Essays on Market Efficiency in Bond and Equity Markets

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Author
Jürgen Klaus, MBA, LL.M.
born April, 30th 1976 in Leverkusen, Germany

First Supervisor
Prof. Dr. Hermann Locarek-Junge
Chair of Finance and Financial Services

Second Supervisor
Prof. Dr. Bernhard Schipp
Chair of Quantitative Methods, esp. Econometrics

Faculty of Business and Economics
Technische Universität Dresden

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Contents

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Abbreviations

General

ATMF	At the money forward
DFR	Deposit Facility Rate
EA	Euro Area
ECB	European Central Bank
EFSF	European Financial Stability Facility
EMH	Efficient Market Hypothesis
EMMI	European Money Market Institute
EMU	European Monetary Union
EURIBOR	Euro Interbank Offered Rate
ESM	European Stability Mechanism
FRN	Floating Rate Note
GFC	Global Financial Crisis
MRR	Minimum Refinancing Rate
N/A	Not applicable
NIRP	Negative Interest Rate Policy
QE	Quantitative Easing
US	United States (of America)
ZIRP	Zero Interest Rate Policy

Model Abbreviations

AR	Abnormal Return
ARCH	Autoregressive Conditional Heteroskedasticity
CAPM	Capital Asset Pricing Model
CAR	Cumulative Abnormal Return
CCAPM	Consumption Capital Asset Pricing Model
CWT	Continuous Wavelet Transform
DCC	Dynamic Conditional Correlation
FFT	Fast Fourier Transform
GARCH	Generalized ARCH
GMM	General Methods of Moments
SABR	Stochastic Alpha Beta Rho (Model)
WTC	Wavelet Transform Coherence

Summary of Notations

Indexes and Number Sets

t	Index for observation times, $t = 1, \ldots, n$
n, n_{sample}	Sample length
N	Number of repetitions of an experiment
$K_{\cdot}$	Number of out-of-sample points with specifier as index
OI	Outperformance Indicator

Parameters

α, β	Estimated regression parameters
P_t	Price of an asset at point t
R_{it}	Return of asset i at point t
R_{mt}	Return of the market m at point t
Θ_{mt}	Information set for market m at time t
u	Error term, normally distributed with a zero mean
X^e	Expected value of forecast variable X
X^{of}	Optimal forecast value of variable X

Other

ATX20	Austrian Traded Index
bp	Basis point (0.01%)
CAC30	Cotation Assistee en Continu
DAX30	Deutscher Aktienindex
FTSE100	Financial Times Stock Exchange
IBEX35	Iberia Index
IRS	Interest Rate Swap
ISEQ20	Ireland Stock Exchange Overall Index
M	Month(s)
MSCI	Morgan Stanley Capital International
PSI20	Portuguese Stock Index
SMI20	Swiss Market Index
Vol	Volatility
Y	Year(s)

1 Introduction

"We are drowning in information but starved for knowledge."
(John Naisbitt)

Understanding asset price and financial market behavior has been of central interest since markets evolved. On the one hand, plenty of areas were widely researched especially since the late 20th century, providing different asset pricing models and concepts. On the other hand, it appears that finance —despite the mathematical framework it often rightly deploys— is (mainly) a social science. The social factor had impacts on the research path during the more recent past. Additional elements were introduced to describe market participants' behavior, as the next sections of this introduction will detail.

Noteworthy, financial markets changed since the time when most of the key research contributions were published. Amongst other factors, the milestone achievements in computer science and information technology were one driver to these market changes. Especially the 1990s and early 2000s marked the rise and fall of various new market segments and indices, complex products, anomalies and asset price bubbles which partly resulted in the financial crises of the recent past.

At the same time, access to financial markets and their products eased over the last decades while common interest in financial markets increased. Asset prices and markets are not only discussed in depth by professional market participants, researchers and policy makers, but by a growing community of retail investors. Today, retail investors have direct market access via online brokerage and electronic trading platforms, and receive information aside the traditional information channels.

Today's markets face a more heterogeneous market participants structure, and a more diverse and advanced information flow including social media channels. Hence, it appears even more challenging to understand, forecast and measure asset pricing behavior and the resulting financial market impacts.

Meanwhile, regulators and political bodies are required to provide a governing framework for markets. Reports about so called flash crashes organized on social media platforms, excessive volatility in dedicated assets, and unprecedented activities of algorithmic trading accounts, draw not only market participant's but also the regulator's attention. In addition, until late 2020, a tweeting former president of the United States (US) used social media as a key policy communication tool to criticize the US-central bank for interfering in financial markets via quantitative easing (QE) programmes. In the Euro Area (EA), record low interest rates under currently higher inflation rates prevailed for years. Similar to other major central banks, the European Central Bank (ECB) implemented QE-bond-buying-programmes as non-standard monetary policy tools since 2014. These programmes are supposed to end soon and markets speculate about the QE-exit strategy (which markets call quantitative tapering—QT for short).

With recently record high inflation rates, potential rate increases are priced into market forward rates for 2022.[1] Together with the exit from its QE-programmes, the ECB's effectiveness in providing the market the relevant information at the right time remains more important than ever.

This thesis observes and analyses forms of market information efficiencies using a set of novel analysis in often special, partly uncharted market situations. The following two sections introduce two academic pillars on investor expectations using available market information, before in Section 2 the individual research contributions are detailed.

1.1 Rational expectations and asset prices

Analyzing asset returns has a long history and has been widely researched over time. Two key research fields focus on asset price predictability and market expectations.[2] Understanding asset price predictability using a mathematical finance framework goes back to the early 1900s when Bachelier (1900) published his thesis on the Theory of Speculation. He states that small asset price changes over a short time distance are independent from the asset's current price. Bachelier indicates further that past prices are not useful to predict future price moves and that future price moves are driven by the market (participants') *expectations*.

In the 1950s and 1960s, researchers used the past behavior of assets to forecast future asset price expectations. This *adaptive expectation approach* states that expectations change only slowly over time (Mishkin, 2016). In the early 1960s, the economist John Muth objected against the adaptive expectation approach by providing an alternative which he referred to as *rational expectations*. Following Muth (1961), they are formed by information, and a rational expectation is one where the market expectation is identical to the best informed analytical forecast for the future *using all available information*. Since the 1960s and into the 1970s, research in

[1] Writing this cover paper finished in July 2022. During the editorial finalisation late July, the ECB raised interest rates by 0.5% ending eight years of negative rates.

[2] This dissertation does not intend to provide a comprehensive literature review on these topics, but to address the key pillars to introduce its own research focus. Plenty of literature reviews on these topics are available as e.g. in Malkiel (2003) and Sewell (2011).

finance resulted in pioneering work on market efficiency, and rational expectations (in markets). Financial historians did not conclude whether the concept of rational expectations and efficient markets were developed independently or if they were inspired by each other. For this introductory section, the work assumption is that Muth's macroeconomic focused equilibrium model of rational expectations was a core inspiration for the efficient market hypothesis in finance.[3]

Following Mishkin (2016), the rational expectations are derived from the idea that the expected value of an asset equals the optimal forecast under using all available information expressed as:

$$X^e = X^{of}, \tag{1}$$

where X is the forecast variable using X^e as the expected value for X and X^{of} as the optimal forecast using all available information in the market. Commonly known implications of the above rational expectation assumptions are:

Change in X leads to a change in X^e	Rational expectations is generalizable to any variable expectations.
Forecasterror for $X^e = 0$	The forecast errors converge over time to zero and cannot be a predicted prior.

During the late 1960s, the concept of rational expectations became adapted to financial assets. Fama provided a seminal study review of the theory and empirical work on capital markets combining the aforementioned elements of asset predictability. He furthermore stated the relevance of information absorption and rational expectations introducing an event study format measuring abnormal market returns (Fama, 1970).[4]

Fama's efficient market hypothesis (EMH) became a cornerstone in analyzing financial markets in the 1970s. The problem Fama faced was to make his hypothesis testable. The joint hypothesis problem was that an applicable asset pricing model is needed. Any tests of expected returns depend on the model efficiency to test market efficiency.

Fama uses a vector P_{t+1} as payoff of any asset at time $t+1$ (including dividends and interest payments) on tradable market assets at t. The joint distribution is given by $f(P_{t+1}|\Theta_{mt})$ of asset payoffs at $t+1$ implied by the information available in the market at time t with Θ_{mt} being a market information set used to set P_t. Fama calls this the vector of equilibrium prices for assets at time t.

The term $f(P_{t+1}|\Theta_t)$ is the distribution of payoffs implied by all information available at t, Θ_t. Following Fama (2013), the hypothesis at t reflecting full available

[3] An overview of the debate between financial historians can be found e.g. in McCallum (2016) and Delcey (2019). The key finding was that stronger connections between finance and economics were envisaged (especially during the 1970s). Mishkin (2016) posits that Fama's efficient market work applied rational expectations based on Muth to other assets under a different name.

[4] A paper by Fama et al. (1969) analyzing information impacts on stock markets using abnormal returns is seen as the start of the event studies in Finance.

information is under a discreet time:

$$f(P_{t+1}|\Theta_{mt}) = f(P_{t+1}|\Theta_t). \tag{2}$$

Under Fama, $f(P_{t+1}|\Theta_t)$ is the distribution from which prices at $t+1$ will be drawn. Notating the changes between different P gives the return as a difference which offers a better performance attribution for P. Hence, the return R as the expected return $E(R)$ on an asset can be written as:

$$E(R_{t+1}|\Theta_{mt}) = E(R_{t+1}|\Theta_t). \tag{3}$$

Noteworthy, Eq. 3 conditions the expected value as $E(R)$ on an given market information set (i.e. Θ_{mt}) as a conditional expected value.

What is needed to assess this expected return is an asset pricing model to compare it with the observed market return. These two components allow to measure abnormal returns. For measuring market efficiency, it is essential to use pricing models allowing to compare *market expected returns* with *actual observed asset returns*. A commonly known and used asset pricing model to derive an expected market return is the Capital Asset Pricing Model (CAPM) based on Sharpe (1964); Lintner (1965); Mossin (1966). Plenty of additions and variations have been introduced within the asset pricing models. For brevity, this section will just mention the behavioral rational investor theory link made from generalizing the initial CAPM into the Consumption Capital Asset Pricing Model (CCAPM). The CCAPM adds an investor utility function based on the work of Merton (1973).

Next to the CAPM, Fama and his colleagues used the standard *market model*. Model dependent, the expected return notation changes from $E(R)$ as in Eq. 3 to R_{it} under the market model. Thus, under this approach, the expected returns of asset i in t is written as R_{it} which is set as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + u_{it}, \tag{4}$$

where R_{mt} is the expected market return, and α_i and β_i the estimated coefficients stemming from a regression on asset i by using the returns R_{it} until the observed event date. The error term is stated as u_{it} to accommodate noise effects which are normally distributed and have a zero mean.

With an expected market return model in use, it is possible to compare an asset's actual observed return to the expected return. For testing market information impacts under event studies (new information hits the market), the *abnormal return* (AR) is computed. Suppose $\tilde{R}_{it}$ as the observed daily returns of the single stock i and —

returning to the initial notation— let $E(R_i)$ be the expected return of asset i, the abnormal return as AR for each stock i at time t notates as follows:

$$AR_{it} = \tilde{R}_{it} - E(R_{it}). \tag{5}$$

This framework offers to measure abnormalities in expected returns on various time frames. Next to intraday observations, multiple observations are commonly used by computing cumulative abnormal returns (CAR) for daily returns over a specified event time frame (Brooks, 2014). Notating these cumulative returns in its basic way follows Eq. 5 and simply adding the sum as:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}, \tag{6}$$

with $t_1 < t_2$ and t_1, t_2 as the defined time frame. Since the early 1930s, abnormal return analysis in event studies are applied to asset analysis and they became commonly used during the decades.[5] Based on Fama's event study computing CAR on a stock split, a vast amount of event studies became available in literature. This makes event studies an established approach to assess price predictability of assets and measuring market efficiency.

1.2 Non rational expectations and asset prices

Rational expectations and the EMH framework as presented by Fama in the early 1970s was a milestone and faced consequently a lot of attention including praise and criticism.[6]

The latter includes methodology discussions (Stiglitz & Grossman, 1982; Malkiel, 2011), historical reviews and connections to other research fields (Delcey, 2018, 2019; Greenwood et al., 2019) and revision proposals (Sewell, 2011; Jarrow & Larsson, 2012). Fama's extensive research in finance also includes various extensions and additional asset pricing tests during the decades (Fama & French, 1993).

In contrast to the rational investor theory and efficient markets, research in the late 1970s and early 1980s also advocated a theory of *non rational* investor behavior expectations. This move was supported by research on economic psychology about human decision making and risk aversion. The 2002 Nobel laureate Daniel Kahne-

[5] On event studies MacKinlay (1997) provides an historical overview including procedural suggestions. Event study tests are discussed in Serra (2007) while Kothari (2007) provides a broader scope in applying econometric methods into event studies. Coding guides (e.g. in Stata) for event studies and their application is e.g. discussed in Pacicco et al. (2017).

[6] A review of EMH specialized research is for example provided by Titan (2015).

mann provided (together with Amos Tversky) the concept of prospect theory in 1979 as a groundbreaking concept why human decisions are not necessarily rational. This influenced the work of different behavioral economists and resulted finally into various *behavioral finance approaches*.[7] Behavioral economists provided research challenging the EMH in showing that irrational investor behavior is not precluded (Shiller, 1979; Shiller et al., 1984; Barberis & Thaler, 2003).

Furthermore, Shiller included psychology concepts and relevant literature into the finance context to support arguments for market overreactions and decision making (using the work of Kahneman and Tversky). With his colleagues, he presented a wide work on investor surveys (Shiller et al., 1991), referring to the EMH as a 'half truth' (Shiller, 2003). One guess is that the second half of the truth in understanding asset price behavior could lie in behavioral finance aspects.

1.3 Information - key element for financial markets

Independent of the model approach or the broader school of thought, EMH-supporters as well as behavioral finance supporters agree on the relevance of information for financial markets and asset pricing. Information efficiency is not only a key part of Fama's three forms of information efficient markets (Fama, 1970) but also well researched by Shiller, Thaler and others in the work of the early 1980s.[8]

Information is the key element for financial markets. The capability to distinguish information as relevant in predicting and determining prices is important as this is not always intuitive. In the recent past, several studies found that sometimes most obvious 'guesses' on relevant information are not neccessarily the key driver for valuations.

Known examples include the pricing impact of weather on orange juice production (Roll, 1984) or valuation changes of stocks when listed in a certain stock index (Shleifer, 1986) even before Fama and French's three factor models. In the early 2000s, information efficiency related research expanded along the market drivers (e.g. technology, new economy). Shiller contributed to research feedback loops and bubbles in asset pricing (Shiller, 2003). In 2015, news media come more into focus, as Shiller details that feedback loops and bubbles are mainly sourced by sociological channels in which the news media and stories are essential in forming financial market sentiment (Shiller, 2015). The relevance of information including its channel, interpretation and consequences remains a critical research topic since the early 1970s work into today's research.

[7]Notably, behavioral finance research is known much longer than early 1970s but became more prominent due to the contradicting views on markets by Fama and Shiller in the late 1970s.

[8]An overview on behavioral finance literature incl. information efficiency related research is detailed in e.g. Shleifer (2002) and Barberis & Thaler (2003).

From personal experience, after spending over twenty years in financial markets, the author considers the EMH framework as one —though not the only one— pillar modeling framework for finance. These findings provide important basic pillars for asset price analysis. Behavioral finance, from the author's practical perception, is complementing and much less contradicting the EMH framework than it may sound in the first place. Market psychology, sentiment and expectations are important for analysing prices. With this view, knowing and applying both approaches helps in practical finance. The aforementioned CCAPM-model shows that rational and behavioral elements can be combined and widen the academic toolkit.

The Nobel prize for Economic Sciences 2013 was awarded to three laureates for their very different, partly contradicting, views of asset price predictability. The first laureate, Eugene Fama, uses efficient markets for understanding asset price predictability in examining whether all publicly available information are incorporated in markets. Fama (1970) provides relevance on short term predictability of stock market returns and the conclusion that short-run predictability is very limited. The second laureate, Niels Hansen, provided core analytical concepts for analyzing markets. His 1982 work on the General Methods of Moments (GMM) is also connected with the two other laureates (e.g. testing the CCAPM assumptions).[9] The third laureate, and foremost contradictory to Fama's work, was Robert Shiller as a key contributor to behavioral finance. In 2013, the Swedish Royal Academy of Sciences paved the way for both concepts to remain in focus and in 2017, the behavioral economist Richard Thaler received the Nobel Prize in economics.

Following this introduction, the remainder of this dissertation is structured as follows: Section 2 provides a contextual frame for the research essays in this cumulative dissertation. Section 3 lists for each of the five essays the abstracts and additional information. Further insights, supplementary results, and topical details are described in Section 4 for selected topics. Section 5 concludes and discusses potential further research in this field.

[9] An introduction of Hansen's work on GMM is provided by e.g. Brooks (2014, p.607ff.).

2 Research Overview

This section details the author's research conducted as part of this cumulative dissertation (esp. relating to the requirements under §10 of the 2018 Doctoral Regulation). The chapters explain the research area, thesis constituents and their topical and content relatedness. The last sub-section lists the contributions to existing research.

2.1 Research focus

This thesis focuses on market information efficiency research on two research objects as asset classes. They are the asset classes of debt securities markets (bond markets) and equity markets (stock markets). The broad research question is if and how new information provided through different channels impacts markets (or not). More specifically, market impacts are analyzed in two ways in this thesis constituents.

First, by analyzing asset performance returns. The thesis contributions use e.g. the aforementioned market model approach measuring abnormal returns as detailed in Section 1, but also present a novel return analysis approach for bond markets.

Second, correlation impacts and information efficiency in the above mentioned asset classes are analyzed. The thesis presents event study based findings and also introduces novel correlation results using advanced filtering techniques. The findings contribute to information efficiency research in today's financial markets.

2.2 Thesis constituents

This cumulative dissertation contains five articles as listed below. The papers are numbered from 1-5 and referenced by when the research work was conducted in chronological order. The individual analytical research work and contributions by the author of this dissertation are detailed under each constituent in Section 3 based on the signed co-author agreements according for each paper as recommended by the Doctoral Regulation. The five essays as research constituents for this dissertation are as follows:

Paper 1 (VOLF):

Measuring Trump: The Volfefe Index and its Impact on European Financial Markets

Paper 2 (NIR):

How floating rate notes stopped floating: Evidence from the negative interest rate regime

Paper 3 (DCC):

Apple, Microsoft, Amazon and Google - A Correlation Analysis: Evidence from a DCC-GARCH Model

Paper 4 (CAR):

Trump tweets and the MSCI World Exposure with China Index- Evidence from an event study deploying Cumulative Abnormal Returns

Paper 5 (WAVE):

Euro Area Sovereign Ratings and the Rescue Funds: A Wavelet Transform Coherence Analysis

The following section describes their interconnections from various angles including content, methodology and other factors.

2.3 Topical relatedness and thematic context

First, all constituents of this thesis study market information efficiency under different information channels, market segments and asset impacts (returns, correlations). Second, the research includes efficient market and behavioral finance as two main concepts for analyzing markets. The essays interpret findings considering the above mentioned concepts to get a better understanding of asset behavior. Third, all research contributions aim to provide also practically relevant findings for contemporary topics.

Studying the sociological channel of tweet sentiment was motivated from the earlier readings on behavioral finance as detailed in Section 1. Twitter sentiment work was very topical after Trump became US president in 2016. His Twitter usage as a policy communication tool drew a lot of attention. Market participants needed to get used to check Twitter ahead of news terminals when markets moved due to an angry Trump tweet. This motivated research on information efficiency and Twitter sentiment. In 2019, the so called Volfefe Index (Salem et al., 2019) was introduced. While studies on this index were not existing yet, Paper 1 (VOLF) was motivated by the idea to extend this index on European markets. The paper received attention and questions from academics, practitioners and some citations confirming the topical relevance even after Trump left the White House and was suspended from Twitter.

Figure 1 shows below an overview for the asset classes (equity- and debt securities markets), the observed impact measure (returns and correlation), and the described essay interconnection. While working on Paper 1 (VOLF), tensions between the US and China trade war increased which initiated Paper 4 (CAR). Motivated by the findings presented in Klaus & Koser (2020), the extension into studying tweet impacts on single assets was elaborated as shown in Figure 1. The design for Paper 4 (CAR) is based on using an event study framework, market model and statistical tests as reliable empirical tools to study a dedicated stock index with firms considered to be highly exposed to China. To the author's knowledge, this combination has not been studied prior and thus extends literature with findings on this stock index.

A parallel research stream in 2018 was the work on impacts of the Negative Interest Rate Policy (NIRP) in the eurozone. The ECB went from a Zero Interest Rate Policy (ZIRP) into a NIRP-framework already in 2014. Initially expected to remain a short measure, the monetary policy path in the EA remained lower for longer which motivated research on impacts of this negative rate regime. Initially, the research design was supposed to focus on a pure financial modeling of the embedded floors of EA floating rate debt.[10]

While market developments hinted into certain legal and financial problems occurring under negative rates, the motivation for Paper 2 (NIR) to become a broader finance and financial law related event study appeared more relevant. The forthcoming Section 4 provides more detail on this relevant research topic.

Figure 1 also shows the methodological connection between Paper 2 (NIR), Paper 4 (CAR) and Paper 5 (WAVE) via an event study framework.

The findings in market structure changes in Paper 2 (NIR) motivated the research for Paper 3 (DCC). Using correlation analysis under the DCC GARCH framework initiated the research design for Paper 5 (WAVE) from a methodological standpoint. The literature on the Fast Fourier Transform (FFT) and filtering methods around the ARCH framework motivated to use wavelets (Addison, 2002; Mallat, 1989; Masset, 2015). As the FFT has its limitations regarding the frequency and time domain, and is less suitable to analyze abrupt changes in the data, the wavelet concept appeared promising for Paper 5 (WAVE). Financial data is usually non-stationary, heterogeneous and asynchronous, and here the continuous wavelet transform (CWT) can show directions of influence between the studied variables. Finally, inspired by the heatmaps in Paper 4 (CAR), the coherence graphs were used in Paper 5 (WAVE) for visualization purposes.

[10] The first idea on embedded floors in floating rates notes was presented 2016 during the 2nd Joint Seminar on Finance: Risk management & Behavioral Finance. Link TU Dresden (retr.20/02/2022).

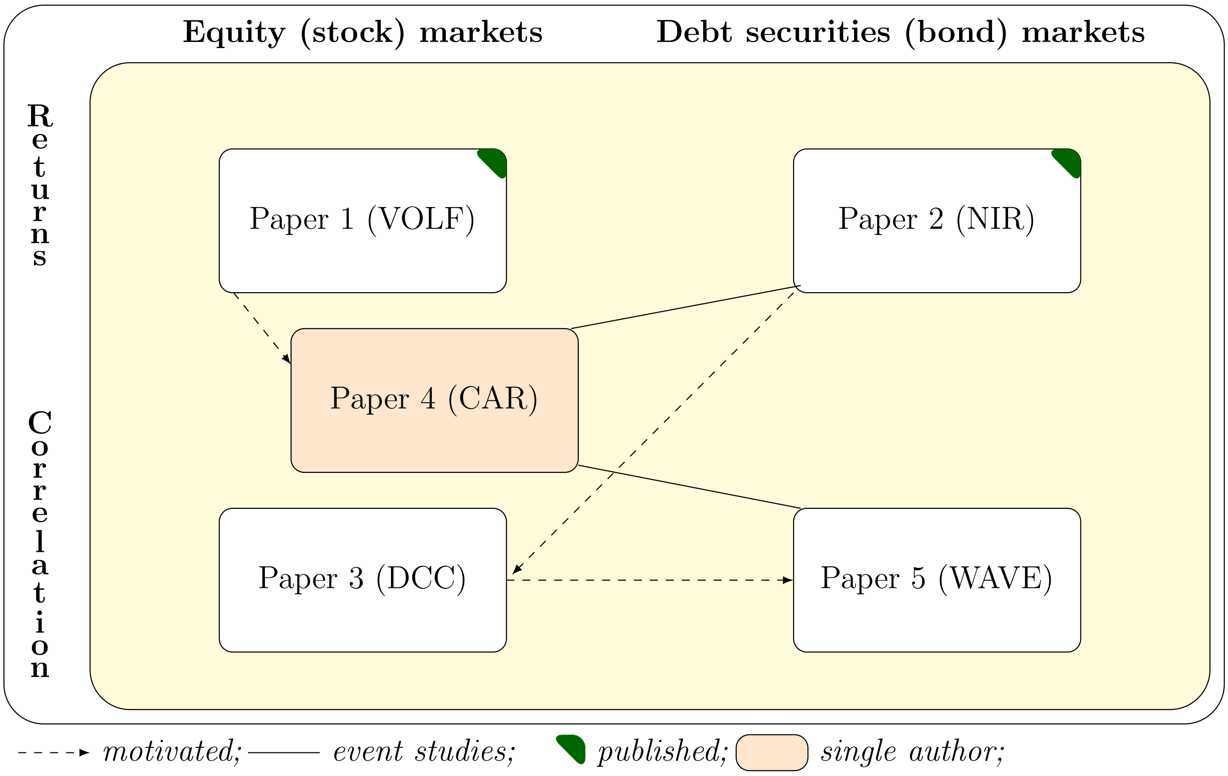


Figure 1: Interrelated overview of published articles and working papers. (own illustration)

2.4 Research contributions

The essays contribute to —and extend existing— research as listed below based on the applied research fields:

Twitter sentiment and asset returns

Klaus & Koser (2020) contribute to Twitter sentiment research and its impact on financial markets. The authors extend literature based on news sentiment modeling work of Barberis et al. (1998) and studies on stock markets (Bouri et al., 2017; Tetlock, 2007). This way, they advance the discussions in e.g. Bollen et al. (2011) on Twitter mood and provide novel findings by examining the predictive power of the quantification factor of the former US president Trump's tweet activity on European stock market returns— using the Volfefe index based on Salem et al. (2019).[11] The findings extend literature on social-media related sentiment and stock markets. It advances previous works e.g. by Fang & Peress (2009) from cross section stock returns in providing the first empirical index extension of the Volfefe Twitter index by applying it to European stock markets. These findings are relevant for different market participants. For private and professional investors for example, the results help

[11]More details on this selected topic are detailed in Section 4.

on market efficiency topics and to better understand interaction on market segments and across countries (has a Twitter user an information advantage compared to a non Twitter user).[12] Furthermore, based on previous studies on China and Trump tweets related to trade balances (Lin & Wang, 2018) and stock returns (Sul et al., 2017), the thesis extends findings on single assets returns measuring abnormal returns in the context of the US and China trade war tensions. This is studied using stocks under an index with a high exposure to China. These findings can support investment choices on a single stock level for market participants. In addition, the analysis reveals and discusses also behavioral finance elements to explain the quantitative return analysis from a different angle.

Negative interest rates and asset returns

Klaus & Selga (2021) contribute to the narrow research on floating rate debt markets including previous studies as in Kim (2013) on asymmetrical bond yield reactions. The authors contribute with findings on information efficiency and market structure changes under negative rates. The impact of negative interest rates and the prevailing EA negative interest rate policy are not only contemporary but also controversial topics. Based on previous studies as in Choi et al. (2011) on stakeholder interactions, and on standard contractual clauses including the pari passu research in Gulati & Scott (2011) and Gelpern et al. (2017), the authors extend this sparse research under negative rates by finding informational inefficiencies due to untested boilerplate templates for debt securities documentation. More broadly, the research tests if and by how far court rulings and other less prominent focused information channels (e.g. press announcements from sovereigns) are efficiently reflected in markets. It also discusses behavioral components. For example, by how far expert knowledge on a market segment may support asset selection as a first mover on an new public information which was not in focus to the broader market at first publication.

Furthermore, based on the concepts provided in Fabozzi & Mann (2000) using the discount margin pricing, the research advances the financial tools to measure asset performance by presenting a novel way to measure the returns of a dedicated security class. The self-developed Outperformance Indicator (Klaus & Selga, 2021) provides a significance-tested way to measure asset performance between different debt securities of the same issuer class. For market analysts and policy researchers, the findings provide insights into market structural changes under the negative interest rate environment. The novel results on micro market structure changes are important for

[12] During the Trump presidency, many investment bankers and trading desks benefitted from having a Twitter account as potential market moving tweets were first published on Twitter. Only shortly after Twitter, the known professional information providers (e.g. Reuters/Refinitiv or Bloomberg) were able to provide the news.

portfolio managers and floating rate debt issuers. Lastly, confirming a lack of informational efficiency, the findings point to prevailing risks in hedging floating rate debt products with interest rate derivatives.

Correlation dynamics in stock and bond markets

The basis of the Autoregressive Conditional Heteroskedasticity (ARCH) model and the multivariate GARCH framework based on Engle (1982) resulted in the Dynamic Conditional Correlation (DCC) model (Engle, 2002). Following correlation modeling work as e.g. in Klein & Walther (2017); Klein (2017), the work of Koser & Klaus (2020) extends research around asset correlation changes. It examines the dynamic correlation between the four most valuable and traded technology stocks using a multivariate model. Using the diversifier assumption formulated in Baur & Lucey (2010), the authors extend research by showing that this assumption does not hold in certain market situations. Concurrently, it confirms previous literature findings as e.g. in Longin & Solnik (2001) on correlation changes under bearish market sentiment—which is an behavioral element. This supports portfolio selection work for investors in these stocks.

On bond markets, the work based on existing literature as e.g. in Mellios & Paget-Blanc (2006) and Kiff et al. (2012) studying drivers of ratings and market impacts under rating changes. Klaus & Benghoul (2022) enhance the work of Candelon et al. (2011) on spillover impacts and extends work as in Beirne & Fratzscher (2013) studying events under the great financial crisis (GFC) and sovereign debt crisis. The authors apply wavelet analysis to another market data set, using the framework presented for financial datasets as in Mallat (1989) and Masset (2011). Extending this application, it provides a novel microscope view on correlation dynamics using wavelets as a filtering technique. This helps in determining rating change impacts of sovereign bond issuers on selected debt security classes.

To sum up, the thesis extends research on market information efficiencies in stock- and bond markets using EMH elements and behavioral aspects. It fills research gaps by investigating informational efficiency in specific market situations (e.g. court rulings, tweets, rating changes) analyzing asset performance and correlations impacts. Methodology wise, it extends literature by introducing a new bond performance measure and extends market sentiment studies.

3 Research Articles

The following sections present the original research article abstracts as part of this cumulative dissertation. Overall, the contributions amount to five papers including two peer reviewed publications in established financial journals.

The research paper on Twitter sentiment as in Paper 1 (VOLF) was published in Finance Research Letters (FRL) as a B-rated journal.[13] Furthermore, Paper 2 (NIR) was successfully peer reviewed and published in the International Review of Financial Analysis (IRFA) as a well respected but not officially rated journal.

The research conducted in Paper 3 (DCC) is a submitted working paper on SSRN. Paper 4 (CAR) is available as an SSRN working paper and was presented and discussed in a workshop for quantitative methods at Technische Universität Dresden. Lastly, Paper 5 (WAVE) is currently an unpublished manuscript planned for a journal submission in 2022.

The abstracts are taken from the journal publication or working paper as applicable. Furthermore, for each article section, conferences and seminars are listed on which the research work was presented and discussed. In case the author of this dissertation was not the presenter of the research work, the presenter (usually a co-author) is listed in parentheses. While the objective was to attend as many conferences in person as possible, the prevailing pandemic since March 2020 limited this possibility so that some events could only be attended in an virtual or hybrid format.

Each description of the five research papers provides an overview of the author's individual analytical contribution and achievements.[14] The listed research achievements and contributions are based on the jointly signed co-authorship certifications as required under the Doctoral Regulation framework and included in the formal PhD submission.

The papers are provided as uploaded/submitted with their individual time stamp and pagination in the Appendix section of this cover paper.

[13]Based on VHB Ranking (retrieved 22.Feb.2022).

[14]For clarification, referring to *the author's* achievements or contributions in the forthcoming relates to the author of this dissertation.

3.1 Measuring Trump: The Volfefe Index and its Impact on European Financial Markets

Referenced as: Paper 1 (VOLF) and Klaus & Koser (2020)

Abstract

We examine the predictive power of the recently constructed Volfefe Index, the quantification of the tweeting activity by the U.S. president Donald J. Trump, by extending the initial index on the dynamics of European stock markets. Using a rolling-window estimation approach, we show that the Trump Tweet Factor contributes to the prediction of stock market returns across European stock markets, after controlling for a set of macroeconomic and financial factors. The results indicate that the relationship is time-varying which is particularly visible when matching daily estimates with corresponding tweets from the Trump Twitter Archive..

Published as:

Klaus, Jürgen; Koser, Christoph (2020): Measuring Trump: The Volfefe Index and its Impact on European Financial Markets, in: Finance Research Letters, Vol.38 , Article 101447, DOI:10.1016/j.frl.2020.101447.

Presented and discussed at:

- PhD seminar Universitat de Barcelona School of Economics, Spring 2020, Barcelona, Spain (Christoph Koser)
- PhD Seminar Doktorandenseminar Ost, Fall 2020, Wörlitz, Germany

Author's research achievements:

- Data collection and preparation
- Research design and research question definition
- Introduction section (research design description, contextualisation into finance research)
- Methodology section (Volfefe index description, esp. focusing on text mining components)
- Data section (description and data set pre-analysis)
- Results and conclusion section (interpretation, financial markets conclusions)
- Corresponding author (submission process, communication with Journals, following up on reviews and re-submission)

Author's comments:
The paper received attention and some citations covering a very topical research on Twitter sentiment related to a tensing geopolitical situation. Methodology wise, it deploys quantitative methods (rolling window regression) in combination with a novel index based on wordmining and neuro-linguistic programming. Based on this Volfefe Index (Salem et al., 2019), this research paper was the first to extend and test the index for european markets. For behavioral finance research, it suggests ways to interpret the sociological channel of information efficiency in markets.

3.2 How floating rate notes stopped floating: Evidence from the negative interest rate regime

Referenced as: Paper 2 (NIR) and Klaus & Selga (2021)

Abstract
We analyse the impact of stakeholder interactions with the market as a consequence of the negative interest rate regime on the pricing of selected Floating Rate Notes (FRNs). The range of reactivity of financial markets and issuers to uncertainty caused by an untested boilerplate term in bond contracts are thoroughly outlined. The subject clause stipulates "not applicable" as the minimum rate of interest, raising confusion regarding payment obligations between issuers and investors. We highlight the range of challenges by drawing parallels with the pari passu saga, noting a comparatively faster qualitative response to legal uncertainty across the FRN industry. We support these findings empirically, by observing that markets do to varying degrees price stakeholder activities with possible impact on the legal certainty of FRNs, like court decisions, industry association statements, and public positions of sovereigns. In turn, issuers are willing to react to legal risks quickly, if costs of inertia are low. This is reflected also in the relevant changes in the FRN issuance structure in the past few years. The announcement of further lower for longer rates in the Euro Area provides evidence that the FRN market appreciates the current protection of negative coupons even under a lower Euribor. Consequently, this appears to confirm a situation where Floating Rate Notes turned de facto into Floored Rate Notes, in part because of legal uncertainty in the N/A clause.

Published as:
Klaus, Jürgen; Selga, Eriks K. (2021): How floating rate notes stopped floating: Evidence from the negative interest rate regime, in: International Review of Financial Analysis Volume 75, May 2021, 101709, DOI: 10.1016/j.irfa.2021.101709.

Presented and discussed at:

- Global Annual Conference on Banking Regulation by the European Banking Institute, Spring 2019, Frankfurt am Main, Germany
- PhD Seminar Doktorandenseminar Ost, Spring 2017, Berlin, Germany

Author's research achievements:

- Research topic idea and design
- Chapter 2: Literature review (finance related part)
- Design and implementation of the Outperformance Indicator (OI)
- Chapter 4: Empirical analysis
  - Data set up (bond pool, bond parameters) and data retrieving
  - Bond clustering and matching
  - Event study design
  - OI calculations and interpretation / descriptive statistics
  - Dummy regression, parameter estimation, analysis and interpretation
- Chapter 5: Concluding remarks (finance aspects)
- Corresponding author (submission process, communication with Journals, following up on reviews and re-submission)

Author's notes:
This interdisciplinary work deploys regression analysis and statistical significance tests under a broad market data set. It introduces a new measure for bond market performance. From a behavioral finance angle, it shows that markets lack information efficiency to a degree under special market situations where expert knowledge is beneficial. Lastly, it shows that established processes in markets do adapt slowly to new risks which signals a lack of informational efficiency.

3.3 Apple, Microsoft, Amazon and Google - A Correlation Analysis: Evidence from a DCC-GARCH Model

Referenced as: Paper 3 (DCC) and Koser & Klaus (2020)

Abstract

In this paper, we examine time-varying correlations among stock returns of Apple, Microsoft, Amazon and Google. Employing a multivariate DCC-GARCH model, we find that there are strong linkages among these four assets. Starting from lower levels, correlation values for most asset pairs exhibit a stable ascending movement in recent upward trended markets to, in an exceptional case, almost hit the perfect positive correlation mark. We show that correlations among these assets jump during downturn market periods, suggesting limits in the diversification of risk within the segment of large cap U.S. technology stocks. Our results are helpful for portfolio management and asset allocation.

Published as:

Koser, Christoph; Klaus, Jürgen (2020): Apple, Microsoft, Amazon and Google - A Correlation Analysis: Evidence from a DCC-GARCH Model. Submitted manuscript, SSRN Working paper. DOI: 10.2139/ssrn.3718788.

Author's research achievements:

- Data collection and preparation
- Research design and research questions definition
- Introduction section (research design description, contextualisation into finance research)
- Data description and data set pre-analysis
- Results interpretation and implications for financial markets
- Commenting and editing of all chapters

Author's notes:

Supported by a strong methodological framework and data set, the paper contributes empirically to correlation analysis under different market sentiment. We extend research in this field by showing that a diversifier assumption from previous work does not always hold depending on the market sentiment. With this, the analytical findings support a behavioral finance aspect of market trend behavior in up- and downside stock market moves.

3.4 Trump Tweet Impacts on the MSCI World Exposure with China Index - Evidence from an Event Study Deploying Cumulative Abnormal Returns

Referenced as: Paper 4 (CAR) and Klaus (2021)

Abstract

I study US-president Trump tweets on the US/China trade relationship and their impact stock valuations of companies with a high China exposure. This event study deploys data from the MSCI World with China Index and identifies potential out- or underperformance using cumulative abnormal returns (CAR). My results are presented based on the full index constituents using heatmaps to show significance of CARs where applicable.

My findings suggest that statistically significant CARs are limited depending on identified tweets and appear volatile depending on the estimation window. A vast amount of statistically insignificant CARs based on Trump tweets on China supports the conclusion that his tweets had an overall low impact on the index companies.

Published as:

Klaus, Jürgen (2021): Trump Tweet Impacts on the MSCI World Exposure with China Index - Evidence from an Event Study Deploying Cumulative Abnormal Returns. SSRN Working Paper. DOI:10.2139/ssrn.3788169 .

Presented and discussed at:

- Research Seminar Multivariate Analytical Methods TU Dresden (online), Faculty of Econometrics and Statistics, esp. in the Transport Sector, Winter 2020, Dresden, Germany
- PhD Seminar Doktorandenseminar Ost, Fall 2020, Wörlitz, Germany

Author's research achievements:

- as single author paper responsible for all chapters

Author's notes:

This paper uses the empirical approach as in the introduction under efficient market tests detailed in Section 1. The findings coincide with suggestions made in multi-factor models regarding stock market capitalization and at the same time show behavioral aspects (e.g. news contagion sentiment). The findings also suggest traces for herding behavior which is possibly market psychology and sentiment driven.

3.5 Euro Area Sovereign Ratings and the Rescue Funds: A Wavelet Transform Coherence Analysis

Referenced as: Paper 5 (WAVE) and Klaus & Benghoul (2022); unpublished manuscript, to be submitted for journal review in 2022.

Abstract

The Euro Area (EA) rescue funds —the European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM)— replace sovereign funding should the EA members lose market access during financial stress or crisis. Importantly, the same EA members are also financial guarantors to these rescue funds and contribute to the funds' credit rating. The funds depend on a strong rating as they finance large volumes in capital markets in crisis times if a guaranteeing member becomes a client. This paper analyses if the funds are impacted by guarantor rating changes and how markets react and incorporate these information. Empirical results from this market efficiency study find overall only small impacts from EA member ratings change to the rescue funds' funding conditions. Furthermore, not all large guarantor rating changes impact the funds alike. The results also suggest a higher correlation resilience for the lower rated and less capitalised EFSF compared to the stronger capitalised and higher rated ESM. The study combines behavioral finance aspects such as prevailing market sentiment and news narratives to interpret the empirical results.

Unpublished manuscript:

Klaus, Jürgen; Benghoul, Maroua (2022): Euro Area Sovereign Ratings and the Rescue Funds: A Wavelet Transform Coherence Analysis.

Author's research achievements:

- Research project idea and design
- Chapter 1: Introduction/research question
- Chapter 2: Literature review
- Chapter 3.2: Financial data application
- Chapter 4: Empirical part
  - Data set up (bond pool, bond parameters) and data retrieving
  - Bond clustering and matching
  - Parameter identification for analysis

- Chapter 5: Results and discussion
- Chapter 6: Conclusions and outlook

Author's notes:
During 2020, Italy was rumored to be a potential next ESM programme candidate. Markets discussed if the rescue funds would be able to finance such a potential programme country (also given Italy's large guarantor amount and considerable debt levels). The research design was inspired by the question whether the fund activities in financial markets are impacted by rating actions of their guarantors.

We provide empirical evidence whether rescue fund ratings and market funding conditions are impacted by these events in a correlation analysis —bearing in mind the causality constraint. In cooperation with a wavelet expert for programming and application, we identify correlation impacts between impacted countries and the rescue funds. Research contributions include also behavioral finance findings as regards signaling effects, including market sentiment effects.

Especially since the political turmoil in Italy in July 2022, the financing costs increased and Italy requiring EU funds and support is discussed again. We intend to bring this thesis constituent into a journal submission process in 2022 given the topical relevance.

4 Selected Topics

This chapter provides further insights into two research and concurrently topical themes of this dissertation. First, the impact of social media platforms —in this case Twitter— on asset prices and market sentiment is detailed including own research contributions. Second, on the ECB's negative interest rate policy, the lower-for-longer narrative is briefly described under practical asset pricing and hedging impacts while also emphasizing the main research contributions.[15] The sections are based on the two peer reviewed articles of Klaus & Koser (2020) and Klaus & Selga (2021). Data and findings were updated if applicable since publication and additional findings are presented based on non-published material stemming from the individual research projects.

4.1 Information efficiency and Twitter sentiment

The following section is based on the work presented in Klaus & Koser (2020) and provides details around the Twitter index based set up which have not been published with this paper. All sections are solely produced and streamlined to the core points for brevity reasons by the author of this thesis. Section 4.1.2 is following the Volfefe source paper in Salem et al. (2019) as a reference.

4.1.1 Information and its transmission

Recalling the introduction Section 1 with the rational based EMH and the irrational elements under behavioral finance aspects, one central point is the relevance of (new) information. Both schools of thoughts agree on the importance of information for asset and market pricing. This holds independent of the information sourcing channel (e.g. newspapers, radio, information platforms like Bloomberg, Reuters). Yet, a key difference is how and with which consequences market participants interpret and decide once information is transferred. The EMH framework follows the assumption that all available information —under three different forms of informational efficiency— is reflected in market prices. Fama rejects to include sociology or psychology impacts into the EMH context (Malkiel, 2003; Delcey, 2019). Under the EMH, there is no anecdotal data, i.e. collective anecdotes without data. Supporters of the EMH refer to forecasts and estimates and not to people's judgments (Thaler, 2018).

