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University of Kent

Essays on Bonds: A Comparative Approach

By

Sherrihan Radi

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in fullfilment of the requirements for the degree of

Doctor of Philosophy in Finance

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Declaration

I confirm the work submitted is entirely my own and have fully referenced my sources as appropriate. Moreover, I confirm that the first two chapters from this thesis were used to draft two papers:

1) A draft paper of the first empirical chapter is submitted for the World Finance Conference's Shark Tank Event taking place the 4th of August 2021, available on:
   Radi, S., Pappas, V. and Alexandridis, A. (2021). Islamic vs. Conventional bond ratings: Determinants and forecastability. *World Finance Conference, 3-6 August, 2021*. Available at: https://www.world-finance-conference.com/papers_wfc/5d0bb9c7b3cb96eac902223ca386f712.pdf

2) A draft paper of the second empirical chapter is uploaded on SSRN:
   Radi, S., Pappas, V. and Alexandridis, A. (2021). Asymmetric and cross-asset herding: Evidence from bond and equity markets. Available at SSRN: https://ssrn.com/abstract=3570518

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Sherrihan Radi

This thesis is dedicated to *my family*

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Abstract

This thesis comprises three comparative empirical chapters that explore distinct areas in bond market literature. The first chapter investigates whether Islamic bonds (sukuk) should be rated the same way as conventional bonds. Using a sample of Malaysian bonds, we address this question by examining the credit rating determinants of each type (conventional and Islamic) and testing the significance of Islamic bond features. Our results based on ordered probit and support vector machines show new evidence of the distinction between the two types of bonds, suggesting that their rating methodologies should differ. Sukuk and conventional bond ratings seem to share some common determinants, but their sensitivity to these determinants vary. Moreover, our findings suggest that conventional bond ratings are driven by a smaller set of financial variables, whilst Islamic bond ratings are triggered by a wider set of variables including Islamic structure variables. The most accurate bond rating predictions are achieved using tailor-made individual Islamic and conventional bond rating models. The support vector machines outperform the ordered probit model across all our samples and increase the bond rating prediction accuracy by more than 20%. Hence, to get the best results we suggest using support vector machines to forecast sukuk and conventional bond ratings, separately.

The second chapter investigates and compares herding in the US corporate bond and equity markets between January 2008 and December 2018. Our initial unconditional tests detect significant herding in speculative grade (high yield) corporate bonds only. However, once we condition for market liquidity and volatility, we find significant asymmetric herding behaviour in both markets and their credit rating portfolios. The results suggest that investors are inclined to collectively herd towards the market consensus during high market liquidity and low volatility. Interestingly, the herding effects are more pronounced in corporate bonds than in equities. The findings are robust even after simultaneously conditioning for both liquidity and volatility market states. Our further tests also provide new empirical evidence of the existence of cross-asset herding spillovers from US corporate bonds to their respective equities. The direction of the cross-herding effect holds during the 2008 global financial crisis, but switches post-crisis from equity to corporate bonds.

The final chapter explores the impact of a wide range (151) of Brexit-related news announcements on UK and EU government bond and stock market volatilities during April of 2010 to February 2020. Using the Heterogeneous Autoregressive (HAR) model, we find strong evidence of the importance of Brexit news carrying valuable information for both markets. Specifically, the initial regressions combining all Brexit news show that the volatility of the Eurozone's government bonds and the UK stock market considerably increased on the announcement days of Brexit news. The detected volatility responses to the news are more substantial in government bonds relative to equities. We also find that the degree and direction of the Brexit news effects varies depending on the news category. Particularly, among the different types of news, the markets seem to be most sensitive to UK votes and UK political

news. In addition, we document leading and lagging effects of the news, suggesting that the volatility responses often extend for more than a day. Interestingly, the findings reveal that the Eurozone markets are more suspectible than the UK to Brexit news. Lastly, the contribution analysis shows that during the 3-day event window, aside from UK votes, all Brexit news categories induce higher levels of volatility that temporarily destabilise the UK and Eurozone markets.

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1 Introduction

Fixed income markets, especially bond markets, have attracted significant interest from both academics and practitioners. Bonds are considered as a stable, cost effective and reliable source of long-term debt financing for governments and corporations around the world. According to the International Capital Market Association, as of August 2020 the global bond markets outstanding value reached $128.3 trillion, which is larger than the global equity market (ICMA 2021). Given the nature of bond debt agreements that often incorporate interest payments and a promise to repay the face value to the holder at maturity, investors consider them safer investments that they shift to during crises and utilise for portfolio diversification. Their importance lies in their relative stability and close links to the economy, where bond market movements are typically observed as key indicators of the health of the economy and future market movements. As a result, this thesis consists of three comparative empirical chapters that focus on bond markets and investigates three current underexplored areas in the literature: Islamic versus conventional bond credit rating prediction, herding behaviour in corporate bonds and the impact of Brexit news on bond volatility.

Recently, there has been an increasing demand for alternative financial investments, most notably in the aftermath of the Global Financial Crisis (GFC) of 2007 when many investors lost trust in the conventional financial market. As a result, a growing number of investors, both Muslim and non-Muslim, became interested in Islamic financial markets that proved to be more resilient during the crisis. In particular, Islamic bonds known as *sukuk* rapidly gained popularity as a Sharia-compliant alternative to the existing conventional bond markets. The Islamic Financial Services Board defines sukuk as Islamic financial certificates with each bond (sakk) representing a "proportional undivided ownership right in tangible assets, or a pool of predominantly tangible assets, or a business venture" (IFSB 2009), noting that these assets must be in a specific project or investment activity that is fully compliant with the Shariah rules and principles. Sukuk come in various types that are based on different structures of Islamic contracts (for example, partnership, lease or another type of agreement).

In 2019, global sukuk issuances hit a record value of USD 146 billion, leading the outstanding sukuk issuances to reach its highest historical value of USD 551.44 billion (IIFM 2020). However, the degree of financial innovation that sukuk offer in comparison to conventional bonds has been a controversial subject of debate in current Islamic finance literature (Wilson 2008; Alam, Hassan and Haque 2013; Azmat, Skully and Brown 2017). As a result, one of the main questions that arises is whether sukuk should be rated using the same determinants and methodology as conventional bonds. We fill in this gap in the literature by studying one of the key features of bonds, their credit ratings. Bond ratings assigned by credit rating agencies serve as a guide to capital market participants and regulators regarding the riskiness of bond issues, which in turn affect the marketability and risk premiums of bonds. Given the importance of bond credit ratings, our first empirical chapter investigates the determinants of Islamic and conventional bond ratings and examines their forecastability using two credit rating forecasting methods: ordered probit and support vector machines (SVM).

The findings of the first empirical chapter offer new empirical evidence which support the view that Islamic bonds, to an extent, differ not only in theory but also in practice from conventional bonds. Using a sample of Malaysian corporate bonds, we show that Islamic and conventional bond ratings share some common financial determinants but are differently affected by them. Interestingly, Islamic bond ratings are driven by a larger set of variables, including their Islamic bond structure. The most accurate bond rating predictions are attained using tailor-made individual Islamic and conventional bond rating models, where the SVM consistently outperform the ordered probit model by more than 20%. Hence, we conclude that Islamic bonds should be treated as a distinct type of bonds, and their rating assignments should be carried out independently taking into account the Islamic features that influence their credit ratings. This research is beneficial for bond issuers and investors that would like to get an estimate of the credit quality of bonds, especially unrated bonds or new issues that would aid them in their decision-making processes.

Another emerging area of finance that has been experiencing an increase in academic interest is Behavioural Finance. Behavioural finance studies the application of psychology to finance, recognising that cognitive factors and emotions can affect investors' financial decision-making and behaviour in markets. It challenges traditional finance as it relaxes its key assumptions regarding investors' expected utility maximisation and rationality in efficient markets. In addition, behavioural finance research attempts to reason observed market anomalies that traditional finance fails to explain. Herding behaviour is one of the most interesting concepts in behavioural finance, where *herding* is the behavioural tendency of investors to suppress their own beliefs and follow the trading patterns of other investors or the collective movements in the market.

Investor herding can dramatically influence not only investors' returns, but may also reduce the benefits of diversification, destabilise prices and potentially undermine financial stability and market efficiency. With the existence of various online trading platforms[1], information and social media[2], the financial markets became more susceptible to herding behaviour. Numerous studies examine the existence of herding towards a market consensus in financial markets, with particular emphasis on equity markets (including Chang, Cheng and Khorana 2000; Chiang and Zheng 2010; Galariotis, Krokida and Spyrou 2016b), yet its presence in bond markets as well as cross-asset classes has been underexplored. Therefore, the second chapter addresses this gap in literature by examining herding behaviour in US

[1] For instance, the online trading platform eToro has introduced a CopyTrader™ function that allows an investor to mimic a particular trader.
[2] Herding based on social media trends. To mention a few, the price explosion (short squeeze) of GameStop attributed to the efforts of the WallStreetBets sub-forum Reddit retail traders and the surge in prices of Etsy, CD Projekt and Dogecoin post Elon Musk's tweets in 2021 (see Goldin 2021; Kelly 2021).

corporate bond and equity markets, paying particular attention to the existence of cross-asset herding between the two markets.

Our initial unconditional tests provide limited evidence of herding in the US bond and equity markets, only present in speculative grade bonds. However, after conditioning for market liquidity and volatility, we document significant asymmetric herding behaviour in both markets, where investors tend to collectively herd when the market is more liquid and less volatile. More notably, the level of herding detected in corporate bonds is substantially higher than in equities. Lastly, we provide novel evidence of cross-asset herding spillovers from corporate bonds to equities, where the direction of the spillover effect persists during the GFC but reverses post-crisis from equities to bonds. The results highlight the importance of studying herding behaviour and cross-asset herding in domestic and international financial markets (across different asset classes) to inform asset allocation decisions and prevent its potential adverse effects on portfolio diversification.

The third empirical chapter of this PhD thesis explores a current topic, the impact of Brexit news announcements on government bonds and equity markets. On 23 June 2016, the UK held an EU referendum vote to exit the European Union. The outcome of the referendum in favour of leaving the trading bloc was an unexpected and monumental event in history; a turning point that is defining the future of UK economic policy. The immediate effect of the referendum was observed the next morning, where the exchange rate of the British Pound against the US dollar significantly dropped (10%) and the global stock markets experienced a sharp slump of more than US$2 trillion. Almost a year after the referendum, the UK triggered Article 50 of the Treaty on European Union on 29 March 2017 and commenced the challenging and lengthy process of UK-EU Brexit negotiations. After three extensions and many hurdles, the two parties came to an agreement and the UK officially left the European Union on 31 January 2020 by sealing the Brexit withdrawal Agreement that contains a transition period and an outline of the future relationship between the UK and the EU.

The current and upcoming impact of Brexit is without doubt widespread, affecting various critical aspects including investment, trade agreements, citizens' rights, migration, labour markets, border arrangements, amongst others. What is more, the duration and countless disputes during the UK-EU negotiations lead to greater ambiguity around the Brexit trade deal and fuelled political, economic and social uncertainty in the UK and the Eurozone. Consequently, an increasing number of studies are taking different approaches to assess the impact of Brexit (e.g. Samitas and Kampouris 2018; Breinlich et al. 2019; Dao, McGroarty and Urquhart 2019); primarily focusing on the Brexit vote or a small number of Brexit-related events. In the last empirical chapter, we extend the previous literature by examining and comparing the effect of a substantial set of (151) Brexit-related news, on the volatility of UK and Eurozone government bonds and equity markets. Furthermore, to gain an in-depth understanding of the impact and importance of the events in question, we classify the news into five categories (UK Brexit, EU Brexit, UK votes, UK political and industry response).

The initial Heterogeneous Autoregressive model (HAR) results which combine all news events at once, indicate that the announcement of Brexit news accelerates the level of Eurozone's government bond volatilities and UK stock market volatility. Interestingly, we capture more significant volatility responses in government bonds in comparison to equities. Although the markets react to most Brexit news categories, their reactions to them vary in magnitude and direction. The most significant volatility responses are documented with the announcement of UK votes and political news. The arrival of the news promotes greater uncertainty; nevertheless, we also detect leading and lagging responses to the news. Unexpectedly, the results reveal that the Eurozone markets' volatilities are more sensitive to Brexit news than the UK is. Lastly, the contribution analysis confirms that, with the exception of UK votes, all other Brexit news categories destabilise the UK and Eurozone market volatilities during our 3-day event window. These findings offer new evidence that reflects the prominence of Brexit events, beyond the day of the EU referendum, for both markets and accentuates the importance of studying and anticipating the influence of political news on domestic as well as relevant international markets.

Overall, this thesis explores how recent developments affect bond dynamics. Newer trends in finance, including Islamic finance and herding behaviour can bring opportunities but also limitations to financial market participants. The study offers further evidence in support of the strong interlink of financial markets; internationally (UK and EU countries) as well as across asset classes (bond and equity markets). It also shows that trading patterns in one market can induce the other. Furthermore, it reveals that political events/news that often influence macroeconomic conditions also affect international financial markets. Therefore, investors and fund managers should explore the potential benefits of investing in newer financial securities, such as, Islamic bonds that have distinct characteristics and risks and could offer portfolio diversification benefits. In addition, financial market participants should hedge and take advantage of relevant political events and examine new behavioural trends in financial markets to incorporate them in their financial decision-making process.

Furthermore, the thesis emphasises the importance of interdisciplinary research. This includes studying human behaviour and psychology in finance, which is becoming increasingly more important with the popularity of social media trends and technological advances (Fintech) that eased online trading for retail or personal investors. Similarly, future work is also recommended in politics and finance; to study the wider effect of political events and unrests as well as investigate how politics and finance shape each other.

The remainder of the PhD thesis is organised as follows: Chapter 2 presents the first empirical study on Islamic vs. conventional bond ratings. Chapter 3 comprises the second empirical study on herding behaviour in corporate bond and equity markets, and Chapter 4 presents the last empirical research that studies the effect of Brexit news announcements on the volatility of government bonds and equities. Each of the aforementioned chapters consists of an introduction, a literature review, data and methodology, empirical results and conclusions. The final chapter provides an overall summary of the conclusions of the thesis and the direction for future work.

2 Islamic vs. conventional bond ratings: Determinants and forecastability

2.1 Introduction

Corporate bond credit ratings are ordinal measures that provide key information to all capital market investors and regulators. They are often used by investors, issuers, and governments as a guide to the riskiness and quality of bond issues. Bond ratings primarily assess whether the issuing firm can meet the coupons and principal payments in a timely manner over the life of the bond issue. Thus, they signify the likelihood of their default or potential missed payments. To indicate this, credit rating agencies (CRAs) typically assign alphabetical symbols to bond issues by corporates or sovereigns. According to White (2010), the purpose of CRAs is to minimise the effects of asymmetric information by providing their judgements, which they prefer referring to them as “opinions” about the credit quality of the corporate bonds.

Credit rating agencies play a vital role in the financial credit markets, as their ratings are heavily used to price risky debt instruments and thus influence their marketability and effective interest rate (Amato and Furfine 2004). Moreover, ratings also allow uninformed investors to quickly assess the riskiness of a large number of securities, using a simple recognised scale (Becker and Milbourn 2011). In fact, they are not only used by uninformed investors, but also by fund managers and institutional investors who consider them when making asset allocation decisions regarding their investment portfolios. The importance of credit ratings is further highlighted by the fact that many regulatory bodies, including the Bank for International Settlements (BIS), base their bond investment regulation and regulatory capital requirements on ratings (Kisgen and Strahan 2010; Löffler 2004). For instance, numerous institutional investors are restricted to holding only investment grade bonds in their portfolios, or are obliged to comply with certain capital requirements based on the credit ratings of the securities they possess (Kisgen and Strahan 2010). As a result, credit ratings have been extensively employed for the development of integrated risk management systems and calibrating internal ratings of primarily banks and financial institutions (Carey and Hrycay 2001).

Credit ratings are usually very expensive to obtain because they require CRAs to invest a substantial amount of time to analyse the firm’s risk. CRAs only list the key rating drivers they assess as part of their rating assignment. Standard & Poor's Ratings Services (2014) explain that they firstly analyse the issuer’s business and financial risk profiles, and then perform forward-looking analysis and use their analytic judgement to assign the final rating. Additionally, Fitch Ratings (2015) explain that they also study the issuer’s industry risk, management strategy, operating environment and group structure. However, they do not disclose the exact details of their rating methodology and emphasise that their analysts' subjective judgement plays a significant role the rating process, which is reflective and interpretive. However, CRAs have been hugely criticised for their lack of transparency, especially following the global financial crisis of 2008, and the sluggish response to credit rating adjustments (White 2010).

Given the significance of credit ratings in financial markets, numerous academics study the determinants of ratings and attempt to predict the credit ratings. Despite the credit rating agencies' claims and denials of the possibility of replicating their ratings, using a variety of methods many researchers have obtained robust results on credit rating prediction (Altman and Katz 1976; Blume, Lim and MacKinlay 1998; Kim 2005; Lee 2007; Kim and Ahn 2012). Moreover, the changes introduced by the Basel II framework further motivates credit rating prediction studies. Basel II encourages banks to determine the capital adequacy requirements needed to cover unexpected losses based on their external credit ratings or, for a limited amount, advanced internal rating approach (Bank for International Settlements 2011). Within the internal rating approach, banks are allowed to construct their own rating models on their collected data, which makes the study of bond rating prediction valuable mainly for issuers and regulators (Van Gestel et al. 2006).

Recently, the sukuk (Islamic bond) market started to gain popularity as a Sharia-compliant alternative for the existing conventional bond markets. According to the International Islamic Financial Market (IIFM 2020), the global sukuk issuance rapidly increased in 2019 (approximately 18.32% jump in year-on-year) totalling USD 146 billion. This caused the outstanding sukuk issuances to reach their highest historical value of USD 551.44 billion, which is a clear indication of the consistent growing interest in sukuk and in Islamic finance in general. As a result of the subprime mortgage crisis, sukuk became of interest not only to Muslim investors, but also to non-Muslim ones who lost trust in the conventional financial markets and wanted to diversify their risks or find alternatives to conventional bonds. Along with the popularity and growth of sukuk issuance, sukuk markets face certain challenges. Credit rating is considered a major challenge as it influences the marketability and risk premiums of the assets. Sukuk are typically rated by the well-known globally recognised credit rating agencies: S&P, Moody's, and Fitch, or by local CRAs. However, due to the high costs associated with external rating mechanisms, some bonds and sukuk remain unrated or unupdated (Huang et al. 2004; Arundina, Omar and Kartiwi 2015).

The current literature is split into two segments with counter arguments regarding the application of sukuk in a modern setting. Some studies including Miller, Challoner and Atta (2007) and Wilson (2008) claim that sukuk are often structured on the basis of the conventional rules of securitisation, which makes them exact substitutes. In contrast, other scholars explain that sukuk do offer some form of financial innovation and therefore differ to some extent from conventional bonds (Cakir and Raei 2007; Akhtar et al. 2016). Kamali and Abdullah (2014) argue that sukuk credibility should not solely rely on the conventional concept of default, but should also incorporate religious factors and degree of compliance to Shariah. Usmani (2002) and Tariq and Dar (2007) explain that non-compliance to Shariah or any deviations increase the chances of potential defaulting or dissolving of the sukuk.

The popularity of sukuk and the on-going debate in literature on the similarity of sukuk and conventional bonds raises serious questions to whether they should be rated using the same methodology and determinants. Hence, this chapter aims to extend the current bond rating prediction literature by comparing sukuk credit ratings to their conventional counterparts. To do so, we investigate three main research questions. i) What are the similarities and differences between the determinants of Islamic and conventional bond ratings? ii) Are the ratings of Islamic bonds affected by non-financial variables? iii) Is a single model sufficient to predict both sukuk and conventional bonds?

This empirical research examines whether sukuk differ not only in theory but also 'in practice' from conventional bonds. To our knowledge, this is the first study to make a direct contrast between the credit rating of sukuk and conventional bonds. It is potentially useful for investors and issuers that do not want to solely rely on external credit ratings or wait for their changes by the CRAs, which can instead base their investment or capital decisions on 'homemade' internal rating. Such predictions are also essential for portfolio managers that need to assess the credit risk of unrated issuers, and new issuers that seek preliminary estimates of their potential ratings prior to their entrance to the financial markets.

To answer the research questions, we use a sample of 541 Malaysian Islamic and 69 conventional long-term Malaysian domestic corporate bonds active on 29th of December 2017. The chapter follows the most recent rating prediction literature (Lee 2007; Bellotti, Matousek and Stewart 2011; Huang et al. 2004) and applies the Ordered Probit model and Support Vector Machines (SVM). The results show that the credit rating of the two types of bonds is not driven by the exact same set of variables, and therefore present new evidence of their distinction. Whilst they share some common determinants, their sensitivities to them differ. Moreover, conventional bond ratings seem to be determined by a smaller set of financial variables, whilst Islamic ones are proven to be triggered by a wider set of variables including Islamic structure ones. In line with previous literature, the SVM method consistently achieves a higher rating prediction accuracy than the ordered probit model, making it a more suitable model for credit rating determination. Furthermore, we show that the best bond rating predictions are achieved with individual Islamic and conventional tailor-made rating models. Thus, we recommend treating sukuk and conventional bonds as distinct bond types and separating them in credit rating assessments.

This chapter contributes to the literature in in several ways. *Firstly*, we contrast between the credit ratings of sukuk and conventional bonds. As a result, we bridge the gap between the bond rating prediction literature and comparative Islamic versus conventional bond literature. We contribute to the extant literature that compares Islamic and conventional bonds by taking a different direction and examining one of their key features, their credit ratings. In terms of bond rating prediction, a lot of research has been done in regards to conventional bond ratings but only a few address the case of sukuk credit rating (Arundina, Omar and Kartiwi 2015; Azmat, Skully and Brown 2017; Elhaj, Muhamed and Ramli 2018; Borhan and Ahmad 2018). Nevertheless, none of the aforementioned studies investigate the differences between conventional and sukuk ratings.

Secondly, this chapter employs a unique set of data that incorporates both types of bonds from a single market, Malaysia[3], which enabled a direct and detailed comparison between their credit ratings assigned by the same local CRAs. By examining and contrasting each bond type's credit rating determinants we explore whether sukuk mirror conventional bonds or if they possess distinct features that distinguish them. We also assess if sukuk ratings are affected by non-financial variables, including Islamic structure ones. We presume that sukuk will have a slightly different set of significant bond specific determinants than their conventional counterparts, which would indicate their distinction.

Lastly, we adopt the SVM method for credit rating prediction that to our best knowledge has not been applied before to the context of the sukuk rating problem. Specifically, we measure the degree of forecastibility of Malaysian sukuk and conventional bond ratings and find the most appropriate method to rate them. To increase the probability of correct classifications, we follow Kamstra, Kennedy and Suan (2001), Lee (2007) and Bellotti, Matousek and Stewart (2011) and examine the effectiveness of, according to the literature, the best performing statistical as well as artificial intelligence methods: ordered probit regressions and support vector machines, respectively. Based on the literature, we hypothesise that for both samples, the SVM will predict the ratings with higher accuracy.

The rest of this chapter is organised as follows: Section 2.2 provides a theoretical background to sukuk and conventional bonds. Section 2.3 provides a brief literature review. Section 2.4 clearly describes the data set, and variables used and 2.5 presents the methods applied. Section 2.6 discusses the empirical findings obtained. Finally, Section 2.7 concludes the chapter.

2.2 Theoretical background

In this subsection, the Islamic bond (sukuk) market is introduced in Section 2.2.1, the different sukuk structures are described in Section 2.2.2 and the similarities and differences between sukuk and Islamic bonds are discussed in 2.2.3.

2.2.1 Brief overview of sukuk market

The Islamic financial industry has grown rapidly over the past decade, reaching a total of USD 2.44 trillion worth in value in 2019, marking a total increase of 11.4% since 2018 (IFSB 2020). One of the

[3] We chose the Malaysian bond market due to data availability and because it dominates 51% of the global sukuk outstanding (IIFM 2018).

key segments of the Islamic financial industry is the Islamic bond market, known as the sukuk market, which has gained popularity as an alternative way of issuing fixed income securities. "Sukuk" is the plural form of "Sakk", the latter being the Arabic term for a legal instrument or deed. In today's financial world it refers to financial instruments, namely, Shariah compliant bonds issued by sovereign or corporate entities. The main driver behind their increase in the Islamic financial industry is the remarkable steady growth rate of sukuk issuance (see Figure 2.1); primarily triggered by the sovereign sukuk issuances by Asia, GCC and Africa. By the end of 2019, the value of sukuk outstanding totalled USD 551.44 billion versus USD 490.78 billion in 2018, of which 47% are sovereign issuances, 20% quasi-sovereign, 24% corporate and 8% financial institutions (IIFM 2020). From the above, it is evident that there has been a clear growing interest in Islamic bonds (sukuk), nevertheless the gap between supply and demand in sukuk remains prevalent, namely for international sukuk.

The sukuk market is dominated by five countries: Malaysia, Saudi Arabia, Indonesia, UAE and Turkey making up nearly 92.25% of the market (IIFM 2020). Given the changes in oil prices and budgetary requirements of certain Muslim countries, these proportions are expected to change a little bit as more and more sovereigns seek sukuk issuance to offer liquidity in their local markets. Thus, a rise in sukuk issuance is anticipated in the GCC area, Indonesia, Pakistan, Turkey amongst others. In fact, several countries (Nigeria and the UK) have expressed their intention to enter or tap into (Morocco, Tunisia and Hong Kong) the sukuk market in 2018 (S&P Global Ratings 2018). This demonstrates that the sukuk market attracts not only Muslim issuers, but also non-Muslim ones that would like to diversify.

The Accounting and Auditing Organisation for Islamic Financial Institutions (AAOIFI) defines sukuk as "certificates of equal value representing undivided shares in the ownership of tangible assets, usufructs and services or (in the ownership of) the assets of particular projects or special investment activity" (AAOIFI 2008, p.307), where the underlying assets must be compliant, both in nature and use, with the Shariah rules and principles. In 2003, AAOIFI issued its Shariah standard FAS 17 in which it specifies 14 different types of sukuk structures, both tradable and non-tradable (AAOIFI 2008). The most common types of sukuk issued are: Ijarah, Murabahah, Musharakah, Mudarabah, Wakalah, Salam and Istisna'a or a hybrid of two or more (Safari, Ariff and Mohamad 2014; IIFM 2018). Figure 2.3 exhibits the types and proportion of sukuk issued in 2017, which is relevant to our study sample. Generally, the current literature classifies the sukuk structures into two main categories: asset-based and asset-backed sukuk (Zulkhibri 2015; Ahroum et al. 2018). The next section will define and describe the differences between them.

Sukuk are typically rated by the internationally recognised credit rating agencies: S&P, Moody's and Fitch, or domestic rating agencies. In Malaysia, sukuk ratings are mainly assigned by two local agencies: RAM Holdings Berhad (RAM) and Malaysian Rating Corporation Berhad (MARC). RAM dominates the market with a share exceeding 70% of sukuk issuances and issuers (RAM 2017).

According to MARC (2016a), their rating approach to sukuk does not fundamentally differ from the conventional bond methodology. Particularly, fixed income sukuk, for example, Ijara sukuk, allows them to implement their standard conventional corporate debt, project or structured finance approaches. However, in the case of limited or no recourse project finance sukuk, MARC bases its assessment on the quality of the project. They claim that they analyse sukuk on an individual basis, taking into consideration their specific characteristics (structures). Furthermore, the agencies emphasise that their credit ratings are an assessment of sukuk credit quality, and thus do not reflect by any means its compliance with Shariah law and principles (RAM 2018). Table 2.1 presents the Malaysian CRAs rating symbols and scale and compares them to the internationally recognised CRAs.

2.2.2 Sukuk structures

Depending on the nature of the tangible asset(s), usufruct or services in question, sukuk certificates can be issued in various structures. The literature often categorises sukuk into two categories: *asset-based* and *asset-backed*. According to Zulkhibri (2015), in asset-based sukuk (for example, Murabahah, Ijarah, Istisna'a, and so forth) the sukuk holders typically have only beneficial ownership or equitable interest in the assets to a special purpose vehicle (SPV) issuer, which is argued to be 'artificial' ownership rights to the physical underlying assets. Although their principal is covered by the capital value of assets, their returns and repayment of face value to the bondholders is not directly financed by the assets in question. On the other hand, asset-backed sukuk (for example, Musharakah and Mudarabah) provide their bondholders with ownership rights that extend to the actual underlying assets. This subsection will introduce a few main sukuk structures.

Murabahah sukuk, also known as debt bonds, fall under the category of contracts of exchange[4] that are classified as asset-based. Murabahah sukuk are structured on the concept of cost plus profit arrangement i.e., buy and resale. This type of sukuk are typically issued to finance the purchase of goods (a real asset). In this type of arrangement, a bank or SPV buys a real asset[5] that the originator (borrower) identifies and instantly sells it back to the originator with the purchase price plus a pre-agreed mark-up creating a debt that the originator periodically repays. Murabahah sukuk could be secured or unsecured, nevertheless, they do not provide the bondholders with direct ownership of the underlying asset. Consequently, they are regarded as less secure than Ijara sukuk (Howladar 2006; Dusuki and Mokhtar 2010). Given the structure of Murabahah sukuk, they are subject to Shariah restrictions in terms of tradability[6] in some countries (Ayub 2007).

Similarly as Murabahah, *Bai Bithaman Ajil* (BBA) structure sukuk are also based on an Islamic contract of exchange (Mohamed, Masih and Bacha 2015). A BBA agreement is said to be an extension of the

[4] Known as 'uqud al-mu'awadat.
[5] The SPV finances the real asset with proceeds from the sukuk issuance.
[6] Trading Murabahah sukuk in the secondary market is viewed as trading debt.

Murabahah with deferred payment terms. In fact, the first sukuk issued was in 1990 in Malaysia by Shell MDS Sdn Bhd who issued RM 125 million BBA sukuk (Abd Rahim and Ahmad 2016). Despite the straightforward structure of BBA sukuk and popularity in the Malaysian market, it was subject to major criticism by Islamic scholars especially due to its constancy of payments and predetermined cash flows (Bacha and Mirakhor 2019). These concerns from a Shariah point of view reduced the popularity of BBA contracts and promoted the issuance of other contracts, such as Ijarah sukuk.

Ijarah sukuk are usually issued to raise funds for the development of long-term finance infrastructure projects through the process of securitisation (on the basis of Ijarah arrangement) of tangible assets for example, hospitals, airports and others (Ayub 2007). Ijara is the Arabic term for renting, which reflects the basis of this type of setting. In an Ijarah arrangement, the originator, typically a corporate or governmental entity, sells the assets to a special purpose vehicle (SPV) that in turn issues Ijarah sukuk. Hence, the assets are financed by the funds obtained from the sukuk investors (Naifar, Hammoudeh and Al Dohaiman 2016). Afterwards, the SPV, acting as a trustee of the investors, leases the assets back to the originator and agrees to sell them back for a pre-determined price at the end of the leasing period (Khan 2010).Thus, Ijarah sukuk represent certificates of investors' undivided ownership in the underlying leased assets. During the course of the leasing contract, the SPV receives the periodic rental payments made by the issuer (lessee) and transfers them to the sukuk holders. At maturity, the assets' ownership reverts to the originator and the sukuk holders receive their cash through the SPV (Azmat et al. 2016; Godlewski, Turk-Ariss and Weill 2013).

According to Bellalah (2013), Ijarah sukuk structure has several benefits. They can be issued for various maturities, ranging from three months to ten years with the condition that the underlying asset, a physical asset, is available and compliant for Ijarah leasing (Wilson 2008). Thus, from a Shariah point of view they are tradable in the secondary market (Bellalah 2013). Moreover, they have a flexibility in their timing of inflows and outflows. Ijarah sukuk are often classified as asset-based but could also be designed as asset-backed. On the other hand, Ijarah sukuk are hugely criticised as their returns are typically benchmarked to the conventional LIBOR on dollar funds or the equivalent local rate (Azmat et al. 2016). This is to ensure that the rental payments on sukuk are comparable to the return on conventional instruments, making them uncannily similar to conventional bonds.

Istisna'a sukuk "are certificates of equal value issued with the aim of mobilising funds to be employed for the production of goods so that the goods produced come to be owned by the certificate holders" (IIFM 2020, p.187). Given that this special contractual agreement is for the sale of assets that will be produced in the future, thus they have been used to finance real estate developments, infrastructure or industrial projects or large equipment such as power plants or aircrafts.

Moving away from asset-based sukuk, Musharakah and Mudarabah sukuk are commonly referred to as asset-backed sukuk or Islamic joint venture bonds (IJV). Both are based on the fundamental profit-and-loss principle of Islamic finance (Azmat, Skully and Brown 2014a; Azmat et al. 2016). In *Musharakah* sukuk structure, the originator seeking the financing, along with an SPV, enter into a fixed period partnership type of arrangement with pre-agreed profit and loss ratios. Both parties become co-owners of a pool of assets or project, where the originator is the provider of the assets or a proportion of cash invested in a project and the SPV acts as the intermediary who contributes cash that it raises through Musharakah sukuk (Godlewski, Turk-Ariss and Weill 2013). Effectively, the investors (sukuk holders) become part owners, and each Musharakah certificate represents the investor's undivided share of ownership in the asset or project. A condition of Musharakah agreement is that the intermediary has to be one of the investors as well (Ayub 2007). Sukuk investors receive their periodic pre-agreed share of profits from the cash returns generated by the partnership, but also bear the losses proportionate to their investment contribution (Azmat, Skully and Brown 2014a). Hence, they are often described as equity-based instruments, as their coupon payments (profit) depend on the performance of the underlying asset or project. Usually, the partners appoint the originator as the managing agent that is in charge of the project or asset(s), who receives a fixed fee plus a variable incentive fee. At maturity, the issuer buys back the shares at the market price rather than at face value (Azmat, Skully and Brown 2014a). Alternatively, in the case of diminishing Musharakah (Musharakah mutanaqisah), the originator purchases (at pre-agreed prices) the SPV's shares periodically, in way that by the end of the contract period the SPV no longer holds any share in the partnership (Godlewski, Turk-Ariss and Weill 2013).

Mudarabah and Musharakah sukuk structures are quite similar. However, in a *Mudarabah* partnership the issuer, corporation or government acts as a 'Mudarib', i.e. an entrepreneur partner. Hence, the issuer only manages the project or asset(s) and in return receives a pre-agreed share of the profits generated. If any losses occur they are entirely borne by the capital owners, the Mudarabah sukuk holders (Ayub 2007; Klein, Turk and Weill 2017). Given the nature of the IJV bonds, they are commonly issued to mobilise funds and finance large long-term projects (Naifar, Hammoudeh and Al Dohaiman 2016). Both Musharakah and Mudarabah certificates are tradable in the secondary market.

When the underlying assets available for supporting the issuance of sukuk consist of a portfolio of assets, then corporations or sovereigns find it useful to issue *Wakalah* sukuk. According to Shariah law, the portfolio also known as Wakalah assets could comprise tangible or intangible assets, including those that typically are not permissible to trade in the secondary market[7], with the condition that at least 30% of the assets are tangible (Razak, Saiti and Dinç 2019). The Wakalah structure is based on the Islamic concept of Wakalah, which is akin to a contract of agency. In the case of Wakalah sukuk, the principal (usually the SPV) appoints a 'Wakeel' (agent) to invest their funds into the Wakalah assets. In this

[7] Such as Murabahah or Istisna'a sukuk.

arrangement, the Wakeel acts on behalf of the investors and manages the portfolio of investments or assets in order to generate a pre-defined profit rate during a certain timeframe. The principal uses the profit return to finance the periodic payments to the sukuk holders. On the other hand, the agent, typically the originator, can keep the surplus profit that exceeds the agreed profit rate as an incentive fee (for more detailed explanation see Razak, Saiti and Dinç 2019). At maturity, the Wakalah portfolio is liquidated and the proceeds are used to pay the dissolution amount to the sukuk holders.

More recently, *Hybrid* sukuk started to emerge and gain popularity. Hybrid sukuk are essentially bonds that are designed on the basis of two or more sukuk structures (Islamic finance arrangements), for example, Istisna'a and Ijarah, Murabahah and Ijarah and so forth.

2.2.3 Similarities and differences between sukuk and conventional bonds

Conventional bonds and sukuk exhibit some similarities, but also vary in different ways. AAOIFI provides in its Shariah standard FAS 17 a clear distinction between sukuk and conventional bonds (AAOIFI 2008). It highlights that sukuk are not debt certificates with a guaranteed fixed income, but instead they are certificates representing proportionate ownership of asset(s) or a project (Godlewski, Turk-Ariss and Weill 2013; Önder 2016). Hence, sukuk holders have ownership rights as opposed to their conventional counterparts. Accordingly, the return made on sukuk is directly linked to the performance of the underlying asset or project rather than the issuer.

Similar to conventional bonds, sukuk can be issued by both government and corporations. They have a maturity date and their income can be fixed (in the case of Ijarah) or variable (Musharakah or Mudarabah) (Godlewski, Turk-Ariss and Weill 2016). However, the investors do not necessarily have a guarantee for the capital or income. Particularly with IJV bonds that are based on the concept of profit and loss sharing, sukuk holders can yield higher returns but also share any losses. At maturity, sukuk holders also get a larger payment, however they do not always receive the original face value. This is visible in the case of equity-like sukuk, for instance, Musharakah sukuk holders receive an amount that is based on the market value (at maturity) of the underlying asset (Azmat, Skully and Brown 2014b).

Dissimilar to bonds, not all sukuk structures can be traded, certain sukuk for example Salam, Istisna'a and Murabahah sukuk, are restricted from trading by Shariah law. In addition, given that the sukuk market is relatively new (the first sukuk were issued in 1990), it still does not have appropriate benchmark sukuk price yield curves that are needed to develop an adequate pricing mechanism for secondary market trading (IFSB 2018). In fact, as mentioned earlier, there is undersupply of sukuk in the Islamic financial market (Archer and Karim 2018). Due to the above reasons, sukuk investors have a tendency to hold on to their sukuk investments, which in turn hinders the liquidity of the sukuk secondary market (Jobst et al. 2008). Apart from the low trading volume, the Islamic bond market is also characterised by wider bid-ask spreads and higher transaction costs (Ahroum et al. 2018).

As demonstrated above, it can be stated that that sukuk markets are considerably less liquid than the conventional bond markets, which has been a longstanding concern of the Islamic financial services industry. The Malaysian sukuk market, which dominates the global sukuk market, is the most liquid, given its persistent strong primary market issuance and secondary market infrastructure (Archer and Karim 2018). Therefore, the observed increase in sukuk issuances gives a positive outlook to sukuk markets, though it must be accompanied with an efficient development of the secondary market's infrastructure and pricing mechanisms.

Although the tax laws do not differ between Islamic and conventional bonds, certain jurisdictions offer tax incentives for sukuk issuance. For instance, the Malaysian government offers tax incentives for sukuk issuers as part of their on-going promotional policy to develop the Islamic markets. Specifically, the Malaysian tax law permits tax deductions on sukuk issuance related expenditures or other additional expenses incurred, exempts asset-backed sukuk issuers/SPVs from stamp duty as well as issuers/originators from real property gains tax accruing on the disposal of chargeable assets that were acquired for the purpose of securitisation (Securities Commission Malaysia 2021). The tax exemptions also extend to investors(foreign investors), where their profit from non-Ringgit (Malaysian Ringgit) denominated sukuk is exempted from income tax. In a similar trend, Bahrain, UAE, Indonesia, Kuwait and Turkey offer tax exemptions to provide tax neutrality and incentivise sukuk issuance (Uddin et al. 2020). Uddin et al. (2020) argues that such tax incentives are necessary as sukuk issuance typically entail multiple underlying buying and selling of assets, which require various asset transfer fees and tax that need to be compensated for to facilitate a level playing field for Islamic and conventional bonds.

Islamic and conventional bonds are subject to similar risks but vary in the degree of their exposure to them. Moreover, given the variety of sukuk structures, distinctions can be observed amongst their risks as well. Both Islamic and conventional bonds face interest rate risk, though in the case of sukuk, predominantly structures that are benchmarked against the LIBOR (for example, Ijara and Salam sukuk) are indirectly exposed to the changes in interest rates (Tariq and Dar 2007). On the other hand, IJV bonds such as Musharakah are the least affected by it, though their holders face another type of market risk that arises from the fluctuations of the variable income (or loss) earned by the underlying asset (Ahroum et al. 2018). As mentioned above, sukuk face liquidity risk which is higher than those observed in the conventional capital market.

Furthermore, analogous to conventional bonds, Islamic bonds also carry foreign exchange rate and credit (default) risks. According to Majid, Shahimi and Abdullah (2011) an Islamic bond defaults when any of its binding contractual obligations set in the original terms of the agreement between the issuer and Islamic bondholders are breached. As a result, the complexity and type of sukuk structure significantly influence the credit rating process of Islamic bonds. In contrast with conventional bonds, sukuk holders hold proportional ownership in an asset, usufruct or project, and thus the credit risk of sukuk not solely rely on the probability of the issuer's default, but also on the performance of the underlying asset or project. This is viewed as a protection for the sukuk holders in the event of a default[8] or bankruptcy of the issuer, as they can utilise them to recover their contributions (Zakaria, Isa and Abidin 2012). For example, in the case of an Ijara sukuk default, the holders can claim possession of the underlying assets. Hence, certain sukuk structures are likely to face lower credit risks than their conventional equivalents; this is in turn reflected in their higher credit ratings documented in emerging markets and relatively low number of defaults[9] (Hassan et al. 2018).

Lastly, but most importantly sukuk face specific Shariah compliance risks; the risk that the Islamic bonds fail to comply with the Shariah rules (Ariff, Iqbal and Mohamad 2013). Shariah law is complex when it comes to specific contracts and interpretations might differ between them[10]. Hence, Shariah advisors play a key role in sukuk issuance as they ensure that each newly issued Islamic bonds are compliant. In fact, Abdul Halim et al. (2019) show that certification of Islamic bonds by reputable Shariah advisors and committees is associated with a significantly lower average bond spread. However, it is worth noting that Islamic securities approved in a certain country might not be approved in another (Ayub 2007).

From the above comparison, it is evident that the two types of bonds have, at least in *theory*, certain similarities but also distinctions. However, the current academic literature is split into two segments with counter arguments regarding the application of sukuk in the modern setting. Some studies including Miller, Challoner and Atta (2007) and Wilson (2008) claim that in practice sukuk are often structured on the basis of the conventional rules of securitisation, thus are no different from conventional bonds. In contrast, other scholars explain that sukuk do offer some form of financial innovation and therefore differ to an extent from conventional bonds (Cakir and Raei 2007).

2.3 Literature review

In the following section, we review empirical studies on credit ratings, methodological studies on corporate bond credit ratings, comparative literature of sukuk and conventional bonds and finally the existing sukuk rating literature.

[8] In the event of a sukuk default, asset-backed sukuk allows their investors to liquidate the underlying asset to recover their investments, whereas asset-based sukuk provide 'beneficial' ownership of the underlying asset, which in turn restricts the investors' rights (Majid, Shahimi and Abdullah 2011).
[9] Since the inception of the global sukuk credit markets, only 0.22% of the total volume of issuances defaulted by the end of 2007 (IFSB 2018).
[10] The differences in opinion may originate from the differing 'Madhab' (Islamic school of thought) that Shariah advisors' adhere to (Azmat, Skully and Brown 2017).

2.3.1 Credit rating literature

Credit ratings have been extensively used by investors, analysts, debt issuers and governments as a representative measure of the creditworthiness (or, alternatively, credit risk) of companies and debt issues. Although credit rating agencies do not publicly disclose the exact method they follow in assigning the ratings, many researchers find promising results on credit rating prediction. Applying various methodologies, rating models have been developed to predict bond ratings (Kamstra, Kennedy and Suan 2001; Huang et al. 2004; Kim 2005; Cao, Lim and Jingqing 2006; Lee 2007; Kim and Ahn 2012; Reusens and Croux 2017), financial institution or bank ratings (Chen and Shih 2006; Van Gestel et al. 2007; Bellotti, Matousek and Stewart 2011) and other corporate issuer credit ratings (Hwang, Cheng and Lee 2009; Golbayani, Florescu and Chatterjee 2020; Yeh, Lin and Hsu 2012; Mizen and Tsoukas 2012; Hwang 2013a; Hwang 2013b).

The credit rating prediction literature seeks to forecast external credit ratings by investigating the relationship between the ratings and financial or business risk. Internationally recognised credit rating agencies (CRAs) use both qualitative and quantitative analysis to assess firms' business as well as financial risks (Van Gestel et al. 2007). Accordingly, prior studies attempt to predict credit ratings using a wide range of variables to analyse how CRAs utilise public information to set the ratings. Most of the studies employ firm specific financial variables in the form of financial ratios, typically measuring firm size, leverage, profitability, liquidity, interest coverage and bond issue subordination status (Ederington 1985; Huang et al. 2004; Kim 2005). Other studies also utilise market variables such as market model beta of listed firms (Blume, Lim and MacKinlay 1998; Mizen and Tsoukas 2012), macroeconomic variables including changes in GDP, unemployment rates and short-term interest rates (Güttler and Wahrenburg 2007; Hwang 2013a), default risk estimates from structural models, amongst others (Pasiouras, Gaganis and Zopounidis 2006; Hwang, Chung and Chu 2010; Doumpos et al. 2015).

The majority of bond rating prediction studies were conducted on industrial corporate bond ratings, and thus included firms from various industrial sectors. However, industries face different degrees of competition, maintain various financial structures, and accordingly comply with different accounting conventions. Hence, studies suggest that they are exposed to distinct risks, which are reflected in their credit ratings (Chava and Jarrow 2004; Kim 2005; Mizen and Tsoukas 2012). Mizen and Tsoukas (2012) explain that credit ratings differ on the basis of industry fundamentals; industries that are highly competitive, capital intensive, instable, cyclical or are in decline are riskier by default. Despite having stable or conservative financial ratios, issuers operating in such industries are less likely to receive the highest rating classification (AAA).

A few studies have attempted to capture the industry effects on credit ratings by adding industry classification dummy variables into their models (Jackson and Boyd 1988; Shin and Han 2001; Mizen and Tsoukas 2012; Hwang 2013b) or by targeting specific industry(ies). For instance, Altman and Katz (1976) studied bond ratings of electric public utility firms, Kamstra, Kennedy and Suan (2001) focused on transport and industrial bonds, Huang et al. (2004) on banks and financial institution bonds and Kim and Ahn (2012) on manufacturing firm bonds. Alternatively, studies exclude certain industries that have distinct financial structures, such as financial institutions and banks, to not distort the model (Kim 2005). Furthermore, other researchers have studied industry difference in bankruptcy prediction (Platt and Platt 1991; Grice and Ingram 2001; Chava and Jarrow 2004; Lee and Choi 2013; Barboza, Kimura and Altman 2017), which are closely related to the bond rating prediction. Their results suggest that a prediction model developed on the basis of a particular industry may not be accurate in predicting the bankruptcy of a firm operating in another industry. Lee and Choi (2013) provide a multi-industry bankruptcy prediction model, which improves the prediction accuracy by a striking 6-12% from the original general prediction model.

The empirical literature expanded to include sovereign credit ratings that are viewed as indicators of sovereign creditworthiness, a country’s financial system development and a determinant o a country’s access to global financial markets. Studies mostly analyse the determinants of sovereign ratings using various sets of historical data. Early studies, such as Cantor and Packer (1996) find that sovereign credit ratings are mainly driven by macroeconomic variables: GDP growth, GDP per capita, inflation, external debt, default history of sovereign debt and economic development of the country. Subsequent studies confirm the importance of these variables in explaining the variability of the sovereign ratings (Bennell et al. 2006; Afonso, Gomes and Rother 2011; Gärtner, Griesbach and Jung 2011). Moreover, further studies investigate the importance other variables next to the macroeconomic indicators, for instance institutional quality, corruption and other political variables (Mellios and Paget-Blanc 2006; Butler and Fauver 2006; Connolly 2007). Butler and Fauver (2006) examine 86 countries’ sovereign bonds and conclude that the quality of political and legal institutions in a country play a significant role in the determination of its sovereign ratings. More recently, Reusens and Croux (2017) observe that the importance of sovereign credit rating determinants change over time. Using a sample of 90 countries covering the period 2002-2015 they notice that after the beginning of the European debt crisis certain variables, a country’s economic development, external debt, and financial balance, became more influential and the Eurozone membership variable effect on ratings switched to negative. Their work demonstrates that the determinants effect is not stable throughout, and that CRAs most likely revised their sovereign credit rating assessment methodology after the beginning of the crisis.

Credit rating agencies’ objective is to provide credit ratings that represent an accurate relative ranking of the credit risk which is valid at each point in time, independent of the time horizon (Cantor and Mann 2003). This implies that the probability of rating migration from one rating classification to another should be constant over time. However, researches analysing rating dynamics and patterns of credit rating transitions detect non-Markov behaviour of rating transitions suggesting the presence of a rating drift and momentum (Carty and Fons 1993; Altman and Kao 1992; Christensen, Hansen and Lando 2004). Empirical evidence shows that ratings tend to have a downward drift, and their probabilities of future rating changes or even defaults do not only depend on the current rating classification, but also on their past rating transitions (momentum effect). In other words, preceding ratings transitions have predicative power for future changes. This rating momentum seems to be more prominent with rating downgrades, wherein ratings that experienced past downgrades are more inclined to further downgrades than others (Jarrow, Lando and Turnbull 1997; Christensen, Hansen and Lando 2004). Moreover, studies also show that the period that an issuer spends on a particular rating classification influences its rating transition to another classification, known as the ageing effect (Kavvathas 2001; Lando and Skødeberg 2002).

CRAs focus on the long-term perspective, lowering the ratings' sensitivity to potential short-term fluctuations in quality (Altman and Rijken 2004). Therefore, they aim to respond to permanent or long-term changes in rating qualities. Accordingly, it is argued that credit ratings should not vary in a procyclical manner, but rather be assigned on a through-the-cycle basis (Bellotti, Matousek and Stewart 2011). However, there are several pieces of evidence which suggest that rating migrations follow the business cycle (Blume, Lim and MacKinlay 1998; Nickell, Perraudin and Varotto 2000; Bangia et al. 2002; Cantor and Mann 2003). Blume, Lim and MacKinlay's (1998) Ordered Probit results suggest that the standards of CRAs became more stringent between 1978-1995, which explains at least part of the increasing number of rating downgrades at that time. Nickell, Perraudin and Varotto (2000) were the first to include a business cycle stage variable into the covariates influencing the rating transitions. Studying the transition matrices of their samples, they observe a higher probability of downgrades during recessions, finding evidence of Moody's ratings cyclicality. They claim that default probabilities strongly depend on the state of the business cycle, and that the cyclicality effect influences especially the lower rated issuers. Using a sample of US S&P issuer ratings, Bangia et al. (2002) confirm that rating transition probabilities fluctuate with business cycles and draw attention to the potential advantage of the regime switching models for credit portfolio stress testing.

On the other hand, Amato and Furfine (2004) extend the work of Blume, Lim and MacKinlay (1998) and find that S&P ratings in general do not demonstrate high sensitivity to the state of business cycle. They claim that the ratings vary with the cyclical changes in the business (firm size, equity risk both systematic and idiosyncratic risks) and financial risks (interest coverage, operating margin and level of gearing) rather than cycle-related changes to rating standards. It is noteworthy that they only detect some degree of procyclicality of investment grade firms, initial ratings and rating changes. A shift in the business cycle state, all other factors constant, can indeed influence the predicted rating of investment grade firms. Furthermore, their results suggest that CRAs have a tendency to treat initial ratings and changes in rating differently than the rest, most likely with an excessively procyclical manner. This observation explains to an extent the massive downgrades that took place during the dotcom bubble and subprime mortgage crisis, which in turn raises some doubts on whether the ratings really see through the cycles (Mizen and Tsoukas 2012).

So far, the credit rating literature discussed here has focused on consistent ratings. Another strand of research analyses different biases or inconsistencies in external credit ratings. According to Livingston, Naranjo and Zhou (2008), approximately 20% of US corporate and sovereign bonds have split ratings. Split ratings occur when two leading CRAs assign a different rating to the same security or issuer. Numerous studies investigate the causes behind split ratings of mainly corporate bonds. For instance, Ederington (1986) argues that new issue split ratings occur due to differences of judgements across the CRAs, i.e. random errors. In contrast, Moon and Stotsky (1993), Cantor and Packer (1997) and Pottier and Sommer (1999) attribute the distinction in assigned ratings to the differences in the CRAs rating methodologies or determinants, rating scales and weighting attached to rating determinants. Moreover, other studies show that corporate issuers operating in industries with more opaque assets, such as financial intermediaries, are more likely to receive split ratings from CRAs (Morgan 2002; Livingston, Naranjo and Zhou 2007; Hyytinen and Pajarinen 2008). Morgan (2002) explains that the disagreement between raters stems from the difficulty of observing and quantifying the risks of these industries or securities.

A few other studies give an alternative reasoning to split ratings, arguing that ratings disagreements can also occur due to home bias, where CRAs seem to rate home country issuers more leniently (Nickell, Perraudin and Varotto 2000; Shin and Moore 2003). This could be due to the conservatism of US CRAs when rating foreign firms operating in markets they are less familiar with. However, this does not appear to be the case of near-to-defaulting firms' credit ratings. Güttler and Wahrenburg (2007) show that within their sample, Moody's and S&P seem to have been more conservative towards US issuers, as they assigned them lower ratings than non-US issuers. They argue that this finding could be ascribed to several reasons: the CRAs have better default forecasting capability in their local US market, enhanced quality of accounting information disclosed in the US or dissimilar regional bankruptcy legislation. The above mentioned researchers believe that split ratings convey valuable information that could potentially affect future rating migrations. Livingston, Naranjo and Zhou (2008) examine this and find that corporate bonds with split ratings are in fact more prone to experience future rating changes.

Analogous qualitative bias was also detected in sovereign credit ratings (Gültekin-Karakaş, Hisarcıklılar and Öztürk 2011; Ozturk 2014; Fuchs and Gehring 2017). The studies document that CRAs assign higher ratings to countries that are closer geographically, culturally, politically and economically to the US. Hence, detecting an upward bias for home country (US) and similar countries.

Gültekin-Karakaş, Hisarcıklılar and Öztürk (2011) observe that emerging markets credit ratings are biased downwards, confirming that sovereign ratings are biased towards developed countries. De Moor et al. (2018) argue that not all foreign or home bias is necessarily spontaneous or unconscious. Credit ratings are known to have a subjective judgement element, though it is unclear how significant their importance is relative to the objective element. It is claimed that this subjectivity might lead to noise or biases in the credit risk assessments (Zheng 2012). De Moor et al. (2018) attempt to measure the subjective component in sovereign ratings and find that it is substantial primarily for lower rated countries. Highly rated countries have a tendency to be positively affected by it, whilst conversely low-rated countries tend to be negatively influenced. They also show that the subjective judgement has a predictive power over sovereign credit rating defaults in the short-term. This lack of transparency of CRAs' rating process has been subject of criticism especially after the subprime mortgage crisis to which regulatory bodies reacted (Dodd-Frank Act in 2010). Amstad and Packer (2015) state that since the regulatory changes took place, CRAs rely more on qualitative analysis which should in theory make their processes more transparent and replicable. However, their further analysis does not show convincing or substantial empirical results to support that.

2.3.2 Bond rating methodologies

There has been an expansion of methodological approaches to corporate bond rating prediction. Generally, the previous empirical literature can be grouped into two broad categories: statistical methods and artificial intelligence (AI) methods.

The first study addressing the bond rating prediction problem using a statistical approach can be traced back to 1966, when Horrigan (1966) utilised OLS to regress accounting data for long-term credit administration. Many subsequent studies applied OLS to predict corporate bond ratings with similar variables obtaining only slightly better results (Pogue and Soldofsky 1969; West 1970). Credit rating agencies report bond credit ratings in an ordinal scale, however all of the studies employing OLS assume that the bond ratings are of an interval scale as they code them into equally spaced discrete intervals from 9 to 1 (Horrigan 1966; West 1970). Therefore, there is a general consensus on the inappropriateness of OLS for predicting bond ratings (Altman et al. 1981; Kamstra, Kennedy and Suan 2001).

The statistical validity and accuracy limitations of regression analysis led subsequent studies to apply Multiple Discriminant Analysis (MDA) that was getting popular at that time (see Pinches and Mingo 1973; Pinches and Mingo 1975; Ang and Patel 1975; Altman and Katz 1976; Belkaoui 1980; Perry, Henderson and Cronan 1984). Although MDA seems like a more appropriate method than OLS it is still subject to criticism. The MDA still does not account for the continuous nature of the bond credit ratings. Moreover, Eisenbeis (1977) argues that the practical application of MDA in finance frequently violates the multivariate normality assumption that the MDA requires for independent variables and accordingly causes biased results.

In order to take into account the ordinal nature of bond ratings, later studies applied Probit and Logit models (Kaplan and Urwitz 1979; Ederington 1985; Gentry, Whitford and Newbold 1988; Blume, Lim and MacKinlay 1998). Ederington (1985), compares all the mentioned statistical approaches, his findings suggest that the logit and probit regressions outperform the rest. More recently, Kamstra, Kennedy and Suan (2001) applied several forecasting methods to predict the Moody's bond ratings in the transportation and industrial sectors. They conclude that a variant of the ordered logit combining method of Kamstra and Kennedy (1998) yields meaningful improvements to the predictions of bond ratings.

