ISCTE Business School
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THE NEWS IMPACT CURVE: AN ANALYSIS OF DOLLAR DENOMINATED CREDIT MARKETS

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Abstract

Financial asset prices mirror investors' expectations and risk perception, which translate into volatility. This volatility, or investment risk, is a key part of the investment decision and has been the target of several studies for several asset classes throughout the years.

This study aims to determine if the conditional volatility of credit markets in dollars can be modelled, and if so, if it can be explained by external regressors. Building on existing frameworks, several ARCH type structures will be tested, including those which allow for leverage and asymmetry effects. Monthly returns of the Bloomberg Barclays Investment Grade USD index are going to be analysed and fitted, and the external variables used, based on literature review, include macroeconomic releases, macro prudential indicators and general news flow that can induce uncertainty, and therefore volatility. For the later, the EPU index will be used as a proxy.

Analysis of the modelled structures conclude that it is possible to model conditional volatility using the aforementioned variables, with an EGARCH model. Further research is recommended to explore interest rate and excess returns components' isolated response to these variables, which could strengthen the model.

Keywords: Financial Econometrics, Financial Markets Modeling, GARCH, Financial Forecasts

JEL Classification: C580, G17

Sumário (Abstract)

Os preços dos ativos financeiros refletem as expectativas e a perceção de risco dos investidores, o que se traduz em volatilidade. Essa volatilidade, ou risco associado ao investimento, é uma parte essencial da decisão de investimento e tem sido alvo de vários estudos para as diversas classes de ativos ao longo dos anos.

Este estudo tem como objetivo determinar se a volatilidade condicional dos mercados de crédito em dólares pode modelizada e, em caso afirmativo, se pode ser explicada por regressores externos. Com base em modelos existentes, várias estruturas do tipo *ARCH* serão testadas, incluindo aquelas que efetivamente apreendem o efeito de alavancagem e assimetria. Os retornos mensais do índice *Bloomberg Barclays Investment Grade USD* serão analisados e ajustados a estas estruturas, e as variáveis externas utilizadas, com base na revisão da literatura, incluem dados macroeconómicos, indicadores macro prudenciais e notícias do espectro geral que podem induzir incerteza e, consequentemente, volatilidade. Para estas últimas será utilizado como *proxy* o índice *EPU*.

A análise dos diversos modelos permite inferir que é possível modelar a volatilidade condicional usando as variáveis supramencionadas com um modelo EGARCH. Estudos futuros neste âmbito deverão explorar a resposta isolada das duas componentes dos índices de crédito, a taxa de juro e o excesso de retorno, a essas variáveis, o poderia fortalecer o modelo.

Keywords: Econometria Financeira, Modelização De Mercados Financeiros, GARCH, Estimativas Financeiras

JEL Classification: C580, G17

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To my parents, José and Anabela, and to my grandfather Anibal, for their support, presence and love. To my sisters, Ana Sofia and Ana Teresa, a constant source of inspiration.

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Sumário Executivo (Executive Summary)

O valor dos ativos financeiros, o preço pelo qual são negociados, incorpora expectativas sobre a economia e, como tal, reflete fundamentos macroeconómicos, como a taxa de crescimento económico, o desemprego ou a inflação. Os investidores desenvolvem essa perceção através de fontes de informações diversas, nomeadamente pela divulgação de dados económicos. Contudo, não obstante estes dados económicos assumam um papel fundamental na construção de expectativas, outras fontes de informação são relevantes. Assim sendo, a análise da variação de preços das classes de ativos supramencionadas, ou da sua volatilidade, assume um cariz fundamental para a decisão de investimento, dado que a compreensão dos fatores indutores de aumentos e quedas nos preços de ativos pode potencializar ganhos e / ou diminuir perdas.

No âmbito desta tese foram analisadas as obrigações de dívida privada, especificamente em títulos com grau de investimento denominados em dólares. Essa classe de ativos foi escolhida por sua importância e, por ser um tema menos explorado. A literatura existente tende a concentrar-se extensivamente no impacto do fluxo de notícias relevantes nos mercados de ações e, em menor grau, no de taxa de juro. Desta forma pretende-se verificar se os modelos de referência existentes permitem uma modelização eficaz da volatilidade condicional dos mercados de crédito e quais as noticias indutoras da mesma. A relação entre a volatilidade e as noticias é um tema relativamente consensual, com a maioria dos autores a concordarem que existe algum grau de correlação entre flutuações de preços e fluxos de notícias. Vários autores abordaram esse assunto, analisando frequentemente classes de ativos específicos e concluíram inclusivamente que há assimetria na resposta do mercado a boas e más notícias (Black, 1976).

Dada a importância dos determinantes da volatilidade, vários modelos foram propostos pela comunidade científica, frequentemente, como mencionado, para classes de ativos específicas e / ou conjuntos de notícias. Em relação a estes últimos, de um modo geral, os tipos de notícias relevantes podem ser divididos em três grupos: (i) divulgações macroeconómicas, (ii) notícias de cariz político, macro prudencial e gerais que geram incerteza e (iii) decisões de política monetária, todas com impacto material (ou concreto)) no mercado, mesmo que a intensidade possa ser diferir de acordo com a classe de ativos analisada.

Conforme supramencionado, notícias recebidas como positivas e negativas para o mercado podem impactar o mercado com uma magnitude diferente (Black, 1976), muitas vezes

relacionadas com a perceção de que as notícias negativas podem ser materializadas no curto prazo ou afetar o valor da empresa de maneira substancial. Por exemplo, notícias com implicações negativas na rentabilidade futura de uma determinada empresa podem alarmar os investidores e aumentar o risco associado ao investimento nesta empresa, levando ao aumento da volatilidade do preço das ações (Boffelli e Urga., 2016).

Ao longo dos anos 80, Engle observou e estudou as variações nos preços, observando que, apesar destas variações, o tratamento de variáveis como parâmetros constantes limitava o poder de previsão dos modelos, e o foco dos modelos financeiros evoluiu para a estacionariedade da volatilidade. Este tipo de análise, nomeadamente da distribuição da volatilidade, está ligado a características específicas da série de retornos e pode permitir o cálculo da probabilidade de futuros aumentos extremos e diminuição do preço.

Estas conclusões foram introduzidas em vários estudos e vários modelos, com o pressuposto mencionado, podem ser usados para garantir que o impacto de notícias positivas e negativas seja diferente, como o Exponential GARCH, apresentado por Nelson (1991), seguido da *NIC - News Impact Curve* (Engle et al., 1993, Boffelli et al. , 2016). A NIC possui uma estrutura para analisar adequadamente a resposta assimétrica dos retornos aos retornos positivos e negativos, avaliando como a volatilidade em t reage às notícias divulgadas em t.

O estudo efectuado permitiu aferir que a volatilidade condicional do mercado de obrigações de dívida privada pode, de facto, ser modelizada com uma estrutura do tipo EGARCH (heterocedasticidade condicional auto-regressiva exponencial) com uma distribuição de erro generalizada. A maioria dos coeficientes para regressores externos é negativa. , o que significa que choques positivos provavelmente implicarão uma variação condicional mais alta em t + 1 do que choques negativos.

I |Introduction

Financial markets are defined, in a simple way, as marketplaces where investors can buy and/or sell assets, including equities, fixed income instruments (such as money market investments and sovereign or credit bonds), currencies and derivatives. As such, they could be perceived as places where not only most companies secure the necessary funding but also the destiny of household's savings, namely in bonds and equity shares.

The importance of financial markets can be perceived by comparing its relative size to global GDP: in October 2018, the world GDP was roughly 80 trillion dollars and the asset size was 213 trillion dollars, or 2.7 times the world GDP (JP Morgan, 2018). In this context, it is understandable that in 2017, equity transactions alone achieved 127% of the world's GDP (Worldbank database).

The value of financial assets, the price at which they are traded, incorporates expectations about the economy and as such, to a high degree, reflects macroeconomic fundamentals, such as economic growth, unemployment or inflation. Investors develop this perception through financial markets related news flows, and although economic releases assume a key role in those expectations, other sources of information are crucial (or vital). The analysis of the variation in prices of those asset classes, or its volatility, is a key step of the investment decision and understanding the triggers of rises and falls in asset prices, which could potentiate gains and/or decrease losses.

1) Research Focus

Considering the importance of financial markets and the relevance of volatility as a key indicator for valuation, this master thesis will focus on one key question - is it possible to model credit returns volatility, while focusing on one of the key components of volatility in financial markets, news releases, specifically the impact of specific types news releases in credit market returns volatility. Understanding the drivers of credit markets volatility is key to potentiate gains and minimize losses.

First, concerning the subject of volatility and news flow, two key questions arise: (i) is volatility predictable through news and (ii) what are the relevant news to explain price fluctuations?

Predictability is a somewhat consensual subject, with most authors agreeing that there is some degree of correlation between price fluctuations and news flows. Several authors have addressed this subject, often analysing specific asset classes, and inclusively concluded that there is asymmetry in the market response to good and bad news (Black, 1976). Recent data seems to indicate, however, that this asymmetry could have changed in the last decade. Given the importance of volatility determinants, several models have been proposed by the scientific community, often, as mentioned, for specific asset classes and/or sets of news.

Concerning the latter, broadly speaking, relevant news types can be divided in three groups: (i) economic releases, (ii) political and other news flows generating uncertainty and (iii) monetary policy decisions, all of which have a material (or concrete) effect in the market, even though the intensity could be different depending of the asset class analysed. Economic releases can be divided into three categories: relevancy, accuracy (or magnitude of diference from the preliminary figure) and "timeliness"(Gilbert, Scotti, Strasser and Veja, 2010). Political events and the perception of political risk are some of the most important news flows impacting markets, hence an uncertainty index mirroring the political framework was considered. As for monetary policy decisions, central banks increase or decrease interest rates according to their macroeconomic projections for the economy and inflation, with repercussions on investors' expectations and hence affecting asset pricing. Overall, this news types are "information" that market agents process and incorporate in their decision making process.

Henceforth, the focus of the thesis will then be to explore the impact of these three groups of news or market relevant information on credit debt, specifically in dollar denominated investment grade bonds. This asset class was chosen for its importance and due to the fact that it is a less explored topic. Existing literature tends to focus extensively on the impact of relevant news flow in equity markets and, to a lesser extent, on interest rate markets, and credit markets are even less analysed. The performance of credit bonds derives from two key components: interest rates and excess returns. Although the first has been the target of extensive analysis, the second part, which is basically the return deriving from credit risk undertaking, has been somewhat overlooked. Therefore, this thesis aims to analyse/study the impact of relevant market news in credit markets, providing an insight into the dynamics of this asset class. Similar to common assumptions in relation to interest rates, dollar denominated bonds are more representative than other currency issued bonds assets and have a significant influence in the market. Furthermore, investment grade issues are the bulk of bonds issued and possess desired features for the analysis, later addressed in the thesis, hence justifying the choice of the Investment Grade Credit Index in dollars denominated bonds as a proxy for credit market analysis.

2) Structure of the thesis

After a brief literature review, relevant data will be presented. To properly access the statistical relationship of these variables – macroeconomic releases, political and other news flow and monetary policy decisions with credit returns volatility, I will then use several econometric models commonly used to model the volatility of an asset return and designated as conditional heteroscedastic models, such as ARCH (Autoregressive Conditional Heteroscedasticity), GARCH (Generalized Autoregressive Conditional Heteroscedasticity) and EGARCH (Exponential ARCH). For the purpose of this thesis, I will analyse the conditional distribution of returns, essentially, considering the three types of news flows referred above. Since 1986 several studies have been made, applying ARCH type models to several asset classes, from equities to foreign exchange rates (Bollerslev,, Engle, & Nelson, 1994).

In section II a brief literature review will be provided to properly assess the relevant news or information sources to be incorporated. In section III, after incorporating this information, I describe the methodology to be applied. In section IV the data collection process is explained and in section V the different models are estimated and tested. Finally, in section VI, I concluded about the fitting of these models and the existence of a News Impact Curve for conditional credit return volatility.

II |Brief literature review

Financial analysis focuses on asset returns rather than asset prices. First, the size of the investment, in a perfectly competitive market should not be relevant for the behaviour of the investment. Using returns instead of prices is a way to have a scale-free measure of the performance of the investment. Second, returns have statistically important properties that prices do not exhibit, namely stationarity, making return series easier to handle (Campbell and Hentschel, 1992).

Forecasting financial time series, i.e., the evolution of asset prices, has been the object of several studies for decades. Due to its complexity, as returns are influenced by several factors, from economic to emotional, the series are quite noisy, with moments (mean, volatility) that change throughout time. The efficient market hypothesis theory addresses this complexity and concludes that to predict tomorrow's price, the best indicator is today's value (Fama, 1970). Taking this into account, past observations and mean returns were usually computed and used as a base for forecasting, assuming stationarity of the series, which was not the best way to proceed. Mean, or average, returns, however, are a limited indicator for financial market analysis, and, additionally to the stationarity assumption, broadly speaking, they are an average for a given period. An average, per se, can dilute the impact of outlier returns. Additionally, these outliers are difficult to forecast, whereas volatility can be easier to model.

Throughout the 1980's, Engle observed and studied the changes in prices, observing that despite these changes in prices, the treatment of the moments of the underlying distribution as constant parameters limited the forecasting power of models, and the focus of financial modelling has evolved from mean return assessment to volatility stationarity investigation of prices. This type of analysis, namely of the distribution of volatility is linked to specific features of the return series and may allow the computation of the probability of future extreme increases and decreases in price.

In fact, history has proven, throughout several financial crises, that a measure of risk, or volatility, is crucial to the decision and investment-making process, increasingly relevant considering that, in recent decades, a risk inducing environment has been somewhat promoted. Dowd (2007) identified several factors that have been increasing financial risk: (i) the negotiation of assets and derivatives continues to grow; (ii) macroeconomic uncertainty and (iii) evolution of information technology. Given this environment, volatility of asset prices, due to its wide range in real implications and potential applications, from risk management to option pricing, is widely investigated not only in the academic community but also at the financial institution level, as a way to manage and optimize risk taking. JP Morgan, for instance, endeavoured a significant amount of resources to understand and quantify market volatility, developing an internal model for the main types of risk incurred by the institution, including market risk called "RiskMetrics", in 1990. The results were so positive at the institution level, that the basic concept and methodology of this model was later made available to customers (JP Morgan, 1994). The analysis of volatility has also been used in the investment banking industry for specific purposes, such as option modelling, influenced by the mentioned increase in derivative trading (Poon & Granger, 2003) or for market timing investment decisions (Andersen, Bollerslev, Christoffersen and Diebold, 2007).

These studies of volatility have concluded that two important features of financial time series, stochastic volatility and volatility clustering, are crucial to model financial assets returns and risk. An empirical inspection of monthly asset returns, for any asset, for a five- or ten-year period, would demonstrate that in some months stationarity seems to be predominant and prices seem almost unchanged, whereas in other time intervals large variations, both up and down, follow one another for a given time period. This particularity of financial time series is denominated volatility clustering and has been a field of study for a long time (Mandelbrot, 1963). Empirical representation and analysis also seem to validate that extreme movements of prices, and therefore returns, are often preceded by large variations. This means that returns are not necessarily independent throughout its time span, a characteristic named stochastic volatility. Assuming that volatility presents this persistence, it becomes relevant to include past observations or autoregressive terms in the model.

Volatility, however, is not directly observable, and can only be estimated and forecasted within a statistical framework. This implies that the inferred conclusions about the level of uncertainty in the market widely depend on the statistical model used as no "true" volatility exists (Alexander, 2008). Another key issue when studying volatility relates to the conditional and unconditional variance. The unconditional variance is computed assuming a constant distribution of returns throughout the analysed time frame, whereas the conditional depends upon all observations conditional on the available history of returns at each observation (Alexander, 2008).

Engle (1982) was the first to present a model contemplating the aforementioned features and introduced the ARCH process. This was the first model to incorporate the assumption that the mean-correct returns are dependent, albeit uncorrelated., or in other words, that the variance of returns presents dependence instead of the returns themselves This model, however, implied the estimation of several parameters to properly catch the dynamics of volatility. To solve this issue, a Generalized ARCH or GARCH model was developed, which has an infinite order ARCH representation (Bollerslev, 1986). In GARCH modelling, the estimated parameters are considerably few and conditional variance is a linear function of past conditional variances and errors. Several authors have, since then, applied this methodology to model returns, particularly concerning the stock market, such as Sabbatini & Linton (1998) for the Swiss Index.

