA Spreads during COVID-19 Pandemic



4.2 COVID-19 Data

For the purpose of our analysis, we chose various COVID-19-related data that we assume could affect the perceived uncertainty of investors and, as a result, the FRA data. We consider a new Government Response Tracker developed by the University of Oxford that provides information about how different countries react to the COVID-19 pandemic measuring 21 indicators.[1] For our analysis, we chose the following indices that aggregate the data into a measure ranging from 0 to 100: an overall response of governments, which contains all the indicators, i.e., *GovernmentResponseIndex*, a measure of closure policies strictness, i.e., *StringencyIndex*, and lastly an index which uses relevant economic policies indicators to measure the government economic support, such as debt relief, i.e., *EconomicSupportIndex*. In Figure 4.2, the respective indices are shown.

Figure 4.2: COVID-19 Data



[1] https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker

Chapter 5

Empirical Results

5.1 Data Analysis

5.1.1 Descriptive Statistics

In this section, we present the first valuable information about the characteristics of our datasets. Table 5.1 summarizes the descriptive statistics for respective time periods.

Table 5.1: Descriptive Statistics

	Period	N	MIN	MAX	μ	σ^2	Skewness	Kurtosis
FRA Spread 1x4 vs 3x6	pre-COVID	1501	-0.160	0.290	0.020	0.005	1.140	1.450
	during COVID	377	-0.390	0.270	-0.020	0.011	-0.910	2.850
FRA Spread 1x7 vs 3x9	pre-COVID	1501	-0.180	0.320	0.030	0.005	1.120	1.320
	during COVID	377	-0.390	0.260	0.010	0.010	-1.100	3.550
Government Response Index	during COVID	377	0.000	81.150	54.400	566.083	-1.180	0.470
Stringency Index	during COVID	377	0.000	82.410	51.650	610.397	-0.750	-0.320
Economic Support Index	during COVID	377	0.000	100	53.750	783.382	-0.400	-0.120

Note: N - number of observations, μ - sample mean, σ^2 - sample variance, Skewness - sample skewness, Kurtosis - sample kurtosis

Looking at the FRA spreads, we can see a decrease in the mean for both examined spreads after the start of the pandemic. Moreover, for the first FRA spread that has a shorter maturity range, the mean deteriorated below zero, signaling pessimistic projections about the state of the economy.

Furthermore, when examining the volatility, a significant increase can be seen during the COVID-19 pandemic. The volatility during this period more than doubled. This discovery confirms one of the hypotheses that after the beginning of the pandemic, the volatility grew significantly. Later, we will investigate whether and to what extent COVID-related data caused this volatility.

Lastly, we inspect the third and fourth statistical moments. Skewness is a measure of asymmetry. It tells us how much the probability distribution of our random variable deviates from the normal distribution. When looking at the skewness of our response variables, we can see that both FRA spreads became negative after the start of the pandemic, which makes perfect sense, since during the pandemic, they exhibit more extreme negative shocks. Kurtosis is also a measure comparing the probability distribution to the normal one. However, unlike skewness, kurtosis is a measure of extreme values in tails. It tells us whether our dataset is heavy-tailed or light-tailed. Since normal distribution has a kurtosis of 3, we distinguish three categories of kurtosis, called platykurtic, mesokurtic, and leptokurtic, based on whether the kurtosis value is less, equal, or more than 3. We can observe that both FRA spreads obtain a higher kurtosis during the COVID-19 pandemic, which is again in hand with our previous assumptions. Nevertheless, we can say that during the COVID period, the FRA spreads are more or less mezokurtic, meaning they have a similar outlier characteristic as a normal distribution.

5.1.2 Stationarity in Data

To estimate ARMA-GARCH models, we need to first ensure that we can use the Box-Jenkins Methodology and its extension to estimate GARCH models. In particular, we need to investigate our time series and determine whether they are stationary. We apply the ADF test for both our samples and FRA spreads.

Table 5.2: FRA Spread Stationarity Test

Series	ADF
1x4 vs. 3x6 COVID	-3.442**
1x7 vs. 3x9 COVID	-3.919***

Note: *** , ** and * mark level of significance at 1% , 5% and 10%.

As there can be seen from Table 5.2, the ADF confirms stationarity for all FRA spreads. However, we will have to be cautious about our conclusions as the data is on the edge of stationarity.