Generally, the above listed studies employing statistical methods to address the bond rating prediction problem reached a prediction accuracy of approximately 50-70%. Despite the methods' limitations, it can be concluded that the previous researchers have shown that relatively simple models with a small number of independent variables based on historical and public information can correctly forecast about two thirds of a sample (holdout) of bond ratings (Huang et al. 2004). Kamstra, Kennedy and Suan (2001) justify the statistical models' lower prediction power explaining that the actual bond rating process is complex and takes into account other unmeasurable variables, for example technological changes and leadership quality. Accordingly consequent studies suggest that the statistical methods can be used as an initial first estimate for the fairly multifaceted and subjective bond rating process (Huang et al. 2004).

Recently, researchers have sought to improve the accuracy of bond rating forecasts using various artificial intelligence (AI) approaches, particularly neural networks (NN) (Dutta and Shekhar 1988; Kim 1993; Moody and Utans 1995; Singleton and Surkan 1995; Kwon, Han and Kun 1997; Maher and Sen 1997), case based reasoning (Shin and Han 1999; Kim and Han 2001), adaptive learning networks (Kim 2005), support vector machines (Huang et al. 2004; Cao, Lim and Jingqing 2006; Lee 2007; Kim and Ahn 2012) and decision trees (Jabeur et al. 2020).

In contrast to the statistical techniques that impose structures on various models, AI methods enable learning the specific structure from the data. Although this is seen as a major benefit of AI methods, it also implies that the results obtained from the models are very complex and hard to interpret (Huang et al. 2004). The most frequently applied AI method is backpropagation neural network (BNN), which is often compared to other methods. Huang et al. (2004) predicted US and Taiwanese corporate bonds with a prediction accuracy of approximately 80% for both BNN and support vector machines (SVM). They explain that SVM offer only a slight enhancement to the BNN. On the other hand, Lee's (2007) empirical results show that SVM outperforms MDA, case based reasoning and standard three-layer fully connected BNN prediction methods by a range of 3.81-7.29%. They explain that SVM prediction might be globally optimal as it attempts to minimise the structural risk, whilst NN tend to minimise the empirical risk.

However, neural networks have several limitations. Studies argue that they have a risk of overfitting, and it is difficult to define the values of control parameters as well as the number of processing elements in the layer (Kim and Ahn 2012). In comparison, SVM do not require tuning of any parameters, except for the upper bound needed in non-separable cases of linear SVM (Barboza, Kimura and Altman 2017). Nevertheless, SVM were originally designed for binary problems, and thus are not naturally suitable for ordinal multi-class classifications, such as credit ratings (Vapnik 1995). To overcome this limitation, Kim and Ahn (2012) extended the SVM analysis to a multi-class classification, and proposed a new SVM classifier by applying an ordinal partitioning strategy named OMSVM. Their proposed model surpasses all other typical multi-class classification techniques in sample and out of sample and requires fewer computational resources. They conclude that their OMSVM is an effective method for solving ordinal multiclass classification problems.

In a more recent study, Jabeur et al. (2020) investigates the effectiveness of six methodologies: Logistic Regression and MDA, SVM, NN, the Cost-Sensitive Decision Tree algorithm and deep NN in predicting a sample of sovereign bonds. Their empirical results suggest that the non-parametric methods (AI) improve the prediction accuracy and can be used as an alternative to the traditional methods. In addition, they find that the Cost-Sensitive Decision Tree algorithm combined with a classifier ensemble provides the most accurate rating predictions, where it outperforms the traditional models and the deep NNs.

The general conclusion that can be made is that artificial intelligence methods, particularly NN and SVM, outperform the traditional statistical methods in most prior studies. Huang et al. (2004) suggest that the prediction accuracy assessment should be adjusted according to the number of prediction rating classes employed. Studies that make predictions using more than five rating classifications, tend to reach an accuracy of between 55-75% (for more detailed comparison see Huang et al. 2004).

2.3.3 Comparative literature on Islamic versus conventional bonds

Recent literature has taken several directions to compare sukuk and conventional bonds. Using the Value-at-Risk (VaR) framework, Cakir and Raei (2007) examine the effect of sovereign sukuk issued on the cost and risk structure of investment portfolios. Employing a sample of sovereign Islamic and conventional bonds from the same issuer, they find that Islamic bond returns are weakly correlated with conventional bond returns and accordingly the inclusion of sukuk in a fixed income portfolio considerably reduces its VaR. This implies that sukuk differ from conventional bonds as they have distinct price behaviour, and therefore offer diversification benefits for investors.

Supporting this view, Godlewski, Turk-Ariss and Weill (2013) applied an event study methodology on a sample of Malaysian listed companies to study the differences in stock market reactions to the announcements of 77 Islamic and 98 conventional bond issues between 2002 and 2009. Following Ross (1977), they argue that debt issuance can send a credible signal to the market regarding the quality of the issuers, which helps tackling the adverse selection problem arising from the information asymmetry between firm insiders and outsiders (investors). Their findings show that the Malaysian stock market negatively reacts to the announcements of Islamic bond issues but is quite neutral to announcements of conventional bonds. This suggests that investors perceive sukuk announcements as negative signals, as they expect the adverse selection mechanism to motivate lower quality (lower profit expectation) firms to issue profit-and-loss sharing sukuk over conventional bonds to be able to share the losses in the case of default. Despite that, the excess demand of sukuk in the Islamic financial market makes it easy for such issuers to sell their sukuk. Moreover, they explain that the negative stock market reaction to sukuk announcements is expected to be lower in a purely Islamic financial market where conventional bonds are not issued.

Covering a wider array of six countries Alam, Hassan and Haque (2013) find similar results before and during the subprime mortgage crisis sample. They argue that the adverse selection mechanism is supported by the characteristics of Islamic bond issuing companies, that are notably less leveraged and less profitable than conventional bond issuers. However, it is interesting to note that they observe an inverse market reaction after the crisis. They attribute the positive market reaction to sukuk in this case to various reasons, including the increased demand for asset-backed sukuk after the crisis. This view is supported by the findings of Khartabiel et al. (2020) who also find a positive response to sukuk issuance announcements in their post-crisis period, but no significant response to the announcements of conventional bonds during this period.

In another event study, Godlewski, Turk-Ariss and Weill (2016) examine the stock market reaction to two key sukuk features: sukuk structure and characteristics of the Shariah scholar certifying the issue. Their event study relies on a sample of eight different countries between 2006 and 2013 and suggests that Shariah scholar reputation and Ijarah sukuk structures positively impact its issuer's share price. These findings are interesting as they support the view that the choice of sukuk structure and Shariah scholar matter to the future market valuation of their issuers. Furthermore, the above studies' results indicate that stock market participants distinguish between the characteristics of Islamic and conventional bonds, which in turn provide evidence of the dissimilarity of the two products. This opposes the major criticism of sukuk by Miller, Challoner and Atta (2007) and Wilson (2008) who claim that sukuk are structured on the basis of conventional rules and thus have great similarity with conventional ones.

In connection to the adverse selection mechanism, several studies attempt to investigate the reasons behind firms preferring the issuance of corporate sukuk as opposed to conventional bonds (Azmat, Skully and Brown 2014b; Mohamed, Masih and Bacha 2015; Klein and Weill 2016; Nagano 2016; Sherif and Erkol 2017; Nagano 2017; Abdul Halim, How and Verhoeven 2017). Studies show that the determinants of Islamic and conventional bond issuance are similar, but the main difference between them lies in the degree of information asymmetry (Klein and Weill 2016; Nagano 2017). Nagano (2017) states that a firm is more likely resort to sukuk funding in underdeveloped financial markets when it requires a large funding size and faces a high degree of information asymmetry to approach the conventional debt market. Analogous to the purely conventional markets, the trade-off and pecking order theories were also found to have explanatory power over the choice of sukuk financing. For example, Mohamed, Masih and Bacha (2015) show that partnership-based sukuk, such as Musharakah or Mudarabah, follow the pecking order view and are preferred when firms face substantially higher information asymmetry. However, they also provide evidence contrary to the interpretations of the theory and Alam, Hassan and Haque (2013). They argue that asset-based sukuk are usually issued by firms with higher growth opportunities, as they offer unique benefits to the issuers in comparison to the conventional bonds. Similarly, Grassa and Miniaoui (2018) claim that in the GCC region, sukuk issuers tend to have higher firm specific characteristics, but older and larger highly rated firms favour issuing conventional bonds instead of Ijarah sukuk. Furthermore, analysing the Malaysian Market, Sherif and Erkol (2017) argue that the tax preferential incentives offered for sukuk issuances and government backing promote funding through sukuk; which in turn supports the development and growth of the sukuk market. Nevertheless, researchers agree that the above evidences underline the need for regulatory framework improvements to balance the growth of the Malaysian and other undeveloped countries' debt markets (Klein and Weill 2016).

Taking a different approach of comparison, Maghyereh and Awartani (2016) investigate the returns and volatility spillovers of Islamic and conventional bonds with equities using four dollar denominated indices. Their dynamic spillover index methodology results show that sukuk markets have different transmission mechanisms than their conventional counterparts. Specifically, they found that sukuk have higher transmission of information from global equities, but a substantially lower or even negligible flow of information from the sukuk market to other markets (including the conventional bond market). Moreover, their findings also signify weak returns spillover and co-jumps between sukuk and global bonds. On the other hand, Hassan et al. (2018) show that sukuk returns in major Islamic markets are less volatile than US and EU conventional bonds, but have a time varying positive conditional correlation with conventional leading bond markets. They observe that this dynamic correlation increases during market recessions and conclude that it is bound by the market conditions for example, stock market uncertainty, liquidity, crude oil prices and other. Other studies confirm that sukuk are distinct from conventional bonds as their co-movement with global and regional uncertainty factors differ, and their returns and volatilities are less sensitive to interest rates surprises (Naifar, Mroua and Bahloul 2017; Akhtar et al. 2017). Although the literature's results are mixed, they shed a light on the potential usefulness and significance of sukuk in portfolio management for strategic asset allocation and hedging which is in line with the findings of Cakir and Raei (2007) discussed earlier in this section.

Concerning the current literature investigating sukuk during periods of economic uncertainty, Kenourgios, Naifar and Dimitriou (2016) studies the contagion effects of the subprime mortgage crisis and Eurozone sovereign debt crisis on Islamic bonds and Islamic equity in general. They find that the Dow Jones sukuk index remained unaffected by the US T-bills during the global financial crisis and were decoupled from the Euro bonds during the sovereign debt crisis. Their empirical results indicate that sukuk were insulated from the crisis, which is in line with a wider set of literature that argues that the religious principles governing the investments of Islamic banks gives them greater stability especially during financial crises (Čihák and Hesse 2010; Beck, Demirgüç-Kunt and Merrouche 2013). In contrast, other studies such as Naifar and Hammoudeh (2016) show that different conditions apply in the bearish GCC market as the global financial crisis and oil price uncertainties have a clear negative influence and causality effects on sukuk returns. More recently, Yarovaya, Elsayed and Hammoudeh (2021) show that sukuk exhibit safe haven properties during the COVID-19 pandemic, and thus can be utilised to diversify portfolios and hedge during periods of market stress, for example the pandemic. Therefore, it can be said that Islamic bonds might provide a cushion against economic downturns or periods of financial instability, however that is subject to the period and to the market in question.

Following the argument of Islamic bond critics, if sukuk mirror their conventional equivalents, then their returns should be comparable (Wilson 2008). In an effort to investigate this, Ariff et al. (2017) contrast the yields of Malaysian Islamic and conventional bonds. They conclude that the average Treasury sukuk yields are significantly higher than conventional Treasury bond yields. On the contrary, AAA corporate sukuk receive lower returns (up to 25 basis points in the case of long-term sukuk) than AAA corporate conventional bonds, which indicates another evidence of their distinction. Using a more recent sample, Asmuni and Tan (2020) find comparable results suggesting that the government (sovereign) sukuk yields are significantly higher than the conventional ones and attribute this positive yield spread to the liquidity factor. Moreover, they detect a small yield spread discount between corporate sukuk and corporate bonds. The observed lower yields or sukuk discount, suggest that they are perceived as safer investments than the their conventional counterparts, which is inconsistent with the event studies showing negative market reactions to sukuk claiming that they are bad news (Godlewski, Turk-Ariss and Weill 2013; Ariff et al. 2017).

Although the yields on sukuk seem to differ, Ayturk, Asutay and Aksak (2017) cross sectional results indicate that the determinants of Islamic bond pricing are comparable to the conventional ones. They show that sukuk credit rating and maturity reduce the primary market spreads, whereas sukuk margin rating seem to increase it. More prominently, sukuk specific factors, such as its type and Shariah scholar reputation, were found to be insignificant contradicting the findings of Godlewski, Turk-Ariss and Weill (2016).

Generally, it can be summarised that the body of literature comparing Islamic and conventional bonds found mixed results. They signify that sukuk have a lot of similarities with conventional bonds, but present several empirical evidence of their special features and distinction. They also show that their differences vary from sukuk structure and from one market to another. This emphasises the need for further empirical research in sukuk literature covering larger samples and geographical areas before a clear conclusion can be made.

2.3.4 Sukuk rating literature

Despite the rapid growth of sukuk markets, sukuk credit rating literature remains largely unexplored. Azmat, Skully and Brown (2014a) examine the suitability of conventional structural credit risk models for capturing IJV sukuk underlying risk. They conclude that the conventional models with Islamic extensions misevaluate the IJV bonds' risk, offering them lower credit ratings and thus recommend evaluating them like equity securities. They explain that the main issue is that the conventional models concentrate on the issuer's ability to return the principal; and does not account the distinct features of IJV sukuk that could potentially offer positive returns. Their work highlights the need of further research in the areas of credit risk and default.

As mentioned earlier, an extensive amount of research has been done to predict bond ratings. However, not much attention has been paid to sukuk credit rating prediction, most likely due to the limited amount of data available. To our knowledge a few studies explore the case of sukuk credit rating (Elhaj, Muhamed and Ramli 2018; Arundina, Omar and Kartiwi 2015; Azmat, Skully and Brown 2017; Borhan and Ahmad 2018). Utilising ordered logit/probit and multinomial logit regressions (MLR), their results indicate that, similar to conventional bonds, firm specific variables, such as, leverage, profitability, size and industry classification seem to influence sukuk credit ratings as well. Additionally, studies show that corporate governance variables (Elhaj, Muhamed and Ramli 2015; Elhaj, Muhamed and Ramli 2018), share price and Islamic bond feature variables, mainly sukuk structure and Shariah advisor also play a significant role in their credit rating determination (Arundina, Omar and Kartiwi 2015; Azmat, Skully and Brown 2017) . Their findings are unique as these variables are not standardly used in credit rating models. Yet, Azmat, Skully and Brown (2017) claim that their results support AAOIFI's concern that the majority of sukuk are structured in a manner similar to conventional ones, with very few differences.

From the above studies, only Arundina, Omar and Kartiwi (2015) attempt to predict sukuk credit ratings. Using a sample of 317 Malaysian corporate sukuk, they compare the performance of two models

MLR and neural network. They find that the Artificial Intelligence method, NN improves the prediction accuracy over the statistical method (96.18% versus 91.72% accuracy). Their results are consistent with prior conventional bond rating literature showing that AI methods mostly outperform the statistical ones (Huang et al. 2004). However, surprisingly the accuracy level of Arundina, Omar and Kartiwi (2015) is significantly higher than those reached in the conventional bond rating prediction literature.

In summary, it is evident that most bond rating literature is concentrated on conventional bond markets, with little attention paid to sukuk credit rating. Recent studies explore the determinants of sukuk credit ratings using traditional methods, but mostly do not provide and evaluate credit rating predictions. Furthermore, as demonstrated above, the comparative literature of sukuk and conventional bonds is growing in an effort to understand the similarity and differences between the two types of bonds. Hence, this highlights the need for greater exploration and comparison between sukuk and conventional bond credit ratings.

2.4 Data

The empirical analysis presented in this chapter is based on data collected from the Bond Pricing Agency Malaysia Sdn Bhd (BPAM). BPAM was the primary source for all bond ratings and for the majority of bond-related and market structure information, including the Islamic structure for Islamic bonds. Moreover, Bloomberg was used to obtain the issuers' company financial information. Data were collected for all rated Malaysian corporate bonds active on 29 December 2017. We chose the Malaysian market as it issues both Islamic and conventional bonds, and dominates 51% of the *global* outstanding sukuk and 73% of total *domestic* sukuk market in 2017 (IIFM 2018). Only long-term domestic corporate bonds rated between January 2016 and December 2017 were included in the sample. After filtering for missing data and excluding financial firms' bonds, our final sample consists of 610 bonds (541 sukuk and 69 conventional bonds). Accordingly, to estimate the models we use the full sample (All), and two sub-samples: the Islamic sample that includes all sukuk, and the conventional sample that includes the conventional bonds. Given that Malaysia is a Muslim country, it is not a surprise that there is a big contrast amongst the subsample sizes. Malaysian firms more commonly issue sukuk that comply with their religious beliefs and are incentivised by government backing and tax advantages offered by the Malaysian government (Sherif and Erkol 2017).

Studies argue that the characteristics of Islamic and conventional issuers or banks can differ (Mohamed, Masih and Bacha 2015; Grassa and Miniaoui 2018; Olson and Zoubi 2008). In order to reduce the self-selection bias and heterogeneity across a sample with Islamic and conventional groups i.e., treated and untreated groups, a few comparative studies test the robustness their results using a reduced sample that is matched based on selected characteristics (Aysan et al. 2018; Duqi, Jaafar and Warsame 2020). There are several matching methods, most notably, the exact matching and propensity score matching (PSM) techniques. Exact matching is only viable when the covariates are discrete and the sample is large (Cameron and Trivedi 2005). Therefore, given that bond credit rating determinants incorporate financial ratios that are continuous in nature, exact matching becomes impractical for this thesis.

PSM is a widely applied inexact matching technique that matches based on the propensity score, which is typically estimated using a logit or probit model (Cameron and Trivedi 2005; Rosenbaum and Rubin 1983). The second stage of this method entails forming matched sets of treated and untreated groups that have a similar propensity score. Various matching approaches have been put forward, including nearest-neighbor matching, caliper matching, radius matching, K-nearest neighbour matching and kernel matching (Dehejia and Wahba 2002; Becker and Ichino 2002). However, the success of PSM implementation is tied to the choice of matching method, whether replacement is allowed and the sample size (Cameron and Trivedi 2005). What is more, the effectiveness of matching methods depends on the appropriateness of the propensity score model chosen (Dehejia and Wahba 2002). King and Nielsen (2019) show that with the use of balanced enough data to approximate complete randomisation, PSM increases the imbalance in comparison to the original data. In regards to the sensitivity of the results to the matching method, Cameron and Trivedi (2005) argues that it varies based on the amount of overlap between the treated and untreated observations. If the comparison group is small, then it is likely to exhaust satisfactory matches, especially if matching was without replacement, and be restricted from using the full treated sample. Given that our conventional sample, that is, the comparison group is limited to 69 bonds, matching methods are unfeasible for our analysis. We do not anticipate any major differences in our findings as we construct our baseline rating model on the rating methodologies published by the Malaysian CRAs as well as the prior literature, which incorporates similar main common bond credit rating determinants for all corporate issuers. In addition, we not only use the full sample, but also separately analyse two separate sub-samples: Islamic bonds and conventional bonds.

2.4.1 Dependent variable

The dependent variable in the bond rating models is the corporate bond credit rating assigned to the bonds by two local Malaysian credit rating agencies: Malaysian Rating Corporation Berhad (MARC) and RAM Holdings Berhad[11] (RAM). In keeping with the standard practice in prior literature, only bonds rated higher than B were considered, and all ratings were categorised without considering the notches or subscripts (i.e., + and – or 1, 2 and 3). The distributions of the credit rating categories of the two sub-samples (Islamic and conventional) and the full sample are presented in Table 2.2. Unlike prior literature, the most common rating assigned by the domestic CRAs is AA rather than A or lower, followed by AAA (Lee 2007; Huang et al. 2004; Kamstra, Kennedy and Suan 2001). This indicates that the Malaysian CRAs seem to be more generous in their rating assignments. Consistent with Azmat,

[11] Formerly known as Rating Agency Malaysia Berhad.

Skully and Brown (2017), sukuk are mostly assigned higher ratings (AAA-A). Comparing the two sub-samples with one another, a higher proportion of Islamic bonds (68.58%) were rated as AA, whilst a larger proportion of conventional ones (56.52% vs. 27.54%) were classified as AAA. Interestingly, the sample does not include any BBB bonds (for which the financials were available) and none of the conventional bonds in the sample were rated BB or lower. As a result, this study considers four ordinal rating categories: AAA, AA, A and BB. In order to run the models, the rating categories were assigned to numerical values, starting with 1 to BB, 2 to A, up until 4 to AA.

2.4.2 Independent variables

In our empirical models, we follow both CRA practice and bond rating literature in measuring the determinants of credit rating. The following subsections explain all explanatory variables we include in our analysis.

2.4.2.1 Firm specific financial variables

CRAs emphasise that the whole rating process is underpinned by the financial analysis of historical financial statements, analytic adjustments and cash flow forecasts (MARC 2017; MARC 2016b; Standard & Poor's Ratings Services 2014). Therefore, the most important set of variables consists of firm financials. The choice of financial variables included into our analysis is guided by previous literature and data availability (Kamstra, Kennedy and Suan 2001; Huang et al. 2004; Kim 2005; Lee 2007; Arundina, Omar and Kartiwi 2015). Six main types of indicators are included: firm size, profitability, leverage, liquidity market value, and cash flow. Since the rating assignments take something between 4 to 6 weeks, thus following Huang et al. (2004) the financial ratios and company financials (apart from share price) variables of the Malaysian issuing firms were collected for two quarters prior to the rating effective date (RAM 2018).

To narrow down the selection of variables we input in our model, we analysed Spearman's rank order correlation matrix of the dependent (ratings) and independent variables and exclude those that cause multi-collinearity. Finally, using a backward ordered probit stepwise approach[12], we include only significant variables in the model. Table 2.4 presents the correlations between the dependent variable and the 10 explanatory variables that we input into the stepwise approach. This approach narrowed down our set of variables from 10 to 7 significant financial variables. Our final set of firm specific financial variables consists of firm size (SIZE), profitability (PM), leverage or debt to assets ratio (LEV), interest coverage (INT_COV), liquidity (LIQUID), and two market value measures: price-to-

[12] Most prior studies select the list of independent variables using the stepwise regression analysis (see e.g. Lee 2007). We set the significance levels as 11% and 10% for the variable removal and addition from the model, respectively.

earnings ratio (PE) and percentage change in firm share price (PRICE_CHANGE). Table 2.3 lists and defines all the variables included in the estimation.

Balance sheet total assets are included to represent size (SIZE) of the issuing firms. This variable has been extensively used in literature, and it has been documented that larger firms, i.e. higher size factor, tend to represent stronger financial soundness and stability which in turn positively influence the credit ratings (Horrigan 1966; Belkaoui 1980; Ederington 1985; Kamstra, Kennedy and Suan 2001). This variable was log transformed, to ensure that larger value inputs do not distort the estimation. In a similar trend, studies also show that profitable firms tend to receive higher ratings (Pinches and Mingo 1973; Kaplan and Urwitz 1979; Blume, Lim and MacKinlay 1998).

To measure the influence of firm profitability on ratings, we follow Kim (2005) and Huang et al. (2004) and take the profit margin (PM) and price-to-earnings ratios (PE). The next two variables we include are leverage ratios: debt to asset ratio (LEV) and interest coverage ratio (INT_COV). Where LEV measures the issuing firm's proportion of assets financed with debt (leverage) and INT_COV determines how easily a company can pay its interest on its outstanding debt for the year. Both ratios have been extensively used in prior literature, which argues that higher levels of leverage imply weaker balance sheet, meaning higher chances of defaulting rating (see e.g. Blume, Lim and MacKinlay 1998; Mizen and Tsoukas 2012; Huang et al. 2004). Therefore, LEV is expected to be inversely related to bond. On the other hand, interest coverage is expected to be positively related to ratings as higher values of the ratio indicate greater ability of servicing the debt, thus greater solvency (Ederington 1985; Kamstra, Kennedy and Suan 2001).

In terms of liquidity, studies employ several measures of liquidity and cash flow, for example current ratio, quick ratio and cash ratio (Huang et al. 2004; Lee 2007). For our LIQUID variable, we concentrate on the moderately conservative measure of liquidity, the quick (acid) ratio. Studies show that higher levels of liquidity positively drive credit ratings (Belkaoui 1980; Hwang 2013b). Lastly, extending the work of Arundina, Omar and Kartiwi (2015), who found that share prices are extremely important in determining sukuk credit rating, we incorporate a share price explanatory variable. Due to the high degree of correlation we observe between log stock prices and the size and leverage ratios, we attempt to capture the market share price effect on the credit risk assessment using the percentage change in firm share price (PRICE_CHANGE). The change is calculated as the percentage difference between the share price on the rating effective date and the share price 200 days before it.

2.4.2.2 *Bond specific variables*

Four bond specific variables are included in the estimation samples (see Table 2.3). The first bond characteristic (ISLAMIC) variable, is a dummy variable that indicates the principle of the bond; it takes a value of 1 if it is an Islamic bond and 0 if it is a conventional one. This variable shows whether the

CRAs distinguish between the two types of bonds in their rating assessment. MARC (2016a) state that they analyse both internal credit enhancements (for example, collateral value) and external credit support provided the issuer or third party. Therefore, the next two variables (GUARANTEE and SECURED) address these supports. GUARANTEE reflects whether the bond is guaranteed by a corporation, financial institution, bank, or other supports that will pay the interest and principal payments in the event of the bankruptcy or default of the issuer. Therefore, having such guarantees is expected to enhance the credit ratings of bonds (MARC 2017). Similarly, SECURED variable refers to whether the bond is secured with some form of a collateral which lowers its riskiness for investors, again secured bonds should be receiving higher ratings than non-secured ones. Furthermore, FIXED_RATE variable specifies if the bond has a fixed rate (coupon), which limits the uncertainty of the cash stream investors will receive. Therefore, it is hypothesised that it will positively influence the credit ratings. Studies show that CRAs assess credit ratings differently, thus our last bond specific variable attempts to capture the effect of credit rating agency firms on credit quality (Cantor and Packer 1997; Livingston, Naranjo and Zhou 2007; Livingston, Naranjo and Zhou 2008). However, since in the Malaysian market bonds are either rated by MARC or RAM, but not both, we incorporate a dummy variable (MARC) that distinguishes between the rating agencies. All variables are constructed as binary indicators (dummy variables), that take a value of 1 in the presence of the characteristic, and 0 otherwise.

2.4.2.3 Market structure variables

There is evidence that industrial sectors characterised by high-risk are expected to receive lower credit ratings i.e. adversely affect ratings, and vice versa (Mizen and Tsoukas 2012). In order to capture the industry effect on credit ratings, sectoral classifications of bond issuers were obtained from BPAM. After filtering for missing values, the total number of sectors included in the full sample are 10. However, due to the small number of observations in certain sectors, we aggregated six sectors that included 6 bonds or less and constructed an ‘other sector’ variable (OTHERSEC). As a result, the number of sector classifications is reduced from 10 to 5. Table 2.2 shows that most Islamic bonds are issued by infrastructure and utility, and construction and engineering firms, which is typical given their specific features (structures) (Ayub 2007). On the other hand, conventional bonds seem to be mostly issued to finance property and real estate or trading and transportation services firms. For the initial estimation, following prior studies (Mizen and Tsoukas 2012; Hwang 2013b) the industrial sectors are included as dummy variables that take a value of 1 if the bond issuer belongs to the sector and 0 if it does not. A total number of 4 dummies are included as shown in Table 2.3, which are benchmarked against the infrastructures and utilities industrial sector with the highest number of observations.

2.4.2.4 Islamic bond structure variables

As mentioned earlier, sukuk come in different Islamic structures (types) with distinct characteristics, where certain structures might inherit more credit risk than others. To capture this, following previous sukuk rating studies we include binary (dummy) indicators for different sukuk structures (Borhan and Ahmad 2018; Elhaj, Muhamed and Ramli 2015; Arundina, Omar and Kartiwi 2015). From the data provided by BPAM, the sample includes eight different sukuk structures as shown in Table 2.2. These variables are included only in the Islamic sample to analyse whether and how the sukuk structures influence the credit ratings. A total number of 7 Islamic structure dummies are included (see Table 2.3), which are benchmarked against the Murabahah sukuk that are often referred to as Islamic debt bonds and are argued to be the closest to conventional ones (Azmat, Skully and Brown 2014a). From Table 2.2, it is evident that the most common sukuk structure included in our sample are hybrid (a mix of two or more structures) and Mudarabah sukuk. In contrast, the least common contractual agreement is Bai Bithaman Ajil (BBA), which is (due to Shariah principles) restricted from secondary market trading.

2.4.3 Descriptive statistics

The descriptive statistics of the selected financial variables from our Islamic, conventional, and full (All) samples are shown in Table 2.5. The table also reports the t-tests (Mann-Whitney test) on the mean (median) difference of the Islamic and conventional bond issuers' financials. Most of the statistics are in line with previous literature. Observing the averages of the size factor, we verify that Islamic firms that issue sukuk are significantly smaller than conventional firms or conventional bond issuers (total assets of RM 47.98 bn against RM 208.16 bn). This is consistent with the findings of Mohamed, Masih and Bacha (2015) and Grassa and Miniaoui (2018), as well as comparative studies of Islamic and conventional banks (Olson and Zoubi 2008; Pappas et al. 2017). Moreover, the profit margins show that sukuk issuers are also less profitable than conventional bond issuers (15.59% and 19.16%), which supports the view that firms with lower profit expectations resort to sukuk (mainly partnership based structures) issuance to be able to share the losses in the event of default (Godlewski, Turk-Ariss and Weill 2013; Alam, Hassan and Haque 2013). Nevertheless, investors seem to be slightly more optimistic about the Malaysian Islamic firms' (sukuk issuers') future prospects indicated by their higher average and median price-to-earnings ratio.

In terms of leverage, Table 2.5 indicates that the Islamic sample firms have higher debt to asset ratios (37.52% versus 23.82%). However, it is noteworthy to mention that this ratio does not take into account the total amount of liabilities firms owe. In fact, when taking into account the total amount of liabilities, the average leverage ratio of Islamic bond issuers become lower than the conventional ones (61.51% against 73.74%), and accordingly they are also more capitalised (38.49% versus 26.26%). These results support the findings of other studies that show that Islamic banks have higher capitalisation (see e.g.

Beck, Demirgüç-Kunt and Merrouche 2013). Despite the Islamic sample firms' lower profitability, their lower liability levels, and accordingly lower interest expenses, allow them to have greater ability to cover their interest payments (15.55 times against 8.76 times).

Furthermore, Islamic banking studies show that Islamic institutions are characterised by higher levels of liquidity. Our descriptive statistics for quick ratio (LIQUID) show consistent evidence, where Islamic bond issuers have a liquidity ratio exceeding 1, opposing to the conventional bond issuers which have a ratio below one (1.12 versus 0.97). This indicates that the Islamic sample firms have a sufficient proportion of liquid assets to instantly cover their current liabilities. Beck, Demirgüç-Kunt and Merrouche (2013) argue that the higher liquidity reserves and capitalisation levels of Islamic banks could potentially explain their reasonably better performance during the subprime mortgage crisis. Lastly, the summary statistics show no significant difference in the growth of share prices of Islamic and conventional firms. All outliers observed in the full sample (for example, PM and PE) have been treated by winzorising at the 1st and 99th percentile.

2.5 Methodology

We use two methods for predicting the bond credit ratings: ordered probit (statistical method) and support vector machines (machine learning method). We perform two types of predictions, namely in-sample and out-of-sample predictions. For in and out-of-sample forecasts, we split the dataset into two subsets: a training set 70% (Islamic: 378, conventional: 48 and All[13]: 427) and a holdout set 30% (Islamic: 163, conventional: 21 and all: 183) of the total sample (610), respectively. The hold-out sample used for producing the out-of-sample measures of predictive performance. The split was done in a way to keep the original proportions of the rating classes (AAA to B) in each of the subsets. Moreover, for the support vector machine estimation and prediction, we scaled the firm specific financial independent variables to the range [-1, 1] to avoid having certain values dominating others or any computational difficulties. The same scaling method was used for both subsets.

2.5.1 The ordered probit model

We estimate an ordered probit (OP) model which is appropriate for ordinal dependent variables, such as credit ratings (Kamstra, Kennedy and Suan 2001; Wooldridge 2010). The model assumes Y^* is an unobservable but predictable index of credit quality determined by:

[13] All is the combined dataset of both Islamic bonds (sukuk) and conventional bonds.

$$Y^* = X\beta + \epsilon \tag{2.1}$$

where X is a matrix of observed K explanatory variables (credit rating determinants for example, firm size, and leverage) that do not contain a constant, β a $K \times 1$ vector of coefficients, and ϵ an error term that follows a normal distribution. The rating classifications are assumed to signify ordered partitionings of the unobserved variable.

Since Y^* is unobservable, the observed credit ratings assigned to corporate bonds, Y, are used instead. Hence, Y is a categorical variable with M response categories, i.e. the four bond rating categories (AAA, AA, A and BB) for the full and sukuk sample, and two categories for the conventional sample (AAA, AA).

If X_j is the vector of independent variables for bond j it is assumed that its rating Y_j is related to the latent variable Y_j^* and their relationship is given by:

$$Y_j = k \qquad if \qquad \alpha_{k-1} < Y_j^* \le \alpha_k \quad for\ k = 1,2,\dots,M \tag{2.2}$$

The α_k represent the cut-off points between the rating classifications. For instance, α_3 represents the division point between AAA and AA ratings. Within this model $\alpha_0 = -\infty$; $\alpha_M = \infty$ and $\alpha_0 < \alpha_1 < \dots < \alpha_M$. Parameters $\alpha_1, \dots, \alpha_{M-1}$ are unknown, and they must be estimated. In our estimation, the effect of constant is absorbed into the cut-off points and thus no constant appears in the equations.

Since the error term is normally distributed, the conditional probability of a given rating k can be derived as follows:

$$Pr\left(Y_j = k\right) = \Phi\left(\alpha_k - X_j\beta\right) - \Phi(\alpha_{k-1} - X_j\beta) \tag{2.3}$$

where $\Phi(.)$ is the standard normal cumulative distribution function. The estimated parameters α and β are estimated using maximum likelihood estimation method, where they are selected to maximise the joint likelihood (log likelihood function) of estimating the actual bond ratings. Given that it is a joint probability, thus its values vary between the bounds of 0 and 1, and taking its logarithm to form the log likelihood function results in a negative value (Brooks 2014). For each j bond the model maximises:

$$L = \prod_{i=1}^{N} Pr\ (Y_i = k_j^*) \tag{2.4}$$

where k_j^* denotes the actual rating of bond issue j. The intervals between the different α's vary from one rating classification to another, hence this model does not associate the same interval scale as the OLS does. In order to measure the goodness of fit of the OP models, three measures are used for comparison: Pseudo R^2 and Akaike information criteria (AIC) and percentage of correct predictions.

2.5.2 Support vector machines (SVM)

Support vector machine (SVM) is a novel machine learning method that was first introduced by Vapnik (1995). SVMs are often used for data classification problems and were initially designed for binary classifications, which were later extended for multiclass classifications (Hsu and Lin 2002). It is a supervised learning method that performs classification on the basis of Structural Risk Minimization principle from computational learning theory (for a detailed discussion of SVM see Vapnik 1995; Scholkopf et al. 1997). In contrast to the statistical techniques that impose structures to various models, machine-learning methods, such as NN and SVM, enable learning the specific structure from the data. Although this is seen as a major benefit of AI methods, it also implies that the results obtained from the models are very complex and hard to interpret (Huang et al. 2004).

In order to construct nonlinear class boundaries, SVM non-linearly maps the input data (vectors) into a high-dimensional feature space in which the optimal separating hyperplane is created (Lee 2007). We follow Bellotti, Matousek and Stewart (2011) and Lee (2007) in our application of SVM. The SVM algorithm can be defined as follows:

Given a training set $l = \{(x_1, y_1), (x_2, y_2), \dots, (x_N, y_N)\}$, with input vectors (determinants of bond ratings for example, firm specific financial variables etc.) $\boldsymbol{x}_i \in \mathbb{R}^n, i = 1, \dots, N$ and target output labels (dependent variable i.e. coded bond ratings) $y_i \in \{1, \dots, M\}$, where M is the number of classes, in our case 4 rating classifications.

The SVM solves the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} \boldsymbol{w}^T \boldsymbol{w} + C \sum_{i=1}^{N} \xi_i \tag{2.5}$$

$$\textit{Subject to} \;\; y_i(\boldsymbol{w}^T \phi(\boldsymbol{x}_i) + b) \geq 1 - \xi_i, \tag{2.6}$$

$$\xi_i \geq 0, i = 1, \dots, N \tag{2.7}$$

where $\boldsymbol{w}$ denotes a vector of weights of the input vectors and b is an intercept. The non-linear function $\phi(.)$ maps the input vectors $\boldsymbol{x_i}$ into a higher-dimensional space. Essentially minimizing $\frac{1}{2} \boldsymbol{w}^T \boldsymbol{w}$ means maximising the margin between two groups of data (classifications) $\frac{2}{\|\boldsymbol{w}\|}$. Since most classification problems are not linearly separable, slack variables ξ_i are included in Eq. (2.5) to permit for misclassifications in the case of inequalities (Hsu and Lin 2002). The above optimisation expression is controlled with the regularisation or tuning hyperparameter $C > 0$ which determines the trade-off between the complexity term ($\frac{1}{2}\,\boldsymbol{w}^T\boldsymbol{w}$) and training errors. Vapnik (1995) showed that the primal problem can be solved by introducing Lagrange multipliers and taking into account the Kuhn-Tucker conditions, which leads to the following dual problem:

$$\min_{\alpha} \frac{1}{2}\boldsymbol{\alpha}^T Q\boldsymbol{\alpha} - \boldsymbol{e}^T\boldsymbol{\alpha} \tag{2.8}$$

$$\textit{Subject to } \boldsymbol{y}^T\boldsymbol{\alpha} = 0, \tag{2.9}$$

$$0 \leq \alpha_i \leq C, \qquad i = 1, \dots, N \tag{2.10}$$

where α_i's are Lagrange multipliers for each data point, $\boldsymbol{e}$ is a vector of ones, and Q denotes an $N \times N$ positive semidefinite matrix $Q_{ij} \equiv y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j)$, and $K(\boldsymbol{x}_i, \boldsymbol{x}_j) \equiv \phi(\boldsymbol{x}_i)^T\phi(\boldsymbol{x}_j)$ is the chosen kernel function. One can pick from a number of kernel choices, for example linear, polynomial, radial basis function (RBF), sigmoid. In this study, we apply the RBF kernel defined as $K(\boldsymbol{x_i}, \boldsymbol{x_j}) = exp\left(-\gamma\left\|\boldsymbol{x}_i - \boldsymbol{x}_j\right\|^2\right), \gamma > 0$ which achieved the best performance in our samples[14]. Note that data instances $\boldsymbol{x}_i$ with non-zero α_i's are known as *support vectors*. Hence, based on Eq. (2.5) the Lagrange multipliers and support vectors determine the Optimal hyperplane, where the optimal $\boldsymbol{w}$ satisfies:

$$\boldsymbol{w} = \sum_{i=1}^{N} y_i \alpha_i \phi(\boldsymbol{x}_i) \tag{2.11}$$

In the above expansion, only support vectors data points $\boldsymbol{x}_i$ are summed, the remaining instances of the training set are irrelevant as their constraint Eq.(2.6) is automatically satisfied with the zero slack variable. Hence, based on the optimal hyperplane the support vectors and their corresponding Lagrange coefficients are used to determine the position of the below decision function (separating rule):

$$sgn(\boldsymbol{w}^T\phi(\boldsymbol{x}) + b) = sgn\left(\sum_{i=1}^{N} y_i \alpha_i K(\boldsymbol{x}_i, \boldsymbol{x}) + b\right) \tag{2.12}$$

To apply the SVM, we used the LIBSVM software package developed by Chang and Lin (2011). A grid search was used for various combinations of γ and C[15] in the SVM application, but only those achieving the highest cross-validation accuracy (CV), i.e. the optimal ones, are reported and used for

[14] Comparable results were observed with the polynomial kernel $K(\boldsymbol{x}_i, \boldsymbol{x}_j) = \left(\gamma \boldsymbol{x}_i{}^T\boldsymbol{x}_j + r\right)^d, \gamma > 0$

[15] $C = 2^{-5}2^{-4}, \dots, 2^{15}$ and $\gamma = 2^{-15}2^{-14}, \dots, 2^{3}$

the in-sample and out-of-sample (holdout) predictions. We apply a 10-fold cross validation procedure on the training set, which is typical in credit rating prediction literature (Huang et al. 2004; Bellotti, Matousek and Stewart 2011). LIBSVM uses the "one-against-one" method (Kressel 1998; Knerr, Personnaz and Dreyfus 1990) to obtain the cross-validation accuracy, thus the same parameter combinations are suggested for all $k(k-1)/2$ two class problems (classifiers), where $k = 4$ is the number of classes.

2.5.3 Research design

We split our empirical results into two stages of analysis. The first stage is to study the determinants of bond ratings using the ordered probit model. We allow for four formulations of the probit model hereafter referred to as Models I to IV:

- Model I (*Baseline model*):
    - Full ('All' sample): Financial variables + ISLAMIC indicator
    - Islamic and conventional bond samples: Financial variables
- Model II: Financial variables + Interactions with ISLAMIC
- Model III: Financial variables + Bond specific variables + Market structure variables
- Model IV: Model III + Interactions of financial variables with ISLAMIC

Model I includes only firm specific financial independent variables (plus an Islamic dummy variables for the combined dataset, i.e. All). Model II adds interaction terms between the firm specific financial variables and the Islamic bond dummy, thus allowing for the sensitivity of the bond ratings to each financial variable to differ between the two bond types (Islamic and conventional). Model III comprises firm specific financials, bond specific and market structures and finally Model IV includes the same variables plus it allows for the interaction terms with the financial variables. Regarding the Islamic sample, we allow for three models:

- Islamic Model I: Financial variables
- Islamic Model II: Financial variables + Islamic bond structure variables
- Islamic Model III: Financial variables + Islamic bond structure variables + bond specific variables

The second stage considers bond credit rating prediction both in-sample and out-of-sample using the ordered probit and SVM. In the in-sample prediction (section 2.6.2.1) we predict the credit ratings of the full sample. On the other hand, in 2.6.2.2 we specify the models using the training sample (70% of the full sample) and then use the model to forecast the training (in-sample) and holdout (out-of-sample) samples.

After estimating the models and using them to predict the bond ratings, a contingency table of actual versus predicted ratings is constructed for both estimation and holdout samples. The percentage of correct predictions is then computed and used as a prediction accuracy measure for comparison.

2.6 Empirical results

2.6.1 First stage analysis: Determinants of bond ratings

In this subsection, we examine the determinants of Malaysian corporate bond credit ratings. Table 2.6 presents coefficient estimates (β) and their respective standard errors and p-values of the ordered probit Model I for the full sample (Islamic and conventional bonds labelled as 'All'), Islamic bonds and conventional bonds, respectively. In addition, we report the marginal effects[16] of the regressions' independent variables (determinants) in Table 2.7. The table shows that the firm specific financial variables are all significant determinants of credit ratings included in the full sample (All). Specifically, the positive and significant SIZE coefficient suggest that larger issuing firms, all other variables constant, have a higher probability of receiving higher credit ratings by the Malaysian CRAs. This is confirmed by the average marginal effects of the SIZE variable on the probability of the credit ratings, which are found to be negative and statistically significant for BB-AA ratings but positive for the highest bond rating, AAA. Hence, this shows that, holding everything else constant, a unit (MYR billion) increase in the size of the firm increases (decreases) the probability of receiving AAA (BB) by 5.1 (0.3) percentage points. This implies that larger firms are seen as more financially sound and thus less likely to default, which is confirms the findings observed in previous literature (Ederington 1985; Kamstra, Kennedy and Suan 2001; Azmat, Skully and Brown 2017).

Opposite to our expectations based on conventional as well as sukuk rating literature (e.g. Kaplan and Urwitz 1979; Blume, Lim and MacKinlay 1998; Arundina, Omar and Kartiwi 2015), firm profitability (PM) seems to adversely affect bond credit ratings, suggesting that CRAs tend to assign lower credit ratings to more profitable firms. Given that the majority of the sample is comprised of Islamic firms' bonds, this could be reflecting the fact that Islamic firms' main objective is not profit maximisation. It is argued that Islamic firms focus more on value maximisation, being responsible for the 'greater good' of the society as a whole, which is bounded by the Islamic ethics (Beekun and Badawi 2005; Saeed, Ahmed and Mukhtar 2001). Inspecting the data more closely, we find that the rated AAA less profitable firm bonds are mostly guaranteed (by banks, financial institutions or other supports) which could also explain this finding.

[16] At the average (mean) of the rest of the covariates. However, given the difficulty of interpreting the marginal effects for ordered choice models, we follow the literature and mainly focus on the coefficients in our analysis (Caporale, Matousek and Stewart 2011; Caporale, Matousek and Stewart 2012).

In line with our expectations, the long-term solvency or leverage indicators' coefficients have the hypothesised signs and are significant (at 1%). The negative LEV and positive INT_COV coefficients (-0.012 and +0.019, respectively) highlight that bond issues by firms with low proportions of existing debt, i.e., leverage ratio or high interest coverage capability, ceteris paribus, have a higher probability of receiving higher ratings classifications. This is particularly clear when observing the instantaneous change in the probability i.e., marginal effect of LEV (INT_COV) on ratings, which is only positive (negative) and significant for AAA. In other words, highly-levered corporate bonds are more likely to be rated in a lower category. This is not surprising as higher proportions of debt impose higher financial obligations including interest payments, which in turn boosts the counterparty risk of the company. Both findings are similar to many other studies, such as Mizen and Tsoukas (2012) and Kamstra, Kennedy and Suan (2001).

In addition, the positive and statistically significant LIQUID coefficient (0.336) and its marginal effects indicate that higher levels of an issuing firm's liquidity increases (reduces) the probability of its bonds receiving higher (lower) credit ratings, which in turn verifies that liquid firms are more stable and prone to fulfil their financial commitments (Belkaoui 1980; Huang et al. 2004). In agreement with Arundina, Omar and Kartiwi (2015), market value variables (PE and PRICE_CHANGE) show that the more optimistic the market is about a company's future prospects, i.e. higher PE ratio and share prices, the higher the credit rating it receives on its bonds. It can be inferred that MARC and RAM take into account the company market valuation and future prospects in their rating assignments. However, the PE effect seems to be weaker in comparison to the rest of the determinants as it is only significant at 5%.

The Islamic binary indicator exhibits an interesting finding. Most notably, the negative Islamic binary (dummy) variable coefficient -0.970 is significant at 1% possibly suggesting that sukuk ratings are biased downwards. Interestingly, the Islamic dummy variable's marginal effects shown in Table 2.7 is negative and statistically significant for AAA bonds, but positive and significant for the rest of the rating classes. Specifically, it indicates that in comparison to a conventional bond, Islamic bonds are on average 36.8% percentage points less likely (lower probability) to receive an AAA rating and 35.6% percentage points more likely to receive to receive an AA rating. According to our findings, Malaysian CRAs are inclined to give lower credit ratings to sukuk relative their conventional bonds. This is evident from Table 2.2 that clearly demonstrates that sukuk tends to receive lower credit ratings than their conventional counterparts. We provide possible explanations for this. Firstly, it could reflect that the CRAs perceive sukuk issuers as less creditworthy, lower quality firms. This argument would support the conclusions of Godlewski, Turk-Ariss and Weill (2013) and Alam, Hassan and Haque (2013), which claim that the market perceives sukuk announcements as negative signals because they are most likely issued by lower quality firms that prefer, amongst others, partnership based contractual agreements to be able to share the losses in the case of default. Alternatively, the effect could have been triggered by the fact that the CRAs are potentially stricter with their sukuk credit rating assignments.

Table 2.6 and Table 2.7 also show the similarities and differences amongst the drivers of Islamic and conventional bond ratings. The Islamic bond sample exhibits very similar results to the combined bond sample, which is not surprising given their larger proportion. Hence, in line with previous literature, it can be inferred from our results that sukuk credit ratings are positively affected by firm size, interest coverage, liquidity, PE ratio and price movements (Elhaj, Muhamed and Ramli 2015; Arundina, Omar and Kartiwi 2015; Azmat, Skully and Brown 2017). Conversely, the credit quality of sukuk is lowered by higher levels of profitability and debt (leverage). Moreover, our findings propose that the conventional bond ratings are driven by a smaller set of financial variables that are examined in our study. Similar to the case of sukuk, size, profitability, interest coverage and PE ratio are found to be strong predictors of conventional bond ratings, which is shown by their significant coefficients at 1%. However, in contrast to sukuk, the conventional sample profit margin coefficient is positive (0.388) signifying that more profitable firms are more likely to receive higher ratings on their conventional bonds. The marginal effect shows that a company with a 1% higher profit margin increases the probability of receiving a AAA bond rating by 15% percentage points. This confirms the main body of literature findings (Pinches and Mingo 1973; Poon 2003; Huang et al. 2004; Kim 2005).

Unlike the case of Islamic bonds, the conventional bond estimates also point that, the Malaysian CRAs do not focus on or consider much the issuers' proportion of leverage and price changes (both are statistically insignificant at 10%) in their credit assessments of conventional bond issues. In addition, it is noteworthy to point out that the size factor[17] has a significant negative effect (β= -0.422) on conventional bond ratings. This contradicts the typical positive effect observed in prior literature (Horrigan 1966; Belkaoui 1980; Ederington 1985; Kamstra, Kennedy and Suan 2001). From Table 2.5, it can be observed that the mean difference between the size of conventional and Islamic firms is statistically significant, where conventional firms are much larger in terms of the total assets they possess (208.16 vs. 47.98 billion Malaysian Ringgit). Perhaps the size effect is positive only up to a certain level of assets, just as typically depicted with economies of scale (McAfee and McMillan 1995). Then the impact can reverse as extremely large firms could be inefficient (diseconomies of scale), hard to manage and accurately report which in turn makes them less credible.

All three models' Wald Chi-square test's p-values are significant at 1%, which *rejects* the null hypothesis: all coefficients (H_0: β=0) except for the constant are zero. Meaning, the models have at least one significant coefficient as we have discussed above. Splitting the bond types into Islamic and conventional bond rating models improve the estimations, which affirmed by the increase in the Pseudo R^2 and lower AIC the independent models exhibit. However, it must be noted that the high Pseudo R^2 of the conventional bond sample (0.591) is most likely compensated by the small sample size (69 bonds).

[17] Given by the natural log of total assets.

Table 2.8 presents the ordered probit estimation results for Models II, III and IV for the full sample combining both bond types[18]. Model II, extends the earlier findings by including interaction terms between the Islamic binary dummy and the firm financial variables to examine if the Islamic and conventional bond ratings experience different sensitivities towards their issuers' financials. As a result, the financial variables' coefficients now represent the effect of the firm specific financial variables on conventional bond ratings, whereas the interactions' coefficients capture the change or 'additive' to their effects when the bonds are Islamic (ISLAMIC = 1).

The results reveal significant differences between the two types of bonds, mainly in the direction of their sensitivities. The differences in the firm specific financial panel are consistent with the dynamics observed in the individual Islamic and conventional models presented earlier. The findings of Model II confirm that the size significantly and negatively affects conventional bond ratings (β_{SIZE} = -0.424), whilst in comparison it positively affects Islamic ones ($\beta_{\mathrm{ISLAMIC\,x\,SIZE}}$ = 0.597). Moreover, as stated above more profitable conventional (Islamic) firms tend to receive higher (lower) bond ratings. In comparison to conventional bonds, higher leverage has significantly more negative impact on sukuk ratings, which is understandable given the restrictions on debt financing (interest prohibition) imposed on Sharia compliant firms (Aggarwal and Yousef 2000). Similarly, liquidity affects each bond type differently. This is expected as Islamic firms are more constrained in terms of their access to funds as they cannot utilise debt instruments or invest in short term derivatives, and thus higher liquidity reduces their necessity to acquire external funds and ensures they can pay off their financial obligations (higher rating). On the other hand, high quick ratio in conventional firms significantly (at 5%) lowers the credit ratings, potentially because excessive liquidity could signify ineffective liquidity management and forgone investment opportunities. PE seems to have a similar positive influence on both bond types, though its overall effect on sukuk is slightly lower (0.145 - 0.128 = 0.017). Lastly, in this table, the changes in stock price are insignificant for all bond types, which contradicts the findings observed in Table 2.6 and Arundina, Omar and Kartiwi (2015). Overall, these results emphasise that the drivers of bond ratings do not affect the Islamic and conventional bonds in the same way.

In both Models III and IV in Table 2.8, we expand our explanatory variables (credit rating determinants) by incorporating the bond specific and market structure variables. The difference between the two models is that Model III excludes the Islamic dummy variable interactions with the financial variables. As a result, Model III can be viewed as an extension of Model I, whereas Model IV as an extension of Model II. The findings of Model III presented in Table 2.8 are consistent with our earlier full sample's Model I findings. The only difference observed amongst the coefficients of the firm specific financial variables is that the liquidity ratio here is only significant at 10% (p-value of 0.68), which suggests its

[18] We do not report the marginal effects for Model II-IV as interaction terms do not have marginal effects. Instead, we focus on the signs and significance of the determinants' coefficients that are of our interest and are easier to interpret and compare to the baseline model (Model I).

lack of significance, i.e., it has a smaller role in the credit rating determination as observed in a few other studies (Hwang, Chung and Chu 2010; Horrigan 1966; Kaplan and Urwitz 1979). Similarly, the signs and statistical significances of the firm specific financial variables of Model IV are comparable to those from Model II.

Focusing on the bond specific determinants in Models III and IV, our results demonstrate that guaranteed bonds receive higher credit ratings than non-guaranteed ones; confirming the guidelines of MARC (2016a) rating methodology. This is reflected by the GUARANT positive and significant (at 1%) coefficients. Unexpectedly, the bond security indicator was found to be insignificant in all samples. We presume that the guarantee variable could have captured the secured effect because it includes bonds with other forms of supports which possibly comprises even collaterals put as a security. Furthermore, the results suggest that fixed coupon rate (FIXED_RATE) increase the credit rating of bonds, which is reasonable as it limits the uncertainty of the cash stream investors will receive. The last bond specific variable capturing the effect of the CRAs is only significant in Model IV. Model IV suggests that MARC seems to rate bonds harsher than RAM which supports the view that CRAs assess credit ratings differently (Cantor and Packer 1997; Livingston, Naranjo and Zhou 2007; Livingston, Naranjo and Zhou 2008).

The last set of variables shown in Table 2.8 indicate that construction and engineering, property and real estate (significant at 10%) and other industries (for more details see Table 2.2) receive lower credit ratings than the benchmark industry - infrastructures and utilities. This implies that they are viewed as higher-risk sectors. These findings are consistent with Mizen and Tsoukas (2012), as the aforementioned industries are mostly competitive, capital intensive, and are judged accordingly as high-risk industries and should have correspondingly lower chances of receiving high ratings. Comparing the three models II-IV, Model IV has the lowest AIC and highest Pseudo-R^2 (almost 40%) suggesting that it is a better-fit model.

Table 2.9 presents the ordered probit regression results of Islamic Models I, II and III estimated for the Islamic bond (sukuk) sample. Here we compare and extend the Islamic bond specific model presented in Table 2.6, that is Islamic Model I, by including a wider set of explanatory variables. Islamic Model II adds the Islamic bond structure variables and Islamic Model III in addition incorporates the bond specific variables. Both Islamic Models II and III have consistent coefficients to the baseline Model I, except that the liquidity and PE ratios explanatory powers decrease or disappear (PE is insignificant in Model II and LIQUID in Model III) when including the Islamic bond structure variables. From the Islamic Model III, it can be inferred that sukuk ratings seem to be also driven by two bond specific variables, guarantee status and the CRA its rated by. Their marginal effects presented in Table 2.10 indicate that guaranteed (MARC rated) bonds on average have a remarkable 45% (25.2%) additional higher (lower) probability of being rated AAA. Comparable guarantee status effect is detected in previous sukuk rating literature (see Arundina, Omar and Kartiwi 2015; Borhan and Ahmad 2018). Furthermore, MARC variable is negative (-1.632) and statistically significant[19], indicating that MARC is more stringent or gives lower credit ratings to sukuk than RAM.

In line with previous literature, Table 2.9 shows that Islamic bond structures significantly influence their credit ratings (Borhan and Ahmad 2018; Elhaj, Muhamed and Ramli 2015; Arundina, Omar and Kartiwi 2015). Clearly, the Islamic specific variables (Islamic Model II) significantly improve the original Islamic Model I as the pseudo-R^2 of the model increases nearly by one-fold (from 0.220 to 0.418). These results offer primary evidence of the distinction between the determinants of Islamic and conventional bonds.

