THE IMPACT OF MEDIA TONE ON DOLLAR EXCHANGE RATE VOLATILITY: GARCH APPLICATIONS

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ABSTRACT

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Abstract

Using several million news and social media articles related to US dollar, I examine the role of Media tone in predicting daily dollar exchange rate returns from 1998 to 2021. In this study, I use GARCH specifications to explore the relationship between currency Media tone and dollar exchange rate volatility. I include currency Media tone as an external regressor into both mean and variance equations of different specifications following the significance and sign of the causal relationship. The results reveal that the impact of currency Media tone to be time-dependent, source-dependent, statistically significant but economically insignificant. The inclusion of the currency Media tone into the variance equation of the GARCH specification increases the explanatory power of the model from 10,43% to 10,85%. The sign of the impact has been varying from specification to specification, however in most cases the sign of the coefficient for currency Media tone was positive in the mean equation and negative in the variance equation. This means that information about US dollar increases the dollar exchange rate returns but decreases the exchange rate volatility.

Key words

Exchange Rate Volatility; GARCH; Media Tone; Social Media; News; Sentiment

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 Research Background

Recently many countries have adopted a flexible exchange rate system and together with worldwide trends towards liberalization, globalization of the economies and increased economic cooperation and trade between countries, the phenomenon of high exchange rate volatility has arisen. The centre of debates around this phenomenon is its nature and since there is a lack of clarity on this issue, the high risk of implementing suboptimal economic policies emerges. At the macro level, wild currency fluctuations can create economic uncertainty and instability which, in turn, affect capital flows and international trade. Today in the COVID-19 times the overall uncertainty about exchange rate volatility has increased and, therefore, it has become even more important to explore the nature of excessive exchange rate volatility.

Understanding the nature of volatile foreign exchange rates has been a hot topic for discussions to many researchers for another solid reason: at the micro level, exchange rate fluctuations affect the corporate world a lot. The most unfavorable for a company consequence exchange rate volatility can have is deterioration of its financial health: for example, exchange rate fluctuations can decrease a company's future cash flows and market value and even if a company is not involved into foreign transactions, this can still affect company's competitiveness. Exchange rate risk exposure turns to be an important aspect to take into account by especially those companies who are involved into export/import transactions: exchange rate volatility makes the profit of a company, which is formed of international trade and foreign direct investment, uncertain. Therefore, understanding the factors which can explain and help to forecast exchange rate volatility is of a great importance for the prosperity of a business both in the long-run and in the short-run.

The problem of exchange rate volatility is gaining a special attention in emerging countries rather than developed countries because these markets are highly volatile and, therefore, the phenomenon of exchange rate volatility is more pronounced there. One of the emphasis of this research paper is going to be the comparative analysis of the impact of information about emerging and advanced economies on exchange rate volatility.

The excessive exchange rate volatility is a volatility that can't be explained through the variation in fundamental variables. The existence of excessive exchange rate volatility in the financial markets is a counterargument against Efficient Market Hypothesis introduced by Eugene Fama (1970): EMH assumes that (i) the value of a currency reflects all the available information that is relevant to the fundamental value of the exchange rate and that (ii) the traders are rational in their actions and, therefore, it is not possible to predict changes in the value of currency. Thus, excess exchange rate volatility means that changes in the value of currency are forecastable and this is a direct contrast to EMH. A positive causal relationship between excess volatility and exchange rate returns exists: the higher is the excess volatility, the higher are the exchange rate returns.

According to the empirical literature, exchange rate volatility can be explained by macroeconomic fundamental variables in the long-run, but not in the short-run period, this is called exchange rate puzzle (Meese and Rogoff (1983); Rossi (2013)). Though currency markets have a long research history, there is still no consensus in the literature regarding the predictors of exchange rates. There are many theoretical explanations and empirical models that have been proposed for the excessive volatility in the short-run period.

The role of public and private information in the market

DeGennaro and Shrieves (1997) in their empirical research conclude that both private information and news effects are vital in determination of exchange rate volatility. In line with DeGennaro and Shrieves (1997), Taylor et al. (2001) claim that both macroeconomic news releases and private information such as order flow and bid-ask spread have a significant impact on volatility. In contrast, Opschoor et al. (2014) infer from the empirical analysis that private information measured by order flow has a much larger effect on volatility than the most influential macroeconomic announcements. In line with Opschoor et al. (2014), Evans and Lyons (2002) state that order flow performs really well in explaining exchange rate dynamics.

The different trading strategies of heterogeneous agents

In the model of Farmer and Joshi (2002), it is claimed that different trading strategies of heterogeneous agents result in excess volatility in the market. The model considers two types of traders: chartists whose trading strategies depend only on the price history and fundamentalists who make subjective assessment of the long term fundamental value using external information. The authors assert that the combination of value investing strategies and trend following strategies lead to excess volatility since both strategies strengthen noise in the heterogeneous settings. There are several other chartists and fundamentalists models that take into account heterogeneous beliefs of foreign exchange market participants in attempt to explain a short term movements of exchange rates: the models provide a time varying nonlinear combination of lagged chartist and fundamentalist predictions as a reasoning for excess exchange rate volatility (Frankel and Froot (1986); De Long et al. (1990); Lux (1995); Sethi (1996)).

Psychological choices

Another possible explanation for the excess volatility is behavioral patterns of economic agents. In the behavioral models of Gennaioli and Shleifer (2010) and Bordalo et al. (2016) investors have diagnostic expectations which means that when forming their beliefs investors overweight future outcomes that have turned to be more likely in the light of most recent data and this can be a possible explanation for high volatility in the foreign exchange market and overreaction to new information. Barberis et al. (1998) suggest another psychological issue of an investor as a probable explanation for an excess volatility – conservativeness: investors identify only two regimes, trend and mean reverting regimes, and if they face new evidence (news), they act reluctant to change to the correct regime which result in underreacting to news in the short-run period and overreacting to news in the long-run period. Daniel et al. (1998) in his model introduce overconfidence of investors as a reason for excess volatility in the market: the overconfident investors overvalue the accuracy of private information and undervalue the accuracy of public information causing them to overreact to private information and underreact to public information. In the behavioral models of Manzan and Westerhoff (2005), it is suggested that excess volatility can be the result of underreacting to news in quiet economic periods and overreacting to news in volatile economic periods and the psychology underlying such a behavioral pattern is that investors believe that if historical volatility is low, then new evidence must be insignificant.

Imperfect information

There is a couple of theories which highlight the role of imperfect information for the excess volatility. In the model of Damodaran (1985), it is assumed that information is reported promptly but with an error which arises from a competitive zeal to report news quickly which, in turn, leads to excess return volatility. However, in the model of Veronesi (2000), the assumption is opposite: the reported information is assumed to contain errors and investors know about it and try to hedge against the risk of imprecision of news causing higher or lower volatility. In the earlier paper of Veronesi published in 1999, the model's underlying assumption is that investors are concerned about future state of the economy and this concern acts as an additional risk for risk-averse investors leading them to underreact to good news in bad times and overreact to bad news in good times.

Some of the factors that theoretically have an impact on exchange rate volatility such as, for example, overconfidence of investors is really difficult to measure and some of the factors like private information which is also considered to be a determinant of exchange rate volatility is really expensive to get access to. Hence, in this research I am going to use the information provided by the Thomson Reuters Media tone, which is private but easily accessible.

In this Master's thesis, I present Media tone as another currency predictor and solution to exchange rate puzzle. Media tone not only includes news related to macroeconomic fundamentals of exchange rates but also information related to non-fundamentals, for example, sentiment, from social media which makes this predictor superlative to either macroeconomic variables or variables which reflect simple number of news related to macroeconomic announcements.

1.2 Research Aim and Objectives

The aim of this research is to find out whether Media tone information has a significant impact on dollar exchange rate volatility. To achieve this goal, the study examines the following specific objectives:

i. Review empirical literature devoted to the impact of new information on exchange rate volatility and identify the gaps to fill in
ii. Find out a suitable econometric model to use to explore the impact of new information on exchange rate volatility
iii. Explore the impact of news and social media sentiments on dollar exchange rate volatility
iv. Estimate quantitatively (in terms of R^2) the role of Media tone in explaining dollar exchange rate volatility
v. Investigate the difference in the impact of news and social media sentiments on dollar exchange rate volatility against currencies of advanced and emerging economies
vi. Explore the role of Global Financial Crisis in the impact of Media tone on dollar exchange rate volatility
vii. Identify the difference in the impact of information from different sources of media (Financial Times, Wall Street Journal, The Economist and New York Times) on dollar exchange rate volatility

1.3 Research Structure

This study is organised into five chapters, with chapter one focusing on the background of the topic and relevance of the research topic. Also the chapter offers the main aim of the study together with the related study objectives. Chapter two is the literature review. The chapter first gives a review of previous research conducted in the same topic. This is followed by the identification of main gaps in the research topic. Afterwards, chapter three gives the research procedures and methodologies used in conducting the research, whereas chapter four covers data and variables description as well as formulation of working hypotheses of the research. Chapter five is a presentation of the findings and analysis of the study. Chapter six, which is the last chapter gives the conclusion of the research findings, limitations of the study and as well as recommendations for further research.

2 LITERATURE REVIEW

2.1 The impact of new information on exchange rate volatility

One of the key implications of the rational expectations hypothesis is that unexpected events like news may play the most important role in dynamics of real variables. Many empirical researches indicate a connection between exchange rate volatility and news or information on macroeconomic fundamentals.

Frankel (1981) was among the first researchers who pointed out that exchange rate changes can be caused by "new information": the author found out that the variances of monthly percentage changes in exchange rates are much larger than the variances of monthly forward premium. Another result of the study which strengthen the conclusion about the role of news in exchange rate volatility is that exchange rate changes depend on the unexpected changes in the interest rates.

Almeida et al. (1998) infer that the DEM/USD exchange rate has a high frequency reaction to publicly announced macroeconomic information about the U.S. and German economies. The authors point out that the effect of German announcements on exchange rate is much smaller than the U.S. announcements and that German macroeconomic announcements incorporate into DEM/USD exchange rate much more slowly than the news emanating from the U.S.

Cheung and Chinn (2001) provide an evidence from a survey of U.S. foreign exchange traders that news related to macroeconomic fundamentals is rapidly incorporated into exchange rates. The researchers find out that an adjustment of the exchange rate to announcements about unemployment, the trade deficit, inflation, GDP and the interest rate takes place within a minute.

Andersen et al. (2003) claim that high-frequency U.S. dollar spot exchange rate is linked to announcement surprises about macroeconomic fundamentals and bad news have a greater impact on U.S. dollar spot exchange rate than good news.

In line with Andersen et al. (2003), Laakkonen (2007) in her research states that US and European macroeconomic news increase USD/EUR volatility significantly and bad and conflicting news concerning the state of the U.S. economy have a greater impact on exchange rate volatility rather than good and consistent news. In order to examine the influence of the US and European macroeconomic news on the USD/EUR volatility, the researcher uses the Flexible Fourier Form method. In line with Almeida et al. (1998), the authors highlight the predominant role of the U.S. news in exchange rate volatility.

Overall, it can be concluded that the impact of news on exchange rate volatility is asymmetric and can be decomposed by different factors.

2.2 ARCH models as a benchmark in volatility modelling

The most frequently addressed problems researchers face when modelling exchange rate volatility is time-varying volatility, so called volatility clustering, and leverage effects. For example, Friedman and Stoddard (1982) highlight that daily foreign exchange rate returns follow a stochastic process with time varying parameters and, therefore, cast doubt on the implication of ARIMA technique in modelling exchange rate returns. In line with Friedman and Stoddard (1982), Hsieh (1989) highlight the presence of nonlinearity of variances in a multiplicative form for five exchange rates and mention the importance of usage of models which account for nonlinear behaviour of daily exchange rate returns in the short term modelling.

The most known applied models that are designed to model exchange rate volatility clustering and leverage effects successfully are the autoregressive conditional heteroscedastic (ARCH) model developed by Engle (1982) and generalized (GARCH) model developed by Bollerslev (1986) and Taylor (1986). Engle (1982) in his research paper introduces a new type of autoregressive conditional heteroscedastic (ARCH) stochastic model which takes into account non-constant variances conditional on past.

Engle (1982) introduced the autoregressive conditional heteroscedastic model to address the problem of fat tailed distributions and volatility clustering in the financial data. Whilst traditional econometric models assume a constant variance, the ARCH process was introduced to tackle this improbable for financial data assumption. The ARCH process assumes a mean zero, serially uncorrelated process with non-constant variance conditional on the past, however constant unconditional variance.

Definition of ARCH(q) process

ARCH process can be defined in different contexts. Here we will define it as a distribution of the errors of a dynamic linear regression model and describe its properties (Bera and Higgins, 1993). Let y_t denote the univariate discrete time real-valued stochastic process with x_t is a $k \times 1$ vector of endogenous and exogenous explanatory variables which can include lags of the dependent variable and β is a $k \times 1$ vector of regression parameters:

$$y_t = x_t\beta + \varepsilon_t, \quad t = 1, \dots, T$$

The ARCH model describes the distribution of the stochastic errors ε_t conditional the information set $I_{t-1} = \{y_{t-1}, x_{t-1}, y_{t-2}, x_{t-2}, \dots\}$. The ARCH model assumes that error term is normally distributed with the zero mean and a time varying conditional variance equal to h_t:

$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

The conditional variance h_t is a linear or nonlinear function of lagged values of ε_t and predetermined variables x_t as they enter information set as well:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{i-q}^2$$

with $\alpha_0 > 0$ and $\alpha_i \geq 0, i = 1, \dots, q$ as conditional variance must be positive.