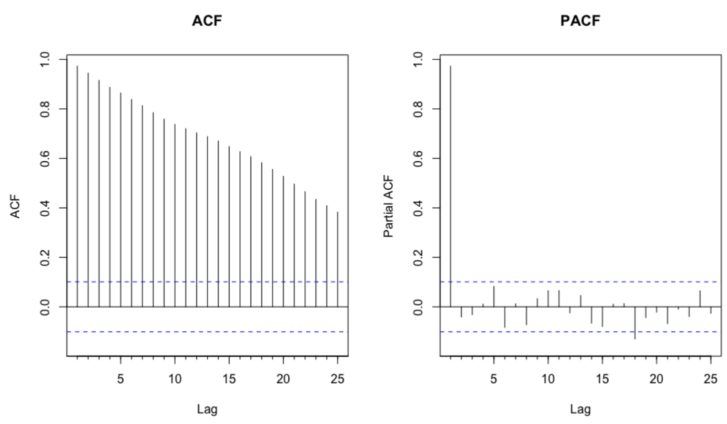
Next, we begin with the ARMA-GARCH specification for our FRA spreads during the COVID period. First, we start with FRA spread 1x4 vs. 3x6, and then FRA spread 1x7 vs. 3x9 accordingly.

5.2 FRA Spread 1x4 vs 3x6

5.2.1 ARMA Model

The purpose of this section is to find the most parsimonious ARMA model. We already presented that the FRA Spread 1x4 vs. 3x6 can be considered stationary. To estimate the most efficient ARMA specification, we further have to examine the correlation across the series lags. We employ ACF and PACF to help us identify the appropriate order of the ARMA(p,q) model. After looking at the ACF in Figure 5.1, we can say that our data has preserved a long memory, which makes sense since FRA is an interest rate derivative; hence it is dependent on the interest rates that do not change that often. Because of that, we can see the strong dependency. This is further confirmed after computing the Ljung-Box test, which tests whether there is any autocorrelation in the time series, where we strongly reject the null hypothesis with the p-value being smaller than $2.2 * 10^{-16}$. When looking at the PACF, we can also observe an extreme result for the first lag, which is not a surprise since ACF and PACF give the same value for the first lag, as already discussed in the Methodology section.

Figure 5.1: ACF and PACF of the FRA Spread 1x4 vs 3x6



Following this, we minimize the information criteria to find the right balance between the number of parameters and the goodness of fit. However, before we do so, we include the following variables representing the COVID-19 data as external regressors that will help us to better determine the data-generating process.

$$externalregs = \delta_1 GovernmentResponseIndex + \delta_2 StringencyIndex + \delta_3 EconomicSupportIndex, \quad (5.1)$$

where the respective variables are defined in the Section 4.2. By using these external regressors, we would like to find out whether there was any effect of COVID-19 data that affected the FRA spread.

After minimizing AIC and BIC, we find the best fit for our model is ARMA(1,0). Looking at the Table 5.3, we can observe that our autoregressive coefficient is strongly significant and close to 1, which threatens the stationarity condition. Nevertheless, we will not further discuss the ARMA model coefficients, since they will be slightly changed when estimating later employing GARCH models.

Table 5.3: ARMA Model of the FRA Spread 1x4 vs 3x6

	Coefficient	S.E
ϕ_0	0.154**	0.086
$\phi_1(AR1)$	0.989***	0.007
$\delta_1(GovernmentResponseIndex)$	-0.007***	0.001
$\delta_2(StringencyIndex)$	0.004***	0.001
$\delta_3(EconomicSupportIndex)$	8e-04***	3e-04

AIC = -1836.31 BIC = -1812.72

Note: ***, ** and * mark level of significance at 1%, 5% and 10%.

5.2.2 ARCH Effect

As already discussed in the methodology section, there are weaknesses of working with ARMA models. Specifically, the constant variance assumption is usually not satisfied when working with financial time series. Before we get to GARCH modeling, we investigate whether there is an ARCH effect present. We do so by employing the Lagrange Multiplier test, which tests for the null hypothesis that the residuals of an ARMA model are homoscedastic. After receiving a p-value that is virtually zero, we reject the null hypothesis of homoscedasticity and conclude that there is an ARCH effect present in the residuals, and thus we can proceed with our estimation using GARCH models.

5.2.3 GJR-GARCH Model

We choose the GJR-GARCH model for modeling the volatility of this spread. As described before, the GJR extension is able to capture the leverage effect, i.e. the negative relationship between the positive and negative news and market volatility. For the purpose of this analysis, we will use GJR-GARCH(1,1). In many economic applications, the GARCH(1,1) is employed, and according to Brooks & Burke (2003), this order should be considered sufficient when examining financial time series.