In addition to the statistical framework, the main question arising when analysing volatility is linked with its determinants. What are the key drivers of volatility? Can we estimate conditional volatility to macroeconomic and political news flows? Research made for stock markets by Engle and Ng (1993) proved that this is indeed possible, and volatility is influenced by available and relevant information in the market. Ng and Fu (2003) concluded that share prices, specifically, are influenced by political and economic news flow. Christiansen, Schmeling and Schrimpf (2012) furthermore concluded that macroeconomic variables, namely inflation and those linked with output, such as industrial production, have predictive value to model volatility, for equity, bonds, foreign exchange and credit markets.

1) Macroeconomic data and monetary policy

Asset classes pricing mirrors investors' expectations on the economy as a whole, therefore, macroeconomic news and monetary policy decisions impact valuation and volatility of financial instruments. For instance, in a buoyant economy pricing power is likely to be high, driving consumption and savings. An increase in consumption will possibly pressure prices, increasing inflation and supporting a more "hawkish" monetary policy.

Economic data, such as GDP growth, core and baseline inflation, the employment report, among others, as well as central bank policy announcements, are important indicators of economic health and are released/announced in specific dates or within specific time frames. Output based measures, such as industrial production growth, were incorporated in several studies of return predictability in specific asset classes, such as bonds, given its value as a predictor of the growth of the economy (Ludvigson and Ng (2009); Fornari and Mele (2010) and Chauvet, Senyuz, and Yoldas (2010)). These releases could be above or below analysts' expectations, and the surprise itself, more than the actual figure, could have an impact on markets. An expressive difference between the released and forecasted number might force investors to reassess their expectations for the economy and hence changing their investment stance, influencing prices. Although economic announcements surprises may already be incorporated by the market or have a transitory impact, some indicators have a statistically significant and long-term effect on financial markets. Several authors have analysed this issue, namely Bartolini, Goldberg and Sacarny (2008), when analysing USA assets, concluded that nonfarm payrolls, the GDP[1] advance release and the ISM Manufacturing[2] have the most lasting and significant impact on prices, whilst others, such as housing starts, do not have a persistent effect. Bauhmol (2012) remarks that several leading indicators, such as initial jobs claims, have an impact on the bond market, namely with large rises, given that new fillings may indicate a weaker economy, and hence investors choose a more cautious investment approach. Stock, on the other hand, have the opposite reaction, given its pro-cyclical features. In the long run, these statistics are closely related to the labour market report (Tainer, 1993), which further supports the closely watch of investors. Sentiment indicators, such as the Philadelphia Feed Business Outlook, are also closely monitored, although apparently without an immediate impact, and are a hint for the ISM, released days later (Bauhmol, 2012).

Furthermore, given the importance of the USA for the world economy, the mentioned macro data and Fed announcements often have a material impact in other countries' assets, namely in bonds. Andersson, Hansen and Szabolcs (2006) verified this, when analysing the prices of German treasury bonds, inclusively concluding that, before 2006, these bonds were more sensitive to USA information than European or German data. One of the hypotheses advanced was the delay between the release of European Union (EU) GDP and the release of the GDP of its member states, which are released previously, hence undermining the surprise effect. Despite this hypothesis, most of the studies made are, in fact, based on the American market, richer and with more data than any other.

[1] GDP – Gross Domestic Product
[2] Institute for Supply Management® (ISM®) Manufacturing Business Survey Committee

All in all, macroeconomic and monetary policy announcements are events which have a statistically relevant influence in prices. However, the way these news affect the value of financial instruments is heterogeneous and may be asymmetric when the economy is buoyant or contracting.

The behaviour of interest rates seems more straightforward (Andersson et al., 2006; Bartolini et al., 2008): in a strong economy, with favourable growth rates, there's typically inflation, supporting a more hawkish stance on monetary policy, driving interest rates higher. On the other hand, when the economy shows signs of a downward cycle, interest rates often fall due to decreases by Central Banks of their respective reference rates to stimulate the economy. Guégan and Ielpo (2008) addressed this issue concluding that volatility may be explained, not only by the reaction of term structure of interest rates to news, but by the dynamic of news in the economic cycle of the economy. An example is the Nonfarm Payroll figure, which, according to the author, seems to be considered by the market as an indicator of potential changes in monetary policy in expansion cycles, albeit ignored in other moments.

Gilbert et al. (2010) explore this asymmetry of reaction in the USA market, reaching another conclusion. The authors divided the information news flow into three drivers of volatility: relevance, revision differential and "timeliness". The relevance of the data refers to the value of the input to forecast FOMC[3] rate decisions, as these derive of GDP and economic policy forecasts. As for the latter two drivers, the revision differential, or "noise", is the difference between the preliminary released figure and the final one, while the "timeliness" concerns the interval between the release date and the period the announcement refers to. "Noise" was considered a less relevant variable in price impact, even though more expressive when variations are large.

Equity markets have a less straight reaction. In a positive economic environment, corporate revenues and net income are expected to increase, thus theoretically driving prices higher. However, this context also implies rising interest rates, which means that future cash flows from companies, namely dividends, will be discounted at a higher rate, and that debt costs will also be higher, hence decreasing its present value. Bartolini el al. (2010) conclude that equity markets are the less impacted by economic and monetary policy news, although, in a positive

[3] The Federal Open Market Committee (FOMC) from the US Federal Reserve, holds scheduled meetings throughout the year to analyse economic and financial conditions and decide upon monetary policy

economic cycle, there is a statistically positive response to data such as GDP, inflation measures or ISM.

Analysing exchange rates also leads to conclude, according to the existent literature, that there is a lack of obvious correlation of this variable with macroeconomic news. At a first glance, expectations of rising inflation should pressure the currency in the long term. However, this inflation scenario is consistent with rising interest rates, supporting the currency, at least in the short term. Several studies present evidence that, more than the news, the interest rate is the key driver of exchange rates (Andersen et al., 2007), furthermore concluding that the immediate or intraday impact is more visible that daily or weekly numbers.

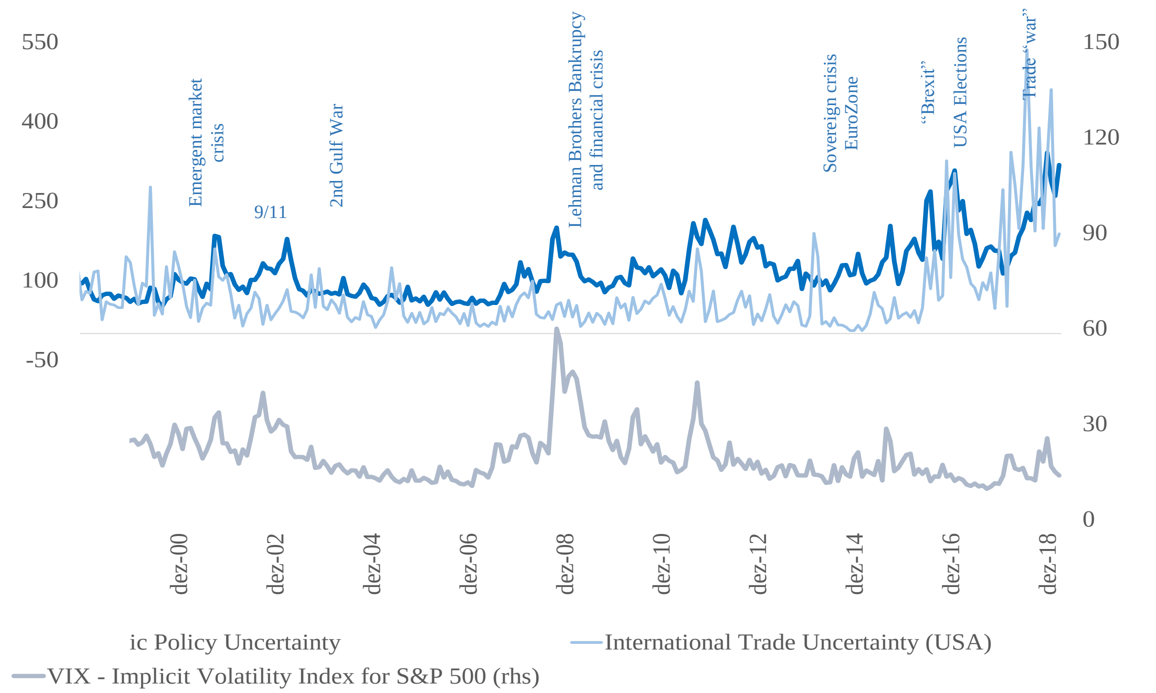
2) Measuring economic uncertainty and geopolitical risk

Macroeconomic and prudential information seem to be a relevant source of volatility and a driver of investor expectations. However, political and economic uncertainty at the global level, seem to be increasingly more relevant in a deeply connected world. Following the sovereign crisis in 2009-2012, several international institutions advised against the risk that uncertainties concerning fiscal policies, regulatory framework and overall political risk, such as the sovereign crisis, posed to the economy, increasing volatility in markets (IMF, 2013). For instance, the US presidential election, the Brexit referendum in 2016 or more recently the EUA-China bilateral trade negotiations, triggered peaks of volatility in the market, as the market feeling changes often and the result is unknown.

Geopolitics is also a theme analysed concerning uncertainty and is usually defined as the influence a given country has on all others given its specific features, namely size, economic power and military position. In a global world, any alteration in the relationship between two countries has implications worldwide, although the impact varies among asset classes (Middeldorp and Nauta, 2018). For instance, the renegotiation of trade terms between the US and China since 2017 has affected financial markets. First, considering the weight that international trade has in global output, and the size of these economies, any disturbance in the renegotiation between these two economies can produce a slowdown not only in both countries but worldwide (and therefore, disrupt global growth). Second, the ramifications in financial markets can be diverse. Some analysts (Middeldorp et al., 2018) noted that, despite the lack of response of US government bonds to geopolitical risk in the past, this specific event, i.e., the renegotiation of Chinese-American trade terms, triggered an increasing sensitivity of US treasuries yields to fluctuations in perceived increases in risk. These analysts theorize that this shift in the response could be linked to fears that China, one of the main foreign holders of US Treasuries, might stop to buy them if tensions escalate. A decrease of the buying interest in these assets can pressure prices and therefore reduce profitability.

For a more comprehensive analysis of the impact that uncertainty could have in the economy, Baker, Bloom and Davis (2016) created the EPU – Economic Policy Uncertainty Index for the USA (see Exhibit 1). To compute this index, the authors gathered news from the main 10 newspapers in the country with specific headlines, including “deficit”, “regulation” and “uncertain”. The authors went as back as 1900 for the USA (using six newspapers) and later constructed indexes for 12 other countries. Using VAR models, Baker et al. concluded that an increase in EPU in similar magnitudes to the 2005/2006-2011/2012 interval implies a contraction of 6% in gross investment, 1.2% in industrial production and 0.35% in employment. As for volatility, the authors concluded that a 1% increase in EPU implies an increase of approximately 0.43% in stock price volatility. Using the Chicago Board Options Exchange Volatility Index, simply known as “VIX”, as a proxy for S&P500’s Index volatility, the correlation is presented in Exhibit 1. The VIX, produced by the Chicago Board Options Exchange measures implied volatility of the S&P500 based on option on that index.

Exhibit 1 - Economic Policy Uncertainty (EPU) Index



Source: Baker, Bloom and Davis

Based on this index, NBER – National Bureau of Economic Research - developed a Global EPU. The data is gathered in a similar way for 16 countries, which account for 2/3 of global output, and an individual index is computed for each country. Following this calculation, the authors built a GDP weighted average of those 16 local indexes, producing a global index (Davis, 2016). There are a variety of other indexes aiming at capturing specific sources of uncertainty and hence volatility of asset classes prices. The American Federal Reserve, for instance, also built a Geopolitical Risk (GPR) Index using this methodology. This monthly index, counts specific words, ranging from military tensions to war threats, in 11 international newspapers. Another example is the World Uncertainty Index WUI index, released on a quarterly basis, analysing the frequency of "uncertainty" and related words in the Economist Intelligence Unit reports of 143 countries. All indexes spiked near the European debt crisis, Gulf War II and the European border control crisis.

III |Methodology

To model volatility of credit price returns conditional to a set of variables, I will ensue a process which begins with the collection of data. Following this, I will analyse the raw figures and the returns, namely performing tests to infer if the financial time series present desired features briefly approached in the literature review, such as the importance of past observations and volatility clusters and persistence. These features imply that an autoregressive non-parametric approach must be used to model volatility. Therefore, the last step will be to build upon the results of the tests to estimate a model for the mean return, which will be an ARMA – Autoregressive Moving Average structure, and for the volatility, I will assume an ARCH – Autoregressive Conditional Heteroscedasticity type model.

- **A) Steps to model credit returns conditional volatility:**

1. Gathering raw relevant data is the first step, such as the monthly closing prices[4] for the following variables.
    a. Dollar denominated credit index market closing prices
    b. Relevant economic data
        i. GDP (Gross Domestic Product) in billions of dollars
        ii. CPI (Consumer Price Index)
        iii. Industrial production in billions of dollars
        iv. South Korean Exports in thousands of dollars
        v. Produces Manufacturing Index for industry
        vi. Philadelphia Fed Business Outlook Index
        vii. Initial Jobless Claims, thousands of claims
    c. EPU Index as a measure of monetary policy uncertainty and geopolitical risk
    d. Monetary policy
        i. Federal Reserve Effective Reference rates

2. The data is then analysed to infer if it possesses certain characteristics which will allow the development of a framework to explain volatility. Both raw series (in levels) and the

[4] "Closing prices" is a term used to characterize the closing value at a specific date or range (e.g. weekly, monthly) of a given indicator or index.

difference of the logarithm (price returns) will be analysed. Price returns tend to exhibit certain features observed in many studies, therefore designated as "stylized facts" (Cont, 2001).

Cont (2001) summarizes the "stylized facts" facts the as following:
1. Log returns do not present a normal distribution and have a "heavy" tail;
2. Absolute and squared log returns are correlated, with a decay over time, although log returns do not present this relationship;
3. These autocorrelations are highest for the recent observation (Taylor effect);
4. "Aggregational gaussianity", i.e., in the long term or at a large-scale analysis the distribution resembles a normal distribution;
5. High volatility periods tend to group in time (volatility clustering);
6. Asymmetry of gains and losses;
7. Intermittency or high variably throughout time;
8. Volatility clustering, which means high volatility peaks tend to follow high volatility observations (positive autocorrelation of volatility);
9. Heavy tails even with correcting returns for the clusters in volatility;
10. Negative relationship between volatility and returns (leverage);
11. Correlation between trading volume and volatility and
12. Volatility measures are best predicted for monthly returns than daily returns.

3. Credit price returns will be the target of a specific analysis concerning the existence of a unit root, to assess if the series is stationary and to analyse the autocorrelation observed between observations.

Stationarity influences the properties of the time series, namely considering that (i) if the series is not stationary, the effect of a given shock will be infinite whereas in a stationary series there is the decay factor, which means that the effect of a shock in t is smaller in t+2 than in t+1 and (ii) a regression based on non-stationary series may produce spurious estimates, which means that the produced estimates appear to have statistical significance when in fact it is worthless as it reflects the mentioned infinite impact of the unit root. I will apply a variety of tests to infer about the existence of stationarity.

Auto-regression modelling studies the correlation between present and past (or lag) observations, using it to predict future ones. The existence of this relationship implies that to forecast a given return in period t, r_t, the lagged observation , r_{t-1} has statistical significance (Tsay, 2003), a relationship I will also analyse.

Therefore, the results of these tests will allow the computation of an ARMA model. One of the main assumptions of AR structures is the existence of at least “weak stationarity” (Tsay, 2003), implying that the first two moments of the distribution, i.e., mean, variance and autocorrelation, remain constant over time. This is a very common and important assumption adopted in the financial time series literature, allowing the implementation of specific forecasting methods. However, if necessary, when stationarity is not verified, it can be transformed using specific techniques (Prins, Croarkin and Tobias, 2012). Furthermore, return modelling can also be performed by using moving average (MA) models, which imply the existence of a linear relationship between the dependent variable, r_t in period t, and its current and past errors. This model can either be approached as a combination of white noise series or as a finite AR(q) model subject to some constraints. It is commonly known as a “finite-memory” model, considering that the mentioned linear relationship is valid for the first q lagged variables, i.e., the older ones are not statistically significant and its influence “decays” as times goes by.