The conditional variance function can also be expressed in the following way:

$$h_t = h(\varepsilon_t^2, \dots, \varepsilon_{t-q}^2, x_t, \dots, x_{t-q}, \alpha)$$

or simply

$$h_t = h(I_{t-1}, \alpha)$$

It is possible to use ordinary least squares to estimate an ARCH(q) model. Below in this section I am going to describe the procedure proposed by Engle (1982) to test or the lag length of ARCH errors using the Lagrange multiplier test:

1. Estimate the most precise autoregressive model AR(q)
$$y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, y_{t-i} + \varepsilon_t$$
2. Regress the squared errors on a constant and q lagged values:
$$\hat{\varepsilon}_t^2 = \gamma_0 + \sum_{i=1}^{q} \gamma_i \hat{\varepsilon}_{t-i}^2 + v_t$$

where v_t is independent and identically distributed.

3. The last step is to test for "ARCH effects": the test statistic is defined as TR^2 which is equal to the number of observations multiplied by the coefficient of multiple correlation from the last regression and follows χ^2 distribution with q degrees of freedom. The null and alternative hypotheses are:
H_0: $y_1 = y_2 = \cdots = y_q = 0$
H_1: $y_1 \neq y_2 \neq \cdots \neq y_q \neq 0$
If the value of the test statistic is greater than the critical value from the χ^2 distribution, then the null hypothesis is rejected and we conclude that there is an ARCH effect. If the value of the test statistic is smaller than the critical value from the χ^2 distribution, then the null hypothesis is not rejected and we conclude that there is no an ARCH effect.

ARCH models have gained their popularity through the application to financial data modelling and have been marked as successful in volatility forecasting by many researchers, for example, Bera and Higgins (1993) mention the following benefits of use of ARCH models:

- ARCH models are simple and easy in understanding and use
- ARCH models account for clustered volatility
- ARCH models account for nonlinearities
- ARCH models allow to forecast changes for one period to another

Definition of GARCH (p,q) process

In empirical research, an ARCH(q) model is often blamed for negative variance parameter estimates because of a relatively long lag structure of the conditional variance equation. To address this problem, Bollerslev (1986) introduced the generalized ARCH models which allow past conditional variances to be included into the current conditional variance equation. The GARCH model is a more parsimonious extension of ARCH model that is less likely to breech non-negativity constraints.

In the case of GARCH(p, q) model, p is the order of the GARCH terms $\sigma^2(h)$ and q is the order of the ARCH terms ε^2. The original paper published by Bollerslev (1986) gives the following notation of the model:

$$y_t = x_t\beta + \varepsilon_t, \quad t = 1, \dots, T$$

$$\varepsilon_t | I_{t-1} \sim N(0, h_t)$$

$$h_t = \alpha + \sum_{i=1}^{q} \beta_i \, \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \gamma_i \, h_{t-i} + \nu_t$$

with $\alpha > 0$ and $\beta_i \geq 0, i = 1, \dots, q$ and $\gamma_i \geq 0, i = 1, \dots, p$ as conditional variance must be positive.

The conditional variance function in the GARCH model can also be expressed in the following way:

$$h_t = h(\varepsilon_{t-1}^2, \dots, \varepsilon_{t-q}^2, h_{t-1}, \dots, h_{t-p}, x_t, \dots, x_{t-q}, \alpha)$$

The procedure proposed by Bollerslev (1986) to establish the lag length p of a GARCH(p,q) is described above:

1. Estimate the most precise autoregressive model AR(q)

$$y_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, y_{t-i} + \varepsilon_t$$

2. Calculate and plot autocorrelation functions of ε_t
4. Autocorrelation coefficients that are larger than their value plus standard deviation which is approximated as $1/\sqrt{T}$ for larger samples indicate the presence of GARCH errors. To estimate the number of lags of the GARCH terms, the Ljung-Box test is used until the value of lags is less than 10%. The null and alternative hypotheses are:

   H_0: There are no ARCH or GARCH errors in the conditional variance
   H_1: There are ARCH and GARCH errors in the conditional variance

2.3 The use of ARCH and GARCH specifications in modelling dollar exchange rate volatility

ARCH and GARCH models have been used extensively to analyse exchange rate volatility in the empirical research.

Lastrapes (1989) apply ARCH specification to model the impact of the U.S. monetary policy on dollar exchange rate volatility. The author uses weekly exchange rate volatility data and five exchange rates: British pound, Canadian dollar, Deutsch mark, Japanese yen and Swiss franc. The author finds out that the U.S. monetary policy has a significant impact on the dollar exchange rate volatility however the results are not uniform across the currencies. The author also infers that it is important to account for possible changes in unconditional variance in ARCH specification.

Tse and Tsui (1997) uses a new class of Asymmetric Power ARCH model to explore the conditional volatility of the exchange rates of two Asia-Pacific currencies against dollar: The Malaysian ringgit and the Singapore dollar. The researchers employ APARCH model to capture the possibly asymmetric effects of exchange shocks on future volatilities. The authors infer that the conditional heteroscedasticity demonstrated by the exchange rates of the two Asia-Pacific currencies is described adequately by the APARCH model and that a depreciation shock in the Malaysian ringgit against the US dollar has a larger effect on future volatilities than an appreciation shock of the same magnitude.

Brooks and Burke (1998) use a set of modified information criteria to select an optimal model orders for predicting the conditional variance of weekly exchange rate returns on the U.S. dollar against the Canadian dollar, German mark and Japanese yen. The authors conclude that GARCH (1,1) turns to be an optimal specification for modelling dollar exchange rate volatility.

Longmore and Robinson (2004) model Jamaican dollar against the U.S. dollar exchange rate volatility using non-linear asymmetric specifications of GARCH. The researchers claim that linear GARCH model can't capture some features in the exchange rate volatility data, for example, significant thick tails in the unconditional distribution. Moreover, according to the authors, linear form of GARCH model has been found to be "deficient in correcting bias in the forecast and forecast error variance associated with a skewed distribution". The authors conclude that non-linear GARCH models perform better than linear form of GARCH in terms of the explanatory power and in the out-of-sample forecasting and, in line with Tse and Tsui (1997), infer that negative shocks in Jamaican dollar against the U.S. dollar tend to generate more volatility than positive exchange rate shocks.

Dritsaki (2019) explores the volatility of euro/dollar exchange rate using ARCH, GARCH and EGARCH specifications. The results of the study show that EGARCH (1,1) model describes exchange rate returns most precisely and, in addition, captures the leverage effect existing in the data.

Having analysed several research papers, we can conclude:

- GARCH models and their many extensions perform better in modelling and forecasting exchange rate volatility than ARCH models.
- Non-linear GARCH specifications can outperform linear GARCH in some cases.

2.4 The impact of new information on exchange rate volatility using GARCH models

There has not been much research done to find out the impact of new information on exchange rate volatility using GARCH specification since this topic is quite new. However, in this section I am going to provide an overview of several research papers that have contributed to this research topic so far.

Radovan and Horvath (2010) investigate the impact of the Czech National Bank communication, macroeconomic news and interest rate differential on exchange rate volatility by means of generalized autoregressive conditional heteroscedasticity model. The baseline specification of the research is GARCH (1,1) that looks as follows:

$$\Delta s_t = \mu + \varepsilon_t$$

$$\sigma_t^2 = \gamma_1 + \gamma_2 \varepsilon_{t-1}^2 + \gamma_3 \sigma_{t-1}^2 + \phi_i \sum_{i=1}^{n} CB_{it} + \rho_1 news_t + \rho_2 intdiff_t + \varpi_{jt}$$

To capture the central bank communication effect, the authors use the following dummy variables:

- $Comment_t$ which takes a value of 1 on the days when a member of Czech National Bank Board makes a verbal comment regarding price stability, economic outlook, interest rates or exchange rate.
- $Timing_t$ which is a product of $comment_t$ and a categorical variable that is equal to 30 on the day of monetary policy meeting, 29 on the day before the meeting, 28 on two days before the meeting and so on.
- $Minutes_t$ which takes a value of 1 on the day when monetary policy minutes are published.

$News_t$ is a dummy variable which takes a value of 1 on the days when macroeconomic news is released. $Intdiff_t$ is the interest rate differential between Czech and the euro area money market rates.

The researchers estimate the model and conclude that both central bank communication and macroeconomic news decrease the exchange rate volatility. Whilst the central bank communication effect reflects the aim of CB to decrease the noise in the financial markets, macroeconomic news effect is associated, in opinion of the authors, with the fact that emerging markets are highly uncertain and news does have a calming effect on the market.

Hua and Gau (2006) investigate the impact of the public news arrivals, inventory risk and central bank interventions on intraday Taiwan dollar/ U.S. dollar exchange rate volatility using periodic generalized autoregressive conditional heteroscedasticity model (P-GARCH). In contrast to the findings of Radovan and Horvath (2010), the results of the research indicate that public news arrivals lead to a higher NTD/USD volatility on days when central bank interventions are reported.

Bauwens et al. (2005) explore the influence of information arrival on the exchange rate volatility of Norwegian krone using the EGARCH. The researchers infer that the impact of changes in the number of information events is positive and statistically significant and quite stable across different exchange rate regimes.

Stančík (2007) estimates the impact of news factors, economic openness and exchange rate regime on euro/ U.S. dollar exchange rate volatility in six Central and Eastern European countries using the threshold ARCH (TGARCH) model. The researcher concludes that news significantly affects exchange rate volatility.

To sum up, it is clear that some exchange rates may contain non-linear component and in that case it should be considered in exchange rate volatility modelling and more complicated GARCH models should be applied. Most of the researchers claim that new information significantly increases the exchange rate volatility rather than decreases.

2.5 The role of sentiment in stock pricing and exchange rate research

Another explanation for the exchange rate volatility can be foreign exchange market sentiment. Whilst the impact of sentiment on asset pricing has been extensively researched, its influence on exchange rates has not gained that much attention. Baker and Wurgler (2007) claim that the question is no longer whether investor sentiment has an effect on stock prices, but instead how to measure and quantify it. De Long et al. (1990) state that sentiment is usually attributed to the behaviour of noise traders whose actions based to their moods and emotions drive the asset price away from fundamental value of an asset. There are several studies which examine the role of market sentiment in stock pricing. Baker and Wurgler (2006) find out that when investor sentiment is high, stocks whose valuations are highly subjective or difficult to arbitrage earn relatively low returns. Kumar and Lee (2006) introduce systematic retail trading as a reason for return co-movements for stocks with high retail concentration. The authors highlight that macroeconomic news can't explain these results and, in this way, the findings of the paper support a role of investor sentiment in the formation of stock returns. In line with Baker and Wurgler (2006), Baker et al. (2012) find out that global and local sentiment constructed by the authors for six major stock markets predict the time-series of cross-sectional returns within markets. Ben-Rephael et al. (2012) measure investor sentiment using mutual fund flows: they researchers conclude that the investor sentiment is positively correlated with aggregate stock market excess returns. Da et al. (2015) construct a market-level investor sentiment using daily Internet queries related to household concerns and find out that the index predicts short term return reversals as well as temporary increases in volatility. Jiang et al. (2019) constructs a manager sentiment index based on the aggregated textual tone of corporate financial disclosures: in the study it is found out that manager sentiment acts as a negative predictor of future aggregate stock market returns.

The construction of a media sentiment seems to be sophisticated since the empirical literature is inconclusive about the ability of text-based measures to capture a sentiment. Several studies state that their lexical-based measures capture a sentiment. Tetlock (2007) uses daily media content from a Wall Street Journal to measure a sentiment and estimate its impact on stock market prices: the author concludes that high media pessimism forecasts decreasing pressure on market prices. Garcia (2013) uses the fraction of positive and negative words in two columns of financial news from the New York Times to capture a sentiment and estimate its influence on stock returns: the author highlights the news' content's ability to predict stock returns during recessions. Soo (2018) infers that housing media sentiment for 34 cities across the United States is able to predict future house prices for nearly two years ahead.

However, there are some research papers that claim that their measures of new information are related to asset fundamentals rather than sentiment. For example, Tetlock et al. (2008) employ a linguistic media content measure to predict individual firms' stock returns and conclude that the predictability is the largest for the stocks that concentrate on fundamentals.

As it has been mentioned above, the empirical currency literature lacks the research on the role of sentiment, however there is a couple of studies that address this specific question. Menkhoff and Rebitzky (2008) find out that professional investors' currency expectations can predict EUR/USD exchange rate for up to 2 years. Yu (2013) uses three types of sentiment data to analyse its impact on real exchange rate changes: Baker and Wugler's (2006) monthly data on US sentiment, Baker et al. (2012)'s annual sentiment data for the largest industrialized countries and survey-based sentiment measures for the other seven countries. The conclusion of the research is that investor's misperception sentiment has a positive and significant influence on the changes in the real exchange rate.