We examined several versions of the model, but we did not find any effect of the COVID-19 variables on the FRA spread volatility. Hence, we decided to include them only in the mean equation.

Consider a following set of equations used for ARMA(1,0)-GJR-GARCH(1,1) specification:

$$y_t = \mu_t + a_t,$$

$$\mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \delta_1 GovernmentResponseIndex + \delta_2 StringencyIndex + \delta_3 EconomicSupportIndex$$

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma a_{t-1}^2 S_{t-1},$$

where p equals 1. After estimating the above-specified model, we receive the estimated coefficients in Table 5.4. To begin with the autoregressive coefficient ϕ_1, we can observe that it is still extremely high, implying strong dependency. Its positive value of 0.994 indicates that if the FRA spread increases by 100bps, it is expected to increase another 99bps the following trading day, holding all the other variables fixed.

Looking at the included variables representing the COVID-19 data in the mean equation, we can see that all of them are significant at their respective significance levels. This confirms our central hypothesis that COVID-19 data affected the FRA spread. To begin with δ_1, representing the overall government response to the pandemic, we can see a negative impact of the variable on the FRA spread. This is expected since this index contains all the indicators, including containment and closure policies, health system policies, and vaccine policies, and thus it is an adequate measure of the overall response from the government. We proceed by looking at the indices measuring specific indicators.

Table 5.4: FRA Spread 1x4 vs 3x6 ARMA-GJR-GARCH estimates

	Coefficient	S.E
ϕ_0	0.062***	0.014
$\phi_1(AR_1)$	0.994***	0.003
$\delta_1(GovernmentResponseIndex)$	-0.007***	0.001
$\delta_2(StringencyIndex)$	0.003***	0.001
$\delta_3(EconomicSupportIndex)$	0.001**	0.000
ω	0.000***	0.000
α_1	0.053***	0.012
β_1	0.894***	0.013
γ	0.104***	0.036

Note: ***, ** and * mark level of significance at 1%, 5% and 10%.

What comes as a surprise is the positive value of δ_2 coefficient measuring the strictness of lockdowns and policies restricting people's behavior. We would expect that more restriction policies would cause a stronger toll on the country's economy and thus decrease the FRA spread. One possible explanation of the coefficient's positive value might be that when restrictions were implied, people were able to adjust to them. However, since they did not know when the restrictions would end, they could feel a stronger uncertainty about the future, as they were not able to predict the future steps of the government. As for the last variable from COVID-19 data, the respective coefficient δ_3 is positive, which is according to our expectations, as more financial help from the government side should decrease the perceived uncertainty of individuals and thus increase the FRA spread.

When examining estimates of the variance equation, we observe the ω coefficient, which stands for the lowest possible variance being generated, is zero. We can also see that the stationarity condition for GARCH models ($\alpha_1 + \beta_1 < 1$) is satisfied. However, the sum is close to 0.95, which suggests the presence of both ARCH and GARCH effects, and we can consider this model to be persistent. Moreover, the β_1 coefficient is strongly significant and of high magnitude reaching 0.894, which implies that the volatility at time t is strongly affected and estimated closely to volatility from *t-1*. The significant α_1 coefficient as a measure of volatility shock means that our model reacts significantly to incoming information. Lastly, the GJR-GARCH model added γ coefficient capturing the leverage effect is positive, implying that the volatility should increase even more after negative shock. Since the γ coefficient is statistically significant at 1% level, we can conclude that the GJR extension was a relevant choice that helped us to model the variance in a more realistic way.

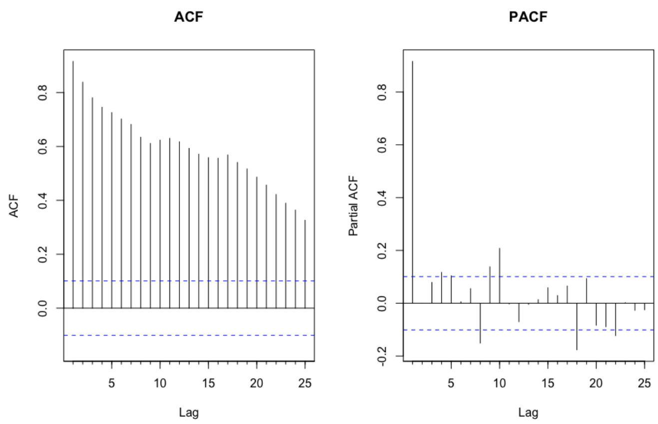
5.3 FRA Spread 1x7 vs 3x9

In this section, we will examine the FRA Spread 1x7 vs. 3x9 using the same procedure. However, we will not go into detail as in the previous section since the respective steps of the analysis were already described. We believe looking at the FRA spread of different maturities will bring other interesting discoveries.