The combination of the two mentioned statistical approaches is designated as an Auto Regressive Moving Average (ARMA) process, first addressed by White (1951). This concept merges the auto regressive and moving average models to capture more dynamic and complex structures/relationships without the need to estimate a large number of parameters. An ARMA (1,1) model can be expressed as follows (Tsay, 2003):

$$\text{ARMA (1,1)}: \; r_t = \varphi_1 r_{t-1} - \varphi_0 + a_t - \theta_1 a_{t-1} \qquad (1)$$

where

$\{a_t\}$ - white noise series,

$r_t - \varphi_1 r_{t-1}$ is the AR component of order 1 and

$\theta_1 a_{t-1}$ is the MA component of order 1.

Several methods can be used to estimate the parameters of the model, however, maximum likelihood is often used (Box, Jenkins and Reinsel, 2015). In order to choose the best parameterization for the model, several criteria can be used, namely the Akaike's Information Criteria (AIC), the Final Prediction Error of Akaike (FPE) or the Bayes Information Criteria (BIC) (Goojjer and Hyndman, 2006).

4. Before modelling the volatility of the ARCH structure of credit returns, it is necessary to perform an analysis of the residuals of the series. The purpose of these structures is to model the unexplained part of volatility conditional to specific sources of uncertainty or risk. This unexplained part, the residuals, should also present some desired features. Broadly speaking, a dynamic conditional process can still be found in an uncorrelated time series, therefore it is possible to classify the series as serially dependent (Engle, 1982). Hence, when there is a high persistence of squared returns in the series, i.e., when there are signs of conditional heteroscedasticity, the series exhibits ARCH residuals. Engle proposed a Lagrange multiplier (LM) test to properly measure the significance of these signals. Following this test, ARCH type models are analysed to properly infer about the best model to adopt.

5. If the test confirms those properties, several ARCH type structures will be tested and estimated, first without and then with external regressors. To evaluate the models, I analyse features such as the underlining distribution, the number of lags and the existence or not of leverage effect.

- **B) ARCH model and ARCH-type models**

Frequently financial time series exhibit low serial correlation, i.e. correlation between returns, although some dependence is visible. They also present high autocorrelation between absolute and square returns. This autocorrelation is statistically more significant for recent data, still the "decay" factor previously mentioned seems to decrease slowly, a phenomenon that can also be interpreted as dependence. The purpose of ARCH type volatility models is to try to capture this dependence, using the conditional mean and conditional variance of the return given the information available in the previous periods as indicators (Tsay, 2003).

In this analysis, the non-stationarity of volatility is a common feature of financial time series, that is, small absolute returns tend to follow small absolute returns, and large absolute returns also tend to follow identically large absolute returns, a dynamic called clustering of volatility (Goojjer et al., 2006). Modelling time-changing volatility over time is a challenge, answered by Engle (1982), through the presentation of ARCH – Auto Regressive Conditional Heteroscedasticity.

Given its simplicity and wide applications, ARCH models became so popular that by 1992, Bollerslev concluded that it had been quoted in over 200 papers. Considering y_t as the return between prices p_t and p_{t-1} and F_{t-1} as the past information for realized values in t-1, it is possible to write (Engle, 2003):

$$m_t = E(y_t \,|F_{t-1})$$

as the conditional expected value of y_t given the information available at t-1 and

$$h_t = Var(y_t \,|F_{t-1})$$

as the conditional variance of y_t given the available information available at t-1.

Furthermore, considering that the unexpected return can be defined as $\varepsilon_t = y_t - m_t$, Engle suggests that the conditional volatility could be expressed as a result of lagged unexpected returns. This type of parametrization such as this has an underlying assumption that this unexpected return features some dependence concerning past information.

An ARCH model can then be written as:

$$\text{ARCH (m)} : \sigma_t^2 = \alpha_0 + \sum_{i-1}^{m} \alpha_m a_{t-m}^2 \tag{2}$$

with a_t = $\sqrt{h_t}\varepsilon_1$,

$a_0 > 0$ and

$a_1 \geq 0$.

where

a_t - mean corrected asset return

$a_0 > 0$ and $a_1 \geq 0$

h_t - conditional variance

$\{\varepsilon_t\}$ - sequence of i.i.d. random variables, with $E(\varepsilon_t)$ - μ and Var $(\varepsilon_t) - 0$

ARCH structures, however, show some limitations (Tsay, 2003 and Becketti, 2013):

a. The signal of the shock is irrelevant, as the effect in volatility is the same for positive and negative changes;
b. The values attributes to "α_1" are limited to ensure positive variance and finite kurtosis;
c. Nothing new is provided concerning the source of the shock and
d. Volatility can be overstated considering the slow response to high contained shocks.

Regardless of the major advantages of this model and its wide use in financial mathematics, these limitations and the high number of parameters often needed to be estimate to model a financial time series, have promoted further developments in ARCH structures. Tsay(2003) for instance, underlines that to analyse the volatility dynamics of the S&P500 monthly returns an ARCH (9) model has to be used. One of the best know and used extensions of this structure is the GARCH parametrization, introduced by Bollersev (1986).

- **GARCH Structure**

Bollersev (1986) introduced an additional parameter in the ARCH model, presenting the Generalized ARCH or GARCH. This powerful extension implied that the variance equation of the process can be described using an ARMA structure. This model translates in a more robust forecast method, first because in some occasions a good fit is possible without many parameters and because the model itself allows the shock in volatility of past news to decrease geometrically with time (Becketti, 2013 and Tsay, 2003):

$$\text{GARCH (m,s)} : \sigma_t^2 = \alpha_0 + \sum_{i-1}^{m} \alpha_m a_{t-m}^2 + \sum_{j-1}^{s} \beta_j h_{t-j} \qquad (3)$$

with $a_t = \sqrt{h_t}\varepsilon_1$,

$\alpha_0 > 0$,

$\alpha_m \geq 0$ and

$\beta_j \geq 0$.

where

a_t - mean corrected asset return

h_t - conditional variance

$\{\varepsilon_t\}$ = sequence of i.i.d. random variables, with $E(\varepsilon_t) = \mu$ and Var $(\varepsilon_t) = 0$

The constraints imply that the unconditional variance is finite whilst the conditional can vary over time. Interestingly, considering the unconditional mean in an ARMA model, it is possible to re-write GARCH as an ARMA type structure of the square series of a_t^2. The model also presents similar features to ARCH structures, namely concerning outliers, which also have a higher a probability to happen. Modelling volatility using a GARCH approach allows the shock in volatility to decrease geometrically with time and is more parsimonious in the number of parameters needed. However, this model presents the same limitations than ARCH, specifically it does not capture asymmetry or leverage in the shock (French, Schwert and Stambaugh, 1987).

- **Asymmetric GARCH models**

News seen as positive or negative to the market can impact the market differently (Black, 1976), often related with the perception that negative news can be materialized in the short term or affect the value of the company in a substantially manner. For instance, news with negative implications on future profitability of a given firm can alarm investors and increase the risk they associated with an investment in such a firm, leading to increasing stock price volatility (Boffelli and Urga., 2016).

Several models can be used to ensure that the impact of positive and negative news is different, such as the Exponential GARCH, introduced by Nelson (1991), followed by the **NIC – News Impact Curve** (Engle et al., 1993, Boffelli et al., 2016). The NIC provides a framework to properly analyse the asymmetric response of returns to positive and negative returns, assessing how the volatility in t reacts to news released in t-1, assuming:

- Information up to t-2 is constant and
- Lagged conditional variance are assessed at the conditional volatility level.

An EGARCH (m,s) can be written as such (Tsay, 2001):

$$\text{EGARCH (m,s)} : \ln(\sigma_t^2) = \alpha_0 + \left(\frac{1+\sum_{j-1}^{s} \beta_j B^s}{1-\sum_{i-1}^{m} \alpha_m B^m}\right) * (g\ (\varepsilon_{t-1})) \qquad (4)$$

with

a_t - $\sqrt{h_t}\varepsilon_1$.

where

a_t - mean corrected asset return

h_t - unconditional variance

$\{\varepsilon_t\}$ - sequence of i.i.d. random variables, with $E(\varepsilon_t) = \mu$ and Var $(\varepsilon_t) = 0$

B - lag operator

IV |Data

The data set analysed in this thesis comprises monthly closing prices dollar denominated credit indexes between December 31st, 1997 and June, 28th, 2019. All the data concerning macroeconomic releases, monetary policy decisions and economic policy uncertainty was also retrieved for those time frames, although some macroeconomic releases and monetary policy decisions are punctually released, i.e., quarterly or in specific dates.

1) Credit markets

I choose to analyse indexes to properly infer the impact of relevant newsflow in credit market volatility, considering that these aggregates already allow for an interesting and deep screening of the market. Several bonds placed in the market may not have liquidity, i.e., are not traded by market agents, are of small dimension, i.e., below 500 million of the base currency or are close to maturity. Bonds such as these will present price and volatility clusters unrelated with the news flow, thus undermining the analysis. For example, a bond issued by Mota-Engil, a small Portuguese construction company, with EUR 95 million of face value, is only traded by a few investment houses (Exhibit 2). It is possible to observe a surge in price whenever the bond is traded, unrelated to a specific news flow or release.

Exhibit 2 - Transaction of a bond with reduced liquidity EGLPL 3.9 02/20

Source: Bloomberg

Even if a bond has a larger issued amount and rating, it might be a private placement or issued for specific issues and only occasionally traded. Using indexes, specifically the Bloomberg Barclays Indexes, allows a deeper analysis in a representative and liquid universe of bonds in credit markets, avoiding pricing, and hence volatility, issues arising from the aforementioned factors. Furthermore, almost all bonds have credit ratings issued by renowned credit risk rating agencies, such as Standard & Poors and Moody's. In fact, most fixed income indexes are organized by ratings: Investment Grade (IG), and High Yield (HY). IG indexes are high quality indexes, normally with bonds of higher seniority of companies with strong financial ratios, whereas HY comprehend speculative grade bonds. Given that HY indexes are (i) smaller, (ii) often have lower seniority bonds of IG issuers which already have bonds in IG indexes and (iii) historically track equity market performance with a higher correlation than IG bonds (Distenfeld et al., 2014), I choose to analyse the volatility in credit markets using Bloomberg Barclays IG dollar denominated bonds Index (Exhibit 3).

The performance of credit markets results from two key components, interest rates and credit spreads, hence it is possible to compute the return either using a "total return" or "excess return" formula. Excess return only captures the credit spread variation component. Therefore, a total return index was used, although the subject of the thesis is credit markets, considering that volatility could arrive from either component the total return of the index, i.e., interest rate and excess return, and that when investment is made, it is usually made in a bond without hedging a specific risk, a total return index was used.

Exhibit 3 - Barclays IG dollar denominated bond Index features

Index analysed	**Source**	**Periodicity**	**Unit**
Bloomberg Barclays US Corporate Total Return	Bloomberg	Daily	Value

Source: Bloomberg

2) Time series - news

a) Economic releases

Considering the intakes from the literature review, namely of Christiansen et al. (2012) concerning the relevance of macroeconomic variables, namely CPI and output measures such as industrial production, as well as of of Bartolini et al.(2008), which analysed advanced releases of GDP and some leading indicators, such as ISM releases, the macroeconomic data used will be along those lines. Macro data can be divided, for this analysis purpose, into two groups: macroeconomic data and leading indicators. As such, the economic figures considered were those providing an image of the overall actual state of the economy for a given date: GDP growth, CPI, Industrial Production and South Korean Exports. These numbers, however, are often released with a lag. Leading indicators are those assessing business confidence and the overall current feeling of the economy, namely Purchasing Manufacturing Index, from ISM, and confidence indicators.

- Macroeconomic data

GDP (Gross Domestic Product) is a key variable to perceive the change in the wealth of the countries and a relevant macroeconomic indicator for the cycle of the economy. This indicator is released on a quarterly or annual basis, and considering our monthly cadence of date, the date had to be transformed. The quarterly values were retrieved from the Federal Reserve database and transformed to seasonally adjust monthly values through the Litterman process (Exhibit 4).

CPI (Consumer Price Index) measures the variation of prices of a standard basket of goods and could indicate the point of the economic and business cycle. Usually, a growing economy promotes an increase in consumption, prompting an increase in prices. Initially, when prices increase, corporate margins and hence profitability (all else equal), also rises. Monthly values of US CPI index were retrieved from the Bureau of Labour Statistics (Exhibit 4).

Industrial production is defined by the Federal Reserve as the "real output for all facilities located in the United States manufacturing, mining, and electric, and gas utilities". An increase in production usually signals an expanding economy and possible a support for higher inflation, if this increase is accompanied by an increase in capacity utilization. The monthly output values in billions, retrieved from the Federal Reserve database, were used (Exhibit 4).

I added **South Korean Exports**, based on the conclusions of the previous research claiming that output measures have a statistically relevant impact in volatility, and considering the relevance of international trade in market disruptions, particularly since 2017, when several countries, including US and China initiated the renegotiation of trade terms. On one hand, South

Korea exports a significant amount of capital goods to China, its largest commercial partner since 2003, as well as to the US and Japan. The exchanges between these countries, the largest economies in the world, are mirrored in South Korean exports indicators, which acts as a compass for the state of international trade and hence of global economy. On the other, according to a study released by OECD in 2017, over 33% of economic activity in South Korea depends from foreign countries. Monthly values from South Korean International Trade Association in thousands of dollars (KOSPI) were retrieved Exhibit 4).

- Leading indicators

PMI (Purchasing Managers' Index) Manufacturing, the headline indicator of ISM's business conditions report, is a survey conducted which mirrors business conditions in the industry and is seen as a warning bell for potential downturns, often prompting financial market prices reactions. A PMI above 50 indicates growth and below this threshold could signal contraction. **PMI Composite**, which also includes the service component, is also included in the analysis to provide a broader range of inputs. Both Markit and ISM produced PMI indexes, however the first has a wider spectrum of countries in its portfolio (Exhibit 4).

Philadelphia Fed Business Outlook Survey is one of the oldest surveys conducted by Fed, dating back to 1968, providing an assessment for the short-term evolution of the activity. The process is fairly simple as an inquiry is made, in the beginning of every month, to the main companies in the Philadelphia about changes of activity in the last month and perspectives for the following. As referred in the literature review, this indicator is closely monitored, even without an immediate impact, as it is seen as a hint for the ISM, released days later (Bauhmol, 2012). Data from the Philadelphia Federal Reserve was retrieved concerning monthly survey index (Exhibit 4).

Initial jobless claims are unemployment compiled weekly to assess the number of first time unemployed. Baumohl, 2013, classifies this indicators as a "good coincident" measure, which broadly means that it is an accurate reflection of the current status economy, whilst possessing great power as an indicator of future strength of economic activity, given that more jobs, i.e., less unemployment, translates into more household income and spending power. The number of monthly request was retrieved from the Bureau of Labour (Exhibit 4).

Exhibit 4 – Features of utilized macroeconomic sources of information

	Indicator			Source	Periodicity	Unit for raw data	Other information
Macroeconomic Data	GDP Growth rate	GDP	US	US Bureau of Economic Analysis	Quarterly	Billions dollars	**Transformation made to raw data before input**: Released quarterly; converted to monthly values through a Litterman process.
	Inflation	CPI	US	Bureau of Labor Statistics	Monthly	Percent	Index
	Industrial Prodution	INDPROD	US	Federal Reserve	Monthly	Billions dollars	
	International Trade	SKEXPORTS	South Korea Exports	Korea International Trade Association, Foreign Trade Statistics	Monthly	Thousands of dollars	
Leading Indicators	Business conditions Indicator	ISMMAN	PMI Industry US	Institute for Supply Management (ISM)	Monthly	Value	Index, Seasonal adjustment
		ISMCOMP	PMI Composite US	Markit	Monthly	Value	Index, Seasonal adjustment
		INTJOBCL	Initial Jobs Claims	Department of Labour	Monthly	Thousands, number of requests	
	Business Sentiment	PHILYFED	Philadelphia Fed Business Outlook Survey	Philadelphia Federal Reserve	Monthly	Value	Index, Seasonal adjustment

Source: US Bureau of Economic Analysis, US Bureau of Labor Statistics, Federal Reserve, Institute for Supply Management (ISM), Markit, Philadelphia Federal Reserve, Korea International Trade Association, Foreign Trade Statistics

b) Measuring uncertainty

For the purpose of this thesis, uncertainty will be treated as a measure of risk and EPU will be used as a proxy for uncertainty linked to geopolitics and economic policy. As previously mentioned, the index spiked near the European debt crisis, Gulf War II and more recently international trade instability from the ongoing "trade war" between US and China. The values for the index were retrieved from the database of Baker, Bloom and Davis (2016) (Exhibit 5).