All structures', apart from BBA[20], coefficients are significantly different from Murabahah[21] sukuk. Ijarah, Musharakah, Wakalah and Hybrid structures positively boost the sukuk ratings. This is evident from their marginal effects (see Table 2.10) that show that, on average, Ijarah, Musharakah, Wakalah and Hybrid sukuk are 25.6, 19.4, 44.3 and 26.9 percentage points more likely to receive a AAA rating than Murabahah bonds, respectively. CRAs seem to perceive them 'safer' than Murabahah sukuk (direct buy and resale cost-plus bond) and therefore assign them higher ratings. Ijarah sukuk are supposed to be more secure than Murabahah as the certificates represent the investors' undivided ownership in the underlying leased assets, hence their bondholders should be able to claim their ownership at default (Usmani 2002). On the other hand, Musharakah, profit-and-loss sharing partnership based agreement, are argued to resemble equity with no guarantee of any return of principle (Azmat, Skully and Brown 2014a). In fact, their returns depend on the performance of the issuer. Therefore, the positive significant effect of the Musharakah ($\beta_{\mathrm{MUSHARAKAH}}$ = 0.767 and 1.255 in Models II and III) contradict the expectations. However, this has been previously observed in prior literature (Azmat, Skully and Brown 2017). Similarly, Wakalah sukuk (agency agreement) seem to also have positive and significant coefficients, β_{WAKALAH} = 1.482 and 2.867 in Models II and III. This finding could be partially explained by their special structure, where their underlying is a portfolio that consists of tangible assets (at least 30% of the portfolio) that could reduce their credit quality. On the other hand, their performance still depends on the agent[22]. According to Azmat, Skully and Brown (2017) this finding could also imply that the Musharakah, and in our case also Wakalah, sukuk in the sample might have been inappropriately structured making them more similar to conventional debt bonds and thus achieved higher ratings. The Hybrid sukuk could be rated higher or lower than Murabahah sukuk, depending on

[19] This finding is persistent even when including industry effects.
[20] Most likely because the sample includes only 5 BBA bonds (see Table 2.2).
[21] Our benchmark sukuk structure, which are considered to be the most similar to conventional bonds.
[22] In Wakalah sukuk the expected profits are agreed upon, and any excess profit made is paid to the agent (special purpose vehicle) as an incentive. However, all risks and losses (if any) are borne by the investors.

the combination of structures incorporated in them. From the results, it seems like less risky structures (for example, Ijarah) were mostly used in the construction of the hybrids.

On the contrary, Istisna'a and Mudarabah sukuk structure coefficients are found to be negative and statistically significant at 1%. This means that they tend to receive lower credit ratings than Murabahah sukuk, especially Istisna'a sukuk, which is confirmed by their negative marginal effect (change in probability) for AAA bond rating. Istisna'a and Murabahah sukuk have similar structures and are often classified as Islamic debt bonds, which makes them according to the Sharia law non-tradable on the secondary market (Usmani 2002). As defined earlier, Istisna'a sukuk "are certificates of equal value issued with the aim of mobilising funds to be employed for the production of goods so that the goods produced come to be owned by the certificate holders" (IIFM 2020, p.187). From the definition it is evident that at issuance the assets or project to be funded do not exist yet, which increases the uncertainty of investors in case of bankruptcy as well as their chances of receiving their proceeds from the intended deferred mark-up sale to the issuer (Tariq and Dar 2007). Hence, given the additional complexity of Istisna'a contracts in comparison to Murabahah (cost-plus) sukuk arrangement could be the reason of the harsher ratings.

Lastly, Mudarabah sukuk are very different to Murabahah. Essentially, they are similar to Musharakah sukuk, but in the case of Mudarabah partnership the issuer (known as 'mudarib') acts as the entrepreneur partner that is in charge of managing the project or assets and accordingly receives a pre-agreed share of profits without bearing the burden of losses if any (Klein and Weill 2016). Therefore, logically Mudarabah sukukholders face greater credit risk than Murabahah sukukholders, which in turn reduces their ratings.

The above findings support the view that sukuk are different from their conventional counterparts, as they are driven by a wider set of bond rating determinants and have different sensitivities to the firm specific financial determinants. In particular, firm size, profitability, liquidity, interest coverage, PE ratio and the guarantee status are found to be the common bond credit rating determinants for both types of bonds. Islamic bonds ratings are additionally influenced by the amount of debt the issuer owes as well as the movements in its share price. More importantly, the Islamic principle (structure) that an Islamic bond is structured on is critical for its bond rating determination. Certain Islamic structures e.g. Ijarah and Wakalah structures boost the credit ratings, whereas others including Istisna'a and Mudarabah deteriorate it as they increase the likelihood of default. As a result, raters, investors and issuers should acknowledge the contrast between conventional and Islamic bonds, as well as different types of Islamic bonds in their rating and decision-making processes.

2.6.2 Second stage analysis: Bond rating prediction

2.6.2.1 In-sample bond rating prediction

In this subsection, we use four different models to forecast the bond credit ratings of our three samples: combined (All), Islamic and conventional bonds. The aim is to compare how well can a model based on, for example, the Islamic sample forecast all bond ratings included in All, Islamic and conventional and vice versa. Table 2.11 summarises all in-sample forecasts (number of correct predictions and accuracy), based on four models: All Model I, All Model II, Islamic Model I and conventional Model I predicted using the ordered probit and SVM.

From Table 2.11 it can be inferred that the baseline ordered probit Model I based on the full (All) dataset predicts slightly over 70% of all bond ratings. However, it is more geared towards sukuk (406/541 sukuk ratings are correctly predicted), which is not surprising as the number of sukuk in the sample outweighs the conventional bonds. Only 33% of the conventional bonds were accurately forecasted. When forecasting using tailor made models i.e., individual Islamic or conventional, the respective bond type forecasts improve. The individual Islamic (conventional) model predicts the Islamic (conventional) bond ratings quite well but cannot predict the other type with the same accuracy. This finding is consistent using both methods OP and SVM. For instance, The Islamic model I correctly forecasts 70.43% (99.82% using the SVM) of the sukuk ratings, whilst it can only accurately classify 37.68 (59.42% using the SVM) of the conventional bonds. The biggest improvement is observed in the conventional bond rating forecasts, where the individual conventional Model I managed to predict 82.61% of the ratings versus the original 33.33% prediction accuracy using the baseline model yielding an outstanding 49.28% improvement. As a result, we can conclude that a model with a single Islamic binary variable (All Model I) is not sufficient to capture the differences between the Islamic and conventional bonds.

The most efficient model in Table 2.11 is arguably All Model II, which takes into account the interactions between the Islamic dummy indicator and the firm specific financial variables. It seems to have the best of both worlds, as it reaches higher prediction accuracy of the combined dataset (using ordered probit 70.33% in All Model I versus 71.80% All Model II) and maintains the exact same accuracies of the individual models for the Islamic and conventional samples. This is due to the fact that the interactions take into account the distinct sensitivities of the bond types towards their issuers' financials, which also confirms earlier findings and signifies that sukuk are distinct from their conventional counterparts. Lastly, the table also shows that irrespective of the choice of model or sample, the SVM in-sample forecasts consistently outperform the ordered probit forecasts with the highest accuracy (98.55% to 99.67%) observed employing Model II.

2.6.2.2 In-sample and out-of-sample prediction accuracy analysis

Table 2.12 exhibits the bond rating predictions in terms of the number of correct predictions and prediction accuracies of the samples (All, Islamic and conventional bonds) using ordered probit and SVM methodologies. For each model estimated, we present the cross-validation, in-sample (training 70%) and out-of-sample (holdout 30%) rating forecasts.

The results indicate that the ordered probit model based on the financial determinants (Model I) predicts around 68% of the 'All' out-of-sample bond ratings. This finding is consistent with the prior literature that has shown that relatively simple statistical models based on a few firm financial variables can correctly classify more than two thirds of the holdout sample (Huang et al. 2004; Kamstra, Kennedy and Suan 2001; Ederington 1985). Furthermore, the table also confirms our earlier finding that adding Islamic binary variable interaction terms improve the probit model estimation (All Model I vs. Model II) as it increases the number of correct credit rating predictions. Specifically, the holdout set's prediction accuracy increases from 68.31% to 71.58%, where 6 additional bonds are correctly rated.

Looking across all samples, the SVM method significantly outperforms the ordered probit model. It increases the prediction accuracy (on average) by more than 20%. Therefore, this provides additional evidence to the existing literature (Lee 2007; Cao, Lim and Jingqing 2006; Bellotti, Matousek and Stewart 2011) supporting the view that artificial intelligence methods, namely SVM, predict bond ratings more accurately than the traditional ordered probit regression. However, it is worth noting that the holdout sample's SVM classification accuracies achieved are higher than the ones observed in Huang et al. (2004) and Lee (2007). According to Table 2.13, most misclassifications of Model II are between AAA and AA rating classifications. The ordered probit model has a tendency (29 out of 52 misclassifications) to underrate AAA to AA. Moreover, unlike the SVM, it fails to distinguish between A, BB and AA ratings.

When comparing the combined dataset to the individual tailor-made models (Islamic Model I and conventional Model I), it is clear that the individual models, both ordered probit and SVM, are able to predict the bond ratings more accurately. This suggests that sukuk and conventional bonds are indeed two individual bond types and it is vital to distinguish between them in their credit assessments. However, the forecasting accuracy improvement is more notable in the conventional sample, where the holdout set forecasts increased from 68.31% to 80.95% using the ordered probit and 97.81% to a remarkable 100% using the SVM. Nevertheless, it is worth noting that the conventional bond holdout set is relatively small (21 bonds) and the SVM classification is binary (two rating classifications), which mostly likely helped in achieving better results. Despite that, it is the sample that achieved the highest accuracy in our study, suggesting that models based on a small set of financial firm specific variables suffice to predict the majority if not all of the conventional bond ratings. The Malaysian bond rating agencies seem to heavily rely on firm specific variables in their conventional bond rating assignments.

When focusing on Islamic bonds solely, in comparison to the full (All) sample, the accuracy of the ordered probit Model I holdout predictions only slightly improve from 68.31% to 69.33%. Similarly, as with the full sample, most misclassifications of the basic Islamic Model I are misclassifications of AAA sukuk rating to AA (see Table 2.13). However, when introducing the Islamic bond structure variables (Musharakah, Ijarah, and so forth) the predictions increase both in-sample and out-of-sample. The Islamic structure variables (Islamic Model II) improve the holdout sample forecasts by approx. 7.36% and 14.72% using the ordered probit and SVM models, respectively. With the new Islamic structure variables, the ordered probit model starts to distinguish between BB and AA classes, and the SVM stops underrating AAA bonds. ‘A’ class is poorly predicted in all models, which was anticipated due to its small overall sample size (5 A-rated Islamic bonds of which 3 are training and 2 holdout). The Islamic Model II is the most effective in forecasting sukuk ratings, achieving an outstanding forecasting accuracy of 98.77% using SVM. Our findings are in line with prior sukuk rating literature that also found Islamic variables to be significant (Arundina, Omar and Kartiwi 2015; Azmat, Skully and Brown 2017). However, our sukuk SVM classification accuracy (98.77%) is higher than NN’s accuracy (96.18%) documented in an earlier study by Arundina, Omar and Kartiwi (2015).

From above analysis, it can be inferred that more than two thirds of Malaysian bond ratings can be forecasted using a simple statistical model with a relatively small sample of publicly available information. Although the Islamic and conventional bonds share similar financial firm specific determinants, they are not solely enough to predict the Islamic bond ratings with great accuracy. Our study shows that they should be accompanied with sukuk structure variables that play a big role in determining the credibility of Islamic bonds. As a result, their rating assignments should be partitioned. Following our methodology, financial market participants and issuers that do not want to wait or rely on external ratings can apply our method to predict the credit ratings of Islamic and conventional bonds. However, once the determinants of bond ratings are classified using the ordered probit model, we advise employing SVMs to gain superior forecasting accuracy.

2.7 Conclusions

This chapter bridges the gap between the bond rating prediction literature and the comparative literature of Islamic (sukuk) versus conventional bonds. We take a different direction than previous studies, focusing on the credit ratings of both types of bonds using a comparable sample of Malaysian bonds. Specifically, we examine and compare the determinants of Islamic and conventional bond ratings, and accordingly find the most suitable model to predict their credit ratings. In order to obtain robust results, we base our analysis on two methods: ordered probit regressions (statistical method) and SVM (artificial intelligence method).

We find that the credit ratings of Malaysian conventional as well as Islamic bonds are also predominantly determined by their issuers' financial variables. Using the ordered probit model, our first stage analysis provides strong evidence of the distinction between sukuk and conventional bonds. We identify multiple contrasts between their credit ratings' sensitivities to their issuers' financial variables. The results also suggest that conventional bond ratings are driven by a smaller set of financial variables. More interestingly, our findings show that sukuk ratings are biased downwards, where Malaysian credit rating agencies are inclined to give lower credit ratings to sukuk relative to their conventional counterparts. Lastly, we show that the Islamic structure of sukuk (Ijara, Musharakah and so forth) significantly influence their credit ratings, suggesting that certain structures increase or lower the credit risk of sukuk. These findings highlight the fact that raters should assess the financials of sukuk issuers in the context of Islamic finance (including Sharia compliance) and take into account the specifics that sukuk structures impose in their credit assessments.

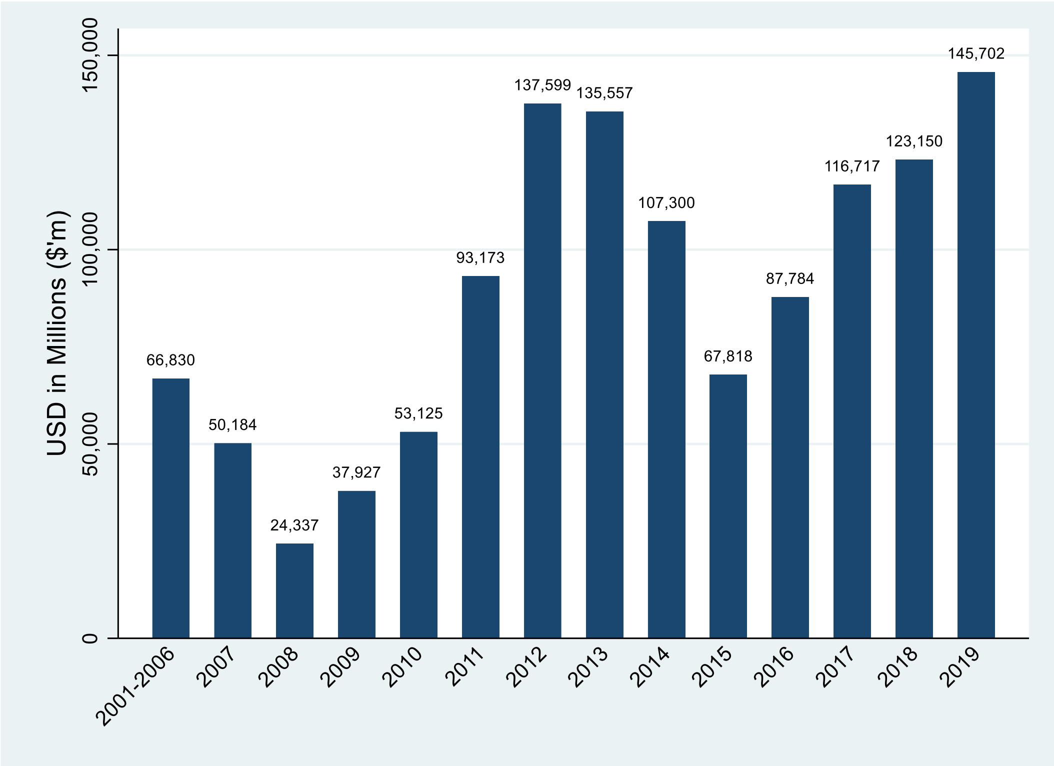
The second stage analysis' bond rating predictions show the baseline Model I with financial variables and Islamic indicator dummy correctly predicts slightly over 68% of the out-of-sample bond ratings. The model was found to be more geared towards sukuk, which is not surprising as the number of sukuk in the sample outweighs the conventional bonds. Adding interaction terms between the Islamic bond indicator dummy variable and the financial variables increases number of correct credit rating predictions, both in-sample and out-of-sample. This improvement stems from the interaction terms that capture the bonds' distinct sensitivities, which in turn supports our first stage analysis. Furthermore, these results indicate that including a single Islamic binary dummy is not sufficient to capture the differences amongst the bonds, but instead they should be treated as distinct types of bonds.

Splitting the sample into individual sukuk and conventional bond tailor-made baseline models improve the forecasting accuracy, though the improvement is more notable in the conventional sample reaching a remarkable accuracy of 80-100% across our samples. Hence, we conclude that the conventional model based on a small set of financial firm specific variables is sufficient to predict the majority, if not all, of the Malaysian conventional bond ratings. On the other hand, our results indicate that the same financial variables are not merely enough to predict the Islamic bond ratings with the same accuracy. Our further empirical analysis show that sukuk structure variables enhance the out-of-sample (holdout) prediction accuracy by 7.36% and 14.72% using the ordered probit and SVM models, respectively. As a result, we suggest that Islamic bond rating models are supplemented with sukuk structure variables that play a big role in determining their credit ratings. We conclude that sukuk should not be rated using the same methodology as conventional bonds. All results are consistent using both methods, nonetheless the findings clearly show that the SVM method consistently outperforms the ordered probit model in all samples. It increases the prediction accuracy by more than 20% (on average). Hence, to yield most accurate results we recommend using the SVM methodology and separating Islamic and conventional bonds for credit rating prediction models. In particular, this is potentially useful for issuers, investors and analysts that would like to predict the bond credit ratings or anticipate changes in them.

Our results provide novel evidence of the distinction, not only in theory but also in practice, between the credit ratings of sukuk and conventional bonds. Hence, investors should take advantage of their differences and explore the benefits they can obtain from them. It would be interesting to see if these results are consistent in other markets that also trade both types of bonds. Further studies could extend this comparison and differentiate sukuk rating prediction models according to their Islamic structures (for example, Islamic debt bonds, partnership-based sukuk etc), to gain a better understanding of their differences in terms of credit risk.

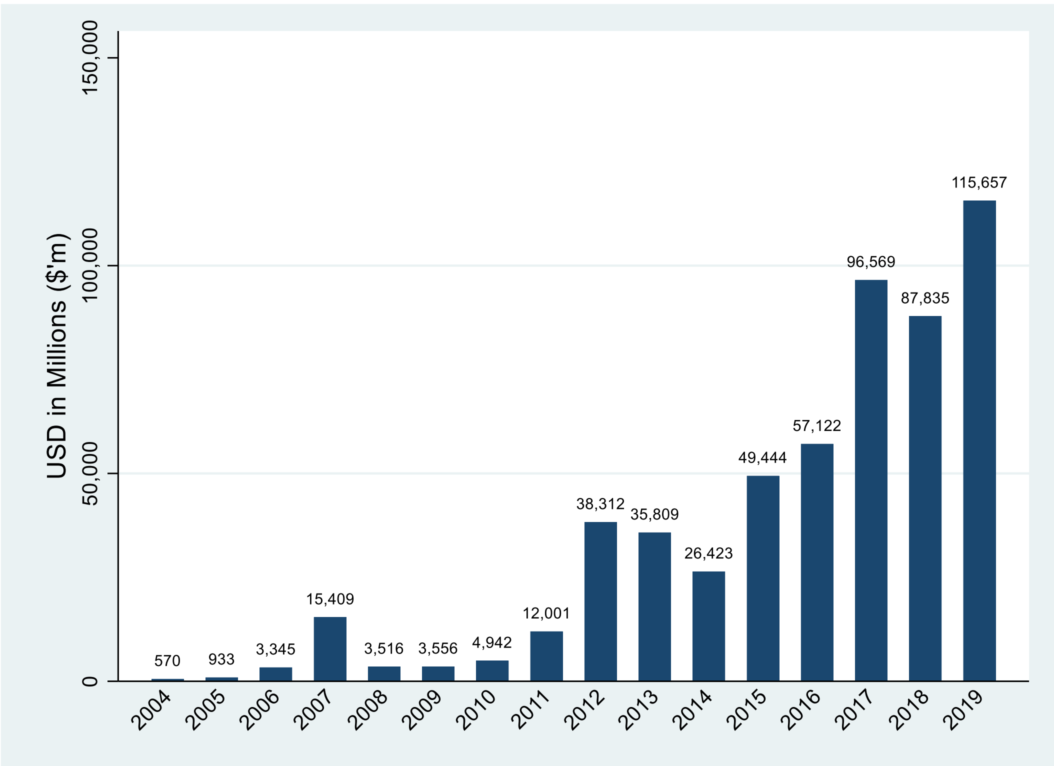
2.8 Tables and figures

Figure 2.1: Total value of global sukuk issuances (2001-2019) all tenors and currencies, in USD Millions



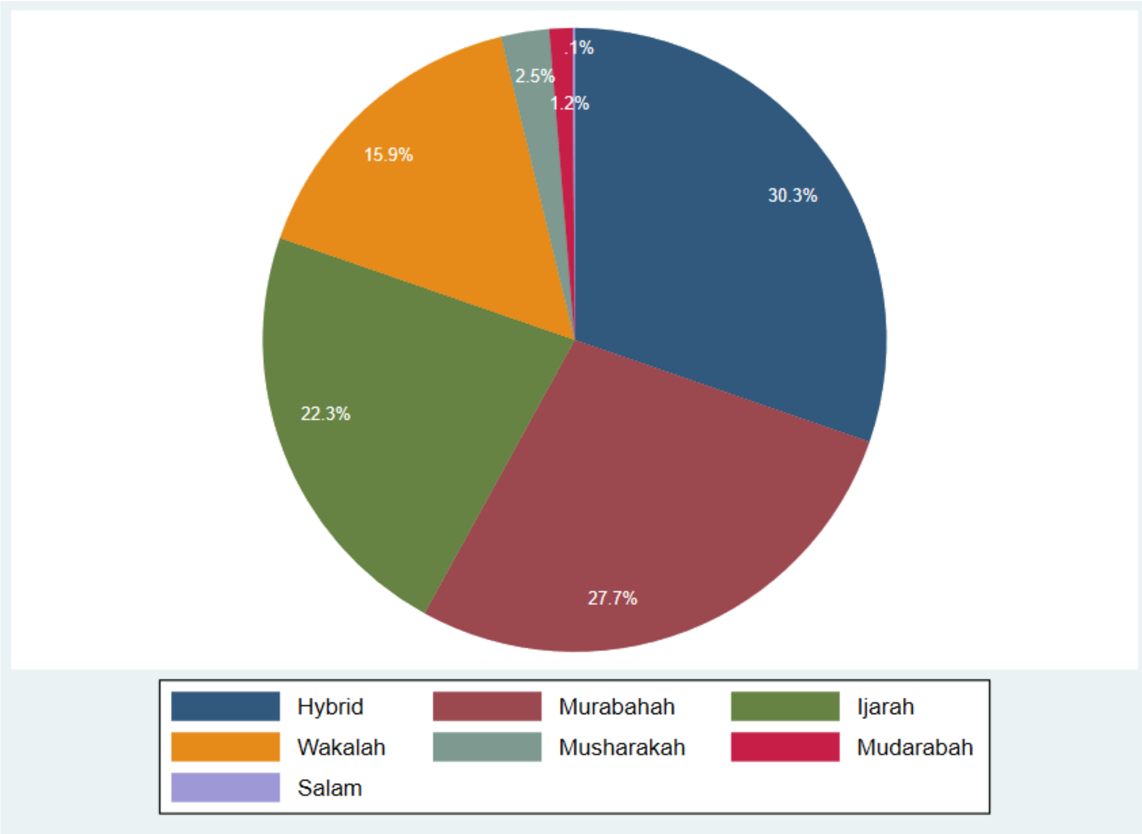
Source: (IIFM 2020, p.28)

Figure 2.2: Total global sukuk outstanding as of 31 December 2019, in USD Millions



Note: Total Global Sukuk outstanding USD 551.44 Billion. Source: (IIFM 2020, p.92)

Figure 2.3: New sukuk issuances (2017) by structure



Source: IFSB (2018, p.105)

Table 2.1: Rating symbols by credit agency

Moody's	S&P	Fitch	MARC	RAM	Rating description
Long-term	**Long-term**	**Long-term**	**Long-term**	**Long-term**	
Aaa	AAA	AAA	AAA	AAA	Prime
Aa1	AA+	AA+	AA+	AA1	High grade
Aa2	AA	AA	AA	AA2	
Aa3	AA−	AA−	AA−	AA3	
A1	A+	A+	A+	A1	Upper medium grade
A2	A	A	A	A2	
A3	A−	A−	A−	A3	
Baa1	BBB+	BBB+	BBB+	BBB1	Lower medium grade
Baa2	BBB	BBB	BBB	BBB2	
Baa3	BBB−	BBB−	BBB−	BBB3	
Ba1	BB+	BB+	BB+	BB1	Non-investment grade speculative
Ba2	BB	BB	BB	BB2	
Ba3	BB−	BB−	BB−	BB3	
B1	B+	B+	B+	B1	Highly speculative
B2	B	B	B	B2	
B3	B−	B−	B−	B3	
Caa1	CCC+	CCC+	C	C1	Substantial risks
Caa2	CCC	CCC		C2	
Caa3	CCC−	CCC−		C3	
Ca	CC	CC			Extremely speculative
	C	C		D	Default imminent
C	RD	DDD	D		In default
/	SD	DD			
/	D	D			

Table 2.2: Number of observations by bond rating classification and type. The table presents the number of Islamic (sukuk), conventional and combined (All) bonds available in the sample per: (A) rating classification (B) industrial sector. Assigned number denoted the numerical code assigned in the models applied. Panel (C) shows the number of Islamic bonds per sukuk structure. All refers to the combined number of Islamic and conventional bonds together.

Panel A: Bond Rating	**Assigned Number**	**Islamic**		**Conventional**		**All**
AAA	4	149	27.54%	39	56.52%	188
AA	3	371	68.58%	30	43.48%	401
A	2	5	0.92%			5
BB	1	16	2.96%			16
Total issues		541	100%	69	100%	610

Panel B: Industrial Sector	**Variable Code**	**Islamic**	**Conventional**	**All**
Infrastructures and Utilities	INFRA&UTIL	402	6	408
Construction and Engineering	CONST&ENG	83	12	95
Property and Real Estate	PROPERTY&RE	31	20	51
Trading and Services	TRADING&SERV	15	19	34
Asset-Backed Securities		-	6	6
Plantation and Agriculture		5	-	5
Diversified Holdings	OTHERSEC	-	4	4
Industrial Products		3	-	3
Consumer Products		-	2	2
Mining and Petroleum		2	-	2
Total		541	69	610

Panel C: Sukuk (Islamic Bond) Structure	Variable Code	Islamic
Bai Bithaman Ajil	BBA	5
Ijarah	IJARAH	48
Istisna’a	ISTISNA	16
Mudarabah	MUDARABAH	20
Musharakah	MUSHARAKAH	64
Murabahah	MURABAHAH	166
Wakalah	WAKALAH	15
Hybrid	HYBRID	207
Total		541

Table 2.3: Explanatory variables used in the analysis. The table shows the variables considered in the models and their variable codes, potential expected sign and definitions. Bloomberg was used to obtain all firm specific variables and BPAM for all other variables.

Variable	Variable Code	Expected Coefficient Sign	Description
Firm Specific Financial Variables			
Size of Firm	SIZE	+	Natural logarithm of total assets of the firm
Profit Margin	PM	+	Net Profit/Sales
Leverage	LEV	-	Debt to Asset = Debt/Total Assets
Interest Coverage	INT_COV	+	EBIT/Interest Expense
Liquidity	LIQUID	+	Quick Ratio = Cash & Cash Equivalents + Marketable Securities + Receivables /Current Liabilities
Price to Earnings	PE	+	Market Price/EPS
Price Change	PRICE_CHANGE	+	Percentage change in price from the rating effective date and 200 days before
Bond Specific Variables			
Principle	ISLAMIC	+ or -	Binary Indicator 1=Islamic bond 0 = Conventional bond
Guarantee Status	GUARANTEE	+	Binary Indicator 1 = guaranteed bond 0 = non-guaranteed bond
Secured	SECURED	+	Binary Indicator 1 = secured bond 0 = non-secured bond
Fixed Rate	FIXED_RATE	+	Binary Indicator 1 = bond with fixed rate 0 = bond with non-fixed rate
Credit Rating Agency	MARC	+ or -	Binary Indicator 1 = bond rated by MARC 0 = bond rated by RAM
Market Structure Variables			
Construction and Engineering	CONSTR&ENG		Binary Indicator 1 = Construction and Engineering 0 = otherwise
Property and Real Estate	PROPERTY&RE		Binary Indicator 1 = Infrastructures and Utilities 0 = otherwise
Trading and Services	TRADING&SERV		Binary Indicator 1 = Trading and Services 0 = otherwise
Other sectors	OTHERSEC		Binary Indicator 1 = other industrial sector

		0 = otherwise
Islamic Bond (Sukuk) Structure Variables		
Bai Bithaman Ajil	BBA	Binary Indicator 1 = Bai Bithaman Ajil sukuk 0 = otherwise
Ijarah	IJARAH	Binary Indicator 1 = Ijara sukuk 0 = otherwise
Istisna'a	ISTISNA	Binary Indicator 1 = Istisna'a sukuk 0 = otherwise
Mudarabah	MUDARABAH	Binary Indicator 1 = Mudarabah sukuk 0 = otherwise
Musharakah	MUSHARAKAH	Binary Indicator 1 = Musharakah sukuk 0 = otherwise
Wakalah	WAKALAH	Binary Indicator 1 = Wakalah sukuk 0 = otherwise
Hybrid	HYBRID	Binary Indicator 1 = Hybrid sukuk 0 = otherwise

Table 2.4: Spearman's rank correlation matrix of all considered variables

	RATING	SIZE	PM	PE	ROE	LEV	INT_COV	LIQUID	CASH RATIO	CFO_INTEREST	PRICE_CHANGE
RATING	1.000										
SIZE	0.162	1.000									
PM	-0.154	0.234	1.000								
PE	0.117	-0.056	-0.178	1.000							
ROE	-0.035	0.216	0.611	-0.260	1.000						
LEV	-0.073	-0.343	-0.415	-0.317	-0.365	1.000					
INT_COV	0.222	0.271	0.451	0.177	0.480	-0.633	1.000				
LIQUID	0.053	0.366	0.378	0.060	0.343	-0.230	0.260	1.000			
CASH RATIO	0.075	0.465	0.387	0.066	0.391	-0.266	0.308	0.780	1.000		
CFO_INTEREST	0.071	0.408	0.560	-0.037	0.588	-0.655	0.611	0.397	0.473	1.000	
PRICE_CHANGE	0.104	-0.215	-0.161	-0.310	-0.272	0.171	-0.042	-0.234	-0.410	-0.289	1.000

Table 2.5: Descriptive statistics of firm specific financial variables. The table reports the descriptive statistics for the firm specific financial variables considered in our analysis. The sample includes the financials of bond issuers of all active domestic bonds on 29 Dec2017 rated between Jan 2016 – Dec 2017. The RM bn denotes Malaysian Ringgit in billions. The St.Dev is the standard deviation. The Obs is the number of company specific financial information available for the bond classification (Islamic, conventional and all). The table also reports the t-tests (Mann-Whitney tests) of the mean (median), where the hypothesis of the t-test (Mann–Whitney test) is that the mean (median) of the financial variable is equal for Islamic and conventional bonds. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

Firm Specific Financial Variable			**Islamic**				**Conventional**				**All**					
Size	***Variable Name***	***Unit***	***Mean***	***Median***	***St.Dev***	***Obs***	***Mean***	***Median***	***St.Dev***	***Obs***	***Mean***	***Median***	***St.Dev***	***Min***	***Max***	***Obs***
SIZE	SIZE	RM bn	47.98	13.16	78.07	650	208.16	66.27	254.50	185	83.47***	16.64***	153.18	0.06	745.48	835
Profitability																
Profit Margin	PM	%	15.59	12.59	18.51	650	19.16	19.81	20.43	185	16.39**	13.28***	18.99	-48.31	113.89	835
Leverage																
Leverage (debt to assets)	LEV	%	37.52	32.04	15.94	650	23.82	15.24	15.40	185	34.48***	31.29***	16.80	2.98	78.02	835
Interest Coverage	INT_COV	Times	15.55	4.79	45.29	626	8.76	3.11	24.14	96	14.65	3.84***	43.13	-19.82	234.59	722
Liquidity																
Liquidity	LIQUID	Times	1.12	1.23	0.72	614	0.97	0.67	0.97	93	1.10*	1.14***	0.76	0.06	3.95	707
Market Value																
Price to Earnings	PE		19.88	15.09	31.73	577	14.30	12.80	5.50	158	18.68**	14.50***	28.32	4.25	345.77	735
Price Change	PRICE_CHANGE	%	6.93	2.34	26.28	646	5.12	7.12	18.26	185	6.53	2.38	24.72	-35.00	122.12	831

Table 2.6: Determinants of bond credit ratings. The table presents the ordered probit Model I (only firm specific financial variables) estimation results for the full sample (All), Islamic bonds, and conventional bonds. It reports the expected signs based on prior literature, β coefficients (Coef.) from Eq. (2.1), standard errors in parentheses and their corresponding p-values. Wald Chi2 is the Chi-square test with k (no. of parameters) degrees of freedom testing the null hypothesis that all coefficients (H_0: β=0) except for the constant are zero. The overall goodness-of-fit is measured by the Akaike Information Criterion (AIC) and Pseudo-R^2. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

			All		**Islamic**		**Conventional**	
Y: Credit Rating	Variable Name	Expected Sign	Coef.	P-value	Coef.	P-value	Coef.	P-value
Independent variable								
Firm Specific Financials	SIZE	+	0.147	0.000***	0.170	0.000***	-0.422	0.008***
			(0.038)		(0.044)		(0.160)	
	PM	+	-0.037	0.000***	-0.049	0.000***	0.388	0.000***
			(0.005)		(0.006)		(0.076)	
	LEV	-	-0.012	0.002***	-0.011	0.007***	0.013	0.235
			(0.004)		(0.004)		(0.011)	
	INT_COV	+	0.019	0.000***	0.023	0.000***	-0.193	0.000***
			(0.003)		(0.003)		(0.047)	
	LIQUID	+	0.336	0.000***	0.576	0.000***	-0.627	0.026**
			(0.083)		(0.091)		(0.281)	
	PE	+	0.015	0.035**	0.0171	0.029**	0.170	0.000***
			(0.007)		(0.008)		(0.039)	
	PRICE_CHANGE	+	0.016	0.000***	0.016	0.000***	-0.000	0.980
			(0.003)		(0.004)		(0.020)	
Islamic indicator	ISLAMIC		-0.970	0.000***				
			(0.191)					
Observations			610		541		69	
Diagnostics	Wald Chi2		149.16***		146.39***		187.77***	
	AIC		787.934		662.525		54.604	
	Pseudo-R^2		0.188		0.220		0.591	

Table 2.7:Marginal effects of bond credit rating determinants. The table presents the average marginal effects (at means) of the ordered probit Model I (only firm specific financial variables) independent variables presented in Table 2.6 for the full sample (All), Islamic bonds, and conventional bonds. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. It reports the marginal effects per each rating category BB to AAA that were assigned to ascending numerical values 1 to 4, respectively

Variable (Determinant)	Rating	All	Islamic	Conventional
SIZE	**AAA**	0.051***	0.055***	-0.164***
	AA	-0.047***	-0.052***	0.164***
	A	-0.001**	-0.001**	
	BB	-0.003**	-0.003**	
PM	**AAA**	-0.013***	-0.016***	0.150***
	AA	0.012***	0.015***	-0.150***
	A	0.000**	0.000**	
	BB	0.001***	0.001***	
LEV	**AAA**	-0.004***	-0.004***	0.005
	AA	0.004***	0.003***	-0.005
	A	0.000*	0.000*	
	BB	0.000**	0.000**	
INT_COV	**AAA**	0.006***	0.007***	-0.075***
	AA	-0.006***	-0.007***	0.075***
	A	-0.000**	-0.000**	
	BB	-0.000***	-0.000***	
LIQUID	**AAA**	0.116***	0.188***	-0.243**
	AA	-0.108***	-0.175***	0.243**
	A	-0.003**	-0.004**	
	BB	-0.006**	-0.009**	
PE	**AAA**	0.005**	0.006**	0.066***
	AA	-0.005**	-0.005**	-0.066***
	A	-0.000	-0.000	
	BB	-0.000*	-0.000*	
PRICE_CHANGE	**AAA**	0.005***	0.005***	-0.000
	AA	-0.005***	-0.005***	0.000
	A	-0.000**	-0.000**	
	BB	-0.000***	-0.000**	
ISLAMIC	**AAA**	-0.368***		
	AA	0.356***		
	A	0.004**		
	BB	0.008***		
Observations		610	541	69

***Table 2.8: Full sample ordered probit estimates*.** The table presents the ordered probit Models II to IV estimation results for the full sample (All). Model II considers firm specific financial variables and their interactions with the Islamic binary dummy. Model III incorporates firm specific financials, bond specific and market structure variables. Model IV includes all variables in II and III. It reports the expected signs based on literature, β coefficients (Coef.) from Eq. (2.1), standard errors in parentheses and their corresponding p-values. Wald Chi2 is the Chi-square test with k (no. of parameters) degrees of freedom testing the null hypothesis that all coefficients (H0: β=0) except for the constant are zero. The overall goodness-of-fit is measured by the Akaike Information Criterion (AIC) and Pseudo-R2. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively

			Model II		**Model III**		**Model IV**	
Y: Credit Rating	**Variable Name**	**Expected Sign**	**Coef.**	**P-value**	**Coef.**	**P-value**	**Coef.**	**P-value**
Independent variable								
Firm Specific Financials	SIZE	+	-0.424	0.002***	0.162	0.003***	-1.016	0.000***
			(0.136)		(0.054)		(0.173)	
	PM	+	0.333	0.000***	-0.029	0.000***	0.382	0.000***
			(0.044)		(0.007)		(0.060)	
	LEV	-	-0.014	0.157	-0.022	0.000***	0.054	0.000***
			(0.010)		(0.005)		(0.011)	
	INT_COV	+	-0.161	0.000***	0.011	0.010**	-0.187	0.000***
			(0.029)		(0.004)		(0.036)	
	LIQUID	+	-0.453	0.026**	0.185	0.068*	-0.640	0.007***
			(0.204)		(0.102)		(0.235)	
	PE	+	0.145	0.000***	0.017	0.029**	0.191	0.000***
			(0.032)		(0.008)		(0.030)	
	PRICE_CHANGE	+	-0.001	0.903	0.019	0.000***	0.024	0.069*
			(0.012)		(0.003)		(0.013)	
Islamic bond Interactions	ISLAMIC x SIZE		0.597	0.000***			1.235	0.000***
			(0.143)				(0.171)	
	ISLAMIC x PM		-0.383	0.000***			-0.421	0.000***
			(0.044)				(0.061)	
	ISLAMIC x LEV		-0.026	0.016**			-0.074	0.000***
			(0.011)				(0.012)	

	ISLAMIC x INT_COV		0.185	0.000***			0.204	0.000***
			(0.029)				(0.037)	
	ISLAMIC x LIQUID		1.041	0.000***			1.030	0.000***
			(0.224)				(0.272)	
	ISLAMIC x PE		-0.128	0.000***			-0.180	0.000***
			(0.033)				(0.031)	
	ISLAMIC x PRICE_CHANGE		0.018	0.151			-0.001	0.934
			(0.012)				(0.013)	
Bond Specific	ISLAMIC	+ or -	2.305	0.008***	-1.049	0.000***	3.768	0.000***
			(0.870)		(0.246)		(0.865)	
	GUARANTEE	+			1.778	0.000***	0.977	0.000***
					(0.243)		(0.260)	
	SECURED	+			0.216	0.127	-0.108	0.554
					(0.142)		(0.183)	
	FIXED_RATE	+			1.252	0.000***	2.113	0.000***
					(0.300)		(0.400)	
	MARC	+ or -			-0.164	0.219	-0.648	0.000***
					(0.134)		(0.132)	
Market Structure	CONSTR&ENG				-0.558	0.017**	-1.382	0.000***
					(0.234)		(0.257)	
	PROPERTY&RE				-0.560	0.055*	-0.495	0.137
					(0.292)		(0.333)	
	TRADING&SERV				-0.484	0.106	-0.087	0.750
					(0.299)		(0.274)	
	OTHERSEC				-1.312	0.001***	-0.673	0.075*
					(0.395)		(0.378)	
Observations			610		610		610	
Diagnostics	Wald Chi2		501.24***		381.14***		911.35***	
	AIC		720.544		689.523		619.418	
	Pseudo-R^2		0.275		0.310		0.399	

Table 2.9: Islamic sample ordered probit estimates. The table presents the ordered probit Islamic models I to III estimation results for the Islamic bond (sukuk) sample. Model I considers firm specific financial. Model II incorporates also Islamic bond structure variables. Model III includes all variables in I and II and adds to them bond specific variables. It reports the expected signs based on literature, β coefficients (Coef.) from Eq. (2.1), standard errors in parentheses and their corresponding p-values. Wald Chi2 is the Chi-square test with k (no. of parameters) degrees of freedom testing the null hypothesis that all coefficients (H0: β=0) except for the constant are zero. The overall goodness-of-fit is measured by the Akaike Information Criterion (AIC) and Pseudo-R2. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively

Islamic Model:			**Model I (financial variables)**		**Model II (financial+islamic)**		**Model III (financial+islamic+bond)**	
Y: Credit Rating	**Variable Name**	**Expected Sign**	**Coef.**	**P-value**	**Coef.**	**P-value**	**Coef.**	**P-value**
Independent variable								
Firm Specific Financials	SIZE	+	0.170	0.000***	0.107	0.023**	0.340	0.000***
			(0.044)		(0.047)		(0.062)	
	PM	+	-0.049	0.000***	-0.050	0.000***	-0.043	0.005***
			(0.006)		(0.009)		(0.015)	
	LEV	-	-0.011	0.007***	-0.022	0.000***	-0.056	0.000***
			(0.004)		(0.006)		(0.010)	
	INT_COV	+	0.023	0.000***	0.019	0.000***	0.024	0.010**
			(0.003)		(0.004)		(0.009)	
	LIQUID	+	0.576	0.000***	0.296	0.013**	-0.307	0.116
			(0.091)		(0.119)		(0.195)	
	PE	+	0.0171	0.029**	-0.002	0.767	-0.018	0.071*
			(0.008)		(0.007)		(0.010)	
	PRICE_CHANGE	+	0.016	0.000***	0.018	0.000***	0.018	0.000***
			(0.004)		(0.004)		(0.004)	
Bond Specific	GUARANTEE	+					2.920	0.000***
							(0.383)	
	SECURED	+					0.420	0.121
							(0.271)	
	FIXED_RATE	+					0.243	0.548
							(0.404)	

	MARC	+ or -				-1.632 (0.292)	0.000***
Islamic bond structure	BBA			-1.276 (1.062)	0.229	0.743 (1.101)	0.500
	IJARAH			1.189 (0.270)	0.000***	1.661 (0.342)	0.000***
	ISTISNA			-12.855 (0.932)	0.000***	-15.168 (1.181)	0.000***
	MUDRABAH			-0.767 (0.227)	0.001***	-2.432 (0.569)	0.000***
	MUSHARAKAH			0.767 (0.303)	0.011**	1.255 (0.348)	0.000***
	WAKALAH			1.482 (0.353)	0.000***	2.867 (0.314)	0.000***
	HYBRID			0.638 (0.224)	0.004***	1.739 (0.310)	0.000***
Observations			541	541		541	
Diagnostics	Wald Chi2		146.39***	15738.94***		24126.75***	
	AIC		662.525	513.005		420.789	
	Pseudo-R^2		0.220	0.418		0.540	

Table 2.10: Islamic sample marginal effects of a selection of bond credit rating determinants. The table presents the average marginal effects (at means) of the ordered probit Islamic models II and III independent variables presented in Table 2.9 for the Islamic bond (sukuk) sample. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively. It reports the marginal effects per each rating category BB to AAA that were assigned to ascending numerical values 1 to 4, respectively.

Variable (Determinant)		Rating	Model II (financial+islamic)	Model III (financial+islamic+bond)
Bond specific	GUARANTEE	AAA		0.451***
		AA		-0.450***
		A		-0.001
		BB		-0.000
	MARC	AAA		-0.252***
		AA		0.252***
		A		0.000
		BB		0.000
	IJARAH	AAA	0.246***	0.256***
		AA	-0.241***	-0.256***
		A	-0.005	-0.000
		BB	-0.000	-0.000
	ISTISNA	AAA	-2.662***	-2.342***
		AA	2.604***	2.339***
		A	0.058	0.003
		BB	0.000	0.000
	MUDARABAH	AAA	-0.159***	-0.375***
		AA	0.155***	0.375***
		A	0.003	0.000
		BB	0.000	0.000
	MUSHARAKAH	AAA	0.159**	0.194***
		AA	-0.155**	-0.193***
		A	-0.003	-0.000
		BB	-0.000	-0.000
	WAKALAH	AAA	0.307***	0.443***
		AA	-0.300***	-0.442***
		A	-0.007	-0.001
		BB	-0.000	-0.000
	HYBRID	AAA	0.132***	0.269***
		AA	-0.129***	-0.268***
		A	-0.003	-0.000
		BB	-0.000	-0.000
	Observations		541	541

Table 2.11: In-sample bond rating forecasts. The table reports the number of correct predictions and in-sample bond credit rating prediction accuracies (%) of all three samples: All bonds, Islamic bonds, and conventional bonds. The entire set of bond ratings included in each sample are predicted using the ordered probit and SVM. The prediction accuracies of the ordered probit are based on the predicted rating for each bond, which corresponds to the category (rating class) with the highest probability outcome. The in-sample SVM predictions are based on the optimal combination of parameters γ and C. We do not report any SVM All sample prediction accuracies for Model I as the SVM takes into account independent variables' interaction terms.

Model Used	**Forecasted Sample**	**Ordered Probit**		**SVM**	
		No. of correct predictions	Accuracy (%)	No. of correct predictions	Accuracy (%)
All (Model I)	All	429/610	70.33%	-	-
	Islamic	406/541	75.05%	-	-
	Conventional	23/69	33.33%	-	-
All (Model II)	All	438/610	71.80%	608/610	99.67%
	Islamic	381/541	70.43%	540/541	99.82%
	Conventional	57/69	82.61%	68/69	98.55%
Islamic (Model I)	All	407/610	66.72%	581/610	95.25%
	Islamic	381/541	70.43%	540/541	99.82%
	Conventional	26/69	37.68%	41/69	59.42%
Conventional (Model I)	All	261/610	42.79%	440/610	72.13%
	Islamic	204/541	37.71%	372/541	68.76%
	Conventional	57/69	82.61%	68/69	98.55%

Table 2.12: Number of correct predictions and prediction accuracies. The table reports the number of correct predictions and bond credit rating prediction accuracies (%) of the samples using the ordered probit and support vector machines (SVM). The prediction accuracies of the ordered probit are based on the predicted rating for each bond, which corresponds to the category (rating class) with the highest probability outcome. The 10-fold cross validation was performed on the training set. We only report the results of the optimal model with the highest cross-validation accuracy obtained from the grid search. The in-sample (training 70%) and out-of-sample (holdout 30%) SVM predictions are based on the optimal combination of parameters γ and C. We do not report any SVM All sample prediction accuracies for Model I as the SVM takes into account independent variables' interaction terms.

Sample	**Model**	**Subset**	**Ordered Probit**		**SVM (RBF)**	
				%		%
All	Model I	Cross validation (10-fold)		71.43%		-
		Training set	300/427	70.26%	-	-
		Holdout set	125/183	68.31%	-	-
	Model II	Cross validation (10-fold)		71.20%		97.89%
		Training set	304/427	71.19%	426/427	99.77%
		Holdout set	131/183	71.58%	179/183	97.81%
Islamic	Islamic Model I	Cross validation (10-fold)		70.33%		98.68%
		Training set	265/378	70.11%	323/378	85.45%
		Holdout set	113/163	69.33%	137/163	84.05%
	Islamic Model II	Cross validation (10-fold)		75.91%		98.41%
		Training set	287/378	75.93%	377/378	99.74%
		Holdout set	125/163	76.69%	161/163	98.77%
Conventional	Model I	Cross validation (10-fold)		83.50%		97.92%
		Training set	40/48	83.33%	47/48	97.92%
		Holdout set	17/21	80.95%	21/21	100.00%

Table 2.13: Comparison of actual and predicted rating classifications. The table presents our holdout samples' predicted rating classifications and compares them to the actual ones. The comparison is made for both methods: ordered probit and support vector machines (SVM). We report the optimal SVM parameters: C the regularisation hyperparameter and γ RBF kernel's gamma, which were selected based on the cross-validation of the training sets. The table reports the number of correct predictions of each model and its corresponding percentage of accuracy.

All (Model II)											
Ordered Probit						SVM ($C=2^{15}$ $\gamma=2^{0}$)					
Actual Rating	*Predicted Rating*					*Actual Rating*	*Predicted Rating*				
	AAA	AA	A	BB	Total		AAA	AA	A	BB	Total
AAA	27	29			56	AAA	54	2			56
AA	16	104			120	AA	2	118			120
A		2			2	A			2		2
BB		5			5	BB				5	5
No. of correct predictions: 131/183 Prediction accuracy: **71.58%**						No. of correct predictions: 179/183 Prediction accuracy: 97.81%					

Islamic Model I (Firm Specific Variables)											
Ordered Probit						SVM ($C=2^{15}$ $\gamma=2^{0}$)					
Actual Rating	*Predicted Rating*					*Actual Rating*	*Predicted Rating*				
	AAA	AA	A	BB	Total		AAA	AA	A	BB	Total
AAA	16	29			45	AAA	22	23			45
AA	14	97			111	AA	2	109			111
A		2			2	A	1		1		2
BB		5			5	BB				5	5
No. of correct predictions: 113/163 Prediction accuracy: **69.33%**						No. of correct predictions: 137/163 Prediction accuracy: 84.05%					

Islamic Model II (Firm Specific+ Islamic Structure)											
Ordered Probit						SVM ($C=2^{15}$ $\gamma=2^{-1}$)					
Actual Rating	*Predicted Rating*					*Actual Rating*	*Predicted Rating*				
	AAA	AA	A	BB	Total		AAA	AA	A	BB	Total

AAA	14	31			45	AAA	45				45
AA	5	106			111	AA	1	110			111
A		2			2	A	1		1		2
BB				5	5	BB				5	5
No. of correct predictions: 125/163 Prediction accuracy: **76.69%**						No. of correct predictions: 162/163 Prediction accuracy: 98.77%					

Conventional							
Ordered Probit				SVM (C=2^{15} γ=2^3)			
Actual Rating	*Predicted Rating*			*Actual Rating*	*Predicted Rating*		
	AAA	AA	Total		AAA	AA	Total
AAA	11	1	12	AAA	12		12
AA	3	6	9	AA		9	9
No. of correct predictions: 17/21 Prediction accuracy: **80.95%**				No. of correct predictions: 21/21 Prediction accuracy: 100.00%			

3 Herding behaviour in corporate bond and equity markets: A comparative approach

3.1 Introduction

In behavioural finance literature, *herding* is used to describe a process where individuals suppress their own beliefs and make investment decisions entirely based on their peers' actions or collective movements in the market. It is debated that herding might produce efficient outcomes (for example, fundamentals-driven spurious herding, see Bikhchandani and Sharma (2001)). However, herding can destabilise prices, precipitate bubble-like effects and potentially undermine financial stability (Spyrou 2013; Demirer and Kutan 2006). In essence herding can lead to observable correlated trading patterns that could induce systematic, erroneous decision making by market participants (Bikhchandani, Hirshleifer and Welch 1992). This increase in the degree of co-movement of asset returns decreases portfolio diversification benefits and induces systemic risk. As a consequence, investors might need to hold a larger pool of securities to achieve the desirable reduction of idiosyncratic (unsystematic) risk, or in the extreme scenario of perfectly correlated asset returns the diversification of risk might be unachievable (Chang, Cheng and Khorana 2000; Morelli 2010). Furthermore, correlated trading patterns can also result in asset prices to deviate from their fundamentals, causing mis-pricings that could present profitable trading opportunities for investors (Chiang and Zheng 2010; Tan et al. 2008).

Empirical research in herding behaviour has typically followed two broad directions: the first examines institutional investor herding (e.g. Lakonishok, Shleifer and Vishny 1992; Sias 2004; Choi and Sias 2009), whilst the second concentrates on herding towards a market consensus (e.g. Christie and Huang 1995; Chang, Cheng and Khorana 2000). This chapter focuses on the latter. A sizeable empirical literature examines herding towards a market consensus predominantly in equity markets (Chiang and Zheng 2010; Demirer, Kutan and Chen 2010; Galariotis, Krokida and Spyrou 2016b; Andrikopoulos et al. 2017; Guney, Kallinterakis and Komba 2017). Focusing on the US market, early studies fail to find evidence of investor herding around the market return (Christie and Huang 1995; Chang, Cheng and Khorana 2000), recent ones do (Hwang and Salmon 2004; Galariotis, Rong and Spyrou 2015). The extent to which investors follow each other's trades seems to vary across markets and time. Asymmetric herding effects are evidenced when conditioning on market volatility, trading volume and liquidity, which appear to be heterogeneous across markets (Tan et al. 2008; Economou, Kostakis and Philippas 2011; Galariotis, Krokida and Spyrou 2016b; Cui, Gebka and Kallinterakis 2019). Despite this apparent focus on equity markets, herding in corporate bond markets remains largely underexplored with only two studies exploring bond markets (Galariotis, Krokida and Spyrou 2016a; Cai et al. 2019). The first study by Galariotis, Krokida and Spyrou (2016a) tests for herding in European government bond prices, whilst Cai et al. (2019) examine the level of institutional herding in the US corporate bond market. The studies show that herding exists in bond markets and should be explored further to understand its nature and drivers.

From the above evidence it is clear that herding behaviour could have a substantial impact on financial markets and thus is worth examining and documenting. So far, studies have investigated herding behaviour in stock and bond markets in isolation. Furthermore, as bond trading is conducted primarily by well-informed institutional investors, the existence of cross-asset herding between bond and equity markets receives renewed attention.[23] Yet, and to the best of our knowledge, no study exists to address these issues. Hence, this chapter aims to fill in this gap by examining unconditional and conditional herding in US corporate bond and equity markets as well as evidence of cross-herding between them. We study and compare both markets at the same time using the same sample and examine if herding is contagious across markets. Against this background, our study aims at addressing the following three main questions: i) Do investors herd in US corporate bond and equity markets? ii) How is the herding activity associated with the level of liquidity and volatility in corporate bond and equity markets? iii) Is there a cross-asset herding spillover between corporate bonds and equities?

To address our research questions, we apply the methodology of Chang, Cheng and Khorana (2000) to conduct the standard herding tests towards the market consensus. Using a unique dataset comprising of 794 stocks and 8,623 corporate bonds issued by the same firms that were listed on the S&P 500 between January 2008 – December 2018. Our initial unconditional tests show little evidence of investor herding, only present speculative grade (high yield) bonds. However, after controlling for herding asymmetries (up/down markets, high/low liquidity and high/low volatility), we detect significant herding effects in both corporate bond and equity markets. Particularly, our results suggest that investors tend to herd when the market is more liquid and less volatile. This indicates that investors herd more intensively around the market average in clamer periods, during which investors are more optimistic or certain about the direction of the market. Interestingly, the level of herding detected in corporate bonds is substantilly higher than in equities. The results are consistent through the full samples as well as the portfolios constructed based on the bonds'/issuers' credit rating (investment grade, high yield and non-rated). However, we find that during liquid (less volatile) days investors herd more actively in investment grade (speculative grade) assets. Our additional analysis show that the detected herding asymmetries hold for all liquidity (volatility) sub-samples and indicate that herding is mostly positively related to liquidity, whilst the level of market volatility act as a catalyst that amplifies the herding effect further. Our results also reveal significant cross-asset herding spillover effects from US corporate bonds to equities. This may be attributed to the difference in the composition of market participants in each market; stock market participants include a large proportion of retail investors that are more likely to follow the trading patterns of the well-informed institutional investors prevailing in bond markets. The

[23] We refer to this as "cross-herding" in the rest of the chapter.

cross-herding effect from bonds to equity holds during the 2008 Global Financial Crisis (GFC) period but shifts post-crisis from equity to bonds. This shift in cross-herding informational content is likely to be due to the aftermath of the crisis that was characterized by informational asymmetry.

This chapter contributes to the literature in three distinct ways: *Firstly*, we investigate a specific gap in the literature: cross-asset class herding spillover that has been neglected in prior literature. Extant literature has either focused extensively on isolated asset classes (for example, equities, bonds), performed cross-country herding evidence e.g. from a major country such as the US to other countries (Chiang and Zheng 2010; Galariotis, Rong and Spyrou 2015), or used the underlying market (equity) to draw inferences about the typically forward-looking option and futures markets herding (Demirer, Lee and Lien 2015; Voukelatos and Verousis 2019). This part of the research is motivated by the stock-bond contagion and flight literature. Specifically, we extend the previous literature by examining whether there is a persistent pattern in the corporate bond and equity investors' trades that spills over from one asset class to another i.e., if investors' herding in stock markets induce herding in corporate bond markets, and vice versa.

Secondly, this is the first study to assess herding behaviour in corporate bond and equity markets in a comprehensive manner, providing a direct comparison of herding behaviour in corporate bonds and stocks. To enable this comparison, we utilise bonds and equities issued by the constituents of the S&P 500 index which makes it interesting to see if the behaviours of investors vary in trading different assets of the same firms. Furthermore, since issuers and bonds are often independently assigned credit ratings that reflect their distinct credit quality and specifics[24], we extend our analysis to examine the presence of herding and analyse the differences (if any) in investors' trading behaviour across different rating classes. We build on the assumption that assets with diverse or no rating classification are subject to different levels of informational asymmetry and could attract distinct types of investors with specific trading strategies and preferences, which could potentially imply different degrees of herding activity.