2.6 The foreign exchange market participants

A more general goal of this Master's thesis is to understand the nature of dollar exchange rate returns. In general, exchange rates - like asset prices – move in response to new information about their fundamental value. To understand what kind of information can affect dollar exchange rate volatility, it is necessary to understand who is actually trading in foreign exchange market. So far, microstructure research revealed different categories of FX market participants. In this section, I am going to review the structure of the FX market and its evolution.

Dealers

Dealers act as the biggest player in the foreign exchange market. Sometimes in the literature, they are also called as broker dealers. The majority of the foreign exchange market dealers in the world are the banks. Quite often, the market in which dealers cooperate with each other is also referred as interbank market. However, there are some non-bank financial organizations that act as dealers in the foreign exchange market.

Historically, dealers appeared in a natural way to act as a search engine for trading counterparties. Dealers are ready to trade with anybody who is interested in trading one currency for another. FX trade is initiated by an agent: he calls a dealer, indicate a currency, quantity he wants to trade and ask for the price. The dealer tells the price at which he is ready to buy (known as "bid" price) and a price at which he is ready to sell (known as "ask" price). At last, the customer decides what he want to do: buy, sell or pass. The dealer is compensated by a gap between the quoted buy and sell prices, so-called "bid-ask spread."

Brokers

Brokers are often mistakenly mixed up with dealers but here I am going to provide a clear distinction between these two FX market participants and their roles in the FX market. In case a person has sufficient knowledge, he can call directly to a dealer and obtain a favourable rate. However, if a person does not have enough knowledge, the broker is here to find the best quote. For example, a broker can help a client to get the lowest buying price or the highest selling price by making available quotes from several dealers.

Hedgers

Many companies create an asset or liability priced in foreign currency as a regular activity of their business. For example, companies-importers or companies-exporters that are involved in foreign trade might have open positions in couple of foreign currencies. Therefore, these companies may be affected in case the value of foreign currency is fluctuating. In order to protect themselves against these losses, hedgers take opposite positions in the market. In this way, any unfavorable movement in their original position is offset by an opposite movement in their hedged positions. The sum of profits and losses is then equal to zero and their business starts to operate steadily.

Speculators

Speculators are a category of traders that do have a good reasoning behind their trading activities. They buy and sell currencies in the hope to make more profit.

In general, the number of speculators in the FX market is not big compared to other categories but is usually increasing when the market sentiment is high. As a rule, speculators do not keep open positions in any currency for a long time – speculators take short position, a technique used when an investor anticipates that the price will decline in the short-term, to make a short-term profit.

Arbitrageurs

Arbitrageurs are traders that take advantage of the price discrepancy in different markets in order to make a profit. Arbitrageurs play a very important role in the foreign exchange market. Their operations ensure that market is large, decentralized, diffused, and efficient and provides uniform price quotations all over the world. When arbitrageurs find a price discrepancy in the market, they buy in one market and sell in another market till the price discrepancy disappears.

Central Banks

Central Banks of all countries are participants of the Forex market, however the extent of participation varies from one country to another. The participation of Central Bank is official which makes this category of foreign exchange market participants different from others. Every Central Bank has a target range within which they want their currency to fluctuate and when the currency gets out of the range, Central Bank starts to conduct open market operations for the currency to get back in range. Central Banks also intervene into the market to defend their currency when the currency is under speculative attack.

Retail Market Participants

Retail market players are ordinary people like tourists, for example, and small businesses that involve into foreign trade. Whilst the majority of retail market players participate in the spot market, people with long-term goals operate in the futures market. Retail market participants buy or sell currency when they have an individual/professional motive – dealing with foreign currency is not part of their regular business.

Figure 1 below presents how complex the FX market structure has become by 2010. The trading structure has become more segmented as in other financial markets. Clients can now trade not only directly with dealers but also through Multi-bank platforms, Prime Brokerage accounts on the EBS, Reuters electronic limit order books, and on platforms called Retail Aggregators.

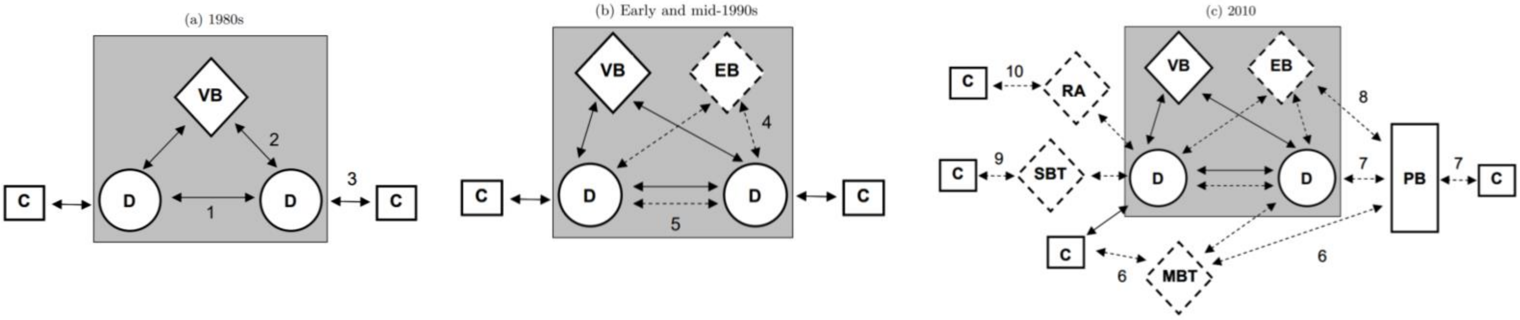

FIGURE 1. Evolution of FX market structure

NOTES: D=dealer, C=client, VB=voice broker, EB=electronic broker, PB=prime broker, MBT = multi-bank trading system, SBT=single-bank trading system, RA=retail aggregator. Solid lines mean voice execution methods. Dashed lines stand for electronic execution methods. Source: King et al. (2012).

To sum up this section, it can be inferred that the structure of the FX market has become more complex in recent decades and most of the FX market participants nowadays are professional traders that use macroeconomic fundamentals in their decision-making rather than news and social media information. Therefore, we can expect that the impact of news and social media information is not going to be the main factor that contributes to the dollar exchange rate volatility even in the short-run period.

3 METHODOLOGY

In the empirical part, I am using different GARCH family specifications to model effective nominal dollar exchange rate volatility and the impact of Media tone information on it and here I am going to give a brief description of each model. Overall, GARCH models can be divided into two categories: symmetric and asymmetric. Symmetric GARCH models assume that conditional volatility depends on the magnitude but not the sign of the exchange rate returns whilst asymmetric GARCH specifications are based on the assumption that positive and negative returns of the same magnitude have different impact on future volatility.

Symmetric GARCH models

Standard GARCH model

In the standard specification of general autoregressive conditional heteroscedasticity model, the conditional volatility is a linear function of its own lags. The general form of GARCH (p,q) looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t, \;\; y_t = h_t \varepsilon_t$$

$$\textit{Variance equation}: h_t = \alpha + \textstyle\sum_{i=1}^{q} \beta_i y_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

Asymmetric GARCH models

GJR-GARCH model

The GJR-GARCH model is another form of asymmetric GARCH models. The specification of GJR-GARCH (p,q) model looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t, \;\; y_t = h_t \varepsilon_t, \;\; \varepsilon_t \sim N(0, h_t)$$

$$\textit{Variance equation}: h_t = \alpha + \textstyle\sum_{i=1}^{q} \beta_i y_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j} + \rho_i I_{t-i} \varepsilon_{t-i}$$

where I is a dummy variable which take a value of 0 when y_{t-i} is positive and value of 1 when y_{t-i} is negative. Significant and positive ρ means that bad news has a greater impact than positive news.

Exponential GARCH model

The general form of Exponential GARCH (p,q) model is given by:

$$\ln(h_t) = \alpha + \sum_{i=1}^{q} \beta_i \left| \frac{y_{t-i}}{\sigma_{t-i}} \right| + p_i \frac{y_{t-i}}{\sigma_{t-i}} + \sum_{j=1}^{p} \gamma_j h_{t-j}$$

where ρ is the asymmetric response parameter that can be either positive or negative depending on the impact of the future uncertainty.

Asymmetric Power ARCH (APARCH) model

Asymmetric power ARCH model was introduced as another method to deal with asymmetries. The specification of APARCH (p,q) model looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t,\ \ y_t = h_t\varepsilon_t,\ \ \varepsilon_t \sim N(0, h_t)$$

$$\textit{Variance equation}: h_t^{\delta} = \alpha + \sum_{i=1}^{q}(\beta_i|y_{t-i}| - \rho_i y_{t-i})^{\delta} + \sum_{j=1}^{p}\gamma_j h_{t-j}^{\delta}$$

where ρ is the leverage parameter and δ is the parameter for the power term.

4 DATA AND VARIABLES

4.1 Independent Variable: Thomson Reuters Currency Media Tone

In this Master's thesis I am going to introduce currency Media tone as a currency sentiment measure. Currency Media tone is a text-based measure developed by Thomson Reuters MarketPsych Indices for the American dollar. The TRMI currency Media tone data consist of all the currency-related global and social media news. Media tone data include both information related to exchange rate fundamentals and non-fundamental component. Therefore, Media tone is going to be superlative to either news variables or sentiment measures introduces in previous studies and capture all the possible new information that might cause the exchange rate volatility.

Thomson Reuters MarketPsych Indices as variables are available for 3 different content sets: news, social media and the combined content. Only English-language texts are used for the analysis. The data is available at the daily frequency from 1st of January, 1998 to 20th of May, 2020. For the analysis, I am going to use two variables: news dollar sentiment and social media dollar sentiment.

The news sentiment includes the Reuters news and Internet news gathered by LexisNexis the content of which is restricted to top international and business sources. The social media sentiment comprises of a larger number of sources: Internet forum and message board content, LexisNexis social media content and tweets.

Both sentiments' values are in range from -1 to +1 and reflect overall positive references in news/social media, net of negative references in news/social media.

Lehkonen, Heimonen and Pukthuanthong (2020) describe the TRMI data formation in their research paper and present several specific cases how Media Tone is scored. TRMI data is formed using word recognition techniques that are used to extract economics, finance, business and psychological related information from the following sources: financial news, social media, conference calls transcripts and executive interviews. TRMI data covers:

- More than 7750 organizations from over 30 countries
- The 15 largest markets from 1998 onwards at the index level
- 130 countries in general

Lehkonen, Heimonen and Pukthuanthong (2020) point out that word recognition technique used to construct TRMI data is a superior method compared to lexical analysis that is used mostly in the previous research papers since it concentrates not only on positive and negative dimensions of Media tone but also on other interrelated dimensions – various grammatical frameworks to various text sources and the structure of the sentences and articles. The score that lies in the range from -1 to +1 is calculated based on the word interrelationships rather than frequency analysis of separate words.

Another aspect concerning the construction of the Media tone pointed out by the authors of the research is source type differences. Word recognition technique is quite sensitive to different source types such as traditional news and social media and, therefore, requires customization for each source during data processing. In general, tone of social media is more emotional than news media as it can contain emoticons and acronyms. The emotional nature of social media is also attributed to the absence of journalists that process several viewpoints and make news media more neutral. Due to above-mentioned differences of sources, different text analytical models are applied to traditional news, social media forums, tweets and so on.

One more characteristic of the nature of TRMI data is entity identification. Anti-correlate filters are applied to eliminate irrelevant entities: "For example, gold and silver are typically mentioned every two years during the Olympic Games but they are not related to gold and silver commodities". Except entity identification, TRMI takes into account difference between expectations and past events. Modifiers and negations are also considered when the TRMI score is calculated: for example, word "large" in a phrase "large loss" will have a higher multiplicative weight than a more frequent word "new". Multiplicative weights also vary between headlines, subtitles and article bodies that have the smallest multiplicative weight.

The data includes three feeds: news, social media and a combination of news and social media. During the day, TRMI processes more than 2 million articles and every minute the data is updated. As for sources of texts, TRMI is based on the data from:

- The most influential news organizations
- Global internet news coverage
- A wide range of social media sources

In addition, the data also includes hundreds of financial news sites and finance specific sources widely followed by professionals. Social media content has been derived from public social media sites from 1998 and from Moreover Technologies' aggregate social media feed from 2009.

Every TRMI indicator consists of a mixture of components called PsychVars. In order to create a TRMI variable, the absolute values of PsychVars are first set using 24 hours of observations. Then the Buzz-variable is calculated as the sum of those absolute values for all components. Mathematically it looks as follows:

$$Buzz_t(a) = \sum_{c \in C(a), p \in P} \left| PsychVar_{c,p,t} \right|$$

where t – time, a – the entity, C(a) - the set of all components of a, P(s) – the set of all PsychVars related to a specific TRMI indicator s.