Exhibit 5 – Features of utilized uncertainty indexes

Indicator		Source	Periodicity	Unit
FF	Effective federal funds rate	Federal Reserve	Daily	Yield

Source: Baker, Davis and Bloom

c) Monetary policy announcements

Central banks meetings and decision impact the markets in two different ways: directly, through changes in monetary policy, such as the setting of interest rates or asset purchasing programmes, and the "tone" of the speech. Often enough, particularly recently, even when no specific changes are made, if the speech of the president indicates more measures to come or the intention to keep rates unchanged, the reaction is immediate. Usually it is said that the speech is "dovish" when a loose monetary policy is preferred and "hawkish", otherwise.

Considering these two types of effects, two vectors of measures will be used: central banks effective reference rates for USA, as well as an index measuring the perceived uncertainty of future monetary policy through a "hawkish" or "dovish" tone of the speech. The Economic Policy Index (EPU) Index, will be used as a proxy. Surprises concerning fed funds, policy changes and forward guidance are effectively captured by the index (Baker et al., 2013). Effective reference rates were chosen because these rates are released on a daily or monthly basis (Exhibit 6) The upper or lower bond of the reference rate is only changed periodically.

Exhibit 6 – Features of utilized monetary policy reference rates

Indicator		Source	Periodicity	Unit	Other information
EPU	Economic Policy Uncertanty Index	Baker, Bavis and Bloom	Quarterly	Rate	No Seasonal adjustment

Source: Federal Reserve, European Central Bank

V|Data analysis and modelling

a) Features of selected time series

As can be observed in Exhibits 8 through 14, considering that the time series lacked the desired features of normality, confirmed through the analysis of the moments of the distribution in Exhibit 15, the log returns[5] were computed. The graphic depiction of the log returns, on the other hand, seem to show some evidence of normality. The difference of the logarithm was computed for all the variables with the exception of the Philly Fed Index; due to the building features of this index, it can assume negative values.
For the computation of Philly Fed return, the following formula was used:

$$(Pt – Pt\text{-}1)/Pt$$

For the remaining series, the procedure was as following:

$$(\log(Pt) – \log(Pt\text{-}1))$$

These intakes are validated when the date is further analysed and a normality test, Jarque Bera (JB), is conducted (see Exhibit 7), rejecting normality of the raw data and log returns. The null hypothesis of the JB test states that the data is normally distributed, against the alternative that it isn't.

- **Credit markets analysis:** Credit market returns do not appear to have an approximately normal distribution, given its zero average and a standard deviation of 0.2. The data also shows some noticeable negative skewness and excess kurtosis. The p-value of the JB is lower than 0.05 and hence the null hypothesis, i.e., the normality of the data distribution, is rejected (Annex I and Exhibit 7).

- **Time series:** The series show some noticeable negative skewness, negative for economic releases and positive for leading indicators and, when possible to infer, excess kurtosis. For Philly Fed the monthly difference was assessed, where the expected return is around zero, holding the conclusions. The p-value of the JB is lower than 0.05 and

[5] "Return" is used in this section to describe the monthly variation of all time series.

hence the null hypothesis, i.e., the normality of the data distribution, is rejected (Annex I and Exhibit 7).

- **Economic Uncertainty index:** The difference of the logarithm of the values of EPU has a zero average and a standard deviation of 0.18. The data also shows some noticeable positive skewness and excess kurtosis. The p-value of the JB is lower than 0.05 and hence the null hypothesis, i.e., the normality of the data distribution, is rejected (Annex I and Exhibit 7).

- **Monetary policy empirical data analysis:** The difference of the logarithm of the values Reference Rate have a near zero average and a standard deviation of 0.19. The data also shows some noticeable negative skewness and excess kurtosis. The p-value of the JB is lower than 0.05 and hence the null hypothesis, i.e., the normality of the data distribution, is rejected (Annex I and Exhibit 7).

Exhibit 7 – Empirical data analysis

Variable	number of obs.	mean	standard deviation	median	trimmed	mad	min	max	range	skewness	kurtosis	Jarque Bera Test
USTR	259	1870,94	639,68	1661,7	1856,36	801,88	938,42	3107,73	2169,31	0,21	-1,35	*
$(R_t(USTR))$	258	0	0,02	0,01	0	0,01	-0,08	0,07	0,15	-0,87	5,94	*
GDP	259	5140,7	624,21	5168,87	5138,4	714,98	3917,49	6345,62	2428,14	0	-0,84	*
$\log(GDP_t) - \log(GDP_{t-1})$	258	0	0	0	0	0	-0,01	0,01	0,02	-0,96		*
CPI	259	209,5	27,84	213,15	209,96	36,04	161,8	255,31	93,51	-0,16	-1,28	*
$\log(CPI_t) - \log(CPI_{t-1})$	258	0	0	0	0	0	-0,02	0,01	0,03	-1,35	10,5	*
INDPROD	259	98,47	6,01	99,31	98,52	7,23	86,2	110,55	24,35	-0,07	-0,97	*
$\log(INDPROD_t) - \log(INDPROD_{t-1})$	258	0	0,01	0	0	0,01	Inf	0,02	0,06	-1,82	9,95	*
SKEXPORTS	259	3,151E+07	1,415E+07	3,221E+07	3,168E+07	2,046E+07	9,000E+06	5,512E+07	4,611E+07	-0,13000	-1,52	*
$\log(SKEXPORT_t) - \log(SKEXPORT_{t-1})$	258	0	0,09	0	0,01	0,08	-0,32	0,22	0,55	-0,36	1,09	*
ISMMAN	259	52,71	4,79	52,9	53,12	4,3	34,5	61,4	26,9	-0,99	1,61	*
$\log(ISMMAN_t) - \log(ISMMAN_{t-1})$	258	0	0,04	0	0	0,03	-0,21	0,1	0,31	-0,93	5,05	*
ISMCOMP	259	54,3	3,83	54,9	54,75	2,97	37,5	61,1	23,6	-1,47	3,17	*
$\log(ISMCOMP_t) - \log(ISMCOMP_{t-1})$	258	0	0,03	0	0	0,03	-0,16	0,08	0,24	-0,72	3,24	*
PHILYFED	259	7,45	14,88	8,8	8,51	12,31	-40,9	37,8	78,7	-0,76	0,87	*
$(PHILYFED_t) - (PHILYFED_{t-1})$	258	-0,06	8,85	0	0,13	8,01	-39,9	22,6	62,5	-0,48	1,6	*
INTJOBCL	259	346,56	86	331	338,84	74,13	204	665	461	1,03	1,38	*
$\log(INTJOBCL_t) - \log(INTJOBCL_{t-1})$	258	0	0,06	0	0	0,05	-0,18	0,25	0,43	0,51	1,88	*
FF	259	2,11	2,1	1,26	1,9	1,69	0,07	6,54	6,47	0,69	-1,05	*
$\log(FF_t) - \log(FF_{t-1})$	258	0	0,14	0	0	0,05	-0,91	0,69	1,6	-1,73	14,4	*
EPU	259	117,37	51,11	105,6	110,56	44,69	50,93	311,85	260,92	1,3	1,7	*
$\log(EPU_t) - \log(EPU_{t-1}))$	258	0	0,18	0	0	0,17	-0,56	0,76	1,32	0,59	1,76	*

Note: the asterisks ***, **, * indicate significance at 1, 5, 10% respectively

Source: Own calculations using R project software and Psych package

b) Testing stationarity

- **Unit root and stationarity tests**

One of the most important characteristics of the ARCH type models is the stationarity of the time series. To test this property, we use the Augmented Dickey Fuller (ADF) test, which uses a parametric approach to simulate the ARMA structure of the errors. The null hypothesis assumes that the series has a unit root, i.e., is not stationary, against the alternative that it is stationary. Log prices show, both visually and through the test, that they are non-stationary: the test statist is -2,499 for critical values of -3,98, -3,42 and -3,13 for 1%, 5% and 10% significance level. The ADF test on log returns, on the other hand, allows for the rejection of the null hypothesis of a unit root in favour of the alternative hypothesis (see Exhibit 8).

Exhibit 8 – ADF and PP tests

Variable	Augmented Dickey Fuller (ADF) test			Phillips-Perron (PP)		
	P-value < x	t-statistic		P-value < x	t-statistic	
USTR	5,0E-03	-1,19929		2,2E-16	-2,44640	
$(R_t(USTR))$	2,2E-16	-1,19929		3,6E-02	-13,40520	*
GDP	2,2E-16	1,79260		2,2E-16	-1,56860	
$\log(GDP_t) - \log(GDP_{t-1})$	2,2E-16	-3,21350	***	2,2E-16	-4,79760	*
CPI	2,7E-13	-2,18260		2,2E-16	-2,12090	
$\log(CPI_t) - \log(CPI_{t-1})$	2,2E-16	-10,53420	*	3,7E-11	-10,00700	*
INDPROD	8,8E-11	-3,30790	***	2,2E-16	-2,11330	
$\log(INDPROD_t) - \log(INDPROD_{t-1})$	2,2E-16	-3,99935	*	2,4E-03	-13,73410	*
SKEXPORTS	2,2E-16	-2,19850		2,2E-16	-4,17190	*
$\log(SKEXPORT_t) - \log(SKEXPORT_{t-1})$	2,2E-16	-3,65570	**	1,5E-05	-25,44780	*
ISMMAN	3,8E-03	-3,54610	**	2,2E-16	-3,64620	**
$\log\ (ISMMAN_t) - \log(ISMMAN_{t-1})$	2,2E-16	-9,14730	*	7,6E-01	-15,36160	*
ISMCOMP	2,8E-03	-3,06860		2,2E-16	-3,45160	**
$\log\ (ISMCOMP_t -) - \log(ISMCOMP_{t-1})$	2,2E-16	-12,79970	*	1,4E-01	-18,18050	*
PHILYFED	1,8E-06	-3,65490	**	2,2E-16	-4,87570	*
$(PHILYFED_t - PHILYFED_{t-1})$	2,2E-16	-13,27400	*	2,1E-05	-21,78900	*
INTJOBCL	1,5E-02	-2,02570		2,2E-16	-2,00580	
$\log\ (INTJOBCL_t) - \log(INTJOBCL_{t-1})$	2,2E-16	-13,27990	*	8,4E-04	-20,51130	*
FF	2,2E-16	-1,63980		2,2E-16	-4,72200	*
$\log(FF_t) - \log(FF_{t-1})$	2,2E-16	-8,78840	*	2,1E-12	-10,13210	*
EPU	3,0E-05	-4,55610	*	2,2E-16	-1,14760	
$\log\ (EPU_t) - \log(EPU_{t-1}))$	2,2E-16	-13,11280	*	2,0E-01	-18,88250	*

Note: the asterisks ***, **, * indicate significance at 1, 5, 10% respectively

Source: Own calculations using R project software and URCA package

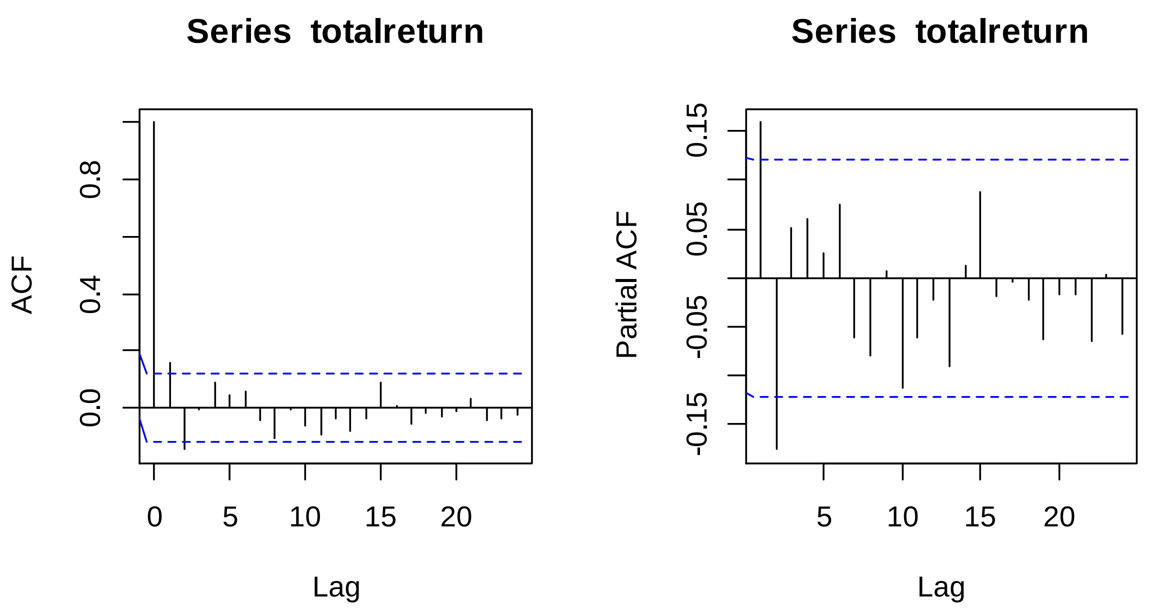
As an alternative and to complement to the stationarity analysis the Phillips-Perron (PP) test was used. Although the null and alternative hypothesis are similar, the PP deals differently with errors' heteroscedasticity and autocorrelation by adjusting the standard errors according to the Newey-West procedure. This introduction of a non-parametric correction feature makes the test more robust than the ADF to heteroscedasticity (Boffeli et al., 2016). PP tests confirm the previous conclusions of non- stationarity of log-prices and stationarity of log returns (see Exhibit 8).

The Kwiatkowski–Phillips–Schmidt–Shin (KPSS) was also performed to confirm these results. Contrary to the previous tests, the null hypothesis is of stationarity, tested against the alternative hypothesis of non-stationarity. If the test statistic is lower than the critical values, the null hypothesis is not rejected and the series can be considered stationary. Otherwise, when the test statistic is higher, the null hypothesis is rejected and the series can be considered non-stationary. A five-lag test regression was computed and as the test values are lower than the critical ones, the null hypothesis was not rejected and the series can be considered stationary. As for log returns, the conclusion is opposite, given that the value of the test statistic is higher and hence these series are not stationary. The detailed results are in Annex II.

c) Autocorrelation

Additionally, to the stationarity of returns, an analysis of the statistical relevance of the lags was also conducted. This structure of returns autocorrelation can be evaluated based on Auto Correlation Function - ACF and Partial Auto Correlation Function - PACF functions. In other words, the PACF provides information concerning the added value of per lag to the time structure. Using URCA package in R a graphic visualization was generated for the ACF and the PACF (Exhibit 9).

Exhibit 9 - USTR PACF and ACF graphic depiction



Source: Own calculations using R project software and tseries package

The estimated coefficients (represented by the vertical lines) fall within the dotted lines when the sample autocorrelation is not statistically significant and there is no correlation between the observations separated by the lag considered in the X-axis. In this data there are two significant peaks in the graphic depiction of the time series of PACF credit price returns, hence it possible to deduct that there is autocorrelation and a second order lag is relevant for AR specification. To model the conditional mean return, the possible models would be an AR(2), an MA(1), according to the significance of the first autocorrelation coefficient or an ARMA(2,1). Using the Akaike criterion (Exhibit 10), which stipulates that the model with the lower AIC is the best model because the lost information is lower (Burnham and Anderson, 2004), an AR (2) will be used.

Exhibit 10 – Comparison of ARMA models using Akaike criterion

	ARIMA(2,0,0)	ARIMA(0,0,1)	ARIMA(2,0,1)
AIC criteria	-1438,8	-1435,8	-1437,2

Source: Own calculations using R project software and URCA package

A complimentary test to conclude about the autocorrelation is the The Ljung-Box Q-test, as it analyses the autocorrelation of multiple lags jointly. The null hypothesis is then that the first j autocorrelations are jointly zero (H0: ρ1=ρ2=…=ρj=0), tested against the alternative that at least one is not (Ljung, 1978). The test rejects the null hypothesis and hence the autocorrelation is significant in at least one of the lags (Exhibit 11).