Thirdly, given the distinction between bond and equity markets' characteristics and liquidity, we comprehensively explore the relationship between market liquidity, volatility and investors' herding in a wider context. Further, we investigate whether the asymmetric effect of one supersedes or outweighs the other. It is specifically important to study the relationship between of liquidity and herding behaviour as studies suggest that liquidity predicts equity returns and corporate bond yield spreads (Amihud and Mendelson 1986; Helwege, Huang and Wang 2014; Friewald, Jankowitsch and Subrahmanyam 2012). High liquidity can be viewed as a positive externality that could induce investors' clustering in a particular market (Devenow and Welch 1996), however, one could also expect investors to herd more in less liquid assets that commonly suffer from asymmetric information (Taylor

[24] Studies show that the specifics of investment grade and high yield assets differ, where the latter are more fragile and sensible to different risk factors (Raffestin 2017).

2002). Our research expands on the work of Galariotis, Krokida and Spyrou (2016b) by examining the impact of liquidity on herd behaviour in corporate bond markets. The general illiquidity of bonds in comparison to equities (Bao, Pan and Wang 2011) and the diverse liquidity conditions that different bond grades maintain, suggest that bond market liquidity could hugely impact the behaviour of market participants; which is an exciting underexplored testing ground in herding that we aim to fill. Furthermore, a number of studies have documented a strong relationship between market liquidity and volatility, though the nature of the relationship between these two most important features of financial markets is complex and does not appear to be constant. Hence, this chapter attempts to appropriately account for them in two different markets and provides new insights into their relationship in connection with asymmetric herding behaviour.

The rest of the chapter is organised as follows. Section 3.2 provides a literature review. Section 3.4 presents the methodology employed and 3.3 describes the sample data. Section 3.5 discusses the empirical findings and implications. Section 3.6 concludes.

3.2 Literature review

In financial markets, herding arises when investors follow and imitate their peers' actions or trades; ignoring their own opinions (or information based on fundamentals) (Cui, Gebka and Kallinterakis 2019). As a result of herding behaviour, investors simultaneously trade in the same direction over a period of time (Nofsinger and Sias 1999). Studies explain that herding behaviour can be motivated by various reasons. For instance, investors might anticipate informational gains by inferring some information from the previous trades of better informed investors[25] (Banerjee 1992; Bikhchandani, Hirshleifer and Welch 1992). Herding can also occur as a reaction to the announcement of certain fundamental information (Spyrou 2013), low quality analysts and investment managers might mimic their peers to appear as equally talented and protect their reputation, institutional investors might herd for remuneration purposes (Scharfstein and Stein 1990; Jiang and Verardo 2018). Studies also argue that fads and style investing can trigger herding by inducing the level of correlation in the trades of investors following popular industries or specific investment strategies (Barberis and Shleifer 2003; Choi and Sias 2009; Celiker, Chowdhury and Sonaer 2015). Furthermore, herding can simply be a product of irrational behavioural biases that stem from psychological or social factors systematically affecting investors' trading decisions (Barber, Odean and Zhu 2009a; Barber, Odean and Zhu 2009b).

Bikhchandani and Sharma (2001) distinguish between two types of herding: "spurious herding" where market participants take similar trading decisions based on a similar set of information they face (typically changes in fundamentals), and "intentional herding" where investors purposely mimic each other's actions. As mentioned above, herding empirical literature can be split into two strands: studies

[25] This is known as informational cascades.

that concentrate on that rely on microdata and investigate institutional investor herding, while others explore price and market activity to examine herding towards a market consensus (for a more detailed review see e.g. Spyrou 2013). The subsections below – 3.2.1 and 3.2.2 – review the main studies in these two categories, whilst subsection 3.2.3 briefly presents further evidences of herding in various asset classes.

3.2.1 Institutional investor herding

This body of literature is based on the view that institutional investor herding heavily affects the individual stock prices and is mainly responsible for large movements in prices. This argument supported by the fact that institutional investors are the most active investors with largest proportions of holdings in the financial markets, and accordingly changes in their demand have a stronger effect on stock prices than individual investors' demand. According to this view, institutional investors destabilise stock prices as their trading can divert stock prices away from their fundamental values causing a long-term price volatility. The earliest study documented investigating institutional herding is the work of Lakonishok, Shleifer and Vishny (1992; LSV hereafter) that examines the trading patterns of US equity pension fund managers. Using 769 all all-equity pension funds managed by 341 institutional managers, they construct their sample consisting of end of quarter portfolio holdings of the managers between January 1985 and April 1989. LSV propose a metric that measures if, in a given period of time, a disproportionate number of institutional investors (money managers) are buying (selling) a specific asset more intensively than the market-wide buying (selling). Their findings show no evidence of herding or positive-feedback trading by pension fund managers within large cap stocks, which form the majority of institutional holdings and trades, and limited evidence in smaller stocks. Accordingly, they conclude that within their sample institutional investors do not destabilise the prices of individual stocks, but instead the wide range of styles and strategies of they follow in their trades seem to offset each other without heavily influencing the prices.

Following LSV, earlier studies from the US such as, Grinblatt, Titman and Wermers (1995) and Wermers (1999) find weak evidence of herding by US mutual fund managers, predominantly in the trades of small-stock growth-oriented funds. Other studies (Froot, Scharfstein and Stein 1992; Hirshleifer, Subrahmanyam and Titman 1994) show that institutional herding can push prices towards (rather than away from) the equilibrium prices; possibly due to the fact that they are typically well informed and thus more likely to herd towards undervalued stocks and away from overvalued ones. However, empirical studies employing more recent stock market data find some non-negligible price destabilising effects of institutional herding (Sias 2004; Choi and Sias 2009; Brown, Wei and Wermers 2014). Sias (2004) argues that the demand of institutional investors for an asset in a certain quarter is positively correlated with their demand for the same asset in the previous quarter if they follow (herd) their own lag trades of the same assets. Based on this concept, he proposes a new approach to measure institutional herding by evaluating the '(…) cross-sectional temporal dependence in institutional demand over adjacent quarters' (Sias 2004, p.200). He finds evidence supporting this argument and his further analysis show that institutional investors herd as a response to the information they infer from each other's activities.

Generally, the institutional herding literature results are mixed, suggesting that fund managers or institutional investors herd in various degrees internationally. Kim and Nofsinger (2005) show that Japanese institutional investors exhibit lower levels of herding than US ones, whilst Wylie (2005) detects a moderate amount of fund manager herding in the UK, concentrated within the largest and smallest UK stocks. On the other hand, Goodfellow, Bohl and Gebka (2009) found no signs of Polish institutional traders' herding behaviour at any state of the market. Stronger institutional herding effects are captured amongst other markets e.g. German mutual funds (Walter and Moritz Weber 2006; Kremer and Nautz 2013), Chilean pension funds (Olivares 2008) and Portuguese equity funds (Holmes, Kallinterakis and Ferreira 2013).

Furthermore, earlier studies find very little evidence of return reversals post herding (Nofsinger and Sias 1999; Wermers 1999; Sias 2004). However, more recent papers detect subsequent return reversals in both short-term and long-term horizons (e.g. Brown, Wei and Wermers 2014; Dasgupta, Prat and Verardo 2011). Brown, Wei and Wermers (2014) empirical results attribute these reversals to trading managers that typically have short-term career concerns and thus have a tendency to overreact to analyst revisions. Focusing on the long-term horizon, Dasgupta, Prat and Verardo (2011) find complementary evidences and proposes three explanations for the price impact (reversals) of institutional herding. The first hypothesis is that institutional investors are influenced by behavioural biases that could direct them to trade on stale information and accordingly pushing the prices away from their fundamental values. Their second hypothesis suggests that reversals are a consequence of the reputational concerns of delegated portfolio managers that are inclined to trade in a correlated manner, which in turn leads to mispricing and subsequent return reversals. Their last explanation attributes the return reversals to the fact that institutional investors trade against insider ones that have superior information regarding the future cash flows.

3.2.2 Herding towards a market consensus

This strand of literature uses aggregate market data to measure herding towards the market average. The pioneering studies in this area are the works of Christie and Huang (1995) and Chang, Cheng and Khorana (2000). Christie and Huang (1995) were the first to suggest and measure herding using the cross-sectional deviation of equity returns (dispersions). Their methodology is based on their hypothesis that during periods of market stress, investors have a tendency to ignore their own beliefs and herd towards the market average. Thus, in such situations, the individual returns will not deviate much from the market return and consequently the dispersions are predicted to be relatively low. To test for the price implication of herding, they use a sample of daily NYSE and Amex equity returns from July 1962 to December 1988 and monthly NYSE equity returns from December 1925 to December 1988. Their daily and monthly results show that, opposing to their hypothesis, the equity return dispersions in their samples significantly increase during extreme market conditions (price movements), providing no evidence of herding activity. They explain that their results are consistent with the rational asset pricing models, which suggest that individual stocks have different sensitivities towards the market return that in turn push the returns away from the market average. Their further analyses detect an asymmetry during up and down markets, where the dispersions seem to increase more dramatically during up markets relative to down markets.

Chang, Cheng and Khorana (2000) build on the methodology of Christie and Huang (1995) and propose their own herding measure that they use to examine the existence of herding behaviour within a wider set of countries: advanced countries (US, Hong Kong and Japan) and emerging ones (South Korea and Taiwan). Interestingly, they document significant herding activity in emerging markets, and weaker evidence in Japan. However, they do not detect any herding in US and Hong Kong. Their results seem to be consistent and robust across time and different size-based portfolios. They attribute the variation in herding behaviour to the relatively high level of government intervention in the emerging markets and lack of reliable micro-information. Furthermore, they suggest that the presence of a higher number of speculators with shorter investment horizons in South Korea and Taiwan could have also promoted herding activity. This proposition is in line with the findings of Froot, Scharfstein and Stein (1992) who demonstrate that the presence of short-term speculators can induce some types of information inefficiencies, where they might herd on a single source of information resulting in a less prevalent return dispersion. Focusing on South Korea and Taiwan that exhibit herding, Chang, Cheng and Khorana (2000) further find that the macroeconomic information, rather than firm-specific, have a significant impact on investors' behaviour in these markets.

In the same spirit as Christie and Huang (1995), Hwang and Salmon (2004) introduce a new approach to measure herding activity that is found on the cross-sectional dispersion of asset sensitivity (betas) to several fundamental factors (size and book-to-market factors of Fama and French (1993)) in a particular market. In contrast to the previous studies, they find persistent evidence of herding behaviour towards the US and South Korean stock markets within their sample period from January 1993 to November 2002. They also demonstrate that the herding effect is independent of the state of the markets and macroeconomic factors, which challenges the findings of Chang, Cheng and Khorana (2000). Based on their empirical results, they claim that periods of market stress, particularly the Asian and Russian Crises within their sample, are important turning points that decrease the herding effects and help in restoring the markets back to their equilibrium. Their results provide a more comprehensive understanding to herding effects around market turbulences, suggesting that during crisis investors are likely to rely on fundamentals, which could potentially explain why Christie and Huang (1995) did not detect any herding during crises. Lastly, they claim that their results do not conflict with Christie and Huang (1995), but instead they stress that herding is more pronounced when the market is more stable and investors are more certain of the direction of the market. More interestingly, they show that herding effects in the US market change over time, as in their study it began to disappear from early 2000, before the market boomed and crashed, and then regained later in the year until the end of their sample.

Employing the herding methodologies of Christie and Huang (1995) and Chang, Cheng and Khorana (2000), studies found varying results in different countries. For instance, Caparrelli, D'Arcangelis and Cassuto (2004) tests for the presence of herding in the Italian stock market and find evidence of herding activity during extreme market conditions. Similarly, Demirer, Kutan and Chen (2010) detects herding activity in all sectors of the Taiwanese stock market and Guney, Kallinterakis and Komba (2017) in eight African frontier stock markets. However, Demirer and Kutan (2006) fails to find signs of herding activity, using individual-firm and sector level data, in Chinese markets. Conversely, using the same Chinese stock exchanges (Shanghai and Shenzhen) and a slightly wider sample time frame, Tan et al. (2008) detect herding behaviour in both Chinese A and B-share stocks during rising and falling markets. Additionally, they test for a variety of herding asymmetric behaviour and note that A-share markets (dominated by domestic individual investors) on the Shanghai stock exchange is more prevalent when markets are rising, characterised by higher trading volume and volatility. Interestingly, they further find that the herding effect becomes weaker with the weekly and monthly data, signifying that herding is most likely circumscribed to shorter time horizons.

Chiang and Zheng (2010) study herding at a global level and tests investors' herding activity in 18 countries. Employing a sample from May 1988 to April 2009, they find strong evidence of herding activity in nearly all, except US and Latin America, individual markets examined in both up and down markets. Their results show that herding exists even in developed markets (for example, Australia, Germany, France, and the UK, amongst others) and is not specific to developing countries as earlier studies suggest (Chang, Cheng and Khorana 2000). Chiang and Zheng (2010) were also the first to examine herding spillover effects. Their empirical findings indicate that the US return dispersions play an important role in explaining the other markets' (in their sample) herding activity. Non-US investors seem to herd not only with their domestic peers, but also with the US stock market. Challenging the findings of Hwang and Salmon (2004), they claim that crisis stimulate herding activity in the country that caused the crisis, which spreads the financial crash to the neighbouring countries (contagion effect).

Similarly, Economou, Kostakis and Philippas (2011) document herding effects in their Greek and Italian samples, but find either no evidence or weak evidence of herding in the Spanish and Portuguese markets. In line with previous literature (e.g. Tan et al. 2008), they also detect significant asymmetries in the herding activity observed during different states, trading volume and volatilities of the market. More importantly, they find compelling evidence of cross-country herding effects, implying a great degree of co-movement between the cross-sectional returns' dispersion of the countries examined. However, in contrast with Chiang and Zheng (2010), their analysis suggest that the most recent subprime mortgage crisis did not particularly trigger a more extreme herding activity in their sample.

In a more recent study, Galariotis, Rong and Spyrou (2015) show differences in the herding activity of US and UK leading stocks. They find that US investors tend to herd on macro data (e.g. changes in the US federal funds rate, unemployment and inflation rates etc) and highlight there have been some herding spillover effects from the US to the UK during the Asian and Dotcom crises. They are also the first to empirically differentiate between herding due to fundemental information (spurious herding) and non-fundemental information (intentional herding); originally defined by Bikhchandani and Sharma (2001). Their findings show much stronger evidences of US investors' herding attributable to both fundementals and non-fundementals, during multiple past financial turmoils. Using intraday data, Andrikopoulos et al. (2017) show that investors herd in the Euronext as a group before, during and after the GFC crisis, with the herding effects being less intense during the crisis. In addition, they find that the trading dynamics of the group's member markets severely impact each other and in some cases can induce herding behaviour.

From the above evidence, one can notice that in terms of herd spillover effects, studies mainly focus on cross-country spillovers. Against this trend, Demirer, Lee and Lien (2015) extends the prior literaure and look into herd spillover between different commodity sectors and investigate the effect of the S&P 500 stock market on the herd behaviour they observe in the commodity futures market. They find that significant changes in the prices of energy and metal sectors largely influence the herd behaviour in grains sectors. However, they fail to find any herding spillover effects from the stock market to the commodity futures. In contrast to the previous literature, Bernales, Verousis and Voukelatos (2016) document an inverse relationship between the clustering of individual option returns and stock returns, which they explain by the divergence in the investors' opinions in the respective markets.

Galariotis, Krokida and Spyrou (2016b) is the first to investigate the relationship between herding behaviour and stock market liquidity in the context of herding towards a market average. When conditioning on the liquidity of the G5 market stocks, they document herding activity at high liquidity days. As liquidity rises, investors have an increased inclination to herd around the mean. This finding is consistent in most countries studied (apart from Germany) and is robust across different sub-periods and measures of liquidity. Their further tests also show that there is a two-way Granger causality effect between the market liquidity and herding. Their results provide strong evidence of the unexplored relationship between equity market liquidity and herding.

Moving away from static models, a few studies explore time-variations (dynamic) in herding behaviour using regime-switching models (Fang, Shen and Lee 2017; Balcilar, Demirer and Hammoudeh 2013; Klein 2013) and state-space Kalman filter (Arjoon and Bhatnagar 2017; Chiang et al. 2013). More recently, Voukelatos and Verousis (2019) investigate if investors herding in US equity markets can be explained by option-implied information. Whilst Krokida, Makrychoriti and Spyrou (2020) examine the relationship between monetary policy (conventional and unconventional) and herd behaviour in US and Eurozone equity markets.

From above, it is evident that the results of the mentioned studies are mixed, where some detect herding behaviour and asymmetries whereas others do not. The researchers also find different results regarding the intensity of herding activity during crises. What is more, studies examining the same country (market) find contrasting results using different periods. Hence, it can be concluded that the drivers of herding behaviour are time period specific and country specific (Galariotis, Rong and Spyrou 2015).

3.2.3 Herding behaviour in different asset classes

Most of the existing herding literature focuses on herding in equity markets. However, a few researchers explore other asset classes and find evidences suggesting that the herding behaviour also exists in commodity futures markets (Demirer, Lee and Lien 2015), option contracts (Bernales, Verousis and Voukelatos 2016), REIT markets (Philippas et al. 2013), closed-end funds (Cui, Gebka and Kallinterakis 2019) and other. In contrast, other studies, such as, Gleason, Mathur and Peterson (2004) fail to detect herding activity in exchange traded funds asset classes.

Focusing on bond markets, only two studies examine the existence of herding in them (Galariotis, Krokida and Spyrou 2016a; Cai et al. 2019). In particular, Galariotis, Krokida and Spyrou (2016a) examine herding activity in European government bond prices. They find no indication of investor herding prior or post the EU crisis. However, interestingly, they detect macroeconomic information induced bond herding during the crisis. These findings challenge the common belief that irrational herding aggravated the EU crisis and was partially accountable for the soaring of yield spreads. They also spot herding spillover effects amid the crisis from the relatively financially stable Northern European markets (Finland, the Netherlands, and Germany amongst others) to the financially distressed Southern European markets (Greece, Spain, Portugal and Ireland).

On the other hand, the recent study by Cai et al. (2019) looks into institutional herding in the US corporate bond market. They detect a high level of institutional herding in corporate bonds, where sell herding is found to be substantially stronger and more persistent than buy herding. Their further evaluation shows that buy herding tends to have a permanent price impact as it facilitates price discovery, whilst sell herding induces temporary large price distortions. Furthermore, the destabilising effect of sell herding seems to be more pronounced during the global financial crisis and within speculative-grade, small and illiquid bonds.

In a summary, the above literature proves that investors follow each other's trades in various asset classes and markets. It is also evident that research in corporate bond investor herding and cross-asset herding spillover is underexplored. Hence, this chapter aims at filling these gaps by testing for the existence of herding in corporate bond and equity markets across different rating classifications; and explore the potential herding spillover effects between them.

3.3 Methodology

3.3.1 Detecting herding activity in financial markets

To test for the existence of herding activity in bond and equity markets we follow Chang, Cheng and Khorana (2000) herding model (CCK hereafter), which measures herding towards a market consensus. It is argued that during extreme market conditions investors are more likely to supress their own beliefs and conform to the market consensus (Christie and Huang 1995). In the presence of herding, individual asset returns are not expected to deviate much from the market return and, as a consequence, the typically expected linear and positive relationship between the cross-sectional return dispersions and market returns may not hold. CCK measure the cross-sectional absolute deviations (CSAD) as follows:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}\left|R_{i,t} - R_{m,t}\right| \tag{3.1}$$

where N is the number of assets, $R_{i,t}$ is the daily log return of asset i at day t, given by $R_{i,t} = ln(P_t/P_{t-1})$ where P_t and P_{t-1} are the daily closing prices of the asset i on days t and $t-1$. $R_{m,t}$ is the cross-sectional average return of N assets (equally weighted market portfolio) in each market at time t. To test for the existence of herding behaviour, Chang, Cheng and Khorana (2000) propose the following regression:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \varepsilon_t \tag{3.2}$$

In Eq. (3.2)$\left|R_{m,t}\right|$ is the absolute market return and $R_{m,t}^2$ is the squared market return at day t. Based on the asset pricing models the relationship between $CSAD_t$ and the absolute market return captured by β_1 is expected to be significantly positive and linear. In the presence of herding at days characterised with extensive market movements (high or low), the relationship between $CSAD_t$ and the market return is expected to be non-linear and thus the coefficient β_2 of the non-linear term ($R_{m,t}^2$) is expected to be significant and negative. Consequently, herding is detected by the negative relationship between $R_{m,t}^2$ and $CSAD_t$, as picked up by β_2, and it is presumed to decrease the cross-sectional deviations of the returns.

3.3.2 Extensions to herding models

3.3.2.1 Herding in rising and declining markets

We expand the CCK model in three ways. First, to allow for asymmetries in line with market performance we run the following separate regressions:

$$CSAD_t^{UP} = \beta_0 + \beta_1^{UP}\left|R_{m,t}^{UP}\right| + \beta_2^{UP}\left(R_{m,t}^{UP}\right)^2 + \varepsilon_t \tag{3.3}$$

$$CSAD_t^{DOWN} = \beta_0 + \left|R_{m,t}^{DOWN}\right| + \beta_2^{DOWN}\left(R_{m,t}^{DOWN}\right)^2 + \varepsilon_t \tag{3.4}$$

where UP (DOWN) markets are defined as the days when the equally-weighted average market return, $\mathrm{R_{m,t}}$, is positive (negative). $\mathrm{CSAD_t^{UP}}$ ($\mathrm{CSAD_t^{DOWN}}$) is the CSAD at day t, when the market is rising (declining), $\left|\mathrm{R_{m,t}^{UP}}\right|$($\left|\mathrm{R_{m,t}^{DOWN}}\right|$) is the absolute positive (negative) market return at day t and $\left(\mathrm{R_{m,t}^{UP}}\right)^2$ ($\left(\mathrm{R_{m,t}^{DOWN}}\right)^2$) is the squared positive (negative) market return at day t.

Afterwards, instead of splitting the sample into two separate equations, we employ a more robust approach applied in Chiang and Zheng (2010) and Economou, Kostakis and Philippas (2011) that incorporates a binary dummy in a single model as follows:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 D^{UP} R_{m,t}^2 + \beta_3(1 - D^{UP})R_{m,t}^2 + \varepsilon_t \tag{3.5}$$

where $D^{UP} = 1$ on trading days with positive $\mathrm{R_{m,t}}$ and 0 on days with negative $\mathrm{R_{m,t}}$. Significant and negative values of β_2 and β_3 (or either) would suggest the existence of herding towards a market consensus in rising (declining) markets, respectively.

3.3.2.2 Herding and market liquidity

Second, to account for the interaction between market liquidity and herding we follow Galariotis, Krokida and Spyrou (2016b) and use the following regression:

$$CSAD_t = \beta_0 + \beta_1\left|R_{m,t}\right| + \beta_2 R_{m,t}^2 + \beta_3 D^{LLiq} R_{m,t}^2 + \beta_4 D^{HLiq} R_{m,t}^2 + \varepsilon_t \tag{3.6}$$

Here, $\mathrm{D^{LLiq}} = 1$ ($\mathrm{D^{HLiq}} = 1$) if the average market liquidity on day t lies in the extreme (5%, 10 and 25%) lower (upper) tail of the liquidity distribution and zero otherwise. Consequently, the two coefficients β_3 and β_4 detect the marginal change in the herding behaviour when the market is operating at the bottom or upper end of the liquidity distribution respectively; whereas β_2 captures herding at medium liquidity (the remaining days that are not included in $\mathrm{D^{LLiq}}$ and $\mathrm{D^{HLiq}}$). In line with Galariotis, Krokida and Spyrou (2016b), we proxy the market liquidity with the Amihud illiquidity measure. Studies show that the measure is a reliable proxy to estimate the price impact of trades and its effectiveness lead to its wide range of application in in both equity and bond market literature (Acharya and Pedersen 2005; Lesmond 2005; Goyenko, Holden and Trzcinka 2009; Friewald, Jankowitsch and Subrahmanyam 2012; Dick-Nielsen, Feldhütter and Lando 2012; Cai et al. 2019). Moreover, unlike other liquidity proxies, it does not require a large amount of microstructure data that is not necessarily available in all markets; which also makes it a suitable measure for our study that includes over-the-counter traded corporate bonds that are less liquid (in comparison to related equity markets) with limited data availability (Amihud 2002). In order to define liquidity (rather than illiquidity) of individual assets, we use the modified Amihud measure according to Karolyi, Lee and van Dijk (2012) given by:

$$Liq_{i,t} = -log\left(1 + \left(\frac{|R_{i,t}|}{V_{i,t}}\right)\right) \tag{3.7}$$

where $|R_{i,t}|$ is the absolute return and $V_{i,t}$ is the trading volume (in \$'000) of asset i on day t. Similar to earlier studies (e.g. Galariotis, Krokida and Spyrou 2016b; Cai et al. 2019; Friewald, Jankowitsch and Subrahmanyam 2012) the equity trading volume is taken as the daily trading volume (number of shares in thousands) of share i multiplied by the closing share price of that day ($P_{i,t}$), and the bond trading volume as the par value volume of all reported trades (in \$'000) of bond i on day t. A constant is added to Amihud's measure and the log is taken to decrease the effect of the outliers. Furthermore, the whole term is multiplied by -1 to reach a number that is increasing with the higher liquidity of assets (Karolyi, Lee and van Dijk 2012). After computing the individual assets' liquidities, we obtain the cross-sectional average daily market liquidity (across all assets) as follows:

$$Liq_{m,t} = \frac{1}{N}\sum_{i=1}^{N} Liq_{i,t} \tag{3.8}$$

Based on Eq. (3.7) and (3.8), a larger modified Amihud market liquidity proxy $Liq_{m,t}$ implies greater liquidity.

3.3.2.3 Herding and market volatility

Third, we examine if herding varies during low, medium and high volatility days applying the following regression:

$$CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D^{LVol} R_{m,t}^2 + \beta_4 D^{HVol} R_{m,t}^2 + \varepsilon_t \tag{3.9}$$

The dummy variable $D^{LVol} = 1$ ($D^{HVol} = 1$) if the market volatility on day t lies in the extreme (5%, 10 and 25%) lower (upper) tail of the volatility distribution and zero otherwise. Unlike the previous literature (e.g. Cui, Gebka and Kallinterakis 2019), we do not proxy the market volatility using the squared returns ($R^2_{m,t}$) that have been known to be noisy for conditional volatility estimates (Patton 2011), instead we employ a GARCH(1,1) model to obtain the conditional volatility of the market portfolio of returns. Studies have shown that GARCH models and realised measures[26] are far superior in estimating volatility (e.g. Hansen and Huang 2016; Barndorff-Nielsen and Shephard 2002). However, since our study is based on daily data and realised measures require high-frequency data, a GARCH model is deemed as most fit. The coefficient β_3 (β_4) capture the marginal change in the herding behaviour when the market is operating at the bottom (upper) end of the volatility distribution, whilst β_2 captures herding at medium volatility days (the market volatility that lie in the area that is not covered by D^{LVol} and D^{HVol}).

Following recent literature (e.g. Galariotis, Krokida and Spyrou 2016b; Cui, Gebka and Kallinterakis 2019), we estimate all regressions given by equations (3.2) – (3.6) and (3.9) using the method suggested by Newey and West (1987) with automatic lag selection (bandwidth) selection procedure to account for heteroscedasticity and autocorrelation in the estimated coefficients (Newey and West 1994).

3.3.3 Cross-asset class herding spillover

Extant literature examined cross-country herding spillover, i.e. whether investors' herding behaviour in a particular market is affected by events in other markets (Chiang and Zheng 2010; Galariotis, Rong and Spyrou 2015). In a similar spirit, we explore if herding in bond markets might be related to herding in equity markets, and vice versa. We examine the existence of cross-asset class herding spillover by adding an additional CSAD term and squared market return term of the other market in the original equation (3.2) as represented in the following system of equations:

$$CSAD_{B,t} = \beta_0 + \beta_1 |R_{Bm,t}| + \beta_2 R^2_{Bm,t} + \beta_3 CSAD_{S,t} + \beta_4 R^2_{Sm,t} + \varepsilon_{B,t} \tag{3.10}$$

$$CSAD_{S,t} = \gamma_0 + \gamma_1 |R_{Sm,t}| + \gamma_2 R^2_{Sm,t} + \gamma_3 CSAD_{B,t} + \gamma_4 R^2_{Bm,t} + \varepsilon_{S,t} \tag{3.11}$$

where the the subscripts B, S refer to the Bond and Stock sample respectively, all other variables are defined in the same way as before. To account for the endogeneity problem, we estimate the system using two stage least squares (2SLS) with robust standard errors. In the presence of herding spillover effects from one asset class market to another, we expect the respective coefficients (β_4 and γ_4) to be negative and statistically significant. We perform the same tests for each credit rating portfolio of assets (investment grade, high yield and non-rated), where we test for herding spillover effects between the same rating grade for example, from investment grade bonds to investment grade issuers' stocks and vice versa.

[26] Realised measures require high-frequency data to be computed.

3.4 Data

Our analysis relies on a comprehensive US corporate bonds and equities of from 1 January 2008 to 31 December 2018. We restrict the sample to stocks and bonds that have some pricing data available; and firms that were constituents[27] of the S&P 500 index at some point within our sample period, which covers approximately 80% of the available equity market capitalization. Similarly, for our corporate bond sample, we include those that were listed on the S&P 500 Bond Index[28]. After filtering for missing pricing data, our sample incorporates a total of 794 stocks and 8,623 corporate bonds[29] (issued by 569 corporations).

For the stocks, we obtain the daily closing prices and trading volume of S&P 500 constituents from Bloomberg. In order to facilitate for a direct comparison between the herding effects in US equity and corporate bond markets; we use the closing bond prices[30] and par value volume of bonds[31] ($ amount of trade) listed on the S&P 500 Bond Index downloaded from the Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engines (TRACE). We also obtain the corporate bond and long-term issuer credit ratings assigned by the three major credit rating agencies (CRAs): S&P, Moody's and Fitch. We use the corporate bond (long-term issuer) ratings to split our bond (equity) sample into investment grade, high yield/speculative and unrated bond (stock) portfolios i.e., sub-samples. Based on the CRAs' rating definitions, we include a bond or issuer in our investment grade portfolio if it is rated as BBB-/Baa3/BBB-[32] or higher, and consider it in our high yield (speculative) portfolio if its rating falls on or between BB+/Ba1/BB+ and D/C/D. We rebalance our portfolios annually, where the lowest credit rating assigned by the CRAs at the end of a year (for example, 31/12/2017) is used to classify the assets for the following year (in this case the year of 2018).

In order to test for the stability of our results throughout our sample period that includes the Global financial crisis, we split our sample into two sub-periods. Following the recent literature (Galariotis, Krokida and Spyrou 2016b; Baur 2012; Forbes and Rigobon 2002), we identify the crisis period as based on the timelines offered by the Federal Reserve Board of St. Louis and the Bank of International settlements. According to the official timelines, the first signs of stabilisation were observed in mid-March (BIS 2009, p.34). Therefore, we define our two sub-periods as follows: crisis period (1 January 2008 - 15 March 2009) and the post-crisis period (16 March 2009 - 31 December 2018).

[27] We obtained the annual list of S&P 500 constituents from Bloomberg and included the union of all firms listed within the sample period.
[28] We obtained the annual list of S&P 500 Bond Index constituents from S&P Dow Jones Indices, LLP.
[29] Since our dependent variable in all regressions is a cross-sectional measure (CSAD), we include in our samples all bonds and stocks with available prices and treat missing values as unavailable data for the day. We only exclude assets with no observations in our sample.
[30] Price at which the last trade was executed as a percentage of par (FINRA 2017, p.23).
[31] The reported TRACE par value of a trade is capped at $1 million for high yield and unrated bonds and $5 million for investment grade bonds.
[32] S&P/Moody's/Fitch rating

3.4.1 Descriptive statistics

The evolution of the CSAD measure along with the market return for both samples (corporate bonds and equity) are presented in Figure 3.1. Generally, it is evident that the CSAD measure is relatively stable post 2009, with significantly larger deviations at the beginning of our sample. It seems like the return deviations from the market consensus (CSAD) increase with the fluctuations of the market return, as the highest CSAD figures are observed during 2008-2009 period coinciding with the Subprime mortgage crisis.

Table 3.1 presents the descriptive statistics for the daily market return, CSAD, market liquidity proxy and market conditional volatility, for our US corporate bond and stock market for the period between 2008 and 2018 (2,769 observations for each market). The average return on the equally weighted equity market portfolio (R_m) is approximately seven times larger than the return on the equivalent bond market portfolio (0.014% vs. 0.002%). Accordingly, the mean volatility ($CondVol$) of the bond market sample is lower than the volatility observed in the stock market sample. Furthermore, the corporate bond (equity) CSAD measure has an average value of 0.972% (1.198%) and a standard deviation of 0.718% (0.580%), suggesting that, on average, corporate bonds have smaller cross-sectional absolute return dispersions from the market return, but their CSAD values vary more (from the mean) through time. Corporate bonds are significantly less liquid than equities, as reflected on the average of Amihud liquidity proxy (Liq) of -0.0160 versus -0.0001. This signifies the illiquidity of corporate bonds in comparison to stocks, a well-known phenomenon in literature (e.g. Bao, Pan and Wang 2011; Goldstein, Jiang and Ng 2017). However, it is also worth noting that the liquidity measure for bonds, calculated using Eq. (3.7), incorporate the par value volume of all reported trades in the denominator as the proxy for bond trading volume $\mathrm{V}_{\mathrm{i,t}}$ (in $'000), where most of our bonds' par value is $1,000 - which is considerably larger than that of the stocks that discourage retail investors from trading in these instruments. The scatter plots of the CSADs with corresponding squared market return, liquidity and volatility are exhibited in Figure 3.2 to Figure 3.4. Table 3.2 presents the full sample correlation coefficients between the CSAD, market return, liquidity and volatility for the bonds and stocks, respectively. A brief inspection shows that that the CSAD of each market is inversely related to market liquidity, but positively correlated with conditional market volatility. Furthermore, we provide a scatter plot of the relationship between market liquidity and volatility in Figure 3.5 and per bond (stock) correlations (Figure 3.10 to Figure 3.12).

Figure 3.5, depicts the relationship between market liquidity and volatility for the bonds and stocks across the full sample and histograms of their daily correlations (Figure 3.7 and Figure 3.8). In addition, Figure 3.9 presents these correlations on a year-by-year basis and Figure 3.10 shows how the relationship is dispersed across the individual assets. At the broadest of strokes, the relationship between liquidity and volatility is a complex one, and we observe that: i) it is strong in the period leading to the

2008 Global Financial Crisis; ii) it is largely negative, and this is more pronounced for the equity sample; iii) a positive relationship between liquidity and volatility is observed for some bonds. Overall CSAD, the key measure for herding is significantly related to both liquidity and volatility. However, the complex relationship of the latter necessitates a detailed investigation of herding around periods of extreme liquidity/volatility times.

3.5 Empirical results

3.5.1 Herding in US corporate bond and equity markets

Table 3.3 presents the results for the herding equations (3.2) to (3.5), estimated for our full S&P 500 corporate bonds and equity samples (Panel A) and the three portfolios based on the bonds'/issuers' credit ratings: investment grade (Panel B), high yield (Panel C) and non-rated (Panel D) assets for the entire sample period. The table presents the coefficients of the linear ($|\mathrm{R}_{\mathrm{m,t}}|$) and nonlinear ($R_{m,t}^2$) terms of the regressions and their respective standard errors, where the coefficient on the nonlinear term is of our interest.

Table 3.3 column (1) reports the initial unconditional herding tests based on the full samples (Panel A) show no evidence of herding in our US corporate bond and stock markets. The β_2 coefficient of $R_{m,t}^2$ term fails to reach conventional significance levels for the bonds, while for the equities a positive coefficient ($\beta_2 = 0.012$) suggests adverse herding effects (i.e., investors following their own judgement). The positive and significant coefficient of $|\mathrm{R}_{\mathrm{m,t}}|$ that both samples have provide evidence of supporting the view that the CSAD increases linearly with the average equally weighted market portfolio return, which is consistent with standard rational asset pricing model (Chang, Cheng and Khorana 2000). These results are in line with prior literature on herding in US stock markets (e.g. Galariotis, Rong and Spyrou 2015). In addition, we do not find significant evidence of herding behaviour across most of the credit rating portfolios in both the bond and the equity samples. Speculative grade bonds are the notable exception, where a negative and statistically significant (at 1%) β_2 = -0.111 coefficient provides evidence in support of herding behaviour among this class of investments. This may be plausibly attributed to the fact that speculative grade bonds are typically more sensitive to risk factors, less liquid and often subject to higher levels of informational asymmetry leading investors to herd around the market average (Raffestin 2017; Lu, Chen and Liao 2010). This confirms the findings of Cai et al. (2019), who found stronger level of institutional herding in speculative grade bonds, explaining that herding tends to be stronger in riskier bonds.

Columns (2)-(4) in Table 3.3, allow for herding asymmetries in rising (UP) and declining (DOWN) markets. The second and third columns, present the herding test results of equations (3.3) and (3.4). Similarly, as with the unconditional test, in the presence of herding towards the consensus, we expect β_2 to be negative and significant. In contrast, last column employs the entire sample incorporating dummy variables for rising and falling market days (see equation (3.5)), allowing us to test for herding in both market states at once. Here, β_2 (β_3) detect investor herding during up (down) market days. The results in these columns show differences in the behaviour of investors in corporate bonds and equity markets. As far as the bond sample is concerned, we detect weak evidence of herding only during rising bond markets (column 2 Panel A) as β_2= -0.132 is inversely related (significant at 10%) to the CSAD. This observation is contrary to the shared belief in early herding literature (Christie and Huang 1995; Chang, Cheng and Khorana 2000), which hypothesises that investors are likely to disregard their own beliefs and herd towards the market average during periods of market stress (downturns). However, these results are not confirmed in column (4), as the coefficients on both dummy variable interactions, for up and down periods, with the squared market return (β_2 and β_3) are negative but statistically insignificant. In contrast to the bonds, we do not find any evidence of herding in the equity sample.

Inspecting the results based on credit rating portfolios, they are consistent to our unconditional tests, with the speculative grade bonds showing significant evidence of herding behaviour. We find evidence of speculative grade investors' (Panel C) herd behaviour in both, rising and falling markets, where the latter is 25% more pronounced. Furthermore, the significant F-statistic of 3.67 (p-value = 0.055) in Panel C, examining the difference between the pair of coefficients β_2 and β_3 in Eq. (3.5), shows that there is a herding asymmetry between up and down markets in speculative grade bond markets. Hence, speculative bond investors are more likely to disregard their own judgment over herd information during declining markets, a finding which is in line with the early herding literature (Christie and Huang 1995; Chang, Cheng and Khorana 2000). On the other hand, investment grade and non-rated bond portfolios show no evidence of herd behaviour in these series of tests. In fact, we find that the coefficients of $R^2_{m,t}$ for falling market days in Panel D for non-rated bond portfolio is positive and significant (β_2 = 0.503 in column 3 and $\beta_3 = 03.67$ in column 4), signifying the presence of adverse herding behaviour i.e., the investor's tendency to follow their own opinion when trading non-rated bonds. Lastly, in contrast to the corporate bonds, we fail to find any evidence of investors' herding in our full equity sample as well as equity credit rating sub-samples.

3.5.2 Herding and market liquidity

Table 3.4 presents the estimates of regression (3.6), where we condition on the level of liquidity in the market for the full sample period for both corporate bond and equity samples (Panel A) as well as their credit rating based portfolios (Panel B to D). In this set up, β_3 (β_4) captures the marginal change in herding during extremely low (high) aggregate market liquidity days and β_2 captures herding at medium liquidity. For robustness purposes, we employ the same regression three times for each sample (sub-sample), alternating the cut-off points to 5%, 10 and 25% thresholds of the lower and upper extreme tails of the market liquidity distribution each time.

A first inspection of the results shows that the β_2 coefficient is negative and significant in the bond sample, which is suggestive of herding effects when the liquidity is moderate (medium market liquidity periods). The F-tests and their p-values, used to test for the significance of the dissimilarity between β_3 and β_4 , show that the herding is significantly asymmetric in high and low liquidity days. In low liquidity herding is zeroed, a result that is consistent across all three liquidity cut-off thresholds. By contrast, the regressions consistently yield significant and negative β_4 coefficients on the non-linear term during high market liquidity days, which increases around 130% compared to the medium liquidity case.[33] We find that equities exhibit herding behaviour only in periods of high liquidity, as verified by the negative and significant β_4 coefficient. Yet the economic magnitude of the herding effect is more pronounced in the bond samples as verified by the larger (in absolute value) coefficient. The strongest herding effects are captured using the extreme 5% liquidity cut-off criterion in the full bond sample, which have outstanding β_4 value of -14.029 versus its significantly smaller (in absolute value) equity equivalent of -0.242. These results strongly suggest that, both bond and stock market investors are inclined to collectively herd towards the consensus during periods of high liquidity, a finding that is consistent with Galariotis, Krokida and Spyrou (2016b) observations in their major equity market samples. In addition, it extends on the work of Galariotis, Krokida and Spyrou (2016a) by showing that herding also exists in corporate bonds.

In addition, bond portfolios organized by credit rating suggest that it is the investment grade that shows the stronger herding as judged by the absolute size of the β_2 coefficients. In line with the main results, the herding effect on these portfolios increases during periods of high liquidity. By contrast, investment grade equity portfolios only show herding during high liquidity periods. Conversely, in low liquidity days we find evidence of adverse herding effects, mainly in our bond sample, whereby investors place more weight on their own opinions. This attests to the positive and significant β_3 coefficient across credit rating portfolios and liquidity cut-off points. For example, in the full bond sample β_3= 2.586, 3.334 and 4.472 at the 5%, 10% and 25% cut-off points, respectively.

The above results indicate that there is a positive relationship between herd behaviour (detected by inverse relationship between CSAD and squared market return) and market liquidity, which is affirmed by the negative pattern captured in the scatter diagram of the CSAD and market liquidity (see Figure 3.3) and their significant pairwise correlations in Table 3.2. High levels of market liquidity seem to be associated with lower cross-sectional absolute individual assets' return deviations from the market return (due to herding), and vice versa. Moreover, although the impact of liquidity on herding is consistent in both markets, the difference in the magnitude of the coefficients suggest that the economic impact of herding is more pronounced in bonds compared to equities. This finding is in agreement with Cai et al. (2019) statement regarding the higher levels of bond *institutional* herding. This may be

[33] These are calculated as ln $(-13.861/(-3.648))$ using the 10% liquidity cut-off threshold.

plausibly attributed to the larger participation of institutional investors in bond markets due to the typically larger denominations of the financial instruments.

Studies suggest that liquidity can be seen as a proxy for investor sentiment i.e. investors' propensity to speculate or overall attitude towards a market, as they find that markets are more liquid when investor sentiment is high (Galariotis, Krokida and Spyrou 2016b; Baker and Stein 2004). Additionally, they further explain that investor sentiment indicate the existence (absence) of irrational investors in a financial market and show that it Granger-causes market liquidity (Liu 2015; Baker and Stein 2004). On this basis, it may be argued that a high market liquidity reflects positive irrational investors' sentiment, which in turn could explain the strong and consistent herding we observe in high liquidity market states. In this case, our findings support the view that high liquidity is a positive externality that could induce investors' clustering in a particular market (Devenow and Welch 1996).

3.5.3 Herding and market volatility

Similar to the herding and liquidity analysis, in Table 3.5 we condition on the level of market volatility measured by the conditional volatility obtained using a GARCH(1,1) fitted model on the market return. It presents the estimates for equation (3.9) for the corporate bond and equity samples (Panel A) and the credit rating- based portfolios (Panel B to D). To account for the asymmetric effect of volatility, we split the sample into high-medium-low volatility using three cut-off points (5%, 10 and 25%) of the lower and upper extreme tails of the market volatility distribution for robustness, displayed in the first to third column. Here β_3 (β_4) captures the marginal change in herding during extremely low (high) market volatility days and β_2 detects herding at medium liquidity. The bond and equity samples produce comparable results, we observe a negative and significant β_2 coefficient in both samples, which is suggestive of herding effects in medium volatility days. The F-tests reveal significant differences between the β_3 and the β_4 coefficients. The null hypothesis ($H_0: \beta_3 = \beta_4$) is rejected at 1%; indicating an asymmetric herding effect in low and high volatility markets as their coefficients are statistically different from each other.

Furthermore, we detect strong herding effects in low volatility days, as evidenced by the negative and significant β_3 coefficient, which measures the marginal increase in the herding effect compared to the baseline, medium volatility scenario. Focusing on the full samples (Panel A) at the 10% cut-off criterion, the bond market sample has a $\beta_2 =$ -3.153 and β_3= -4.558 (significant at 1%), whilst the stock market sample coefficients $\beta_2 =$ -0.062 and β_3= -0.087 (significant at 5%). As a result, we detect an 89% (87%) increase in herding during low volatility compared to the medium volatility[34] in our bond (equity) samples. This suggests that as the market volatility drops, investors herd more and more. In a

[34] These are calculated as ln $(-7.711/(-3.153))$ using the 10% volatility cut-off threshold.

similar pattern as with the liquidity conditioning, the economic magnitude of the effect is more prominent in the bond samples as verified by the larger (in absolute value) β_2 and mainly β_3 coefficients. By contrast, in cases of high volatility, herding is not observed in either market as the estimates β_4 are steadily positive and significant (at 1%) throughout the samples. These findings indicate that investors follow their own judgement (adverse herding) during highly volatile market conditions.

The analysis by credit rating portfolios provides consistent results with the full samples and offer further interesting insights. With regards to the bond sample, in medium volatility days it is the investment grade (Panel B) that exhibits the strongest herding evidence. A similar conclusion is obtained within the equity sample, albeit the economic magnitude of herding is more muted. However, in low volatility days, it is the speculative grade that is more prone to herding in the bond sample. The most substantial herding effects are captured in speculative bonds (Panel C) at 10% volatility cut-off in bonds, where the coefficient of low volatility reaches a significant value of $\beta_3 =$ -11.050. In comparison, within the equity sample, the investment grade retains its status as the most prone to herding. This evidence confirms our earlier results and signify the existence of herding during medium and, especially, low volatility market days.

From above, it is evident that herding is related to market volatility, a finding that has been observed in other studies (e.g. Tan et al. 2008; Economou, Kostakis and Philippas 2011; Cui, Gebka and Kallinterakis 2019). The relationship between CSAD and market volatility, in both samples is depicted in the scatter diagrams Figure 3.4 and their pairwise correlations presented in Table 3.2. The diagrams and correlations confirm our results as it shows the positive relationship between CSAD and market volatility, that is when the market volatility is low (high) return clustering around the aggregate market return is more (less) intense.

In general, these results suggest that investors tend to strongly herd towards the market consensus during periods of low volatility. It is plausible that low volatility periods may encourage a higher degree of collusion in investors practices, as no abrupt changes take place in a trading day. This is supported by the fact that low volatility periods often experience strong downward or upward trends, which may induce investors to follow the trend by taking the same position. In addition, it could be argued that tranquil periods can induce 'bad' fund managers or less informed investors to herd more intensively, as the low volatility makes it easier for them to follow the trades of their better informed peers (Gavriilidis, Kallinterakis and Ferreira 2013). Our findings are particularly in line with Economou, Kostakis and Philippas (2011) and Guney, Kallinterakis and Komba (2017) who find an inverse relationship between herding and volatility. However, they challenge the findings of Tan et al. (2008) and Cui, Gebka and Kallinterakis (2019), that detect stronger herding evidences during high volatility periods in Chinese stock markets and US close-end funds, respectively.

Opposite to the common belief of earlier literature (Christie and Huang 1995; Chang, Cheng and Khorana 2000; Chiang and Zheng 2010), our empirical findings show that herding in the US bond and equity markets is not intensified or triggered by turbulent periods characterised by high market volatility, usually seen in crises, but is instead present in calm or stable periods when investors are more optimistic or certain about the direction of the market. In fact, the adverse herding effects we detect in high volatility days seem to confirm the findings of Hwang and Salmon (2004), who explain that crises appear to encourage investors to turn towards fundamentals rather than the trading patterns of the overall market; pushing the returns towards efficiency. These findings complement well our results in the previous sections, as low volatility periods are often accompanied with higher liquidity; typically observed in non-crisis (rising) markets, all which we have detected herding activity in. Furthermore, we believe that our results are reflective of the unique nature of the 2008 Global Financial Crisis, which was characterized by the uncertainty around the exposure of market participants in credit derivatives and securitized products that were blamed for the intensity of the crisis. Hence, as financial crises reveal new information, the pre-crisis consensus is broken and any herding nurtured by it.

3.5.3.1 Crisis and post-crisis analysis

As exhibited in in Figure 3.6, the volatilities mainly peak in 2008, reflecting the crisis period, and then gradually decline in 2009 onwards. According to the Bank of International Settlements 'volatilities declined and asset prices recovered from their previous lows, as further and more determined policy action induced markets to show some optimism in the face of what remained a largely negative macroeconomic and financial outlook' (BIS 2009, p.34). In Table 3.6 we examine the stability of our herding and market volatility results during the crisis (1 January 2008 – 15 March 2009) and post crisis (16 March 2009 – 31 December 2018) sub-periods in our corporate bond and equity samples (Panel A) as well as the three credit rating based portfolios (Panel B to D). Column (1) of both sub-periods present the findings of the main herding equation (3.2) and column (2) displays the estimates of equation (3.9), where we condition on the different market volatility states using the 5% lower and upper extreme tails of the market volatility distribution. All variables are defined in the same way as before.

Focusing on the unconditional herding test on corporate bonds, column (1), we observe noteworthy herding effects during the crisis sub-period given by the significantly negative β_2 in the full bond sample as well as the investment and speculative grade portfolios. On the other hand, the initial tests on post-crisis period shows no evidence of herding behaviour in corporate bonds. These results indicate that the level of herding during the crisis sub-period is more intense, which affirms the findings of Chang, Cheng and Khorana (2000) that herding behaviour changes over time. In line with our earlier results, the equity sample does not exhibit any signs of herding in the crisis and post-crisis sub-periods, suggesting that the crisis does not affect investors' herding in equity markets.

Once we condition on market volatility, column (2), the sub-periods produce consistent results with our full sample ones observed in the earlier section 3.5.3. We detect herding behaviour during low volatility days and occasionally in medium volatility days, with the herding effects being more consistent and intense in the US corporate bond market[35]. During the lowest volatility days of the crisis period, investors appear to herd most in investment grade bonds, where the coefficient measuring the marginal change in herding during low market volatility reach a negative and statistically significant (at 1%) value of β_3 = -6.398. In times of economic distress, investors become increasingly risk averse often leading them to rebalance their portfolios and shift their funds to towards more liquid and less risky instruments, a phenomenon known as flight-to-liquidity and flight-to-quality, respectively (for more info see Beber, Brandt and Kavajecz 2008). This could explain why we observe, during the crisis, more herding (most likely herding based on fundamentals) in investment grade corporate bonds, which are typically more liquid and are subject to lower credit risk than speculative grade bonds (Friewald, Jankowitsch and Subrahmanyam 2012; Ericsson and Renault 2006). This is also in line with the work of Bethke, Gehde-Trapp and Kempf (2017), who show that when the investor sentiment is bad, investors are less likely to invest in bonds with high credit risk (lower credit ratings); which lead to flight-to-quality behaviour and eventually high bond correlations.

However, in the post-crisis period, investors seem to shift and herd more intensively in high yield bonds followed by non-rated bonds, where β_3 = -7.197 and β_3= -2.568 (both significant at 1%), respectively. This suggests that after the subprime mortgage crisis, investors became gradually more optimistic and confident in the market, leading them to change their behaviour and herd more in lower rated bonds that face more informational uncertainty and asymmetry in hopes of obtaining informational gains from the trades of better informed investors (Lu, Chen and Liao 2010). Studies argue that the impact of credit risk is aggravated during financial meltdowns and that the flight-to-liquidity phenomenon also holds for stock markets (Rösch and Kaserer 2013), which our results seem to confirm as we observe a similar pattern of the bonds in our equity sample (see columns (2) in Table 3.6).

3.5.4 Two-way splits of liquidity and volatility

In this section, we perform additional herding tests to investigate further the relationship between market liquidity, volatility and herding. We examine if herding activities in bond and equity markets persist even after conditioning on both volatility and liquidity at the same time to see if any of the above-detected herding asymmetries outweigh the other.

In order to investigate the persistence of the observed herding asymmetries conditional on market liquidity during different market volatility states, we split our full sample period to three sub-samples based on the daily level of market (corporate bond or equity) volatility. To do that, we identify the 25%

[35] These results are robust when we use a different cut (10% and 25%) of the extreme tails of the market volatility distribution. The results are available upon request.

lower and upper tail of the market volatility distribution and accordingly define the following sub-samples: low volatility sample (25% of the sample with lowest daily market volatility), medium volatility sample (50% of the sample with moderate daily market volatility) and high volatility sample (25% of the sample with the highest daily market volatility). Table 3.7, presents the estimates of regression (3.6) for the bottom-mid-upper volatility sub-samples in corporate bond and equity markets. Similar to our previous analysis, we employ the regression three times on each sub-sample by changing the cut-off points (5%, 10 and 25% criterion) of the lower and upper extreme tails of the market liquidity distribution each time.

Generally, the results are consistent with our previous analysis; herding effects are mainly detected during high liquidity days and are more prominent in corporate bonds. In addition, herding effect is further magnified in periods of high volatility. For instance, focusing on the high volatility sub-sample and 5% liquidity criterion, we find that the magnitude of herding in corporate bond markets is 5 times higher[36] than in equity markets as corroborated by the relative magnitude of the β_4 coefficient. The most profound evidence of herding is reflected in the high (low) volatility sub-sample for corporate bonds (equities). The difference in herding across the two asset classes could be explained by the more negative relationship between liquidity and volatility (per asset correlations) documented in stocks compared to bonds across the full sample (see Figure 3.10). It is worth also noting that the correlations between market liquidity and conditional volatility change over time as shown in Figure 3.9, where the most inverse relationship is clearly depicted in 2008 that covers most of the crisis period (see also Figure 3.11 and Figure 3.12). We also observe some herding at medium market liquidity periods in corporate bonds only, where the coefficient β_2 is negative and significant mainly in the high and medium volatility sub-samples. In line with our full sample results, the positive and significant β_3 coefficient reveals that herding in low liquidity periods is inexistent for either asset class or across volatility splits. Overall, herding is positively related to liquidity, with volatility acting as a catalyst and magnifying the herding effect further.

Similarly, we examine the robustness of the detected herding asymmetries conditional on market volatility during different market liquidity periods by splitting the sample into bottom-mid-upper liquidity using the 25% cut-off threshold. We find the 25% lowest and highest market liquidity days in our sample and subsequently define the following sub-samples: low liquidity sample (25% of the sample with lowest daily market liquidity), medium liquidity sample (50% of the sample with moderate daily market liquidity) and high liquidity sample (25% of the sample with the highest daily market liquidity). Table 3.8, presents the output of regression (3.9), where we examine the existence of herding activity in bond and equity markets whilst controlling for the level of market volatility in the three liquidity sub-samples. We re-estimate the regression three times on each liquidity sub-sample, varying

[36] These are calculated as ln $(-20.175/(-0.173))$.

the cut-off points (5%, 10 and 25% criterion) of the lower and upper extreme tails of the market volatility distribution each time.

Both bond and equity samples exhibit some evidence of herding behaviour during moderate volatility periods, captured by β_2, in the low liquidity sub-sample. Focusing on the corporate bond sample, we observe herding effects in low market volatility days across all sub-samples and volatility cut-offs, evidenced by the consistently negative and statistically significant β_3 coefficient that measures the marginal increase in the herding effect in comparison to the medium volatility days. The strongest herding effects are found in the low liquidity sub-sample. For instance, when conditioning on 5% volatility criterion the coefficient on low volatility dummy variable β_3 = -22.515 is statistically significant at 1%. These results confirm our earlier findings, implying that investors are inclined to herd during calm market periods (low volatility days). The equity sample seem to exhibit a similar pattern as the bond sample, though magnitude and significance of the β_3 coefficient is somewhat weaker. Finally, β_4 is found to be mostly statistically significant but positive, suggesting adverse herding behaviour amid unstable high volatility days. These results affirm our earlier findings and highlight that the relationship between herding behaviour and market volatility is preserved despite the level of liquidity in the market. Hence, it can be concluded from this section that investors' herding towards the market consensus is related to both market liquidity and volatility, where one does not offset the other.

3.5.5 Cross-asset herding spillover

Table 3.9 presents the estimates of equations (3.10) and (3.11), in which we examine the herding spillover effects between corporate bond and equity markets, as such effects could potentially explain the movements observed in the two markets. To test for herding spillover effects, we follow Chiang and Zheng (2010) and add an additional CSAD term and squared market return of the stock market sample in the bond market herding regression and vice versa. In the presence of herding spillover effects from one asset class market to another, we expect β_4 and γ_4 from equations (3.10) and (3.11) respectively, to be negative and statistically significant. All regressions are employed on the entire sample period from January 2008 to December 2018, for each asset class (US corporate bond and equity) and separately for their corresponding credit rating portfolios: investment grade, speculative grade and non-rated. In the case of the credit rating portfolios, we test for herding spillover effects between the same rating grade, for example from investment grade bonds to investment grade issuers' stocks and vice versa.

A cursory observation of the results shows that including the cross-herding terms does not change our earlier unconditional herding results. With the exception of speculative grade bonds, we fail to find evidence of unconditional herding. Focusing on cross-asset herding, we observe that the positive coefficient of the CSAD reflects the dominant influence of the equity market return dispersions upon the bond market and vice versa. The fact that the β_3 and γ_3 coefficients share the same sign, suggests that a positive co-varying risk associated with the trading dynamics of these markets is verified, in line with (Chiang and Zheng 2010; Demirer, Lee and Lien 2015) studies.