Under behavioral finance aspects, it is not only the information itself but also the way participants judge and interpret information provided. Market participants' biases and judgments influence their decisions. The narrative around information

[15] In March 2022, the ECB's latest press conference statements indicated a phase out of the current negative rate regime. Rates were hiked during finalization of this paper in July 2022. Forward rates for the Euro Area signal further strong rate increases around 100bps or 1% into 2023 as likely.

and its channels is one additional element behavioral finance adds to the model assumptions. Researching information channels is part of Shiller's extensive Nobel price awarded work centering around the concept that information is brought in stories and mainly via sociological channels (Shiller, 2017, 2015, 2003; Shiller et al., 1991).

Importantly, the role of the news media and other social media channels is key due to their contagion impacts. Furthermore, these channels gain attraction due to increasing usage also by politicians, celebrities and business leaders telling their narratives often unfiltered, with high-speed and partly surprising timing.[16] Research within this strand of literature will likely increase given the changes in information technology allowing to perform news and word mining searches in a more advanced fashion than in the recent decades (see also chapter 5).

4.1.2 Twitter market impact measures

As Klaus & Koser (2020) detail in their literature review, research on Twitter sentiment and its impact and relevance for asset pricing is increasing. Using word-mining techniques under big data analysis, today's stories and narratives appear to be much easier to research than in recent past (e.g.compared to reviewing old newspaper archives to extract information (Shiller, 2017, p.273)). Researchers try to find appropriate ways to model Twitter impacts including outreach, followers and impact using different combined tools from psychology, sociology and data analysis. The Twitter platform attracted special attention in 2016 with Donald Trump becoming the US president elect. Before being known as the Tweet-President, he was using Twitter as a key communication tool in his election campaign.[17]

Consequently, research on Trump and Twitter remained in focus even after he left the White House (Monahan & Maratea, 2021; Ajjoub et al., 2021) and in connection with EMH assumptions (Born et al., 2017) and market impacts (Benton & Philips, 2020). It was in 2019, when two researchers from the US Investment Bank JP Morgan introduced an Index on Trump's tweet activities to find whether his tweets impact markets. Salem et al. (2019) named the index by a misleading Trump tweet in 2017 the Volfefe index.[18] Based on the results and methodology presented by Salem et al. (2019), the index is constructed using Twitter Archive data (@realDonaldTrump).[19] From over 14,000 tweets (of which over 10,000 tweets refer to the time he was presi-

[16]Browne (2021)"*Bitcoin falls after Elon Musk tweets breakup meme*" (retrieved 11.01.2022).

[17]Johnson (2016) "*Donald Trump tweeted himself into the White House*" (retrieved 29.12.2021).

[18]Trump's *covefe* tweet in May 2017 confused many journalists and served as a media attention tracking inspiration for Salem et al. to name their sentiment index Volfefe (Dorfer, 2017).

[19]Trump tweeted under @realDonaldTrump. His account was disabled in January 2021. The official US president Twitter account is @POTUS (President of the United States).

dent), the authors firstly define a market moving tweet. This is a tweet immediately followed by a net move in 10Y-US-Treasury yields of at least 0.5 basis points (bps) or 0.005% within five minutes of tweet publication. Using high resolution intraday treasury market trading data, Salem and his colleagues plot tweets causing market moves using a rolling one-month-count of tweets. Plotted against the 3M/10Y swaption volatility (vol) for ATMF-swaptions, this rolling 1M-tweet window shows a series of increased market moving tweets along increased interest rate vol across the time series. Salem et al. (2019) declare 146 tweets as real market moving ones based on this analysis. The authors identify for these market moving tweets a focus on a dedicated word subset (identified key words relate to e.g. China, dollar, trade, tariff and monetary policy related words e.g. economy, inflation, federal reserve).

The objective is to look at the ratio of word frequency used in market moving tweets against the word usage frequency within the tweet pool data set.[20] Finally, a random forest based classifier using a market move score is applied to form the index. The index output is a unitless rolling 21-day sum of a market move score in Figure 2.

Based on Salem et al. (2019) index work, Klaus & Koser (2020) provide the first empirical extension (at the time of writing in early 2020) of the Volfefe index on european stock markets. The paper received some attention as it extends the narrow social media sentiment literature.[21] Empirical contributions to research include the control results revealing a heterogeneous effect of the Volfefe index on European stock markets. The authors find that this effect is time-varying but broadly matching with the presidential tweets.

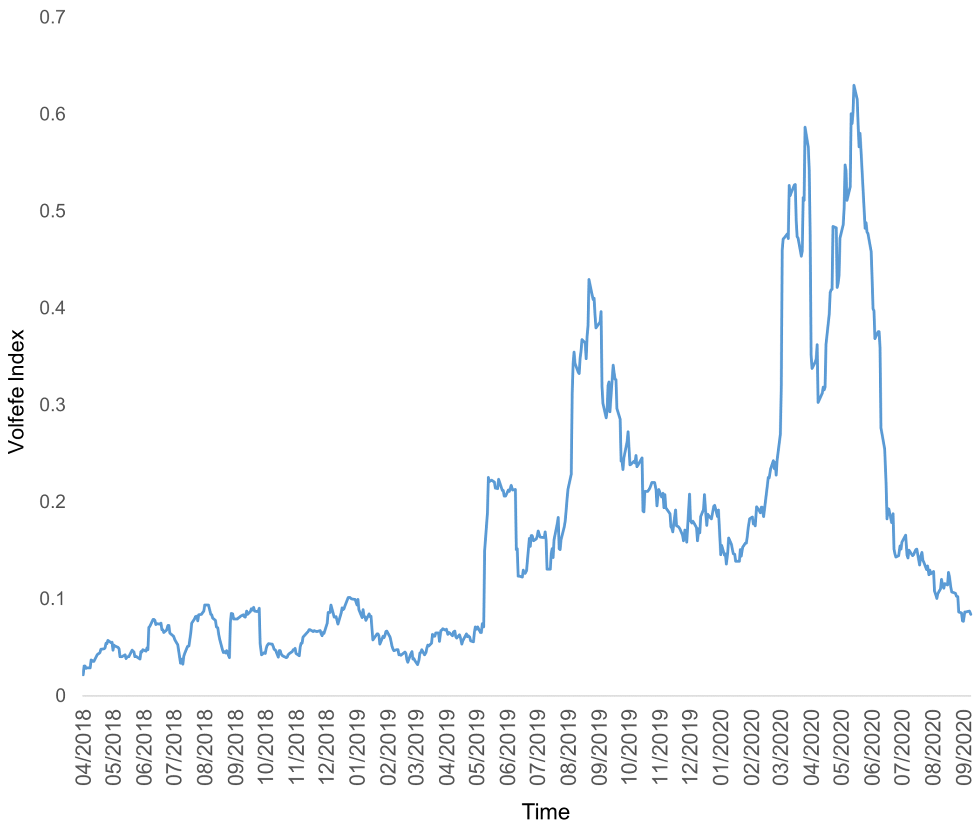
The paper covers also important market efficiency questions. Related to information efficiency, the paper contributes to research discussions around information channels how markets actually receive and digest information. From a behavioral finance standpoint, the work contributes to research on contagion effects (news going viral) and communication clarity (tweets bear biased, manipulative content). The authors further found signs of tweet-habiting-behavior which appears to show that the market gets used to a communication style under Trump. One consequence is that at inception markets react much stronger on certain messages and after time gets used to a communication style. From a behavioral finance perspective, this would require additional future research.

Klaus & Koser (2020) also critically question the predictive power of this Twitter index. The methodological setup remains partly unclear and appears random. The

[20] For brevity, the technical details of word mining are neglected here—index model details are available in the source paper Salem et al. (2019). Silge & Robinson (2017) provide a use case on Twitter word mining similar to Salem's approach.

[21] See *Volfefe paper tweets* (retrieved 20/03/2022)

Figure 2: Volfefe Index from Jan2018 to Sep2020.



Source: own illustration based on JP Morgan data.

Note: This figure shows the time-series Volfefe Index exclusively provided by JP Morgan Chase. It has been updated compared to the submitted paper script which initially covered 383 observations until Oct 2019. In September 2019, JP Morgan Chase released the visual Volfefe Index time-series representation publicly. Since then, the index has received global media attention from practitioners and the general public.

authors point out these shortcomings for more research in this field and propose further ideas to extent this index to other areas. Based on this research, this index appears less suitable for predictive purposes but maybe beneficial to estimate possible volatility changes.

4.2 Negative interest rates in the Euro Area

The following chapter focuses on the negative interest rates and their impact in financial markets following Klaus & Selga (2021). Parts of the following sections include content from an earlier, unpublished manuscript[22] and unpublished parts of Klaus & Selga (2021). However, the following sections are solely written by the author of this thesis. Data as presented in Figure 3 were updated to illustrate the relevance of this topical research.

4.2.1 Bond markets in uncharted territory

Since the inception of the Euro around twenty years ago, the ECB reduced interest rates in the Eurozone to historically low levels. After the austerity measures engaged in the GFC, interest rates have further been brought into an unprecedented negative rate level. With this, the ECB's monetary policy changed from a zero interest rate (ZIRP-regime) into a negative interest rate stance (NIRP- regime).[23] The NIRP-regime —and non-conventional monetary policy tools in general— had impacts on market levels and practices. Additionally, these ECB measures provoked legal issues and lawsuits ranging from claims of monetary financing via the ECB to challenges regarding the ECB's mandate.

At the time of writing this section in February 2022, the ECB deposit facility rate (DFR) was set at -0.50% while the main refinancing rate (MRR) was set to 0% already since 2016. Main EA-market rates yielded negative consequently to the ECB policy rates ahead of the invasion of Ukraine by Russia.

Figure 3 shows on the next page, together with the EA key policy rates, the benchmark rates for money markets using the 3M- and 6M- Euro Interbank Offered Rates (EURIBOR) fixing around the mark of -0.50%. Similar for bond markets, using the German Bund market as a benchmark, the market trades up to around 10y-maturities at negative yields as of February 2022.

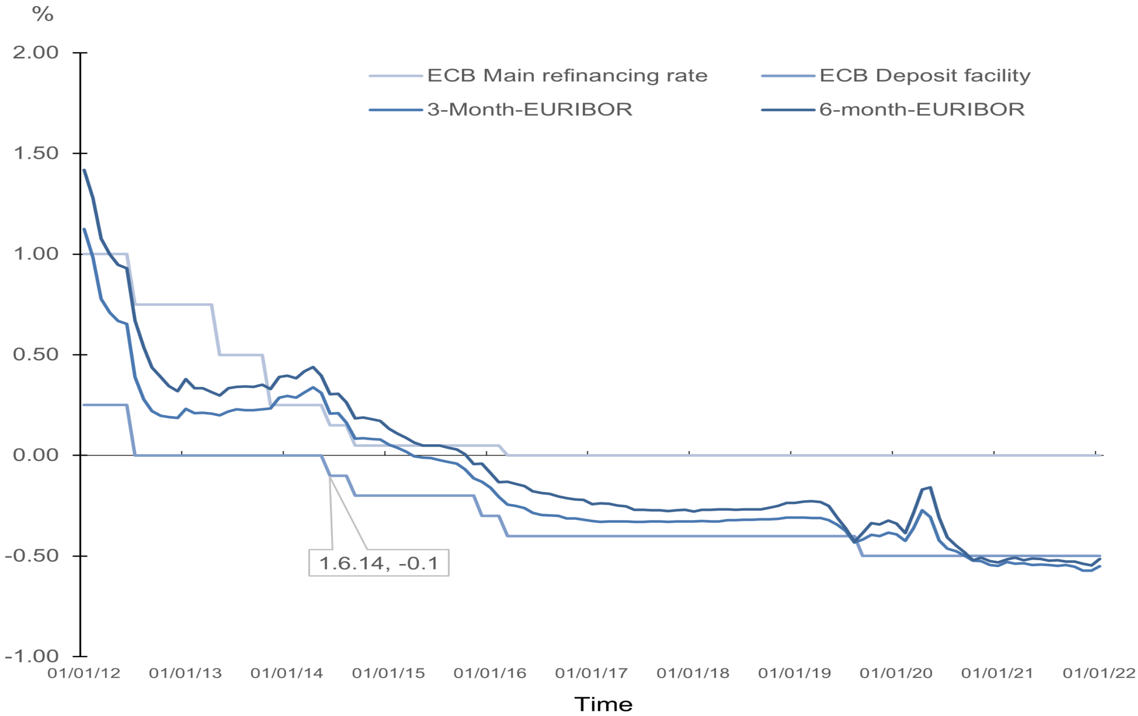
Negative yields are common and known in fixed income bond markets—but not negative coupons.[24] Notably, since the invasion of Ukraine by Russia in late February, rate hike expectations increased due to high inflation rates. Similar for the US central bank, which is expected to hike rates faster and more aggressively to fight inflation levels into 2022.

[22]The unpublished first version was part of the EBI working papers 2019. Revised later versions ended finally in the Paper 2 (NIR).

[23]This dissertation takes a market impact angle and neglects the wide monetary economics discussion. For the ECB, the ECB research and publications website provides further information on macroeconomic NIRP-research (retrieved 15.January 2022).

[24]Common market practice applies a 0% coupon to fixed coupon bonds and adjusting the issuance price to accommodate negative yields. Klaus & Selga (2021) provide more technical details on negative yield and coupons.

Figure 3: ECB policy and money market interest rates (as of Feb.2022).



Source: own illustration based on ECB and EMMI data

Note: This figure shows the ECB main policy rates using the deposit facility (DFR) and the minimum refinancing rate (MRR) with the two money market benchmark rates for 3M- and 6M-EURIBOR. Pointed in the chart is the NIRP-entry point with the ECB entering unchartered territory. Shortly after, during 2015, the EURIBOR rates followed into negative territory.

4.2.2 Impacts on pricing and trading for non linear products

Entering the NIRP-regime revealed various caveats and challenges for financial market participants. Although not in main scope for this dissertation, some selected valuation and execution topics are presented hereafter as it shows the topical relevance of the research started in 2018. Within the fixed-income market, linear products with known cash flows (e.g. fixed coupon bonds) were not impacted as discounting the cash flow can be performed independent from positive or negative rates. However, this was different for the valuation of non-linear products.

Challenges occurred for non-linear products like options and especially Floating Rate Notes (FRN). For interest rate options, valuations became more complex with payments subject to a probability distribution which is contingent to future rate levels becoming negative. Traditional pricing models based on a log-normal distribution do not allow negative rates (e.g. Black-Scholes). Furthermore, implied volatility is trending to infinity once forward rates reach zero levels. Various model adjustments were applied in practice (e.g. using a displaced log normal model by shifting the distribution slighlty to allow for negative rates) while the state of the art approach appears to be the Stochastic Alpha-Beta-Rho-model (SABR) based on the work of Hagan et al. (2002). For options, the SABR-model appears most practical as it allows volatility itself to be a stochastic variable and allows correlating (negative) forward rates and volatility.

For FRN-markets, that is the market of floating rate debt linked to a floating rate index (e.g. EURIBOR as shown in Figure 3), negative rates impose even more problems. Klaus & Selga (2021) contribute to research with findings on market structure- and valuation changes and by introducing an Outperformance Indicator (OI) measure as a novel way to trace abnormal returns and extract legal uncertainties with FRN-bond documentations under NIRP.

Meanwhile, the impacts of de-facto —but not de-jure— floored floating rate coupons also bear an optional component in the FRN price. With the formal agreement by some bond issuers to never impose a negative coupon rate, FRN debt securities bear an implicit floor option with a exercise level (strike) of zero per-cent. Using the OI as presented in Klaus & Selga (2021), the authors traced changed in FRN pricing. For further research, the aforementioned SABR-model could be applicable to extract the value of this embedded option and by using the newly introduced OI to allow a more detailed decomposition of pricing impacts for FRN markets.

More generally, negative interest rates are also relevant for some countries where floating retail mortgages are commonly used (e.g. in the Baltic countries, the Netherlands and also in the United Kingdom). While submitting this dissertation, EA markets show a flatter yield curve driven by higher short end rates while longer term rates remain relatively lower due to upcoming recession fears. Thus, despite the current exit from negative rate regimes, the ECB may face a dilemma with high inflation rates while also discussing rate reductions due to mitigate impacts from a possible recession.

5 Conclusions and Outlook

This dissertation enhances the understanding of market information efficiency. It contributes to research on return and correlation impacts in bond and equity markets. The five constituting papers combine analytical tools and techniques under the efficient market framework and also include behavioral finance aspects. The thesis also introduces a novel performance indicator to measure bond market returns. Hence, the thesis contributes to research with topical and relevant findings while also enhancing the method toolbox in finance.

Based on the observation space in this thesis, the results do not suggest fully information efficient markets after all, confirming previous literature e.g. in Stiglitz & Grossman (1982); Malkiel (2003). For return analysis findings, different market segments show different results and markets appear to react on information based on the perceived relevance (of the incoming information) under prevailing market assumptions and expectations differently. For example, findings from a return analysis in a specialised bond market segment (Klaus & Selga, 2021) indicate slow reaction to new information from specialised channels (court rulings, issuer statements) which would allow for expert knowledge to 'beat the market' due to an earlier and more sound conclusion of the information impacts. This indicates a lack of informational efficiency and extends literature on asymmetrical bond market reactions (Kim, 2013), and also on bond contractual design (Gulati & Scott, 2011; Gelpern et al., 2017).

Informational efficiency is different —but not better— when looking at asset and market return impacts of the social media channel Twitter on equity markets (Klaus & Koser, 2020; Klaus, 2021). The results suggest that impacts are time-varying, and information is spread much more systemic and often to a more like-minded audience, but overall show low impacts on valuations in this sector. This is somehow surprising given the tweet impacts in other areas. Under a behavioral finance angle, this relates and confirms to findings due to sociological channeling and contagion effects of information (Akerlof & Shiller, 2010; Shiller, 2015). Another possible reason for these different findings could lie in the market participant structure and the development grade of the market segment. These findings extend literature around social media sentiment as in Barberis et al. (1998) and stock markets as in Tetlock (2007); Bouri et al. (2017). Furthermore, Klaus (2021) extends research around China and Trump asset price impacts due to trade balances (Lin & Wang, 2018) and stock returns (Sul et al., 2017) with findings on single assets returns in the context of the US and China trade war tensions.

Regarding correlation analysis related findings, Koser & Klaus (2020) reveal informational inefficiency on a single stock level especially during market sell-offs and downturns where correlations jump. The research extends the work of Baur & McDermott (2010) showing that their diversifier assumption does not hold in certain market situations. The results also confirm previous literature as in Longin & Solnik (2001) on correlation changes under bearish market sentiment. This supports portfolio selection work for investors in these stocks. Interpreting this from a behavioral finance perspective suggests that it is market sentiment driven as a overreaction (herd behavior) limiting the risk diversification and hedge efficiency. Knowing these features can help to improve market efficiency by participants trying to mitigate these impacts for their risk management.

The findings on bond market correlation changes (Klaus & Benghoul, 2022) are relevant also on the contextual nature of financial data and its narrative. The work contributes to rating drivers and asset prices research (Mellios & Paget-Blanc, 2006; Kiff et al., 2012). Specifically, it extends research around rating spillover impacts (Candelon et al., 2011; Beirne & Fratzscher, 2013). The results in both bond market studies also show that not all intuitively relevant information hitting the market do actually matter empirically. With this, the findings coincide with existing earlier studies on information efficiency (Roll, 1984; Shleifer, 2002; Shiller, 2015). For bond portfolio managers and practitioners, the results contribute to risk management related to hedge efficiency and correlation modeling.

The introduction indicated market structure changes which could impact asset prices and informational market efficiency. The thesis contributes to research by identifying and analysing some of these changes supported by empirical results. For floating rate bond markets under negative rate regimes, this thesis provides novel insights about a lack of information efficiency and legal uncertainties resulting in asset price and market structure changes (Klaus & Selga, 2021). The findings point out risks stemming from the negative rate regime and identifies repricing related to policy announcements. Still, even with markets exiting negative rates in 2022, researching impacts of negative rates remains contemporary as markets learned since 2014 that low and negative interest rate regimes could last longer than initially anticipated. Economists are partly expecting a recession with possible lower rates again into the near future. It therefore also contributes to research around negative rate regimes going ahead.

Klaus & Benghoul (2022) advance the application of wavelets in finance as a time-frequency-filter method which is long known in other scientific areas yet less so in finance. This method allows to study drivers of correlation changes and is important for analysing informational market efficiency. The authors extend the existing work on the rescue funds (Rocholl, 2012; Dieckmann, 2012) with a new study and also provide another practical use case for studies using IRS and credit spread measures (Afonso & Strauch, 2007; Liu et al., 2006). Methodology wise, the work provides insights for researchers in this field and exemplary shows the advantages using the continuous wavelet transform for financial data following the suggestions from literature (Mallat, 1989; Masset, 2011).

Further research includes applied and methodological areas of informational market efficiency. Bond market studies face a caveat stemming from the still prevailing quantitative easing programmes. They can influence studies via prices, spreads, liquidity, correlations and available free float of securities. While the ECB claims to execute their programmes market neutral, it remains an important point to recall when analyzing bond markets. Future research work could extend the presented studies and test market efficiency under a different monetary policy regime regime. With the introduction of the Next Generation EU Fund in 2020, there is more room to extend the research on correlation impacts and market structure changes once the market data allows thorough analysis. The wavelet spectrum offers further research ideas to advance the understanding of correlation changes. On Twitter sentiment and market impacts, research can extend via various angles including methodological work on Twitter indices related to the selected parameters and observation instruments used to trace impacts. In relation to the abnormal return studies presented, applying different asset pricing models on top of the market model may provide additional findings.

More broadly, researching information flows and economic and financial narratives remains topical. Getting a better understanding of how information and narratives distribute within markets, the economy and the society at last, is important to prevent the spread of fake news and to understand news contagion effects. Despite different schools of thoughts about understanding asset prices and investor expectations in finance, the one core element for markets and asset pricing remains —this is information. Importantly, how today's market participants form their expectations —they may be rational or irrational— is depending on how information spreads. Available information in markets is not only a pure content message or a number, but also the narrative and sentiment behind the information.

Finally, the combination of available research approaches and concepts in finance ranging from efficient markets paradigms to behavioral finance approaches can complement each other in order to better understand drivers of asset price valuation in markets. This finally adds to policy goals (e.g. capital market union) and contributes to financial stability in today's financial markets.

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Original Research Articles

Measuring Trump: The Volfefe Index and its Impact on European Financial markets*

Jürgen Klaus[a], Christoph Koser[b,*]

[a]*Faculty of Business and Economics, Technische Universität Dresden, Germany*
[b]*Department of Econometrics and Statistics, University of Barcelona, Spain*

Abstract

In this study, we examine the predictive power of the recently constructed *Volfefe* Index, the quantification of the tweeting activity of the U.S. president Donald J. Trump, on the dynamics of European stock markets. After controlling for a set of macroeconomic and financial factors, we show that the Trump Tweet factor contributes to the prediction of European stock market returns. The results obtained from a rolling-window regression approach indicate that the relationship between the Volfefe Index and European stock market returns is heterogeneous and time-varying. These dynamics coincide surprisingly well with a series of presidential tweets, identifying the directional effect of the Trump Twitter factor.
Keywords: European Financial Markets, Twitter, Sentiment, Donald Trump, Volfefe Index

JEL classification: G12, G14, G15, G40

1. Introduction and literature

Investor sentiment and stock market performance have long been in the focus of the financial literature. Early studies refer to noise or irrational traders who move prices away from its fundamental value, leading to higher expected returns and redundant volatility in the market (De Long et al., 1990a,b). Contemporaneously, the formation of sentiment has radically changed with the introduction of web-based applications and networks (i.e.

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*Corresponding author, email:j.klaus@esm.europa.eu .

social media) and created a platform where market participants can extract relevant content with much faster pace and accuracy than before.

According to Fang & Peress (2009), the micro-blogging platform Twitter is the tenth most-trafficked website on the world wide web and records over 330 million monthly active users as of 2019.[1] Thus, it seems not surprising that (global) institutions and leading figures use Twitter to convey political, social, and economic concerns (Ranco et al., 2015) to a global audience but may unintentionally fuel the development of (stock market) sentiment. One of them is Donald J. Trump whose style of communication is utmost distinctive from his predecessors. Although many major politicians tend to use Twitter nowadays, Trumps' communication through Twitter appears to be less predictable, timely-independent, and perhaps unintentionally amplified by re-tweeting activities via followers. To the extent that presidential tweets create sentiment and market movements, JP Morgan Chase (hereafter: JPM), in particular Salem et al. (2019), have constructed a time-series index based on a sequence of keywords used within Trump's vocabulary (i.e. "tariffs," "trade," "products," "billion," and "China") and relate it to the U.S. interest rate market. They show that Trump's tweeting activity impacts sentiment for money markets and large cap stocks. These findings suggest that Trump's tweeting activity may induce investor sentiment across a broader range of asset classes and potentially for markets outside of the U.S.

In this paper, we address the impact of Donald J. Trump's tweeting activity on European stock market returns. To do so, we utilize the recently constructed Trump twitter index by Salem et al. (2019) within a rolling-window regression model. After controlling for a set of macroeconomic and financial variables, we obtain dynamic estimates for the Trump Twitter factor on a daily level and compare them with the results of the mean regression method.

There have been a number of studies devoted to sentiment and stock market (e.g. Bouri et al., 2018a,b). For instance, the theoretical model by Barberis et al. (1998) shows that investors underreact to news and overreact to persistently good or bad news. Tetlock

[1] see https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/

(2007) finds that high media pessimism results in a downward pressure on intraday prices and a jump in trading volume. Fang & Peress (2009) document a significant premium on small stocks that are not covered in the media and with low analyst followings. As for the measurement of investor sentiment, a variety of proxies have been in use. Baker & Wurgler (2006) measure investor sentiment, using a composite index based on six underlying proxies.[2] They find an effect on stock markets in general and particularly on stocks that are difficult to value or arbitrage.[3] A second strand of the literature measures sentiment with survey data. More recent studies focus on the impact of Twitter sentiment on stock returns. Bollen et al. (2011) use a sentiment analysis application tool to filter out emotional polarity in the sentence structure of 9.853.498 tweets from 2.7 million users. Constructing six different mood-dimensional daily time-series, they find a positive association between "calmness" and the stock market performance. A similar study by Sul et al. (2017) groups tweets into emotional valence and match daily firm level twitter content to the corresponding return(s). They show that tweets about a specific firm are positively related to its returns and can further be utilized to predict returns ten days after the initial tweets. Oliveira et al. (2017) construct Twitter sentiment indicators and analyze their predictive power for returns of the S&P500 index and portfolios of lower market capitalization.

This paper is the first to examine the recently constructed quantification factor of Trump's tweeting activity outside of U.S. financial markets. We extend previous studies on sentiment and financial markets and specifically contribute to the above mentioned literature on twitter sentiment and stock market performance. We find that the mean impact of the Trump Twitter factor is of heterogeneous nature in its prediction of European stock market returns. More importantly, we document that these coefficients exhibit time-varying pattern and coincide surprisingly well with a series of presidential tweets, indicating the directional effect of the Trump Twitter factor.

[2]That is closed-end fund discount, NYSE share turnover, the number and average of first-day return on IPOs, the equity share in new issues and the dividend premium.

[3]Schmeling (2009) proxies sentiment with consumer confidence and shows its impact on stock returns across countries. This effect is particularly strong for countries with weak institutions and herd-like behaviour among investors.

The remainder of this paper is structured as follows. Section 2 presents the methodological approach of computing the quantification factor of Trump's tweeting activity. Section 3 describes the data and our estimation technique. Section 4 presents some preliminary statistics and the main results. Finally, Section 5 concludes and provides further outlook on the potential research in this field.

2. Volfefe Index - Trump Twitter Factor

The study by Salem et al. (2019) finds strong evidence that Trump's tweets have a market moving impact on U.S. treasury rates. The authors build a trained classifier based index to identify market moving tweets. First, they perform a tweet analysis and find a persistent daily presence as Trump's average activity on the platform, amounting to 10 tweets per day which extends to around 25 tweets if re-tweets are included. The Volfefe index, named in reference to Trump's viral *covefe* tweet on May 31st, 2017, considers over 14,000 tweets since 2016 of which around 10,000 appeared after he became president-elect. Second, Salem et al. (2019) define a market mover tweet as one immediately following a substantial move in U.S. treasury yields. The authors use intraday market turnover data, based on five-minute frequency to identify and tag price movements. Third, the paper deploys elements of natural language processing (NLP) techniques to identify a relative frequency of key words used within Trump's vocabulary. The results show that market moving tweets predominately focus on a subset of Trump's tweet horizon. By using a random forest classifier tree algorithm, the study models a word ranking which reveals trade and monetary policy as key topics. Lastly, this final classifier is used to construct an index computing the likelihood of a tweet being market moving under the above definition. The computational results are mapped via a one month rolling sum index of this score considering all tweets during market hours.

While the authors introduced a rather narrow observation space (i.e. U.S. interest rate markets), we aim to extend the study with a more European focus. In particular, we relate the time-series JPM Volfefe index on stock market index return to find market moving effects.

3. Data and Methodology

We collect daily closing prices for the following European stock market indices, DAX30, CAC40, IBEX35, FTSE100, ATX20, SMI20, PSI20, and ISEQ20, representing around 71% of the entire European stock market capitalization. These indices are comprised of the largest and most liquid stocks, weighted by its market capitalization. Our sample period is primarily selected upon the availability of the Volfefe Index provided by JPM and spans from April 4, 2018 to October 2, 2019, resulting in a total of 383 daily observations. Data on these indices is retrieved from Thomson Reuters Datastream and Bloomberg. We employ a 20-day rolling-window regression model to estimate time-varying coefficients for each index. Using OLS with Newey & West (1987) corrected standard errors, the time-series regression model can be written as follows:

$$r_{it} = \alpha_{it} + \Phi_{it} Volfefe_{it} + \Psi_{it} X_{it} + \epsilon_{it} \tag{1}$$

where r_{it} are the daily returns of the stock market index i; $Volfefe$ is the Trump Tweet factor, as constructed by JPM, and Φ_{it} the corresponding regression coefficient. X_{it} and Ψ_{it} denote a $N \times 4$ and a $4 \times N$ matrix which collects a set of macroeconomic and financial control variables and its estimates, respectively. Finally, ϵ_{it} denotes the error terms, assumed to be independent with zero mean and variance σ^2.

We control for short-term market expectation with the implied-option based volatility measure for the EuroStoxx50.[4] This proxy seems plausible as volatility changes are inverse related to concurrent stock returns, see French et al. (1987). We also include the Brent Crude Oil Price with the notion that higher oil prices correspond to the fear of higher cost of (world) production, less company earnings and hence a depression of stock prices, Sadorsky (1999). The inclusion of the German government bond yield controls for potential shifts between the EU stock and bond markets, known as flights-to-quality, see Beber et al. (2008), Baele et al. (2013). Ajayi & Mougouė (1996) show in a dynamic model

[4] This measure for volatility is constructed in the same fashion as the CBOE Volatility Index on the S&P500.

that a currency depreciation has a negative impact on current aggregate stock prices. To isolate the effect of exchange rates movements, we include the EUR/USD exchange rate. All variables are transformed into first differences to ensure stationarity. Table A1 reports the corresponding statistics that support the non-existence of any unit root for all series.

4. Results and discussion

4.1. Summary statistics

Table 1 shows the summary statistics for daily returns of all eight European stock market indices for the period from April 4, 2018 to October 2, 2019. Daily mean returns, measured in absolute values, are the highest for the ATX20 index, followed by the ISEQ20 and the DAX30 index. Moreover, these same markets are also the most volatile. Conversely, the lowest daily mean returns are to be found for the Swiss stock market (SMI20). All series are negatively skewed and exhibit an excess kurtosis slightly above 3, similar as in a normal distribution. The Jarque-Bera statistics however reject the null hypothesis, providing sufficient evidence for non-normality in all cases.

Table 1: Summary statistics of European stock markets indices

Indices	Mean	Max	Min	Std.Dev.	Skewness	Kurtosis	Jarque Bera
DAX30	0.70817	3.3144	-3.5373	0.93598	-0.3769	4.1000	28.39
CAC40	0.64606	2.6878	-3.6355	0.8753	-0.5176	4.6956	62.98
IBEX35	0.63728	2.4855	-2.8069	0.8259	-0.3158	3.7074	14.35
FTSE100	0.58213	2.3255	-3.2839	0.7810	-0.4515	4.6812	58.11
ATX20	0.7440	3.0923	-3.3384	0.9704	-0.2745	3.7297	13.30
PSI20	0.62581	2.7832	-2.6436	0.8054	-0.2308	3.4416	6.51
SMI20	0.57985	2.8111	-3.1813	0.7868	-0.2825	4.6564	48.88
ISEQ20	0.71882	3.148	-3.9057	0.93879	-0.3443	4.0814	26.23

Note: This table shows the summary statistics of daily changes of eight European stock market indices. The sample period ranges from April 4, 2018 to October 2, 2019, resulting in a total of 383 observations.

4.2. Regression Results

Table 2 presents the time-series regression results for eight European stock market indices from April 4, 2018 to October 2, 2019. The coefficients are obtained through the mean OLS estimation method and standard errors are computed with the Newey & West (1987) technique to correct for serial dependent error terms. To ensure appropriate stationarity conditions, all variables are transformed into first differences before estimating. The model specifications are jointly significant for all models and the adjusted R^2 ranges from 36 to 84%.

Table 2: Time-Series Regression Results - Volfefe Index & European Stock Market Returns

Variables	DAX30	CAC40	IBEX35	FTSE100	ATX20	PSI20	SMI20	ISEQ20
Volfefe Index	0.0082	-0.0105	-0.0211	0.0071	0.0168	-0.0059	-0.0066	-0.0058
	(0.97)	(-1.49)	(**-3.56**)	(0.40)	(1.28)	(-0.41)	(-0.63)	(-0.32)
Brent Crude Oil Price	0.0118	0.0038	0.0298	-0.0292	0.1310	0.0847	-0.0111	-0.0365
	(0.75)	(0.27)	(1.64)	(-0.86)	(**6.41**)	(1.94)	(-0.51)	(-0.63)
EuroStoxx50 Volatility	0.1161	0.1319	0.1172	0.0994	0.0822	0.0615	0.0955	0.0949
	(**-7.78**)	(**-8.93**)	(**-9.51**)	(**-3.59**)	(**-7.53**)	(**-4.57**)	(**-8.10**)	(**-6.21**)
German Treasury Bond Yield	-0.0034	0.0005	-0.0297	0.0211	-0.0029	-0.0229	0.0282	-0.0509
	(-0.41)	(0.03)	(-1.87)	(1.22)	(-0.24)	(-1.02)	(1.91)	(-1.43)
EUR/USD Currency Rate	-0.5099	-0.5870	-0.7576	-0.8331	0.3605	-0.1009	-0.2032	-1.8226
	(-1.69)	(-1.59)	(**-4.64**)	(-1.91)	(1.09)	(-0.17)	(-0.52)	(- 1.63)
Constant	0.0929	0.0194	0.0896	-0.0178	0.1943	0.0098	0.0456	0.1131
	(1.58)	(0.38)	(1.47)	(-0.15)	(**2.77**)	(0.08)	(0.64)	(0.54)
F-Statistic	20.36	21.82	18.68	4.34	10.80	3.17	7.86	3.76
Adjusted R^2	0.83	0.84	0.82	0.46	0.72	0.36	0.64	0.42
Durbin-Watson Statistic	1.71	2.00	1.74	2.00	1.80	2.38	2.07	2.01

Note: This table presents the mean OLS regression results for eight European stock markets for the period from April 4, 2018 to October 2, 2019. Standard errors are corrected for serial dependence in the error terms with the Newey & West (1987) method.

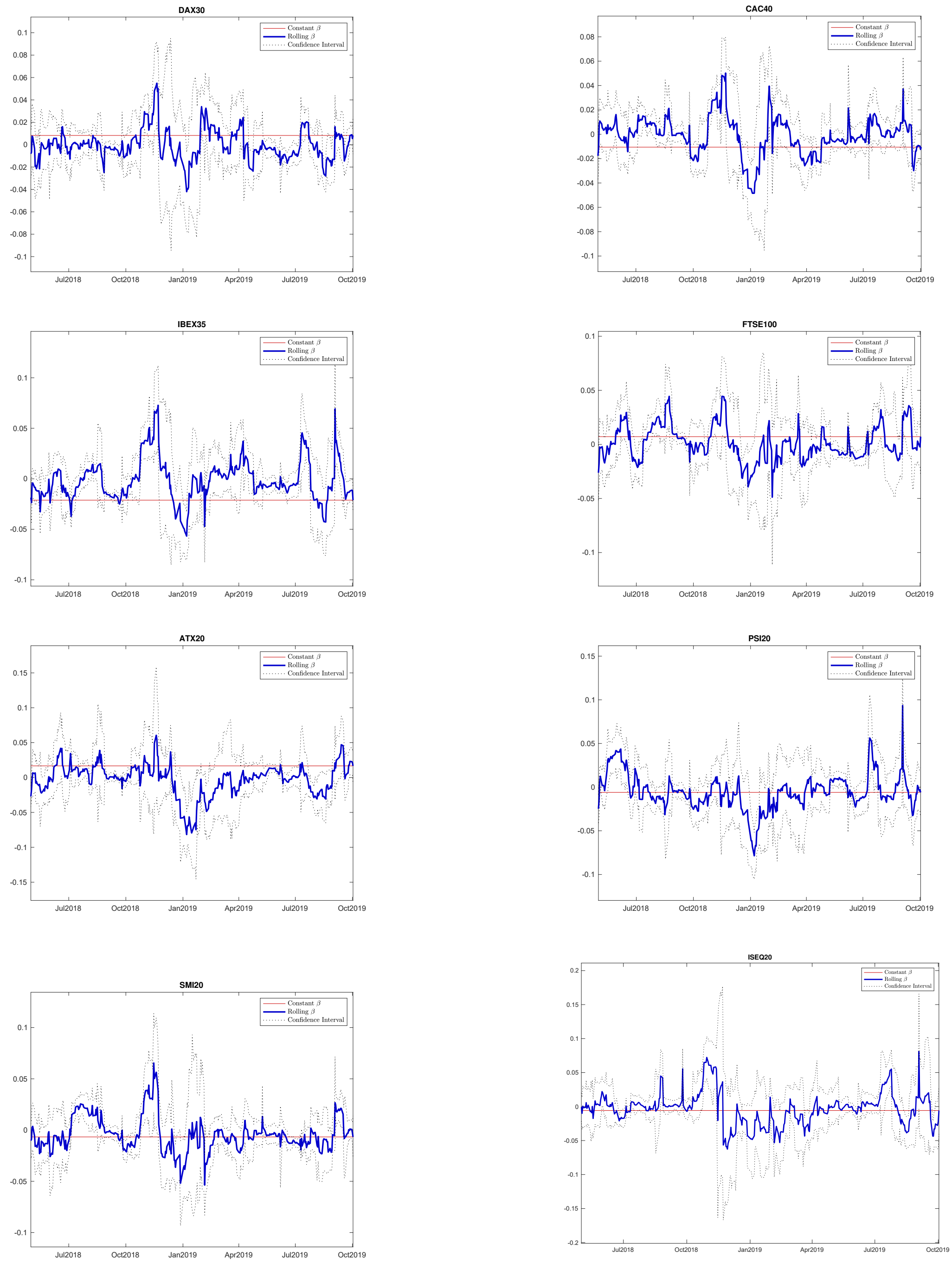
Evidently, the mean coefficient of the Volfefe index does not depict a persistent effect across markets. For instance, we document a positive but statistically insignificant relationship for the DAX30 and the FTSE100. Conversely, there is also evidence for a negative association between the Volfefe index and returns of the SMI20 and the ISEQ20 indices, but the effect is also insignificant. The only market that exhibits a significant exposure to the Volfefe index is the Spanish IBEX35. These findings suggest that sentiment based on presidential tweets does only partially explain European stock market returns over a longer horizon. As for the control variables, estimates show a consistent pattern for most markets. In all cases, we find a negative and statistically significant relationship between stock returns and volatility. This is consistent with French et al. (1987), who argue that changes in volatility increase future expected risk premiums but decrease concurrent stock prices. Changes in the short-term yield of German government bonds are inversely related with most stock market returns. These findings are also plausible as an increase in the yield for risk-free assets strengthens the flights-to-quality argument for investors, see Baele et al. (2013), Beber et al. (2008), Vayanos (2004). Noteworthy, different than what one may expect from the literature, oil price changes tend to have a positive association with returns in this sample period. Finally, we find that an increase in the EUR/USD currency rate, resulting in a dollar depreciation, depresses concurrent stock returns in Europe. To better understand if the coefficients for the Volfefe index are time-varying, we adopt a dynamic estimation approach with a rolling-window technique. The dynamics of the coefficients of the Volfefe index are plotted in Figure 1. We document some consistent patterns across markets. For instance, the dynamic estimates of the Volfefe index exhibit a major peak around October/November 2018 for all stock markets. Contemporaneously, these dynamics match with a sequence of presidential tweets that might partially count as contributors to the stock market performances across Europe at that moment in time.

- *October 31, 2018, 08:04:26 AM - "Stock Market up more than 400 points yesterday. Today looks to be another good one. Companies earnings are great!"*
- *October 30, 2018, 07:33:39 PM - "The Stock Market is up massively since the Election, but is now taking a little pause - people want to see what happens with the Midterms. If you want your stocks to go down, I strongly suggest voting Democrat. They like the Venezuela financial model, High Taxes & Open Borders!"*

In contrast, and common across most markets, this peak reverses with a sharp decline around the beginning of December 2018. Further, we find that one of the lowest return series across markets in the entire sample period occurs on December 6, 2018. This coincides with another sequence of presidential tweets that match the time-varying Volfefe coefficient and subsequently provide evidence to may drive daily returns at this point in time.[5] After the estimates of the Volfefe index reach their lowest value in our observations

[5]The appendix lists some further examples of Trump Tweets taken from the Trump Twitter Archive (`http://www.trumptwitterarchive.com`).

Figure 1: Rolling Estimates - Volfefe Index



Note: This figure shows the rolling-window estimates for the Volfefe index for the period from April 4, 2018 to October 2, 2019. The window length is 20 days. Our results are robust to different window sizes.

space, we see a positive reversal of the coefficients. This reversion is accompanied by another series of early 2019 presidential tweets that contains a strong selection of keywords, namely "Tariffs and Trade" that tend to affect market sentiment. This is also in line with the findings of Salem et al. (2019), who state that a series of keywords in Trump tweets, "Tariffs" or "Trade" among them, are likely to be market moving.

- *January 3, 2019, 09:52:13 AM - "The United States Treasury has taken in MANY billions of dollars from the Tariffs, we are charging China and other countries that have not treated us fairly. In the meantime, we are doing well in various Trade Negotiations currently going on. At some point this had to be done!"*
- *January 8, 2019, 08:16:09 AM - "Talks with China are going very well"*

Overall, this study provides interesting insights on the dynamic effects of the Volfefe index on European stock market returns.

5. Concluding remarks

In this paper, we examine the predictive power of the quantification factor of Trump's tweeting activity - the Volfefe index - on European stock market returns. After controlling for a set of macroeconomic and financial factors, we show that there is a heterogeneous effect of the Trump Twitter factor on stock market movements across Europe. Using a 20-day rolling-window regression model, we find that this effect is time-varying for all European indices, matching time-wise with presidential tweets.