5.3.1 ARMA Model

Looking at the Figure 5.2, we can see a similar result as for the previous FRA spread. There is a strong dependency in the data. After computing the Ljung-Box test, we can confirm that there is autocorrelation in the series as the p-value is smaller than $2.2 * e^{-16}$. Before minimizing the criteria, we include the external regressors that were described in Equation 5.1.

Figure 5.2: ACF and PACF of the FRA Spread 1x7 vs 3x9



We find that ARMA (1,1) specification describes our data most efficiently. The respective estimated coefficients can be seen in Table 5.5. Both the autoregressive coefficient ϕ_1 and moving-average coefficient θ_1 are statistically significant. Moreover, we can observe that the ϕ_1 is close to 1 as we have a significant dependency in the data.

Table 5.5: ARMA Model of the FRA Spread 1x7 vs 3x9

	Coefficient	S.E
ϕ_0	0.171***	0.084
$\phi_1(AR1)$	0.979***	0.012
$\theta_1(MA1)$	-0.138***	0.059
$\delta_1(GovernmentResponseIndex)$	-0.017***	0.002
$\delta_2(StringencyIndex)$	0.013***	0.002
$\delta_3(EconomicSupportIndex)$	2e-03	5e-04

AIC = -1836.31 BIC = -1812.72

Note: ***, ** and * mark level of significance at 1%, 5% and 10%.

Further, we examine the residuals of an ARMA model to find out whether they are homoscedastic. After computing the Lagrange Multiplier test, we can reject the null hypothesis and thus conclude that there is an ARCH effect present.

5.3.2 GJR-GARCH Model

We employ the GJR-GARCH extension as we do not have a reason to use another type, since we are working with the same type of financial data. We again use the (1,1) specification, and thus our joint model is ARMA(1,1)-GJR-GARCH(1,1). After examining various versions of the model, we find no effect of the COVID-19 data on the FRA spread volatility, which further confirms our result from the previous FRA spread. Thus, we include them only in the mean equation.

$$y_t = \mu_t + a_t,$$

$$\mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \delta_1 GovernmentResponseIndex + \delta_2 StringencyIndex + \delta_3 EconomicSupportIndex$$

$$a_t = \sigma_t \varepsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma a_{t-1}^2 S_{t-1}, \tag{5.2}$$

where p and q equal 1. After estimating the above-specified model, we receive estimated coefficients presented in Table 5.6.

Table 5.6: FRA Spread 1x7 vs 3x9 ARMA-GJR-GARCH estimates

	Coefficient	S.E
ϕ_0	0.065***	0.022
$\phi_1(AR_1)$	0.938***	0.026
$\theta_1(MA_1)$	-0.315***	0.068
$\delta_1(GovernmentResponseIndex)$	-0.001	0.001
$\delta_2(StringencyIndex)$	0.001	0.001
$\delta_3(EconomicSupportIndex)$	-0.001***	0.001
ω	0.000***	0.000
α_1	0.146***	0.038
β_1	0.823***	0.025
γ	0.060	0.050

Note: ***, ** and * mark level of significance at 1%, 5% and 10%.

Beginning with the autoregressive coefficient ϕ_1, we can observe a very similar pattern that was found in the previous spread. The coefficient slightly decreased but is still close to 1, indicating that after a 100bps increase of the FRA spread, it is likely to increase another 94bps the next trading day, holding other factors fixed. Furthermore, we can see that the moving-average coefficient μ_1 is also significant and negative, hence slightly decreasing the power of the autoregressive coefficient.

When examining the mean equation variables, we can see different results in comparison with the previous FRA spread. Both δ_1 and δ_2 coefficients are not significant for this spread. The only significant COVID-19 variable in this model remains the *EconomicSupportIndex*. However, the sign of the δ_3 coefficient is surprising. We would expect that stronger government financial support would increase the FRA spread, as it should ease the perceived fear of individuals.

Following, we look at the variance equation estimates, and we can see that the ω is again zero. Moreover, the stationarity condition is satisfied, as there can be seen by looking at the sum of the α_1 and β_1, which is less than 1. Examining the β_1, we can see its strong significance and high value of 0.824, which indicates the volatility persistence, as already found in the previous spread. Furthermore, the α_1 coefficient is also significant, meaning that this model is significantly affected by the incoming information. However, looking at the γ coefficient, we see that it is not significant, which comes as a surprise, considering its strong significance for the previous spread.