Moreover, the results of the herding spillover tests show a distinction in the US corporate bond and equity samples. A negative β_4 (γ_4) coefficient captures the cross-asset herding spillover upon bond (equity) markets induced from large swings in equity (bond) markets. Inspecting the bond full sample results, we find that although the coefficient on the squared equity market return is negative, β_4= -0.003 it is statistically insignificant, suggesting no herd spillover from equities to bond markets. The same pattern is detected across two out of the three credit rating bond sub-samples. On the other hand, our results suggest that equity market herding is significantly influenced by bond market dynamics, as corroborated by the negative γ_4 coefficient.

For example, entire equity sample's coefficient on the corporate bonds' non-linear term γ_4= -0.076 is negative and statistically significant at 1%. Since this term measures the extreme movements in the US corporate bond market, its statistically negative coefficient signifies that stock market herding could be explained by corporate bond market conditions. Large swings in the bond market seem to decrease the dispersion of equity returns from the market, in other words, induce clustering around the equity market consensus. By contrast, bond market herding is unaffected by equity market swings, except for unrated bonds. This provides novel empirical evidence suggesting the existence of herding spillovers from US corporate bond market to US stock market. This effect seems to be consistent through all credit rating classifications, where γ_4= -0.099 (investment-grade) and -0.021 (high-yield) and -0.033 (non-rated issuers) is negative and statistically significant for all. The most pronounced herding spillover effects (most negative γ_4) are observed within the investment grade issuers' assets.

Since the subprime mortgage crisis, the corporate bond market rapidly expanded[37] with the majority of bonds being held by institutional investors[38] (Cai et al. 2019). Hence, the trades of bondholders are typically made by more informed institutional investors[39] with larger trading volumes (mainly in investment grade bonds). This could explain the herding spillover effects we detect from bonds to equities, as a large proportion of stock market participants are retail (typically less informed) investors which are likely to follow the trading patterns of the typically institutional, bond market investors anticipating informational gains. As a result, stock market investors' herding could be affected by the corporate bond institutional investors' trades that is captured by the herding spillover. On the other hand, we believe that the cross-herding from unrated equities to bonds is possibly reflective of the lack

[37] According to the Securities Industry and Financial Markets Association (SIFMA), the US corporate bond market reached $9.2 trillion (outstanding) as of the end of 2018, which is the highest historical value recorded.
[38] "According to the Financial Accounts of the United States, about three-quarters of US corporate bonds, including foreign bonds issued in the US, are held by institutional investors" (Cai et al. 2019, p.1).
[39] Tsai (2014) shows that US corporate bonds with the lowest credit ratings (speculative grade) are traded most by institutional investors, whilst bonds with the highest credit ratings attract more trading volume from institutional investors.

of credit information about these bonds; hence information content from equity markets becomes more relevant.

In order to test for the stability of the spillover effects during the entire sample, in Table 3.10 we apply the same cross-herding regressions to the crisis (1 January 2008 – 15 March 2009) and post crisis (16 March 2009 – 31 December 2018) sub-periods. In both sub-periods we observe positive and significant CSAD coefficients (β_3 and γ_3) suggesting that both equity and bond markets cluster around the market consensus at the same time and that the dispersions in one market help to explain the dispersions in the other. In alignment with the full sample period estimates, except for the unrated issues, the bond sample results show no evidence of herding spillover from equity markets to corporate bonds during the crisis period. Although the spillover detecting coefficient (β_4) is found to be negative for the full sample as well as the credit rating portfolios, it mostly statistically insignificant at 10%. For instance, the crisis period full bond sample β_4= -0.007 and the investment grade bonds' regression β_4 = -0.009, where both are insignificant implying no cross-herding spillover from equities to bonds during the crisis. Looking at the equity sample results, we observe that the cross-herding spillover from bonds to equity remains strong in the crisis period. The coefficients on the corporate bonds' squared market return term are negative and statistically significant, which show that large movements in bond returns significantly contribute to clustering of equity returns towards the market consensus i.e. herding. The level of significance of γ_4 varies across the credit rating portfolios, with the investment grade one γ_4 = -0.072 being the most statistically significant (at 1%). These findings confirm our earlier results regarding the link between the US corporate bond and stock market investors' herding behaviour, where equity herding formation is influenced by the bond market conditions. In addition to our earlier reasoning, the crisis period results could also be the product of flight-to-quality that prevail in periods of distress, where investors pull out of riskier markets to invest in safer, more reliable bond issuers (Brière, Chapelle and Szafarz 2012).

By contrast, during the post-crisis period we observe a shift in the cross-herding, whereby informational content from the equity sample significantly contributes to herding in the bond market. For the equity post-crisis sample, the γ_4 coefficients for the full, investment grade and speculative grade samples are now positive and insignificant. This suggests that, apart from unrated issuers' stocks, the observed herding spillover from corporate bonds to equities disappeared after the market downturn. Nevertheless, we detect cross-herding spillover effects from US equities to US corporate bonds in the post crisis period, evidenced by the negative β_4. For instance, the post-crisis period full bond sample has β_4= -0.014, which is statistically significant at 1%. We believe this may plausibly be attributed to the aftermath of the global financial crisis when the exposure of institutional investors to toxic securities had been well-documented, and which could have culminated to institutional investors utilising information from any available source, including the equity markets.

From above, we conclude that there is a close link between the trades of corporate bond and equity investors and that the direction of the cross-herding spillover effects is not constant. Moreover, the results emphasise the importance of studying herding behaviour and cross-herding spillovers across different asset classes in a domestic as well as international setting. These findings are partially in line with Galariotis, Rong and Spyrou (2015), who detect herding spillover effects from the US stock market to the UK only during the Asian crisis and the Dotcom bubble sub-samples, suggesting that herding spillover effects can be period-specific.

3.6 Conclusions

This chapter provides detailed investigation of herding behaviour towards a consensus in US corporate bond and equity markets; with particular empahsis on the existence of cross-asset herding between the two markets. We apply the commonly employed methodology of Chang, Cheng and Khorana (2000) to conduct the standard herding tests and expand on it to examine asymetric herding effects (up/down markets, high/low liquidity and high/low volatility). Using a sample of 794 stocks and 8,623 corporate bonds that were listed on the S&P 500 between January 2008 – December 2018, we perform and compare all herding regressions on the full bond and equity samples, as well as three credit rating portfolios: investment grade, high yield (speculative grade) and non-rated assets. To capture the bond and equity markets' liquidity we follow Galariotis, Krokida and Spyrou (2016b) and apply the widely used Amihud (2002) illiquidity measure, whilst the markets' volatlity is meausred using the conditional volatility from the GARCH(1,1) fitted model on the market return.

Our initial unconditional tests show limited herding effects in US corporate bond markets, present only in speculative grade bonds, and no evidence of investor herding in US equity markets. However, when allowing for herding asymmetries, we find significant evidences of herding in bond and equity markets. Our corporate bond and equity findings show consistent results, suggesting that in both markets investors collectively herd towards the consensus when the market is more liquid and less volatile, i.e. stable days when investors are more optimistic or certain about the direction of the market. The strongest and most persistent herding effects are observed in high liquidity and low volatility market days. On the other hand, the estimates also suggest that investors follow their own opinions (adverse herding) during dry and highly volatile market conditions. Interestingly, we observe a substantially higher level of investor herding in corporate bonds in comparison to equities, which is verified by their larger (in absolute value) herd detecting coefficients. This is a key finding of our study that is worth exploring in future studies.

The results are consistent through all credit rating portfolios (investment grade, speculative grade and non-rated), though herding is stronger in investment grade (speculative grade) bonds during extremely liquid (low volatility) market days. In addition, we show that the observed herding asymmetries persist even after conditioning on both volatility and liquidity at the same time, confirming that investors' herding is related to both and that their asymmetries do not offset each the other. Furthermore, we find herding to be positvely related to liquidity, with market volatility acting as a catalyst to the herding effect. What is more, further analysis indicate that herding conditional on market volatility hold during crisis and post-crisis sub-samples, demonstrating similar patterns as observed in the full period with more notable herding in investment grade bonds during crisis and speculative grade bonds post-crisis.

More importantly, we provide new empirical evidence of the existence of cross-asset herding spillovers. We document cross-herding from US corporate bonds to US equities, which may be in part attributed to the different profile of investors. Specifically, stock market participants include a large percentage of retail investors that are more likely to mimic the trading patterns of the better-informed institutional investors that dominate the bond markets. We show that the dynamics of corporate bond market can contribute to stock market herding and seem to inform its trading strategies particularly during crises. In the post-crisis period, when higher level of informational asymmetry is observed, the converse direction of cross-herding is evidenced. This finding is another interesting result that provides further evidence of the close relationship or connection between corporate bonds and equities.

Our results may be useful to investors and portfolio managers since herding behaviour can affect asset allocation in varying degrees across liquid and volatile market periods. The closer clustering of asset prices around the market consensus during these periods and cross-herding spillover could reduce the benefits of diversification. Further research may be directed to exploring the nature and motives behind this consistent and intense herding observed in corporate bond markets. For instance, if the investors' herding behaviour is dynamic and whether it is based on fundamentals (e.g. see Galariotis, Rong and Spyrou 2015; Chiang et al. 2013). In regards to the herding asymmetries, it would be useful to examine the causality between liquidity, volatility and herding. Furthermore, given the possible destabilizing effects and financial instability risks of herding, it is critical to further investigate cross-asset spillovers domestically and internationally and study its implications.

3.7 Tables and figures

Figure 3.1: Cross-sectional absolute deviation and market portfolio return for the corporate bond and stock (equity) markets over time (1 Jan 2008 – 31 Dec 2018).

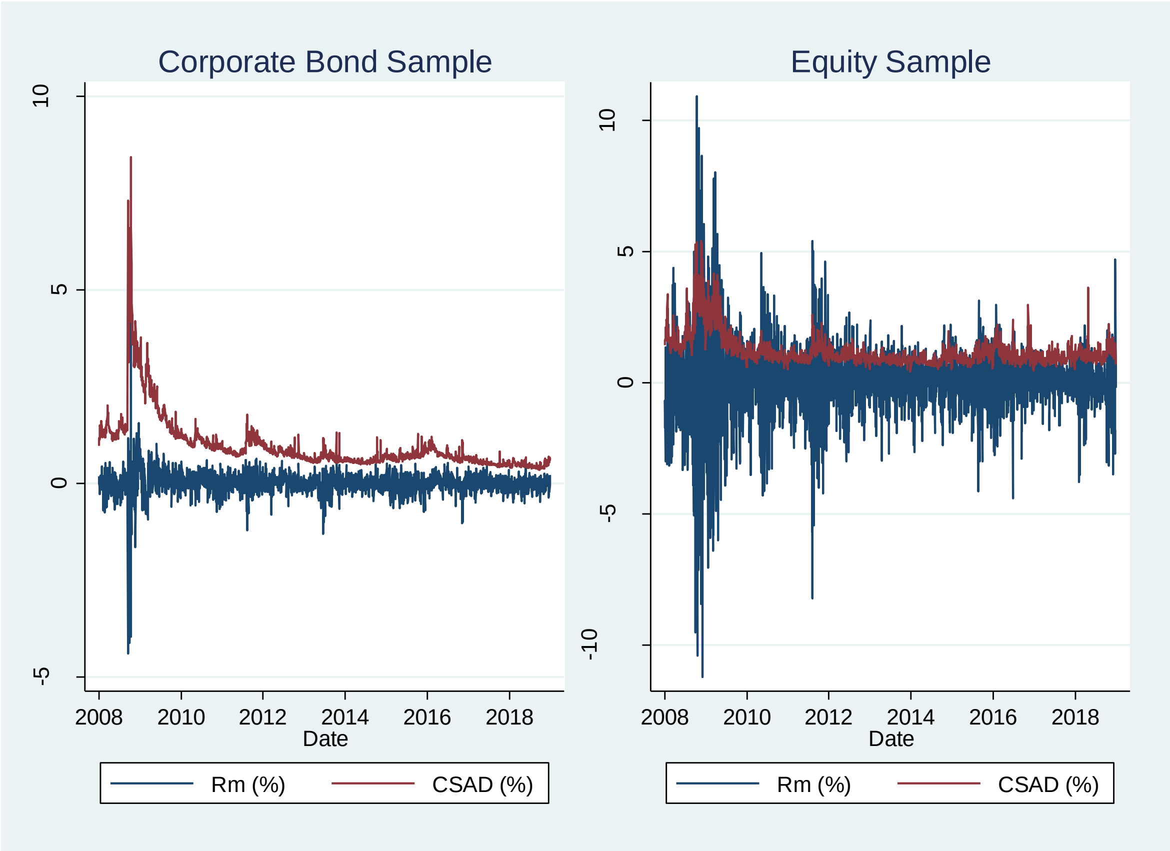


Figure 3.2: Cross-sectional average deviation and market portfolio return (Jan 2008 - Dec 2018).

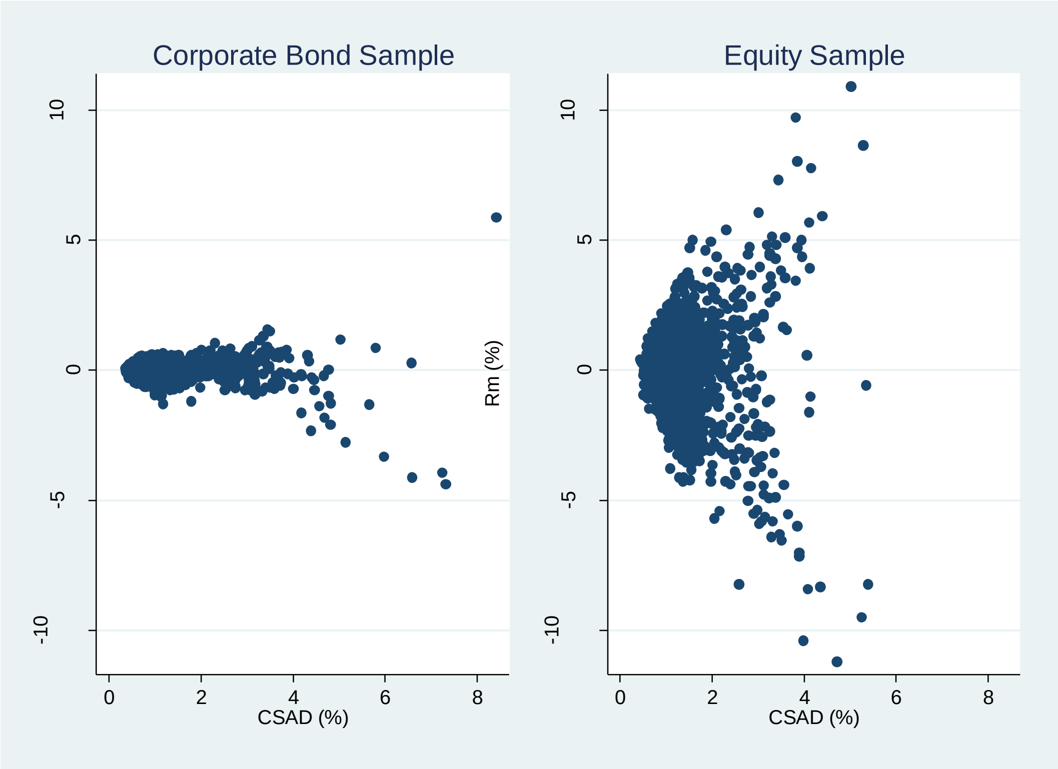


Figure 3.3: Cross-sectional average deviation and market liquidity (Jan 2008 - Dec 2018).

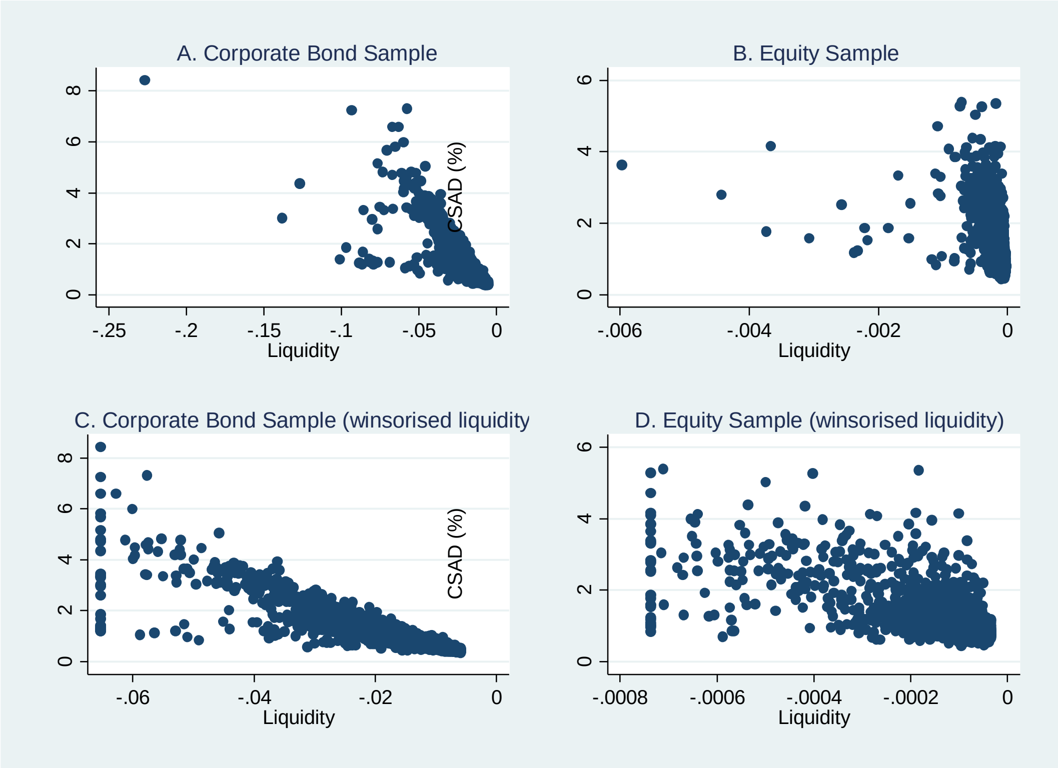


Figure 3.4: Cross-sectional average deviation and conditional volatility (Jan 2008 – Dec 2018).

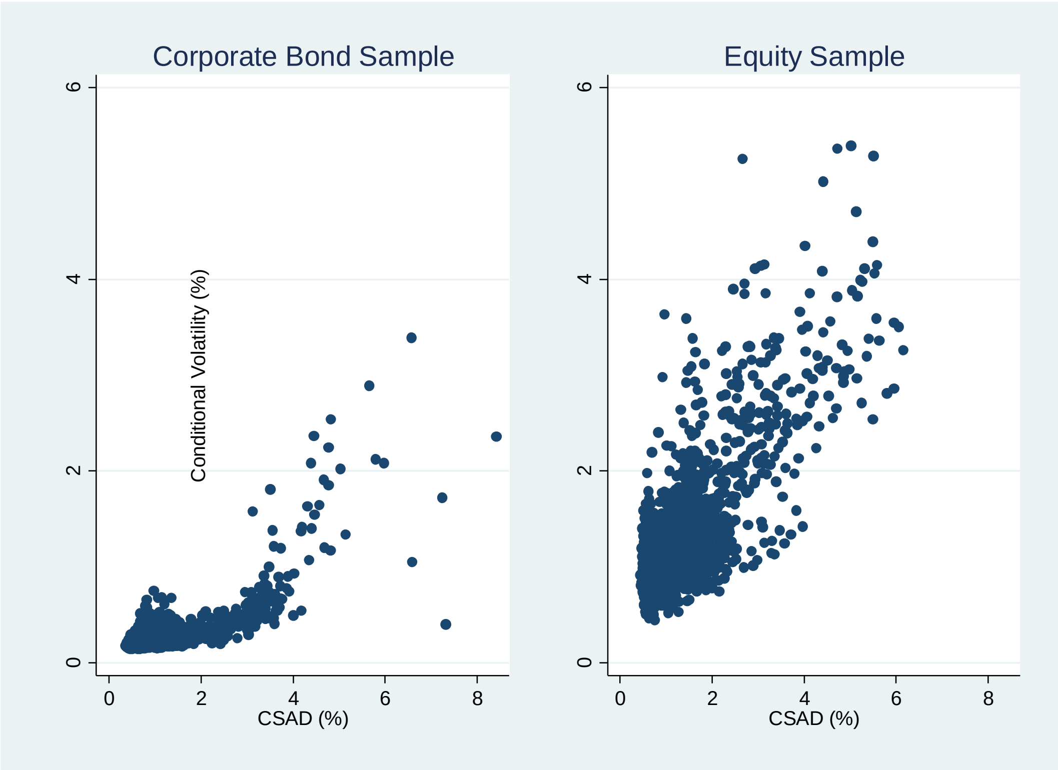


Figure 3.5: Market liquidity and conditional volatility (Jan 2008 – Dec 2018).

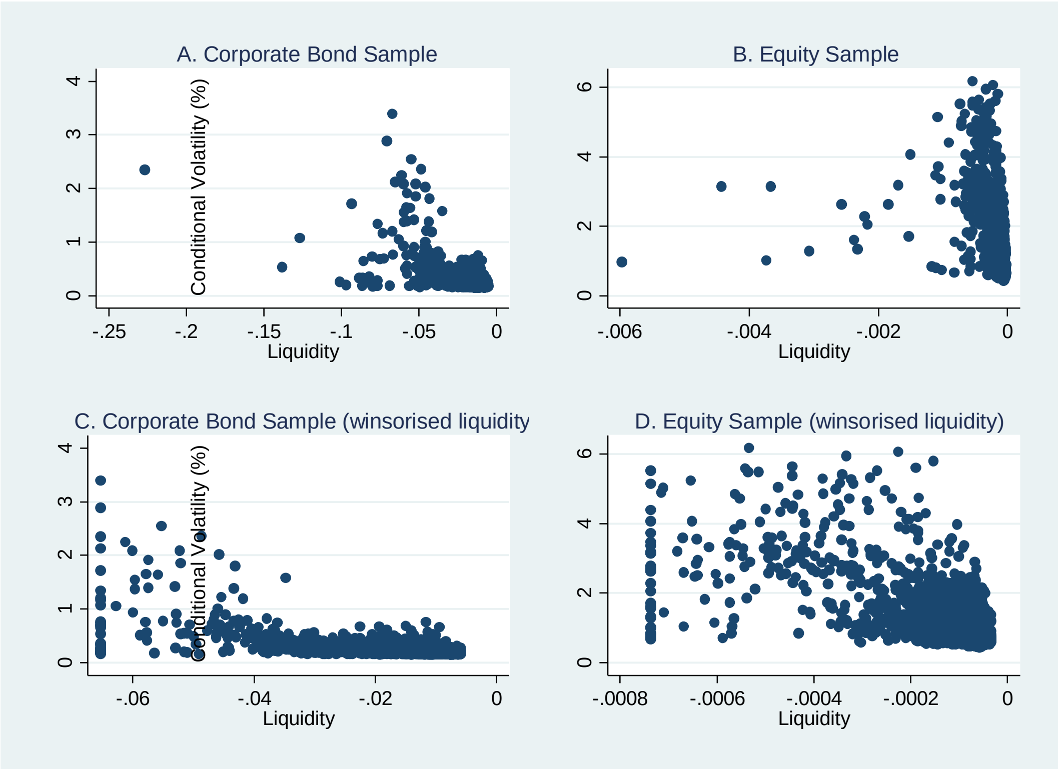


Figure 3.6: Corporate bond and equity conditional market volatility (GARCH 1,1) markets over time (Jan 2008 – Dec 2018).

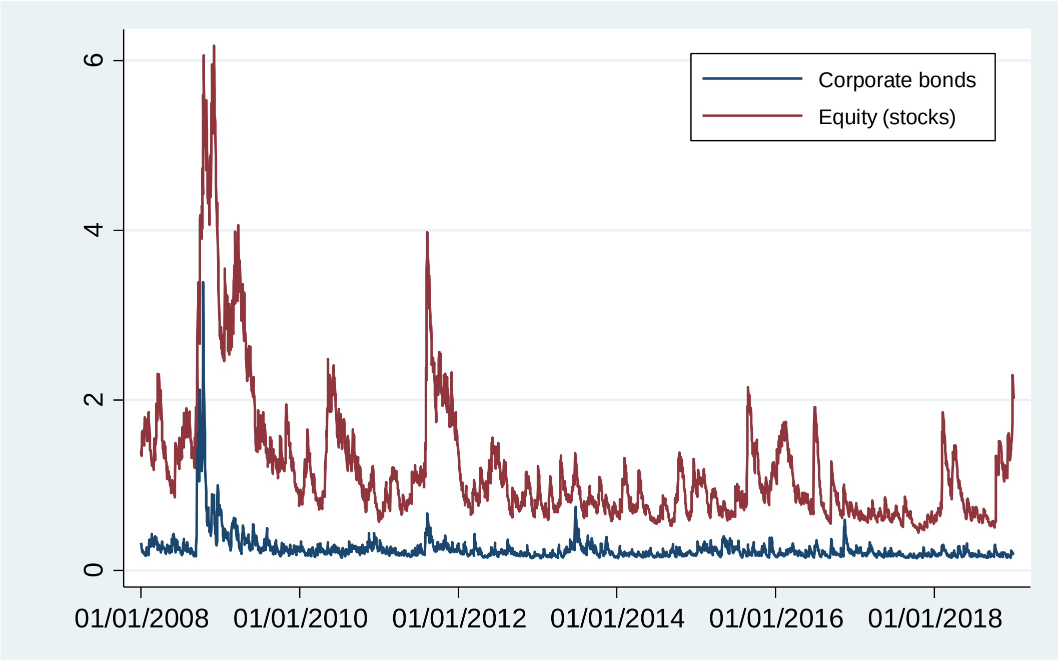


Figure 3.7: Histogram of US corporate bond market daily moving window (252 trading days) liquidity and volatility correlation coefficient (Jan 2009 – Dec 2018)

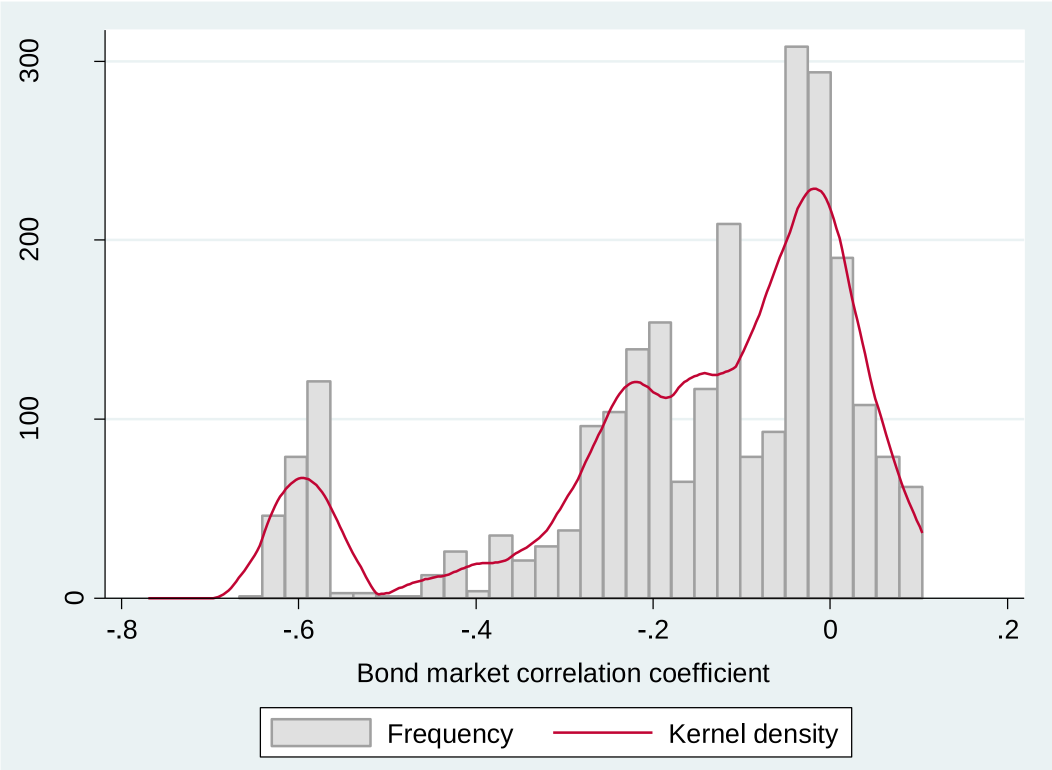


Figure 3.8: Histogram of US equity stock) market daily moving window (252 trading days) liquidity and volatility correlation coefficient (Jan 2009 – Dec 2018)

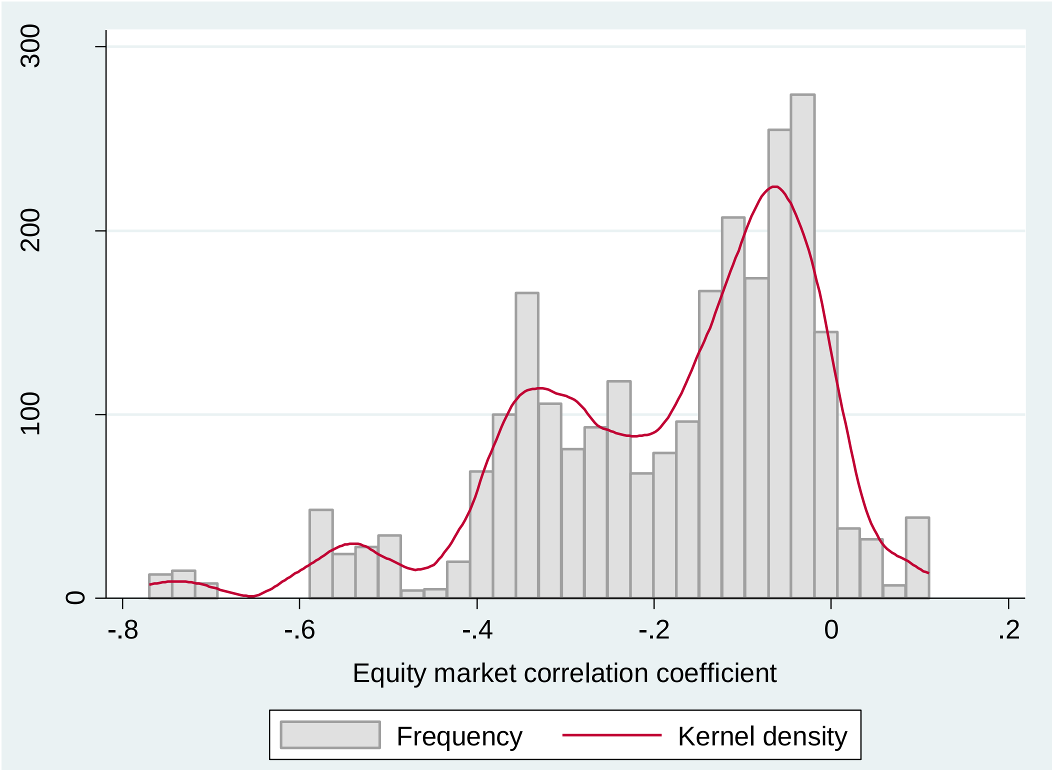


Figure 3.9: Annual corporate bond and equity (stock) market liquidity and volatility correlation coefficients

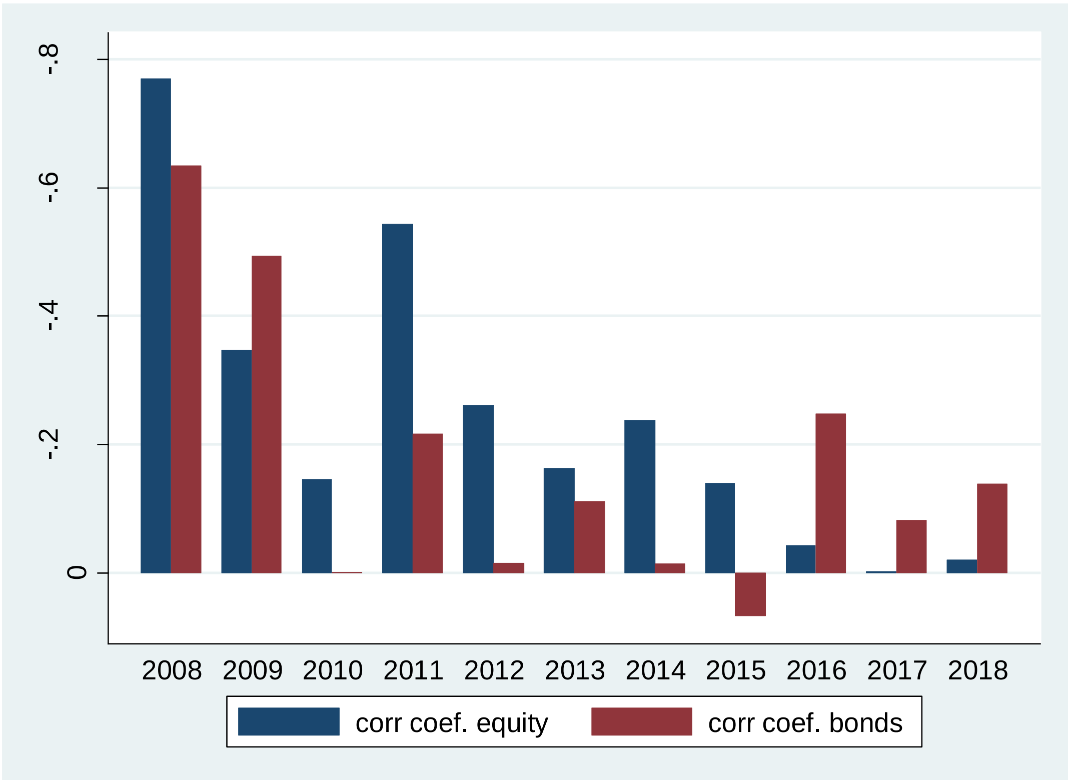


Figure 3.10: US corporate bond and equity histogram of liquidity and volatility correlation coefficients (per asset)

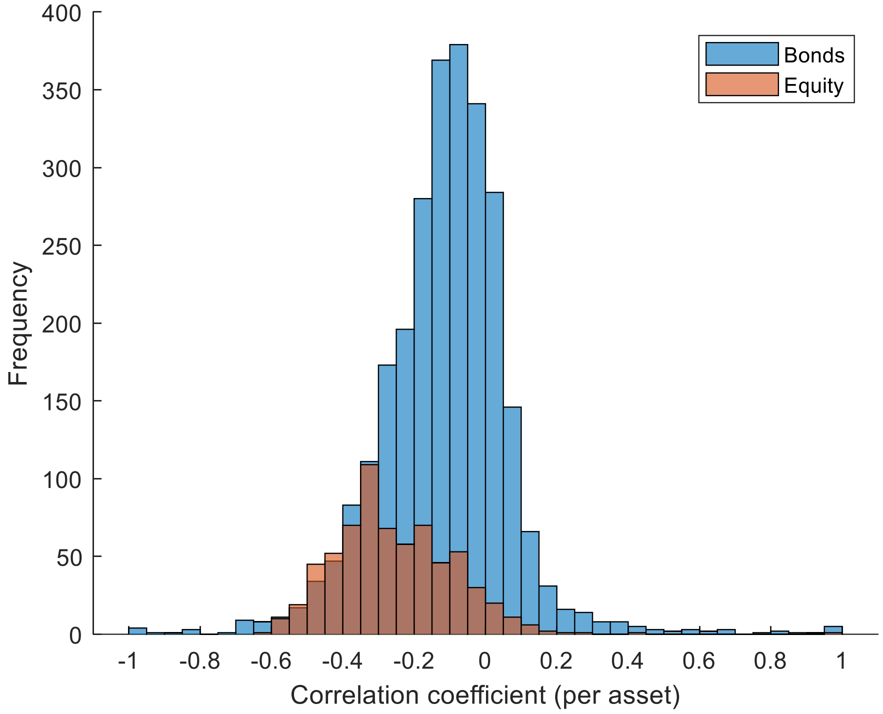


Figure 3.11: Annual (2008-2018) histogram of individual US corporate bonds' liquidity and volatility correlation coefficients (per bond)

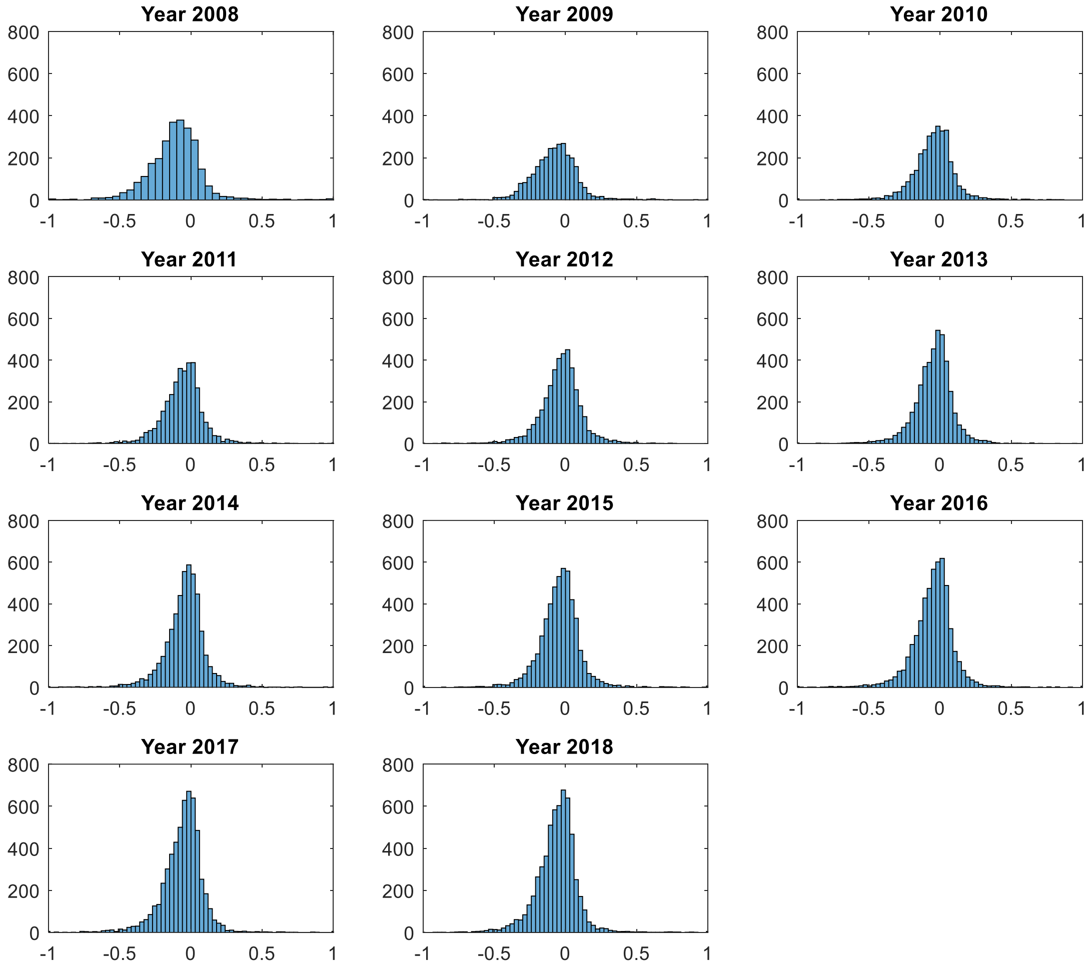


Figure 3.12 : Annual (2008-2018) histogram of individual US stocks' liquidity and volatility correlation coefficients (per stock)

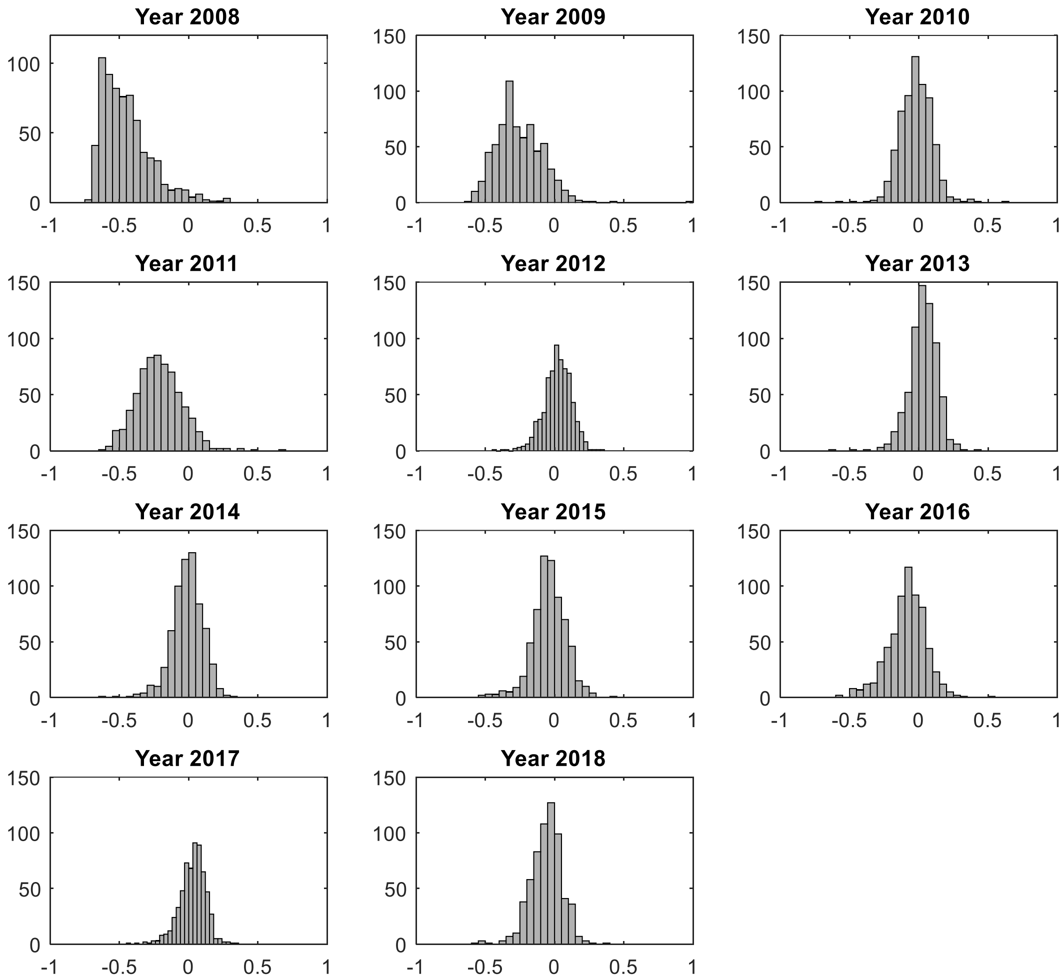


Table 3.1 Descriptive statistics. The table reports the descriptive statistics for the daily cross-sectional equally-weighted market return (R_m), the cross-sectional absolute deviations ($CSAD$), Amihud market liquidity proxy (Liq) and GARCH(1,1) market conditional volatility ($CondVol$) for our US corporate bond and stock (equity) samples, for the period January 2008 to December 2018. The $CSAD$ is given by $CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|$, where $R_{i,t}$ is the daily log return of asset i at day t and $R_{m,t}$ is the cross-sectional average (market) return of Nassets at time t.

	Corporate Bonds				**Stocks (Equity)**			
	R_m	$CSAD$	Liq	$CondVol$	R_m	$CSAD$	Liq	$CondVol$
Mean	0.00197	0.97228	-0.01602	0.25526	0.01436	1.19813	-0.00014	1.20501
Median	0.01973	0.74348	-0.01264	0.21475	0.06888	1.02754	-0.00009	0.94599
Std. dev	0.32570	0.71773	0.01177	0.19032	1.45305	0.57991	0.00024	0.79611
Minimum	-4.40262	0.35767	-0.22713	0.13969	-11.20799	0.43875	-0.00598	0.44545
Maximum	5.85506	8.41964	-0.00503	3.38931	10.90546	5.39447	-0.00002	6.16751
Skewness	-1.16647	3.62958	-5.02919	8.05212	-0.49011	2.83242	-12.78093	2.78585
Kurtosis	77.31727	21.82020	55.20532	88.96104	12.47388	13.40708	231.38010	12.59169
Observations	2769	2769	2769	2769	2769	2769	2769	2769

Table 3.2: Pairwise variable correlations. The table reports the pairwise correlation coefficients of the daily the cross-sectional absolute deviations ($CSAD$), cross-sectional squared market return (R_m), Amihud market liquidity proxy (Liq) and GARCH(1,1) market conditional volatility ($CondVol$) for our US corporate bond (Panel A) and equity (Panel B) samples, for the period January 2008 to December 2018. *, **, and *** represent statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A: Corporate Bonds				
	$CSAD$	R_m^2	Liq	$CondVol$
$\boldsymbol{CSAD}$	1.0000			
$\boldsymbol{R_m^2}$	0.4580***	1.0000		
$\boldsymbol{Liq}$	-0.8246***	-0.4413***	1.0000	
$\boldsymbol{CondVol}$	0.7598***	0.3877***	-0.5965***	1.0000
Panel B: Stocks (Equity)				
$\boldsymbol{CSAD}$	1.0000			
$\boldsymbol{R_m^2}$	0.6395***	1.0000		
$\boldsymbol{Liq}$	-0.4257***	-0.3255***	1.0000	
$\boldsymbol{CondVol}$	0.7888***	0.5042***	-0.3568***	1.0000

Table 3.3: Testing for unconditional and conditional (rising and declining markets) herding in US corporate bond and equity markets. The table presents the coefficient estimates from the following regressions:

(1) $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t$

(2) $CSAD_t^{UP} = \beta_0 + \beta_1^{UP}|R_{m,t}^{UP}| + \beta_2^{UP}(R_{m,t}^{UP})^2 + \varepsilon_t$

(3) $CSAD_t^{DOWN} = \beta_0 + |R_{m,t}^{DOWN}| + \beta_2^{DOWN}(R_{m,t}^{DOWN})^2 + \varepsilon_t$

(4) $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 D^{UP} R_{m,t}^2 + \beta_3(1 - D^{UP})R_{m,t}^2 + \varepsilon_t$

The equations are estimated for the 01/01/2008 – 31/12/2018 sample period, for our full bond and equity samples (Panel A) and credit rating portfolios: investment grade (Panel B), high yield (Panel C) and non-rated (Panel D) sub-samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients β_2 and β_3. $\mathrm{CSAD_t}$ is the daily cross-sectional absolute deviation of our US bonds (equity) returns and $\mathrm{R_{m,t}}$ is their daily equally-weighted average return at time t. Regression (2) is estimated for the days that the market is rising ($\mathrm{R_{m,t}} > 0$), whilst regression (3) is estimated for the days that the market is falling ($\mathrm{R_{m,t}} < 0$). $D^{UP} = 1$ when $\mathrm{R_{m,t}} > 0$ and zero otherwise.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds				**Stocks (Equity)**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Full sample								
β_1	1.861***	2.162***	1.555***	1.857***	0.290***	0.312***	0.266***	0.288***
	(0.418)	(0.416)	(0.529)	(0.435)	(0.063)	(0.071)	(0.059)	(0.063)
β_2	-0.073	-0.132*	0.015	-0.074	0.012*	0.013	0.013**	0.016*
	(0.092)	(0.074)	(0.137)	(0.085)	(0.007)	(0.009)	(0.007)	(0.008)
β_3				-0.070				0.011
				(0.108)				(0.007)
Constant	0.622***	0.583***	0.661***	0.622***	0.903***	0.878***	0.929***	0.903***
	(0.048)	(0.050)	(0.056)	(0.049)	(0.028)	(0.032)	(0.030)	(0.028)
Observations	2,769	1,507	1,262	2,769	2,769	1,476	1,293	2,769
R-squared	0.369	0.356	0.386	0.369	0.484	0.474	0.496	0.485
F-stat (H_0: $\beta_2 = \beta_3$)				0.01				2.23
p-value				0.904				0.135
Panel B: Investment grade								
β_1	1.589***	1.801***	1.381***	1.576***	0.301***	0.332***	0.269***	0.299***
	(0.399)	(0.369)	(0.485)	(0.392)	(0.066)	(0.080)	(0.059)	(0.066)
β_2	-0.007	-0.067	0.057	-0.022	0.015*	0.015	0.016**	0.019**
	(0.085)	(0.069)	(0.108)	(0.080)	(0.008)	(0.011)	(0.007)	(0.010)
β_3				0.008				0.013*
				(0.085)				(0.008)
Constant	0.607***	0.585***	0.629***	0.610***	0.761***	0.731***	0.792***	0.761***

	(0.046)	(0.043)	(0.055)	(0.045)	(0.025)	(0.031)	(0.029)	(0.025)
Observations	2,769	1,480	1,289	2,769	2,769	1,482	1,287	2,769
R-squared	0.353	0.308	0.395	0.354	0.501	0.502	0.504	0.503
F-stat ($H_0: \beta_2 = \beta_3$)				1.71				2.01
p-value				0.191				0.157
Panel C: High yield (speculative grade)								
β_1	1.964***	2.277***	1.714***	1.964***	0.261***	0.295***	0.226***	0.258***
	(0.250)	(0.224)	(0.276)	(0.253)	(0.058)	(0.067)	(0.055)	(0.059)
β_2	-0.111***	-0.149***	-0.078*	-0.094**	0.011**	0.011*	0.013**	0.015**
	(0.039)	(0.040)	(0.041)	(0.048)	(0.005)	(0.007)	(0.005)	(0.006)
β_3				-0.121***				0.009*
				(0.038)				(0.005)
Constant	0.858***	0.805***	0.898***	0.858***	1.255***	1.209***	1.302***	1.256***
	(0.048)	(0.038)	(0.062)	(0.048)	(0.038)	(0.042)	(0.039)	(0.038)
Observations	2,769	1,488	1,281	2,769	2,769	1,448	1,321	2,769
R-squared	0.562	0.584	0.554	0.563	0.438	0.433	0.450	0.440
F-stat ($H_0: \beta_2 = \beta_3$)				3.67*				4.29**
p-value				0.055				0.038
Panel D: Non-rated								
β_1	1.541***	1.493***	0.542**	1.148***	0.226***	0.257***	0.196***	0.226***
	(0.358)	(0.248)	(0.251)	(0.173)	(0.048)	(0.053)	(0.047)	(0.048)
β_2	0.010	-0.021	0.503***	0.024	0.012**	0.010	0.015***	0.014**
	(0.041)	(0.029)	(0.151)	(0.037)	(0.005)	(0.006)	(0.005)	(0.006)
β_3				0.367***				0.011**
				(0.140)				(0.005)
Constant	0.449***	0.462***	0.652***	0.529***	0.983***	0.946***	1.022***	0.983***
	(0.085)	(0.059)	(0.052)	(0.039)	(0.027)	(0.029)	(0.030)	(0.027)
Observations	2,768	1,501	1,267	2,768	2,769	1,499	1,270	2,769
R-squared	0.530	0.593	0.659	0.616	0.386	0.389	0.385	0.386
F-stat ($H_0: \beta_2 = \beta_3$)				7.94***				1.22
p-value				0.005				0.270

Table 3.4: Herding conditional on market liquidity in US corporate bond and equity markets. The table presents the coefficient estimates from the following regression: $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D^{LLiq} R_{m,t}^2 + \beta_4 D^{HLiq} R_{m,t}^2 + \varepsilon_t$. The equation is estimated for the 01/01/2008 – 31/12/2018 sample period, for our full bond and equity samples (Panel A) and credit rating portfolios: investment grade (Panel B), high yield (Panel C) and non-rated (Panel D) sub-samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients β_3 and β_4. $CSAD_t$ is the daily cross-sectional absolute deviation of our US bond (equity) returns and $R_{m,t}$ is their daily equally-weighted average return at time t. $D^{LLiq} = 1$ ($D^{HLiq} = 1$) if the Amihud market liquidity proxy on day t lies in the extreme 5%, 10 and 25% lower (upper) tail of the liquidity distribution and zero otherwise. The liquidity proxy is based on Karolyi, Lee and van Dijk (2012) and is constructed as: $Liq_{i,t} = -log\left(1 + \left(|R_{i,t}|/V_{i,t}\right)\right)$, where $|R_{i,t}|$ and $V_{i,t}$ are the absolute return and the trading volume of bond (stock) i on day t, and the cross-sectional average daily liquidity across bonds (stocks) is obtained as: $Liq_{m,t} = \frac{1}{N}\sum_{i=1}^{N} Liq_{i,t}$. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds			**Stocks (Equity)**		
	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion
Panel A: Full sample						
β_1	2.914***	2.992***	2.756***	0.360***	0.361***	0.330***
	(0.342)	(0.317)	(0.258)	(0.054)	(0.081)	(0.069)
β_2	-2.883***	-3.648***	-4.744***	-0.017	-0.029	-0.051
	(0.528)	(0.743)	(0.666)	(0.015)	(0.028)	(0.034)
β_3	2.586***	3.334***	4.472***	0.024*	0.034	0.059**
	(0.463)	(0.679)	(0.618)	(0.013)	(0.021)	(0.028)
β_4	-14.029***	-10.213***	-4.580***	-0.242**	-0.261***	-0.133*
	(1.939)	(1.842)	(0.668)	(0.095)	(0.092)	(0.070)
Constant	0.574***	0.586***	0.628***	0.881***	0.888***	0.910***
	(0.039)	(0.041)	(0.033)	(0.023)	(0.030)	(0.027)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.444	0.493	0.515	0.495	0.497	0.496
F-stat ($H_0: \beta_3 = \beta_4$)	59.26***	40.09***	89.4***	7.83***	9.42***	4.97**
p-value	0.000	0.000	0.000	0.005	0.002	0.026
Panel B: Investment grade						
β_1	2.750***	2.785***	2.513***	0.401***	0.370***	0.323***
	(0.414)	(0.363)	(0.359)	(0.073)	(0.083)	(0.074)
β_2	-2.896***	-3.292***	-4.222***	-0.034	-0.037	-0.051
	(0.728)	(0.750)	(0.822)	(0.021)	(0.032)	(0.055)
β_3	2.653***	3.041***	4.019***	0.040***	0.044*	0.063
	(0.644)	(0.676)	(0.750)	(0.014)	(0.025)	(0.048)
β_4	-11.643***	-8.598***	-3.486***	-0.304**	-0.208**	-0.153**
	(1.586)	(1.500)	(0.806)	(0.134)	(0.084)	(0.063)
Constant	0.547***	0.554***	0.598***	0.734***	0.750***	0.772***

	(0.038)	(0.038)	(0.042)	(0.026)	(0.027)	(0.023)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.437	0.471	0.489	0.521	0.513	0.508
F-stat ($H_0: \beta_3 = \beta_4$)	51.59***	39.41***	35.15***	6.41**	8.00***	7.41***
p-value	0.000	0.000	0.000	0.011	0.005	0.007
Panel C: High yield (speculative grade)						
β_1	2.246***	2.383***	2.310***	0.291***	0.328***	0.295***
	(0.232)	(0.219)	(0.221)	(0.056)	(0.067)	(0.070)
β_2	-0.458***	-0.930***	-1.189***	0.001	-0.015	-0.016
	(0.084)	(0.187)	(0.248)	(0.009)	(0.016)	(0.023)
β_3	0.306***	0.755***	1.023***	0.010	0.021	0.024
	(0.071)	(0.157)	(0.220)	(0.009)	(0.013)	(0.019)
β_4	-8.838***	-1.173	-1.592**	-0.021	0.002	0.020
	(1.327)	(1.061)	(0.682)	(0.091)	(0.070)	(0.030)
Constant	0.839***	0.831***	0.853***	1.242***	1.228***	1.245***
	(0.047)	(0.044)	(0.050)	(0.037)	(0.039)	(0.039)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.576	0.600	0.611	0.442	0.447	0.443
F-stat ($H_0: \beta_3 = \beta_4$)	47.75***	3.18*	11.44***	0.11	0.07	0.01
p-value	0.000	0.075	0.000	0.737	0.797	0.912
Panel D: Non-rated						
β_1	1.498***	1.462***	1.877***	0.268***	0.290***	0.272***
	(0.201)	(0.262)	(0.339)	(0.045)	(0.064)	(0.055)
β_2	-0.061**	-0.050*	-1.311***	-0.005	-0.024	-0.046*
	(0.025)	(0.027)	(0.268)	(0.013)	(0.024)	(0.025)
β_3	0.138***	0.117***	1.276***	0.014	0.029	0.052***
	(0.030)	(0.025)	(0.246)	(0.012)	(0.019)	(0.020)
β_4	-1.672***	-1.896***	-1.291***	-0.186*	-0.109**	-0.122***
	(0.486)	(0.472)	(0.417)	(0.100)	(0.054)	(0.045)
Constant	0.474***	0.487***	0.473***	0.969***	0.968***	0.987***
	(0.050)	(0.063)	(0.075)	(0.025)	(0.029)	(0.027)
Observations	2,768	2,768	2,768	2,769	2,769	2,769
R-squared	0.569	0.562	0.576	0.392	0.396	0.403
F-stat ($H_0: \beta_3 = \beta_4$)	13.81***	17.90***	22.11***	4.04**	5.80**	10.22***
p-value	0.000	0.000	0.000	0.045	0.016	0.001