We contribute to the existing literature on market sentiment and stock market performance. Specifically, we extend the narrow literature on social-media related sentiment and stock markets. Further, we provide the first empirical extension of the recently proposed Volfefe index with an application on European stock markets. Policy implications of our findings relate to market efficiency topics (could market participants as Twitter users beat the market compared to non Twitter users) as well as to inter-linkages between market segments and across countries. Further, in contrast to the discussion on capital market union in Europe our research raises the discussion into how market participants receive and digest relevant information. Noteworthy, given Trump's communication style, it appears interesting to analyse by how far markets adjust to a certain political communication style. Policy makers may seek to better understand how the combination of potential information inefficiencies (channelled via social media platforms) alongside a less streamlined, predictable and concise output (related to the *covefe* quote) may require policy responses.

Although we consider a certain degree of financial market integration between U.S. and European markets, there are still certain areas which require further research. Firstly, future research is encouraged to analyze the impact of Trump's tweeting activity on different European market segments, e.g. interest rate volatility in order to complement the initial approach taken by JPM. Secondly, the index can be widened in the sense that underlying U.S. treasury data is substituted with European benchmark data, i.e. European interest rate yields or equity. Thirdly, additional research could evaluate Trump's comments on European institutions and political leaders and hence reconstruct the index with a more European focus. Finally, research could address the impact of the Volfefe index on Asian financial markets, which is of particular interest in light of concurrent trade conflicts. Broadly, more research is needed to improve the predictive power of the presidential tweets on market pricing and market sentiment.

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Appendix A. Additional Tables and Figures

Table A.3: Unit Root Tests

	ADF-Test	PP-Test
Volfefe Index	-16.478*	-16.617*
DAX30	-19.978*	-19.976*
CAC40	-19.193*	-19.214*
IBEX35	-19.011*	-19.038*
FTSE100	-19.439*	-19.432*
ATX20	-18.479*	-18.533*
PSI20	-18.681*	-18.743*
SMI20	-20.292*	-20.305*
ISEQ20	-19.871*	-19.882*
Brent Oil	-20.409*	-20.421*
VIX-EuroStoxx50	-20.571*	-20.608*
German Treasury Bond	-19.295*	-19.300*
FX Rate USD/EUR	-18.901*	-18.915*

Note: This table reports the results of the Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) unit root tests for the Volfefe Index, the stock market indices and a set of explanatory variables. The sample period spans from April 4, 2018 to October 2, 2019.

Appendix B. Selection of Trump Tweets

We list a series of Trump tweets that seem valuable in light of the above analysis. All presidential tweets are taken from the following website: `http://www.trumptwitterarchive.com`.

- *August 28, 2018, 04:57:51 AM - "NASDAQ has just gone above 8000 for the first time in history!"*
- *October 23, 2018, 11:43:46 AM - "Billions of dollars are, and will be, coming into United States coffers because of Tariffs. Great also for negotiations - if a country won't give us a fair Trade Deal, we will institute Tariffs on them. Used or not, jobs and businesses will be created. U.S. respected again!"*
- *December 4, 2018, 07:21:41 PM - "China does not want Tariffs!"*
- *December 4, 2018, 07:20:27 PM - "We are either going to have a REAL DEAL with China, or no deal at all - at which point we will be charging major Tariffs against Chinese products being shipped into the United States."*
- *December 14, 2018, 11:25:59 AM - "China just announce that their economy is growing much slower than anticipated because of our Trade War with them. They have just suspended U.S. Tariff Hikes. U.S. is doing very well. China wants to make a big and very comprehensive deal. It could happen, and rather soon."*
- *August 1, 2019, 12:26:10 PM - "...during the talks the U.S. will start, on September 1st, putting a small additional Tariff of 10% on the remaining 300 Billion Dollars of goods and products coming from China into our Country. This does not include the 250 Billion Dollars already Tariffed at 25%."*
- *August 3, 2019, 07:46:45 AM - "Things are going along very well with China. They are paying us Tens of Billions of Dollars, made possible by their monetary devaluations and pumping in massive amounts of cash to keep their system going. So far our consumer is paying nothing - and no inflation. No help from Fed"*

How Floating Rate Notes Stopped Floating: Evidence from the Negative Interest Rate Regime☆

Jürgen Klaus[a,*], Ēriks K. Selga[b]

[a] *Faculty of Business and Economics, Technische Universität Dresden, Germany*
[b] *Faculty of Law, University of Hong Kong, Hong Kong*

Abstract

We analyse the impact of stakeholder interactions with the market as a consequence of the negative interest rate regime on the pricing of selected Floating Rate Notes (FRNs). The range of reactivity of financial markets and issuers to uncertainty caused by an untested boilerplate term in bond contracts are thoroughly outlined. The subject clause stipulates 'not applicable' as the minimum rate of interest, raising confusion regarding payment obligations between issuers and investors. We highlight the range of challenges by drawing parallels with the pari passu saga, noting a comparatively faster qualitative response to legal uncertainty across the FRN industry. We support these findings empirically, by observing that markets do –to varying degrees– price stakeholder activities with possible impact on the legal certainty of FRNs, like court decisions, industry association statements, and public positions of sovereigns. In turn, issuers are willing to react to legal risks quickly, if costs of inertia are low. This is reflected also in the relevant changes in the FRN issuance structure in the past few years. The announcement of further lower for longer rates in the Euro Area provides evidence that the FRN market appreciates the current protection of negative coupons even under a lower Euribor. Consequently, this appears to confirm a situation where Floating Rate Notes turned de facto into Floored Rate Notes, in part because of legal uncertainty in the N/A clause.

Keywords: Sovereign Bond Markets; Floating Rate Notes; Negative Interest Rates; Legal Uncertainties
JEL classification: C53; G17; Q14

1. Introduction

Eurozone key interest rates may stay lower for longer.Since the inception of the European Sovereign Debt Crises in 2009, the European Central Bank (ECB) reduced interest rates in the Euro area to historically low levels. As of now, the deposit facility rate has been negative for over five years at currently −0.50%. Meanwhile, the Euro Interbank Offered Rate (EURIBOR) fixes in negative territory while main Euro area sovereign bonds

*Corresponding author, email: j.klaus@esm.europa.eu

trade with negative yields.[1] This research investigates the impact of the unprecedented dip on pricing behaviour of the market towards Sovereign Floating Rate Notes (FRNs), which have been subject to a unique type of legal uncertainty as a result of the shift into negative rates.

The locus of distress in FRNs is a clause in the boilerplate bond contracts that stipulates 'not applicable' (N/A) as the minimum rate of interest. FRNs worth up to EUR200bn are subsequently at risk of their coupon turning negative, which may allow for the unlikely interpretation that would reverse payment obligations in an favour of the issuer and cause a market-wide upset reminiscent of the pari passu saga. The structure of market issuances has already changed to adapt to this risk. For example, issuances of FRNs without an explicit minimum interest rate have increased exponentially at the beginning of the low-interest period, only to come to a crawl upon entry into negative benchmark rates. In their stead, there has been a resurgence of FRNs with explicit minimum rates.While negative coupons have not been charged to investors yet, attempting to enforce payments from noteholders carries crowding risks for issuers, pushing investors into other FRNs. Stakeholders have attempted mitigating the lack of clarity surrounding FRNs without a minimum interest rate with a myriad of unconventional activities.[2]

The FRN market thus calls for a two-pronged investigation. First, into whether the industry found sufficient legal risks in the interpretation of the N/A clause to attempt rectification. While markets could cope with negative yields, the potential of negative coupons triggered key participants to argue that a reversal of a coupon payment is legally and operationally impossible. A series of court decisions in other financial segments of the Eurobond area[3] have highlighted the disagreement on this stance, and could warrant mitigatory action.[4] The second prong is into the impacts on the financial aspects of FRN markets. Changes in the standard market practice of flooring coupons have required re-calibrating pricing and risk management of FRNs.

The interdisciplinary nature of the study—from a legal and a empirical perspective—supplies certain limitations to the depth of both legal and finance investigations. The legal discussion does not holistically analyse the contractual aspects associated with the

[1]This includes core sovereign fixed coupon bonds with maturities up to ten years. German sovereign bonds yield negative across the full yield curve; 30y Bunds reached negative territory beginning of August 2019.

[2]A sovereign publicly announced their legal stances in the debate, clearing houses have released a united guidance document exclaiming the operational impossibility of reversing coupon payments, and a range of courts in the Euro area have been circling in on the FRN issue through claims about International Swap Dealers Association (ISDA) collateral and retail loan cases.

[3]Eurobonds are securities issued outside the country of the issuer's origin. Since the early 1960s it is the issuance format for bonds as a Global Note dematerialized format. They should not be confused with the debate on joint bond issuances from EA member states or a reference to specific currency only.

[4]For example, the Opinion of Advocate General Mengozzi delivered on 13 July 2016 affirming the validity of Spain in limiting 'floor' clauses in bank loan contracts to retail consumers in judgments No 139/2015 (ES:TS:2015:1280) and judgment No 222/2015 (ES:TS:2015:2207).

boilerplate documents—the variety in legal treatment of bonds, negative interest rates, and related matters among different jurisdictions require individual investigation; nor do we explore the legal standing of certain stakeholder activities. Instead, we aim to highlight the sources of uncertainty across various European jurisdictions, gauge their impact on markets and bring the matter into the wider standard clause debate through juxtaposition with the discourse on the pari passu clause. Regarding determinants and the event study, the investigation on market structure uses the interest rate path and pricing relationships as core signifiers of impact to stakeholder events. The sampling for the empirical data also compromises between liquidity, market size, and closeness to negative coupons, resulting in sovereign FRNs issued by Italy as the main source of samples.

The remainder of the paper is structured as follows. Section 2 presents relevant literature from both legal and finance, highlighting a consensus on pricing impacts of contractual clauses, but a lack of relevant research on FRN terms. Section 3 discusses legal uncertainty and finance challenges stemming from the low-interest rate period , divided into discussions of bond documentation characteristics, interpretability of the N/A clause, parallels of FRN documentation with the pari passu saga, and subsequently - FRN idiosyncrasies. Section 4 outlines an empirical study of FRN markets, investigating the change in available FRNs, their pricing, and providing results. Section 5 concludes and reiterates the links between the legal discussion with the empirical study.

2. Literature Review

In the following section, we outline the research on bond price sensitivity generally during zero interest rate policy (ZIRP) and negative interest rate policy (NIRP), the pricing impacts of litigation and contractual terms, as well as stakeholder reactions to the aforementioned determinants.

Research concerning aspects of low rate regimes is manifold and includes topics such as monetary policy debates, financial stability and growth impacts as well as microeconomic impacts of factors like bank business models (Coere, 2014, Borio et al., 2017, Nucera et al., 2017). However, research on FRN markets under negative rates is limited to several bank research papers from a practitioner's perspective that have drawn attention to the topic. Research is also scarce in providing general principles for FRN markets. Fabozzi & Mann (2000) provide an FRN specific framework explaining its characteristics and valuation principles. It is pointed out that margin based pricing of FRNs and the discount margin as an appropriate price determinant are of significant importance to markets.[5] The calculation of the discount margin in lined out in the Appendix.

In literature, it is generally agreed that pricing based on traditional approaches has

[5]For reference to the commonly used margins as spread for life, adjusted simple margin, adjusted total margin, and discount margin refer to Fabozzi & Mann (2000).

changed during ZIRP and NIRP periods. Arteta et al. (2018) builds on these findings by highlighting that markets have also not been correct in their predictions in interest cuts. Xia & Wu (2018) have drawn a strict line denoting the increase of borrowing and lending costs upon reaching the negative zone. However, while Kim (2013) finds that interest rate ambiguity contributes to yields, it does not do so linearly, implying that conventional yield factors are not fully accountable for premia variation.[6] Our investigation considers the low-interest rate period as a period of heightened market vigilance and uncertainty, where non-traditional factors like stakeholder activities and court decisions may have heavier impacts.

A broad literature has aimed to assess the impact of various non-traditional on market behaviors. Kim (2013) finds that bond yields asymmetrically respond to news from authorities, with stronger changes upon the day of bad news than good news.[7] Ahmed & Alfaro (2017) and Hébert & Schreger (2017) find sovereign-debt related litigation chains have an impact on yields, noting an impact from investor perceptions on contract enforceability. Investigation has also been conducted on the role of particular provisions in bond documentation in market behavior, with scholars finding various degrees of pricing impacts depending on proximity and clause (Bradley et al., 2010, Dufour & Nguyen, 2012, Peiers, 1997).

Research on the effects of contractually unclear terms is sparse. Choi et al. (2011) find markets reacting generally slow to changes, with significant inertia costs. The potential risk arising from interpretation of stipulation from litigation is, by itself, not the most important factor in alterations of contracts. Markets also ignore historical evidence on clause interpretation on the basis of contemporaneous contextual differences, industry leaders and stakeholder interactions (Choi et al., 2017). While markets may react quickly in pricing activities, changes in contractual clauses may not have taken places because contractual clauses in standard clause persist until an exogenous factor requires change (Choi et al., 2011). Even with such an event, the change must be capable of overcoming the aggregated cost of ex-ante and ex-post inertia. The inertia costs attributed to the belated change in the pari passu cited by Gulati & Scott (2011) appear in four distinct categories: legacy debt costs, market reaction uncertainty, idiosyncrasy costs, and legal uncertainty. Gelpern et al. (2017) supports the stance from a qualitative investigation from the perspective of debt managers; reluctance to change derived from fear of markets misreading the signals from edited contracts, and a need to blend in with their cohort. Choi et al. (2017) posit that such a cost can be overcome only when market participants solve a collective action problem required to prevent the isolation of a single issuer imple-

[6]Conventional yield factors generally consist of Interest rate, inflation, debt to GDP ratio, deficit to GDP ratio, GDP growth rate, and equity indexes.

[7]For example, the Federal Open Market Committee issuing news on decreasing interest rates is considered bad news by bond market participants (Kim, 2013).

menting changes in standard agreements. Recent studies further highlight the difficulty of effectively pricing terms, especially when they are market-standards (Scott, 2020, Gelpern et al., 2019, Scott et al., 2020).

This contribution aims to build on the aforementioned areas of study through three core aspects. First, it extends research on the impact of general non-traditional events on pricing behavior and spillover events to the Euro area. Second, it adds to the discourse on unclear boilerplate clauses, and how markets react when they are put under the spotlight in a conservative financial industry. Third, it provides a new methodological model with which to examine such event-tied behaviours.

3. The Legal Uncertainties of the Low-interest Rate Regime

In the following section we outline how ZIRP has brought legal uncertainty to FRN contracts, and how such uncertainty can have a market-wide impact. First, we outline the unique characteristics of FRN bond documentation, especially the N/A clause. Second, we discuss how the N/A clause may cause significant uncertainty depending on the legal environment. Third, we compare the uncertainty of FRNs with the pari passu saga, where a single clause caused systematic market changes. Last, we highlight the differences and idiosyncracies of FRN bond documentation.

3.1. Bond documentation

The structural changes in the market in favor of FRN issuances with explictly delineated floors instead of 'N/A' are ultimately a consequence of the term's opaqueness in the *Final Terms* (FT) legally detailing the individual bond characteristics. The FT of a bond's documentation contains a series of core transaction related information, like the International Security Identification Number (ISIN), bond pricing, governing law, and maturity details. They are publicly available for bond issuances, and are considered legal supplements to the prospectus, which they are subordinated to. They also contain the applicable minimum interest rate to the bond. As a market practice for FRN agreements there are two types of interest variations:

1. an *initial explicit floor*, stating a minimum rate of interest to the investor as of the issue date;
2. an *assumed implicit floor*, which does not explicitly state a minimum rate of interest.

These floors are denoted by express statements following the minimum interest rate clause of the document, as either 0% or above, or by the phrase 'not applicable' (N/A). In positive rate markets, the latter would generally be interpreted as providing for an implicit floor of 0%. However, in NIRP the intuitive inference of N/A would differentiate the meaning from the explicit floor of 0%, just by the variation in the construction of the term. This surfaces the question of the meaning of the phrase among industry practitioners. A possible fringe interpretation is that there is no floor, and that interest rates can enter negative areas. Such an interpretation strongly differs from market practice, and brings challenges from both legal and financial perspectives.

3.2. Interpreting N/A

Legally, the contractual core principles of bonds and securities are founded in debtor and borrower relationships. Negative interest rates can, prima facie, result in two unconventional alterations of this relationship. In the case of a loan, the borrower may receive interest on borrowed money, and a lender may have to pay the borrower this money. In the case of a deposit, the depositor may have to pay interest on his deposit, receiving less in output than input.

Applied to FRNs, if the floating rate coupon rate is negative, reversing the standard cash flow may result in debiting the bondholder. Other unconventional methods of settling coupon payments may also arise. An issuer could intend to redeem less than par at maturity to compensate for any theoretical negative coupons not imposed. Additionally, an issuer may consider adjusting positive coupons by compensating previous theoretical negative coupons over the bond's lifetime. Any of these variants create legal risks ranging from a credit event (below par principal redemption) to lengthy legal discussions (e.g. averaging coupons). When issuing floating rate debt, the issuer faces the risk that the total coupon payments increase with the reference interest rate increasing. The issuer may also have conducted an interest rate swap agreement to protect the floating rate payment obligation against a rate increase. If the rates decrease below zero, both contracts may be affected. Myriad challenges would also be transposed to derivative hedges and other related instruments.

The proposed reversal of payments has not yet materialized in practice; although there are exceptional instances of bonds with a negative fixed coupon, the question remains if negative coupon payments for implicitly floored FRNs could be legally enforced and who would carry the legal and financial burden. The stance of the legal industry is, generally, that an interpretation in favor of a 'no-floor' would be unlikely, given the aberrant nature of such a decision to the legal order, the lack of express indication of such intention in bond contracts, and operational limitations impinged upon. The evident vacuum left by a leading court is also allowing divergences across various legal systems, where bonds under the negative facility rates could be considered outside the framework of a monetary loan.[8] The situation becomes increasingly confusing regarding the vast amounts of structured bonds.

[8]It has been proposed that a bond issued in a negative rate from the beginning could be considered a custody agreement, as it would result in a party entrusting money to another for a guarantee of solvency. See further: Endréo (2015).

3.3. *Pari passu parallels*

The state of the N/A interpretation issue parallels the infancy of the pari passu saga, in several salient ways. The pari passu chronology begins in 2000, when the Republic of Peru was taken to court in Brussels by a hedge fund on a claim of non-payment of debts. The court ruled, on an ex parte motion, that the Peruvian debt contracts contained a pari passu clause that prevented Peru from paying other creditors without paying a pro-rata share to the hedge fund (Cohen, 2011). Additionally, the hedge fund could place an injunction against the Euroclear financial clearing house, preventing payments to restructured bond holders lest the fund received its full payment on the unrestructured amount. This reading of the pari passu clause received near-universal criticism from the international financial community, for providing a severely aberrant interpretation. However, even with the noise surrounding the clause, sovereign debt contract provisions were not modified to clarify the anomalous interpretation. Lawyers explained the lack of editing as unnecessary, as more authoritative courts in New York or London would never repeat such an interpretation.[9]

In 2011, in a similar case concerning Argentinian bond pari passu interpretation, a federal judge in New York decided the case the same way as the Brussels court. In 2012, in appeal, the Second Circuit court affirmed the previous interpretation, even in light of extensive amicus briefs from three different countries, industry organisations, and even a Nobel laureate expert in sovereign debt. The Supreme Court declined to hear the case. The pari passu saga was epilogued by a series of high-level meetings between the International Monetary Fund (IMF), the International Capital Market Association (ICMA), the World Bank, and G-20, all of them endorsing the necessary changes to the clause. The shocking interpretations of the courts were heralded as a major threat for the sovereign bond market, as it would make debt restructuring even more difficult, harming both sovereigns and creditors.

Our analysis highlights similar points of inflection between N/A and pari passu clauses. First, both concern the reading of a boilerplate term, from the very standardized capital markets framework. The initial uncertainty in the meaning of pari passu was signalled by a decision in what was considered a minor court, lacking authority to change the vector of the markets. While courts generally have not been in favor {blue of implying payment obligations related to negative interest, there have been variations on the extent of this attitude across jurisdictions.[10] An attentive market would presumably be vigilant to such sentiments (Choi et al., 2011).

[9] Instead, the market chose to ameliorate the issue by coordinating revision of the no-modification clauses in New York governed law bonds, to require the approval of only 75% instead of unanimity as a method of encumbering holdouts seeking a blocking position (Gulati & Scott, 2011).

[10] See for example the Austrian cases Decision on case OGH, March 21, 2017, 10 Ob 13/17k and Decision on case OGH, May 3 2017, 4 Ob 60/17b on negative interest rates in mortgage contracts.

Second, the pari passu issuance ratio was not significantly affected by professional industry associations (Gelpern et al., 2017). Many of the contractual ambiguities have been elucidated in a collective effort by stakeholder in the form of various guidelines, explanatory notes, and practical proclamations. Industry organisations like ICMA and the International Swap Dealers Association (ISDA) have introduced the ISDA Collateral Agreement Negative Interest Protocol, updating and clarifying swap and derivative contracts on negative interest rates. The Loan Markets Association has introduced an option clause that can be implemented in loan agreements governed by English law (Frankel, 2014). The general solution offered has been to create floors for the interest rate or amend contracts. The impact of such endeavors remains to be explored later in the paper.

Third, in both cases, issuers have attempted to mitigate the uncertainty around a clause through methods beyond altering the contracts. For example, in Argentina's petition for Supreme Court review of the 2nd Circuit Court of Appeals decision in favor of holdouts, France, Mexico, and Brazil submitted amicus briefs in its support (Frankel, 2014). In the case of the N/A discussion - the Italian government took a much stronger stance, and issued the Attorney General's opinion on the action on coupons in the event of certain securities entering the "recent[ly]...inconceivable" phenomenon of negative coupon rates in the Official Gazette in 2016 (Ministry of Economy and Finance, 2016). The opinion notes that the issuances decrees have no explicit rule in assuming negative coupons, and there is a question about how they are interpreted. In accordance with the official's opinion, the Italian Civil Code allows the maximum risk for the lender to be the "gratuitousness" of the contract. Concurrently, services qualified as interest must be for the account of the borrower, preventing them being on account of the lender. The attorney general concludes that "the regulation of the relationship includes an implicit provision, whereby, in the event of negative interest rates, the minimum coupon is equal to zero" (Ministry of Economy and Finance, 2016).

Similarly in the case of the N/A clause for the Eurobond markets, the two International Central Securities Depositories (ICSDs) Euroclear and Clearstream launched guidelines on securities held in their systems with negative interest rates. The guidelines described situations when coupons are negative as ones that would "usually" be considered floored, and claim that "in principle", the ICSDs do not facilitate the collection of cash due to negative interests on coupons from their noteholders (ICMSA, 2015). Leading lawyers and institutions like the ECB also professed necessity of wider adaptation to the NIRP regime throughout the market (Coere, 2014). Collectively, through strong and opinionated stances, the industry has reacted to the ZIRP and N/A issue by sending strong signals regarding the impossibility of an aberrant interpretation, which was also the case in the pari passu sage - which resulted in a surprising upset.

3.4. FRN idiosyncrasies

The aforementioned similarities create a base for further investigation into current market reactions to stakeholder activities. There are, however, also several major differences. For one, the slow reaction of markets and issuers to the growing pari passu risks, by ignoring the recommendations of industry associations, and mistaking the earlier decisions, are inapplicable to the no-floor clause debate. Significant structural changes in the volume of issuances of FRNs took place within a relatively short period of ZIRP and NIRP. At the beginning of the low-interest period, N/A FRN issuances begin increasing exponentially, coming to a swift halt exactly at the dip of the benchmark rates into negative territory. The questions posed by Gelpern et al. (2017) and Gulati & Scott (2011) regarding the slow speed of issuer adaptation to risks in their contract forms, are made partly moot in this case. At first sight, the reaction of markets does not coincide with the collective action thesis of Choi et al. (2017); no traceable series of meetings between market players triggered the change. Instead, the decision appears endogenous to issuers. This can partly be explained by the anticipation of the dip by market participants, contrary to the aberrant decisions in the pari passu cases.

It also alludes to the different levels of encumbrance in altering the clause. The prospectus carries significant inertia costs. Investors, underwriters, and issuers alike cannot make any significant changes to the prospectus, especially without collective support (Gelpern et al., 2017). The FTs, on the other hand, are altered freely, allowing multiple types of characteristics under a single issuance, thus decreasing issuer fear of crowding risks.

The role of court decisions is another material difference between the two topics. The NIRP regime has provided a series of decisions in the Eurobond area, relevant to the interpretation of negative interest rate impacts on debt contracts. Unlike the pari passu saga, which revolved around several critical decisions concerning the terms' specific interpretation in regards to holdouts, none of the cases have tested the term in regards to bonds. The thematically closest case was decided in the English High Court, concerning the interpretation of a 1995 ISDA Credit Support Annex (CSA) in NIRP environments, in regards to how cash collateral should be paid under such a regime. The Netherlands lost to Deutsche Bank AG, as the judge found that the agreement as a whole did not include an obligation on the transferor if interest mount is negative, unless the obligation were "spelled out."[11]

As the ISDA 2013 Statement of Best Practices, allowing for negative interest obligations was not around at the time of contracting, it would not be applicable to the case. While the case is confined to a specific CSA and the derivatives market, the subject mat-

[11]Decision in the State of the Netherlands v Deutsche Bank AG [2018] EWHC 1935 (Comm) (25 July 2018).

ter is in the orbit of bonds, and provides a vector for judicial sentiment - particularly important as it is an English court. For bonds issued in NIRP environments, the decision necessitated a review of whether N/A could be understood as sufficiently similar in meaning to explicit floored terms, to receive a similar finding from the court. The decision was also appealed, further increasing its possible relevance to bonds.[12] The appeal to the case affirms the previous decision, with certain derivations. First, the judges argue that on a more general level, while "the commercial background can be argued both ways," the CSA does not intend to give the impression that negative interest is "contemplated or intended." The court does allow more room for a reading that supports the aberrant position, instead confirming the decision of the previous court by reference to the relevant ISDA documentation depended on by the parties. The User's Guide of the ISDA forms depended on by the contracting parties in 1999, makes no reference to negative interest being provided for, even though they were a possibility at the time. Only in the 2010 Best Practices statement amendment are interest rate accruals fixed from dropping into negative figures, highlighting that it was generally not anticipated that interest rate accrual should be negative significantly prior to 2010. As such, the appeal expands the are for interpreting negative interest payments in bonds, by setting the authority for analysing several levels of non-binding industry documentation to understand the possible extent of meeting of minds.[13]

While the aforementioned cases concern sophisticated parties and contracts in financial markets, several cases address the interpretation of negative interest rates towards consumers. Two Austrian Supreme court cases find that a bank cannot unilaterally fix an agreed reference rate to zero, even if it becomes negative.[14] In turn, a reversal of payments could also not be enforced as the parties to the contract bilaterally agree on sharing the risks from fluctuations of reference interest rates. A Dutch Financial Services Complaints Tribunal, however, ordered a bank to pay negative interest to its client on the basis of no interest rate floor in the agreement.[15] The bank had also tried to introduce an implicit floor of 0%, which the tribunal found as an unreasonable interpretation without explicit stipulations to such an effect in the agreement. The variance among decisions on negative interest rates may be enough for markets to interpret uncertainty - this, we examine in the following section.

[12]Decision in Appeal on The State of the Netherlands v Deutsche Bank AG [2018] EWHC 1935 (Comm) (25 July 2018).

[13]Decision in Appeal on The State of the Netherlands v Deutsche Bank AG [2019] EWCA Civ 771 (2 May 2019).

[14]Decisions OGH, March 21 2017, 10 Ob 13/17k and OGH, May 3 2017, 4 Ob 60/17b, respectively.

[15]Judgment (Binding Advice) Nr. 2016-143 of the Dutch Financial Services Complaints Tribunal (Geschillencommissie Financiële Dienstverlening).

4. An Empirical Analysis of Floating Rate Debt Markets

In the following section, we conduct an empirical analysis of FRN debt markets to study pricing changes. First, we elaborate on how the ZIRP regime impacted the dynamics of the FRN market based on shifts between FRNs and fixed coupon market segments and their pricing. Second, we outline an empirical study on bond matching and elaborate on the event study methodology used. Key stakeholder events with impact on legal interpretation of the N/A clause are then defined, and the study performed. Last, we discuss the results.

4.1. Changes in market structure

The boilerplate legal templates of floating rate debt securities are tied to their character as traditional financial products. They replaced bank loans as a major borrowing form in the early 1980's along with the development of the swap market. The gross issuance of sovereign bonds in 2017 reached around EUR 2.5 trillion with a total outstanding of around EUR 10 trillion. The average daily trading volume for sovereign bonds amounts to around EUR 57 billion per day. The outstanding amount of FRN sovereign bonds amounts to around EUR 180 billion. This quantity increases to well above EUR 200 billion when non-sovereign floating-rate note issuers are included (Association for Financial Markets in Europe, 2017). Due to their resetting coupon nature which regularly adjusts the coupon to an on-market level (e.g. every six months), their interest rate sensitivity is naturally very low. Thus, FRNs are often considered risk conservative products.

We analyse the tensions stemming from legal uncertainty in the FRN market through a comparative lens of two market segments - an issuer's fixed coupon market and the FRN market. We use two price parameter variables under a given data sample of FRNs - outlined below in greater detail - to assess whether a change in structure took place independently of key industry reactions on the N/A interpretations. We include FRN market structures during the ZIRP and NIRP cycles to reduce the sample set to selected liquid FRNs to complement our legal argumentation with price and market structure changes.

We note particular changes in FRN issuance activities regarding volumes in relation to interest rate changes and changes in the contractual design of FRN issuances highlighted below in Fig. 1.

We find that monthly averaged FRN issuance volumes stand around EUR 14bn over the time series. The average issuance volumes until March 2016, when ECB rates (expressed as the main refinancing operations rate) turned to 0%, are EUR 9.8bn. representing around 74% of the total average volumes. Issuance volumes doubled from April 2016 onward and result in a much higher average monthly issuance volume of EUR 19.5bn. being 1.99 times above the total monthly average.

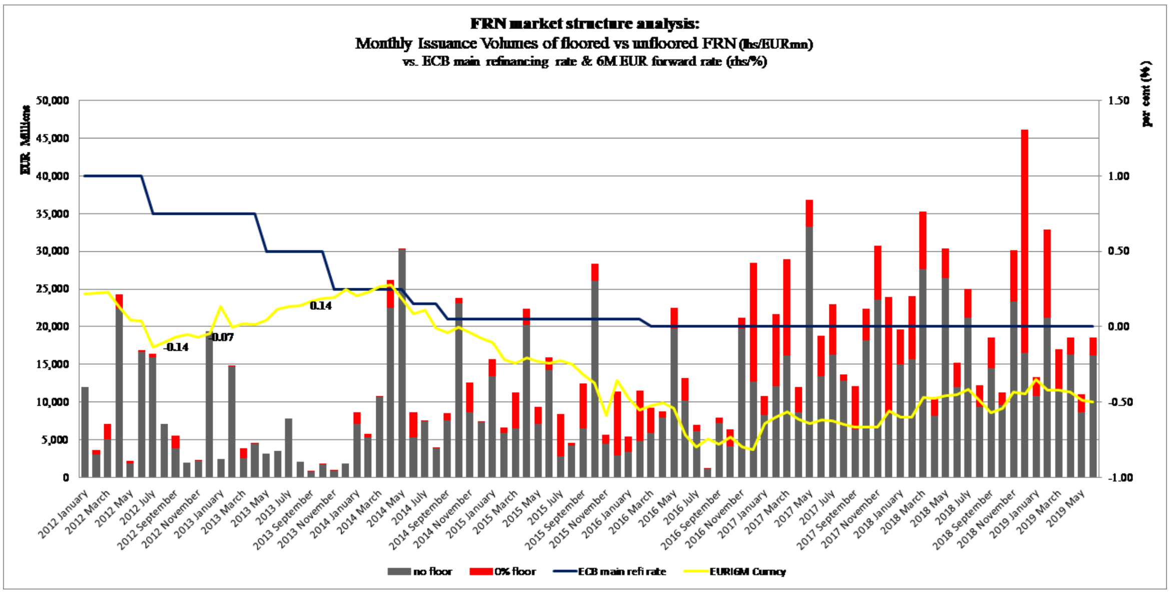

Figure 1: FRN Market Structure Analysis and issuance volume (bar charts), interest rate path (blue line), and 6M implied forward (yellow line) from January 1, 2012 to June 30, 2019.

We added the 6M EUR forward rate (EURI6M) in Fig. 1. This forward rate became negative in July 2012 and the overall monthly issuance volumes decrease until April 2014, which is also observable in the decrease in grey bars around that time. Meanwhile, issuance activity since 2017 increased to over EUR 21bn. per month and continued to hold around these levels until the end of the observation period. As shown in Fig. 1, floating rate debt issuance volumes remains high while the forward rate tends lower in 2016/17 and oscillates around -0,5% .

Floored vs. unfloored issuance structure

Until the end of 2014 explicit floors were underrepresented with only 7% of total volumes applying zero floored coupon in the final terms. During the next two years of time series (January 2015-2017) this share increases to 26% of FRN using explicit floors and remains around this level until end of November 2018. Notably, apart from one outlier in the typically quiet summer period (August 2016), we find around 28% of monthly FRN issuances include explicit floored coupons. Peak month even reach over 60% of total issuance sizes.[16]

FRN market structure analysis findings

First, the analysis of Fig. 1 indicates that issuance structures changes. Monthly average volumes increase during the observation time (shown on the left hand scale). Until the end of 2014, the share of explicit floors includes around only 7% of total FRN volumes issued. From March 2014 onwards, the implicitly floored issuances fall sharply, and

[16]A breakdown into monthly data show peaks of floored coupons in H2/2017 and December 2018 between 47-64%.

a gradual increase in explicitly floored bonds emerges. The change in behavior towards explicit rates suggests a lack of certainty in the applicability of the N/A clause. However, as implicitly floored notes keep being issued at varied rates, the certainty is either not affecting the market at an equivalent rate, or the costs of altering documentation are too high. Notwithstanding, FRN with implicit floors are being issued at varied rates.

Second, regarding the interest rate path correlation with the implied 6M forward rate, we find no direct match between rates turning negative and decrease in issuance activities. However, changes in issuance behaviours include lagging effects. These effects may stem from time needed to interpret the market rate expectations, as at this point in time EURIBOR was low but still positive as the 3M EURIBOR turned negative in April 2015 and 6M in November 2015, respectively.

Third, from a game theory perspective, the results require further analysis. Why would issuance activities in FRN increase when issuers open themselves to wider exposure to higher and, most importantly, uncapped interest rate risks? The cost burden for issuers increases when reference rates increase. Concurrently, an issuer will not benefit on the downside in case rates decrease further. An answer could be found in the trade off decision issuers have to conduct. On the one hand, opportunistic cheap funding appears attractive, depending on the credit spread expressed in the quoted margin - in the best case, at zero cost. On the other, the instrument's characteristics of being implicitly floored rate notes but to the upside, still floating rate notes, bear legal and financial risks. These one way risks stem from a unilateral change of the final terms using the non-applicable phrase of the interpretation that with rates negative issuers cannot benefit to the one side while being fully exposed to the other side of the rate movement spectrum. As investors should have increased demand for floored FRN—independent whether the floor is implicit or explicit—the trade off to secure funding while paying only the increased interest rate risk can be favorable. The practical problem is that a hedging instrument such as an interest rate swap (IRS) bears additional risks as negative rates apply in standard interest rate derivatives.

4.2. Data sets and bond matching

We obtain Bloomberg data on an ISIN basis by filtering for EUR denominated, plain vanilla[17] active FRN from corporate and governments issuers. While the regression aims to complement the legal argumentation, we filter for FRN governing law groups related to the legally and regulatory events as described in the event study section. These issuers include – amongst others - the largest and most liquid FRN sovereign issuer, the Republic

[17]This means we include standard FRN bonds with floating rates vs. EURIBOR and exclude all non standard payment FRN (e.g. amortizing, non bullet bonds) as well as FRNs explicitly including any embedded options (e.g. capped or floored FRN).

of Italy (Italy), as well as the SSA[18] regular FRN issuer European Investment Bank (EIB) and the European Financial Stability Facility (EFSF). Narrowing down further, we include only FRNs with a minimum outstanding amount of EUR500mn. Applying this filter set reduces the applicable securities from over 14,000 FRNs to 169 securities. We retrieve standard FRN descriptive data labels including the quoted margin (QM) and the discount margin (DM). FRN cash flows are unknown and as a result in bond trading, there are different margin measures computed to express the FRN return/price. The most common ones called spread for life (also called 'simple margin') and, more importantly, the discount margin. In Appendix A, details on calculation of the discount margin are given.

Importantly, we obtain whether the FRN has an explicit floor included. For the main regressor data set, we retrieve for each issuer the generic 2 year fixed coupon bond yield against the 2 year EUR IRS rate as a basis point differential.

We apply similar bond matching techniques outlined in Osvaldo Picarelli et al. (2018). Notably, analysing floating rate debt has caveats regarding data available compared to the fixed income sovereign bonds. Floating rate debt has limited bonds available within issuer groups (e.g. sovereigns), small outstanding FRN issue amounts (often insufficient under corporate FRNs thus we excluded them from filtering) as well as less pricing sources and turnover data. Further, different as for fixed coupon bonds, we are not aware of any generic reliable FRN datasets. This results in different time series sets available depending on the issuer type and frequency.

To cope with the aforementioned we identify the following key issuers as proxy sets for the FRN market. We look to set issuer proxies for sovereign, sub-sovereign and agency issuers. These proxies need to coincide with relevant stakeholder decisions we identified for jurisdictions in Italy, Austria, Germany. Additionally, for the sovereign sector we analyse Italy as the largest and most liquid issuer with their FRN issuances ('CCTS'). Further, for sub-sovereign class issuers, we consider the EIB and EFSF and lastly Erste Group Bank as a financial institution issuer for AT in absence of any further applicable FRN outstanding.

Applying this issuer selection results in a list of securities 23 FRNs (from 169 in the previous step). Next, we selected three FRNs per issuer including four different governing laws (IT, AT, LU, EN), implicit and explicit coupon floors as well as FRNs which would de facto bear a negative coupon and those FRN close to become coupon negative. Cross checking the data sets for Austria as the only additional sovereign for which we identified a key decision event, we decide to neglect this sovereign with only one FRN outstanding. Similar for the EFSF FRNs which do not provide sufficient data samples due to their illiquidity.

[18] Supranational Sub-Sovereigns and Agencies (SSA) define a dedicated issuer segment of the bond market.

Our empirical strategy is to estimate market tension impacts (tensing/relaxing market conditions) of identified key events. We measure this using the price path determining spread for FRNs. Consequently we seek out time series data for the pre-selected FRN market proxies, which we retrieve via Bloomberg from the 2nd January 2012 until the 30th of June 2019. We obtain historical daily data sets for each FRN by retrieving the DM (in bps), the bid and ask price (in %) on an end of day basis.

While working on an ISIN basis we experience data issues as bonds were issued at different dates during the recent path. This makes the data sampling inconsistent yet still employable, as historical data can be retrieved between 2012-2016 thus covering at least two years of data. For the main market proxy, Italy, we build a time series by including one matured bond to be able to test data prior to 2016.

4.3. Methodology

First, we identify key stakeholder events and apply a basic event study methodology to identify in the analysis if floating rate debt markets reacted on these events. Second, we apply a multi linear regression onto a pre-defined data set. We study potential changes in the regression linearity at exemplary key event days. Third, with findings arising from the regression model, we construct a simple outperformance indicator to interpret changes in pricing of floating debt on certain key events in the event study. Changes in FRN pricing rates are compared against comparable fixed rate bonds to measure the FRN's relative performance. Where possible, from a data feeding perspective,[19] we aim to use historical data from the beginning of zero/negative interest rate regime which we set as the 1st of January 2015. The objective is to understand if and how this dedicated market segment reacted compared to the standard bond market.

Event study methodology

Our event study methodology for assessing market reactions to non-standard events draws on the key event study of the US Federal Reserve maturity extension program utilized by Foley-Fisher et al. (2016). We also apply a simple event study for our analysis similarly to Jorgensen & Kirshnamurthy (2011) for impact caused by quantitative easing (QE) programs. The aforementioned authors identified key events (e.g. rate decisions, QE announcements) and studied market reactions on the aforementioned. Noteworthy, the difficulty of selecting 'market impacting events' can be challenging. Markets may react to even the most trivial events (from a legal or economic impact perspective) while severe 'confirmed and published' events can be a market wise non-event in case the market already 'priced in' the event outcome. Particularly for our studies, the question when

[19] We refer to the first times where EURIBOR rates as the FRNs underlying reference rate turned negative. Notably, the ECB's deposit facilty rate was set to -0.10% on June 30, 2014 and the main refinancing rate in the Euro area was reduced to the current level of 0.00% on March 31st 2016.

markets react on negative rates is challenging. Do markets immediately react when rates turn negative or when the discussion or anticipation (e.g. via the forward rates) imply negative rates is a key question. Thus, the event study approach looks at an event k on a certain date t and describes market price changes of assets.

Key events that might have an impact on FRNs and tested subsequently are presented in Tab. 1.

Table 1: Key event dates and description used in this research.

Event	Entity	Date	Event type
1	International Swaps and Derivatives Association	12/05/2014	Publication of ISDA 2014 Collateral Agreement Negative Interest Protocol
2	European Central Bank	30/04/2015	Entry into NIRP of (3M) Euribor
3	Euroclear and Clearstream	11/08/2015	Publication of Guidelines concerning negative interest rate securities held through Euroclear Bank and Clearstream Banking ('the ICSDs')
4	European Central Bank	30/11/2015	Entry into NIRP of 6M Euribor
5	Republic of Italy	21/03/2016	Publication in Offical Gazette of Italian Government Determination in Case of Negative Interest Rates
6	Austrian Supreme Court	21/03/2017	Publication of Decision on case OGH, March 21 2017, 10 Ob 13/17k
7	Austrian Supreme Court	03/05/2017	Publication of Decision on case OGH, May 3 2017, 4 Ob 60/17b
8	English High Court	25/07/2018	Publication of decision in case The State of the Netherlands v Deutsche Bank AG [2018] EWHC 1935 (Comm)
9	English Court of Appeal	26/09/2018	Publication of submission of Appeal on The State of the Netherlands v Deutsche Bank AG [2018] EWHC 1935 (Comm)
10	English Court of Appeal	02/05/2019	Hadning in its judgement in the State of Netherlands v Deutsche Ban [2019] EWCA Civ 771
11	European Central Bank	18/06/2019	Sintra Speech of ECB President Draghi hinting interest rate expectations of lower for longer lower rate environment

Our approach in selecting events is not to optimize the number of events as such. Instead, we aim to cover a wider time span from 2014-2019 and include different stakeholder activities (i.e. messages sent to the market by stakeholders) of legal significance, that may impact the interpretation of the N/A clause, and affect the nature of the consequent obligations. We also include intra-market events; for example whether the first negative EURIBOR fixing had any impact on the discussion at hand. We first identify and categorize eleven key events by stakeholder and type of market information (e.g. issuer press release, court rulings) and include key market indicator tests (e.g. EURIBOR reference rate turning first time negative).

We study these events by analysing whether the observed FRN market segment of a certain issuer shows pricing impacts around the dedicated event. We categorize events in the findings by two impact types stemming from the legal and regulatory narratives outlined above. First, we investigate events which should contribute to legal/regulatory certainty and thus shall result in an increased demand of the FRN segment which consequently should be reflected in the relative (out-)performance. Second, events which may contribute to increased market insecurity or uncertainty which shall lead to an underperformance of the FRN market against the fixed coupon bond market.