The values for other TRMI indicators are calculated as follows:

$$TRMI_{s,t}(a) = \frac{\sum_{c \in C(A), p \in P(s)} (I_t(s,p) * PsychVar_{p,t}(c))}{Buzz_t(a)}$$

where $I_t(s,p)$ describes if a PsychVar $p \in P(s)$ is either additive or subtractive to a TRMI indicator s at time t:

$$I_t(s,p) = \begin{cases} +1, & if\ additive\ at\ time\ t \\ -1, & if\ subtractive\ at\ time\ t \end{cases}$$

4.2 Dependent Variable: Effective Nominal Dollar Exchange Rate Returns

As a dependent variable, I am going to use an effective nominal dollar exchange rate from the Bank for International Settlements Database. An effective dollar exchange rate serves as a better indicator of the macroeconomic effects of dollar exchange rate than any single dollar bilateral rate. A nominal effective dollar exchange rate is an index of dollar geometric weighted average of a basket of bilateral exchange rates. The weights represent trade flows and account for time-varying trade patterns. The trade-based weights capture not only direct bilateral trade, but also third-market competition.

There are two types of effective nominal dollar exchange rate index available: the broad index and the narrow index. The narrow index captures better the competitiveness among advanced economies whilst the broad index gives a more global picture by taking the emerging market economies into account. In this study, I am going to use both broad and narrow indexes to point out the difference in the effect of media on currencies of emerging and advanced economies.

Except an aggregate dollar exchange rate indicator, bilateral dollar exchange rates of three major currencies: British pound, Japanese yen and euro, - are going to be tested for the influence of news and social Media tone. Daily bilateral dollar exchange rates are gathered through the DataStream.

4.3 Overview of the findings of research papers using TRMI and financial data

There is a couple of research papers that have already explored the TRMI data and its relationship with the financial data. In this section, I am going to review the findings of other researchers about the nature of the TRMI data.

Gan et al. (2020) examine the relationship between social and news media using TRMI dataset across the time as well as the dynamic relationships between media activities and stock market activities. The authors use Sentiment and Buzz indices from TRMI and the implied volatility of stock index futures (VIX) at the daily frequency in their analysis. As for the econometric framework, the authors claim that a rolling-window vector autoregressive approach is the most suitable for this data as it not only captures the interdependence between news and social media but also allows to avoid assumptions of explicit exogeneity. The authors run the empirical analysis through 3 periods:

- *Pre-transition period* – period from January 2011 to December 2013 when the news media coverage stimulated activity in social media
- *The transition period* – period from January 2014 to December 2015 when news and social media activities tend to intertwine
- *The post-transition period* – period from January 2016 to November 2017 when social media activity starts to dominate news activity

The authors make several conclusions from their analysis:

a) The social media is becoming more dominant than traditional media.
b) The reaction of media sentiment to changes in stock market return and volatility is much stronger than the other way round.
c) The connection between volatility and media sentiment is more stable than the linkage between returns and media sentiment.
d) In the post-transition period, the effect of social media sentiment on returns is twice as much as in the pre-transition period.
e) In the post-transition period, the effect of news media sentiment on returns is twice as less as in the pre-transition period.

In line with Gan et al. (2020), Jiao et al. (2016) explore the impact of traditional news media and social media on stock market volatility. Unlike in previous research paper, the researchers use Buzz metric that is an indicator of how much activity market-moving themes, such as Litigation, Mergers, and Volatility are discussed and constructed parametric measure of realized idiosyncratic volatility in their analysis. In this study, the authors use three methods:

- Panel regression method since the dataset is by stocks and across time
- Panel vector autoregression (VAR) that allowed to test for Granger causality between variables
- GJR-GARCH model that allows to capture potential asymmetry in volatility

The main finding of the research is that whilst coverage by traditional news media decreases stock market volatility, coverage by social media increases stock market volatility. The authors explain this finding with a model of "echo chambers" which implies that social media repeats news but then this information is interpreted as completely new by some investors.

Another study that uses daily TRMI observations in the analysis (Nooijen and Broda, (2016)) is devoted to the predictive capabilities of Media Tone for the returns and volatility of MSCI U.S. Equity Sector Indices. The authors exploit EGARCH and Markov Switching EGARCH models for their analysis and find that Media tone has a higher predictability for stock volatility rather than for return.

The TRMI data is also available at frequencies that are more granular. Sun et al. (2016) focus on intraday (30 min) TRMI data and its predicting ability for stock index returns. They find out that TRMI Media tone during the first half trading hour acts as a strong predictor of the last two trading hours' stock index returns pointing out a slow adjustment of stock index returns to TRMI Media tone.

The consistency and validity of TRMI variables in measuring media-related investor sentiment has been already checked by many researchers. For example, Michaelides et al. (2015) confirm the efficiency of TRMI dataset by matching the manually collected sovereign downgrade news events with TRMI indictors. In the further research, Michaelides et al. (2019) control for media based public information using TRMI and manually created foreign exchange currency related news and in this way present another evidence of consistency of these two metrics.

Having analysed previous empirical literature using TRMI data, here I will formulate a couple of working research hypotheses:

1. *The impact of Media tone on dollar exchange rate volatility is expected to be time-varying*
2. *Social media is expected to have a stronger impact on exchange rate volatility than traditional news media*

5 EMPIRICAL ANALYSIS AND RESULTS

5.1 Modelling effective nominal dollar exchange rate volatility

Graphical analysis and descriptive statistics

A visual inspection of Figure 2 shows that daily effective nominal dollar exchange rate index is not stationary.

FIGURE 2. Daily US Dollar Broad Effective Nominal Exchange Rate Index (1998-2020)

In order to test for stationarity an Augmented Dickey–Fuller test (ADF) for a unit root in a time series sample is implemented. The calculated ADF test-statistic (Table 1) is equal to -0.72 and it is greater than the critical values at all the significance levels. Therefore, we fail to reject the null hypothesis that there is a unit root and that the series needs to be either differenced or transformed in order to make it stationary.

TABLE 1. Augmented Dickey-Fuller test of the daily index

ADF Test Statistic	1 % Critical value	-3,43
-0,72	5% Critical value	-2,86
	10% Critical value	-2,57

As in most empirical finance literature, the dollar exchange rate index is transformed into daily logarithmic returns using the following returns formula:

$$r_t = 100 * \log(\frac{P_t}{P_{t-1}})$$

Now let's visually analyse exchange rate return series. From Figure 3 we can already notice that clustering volatility exists in the series which indicates that traditional techniques of time series modelling such as ARIMA specifications may not be applicable in this case. Upward movements tend to be followed by other upward movements and downward movements also followed by other downward movements.

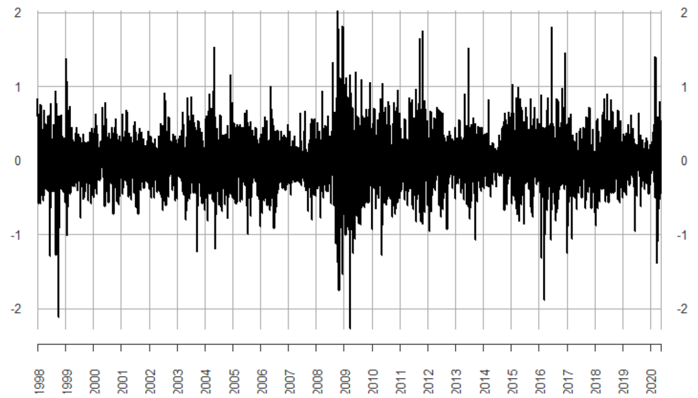

FIGURE 3. Daily US Dollar Broad Effective Nominal Exchange Rate Returns (1998-2020)

This indicates that the logarithm of effective nominal dollar exchange rate index is stationary after taking the first difference, and the ADF test results in Table 2 confirm the stationarity of the return series data. The computed ADF test-statistic is equal to -54.53 and it is smaller than all the critical values.

TABLE 2. Augmented Dickey-Fuller test of the daily returns

ADF Test Statistic	1 % Critical value	-3,43
-54,53	5% Critical value	-2,86
	10% Critical value	-2,57

A summary of the statistics of the return series data is given in Table 3. The mean is positive, suggesting that dollar exchange returns increase slightly over time.

TABLE 3. Summary Statistics for the returns of USD exchange rates

Number of Obs.	5839
Max.	2.02
Min.	-2.28
Mean	0.00
Median	0.00
Variance	0.10
Skewness	0.076
Kurtosis	6.50
Jarque-Bera test statistic	2987.30
JB p-value	0.00

Apart from the problem of volatility clustering existing in the series, the return series seem to be asymmetric:

a) The histogram of the return series is not bell-shaped indicating that the distribution of the return series is not normal (Figure 4).
b) Q-Q normal plot (Figure 5) reflects the stylized fact about exchange rate returns – fat tails: exchange rate returns have more extreme values than would be expected if they truly came from a normal distribution.
c) Another evidence of "fat tails" of exchange rate returns is its kurtosis, which is equal to 6.5 (Table 3), so called leptokurtic returns. The standard normal distribution has a kurtosis equal to approximately 3.
d) The skewness of 0.076 (Table 3) indicates that the returns are skewed right.
e) The Jarque Bera test statistic has a p-value of 0 (Table 3) which means that at 5% significance level we can reject the null hypothesis of the test that the distribution of exchange rate returns is normal.

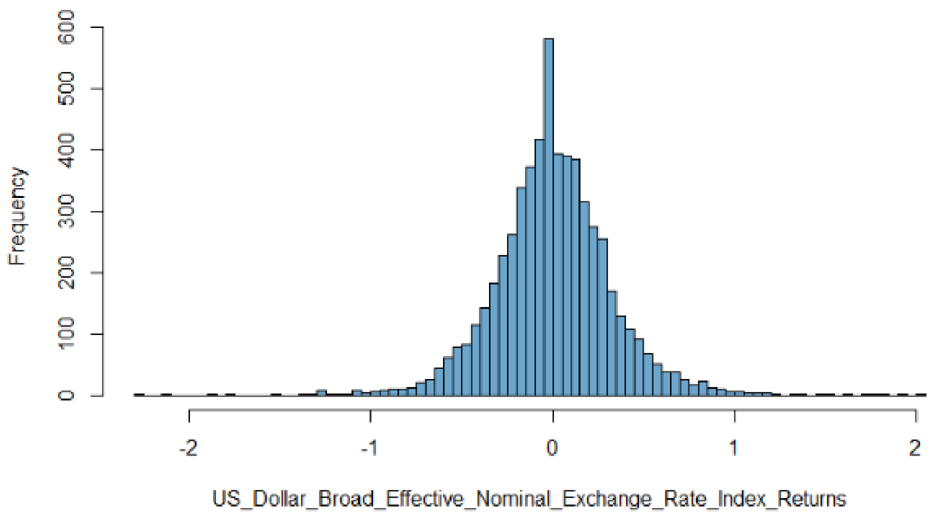

FIGURE 4. Histogram for Daily US Dollar Broad Effective Nominal Exchange Rate Returns (1998-2020)

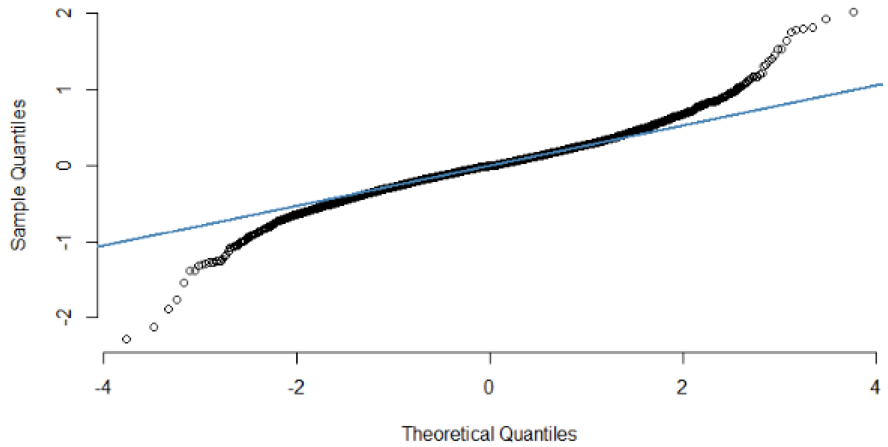

FIGURE 5. Q-Q normal plot for Daily US Dollar Broad Effective Nominal Exchange Rate Returns (1998-2020)

In this part, I will be modelling exchange rate volatility without any external regressors. Let's first check how well GARCH family models can fit the effective nominal dollar exchange rate volatility.

Testing returns for heteroscedasticity

Before applying the generalized autoregressive conditional heteroscedasticity methodology, it is first necessary to examine the residuals of the return series of exchange rate for evidence of heteroscedasticity.

In the first step of procedure, we obtain the residuals from the ordinary least squares regression of the conditional mean equation which is given by:

$$NERR_t = \alpha + \varepsilon_t$$

After obtaining the residuals ε_t, the next step is to regress the squared residuals on a constant and q lags. Let's use only one lag in our specification:

$$\varepsilon_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \upsilon_t$$

The estimated equation is given by:

$$\hat{\varepsilon}_t^2 = 0{,}084 + 0{,}198\varepsilon_{t-1}^2$$
$$(0{,}003) \quad (0{,}013)$$

The null hypothesis is that there are no ARCH effects up to order q and can be written as:

$$H_0: \alpha = \beta = 0$$

In the estimated equation, both constant and lagged value of the squared residuals are significantly different from zero value at the 5% significance level and, therefore, we can claim that there are ARCH effects in the dollar exchange rate return series up to order 1.