Table 3.5: Herding conditional on market volatility in US corporate bond and equity markets. The table presents the coefficient estimates from the following regression: $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R^2_{m,t} + \beta_3 D^{LVol} R^2_{m,t} + \beta_4 D^{HVol} R^2_{m,t} + \varepsilon_t$. The equation is estimated for the 01/01/2008 – 31/12/2018 sample period, for our full bond and equity samples (Panel A) and credit rating portfolios: investment grade (Panel B), high yield (Panel C) and non-rated (Panel D) sub-samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The F-test is used to test for the significance of the difference between the pair of coefficients β_3 and β_4. $CSAD_t$ is the daily cross-sectional absolute deviation of our US bond (equity) returns and $R_{m,t}$ is their daily equally-weighted average return at time t. $D^{LVol} = 1$ ($D^{HVol} = 1$) if the GARCH(1,1) conditional market volatility on day t lies in the extreme 5%, 10 and 25% lower (upper) tail of the volatility distribution and zero otherwise. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds			**Stocks (Equity)**		
	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion
Panel A: Full sample						
β_1	1.920***	2.791***	2.505***	0.337***	0.431***	0.396***
	(0.409)	(0.351)	(0.411)	(0.067)	(0.084)	(0.076)
β_2	-0.179	-3.153***	-3.558***	-0.007	-0.062**	-0.088***
	(0.116)	(0.676)	(0.899)	(0.012)	(0.027)	(0.032)
β_3	-5.923***	-4.558***	-0.566	-0.066**	-0.087**	-0.083***
	(1.328)	(0.798)	(0.712)	(0.028)	(0.035)	(0.027)
β_4	0.110	2.879***	3.343***	0.018**	0.060***	0.088***
	(0.082)	(0.607)	(0.812)	(0.007)	(0.018)	(0.024)
Constant	0.623***	0.593***	0.616***	0.887***	0.865***	0.892***
	(0.047)	(0.036)	(0.042)	(0.029)	(0.030)	(0.028)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.378	0.453	0.439	0.493	0.521	0.526
F-stat ($H_0: \beta_3 = \beta_4$)	20.75***	45.75***	13.73***	8.57***	11.81***	18.41***
p-value	0.000	0.000	0.001	0.003	0.000	0.001
Panel B: Investment grade						
β_1	2.404***	2.512***	2.218***	0.331***	0.445***	0.405***
	(0.464)	(0.439)	(0.436)	(0.068)	(0.083)	(0.078)
β_2	-1.846***	-2.714***	-2.852***	0.002	-0.066**	-0.097***
	(0.662)	(0.738)	(0.829)	(0.014)	(0.029)	(0.035)
β_3	-5.064***	-4.076***	-0.773	-0.071**	-0.082**	-0.091***
	(1.140)	(0.796)	(0.738)	(0.030)	(0.037)	(0.031)
β_4	1.676***	2.517***	2.713***	0.012	0.066***	0.099***
	(0.578)	(0.649)	(0.739)	(0.010)	(0.020)	(0.027)
Constant	0.558***	0.569***	0.592***	0.752***	0.724***	0.753***
	(0.043)	(0.041)	(0.042)	(0.027)	(0.026)	(0.026)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.400	0.426	0.416	0.505	0.535	0.540

F-stat ($H_0: \beta_3 = \beta_4$)	23.96***	30.17***	10.61***	7.76***	11.5***	17.49***
p-value	0.000	0.000	0.001	0.005	0.000	0.000
Panel C: High yield (speculative grade)						
β_1	2.318***	2.319***	2.125***	0.332***	0.403***	0.350***
	(0.259)	(0.242)	(0.245)	(0.068)	(0.083)	(0.073)
β_2	-0.603***	-0.910***	-1.254***	-0.013	-0.049**	-0.049**
	(0.186)	(0.219)	(0.419)	(0.011)	(0.021)	(0.023)
β_3	-9.364***	-11.050***	-4.539***	-0.178***	-0.066**	-0.057***
	(2.031)	(2.178)	(1.172)	(0.040)	(0.028)	(0.019)
β_4	0.440***	0.744***	1.116***	0.023***	0.047***	0.050***
	(0.157)	(0.183)	(0.392)	(0.006)	(0.014)	(0.018)
Constant	0.832***	0.852***	0.888***	1.230***	1.206***	1.239***
	(0.048)	(0.048)	(0.049)	(0.041)	(0.042)	(0.039)
Observations	2,769	2,769	2,769	2,769	2,769	2,769
R-squared	0.583	0.601	0.594	0.463	0.478	0.469
F-stat ($H_0: \beta_3 = \beta_4$)	23.00***	28.21***	21.00***	24.68***	10.95***	16.74***
p-value	0.000	0.000	0.000	0.000	0.001	0.000
Panel D: Non-rated						
β_1	1.639***	1.749***	1.697***	0.296***	0.352***	0.321***
	(0.343)	(0.387)	(0.362)	(0.059)	(0.070)	(0.060)
β_2	-0.064	-0.208*	-0.281**	-0.016	-0.049**	-0.062***
	(0.045)	(0.113)	(0.117)	(0.012)	(0.021)	(0.024)
β_3	-1.908***	-2.381***	-2.611***	-0.116***	-0.129***	-0.085***
	(0.674)	(0.772)	(0.569)	(0.034)	(0.029)	(0.023)
β_4	0.075**	0.205***	0.281***	0.025***	0.048***	0.062***
	(0.036)	(0.077)	(0.091)	(0.007)	(0.014)	(0.018)
Constant	0.436***	0.427***	0.461***	0.960***	0.948***	0.969***
	(0.082)	(0.087)	(0.082)	(0.029)	(0.029)	(0.027)
Observations	2,768	2,768	2,768	2,769	2,769	2,769
R-squared	0.539	0.557	0.571	0.404	0.424	0.427
F-stat ($H_0: \beta_3 = \beta_4$)	8.78***	10.71***	24.56***	15.95***	23.92***	21.15***
p-value	0.003	0.001	0.000	0.000	0.000	0.000

Table 3.6: Herding conditional on market volatility in crisis and post-crisis periods. The table presents the coefficient estimates from the following two regressions:
(1) $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \varepsilon_t$
(2) $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D^{LVol} R_{m,t}^2 + \beta_4 D^{HVol} R_{m,t}^2 + \varepsilon_t$
The equations are estimated for two sub-sample periods: crisis period 01/01/2008 – 15/03/2009 and post-crisis period 16/03/2009 – 31/12/2018, for our full bond and equity samples (Panel A) and credit rating portfolios: investment grade (Panel B), high yield (Panel C) and non-rated (Panel D) sub-samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. $\mathrm{CSAD_t}$ is the daily cross-sectional absolute deviation of our US bond (equity) returns and $\mathrm{R_{m,t}}$ is their daily equally-weighted average return at time t. In regression (2), $\mathrm{D^{LVol}} = 1$ ($\mathrm{D^{HVol}} = 1$) if the GARCH(1,1) conditional market volatility on day t lies in the extreme 5% lower (upper) tail of the volatility distribution and zero otherwise and the F-test is used to test for the significance of the difference between the pair of coefficients β_3 and β_4. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds				**Stocks (Equity)**			
	Crisis period		*Post-crisis period*		*Crisis period*		*Post-crisis period*	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Full sample								
β_1	2.072***	2.178***	0.642***	0.874***	0.308***	0.305***	0.167***	0.258***
	(0.188)	(0.207)	(0.189)	(0.198)	(0.047)	(0.044)	(0.033)	(0.071)
β_2	-0.170***	-0.229***	0.311	-0.298	0.001	-0.001	0.023**	-0.021
	(0.042)	(0.061)	(0.312)	(0.196)	(0.006)	(0.005)	(0.011)	(0.022)
β_3		-3.900***		-2.893***		-0.150***		-0.017
		(0.799)		(0.834)		(0.039)		(0.020)
β_4		0.053		0.955**		0.020***		0.040*
		(0.036)		(0.439)		(0.004)		(0.024)
Constant	1.507***	1.498***	0.692***	0.680***	1.590***	1.605***	0.910***	0.882***
	(0.146)	(0.167)	(0.034)	(0.033)	(0.107)	(0.109)	(0.019)	(0.025)
Observations	302	302	2,467	2,467	302	302	2,467	2,467
R-squared	0.508	0.520	0.102	0.123	0.530	0.557	0.340	0.367
F-stat (H_0: $\beta_3 = \beta_4$)		24.05***		13.45***		19.27***		3.04*
p-value		0.000		0.000		0.000		0.081
Panel B: Investment grade								
β_1	1.843***	1.835***	0.590***	0.757***	0.293***	0.306***	0.151***	0.266***
	(0.247)	(0.252)	(0.151)	(0.180)	(0.044)	(0.047)	(0.037)	(0.086)
β_2	-0.106**	-0.103*	0.222	-0.187	0.005	0.003	0.033**	-0.027
	(0.051)	(0.056)	(0.194)	(0.188)	(0.005)	(0.005)	(0.013)	(0.029)

β_3		-6.398**		-2.488***		-0.133***		-0.005
		(2.569)		(0.709)		(0.023)		(0.019)
β_4		-0.004		0.685**		0.004		0.053*
		(0.012)		(0.327)		(0.010)		(0.030)
Constant	1.495***	1.510***	0.652***	0.644***	1.478***	1.478***	0.774***	0.742***
	(0.217)	(0.221)	(0.031)	(0.031)	(0.150)	(0.152)	(0.018)	(0.027)
Observations	302	302	2,467	2,467	302	302	2,467	2,467
R-squared	0.493	0.498	0.097	0.113	0.524	0.536	0.359	0.396
F-stat (H_0: $\beta_3 = \beta_4$)		6.17		13.43***		32.28***		2.47
p-value		0.013		0.000		0.000		0.116
Panel C: High yield (speculative grade)								
β_1	1.627***	1.684***	1.406***	1.470***	0.357***	0.371***	0.186***	0.262***
	(0.216)	(0.202)	(0.284)	(0.276)	(0.076)	(0.075)	(0.031)	(0.054)
β_2	-0.086***	-0.109***	0.024	-0.271**	-0.004	-0.007	0.010	-0.019
	(0.031)	(0.029)	(0.163)	(0.131)	(0.007)	(0.007)	(0.008)	(0.013)
β_3		-2.579***		-7.197***		-0.133***		-0.125***
		(0.473)		(2.040)		(0.037)		(0.035)
β_4		0.031***		0.558***		0.005		0.026*
		(0.006)		(0.153)		(0.004)		(0.015)
Constant	1.885***	1.894***	0.864***	0.869***	1.866***	1.867***	1.255***	1.227***
	(0.257)	(0.226)	(0.036)	(0.036)	(0.137)	(0.136)	(0.025)	(0.027)
Observations	302	302	2,467	2,467	302	302	2,467	2,467
R-squared	0.557	0.569	0.376	0.413	0.528	0.541	0.275	0.297
F-stat (H_0: $\beta_3 = \beta_4$)		3.39***		14.41***		14.43***		13.23***
p-value		0.000		0.000		0.000		0.000
Panel D: Non-rated								
β_1	1.802***	1.917***	1.135***	1.035***	0.216***	0.203***	1.135***	1.035***
	(0.673)	(0.640)	(0.194)	(0.166)	(0.053)	(0.048)	(0.194)	(0.166)
β_2	-0.024	-0.071	-0.029	-0.073**	0.004	0.004	-0.029	-0.073**
	(0.075)	(0.070)	(0.065)	(0.037)	(0.006)	(0.005)	(0.065)	(0.037)
β_3		-1.173***		-2.568***		-0.233***		-2.568***
		(0.354)		(0.513)		(0.062)		(0.513)

β_4		0.068		0.279***		0.015***		0.279***
		(0.041)		(0.066)		(0.004)		(0.066)
Constant	0.953***	0.920***	0.488***	0.518***	1.659***	1.685***	0.488***	0.518***
	(0.326)	(0.312)	(0.041)	(0.040)	(0.107)	(0.105)	(0.041)	(0.040)
Observations	301	301	2,467	2,467	302	302	2,467	2,467
R-squared	0.552	0.567	0.331	0.377	0.436	0.458	0.331	0.377
F-stat ($H_0 : \beta_3 = \beta_4$)		12.46***		33.98***		16.55***		3.98***
p-value		0.000		0.000		0.000		0.000

Table 3.7: Herding conditional on market liquidity in low, medium and high market volatility days. The table presents the coefficient estimates from the following regression: $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D^{LLiq} R_{m,t}^2 + \beta_4 D^{HLiq} R_{m,t}^2 + \varepsilon_t$. The equation is estimated for our full bond and equity samples during low, medium and high market volatility days. We split the full sample period (01/01/2008 – 31/12/2018) into three sub-samples based on the GARCH(1,1) conditional market volatility on day t, where the low (high) volatility sample is defined as the days with lowest (highest) 25% conditional market volatility and the medium volatility sample covers the middle 50% market volatility days (the remaining days that are not included in the low and high sub-samples). Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. $CSAD_t$ is the daily cross-sectional absolute deviation of our US bond (equity) returns and $R_{m,t}$ is their daily equally-weighted average return at time t. $D^{LLiq} = 1$ ($D^{HLiq} = 1$) if the Amihud market liquidity proxy on day t lies in the extreme 5%, 10 and 25% lower (upper) tail of the liquidity distribution and zero otherwise. The liquidity proxy is based on Karolyi, Lee and van Dijk (2012) and is constructed as: $Liq_{i,t} = -log\left(1 + \left(|R_{i,t}|/V_{i,t}\right)\right)$, where $|R_{i,t}|$ and $V_{i,t}$ are the absolute return and the trading volume of bond (stock) i on day t, and the cross-sectional average daily liquidity across bonds (stocks) is obtained as: $Liq_{m,t} = \frac{1}{N}\sum_{i=1}^{N} Liq_{i,t}$. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds								
	25% Low volatility sample			*50% Medium volatility sample*			*25% High volatility sample*		
Liquidity distribution tail (%)	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion
β_1	0.452***	0.520***	1.180***	0.834***	1.026***	0.919***	2.861***	2.780***	2.420***
	(0.141)	(0.148)	(0.231)	(0.226)	(0.244)	(0.240)	(0.125)	(0.147)	(0.206)
β_2	0.361	0.276	-1.093**	-0.412	-1.064***	-1.433***	-2.875***	-3.511***	-5.333***
	(0.297)	(0.288)	(0.509)	(0.339)	(0.406)	(0.530)	(0.348)	(0.678)	(0.994)
β_3	2.018***	2.863**	1.124***	3.926**	3.635***	3.411***	2.564***	3.217***	5.110***
	(0.783)	(1.303)	(0.430)	(1.700)	(0.796)	(0.501)	(0.331)	(0.655)	(0.968)
β_4	-4.799***	-3.668***	-2.625***	-14.169***	-9.531***	-3.216***	-20.175***	-11.792***	-4.955**
	(0.850)	(0.762)	(0.423)	(1.994)	(1.652)	(0.650)	(5.136)	(2.317)	(2.011)
Constant	0.573***	0.571***	0.534***	0.729***	0.723***	0.730***	0.961***	0.973***	1.045***
	(0.026)	(0.027)	(0.027)	(0.036)	(0.035)	(0.036)	(0.144)	(0.145)	(0.066)
Observations	693	693	693	1,384	1,384	1,384	692	692	692
R-squared	0.170	0.217	0.258	0.099	0.168	0.266	0.494	0.528	0.522
	Stocks (Equity)								
β_1	0.052	0.053	0.066	0.131***	0.123***	0.149***	0.315***	0.292***	0.242***
	(0.040)	(0.041)	(0.047)	(0.033)	(0.034)	(0.035)	(0.056)	(0.075)	(0.070)
β_2	0.042**	0.042**	0.024	0.018	0.020	-0.012	-0.021	-0.026	-0.034
	(0.019)	(0.019)	(0.025)	(0.013)	(0.015)	(0.018)	(0.015)	(0.026)	(0.039)
β_3	-0.050***	-0.013	0.029*	0.044*	0.014	0.034***	0.026**	0.032	0.045
	(0.010)	(0.046)	(0.018)	(0.023)	(0.015)	(0.012)	(0.013)	(0.020)	(0.034)
β_4	-0.344***	-0.163**	-0.006	-0.125*	-0.120*	-0.107**	-0.173***	-0.192***	-0.071
	(0.103)	(0.070)	(0.048)	(0.074)	(0.063)	(0.047)	(0.033)	(0.056)	(0.083)

Constant	0.884***	0.883***	0.878***	0.927***	0.931***	0.930***	1.275***	1.296***	1.326***
	(0.023)	(0.024)	(0.023)	(0.016)	(0.016)	(0.016)	(0.073)	(0.076)	(0.076)
Observations	693	693	693	1,384	1,384	1,384	692	692	692
R-squared	0.085	0.080	0.079	0.215	0.210	0.221	0.458	0.454	0.444

Table 3.8: Herding conditional on market volatility in low, medium and high liquidity days. The table presents the coefficient estimates from the following regression: $CSAD_t = \beta_0 + \beta_1|R_{m,t}| + \beta_2 R_{m,t}^2 + \beta_3 D^{LVol} R_{m,t}^2 + \beta_4 D^{HVol} R_{m,t}^2 + \varepsilon_t$. The equation is estimated for our full bond and equity samples during low, medium and high market volatility days. We split the full sample period (01/01/2008 – 31/12/2018) into three sub-samples based on Amihud market liquidity proxy on day t, where the low (high) liquidity sample is defined as the days with lowest (highest) 25% market liquidity and the medium liquidity sample covers the middle 50% market liquidity days (the remaining days that are not included in the low and high sub-samples). Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. $CSAD_t$ is the daily cross-sectional absolute deviation of our US bond (equity) returns and $R_{m,t}$ is their daily equally-weighted average return at time t. $D^{LVol} = 1$ ($D^{HVol} = 1$) if the GARCH(1,1) conditional market volatility on day t lies in the extreme 5%, 10 and 25% lower (upper) tail of the volatility distribution and zero otherwise. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	25% Low liquidity sample			*50% Medium liquidity sample*			*25% High liquidity sample*		
Volatility distribution tail (%)	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion	5% criterion	10% criterion	25% criterion
Corporate bonds									
β_1	1.760***	2.296***	2.025***	0.305***	0.339***	0.306***	0.110	0.042	0.119
	(0.321)	(0.215)	(0.277)	(0.091)	(0.091)	(0.090)	(0.095)	(0.086)	(0.080)
β_2	-0.160**	-2.817***	-4.389***	0.017	-0.069	-0.020	0.622**	0.904***	0.756***
	(0.081)	(0.568)	(1.050)	(0.164)	(0.154)	(0.154)	(0.264)	(0.223)	(0.222)
β_3	-22.515***	-5.050**	1.502**	-0.813**	-0.893**	-0.371**	-0.792***	-0.806***	-0.617***
	(5.536)	(2.014)	(0.742)	(0.330)	(0.406)	(0.184)	(0.245)	(0.176)	(0.165)
β_4	0.082	2.611***	4.237***	0.198	0.296*	0.244	3.449***	1.694***	0.278
	(0.067)	(0.528)	(0.997)	(0.154)	(0.154)	(0.151)	(0.204)	(0.594)	(0.267)
Constant	1.282***	1.287***	1.330***	0.726***	0.724***	0.726***	0.509***	0.512***	0.509***
	(0.101)	(0.115)	(0.116)	(0.021)	(0.022)	(0.022)	(0.015)	(0.015)	(0.015)
Observations	693	693	693	1,384	1,384	1,384	692	692	692
R-squared	0.427	0.511	0.490	0.063	0.067	0.069	0.143	0.169	0.153
Stocks (Equity)									
β_1	0.281***	0.377***	0.295***	0.077	0.071	0.151***	-0.109	-0.105	0.060
	(0.075)	(0.082)	(0.076)	(0.053)	(0.050)	(0.055)	(0.073)	(0.070)	(0.055)
β_2	-0.005	-0.064**	-0.078**	0.039	0.038	-0.035	0.262***	0.266***	0.056
	(0.014)	(0.027)	(0.033)	(0.032)	(0.030)	(0.025)	(0.077)	(0.074)	(0.066)
β_3	-0.032*	-0.034	-0.055	-0.047**	-0.066**	-0.047*	-0.223**	-0.139**	-0.057
	(0.017)	(0.029)	(0.036)	(0.024)	(0.028)	(0.024)	(0.105)	(0.068)	(0.044)
β_4	0.018**	0.063***	0.085***	0.144***	0.115***	0.105***	0.570***	0.569***	0.182**
	(0.008)	(0.019)	(0.026)	(0.022)	(0.033)	(0.033)	(0.211)	(0.211)	(0.078)
Constant	1.137***	1.111***	1.180***	0.994***	0.997***	0.981***	0.913***	0.912***	0.891***
	(0.100)	(0.104)	(0.104)	(0.028)	(0.028)	(0.030)	(0.021)	(0.020)	(0.018)
Observations	693	693	693	1,384	1,384	1,384	692	692	692
R-squared	0.450	0.497	0.483	0.147	0.154	0.184	0.095	0.098	0.115

Table 3.9: Testing for cross-herding spillover effects between US corporate bond and equity markets. The table presents the coefficient estimates from the following regressions:

$$CSAD_{B,t} = \beta_0 + \beta_1 \left|R_{Bm,t}\right| + \beta_2 R^2_{Bm,t} + \beta_3 CSAD_{S,t} + \beta_4 R^2_{Sm,t} + \varepsilon_{B,t}$$

$$CSAD_{S,t} = \gamma_0 + \gamma_1 \left|R_{Sm,t}\right| + \gamma_2 R^2_{Sm,t} + \gamma_3 CSAD_{B,t} + \gamma_4 R^2_{Bm,t} + \varepsilon_{S,t}$$

The equations are estimated using two stage least squares over the full period (01/01/2008 – 31/12/2018) for our bond and equity samples and credit rating portfolios. Numbers in parentheses are the Huber-White heteroscedasticity robust standard errors. $CSAD_t$ is the daily cross-sectional absolute deviation of our US Bond (subscripted B) and Stock (subscripted S) returns and $R_{m,t}$ is the respective daily equally-weighted average return at time t. The Chi^2 is the Wald statistic of the joint significance of the parameters W ~ χ^2(4), with the exception of the constant. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds					Stocks (Equity)			
	Full Sample	*Investment Grade*	*Speculative Grade*	*Non-rated*		*Full Sample*	*Investment Grade*	*Speculative Grade*	*Non-rated*
β_1	0.690***	0.540***	1.008***	0.982***	γ_1	0.135***	0.136***	0.134***	0.148***
	(0.096)	(0.091)	(0.111)	(0.182)		(0.020)	(0.023)	(0.020)	(0.019)
β_2	0.048	0.102***	-0.036**	0.056	γ_2	0.006*	0.010**	0.003	0.012***
	(0.033)	(0.034)	(0.015)	(0.051)		(0.004)	(0.004)	(0.003)	(0.003)
β_3	0.898***	0.889***	0.862***	1.095***	γ_3	0.553***	0.576***	0.433***	0.259***
	(0.073)	(0.081)	(0.119)	(0.164)		(0.037)	(0.050)	(0.030)	(0.037)
β_4	-0.003	-0.007	-0.000	-0.020**	γ_4	-0.076***	-0.099***	-0.021*	-0.033***
	(0.005)	(0.006)	(0.005)	(0.008)		(0.019)	(0.016)	(0.011)	(0.012)
Constant	-0.235***	-0.119*	-0.276*	-0.680***	Constant	0.530***	0.394***	0.844***	0.819***
	(0.068)	(0.067)	(0.153)	(0.164)		(0.026)	(0.033)	(0.029)	(0.024)
Observations	2,769	2,769	2,769	2,768	Observations	2,769	2,769	2,769	2,768
R-squared	0.757	0.760	0.724	0.583	R-squared	0.762	0.769	0.669	0.480
Chi^2	1778.72***	1409.19***	2413.35***	480.57***	Chi^2	2338.82***	1757.73***	2027.88***	1107.97***

Table 3.10: Testing for cross-asset herding spillover effects in crisis and post-crisis periods. The table presents the coefficient estimates from the following regressions:

$$CSAD_{B,t} = \beta_0 + \beta_1 |R_{Bm,t}| + \beta_2 R^2_{Bm,t} + \beta_3 CSAD_{S,t} + \beta_4 R^2_{Sm,t} + \varepsilon_{B,t}$$

$$CSAD_{S,t} = \gamma_0 + \gamma_1 |R_{Sm,t}| + \gamma_2 R^2_{Sm,t} + \gamma_3 CSAD_{B,t} + \gamma_4 R^2_{Bm,t} + \varepsilon_{S,t}$$

The equations are estimated using two stage least squares over the crisis period 01/01/2008 – 15/03/2009 and post-crisis period 16/03/2009 – 31/12/2018, for our bond and equity samples and credit rating portfolios. Numbers in parentheses are the Huber-White heteroscedasticity robust standard errors. $CSAD_t$ is the daily cross-sectional absolute deviation of our US Bond (subscripted B) and Stock (subscripted S) returns and $R_{m,t}$ is the respective daily equally-weighted average return at time t. The Chi^2 is the Wald statistic of the joint significance of the parameters W ~ χ^2 (4), with the exception of the constant. *, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Corporate bonds					Stocks (Equity)			
	Full Sample	*Investment Grade*	*Speculative Grade*	*Non-rated*		*Full Sample*	*Investment Grade*	*Speculative Grade*	*Non-rated*
					Crisis period				
β_1	1.052***	0.892***	0.730***	1.154**	γ_1	0.180***	0.168***	0.203***	0.142***
	(0.199)	(0.221)	(0.170)	(0.474)		(0.045)	(0.051)	(0.061)	(0.054)
β_2	-0.037	0.026	-0.019	0.032	γ_2	0.002	0.006	-0.002	0.009
	(0.038)	(0.047)	(0.025)	(0.060)		(0.005)	(0.006)	(0.006)	(0.005)
β_3	0.969***	0.886***	1.334***	2.112***	γ_3	0.383***	0.445***	0.294***	0.158***
	(0.176)	(0.209)	(0.215)	(0.590)		(0.067)	(0.099)	(0.073)	(0.056)
β_4	-0.007	-0.009	-0.010	-0.047***	γ_4	-0.042**	-0.072***	-0.007	-0.020**
	(0.006)	(0.009)	(0.007)	(0.016)		(0.018)	(0.020)	(0.015)	(0.009)
Constant	-0.246	0.005	-0.962**	-2.730***	Constant	0.994***	0.795***	1.320***	1.432***
	(0.295)	(0.328)	(0.443)	(0.988)		(0.105)	(0.150)	(0.132)	(0.073)
Observations	302	302	302	301	Observations	302	302	302	301
R-squared	0.782	0.752	0.741	0.516	R-squared	0.749	0.734	0.718	0.462
Chi^2	663.20***	509.02***	644.50***	93.38***	Chi^2	594.03***	440.12***	510.82***	329.52***
					Post-crisis period				
β_1	0.331***	0.292**	0.874***	0.921***	γ_1	0.094**	0.083*	0.111***	0.123***
	(0.128)	(0.138)	(0.164)	(0.105)		(0.040)	(0.046)	(0.018)	(0.018)
β_2	0.034	0.035	0.017	0.004	γ_2	0.019***	0.030***	0.007**	0.014***
	(0.242)	(0.263)	(0.116)	(0.060)		(0.006)	(0.009)	(0.003)	(0.005)
β_3	0.916***	0.982***	0.781***	0.859***	γ_3	0.456*	0.420	0.381***	0.150***

	(0.093)	(0.127)	(0.202)	(0.172)		(0.237)	(0.281)	(0.058)	(0.033)
β_4	-0.014***	-0.024**	-0.008	-0.014*	γ_4	0.044	0.018	0.010	-0.020**
	(0.005)	(0.010)	(0.009)	(0.008)		(0.303)	(0.306)	(0.061)	(0.009)
Constant	-0.207**	-0.164	-0.152	-0.397**	Constant	0.600***	0.504***	0.893***	0.877***
	(0.088)	(0.101)	(0.257)	(0.175)		(0.150)	(0.169)	(0.053)	(0.023)
	2,467	2,467	2,467	2,467	Observations	2,467	2,467	2,467	2,467
Observations	0.398	0.372	0.449	0.347	R-squared	0.541	0.557	0.423	0.298
R-squared	693.29***	545.62***	788.15***	463.58***	Chi^2	877.14***	649.39***	997.23***	540.55***

4 The effect of Brexit news announcements: Evidence from UK and Eurozone government bond and equity markets

4.1 Introduction

On 23 June 2016, the United Kingdom (UK) held a referendum vote[40] to exit the European Union (EU). Most of the participating voters (51.9% versus 48.1%) voted in favour of leaving the EU, which led the UK to plan the process of their way out of the EU, known as "Brexit". The unexpected result of the Brexit referendum is undeniably one of the major events since the Global Financial Crisis of 2007-2008 that is and will continue to shape the UK economic policy for decades. The effect of the vote was instantly observed the following morning, 24 June, as the value of the British Pound (GBP) against the US Dollar (USD) dropped by a dramatic 10% reaching its lowest record since 1985. On a global scale, the stock markets lost more than US$2 trillion with the FTSE 100 losing approximately £85 billion (Samitas and Kampouris 2018). Specifically, the EU banking industry stocks suffered more substantial losses due to the referendum than to Lehman Brothers' bankruptcy (Schiereck, Kiesel and Kolaric 2016).

Less than a year after the EU referendum, the UK triggered Article 50 of the Treaty on European Union on 29 March 2017 and started the lengthy process of UK-EU Brexit negotiations. After 47 years of membership and three extensions to the Brexit date, the UK officially left the European Union on 31 January 2020 and entered an 11-month transition period. Until the end of 2020, it was still not clear as to what deal the UK will be able to strike with the EU. Hence, it is no surprise that the Brexit accelerated the political and economic uncertainty as well as raised social concerns in the UK and EU. As a result, there has been a growing number of academic literature investigating the impact of Brexit on for example, GDP (Born et al. 2019), inflation (Breinlich et al. 2019), foreign exchange (Dao, McGroarty and Urquhart 2019; Andrikopoulos, Dassiou and Zheng 2020), stock markets (Samitas and Kampouris 2018; Davies and Studnicka 2018; Nishimura and Sun 2018), foreign direct investments (Breinlich et al. 2020) and other (Hudson, Urquhart and Zhang 2020). The research up to date, confirm the significance of the Brexit vote, particularly in the short-term. Nevertheless, most of the literature focuses on the impact of one or two major events, the EU referendum and the subsequent invocation of Article 50. To our knowledge there are only four studies that examine a few additional Brexit related events leading up to the triggering of Article 50 (Davies and Studnicka 2018; Kadiric and Korus 2019; Shahzad et al. 2019; Hudson, Urquhart and Zhang 2020). Davies and Studnicka (2018) and Shahzad et al. (2019) show that Brexit related events adversely affect the returns of UK firms, whilst Kadiric and Korus (2019) find that they influence the risk conditions in UK and Eurozone corporate bond markets.

[40] Commonly referred to as the EU referendum or the Brexit referendum.

Nevertheless, the markets seem to react more severely to the EU referendum. Interestingly, Shahzad et al. (2019) highlight that there is a distinction in the markets' reaction during pre and post-referendum Brexit events. In a more recent study, Hudson, Urquhart and Zhang (2020) demonstrate that Brexit events negatively affect the risk and returns of stock indices, though the returns on event days are for the most part explained by the risk and the risk premium associated with those days. The studies show that Brexit events could have severe impact on markets and should be explored further to understand the extend of the effects and investigate which news are likely to affect markets more than other.

Motivated by the significance of Brexit internationally and the impact of political and economic policy events on financial markets (Białkowski, Gottschalk and Wisniewski 2008; Boutchkova et al. 2012; Pástor and Veronesi 2012; Karanasos and Yfanti 2020; Ma, Wang and He 2020) we examine and compare the effect of a wide range of Brexit-related news on UK and Eurozone government bond and equity markets. Since the effects of news tend to be more prominent on volatility in comparison to prices, we focus our study on the effects of the Brexit-related news on market volatility. Against this background, our research aims at addressing the following three main research questions: i) Do Brexit news announcements affect UK and Eurozone government bond and equity market volatilities? ii) Which Brexit news category(ies) influence the market volatilities most? iii) How do the Brexit news categories contribute to the market volatilities?

To address our research questions, we employ an extension of Corsi's (2009) Heterogeneous Autoregressive model (HAR) to model the volatility of the UK and Eurozone government bond and equity markets from 1 April 2010 to 28 February 2020. In order to capture the news' impact more sensitively that are likely to cause market turbulences with drops and recoveries, we avoid the use of traditional close-to-close volatility estimates that fail to reflect the information content between the one closing price and another. Hence, we estimate the volatility using two measures: Parkinson's (1980) high-low range estimator and realised volatility; though due to data availability constraints our sovereign bond sample is limited to the high-low range volatility estimator. The initial tests combining all Brexit news together show that the arrival of Brexit news announcements significantly increase the level of Eurozone's sovereign bond volatilities and UK stock market volatility. What is more, we find that the Brexit news announcements' effect in sovereign bond markets extend beyond the announcement day, where half of the markets anticipate the arrival of the news one day before their announcement. Another important finding of our study is that we capture a greater response to the news in the government bond markets. Classifying the news into five different categories enabled us to get greater insights into the impact and significance Brexit news. We show that government bond and equity market volatilities react to most news categories, but the magnitude and direction of their reaction to them varies. Unexpectedly, the strongest volatility responses are captured with the arrival of UK votes and political news, whereas the weakest ones to the UK Brexit news. Similar to our initial tests, we find that the different categories of news announcements induce greater market uncertainty (risk) on the news reporting day and detect some leading and lagging effects of the news. Contrary to our expectations, we observe that the impact of Brexit news is more pronounced in Eurozone countries.

Our contribution and proportion analysis further highlight the importance of UK votes and political news for both markets, as they account for more than 55% of the volatility responses to all Brexit news. In addition, the contribution analysis show that, apart from UK votes, all Brexit news categories have a destabilising effect on the UK and EU markets across the 3-day event window. The equity results based on the high-low range and realised volatility estimators are for the most part consistent, though the latter provides a better-fit model and exhibit greater responses to the news. Hence, we encourage the use of the realised volatility measure based on intra-day data (when available) in order to increase the estimation accuracy and limit the adverse effects of market microstructure frictions. Our findings provide new evidence of the significance of Brexit news carrying valuable information for both markets and highlight the importance of recognising and studying the effect of Brexit and other political votes and news, beyond the EU referendum and elections, on the UK and mainly EU markets by all market participants. They also show that global news announcements are no less valuable than local ones, which in turn signifies the prevailing close ties between the UK and Eurozone.

This chapter contributes to the literature in three distinct ways: *Firstly*, we explore the effect of a wide range of Brexit related events (151 news announcements) spanning from the early mention of the possibility of holding an EU referendum in 2013 up to the Brexit date – 31 January 2020. *Secondly*, we allow for more detailed analysis of the impact of the events by classifying the news into five broad categories: UK Brexit, EU Brexit, UK votes, UK political and industry response. Hence, we include a variety of news which includes Brexit news announcements from the UK as well as the EU side, different crucial votes, the appointment and resignation of key figures amid the Brexit uncertainty and news reported from different industries as a response to the Brexit. As a result, the news captures the direct and indirect Brexit news announcements. We believe that this categorisation enables us to grasp a greater understanding of the type(s) of Brexit related news that the markets more are sensitive to and should be observed more closely. Hence, in comparison to prior literature that examine a handful of Brexit events or uses a single Economic Policy Uncertainty Index combining all news together, our approach is considered more comprehensive and detailed.

Thirdly, we examine and compare the impact of Brexit events on the volatilities of not only equity markets, but also government (sovereign) bonds that have not been explored in the context of Brexit. This contribution is motivated by the sensitivity of sovereign bonds to public news announcements. Studies have shown that government bond prices and volatility are sensitive to public news announcements, namely macroeconomic news (Balduzzi, Elton and Green 2001; de Goeij and Marquering 2006), with the effects on volatility being more prominent and persistent than on prices

(Fleming and Remolona 1999; Nowak et al. 2011). In fact, given the responsiveness of government bond markets to news announcements, studies have used their yields and implied volatility as a proxy for macro-effects (see e.g. Karanasos and Yfanti 2020). Therefore, our research extends the existing literature by examining the effect of another type of public news (Brexit) that influences the macroeconomic conditions in the UK and EU on the volatility of government bond markets and compare it to equities. Although the literature document that the government bond markets seem to adjust to the public news relatively quickly, they also show that bond market responses vary depending on the type of the macroeconomic news and the element of surprise it carries, which draws the attention to the importance of distinguishing between the types of news (de Goeij and Marquering 2006).

The remainder of the chapter is organised as follows: Section 4.2 provides a literature review. Section 4.3 describes the applied methodology and 4.4 the sample data. Section 4.5 discusses the empirical findings and implications and Section 4.6 concludes the chapter.

4.2 Literature review

4.2.1 News announcement literature

A sizable amount of literature investigates financial markets' reactions to different news releases or events. The seminal event studies (Ball and Brown 1968; Fama et al. 1969) examine whether the market efficiently incorporates information. Since the late 1970's, numerous event studies have been published (for a detailed review see Binder 1998; MacKinlay 1997; Kothari and Warner 2007; Corrado 2011) focusing on various news announcements including: macroeconomic news (Schwert 1981; McQueen and Roley 1993; Andersen and Bollerslev 1998), stock splits (Fama et al. 1969; Ikenberry, Rankine and Stice 1996; Chern et al. 2008), dividend and earnings announcements (Charest 1978; Anderson 2009), public information (Mitchell and Mulherin 1994), political and financial news (Pantzalis, Stangeland and Turtle 2000; Białkowski, Gottschalk and Wisniewski 2008; Kutan, Muradoglu and Sudjana 2012; Beetsma et al. 2013; Kosmidou, Kousenidis and Negakis 2015) among other studies.

A heterogeneous news impact upon asset classes is observed. For instance, firm specific news mainly affect stock markets, whilst macroeconomic ones drive government bonds (McQueen and Roley 1993; Fleming and Remolona 1999; Andersen et al. 2007). This is not a surprise as macroeconomic factors are the main determinants of the yield curve that directly affect government (sovereign) bond prices. Whilst news is typically unpredictable, some announcement releases, especially macroeconomic ones, are known. Hence, studies distinguish between pre-scheduled and non-scheduled news (de Goeij and Marquering 2006).

Balduzzi, Elton and Green (2001) analyse the effects of scheduled macroeconomic news releases on the prices, trading volume and bid-ask spreads of three treasury instruments: three-month treasury bill, two-year note and 30-year bonds. Utilising the announcement values and expectations from the Money

Market Services (MMS) forecast surveys, they construct a standardised measure of surprises (unexpected shocks) of the announcements. Using regression techniques we find that a total of 17 news announcements have a significant effect on at least one of the treasury instruments. They also observe persistent increase in price volatility and trading volume post-announcements. What is more, the news is found to have a high explanatory power in explaining the post-announcement price volatility. Using a similar methodology, Beechey and Wright (2009) show that long-term nominal yields and forward rates are sensitive to macroeconomic news, whilst inflation compensation is sensitive to price indices and monetary policy announcements.

Andersen et al. (2003b) argue that while OLS would yield consistent parameters, the disturbance terms for high-frequency (5-minute) return regressions are heteroskedastic. Hence, to improve the efficiency of the coefficient estimates they first estimate the conditional mean equation using OLS, then estimate time-varying volatility using the absolute values of the regression residuals, which is subsequently utilised to run weighted least squares estimation of the returns. Their findings suggest that high-frequency US dollar spot exchange rates dynamics are related to fundamentals as the news surprises cause conditional mean jumps. In line with prior literature, they further show that the market reaction to news is rather asymmetric, bad news has stronger effects than good ones. Similarly, Andersen et al. (2007) prove that US, German and UK stock, bond and exchange rate dynamics are also linked to macroeconomic fundamentals as their news systematically produce jumps in their conditional means. Moreover, their results further provide evidence that support the view that Treasury bond markets exhibit the strongest reaction to macroeconomic news. Nowak et al. (2011) find comparable results in emerging bond markets, where the price response to the selected macroeconomic news surprises is nearly instantaneous. However, the effects of the news on volatilities seem to be more pronounced and last longer in comparison to the prices. Furthermore, they show that global and regional news are not less important than local ones, signifying the close ties between emerging and developed economies.

Jiang, Konstantinidi and Skiadopoulos (2012) extend on the above studies and examine the impact of scheduled and unscheduled economic and other news announcements on the transmission of implied volatilities across the US and European stock markets. They detect an interesting contrast between the two types of news, where scheduled (unscheduled) news announcements are found to resolve (generate) information uncertainty causing a drop (surge) in implied volatility. In addition, they show that although the announcements influence the intensity of the observed implied volatility spillovers, they do not fully explain them, which in turn provides evidence of volatility of contagion.

Focusing on the dynamics of conditional volatility, some new announcement studies base their work on ARCH and GARCH models developed by Engle (1982) and Bollerslev (1986). For instance, to test for the reaction of US Treasury futures to macroeconomic announcements Li and Engle (1998) apply a filtered GARCH model that incorporates dummy variables in the conditional volatility equation for each of the following: the time-of-the-week effects, pre-announcement days and announcement days. Their findings reveal heterogeneous persistence from scheduled versus unscheduled announcements, and particularly stronger persistence after bad news. They present evidence of strong asymmetric effects from scheduled announcements, where positive (negative) shocks reduce (increase) volatility on successive days. News release day shocks show little persistence, but immense influence on volatilities in the short-run. In addition, they fail to find statistically significant risk premium for macroeconomic news release dates.

Similarly, using GARCH(1,1) model Jones, Lamont and Lumsdaine (1998) investigate the reaction of US Treasury bond prices to scheduled producer price index (PPI) and employment data releases by the US government. Their results also show that bond market volatilities surge on announcement days but do not persist, suggesting that bond prices immediately incorporate the scheduled information. Comparable results are also found in Ederington and Lee (1993) and Fleming and Remolona (1999). Extending on prior literature, Christiansen (2000) studies the effects of macroeconomic announcements not only on conditional variances, but also on covariances and correlation coefficients of US government bond returns. Their multivariate GARCH results show that news announcements significantly increase all three, proposing that macroeconomic news promote common movement in the bond market. More recently, de Goeij and Marquering (2006) explore the relationship between announcements and asymmetric volatility of bond returns. Using an extended GJR specification they confirm that conditional variances increase on announcement days, but do not persist. Focusing on euro/dollar FOREX returns, Bauwens, Ben Omrane and Giot (2005) EGARCH model results indicate that during pre-announcement periods volatility tends to rise, mainly before scheduled events. Rangel (2011) presents an alternative approach, a Poisson–Gaussian-GARCH process with time-varying jump intensity, to examine the effects of schedules news releases on stock market volatility. Contrary to prior literature, the results indicate that announcement days, apart from unemployment announcements, do not have a great impact on stock market conditional volatility. Only after considering the surprise component of the fundamental news, their effects become more significant.

Lyócsa, Molnár and Plíhal (2019) argues that GARCH models based on a single observation per day does not estimate the volatility accurately. Furthermore, they question the suitability of implied volatilities for studying the impact of the event day of scheduled announcements, as the daily value of implied volatilities measure the 30-day forward looking (expected) volatility and thus should decrease making it difficult to identify the stabilising (destabilising) effect of the news. As a result, they base their research on realised volatilities that are calculated using high-frequency data and assess the effect of monetary policy news releases on them. They apply a variant of Heterogeneous Autoregressive model (HAR) with exogenous variables and GARCH errors and find that the realised volatilities significantly increase on the day of an interest rate announcement but decrease in the five days after it. Their results are consistent across all the developed countries in their sample.

Furthermore, studies also explore the effect of announcements on volatility spillovers. For example, Kim and Nguyen (2009) investigate the effects of the US Fed and the European Central Bank target interest rate news announcements on the returns and volatilities of 12 Asian Pacific stock markets. Their results show that most stock markets significantly and negatively react to unexpected rate rises. Interestingly, they detect higher responses of return volatilities to the interest rate news from both sources, where some of these responses are delayed or persistent. Similar studies extend to other asset classes such as, bond markets (Antonakakis and Vergos 2013), foreign exchange markets (Ben Omrane and Hafner 2015), commodities (Hamadi, Bassil and Nehme 2017), cryptocurrencies (Corbet et al. 2020) and other.

From the above discussion, it is evident that different types of news could have significant impact on financial markets. In addition, it appears that different asset classes respond to certain news announcements more than other. Lastly, the studies also show that the volatility responses seem to be more pronounced and persistent than returns. Hence, this highlights the importance of comparing of the volatility responses of different asset classes to news.

4.2.2 Political events literature

Previous literature shows that political factors and political uncertainty may influence the returns and volatility of financial assets (Pantzalis, Stangeland and Turtle 2000; Białkowski, Gottschalk and Wisniewski 2008; Chau, Deesomsak and Wang 2014). A large proportion of the studies that examine the effects of political cycles and presidential elections focus on the US stock market (Niederhoffer, Gibbs and Bullock 1970; Riley and Luksetich 1980; Johnson, Chittenden and Jensen 1999; Nippani and Medlin 2002; Santa-Clara and Valkanov 2003; He et al. 2009). Early US studies, such as Niederhoffer, Gibbs and Bullock (1970) and Riley and Luksetich (1980) provide evidence suggesting that the US stock markets are affected by presidential elections in the short-run; where the markets tend to rise after the win of a Republican candidate and fall after the election of a Democratic one. On the other hand, Pantzalis, Stangeland and Turtle (2000) examine the stock market behaviour around political elections in an international scale, a total of 33 countries, from 1974 to 1995 and evidence positive abnormal returns in the two weeks prior to the election. They show that the positive reaction depends on the country's degree of political, economic and press freedom, as well as the election timing and the success of the current candidate being re-elected. Studies also show that the effect of US presidential elections and cycles transmit to international stock returns (Foerster and Schmitz 1997; Nippani and Arize 2005)

Focusing on the long-run effect, Santa-Clara and Valkanov (2003) find that stock markets exhibit higher excess returns under Democratic presidencies, than those observed during Republican presidencies which is known as the presidential puzzle. Interestingly, they show that the difference is not justified with business cycle variables nor is intensified around election periods. In another study, Li and Born (2006) uses candidate preference (i.e. polling) data from US presidential elections between

1964-2000, and document a rise in average daily stock returns approximately three months prior to a presidential election that has uncertain outcome. Conversely, Döpke and Pierdzioch (2006) detect weak evidence of the impact of political process on German stock market returns between 1960-2003. Nevertheless, their results indicate that, unlike the US, German stock market returns tend to be higher under right-wing governments than under left-wing ones. In addition, their VAR-based results suggest that stock market returns impacted the popularity of German governments.

In contrast to the above, more recent studies fail to find robust evidence of an association between stock returns and different presidencies or partisan control of the government after controlling for estimation biases (Powell et al. 2007; Jones and Banning 2009; Sy and Al Zaman 2011). For example, Sy and Al Zaman (2011) show that the systematic risk varies across presidential cycles and attribute the presidential puzzle to the difference in market and size premiums though the cycles.

While numerous studies examine the relationship between elections or political cycles and stock returns, surprisingly only a few studies investigate the effect of elections on market volatility. For example, Białkowski, Gottschalk and Wisniewski (2008) study the stock market volatility of 27 OECD counties and find that the country-specific component of volatility may double in the week around an election. They argue that despite the efforts of predicting election outcomes, market participants are still surprised by the results which is reflected in the strong response of stock market prices. They identify several factors that influence the magnitude of the election shock, including the margin of victory, the absence of compulsory voting laws, changes in the political orientation of the government and the inability to form a government with parliamentary majority. In addition, they find evidence suggesting that market indices with limited trading history exhibit a stronger response. Boutchkova et al. (2012) show that certain industries tend to be more sensitive to political events than others. In particular, industries that rely more heavily on trade, contract enforcement and labour experience higher volatility during periods of higher local political risks. Notably, global political uncertainty, for example elections and elevated political risk in trading partner countries influence the level of volatility in trade-dependent domestic industries. Adapting the implied volatility as a measure of stock market volatility (risk), Goodell and Vähämaa (2013) documents a positive association between the VIX volatility index and the changes in the probability of success of the eventual winner over five US presidential elections between 1992 and 2008. Their findings hold even after controlling for the changes in the overall election uncertainty, which suggests that elections may imperil stock market anxiety.

Studies explored other political factors, beyond elections and presidential terms. For instance, Pástor and Veronesi (2012) investigate how the changes in government policy affect stock prices and note that they often decrease stock prices on announcement day. They argue that the magnitude of the adverse effect depends on the extent of uncertainty about government policy and whether the event is preceded by a short or shallow downturn. In another study, Chau, Deesomsak and Wang (2014) test the influence of the increased political uncertainty due to the Arab Spring on the volatility of major MENA stock markets. Their GARCH results reveal differences amongst their samples, where the volatility of Islamic indices significantly increased with the surge in political unrest. On the other hand, the increased political uncertainty seems to have little or no impact on the volatility of conventional indices. Using the economic policy uncertainty (EPU) index, Ma, Wang and He (2020) examine the dynamic and frequency spillover between EPU and the realised volatility of the G7 stock markets. They find strong evidence of spillover effects of EPU on market volatilities, which have regional patterns and seem to last longer (3-18 months) in France, Germany and Italy. More importantly, they show that significant economic events, such as the global financial crisis and Brexit amplify the observed spillover level and duration. Lastly, Karanasos and Yfanti (2020) find that UK Policy Uncertainty (measured by the EPU), credit crunch and commodity factors drive EU stock market volatility and can potentially distort financial stability.

To summarise, a large number of studies examine the effect of elections and political cycles on markets, with a focus on the US market. However, a growing number of more recent studies explore the relationship between political uncertainty and financial markets, with emphasis on market volatilities. Nevertheless, a great deal of those approximate political uncertainty with available indices such as the EPU index that captures the ‘broad’ concept of economic uncertainty utilising news from the digital archives of the Access World News NewsBank service. Overall, the studies prove that political uncertainty seems to amplify market volatility and contribute to some spillover effects that could be relatively long-lasting.

4.2.3 Brexit literature

Since the Brexit referendum, a new stream of literature has emerged taking different directions to study the effect of Brexit on financial markets. For instance, Schiereck, Kiesel and Kolaric (2016) find that the short-run decline of stock prices, especially for EU banks, as a reaction to the Brexit referendum announcement is more severe than the one observed to Lehman Brother’s bankruptcy filing. Focusing on the period 1 April to 22 June 2016 leading up to the referendum, Belke, Dubova and Osowski (2018) examine the effect of the Brexit probability on UK and international stock returns, sovereign CDS and 10-year interest rates. They employ two measures of the perceived probability of Brexit prior to the vote: the online betting exchange (Betfair) data and results of surveys (polls) published by Bloomberg. Their panel and single-country Seemingly Unrelated Regressions (SUR) results indicate that increases in the probability of a Brexit happening have strong effects on EU stock markets. Conversely, the impacts of the probability of Brexit on long-term interest rates and CDS seem to be heterogeneous, which is likely to be due to the differences in their sovereign credit risk. They conclude that the Brexit is likely to carry on promoting policy uncertainty and market instability, which in turn could cause a damage to the real economy in the UK and other EU countries.

Ramiah, Pham and Moosa (2017) conduct and event study to examine the impact of the referendum on different UK sectors across June - July 2016 period. They show that the effect of the referendum is sector specific, with the banking and travel sectors being most negatively affected. In another event study, Oehler, Horn and Wendt (2017) demonstrate that after the referendum firms with higher percentages of domestic sales i.e. a lesser degree of internationalisation, generated more short-term negative abnormal returns than those with higher levels of internationalisation. However, this finding is mainly observed in the first few minutes of the day following the vote and quickly disappears on the next day.

Similarly, Davies and Studnicka (2018) find that the referendum's unexpected results adversely affected most FTSE 350 firm returns. In addition, their event study of the referendum and five other Brexit related events, including the triggering of Article 50, yields three other key findings. First, they show that firms with predominantly European global value chain structure or rely on imported intermediates, perform worse than the rest of the market. However, the latter is partially offset though intra-firm trade in intermediaries. Second, the primary stock market reactions are observed during the first two days following the announcement of the vote's result but were persistent over long event windows (up to four weeks). Lastly, they detect weaker market reactions to the events succeeding the referendum and argue that it could be due to the market's greater anticipation of them. Using a wider selection of Brexit events, Shahzad et al. (2019) explore the UK's stock market response to a total of 27 events related to the likelihood of Brexit. Their event study indicates that the general reaction of the market to these events is negative. However, they reveal a distinction between the market responses before and after the EU referendum. They observe a negative and significant reaction to the events leading up to and including the referendum, whereas they detect a positive reaction to the events after the referendum. They argue that their results support the view that post referendum the future economic relationship between the UK and EU started to gain some clarity, which could have caused the positive responses.

Focusing on the currency markets, Plakandaras, Gupta and Wohar (2017) study the impact of the Brexit vote on the sudden plunge in the USD/GBP exchange rate (FX). They debate that their daily exchange rate forecasts accounting for the Brexit uncertainty[41] closely adhere to the development of the observed exchange rate, which suggests that the main reason behind its depreciation is the increasing uncertainty caused by the Brexit. Dao, McGroarty and Urquhart (2019) find that the referendum vote induces the correlations between safe-haven currencies (Swiss Franc and Japanese Yen and gold), whilst decrease their correlations with the directly involved currencies i.e., the British Pound and Euro. They associate these changes to the appreciation (depreciation) of the safe-haven (directly involved) currencies,

[41] They approximate the Brexit uncertainty with an Economic Policy Uncertainty (EPU) index.

highlighting the post-Brexit vote flight to quality behaviour of investors. Furthermore, they observe a substantial drop (64%) in the volatility transmission between the British Pound and the Euro after the vote, which is the result of the weaker market integration. Their results are consistent with prior literature that suggests that the strength of the market integration positively contributes to the intensity of volatility spillovers (Baele 2005; Christiansen 2007). On the other hand, Andrikopoulos, Dassiou and Zheng (2020) show that the EU referendum had a significant positive effect on the returns of UK non-financial firms. Moreover, their post-referendum analysis reveal that it increased their firm-level FX exposures but reduced the market-level FX in the UK, Germany and Spain.

A few other studies explore the impact of Brexit on market volatilities. For example, Adesina (2017) uses an augmented GARCH (1,1) to model the volatility dynamics and persistence in the returns of the FTSE100 and GBP/USD foreign exchange rate. Interestingly, the find that after the Brexit vote, the volatility persistence significantly increased in the stock market, whereas it decreased in the FX market. Despite that, they reveal analogous patterns in the dynamics of both markets' volatilities, where the impact of the news starts to weaken after the vote. Furthermore, they state that the increasing volatility persistence seem to be borne by the past period variance forecast, which might indicate that investors had already priced the effect of the Brexit vote. Arshad, Rizvi and Haroon (2019) provides sectorial analysis of the impact of the vote on the London Stock Exchange (LSE) and show that in the long-term the overall volatility decreased, while some of the sectors within the exchange behaved differently. Consistent with previous studies they find that the LSE exhibited higher levels of volatility prior to the referendum than during or after it. In another study, Ben Sita (2017) investigates how sentiment contributed to the volatility patterns of FTSE 100 stocks in the wake of the Brexit referendum and document a damped U-shaped volatility pattern, indicating how rational investors drifted away from low trading stocks to acquire high trading ones.

Samitas and Kampouris (2018) employ dependence dynamics through copulas with regime switching to detect contagion among 43 developed and emerging stock markets and examine the effect of the Brexit vote and the invocation of Article 50. Their results provide evidence of immediate financial contagion and increased uncertainty due to the referendum outcome. In addition, they detect higher levels of elevated volatility (high dependence regime) in their pre-referendum and post-referendum sub-samples compared to the after Article 50 period. However, they show that the effect is short-lived, as most of the markets fully recovered within a few days after the polling day. On the other hand, Nishimura and Sun (2018) extend on the work of Diebold and Yilmaz (2012) by proposing an Intraday Volatility Spillover Index that they use to investigate the influence of the Brexit vote on the volatility spillovers between five major EU stock markets. Their empirical results based on the three months after the vote, do not depict any evident changes in the connectedness of the markets. However, when narrowing down the sample to one month post the vote, the volatility spillovers change mechanism and increase. Using a wider sample, Li (2020) show that the UK's influence on other markets began to drop since the campaign for the referendum started early 2016, which is exhibited by the UK's reduced and less frequent positive net volatility spillovers. They also provide evidence that the referendum not only increased the stock market volatilities, but also instantly and diversely impacted market co-movements. The markets adjust within five days, yet the effect of the votes on their co-volatilities remains substantial and persists.

In a more recent study, Hudson, Urquhart and Zhang (2020) examine if the effect of Brexit events on financial markets support the rational asset pricing model. To conduct their analysis they explore 17 Brexit events between 2013 and 2017 on a sample of 34 indices. Their GJR-GARCH results show that the Brexit events negatively affect a large proportion of the indices' risk and returns, nevertheless the returns on event days are for the most part justified by the risk and the risk premium associated with those days. Hence, they argue that their results support the suitability rational asset pricing models even during periods of increased political uncertainty. Furthermore, their event study findings provide limited evidence of pre- and post-event drift, mainly captured after anti-Brexit events that seem to be short-lived. They conclude that the market prices generally quickly adjust to the announcement of Brexit news, which is in line with the semi-strong form EMH.

In terms of bond markets, the literature remains largely underexplored. To our knowledge there is only one study that addresses the effect of the Brexit on bonds (Kadiric and Korus 2019). Kadiric and Korus (2019) use an event study to examine the impact of the EU referendum and 16 other Brexit related events on the UK and Eurozone corporate bond yield spreads. Their results show that the Brexit events influenced the risk conditions in both markets, though only the referendum outcome directly affected the credit spreads. Specifically, the outcome of the vote is associated with wider credit spreads and its effect seem to be stronger on UK credit spreads.

From the analysis outlined above, it is evident that most Brexit literature is concentrated on stock and foreign exchange markets, with little attention paid to bond markets. More recent studies explore the effect of Brexit on volatility, though the majority focus on the EU referendum or a few Brexit events. The literature clearly indicates that the Brexit has a substantial impact on financial markets, though some of the events such as the EU vote have stronger or longer lasting effects than other. Furthermore, studies show that there seem to be a distinction in the market responses to pre and post the vote, which highlights the importance of studying a wider set of Brexit news and distinguishing between their different types.