These events are thus classified across four major categories, building on event typology in previous studies (Deng et al., 2014, Jiang et al., 2016, Galil & Soffer, 2011). First, we analyse statements of industry associations and participants like ISDA, Euroclear and Clearstream with express relevance to the relationship between negative interest rates and bonds. Second, market shifting events, like publication days of movement into negative interest rates for the 3M and 6M Euribor. Third, we test the declaration of Italy regarding practicing zero-floors for its issued bonds. Last, we assess various court decisions and filings from the United Kingdom and Austria, as well as the ECB's announcement signalling further rate cuts which are in the theme of negative interest rates, but are not specifically related to FRN bonds. Pricing impacts are measured via the Outperformance Index (OI) detailed in the section below.

Using a dummy regression, we measure the daily changes in each FRN's discount margin ($\Delta DM_{i,t}$) against the changes in regressed variables being the daily change in the swap spread ($\Delta SWSPR_{i,t}$) of the generic fixed coupon bond for an issuer, further as control variables the daily 3M and 6M EURIBOR fixings ($EUR3M_t$, $EUR6M_t$) as well as the daily change in EURUSD exchange cross rate ($EURUSD_t$) and against the changes in the Euro Stoxx Index ($EURST_t$).

For asset i, the regression for p possible dummy dates reads

$$\begin{aligned}\Delta DM_{i,t} = \beta_0 + \sum_{j=1}^{p} \beta_j D_{j,t} + \beta_{p+1} \Delta SWSPR_{i,t} + \sum_{j=1}^{p} \beta_{p+1+j} \Delta SWSPR_{i,t} * D_{j,t} \\ + \beta \Delta Controls + \varepsilon_{i,t},\end{aligned} \tag{1}$$

where $D_{j,t}$ denotes the dummy variable $j = 1, \dots, p$ which is 1 after dates of interest and 0 otherwise. First differences are defined as $\Delta Var_t = Var_t - Var_{t-1}$ for each variable $DM_{i,t}$, $SWSPR_{i,t}$, and controls: $EUR3M_t$, $EUR6M_t$, $EURST_t$, and $EURUSD_t$. For the disturbance term, we assume zero mean and unit variance. Robust standard errors are calculated with White's heteroskedasticity-adjusted approach.

In addition to using discount margin changes, we set up a simple outperformance indicator (OI). The objective is to study whether and how much the FRN market segment of an observed issuer has reacted differently to the fixed coupon bond market. In applying this logic we form the hypothesis that the stakeholder key events shall impact FRN markets particularly while the fixed coupon bond market would not be impacted. The OI shall further eliminate exogenous impacts such as rating changes in the issuer market.

Notating the OI follows the simple formula:

$$OI_{i,t} = \Delta DM_{i,t} - \Delta SWSPR_{i,t}. \tag{2}$$

For each issuer i and events $k = 1, \dots, 11$, we sum $OI_{i,t}$ five days prior and past the event date (t) as

$$E_i^k = \sum_{s=t-5}^{t+5} OI_{i,s}. \tag{3}$$

Given the above formula, the lower the OI the higher the outperformance of the FRN; meanwhile the more positive the higher the underperformance (the lower the outperformance) of the FRN relative to fixed coupon markets.

4.4. Empirical results

The results confirm the significance of the issuer's fixed coupon market ($SWSPR$) on the FRN market segment (DM). Detailed results for an example regression using the data for the largest FRN sovereign market Italy and other issuers described in what follows.We run several key event dates with $p = 2$ dummy variables; dates used in this example are 24/03/2016 and 25/07/2018. The results for other key events are qualitatively the same and available upon request.

Table 3 provides example estimation results for the dummy regression defined in Eq. (1) for three choices of benchmark FRNs of Italy and exemplarily of the EFSF, EIB, and Austria.[20] For Italian FRNs, the regression results from January 2012 until the first dummy date (24/03/2016) confirm the explanatory significance of the issuer's fixed income market segment ($SWSPR$, measured with β_3) in explaining the changes of the FRN market segment. Further, we find that with the first event date, 24/03/2016, the explanatory impact of the SWSPR decreases (from a factor load of $\beta_3 = 0.6524$ by $\beta_4 - 0.2171$ to 0.4353 for the Italy DM_1) with strong significance levels in relating p values. From a legal narrative, the key event studied is the announcement of the Italian Ministry of Finance to skip the right to enforce negative coupons from its investors. The decrease in explanatory significance suggests to us that the FRN market reacted on this event by decoupling from the remaining market segment and increased its own dynamics. This event is categorized to increase demand for FRNs and findings on the OI values shall deliver details on the magnitude and direction of the event.

As for the next break point observed on 25/07/2018, regressing the time frame from 24/03/2016 until the 25/07/2018, we see a reversing effect which coincides wth a court ruling of the non-applicability of negative rates under the collateralization of swap agreements. We find that the second dummy date triggers a change in the linearity of the regression which counteracts the aforementioned event ($\beta_5 = 0.1602$). While from a legal and regulatory narrative this event should also contribute to clarity and increased demand we find that the FRN market increases its correlation with the fixed coupon market. Further, the results show no significance in the controls apart from the stock market control

[20] We only present selected FRNs. Results for all FRNs analysed in this study are available upon request.

($EURST$). The regression results for the other issuer segments in the sample show no significance albeit using the same set of variables. The observed effects seem to be valid only for Italian FRNs. For FRNs issued by EFSF, EIB, or Austria, no such effects are identifiable and the regressors surpisingly fail to provide *any* explanatory power of the discount margin of the respective FRNs.

Table 3: Parameter estimations of the regression outlined in Eq. (1) for six selected FRNs and $p = 2$ selected dates for the dummy variables, 24/03/2016 and 25/07/2018, respectively. Daily $DM_{i,t}$ observations end on 30/11/2018 while the start dates vary by FRN (Italy: DM_1 02/01/2012, DM_2 26/04/2016, DM_3 27/10/2016; EFSF 25/11/2013; AT 03/06/2014; EIB 02/01/2012).

	Italy DM_1	Italy DM_2	Italy DM_3	EFSF DM	AT DM	EIB DM
β_0	−0.1765	0.1427	0.1905	−0.0186	−0.0094	−0.0500**
	(0.12811)	(0.1572)	(0.1914)	(0.9376)	(0.0718)	(0.0692)
β_1	0.4351**	—	—	0.0193	−0.0003	0.0162
	(0.2017)	—	—	(0.1598)	(0.0925)	(0.0338)
β_2	−0.1722	−0.1734	−0.1869	−0.6130	0.0107	0.0864*
	(0.3098)	(0.2910)	(0.3226)	(0.7152)	(0.1066)	(0.0506)
β_3	0.6524***	0.4870***	0.4265***	−0.0249	−0.0406	0.0047***
	(0.0137)	(0.0151)	(0.0163)	(0.9197)	(0.0474)	(0.0039)
β_4	−0.2171***	—	—	0.0645	−0.0369	0.0632*
	(0.0208)	—	—	(0.1288)	(0.0374)	(0.0346)
β_5	0.1602***	0.1892***	0.2156***	−0.1685	0.0901	−0.1192
	(0.0347)	(0.0324)	(0.0000)	(0.2751	(0.0854)	(0.0836)
β_6	0.2329	0.4370	0.068	−0.1882	0.4986	0.1275
	(0.6405)	(1.4448)	(1.9213)	(0.4702)	(0.3173)	(0.1046)
β_7	0.5847	0.8964	0.9034	0.1912	−0.3600	0.0837
	(0.6125)	(1.0401)	(1.2671)	(0.4231)	(0.3174)	(0.1000)
β_8	−0.0266***	−0.0290***	−0.0419***	−0.0008	0.0002	−0.0002
	(0.0000)	(0.0040)	(0.0006)	(0.0017)	(0.0011)	(0.0004)
β_9	−27.762*	−25.747	−51.239	6.5291	2.7343	0.7059
	(15.474)	(26.009)	(31.290)	(8.9263)	(6.7542)	(2.5584)
R^2_{adj}	0.6810	0.683	0.6510	0.0055	0.0037	0.0189
n	1 948	822	690	1 453	1 317	1 948

Note: The regression including two dummy variables read $\Delta DM_{i,t} = \beta_0 + \beta_1 D_{1,t} + \beta_2 D_{2,t} + \beta_3 \Delta SWSPR_{i,t} + \beta_4 \Delta SWSPR_{i,t} * D_{1,t} + \beta_5 \Delta SWSPR_{i,t} * D_{2,t} + \beta \Delta Controls + \varepsilon_{i,t}$. Robust standard errors are given in parenthesis. ***,**, and * denote the 1%, 5%, and 10% level of significance, respectively.

The analysis confirms the statistical relevance of the FRN market expressed by its discount margin pricing against the fixed coupon swap spread for the Italian market. Bearing this caveat in mind we run a performance measurement for the four issuers expressed by the OI index over the bond sample as described in the bond matching section. As mentioned in the data set and bond matching section we find that due to the data availability and reliability no sufficient findings to interpret for the likes of EIB, EFSF and AT. The table below shows the OI values for the issuer sets from which we conclude to focus on the most reliable data set from the Italian market analysis.

Next we combine the OI values for Italy in Tab. 5 with the expected market impacts stemming from the legal narrative. Shown in (i) is the legal narrative interpretation of each event categorized by either relaxing or tensing market uncertainty for FRN markets. We then link this impact assumption into a relative value financial impact of the market segment in (ii) where we categorize if FRN markets to either out-/underperform against the fixed coupon bond market. The simple logic is to assume increased demand due to

Table 4: Outperformance index for eleven key dates for different FRNs.

		Outperformance Index in bps			
Event	Date	OI IT	OI EIB	OI EFSF	OI AT
1	12/05/2014	0.049	−0.478	n.a.	n.a.
2	30/04/2015	4.007	−0.389	n.a.	−3.379
3	11/08/2015	−4.348	0.782	n.a.	2.942
4	30/11/2015	6.191	−1.706	3.504	−2.913
5	21/03/2016	−5.570	3.869	2.899	3.321
6	21/03/2017	0.937	1.233	0.480	−15.467
7	03/05/2017	4.132	1.058	0.561	−0.030
8	25/07/2018	9.373	−1.326	−0.248	−2.408
9	26/09/2018	4.305	−0.796	0.209	6.946
10	02/05/2019	−0.173	0.986	−0.635	1.513
11	18/06/2019	−12.640	1.151	−0.002	−1.910

(i) and hence higher prices, lower yields which is put in a relative value analysis in the OI turning (iii) more negative.

Table 5: Expected market impacts of decisions made on the identified key dates.

Event No.	Date	(i) legal narrative	(ii) financial impact	(iii) OI IT
1	12/05/2014	relaxing FRN uncertainty	FRN outperformance	0.049
2	30/04/2015	tensing FRN uncertainty	FRN underperformance	4.007
3	11/08/2015	relaxing FRN uncertainty	FRN outperformance	−4.348
4	30/11/2015	tensing FRN uncertainty	FRN underperformance	6.191
5	24/03/2016	relaxing FRN uncertainty	FRN outperformance	−5.570
6	21/03/2017	tensing FRN uncertainty	FRN underperformance	0.937
7	03/05/2017	relaxing FRN uncertainty	FRN outperformance	4.132
8	25/07/2018	relaxing FRN uncertainty	FRN outperformance	9.373
9	26/09/2018	tensing FRN uncertainty	FRN underperformance	4.305
10	02/05/2019	relaxing FRN uncertainty	FRN outperformance	−0.173
11	18/06/2019	relaxing FRN uncertainty	FRN outperformance	−12.640

We find for the eleven events observed in (iii) the out-/underperformance of the FRN market in basis points. From a pure pricing change perspective movements of less than one basis point are negligible. Thus we observe three events (1, 6 & 10) without any impact. Six events match along the legal narrative. However, we also find a contrary market pricing move in two events (7 & 8).

Market reactions are observed and to understand their impact we use a simple significance test with the expected value (μ) and the standard deviation (SD) for each category of OI indicators. First, for positive OI values (implying tensing market uncertainty and FRN underperformance) we find μ at 4.14bps while the SD is at 2.89bps. This indicates significance for the OI under tensing market uncertainty. Second, for relaxing market uncertainty and FRN outperformance, we retrieve $\mu = -5.68$bps with the SD at 4.49bps. This result indicates non-significance.[21]

In conclusion, we find that while the statistical significance of the break dates holds, the findings of the second analysis (OI values) impose a caveat. The OI is introduced based on the author's practical approach trade/price FRN markets.[22] The OI categorizes events by

[21]For brevity, we do not report details here. These results are available upon request.

[22]Notably, the market practice is to solely quote and trade FRN markets based on the discount margin.

positive/negative values under a price pattern narrative. Under the applied samples the statistical significance can be obtained only for events under tensing market uncertainty and—consequently—positive OI values. With the available data set, for relaxing market uncertainty and negative OI values price reactions can be identified. However, they cannot be considered statistically significant.

With regard to the legal analysis, the publication of Italy to skip the right to enforce negative coupons (event 5) led to an outperformance of 6bps, yet stays below our expectations as this was considered to be the key event for outperformance. Confirming our expectations of outperforming FRN markets is the July ECB press conference (event 11) indicating lower rates for longer. This event resulted in the larget outperformance in FRN markets seen in the case study. As for other event results we find mismatches within our narrative in the court ruling on negative interest application on collateral agreements (events 7-8) while event 8 reveals the highest underperformance score. Though the ruling offered significance as a potential authority in the interpretation of bond documentation in future litigation, markets did not connect the outcome to a notable change risk.

5. Concluding Remarks

This contribution aims primarily to analyse the impact of stakeholder interactions with the market on the pricing of selected FRNs during the negative interest rate regime. Secondly, we analyse the range of reactivity of financial markets and issuers to uncertainty caused by an untested boilerplate term—N/A minimum rate of interest. Sovereign issuers react similarly to avoid the costs of moral hazard and expensive sovereign debt litigation. For this, we measure the change of FRN prices in the intra-bond market segment to differentiate them from other bond classes—namely the fixed coupon bond market segment.

Our findings suggest that attention has been placed on stakeholder activities, confirming our hypothesis with a caveat. We find that the markets gauge stakeholder activities regarding the N/A clause, but only to a limited extent. The Italian event concerns the Italian issuances, which also make up the majority of the FRN market. A notable pricing effect presents itself, tied to an endogenously instanced event. The English decisions illuminate the stances of courts in the orbit of negative interest rates of a dominating governing law, to which price reactivity indicates market sense toward court inclinations, albeit limited to the hard ruling of the court without particular care for argumentative nuances.

The announcement of further lower for longer rates in the Euro Area (event 11) shows the highest outperformance. We interpret this as evidence that the FRN market appreciates the current protection of negative coupons even under a lower Euribor. Consequently, the markets crowds into FRN markets while yields on comparable bonds decrease and a debate on potential negative fixed coupons sparks again while rates trend lower.Thus, while the Eurobond area is harkened as a legally convergent market with an appetite for harmonization, our findings suggest that markets have not reached the same conclusion.

We are also alerted by the significant changes in the FRN market structure. Despite very low interest rates, issuers increase their activities while bearing additional risks in hedging transactions. This supports the strand of scholarship finding that markets are limited by reputational or legal factors, adding that these issues do not need to be urgent, or post-factum in the case of a finding negative coupon applicable. We can also add to the findings of change in boilerplate terms in bond markets. The speed and relative severity of changes in issuances of FRNs with N/A in the NIRP timeline accentuates a high issuer awareness of potential legal risks, and a willingness to change legal documentation when inertia costs connected to sticky standardized documents with many stakeholders are not involved. Even more noteworthy is that the timing of the structural shift coincided closely to the dip into negative territory, highlighting, at the very least, consciousness of the associated risks, if not also opportunistic foresight to take advantage of the cheap funding in the prior ZIRP period. Our findings thus suggest a limit to the power of financial boilerplate in halting change.

Our study also provides implications for the broader debate on integration. Even with a single internal market and strides in the banking union, convergence in capital markets union is lagging behind in regards to their core behaviors. In the eyes of the market, different sovereigns, their activities, and legal positioning are still capable of forming isolated islands. As risk sharing is becoming a growing priority to secure the international role of the Euro, further legal harmonization is necessary to connect the islands. This is particularly important considering current Brexit debates. Concurrently, the experiences on the EURIBOR benchmark reform matter after the experience that the first reform attempt—solely left to the industry—failed. Our research highlights that the themes of the aforementioned debates are capable of having material repercussions in markets. They are important to building a more secure Euro area but necessitate deeper analysis.

Future research could focus on a more encompassing analysis of discount margins and their evolution. In particular in view of the outperformance indicator, it remains open as to what the expected discount margin would be in some comparison to a market model. Using a market model leaves room to deploy different return measures (e.g. AR, CAR) to compare results. Additionally, more complex frameworks could address fixed or random effects across the panel of FRNs of different issues and issuers.

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Appendix A. FRN pricing and discount margin (DM) computation

Consider a classic fixed coupon bond has the advantage that the cash flows are known; thus standard yield measures (e.g. yield to maturity) can be computed. However, FRN cash flows are unknown and as a result, in bond trading, there are different margin measures computed to express the FRN return/price. The most common ones called spread for life (also called 'simple margin') and, more importantly, the discount margin.[23] A FRN's coupon rate can be generally expressed as follows:

Coupon FRN = reference rate ± quoted margin.

The quoted margin is simply an adjustment to the reference rate expressed in basis points (e.g. 6M EURIBOR +4bps (QM)). From a required yield perspective, the quoted margin which was fixed at issuance represented the additional credit spread required by the market at the time of issuance.

Now, assume a FRN would trade at a premium or discount to par value – this means the required yield is unequal to the QM + reference rate. For pricing, we need to consider this variation to par-value as it implies an additional income/loss for a bondholder due to changes in the required yield. In practice, FRNs are usually quoted using their DM as it is one common method of measuring potential return that employs discounted cash flows (Fabozzi & Mann, 2000, p.358).

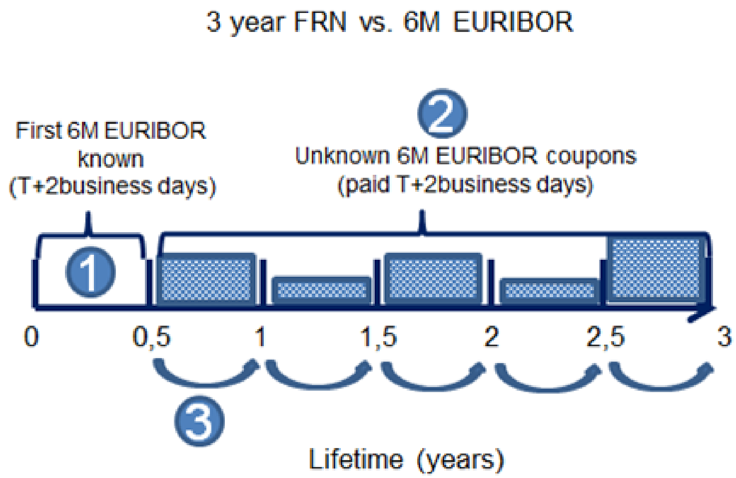

Figure A.2: Cash flow principles of a floating rate note.

In Figure A.2, we mark the initial known EURIBOR coupon (1), the unknown next coupons (2) and the resetting nature (3). The value determined on the day when the reference rate is applied ('T' is the fixing/reset day) is used to calculate the FRN's coupon payment. Being indexed, the FRN coupon rate generally moves in the same direction as the underlying reference rate moves. As a result, a bondholder expecting rate increases would choose a FRN over straight coupon bond and vice versa. Interestingly, being the topic of this paper, the investors is protected to the downside due to a floored 0% coupon. FRN allow, different to fixed coupon bonds, no ex-ante yield to maturity calculation. To price a FRN we apply the same principle of discounting cash flows as for fixed coupon bonds. The assumption is for FRN pricing that a presumed same EURIBOR coupon for the remaining life of the FRN. As shown in Figure A.3 above, for FRN pricing we

[23] There are further variations possible such as effective margin or total adjusted margin which we neglect for the purpose of this work

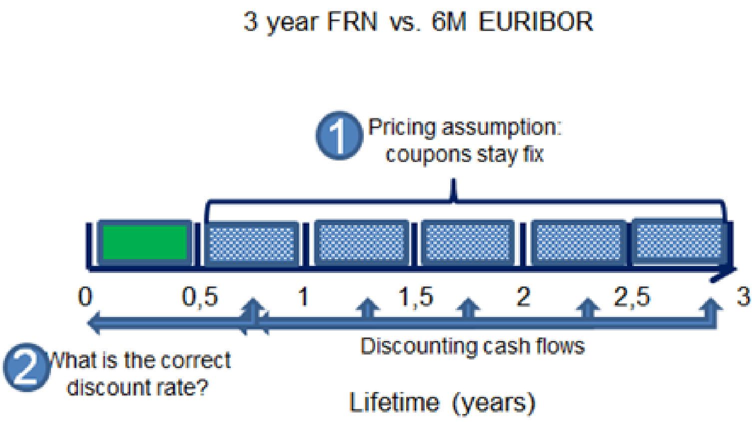

Figure A.3: Cash flow discouting principles of a floating rate note.

assume one constant coupon (1) which is then discounted. The challenge is to find the correct discount rate (2). As a result, in bond trading, there are different margin measures computed to express the FRN return/price. The way FRN prices are quoted in markets is by using the DM quotation (in bps). Figure A.4 below shows the main principle of identifying the correct discount (rate) margin. Computing the DM follows a recursive

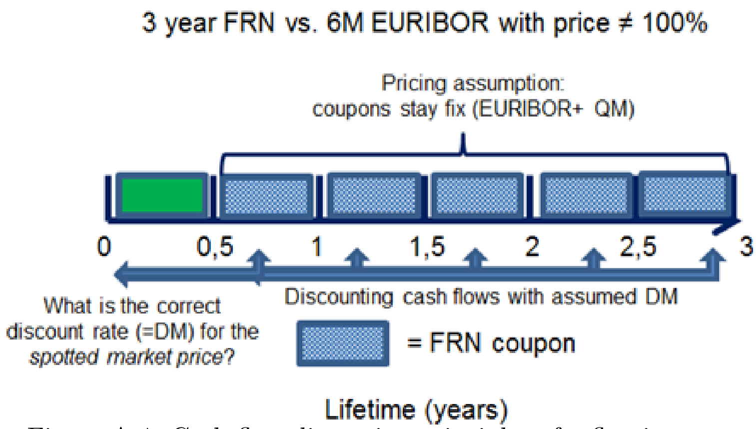

Figure A.4: Cash flow discouting principles of a floating rate note.

approach:

a) Cash Flows: Defining the cash flows by applying a constant reference rate over the FRN lifetime;

b) Define a DM: Add/deduct a DM to the assumed constant reference under a);

c) Compute present value (PV): Discount the cash flows a) with the applied rate including the DM of b);

d) Identify market price, then market price comparison: the PV of c) is compared with the market price in d). If c) $\neq$ d) $\rightarrow$ adjust the assumed margin chosen in b) and iterate the steps until we compute the market price spotted;

e) If c) = d): once the PV c) equals the market price d) we identified the corresponding DM

Apple, Microsoft, Amazon and Google - A Correlation Analysis: Evidence from a DCC-GARCH Model

Jürgen Klaus[a], Christoph Koser[b,*]

[a] *Faculty of Business and Economics, Technische Universität Dresden, Germany*
[b] *Department of Econometrics and Statistics, University of Barcelona, Spain*

Abstract

In this paper, we examine time-varying correlations among stock returns of Apple, Microsoft, Amazon and Google. Employing a multivariate DCC-GARCH model, we find that there are strong linkages among these four assets. Starting from lower levels, correlation values for most asset pairs exhibit a stable ascending movement in recent upward trended markets to, in an exceptional case, almost hit the perfect positive correlation mark. We show that correlations among these assets jump during downturn market periods, suggesting limits in the diversification of risk within the segment of large cap U.S. technology stocks. Our results are helpful for portfolio management and asset allocation.
Keywords: Dynamic Conditional Correlation, Return Dynamics, DCC-GARCH Model
JEL classification: C10, C58, G1, G10, G11

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*Corresponding author, Email: chkoserk11@alumnes.ub.edu

1. Introduction

At the forefront of technology, centred around the digitalization and the continuing innovation process of the world wide web, there are four companies - Apple, Microsoft, Amazon and Alphabet(Google) - that have brought along structural change in the core infrastructure of the world wide web, the shaping of products and services and the communication opportunities among its users and related devices, Dolata (2017). According to Bloomberg[1], financial markets have valued these firms at USD 1.663T; 1.620T; 1.596T and 1.052T, respectively, (by July 2020), which make them the four largest companies by market valuation worldwide.[2] The price of a stock by Microsoft has risen exponentially since decades to finally peak at USD 213.67 in July 2020. Similarly, Amazon's stock price has peaked at USD 3200.00. Apple and Google share prices show similar upward trends in recent times and future demand for these assets is likely to rise in the light of the continuing, cutting-edge progress made in the fields of technology. However, there is no research on how these four stocks are correlated in their return dynamics.

In this paper, we address this issue and extend the existing literature by examining time-varying conditional price correlations via the *Dynamic Conditional Correlation (DCC)-GARCH* modelling approach by Engle (2002). We believe that a rather high number of asset managers include some or all of these tech giants in their portfolios. Thus, studying dynamic correlations among these four financial assets benefits the diversification of risk in the asset allocation process. We find this class of GARCH models an ideal methodological approach to dynamically model co-movements in the return dynamics of these assets. Previous studies use the DCC-GARCH modelling approach in various settings (financial and macroeconomic risk assessments). For instance, Cappiello et al. (2006) employ an asymmetric version of the DCC-GARCH specification (ADCC) to analyze time-varying conditional correlations in international equity and bond returns. Similarly, Gjika & Horvath (2013) examines stock market co-movements in Central Europe. Celık (2012) uses a DCC-GARCH approach to examine contagion in foreign ex-

[1] `https://www.bloomberg.com`

[2] We exclude Facebook from our sample size as its IPO (initial public offering) took place in 2012 while this correlation analysis focuses on a longer horizon, starting in 2004.

change markets in emerging and developed economics during the U.S. subprime crisis. Jones & Olson (2013) investigate time-varying correlations between uncertainty, output and inflation. More recent, Mensi et al. (2017) examine correlations between developed and BRICS stock markets.[3] Under the flight-to-quality scenario, Klein (2017) analyses dynamic correlations between precious metals and stock market indices in developed countries, accounting for long-memory in the estimation of the variance in the DCC model. Using a multivariate DCC-GARCH model, Canh et al. (2019) find a strong positive correlation among six out of seven cryptocurrencies. Finally, Klein et al. (2018) use a BEKK-GARCH approach to model conditional correlations among Gold and Bitcoin and the S&P500.

When examining the returns of these assets by means of dynamic correlations, we refer to the definition of a hedge, diversifier or safe haven as formulated in Baur & Lucey (2010). If an asset is uncorrelated or negatively correlated with another asset or portfolio, they refer to the asset as hedge. A safe haven asset shares the exact same explanation of a hedge but applies only in times of market distress. Finally, a diversifier is an asset that is positively but not perfectly correlated with another asset or portfolio. Our results show that there are strong linkages in the return dynamics among these four assets. We find that most asset pairs exhibit a stable upward movement in their correlation values, in some cases to almost hit the perfect positive correlation mark. Parallel to this general upward trend, there are abrupt jumps in the correlation during recent market distress.

This paper is organized as follows: Section 2 describes the data and presents some descriptive statistics. Section 3 formulates the methodological pathway of this study. Section 4 reports our findings and discusses implications for risk management. Section 5 concludes.

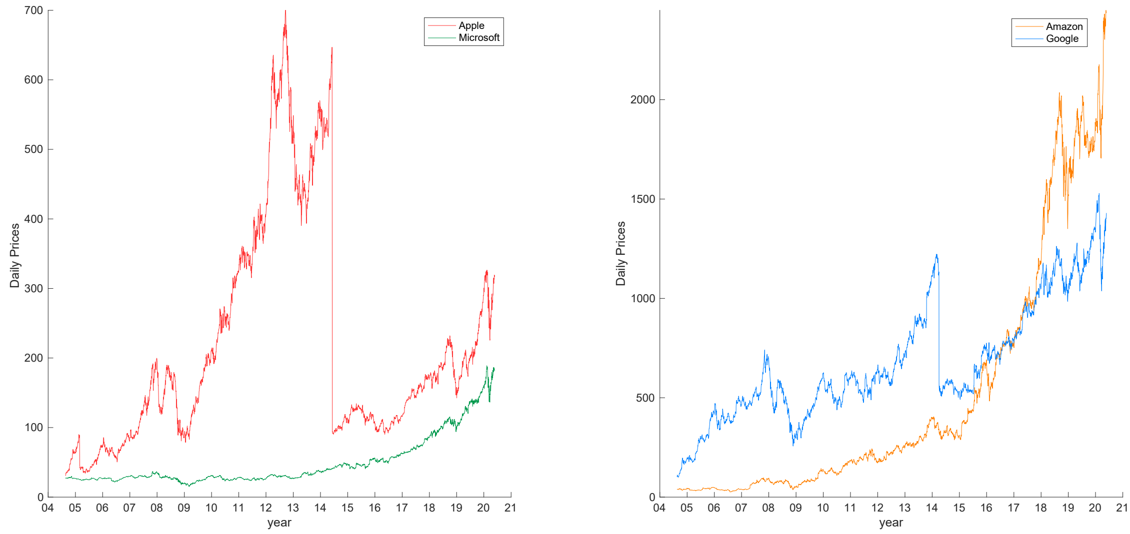
2. Data and Preliminary Analysis

The dataset is comprised of daily average prices of the following stocks: Apple, Microsoft, Amazon and Alphabet(Google). The sample period ranges from August 20, 2004

[3]BRICS stands for Brazil, Russia, India, China and South Africa.

to May 26, 2020, (n=3964), covering the most recent periods of market distress and recovery. Prices of Apple, Microsoft, Amazon and Google are obtained from the WRDS - Wharton Research Data Service.[4] Figure 1 presents the plots.

Figure 1: Dynamic Correlations - Apple, Microsoft, Amazon and Google



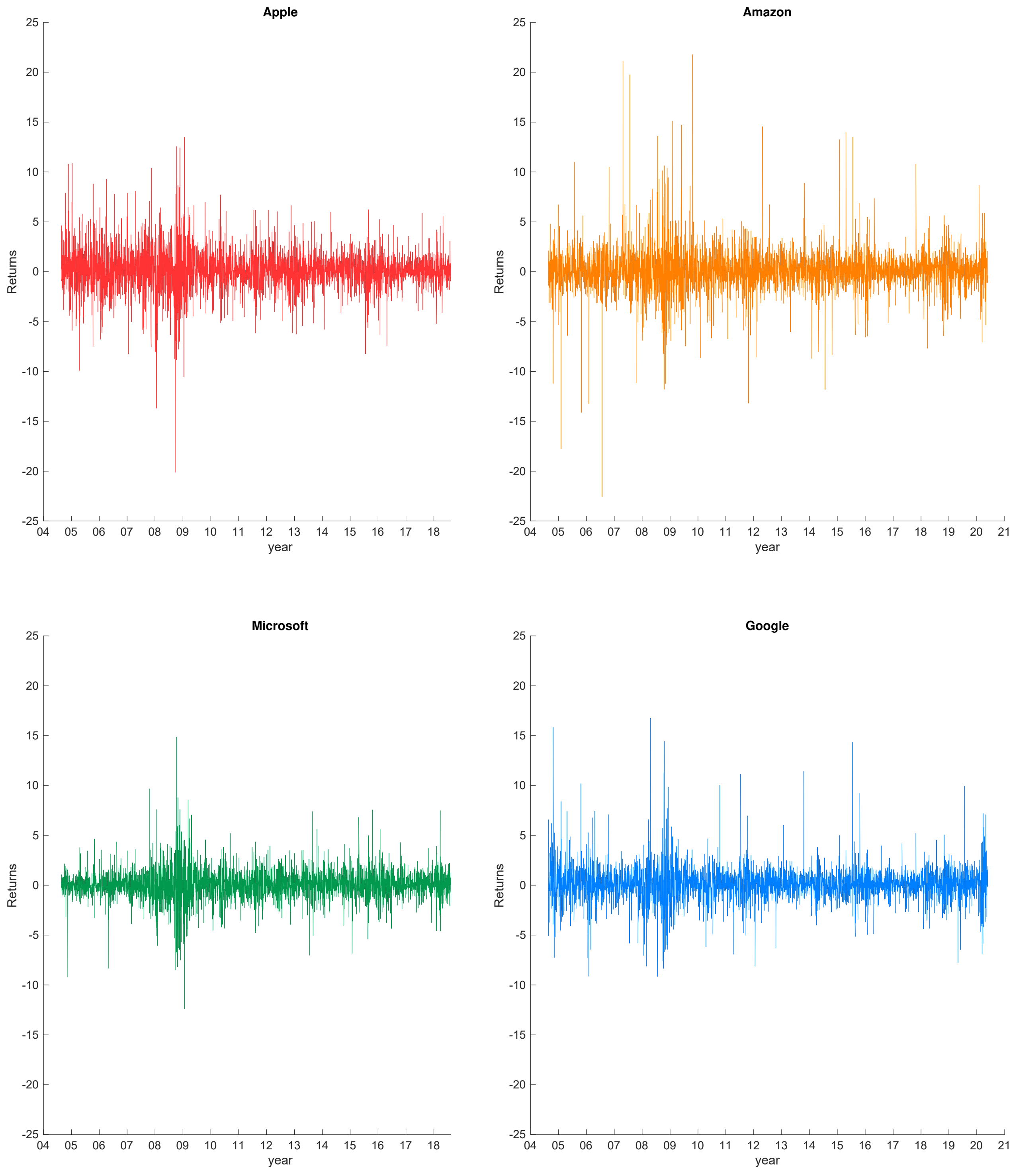
Plots of daily average prices of Apple, Microsoft, Amazon and Google. The sample period ranges from August 20, 2004 to May 26, 2020.

We observe that all stocks exhibit an almost exponential-like increment over the time horizon of 16 years. At the same time, as can be seen, there are straight-lined downward jumps in the average prices of the stock of Apple and Google. This is due to stock splits on February 28, 2005 and June 9, 2014 in the case of Apple and on April 3, 2014 and April 27, 2015 in the case of Google (four observations in total). We calculate the natural logarithmic returns from daily average prices as $r_t = 100 \cdot ln(P_t/P_{t-1})$, where P_t denotes the price at time t. Returns are plotted in Figure 2. From a technical aspect of the analysis, we delete the return observations on those days on whose the stock-split of the respective stock has taken place. As is evident, all series exhibit volatility clustering. Remarkably, the second largest volatility cluster after the financial crisis coincides with the COVID-19 outbreak from March 2020 onwards to the end of this sample period.

Table 1 summarizes the descriptive statistics for the four return series. The Apple

[4]We use the average price (from high and low prices) as listed in the intraday indicator dataset which is similar to using the official closing prices from the CRSP database.

Figure 2: Dynamic Correlations - Apple, Microsoft, Amazon and Google



Note: Plots of daily log returns series of Apple, Microsoft, Amazon and Google. The sample period ranges from August 20, 2004 to May 26, 2020.

Table 1: Descriptive Statistics - Logarithmic Returns Series

Stocks	Mean	Std.Dev.	Min	Max	Skew.	Kurt.	JB (x 10^3)	ADF	Q(5)	ARCH(5)
Apple	0.12426	2.1041	-20.121	13.491	-0.17733	9.6887	7.4***	-64.946***	12.743**	288.94***
Microsoft	0.04844	1.6145	-12.47	14.866	0.00868	11.742	12.6***	-67.628***	30.062***	581.60***
Amazon	0.10518	2.1709	-22.53	21.765	0.46061	19.928	47.4***	-57.159***	45.054***	23.113***
Google	0.08384	1.6886	-9.1536	16.757	0.91915	15.057	24.5***	-55.233***	72.668***	87.035***

Note: This table presents preliminary statistics and test of log returns of Apple, Microsoft, Amazon and Google. The sample runs from August 20, 2004 to May 26, 2020, n = 3964 observations. We exclude the returns on the days on which the stock splits happened from the sample, that is February 28, 2005; June 9, 2014 for Apple and April 3, 2014 and April 27, 2015 for Google. ADF is the Augmented Dickey-Fuller test for unit roots. Q(5) is the Ljung-Box Q-test for serial correlation. ARCH(5) is the test for autoregressive conditional heteroskedasticity at the 5th lag. ***, (**) indicates statistical significance at the 1%, (5%) level.

stock offers the highest mean return (0.12%), followed by Amazon (0.10%). Apple and Amazon also exhibit higher daily standard deviations and the other two large tech stocks, 2.10% and 2.17%, respectively. Supported by the kurtosis, the Jarque-Bera test (JB, Jarque & Bera (1987)) rejects the null hypothesis for normally-distributed return series at the 1% level, indicating leptokurtotic returns. Employing the Ljung-Box Q-test, we reject the null hypothesis of no autocorrelation for all series. The results for the ARCH-LM test show autocorrelation in the squared returns, (ARCH-effects). The Augmented Dickey-Fuller test (ADF, Dickey & Fuller (1979)), computed with a trend component, rejects the null hypothesis which confirms the non-existence of a unit root for all series.

We provide a first indication of pairwise Pearson correlations between the four stocks in Table 2. We find that Apple and Microsoft share a positive correlation of 0.5, providing a first indication for a diversifier relationship here. In comparison, Apple's correlation with Amazon and Google is 0.26 and 0.31, respectively. Interestingly, Amazon and Google have a correlation of 0.44, again suggesting a diversifier relation. In the following section, we fit GARCH models to the returns series and derive time-varying correlations from its conditional covariance matrix.

Table 2: Pairwise Pearson Correlation Matrix, n= 3964 obs.

	Apple	Microsoft	Amazon	Google
Apple	1.00000	0.50093	0.26258	0.31973
Microsoft		1.00000	0.30956	0.35104
Amazon			1.00000	0.44444
Google				1.00000

3. Methodology

The DCC-GARCH modelling by Engle (2002) is based on a two-stage estimation, that is, first the fitting of the univariate GARCH models for each return series and second the estimation of the time-varying, conditional covariance matrix H_t. The DCC model, (seen as generalization of the constant conditional correlation estimator by Bollerslev (1990)), assumes a $kx1$ vector of asset returns r_t with mean zero and covariance H_t, here for a pair of two assets, i and j, which reads as follows

$$r_t|\Im_{t-1} \sim St - t_v(0, H_t), \tag{1}$$

where $\Im_{t-1}$ is the information set at time $t-1$. Based on the non-normal structure of the set of returns, we assume a Student-t distribution of the innovation terms in our estimation setting, $\varepsilon_t \sim St - t_v(0, 1, \kappa)$[5]. The variance-covariance matrix H_t is decomposed in the following way:

$$H_t = D_t \cdot R_t \cdot D_t, \tag{2}$$

with $D_t = diag\{\sqrt{h_{i,t}}\}$ is the kxk matrix of the square root of conditional variances as estimated by univariate GARCH models. R_t is a matrix that contains the correlation coefficients that are allowed to be time-varying. Using the standardized residuals from the estimation of the models, $\varepsilon_{it} = r_{it}/\sqrt{h_{it}}$, the correlation dynamics of Engle (2002)'s DCC specification is given by

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha(\varepsilon_{t-1}\varepsilon_{t-1}) + \beta Q_{t-1}, \tag{3}$$

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}, \tag{4}$$

where $\bar{Q} = E[\varepsilon_t\varepsilon_t']$ is the unconditional correlation matrix of standardized residuals. α and β are scalars with $\alpha, \beta > 0$, satisfying the mean reverting condition, $\alpha + \beta < 1$; $diag\{Q_t\} = [q_{ii,t}] = \sqrt{q_{ii,t}}$ is a diagonal matrix that contains the square root of the i^{th}

[5] κ represents the number of degrees of freedom (df).

diagonal element of Q_t on the i^{th} position in the matrix. In fact, $diag\{Q_t\}$ guarantees that R_t is a correlation matrix with the value of ones on its diagonal, if and only if Q_t is positive definite.[6]

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & 1 \end{bmatrix}$$

A dynamic correlation estimator is then obtained by calculating $\rho_{ij,t} = q_{ij,t}/\sqrt{q_{ii,t}q_{jj,t}}$ (on the off-diagonal elements in R_t). Assuming a bivariate Student-t distribution, parameters are computed in an iterative procedure through the quasi-maximum likelihood (QML) estimator which reads as follows

$$\begin{aligned} ll_t = {} & log\Gamma\left(\frac{\kappa+m}{2}\right) - log\Gamma\left(\frac{\kappa}{2}\right) - \frac{m}{2}\{(\kappa-2)\pi\} \\ & -\frac{1}{2}log\{det(R_t)\} - log\{det\left(D_t^{1/2}\right)\} - \frac{(\kappa+m)}{2}log\left(1+\frac{1}{(\kappa-2)}\varepsilon_t' R_t^{-1}\varepsilon_t\right), \end{aligned} \quad (5)$$

where Γ is the Gamma function and κ is the degree of freedom associated with the Student-t distribution. Estimated parameters are reported in Appendix A1.

4. Results

Figure 3 presents the time-varying correlations of return dynamics of Apple, Microsoft, Amazon and Google. For the Apple-Microsoft pair, the correlation starts moderately at 0.2 to 0.4 with some downward spikes, while values of the remaining pairs begin in the [0 - 0.1] interval with less alternating swings. During the financial crisis, most correlation values increase immensely, in some cases with abrupt jumps to higher levels (Apple-Amazon, Apple-Google and Microsoft-Google), and persistently oscillate on these levels. This phenomenon of rapid increments in return correlations across asset pairs can generally be attributed to extreme market scenarios with selling pressure across many industries and asset classes. In this regard, the correlation of Apple-Microsoft clearly marks the highest

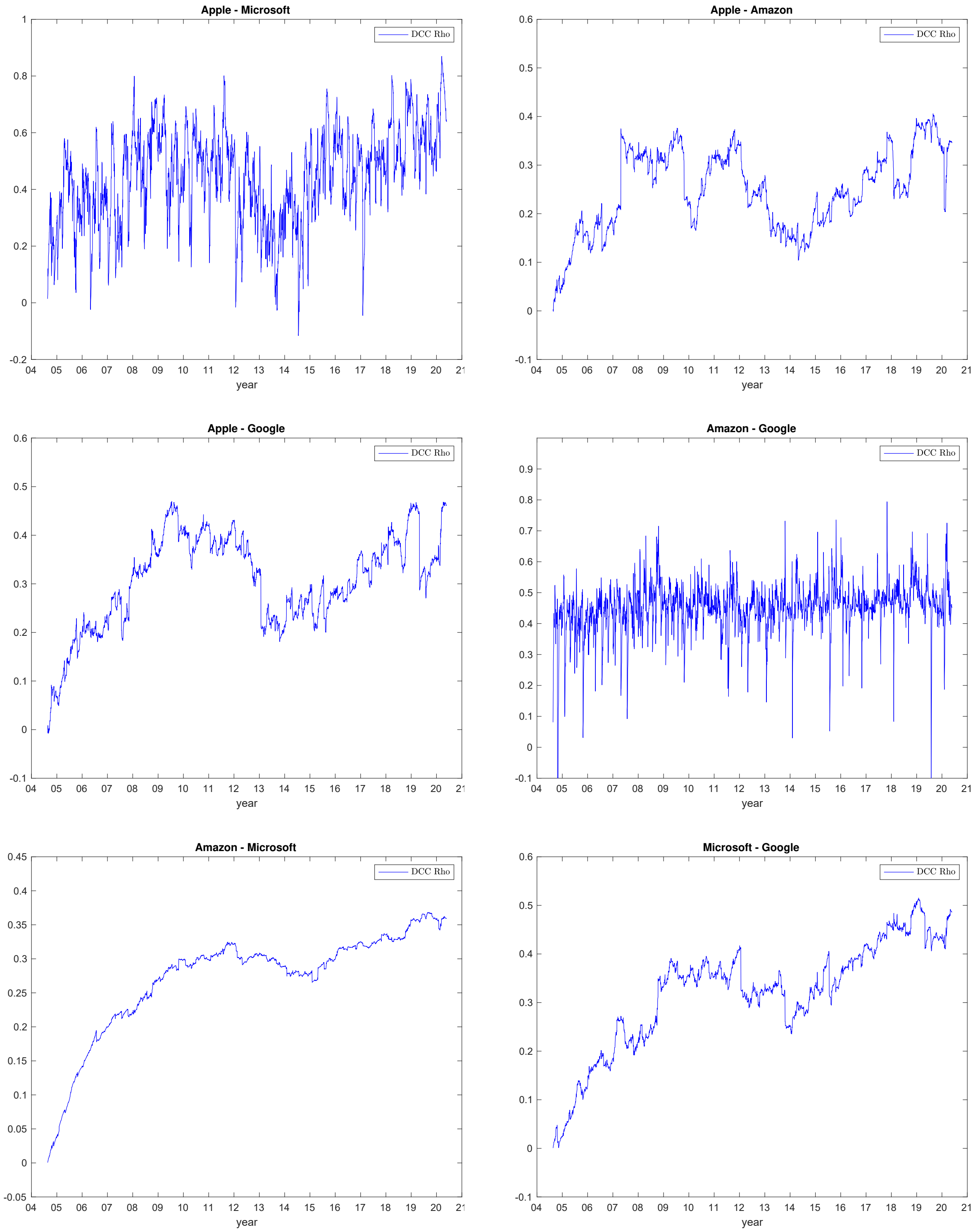
[6] See Cappiello et al. (2006) for an extended formulation of the model.

one in comparison when hitting the 0.8 bar in early 2008 but, with a focus on portfolio rebalancing strategies, correlations of assets price dynamics in these highs clearly signal no longer a diversifier relationship in the definition of Baur & Lucey (2010). Such a scenario limits options in the diversification of risk within the segment of large cap U.S. technology stocks. Surprisingly, correlation values for the Amazon-Google pair remain around a set range of 0.3 and 0.6 during the entire sample period - in times of market distress and recovery, suggesting a strong sign to be characterized as diversifier in the above-mentioned definition over a longer time horizon. Moreover, and irrespectively of the recent market downturn, time-varying correlations in the Amazon-Microsoft return dynamics show a continuous upward trend to reach its maximum value of 0.36 in late 2019.