Exhibit 11 - The Ljung-Box Q-test autocorrelation test

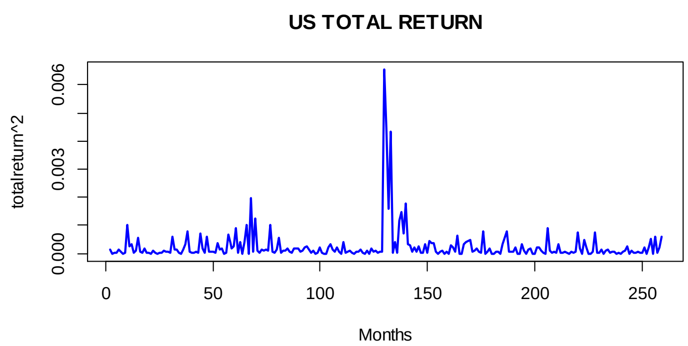
Variable	Box-Ljung test		
	p - value	x - sqrd	lags considered
$(R_t(USTR))$	0,00224	12,044	2

Source: Own calculations using R project software and URCA package

d) Heteroscedasticity analysis

Considering the previous results, an AR(2) will be used to model the conditional mean of credit returns The next step will be to analyse the square returns to conclude about the existence of conditional heteroscedasticity. The pattern of squared returns exhibits phases of high volatility and others of low volatility, a feature known as volatility clustering. The dot.com bubble in the early 2000's, the financial crisis in 2007/08, the European sovereign crisis between 2010 and 2012/13 and recently the uncertainty surrounding international trade (Exhibit 12).

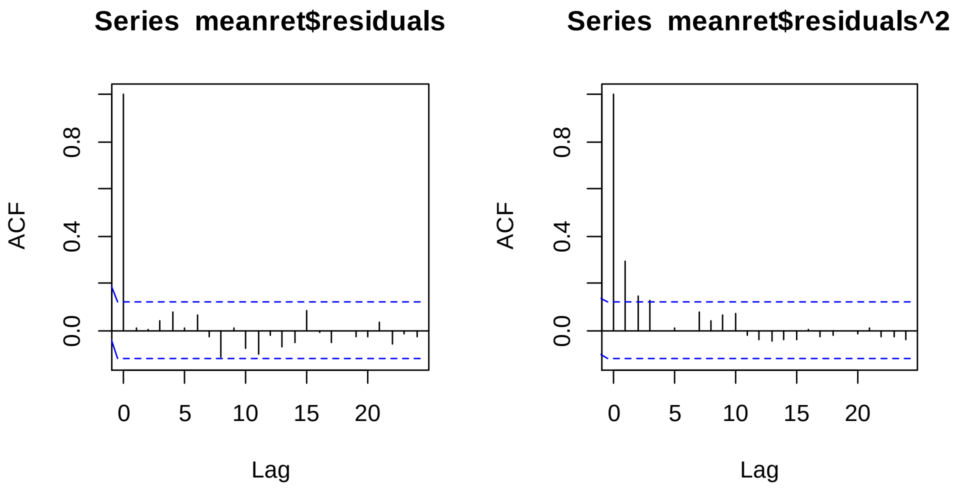
Exhibit 12 – USTR squared returns visualization



Source: Own calculations using R project software and tseries package

To conclude about conditional heteroscedasticity, the ACF and PACF of squared residuals were build, through which was inferred the presence of a high persistence of square residuals, implying that an appropriate model to capture this feature can have an ARCH like structure (Exhibit 13).

Exhibit 13 – Autoregressive squared returns visualization



Note: An ARIMA (2,0,0)-AR(2) was be used, which implies that only the Autoregressive component is being estimated using a second order lag.

Source: Own calculations using R project software and tseries package

e) ARCH effect

The ARCH effect (which points for conditional heteroscedasticity of the errors) is analysed through an LM test, where in the null hypothesis test the inexistence of ARCH effects. A second test, the Portmanteau Q test, is similar to one used to test the joint autocorrelation on the squared residuals, the Ljung-Box test. The null hypotheses in the Portmanteau is the inexistence of a joint correlation in the square residuals, i.e., they are a sequence of white noise, against the alternative, which implies they have autocorrelation (Engle, 1982). Both tests, with the exception of LM with 24 lags, strongly reject the null hypothesis and suggest the statistical significance of the lags, i.e., the existence of conditional heteroscedasticity (Exhibit 14). A graphic analysis of square residuals also evidences statistical significance of previous observations (Exhibit 15).

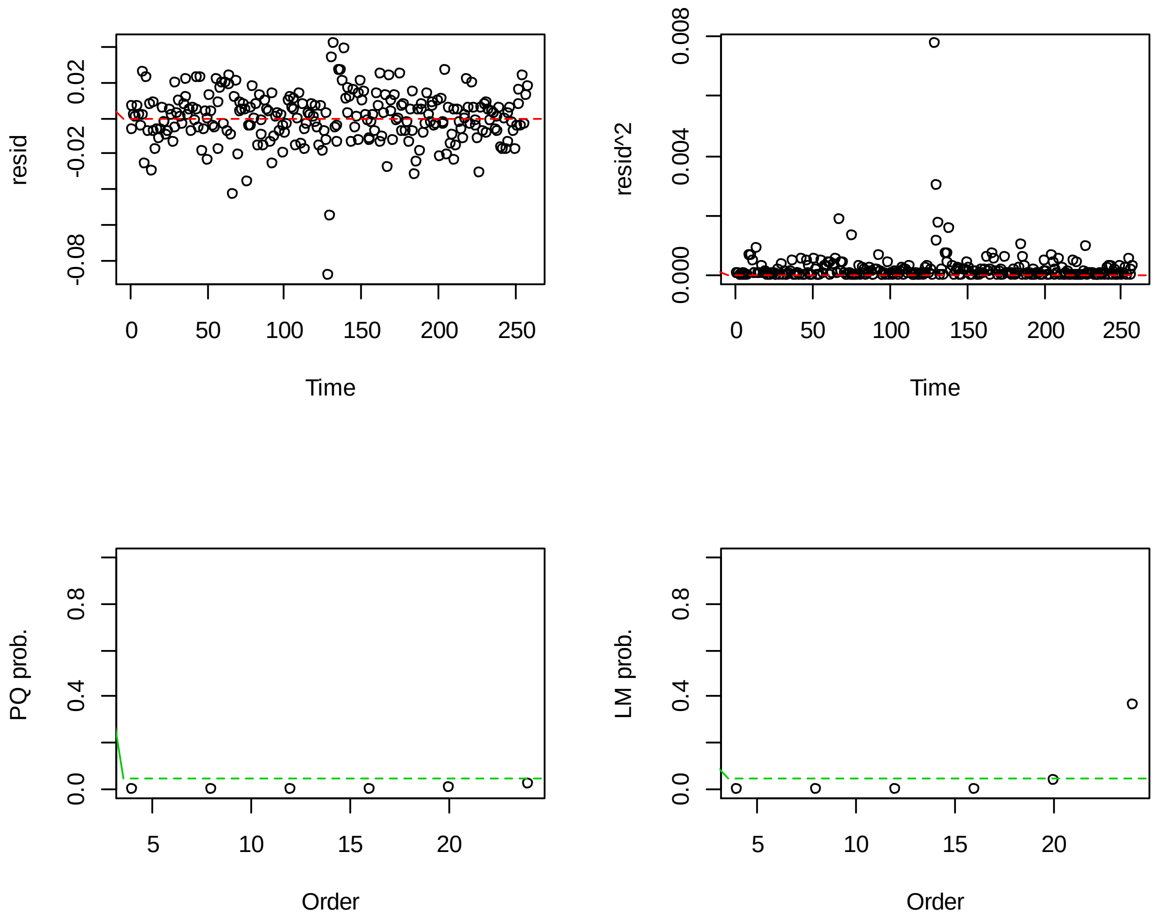
Exhibit 14 – ARCH LM tests

	test order	Portmanteau-Q	Lagrange-Multiplier
[1,]	4	31,6 *	201,9 *
[2,]	8	33,8 *	89 *
[3,]	12	36,5 *	57,8 *
[4,]	16	37,9 *	41,4 *
[5,]	20	38,3 **	31,5 **
[6,]	24	39,2 **	24,8

Note: the asterisks ***, **, * indicate significance at 1, 5, 10% respectively

Source: Own calculations using R project software and tseries package

Exhibit 15 – Residuals and square residuals graphic visualization



Source: Own calculations using R project software and tseries package

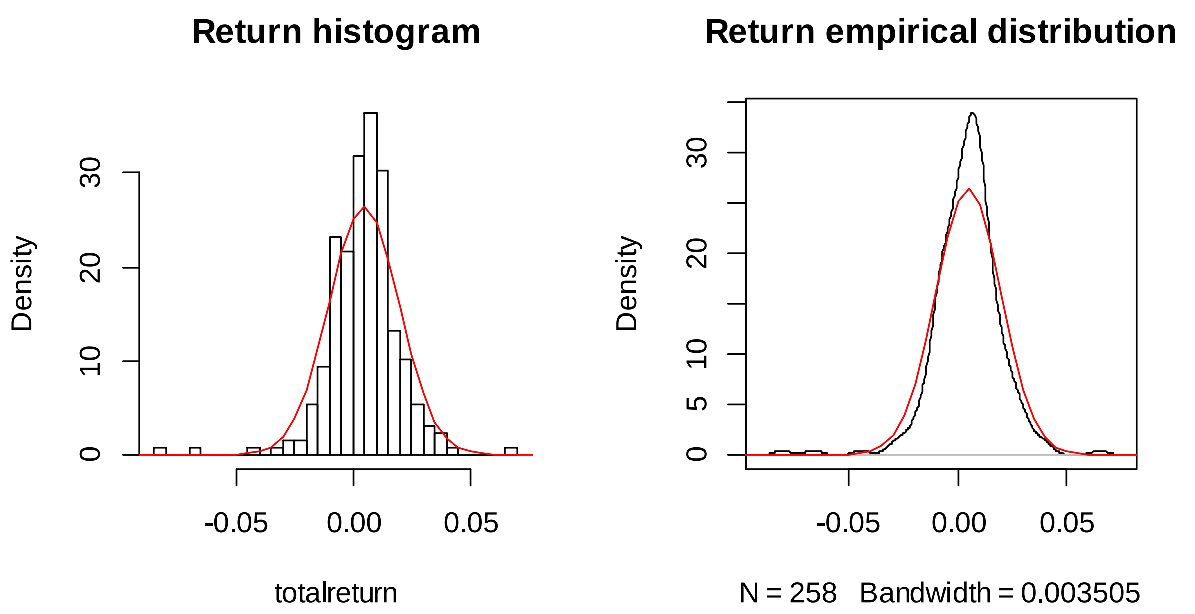
V | Results - Modelling volatility

Formal statistical tests and ACF graphical representation of the data show that the autocorrelation of squared returns is statistically significant, thus we can proceed to (i) estimate ARCH like structures given the existence of conditional heteroscedasticity of the errors, (ii) specifying firstly an AR (2) structure for the conditional mean equation. The first approach will be to test the mentioned ARCH type structures without external regressors, followed by the inclusion of explanatory variables for the conditional volatility.

a) Testing ARCH type models

The choice of the structure as well as the underlying distribution are the first step to model volatility. In spite of graphical depiction and initial tests pointing for the non-normality of the data, the first distribution for the errors considered was a normal distribution. However, an analysis of the returns histogram in Exhibit 16 validates what previous empirical tests show, namely some skewness and heavy left tails, which means that other distributions, such as Student's t or Generalized Error distribution, could provide a better fit. The estimation results of the AR-GARCH models are in Exhibit 17 and Exhibit 18.

Exhibit 16 - USTR PACF and ACF graphic depiction



Source: Own calculations using R project software and tseries package

Using the RUGARCH package in R, I estimated a GARCH (1,1) model using (3) for the returns of USTR and using an AR (2) structure for the conditional mean returns. According to the test for white noise behaviour of the residuals, the Ljung-Box test, the residuals have a p-value>0.05, and therefore the null hypothesis is not rejected, i.e., there is no evidence of autocorrelation. The test on the standardized squared residuals, which tests for ARCH effect in the residuals, also implies the inexistence of serial correlation in squared residuals as the p-value>0.05.

However, the Pearson test strongly suggest that the normal distribution is rejected and the negative bias test implies some leverage in the data. The p-value for the AR coefficient estimates (ar1 and ar2) are statistically significant, as well as the gamma (leverage) coefficient.

Considering the existence of leverage and building upon the key intakes of the literature review, an exponential GARCH, EGARCH (1,1) using formula (5) was estimated with an underlying normal distribution. The fitting of the model (see Exhibit 19) shows some improvements, namely in the AR model parameters. However, the estimation of alpha1, the coefficient for the "spikeness" of the volatility is not statistically significant, as its p-value is now greater than 0.05.

Testing an EGARCH structure with a student-t reveals an improvement, considering that the coefficients are now statistically significant. Furthermore, the "shape" coefficient has a p-value close to 5% and the information criteria, such as the AIC, improve. Regardless, the "shape" still does not have the best fit and the gamma (leverage) coefficient is not significant.

The best fit and "shape" coefficient was achieved when an EGARCH(1,1) with a generalised error distribution was considered. However, several estimates for the parameters were still not statistically significant.

Exhibit 17 - Coefficient comparison with robust standard errors GARCH and EGARCH

	GARCH(1,1)		EGARCH_N (1,1)		EGARCH_T (1,1)	
distribution	normal		normal		t-student	
Coefficients:	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
mu	0,003806	0,000940 *	0,003711	0,000970 *	0,004189	0,000874 *
ar1	0,100904	0,068302	-0,831348	0,117627 *	0,086281	0,067954
ar2	-0,030189	0,070523	0,093760	0,036092 *	-0,006057	0,069419
omega	0,000043	0,000018 **	0,950728	0,139369 *	-0,136332	0,847407
alpha1	0,101872	0,043111 **	0,000044	0,000017 **	0,014390	0,081438
beta1	0,691283	0,109734 *	0,107246	0,042242 **	0,840163	0,098977 *
gamma1			0,682249	0,105218 *	0,323322	0,118331 *
skew	0,766090	0,060578 *	0,756696	0,060362 *	0,874703	0,078899 *
shape					0,588014	2,133485 *
Robust						
mu	0,003806	0,001126 *	0,003711	0,001169 *	0,004189	0,000913 *
ar1	0,100904	0,061373	-0,831348	0,197129 *	0,086281	0,068951
ar2	-0,030189	0,089307	0,093760	0,073158	-0,006057	0,081424
omega	0,000043	0,000017 *	0,950728	0,181593 *	-0,136332	0,629464 **
alpha1	0,101872	0,035724 *	0,000044	0,000016 *	0,014390	0,080725
beta1	0,691283	0,074663 *	0,107246	0,043789 **	0,840163	0,073353 *
gamma1		*	0,682249	0,071583 *	0,323322	0,125493 *
skew	0,766090	0,088164 *	0,756696	0,087878 *	0,874703	0,064784 *
shape					0,588014	2,494630 **

Source: Own calculations using R project software and ruGARCH package

Exhibit 18 - Overview of tests results with a GARCH framework

	GARCH(1,1)			
distribution	normal			
Information criteria				
Akaike	-5,6838			
Bayes	-5,5874			
Shibata	-5,6852			
Hannan-Quinn	-5,6450			
eighted Ljung-Box Test Standardized Residuals				
	statistic	p-value		
Lag[1]	0,0743	0,7852		
Lag[2*(p+q)+(p+q)-1][5]	1,1423	0,9999		
Lag[4*(p+q)+(p+q)-1][9]	3,4878	0,8038		
Veighted Ljung-Box Test Standardized Squared				
	statistic	p-value		
Lag[1]	0,4830	0,4870		
Lag[2*(p+q)+(p+q)-1][5]	0,6597	0,9305		
Lag[4*(p+q)+(p+q)-1][9]	0,7860	0,9934		
d,o,f=2				
Weighted ARCH LM				
	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0,2027	0,5000	2,0000	0,6526
ARCH Lag[5]	0,2587	1,4400	1,6670	0,9510
ARCH Lag[7]	0,3359	2,3150	1,5430	0,9907
Nyblom stability test				
Joint Statistic:	1,1613			
Individual Statistics:				
mu	0,0909			
ar1	0,0862			
ar2	0,4687			
omega	0,0790			
alpha1	0,1752			
beta1	0,0925			
gamma1	---			
skew	0,1434			
shape	---			
Individual Statistics:				
Asymptotic Critical Values	10%	5%	1%	
Joint Statistic:	1,6900	1,9000	2,3500	
Individual Statistic:	0,3500	0,4700	0,7500	
Sign Bias Test				
	t-value	prob		
Sign Bias	1,0076	0,3146		
Negative Sign Bias	0,4980	0,6189		
Positive Sign Bias	0,5839	0,5598		
Joint Effect	1,0186	0,7967		
Adjusted Pearson Goodness-of-Fit				
	group	statistic	›-value(g-1)	
1	20	14,2500	0,7690	
2	30	21,7700	0,8297	
3	40	41,2200	0,3735	
4	50	52,4700	0,3412	