4.3 Methodology

4.3.1 Brexit news (event) dates and classification

Our news horizon covers the period January 2013 – January 2020. It starts at the beginning of 2013, when the UK Prime Minister David Cameron pledged on to hold an in/out referendum on EU membership if the Conservative party won the next general election and ends when the UK officially left the EU on 31 January 2020. We include news prior to the EU referendum to capture the full impact of the Brexit from its early mention in 2013 until it took effect. The chosen period includes many significant events, concentrated mainly after the referendum date (23 June 2016).

The most important and challenging task in this study was to identify and classify the key news. We started to build the list of news using the official Brexit timeline published by the House of Commons Library that lists the events that took place leading to the UK's exit from the EU (Walker 2021). In addition, we have reviewed and included the most read news published by BBC, Bloomberg, Reuters and the Financial Times (FT). Furthermore, to narrow down the selection of news and define the importance of including the news announcement in our study, we assessed and ranked each Brexit news in terms of the effect that each event had on the annualised CBOE/CME FX British Pound Volatility Index (BPVIX) and the percentage change in GBP/EUR exchange rate. Table 4.1 chronologically presents all 151 news we have included in our sample. From the table it can be observed that we only include 7 news prior to the EU referendum, whilst the majority of news come after it when the different negotiations of the Brexit took place. We deem it necessary to include a few key news prior to the Brexit vote (for example, the speech of David Cameron to Chatham House reaffirming his commitment to an EU referendum in November 2015 and his subsequent announcement of the official EU referendum vote date) as we expect the markets to react to these Brexit-related news announcements that clearly voice that there is a realistic possibility of the Brexit taking place.

Column (1) shows the calendar date the news was published on, column (2) briefly describes the event (or headline of the news) and columns (3) the category it was classified to. Since Bloomberg database that we use for pricing information excludes weekends, we limit our sample to working days and transfer the small number of weekend news[42] in our sample to the next working day (i.e. Monday).

To allow further analysis of the impact of the events, we classify the list of news into five broad categories:

1. **UK Brexit:** this category includes various news or announcements of the UK government or other important UK political figures related to Brexit. These news announcements are clearly and specifically about the Brexit (updates, direction of negotiations etc) released from the UK

[42] A total of nine news events fall on weekend days (25/06/2016, 02/10/2016, 08/01/2017, 20/10/2018, 25/10/2018, 28/07/2019, 24/08/2019, 19/10/2019 and 18/01/2020).

side. For example, the UK Prime Minister's statements, the publication of Brexit proposals or reports, new Brexit deal plans, the Queen's approval (Royal Assent) of Brexit related acts and the European Union Bill etc. To mention a few: David Cameron's announcement of the EU referendum date (22 Feb 2016), the publication of Boris Johnson's Brexit proposal (2 Oct 2019), Queen Elizabeth's II approval of the Benn Act (9 Sep 2019) and the European Union Bill (23 Jan 2020).

2. **EU Brexit:** this category is similar to UK Brexit but consist of Brexit announcements or news events from the EU. For instance, European Council Meeting outcomes, EU 27 agreements of Brexit extensions (21 Mar 2019 and 28 Oct 2019), the European Commission and European Union Presidents' statements. This category is included to capture the impact of Brexit news announcements from the other relevant party to the Brexit, the EU. This ensures we study both sides of the news events, from the UK as well as EU. In addition, including both the UK and EU Brexit news categories enables us to contrast between their effects on the UK and EU volatilities.

3. **UK votes:** to facilitate the UK leaving the EU bloc, a series of votes took place in the UK during our sample period. Votes are typically scheduled events with expected outcomes, which distinguishes them from the other Brexit announcements in our study that are predominantly unscheduled and possibly contain a larger surprise element. As a result, we deem it appropriate to group the votes in a standalone 'UK votes' category. Examples of votes incorporated in this category include: the EU referendum vote (23 Jun 2016), Parliamentary votes on Brexit (meaningful vote 12 Mar 2019) confidence vote (16 Jan 2019), UK general election (12 Dec 2019), votes in the UK Parliament including in the House of Commons and the House of Lords and the second and third readings of the EU withdrawal bills.

4. **UK Political:** this includes (but is not limited to) the candidacy, appointment and resignations of key figures in UK politics for example, the UK Prime Minister Theresa May's announcement of her intention to resign (24 May 2019), the appointment of Boris Johnson (24 Jul 2019), and the resignation of the UK's Permanent Representative to the EU – Ivan Roger. It also incorporates the call for a general election, relevant high court rules (such as the Gina Miller Case 3 November 2016) and government post-Brexit plans. This category is designed to detect the indirect effect of the Brexit, as it contains important news regarding the UK politics released during the sample period, which are not concerning the Brexit specifically but are closely related to it. For instance, the UK Prime Minister Theresa May's resignation announcement is not new information (news) explicitly regarding the development of the Brexit or its deal. Instead, it is a political event that, despite being mainly motivated by the direction of the Brexit

negotiations, it has a widespread implication for the UK and is expected to affect the future of the Brexit.

5. **Industry Response:** in this category we broaden the indirect news selection and study the impact of Brexit-related key news that are out of the UK politics. It incorporates news published by various influential investment banks, companies, credit rating agencies, the Bank of England and industries as a response to Brexit plans. For instance, Moody's UK credit rating cuts (22 February 2013 and 22 September 2019), investment banks' relocation of assets and headquarters and companies' delayed spending decisions.

Including these five Brexit news categories gives a well-rounded overview of the relevant news. It also enables studying the direct and indirect impact of Brexit news and facilitates comprehensive and comparative analysis of the news depending on their category i.e., nature or announcer. Figure 4.1 to Figure 4.4 exhibit the development and response of the BPVIX and GBP/EUR around key Brexit news. For example, Figure 4.1 clearly shows the impact the referendum vote (23 Jun 2016) had on the series, where the BPVIX volatility index increased prior to the scheduled vote and dramatically dropped along with the GBP/EUR exchange rate right after. Similarly, the BPVIX was high before the UK general election date (12 December 2019), most likely due to the anticipation of the election and quickly fell after the announcement of the results that seem to have weakened the exchange rate (see Figure 4.3). On the other hand, the BPVIX dropped shortly before the Brexit date in which the UK officially left the bloc (31 January 2020, Figure 4.4). Our final sample of news categories are presented in Table 4.2 include a total of 151 news, spread across on 143 working days. The classification of each piece of news is shown in the fourth column of Table 4.1. Given the nature of the Brexit and sequence of events, 5% (8 news) of our events overlap; this happens when two significant news were announced on the same day. The overlap percentage is small; thus it is unlikely to have any material effect on our findings.

4.3.2 The HAR model

Volatility is a persistent process, where historical volatility has a persistent impact on future volatility. Hence, traditionally it has been modelled via means of long-memory FIGARCH and ARFIMA specifications that arguably lack clear economic interpretation (Hwang and Shin 2014). More recently, Corsi (2009) introduced the Heterogeneous Autoregressive model of realised volatility (HAR-RV)[43], which offers an approximation that captures the long-memory property of the volatility process while being flexible and easy to estimate. The HAR model of Corsi (2009) can be defined as an additive cascade model of three heterogeneous volatility components corresponding to their time horizons of

[43] We refer to it as HAR model hereafter.

one day, one week and one month. The time-series representation of the HAR model can be written as follows:

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \varepsilon_t \tag{4.1}$$

where RV_{t-1} denotes the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities respectively, given by:

$$RV_{t-1}^{(w)} = \frac{1}{5}(RV_{t-1} + \cdots + RV_{t-5}) = \frac{1}{5}\sum_{i=1}^{5} RV_{t-i} \tag{4.2}$$

$$RV_{t-1}^{(m)} = \frac{1}{22}(RV_{t-1} + \cdots + RV_{t-22}) = \frac{1}{22}\sum_{i=1}^{22} RV_{t-i} \tag{4.3}$$

Note that the upper scripts (w) and (m) indicate the aggregation period. In Eq.(4.1), the lagged realised volatilities approximate the daily, weekly and monthly movements and capture the diversity in investors' trading frequency and time horizon (Lyócsa, Molnár and Plíhal 2019).

To capture the effect of our selected Brexit related events (news) on volatility, we extend on Corsi's HAR model by adding a dummy variable for the Brexit news announcement days as well as interaction term between the news dummy and the lagged RV. This procedure is similar to the methodology of Lyócsa, Molnár and Plíhal (2019). As such, Eq. (4.1) is extended as follows:

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma D_t + \mu I_t + \varepsilon_t \tag{4.4}$$

where D_t is a Brexit news dummy that takes a value of 1 if there is a Brexit news announcement on day t and zero otherwise. Accordingly, its coefficient (γ) captures the changes in volatility at the announcement day. We expect it to be significant and positive, as the literature suggests that asset volatility should increase on the day of the announcement (Lyócsa, Molnár and Plíhal 2019). Moreover, to show how the news announcements influence the process, we allow for interactions between the Brexit news dummy with the daily lagged RV component i.e., $I_t = D_t \times RV_{t-1}$.

Next, following the literature we expand on the event (news) window and examine the impact of the news prior to the announcement as well as after it (Bauwens, Ben Omrane and Giot 2005; Falagiarda and Reitz 2015; Lyócsa, Molnár and Plíhal 2019). We adjust Eq.(4.4) as below:

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma_1 D_t^{Before} + \gamma_2 D_t + \gamma_3 D_t^{After} + \sum_{\tau=1}^{3} \mu_\tau I_{\tau,t} + \varepsilon_t \tag{4.5}$$

In the above expression, the *Before* news announcement dummy $D_t^{Before} = 1$ if t falls one day before the Brexit news announcement and zero otherwise. In addition, we allow for one lag effect by introducing an *After* news announcement dummy D_t^{After} which returns 1 if t is a date one day after the announcement of a Brexit related news and zero otherwise. By extending the event window beyond the announcement day (total of 3-days[44]), we allow our model to capture anticipated and delayed responses to Brexit news by of the market. In this set up, the coefficients $\gamma_1, \gamma_2$and γ_3 measure the change in the RV prior to, on the day of and after the Brexit announcement, respectively. If the Brexit related news contain were anticipated, such as a scheduled election or vote, then we expect γ_1 to be positive and statistically significant. Likewise, if the news announcement contained valuable information to the market, we hypothesise that the daily volatility would increase on the announcement day (captured by γ_2) and could either fall back or further increase post the announcement day (γ_3); depending on the importance of the news to the market and the speed by which it processes it. Similarly, as in Eq.(4.4), we interact all Brexit news dummies with the lagged volatility (RV_{t-1}). The index τ indicates the event period: before announcement period ($\tau = 1$), the day of the announcement ($\tau = 2$) and after announcement period ($\tau = 3$) and $I_{\tau,t}$ refer to the interaction terms of the mentioned dummies with the previous period RV.

In a similar spirit as in Eq.(4.4) and (4.5), we explore the effect of the five individual Brexit news categories by factoring them as below:

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \gamma_j D_{j,t} + \sum_{j=1}^{5} \mu_j I_{j,t} + \varepsilon_t \tag{4.6}$$

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \left(\gamma_{1,j} D_{j,t}^{Before} + \gamma_{2,j} D_{j,t} + \gamma_{3,j} D_{j,t}^{After} \right) + \sum_{j=1}^{5} \sum_{\tau=1}^{3} \mu_{j,\tau} I_{j,\tau.t} + \varepsilon_t \tag{4.7}$$

Here, the subscript j ($j = 1, 2, 3, 4, 5$) denotes the Brexit news category in the following order (UK Brexit, EU Brexit, UK votes, UK political and industry response). Accordingly, each news category is represented by its own dummy variable $D_{j,t}$, which equals 1 the date of the arrival of the news and zero otherwise, and its corresponding interaction with the lagged RV is denoted as $I_{j,t}$. Eq. (4.7) extends on (4.6) by adding additional dummy variables ($D_{j,t}^{Before}$ and $D_{j,t}^{After}$) that attempt capturing the effect of the news of each category j before and after the announcement day t. $D_{j,t}^{Before} = 1$ if t belongs to an n-

[44] Pre-announcement day, the announcement day and post- announcement day.

day window before category j's Brexit news announcement and zero otherwise. For robustness, we consider two event windows n=1 and n=3 days pre-announcement[45]. In the main results of this chapter, we report and discuss the results for n=1. On the other hand, we keep only 1-day lag effect after the news announcement. The rest of the variables are defined similarly as before. Our focus here is on the statistical significance and the signs of each Brexit news category j coefficients γ_j in Eq. (4.6),$\gamma_{1,j}$, $\gamma_{2,j}$ and $\gamma_{3,j}$ in Eq. (4.7).

In line with the prior literature, we correct for autocorrelation and heteroscedasticity in all regressions using Newey and West (1987) HAC covariance estimator and Newey and West (1994) automatic lag selection (bandwidth) procedure.

4.3.3 Brexit news (event) contributions and proportions

Motivated by Kosmidou, Kousenidis and Negakis (2015) and Beber, Brandt and Kavajecz (2008), we compute the contribution and proportion of each Brexit news category to the total shift in the volatility as follows:

$$Contribution\ of\ Brexit\ News\ Category\ j = \gamma_{1,j} \times \overline{D_j^{Before}} + \gamma_{2,j} \times \overline{D_j} + \gamma_{3,j} \times \overline{D_j^{After}} \tag{4.8}$$

However, since $\overline{D_j^{Before}}$, $\overline{D_j}$ and $\overline{D_j^{After}}$ are dummy variables; taking the value of 1 or 0, thus we simplify the above contribution equation to:

$$Contribution\ of\ Brexit\ News\ Category\ j = \gamma_{1,j} + \gamma_{2,j} + \gamma_{3,j} \tag{4.9}$$

$$Proportion\ of\ Brexit\ News\ Category\ j = \frac{|\gamma_{1,j}| + |\gamma_{2,j}| + |\gamma_{3,j}|}{\sum_{j=1}^{5} |\gamma_{1,j}| + |\gamma_{2,j}| + |\gamma_{3,j}|} \tag{4.10}$$

where $\gamma_{1,j}$, $\gamma_{2,j}$ and $\gamma_{3,j}$ are the estimated regression coefficients of the j^{th} Brexit news category dummies extracted from Eq. (4.7).

The above equations calculate the contribution and proportion of the j^{th} Brexit news category to the total change in the volatility of government bonds and equities. The contribution value might take a positive or negative value, depending on the summation of the Brexit news category's dummy coefficients. The sign of these figures indicates where the news announcements of a Brexit news category on average increase or decrease the market volatility throughout the 3-day event window. On the other hand, the proportion figures are always positive, as we take the absolute values of the

[45] This extends the total event window, from 3-day to 5-day window, that we study in our robustness analysis.

coefficients, and sum up to 1. This analysis complements our estimation results, providing additional information about the impact of the news categories on the changes in market volatility. Specifically, the contribution designates the direction and magnitude of the shift in the volatility by the news, whereas the proportion measures the relative impact of each news category on the total news response of the volatility.

4.4 Data

To conduct our study, we use daily high and low data of 10-year government bond yields and stock market indices collected from Bloomberg for the UK, four EMU countries (Germany, France, Netherlands, and Belgium) and the Eurozone. Table 4.3 presents the government bond and stock series we incorporate in our study. Following the trend in literature, we also provide additional analysis for the equity sample using the daily realised variance (based on high frequency 5-minute returns) series obtained from the Oxford-Man Institute of Quantitative Finance Realised Library. Unfortunately, the realised variances are limited to the equity sample, as no intraday data are available for the government bond sample. Our sample period spans from 1 April 2010 to 28 February 2020 (i.e., a total of 2,514 observations), which includes all important Brexit related dates but excludes the beginning of the Coronavirus (COVID-19) pandemic[46].

4.4.1 Volatility estimators

Studies argue that GARCH and SV models provide inaccurate and inefficient estimates of volatility as they are based on a single observation (closing prices) per day which fails to incorporate the information content between one closing price and another (Alizadeh, Brandt and Diebold 2002; Chou 2005). Since our study aims at capturing the effect of the Brexit news on market volatilities, which are likely to include turbulent days with peaks and recoveries, thus we do not utilise the traditional close-to-close volatility measures and favour volatility estimates that incorporate higher frequency data or high and low prices with greater information content. Based on the data availability, we apply two measures of volatility, a range-based volatility estimator and high-frequency realised volatility, to examine and contrast the impact of Brexit news announcements on government bond and equity market volatilities.

Due to the unavailability of government bonds' intraday data, we follow the tradition of a large body of literature (e.g. Diebold and Yilmaz 2012; Fernández-Rodríguez, Gómez-Puig and Sosvilla-Rivero 2015; Fernández-Rodríguez, Gómez-Puig and Sosvilla-Rivero 2016) and firstly estimate the daily variance using Parkinson (1980) high-low range estimator, which is also known as the extreme-value estimator. Studies show that the Parkinson's high–low range estimator, is an unbiased estimator of daily volatility and appears to up to 8.5 times more efficient than the squared daily close-to-close log squared

[46] Comparable results are obtained when extending the sample period to 1 April 2020, the results are available upon request.

return (Parkinson 1980; Chan and Lien 2003; Martens and van Dijk 2007; Lyócsa, Molnár and Výrost 2021). To estimate Parkinson's (1980) measure, we employ two prices (yields for government bonds) per day: the daily high and low prices for each market i on day t as follows:

$$PK_{it} = 0.361[ln(P_{it}^{max}) - ln(P_{it}^{min})]^2 \tag{4.11}$$

where P_{it}^{max} (P_{it}^{min}) denotes the maximum (minimum) i.e., high (low) price in the market i on day t. Given that PK_{it} is a proxy for the daily variance, we define the corresponding daily volatility (percent standard deviation)[47] as follows:

$$\hat{\sigma}_{it} = \sqrt{PK_{it}} \times 100 \tag{4.12}$$

To enable comparability and consistency amongst the two asset classes, we approximate the daily realised volatility (RV_t) used in our HAR regressions with the above daily volatility measure for both government bond and equity samples. This choice of volatility proxy is in accordance with recent literature, for example Clements and Preve (2019) who show that Parkinson's high-low range estimator often provide similar quality forecasts to those produced using high-frequency realised volatility. They also recommend replacing the RV_t in the HAR model with the high-low range estimator when high-frequency data are not readily available to estimate the realised volatility.

Secondly, in our additional analysis we use the realised volatility measure that is based on intraday data (high frequency 5-minute returns), which only is available for our equity sample. The simplest and most common estimator of daily realised variance[48], econometrically formalised by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002), is given as follows:

$$RM_t = \sum_{j=1}^{N} r_{j,t}^2 \tag{4.13}$$

where $r_{j,t}^2$ is the j^{th} squared intraday return of a stock market index at day t and N denotes the number of intraday returns, which depends on the length of the trading hours and sampling frequency. However, given that microstructure noise may impact realised variances, following Shephard and Sheppard (2010) we use estimators that are robust to noise. The realised variances we use are estimated employing a Parzen kernel function, defined as:

[47] We also use the annualised daily volatility in our descriptive statistics which we define as follows: $\hat{\sigma}_{it} = 100\sqrt{252 \times \tilde{\sigma}_{it}^2}$

[48] For more information on the background to realised measures please refer to Andersen, Bollerslev and Diebold (2010) and Barndorff-Nielsen and Shephard (2007).

$$RM_t = \sum_{h=-H}^{H} k\left(\frac{h}{H+1}\right)\gamma_h \quad , \quad \gamma_h = \sum_{j=|h|-1}^{n} r_{j,t}\ r_{j-|k|-1,t}$$

(4.14)

where $k(x)$ is the Parzen kernel function given by:

$$k(x) = \begin{cases} 1 - 6x^2 + 6x^3 & 0 \le x \le 1/2 \\ 2\,(1-x)^3 & 1/2 \le x \le 1 \\ 0 & x > 1 \end{cases}$$

According to Shephard and Sheppard (2010), it is essential that H increases with the sample size so that, in the presence of noise, it consistently estimates the increments of quadratic variation. The bandwidth of H is determined following Barndorff-Nielsen et al. (2009). Similarly, as above, we define the daily realised volatility RV_t that we utilize in our HAR regressions as:

$$RV_t = \sqrt{RM_t} \times 100$$

(4.15)

4.4.2 Descriptive statistics

The descriptive statistics of the annualised daily volatilities for both treasury bonds and equities are summarised in Table 4.4. Focusing on our full sample period (Panel A), the Eurozone experienced the highest average daily volatility in both bonds and stock samples. Moreover, the t-tests (Mann-Whitney tests) of the means (medians) in Panels B show that the level of volatility on news announcement days are consistently significantly different from non-announcement days. This finding is consistent for nearly all treasury bonds as well as equity samples, with the exception of the mean of the UK FTSE 100 volatility series. Similar patterns are detected in Panels C to G, where this observation is more pronounced in bond volatilities. This indicates that the news announcements potentially influence the level of daily volatility that we aim to explore in this study. Interestingly, the annualised average daily bond (equity) volatility on announcement days seems to be higher (lower) than those recorded in the full sample. Since the descriptive statistics of the sub-sample news categories were computed using the announcement day only, then one way to explain the observed lower equity indices' volatilities on these days is that the equities could have reacted to the news before or after the announcement day took place. This motivated us to take a wider event window in our regressions. Furthermore, it is worth mentioning that the differences in the minimums and maximums and magnitude of the bond versus equity volatility series is due to the government bonds' daily volatilities being computed using their high and low yields rather than prices. The Eurozone and German government bond statistics are identical, which is not a surprise as the EU treasury bond is approximated by the German one (bund) on Bloomberg. Finally, the values of the ADF test show that the daily volatilities are stationary.

The per-country government bond and stock market daily volatilities are depicted in Panel A of Figure 4.5 and Figure 4.6. Panel B exhibits only the UK and Eurozone's daily volatilities. It is evident that the daily volatilities surged at the date of the Referendum (23 June 2016). However, it is noteworthy that in both samples, the Eurozone seems to experience greater volatility (risk) than the UK, which is affirmed by the sample's standard deviations. Furthermore, the effect of the referendum appears to be instantaneous and short-termed in equities, whilst the higher volatility post-referendum seemed to have persisted for a longer period in the government bonds. In addition, opposing to the equity volatilities, the Eurozone and UK government bond volatilities did not accelerate much at the Brexit date (31 January 2020). However, France and Belgium's volatilities peaked around the time leading to the Brexit date i.e., early 2020. Figure 4.5 also shows that the treasury bonds' risk visibly increased in the spring/summer of 2019, which corresponds to the time of the Brexit negotiations and extension requests.

Table 4.5 summarises the descriptive statistics of our equity samples' realised volatilities that are based on high frequency 5-minute returns (see Figure 4.7) that we use in our additional analysis. Overall, the descriptive statistics of both equity sample volatilities measured by the high-low range estimator and realised volatilities are comparable and consistent.

4.5 Empirical results

4.5.1 Effect of Brexit news announcements

Table 4.6 presents the results for the HAR regressions estimated for our government bonds (Panel A) and equity (Panel B) samples for the entire sample period 1 April 2010 to 28 February 2020. Columns (1) in Table 4.6 reports each country's estimation coefficients of equation (4.4), and their respective standard errors, where the coefficient on the Brexit news dummy (D_t) is of our interest. In this set up, D_t captures the effect of all 151 Brexit events (news) on the market volatility at once, where the volatility is approximated using the Parkinson's (1980) high-low range estimator.

The estimated results suggest that the lagged daily ($RV_{\mathrm{t}-1}$), weekly ($RV_{t-1}^{(w)}$) and monthly ($RV_{t-1}^{(m)}$) volatility components help in explaining the behaviour of the daily volatility of both government bond and equities as their coefficients are highly statistically significant (mostly at 1%). This is in line with prior literature that also found that bond and mainly stock market volatilities have long memory (Bollerslev, Cai and Song 2000; Corsi 2009; Busch, Christensen and Nielsen 2011). There only a few exceptions that are observed in the government bond sample, where the lagged monthly volatility is not statistically significant for Germany[49] (and accordingly the Eurozone) and France.

Focusing on the sovereign bond results (Panel A) clearly indicate that on the announcement day of Brexit related news, the volatility of the bond market increased in most of the countries. The Eurozone

[49] Bloomberg approximates the Eurozone treasury bond with the German government bond (bund).

and all individual EMU markets show positive and significant (at 1%) coefficients for the Brexit news dummy (D_t) on the announcement day, which suggests that, in comparison to non-announcement days, Brexit news announcement days experience significant volatility responses (higher volatility) to the news. For example, the coefficient on the Brexit news dummy of the Eurozone government bond sample suggests that the Eurozone's daily volatility on average increases by 1.971% on announcement days. The highest sensitivity (strongest response) is observed in the Belgian government bond volatility. These results indicate that the Brexit news announcements most likely contain valuable information to the bond markets, which in turn affect the level of volatility. Interestingly, we do not observe significant change in the volatility of the UK treasury bonds. In contrast, the UK stock market daily volatility (Panel B) is the only market that has a significantly positive Brexit dummy coefficient at the announcement day. Furthermore, the markets with significant news dummy have a negative and significant coefficient on the interaction term (I_t) between the Brexit news dummy with the lagged daily volatility. Hence, the explanatory power of the previous day's volatility significantly drops on announcement days, indicating that the level of volatility on these days are influenced by other factors, potentially the news that we examine.

Next, we extend the news event window to three days, allowing for possible anticipated and delayed responses to the Brexit news by market participants. Columns (2) in Table 4.6 presents the estimation results of equation (4.5), in which we add two additional dummy variables (D_t^{Before} and D_t^{After}) that capture what occurs one day prior and post the Brexit news announcement day, respectively. The dummy variable prior to the news announcement is found to be significant in half of the sovereign bond markets examined. Specifically, we find a significantly positive coefficient of 0.915 and 1.098 in France and Belgium, implying that the countries' sovereign bond markets most likely anticipated the arrival of the Brexit-related news as their volatilities increase one day before the announcement of the news. On the other hand, the UK before the announcement day dummy is negative (-0.594) and statistically significant at 10%, suggesting a decrease in the Gilt's volatility one day ahead. This finding could be a sign of a higher degree of UK bond market efficiency resultant from the speedy adjustment of the UK bond yield to Brexit news. Furthermore, we observe lagging responses in Germany and Netherlands, where their bond market volatilities increase one day after the announcement, though this effect seems to be weaker than the one observed on the announcement day. Widening the event window to three days to some extent increases the explanatory power of the model (R-squared). In contrast, none of the country stock market volatilities have significant before or after the news announcement dummy, providing no evidence of leading or lagging volatility responses to the news.

The above analysis suggest that the Eurozone and EMU treasury bond markets are more sensitive to the news announcements as their risks increase one day before the announcement and continue to increase further on the day of the announcement. Whereas the initial regressions on the equity sample propose that the UK equity market is the only market that experiences higher levels of volatility on

Brexit announcement days. The results clearly indicate that government bonds, in comparison to equities, are more sensitive to Brexit news announcements that carry valuable information to the markets. Given the ongoing impact of the Brexit on the UK and EU macroeconomic conditions, it is not a surprise that bonds greatly react to the news as the macroeconomic conditions drive the benchmark curve. The stronger reaction of treasury bonds to news has been documented in other studies on macroeconomic news (e.g. Andersen et al. 2007; Kim, McKenzie and Faff 2004). Furthermore, our results show some distinctions between the government bond and equity markets and point out the importance of investigating the effect of Brexit news on volatility in more detail. This could be attributed to the nature of the prevailing investors in the markets, where bond market investors are typically more informed institutional investors whereas stock market participants include a large proportion of retail (less informed) investors.

4.5.2 Effect of Brexit news categories

In this section, we attempt answering the second research question investigating the markets' responses to the different Brexit news categories that we have classified. Table 4.7 and Table 4.8 report the regression results estimated for the government bond and equity sample, respectively. Similarly, as above, we present the results firstly with a single at the 'announcement day' dummy, but this time we include a dummy for each news category and then widen the event window to three days.

4.5.2.1 At the date of Brexit news announcements

Columns (1) present the individual countries' extended HAR model estimation coefficients[50] of equation (4.6) and their respective standard errors. Here, each of the five Brexit news categories (UK Brexit, EU Brexit, UK votes, UK political and industry response) has a dummy variable ($D_{j,t}$) that takes a value of 1 at the day of the news announcement, detecting the market's volatility response to the event. Consistent with our earlier results, the estimates for both sovereign bond and equity markets show that the lagged market volatilities aggregated over the three separate time horizons (daily, weekly and monthly) are positive and highly significant for nearly all countries[51]. When investigating the effect of each Brexit news category separately, our findings provide interesting insights.

Firstly, the arrival of Brexit-related news from the UK (UK Brexit) seem to affect the volatility of Eurozone, German, and French government bonds but not UK bonds. In particular, their announcement days are associated with significantly higher bond market volatilities captured by the positive UK Brexit dummy coefficient ($D_{1,t}$). For example, the Eurozone's UK Brexit dummy equals 1.606 and is statistically significant at 5%. In contrast, the only set of news announcements that appear to reduce the

[50] Excluding the coefficients on the interaction terms that for space reasons were not included but are available upon request.
[51] The only exception are once again the lagged monthly volatility for the German and French government bonds, affirming our earlier findings.

level of government bond market volatilities are Brexit news announced by the EU (EU Brexit). For instance, the coefficient on the EU Brexit news category dummy for the UK is -1.006 negative and statistically significant at 1%. Based on our results this could be interpreted as the average percentage drop in the daily volatility of the UK government bonds at the date of the announcement of EU Brexit news in comparison to non-announcement days. These findings suggest that the news announced by the EU potentially provide some stability (less uncertainty) to government bond markets, which could be explained by the nature of some of the EU Brexit news, for example, European Council meetings addressing Brexit, and the approval of the extension of the Brexit date. In addition, this provides evidence that the reaction of the bond market differs depending on the side taking action in the event, the UK side Brexit news present greater uncertainty in major Eurozone government bonds whereas the EU side Brexit news limits the uncertainty in the UK as well as Germany and Netherlands. On the other hand, the equity sample shows a different reaction to the above-mentioned news. Interestingly, the UK Brexit news coefficient is not significant for any of the stock markets, whilst the EU Brexit event coefficient is positive and statistically significant for the Eurozone index (γ_2= 0.187), Germany and Belgium (0.321 and 0.133).

Secondly, the UK political event dummies are found to be highly positive and statistically significant at 1% for all countries in our sovereign bond sample. France, followed by Belgium experienced the largest increases in volatility (%) as a response to the UK political news (γ_4= 2.628 and 2.620, respectively), which are both slightly higher than the one observed in the UK (2.450). Thus, we find strong evidence that not only the UK, but also Eurozone sovereign bond market volatility (uncertainty) rises with the arrival of UK political news – for example, the resignation/appointment of the UK Prime Minister or other key figures in UK politics, Brexit relevant high court rules and government post-Brexit plans. These results provide new evidence that extend on earlier studies, such as, Pástor and Veronesi (2012) highlighting the importance of political events beyond elections and presidential terms. Similarly, apart from the UK bond market, all other bond markets show a significantly higher volatility in response to the UK votes and Industry response news categories. The most significant response to the UK votes (Industry response) is captured in Germany (Belgium), where the coefficient on the news dummy reached 2.190 (6.553) that is significant at 1% (10%). This result was expected as the UK votes included the referendum vote which other studies found to be an impactful event that amplified market volatility (e.g. Adesina 2017; Kadiric and Korus 2019; Li 2020). However, we extend this literature by providing novel evidence on government bonds that have not been explored and showing that, apart from general elections and the referendum, other Brexit votes that took place in the UK parliament induce greater uncertainty within the Eurozone.

From the above analysis, it appears that at the date of the announcement the UK bonds seem to react to UK political and EU Brexit news the most, whereas the Eurozone bonds reacts most to the industry response and UK votes. These results show that global news announcements are not less valuable and influential than local ones, which in turn highlights the close ties between the UK and Eurozone.

When contrasting the government bond and equity volatility samples, it is evident from our results that the bond market has a stronger response to the news arrivals, which is consistent with our initial analysis. However, when we categorize the news, the level of the UK (FTSE 100) stock market volatility does not seem to be statistically different on the announcement day of any of the specific Brexit news categories. On the other hand, we find some evidence of an increase in the daily volatility of the Eurozone (German) stock index volatility levels with the arrival of EU Brexit as well as UK voting (Industry response) news. These results are consistent with the earlier studies on the EU referendum (e.g. Schiereck, Kiesel and Kolaric 2016; Samitas and Kampouris 2018; Davies and Studnicka 2018; Li 2020) and highlights the importance and impact of numerous Brexit news on UK and mainly Eurozone government bond and equity market volatilities, which are worth exploring in more detail.

4.5.2.2 Pre- and post-Brexit news announcements

Columns (2) of Table 4.7 and Table 4.8 present each country's HAR model's estimation results[52] of equation (4.7). In this set up, we extend the news event window to include one day before and after the news announcement. Hence, in addition to the five Brexit news categories' dummy variables, we include two extra dummy variables for each news category, $D_{j,t}^{Before}$ and $D_{j,t}^{After}$ where their coefficients capture the average change in the level of the markets' volatility pre and post the news announcements.

When we expand the event window to three days, we find further strong evidence to support the importance of Brexit related news. Columns (2) in Table 4.7 show that the UK Brexit news carry important information, where all the examined sovereign bond markets anticipate the arrival of Brexit news from the UK as their 'before' news coefficient is mostly positive and statistically at 1%. Despite the fact that the individual countries' UK Brexit announcement day coefficient is insignificant, their coefficient on the day 'after' the UK Brexit news announcement is significantly positive for all Eurozone bond markets. The reaction post announcement seems to be stronger (given by the larger coefficient values) than pre-announcement of UK Brexit news. For instance, the coefficients on $D_{1,t}^{Before}$ and $D_{1,t}^{After}$ for the Eurozone are 1.192 versus 1.597. This suggests that the Brexit news from the UK is not only anticipated, but that their effect persists as the volatility on the day after the announcement significantly increases. This is not a surprise as some of the UK Brexit news, for instance, the publication of the Brexit White Paper, Brexit proposals (deal), the formal announcement of the UK Prime Minister's extension requests for Article 50, the beginning of MPs Brexit deal/Meaningful Vote

[52] Excluding the coefficients on the interaction terms that for space reasons were not included but are available upon request.

debates and the Royal Assent of the relevant acts/European Union Bill, were awaited news that explain the increase in the volatility levels prior to the announcement. On the other hand, some UK Brexit news potentially had a surprise element, for example details of the proposed Brexit deals, the resignation of the Brexit Secretary David Davis (9 July 2018) or Chancellor Philip Hammond's announcement of the UK Budget that includes £500m for no-deal Brexit preparations (29 October 2018), which consequently induced the uncertainty levels after the news announcement. However, these findings were not observed in the equity sample (Table 4.8), highlighting distinctions between the government bond and equity markets.

Similarly, as before, four out of the six government bond markets positively react to the release of EU Brexit news as their volatilities drop on that day. However, this extended analysis show that prior to the drop in market volatility on the announcement day; the markets mostly experience a rise in the volatility one day ahead as evidenced by the positive 'before' news coefficient. Furthermore, we observe a delayed response to some of the EU news in the Eurozone, France, and Belgium. Most notably, the results suggest that in comparison to non-announcement days, the Eurozone (and respectively the German) government bond market's volatility on average increase by 7.07% post the news release day. The equity market exhibits partially comparative findings, where the coefficients before and after the EU Brexit news announcements are positively significant in some of the markets, namely the German one.

In addition to the above, the extension of the event window shows that the sovereign bond markets' reaction to UK votes and UK political news is much more significant than initially observed. Apart from having a higher daily volatility on the UK votes and political news announcement day (positively significant coefficients on the day of the news announcement dummies $D_{3,t}$ and $D_{4,t}$), most of the bond markets' volatilities respond a day preceding the news announcement. Specifically, all Eurozone bond markets have a negative and statistically significant (at 1%) coefficients on the before the UK votes' announcement day dummy, with the German and accordingly Eurozone market having the most substantial negative coefficient of -22.091. This finding suggests that in comparison to non-vote announcement days, Germany's bond market volatility drops one day prior to the UK votes take place, and then significantly increases on the voting day in the UK. The drop in volatility prior to the votes could be due to the anticipation of the votes that are typically scheduled, whereas the subsequent increase in uncertainty on the day of the votes could be interpreted as the reaction to the 'surprise' element in the votes' outcome. Conversely, the UK bond market's volatility does not show any reaction to the UK votes before or at the day of the announcement, potentially indicating the higher informational efficiency of the market. This finding is supported by the plunge in the UK bond's volatility a day after the votes, captured with the significantly lower coefficient on the 'after' UK votes' dummy variable -2.738. Similarly, as with the UK bonds, the equity sample shows fewer responses to the UK votes, with the strongest responses observed after they have taken place. Specifically, the Eurozone, French and

Dutch stock market volatilities are significantly lower one day after the UK votes' announcements. Hence, our findings support the view that the Brexit and other votes' impact is rather short-lived, where the markets seem to recover much faster than what is observed in the literature after the EU referendum vote (Adesina 2017; Samitas and Kampouris 2018; Li 2020)

In contrast with the UK votes, we observe a reverse response of the bond markets prior to the UK political news announcements. We find that, with the exception of the UK, all Eurozone bond markets' volatilities significantly increase prior to the UK political news release as observed with their significantly positive coefficients. On the publication day of the political news, the daily volatilities of all bond markets significantly increase in comparison to days with no-political news with the average increase in volatility is just over 2%. However, we do not detect any lagging responses to political news in our bond samples. Contrary to the bonds, the Eurozone equity samples in our study have positive and significant coefficients on the day after the UK political news announcement, which reflects the delayed response to the news, in this case, an increased uncertainty in EU stock markets during these days. Lastly, our extended analysis provides no (limited) evidence of leading (lagging) responses of government bond and equity market volatilities to industry related Brexit news. Most reactions are captured at the day of the announcement and seems to quickly disappear after that.

Our findings clearly indicate that the different Brexit news categories carry valuable information that influence the level of uncertainty in the markets, which signifies the importance of not only local but also global news announcements and the existing close ties between the UK and Eurozone. The government bond and equity market responses slightly differ, with the former being more sensitive to Brexit news releases. Furthermore, we show that the impact and direction of the Brexit news categories vary, which affirms the importance of categorising news in general. The markets seem to anticipate and process certain news more quickly than other, with the speed of recovery often extending beyond one day in government bond markets.

4.5.3 Contribution and proportion of Brexit news categories

To study the effect of the Brexit news (event) categories across the 3-day event window in greater detail, we estimate the contribution and proportion of each news category using equations (4.9) and (4.10) for our sovereign bond as well as equity samples. Table 4.9 presents these results. As mentioned earlier, the contribution reflects the direction and scale of the change in the volatility (news response) within the event window, whereas the proportion values weigh the relative effect (in %) of every Brexit news category on the total variation in volatility as a response to the Brexit news.

Most of news category contributions in Table 4.9 are positive, suggesting that the UK and Eurozone bond and equity volatilities react in the same direction to the majority of Brexit news categories. Hence, one could say that in general Brexit news increase the level of volatilities across the 3-day event window in UK and Eurozone bond and equity markets. This is affirmed by the mostly positive total per country contributions figures. Interestingly, the consistent exception is the UK votes news category that has a negative overall contribution for all countries in our sample. This finding is consistent across our bond as well equity samples, which suggests that across the 3-day window period the UK votes announcement seem to reduce (negatively shift) the daily volatility. Meaning that the magnitude of the observed reduction in volatility one day prior/post the votes' announcement outweighs the increase in volatility on the announcement day. Hence, the observable implication of these results is that apart from UK votes, all other news categories have a tendency of inducing greater volatility. On the other hand, UK voting outcomes overall calm UK and Eurozone government bond and equity markets and reduce their uncertainties. This could be due to the fact that the majority of the votes are scheduled, and their outcomes are anticipated. Thus, the votes' announcements element of surprise or adverse effect is not as substantial, but instead they overall bring some certainty (clarity) on critical issues regarding the Brexit and the direction of the negotiations.

In terms of magnitude, unexpectedly most Eurozone markets exhibit a stronger reaction (larger total contributions) to Brexit news than the UK. This is a clear indication of the strong interlink between UK and Eurozone countries and that the Brexit news, even UK focused ones, are sources of greater uncertainty in Eurozone markets as the outcomes of Brexit could strongly affect them. Our findings are into an extent in line with other studies that find evidences of EU (incl. the UK) market integration and spillovers across their member states (Baele 2005; Skintzi and Refenes 2006; Christiansen 2007; Virk and Javed 2017). Furthermore, our results also complement the findings of Nishimura and Sun (2018) that show that there has been a temporary increase in the volatility spillovers between EU countries after the Brexit vote.

Considering the proportions of the news in Table 4.9, we note that relative to all news categories, the UK votes explain the largest percentage of the variation in the volatility of Eurozone, German, and Dutch government bond markets. On the other hand, the UK political news, directly followed by the UK votes, seem to have the greatest impact on UK and French bond market volatilities. Focusing on the equity (stock) sample, most markets, including the UK, experience the largest percentage of total shifts in response to UK votes, signifying the importance of UK votes not only in bond but also equity markets. The votes seem to most severely impact the Eurozone benchmark (index) bond and equity volatilities, where the event's significance is relative to the other news categories reach 52.61% and 54.66%, respectively.

The rankings of the events' significance across our bond sample are mostly consistent, where the UK votes and UK political news are often ranked as the two most significant Brexit news, together on average explaining more than 55% of the Brexit news responses of which the votes account for 35.15% on average. The Industry response was found have the greatest impact on Belgian government bond volatility (30.13%), followed by the Netherlands (25.92%) and France (21.50%). According to Tata (2018), 20-30% of UK-based corporates and investment banks are likely to relocate to EU after the Brexit, which could explain our findings as the mentioned three EU counties are closest neighbouring EMU countries to the UK that are likely to experience the biggest effects of the new regulations imposed by the Brexit deal. In contrast, the news category with the weakest effect on bond volatilities is UK Brexit, with an average proportion of 9.25%. The analysis of proportions in the equity sample demonstrate some similarities with the government bonds. Four out of the six indices rank the UK votes as the most important class of news with an average proportion of 37.54%, often followed by the UK political news. Moreover, the equity sample confirms that the least impactful set of news are UK Brexit ones with a lower average proportion of approx. 4.69%. In contrast to the bonds, the German and Belgian equity indices' proportions show that the EU Brexit news explain more than 30% of their volatility responses to all Brexit news.

4.5.4 Additional analysis: equity (stock) results based on realised volatilities

Our earlier equity results provide some evidence of the effect of Brexit news on UK and Eurozone stock markets' volatilities. However, when we run the same regressions on the same equity indices' *realised* volatilities we find greater evidence of equity markets' responses to the news announcements. Similar as above, Table 4.10 presents the initial HAR estimation results for equations (4.4) and (4.5) with a single Brexit news dummy for all news, whilst Table 4.11 analyses the impact of each Brexit news category using equations (4.6) and (4.7).

Columns (1) in Table 4.10 show that in addition to the UK, the Eurozone, Netherlands and Belgium stock market realised volatilities seem to respond to the announcement of the Brexit news as their coefficient of the news announcement day (D_t) is positive and significant mostly at 1-5%. This provides evidence of an increase in the stock markets' realised volatilities on the day the news is announced. Furthermore, the estimation results in columns (2) confirm these results, though we fail to find any leading or lagging volatility responses to the Brexit news (in total) in equity markets. Lastly, the regressions on the realised volatilities for the equity sample yield visibly higher R-squared (on average higher by 15.63%) than those on the volatility measured by the high-low range volatility estimator (Table 4.6). For instance, the R-squared of the Eurozone index (EURO STOXX 50) improved by more than 15% (from 0.410 to 0.568). These results encourage the use of the robust[53] realised volatility estimator based on 5-min intervals as it seems to increase the accuracy of the model and is known to also limit the adverse effects of market microstructure frictions (Andersen et al. 2003a; Fleming, Kirby and Ostdiek 2003; Martens and van Dijk 2007)

[53] Realised volatility estimates that are robust to noise estimated using a Parzen kernel function, for more information see Shephard and Sheppard (2010).

Table 4.11 examines the impact of the Brexit news categories on the realised volatilities of the country equity indices. Consistent with our earlier results, the equity realised volatilities seem to react most to UK votes and UK political news. The nature of the realised volatilities' responses to UK vote announcements, are into an extent comparable to the bond volatility sample. The stock markets' uncertainty increases on the day of the announcement (positive and significant coefficients of $D_{3,t}$) in nearly all countries in our sample, with the results being more significant after expanding on the event window. However, the realised volatilities quickly reduce one day after the votes (captured by the negative and significant coefficients of $D_{3,t}^{After}$). Conversely, with the exception of Belgium, the equity samples do not exhibit any significant volatility responses in anticipation of the Brexit votes. These results complement the findings of Białkowski, Gottschalk and Wisniewski (2008), confirming the importance of elections that induce stock market volatility. However, we show that not only elections are of significance, but also Brexit votes that have strong effects extending beyond the UK to the other EU member states.

Across all countries, the UK political news announcement day dummy ($D_{4,t}$) coefficient is positive and significant, with the Eurozone having the highest coefficient 0.202 that is significant at 1%. Similar to the prior equity analysis, the equity realised volatilities continue to be significantly higher than non-announcement days, which is captured by the reported significantly positive coefficients after the UK political news announcement ($D_{4,t}^{After}$). In fact, the post UK political news announcements coefficients appear to be consistently larger in magnitude than the day of the announcement. For instance, in comparison to no UK political news days, the UK (French) stock realised volatility increases on average by 0.246% (0.162%) on the political news announcement days, whilst it surges by 0.298% (0.310%) post-announcement. This finding proves the distinction between the bond and equity volatility responses to UK Political news, where only equities exhibit delayed responses to the news suggesting that the UK Political news have a longer lasting effect on UK and Eurozone equity markets' uncertainty.

Apart from the UK votes and political news, the Eurozone's equity realised volatilities show little responses to EU Brexit news. The uncertainty in the German and Belgian stock markets rise on the announcement day of EU Brexit news, whilst France and the Netherlands show lagging responses to the news. In contrast to our bond sample, we detect minimal impact of the UK Brexit and Industry response news on the realised volatilities of our equity samples. As observed earlier, the regressions on the realised volatilities for the equity sample yield visibly higher R-squared, mainly in Eurozone countries where their R-squares improve on average by 17.36% in comparison to those based on the equity volatility measured by the high-low range estimator (Table 4.8).

The final table, Table 4.12, presents the contributions and proportions of each news category using equations (4.9) and (4.10) for realised volatility equity sample. The results are for the most part consistent with our earlier findings. The estimated contributions show that realised equity volatilities positively respond to EU Brexit, UK political and industry response news, implying that they induce greater risk levels across the 3-day news announcement window. As observed earlier, UK votes' news have the opposite, rather stabilising, overall effect on equity volatilities. The only observed difference is that the UK Brexit news seem to have negative, but relatively small magnitude contributions. Overall, the total contributions are positive with an average figure of 0.44, which supports our earlier findings pointing at the fact that the Brexit news studies generally induce greater volatility (risk) in equity markets. The proportions demonstrate that UK votes are consistently explain the largest percentage (on average 41.59%) of the total realised equity volatility responses to Brexit news. The UK political news are mostly ranked as second most significant Brexit news category, followed by the EU Brexit. Once again, the EU Brexit appear to have a greater effect on namely German and Belgian equity volatilities. Lastly, the least impact or relative effect is prompted by UK Brexit news.

From above it can be stated that our additional equity analysis using the realised volatilities are mostly in line with our earlier findings. However, it is notable that we find greater evidence of the effect and importance of the Brexit news using the realised volatility measure and the accuracies of the models improved across all country stock indices.

4.5.5 Robustness checks

In this section, we examine the robustness of our earlier results that test for the impact of the five Brexit news categories on the volatility. Similar as above, Table 4.13 presents each country's HAR model's results by re-estimating equation (4.7), where the RV_{t} is measured as the Parkinson's (1980) high-low range estimator for the government bonds, whereas it is the realised volatility for equity indices. Here we extend the news event window to include *three* days before the news announcement and *one* day after it. The impact of the Brexit news category *j* on the day of the announcement is detected by the coefficient of $D_{j,t}$, and the pre- and post-announcement effects are captured with the coefficients $D_{j,t}^{Before}$ and $D_{j,t}^{After}$, respectively.

From the first inspection, the results are for the most part consistent. The results overall confirm the importance of Brexit news, with particular emphasis on the significance of UK Political news. In both markets, the level of volatility significantly increases on the day of the announcement of UK political news and the impact of the news extend for more than a day. Specifically, once again we observe leading (lagging) effects of the news in government bond (equity markets) captured by the statistically significant coefficients of $D_{4,t}^{Before}$($D_{4,t}^{After}$). However, when extending the pre-announcement event window from 1 day to 3 days, the effect of UK votes weakens in the bonds samples. This could suggest that the impact UK votes might be shorter than the new event window and hence the observed insignificancies of the dummy coefficients. On the contrary, the equity sample shows that the UK votes increase the level of realised volatility on the day of the votes (positive and significant

$D_{3,t}$ coefficients), but quickly drop the day after. The coefficients after the vote's announcement day are negative and typically larger (in absolute terms) than the day of the announcement. This is observed in nearly all equity indices and is line with our earlier results.

In addition, we observe consistent patterns and coefficient signs in the results regarding the effect of the reminder of Brexit categories. The arrival of UK Brexit news influences the Eurozone's government bond volatility, where the volatilities of the Eurozone, Germany and France government bonds significantly surge in anticipation of the announcements of the news, whereas the Netherlands and Belgium demonstrate lagging effects. Moreover, both government bond and equity samples show that the EMU markets are visibly more sensitive to EU Brexit and Industry response news than the UK. In line with our main findings, the bond volatility response to EU Brexit news differs from equities. In comparison to no-EU Brexit news announcement days, three out of the six government bond markets' volatilities increase prior to the EU Brexit news release and fall on the day of the announcement. This is not detected in equities that experience an escalation in the uncertainty on or after the announcement day. Overall, we conclude that the robustness analysis confirms our earlier findings and show that certain news (specifically UK votes) has a shorter impact than others. Hence, this suggests that it might be more appropriate to take a shorter event window of 3-days for Brexit news studies.

4.6 Conclusions

This chapter offers a comprehensive analysis of the effect of Brexit news announcements on financial markets. Given the significance of Brexit, unsurprisingly a growing number of studies emerged investigating its impact on financial markets, mainly focusing on the EU referendum date or a handful of subsequent events. To the best of our knowledge, this is the first study examines the impact of a wide sample of Brexit related news (a total of 151 news) announcements on the volatility of UK and Eurozone government (sovereign) bond and equity markets. We analyse a broad sample covering not only the UK, but also a Eurozone benchmark and four Eurozone countries that are closely linked to the UK: Germany, France, Netherlands, and Belgium.

To test for the impact of the news, we employ an extension of Corsi's (2009) Heterogeneous Autoregressive model for volatility. Our HAR regressions depict similarities as well as distinctions between the volatility responses of sovereign bond and equity markets. Firstly, the results indicate that government bond and mainly stock market volatilities have a long memory, where the lagged daily, weekly, and monthly volatility components help in explaining the behaviour of the daily volatility. Furthermore, our initial tests combining all Brexit news together show that the Eurozone countries' sovereign bond volatilities significantly increase with the arrival of Brexit news. In contrast, the UK stock market volatility is the only stock market that exhibit higher uncertainty on the announcement day. Once we extend on our event window to three days, half of the sovereign bond markets examined seem to anticipate the arrival of Brexit news one day ahead. Our results provide novel evidence of the importance of Brexit news announcements that contain valuable information, beyond the EU referendum, which tend to induce market uncertainty. In addition, our initial tests that the government bond markets are more sensitive to Brexit news than equity markets.

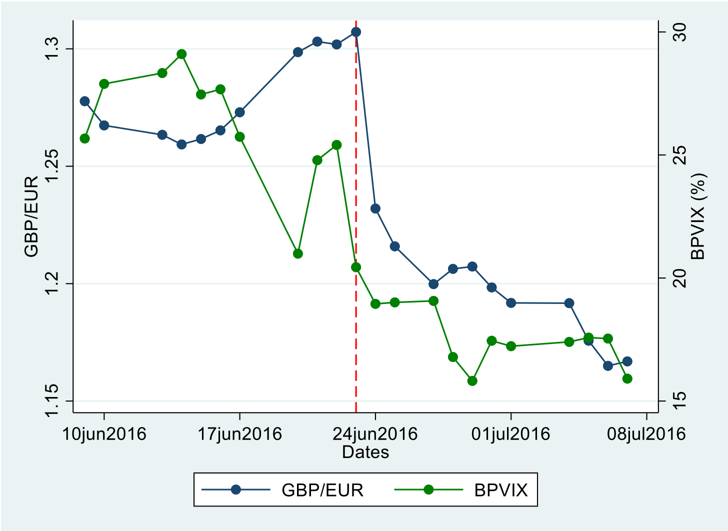
Classifying the news to five different categories (UK Brexit, EU Brexit, UK votes, UK political and Industry response) provide us with further insights into the significance of the different Brexit news. The market volatilities strongly react to certain Brexit news more than others. Specifically, the markets strongly respond to the arrival of UK votes and political news, moderately to Industry response and EU Brexit news, and much less to UK Brexit news. When contrasting the government bond and equity volatility samples, it is evident from our results that the bond market has a stronger response to the Brexit news, which could be explained by the nature of the bond market participants and the drivers of government bond yields. Furthermore, we find that the market volatilities tend to increase on the news' announcement days implying greater market uncertainty. We also find leading and some lagging effects the Brexit news categories. Most notably, on average, sovereign bond (stock) market volatilities significantly decrease one day before (after) the announcement of UK votes. Interestingly, the bond markets seem to also anticipate the arrival of UK political news one day before their announcements, whereas the stock market reactions seem to lag and persist one day after the announcement. As a result, we conclude that although the UK votes are scheduled, they still carry an element of surprise that induces greater risk on the day of the announcement. However, their impact is rather short-lived as the markets seem to recover rather quickly from them. On the other hand, the effect of the UK political news seems to persist longer (two to three days), especially in the stock markets. Contrary to our expectations, we observe that the impact of Brexit news is more pronounced in Eurozone countries, which highlights the importance of global news announcements and affirms the strong ties between the UK and other EU countries.

Our contribution and proportion analysis confirm our earlier results. The majority of news categories' contributions are found to be positive, indicating that Brexit news generally promote greater uncertainty (risk) during the 3-day event window in UK and Eurozone bond and equity markets. The consistent exception are UK votes that have a negative overall contribution, suggesting that, on average, the degree of reduction in volatility one day prior/post the votes' announcements outweigh the increase in volatility on the announcement day. Hence, we conclude that UK votes have an overall stabilising effect on government bond and equity market volatilities and attribute this finding to the fact that the votes tend to bring some clarity on the key issues and direction of the Brexit negotiations. In addition, our proportion analysis enables us to rank the relative effect of each Brexit news category. The rankings highlight that UK votes and UK political news are the two most significant types of Brexit news for government bond and equity market volatilities. The proportion analysis show that these two categories together explain more than 55% (on average) of the markets' volatility responses to Brexit news. On the other hand, the least impactful set of news are found to be UK Brexit announcements. Therefore, our findings offer new empirical evidence of the importance and effect of a large set of Brexit votes, in addition to general elections and the EU referendum, as well as political news. Hence, the observable implication of these results is that it is critical that investors and other market participants study and anticipate the potential impact of Brexit-related news, other parliamentary votes and political news beyond elections and presidential terms, in their decision-making. Furthermore, given the destabilising effects of political news, we believe that it is worth exploring them in a greater detail and wider context.

Lastly, we provide additional analysis for our equity sample applying the same methodology, but this time estimating the volatilities using a realised measure based on intraday (5-min) returns. The equity sample results using the realised volatilities are comparable to those based on the volatilities measured by Parkinson’s range-based volatility (high-low range) estimator. However, the effect and importance of the Brexit news are more notable on the realised equity volatilities. In addition, we find that employing the realised volatilities significantly improve the accuracy (average increase of 17.36% in R-squared) of the HAR regressions across all country stock indices. Therefore, we encourage the use of robust realised volatility estimators based on 5-min intervals over the range-based volatility estimator to increase the estimation accuracy and limit the adverse effects of market microstructure frictions. However, further evidence from other financial asset samples, including the sovereign bonds and exchange rates, is required to determine whether our findings on realised volatilities can be generalised.

4.7 Tables and figures

Figure 4.1: Daily historical time-series of the GBP to EUR exchange rate (GBP/EUR), the annualised CBOE/CME FX British Pound Volatility Index (BPVIX) and their corresponding logarithmic returns (logr). Sample period: 9 Jun - 7 Jul 2016. Notes: the red vertical line represents the date of the referendum (23 Jun 2016).