In the years after the financial crisis, correlation values for most asset pairs dropped again from 2012 to reach a local minimum in late 2013, early 2014, (except for Amazon-Google and Amazon-Microsoft). This could indicate that investors start to rebalance portfolios with other stock or asset segments and reduce demand for large cap technology stocks, which dampen the upward correlation trend(s).

As from 2015 onwards, there is a stable upward movement in correlation values for most asset pairs (except for Amazon-Google). Again, we find that within this trend, the correlation for the Apple-Microsoft pair is the highest, peaking at 0.87 on March 17, 2020. This finding may directly be related to the uncertainty around the COVID-19 outbreak as experienced by global stock markets but shows again that Apple and Microsoft are by far no diversifier assets in times of stock market uncertainty. Instead, Amazon and Google perfectly serve as diversifier in the latest trend of the market. For the remaining assets, we generally observe that correlations in return dynamics among this set of technology stocks become stronger in the second half of the sample period, most likely as a result of the recently rising market until the COVID-19 outbreak, nevertheless mostly fall into the definition of diversifier assets, Baur & Lucey (2010) . These findings are in line with the broad literature such as by Longin & Solnik (2001) who finds that correlation among international equity markets increase in bearish market states and with market trends.

Figure 3: Dynamic Correlations - Apple, Microsoft, Amazon and Google



Dynamic correlations among the Apple, Microsoft, Amazon and Google returns obtained through a multivariate GARCH model between August 20, 2004 and May 26, 2020, n = 3964.

5. Conclusion

In this paper, we examine the dynamic correlation between the four most valuable stocks worldwide, that is Apple, Microsoft, Amazon and Google. We use a multivariate DCC-GARCH model to identify linkages in the return dynamics of this set of stocks. Our results show that time-varying conditional correlations for all asset return pairs exhibit a steady increase parallel to an upward trended market. Despite the dynamics, we find that correlation values alternate in ranges where the definition of a diversifier asset still holds. Moreover, we observe that conditional correlation dynamics increase abruptly during extreme market conditions, suggesting limitations in the diversification of risk within the large cap U.S. technology stock sector. Our study has implication for the construction of an adequate risk-return profile or portfolio rebalances.

Future research is encouraged to examine time-varying, conditional correlations in liquidity and trading activity among these four assets as the underlying price discovery mechanism is usually driven by market microstructure characteristics which directly impacts liquidity and prices.

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Appendix

Table A1: Parameters of the DCC-Model - Pairwise Return Combinations

	Apple-Microsoft	Apple-Amazon	Apple-Google	Amazon-Google	Microsoft-Amazon	Microsoft-Google
Average COR.	0.4992***	0.4155***	0.5274***	0.6004***	0.5799***	0.6203***
	(0.0362)	(0.0675)	(0.0927)	(0.0153)	(0.0782)	(0.1052)
α	0.0489***	0.0051***	0.0055***	0.0516***	0.0009***	0.0039***
	(0.0155)	(0.0014)	(0.0014)	(0.0141)	(0.0013)	(0.0011)
β	0.9245***	0.9913***	0.9918***	0.7758***	0.9973	0.9941***
	(0.0299)	(0.0015)	(0.0010)	(0.0527)	(0.0008)	(0.0009)
κ	4.4296***	3.8011***	4.3069***	3.353***	3.8228***	4.3125***
	(0.2338)	(0.1718)	(0.2113)	(0.1353)	(0.1713)	(0.2125)

Note: κ denotes the degree of freedom from the Student-t distribution. Standard errors are provided in parentheses. *** indicate statistical significance at the 1% level.

Trump tweet impacts on the MSCI World Exposure with China Index - evidence from an event study deploying Cumulative Abnormal Returns

Jürgen Klaus[a]

[a] *Faculty of Business and Economics, Technische Universität Dresden, Germany*

Abstract

This paper studies former US-president's Trump tweets on the US/China trade relationship and their impact stock valuations of companies with a high China exposure. Based on selected tweets, this event study deploys data from the MSCI World with China Index and identifies potential out-/underperformance using cumulative abnormal returns (CAR). In applying different event-estimation-windows, I also aim to identify whether valuations change depending on the pre-event window of incoming tweets to test for a potential surprise factor of tweets on stock performances. My results are presented based on the full index constitutes using heatmaps to show significance of CARs where applicable. My findings suggest that statistically significant CARs are limited depending on identified tweets and appear volatile depending on the estimation window. A vast amount of statistically insignificant CARs based on Trump tweets on China supports the conclusion that his tweets had an overall low impact on the index companies.
Keywords: CAR return event study, Twitter, Trump and China, MSCI Exposure with China Index, Volfefe Index

1. Introduction and literature

Prior to Joe Biden's inauguration in January 2021, his predecessor Donald Trump was facing his second impeachment tribunal after the US capitol being hit by an attack led by Trump supporters. Trump was accused of having verbally heated up the situation further. Earlier in January already, Trump's Twitter account got deactivated due to "the risk of

*email:j.klaus@esm.europa.eu / Tel.:+352-621-833-872

further incitement of violence"[1]. This was the shutdown (for now) of Trump's twitter activities after tweeting over fifty thousand tweets. Trump's Twitter politics may remain an exception for an US president. Amongst other policy areas, Trump's communication style in using social media platform for key policy messages was utmost distinctive from his predecessors. With this, he contributed to sentiment changes and could impact stock market performance. One particular area for Trump's policy tweets was the trade negotiations ('trade war') with China.

Many may argue his tweets should impact markets yet the question is if we can we quantify and measure them. This paper contributes to this question by studying stock market evaluation changes on selected Trump tweets. I study whether stock companies with a high China exposure do under-/outperform under changes in policy uncertainty with different tweets including the trade war between the U.S. and China.

Measuring economic policy uncertainty is studied extensively in literature. For example, Baker et al. (2016) develop a policy uncertainty index based on word mining tools covering over twelve thousand newspaper articles. By using firm levels data, they find that news sourced policy uncertainty is associated with stock price valuations (both their valuation and volatility). Fear linkages between US trade relations and the BRIC stock markets are presented by a the theoretical model by Barberis et al. (1998). They find that investors overall underreact to news and overreact to persistently good or bad news. Tetlock (2007) discover that high media pessimism results in a downward pressure on intraday prices and a jump in trading volume. Fang & Peress (2009) identify in their study a significant premium on small stocks in niche markets that are not covered in the media and with low analyst followings.

Sentiment analysis is another large strand of literature. For measuring investor sentiment, a variety of proxies have been in use. Baker & Wurgler (2006) measure investor sentiment by deploying a composite index based on six underlying proxies.[2] They find a

[1] see Twitter press release `https://blog.twitter.com/en_us/topics/company/2020/suspension.html` (retrieved 20. Jan.2021)

[2] That is closed-end fund discount, NYSE share turnover, the number and average of first-day return on IPOs, the equity share in new issues and the dividend premium.

general effect on stock markets and particularly on stocks that are difficult to value or arbitrage.[3] Within investor sentiment studies, another area of existing literature measures sentiment with survey data. These impacts of investor sentiment on stock market performance are for example studied by (De Long et al., 1990a,b). The study concludes that noise or irrational traders move prices away from its fundamental value, leading to higher expected returns.

As far as information efficiency in markets is concerned, social media platforms are special. Social Media platforms as web-based applications and networks created an information channel where market participants can extract relevant content with much faster pace and accuracy than before. Furthermore, this information is not only for financial experts available (e.g. using information platform like Reuters or Bloomberg) but immediately accessible for a much wider audience following tweets of a dedicated person. The results of Fang & Peress (2009) indicate that stock companies show different returns depending on their media coverage after controlling for other classic market factors. As for Twitter, it is the micro-blogging platform that records over 330 million monthly active users as of 2019.[4] It is the tenth most-trafficked website on the world wide web which may explain why Twitter is a tool to convey political, social, and economic concerns to a global audience (Ranco et al., 2015). However, depending on the content this may unintentionally fuel the development of (stock market) sentiment.

More recent studies focus on the impact of Twitter sentiment on stock returns. Bollen et al. (2011) use a sentiment analysis application tool to filter out emotional polarity in the sentence structure of 9.8 million tweets from 2.7 million users. Constructing six different mood-dimensional daily time-series, they find a positive association between "calmness" and the stock market performance. A similar study by Sul et al. (2017) groups tweets into emotional valence and match daily firm level twitter content to the corresponding return(s). They show that tweets about a specific firm are positively related

[3]Schmeling (2009) proxies sentiment with consumer confidence and shows its impact on stock returns across countries. This effect is particularly strong for countries with weak institutions and herd-like behaviour among investors.

[4]See https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users/.

to its returns and can further be utilized to predict returns ten days after the initial tweets. Oliveira et al. (2017) construct Twitter sentiment indicators and analyze the predictive power for returns of the S&P500 index and portfolios of lower market capitalization. Twitter is nowadays used by a variety of other politicians too yet Trump's communication during his presidency appeared less predictable, partly random and mood based. This particularly holds for his over 14 thousand tweets available in the Trump Twitter archive since his inauguration in 2016. His tweets are placed timely-independent, partly unclear and perhaps unintentionally amplified by re-tweeting activities via followers.

Also Trump's presidency covers a variety of studies. Angelini et al. (2018) study market sentiment changes between Trump's election 2016 and financial markets. They found evidence for stock market returns, treasury bond yields and gold using a co-integration analysis. Trump and China is studied by Lin & Wang (2018) who identify the large trade balance deficit with China as a key issue for Trump's political pressure on the US-China trade relations. Stiglitz (2018) discusses the effects of Trump's major change to the US economic policy and finds that the US turned away from the WTO's rule based system. With Trump using tweets as a policy tool it was immanent to ask whether they have an impact on markets. A team of US analysts from the investment bank JP Morgan Chase as in Salem et al. (2019) introduced the so called Volfefe Index (a Trump twitter index). In this study, the authors construct a time-series index based on a sequence of keywords used within Trump's vocabulary (i.e. "tariffs", "trade", "products", "billion" and "China") and relate it to the U.S. interest rate market. This index includes word mining techniques using a random-forest-based classifier approach in combination with neuro linguistic programming techniques. The authors find that Trump's tweeting activity impacts money market sentiment and large cap stocks. As Salem et al. (2019) further find, Trump's tweeting activity potentially also impacts market segments also outside of the U.S. On this hypothesis, the work of Klaus & Koser (2020) provides an approach to extend Trump tweets into European markets. The authors study Trump tweet impacts - using the Volfefe Index - on European financial markets. This extends previous studies on sentiment and financial markets and specifically contributes to the above mentioned literature on twitter sentiment and stock market performance. Klaus & Koser (2020) find that the mean impact of the Trump twitter factor is of heterogeneous nature in its prediction of European stock market returns. The contribution documents that these coefficients exhibit time-varying pattern and coincide well with a series of presidential tweets, indicating the directional effect of the Trump Twitter factor. Lastly, as a reference for this contribution, the authors provide selected market significant tweets on the trade war between the U.S. and China and other events, serving as a event base for the following event study conducted in this paper (see section 3).

Event studies are a very common technique in finance and research projects as discussed in the work of Kothari (2008). This basic statistical technique and tool-kit is used in almost 600 studies between 1974 and 2000 within various fields based on the Kothari's observations. Event studies include bond markets (e.g. in Klaus & Selga (2021) on market structure changes or based on credit default swaps as in Andres et al. (2016)) yet mainly involve common stocks markets. Many event studies include stock market events ranging from studying merger and acquisitions, short selling transactions and other key events. Measuring stock returns in event studies has a long history since perhaps 1933 when Dolley observed price effects of stock splits (Mac Kinlay (1997)). During defined events, various stock returns can be measured and compared within the framework of expected market returns against abnormal returns (AR). These ARs are used in various variations and tested on significance to derive conclusions on any abnormal moves in the observed stock due to the event (see 3). Research deploying a similar methodology combining event- and stock return studies are manifold available. For example, Asian stock performance reactions to mergers and acquisitions (MA) are studied by Ma et al. (2009). They find find that the stock markets have expected positive cumulative abnormal returns (CARs) and that valuation effects of information leakage about MA deals are statistically significant.

This paper studies studies CARs on stocks with a high exposure to China on selected tweet events using stock data of large listed companies from the MSCI World with China Index. Tweets are tested on market significant Trump tweet events on China based on the findings from Klaus & Koser (2020). The research question is if and by how far Trump's China tweets impact selected stocks based on different CAR measures. This research contributes in novel way in combining tweets on China/U.S trade negotiations with an established China exposure index (from MSCI). The paper adds to research findings on twitter sentiment and out- or underperformance stock returns from this specific index being the benchmark for stocks with large China exposure. While I am using an established methodology (event study in combination with return studies) it is the topical data combination which bears some novelty. I contribute to literature by reviewing Trump's twitter impact on selected stocks based on findings for relevant market moving tweets by extending one of our very recent (2020) papers. Additionally, while I am not focusing on single companies but the full index constitutes, I also offer a 'back testing' of the MSCI World with China Index as my findings help to conclude if such an index is indeed - related to the Twitter effect scope - representative or not.

The remainder of this paper is structured as follows. Section 2 describes the data set in greater detail, its relevance and my estimation technique. Section 3 details the methodological approach of computing the quantification factor of Trump's tweeting activity using the aforementioned event study methodology in identifying abnormal returns. Section 4 presents and discusses the results of the analysis with some preliminary statistics and the main results. Finally, section 5 concludes, discusses caveats and potential shortcomings of my analysis and provides further outlook on the research in this field.

2. Data

This section details the data selection and data set building process.

2.1. Selecting Trump tweets for event studies

I face the challenge to identify a selected set of market significant Trump tweets from the Trump archive with over thousand of tweets. One potential solution could be to deploy word mining tools and techniques to extract US/China tweets based on a pre-selected word set; which is not my prior research focus. Given the large number of tweets available and the consequence on the size of the dataset, it would be very useful to deploy a set of tweets on the China/US trade relations which can be considered as market moving (significant). Thus, I conduct the analysis based on our previous studies. I refer to our peer reviewed journal contribution on the Trump Twitter Index Klaus & Koser (2020). This paper provides a set of Trump tweets considered significant for stock market indices. While the paper not solely focuses China related tweets only, I extract the key tweets for the event study framework as they were significant on stock indices benchmarks. From the paper, I focus on Trump tweets related to the trade war discussion between the US/China yet also use less clear China related tweets for cross testing. I consider five tweet events on selected days between which are either grouped as *tensing or relaxing political uncertainty* (they are mapped in a table in section 4). Consequently, in grouping these tweets, I add a qualitative narrative (why I expect them to be tensing/relaxing) and build the event study windows around the tweet dates. While the tweets are significant for European financial markets, I aim to answer the question if they are also for worldwide selected stocks with a large China revenue exposure.

2.2. Selecting companies with a high exposure to China

Having a set of market relevant tweets and considering that I do not intend to study single companies, I searched for a representative index allowing my to study daily index returns as well as the constitutes. With a simple framework, I focus great attention on the reliability of the data - i.e. exchange traded companies from ideally high liquid markets. After researching, I consider the Morgan Stanley Capital International (MSCI) World with China Index as an appropriate measure. This index is tracking companies with a large China exposure in their businesses - more precisely: their revenues. The index was created in 2019 and the dedicated China exposure index is derived from the MSCI World Index as a parent index.

In creating their China index, the index provider concluded a review of the geographic distribution of revenues for each company in the MSCI World Index and the constituents with the highest proportion of revenues derived from China are selected for the MSCI World with China Exposure Index. Constituents average around a stable 50 index constituents representing and concentrating on companies with high revenue exposure to

China. MSCI states in their specification that investors may consider this index a new benchmark for capturing the sizeable business activity in China that is conducted by developed markets companies.

Each of the constitutes carries with a specific index weighting (in per-cent of the index) which I use as defined by MSCI (see A.3). The index is heterogeneous and contains listed companies from different world regions, sectors, jurisdictions and industry segments. To name a few, the index includes companies such as Infenion, Swatch Group, Qualcomm, Texas Instruments and Rio Tinto amongst others. Totally, the 50 worldwide index companies result from a total of nine underlying benchmark stock indices. The constitutes of the MSCI World to China Index was provided by MSCI itself and is available upon request[5].

2.3. Building the dataset

I build the data set by retrieving for each of the 50 stocks [6] including their nine corresponding benchmark stock indices daily market closing prices in each local currency where applicable. For the analysis using the market model (see 3) I further map each single stock to their applicable benchmark market index. The benchmark index table can be found in the appendix and include leading equity indices such as the DAX, S&P, Dow Jones and the Asian main indices with the Nikkei and Hang Seng Index (HSI). For the time series and mapping all data is retrieved from Bloomberg professional and was validity cross checked via Refinitiv (former Reuters Eikon) data.
As stated and detailed further in the methodology section, the observation time series frame is set from 01.January 2018 to the 31. December 2019 for each stock and benchmark index. Finally, the data set includes the time series data of all fifty constituted stocks as well as the applicable and mapped nine benchmarks per index value. This appears sufficient in order to deploy a cumulative abnormal return calculation by first deriving the market model returns for each of the nine applicable indices as detailed in the following methodology section.

[5]MSCI Index info sheet (retrieved 20/01/2021) www.msci.com/documents/10199/e54c552d-3c00-44a0-8172-4dc2bf136200
[6]Data for Budweiser Brewing Co (Stock 49) were not retrievable shown as NaN in the tables.

3. Methodology

Methodology wise I follow Mac Kinlay (1997) and importantly Brooks (2014) detailing event study frameworks. Brooks (2014) explains the origins of standard event study as a modern approach referring to the initial contributions from Fama/Brown in the late 1960s by using time series data. Brooks further details the usage of event studies to test market efficiency. This implies for my research the idea to run various event window frames in order to see if an immedeiate impact from tweets can be observed. Following this spirit, I compute abnormal returns (AR) using a standard market model approach as further detailed in this section. For my studies, I support my data set frequency (daily closing data) with Mac Kinlay (1997) who shows that event studies measuring abnormal returns benefit from the use of daily data. Notably, intraday data are likely to be full of micro structure noise while weekly or monthly data seem inappropriate to measure tweets. This is due to the fact that they are short intraday market information and especially under Trump were often contradicting within a short time frame.

Following Mac Kinlay (1997) the event study framework contains the following steps:

1. *Definition of the event windows*
2. *Computation of normal returns (incl. choice of estimation model as detailed below)*
3. *Estimation of the AR and the cumulative ARs*
4. *Statistical significance testing of the CAR results.*

3.1. Definition of the event windows

As for the first point, one key consideration when measuring abnormal returns is the event window. Following Brooks (2014), there are plenty of different approaches in literature as regards to the 'right event window' when conducting event studies. He suggests that for daily observations an event window can include between 100-300 days while for example monthly basis observations can cover a much longer event horizon. For the event windows I deploy in this paper two variations for comparison of the potential 'surprise' factor of Tweets. First, following the suggestions in Mac Kinlay (1997), I deploy each ten days as a pre-event- and post-event window including the event (tweet) day. This results in 21 observations per tweet. Second, I re-run the analysis by adjusting the pre-/post-event windows to five days/each. This consequently reduces the dataset and results in eleven observations to compute returns. Third, to add for the two prior mentioned computations, I re-run another data set *without any pre-event window*.

My intention is to identify/test for a *tweet surprise factor*. My motivation for deploying this is the key difference compared to event studies conducted on known events (e.g. merger announcement, dividend days) and my analysis. As tweets are by nature without pre-announcement and spontaneously sent to markets, I like to consider and test for a degree of 'surprise' effect stemming from a spontaneously sent tweet. In trying to re-run the study without any pre-event window should help to understand if after a tweet the study finds any significant impacts on stock prices or not.

3.2. Computation of normal returns (and expected returns)

Referring to the second step being the normal return computation and the estimation model choice I define the return for each firm i on each day t and each event window as R_{it}. This simple return is calculated based on the change in percent for each stock or index value for each trading day based on the retrieved data set following the simple equation:

$$R_{it} = \frac{\Delta p_{t,t-1}}{p_t} \tag{1}$$

where R_{it} is the return of stock i on day t in decimals based on the daily change of the stock or index observed ($\Delta p_{t,t-1}$) in relation to the current price (p_t).

The next part includes the computation of the *expected* return for each instrument using the standard market model. From the variety of possibilities (Brooks (2014)[573ff.]) to compute expected returns I apply the standard market model. It offers a more advanced solution than the constant mean return assumption (which implied a simple average of R_I). The market model approach implies to construct the excepted return using a regression of the return to stock i on a constant and the return to the market portfolio using the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + u_{it} \tag{2}$$

where the *expected* return R_{it} of each stock company would be calculated as the $beta - estimate$ of the regression multiplied with the market (or more precise here the *mapped benchmark index*) return on the day t.

3.3. Estimation of the AR and the cumulative AR

The AR as the abnormal return is simply the difference between the *actual* and the expected return ($E(R_{i_t})$) of each stock over a certain event window framework. For each applied event window calculation I define the event day (*t=0*) and depending on the pre-/post-event window with either for the *10* day-event-window with $t = -10, -9, \ldots, 0, 1, 2, \ldots, 10$ or for the ± 5 day-event-window with *(t=-5,-4,-3, ...,0,1,2,3, ...,5)*. I compute the AR for each stock and mapped benchmark index following the below equation:

$$AR_{i_t} = R_{i_t} - E(R_{i_t}) \tag{3}$$

where R_{it} is the daily returns of the single stock i; and with E being the expected return for each stock i on t. I am interested cumulative AR's for the given event windows. Consequently, I consider the event window as a multi-day period and compute aggregation of ARs resulting in *cumulative* abnormal returns (CAR) as below:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t} \tag{4}$$

with $t_1 < t_2$ and t_1, t_2 as the defined event window.

After having performed these CAR calculations I have a result matrix per event window and stock as provided in the section 5.

3.4. Statistical significance testing of the CAR results

As the name indicates to be *abnormal* returns, it is still of course relevant to study their statistical relevance. Literature offers a variety (see e.g. Brooks (2014)) of tests available with in the parametric and non-parametric tests. I assume normally distributed securities and market returns. Consequently, given that my hypothesis testing framework is also that (C)ARs follow a Normal distribution with mean 0 and variance σ_{CAR}. Given this, I can construct the test statistics based on the standardised abnormal performance. Considering the asymptotically normally distributed test statistics pattern, I use the time-series data from expected returns estimations. The variance of the residuals from the applied market model states as follows for ARs:

$$\hat{\sigma}^2(AR_{it}) = \frac{1}{\tilde{T} - 2} \sum_{k=1}^{t-v} \hat{u}_{ik}^2, \tag{5}$$

where $\tilde{T}$ is the number of observations in the estimation window period until the start of the event window defined above with v as the number of days prior to the event at time t. This equally holds for the variance of the CAR while their variance is driven by the number of observations from the event window plus one multiplied by the daily AR variance as stated above.

In further following Brooks the CAR variance details as:

$$\hat{\sigma}^2(CAR_i(T_1, T_2)) = (T_2 - T_1 + 1)\hat{\sigma}^2(\hat{AR}_{it}) \tag{6}$$

This returns the sum of the applicable daily variances between T_1 to T_2 inclusively. With this the CAR test statistic under standard normally distribution assumptions is given by:

$$\widehat{SCAR}_i(T_1, T_2) = \frac{C\hat{A}R_i(T_1, T_2)}{[\hat{\sigma}^2(CAR_i(T_1, T_2))]^{1/2}} \sim N(0, 1) \tag{7}$$

This includes the full event window with its applicable pre-event-window (e.g. t-10/-5days to t-1) as well as the post-event-window (e.g. t+1 to t+10/+5days).

3.5. Methdology and implementation considerations

Methodology framework and the research objective

Given the above mentioned basic framework I am able to derive CARs from ARs using the simple return data and comparing these with the expected returns based on the standard market model. With these results, I am primary focusing to present a significance heat-map on the MSCI Exposure to China Index basis for each constituting company. As stated earlier, I like to analyse the index constitutes not on a micro level yet rather from a significance framework between *tweets* and their *significance* within the index under *two different methodological approaches*. First, including a *pre-event-window* with two different time frames and, secondly, *without using a pre-event-window* with the intention to test for a *surprise factor*.

As a consequence, given that the dataset - even under only five relevant tweets - gets less handy I focus in the result section on discussing the results based on a heat-map for brevity reasons. The detailed CAR return data is included in the Appendix for completeness. The Matlab implementation is described in the next section.

Matlab implementation notes

Regarding the practical implication I use Matlab and import the stock- and benchmark indices level data as detailed in section 2. The simple percentage returns are computed on a daily basis for the full time series as a matrix. Using Matlab linear model tool delivers the coefficients and data needed for the standard market model approach. I loop along the identified tweet dates to compute results including the test statistics based on the above mentioned sources and concepts. For output convenience, I create a heat-map of significance looping the different CAR into significance levels with p-values $< 0{,}01$ as high significant, values $<0{,}05$ as significant and finally $<0{,}1$ as low significant.The results are discussed in the following section.

4. Results and discussion

Based on the details provided in the methdology section, this chapter details how and why I map the tweets to anticipated market reactions as out- or underperformance of the MSCI China Exposure Index. It also presents and discusses the results based on the index constitutes level using the different event windows. Results are shown as significance heatmaps and discussed in relation to the value tables per event study design (all tables for brevity listed in A.3). The discussion includes findings related to potential limitations and shortcomings of the research design and concludes on the overall results.

4.1. Tweet mapping

If an information based on a tweet hits the market it is neccessary to define a causality or a consequence in what one expects to react upon this information. In other words: tweets as words need to be mapped with an anticipated sentiment shift (positive or negative) or market reaction (stocks up or down). Tweets can be matched along different parameters as for example Sul et al. (2017) shows by using emotional valence of tweets to match with company returns. As stated earlier, another option is to create an own sentiment indicator (index) as proposed by Oliveira et al. (2017). For my analysis on the relevant tweets I refer to the information efficiency of markets and the various studies mentioned in section 1. This means I assume that markets interpret the information transmitted in a tweet as related to an *intended market reaction* on stock valuations. This market reaction is categorized as *relaxing* or alternatively *tensing* political uncertainty. For example, tweets indicating relaxing political impacts include positive progress on trade negotiations (tweet3) which contribute to improve market sentiment for stocks with a large China exposure. On the contrary, tensing tweets include for example threats of economic consequences/tariffs (tweet2) which are considered to worsen market sentiment especially - to be tested - for stocks with a higher exposure to China.

Table 1: Expected market sentiment- and and stock valuation impact on tweet key dates

Tweet Event No.	Date	political uncertainty	market reaction
1	31/10/2018	relaxing	stocks with China exposure outperform
2	04/12/2018	tensing	stocks with China exposure underperform
3	03/01/2019	relaxing	stocks with China exposure outperform
4	01/02/2019	relaxing	stocks with China exposure outperform
5	03/08/2019	tensing	stocks with China exposure underperform

In the following sections the tweet event set stays unchanged while the different event study designs (detailed in section 3) according to the different event windows.

4.2. Event study results and heatmaps

This section presents only the significance heatmaps based on the individual event framework designs and discusses results while referencing to the data tables (provided in

Appendix (A) A.4. I discuss -where possible- the results interdisciplinary. This means I include significance results, simple descriptive statistics and of course the CARs returns. These quantitative data I try to interpret and explain also with the qualitative element (the tweet message and the tweet mapping in Table A.2). For brevity and visibility reasons, the companies are mapped and numbered shown on the x-axis (Stock numbered from 1-50) with the tweets shown on the y-axis (numbered Tweet events as defined in Table A.2). A company name mapping is provided in A.3. The heatmaps show a significance range from levels -3 (for negative CARs) to +3 (for positive CARs). Green values (shown as 0) are considered not significant. The heat mapping is relating to the asterisk parameters for highly significant (-3/+3 imply $p < 0,01$), significant (-2/+2 imply $p < 0,05$) and low significant (-1/+1 with $p < 0,1$).

4.2.1. CAR Event study incl. pre/post event windows

The first results are shown in Figure 1 for the study including a *pre- and post event window of 10days (d)* each including the tweet event day (21 datapoints). For analysing tweets, this is a pretty long observation frame. From a significance perspective all events show different degrees of significant CARs. While three events show higher density (namely tweets 5,4 and 1) there are two event dates with nearly no evidence of any significant out-/underperformance (tweets 3 and esp. 2).
Regarding significance strength, the three main events indicate partly high significant CARs - particularly tweet event 5. For tweet 5 with most significant values, the CAR return tables (A.4) show main descriptive statistics with mean $\bar{x} - 0,029$ close to the mode $\tilde{x}$ at -0,035 and variance σ^2 of 0,012 (SD0,11). From a qualitative narrative, Tweet 5 is a cynical tweet where Trump is criticizing the US Federal Reserve bank for not reacting on Chinas trade policy. This created fear in markets that Trump himself could impose tariffs which may damage in turn high China exposure companies in case China would enter into countermeasures.Overall, the intended market reaction on tweet 5 (negative CARs) fits as 60% of the index constitutes show negative CARs. Two companies however, Advantest (stock1) and ASM Pacific (stock30), in tweet 5 are high significant outperformance against the expected trend. For the other discussed events I find that the narrative fits as

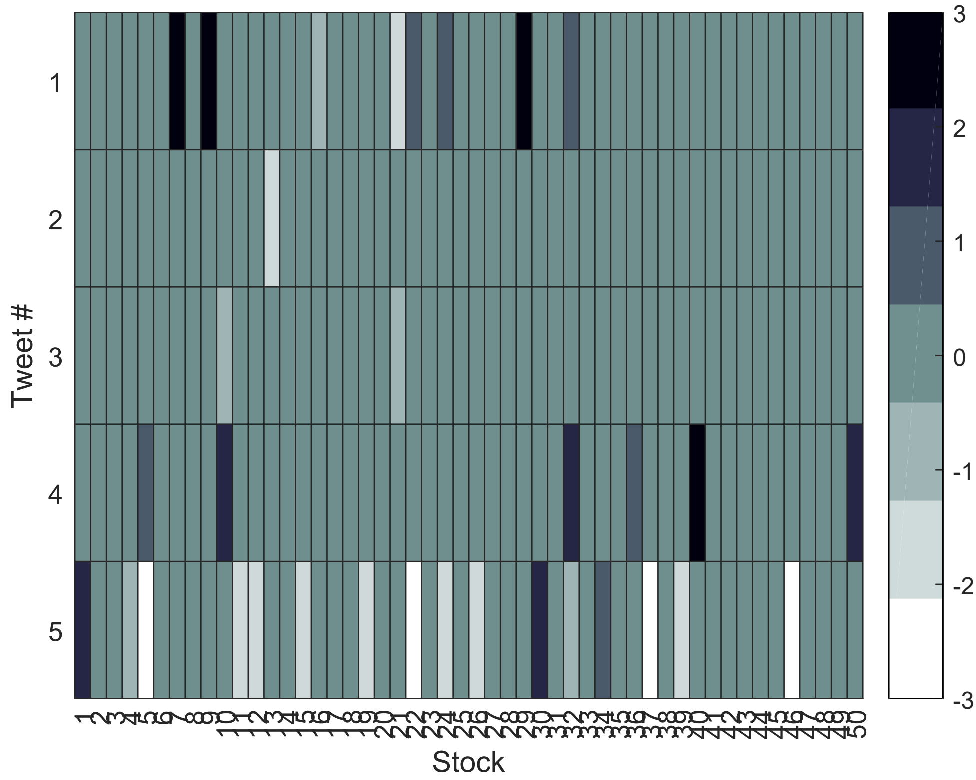

Figure 1: CAR significance heatmap -10d/10d window

I expect tweet 1 and 4 to relax uncertainty and the CARs are supporting this (esp. tweet 1). Tweets 2 and 3 show little significant results which would need further investigation.

The second analysis again includes again pre- and post-event window; yet shorter by halving them to five days each. The results of the total eleven observation days is plotted in heatmap 2. The map shows a higher scattering across tweets; including tweet 2 which was a non event in the previous heatmap. As before, tweet 5 shows the most significant CARs (main stats for the tweet under this framework $\bar{x} - 0,04$, $\tilde{x}$-0,033 and σ^2 0,004 and SD 0,07). For this tweet 74% (from 60% in the 10/10d heatmap) of the stocks were underperforming in line with the qualitative narrative of the tweet. The results show in difference to the previous event study less outlier values (positive CARs by number and significance). Comparing the other tweets from the previous heatmap (tweet 1 and 4), findings again confirm the narrative (relaxing and outperformance).

Notably, under this shorter event frames I would have expected more significant CARs which is not confirmed by the results. In the next sub-section I test results based on my

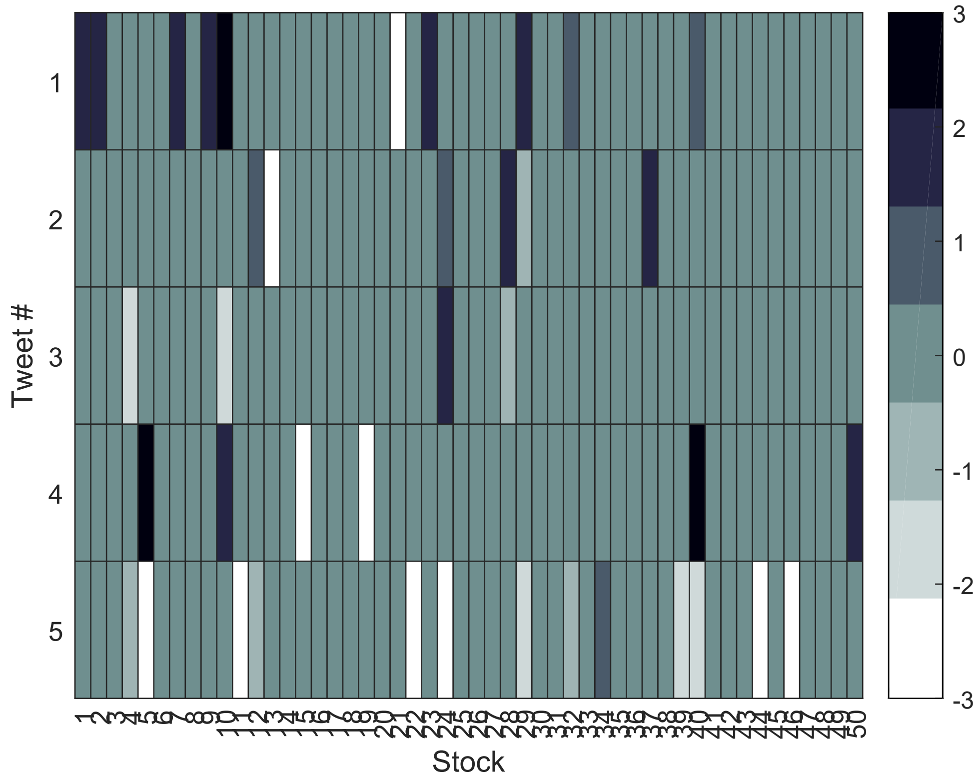

Figure 2: CAR significance heatmap -5d/+5d window

design to also skip the pre-event window completely and start the event study on the tweet day itself with two different post-event-windows as detailed below.

4.2.2. CAR Event study without pre-event windows

The next two event-studies deploy *no pre-event windows* but take the tweet-event day plus each 5d and 10d post-event windows for analysis. As stated in chapter 3 in more detail I test for a *surprise factor* of incoming tweets. My working hypothesis is that an incoming, unexpected tweet should create a market reaction; ideally also much more significant ones than in the previous event studies. Rerunning the analysis with 0d/+10d event study windows provides results as shown in Figure 3.

The heatmap results do not confirm increased significant CARs along the data-set. Comparing the 10d/10d heatmap (Figure 1 two things are noteworthy. First, the significance distribution between tweet 1 and 5. Tweet 5 in Figure 3 shows far less-, and a lower amount, of significant CARs. Tweet 1 (and 2) become key tweets while for the only tweet 1 the narrative holds (outperformance as dark bars). Second, more broadly, the CAR value tables (see A.12ff.) show a stronger - yet not more significant - reaction

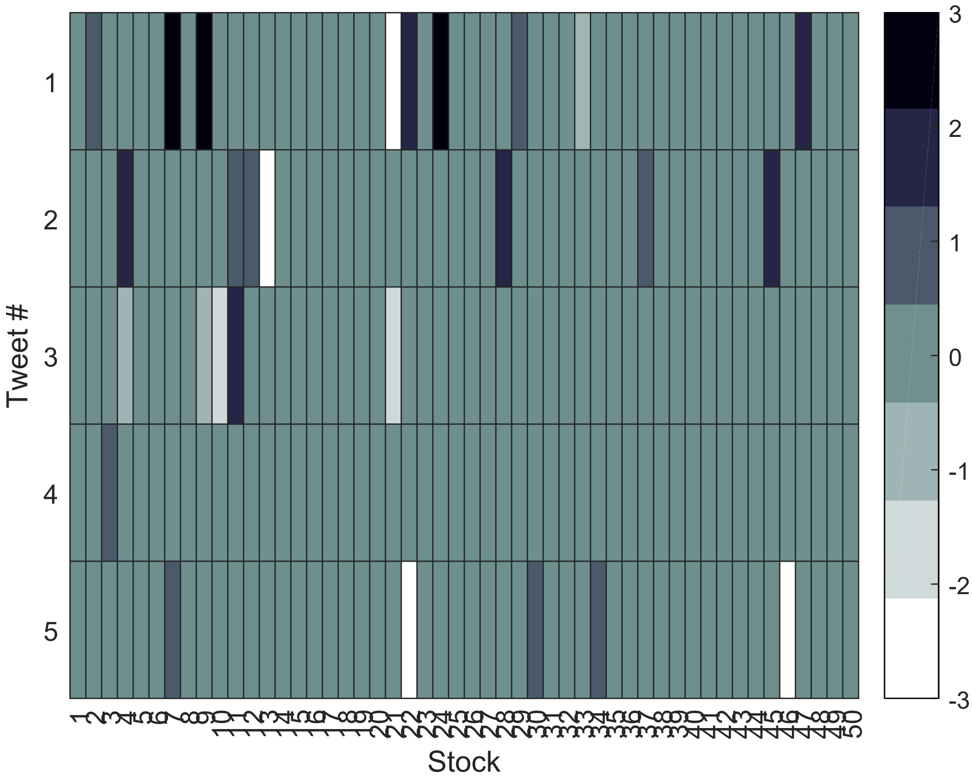

Figure 3: CAR significance heatmap 0d/+10d window

on tweets. For comparison, descriptive statistics of tweet 5 under this event study frames amount to $\bar{x} - 0,009$, $\tilde{x}$-0,013 and σ^2 0,003 and SD 0,06.

The last event study framework includes again no pre-event window and only 5d post-event window. Shown in Figure 4 below is a 0d/5d-event heatmap which similar as the previous 10d heatmaps reduces the number of significant CARs substantially. Tweet 4 also looses significance in the 5d studies once the pre-event window is dropped. Different as for the 0d/10d heatmap, the known focus on the significance of tweets 1 and 5 remains for the 0d/5d heatmap.

Using again tweet 5 as a comparison for main statistics delivers $\bar{x} - 0,01724$, $\tilde{x}$-0,01467 and σ^2 0,002 and SD 0,05. Noteworthy to the previous 5d/5d heatmap for tweet 5 are two high significant outperformers contrary to the narrative match (i.e. tensing uncertainty leads to underperformance). The companies Meiji Holdings (Stock 9) and Smith Group (Stock 34) outperform against the index trend by around 6% each.

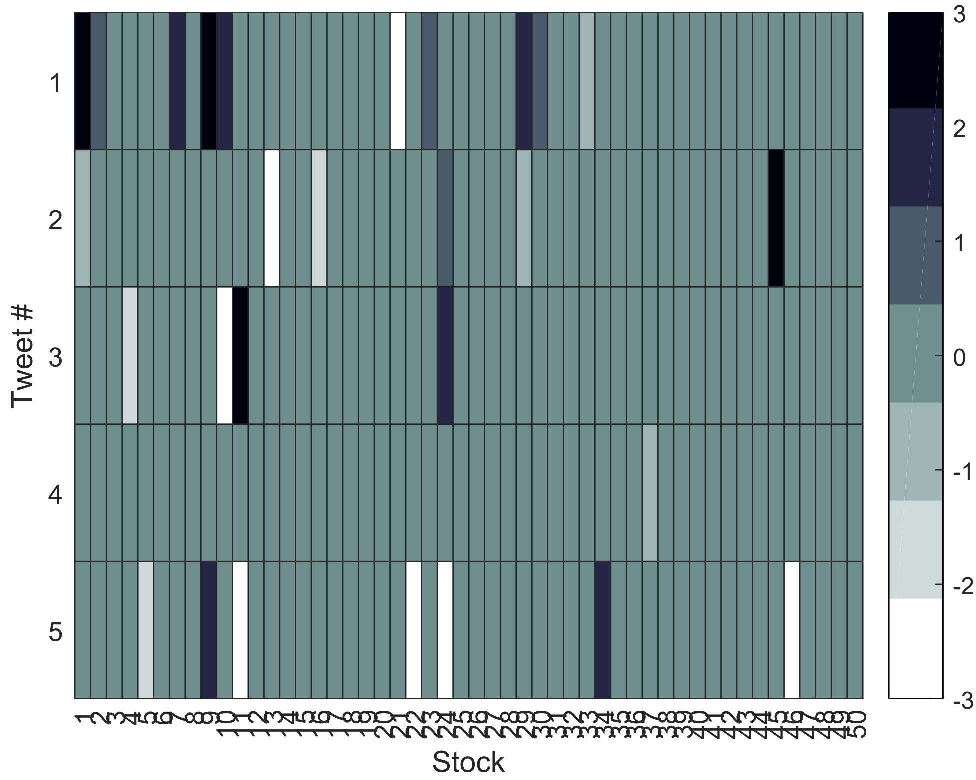

Figure 4: CAR significance heatmap 0d/+5d window

4.3. Reflections on the results

After four event studies using different event window designs and lengths the results are mixed. First, regarding the narrative (does market reactions on tweets follow the matching) I find in the CAR results that most tweets do confirm a match. Second, on the selected tweets for the study, the caveat is that some tweets (mainly tweet 2 and 3) show less significant results and tweet 4 appears to mostly a 'non event' tweet - which is also a finding. Center of the analysis is apparently tweet 1 and 5 with the latter resulting in often high significant CARs. Thirdly, I cannot confirm to have evidence for any *surprise factor* when excluding a pre-event window. Adding to this finding, it seems that also results from the previous event study are not becoming more robust (considering the low significance on the key tweet 5 in both study runs excluding a pre-event window). Lastly, from a holistic standpoint, my results show a majority of insignificant CARs on all studies tweets. This indicates an overall low impact of Trump tweets on these index companies. Certainly, there are a number of caveats, shortcomings and limitations to my analysis and some of them are detailed in the next concluding this contribution.