Source: Own calculations using R project software and ruGARCH package

Exhibit 19 - Overview of tests results with an EGARCH framework

	EGARCH_N (1,1)				EGARCH_T (1,1)			
distribution	normal				t-student			
Information criteria								
Akaike	-5,6801				-5,7301			
Bayes	-5,5700				-5,6061			
Shibata	-5,6820				-5,7324			
Hannan-Quinn	-5,6358				-5,6802			
eighted Ljung-Box Test Standardized Residuals								
	statistic	p-value			statistic	p-value		
Lag[1]	0,0021	0,9631			0,1395	0,7088		
Lag[2*(p+q)+(p+q)-1][5]	3,0743	0,9951			1,2721	0,9998		
Lag[4*(p+q)+(p+q)-1][9]	7,0165	0,5570			3,7371	0,7510		
eighted Ljung-Box Test Standardized Squared								
	statistic	p-value			statistic	p-value		
Lag[1]	0,2829	0,5948			0,2307	0,6310		
Lag[2*(p+q)+(p+q)-1][5]	0,4921	0,9589			0,3354	0,9799		
Lag[4*(p+q)+(p+q)-1][9]	0,6166	0,9970			0,4017	0,9993		
d,o,f=2								
Weighted ARCH LM								
	Statistic	Shape	Scale	P-Value	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0,2542	0,5000	2000,0000	0,6141	0,1306	0,5000	2,0000	0,7178
ARCH Lag[5]	0,2970	1,4400	1,6670	0,9411	0,1824	1,4400	1,6670	0,9696
ARCH Lag[7]	0,3664	2,3150	1,5430	0,9888	0,2111	2,3150	1,5430	0,9967
Nyblom stability test								
Joint Statistic:	0,7978				1,2772			
Individual Statistics:								
mu	0,0797				0,0758			
ar1	0,0811				0,0660			
ar2	0,0893				0,4149			
omega	0,0768				0,0565			
alpha1	0,0849				0,2286			
beta1	0,1728				0,0548			
gamma1	0,0973				0,1628			
skew	0,1428				0,1048			
shape	---				0,0449			
Individual Statistics:								
Asymptotic Critical Values	10%	5%	1%		10%	5%	1%	
Joint Statistic:	1,8900	2,1100	2,5900		2,1000	2,3200	2,8200	
Individual Statistic:	0,3500	0,4700	0,7500		0,3500	0,4700	0,7500	
Sign Bias Test								
	t-value	prob			t-value	prob		
Sign Bias	1,0761	0,2829			1,1678	0,2440		
Negative Sign Bias	0,4850	0,6281			0,3278	0,7433		
Positive Sign Bias	0,5233	0,6012			0,8933	0,3726		
Joint Effect	1,1675	0,7608			1,5023	0,6817		
Adjusted Pearson Goodness-of-Fit								
	group	statistic	p-value(g-1)		group	statistic	p-value(g-1)	
1	20	21,5300	0,3080		20	11,9200	0,8889	
2	30	33,6300	0,2531		30	19,4400	0,9094	
3	40	35,3300	0,6379		40	36,5700	0,5811	
4	50	42,0000	0,7504		50	38,1200	0,8694	

Source: Own calculations using R project software and ruGARCH package

b) EGARCH with exogenous variables

As more than one model can be a good fit to model the conditional variance with external regressors, I used an EGARCH with a t-student distribution and an EGARCH with a generalized error distribution, using all the variables mentioned in IV. As external regressors[6].

Main conclusions with EGARCH(1,1) structure using a t-student distribution (view Exhibit 20 and Exhibit 21):

- Coefficient significance: the autoregressive (ar) parameters are not statistically significant.
- AIC criteria shows an improvement in information of the model when compared to the previous ones and that this approach, according to this criterion, should be preferred to the models without regressors.
- Residual analysis: The Ljung-Box test validates the evidence of autocorrelation and the test on the standardized squared residuals implies the inexistence of serial correlation in squared residuals, confirming that the residuals behave as a white noise process;
- Sign bias and leverage fitting: The model clearly shows leverage, particularly from positive shocks.
- Distribution adequacy: the distribution does not have a perfect fit according to the Pearson Godness of Fit distribution.

Main conclusions with EGARCH(1,1) structure using a generalized error distribution:

- Coefficient significance: all parameters are statistically significant, hence the equations for the mean return and variance are adequate.
- AIC criteria shows an improvement versus models without external regressor but a slight loss when compared to the same structure using a t-student.
- Residual analysis: The Ljung-Box test validates the evidence of autocorrelation and the test on the standardized square residuals implies the inexistence of serial correlation in squared residuals, confirming that in this structure the residuals also behave as a white noise process;

[6] The explanatory variables were subject to a multicollinearity diagnostic to infer the need to exclude a variable and all were considered relevant as multicollinearity among variables was not significant (Annex III).

- Sign bias and leverage fitting: The model clearly shows leverage, particularly from positive shocks.
- Distribution adequacy: the p-value in the Pearson Godness of Fit test is almost 5% and hence this is the best fit of all the structures tested.

All in all the best fit to model credit returns volatility is an EGARCH structure with a generalized error distribution. An analysis of the coefficients of this model shows the relevance of the regressors.

Exhibit 20 - Coefficient comparison with robust standard errors - models with external regressors

	EGARCH_T (1,1) with external regressors		EGARCH_GED (1,1) with external regressors	
distribution	t-student		ged	
Coefficients:	Estimate	Std. Error	Estimate	Std. Error
mu	0,004952	0,000930 *	0,004859	0,000005 *
ar1	0,060245	0,077221	0,050588	0,000118 *
ar2	-0,033788	0,068717	-0,106605	0,000178 *
omega	0,000053	0,000014 *	-1,030305	0,000803 *
alpha1	0,129972	0,159277	0,045795	0,000218 *
beta1	0,616508	0,109589 *	0,882081	0,000461 *
gamma1	-0,018564	0,165053	-0,329057	0,001012 *
skew	0,000000	0,007318	---	---
shape	1,304075	0,233182	1,873991	0,001741 *
vxreg1 = retGDP	-0,018564	0,165053	-0,277613	0,001187 *
vxreg2 = retCPI	0,000000	0,007318	-1,644668	0,001020 *
vxreg3 = retINDPROD	0,000000	0,005725	-16,186347	0,015079 *
vxreg4 = retSKEXPORTS	0,000000	0,002813	3,038934	0,002851 *
vxreg5 = retISMMAN	0,000000	0,000458 *	-8,952784	0,008423 *
vxreg6 = retISMCOMP	0,000000	0,000826	5,968180	0,012064 *
vxreg7 = retPHILYFED	0,000000	0,001718	0,018819	0,000046 *
vxreg8 = retINTJOBCL	0,000001	0,000000 *	0,595462	0,017972 *
vxreg9 = retEPU	0,000000	0,000393	-0,126720	0,002930 *
vxreg10 = retFF	0,000000	0,000120	-0,336776	0,000526 *
Robust				
mu	0,004952	0,001279 *	0,004859	0,000177 *
ar1	0,060245	0,098569	0,050588	0,001735 *
ar2	-0,033788	0,102826	-0,106605	0,022947 *
omega	0,000053	0,000017 *	-1,030305	0,035216 *
alpha1	0,129972	0,173977	0,045795	0,003020 *
beta1	0,616508	0,165245 *	0,882081	0,210538 *
gamma1	-0,018564	0,178031	-0,329057	0,142371 **
skew	0,000000	0,000000 *	1,873991	0,025687 *
shape	1,304075	0,260839 *	1,873991	0,025687 *
vxreg1 = retGDP	0,000000	0,007547	-0,277613	0,040324 *
vxreg2 = retCPI	0,000000	0,006862	-1,644668	0,042128 *
vxreg3 = retINDPROD	0,000000	0,002478	-16,186347	0,285550 *
vxreg4 = retSKEXPORTS	0,000000	0,000650	3,038934	0,095440 *
vxreg5 = retISMMAN	0,000000	0,001069	-8,952784	0,284068 *
vxreg6 = retISMCOMP	0,000000	0,002673	5,968180	0,229710 *
vxreg7 = retPHILYFED	0,000001	0,000000 *	0,018819	0,000541 *
vxreg8 = retINTJOBCL	0,000000	0,000329	0,595462	0,252190 **
vxreg9 = retEPU	0,000000	0,000131	-0,126720	0,044003 *
vxreg10 = retFF	0,000000	0,000206	-0,336776	0,063376 *

Source: Own calculations using R project software and ruGARCH package

Exhibit 21 - Overview of test results - models with external regressors

	EGARCH_T (1,1) with external regressors				EGARCH_GED (1,1) with external regressors			
distribution	t-student				ged			
Information criteria								
Akaike	-5,6355				-5,7895			
Bayes	-5,3876				-5,5416			
Shibata	-5,6444				-5,7984			
Hannan-Quinn	-5,5358				-5,6898			
eighted Ljung-Box Test Standardized Residuals								
	statistic	p-value			statistic	p-value		
Lag[1]	0,5894	0,4427			1,4520	0,2282		
Lag[2*(p+q)+(p+q)-1][5]	#########	0,9984			3,5410	0,1900		
Lag[4*(p+q)+(p+q)-1][9]	#########	0,7490			5,4490	0,3571		
eighted Ljung-Box Test Standardized Squared								
	statistic	p-value						
Lag[1]	0,5166	0,4723			0,0294	0,8638		
Lag[2*(p+q)+(p+q)-1][5]	0,6527	0,9318			0,5391	0,9515		
Lag[4*(p+q)+(p+q)-1][9]	0,7898	0,9933			1,3489	0,9670		
d,o,f=2								
Weighted ARCH LM								
	Statistic	Shape	Scale	P-Value	Statistic	Shape	Scale	P-Value
ARCH Lag[3]	0,1740	0,5000	2000,0000	0,6766	0,4774	0,5000	2,0000	0,4896
ARCH Lag[5]	0,2267	1440,0000	1667,0000	0,9591	0,6589	1,4400	1,6670	0,8359
ARCH Lag[7]	0,3174	2315,0000	1543,0000	0,9918	0,9852	2,3150	1,5430	0,9160
Nyblom stability test								
Joint Statistic:	12,3710				n.a.			
Individual Statistics:								
mu	0,1530				0,0540			
ar1	0,0652				0,0582			
ar2	0,2730				0,0520			
omega	0,1037				NaN			
alpha1	0,1653				0,0545			
beta1	0,1156				NaN			
gamma1	0,2212				0,0599			
skew	0,0000				---			
shape	0,0285				0,0546			
Individual Statistics:								
Individual Statistics for regressors:								
vxreg1 = retGDP	0,4113				0,0551			
vxreg2 = retCPI	0,0513				0,0544			
vxreg3 = retINDPROD	0,7697				0,0554			
vxreg4 = retSKEXPORTS	0,0973				0,0536			
vxreg5 = retISMMAN	0,4472				0,0577			
vxreg6 = retISMCOMP	0,1728				0,0596			
vxreg7 = retPHILYFED	0,2488				0,0564			
vxreg8 = retINTJOBCL	0,4466				0,0574			
vxreg9 = retEPU	0,6844				0,0623			
vxreg10 = retFF	2,1642				0,0537			
Asymptotic Critical Values	10%	5%	1%		10%	5%	1%	
Joint Statistic:	3,8300	4,1400	4,7300		0,3500	0,4700	0,7500	
Individual Statistic:	0,3500	0,4700	0,7500		0,0000	0,0000	0,0000	
Sign Bias Test								
	t-value	prob			t-value	prob		
Sign Bias	1,2647	0,2071			0,5883	0,5568		
Negative Sign Bias	0,4914	0,6236			1,5944	0,1121		
Positive Sign Bias	0,8378	0,4030			0,1672	0,8673		
Joint Effect	1,6385	0,6507			2,5831	0,4605		
Adjusted Pearson Goodness-of-Fit								
	group	statistic	-value(g-1)		group	statistic	-value(g-1)	
1	20	14,0900	0,7782		20	30,0600	0,0510	
2	30	26,6500	0,5905		30	40,1400	0,0817	
3	40	36,5700	0,5811		40	59,8300	0,0175	
4	50	48,2000	0,5054		50	52,8500	0,3277	

Source: Own calculations using R project software and ruGARCH package

c) **Coefficient analysis**

The best model to analyse credit market conditional volatility was an autoregressive conditional heteroscedasticity structure with a generalized error distribution, which will now be analysed in greater detail. The estimated coefficients are in Exhibit 22. Most of the coefficients for external regressors are negative, which negative positive shocks will likely imply a higher conditional variance in t+1 than positive shocks. Still, an in depth analysis should be made, as the interpretation of these coefficients has to take into consideration that (i) the credit debt markets are below equity markets in the risk scale and (ii) the investment grade bonds are higher quality debt securities.

Exhibit 22 - Coefficients for external regressors of EGARCH (1,1) model with GED distribution

Coefficients				
	Estimate	p-value	Robust	p-value
mu	0,004859	0,00000	0,004859	0,00000
ar1	0,050588	0,00000	0,050588	0,00000
ar2	-0,106605	0,00000	-0,10661	0,00000
omega	-1,030305	0,00000	-1,03031	0,00000
alpha1	0,045795	0,00000	0,045795	0,00000
beta1	0,882081	0,00000	0,882081	0,00003
gamma1	-0,329057	0,00000	-0,32906	0,02082
shape	1,873991	0,00000	1,873991	0,00000
GDP	-0,277613	0,00000	-0,27761	0,00000
CPI	-1,644668	0,00000	-1,64467	0,00000
INDPROD	-16,186347	0,00000	-16,1863	0,00000
SKEXPORTS	3,038934	0,00000	3,038934	0,00000
ISMMAN	-8,952784	0,00000	-8,95278	0,00000
ISMCOMP	5,96818	0,00000	5,96818	0,00000
PHILYFED	0,018819	0,00000	0,018819	0,00000
INTJOBCL	0,595462	0,00000	0,595462	0,01822
EPU	-0,12672	0,00000	-0,12672	0,00398
FF	-0,336776	0,00000	-0,33678	0,00000

Source: Own calculations using R project software and ruGARCH package

The leverage effect of the model, measured by gamma, is clearly statistically significant, visible in the low p-value. Furthermore, the negative sign indicates that the model is negatively biased, i.e., the reaction to negative news is more pronounced. Focusing on volatility and hence looking at omega, other conclusions arise. Beta's coefficient (the "conditional" or long run volatility coefficient) is statistically relevant and is close to 1, which indicates high persistence of volatility, or in other words, volatility clustering in the model. It is not an unexpected result and frequently observed in financial time series, implying that large changes in volatility can persist for some time[7] (lower decay factor). Alpha, on the other hand, which is the coefficient of the lagged squared residuals (the ARCH effect), is low and positive, indicating that lagged residuals have a low impact on credit return volatility. Beta is the GARCH coefficient, translating into a measure of impact of the variance and it also high, meaning that the decay factor is high.

Concerning the exogenous regressors, the model shows that macroeconomic variables, namely industrial production and the leading indicator for manufacturing production, PMI, have a higher coefficient, i.e., influence, in the volatility of credit markets. This is not an unexpected result. In the 19th century the industrial revolution was the leverage of Great Britain's development, in the 20th century the US, Germany and other countries used industrialization as the path for growth. Nowadays, the high production capacity of China has placed the country growing at one of the highest rate of the world during the last years. National wealth and power, innovation (such as in the technology sector) are linked to strong and fast developing manufacturing sectors. Henceforth, a sign that the industrial production is rising decreases risk aversion and has a negative impact in credit volatility, or in other words, decreases volatility. The explanation is intuitive: credit markets are below the equity in the "spectrum" of investor risk taking. When expectations for the economy are positive, the investment is directed to more cyclical asset classes, i.e., equity. When investors foresee distress signals in the economy, either through industrial production or PMI, the investment is channelled to fixed income assets, i.e., credit markets. The composite index of ISM has a positive impact on volatility, smaller than the manufacturing indicator, which implies that additional information concerning services is relevant but has a positive impact in volatility, i.e., increases credit return volatility instead of decreasing.