Fitting an effective nominal dollar exchange rate volatility with GARCH models

First, we need to define the lag structure of the mean equation of the GARCH specifications. We can make an assumption about an optimal number of AR lags by looking at the partial autocorrelation function plot (Figure 6): the process looks like a white noise.

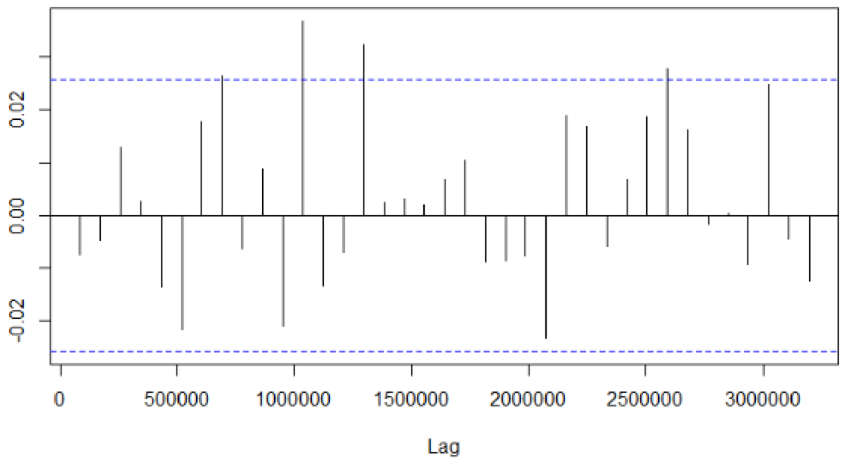

FIGURE 6. PACF Function for Daily US Dollar Broad Effective Nominal Exchange Rate Returns

The results of applying auto.arima() function with Bayesian information criterion as an optimizing parameter (Rstudio) confirm the assumption – optimal p of AR(p) model is equal to 0. Therefore, we will not include the lags of effective nominal dollar exchange rate returns into a mean equation in all GARCH specifications since the lags do not make the models better.

Before any estimations, let's make an assumption about the normal distribution of the standardized residuals of the models we are going to estimate.

Let's write down the specifications of models we are going to estimate. Specification for GARCH (1,1) looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t,\ \ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\textit{Variance equation}: \sigma_t^2 = \varpi + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Several conclusions can be drawn from the estimation of the standard GARCH (1,1) model (Table 4). First of all, the estimates of the model parameters are all significant at the 1% level except the constant μ of the mean equation. Secondly, the statistical significance of the coefficient α1 shows the presence of volatility clustering in the GARCH (1,1) model. Finally, volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is very close to one.

Specification for GJR-GARCH (1,1) looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t,\ \ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\textit{Variance equation}: \sigma_t^2 = \varpi + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1} y_{t-1}$$

Conclusions that can be drawn from the estimation of the GJR-GARCH (1,1) model (Table 4) confirm conclusions from standard GARCH (1,1) estimation as well as offer some new insights about the volatility. In line with GARCH (1,1) results, the estimates of the model parameters are all significant at the 1% level except the constant μ of the mean equation. The statistical significance of the coefficient α1 shows the presence of volatility clustering in the GJR-GARCH (1,1) model. Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is very close to one. The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility. The negative and significant value of γ1 implies presence of the "leverage effect": negative shocks have a greater impact on the conditional volatility than positive shocks.

Specification for EGARCH (1,1) looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t,\ \ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\textit{Variance equation}: \ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}}$$

Conclusions that can be drawn from the estimation of the EGARCH (1,1) model (Table 4) replicate some conclusions from GJR-GARCH (1,1) estimation but also give some opposing to GJR-GARCH (1,1) information regarding an asymmetric behaviour of dollar exchange rate volatility. The estimates of the model parameters are all significant at the 1% level except the constant μ of the mean equation. The statistical significance of the coefficient α1 shows the presence of volatility clustering in the EGARCH (1,1) model. Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is very close to one. The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility. The positive and significant value of γ1 implies presence of the "leverage effect": positive shocks have a greater impact on the conditional volatility than negative shocks.

Specification for APARCH (1,1) looks as follows:

$$\textit{Mean equation}: r_t = \mu + y_t,\ \ y_t = \sigma_t \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2)$$

$$\textit{Variance equation: } \sigma_t^\delta = \varpi + (\alpha_1 |y_{t-1}| - \gamma_1 y_{t-1})^\delta + \beta_1 \sigma_{t-1}^\delta$$

Conclusions based on the estimation of the APARCH (1,1) model (Table 4) coincide with the conclusions made based on GJR-GARCH (1,1) estimations. The estimates of the model parameters are all significant at the 1% level except the constant μ of the mean equation. The statistical significance of the coefficient α1 shows the presence of volatility clustering in the APARCH (1,1) model. Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is very close to one. The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility. The negative and significant value of γ implies presence of the "leverage effect": negative shocks have a greater impact on the conditional volatility than positive shocks.

TABLE 4. Estimations of different GARCH-family models

	GARCH (1,1)	**GJR-GARCH(1,1)**	**EGARCH(1,1)**	**APARCH(1,1)**
μ	-0,0008	0,0007	0,0016	0,0008
	(0,82)	*(0,84)*	*(0,65)*	*(0,82)*
ω	0,0009	0,0009	-0,0246	0,0012
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*
α1	0,0512	0,0570	0,0164	0,0520
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*
β1	0,9402	0,9437	0,9880	0,9435
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*
γ1		-0,0179	0,0117	-0,1025
		(0,01)	*(0,00)*	*(0,01)*
δ				1,7535
				(0,00)
Log Likelihood	-1189,33	-1185,72	-1190,97	-1184,84*
AIC	0,4088	0,4079*	0,4097	0,4079*
HQ	0,4104	0,4079*	0,4117	0,4103
BIC	0,4134*	0,4136	0,4154	0,4148

*Note: p-values are shown in parentheses. * indicates the minimal information criteria across the models.*

Overall, GJR-GARCH (1,1) model seems to have the best quality out of 4 estimated models because:

- It catches an asymmetric behaviour of dollar exchange rate returns compared to GARCH (1,1) model.
- It has the smallest Akaike and Hannan-Quinn information criteria out of three estimated asymmetric models.

In this section, it has been found out that:

a) Asymmetric GARCH specifications perform better than symmetric ones in modelling dollar exchange rate volatility.
b) Volatility shocks are persistent throughout the time, which means that there are some factors which have a continuous effect on the dollar exchange rate volatility.
c) The "leverage effect" is present in the dollar return series: It is not stable across the GARCH specifications but most of them infer that positive returns have a greater impact on conditional volatility than negative returns.

In addition, all the estimations of GARCH specifications confirm that there is a volatility clustering in the dollar exchange rate series.

5.2 Modelling the impact of Media tone on effective nominal dollar exchange rate volatility: Broad Index, Narrow Index and Bilateral Exchange Rates

Now we have understood that impact of dollar exchange rate returns on their volatility is asymmetric. Let's try to solve the exchange rate puzzle (explain dollar exchange rate volatility in the short-run period) by including news and social media dollar sentiments into regression equation.

Figure 7-8 show that on average news dollar sentiment volatility is smaller than social media dollar sentiment volatility but it is more persistent. Based on the visual analysis, we can assume that news and social media dollar sentiments can explain effective nominal dollar exchange rate volatility in the short-run.

From Figure 8 we can also notice that that during 1998-2001 the volatility of daily social media sentiment US dollar sentiment is much higher than afterwards and this can be caused by the massive growth in the use and adoption of the Internet that started in 1995 and resulted into the burst of the so-called dot-com bubble in March 2000. During 1998-2001, positive and negative news were emotionally stronger than after that period when the use of Internet became more like a habit. Therefore, this period of extremely high values of social Media tone can be considered as a period-outlier that should be taken into account when estimating the impact of social Media tone on dollar exchange rate volatility.

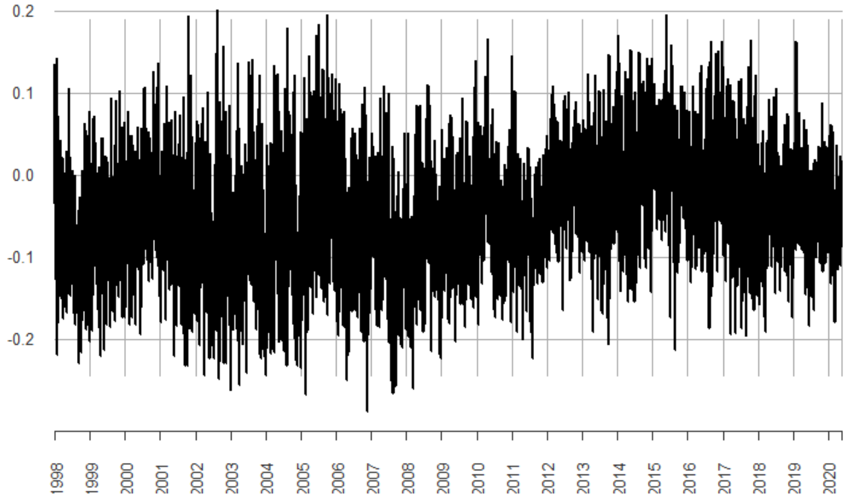

FIGURE 7. Daily News US Dollar Sentiment (1998-2020)

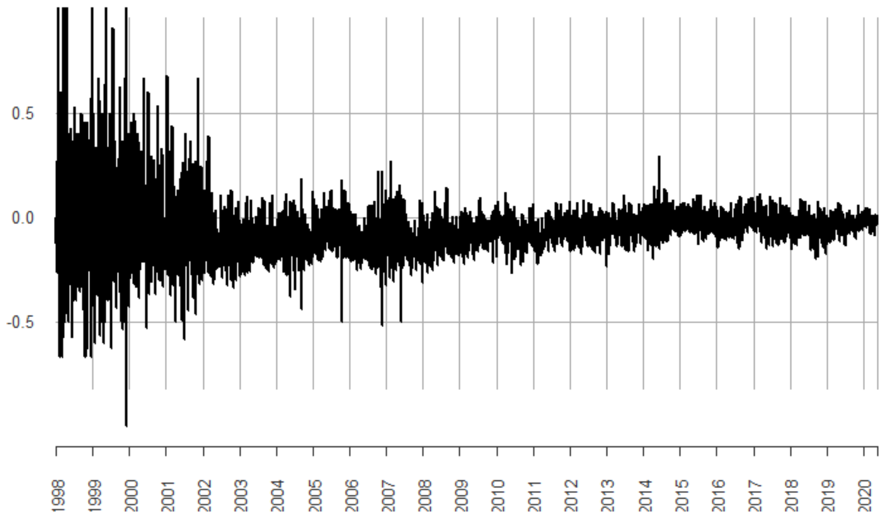

FIGURE 8. Daily Social Media US Dollar Sentiment (1998-2020)

First, let's check whether there are still ARCH effects in the residuals of the return series if we include news and social media dollar sentiments as external regressors into the regression specification.

In the first step of procedure, we obtain the residuals from the ordinary least squares regressions of the conditional mean equations which are given by:

$$NERR_t = \alpha + \gamma News\_Sentiment_t + \varepsilon_t$$

$$NERR_t = \alpha + \gamma Social\_Media\_Sentiment_t + \varepsilon_t$$

After obtaining the residuals ε_t, the next step is to regress the squared residuals on a constant and q lags. Let's use only one lag in our specification:

$$\varepsilon_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \upsilon_t$$

The estimated equations are given by:

News US Dollar Sentiment	*Social Media US Dollar Sentiment*
$\hat{\varepsilon}_t^2 = 0{,}076 + 0{,}217\varepsilon_{t-1}^2$	$\hat{\varepsilon}_t^2 = 0{,}083 + 0{,}198\varepsilon_{t-1}^2$
(0,003) (0,013)	(0,003) (0,013)

The null hypothesis is that there are no ARCH effects up to order q and can be written as:

$$H_0: \alpha = \beta = 0$$

In the estimated equations, both constants and lagged values of the squared residuals are significantly different from zero value at the 1% significance level and, therefore, we can claim that there are ARCH effects in the dollar exchange rate return series up to order 1.

Before the estimations, let's make a couple of assumptions about the models:

- Standardized residuals have Student't t distribution.
- News dollar sentiment has an effect on both conditional mean and volatility of the exchange rate returns whilst social media sentiment has an impact only on conditional volatility of exchange rate returns.

Having run different specifications of GARCH-family models, I have discovered that EGARCH is the one which can reveal the impact of news on conditional volatility of dollar exchange rate returns. Therefore, from now on I will be using EGARCH model in my estimations. Here are the asymmetric EGARCH (1,1) with ARMA (0,0) for the mean specifications I am going to estimate:

Specification I:

Mean equation: $r_t = \mu + y_t + \delta News\_Sent_t,\ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_t$

The conclusions that can be drawn from the estimation of the EGARCH (1,1) model with ARMA (0,0) for the mean (Table 5) are presented below:

a) The estimates of the model parameters are all significant at the 1% level except the λ meaning that news dollar sentiment does not have an immediate impact on conditional volatility of effective nominal dollar exchange rate returns.
b) Estimated δ is positive and significant which means that the 1-unit increase in the news dollar sentiment increases the conditional mean of effective nominal dollar exchange rate logarithmic returns by 1,089.
c) The statistical significance of the coefficient α1 shows the presence of volatility clustering in the EGARCH (1,1) model.
d) Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is very close to one.

e) The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility.
f) The positive and significant value of γ1 implies presence of the "leverage effect": positive shocks have a greater impact on the conditional volatility than negative shocks.