5. Concluding remarks

This paper applies an established and sound methodology set via a CAR-based event study using stock market data from the MSCI World to China Index to test performance impacts on Trump tweets. Its deploys the standard market model including standard significance tests. With the results I provided holistic views on the tweet significance's via illustrated heatmaps for the described p values. With this, I intentionally focused on the index yet less on the individual stock level performance.

In reference to the research question raised in the intro section 1, my findings indicate some impacts of relevant tweets yet to a not fully convincing degree. Put short, most of the CARs appear not significantly impacted by the selected tweets, and are also only partly following the applied narrative of tweet message against expected market reaction. I contribute to the existing literature on market sentiment and stock market performance extending the narrow literature on social-media related sentiment and stock markets. My findings provide an analysis using a combination of data sets in 'testing' twitter impacts on a specific China based companies stock index.

Notwithstanding, there are of course caveats and shortcomings for which future research may extend and elaborate further. First, on the data set itself. I am using an index based on MSCI definition which imposes questions on composition (weightings) as well as the index' rationale (constituents are selected on *revenue* basis to China). For analysis purposes it could be interesting to have a parameter-set defined apart from revenues only. The stock market and benchmark data is heterogeneous with nine benchmark indices who certainly are impacted by other factors including currency effects, index, re-composition (stock prices move due to re-indexing). Idiosyncratic company risks and events are certainly a key caveat. While these can be mitigated by the event study framework there is certainly influence from company related events and news which dilute results.

Second, the research design imposes shortcomings due to the nature of tweets as event triggering. A key characteristic of tweets is their sudden appearance. Tweets can not only be re-tweeted but especially for Trump I find often bundles of tweets intraday (even wihthin minutes) which are often re-tweeted (by replies) and unclear stated. By using daily stock data I run the risk that events are not spotted as they happened intraday. Additionally, and not covered by my analysis, companies also use Twitter and it is possible that e.g. companies reacted even on Trump tweets to limit negative impacts on their business or stock valuations. More concrete, the limited tweet selection and the proposed mapping should be extended. My intention in using 'relevant tweets' as identified in my previous studies was to have a link to 'market relevant tweets'. Yet, after all, these tweets are namely stemming from a study using another index (Volfefe Index). Also the timeline (2018/2019) I deploy should be extended to identify if markets priced in a 'Trump-tolerance-factor' over time. As politicians and markets got used to Trumps behaviour after his inauguration in 2016 it could be interesting to test for 2016/2017 data when markets (and frankly the political fora) were partly shocked by this president's political style. Broadly, one could test *any tweet* on categorized topics for CARs to extend the study (e.g. via wordmining techniques using the Trump Twitter archive).

Thirdly, as part of the methodology used, using event studies include certain assumptions. They include that events are expected to be independent from another and the effect that variances change depending on the event window which also impacts the test statistics. For the significance test (as for my econometric tools in general) I used a very simple and straight approach. Given that stock returns are known to be leptukurtic with uneven tails, the significance tests can be extended to cope with this (e.g. using non-parametric tests). Shortcomings also include the fact that my study does not include different weightings for stocks (could be extended by deploying cross sectional regressions).

Aside these limitations the policy implications of my results relate to market efficiency (could market participants as Twitter users beat the market compared to non Twitter users) as well as to inter-linkages between market segments and across countries. Even with Trump being history (for now) the discussion into how market participants receive and digest relevant information from social media stays an interesting research topic.

This became very topical obvious given the latest GameStop scandal in late January 2021 where stock investors organised a joint squeeze organised on social media platforms against the hedge fund industry. Policy makers may seek to better understand how the combination of potential information inefficiencies (channelled via social media platforms) may require policy responses. Additional future research could contribute to this in analysing social media impacts on markets and financial stability as such.

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Appendix A. Additional Tables and Figures

Table A.2: MSCI World to China Index mapping/stock [alphabetical, based on Bloomberg]

Name (stock)	Benchmark (market return) index
ADVANTEST CORP	TOPIX INDEX (TOKYO)
AMPHENOL CORP	SP 500 INDEX
ANGLO AMERICAN	FTSE 100 INDEX
APPLIED MATERIALS	S&P 500 INDEX
ASM PACIFIC TECHNOLOGY	Hang Seng Index
BANK EAST ASIA	Hang Seng Index
BEIGENE ADR	S&P 500 INDEX
BHP GROUP (AU)	S&P/ASX 200 INDEX
BHP GROUP (GB)	FTSE 100 INDEX
BROADCOM	S&P 500 INDEX
BUDWEISER BREWING CO	Hang Seng Index
CAPITALAND	Straits Times Index STI
CIMIC GROUP	S&P/ASX 200 INDEX
CK INFRASTRUCTURE HLDGS	Hang Seng Index
FIRST QUANTUM MINERALS	Straits Times Index STI
FORTESCUE METALS GROUP	S&P/TSX COMPOSITE INDEX
HANG LUNG PROPERTIES	Hang Seng Index
HIROSE ELECTRIC CO	TOPIX INDEX (TOKYO)
HONGKONG CHINA GAS	Hang Seng Index
HONGKONG LAND (USD)	S&P/ASX 200 INDEX
INFINEON TECHNOLOGIES	Straits Times Index STI
IPG PHOTONICS	DAX INDEX
JARDINE MATHESON (USD)	S&P 500 INDEX
JARDINE STRATEGIC (USD)	Straits Times Index STI
KERRY PROPERTIES	Hang Seng Index
MANULIFE FINANCIAL CORP	Straits Times Index STI
MARVELL TECHNOLOGY GROUP	S&P/TSX COMPOSITE INDEX
MAXIM INTEGRATED PRDCTS	S&P 500 INDEX
MEIJI HOLDINGS CO	TOPIX INDEX (TOKYO)
MURATA MANUFACTURING CO	TOPIX INDEX (TOKYO)
NEW WORLD DEVELOPMENT	Hang Seng Index
NXP SEMICONDUCTORS (US)	S&P 500 INDEX
PATTINSON (WASHINGTON)	Straits Times Index STI
QORVO	S&P 500 INDEX
QUALCOMM	S&P 500 INDEX
RIO TINTO LTD (AU)	S&P 500 INDEX
RIO TINTO PLC (GB)	S&P/ASX 200 INDEX
SEEK	FTSE 100 INDEX
SHARP CORP	TOPIX INDEX (TOKYO)
SINGAPORE AIRLINES	S&P/ASX 200 INDEX
SMITH (A.O.) CORP	S&P 500 INDEX
SWATCH GROUP INH	S&P 500 INDEX
SWATCH GROUP NAM	SWISS MARKET INDEX
DK CORP	TOPIX INDEX (TOKYO)
TEXAS INSTRUMENTS	S&P/ASX 200 INDEX
VENTURE CORP	SWISS MARKET INDEX
WH GROUP	Hang Seng Index
WILMAR INTERNATIONAL	Straits Times Index STI
WOODSIDE PETROLEUM	Straits Times Index STI
YANGZIJIANG SHIPBUILD	S&P/ASX 200 INDEX

#	Name	#	Name	#	Name	#	Name	#	Name
1	ADVANTEST CORP	2	NXP SEMICONDUCTORS (US)	3	BANK EAST ASIA	4	BHP GROUP (AU)	5	RIO TINTO LTD (AU)
6	CAPITALAND	7	HIROSE ELECTRIC CO	8	HONGKONG CHINA GAS	9	MEIJI HOLDINGS CO	10	MURATA MANUFACTURING CO
11	NEW WORLD DEVELOPMENT	12	RIO TINTO PLC (GB)	13	SHARP CORP	14	SINGAPORE AIRLINES	15	SWATCH GROUP NAM
16	TDK CORP	17	TEXAS INSTRUMENTS	18	WOODSIDE PETROLEUM	19	SWATCH GROUP INH	20	APPLIED MATERIALS
21	QUALCOMM	22	JARDINE MATHESON (USD)	23	JARDINE STRATEGIC (USD)	24	HONGKONG LAND (USD)	25	CIMIC GROUP
26	CK INFRASTRUCTURE HLDGS	27	VENTURE CORP	28	BHP GROUP (GB)	29	MANULIFE FINANCIAL CORP	30	ASM PACIFIC TECHNOLOGY
31	INFINEON TECHNOLOGIES	32	AMPHENOL CORP	33	QORVO	34	SMITH (A.O.) CORP	35	MARVELL TECHNOLOGY GROUP
36	KERRY PROPERTIES	37	ANGLO AMERICAN	38	PATTINSON (WASHINGTON)	39	FIRST QUANTUM MINERALS	40	FORTESCUE METALS GROUP
41	SEEK	42	WILMAR INTERNATIONAL	43	IPG PHOTONICS	44	MAXIM INTEGRATED PRDCTS	45	BROADCOM
46	YANGZIJIANG SHIPBUILD	47	WH GROUP	48	BEIGENE ADR	49	BUDWEISER BREWING CO	50	HANG LUNG PROPERTIES

Table A.3: Stock companies mapping MSCI World with China Exposure [source:MSCI]

Tweet	Stocks														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.1023	0.1314	−0.0019	−0.0191	0.0215	0.0107	0.2032	0.0223	0.1821	0.0368	0.0435	−0.0023	−0.0348	0.0084	−0.0624
2	0.0590	−0.0522	−0.0327	0.0310	−0.0328	−0.0033	−0.0053	0.0339	0.0529	0.0537	0.0243	0.0344	−0.2458	0.0087	0.0202
3	−0.0004	0.0698	0.0274	−0.0867	−0.0081	−0.0066	0.0581	0.0041	−0.0525	−0.1414	0.0463	−0.0234	0.1339	−0.0241	0.0278
4	0.1363	0.1286	0.0712	0.0581	0.0962	0.0007	0.0336	0.0228	−0.0037	0.1901	0.0310	0.0460	0.1390	0.0313	−0.0981
5	0.2610	0.0919	0.0403	−0.0972	−0.1587	0.0252	0.0950	−0.0349	0.0388	0.0294	−0.0958	−0.1287	−0.0857	−0.0146	−0.1268

Table A.4: CAR analysis pre/post -10/+10d event window Stocks 1-15 Results

Tweet	Stocks														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	−0.1352	0.0149	−0.0700	−0.0715	0.1009	−0.1339	0.0752	0.0776	0.0701	−0.0422	−0.0190	−0.0617	−0.0024	0.1188	−0.0284
2	−0.0461	0.0090	−0.0554	0.0146	−0.0069	0.1072	0.0219	0.0139	0.0114	0.0394	0.0376	−0.0281	0.0768	−0.0286	0.0875
3	−0.0146	−0.0044	0.0656	0.0225	0.0455	−0.1129	−0.0496	−0.0415	0.0348	−0.0038	0.0433	−0.0035	−0.0820	0.0123	0.0231
4	0.1172	0.0335	0.0417	−0.0782	0.0582	−0.0922	0.0318	0.0608	0.0157	0.0601	0.0309	0.0582	0.0279	−0.0274	0.0978
5	0.0956	0.0880	−0.0159	−0.1230	0.0232	0.0135	−0.1577	−0.0803	−0.0928	−0.0801	−0.0753	0.1105	−0.0814	−0.0726	0.1859

Table A.5: CAR analysis pre/post -10/+10d event window Stocks 16-30 Results

Tweet	Stocks														
	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
1	−0.0146	0.0599	−0.1097	0.0405	−0.0993	0.0449	−0.0149	0.0540	0.0502	0.0955	−0.0502	0.0534	0.0817	0.0522	0.0458
2	0.0788	−0.0014	0.0332	0.0242	0.0674	0.1063	0.0780	−0.1018	0.0239	0.0402	−0.0064	−0.0539	−0.0558	0.0079	0.1374
3	0.0058	−0.0151	−0.0457	0.0467	0.0438	−0.0372	−0.0314	−0.0891	−0.0144	0.0604	−0.0490	0.0112	0.0793	−0.0026	−0.0126
4	0.0587	0.0841	−0.0219	0.0510	0.0783	0.1429	−0.0239	0.0293	0.0083	0.2868	−0.0763	0.0192	0.1347	−0.0081	0.0304
5	0.0230	−0.0697	0.0359	0.1096	−0.0057	−0.0707	−0.1973	−0.0590	−0.3165	−0.1078	−0.0610	0.0122	0.0023	−0.1038	−0.0204

Table A.6: CAR analysis pre/post -10/+10d event window Stocks 31-45 Results

Tweet	Stocks				
	46	47	48	49	50
1	−0.0269	0.1322	0.0306	NaN	0.0515
2	−0.0087	−0.0167	0.0985	NaN	0.0259
3	0.0250	0.0699	−0.0104	NaN	0.0111
4	0.0142	0.0893	−0.1607	NaN	0.1284
5	−0.2626	−0.0800	0.1869	NaN	−0.0110

Table A.7: CAR analysis pre/post -10/+10d event window Stocks 46-50 Results

Tweet	Stocks														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.1733	0.1632	0.0325	0.0099	0.0367	0.0023	0.1244	−0.0139	0.1055	0.1578	0.0107	0.0593	0.0086	0.0308	0.0398
2	−0.0857	0.0145	−0.0433	0.0532	0.0202	0.0005	−0.0375	0.0014	−0.0091	0.0547	0.0144	0.0703	−0.2573	−0.0220	0.0181
3	0.0139	0.0588	0.0097	−0.0876	−0.0118	0.0135	0.0128	0.0017	−0.0397	−0.1415	0.0447	−0.0362	0.0767	−0.0017	−0.0065
4	0.0196	0.0390	0.0370	0.0505	0.1075	0.0049	0.0176	0.0058	0.0402	0.1392	0.0305	0.0283	−0.0235	−0.0007	−0.1343
5	0.0433	0.0245	−0.0158	−0.0703	−0.1148	0.0033	0.0247	−0.0112	0.0614	−0.0120	−0.1327	−0.0752	−0.1005	−0.0126	−0.0676

Table A.8: CAR analysis pre/post -5/+5d event window Stocks 1-15 Results

Tweet	Stocks														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	−0.0074	0.0005	−0.0245	0.0297	0.0256	−0.1454	0.0347	0.0903	0.0188	−0.0260	−0.0260	−0.1054	0.0481	0.0798	0.0268
2	−0.0874	0.0156	0.0176	0.0097	−0.0145	0.0583	0.0171	−0.0103	0.0491	−0.0259	−0.0194	−0.0243	0.0968	−0.0688	−0.0271
3	−0.0388	−0.0035	0.0352	−0.0085	0.0466	−0.0232	−0.0360	−0.0050	0.0599	−0.0224	0.0037	0.0247	−0.0881	0.0211	−0.0027
4	0.0383	−0.0189	−0.0281	−0.1251	−0.0010	−0.0191	0.0329	0.0434	−0.0049	0.0177	−0.0249	0.0117	−0.0122	−0.0134	0.0252
5	0.0717	−0.0018	−0.0005	−0.0651	−0.0041	−0.0240	−0.1201	−0.0626	−0.1254	−0.0473	−0.0389	0.0292	−0.0256	−0.0756	0.0271

Table A.9: CAR analysis pre/post -5/+5d event window Stocks 16-30 Results

Tweet	Stocks														
	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
1	0.0381	0.0480	−0.0315	0.0134	−0.0460	0.0140	0.0305	0.0210	0.0825	0.0997	−0.0583	0.0212	0.0357	0.0644	0.0458
2	0.0480	0.0166	−0.0500	−0.0524	−0.0124	0.0630	0.1164	−0.0558	0.1160	0.0952	−0.0450	−0.0117	−0.1053	−0.0151	0.0969
3	0.0030	−0.0242	0.0013	0.0462	0.0522	0.0140	−0.0442	−0.0241	−0.1217	0.0748	−0.0337	0.0056	0.0669	0.0055	−0.0482
4	0.0044	0.0268	−0.0428	0.0336	0.0086	0.0100	−0.0702	−0.0064	0.0156	0.2416	−0.0628	−0.0111	0.0051	−0.0531	0.0065
5	−0.0097	−0.0517	−0.0096	0.0774	−0.0682	−0.0545	−0.0813	−0.0301	−0.1985	−0.1466	−0.0562	0.0238	−0.0812	−0.1339	−0.0326

Table A.10: CAR analysis pre/post -5/+5d event window Stocks 31-45 Results

Tweet	Stocks				
	46	47	48	49	50
1	0.0726	0.0588	0.0755	NaN	0.0315
2	0.0041	0.0462	−0.0338	NaN	0.0199
3	−0.0103	0.0659	−0.0254	NaN	0.0328
4	0.0394	−0.0015	0.0125	NaN	0.0723
5	−0.2253	−0.0620	0.0779	NaN	0.0177

Table A.11: CAR analysis pre/post -5/+5d event window Stocks 46-50 Results

Tweet	Stocks														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.1177	0.1392	0.0057	0.0074	0.0329	−0.0178	0.1379	0.0049	0.1573	−0.0262	0.0218	0.0142	0.0430	−0.0245	−0.0569
2	−0.0226	−0.0484	−0.0303	0.0800	0.0640	0.0110	−0.0087	0.0124	0.0467	−0.0330	0.0498	0.0775	−0.1935	0.0101	0.0253
3	−0.0616	0.0385	0.0133	−0.0762	0.0027	0.0178	0.0143	−0.0038	−0.0750	−0.1303	0.0727	0.0101	0.0833	−0.0146	0.0396
4	0.0443	0.0357	0.0639	0.0033	0.0110	−0.0264	0.0041	0.0176	0.0246	−0.0066	−0.0013	−0.0163	0.0491	0.0157	−0.0118
5	−0.0575	0.0391	0.0104	−0.0207	−0.0650	0.0190	0.0768	−0.0233	0.0512	−0.0355	−0.0100	−0.0406	0.0069	0.0130	−0.0475

Table A.12: CAR analysis no pre event period (0d) /post +10d event window Stocks 1-15 Results

Tweet	Stocks														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	−0.0899	0.0507	−0.0407	−0.0415	0.0744	−0.1308	0.0788	0.0614	0.0892	−0.0634	0.0103	−0.0361	0.0290	0.0598	0.0663
2	−0.0692	0.0436	−0.0273	0.0241	0.0251	0.0758	−0.0013	−0.0427	0.0156	0.0599	0.0184	−0.0258	0.0919	−0.0244	0.0220
3	−0.0826	−0.0008	0.0236	0.0439	−0.0030	−0.1033	−0.0564	−0.0582	0.0453	−0.0383	0.0291	0.0184	−0.0534	0.0191	0.0324
4	−0.0071	0.0219	0.0410	−0.0145	−0.0364	0.0292	0.0322	0.0032	0.0198	0.0559	0.0108	−0.0141	−0.0085	0.0055	0.0531
5	−0.0131	0.0254	−0.0129	−0.0442	−0.0009	0.0530	−0.1063	−0.0275	−0.0148	−0.0581	−0.0243	0.0850	0.0025	−0.0176	0.1101

Table A.13: CAR analysis no pre event window (0d)/ post +10d event window Stocks 16-30 Results

Tweet	Stocks														
	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
1	0.0142	−0.0259	−0.1298	0.0220	−0.0155	0.0374	0.0144	0.0358	−0.0269	0.0153	0.0170	0.0072	0.0514	0.0593	0.0584
2	0.0063	0.0016	0.0296	0.0453	0.0666	0.0824	0.1100	−0.0069	−0.0629	0.0358	−0.0479	0.0113	−0.0742	−0.0186	0.1403
3	−0.0005	0.0122	0.0105	0.0464	−0.0392	0.0063	−0.0013	−0.0193	0.0902	0.0563	−0.0081	0.0077	0.0965	0.0059	0.0246
4	−0.0038	0.0275	−0.0462	0.0526	−0.0043	−0.0027	−0.0855	0.0451	−0.1184	0.0408	−0.0326	−0.0125	0.1048	−0.0101	0.0243
5	−0.0086	−0.0047	0.0202	0.0756	0.0099	0.0204	−0.0371	−0.0229	−0.1233	0.0508	−0.0353	−0.0192	0.0675	−0.0172	0.0043

Table A.14: CAR analysis no pre event window (0d)/ post +10d event window Stocks 31-45 Results

Tweet	Stocks				
	46	47	48	49	50
1	−0.0007	0.1586	−0.0086	NaN	0.0496
2	0.0510	0.0081	−0.0249	NaN	0.0302
3	−0.0089	0.0888	−0.0076	NaN	0.0372
4	−0.0526	0.0563	−0.0373	NaN	0.0445
5	−0.2375	−0.0632	0.0683	NaN	−0.0432

Table A.15: CAR analysis no pre event window (0d)/post +10d event window Stocks 46-50 Results

Tweet	Stocks														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	0.1599	0.1061	0.0175	0.0080	0.0445	−0.0210	0.0918	−0.0231	0.1012	0.0830	0.0098	0.0399	0.0432	−0.0007	−0.0178
2	−0.1025	0.0018	−0.0222	0.0268	0.0177	0.0036	−0.0463	0.0027	0.0191	−0.0289	0.0171	0.0241	−0.1677	0.0165	0.0232
3	−0.0041	0.0458	−0.0053	−0.0603	0.0108	0.0160	0.0071	0.0032	−0.0405	−0.1365	0.0588	0.0090	0.0870	0.0031	0.0285
4	−0.0075	0.0145	0.0347	−0.0138	0.0146	−0.0145	0.0071	0.0159	0.0440	0.0247	−0.0041	−0.0133	−0.0530	0.0048	−0.0416
5	−0.0146	0.0014	−0.0204	−0.0190	−0.0793	0.0041	0.0219	−0.0147	0.0604	−0.0287	−0.1006	−0.0512	−0.0063	0.0165	−0.0323

Table A.16: CAR analysis no pre event window (0d)/post +5d event window Stocks 1-15 Results

Tweet	Stocks														
	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	−0.0021	0.0155	−0.0376	−0.0080	0.0136	−0.1209	0.0362	0.0545	0.0251	−0.0173	−0.0071	−0.0690	0.0428	0.0550	0.0760
2	−0.1060	0.0240	0.0058	0.0159	0.0040	0.0244	0.0117	−0.0420	0.0405	0.0134	0.0006	−0.0088	0.0331	−0.0443	−0.0416
3	−0.0633	0.0274	0.0254	0.0300	0.0108	−0.0333	−0.0284	−0.0139	0.0518	−0.0235	0.0324	0.0195	−0.0466	0.0103	−0.0076
4	−0.0170	0.0266	−0.0227	−0.0435	0.0183	0.0284	0.0220	0.0257	0.0273	0.0289	−0.0104	−0.0015	−0.0269	−0.0096	0.0138
5	−0.0225	0.0078	0.0107	−0.0268	0.0067	−0.0016	−0.0772	−0.0258	−0.0797	−0.0360	−0.0186	0.0311	0.0074	−0.0224	0.0556

Table A.17: CAR analysis no pre event window (0d)/post +5d event window Stocks 16-30 Results

Tweet	Stocks														
	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45
1	−0.0113	−0.0032	−0.0831	−0.0057	−0.0225	0.0025	0.0342	0.0120	−0.0720	0.0524	−0.0149	−0.0079	0.0185	0.0214	0.0392
2	0.0146	0.0078	−0.0307	−0.0301	0.0235	0.0475	0.0429	0.0095	0.0258	0.0248	−0.0486	0.0110	−0.0787	0.0086	0.1190
3	0.0226	0.0266	0.0556	0.0346	0.0209	−0.0073	0.0150	0.0138	0.0202	0.0631	−0.0014	0.0109	0.0924	0.0263	0.0158
4	0.0008	0.0223	−0.0225	0.0343	0.0366	−0.0204	−0.0724	0.0135	−0.0886	0.0305	−0.0030	−0.0299	0.0091	−0.0011	0.0306
5	0.0105	−0.0164	0.0021	0.0617	−0.0222	−0.0169	−0.0001	−0.0080	−0.0762	−0.0620	−0.0383	0.0250	0.0356	−0.0296	0.0089

Table A.18: CAR analysis no pre event window (0d)/post +5d event window Stocks 31-45 Results

Tweet	Stocks				
	46	47	48	49	50
1	0.0289	0.0877	−0.0477	*NaN*	0.0263
2	0.0315	0.0117	−0.0255	*NaN*	0.0024
3	−0.0339	0.0816	0.0390	*NaN*	0.0365
4	−0.0170	−0.0253	−0.0012	*NaN*	0.0090
5	−0.2511	0.0128	0.0007	*NaN*	−0.0269

Table A.19: CAR analysis no pre event window (0d)/post +5d event window Stocks 46-50 Results

Tweets studied for this analysis [7]

- tweet 1 31/10/2018 relaxing October 31, 2018, 08:04:26 AM- *"Stock Market up more than 400 points yesterday.Today looks to be another good one. Companies earnings are great!*

- tweet 2 04/12/2018 tensing December 4, 2018, 07:20:27 PM- *"We are either going to have a REAL DEAL with China, or no deal at all - at which point we will be charging major Tariffs against Chinese products being shipped into the United States."*

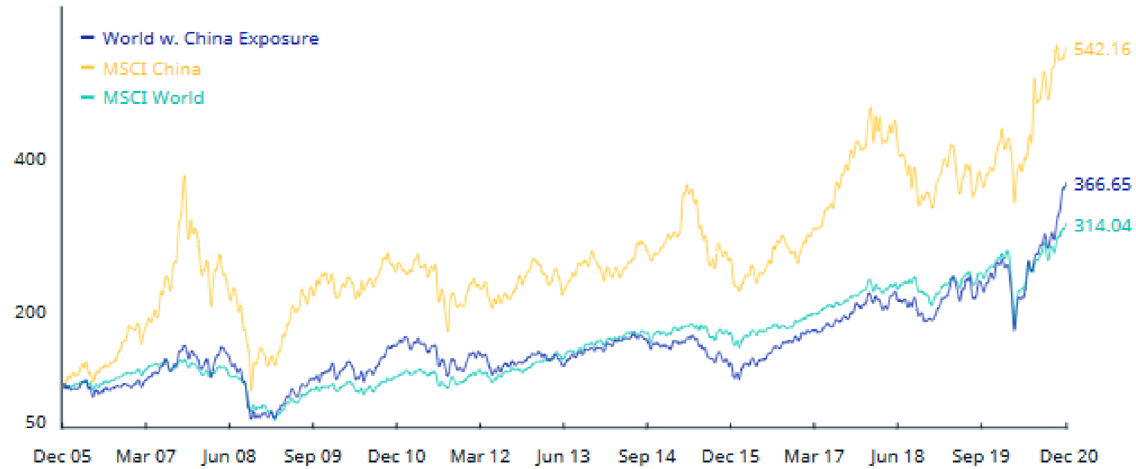
- tweet 3 03/01/2019 relaxing January 3, 2019, 09:52:13 AM- *"The United States Treasury has taken in MANY billions of dollars from the Tariffs, we are charging China and other countries thathave not treated us fairly. In the meantime, we are doing well in various TradeNegotiations currently going on. At some point this had to be done!"*

- tweet 4 01/02/2019 relaxing February 1, 2019, 09:16:32 AM - *"Best January for the DOW in over 30 years. We have, by far, the strongest economy in the world!"*

- tweet 5 03/08/2019 tensing August 3, 2019, 07:46:45 AM- *"Things are going along very well with China.They are paying us Tens of Billions of Dollars, made possible by their monetary devaluations and pumping in massive amounts of cash to keep their system going.So far our consumer is paying nothing - and no inflation. No help from Fed"*

[7] The appendix lists some further examples of Trump Tweets taken from the Trump Twitter Archive (`http://www.trumptwitterarchive.com`).

CUMULATIVE INDEX PERFORMANCE — GROSS RETURNS (USD) (DEC 2005 – DEC 2020)



ANNUAL PERFORMANCE (%)

Year	World w. China Exposure	MSCI China	MSCI World
2020	39.17	29.67	16.50
2019	38.38	23.66	28.40
2018	-9.79	-18.75	-8.20
2017	29.66	54.33	23.07
2016	22.52	1.11	8.15
2015	-15.16	-7.62	-0.32
2014	0.43	8.26	5.50
2013	9.83	3.96	27.37
2012	13.38	23.10	16.54
2011	-19.94	-18.24	-5.02
2010	23.99	4.83	12.34
2009	82.01	62.63	30.79
2008	-51.80	-50.83	-40.33
2007	37.39	66.24	9.57

Figure A.5: MSCI World with China Exposure index performance (source:MSCI)

Euro Area Sovereign Ratings and the Rescue Funds: A Wavelet Transform Coherence Analysis

Jürgen Klaus[a,*], Maroua Benghoul[b,]

[a]*Faculty of Business and Economics, Technische Universität Dresden, Germany*
[b]*Eskişehir Technical University, Faculty of Science, Statistics Department, Eskişehir,Turkey,*

Abstract

The Euro Area (EA) rescue funds —the European Financial Stability Facility (EFSF) and the European Stability Mechanism (ESM)— replace sovereign funding should the EA members lose market access during financial stress or crisis. Importantly, the same EA members are also financial guarantors to these rescue funds and contribute to the funds' credit rating. The funds depend on a strong rating as they finance large volumes in capital markets in crisis times if a guaranteeing member becomes a client. This paper analyses if the funds are impacted by guarantor rating changes and how markets react and incorporate these information. Empirical results from this market efficiency study find overall only small impacts from EA member ratings change to the rescue funds' funding conditions. Furthermore, not all large guarantor rating changes impact the funds alike. The results also suggest a higher correlation resilience for the lower rated and less capitalised EFSF compared to the stronger capitalised and higher rated ESM. The study combines behavioral finance aspects such as prevailing market sentiment and news narratives to interpret the empirical results.

Keywords: Euro area ratings, sovereign ratings, wavelet transform, correlation, European Financial Stability Facility, European Stability Mechanism, financial crises and rating

JEL classification: G1,G4,E44,E47,F32

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*Corresponding author, email: Juergen.Klaus@mailbox.tu-dresden.de

1. Introduction

The European Financial Stability Facility (EFSF) was created 2010 during the euro sovereign debt crisis (euro crisis). Shortly after its inception, Ireland requested the EFSF's financial support. Other euro area (EA) member states followed with Greece and Portugal. In 2013, the European Stability Mechanism (ESM) was created as a permanent intergovernmental financial institution. Additional support programmes for Cyprus, Spain and Greece followed. The EFSF and the ESM (the rescue funds) provide a financial backstop for EA members by raising funds for financial support in capital markets. Since inception, both institutions issued around EUR300bn of debt, making them one of the largest issuers in the european financial debt markets.[1]

From a behavioral finance angle, a negative market and credit sentiment towards the rescue funds could question their mission and impact the EA's financial stability should the funds fail to provide a sound safety umbrella. From an efficient market framework angle —under its semi strong form— it is assumed that markets are informational efficient, and new information about credit quality changes should be reflected in markets. Both funds are owned and guaranteed by the EA member states who are jointly backing the funds' credit strength. Consequently, the rescue funds' credit strength needs to be strong enough to not be negatively impacted in case a guarantor is downgraded or becomes a 'client' by requesting financial support.

The funds are a surrogate to sovereign funding for their beneficiary members who lost either market access to own funding or can only get funding at non sustainable levels. On top of the required large funding capacity, the rescue funds need to fund billions of euros under challenging market conditions with high volatility and stressed markets (e.g. during a financial crisis). Essentially, the funds need to secure financing when their guaranteeing sovereign issuers are not capable to fund. Its a core function for euro rescue funds and essential for the their mission and reliability is a strong credit quality. This

[1] Meanwhile, given the pandemic crisis in 2020, the European Commission launched and even larger recovery fund called *Next Generation EU* with a potential volume of up to EUR750bn. Still, EFSF and ESM additional lending capacity remains over EUR400bn for which they provided up to EUR240bn for a pandemic crisis support programme in May 2020.

mission statement required top ratings from the main credit rating agencies (CRA). It was priority for the institutional reputation and financial reliability as the new EFSF used a guarantee structure solely based on the strength the fund's own guarantors being the EA member states (Regling & Watson, 2010). Both rescue funds benefit from high ratings from the main CRAs.[2] The rescue fund ratings, their programme countries and some large guarantors had various rating and outlook adjustments.

Our motivation is to study rating change impacts on market conditions. Under rational expectations, a rescue institution which is financially supporting its own guarantors bears a one-way-credit risk (guarantors in financial stress also provide guarantees to the rescue). Our work assumption is that due to the lower equity and more complex guarantee structure, the lower rated EFSF should be more vulnerable to guarantor rating changes. Compared to the ESM, the EFSF depends stronger on the guarantee scheme and currently has larger loans outstanding. Hence, we posit that the ESM should be more resilient on rating changes. The ESM is a permament institution for future crises with a stronger capital base as it deploys a paid in capital (PIC) of over EUR80bn provided by agreed callable guarantees per member state. We study correlation impacts on the rescue funds' debt markets against rating actions of its guarantors. From a behavioral finance perspective, the research intends to show results of informational efficiency regarding market sentiment. For example, if rating actions of certain guarantors led to changes of the rescue fund ratings or if market participants differentiate between different ratings levels (e.g. investment grade class). Additionally, we study if markets react differently to rating adjustments of smaller and larger guarantors. Based on a comprehensive multi year data set, we first perform a Spearman correlation anaylsis and, secondly, we zoom into correlation drivers using a wavelet analysis framework.

Section 2 introduces selected literature to identify the research gap, followed by Section 3 on data and methodology. Section 4 presents results on both analyses. Section 5 concludes and provides an research outlook and policy implications.

[2]The EFSF and ESM received top ratings for minimal credit risk at inception (Moody's: Aaa).

2. Literature review

The great financial crisis (GFC) brought CRA-research in focus as the agencies were accused to play a major role in assessing credit risk insufficiently. Already earlier, Cantor & Packer (1996) identified that sovereign ratings can be explained by per capita income, GDP growth, inflation, external debt, the level of economic development and the default history. Later studies confirm these findings by adding more detailed explanatory variables e.g. in Afonso (2005), Afonso et al. (2011). Mellios & Paget-Blanc (2006) have similar results for sovereign ratings as mostly influenced by the aforementioned factors, and adding real exchange rate changes and corruption levels, as measured by Transparency International's Corruption Perceptions Index. D'Agostino & Lennkh (2017) disentangle rating drivers into a 'fundamental' and 'subjective' component using Moody's methodology and recommend CRAs to improve their methodological transparency. Kiff et al. (2012) discuss funding cost impacts with evidence that CRA opinions impact funding costs of sovereign issuers. The authors assess the impact of sovereign rating events on credit default swaps (CDS) concluding that ratings are a concern for financial stability.[3] Poon & Shen (2020) study the information efficiency in United States (US) credit markets and conclude that CRA actions serve as a coordination mechanism between issuers and CRAs.

Literature provides studies on rating information efficiencies in markets during different crisis times, asset classes and information channels. Gande & Parsley (2005) investigate effects of inter-issuer-market sovereign credit rating changes using sovereign credit spreads from 1991 to 2000. The authors find spillover effects and significant rating event impacts on sovereign credit spreads. Further, they find asymmetric effects as positive ratings events impact spreads lower than negative ratings events are associated with an increase in credit spreads. Candelon et al. (2011) discuss spillover effects of sovereign ratings during the GFC in 2007-2010 and find that sovereign rating downgrades show statistically and economically significant spillover effects both across countries and financial markets. Beirne & Fratzscher (2013) find for emerging economies that a deteriorating in

[3] Studying CDS spreads are an interesting study object yet the euro rescue funds do not (yet) provide a CDS market. Hence, we opted for a credit risk measurement using a risk free rate in Section 3.

country fundamentals is a key driver of contagion during the euro crisis. Using credit default- and sovereign spread bond market data, the authors identify sharp contagion effects for a few sovereign issuers (due to an increased market sensitivity to fundamental country data). Reusens & Croux (2017) discuss rating determinants prior and after crisis by comparing the importance of different sovereign credit rating determinants. The authors find that after the start of the GFC in 2009, the importance of the financial balance, the economic development and the external debt increased substantially and the effect of euro area membership switched from positive to negative.

The euro crisis during which the rescue funds were launched provided studies on asset class impacts. Alsakka & ap Gwilym (2013) discuss CRA spillover effects on foreign exchange markets studying credit events prior the great GFC and the euro crisis to find that spillover effects increased during the crisis times. Williams et al. (2013) analyse sovereign rating impacts on banks ratings and find that sovereign rating upgrades (downgrades) have strong effects on bank rating upgrades (downgrades). Borensztein et al. (2013) investigates the link between sovereign- and corporate ratings. Using spread analysis, Gärtner et al. (2011) find that arbitrary rating downgrades trigger processes of self-fulfilling prophecies that may drive even relatively healthy countries towards default.

Literature on the rescue funds includes mainly institutional and legal topics (not in scope of our work). Relevant for our research is a discussion in 2010 regarding the funds' credit strength and institutional set up (Gros & Meyer (2011)). We contribute to this discussion with our results as Gros & Meyer (2011) indicated that the EFSF structure bears a domino effect risk due to the step out guarantor feature.[4] The paper identifies the guarantee based set up as a risk to the EFSF's mission and proposes a bank status with access to the European Central Bank (ECB). Howarth & Spendzharova (2019) discuss governance problems of the two rescue funds related to the set up as international financial institution (IFI) similar to the International Monetary Fund (IMF) while being governed by the Eurozone governance architecture. Gocaj & Meunier (2013) discuss whether the

[4]Under the EFSF, a country receiving financial support is not guaranteeing the initial share anymore and thus becomes a stepping out guarantor for the time of the programme (Art.2(7) of the EFSF framework agreement).

crisis of 2010-2012 provides an instance of historical institutionalism by introducing the rescue funds argueing that it may lead to a broader fiscal union (e.g. joint debt and fiscal policy). The rescue funds' credit strength was part of a short policy briefing discussing the EFSF downgrade on the back of sovereign guarantor downgrades and especially the importance of France ratings in Rocholl (2012). Our research picks up this discussion as the authors did not provide any empirical analysis in their policy contribution. However, Rocholl (2012) shows that EA member state rating actions were a worrisome factor for the rescue funds' ratings and our contribution aims to track impacts measuring its correlation impact and drivers. Dieckmann (2012) studies the announcement effect of the EFSF between 2010-2011 and finds the effect on decreased borrowing rates ambiguous for various guarantors sovereign market rates. Using spread levels, the paper converts the spread effects into a net positive debt effect for the Eurozone of around EUR108bn. Amongst other, our research provides an empirical analysis under the available data set since 2012/2013 to support or reject these previous discussions.

3. Data and Methodology

3.1. Dataset

3.1.1. Issuer and rating data

Our data includes EFSF/ESM and the programme countries Greece, Portugal, Ireland, Cyprus as the most relevant issuers for our studies as we expect to find best results under situations where these countries experienced rating pressures until they decided to apply for an EFSF/ESM programme. We exclude Spain as the fifth the programme country for the detailed wavelet analysis. This is due their short term special support programme and Spain's guarantor share is subsequently lower which makes it less evident for our study purpose.[5] From non-programme countries with a high guarantee share we intend to include the top three stakeholders Germany, France and Italy. However, for Germany, there is no event study background justifying further analysis under wavelets. Germany

[5] The Spain ESM support was special due to the nature (one off banking sector recapitalisation), a short duration (one year), and early repayments (less relevant for our study purpose).

has not experienced any rating action as being AAA rated during the observation time. Thus we exclude Germany from further analysis. We include France based on previous research (Rocholl, 2012) indicating the importance of France ratings for the rescue funds. Lastly, we include Italy as the third largest shareholder with rating events and press rumours and discussion of becoming a potential programme country.

We use Moody's monthly rating history for our time series for the aforementioned issuers. Using Moody's rating history is motivated by the fact that some issuers do not offer all ratings (e.g. ESM had no S&P rating) and that ratings broadly align along their rating cluster between agencies. We convert the ratings from an alphanumeric scale to a numerical scale (Annex Table A2). The highest rating (Aaa) equals to a value of 19. Lower ratings along the Moody scale are numbered with 1 unit lower consequently to the equivalent default ratings with a joint value of 1. Rating outlooks are converted to numeric values as well receiving different outlook keys values (stable/no outlook$= 0$, positive$= 0.25$, negative$= -0.25$) . The use of monthly rating data is sufficient as ratings usually do not change more than once or twice a year and it was extremely unusual to have several actions in the same month.

3.1.2. Market data

Observation time frame is 01. January 2012 until 08 February 2021 for which we retrieve the monthly average 2- and 10 year generic yield-to-maturities for securities of the selected issuers. Generic bond yields provide the best market data regarding liquidity and most accurate bonds.[6] We consider these two maturity tenors as most liquid and useful for our studies. A short and long bond maturity allows to study impact given rating changes on a term structure. As a first observation and caveat retrieving the data, the euro rescue fund issuers data offers only sufficient and complete available data from June 2013 onwards. Prior to that, no sufficient bond and spread data for both funds were available given their ramp-up phase in financial markets. We therefore opted to impute the missing

[6] The disadvantage of using specific bonds via their International Security Identification Numbers (ISIN) is the low price accuracy as these ISINs may not stay the most liquid maturity bond in a certain segment due to the decay of time and new issuances.

observations using the R MICE package's multiple imputation. The data until June 2013 has been imputed based on this method. Additionally, we retrieve the generic euro interest rate swap (IRS) levels for both tenors across the time frame. We include IRS levels as a risk free rate of generic interest rates in the euro area as market practice to compare bond yields on an indexed relative basis. We use Bloomberg professional data and verify the retrieved data by using Refinitiv as a second data source.[7]

3.2. Research design and methodology

3.2.1. Credit spread

We adopt from existing literature using IRS and bond yields as a credit spread (CS) metric for credit rating event studies and analysing credit topics (Liu et al., 2006, Hull et al., 2004). The CS is defined as a difference (spread) between the mid yield to maturity (Bondyield) for each issuer (EFSF and ESM) and the generic IRS market rates in Eq.1. The credit spread CS for a maturity m at time t is expressed in percent as the simple difference of the issuer $j \in \{EFSF, ESM\}$ generic bond yield and the euro interest rate swap rate yield with same maturity m at time t (each 2- and 10year) given by

$$CS^j_{mt} = Bondyield^j_{mt} - IRSyield_{mt}. \tag{1}$$

This delivers for each issuer and maturity spread levels which we consider as most suitable to identify correlation impacts for the rescue funds towards rating changes of their guarantors. This is shown in our analysis output as EFSF-Spread and ESM-Spread for 2Y and 10Y in our Spearman heatmap[8] and as the frequency domain (on the Y axis) in the coherence charts (section 5).

Following previous studies, we use this spread to measure abrupt correlation changes (Gande & Parsley, 2005, Beirne & Fratzscher, 2013). We expect a correlation change and wider spread levels as a market reaction to a downgrade of any guarantor. This

[7]The detailed rics and fields retrieved are available upon request.