Chapter 6

Conclusion

This study provides interesting insight into the perceived uncertainty on financial markets during the COVID-19 pandemic. We found a significant decrease in the mean for both FRA spreads as the COVID-19 pandemic began. The mean for the shorter maturity FRA spread decreased twice as much as the other FRA spread and became negative, indicating a higher sensitivity for the perceived short-term fear and views. Moreover, we observed a strong increase in volatility for both FRA spreads, which doubled since the beginning of the pandemic. These findings confirm that the shock caused by the spread of a new virus could also be seen in financial markets as FRA spreads decreased, meaning that people perceived higher uncertainty about the future.

Furthermore, the results confirm our central hypothesis that there was a significant relationship between FRA spreads and the COVID-19 data. As expected, the overall government response negatively affected both FRA spreads. As for the other COVID-19 data, we could observe mixed effects. Our results show persistent volatility clustering for both FRA spreads. On top of that, the GJR-GARCH model for the first spread showed the parameter capturing the leverage effect as significant, implying the volatility increased even more after negative news.

Comparing the analysis results for the FRA spreads, we found more prominent effects on the shorter maturity FRA spread 1x4 vs. 3x6. This might be explained by the greater importance economic agents attribute to the present and near future in comparison with the distant future, which could be discounted.

However, we have to be highly cautious when drawing the conclusions, as our data were on the edge of the stationarity, which could be observed throughout the whole analysis. On top of that, since we were working with interest rates derivate and during a highly turbulent period, many other behavioral and financial factors might explain the FRA spread movements. It could be interesting to investigate them in future research. Moreover, including other countries that experienced different shocks due to the pandemic would bring a better understanding of how people's perception of the economy changed around the world.

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Appendix A

Figures

Figure A.1: FRA Spread 1x4 vs 3x6 pre-COVID-19

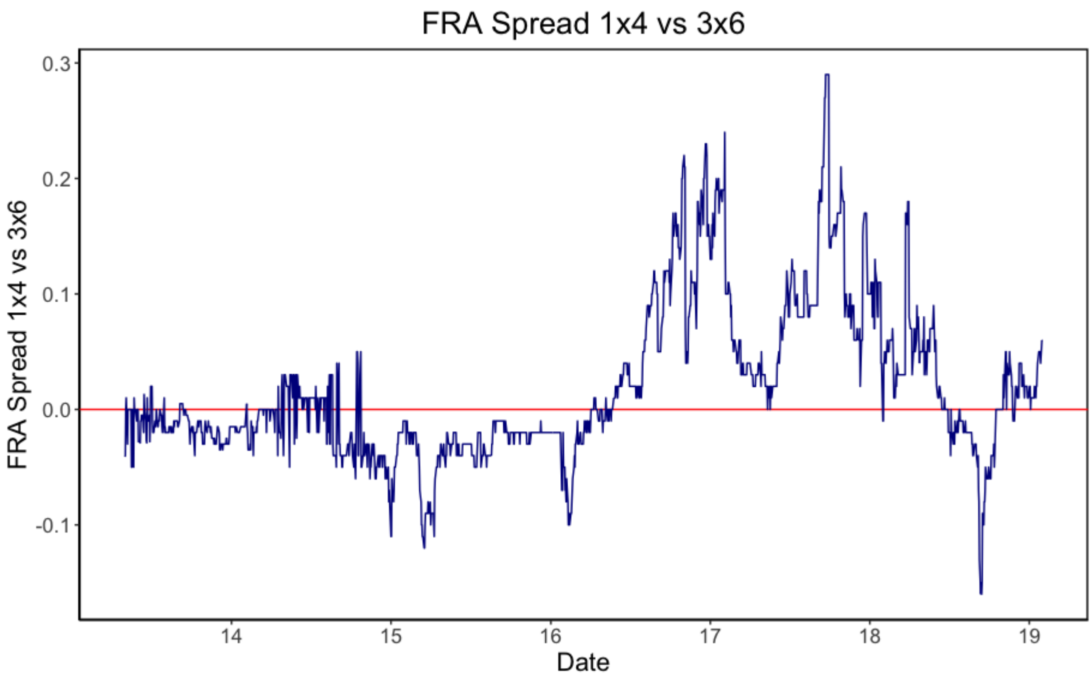

Figure A.2: FRA Spread 1x7 vs 3x9 pre-COVID-19