TABLE 5. Modelling the Impact of News US Dollar Sentiment on Effective Nominal Dollar Exchange Rate Volatility with EGARCH (1,1) and ARMA (0,0) for the mean

	Coefficient	P-value
μ	0,053	0,00
δ	1,089	0,00
ω	-0,032	0,00
α1	0,026	0,00
β1	0,987	0,00
γ1	0,125	0,00
λ	0,011	0,78
Log Likelihood	-807,246	
AIC	0,279	

Let's try to include lagged values of news US dollar sentiment into the variance equation of the specification I:

Mean equation: $r_t = \mu + y_t + \delta News\_Sent_t,\ y_t = \sigma_t\varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_{t-j},\ j = 1,..,18$

Figure 9-10 show that the further is the lag from today, the more significant is the impact of news dollar sentiment on conditional volatility of effective nominal dollar exchange rate returns. The first significant at 10% significance level lambda appeared at the 17th lag meaning that there is a long-run adjustment of effective nominal exchange rate volatility to news information about US dollar.

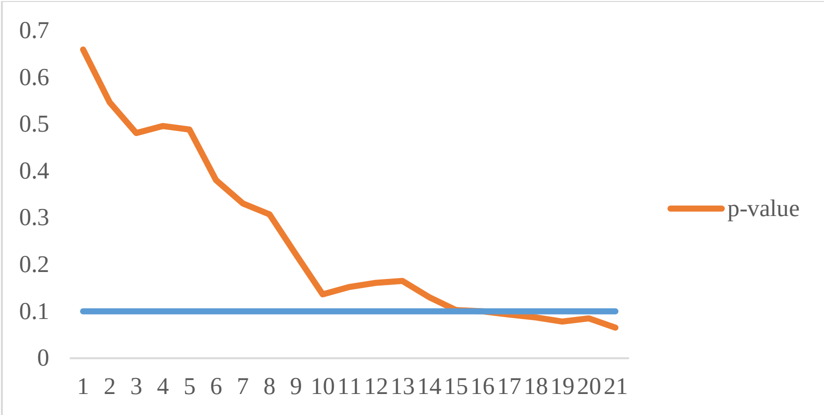

***FIGURE 9.** P-values of lambda coefficients (horizontal axis – number of the lag)*

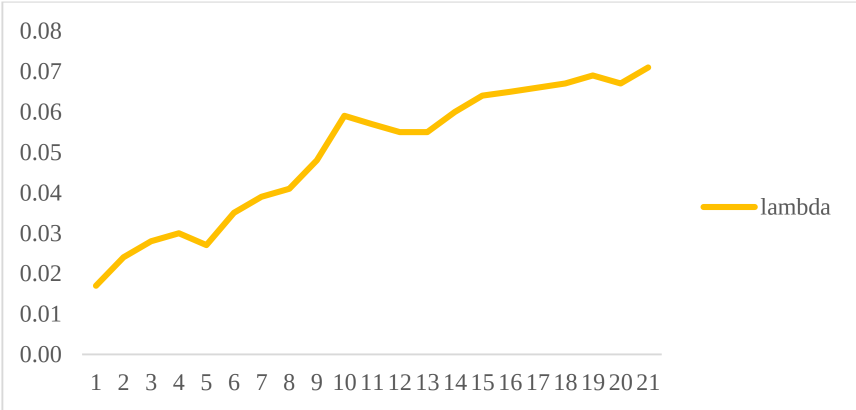

FIGURE 10. Lambda coefficients (horizontal axis – number of the lag)

The specification of the EGARCH (1,1) model with ARMA(0,0) for the mean and lagged news dollar sentiment as an external regressor in the volatility equation looks as follows:

Mean equation: $r_t = \mu + y_t + \delta News\_Sent_t,\ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_{t-17}$

The conclusions that can be drawn from Table 6 are discussed below:

a) The estimates of the model parameters are all significant at the 1% level except the λ which is significant at 10% level.
b) An increase of 1 unit in news dollar sentiment today results in 0,07 increase in volatility of effective nominal dollar exchange rate returns 17 days later.
c) Estimated δ is positive and significant which means that the 1-unit increase in the news dollar sentiment today increases the conditional mean of effective nominal dollar exchange rate logarithmic returns by 1,089 today.
d) The statistical significance of the coefficient α1 shows the presence of volatility clustering in the EGARCH (1,1) model.
e) Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is around one.

f) The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility.
g) The positive and significant value of γ1 implies presence of the "leverage effect": positive shocks have a greater impact on the conditional volatility than negative shocks.

TABLE 6. Modelling the Impact of News US Dollar Sentiment (17th lag) on Effective Nominal Dollar Exchange Rate Volatility with EGARCH (1,1) and ARMA (0,0) for the mean

	Coefficient	P-value
μ	0,053	0,00
δ	1,097	0,00
ω	-0,028	0,00
α1	0,030	0,00
β1	0,988	0,00
γ1	0,122	0,00
λ	0,066	0,093
Log Likelihood	-805,91	
AIC	0,279	

Specification II:

Mean equation: $r_t = \mu + y_t,\ y_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda Social\_Media\_Sent_t$

The conclusions that can be drawn from the estimation of the EGARCH (1,1) model with ARMA (0,0) for the mean (Table 7) are presented below:

a) The estimates of the model parameters are all significant at the 1% level except the λ which is significant at 5% level.
b) An increase of 1 unit in social media dollar sentiment today results in 0,06 decrease in volatility of effective nominal dollar exchange rate returns today.
c) The statistical significance of the coefficient α1 shows the presence of volatility clustering in the EGARCH (1,1) model.
d) Volatility shocks are persistent since the sum of the ARCH and GARCH coefficients (α1+β1) is around one.
e) The coefficient γ1 is significantly different from zero, which indicates the presence of asymmetric behaviour: positive and negative shocks of the same magnitude have different effect on conditional volatility.
f) The negative and significant value of γ1 implies presence of the "leverage effect": negative shocks have a greater impact on the conditional volatility than positive shocks.

TABLE 7. Modelling the Impact of Social Media US Dollar Sentiment on Effective Nominal Dollar Exchange Rate Volatility with EGARCH (1,1) and ARMA (0,0) for the mean

	Coefficient	P-value
ω	-0,030	0,00
α1	0,022	0,00
β1	0,99	0,00
γ1	0,114	0,00
λ	-0,059	0,05
Log Likelihood	-1086,25	
AIC	0,374	

Figure 11-12 show that the further is the lag of social media dollar sentiment from today, the more insignificant lambda coefficient becomes confirming the fact that the effect of social media dollar sentiment on effective nominal dollar exchange rate volatility is immediate and fades away with the time.

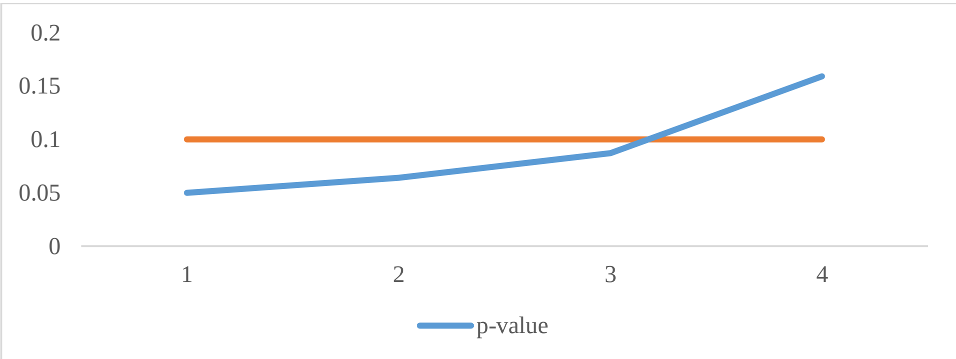

FIGURE 11. P-values of lambda coefficients (horizontal axis – number of the lag)

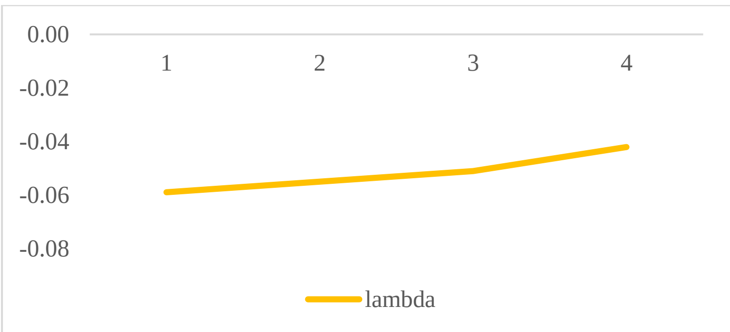

FIGURE 12. Lambda coefficients (horizontal axis – number of the lag)

As it was noticed earlier, the period from 1998-2001 was characterized by much higher values of social Media tone than afterwards and this deserves to be taken care of. Let's estimate the same specification as above but excluding the period from 1998 to 2001.

From Table 8 we can notice that now there is a small significantly positive impact of social Media tone on conditional mean of dollar exchange rate volatility (δ) but now we can not tell anything about the impact of social Media tone on conditional volatility of dollar exchange rate volatility (λ), since $\alpha 1$ is statistically insignificant and, therefore, we can't adequately interpret the coefficients of that equation.

TABLE 8. Modelling the Impact of Social Media US Dollar Sentiment on Effective Nominal Dollar Exchange Rate Volatility with EGARCH (1,1) and ARMA (0,0) for the mean (1998-2001 excluded)

	Coefficient	P-value
μ	0,0004	0,00
δ	0,0082	0,00
ω	-0,0869	0,00
$\alpha 1$	-0,0002	0,97
$\beta 1$	0,9925	0,00
$\gamma 1$	0,1035	0,00
λ	-0,0476	0,09
Log Likelihood	20276,5	
AIC	-8,315	

That was the case of a broad nominal dollar effective exchange rate index. Now let's explore the case of a narrow index (Figure 13): we can already notice that volatility of dollar exchange rate against currencies of advanced countries is a bit higher than against currencies of both advanced and emerging countries.

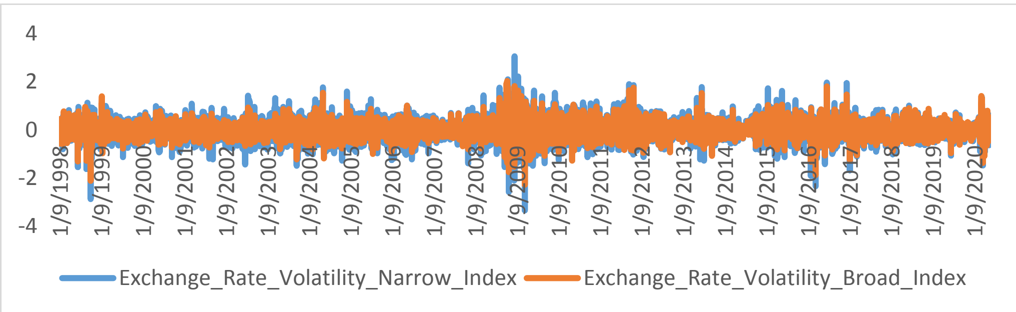

FIGURE 13. Daily returns for Narrow and Broad Nominal Dollar Exchange Rate Indexes

From the estimations given in the Table 9, it is clearly seen that social media and news sentiments significantly increase the conditional mean of dollar exchange rate volatility against currencies of advanced countries. However, it is not possible to conclude about the impact of social and news Media tones on conditional volatility of dollar exchange rate volatility (λ), since α1 is statistically insignificant and, therefore, we can't adequately interpret the coefficients of that equation.

TABLE 9. Modelling the Impact of Media Tone on Effective Nominal Dollar Exchange Rate Volatility with EGARCH (1,1) and ARMA (0,0) for the mean: Case of Narrow Index

	Social Media Sentiment		*News Sentiment*	
	Coefficient	P-value	Coefficient	P-value
μ	0,018	0,00	0,080	0,00
δ	0,347	0,00	1,776	0,00
ω	-0,017	0,00	-0,023	0,00
α1	0,002	0,73	0,005	0,50
β1	0,992	0,00	0,990	0,00
γ1	0,101	0,00	0,117	0,00
λ	-0,032	0,21	-0,046	0,24
Log Likelihood	-2534,24		-2169,56	
AIC	0,904		0,774	

However, let's analyses deeper the nature of the US dollar exchange rate volatility against currencies of advanced economies and consider the impact of news and social media sentiments on the US dollar exchange rate volatility against three major currencies: British pound, Japanese yen and euro (Figure 14-16).