[8]The Spearman correlation analysis (Figure A1) provides results on the different sovereign issuers, the EFSF and ESM and the IRS markets spread proxy. For brevity, the results (section 4) only discuss correlation changes related to EFSF/ESM credit spread.

means, if markets are informational efficient, the rescue fund bond yields rise more (or fall less) than the risk-free IRS yield. If efficiently reflected, the rating event impacts the correlation of this credit spread proxy, as market participants would require a higher or lower credit premium when investing in EFSF/ESM debt. Using this spread levels has multiple advantages. First, it offers a credit risk free component using a generic interest rate derivative curve. Comparing correlation impacts due to rating actions using other sovereign issuers bears the higher risk of idiosyncratic moves which is minimized when using generic derivative curves. Second, IRS markets are highly liquid with sound price information quality and therefore provide a high informational efficiency potential. Third, the IRS market is for many (not all though) issuers in observation used to price new issued bond lines. Especially for new EFSF and ESM issuances, the corresponding marketing levels for new placed bonds are alway quoted against the IRS markets which adds practical relevance. Lastly, as we look at correlation impacts, we can neglect absolute price or yield levels but study the spread differential changes which ignores outright yield moves. While the Spearman table shows significance, the coherence analysis zooms into the drivers of correlation changes of the relationship between the studied variables.

3.2.2. Wavelet analysis

We use the wavelet methodology as it allows analyzing non-normal and non-stationary time series (Masset, 2011, 2015, Struzik, 2001). Wavelet analysis is most applicable to be used in financial data analysis given that financial data is usually asynchronous, contextual and with a lot of noise. Moreover, wavelet analysis allows studying the relationships at different frequencies that helps identifying positive and negative associations at multiple frequencies. We use the credit spread to study the relationship between the rating event and correlation changes and apply the wavelet transform coherence (WTC) to portray the relationship between the variables graphically.

To motivate wavelets, the early Fourier transform has been regarded as a critical mathematical tool since the 18th century, with applications in telephony, computer science, and the audio-visual field. Despite this, a significant flaw in the time information was observed. The Fourier transform reveals the number of signal frequencies but conceals the times at which these frequencies diffuse, as if the signal moments are equivalent (Meyer, 1990, Kaiser, 1995, Burke Hubbard, 1995, Graps, 1995).

To address the issue of fixed temporal resolution, wavelet analysis was introduced as an alternative approach that breaks down a signal in both time and frequency. Wavelets became popular in a variety of fields, including image processing, audio processing, and, more recently, economic and financial areas (Masset, 2011). The wavelets' success was due to a discretization method introduced by Mallat (1989) and later developed as a continued method by Meyer, Daubechies and others (Al-Ani, 2013). Wavelets can decompose non-stationary series with time and frequency localization without any restrictive hypothesis. It was referred as a mathematical microscope by Arneodo et al. (1995) due to its ability to show weak transients and peculiarities in time series (Struzik, 2001). Wavelet transforms are generally classified into three types: continuous wavelet transforms (CWT), discrete wavelet transforms (DWT), and wavelets transformed using multi resolution analysis.

Wavelet transform coherence

Wavelet analysis belongs to the frequency domain analysis sector and was only in the last two decades extended and discovered for financial economical analysis (Masset, 2011). Frequency-domain analysis tools help to understand behaviour of certain financial variables as they permit to get information about the length and the phase of a cycle within the dataset. Masset (2011) contributes a key paper for financial analysis which we base our forthcoming analysis set up upon. The ability to work with non stationary data is further seen as very advantageous especially in econometric financial data sets (Struzik, 2001). Theoretically, a wavelet is simply a time function with a zero mean that follows a basic rule, known as the wavelet eligibility condition:

$$\mathbb{C}_{\psi} = \int_{0}^{\infty} \frac{|\Psi(f)|}{f} df < \infty \tag{2}$$

with

$$\Psi(f) = \int_{-\infty}^{+\infty} \psi(t) e^{-2\pi i f t} dt. \tag{3}$$

The frequency function is given by f for $\Psi(f)$, and Ψ is called the mother wavelet. Eq.3 presents the Fourier transform. To ensure that $C_\psi < \infty$, the following conditions, related to the mother wavelet, must be imposed:

1. $\Psi(0) = 0$, or $\int_{-\infty}^{+\infty} \Psi(t) = 0$
2. $\int_{-\infty}^{+\infty} |\Psi(t)|^2 dt = 1$ (the energy unit).

Wavelet coherence analysis is based on CWT, which decomposes a time series in time-frequency domain by successively convolving the time series with the scaled and translated versions of a mother wavelet function $\Psi 0$ (Mallat, 1989) as

$$W(u, s) = \int_{-\infty}^{\infty} f(t) \overline{\Psi}_(u, s)(t) dt \tag{4}$$

with

$$\Psi_(u, s) = \frac{1}{\sqrt{s}} \Psi(\frac{t - u}{s}). \tag{5}$$

The position (the translation) is determined by u, and the scale (the dilatation) is presented by s. For a signal case, s is the frequency and u is time.

The coefficient $\frac{1}{\sqrt{s}}$ ensures that $\|\Psi_(u, s)\| = 1$.

Using this wavelet transform coherence (WTC) detects transient correlations between signals, primarily to identify correlated areas between signals that would otherwise be uncorrelated (Garg et al., 2013). The WTC is the measurement of the coherency of the Cross-Wavelet Transform (XWT) in the time-frequency space. Following Torrence & Webster (1999), the WTC of two time series is defined as follows:

$$R^2(s) = \frac{\left|S(s^{-1} W_n^{XY}(s))\right|^2}{S(s^{-1} \left|W_n^X(s)\right|^2) S(s^{-1} \left|W_n^Y(s)\right|^2)'}. \tag{6}$$

Eq. 6 includes X, Y as the two time series, and $|W_n^X(s)|, |W_n^Y(s)|$ as the wavelet transforms, n is the time index, s is the scale and S is a smoothing operator. For our analysis, we consider as X the rating events and scores as described in Section 3 and for Y we use the 2Y and 10Y credit spreads.

We use the Matlab toolbox to produce the WTC graphs using Daubechies wavelets and use previous literature methods to interpret results (Grinsted et al., 2004, Boako & Alagidede, 2017) including the MatLab package authors' documentation.[9] Given the research design, we look for ideally look for negative correlation between rating changes to credit spreads per country in each maturity. Interpreting the WTC-charts follows these analytical work assumptions:

Negative rating event → lower rating score	Guarantor downgrade decreases the rescue funds' credit quality.
Positive rating event → higher rating score	Guarantor upgrade increases the rescue funds' credit quality.

To include the second variable, the CS shown as EFSF-Spread and ESM-Spread (Fig.A1), assumes under informational efficient markets that:

Lower rating score → higher credit spreads	Lower credit quality leads to higher credit risk compensation causing abrupt correlation jumps.
Higher credit score → lower credit spreads	The higher credit quality leads to lower credit risk compensation causing abrupt correlation jumps.

We measure informational market efficiency by looking for a negative relationship in the correlation heat maps. The WTC graphs, however, do only show correlation significance while the direction of the arrows indicate the phasing impacts of the two variables (Table A1 5). Hence, left arrows within the cone of influence indicating significant results show negative correlation between rating and spreads (and vica versa for positive correlation).

[9] Detailed in MatLab Wavelet Coherence Documentation and Wavelet Toolbox Author Documentation (retrieved 15.Mar.2022).

4. Results and discussion

4.1. Spearman Correlation

We deploy a Spearman correlation on the full financial data set (Fig. A1). We focus on the correlation between country rating and outlook changes of each guarantor against the EFSF and ESM spread levels (ESM and EFSF Spread 2Y and 10Y in A1).[10]

Results show a high correlation between France (FR) —both in outlook and rating change— and the ESM and EFSF spreads in both maturities. France has a stronger correlation with the ESM than the EFSF. The results for Italy (IT) show low negative correlation with short ESM maturities in Figure A1. In terms of the four programme countries, rating events in Portugal (PT) have a strong positive correlation with short-term ESM bonds but a low correlation with ESM longer maturities and EFSF long and short maturities. The results for Ireland (IE) show high correlations with rating events across the maturities and issuer spectrums, but a low correlation with the ratings outlook. Both Cyprus (CY) and Spain (ES) have moderate correlations between their ratings and ESM 2y and EFSF 10y spreads. Notably, despite the fact that Greece (GR) was the largest beneficiary of support programmes under both rescue fund issuers, we find only a moderate correlation between Greece ratings events and ESM 2y and EFSF 10Yr spreads.

4.2. Wavelet Transform Coherence (WTC) results

The WTC has been used primarily as a mathematical tool to depict a graphical correlation between two variables.[11] Our results show the WTC graphs presented in the Appendix (A3 to A14) as the coherence analysis per country level against the EFSF and ESM credit spread per tenor. We identified in the observation period twenty five rating events (Tab. 5) and run the wavelet analysis across the data set (incl. imputed data areas). As detailed in 3.1.1, we present results for FR/IT/GR/IE/CY and PT. Each sub-section introduces the events and main results along the set of WTC graphs (a-d).

[10] EFSF and ESM guarantors are listed in tables A3 and A4.
[11] A brief instruction how to read and interpret coherence graphs is provided in the Appendix 5.

France (FR) results

The second largest guarantor shows the highest correlations (as also in A1) and the strongest coherence results (A3 and A4). The three rating events (no.4/15/21 in event table 5) indicate high correlation changes in both maturities and especially pronounced in the 10Y ESM maturties (Fig.A3).[12] Looking at the outlook change, the uncertainty area in mid 2015 is noticeable while the May 2018 is further significantly impacting the ESM correlations. The FR rating impacts are less prevailing for EFSF (A4) and stronger in ESM. However, an important finding from the EFSF results is their lower coherence and significance compared to the ESM.

ESM coherence results in Fig. A3 show various significant coherence areas between FR ratings/outlook and ESM 2y/10y spreads. Figure A3-a shows significant high coherence in the period between 2015 and 2016 with indecisive correlation (the directions of arrows show both in phase and out phase relations). In Figure A3-b, three yellow areas can be seen scattered throughout the figure with one represents a significant high coherence. The left downward angle of the arrow during 2014–2016, implies that France ratings outlooks lagging to ESM 2yr spreads. Similar coherence can be found in Figure A3-c between 2015-2016, with two significant coherence areas, the left downward angle of the arrow signifies that France ratings lagging to ESM 10yr spread. Figure A3-d shows mild coherence overall with two scattered areas of strong comovements between France outlooks and ESM 10yr spreads with indecisive correlations. The right downward angle of the arrow during 2014–2016, implies that France ratings lead the ESM 10yr spreads.

Although less prominent compared to ESM coherence, the results in Fig. A4 show strong coherence results for the Sep2015 downgrade (event 15) in A4-a/-b for short/long term maturities. Both results indicate antiphase (neg.correlating) movements while the arrows indicate no clear leading variable.

Italy (IT) results

For IT, we include four rating events (no.2/7/21/22 stated in the event table 5). Event

[12]France events include downgrades in Nov 2012 (event no 4) and in Sep 2015 (event no 15 Aa1/neg to Aa2/sta), and in May 2018 (event no 21 change to positive outlook).

2 is a two notch downgrade in July 2012, followed by a small outlook upgrade (Feb2014, event 7) and two timely close events (mid 2018, event 21/22) and the Oct2018 downgrade to Baa2.

A first findings is that for both issuers we find only very moderate coherence across the two maturities. Rating events show results in 2018 for EFSF and ESM as significant coherence cones in the same time frequency (scattered yellow areas in the graphs). The strong downgrade (event 2) under imputed data shows coherence results yet at the outer range of the cone of influence (Fig. A6 b/c/d). For the ESM, the coherence is less prominent. Following recommendations based on existing literature (e.g. Grinsted et al. (2004)), results at the corner areas of the cone of influence shall be interpreted very carefully. Furthermore, given the imputed data in this part of the time series, we decided to focus on the other event results primarily.

For ESM, results in Fig. A5-a/-b show low coherence in subchart b around the 2014 rating event (no.7) and with a very low significance the other rating events in 2018. Subcharts c-d in Fig. A5 show each two scattered areas around events 21 and 22 in 2018 representing high coherence areas. The arrows in significant coherences around 2018 events (subchart b and c) indicate via right downward angles the rating events as the lagging variable.

Turning to EFSF coherence in Fig. A6, results show less significance and indicating leading variables compared to ESM coherences. In Fig. A6-a results for the 2018 we find around the downgrades an in phase move of both variables led by the rating score as the first variable. We further identify a lot of noise around the significant coherences in late 2018 indicating high uncertainty.

Greece (GR) results

As the largest beneficiary, Greece (GR) includes seven rating events (no.12-15/17/19/23 in table 5). Given their number and directionality (incl. up- and downgrades), we find overall limited coherence results for both issuers. Furthermore, in situations we get significant coherence, it is during times without rating events for ESM. As shown in Fig. A7-a, we get results with strong antiphase coherence during late 2013 in absence of any concrete rating events. This can be interpreted as market volatility and correlation changes at the height of the euro crisis due to the expected default fears related to the Grexit debate (GR was rated with C as 'near default' during that time). Fig. A7-b shows coherence related to short term rating outlook changes. The remaining events since mid 2014 do not show significant coherence albeit notable scattered correlation developments.

Turning to EFSF coherences in Fig. A8, the 2014-2017 rating events show significant results while their drivers remain indecisive (the directions of arrows show both in phase and out phase relations). Fig. A8-a shows in phase results both for the 2015 downgrade events and during the 2017 rating upgrades. The GR results could be explained by the fact that GR was the first client of the rescue funds and impact on the rating and financing stability of the funds were not perceived as relevant as under larger and more financial support programmes. Notably, the strong upgrades in also remain relatively muted showing only small signs of significant changes in the outer range of the cone of influence. Interestingly, the GR outlook events in short term EFSF correlations show stronger results. However, the leading variable cannot be identified with arrows moving into various directions. This could indicate under WTC analysis noise and uncertainty in markets.

Ireland (IE) results

For IE, Table 5 contains six rating events (no.5/6/9/15/16/18) with the specific feature of all being positive rating events. Coherence impacts provide two core findings. First, they are when occuring event window focused around the EFSF programme for IE ending 2014 and around the upgrades 2015-2017. Secondly, coherence results show that EFSF and ESM are differently impacted. For ESM coherence in Fig. A9, the sub charts for the grade changes show overall little significant impacts. While short maturities (subchart a) remain not impacted, the results in Fig. A9-c show coherence in phased with the (positive) rating event during 2013-2015 lagging the credit spread move in 10y ESM maturities. Results further suggest an in phased move driven by-the outlook changes in 2015-2017 (events 15-18) while the driving variable remains indecisive. Outlook upgrade WTC graphs (A9-c,-d) show during the 2015 financial crisis aftermath in phased coherence yet again relatively indecisive regarding the leading variables (esp. in A9-d). The short term EFSF credit spreads show small coherence only in Fig. A10-a. While the scattered area is only partly within the cone of influence, the arrows do show an anti-phase (neg.correlation) and the rating (events 5-9) as leading variables indicated by left downward arrows. The same events impact ratings (Fig. A10-b) alike yet with less clear leading of the outlook changes compare to the rating events in subchart Fig. A10-a. Long term credit spreads (A10-c,-d) show different results compared to the short end spreads. While the aforementioned events do not show relevance, we get results for for the 2015-2017 events (15-18). However, the coherence shows significant in phase behaviour of the variables with the rating events lagging. This supports a view that the upgrades for IE from non investment grade to investment grade class (during 2014 from Ba1 to Baa3 and above) appears to have caused a stronger market reaction compared to the additional upgrades (during 2015-2017).

Cyprus (CY) results

Results for the small ESM programme beneficiary CY includes eight rating events containing up- and downgrades from 2012-2019 (no.3,4,5,8,13,16,18,22,25). The WTC results shown in Fig. A11 display in the sub chart set a-d strong coherence only in the two maturities under rating change graphs (a,c).[13] Fig. A11-a shows for ESM short term correlations coherence scattered areas during the multiple downgrades for CY (events 3-7). Results show an in phase behavior of the variables signilling from the arrows that the rating events are the lagging variable. This could imply that markets went ahead of the curve of any additional downgrades for CY during this time (CY was downgraded from substantial credit risk, Ba3, to near default risk, rated C with negative outlook). For the events around 2015 (events 13-16) in Fig. A11-a we find out phased movements led by the rating events.

This indicates that markets reacted to the rating events impacting market correlations (strong upgrades for CY after the institutional support for CY incl. ESM programme). However, the results also show strong coherence with in phase moves led by rating events

[13]For completeness, sub charts A11-b,-d indicate two tiny low frequency scattered areas which we neglect for brevity reasons

(18-25) which result in higher credit spreads — differently than the efficient market narrative would suggest. The long term coherence in Fig. A11-c show similar results while being less pronounced and decisive. EFSF coherence results are much less pronounced in all four sub charts in Fig. A12. Only small scattered coherence significance is shown around the similar event timing as in ESM. The key finding from this data set is that indeed for CY events, the EFSF was little to not impacted compared to its sister institution. From a behavioral narrative, this is explained by the ESM being responsible for new programmes but would not preclude EFSF correlation impacts. This may be related to the prevailing narrative (in 2016) whether CY would require additional ESM programme support. This programme was by far not as large as for GR but contained various adjustment conditions for CY including a restructuring of the CY banking sector and fiscal consolidation. Results of the ESM coherence charts support this uncertainty during the rating upgrade cycle from C (junk) to Ba2 (close to becoming investment grade).

Portugal (PT) results

Similar to IE, also PT shows a positive rating event history (events 5/9/11/22/24). The country was from 2011 until 2014 under programme and was during the observation period upgraded by three notches (Ba3 to Baa3). Results show for both issuers various phased coherences during this time — however these results are broadly outside the cone of influence (e.g. EFSF in 2years and ESM for 10years in Fig. A13 and A14). Within the cone of influence, results for PT shown in Fig. A13 provide very limited significant coherence areas in the four sub charts. The only strong finding in coherence results is found in the sub chart A13-c for 10years ESM debt correlations with events ranging between end 2013 to 2017 (events 5-9). They show in phase moves of both variables where the rating events lead spreads while arrows directions indicate also uncertainty given the multiple directions. EFSF results for PT show main results only in short end coherence in A14-a,-b. Different to the ESM results, the coherence is anti phased (neg. correlation) with rating events lagging spreads. Looking at the second sub chart (A14-b for outlook changes, results suggest uncertainty and noise stemming from the outlook changes. Unfortunately, the results are largely outside the cone of influence which makes them less reliable.

To sum up, using the results from both correlation analysis, we find supportive results for our analysis with e.g. France ratings a key driver for both euro area rescue fund correlations. Spearman results show the relevance, and the coherence analysis also significant results indicating the FR downgrades as leading variables to drive EFSF correlation changes. Notably, for ESM correlations, there is similar coherence relevance but less interpretative clarity in the leading/lagging variables. Overall, findings from the wavelet coherence provide additional information while the directional indications of lagging- and leading variables (rating impacting spreads) remain limited and reveal noise and uncertainty in the results.

5. Conclusion and outlook

Our work assumption that the EFSF may impose higher vulnerability to member rating changes —as stated in Section 1— cannot be confirmed based on our empirical results. Significant EFSF market correlation impacts are across EA member states lower than for its sister institution ESM. The provided wavelet coherence charts show more areas of insignificance (darker blue with smaller and less pronounced coherence cones of influence). Our findings relate and contribute to previous work on impacts on the rescue funds funding market condition and the importance of a effective coordination between rating agencies and issuers (Kiff et al., 2012, Rocholl, 2012) and findings related to rating outlook relevance as discussed in Poon & Shen (2020). The fact that most beneficiary member states show only low impact on the funds market conditions may support the fact that european institutional efforts to ensure and prepare strong ratings ahead of launching issuances was a sensible thing to do —at least from our research perspective.

Our second work assumption was based on whether the ESM is more resilient to rating changes by members due to the larger capital structure. While indeed the ESM's rating —compared to the sister institution EFSF— remained very stable, we find from the correlation results evidence that ESM correlations are larger impacted overall. This is mainly driven by one large guarantor (France) as our results confirm the relevance of the euro area rescue funds' key guarantors on market correlations and financing conditions. While for the largest guarantor, Germany, the event base was literally non-existent due to a steady highest quality rating, we find evidence that France ratings as a key guarantor are a focal point for the rescue funds' market correlations and financing conditions in the wider angle.

These results contribute to the work on spillover effects of sovereign rating changes (Beirne & Fratzscher, 2013, Gande & Parsley, 2005) and extend previous research by adding findings on the newly created rescue funds for the euro area. Referring to the work on rating assessments criteria before and after crises and the benefuts of being a EA member (Reusens & Croux, 2017), our results contribute and confirm these findings.

Including a behavioral finance and sentiment view, the empirical results on France correlation impacts can be linked to prevailing market narrative and methodological caveats. The rating agency Moody's signalled initially that an ESM rating could unlikely be above the one of France. This could be an explanation why ESM was downgraded from Aaa to Aa1 almost at inception because France was downgraded at that time. Although the ESM's paid in capital and the guaranteed amounts by France are known and the downgrade remained in the very low credit risk class, markets closely monitor changes on Moody's rating of France for the ESM. Later on since ESM's inception, Moody's allowed some decoupling, as currently ESM is rated Aa1 while France is below, at Aa2. With this, we contribute also to existing research on rating methodology by confirming potential subjective rating components which may require more transparency (D'Agostino & Lennkh, 2017). From a behavioral finance perspective, these results indicate to the power of news flow and narrative spillover effects (Shiller, 2003, 2015).

We also provide results on potential market impacts of the news around Italy becoming a potential ESM support candidate. Our results do not support the press noise resulting in significant correlation changes within the observation period (while we have not performed a news event analysis, the lack of coherence results supports this assessment). On the one hand, this is somehow surprising given Italy's large debt-to-GDP-ratio and the sheer size any programme may have. On the other hand, markets do not expect

Italy to access the rescue funds given Italy's known critical stance towards the rescue funds and the political pressure in the country. This is related to the so called ESM-stigma and remains a prevailing and somehow powerful narrative — but not necessarily an economic one (notably, some countries did not assess EFSF/ESM support under a economical comparative cost but rather a political cost basis).

As for the euro area rescue funds' beneficiary EA countries, results suggest some correlation impacts yet not to the extend that market questioned the funds ability to finance the amounts successfully. We hereby contribute and do not find evidence to previous research on doubts about the EFSF's capability to fund without a bank licence (Gros & Meyer, 2011).

Our results under the wavelet transform analysis provided novel insights which contributes to existing literature on wavelet analysis for financial datasets (Masset, 2015, Struzik, 2001). From a methodological angle, however, they came with analytical caveats. First, given the market data set constraints of available sufficient bond yield data and the needed imputations, the interpretation has to apply a high degree of cautiousness. This refers to the outer ranges (2013 and 2019/2020 into the pandemic) which in all charts indicate results but largely remain outside the significance cone of influence. Second, within wavelet analysis, selecting the most suitable mother wavelet remains challenging. We based our motivation on using Daubechies wavelets on previous literature and the prevailing usage in analytical financial tools. Future methodology research is invited to provide more insights on the best application based on the dataset and the topical context (e.g. regime changes, crisis markets). Third, as often in financial datasets, our data includes noise and additional market events within the time series. Our research design offers a coherent and sound setup by reducing outright absolute yield changes using the credit spread metrics, and retaining most applicable generic bond market data from liquid benchmark bonds. However, especially in current market conditions at the time of writing (Q1/2022), caveats include liquidity aspects due to quantitative easing activities, as well as market disruptions and consequently less reliable pricing data. Finally, while we excluded spurious correlation assumptions using the deployed methods. The wavelet results provide a zoom into correlations and coherence and can indicate drivers of changes. However, it does not allow for causality interpretations. Future research in this field can include the methodology framework, extending the observation space to include e.g. the individual support programme events (begin/exit of support programmes), perform news- and word mining analysis to improve the understanding of correlation drivers under such event studies. Our results show areas around the outer cone of influence areas from the very beginning (prior to data and creation in 2012) and very late in pandemic crisis in February 2020. Future research may derive findings also from these events under a differnt data set including the pandemic events since March 2020 which was out of this research scope.

From an institutional standpoint, future work can include to widen the individual country support aspects for further research. This includes to study countries receiving additional crisis support from other funding sources (as nearly all investigated beneficiary states received financial support e.g. from the IMF). Understanding the drivers of market sentiment and correlation shifts for the euro rescue funds is another research angle if it comes to potential future crisis events. If the euro rescue funds would be used for new support, any potential programme would be provided by the ESM as the EFSF is only refinancing outstanding debt. Furthermore, financial support would be likely provided within the new founded Next Generation EU recovery plan.

Finally, our work contributes to literature by back testing the rescue fund's resilience to exogenous rating actions from its guarantors. While we look back for our study into recent crises events, our key research question remains very contemporary. The European supranational issuers —including the EFSF and the ESM— remain an active contributor to the European policy crises responses. This includes, for example, the recent pandemic crisis responses from the European level to mitigate negative financial stability impacts as well as the rescue funds' contribution to strengthening the european monetary union.

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Appendix

Figure A1: Spearman Correlation

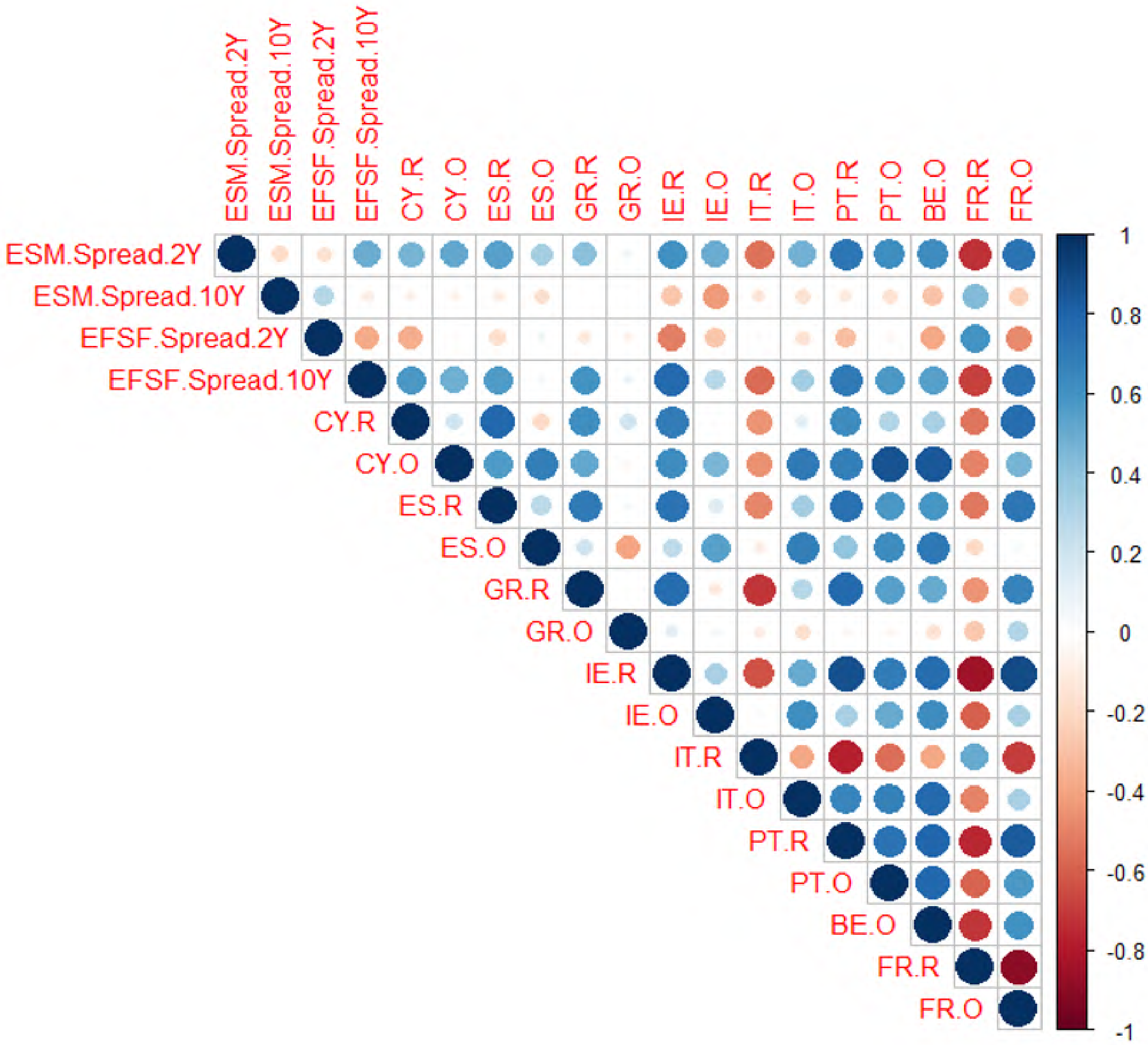


Figure A2: Spearman Correlation Table

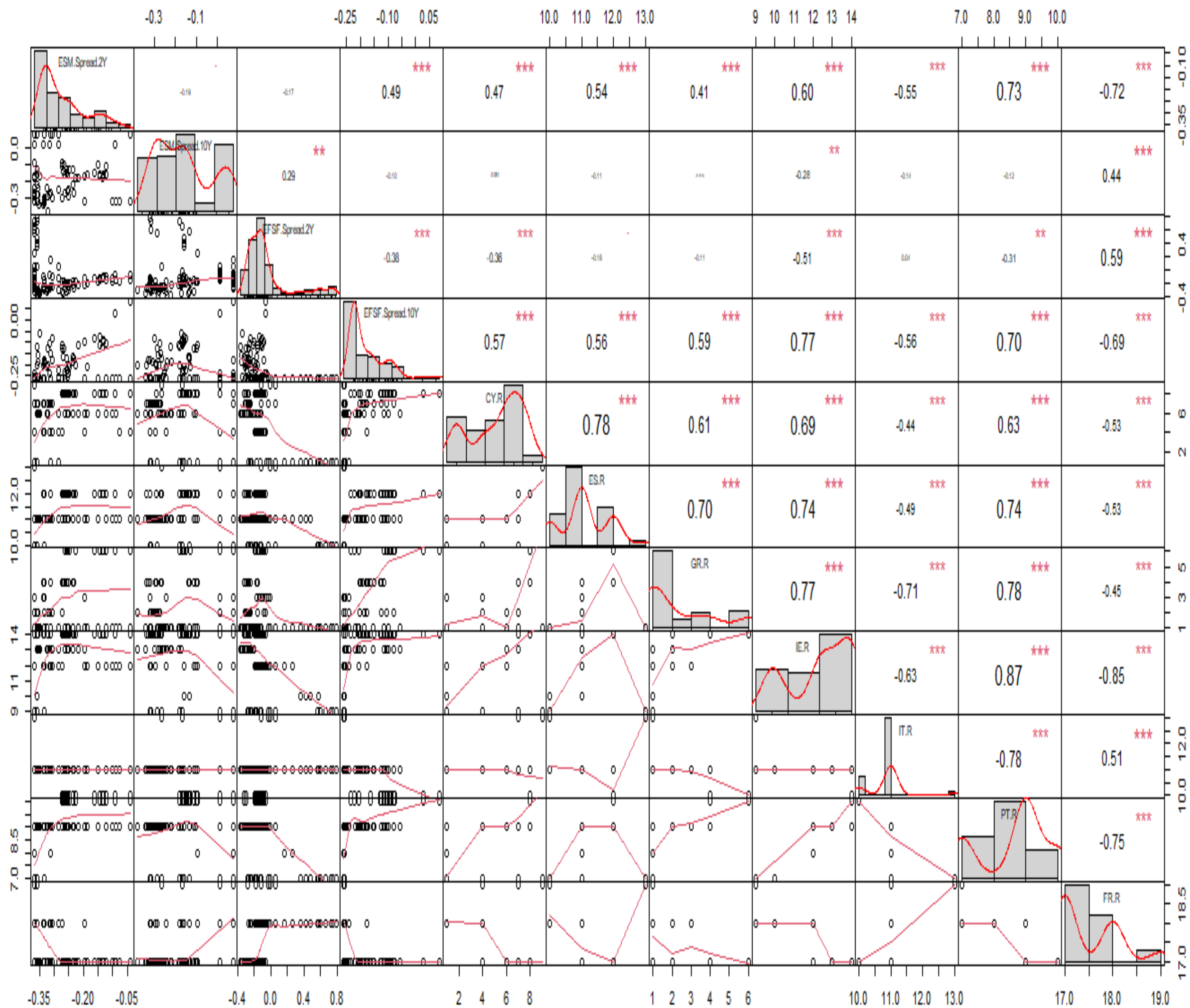
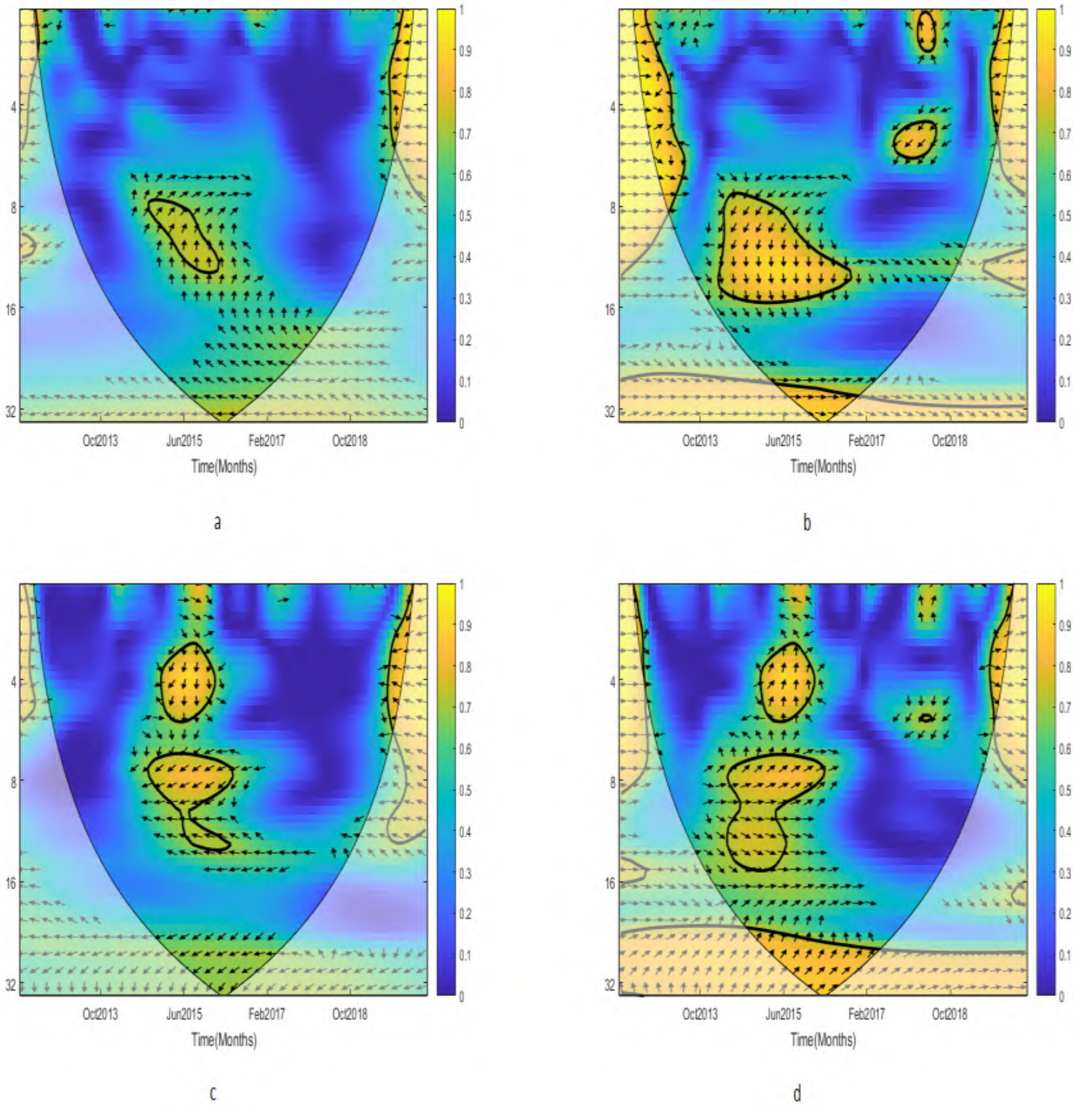
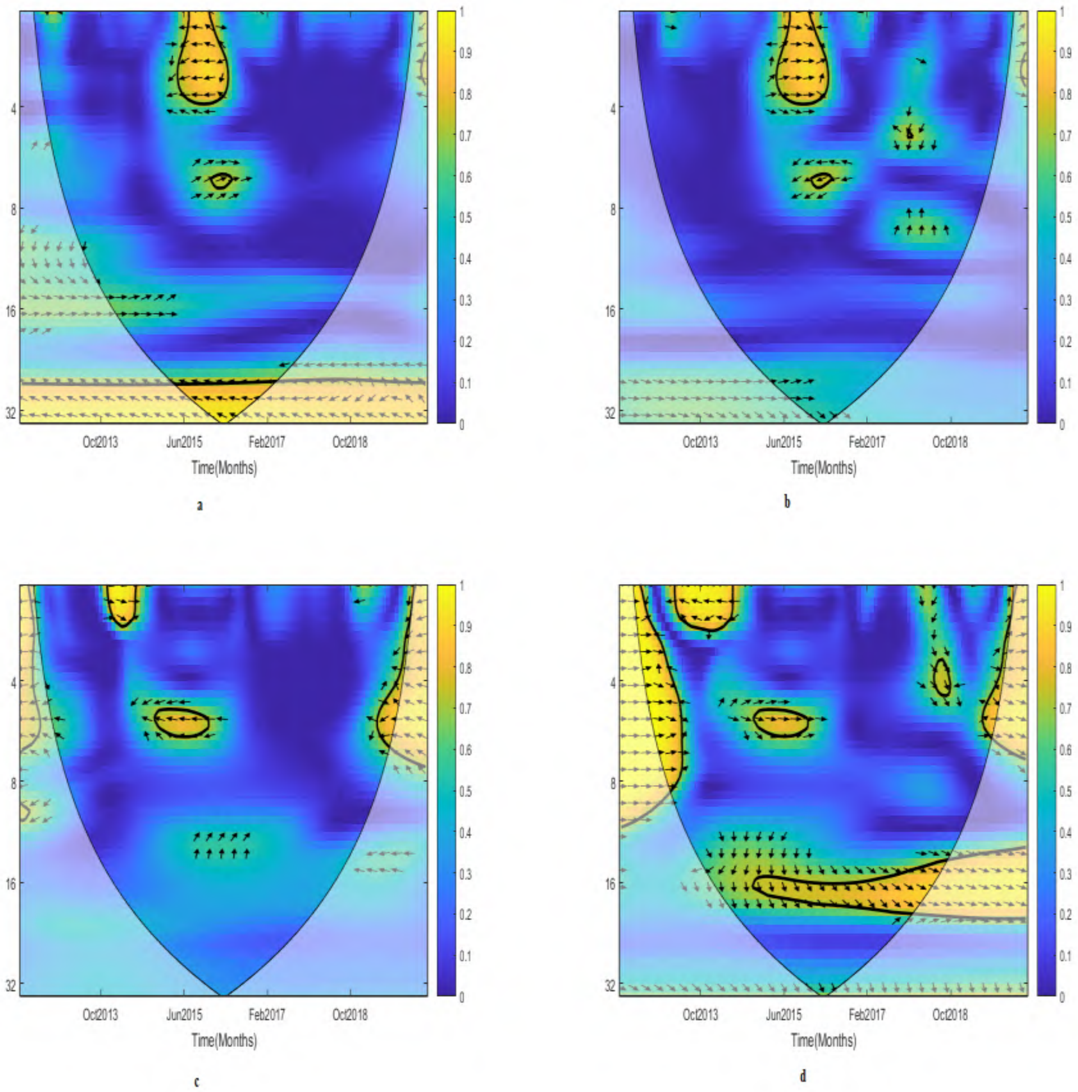


Figure A3: WTC - France ratings and ESM Spread



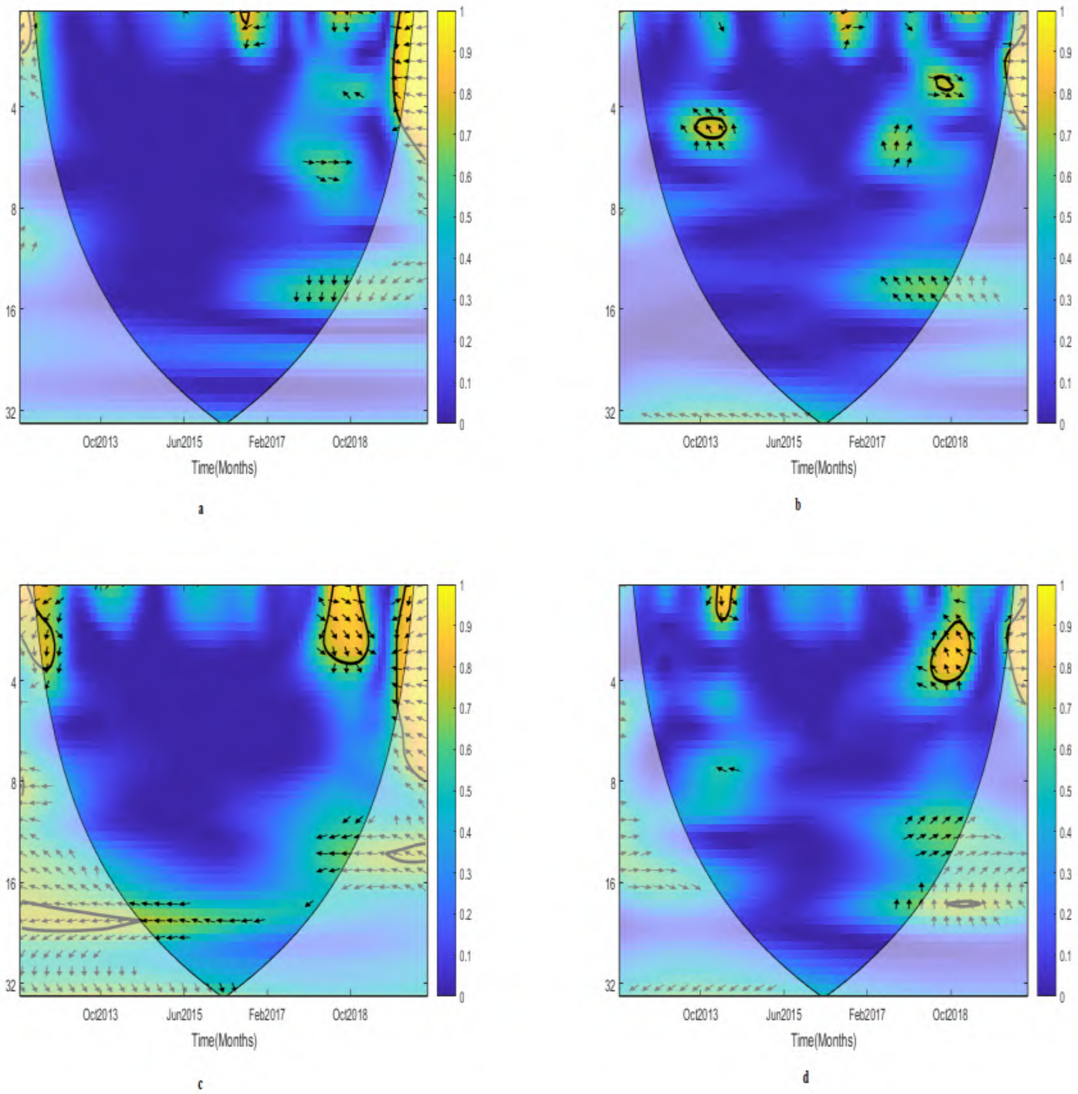
Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and ESM 2Yr spread.
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A4: WTC - France ratings and EFSF Spread