[7] During the Great financial crisis of 2007-2008, for instance.

The GDP indicator is not as strong, although possessing a negative sign, which was expected, due to fact that several information has been perceived by investors through other indicators. First, because GDP is released on a quarterly basis and other indicators are released monthly. Second, because leading indicators give an indication of the undergoing activity and expectations by the companies in the main operating sectors of the economy. CPI has a higher coefficient which suggests that inflation is more significant to credit return volatility, i.e., more relevant for the investor to take decisions than GDP. When inflation rises, returns of credit are more volatile due to the possible implications of this rise, and vice-versa.

South Korean exports have a relevant coefficient, which is positive. This indicator is closely watch because the country releases export data before other countries and has a close connection with China, hence the positive impact on volatility is understandable. International trade instability was enhanced following Donald Trump's election in November, 2016 and its prerogative to renegotiate trade terms. As such, although South Korean exports are a relevant indicator and a barometer per se to see global trade status.

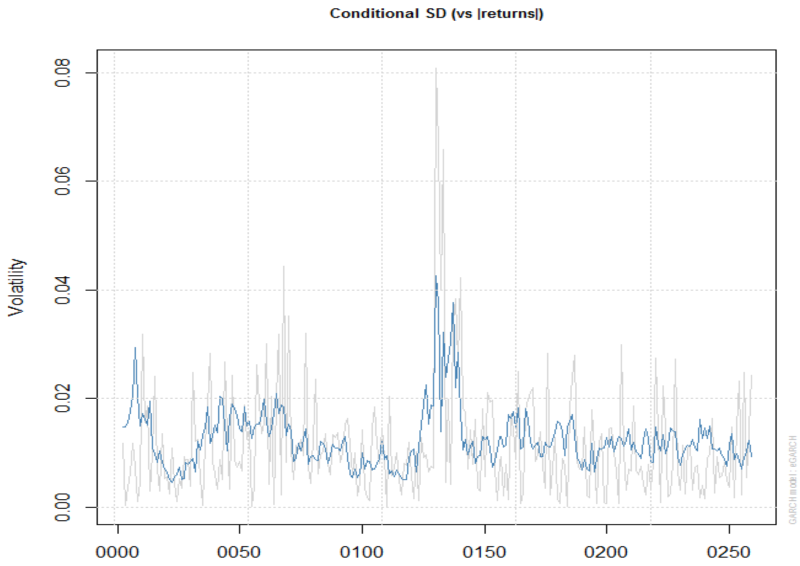
Leading indicators, such as Philadelphia Fed's Business Outlook Survey or Initial Jobs Claims have positive subdued effect on volatility. Regardless, the impact of the "PhillyFed" is marginal and has the smallest coefficient estimate, suggesting that overall volatility results were not greatly impacted by this indicator.

The Economic Policy Uncertainty index has a negative coefficient, suggesting that increases in this variable negatively impact credit returns volatility. EPU is being used as a proxy for monetary policy uncertainty and geopolitical instability, therefore a negative coefficient implies that when uncertainty increases, volatility of credit returns decreases.

Fed Funds also have a negative coefficient, although more pronounced. Rising or decreasing the reference rate is one of the most important tools a central has in order to achieve its main mandate: price stability. When the economy is growing at a high rate and the inflation is rising to a level that might reach hyperinflation, central banks usually increase rates. Borrowing between banks becomes more expensive, ergo consumer lending also becomes expensive, cooling the economy. The inverse is also true: when the economy is slowing down and inflation is very low, the central bank can decrease rates in order to foment lending and borrowing, stimulating the economy. The implications for this model are direct for the interest rate component, if rates are rising, than the economy is in an upward cycle, decreasing volatility of credit market returns.

Plotting the fit data against the real data, it is possible to see that the model provides a suitable fit (Exhibit 23).

Exhibit 23 – EGARCH(1,1) vs. total returns



Source: Own calculations using R project software and ruGARCH package

VI |Final Remarks and next steps

This study aimed to analyse the volatility of investment grade credit market returns and explanatory factors of this volatility. I choose to analyse dollar denominated bonds, due to its large spectrum and representability, and have used several models, building on existing literature, to compute the conditional volatility of credit returns. The variables used to explain the volatility were macroeconomic news, divided between macroeconomic releases and leading indicators, an uncertainty indicators, which mirrors geopolitical and macroeconomic environment, and the reference rate of the Federal Reserve, the authority on monetary policy.

An important limitation to the following conclusions is the time span of the variables: to ensure that all variables were analysed for the same period, the data analysis window starts in December, 1997, i.e., I worked with only 259 observations and 258 returns. However, this time frame captured the recession of 2001, also known as the dot.com recession and the 2008-2009 recession, also known as the “Great Recession”, the biggest recession since the 1929 Great Depression.

The approach to model the conditional volatility of credit returns was based on ARCH type structures, namely those that effectively captured asymmetry in the reaction of the returns to positive and negative news. My conclusion is that volatility of this asset class can efficiently be modelled by an exponential Generalized Auto Regressive Conditional Heteroscedasticity model. The model has the best fit with the distribution and efficiently captures the leverage effect, finding that negative shocks have a more pronounced effect on volatility.

My findings also allow me to conclude that the volatility of dollar denominated credit market is influenced by certain news flows. It is also possible to infer that macroeconomic variables and leading indicators associated with the manufacturing sector are the most relevant and significant to credit return volatility.

The next step would be to replicate the analysis for the high yield market in dollars and for local currency bonds from emergent markets. Even though the factors or news which influence these asset classes are distinct from the investment grade market in dollars, the structure should hold and translate into interesting results.

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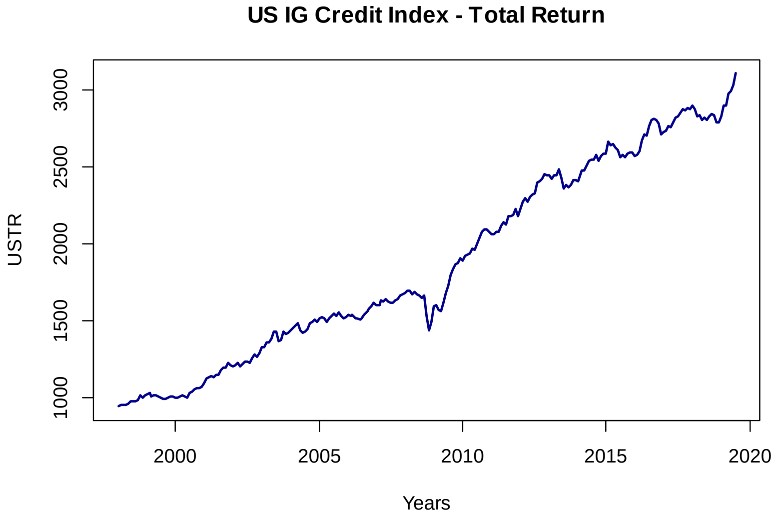
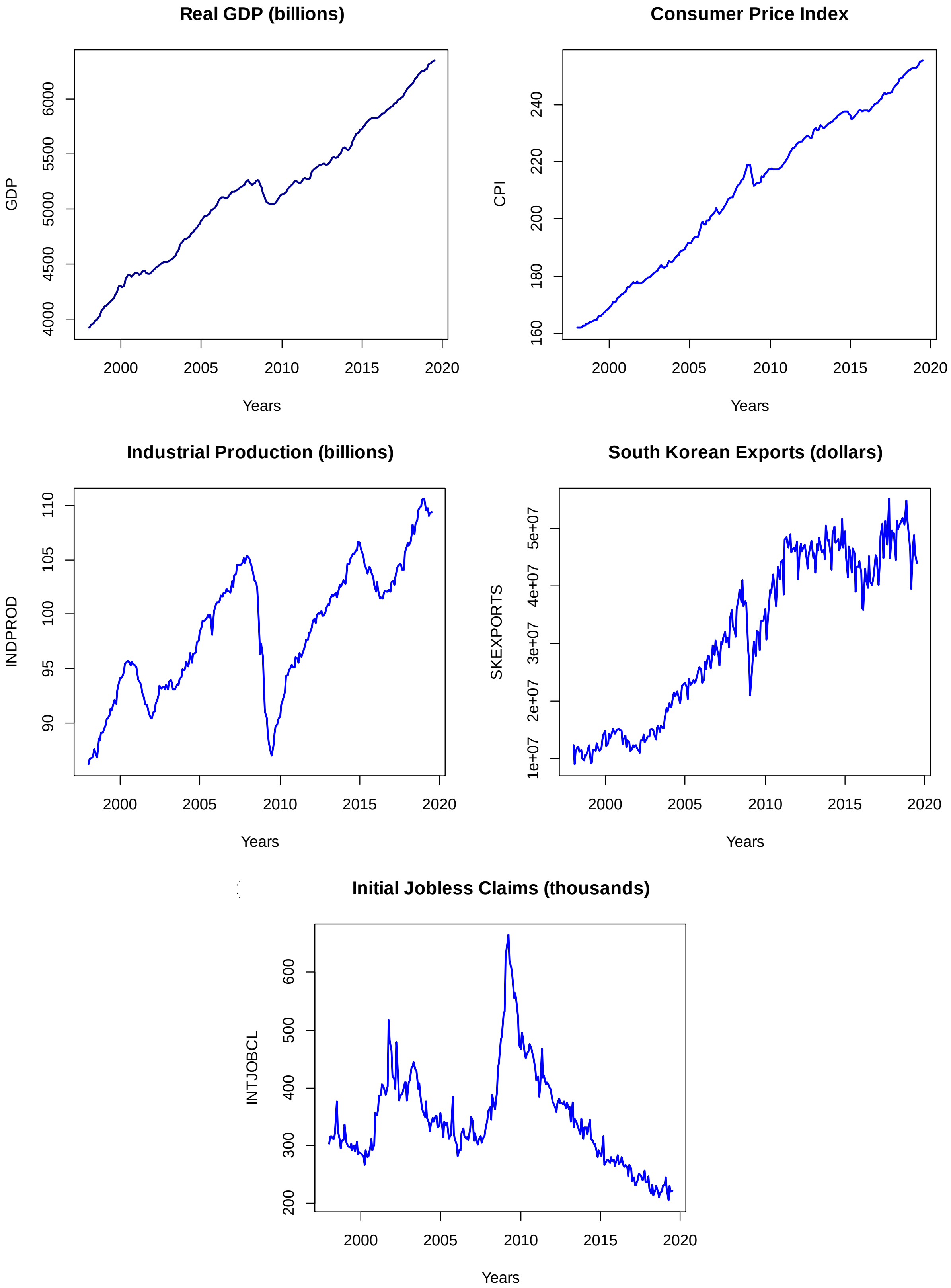
Annex I – Graphical representation of financial time series

Exhibit 24 - Graphic depiction of variables :US Credit Total Return (Index)



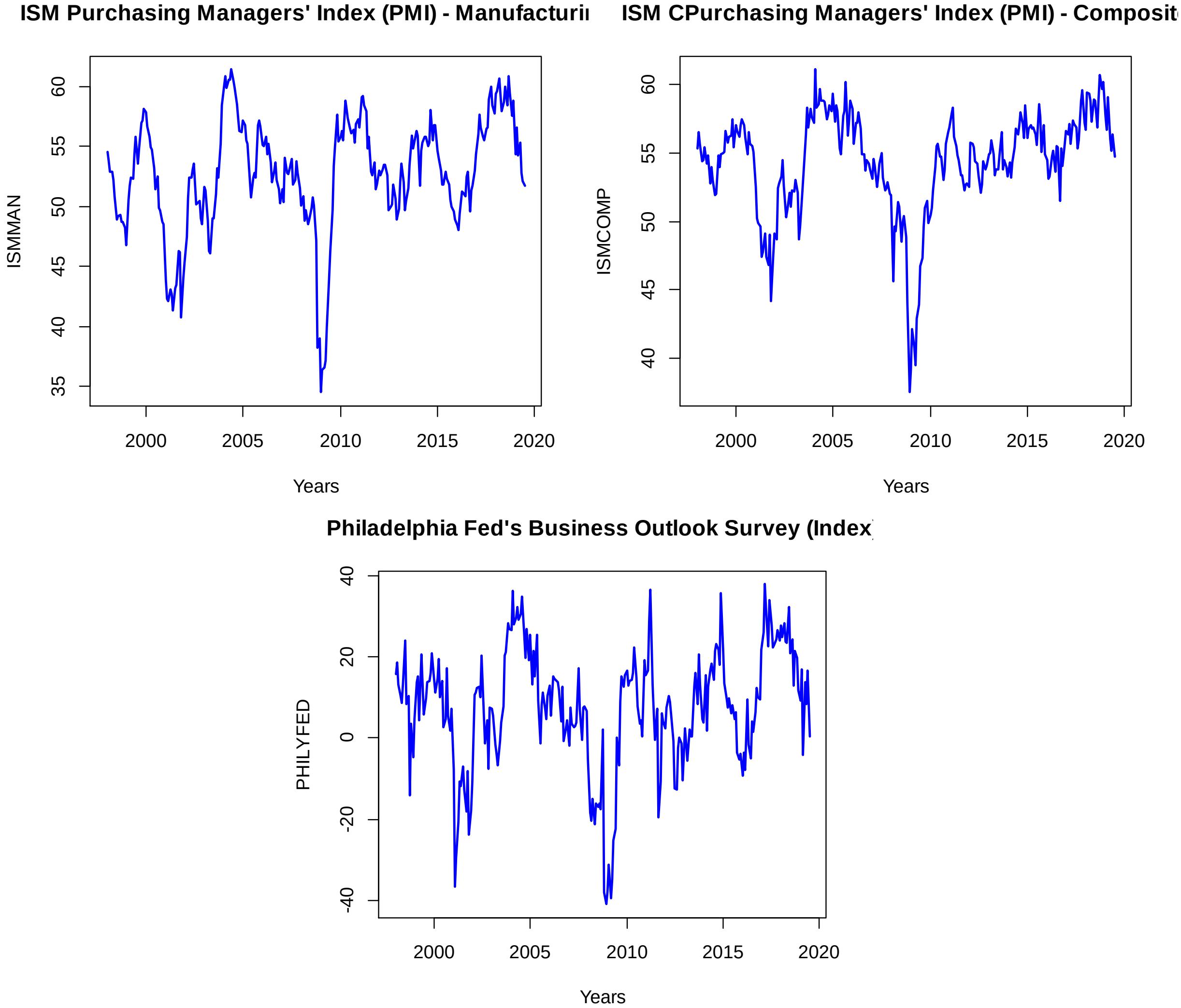
Source: Own calculations using R project software and Psych package

Exhibit 25 - Graphic depiction variables: macroeconomic indicators



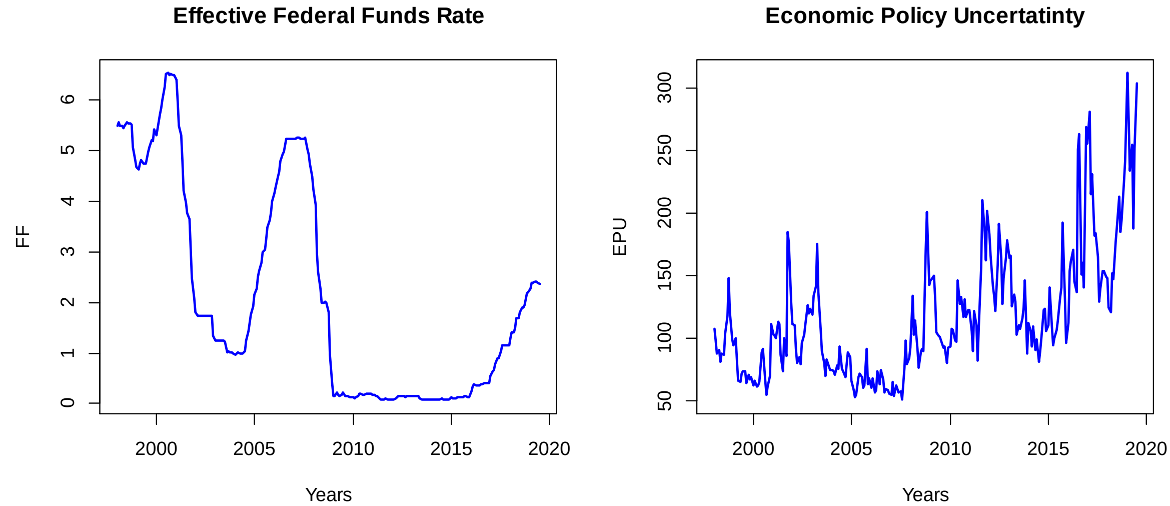
Source: Own calculations using R project software and Psych package