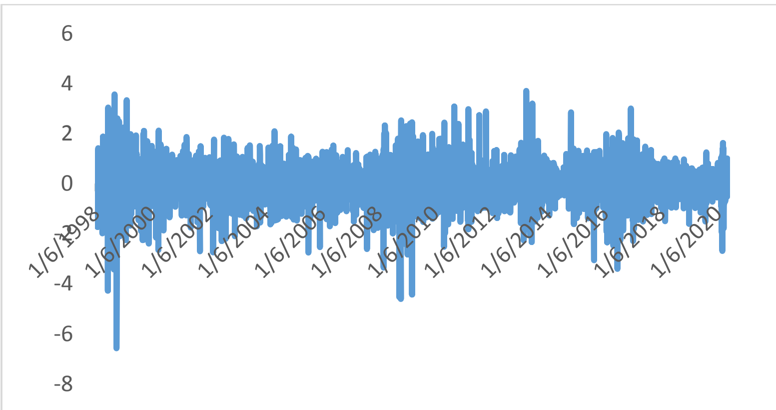

FIGURE 14. US Dollar Exchange Rate Volatility against Japanese Yen

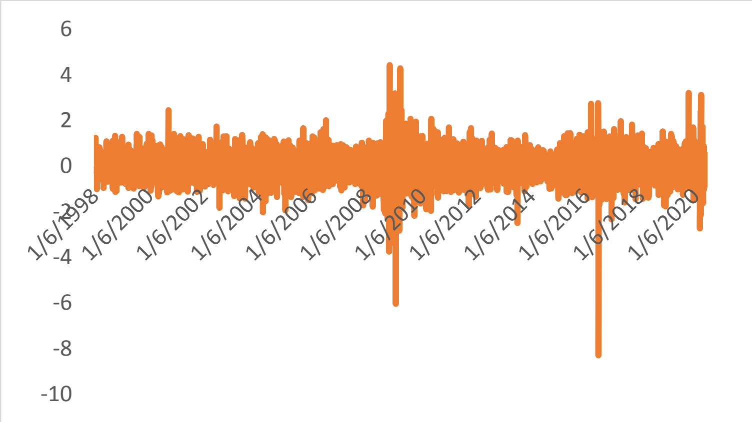

FIGURE 15. US Dollar Exchange Rate Volatility against British Pound

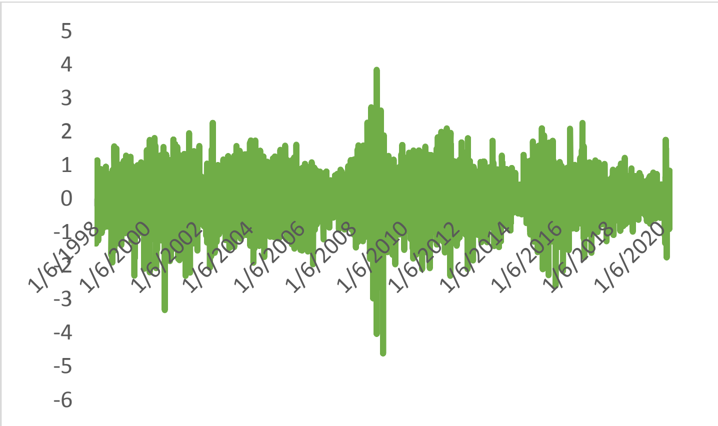

FIGURE 16. US Dollar Exchange Rate Volatility against Euro

Let's analyse coefficients of interest across different specifications (Table 10):

- δ : Apparently the impact of news sentiment on US dollar exchange rate volatility against British pound and Japanese yen is much greater than the impact of social media sentiment. For the Euro case, I did not succeed to find a model that converges when Media tone sentiment is included into the mean equation. The impact of Media tone (both news and social media) is more pronounced in case of Japanese yen rather than British pound. The Media tone increases the conditional mean of US dollar exchange rate volatility against Japanese yen but decreases the conditional mean of US dollar exchange rate volatility against British pound.
- λ : News sentiment decreases the conditional variance of US dollar exchange rate returns against Japanese yen and Euro but in case of Japanese yen the effect is more pronounced. Social Media tone decreases he conditional variance of US dollar exchange rate returns against British pound.

TABLE 10. Modelling the Impact of Media Tone on US Dollar Exchange Rate Volatility against British Pound, Japanese Yen and Euro with EGARCH (1,1) and ARMA (0,0) for the mean

	News Sentiment			*Social Media Sentiment*		
	British Pound	Japanese Yen	Euro	British Pound	Japanese Yen	Euro
μ	-0,067	0,103		-0,019	0,030	
	(0,00)	*(0,00)*		*(0,00)*	*(0,00)*	
δ	-1,371	2,441		-0,332	0,452	
	(0,00)	*(0,00)*		*(0,00)*	*(0,00)*	
ω	-0,009	-0,012	-0,004	-0,013	-0,011	-0,002
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*	*(0,00)*	*(0,09)*
$\alpha1$	-0,025	-0,029	0,014	-0,027	-0,016	0,008
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*	*(0,03)*	*(0,07)*
$\beta1$	0,989	0,987	0,996	0,991	0,989	0,996
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*	*(0,00)*	*(0,00)*
$\gamma1$	0,123	0,136	0,077	0,083	0,118	0,078
	(0,00)	*(0,00)*	*(0,00)*	*(0,00)*	*(0,00)*	*(0,00)*
λ	-0,022	-0,089	-0,043	-0,045	-0,007	0,003
	(0,48)	*(0,02)*	*(0,00)*	*(0,04)*	*(0,80)*	*(0,86)*
Log Likelihood	-4399,09	-4996,88	-4741,61	-4386,93	-5066,91	-4743,39
AIC	1,57	1,78	1,69	1,56	1,80	1,69

In this section, it has been found out that:

- News dollar sentiment has a significant and positive impact on the mean of dollar exchange rate returns meaning that positive news about US dollar increase the mean of dollar exchange rate returns and negative news about US dollar decrease the mean of return series whilst social media dollar sentiment does not affect the mean of the dollar exchange rate returns.
- There is a long-run adjustment of the dollar exchange rate volatility to news about US dollar whereas the effect of social media information about US dollar on dollar exchange rate volatility is immediate.
- News about US dollar increase the conditional volatility of dollar exchange rate returns whereas social media information about US dollar decreases the conditional volatility of dollar exchange rate returns.

5.3 Evaluation of the impact of Media tone information on effective nominal dollar exchange rate volatility

In this part, I am going to compare three GARCH models with effective nominal dollar exchange rate volatility as a dependent variable (without external regressors, with news dollar sentiment as an external regressor and social media dollar sentiment as an external regressor) in order to define the role of different sources of media in modelling dollar exchange rate volatility.

Model I without external regressors: GJR-GARCH (1,1)

Mean equation: $r_t = \mu + y_t,\ \ y_t = \sigma_t \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\sigma_t^2 = \varpi + \alpha_1 y_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 I_{t-1} y_{t-1}$

Model II with news dollar sentiment as an external regressor: EGARCH (1,1) with lagged news dollar sentiment as an external regressor both in the mean and variance equations

Mean equation: $r_t = \mu + y_t + \delta News\_Sent_{t-1},\ \ y_t = \sigma_t \varepsilon_t,\ \ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_{t-1}$

Model III with social media dollar sentiment as an external regressor: EGARCH (1,1) with social media dollar sentiment as an external regressor in the variance equation

Mean equation: $r_t = \mu + y_t,\ y_t = \sigma_t \varepsilon_t, \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda Social\_Media\_Sent_t$

Figure 17 shows the estimated conditional volatility against dollar exchange rate returns based on three asymmetric GARCH specifications described above: it is clear from the graph that the fitted values of conditional volatility of three different models are so similar that we can't even see all the lines since they overlap each other. However, it is worth to notice that visually it seems that estimated conditional volatility explains the returns quite well catching both an overall trend and spikes.

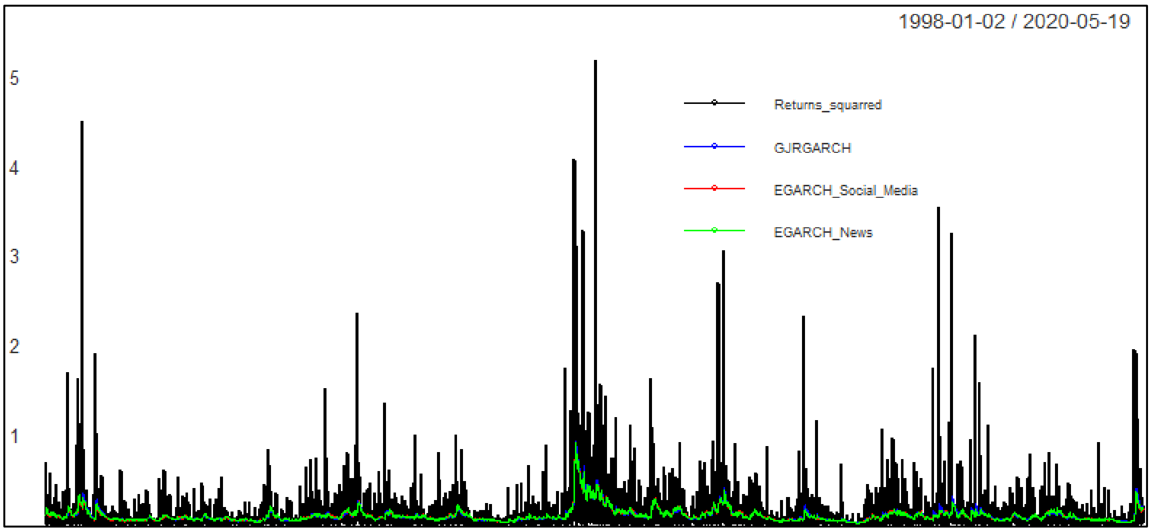

FIGURE 17. Squared dollar exchange rate returns (black) against estimated conditional volatility (blue, red and green)

To understand the quantitated contribution of Media tone information to dollar exchange rate volatility, let's calculate the R^2 from a Mincer-Zarnowitz regression:

$$r_t^2 = \alpha + \beta \hat{\sigma}_t^2 + u_t$$

where squared returns are regressed on the model forecast of conditional variance and a constant.

As we can see from the Table 11., the inclusion of Media tone information into GARCH specifications is statistically significant and helps to explain the dollar exchange rate returns, however quantitatively the contribution of Media tone information in explaining the dollar exchange rate returns is really small since the R^2 is approximately the same across all the three specifications.

TABLE 11. Results of OLS regression of squared dollar exchange rate returns on estimated conditional variance

	Coefficient	**P-value**	R^2
GJR-GARCH(1,1)	0,95	0,00	10,43%
EGARCH(1,1) + Social Media Dollar Sentiment	1,06	0,00	10,84%
EGARCH(1,1) + News Dollar Sentiment	1,05	0,00	10,85%

In this section, it has been found out that both news and social media information about US dollar have a statistically significant impact on the dollar exchange rate returns and their volatility, but the impact is so small that economically it is insignificant.

5.4 Revealing the influence of GFC on the impact of Media tone on effective nominal dollar exchange rate volatility

Global financial crisis of 2007-2008 has become a breaking point in many financial processes. GFC refers to the times of high stress in global financial markets and banking systems. The catalyst for a financial crisis happened to be a downturn in the US housing market. Financial crisis spreaded from the United States to the rest of the world quite fast through linkages in the global financial system. Therefore, GFC is worth to be considered in modelling the impact of news and social media dollar sentiment on effective nominal dollar exchange rate volatility.

Let's use September, 2008 (Lehman Brothers' collapse) as a breaking point in Global Financial Crisis and estimate the impact of news and social media dollar sentiment on effective nominal dollar exchange rate volatility before and after this date. In the estimations below, I will concentrate mainly on conditional volatility and that is why mean equation is set to zero. I am using standard exponential GARCH

(1,1) model to compare the effect of Global Financial Crisis on the impact of news and social media US dollar sentiment on effective nominal dollar exchange rate volatility.

From the Table 12 we can make several conclusions. First of all, it can be noted that if we consider periods before and after GFC instead of a longer combined period, news US dollar sentiment turns to immediately decrease the conditional volatility of effective nominal dollar exchange rate. Together with previous findings, this means that in the short-run the information about US dollar from news decreases the conditional volatility of effective nominal dollar exchange rate whilst in the long-run it actually increases the conditional volatility of effective nominal dollar exchange rate. Secondly, before Global Financial Crisis news about US dollar had a slightly smaller effect on conditional volatility of effective nominal dollar exchange rate than social media information about US dollar and most probably the explanation behind it is the dot com bubble which happened in the United States during 2000-2001. Finally, after Global Financial Crisis news about US dollar turned to have a greater impact on conditional volatility of effective nominal dollar exchange rate than social media information about US dollar: in general, people started to trust official news more than the unofficial information from social media.