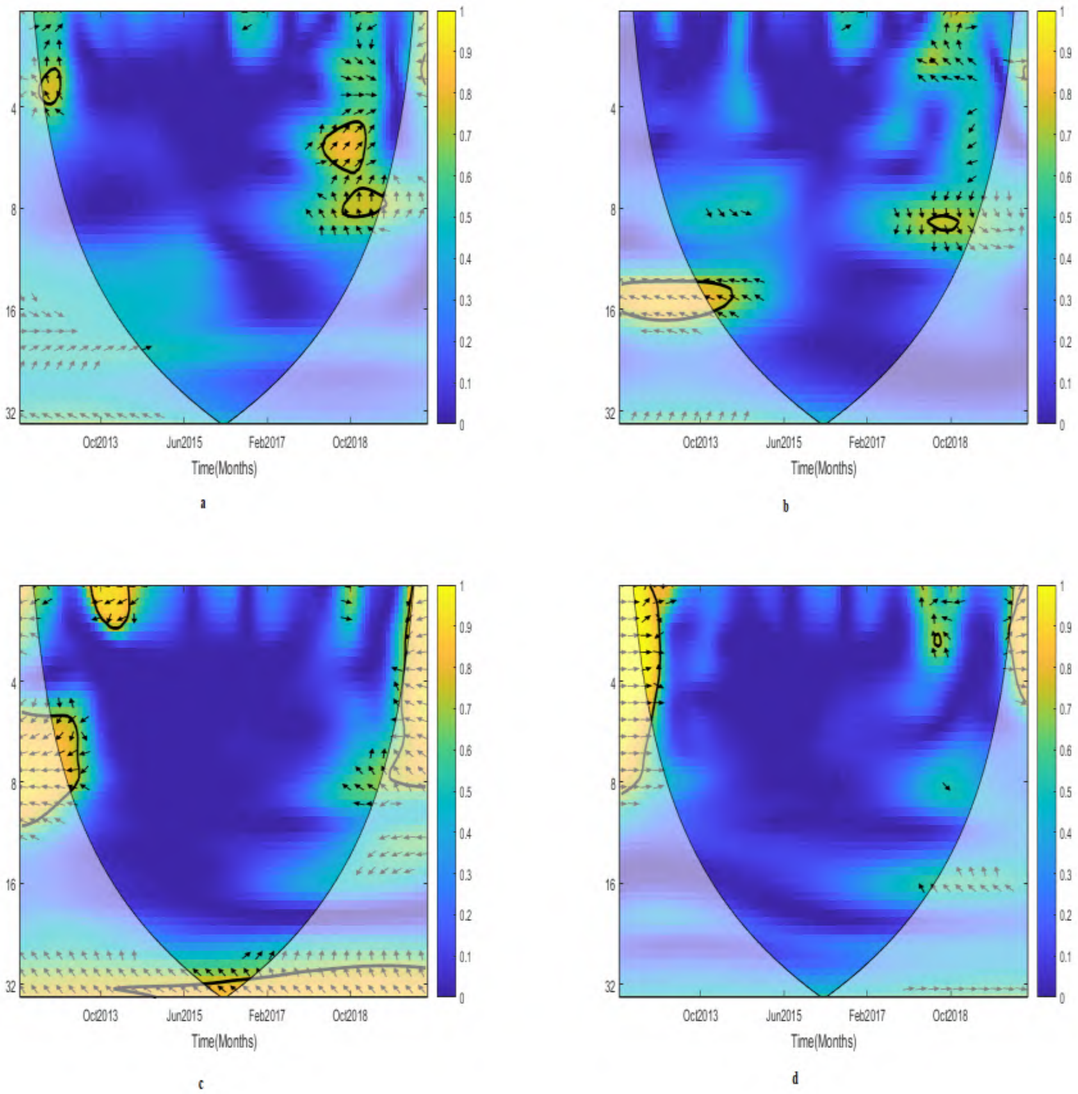
Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and EFSF 2Yr spread.
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Figure A5: WTC - Italy ratings and ESM Spread



Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and ESM 2Yr spread.
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A6: WTC - Italy ratings and EFSF Spread



Four sub charts description (upper left to lower right):
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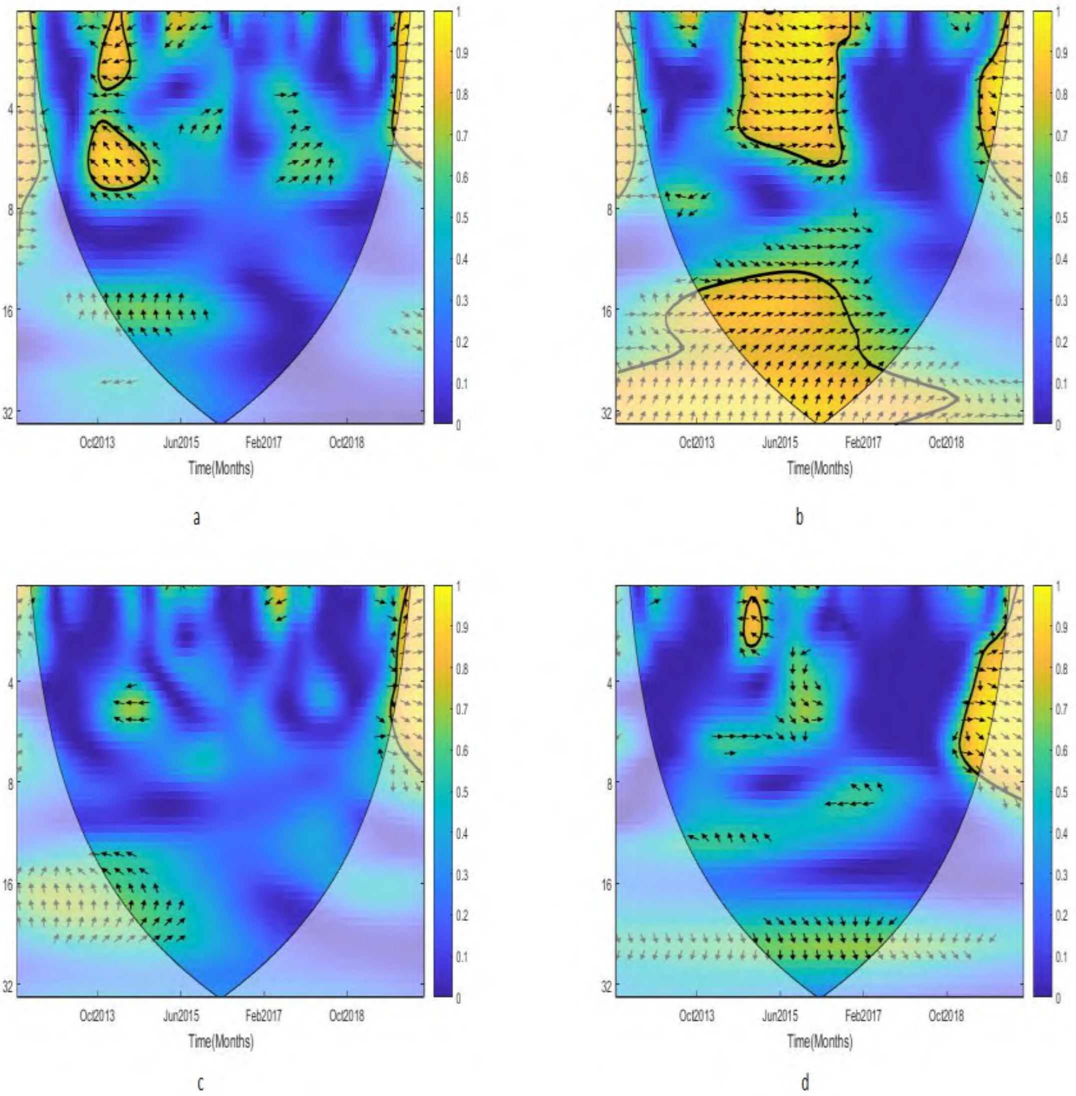
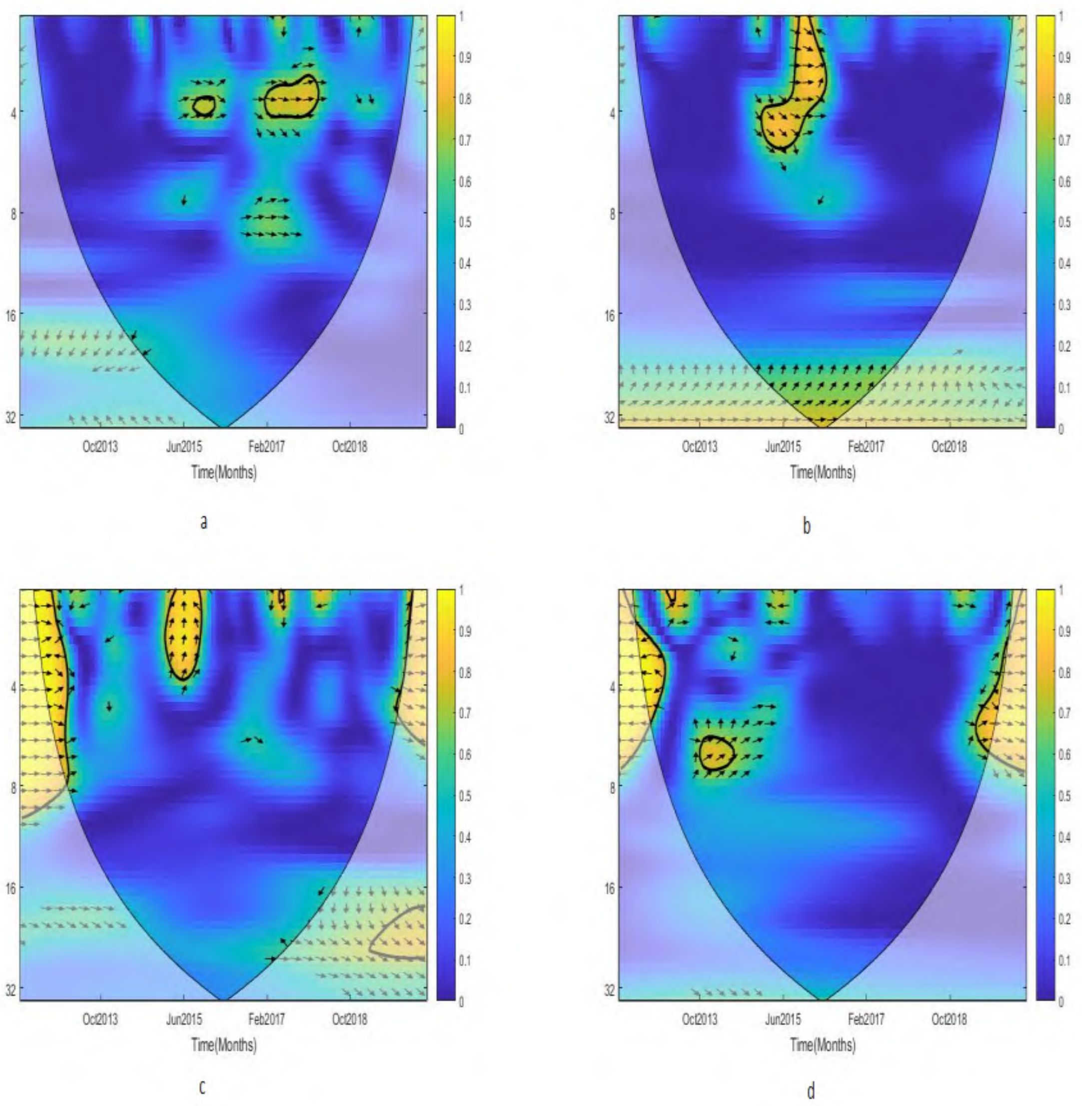
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Figure A7: WTC - Greece ratings and ESM Spread



Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and ESM 2Yr spread.
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A8: WTC - Greece ratings and EFSF Spread



Four sub charts description (upper left to lower right):
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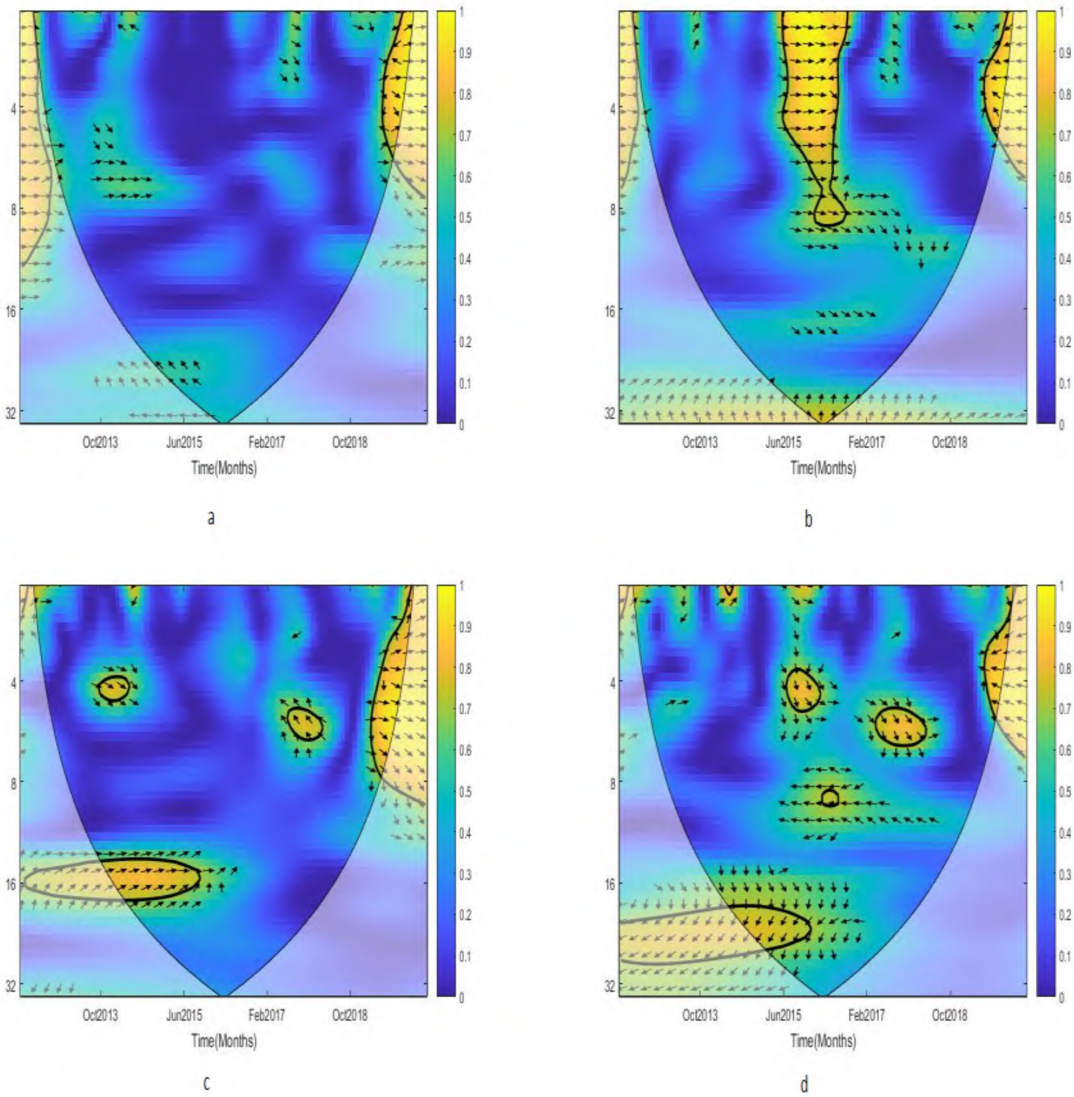
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Figure A9: WTC - Ireland ratings and ESM Spread



Four sub charts description (upper left to lower right):
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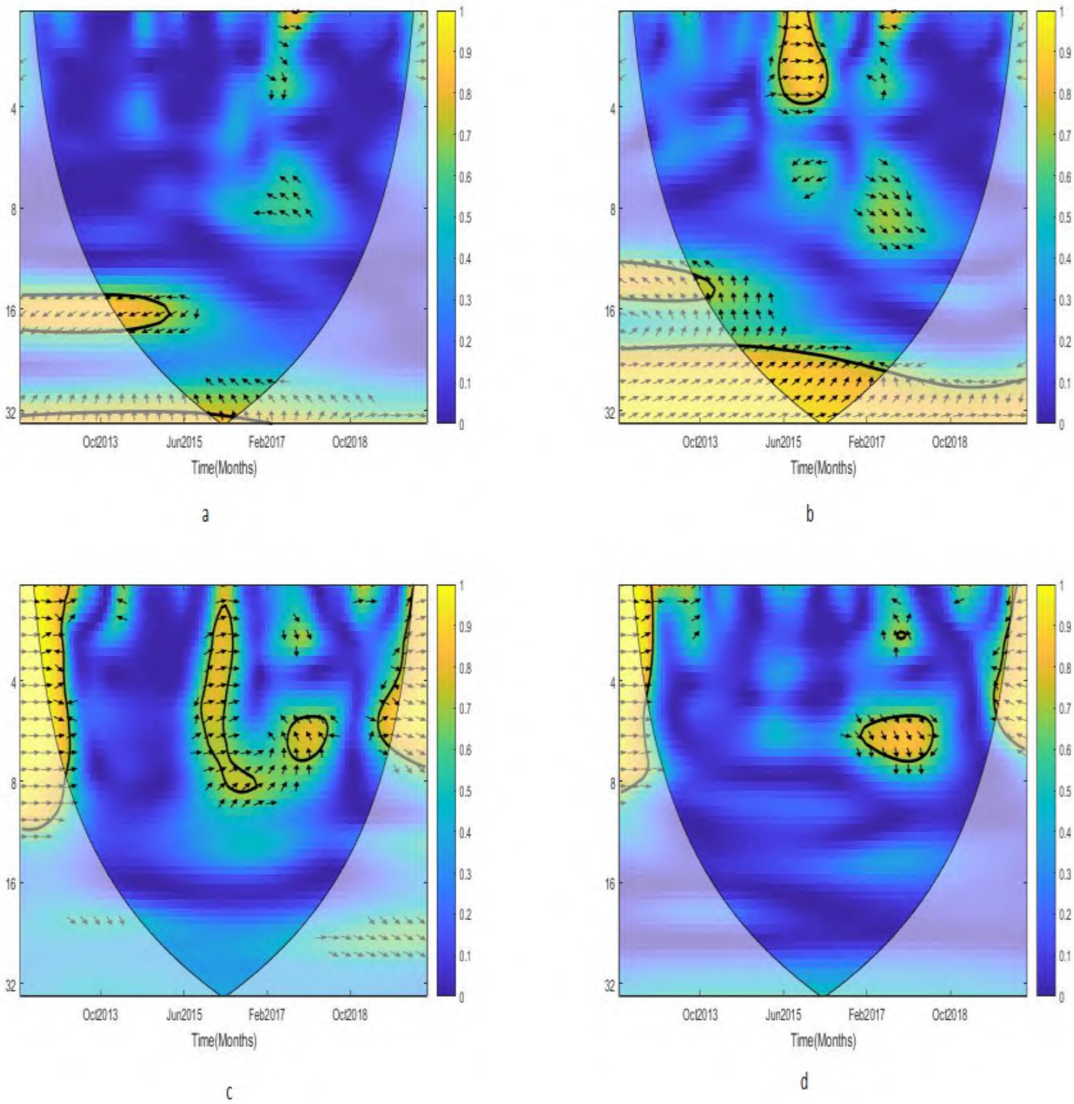
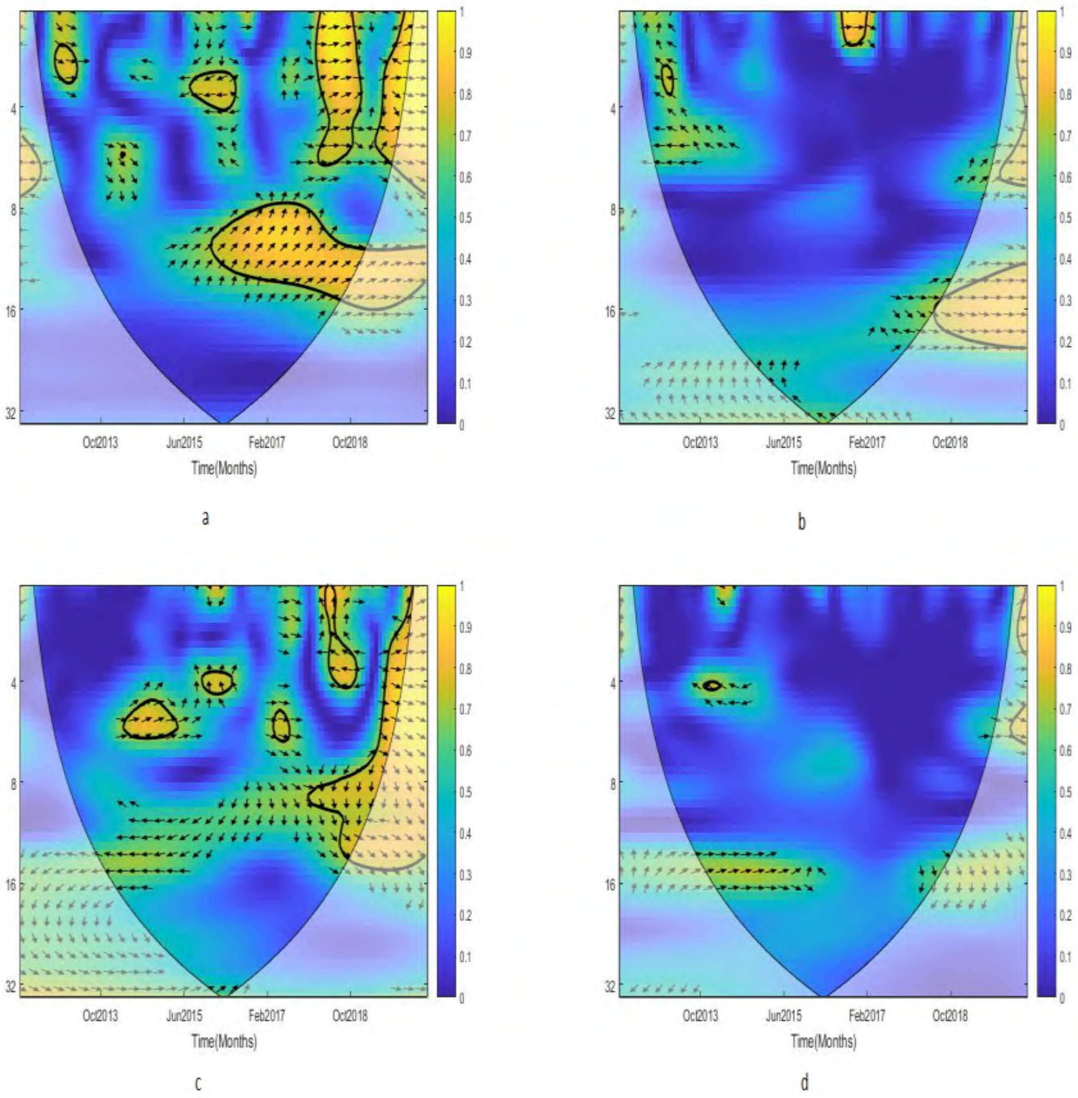
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A10: WTC - Ireland ratings and EFSF Spread



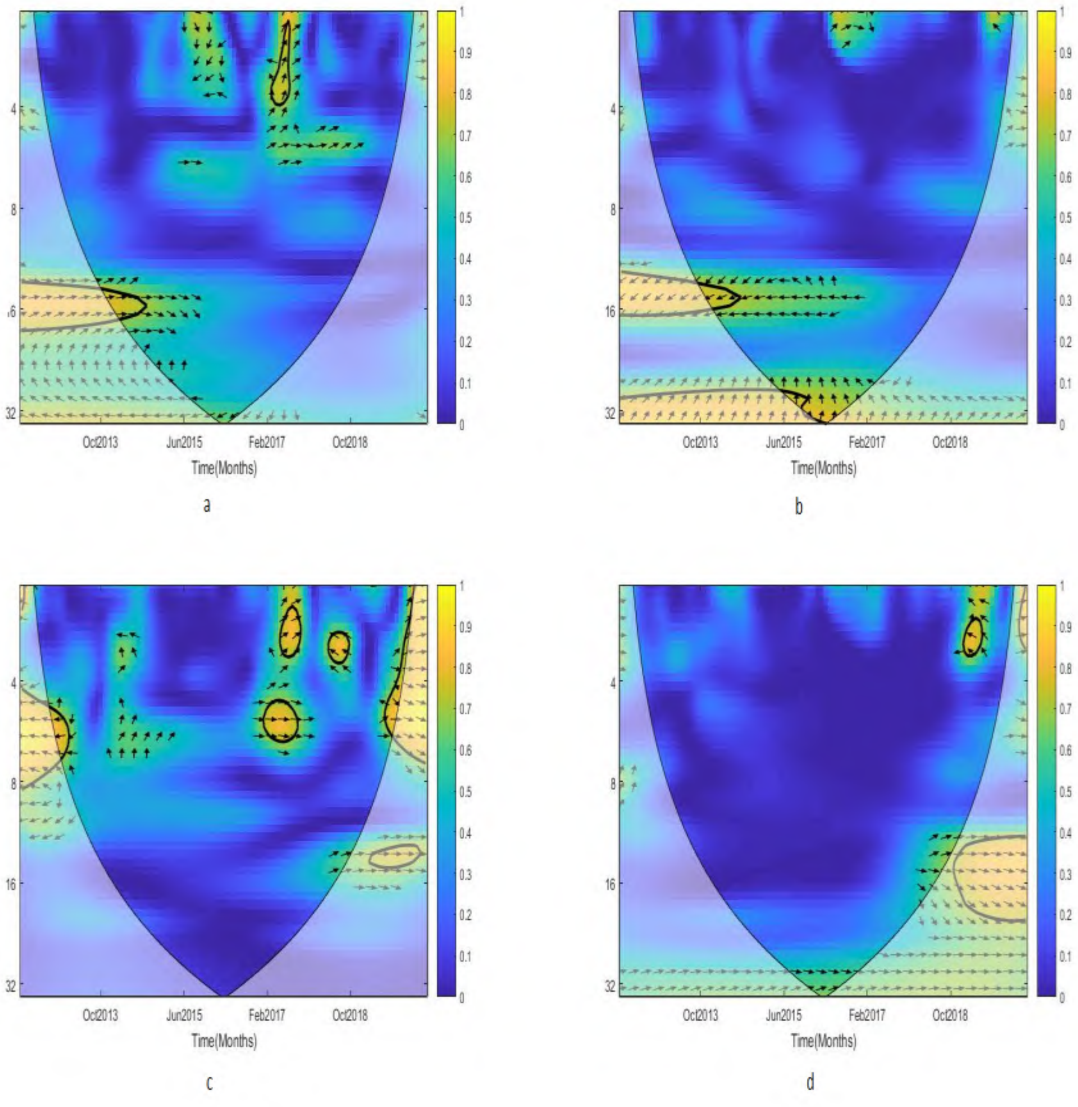
Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and EFSF 2Yr spread.
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Figure A11: WTC - Cyprus ratings and ESM Spread



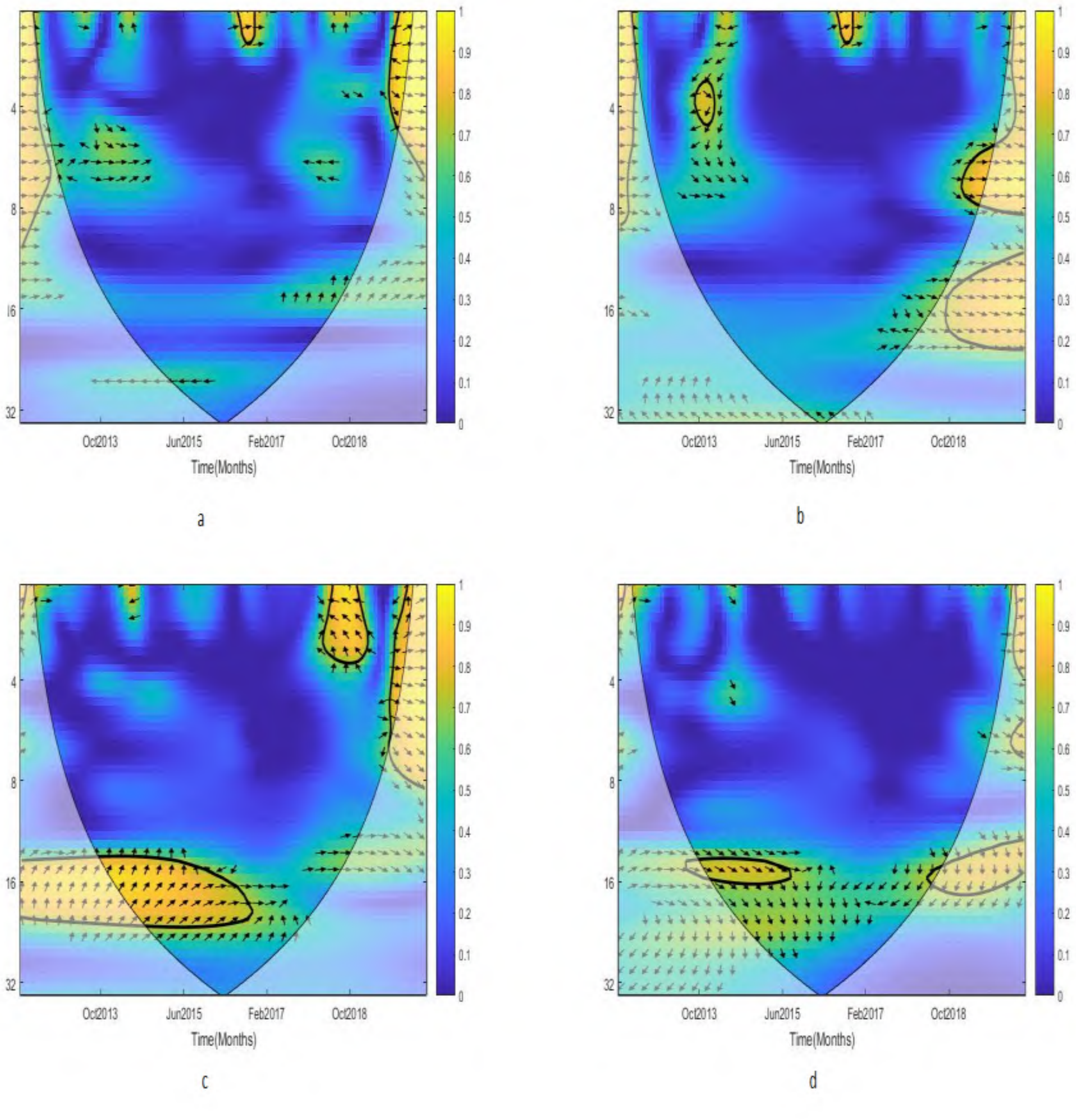
Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and ESM 2Yr spread.
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A12: WTC - Cyprus ratings and EFSF Spread



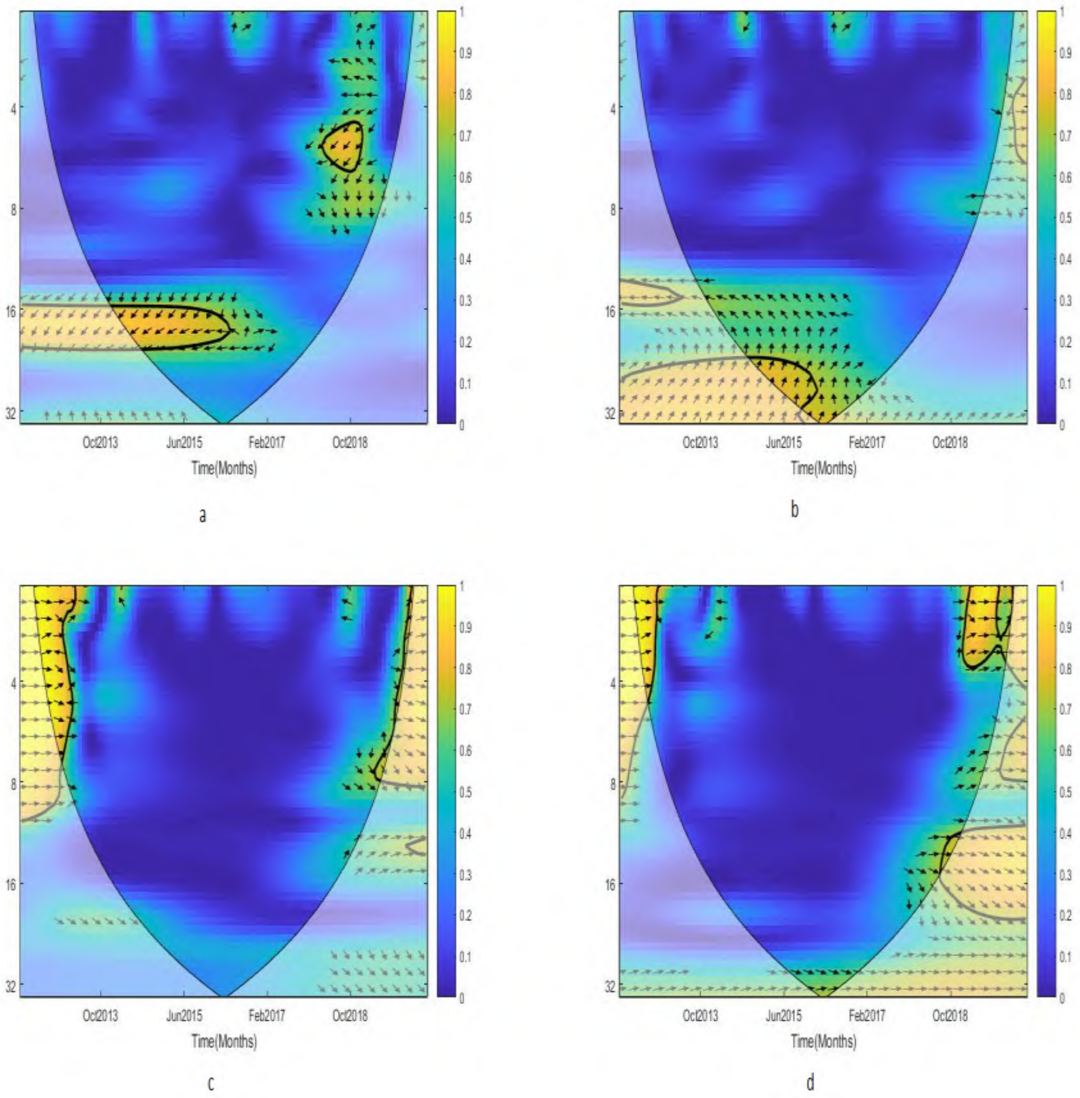
Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and EFSF 2Yr spread.
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Figure A13: WTC - Portugal ratings and ESM Spread



Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and ESM 2Yr spread.
b: Coherence between Moody outlook and ESM 2Yr spread.
c: Coherence between Moody ratings and ESM 10Yr spread.
d: Coherence between Moody outlook and ESM 10Yr spread.

Figure A14: WTC - Portugal ratings and EFSF Spread



Four sub charts description (upper left to lower right):
a: Coherence between Moody ratings and EFSF 2Yr spread.
b: Coherence between Moody outlook and EFSF 2Yr spread.
c: Coherence between Moody ratings and EFSF 10Yr spread.
d: Coherence between Moody outlook and EFSF 10Yr spread.

Event	time	ESM-R	ESM-O	EFSF-R	EFSF-O	FR-R	FR-O	DE-R	DE-O	IT-R	IT-O	PT-R	PT-O	GR-R	GR-O	IE-R	IE-O	CY-R	CY-O	ES-R	ES-O
1	201206	*n.a.*	*n.a.*	19	0	19	−0.25	19	0	13	−0.25	7	−0.25	1	0	9	−0.25	7	−0.5	10	−0.5
2	201207	*n.a.*	*n.a.*	19	−0.25	19	−0.25	19	−0.25	11	−0.25	7	−0.25	1	0	9	−0.25	7	−0.5	10	−0.5
3	201210	19	0	19	−0.25	19	−0.25	19	−0.25	11	−0.25	7	−0.25	1	0	9	−0.25	4	−0.25	10	−0.25
4	201211	18	−0.25	18	−0.25	18	−0.25	19	−0.25	11	−0.25	7	−0.25	1	0	9	−0.25	4	−0.5	10	−0.25
5	201311	18	0	18	−0.25	18	−0.25	19	−0.25	11	−0.25	7	0	1	0	9	0	1	−0.25	10	−0.25
6	201401	18	0	18	−0.25	18	−0.25	19	−0.25	11	−0.25	7	0	1	0	10	0.25	1	−0.25	10	0
7	201402	18	0	18	−0.25	18	−0.25	19	0	11	0	7	0	1	0	10	0.25	1	−0.25	11	0.25
8	201403	18	0	18	−0.25	18	−0.25	19	0	11	0	7	0	1	0	10	0.25	1	0.25	11	0.25
9	201405	18	0	18	−0.25	18	−0.25	19	0	11	0	8	0.5	1	0	12	0	1	0.25	11	0.25
10	201406	18	0	18	0	18	−0.25	19	0	11	0	8	0.5	1	0	12	0	1	0.25	11	0.25
11	201407	18	0	18	0	18	−0.25	19	0	11	0	9	0	1	0	12	0	1	0.25	11	0.25
12	201408	18	0	18	0	18	−0.25	19	0	11	0	9	0	3	0	12	0	1	0.25	11	0.25
13	201502	18	0	18	0	18	−0.25	19	0	11	0	9	0	3	−0.5	12	0	4	0	11	0.25
14	201508	18	0	18	0	18	−0.25	19	0	11	0	9	0	1	−0.5	12	0	4	0	11	0.25
15	201509	18	0	18	0	17	0	19	0	11	0	9	0	1	0	12	0.25	4	0	11	0.25
16	201605	18	0	18	0	17	0	19	0	11	0	9	0	1	0	13	0.25	6	0	11	0
17	201706	18	0	18	0	17	0	19	0	11	0	9	0	2	0	13	0.25	6	0	11	0
18	201709	18	0	18	0	17	0	19	0	11	0	9	0	2	0	14	0	7	0	11	0
19	201802	18	0	18	0	17	0	19	0	11	0	9	0	4	0	14	0	7	0	11	0
20	201804	18	0	18	0	17	0	19	0	11	0	9	0	4	0	14	0	7	0	12	0
21	201805	18	0	18	0	17	0.25	19	0	11	−0.5	9	0	4	0	14	0	7	0	12	0
22	201810	18	0	18	0	17	0.25	19	0	10	0	10	0	4	0	14	0	8	0	12	0
23	201903	18	0	18	0	17	0.25	19	0	10	0	10	0	6	0	14	0	8	0	12	0
24	201908	18	0	18	0	17	0.25	19	0	10	0	10	0.25	6	0	14	0	8	0	12	0
25	201909	18	0	18	0	17	0.25	19	0	10	0	10	0.25	6	0	14	0	8	0.25	12	0

Table A1: Rating event table and scores
Event Time shown as YYYY/MM as e.g. 201909 for Sept'2019
Each issuer (ESM ... ES) according to the country (abbreviation) code in Section 4
Each issuer Rating (R) and Outlook (O) score as detailed in Section 3.1.1
Due to data availability constraints we only find reliable results from event 5 onwards (as detailed in Sections 3.1.1 and 4)

Table A2: Moody's rating classes and alphanumerical mapping [own mapping based on Moody's]

Moody's Rating	Applied Score	Credit Risk
Investment grade		
Aaa	19	minimal
Aa1	18	very low
Aa2	17	very low
Aa3	16	very low
A1	15	low
A2	14	low
A3	13	low
Baa1	12	moderate
Baa2	11	moderate
Baa3	10	moderate
Non investment grade		
Ba1	9	substantial
Ba2	8	substantial
Ba3	7	substantial
B1	6	high
B2	5	high
B3	4	high
Caa1	3	very high
Caa2	2	very high
Caa3	1	very high
Ca	1	in/near default
C	1	in/near default
Outlook scores		
Positive outlook	0.25	
Negative outlook	-0.25	
Stable outlook	0	
No outlook	0	

Table A3: ESM shareholder data (largest to smallest share as of Jan 2022) [ESM website]

ESM Member	ESM capital key (%)	Capital (EUR'000)	Paid in capital (EUR'000)
Germany	26.8992	189,585,400	21,666,900
France	20.2003	142,371,600	16,271,040
Italy	17.7506	125,106,200	14,297,850
Spain	11.7953	83,133,200	9,500,940
Netherlands	5.665	39,926,700	4,563,050
Belgium	3.4454	24,283,200	2,775,220
Greece	2.791	19,671,000	2,248,110
Austria	2.7581	19,438,800	2,221,580
Portugal	2.4863	17,523,600	2,002,700
Finland	1.7811	12,553,100	1,434,640
Ireland	1.5777	11,119,500	1,270,800
Slovakia	0.9849	6,941,800	793,350
Slovenia	0.467	3,291,700	376,190
Lithuania	0.4063	2,863,400	327,200
Latvia	0.2746	1,935,300	221,200
Luxembourg	0.2482	1,749,000	199,890
Cyprus	0.1945	1,370,500	156,630
Estonia	0.1847	1,302,000	148,800
Malta	0.0898	632,700	72,310
Total	100.00	704,798,700	80,548,400

Table A4: EFSF shareholder data (largest to smallest share as of Jan 2022 [EFSF website]

EFSF Member	EFSF capital key (%)	Capital (EUR'000)
Germany	27.06	7,717,062.94
France	20.32	5,795,224.00
Italy	17.86	5,092,439.18
Spain	11.86	3,383,929.63
Netherlands	5.70	1,625,215.34
Belgium	3.47	988,446.50
Greece	2.81	800,708.49
Austria	2.78	791,254.35
Portugal	2.50	713,298.46
Finland	1.79	510,971.74
Ireland	1.59	452,616.89
Slovakia	0.99	282,564.64
Slovenia	0.47	133,987.96
Estonia	0.26	72,943.57
Luxembourg	0.25	71,191.29
Cyprus	0.20	55,787.57
Malta	0.09	25,754.37
total	100.00	28,513,396.92

Table A5: WTC Interpretation following Grinsted et al. (2004), Boako & Alagidede (2017),MatLab (retrieved 15.Mar.2022).

Category	Description
Display structure	each country 4 coherence graphs (a-d)
Sub-graph "a"	2y maturities rating coherence
Sub graph "b"	2y maturities outlook coherence
Sub-graph "c"	10y maturities rating coherence
Sub-graph "d"	10y maturities outlook coherence
X-axis	time series
Y-axis	frequency domain
Color area	from no (blue) to high (yellow) coherence
Black coned line	cone of influence in which results are reliable
Black circles	areas of significance (coherence scattered)
Arrows	indicating direction comovement of variables
left arrows	indicate out phase move of variables
right arrows	indicate in phased move of variables
up/down arrows	indicate lagging/leading of a variable

We provide four coherence charts of EFSF and ESM correlations (for 2y- in the upper two and for 10y in the two lower charts). Each maturity shows rating and outlook changes. Baselines for all coherence charts is March 2012. The direction of small arrows tells the direction of phased moves running from one variable to the other. In contrast, colour inside the circles shows the strength of such a relationship. The cone of influence separates the significant region via a thick black lining drawn from top to bottom on both sides. The arrows help to identify the drivers of the leading and lagging variables.