Exhibit 26 – Graphic depiction variables: Leading macroeconomic releases



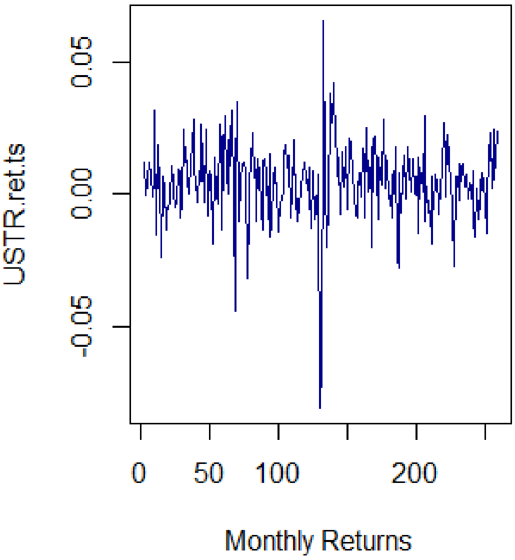
Source: Own calculations using R project software and Psych package

Exhibit 27 - Graphic depiction variables: Fed Funds and EPU Index



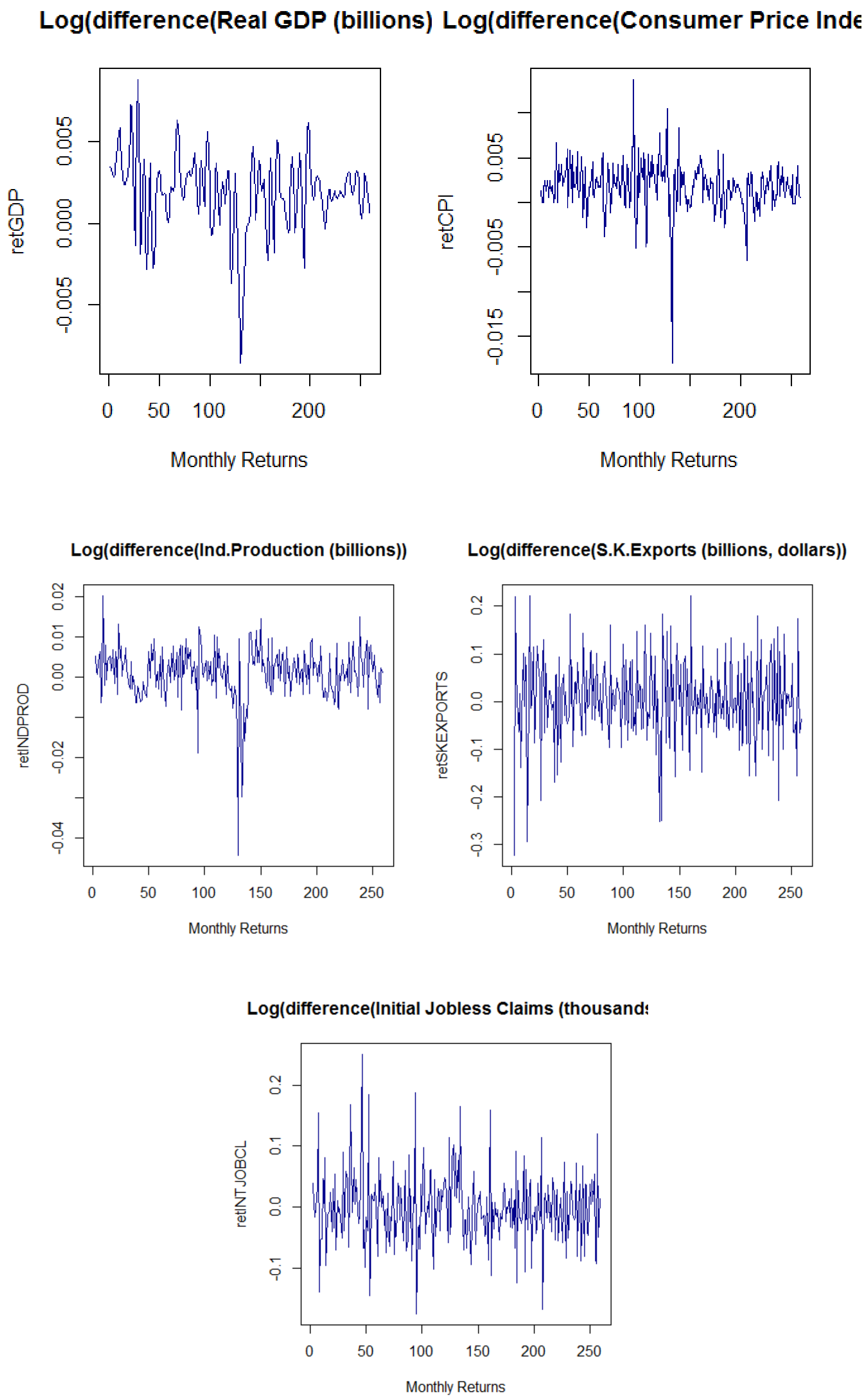
Source: Own calculations using R project software and Psych package

Exhibit 28 - Graphic depiction of the logarithm of the difference : US Credit Total Returns (returns)



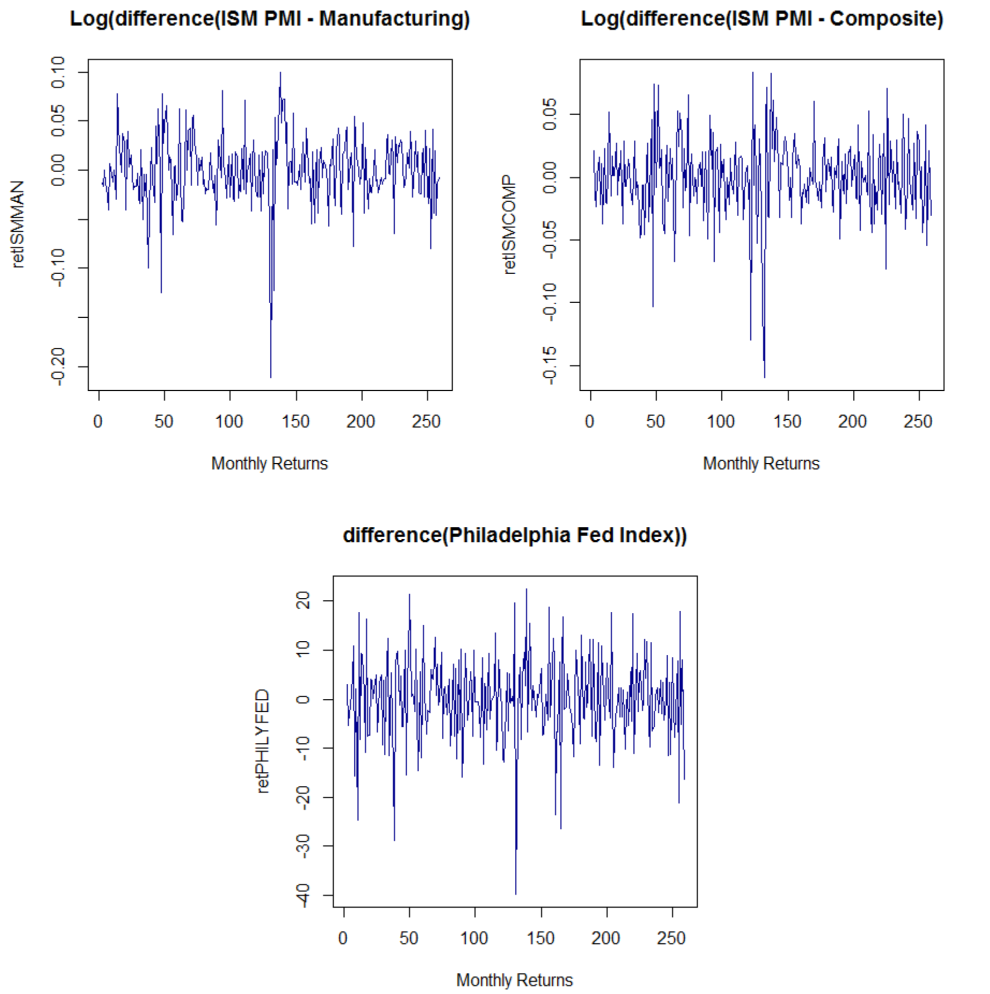
Source: Own calculations using R project software and Psych package

Exhibit 29 - Graphic depiction of the log. difference : macroeconomic variables



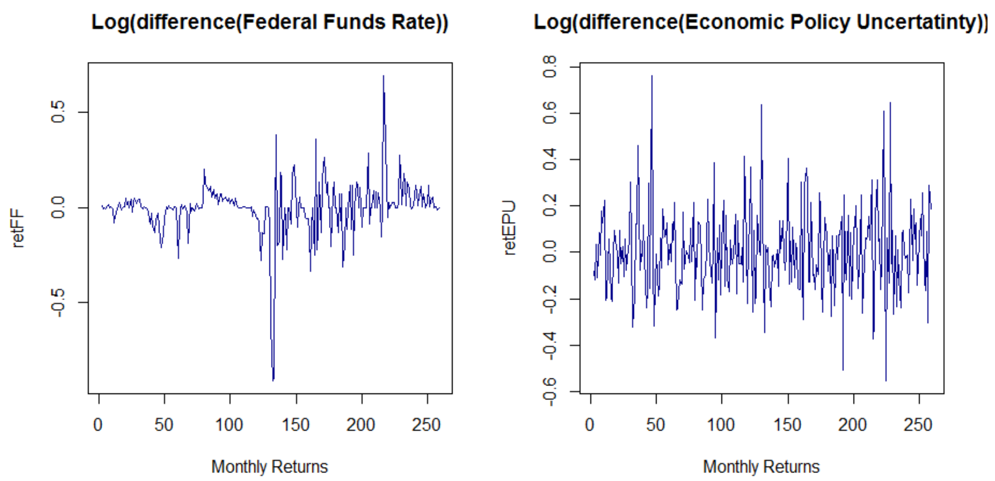
Source: Own calculations using R project software and Psych package

Exhibit 30 - Graphic depiction of the logarithm of the difference : leading indicators



Source: Own calculations using R project software and Psych package

Exhibit 31 - Graphic depiction of the logarithm of the difference : Fed Funds and EPU



Source: Own calculations using R project software and Psych package

Annex II – KPSS tests

Exhibit 32 – KPSS tests

Variable	Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test	
	t-statistic	
USTR		
$(R_t(USTR))$	0,03550	
GDP	0,39560	*
$\log(GDP_t) - \log(GDP_{t-1})$	0,20290	**
CPI	0,66940	*
$\log(CPI_t) - \log(CPI_{t-1})$	0,04620	
INDPROD	0,19500	**
$\log(INDPROD_t) - \log(INDPROD_{t-1})$	0,08020	
SKEXPORTS	0,46590	*
$\log(SKEXPORT_t) - \log(SKEXPORT_{t-1})$	0,06460	
ISMMAN	0,04870	
$\log\ (ISMMAN_t) - \log(ISMMAN_{t-1})$	0,02420	
ISMCOMP	0,23810	*
$\log\ (ISMCOMP_t-) - \log(ISMCOMP_{t-1})$	0,02840	
PHILYFED	0,17520	**
$(PHILYFED_t - PHILYFED_{t-1})$	0,02410	
INTJOBCL	0,57940	*
$\log\ (INTJOBCL_t) - \log(INTJOBCL_{t-1})$	0,04960	
FF	0,28770	*
$\log(FF_t) - \log(FF_{t-1})$	0,16290	**
EPU	0,33380	*
$\log\ (EPU_t) - \log(EPU_{t-1}))$	0,02150	

Source: Own calculations using R project software and URCA package

Annex III – Multicolinearity analysis

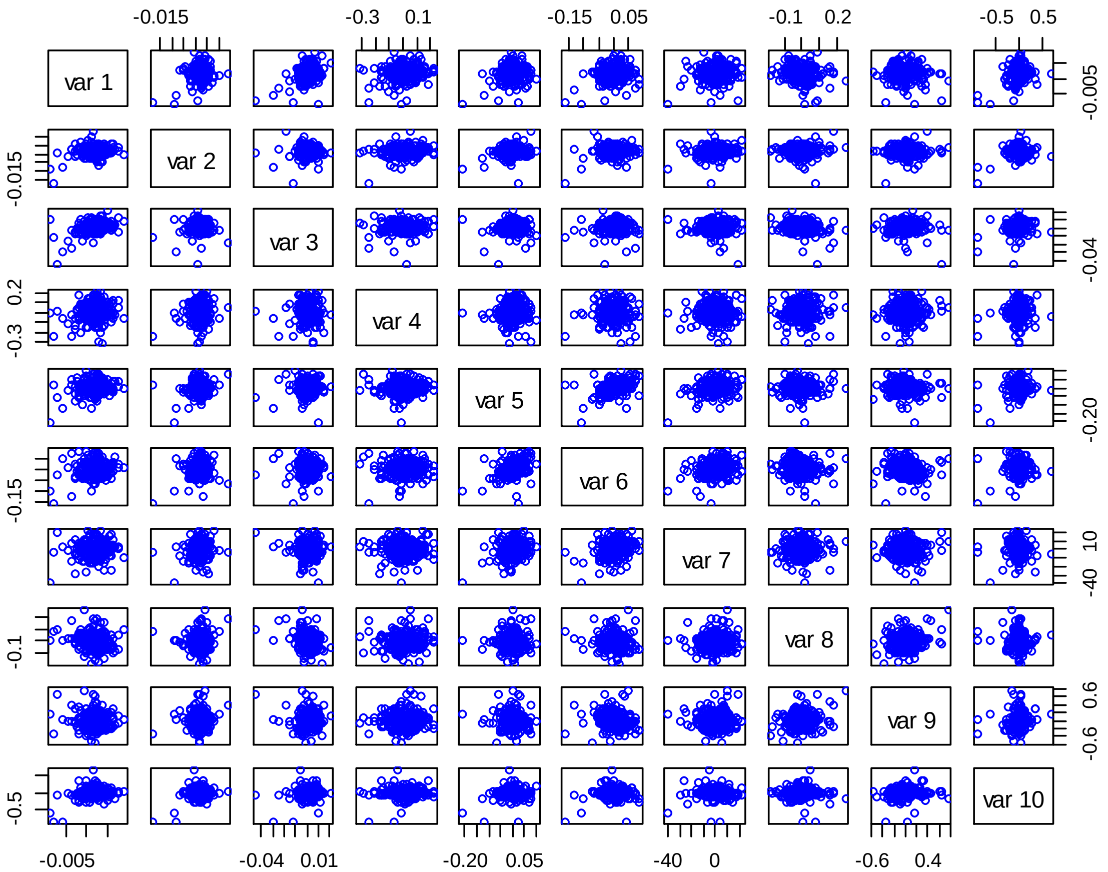
To assess multicollinearity, i.e. the correlation between the variables, two analysis were made: the computation of the VIF (Variance Inflation Factor) and the graphic depiction of the variables. Both analysis reveal a low correlation and hence the inexistence of multicollinearity.

Exhibit 33 – VIF figures for explanatory variables

	GDP	CPI	INDPROD	SKEXPORTS	ISMMAN	ISMCOMP	PHILYFED	INTJOBCL	EPU	FF
VIF	1,421859	1,18015	1,282798	1,053751	1,285917	1,275601	1,158886	1,133641	1,10667	1,262309

Source: Own calculations using R project software and ruGARCH package

Exhibit 34 – Graphic depiction of correlation between explanatory variables



Source: Own calculations using R project software and ruGARCH package