TABLE 12. Modelling the Impact of News and Social Media US Dollar Sentiment on Effective Nominal Dollar Exchange Rate Volatility before and after GFC

	Before GFC				After GFC			
	News Sentiment		Social Media Sentiment		News Sentiment		Social Media Sentiment	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
ω	-0,069	0,040	-0,028	0,000	-0,028	0,000	-0,029	0,003
α1	0,025	0,003	0,033	0,001	0,033	0,001	0,030	0,003
β1	0,977	0,000	0,989	0,000	0,990	0,000	0,990	0,000
γ1	0,113	0,000	0,110	0,000	0,110	0,000	0,113	0,000
λ	-0,153	0,035	-0,167	0,011	-0,167	0,011	-0,132	0,068

From Table 12 we can also notice that before and after GFC we can observe a significantly negative instant effect of news sentiment on dollar exchange rate conditional volatility. A probable explanation for that could be such a huge amount of disperse information, speculation, wrong information existing at those time that official media would have to correct the agents thoughts and lessen the uncertainty in the markets (Figure 18-20):

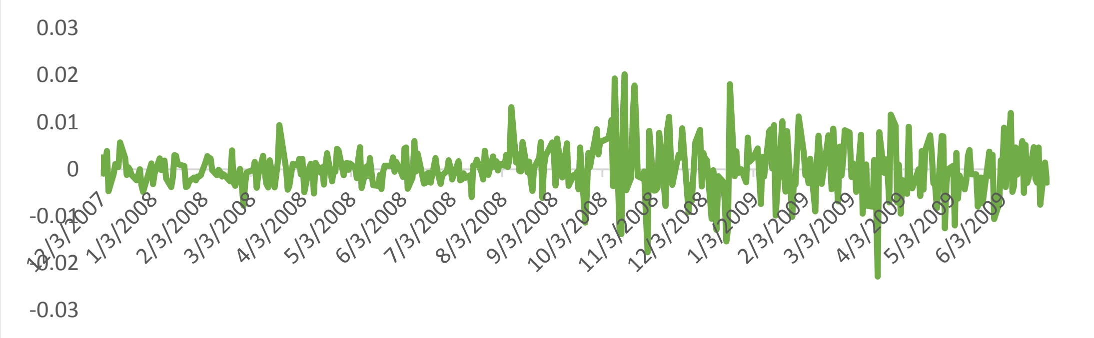

FIGURE 18. Dollar Exchange Rate Volatility around Global Financial Crisis

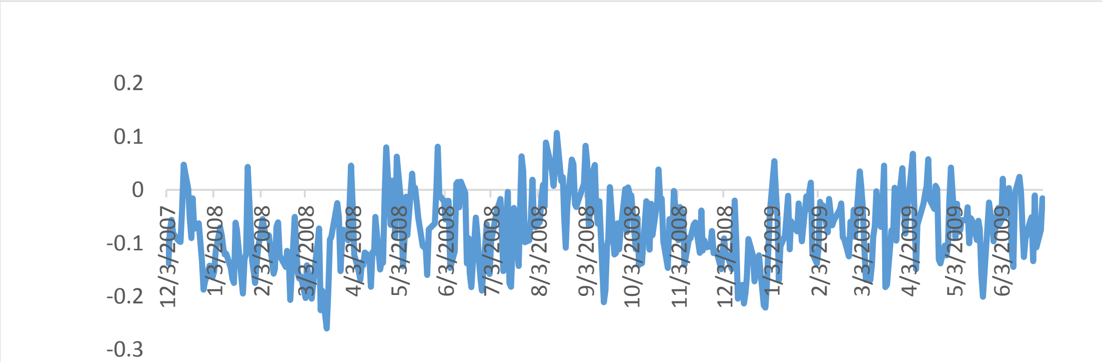

FIGURE 19. News Dollar Sentiment around Global Financial Crisis

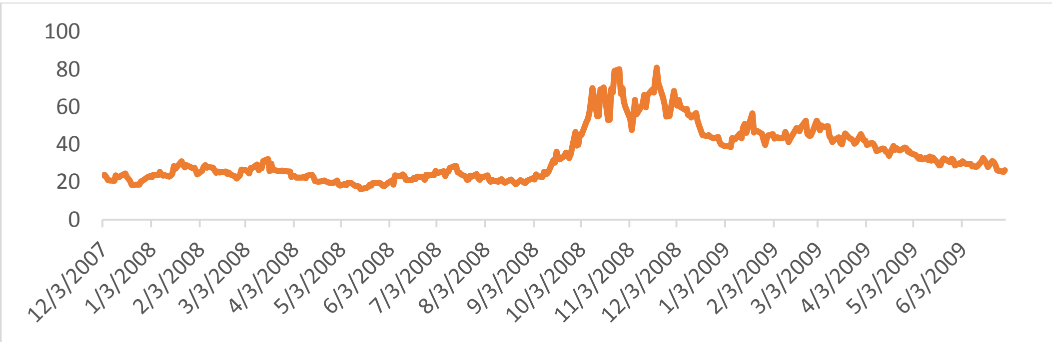

FIGURE 20. VIX around Global Financial Crisis

To test this hypothesis, let's introduce VIX as a general measure of financial uncertainty into our USD conditional volatility model:

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_t + \eta VIX_t + \mu News\_Sent_t * VIX_t$

We will expect that VIX increases the USD volatility whilst the cross estimate (VIX*Media Tone) significantly decreases it and this would mean that media while providing information decreases the impact of the general uncertainty. Now let's check this hypothesis by running exponential GARCH (1,1) excluding the equation for conditional mean.

In the Table 13, we can see the estimations and, unfortunately, I did not manage to find a specification that could allow me to infer anything about the hypothesis since $\alpha 1$ is statistically insignificant meaning that there is no volatility clustering around GFC in the model with external regressors included.

TABLE 13. Modified USD Conditional Volatility Model

	Coefficient	P-value
ω	-3,28	0,02
$\alpha 1$	-0,07	0,23
$\beta 1$	0,73	0,00
$\gamma 1$	0,12	0,19
λ	3,61	0,03
η	0,01	0,09
μ	-0,06	0,17

In this section, it has been found out that Global Financial Crisis has changed the impact of news and social media sentiments on dollar exchange rate volatility: whilst social media sentiment had a greater impact on dollar exchange rate volatility than news sentiment before GFC, news sentiment has turned to dominate social media sentiment in the impact on dollar exchange rate volatility after GFC. Additionally, in this section, there has been an attempt to explain a negative sign of news and social media impact on dollar exchange rate volatility with the financial uncertainty indicator VIX but this attempt has not been successful as there has not been found an adequate for interpretation GARCH model.

5.5 Modelling the impact of Media tone on effective nominal dollar exchange rate volatility across different sources

Except an aggregated data of news dollar sentiment, the data from specific news sources is available in Thomson Reuters Database: Financial Times, New York Times, The Economist and Wall Street Journal. The data from specific sources is quite gappy and, therefore, effective nominal dollar exchange rate returns were calculated from last available date to next available date meaning that returns can't be called daily returns. Let's estimate exponential GARCH (1,1) - ARMA (1,1) specification across different news sources in order to compare the impact of specific news on effective nominal dollar exchange rate volatility:

Mean equation: $r_t = \mu + \eta r_{t-1} + y_t + \nu y_{t-1} + \delta News\_Sent_{t-1},\ y_t = \sigma_t \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_t^2)$

Variance equation: $\ln(\sigma_t^2) = \varpi + \alpha_1 \left|\frac{y_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \ln(\sigma_{t-1}^2) + \gamma_1 \frac{y_{t-1}}{\sigma_{t-1}} + \lambda News\_Sent_{t-1}$

Some conclusions that can be drawn from Table 14:

a) Looking at the estimated δ coefficients across the specifications, it can be inferred that news from all the sources affect the conditional mean of the effective nominal dollar exchange rate returns but the value of this impact is very small: news from Financial Times, New York Times and Wall Street Journal immediately increase the conditional mean whilst news from the Economist instantly decrease the conditional mean of returns series.
b) The estimated equation of conditional variance cannot be interpreted in the case of Wall Street Journal since $\alpha 1$ is not significant but other three sources there are no problems in interpretations of that equation: news from New York Times do not significantly affect the conditional dollar exchange rate volatility whereas news from Financial Times and the Economist decrease the conditional volatility of return series in the short-run.
c) The value of λ coefficient in case of Financial Times is lower than in case of the Economist meaning that news from Financial Times have a larger impact on conditional volatility of dollar exchange rate returns than news from the Economist. Such a difference can be attributed to the fact that FT is published daily and The Economist – weekly.

TABLE 14. Modelling the Impact of News US Dollar Sentiment from different sources on Effective Nominal Dollar Exchange Rate Volatility

	Financial Times		New York Times		The Economist		Wall Street Journal	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
μ	0,00002	0,16	0,00005	0,04	0,00035	0,00	0,00013	0,00
η	-0,35106	0,00	-0,86917	0,00	0,17449	0,00	0,71492	0,00
ν	0,34225	0,00	0,88529	0,00	-0,19268	0,00	-0,72318	0,00
δ	0,00012	0,00	0,00015	0,00	-0,00023	0,00	0,00069	0,00
ω	-0,24504	0,00	-0,36186	0,00	-0,16633	0,00	-0,11134	0,00
$\alpha 1$	0,03846	0,00	0,05813	0,00	0,08384	0,00	0,00175	0,80
$\beta 1$	0,98135	0,00	0,97100	0,00	0,98355	0,00	0,98915	0,00
$\gamma 1$	0,17128	0,00	0,19115	0,00	-0,05702	0,00	0,14708	0,00
λ	-0,03122	0,02	0,01168	0,29	-0,01897	0,00	0,03747	0,00

Now let's estimate the same models but after Global Financial Crisis (Table 15):

a) After GFC news from NYT, TE and WSJ do not have impact on conditional mean of exchange rate returns anymore (δ is insignificant) whilst news from FT still significantly increase it.

b) The equation of conditional volatility in case of WSJ is still not interpretable and news from NYT still do not have an impact on conditional volatility of dollar exchange rate series. However, the effect of FT and TE news on exchange rate volatility becomes more pronounced after Global Financial Crisis.

TABLE 15. Modelling the Impact of News US Dollar Sentiment from different sources on Effective Nominal Dollar Exchange Rate Volatility after GFC

	Financial Times		New York Times		The Economist		Wall Street Journal	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value
μ	0,00004	0,05			0,00082	0,00		
η					-0,05804	0,00		
δ	0,00007	0,00						
ω	-0,3615	0,00	-0,4099	0,01	-0,2420	0,00	-0,2183	0,00
α1	0,0548	0,00	0,0800	0,00	0,1340	0,00	-0,0198	0,16
β1	0,9719	0,00	0,9671	0,00	0,9753	0,00	0,9785	0,00
γ1	0,2315	0,00	0,2584	0,00	-0,0793	0,00	0,1850	0,00
λ	-0,0664	0,00	-0,0066	0,76	-0,0221	0,00	0,0573	0,00

In this section, it has been found out that information from different sources of media has different impact on dollar exchange rate volatility: whilst Financial Times and The Economist have a significant impact on conditional dollar exchange rate volatility, information from New York Times does not affect conditional dollar exchange rate volatility.

6 CONCLUSIONS

This chapter contains contributions of the thesis, its limitations and further research. The present thesis discusses the impact of information from different sources of media on dollar exchange rate volatility.

The first contribution of this thesis to the topic overall is the extensive literature review that identifies the gaps in the topic. There have been many explanations proposed for the phenomena of high exchange rate volatility in the short-term but the exchange rate puzzle remains unsolved. In this thesis, the TRMI currency Media tone from Thomson Reuters has been proposed as a predictor superlative to either macroeconomic variables or variables, which reflect simple number of news related to macroeconomic announcements and are proposed in the existing literature in the following topic. In the current exchange rate research, there has not been done much with sentiment type of data and the use of TRMI currency Media tone also contributes to that. Except the novel predictor, in this thesis I propose the most relevant methodology in this topic identified through an extensive literature review – GARCH applications. New informational data together with the most relevant methodology makes this paper unique in the research topic.

The second contribution of this paper is the results of the GARCH analysis of the impact of currency Media tone on dollar exchange rate volatility. First and foremost, it has been found out that the behavior of the news sentiment and social media sentiment in relation to dollar exchange rate volatility differs: whilst there is a long-run adjustment of the dollar exchange rate volatility to the news sentiment, the impact of social media sentiment on dollar exchange rate volatility is instant. This finding is in line with Sun et al. (2016) who also highlight the slow adjustment of financial indicators to the new information. Secondly, it has been found out that currency Media tone has a significantly positive impact on dollar exchange rate returns and significantly negative influence on dollar exchange rate volatility if considered in the short-run. Moreover, the impact in both cases is quite small and economically insignificant. Finally, in this thesis there has been found another way to point out the shift of the informational effect towards emerging economies rather than advanced ones by considering narrow and broad effective nominal dollar exchange rate indexes. Thirdly, it has been found out that the influence of currency Media tone on dollar exchange rate volatility is time-dependent and has been influenced by the Global Financial Crisis. This discovery supports the findings of Gan et al. (2020) who also point out the differences in the impact across three periods. Finally, it has been identified that the impact of news sentiment on US dollar exchange rate volatility depends heavily on the journal from which those news are collected.

The main limitation of the research is a gappy nature of the currency Media tone at the daily frequency and at the level of different sources of media. This means that coefficients presented in the tables can be interpreted only in a sense of significance and not quantitatively. Another limitation of the study is the negative sign of the impact of currency Media tone on US dollar exchange rate volatility in the conditional variance equation due to the lack of factors that could be considered to explain conditional US dollar exchange rate volatility at the daily frequency.

There are several directions of further research to follow. Next step of the research could be uncovering the nature of the news that have a long-run effect on dollar exchange rate volatility by including macroeconomic fundamentals in the models. For that, the data has to be changed to monthly observations. Another way to proceed could be considering high-frequency data and methodologies in a hope to get more insights about the impact of currency Media tone on US dollar exchange rate volatility rather than returns.

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