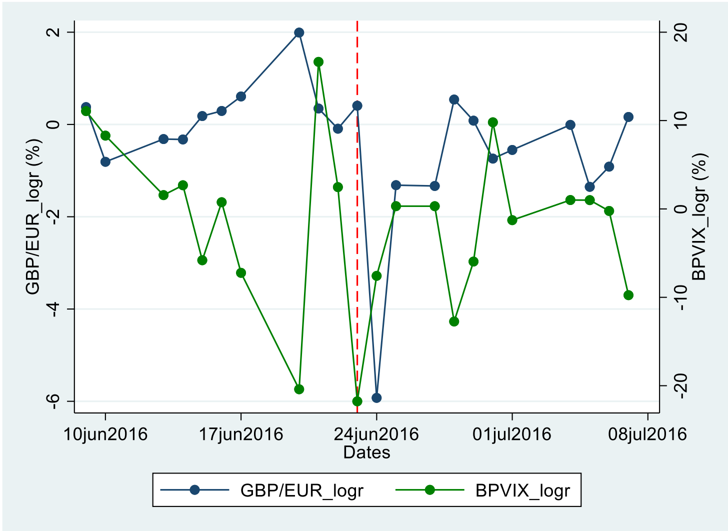
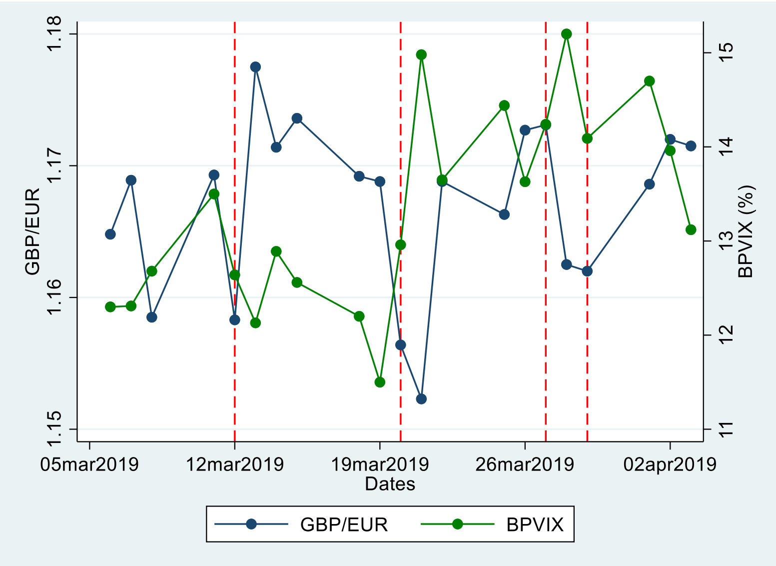


Figure 4.2: Daily historical time-series of the GBP to EUR exchange rate (GBP/EUR), the annualised CBOE/CME FX British Pound Volatility Index (BPVIX) and their corresponding logarithmic returns (logr). Sample period: 6 Mar – 3 Apr 2019. Notes: the red vertical lines represent the date of the second "meaningful vote" (12th Mar 2019), the date that the UK asked the EU for an extension of Article 50 (20 Mar 2019), the date that the Parliament rejected all 8 indicative votes on potential options for Brexit (27 Mar 2019) and the third "meaningful vote" (29 Mar 2019)



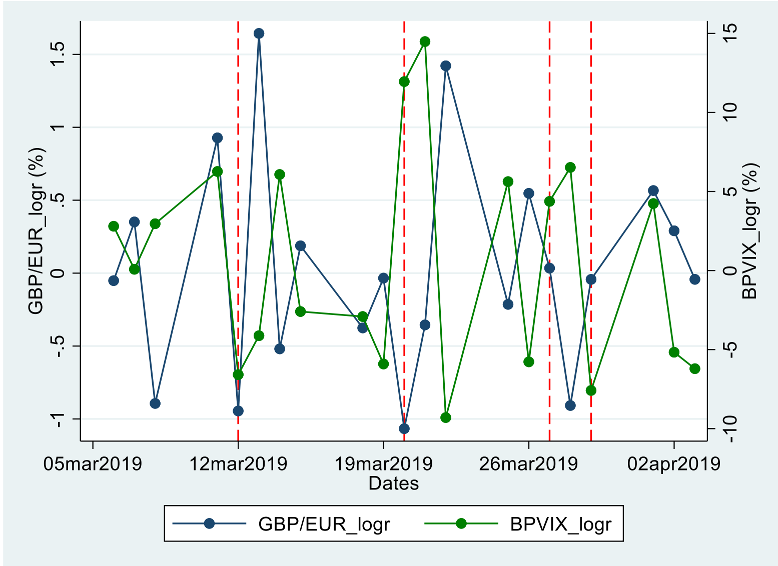


Figure 4.3: Daily historical time-series of the GBP to EUR exchange rate (GBP/EUR), the annualised CBOE/CME FX British Pound Volatility Index (BPVIX) and their corresponding logarithmic returns (logr). Sample period: 29 Nov – 27 Dec 2019. Notes: the red vertical lines represent the UK general election day (12 Dec 2019) and the date that Boris Johnson's speaker announced that the UK intends to outlaw any extension of the Brexit transition period beyond December 2020 (17 Dec 2019).

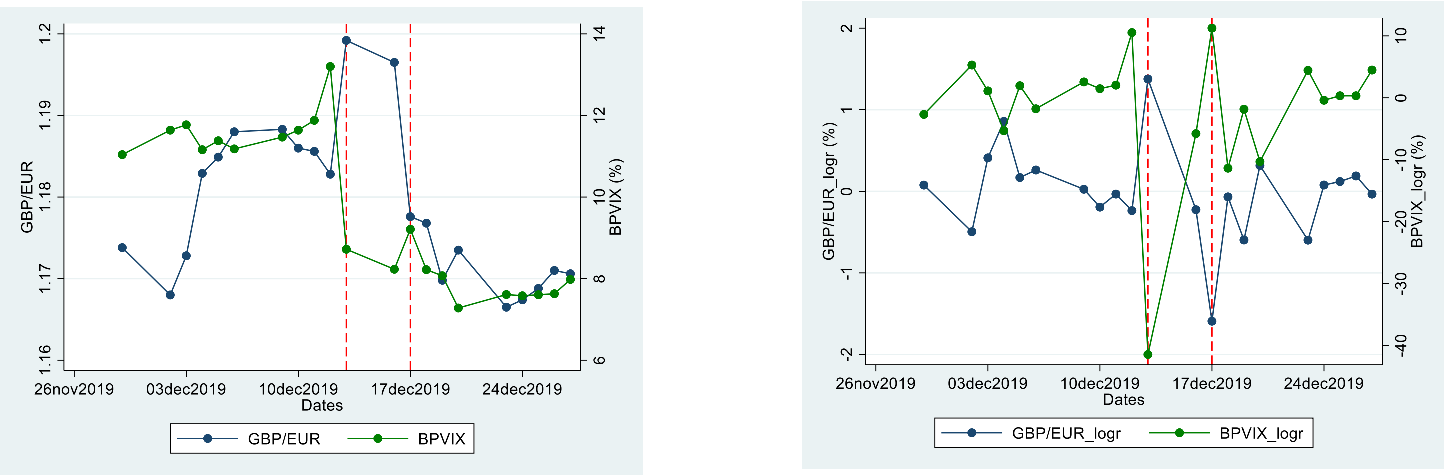


Figure 4.4: Daily historical time-series of the GBP to EUR exchange rate (GBP/EUR), the annualised CBOE/CME FX British Pound Volatility Index (BPVIX) and their corresponding logarithmic returns (logr). Sample period: 17 Jan – 14 Feb 2020. Notes: the red vertical line represent the Brexit date (31 Jan 2020).

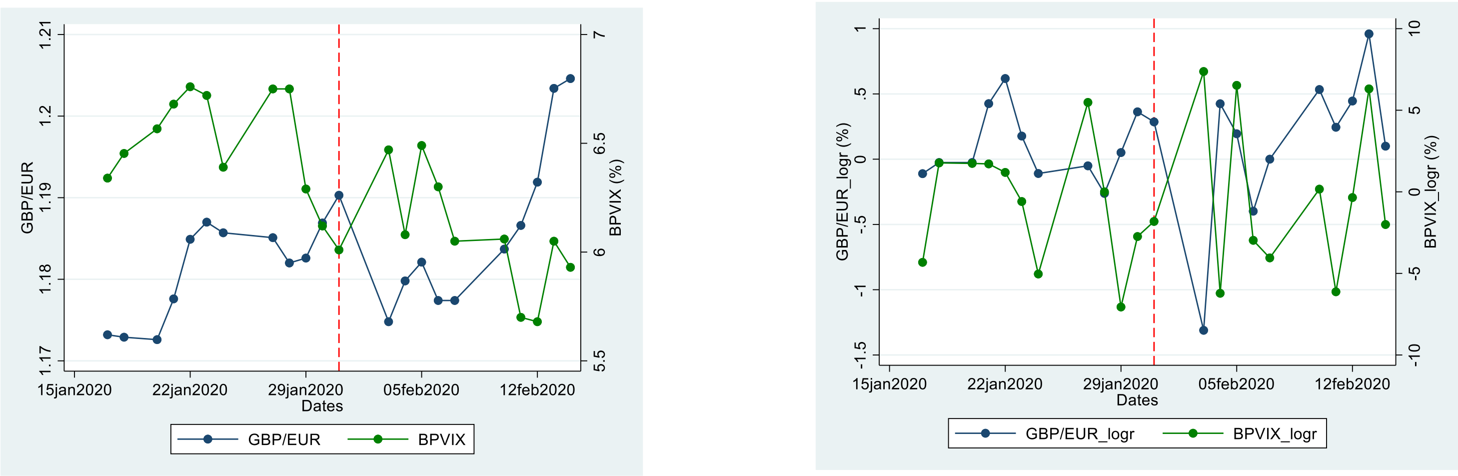


Figure 4.5: Daily 10-year government (sovereign) bond market volatilities (1 April 2010 – 28 Feb 2020). Notes: the red vertical lines represent the date of the referendum (23 Jun 2016) and the Brexit date (31 Jan 2020).

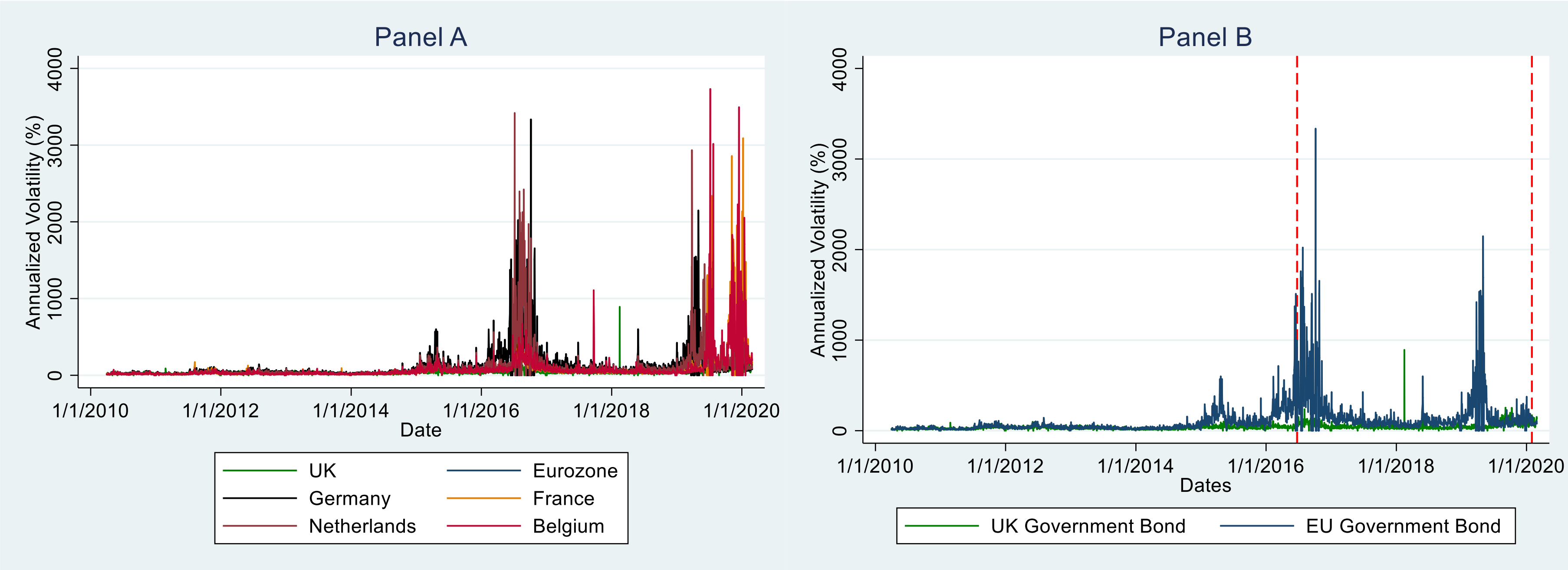


Figure 4.6: Daily stock market volatilities (1 April 2010 – 28 Feb 2020). Notes: the red vertical lines represent the date of the referendum (23 Jun 2016) and the Brexit date (31 Jan 2020).

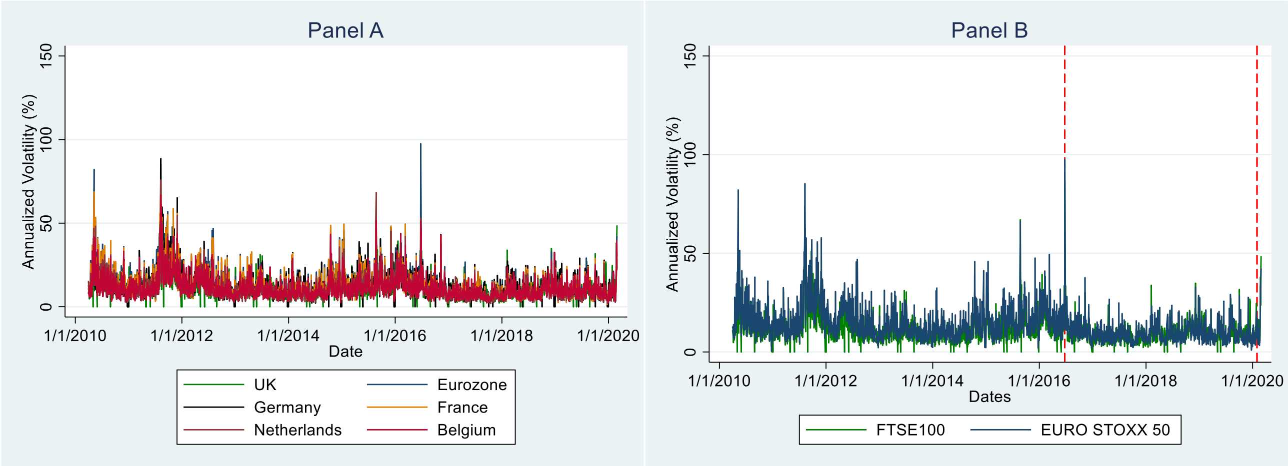


Figure 4.7: Daily stock market realised volatilities (1 April 2010 – 28 Feb 2020). Notes: the red vertical lines represent the date of the referendum (23 Jun 2016) and the Brexit date (31 Jan 2020).

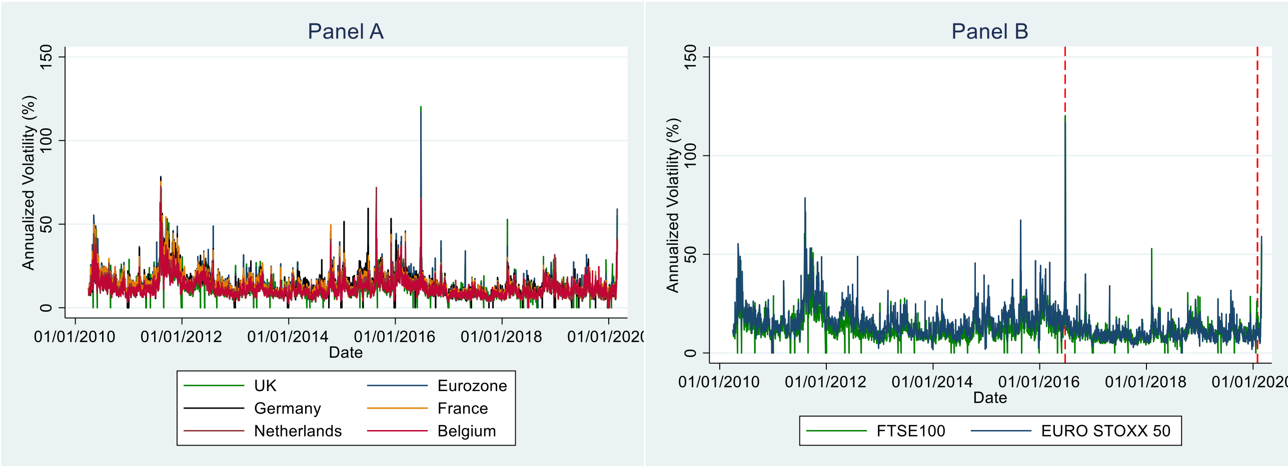


Table 4.1: List of Brexit news included in the sample. This table presents the list of Brexit-related news included in the sample and their Brexit news categorisation. All news (news headlines) were obtained from online sources. **Sources:** House of Commons Library (Walker 2021), BBC, Bloomberg, Financial Times and Reuters.

Date	Brexit event (news)	News (event) category
2013		
23- January	David Cameron promises in/out referendum on EU if the Conservatives win the election.	UK Political
22- February	UK loses triple A credit rating (Moody's downgraded the UK from Aaa to Aa1) for the first time since 1978 on expectations that growth will "remain sluggish over the next few years".	Industry Response
2015		
14-April	Launch of the Conservative Party Manifesto for the 2015 General Election that commits to "hold an in-out referendum on our membership of the EU before the end of 2017".	UK Political
10-November	In a speech to Chatham House, David Cameron reaffirms his commitment to an EU referendum and writes a letter to Donald Tusk setting out the four areas where he is seeking EU reform.	UK Brexit
17-December	The European Union Referendum Act receives Royal Assent.	UK Brexit
2016		
22-February	The Prime Minister announces the EU referendum date (23 June 2016) after securing a deal on the UK's membership of the EU.	UK Brexit
22-June	The Bank of England said some UK businesses may have postponed spending decisions in the run-up to Britain's referendum.	Industry Response
23-June	UK holds referendum on its membership of the EU, with the question posed to the electorate: "Should the United Kingdom remain a member of the European Union or leave the European Union?"	UK votes
24-June	The referendum result is announced, with the majority of voters (51.9%) choosing to leave the EU and the Prime Minister David Cameron announces his intention to resign.	UK Brexit
25-June	The UK's Jonathan Hill resigns as European Union financial-services chief in the wake of the Brexit vote.	UK Political
30-June	Home Secretary Theresa May formally declares her candidacy for the Conservative Party leadership.	UK Political
05-July	Three of the UK's largest real-estate funds freeze assets after the Brexit vote sparked a flurry of redemptions.	Industry Response
13-July	Theresa May becomes the new UK Prime Minister. She names Boris Johnson as foreign secretary, David Davis as Brexit secretary, Liam Fox as trade secretary and Philip Hammond as chancellor of the exchequer.	UK Political
27-July	The European Commission names Frenchman Michel Barnier to lead the EU's Brexit negotiations.	EU Brexit
19-August	Bloomberg reports that Theresa May's team is leaning towards triggering Brexit by April 2017.	UK Brexit
5-September	Theresa May attends her first Group of 20 summit and says she has ruled out a points-based immigration system for EU nationals.	UK Brexit
12-September	David Cameron says he is quitting as a member of the UK Parliament. David Davis says divorce from the EU and a new trade deal can be completed within two years.	UK Political
16-September	European leaders meet without the UK for the first time in four decades, trying at a session in Bratislava to build a shared vision for the bloc.	EU Brexit
2-October	In her speech to the Conservative Party Conference, Theresa May announces a 'Great Repeal Bill' and confirms Article 50 will be triggered before the end of March 2017.	UK Brexit
03-October	Bloomberg News reports financial-services companies will get no special favours in the Brexit talks.	UK Brexit
07-October	The pound plunges more than 6 percent in two minutes to its lowest level in 31 year, most likely due to market concerns about the impact of a "hard Brexit".	UK Brexit

13-October	EU President Donald Tusk says it will be “hard Brexit” or “no Brexit” as he warns there will be “no cakes on the table, for anyone” but rather “only salt and vinegar.”	EU Brexit
03-November	High Court rules that the UK must hold a vote in the Parliament before starting Brexit process (Gina Miller case). The Government announces it will appeal against the decision.	UK Political
15-November	The Financial Times reports the EU is seeking as much as €60bn from the UK when it leaves the bloc.	EU Brexit
23-November	Philip Hammond delivers his budget and reveals the Office for Budget Responsibility estimates Brexit means the government will need to borrow an extra £58.7bn.	UK Brexit
07-December	The House of Commons votes 448 to 75 in favour of Theresa May’s plan to trigger Brexit by the end of March 2017.	UK votes
2017		
03-January	Sir Ivan Rogers, the UK Permanent Representative to the EU, resigns	UK Political
04-January	Sir Tim Barrow is appointed as UK Permanent Representative to the EU.	UK Political
08-January	May signals in an interview with Sky News that regaining control of immigration and law making are her Brexit priorities even if that means leaving Europe’s single market.	UK Brexit
17-January	David Davis gives a statement to the House of Commons on the ‘New Partnership with the EU” and Theresa May gives her Lancaster House speech, setting out the Government’s ‘Plan for Britain’ and the priorities that the UK will use to negotiate Brexit.	UK Brexit
24-January	The Supreme Court rules that the Parliament must vote before triggering Article 50.	UK Political
26-January	Government publishes European Union (Notification of Withdrawal) Bill that will allow the UK to start the process of leaving the EU.	UK Brexit
01-February	The European Union Bill passes its Second Reading in the House of Commons by 498 votes to 114.	UK votes
02-February	The Government publishes its Brexit White Paper, formally setting out its strategy for exiting the EU.	UK Brexit
08-February	The European Union Bill passes its Third Reading in the House of Commons, by 494 votes to 122.	UK votes
21-February	The UK will have to foot a “hefty bill” when it leaves the European Union, European Commission President Jean-Claude Juncker warned.	EU Brexit
28-February	David Davis tells Cabinet colleagues to prepare for the possibility of failing to reach a divorce deal.	UK Brexit
01-March	House of Lords amends the Brexit bill to guarantee the rights of EU citizens in the UK.	UK Brexit
10-March	The UK will leave a €20bn hole in the EU’s budget unless the bloc agrees to give Theresa May the sweeping Brexit trade deal she wants, according to senior British officials.	EU Brexit
16-March	European Union (Notification of Withdrawal) Act received Royal Assent.	UK Brexit
20-March	May’s spokesman confirms that the prime minister will invoke Article 50 on 29 March 2017.	UK Brexit
22-March	EU officials called for the bloc to prepare for the UK to walk out of the Brexit talks without a deal and Michel Barnier says Britain must “settle the accounts” before a trade deal is discussed.	EU Brexit
24-March	European Commission President Jean-Claude Juncker tells the BBC that the exit bill is “around” £50m.	EU Brexit
28-March	Theresa May says she wants “to secure a new deep and special partnership” with the EU and formally signs the letter invoking Article 50.	UK Brexit
29-March	Theresa May triggers Article 50 of the Treaty on European Union and notifies the European Council President Donald Tusk of the UK’s intention to leave the EU -The Brexit deadline is set for 29 March 2019.	UK Brexit
30-March	The Government publishes the Great Repeal Bill White Paper.	UK Brexit
18-April	The Prime Minister calls a General Election to be held on 8 June 2017.	UK Political

06-June	The Economist Intelligence Unit's report showed that the UK's annual health spending would be lower by about £7.5bn pounds by 2021 under a "hard Brexit" than a soft one.	Industry Response
08-June	General Election results in a hung Parliament, with the Conservatives winning the most seats and Theresa May forming a government.	UK Political
19-June	First round of UK-EU exit negotiations begin.	UK Brexit
21-June	State Opening of Parliament. The Queen's Speech includes a 'Great Repeal Bill' in the Government's legislative programme and other Brexit-related Bills.	UK Brexit
26-June	The government publishes a policy paper on the rights of EU citizens in the UK and UK nations in the EU.	UK Brexit
13-July	Government introduces the European Union (Withdrawal) Bill, known as the 'Great Repeal Bill'.	UK Brexit
17-July	Brexit Puts Financial-Trade Tax on ice as banks start moving and the French Finance Minister mentions that Brexit could bring "thousands of jobs to Paris," an opportunity that could be lost if the tax were imposed.	EU Brexit
12-September	EU Withdrawal Bill passes Second Reading in the House of Commons.	UK votes
22-September	Prime Minister delivers her key Brexit speech in Florence, setting out the UK's position on moving the Brexit talks forward. Moody's cut the UK's rating by a further notch to Aa2, underscoring the economic risks that Brexit poses and growth fears.	UK Brexit, Industry Response
19-October	European Council meeting to assess progress on the Phase 1 of the Brexit negotiations.	EU Brexit
13-November	The Government announces a plan for Withdrawal Agreement and Implementation Bill to enshrine the Withdrawal Agreement between the UK and the EU in domestic law.	UK Brexit
08-December	The UK and EU publish a Joint Report progress made during Phase 1 of negotiations. This concludes Phase 1 of negotiations and both sides move to Phase 2. It mentions that there will be no "hard border" with Ireland; and the rights of EU citizens in the UK and UK citizens in the EU will be protected. The so-called "divorce bill" will amount to between £35bn and £39bn, Downing Street sources say.	UK Brexit
11-December	Theresa May insists that the Brexit deal is good for all sides and managed to unite her Conservative party on Brexit, as Tory MPs from all sides lined up to hail her "triumph" in finalising a "divorce" deal".	UK Brexit
2018		
12-January	Goldman Sachs, JPMorgan Chase & Co. and Morgan Stanley are on a hiring drive in Frankfurt to establish new headquarters inside the European Union in time for Brexit.	Industry Response
16-January	European Union President Donald Tusk keeps alive the notion of the UK reversing its plan to leave the bloc.	EU Brexit
17-January	European Commission President Jean-Claude Juncker says the UK can always re-apply for membership after departing.	EU Brexit
18-January	First Reading of the European Union (Withdrawal) Bill in the House of Lords.	UK Brexit
28-February	The European Commission publishes the draft Withdrawal Agreement between the EU and the UK.	UK Brexit
02-March	Theresa May gives a speech at Mansion House stating that the "existing models do not provide the best way forward for either the UK or the EU". The UK still doesn't have a Brexit solution for Northern Ireland.	UK Brexit
14-March	The European Parliament endorses a resolution laying out a possible association agreement framework for future EU-UK relations after Brexit.	EU Brexit
19-March	The amended Draft Withdrawal Agreement is published. The UK and the EU negotiating teams state their aim to finalise the entire Withdrawal Agreement by October 2018.	UK Brexit
16-May	The European Union (Withdrawal) Bill finishes its House of Lords stages and goes into parliamentary ping pong.	UK Brexit

26-June	The European Union (Withdrawal) Bill receives Royal Assent and becomes an Act of Parliament. BMW AG joined a rising chorus of businesses warning they will have to pull back on investment in the UK if a Brexit deal isn't reached that ensures goods can flow freely to the EU.	UK Brexit, Industry Response
03-July	UK companies are delaying spending decisions as they await answers to key questions surrounding the UK's departure from the EU.	Industry Response
09-July	David Davis resigns as Brexit Secretary, telling the BBC he felt the UK was "giving away too much and too easily" to the EU in the Brexit negotiations. Dominic Raab is appointed as his replacement.	UK Brexit
24-July	Government publishes White Paper on future UK-EU relations.	UK Brexit
23-August	The government publishes the first collection of technical notices providing guidance on how to prepare for a no-deal Brexit.	UK Brexit
19-September	EU leaders hold an informal summit in Salzburg in which Theresa May gives a Brexit speech and insists that there could be no deal that splits the UK into two customs territories.	EU Brexit
29-October	UK Budget Day. Chancellor Philip Hammond announces £500m for no-deal Brexit preparations.	UK Brexit
09-November	Goldman Sachs Group Inc., JPMorgan Chase & Co., Morgan Stanley and Citigroup Inc. have presented plans to increase the assets held through their Frankfurt subsidiaries tenfold after the UK's exit from the EU to comply with requirements, the people said.	Industry Response
14-November	The Withdrawal Agreement is agreed and published.	UK Brexit
15-November	In an opposition to the Withdrawal Agreement, the Brexit Secretary Dominic Raab and other Ministers, including Suella Braverman (Junior Brexit Minister) and Esther McVey (Works and Pensions Secretary) resign.	UK Political
25-November	At the special European Council meeting, EU27 leaders endorse the Brexit withdrawal agreement and approve the political declaration on future EU-UK relations.	EU Brexit
04-December	MPs begin the first of five days of Brexit debates, leading up to the 'Meaningful Vote' on 11 December.	UK Brexit
05-December	Government publishes the Attorney General's legal advice to Cabinet on the Protocol to the Withdrawal Agreement on Ireland and Northern Ireland.	UK Brexit
10-December	The CJEU issues its judgment on the Wightman case, finding unilateral revocation of Article 50 TEU is a sovereign right for any Member State to pursue. Later, Theresa May postpones tomorrow's planned Meaningful vote on her Brexit deal.	UK Brexit
11-December	Theresa May wins a vote of confidence in her leadership of the Conservative Party.	UK votes
19-December	Theresa May Unveils Post-Brexit Immigration Plan.	UK Political
2019		
08-January	MPs debate the Report Stage and Third Reading of the Finance (No. 3) Bill. MPs approve an amendment that limits the government's financial powers in the event of a no-deal Brexit.	UK votes
09-January	As five days of Brexit debates begin, an amendment to the business motion is passed, giving the Prime Minister only three days to present a 'Plan B' Brexit plan if she loses meaningful vote.	UK Brexit
15-January	The Prime Minister loses the 'Meaningful Vote' (with 202 voting in favour of the Prime Minister's Brexit deal and 432 against) and the Leader of the Opposition tables a motion of no confidence in the Government.	UK votes
16-January	The Prime Minister wins a vote of confidence in the Government (325 votes to 306).	UK votes
21-January	Theresa May presents the government's 'Plan B' Brexit deal and outlines six key issues that have been at the centre of cross-party talks.	UK Brexit
29-January	MPs debate the Prime Minister's 'Plan B' deal, which is then approved following two amendments, indicating that a majority of MPs are a) against exiting the EU without a deal, and b) against the Northern Ireland backstop in its current form.	UK Brexit
14-February	The government's Brexit plan suffers a defeat in the House of Commons.	UK votes

26-February	The Prime Minister promises MPs a vote on ruling out a no-deal Brexit or delaying Brexit if she loses the second 'meaningful vote' next month.	UK Brexit
12-March	The Prime Minister loses the 'Meaningful Vote 2' by a majority of 149.	UK votes
13-March	In a defeat for the Prime Minister, MPs vote to rule out a 'no-deal Brexit'.	UK votes
14-March	MPs approve the amended government's motion, instructing the government to seek permission from the EU to extend Article 50. President Donald Trump says he anticipates a "large scale" trade agreement with the UK as it faces a delay to its exit from the EU.	UK votes, UK political
20-March	The Prime Minister writes to European Council President Donald Tusk, asking for an extension of the Article 50 period until 30 June 2019.	UK Brexit
21-March	Following a meeting of the European Council, EU27 leaders agree to grant an extension comprising two possible dates: 22 May 2019, if the Withdrawal Agreement gain approval from MPs next week; or 12 April 2019, if the agreement does not get approved.	EU Brexit
27-March	The Commons debates and votes on eight indicative votes, in an attempt to find a Brexit plan that wins the support of the majority of MPs. All options are defeated. Theresa May suggests she will stand down before the second stage of Brexit negotiations.	UK votes
29-March	The Prime Minister loses the vote 'Meaningful Vote 3' for the deal again by 344 votes to 286.	UK votes
01-April	In the second day of indicative votes, all four of the selected options are defeated.	UK votes
02-April	The Prime Minister announces she will seek a further extension to the Article 50 process and offers to sit down with the Leader of the Opposition, to finalise a deal that will win the support of MPs.	UK Brexit
05-April	Theresa May writes to Donald Tusk, asking for a further extension to Article 50 until 30 June 2019.	UK Brexit
10-April	The European Council meets. The UK and EU27 agree to extend Article 50 until 31 October 2019.	EU Brexit
21-May	The Prime Minister unveils her new Brexit deal. According to BBC the new deal isn't all that new, the Withdrawal Agreement, which includes the backstop plan for the Irish border remains exactly the same. Many lawmakers have already decided not to vote for it next month.	UK Brexit
23-May	The UK votes in the European Parliament elections.	UK votes
24-May	Theresa May announces she will resign on 7 June.	UK Political
23-July	Boris Johnson wins the Conservative Party leadership race, securing 92,153 votes to Jeremy Hunt's 46,656.	UK votes
24-July	Boris Johnson formally takes over as Prime Minister.	UK Political
25-July	Prime Minister Johnson makes a statement in the House of Commons and commits to the October date for Brexit and – while hoping for a renegotiation of the Withdrawal Agreement – refuses to rule out the possibility of a 'no-deal' Brexit.	UK Political
28-July	Upon the advice of the Boris Johnson, Queen Elizabeth II approves the suspension of Parliament.	UK Political
21-August	UK Budget Deficit Soars as the UK Prepares for Brexit. According to the Office for National Statistics figures, the budget deficit between April and July stood at £16bn, 60% more than the same period last year.	Industry Response
24-August	Boris Johnson has insisted that any UK-US trade deal would have to work in the interests of British business and that some sectors of the UK economy would be completely off limits in discussions, notably the National Health Service.	UK Political
04-September	MPs debate Hilary Benn's European Union (Withdrawal) (No. 6) Bill and the bill passes its Second Reading and Committee stages. Following this, the Prime Minister moves a motion to hold an early General Election, but the motion is defeated.	UK votes
09-September	Queen Elizabeth II gives her approval to the Benn Act making it a law: the European Union (Withdrawal) (No. 2) Act 2019 and parliament prorogues.	UK Brexit
24-September	The Supreme Court passes a unanimous judgment that the decision to prorogue Parliament was unlawful. The Speaker of the House of Commons announces that the House will sit again the next day.	UK Political

02-October	Prime Minister Boris Johnson publishes his "final" Brexit proposals setting out his alternative to the Irish backstop, which are rejected by the EU.	UK Brexit
08-October	The Government publishes the No-Deal Readiness Report, detailing the UK's preparedness ahead of Brexit on 31 October.	UK Brexit
10-October	The prime minister and his Irish counterpart Leo Varadkar say they see a "pathway" to a deal after talks over the main sticking point - how to keep open the border, for trade and travel, between the British province of Northern Ireland and the Irish Republic.	UK Brexit
11-October	The aerospace, automotive, chemicals, food and drink and pharmaceutical sectors warn they could pose "serious risk to manufacturing competitiveness" and sent a letter to the government highlighting its concerns over the government’s plans for post-Brexit trading arrangements.	Industry Response
17-October	The European Union and the UK announce their agreement on a new draft Brexit agreement.	EU Brexit
19-October	The British parliament sits on a Saturday for the first time in 37 years. Boris Johnson presents his new deal, but MPs vote in favor of delaying (Letwin amendment passes by 322 votes to 306) the decision on the draft deal. The PM later writes to Donald Tusk to ask for a Brexit extension.	UK votes
21-October	The European Union (Withdrawal Agreement) Bill is introduced to Parliament.	UK Brexit
22-October	MPs vote to allow the government's EU bill on it to go forward to the next stage in the parliamentary process, but reject the rapid timetable which would only have allowed three days of debate in the House of Commons.	UK votes
28-October	EU leaders agree to flexible extension (known as "flextension") of Brexit date to 31 January 2020.	EU Brexit
29-October	The government introduces the Early Parliamentary General Election Bill which sets the date for a General Election to take place on 12 December 2019.	UK Political
05-November	Philip Hammond, Chancellor of the Exchequer, Quits Parliament After Expulsion by Johnson for opposing Boris Johnson’s Brexit strategy.	UK Political
12-November	The world’s biggest banks pressed policy makers to pass an urgent Brexit fix to ensure European traders’ access to London derivatives clearinghouses and avoid rupturing £61tn in contracts.	Industry Response
18-November	UK Prime Minister Boris Johnson announced his Conservatives are cancelling plans to cut corporation tax next April so the government can save money to spend more on voters’ priorities, including the state-funded National Health Service.	UK Political
03-December	Moody’s has reduced its outlook on the UK banking system from stable to negative, saying Brexit uncertainty has eroded “the country’s growth prospects” while low interest rates are hitting lenders’ profitability.	Industry Response
04-December	European units of Goldman Sachs Group Inc., JPMorgan Chase & Co., Morgan Stanley and UBS Group AG entered the ECB’s oversight this year as a result of their shift of operations from the UK to the euro area.	Industry Response
12-December	UK General election day.	UK votes
13-December	Boris Johnson wins the biggest Conservative majority in UK election since 1987, trouncing his Labour Party opponent Jeremy Jeremy Corbyn by securing 365 seats with a majority of 80, whilst the Labour won 203 seats. President Trump said the US and UK would now be free to strike a "massive" new trade deal after Brexit. German chancellor Angela Merkel said many fellow EU leaders were relieved British Prime Minister Boris Johnson now had a clear mandate to proceed with Brexit, but said the shortage of time to fix future relations was a major challenge. Credit ratings agency Moody’s said that Brexit uncertainty was likely to return despite Boris Johnson’s comprehensive victory.	UK votes, UK Political, EU Brexit, Industry response
17-December	Boris Johnsons' spokesman said that the British government plans for its new relationship with the European Union to be ready to be implemented in January 2021 and intends to outlaw any extension of the Brexit transition period beyond December 2020.	UK Brexit
19-December	Boris Johnson announces his 'radical' agenda for UK after the Brexit.	UK Brexit

20-December	During the second reading in the House of Commons the MPs voted (358 to 234) in favour of Boris Johnson's Brexit Bill and accordingly backed the PM's plan for the UK to leave the EU on 31 January.	UK votes
2020		
02-January	Bank of England survey shows that the Brexit pessimism in UK businesses decreased in December, though the outlook in the short-term remains challenging.	Industry Response
07-January	The European Union Bill has its first day in Committee Stage in the House of Commons.	UK votes
08-January	The Commission President Ursula von der Leyen warns that Boris Johnson's aim of full Brexit deal in 2020 is 'impossible' as the time is very tight. Johnson says UK won't stay aligned to EU rules and both set out rival red lines for their visions of a post-Brexit deal. The European Union Bill has its second day in Committee Stage in the House of Commons and later passes to the Third Reading.	UK Brexit, UK votes
17-January	The UK government states that EU citizens living in the UK who miss the deadline for applying for "settled status" by mid-2021 will not face automatic deportation.	UK Brexit
18-January	Sajid Javid, the chancellor has warned manufacturers that "there will not be alignment" with the EU after Brexit and insists firms must "adjust" to new regulations. The Food and Drink Federation said it sounded like the "death knell" for frictionless trade with the EU and was likely to cause food prices to rise and affect jobs.	UK Brexit, Industry Response
21-January	Boris Johnson's government suffered a fourth defeat on its Brexit legislation when the Lords voted (300 to 220) to ensure unaccompanied child refugees can continue to be reunited with family in the UK after it leaves the EU. The Bill later passes its Third Reading and is returned to the Commons with amendments.	UK votes
22-January	MPs debate the Lords amendments to The European Union Bill and overturned all five changes made to the legislation. The Lords could have sought to reinstate the changes, but opted not to, allowing the legislation to clear its final hurdle in the UK.	UK votes
29-January	EU Parliament gives the final approval to Brexit deal, paving the way for Brexit to take place on the 31st of January. The UK will enter an 11-month transition period.	UK Brexit
30-January	The Bank of England voted to keep interest rates on hold at 0.75% but dealt a blow to Boris Johnson's government by cutting its longer-term economic forecast.	Industry Response
31-January	Brexit date - The UK has officially left the European Union after 47 years of membership.	UK Brexit

Table 4.2: Brexit news (event) categories and frequencies

News (event) category	# of news	Frequency
UK Brexit	61	40.40%
EU Brexit	20	13.25%
UK Votes	28	18.54%
UK Political	25	16.56%
Industry Response	17	11.26%
Total	**151**	**100.00%**

Table 4.3: Stock and bond samples

Country	Stock Index	10-Year Government Bond (Bloomberg Mnemonic)
UK	FTSE 100	GTGBP10Y Govt
Eurozone	EURO STOXX 50	GTEUR10Y Govt
Germany	DAX 30	GTDEM10Y Govt
France	CAC 40	GTFRF10Y Govt
Netherlands	AEX	GTNLG10Y Govt
Belgium	BEL 20	GTBEF10Y Govt

Table 4.4: Descriptive statistics of annualised daily volatilities (%). The table reports the descriptive statistics for government bond and stocks daily volatilities of our UK and EU sample countries for the period 01/04/2010 – 28/02/2020. The daily volatilities are measured using Parkinson's (1980) high-low range estimator. The Min, Max and St.Dev denote the minimum, maximum and standard deviation, respectively. The table also reports the t-tests (Mann-Whitney tests) of the mean (median), where the hypothesis of the t-test (Mann–Whitney test) is that the mean (median) of the daily volatility is equal for event (news) announcement days and non-event days. ADF is the Augmented Dickey Fuller test statistics. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

	Government Bonds						**Stock (Equity)**					
	UK	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
Panel A: Summary statistics full sample												
Mean	39.198	111.925	111.925	77.975	97.785	81.068	11.175	13.752	13.031	12.978	11.270	11.310
Median	32.572	57.509	57.509	37.052	47.352	35.359	9.514	11.598	11.131	10.974	9.509	9.721
Std. dev	31.461	196.422	196.422	181.039	209.741	202.022	6.929	8.637	8.160	8.046	6.979	6.531
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.407	0.000	1.324	1.847	2.495
Max	891.533	3334.942	3334.942	3089.027	3417.933	3731.258	86.543	97.492	88.584	71.770	75.734	66.777
Skewness	9.327	6.220	6.220	8.551	7.524	9.045	2.518	2.398	2.195	2.236	2.318	2.393
Kurtosis	219.373	59.861	59.861	99.746	78.087	117.511	16.391	14.133	12.636	11.421	12.786	13.100
ADF	-31.582***	-29.278***	-29.278***	-29.251***	-26.167***	-30.653***	-28.987***	-26.618***	-27.366***	-25.998***	-25.766***	-26.993***
Panel B: Summary statistics by Event(news) day												
Mean	63.053***	211.055***	211.055***	210.078***	231.216***	217.153***	10.819	10.812***	10.234***	9.920***	8.950***	9.916***
Median	51.390***	119.055***	119.055***	73.229***	108.146***	68.520***	9.380	8.842***	8.949***	8.253***	7.784***	8.396***
Std. dev	42.049	260.118	260.118	402.743	367.721	387.544	8.304	9.044	6.018	5.829	5.703	6.102
Min	0.000	0.000	0.000	0.000	0.000	0.000	0.000	3.607	0.000	2.521	2.993	3.108
Max	252.511	1581.605	1581.605	3089.027	2933.651	3015.173	86.543	97.492	49.746	44.387	52.948	51.041
Skewness	1.956	2.892	2.892	4.224	4.421	3.802	5.646	6.558	2.926	2.687	3.900	3.709
Kurtosis	7.876	12.239	12.239	24.542	27.390	22.358	49.920	60.905	17.416	13.917	27.329	22.481
Panel C: Summary statistics by UK Brexit												
Mean	57.378***	154.101**	154.101**	168.684*	187.965**	170.080**	11.561	11.091*	10.137***	9.669***	9.074**	9.714*
Median	46.214***	101.723***	101.723***	61.491***	89.635***	65.719***	9.784	8.354***	8.946***	7.945***	6.818***	8.155***
Std. dev	39.593	162.859	162.859	409.331	324.582	271.953	10.977	12.293	6.966	6.559	7.260	6.779
Min	19.745	0.000	0.000	0.000	0.000	0.000	3.150	3.607	0.000	2.521	2.993	3.108

Max	252.511	986.292	986.292	3089.027	2125.505	1291.955	86.543	97.492	49.746	44.387	52.948	51.041
Skewness	2.721	3.169	3.169	6.186	4.386	2.828	5.416	5.873	3.197	2.960	3.937	4.037
Kurtosis	12.313	14.777	14.777	44.037	24.073	10.560	37.134	41.467	18.349	14.890	23.265	24.080
Panel D: Summary statistics by EU Brexit												
Mean	58.575**	244.785	244.785	172.742	230.025*	161.536	8.942*	8.598***	9.004***	8.155***	7.507***	8.099***
Median	44.307***	103.933**	103.933**	56.358***	75.432***	61.536***	7.570*	7.857**	8.401**	7.898***	7.878***	7.680**
Std. dev	39.597	397.062	397.062	297.451	294.178***	259.581	4.880	2.868	2.977	2.736	2.305	2.212
Min	19.049	0.000	0.000	0.000	25.955	0.000	3.736	4.589	4.981	3.678	4.145	4.267
Max	168.599	1581.605	1581.605	1221.745	1214.145	1047.848	26.771	14.579	15.214	15.200	13.203	13.462
Skewness	1.454	2.410	2.410	2.668	2.145	2.509	2.534	0.637	0.741	0.584	0.326	0.604
Kurtosis	4.330	7.901	7.901	9.254	7.352	8.397	10.083	2.481	2.684	3.313	3.044	3.257
Panel E: Summary statistics by UK votes												
Mean	62.596***	290.491***	290.491***	306.740*	338.997**	185.335	10.668	10.766***	10.749***	9.990***	8.610***	10.071
Median	55.531***	190.702***	190.702***	81.962***	168.186***	54.763*	9.106	10.046	9.912	9.184*	7.819**	9.611
Std. dev	29.941	279.848	279.848	643.038	543.929	344.280	4.930	3.768	4.149	3.624	3.571	3.886
Min	23.347	65.805	65.805	0.000	80.251	0.000	4.394	6.018	3.457	4.939	3.987	4.974
Max	157.978	1099.417	1099.417	3089.027	2933.651	1478.948	26.771	23.252	22.012	21.052	21.965	19.377
Skewness	1.483	1.821	1.821	3.358	4.094	2.628	1.517	1.390	0.731	1.482	1.882	1.006
Kurtosis	5.436	5.227	5.227	14.178	19.936	9.187	5.314	5.440	3.404	5.114	8.064	3.449
Panel F: Summary statistics by UK political												
Mean	69.539***	263.910**	263.910**	293.968**	220.304***	374.279**	11.592	11.174	10.510	11.061	9.885	11.532
Median	61.978***	149.773***	149.773***	95.251***	165.871***	128.636***	9.275	7.699**	7.438**	8.080*	8.288	8.351
Std. dev	40.982	302.311	302.311	442.049	216.140	656.451	8.171	8.209	7.681	7.661	5.760	8.526
Min	0.000	29.369	29.369	0.000	29.437	0.000	0.000	3.748	3.879	3.929	3.115	4.272
Max	155.933	1409.802	1409.802	1731.410	939.756	3015.173	28.934	40.058	38.067	37.698	28.765	44.042
Skewness	0.420	2.532	2.532	2.174	1.997	2.939	0.929	1.975	2.131	1.929	1.641	2.465
Kurtosis	2.341	9.631	9.631	6.767	6.544	11.724	2.814	7.178	7.787	6.897	5.845	9.559
Panel G: Summary statistics by industry response												
Mean	85.109***	167.962	167.962	256.332	335.617**	280.8155**	11.505	11.177**	11.230*	10.349**	8.917**	9.893

Median	49.345***	116.704***	116.704***	75.119**	96.290***	65.911**	10.356	11.479	11.56	9.356	9.149	9.345
Std. dev	63.427	135.076	135.076	479.560	401.191	388.704	5.764	4.647	3.588	4.284	3.441	3.593
Min	19.333	27.193	27.193	0.000	34.611	0.000	3.149	4.960	5.883	4.341	4.389	3.601
Max	251.173	464.778	464.778	1953.074	1230.075	1108.081	26.771	21.453	20.863	17.233	16.050	16.188
Skewness	1.114	0.962	0.962	2.860	1.227	1.316	1.056	0.429	0.884	0.273	0.496	0.234
Kurtosis	3.661	2.541	2.541	10.512	2.988	3.094	4.098	2.679	4.252	1.612	2.438	2.174

Table 4.5: Descriptive Statistics of stock annualised daily realised volatilities (%). The table reports the descriptive statistics for stock realised volatilities, of our UK and EU sample counties for the period 01/04/2010 – 28/02/2020. The daily realised volatilities are based on high-frequency 5-minute returns. The Min, Max and St.Dev denote the minimum, maximum and standard deviation, respectively. The table also reports the t-tests (Mann-Whitney tests) of the mean (median), where the hypothesis of the t-test (Mann–Whitney test) is that the mean (median) of the daily volatility is equal for event (news) announcement days and non-event days. ADF is the Augmented Dickey Fuller test statistics. *, **, and *** denote significance at the 10 %, 5 %, and 1 % levels, respectively.

	UK	Eurozone	Germany	France	Netherlands	Belgium
			Panel A: Summary statistics full sample			
Mean	12.243	14.792	13.680	13.795	11.879	11.762
Median	10.739	13.035	12.148	12.167	10.433	10.536
Std. dev	6.946	7.917	7.253	6.973	6.101	5.350
Min	0.000	0.000	0.000	3.320	0.000	0.000
Max	120.259	116.705	77.850	75.418	72.642	64.096
Skewness	3.475	2.708	2.295	2.343	2.610	2.564
Kurtosis	33.732	20.279	13.149	13.284	17.179	16.286
ADF	-26.438***	-20.588***	-19.808***	-18.595***	-18.915***	-19.741***
			Panel B: Summary statistics by Event(news) day			
Mean	11.665	11.843***	10.653***	10.826***	9.962***	10.641**
Median	10.230*	10.278***	9.840***	10.018***	8.779***	9.556***
Std. dev	10.096	9.881	4.941	5.541	5.769	5.837
Min	0.000	5.405	0.000	4.939	4.666	0.000
Max	120.259	116.705	50.613	58.494	65.484	64.096
Skewness	8.858	8.535	3.957	4.821	6.484	5.676
Kurtosis	95.083	90.166	31.568	39.971	61.428	50.823
			Panel C: Summary statistics by UK Brexit			
Mean	12.324	12.049	10.446***	10.567***	9.953*	10.447
Median	9.586	9.555***	8.914***	9.230***	8.390***	8.985***
Std. dev	14.547	14.173	6.305	7.114	7.845	7.622
Min	5.128	5.405	0.000	4.939	4.708	5.700
Max	120.259	116.705	50.613	58.494	65.484	64.096

Skewness	6.859	6.764	4.274	5.156	5.948	5.879
Kurtosis	51.369	50.400	28.178	35.049	42.598	41.688
Panel D: Summary statistics by EU Brexit						
Mean	10.596	10.381***	10.117***	9.8322***	9.275***	9.541***
Median	9.419	8.914***	9.943***	8.693***	8.622**	8.871**
Std. dev	5.135	3.516	2.283	2.832	2.488	2.368
Min	4.780	6.096	6.624	5.824	6.404	6.311
Max	28.624	19.903	14.277	16.305	14.220	14.590
Skewness	2.230	1.220	0.248	0.783	0.717	0.654
Kurtosis	8.698	3.876	2.081	2.698	2.301	2.503
Panel E: Summary statistics by UK votes						
Mean	11.992	12.295***	10.910***	11.355***	10.079***	11.080
Median	10.824	12.054	10.579**	11.105*	9.234	10.870
Std. dev	4.513	4.019	3.635	3.502	3.367	3.416
Min	7.047	5.653	5.094	5.585	4.666	5.736
Max	28.624	25.208	23.609	22.431	22.276	20.223
Skewness	1.918	1.142	1.345	1.049	1.646	0.508
Kurtosis	7.713	5.323	6.336	4.977	7.259	3.014
Panel F: Summary statistics by UK political						
Mean	11.503	12.378*	11.439**	11.745*	10.537	12.091
Median	9.968	10.068**	9.789*	10.062*	9.023	10.569
Std. dev	6.824	6.697	4.779	5.531	4.538	5.320
Min	0.000	5.680	5.719	5.510	5.637	5.119
Max	28.624	31.167	23.778	27.406	24.379	26.163
Skewness	1.217	1.225	0.837	1.134	1.256	1.218
Kurtosis	3.807	3.777	2.934	3.771	4.488	3.841
Panel G: Summary statistics by industry response						
Mean	12.417	11.815***	10.980***	11.214***	10.091**	10.212
Median	12.160	11.205	11.594	11.022	9.593	10.788

Std. dev	5.330	4.043	2.756	3.223	3.332	3.862
Min	6.957	5.661	5.436	5.622	4.787	0.000
Max	28.624	19.903	14.726	16.305	15.942	14.814
Skewness	1.706	0.324	-0.632	-0.038	0.278	-0.985
Kurtosis	6.087	2.219	2.555	2.133	2.091	3.836

Table 4.6: Testing for the effect of the Brexit news announcements on the volatilities of UK and Eurozone government bond and equity markets. The table presents the coefficient estimates from the following regressions:

(1) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma D_t + \mu I_t + \varepsilon_t$

(2) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma_1 D_t^{Before} + \gamma_2 D_t + \gamma_3 D_t^{After} + \sum_{\tau=1}^{3} \mu_\tau I_{\tau,t} + \varepsilon_t$

The equations are estimated for the 01/04/2010 – 28/02/2020 sample period, for our government bond (Panel A) and equity (Panel B) samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The volatility RV_t at day t is approximated by Parkinson's (1980) high-low volatility estimator. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. D_t=1 if there is a Brexit news announcement on day t and zero otherwise and $I_t = D_t \times RV_{t-1}$. Similarly, in (2) D_t^{Before}(D_t^{After})=1 if t is a day before (after) the announcement of a Brexit news and zero otherwise; and $I_{\tau,t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Panel A: Government (sovereign) bonds												
Independent variable	**UK**		**Eurozone**		**Germany**		**France**		**Netherlands**		**Belgium**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\boldsymbol{RV_{t-1}}$	0.057*	0.039	0.527***	0.490***	0.527***	0.490***	0.332***	0.321***	0.408***	0.398***	0.481***	0.465***
	(0.033)	(0.030)	(0.065)	(0.069)	(0.065)	(0.069)	(0.093)	(0.091)	(0.068)	(0.064)	(0.085)	(0.077)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.232**	0.222**	0.474***	0.437***	0.474***	0.437***	0.546***	0.626***	0.329***	0.378***	0.258***	0.356***
	(0.097)	(0.097)	(0.079)	(0.077)	(0.079)	(0.077)	(0.067)	(0.085)	(0.043)	(0.031)	(0.077)	(0.061)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.593***	0.585***	0.051	0.080**	0.051	0.080**	0.065	0.040	0.182**	0.182***	0.191***	0.175**
	(0.092)	(0.087)	(0.034)	(0.039)	(0.034)	(0.039)	(0.047)	(0.042)	(0.071)	(0.070)	(0.072)	(0.070)
$\boldsymbol{D_t^{Before}}$		-0.594*		-0.936		-0.936		0.915**		0.506		1.098**
		(0.314)		(0.802)		(0.802)		(0.398)		(0.429)		(0.489)
$\boldsymbol{D_t}$	0.082	0.138	1.971***	1.819***	1.971***	1.819***	1.849***	1.991***	1.743***	1.808***	2.174***	2.374***
	(0.407)	(0.419)	(0.361)	(0.361)	(0.361)	(0.361)	(0.345)	(0.410)	(0.399)	(0.458)	(0.554)	(0.642)
$\boldsymbol{D_t^{After}}$		-0.105		0.899***		0.899***		-0.037		0.490*		0.350
		(0.234)		(0.285)		(0.285)		(0.310)		(0.293)		(0.546)
$\boldsymbol{I_{1,t}}$		0.193*		0.427**		0.427**		-0.236**		-0.094		-0.260***
		(0.103)		(0.217)		(0.217)		(0.099)		(0.105)		(0.089)
$\boldsymbol{I_{2,t}}$	0.109	0.100	-0.534***	-0.485***	-0.534***	-0.485***	-0.460***	-0.518***	-0.349***	-0.376***	-0.387***	-0.456***
	(0.138)	(0.142)	(0.062)	(0.073)	(0.062)	(0.073)	(0.075)	(0.116)	(0.075)	(0.103)	(0.064)	(0.113)
$\boldsymbol{I_{3,t}}$		0.059		-0.279***		-0.279***		-0.006		-0.174**		-0.134
		(0.078)		(0.099)		(0.099)		(0.088)		(0.077)		(0.139)

Constant	0.281*	0.351**	-0.055	0.021	-0.055	0.021	0.202	0.109	0.251**	0.167	0.221**	0.081
	(0.147)	(0.147)	(0.150)	(0.182)	(0.150)	(0.182)	(0.123)	(0.135)	(0.119)	(0.136)	(0.112)	(0.125)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.350	0.354	0.494	0.511	0.494	0.511	0.528	0.532	0.459	0.460	0.517	0.522
Panel B: Equity (stocks)												
$\boldsymbol{RV_{t-1}}$	0.252***	0.255***	0.229***	0.229***	0.200***	0.202***	0.253***	0.253***	0.253***	0.252***	0.239***	0.243***
	(0.042)	(0.050)	(0.057)	(0.056)	(0.064)	(0.065)	(0.054)	(0.054)	(0.057)	(0.060)	(0.049)	(0.048)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.384***	0.387***	0.362***	0.361***	0.356***	0.353***	0.354***	0.354***	0.373***	0.373***	0.381***	0.380***
	(0.054)	(0.059)	(0.050)	(0.052)	(0.054)	(0.055)	(0.051)	(0.052)	(0.045)	(0.044)	(0.052)	(0.064)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.254***	0.251***	0.289***	0.291***	0.330***	0.332***	0.269***	0.269***	0.248***	0.250***	0.230***	0.229***
	(0.051)	(0.055)	(0.042)	(0.048)	(0.067)	(0.070)	(0.056)	(0.059)	(0.051)	(0.051)	(0.052)	(0.066)
$\boldsymbol{D_t^{Before}}$		0.040		-0.044		0.067		-0.025		-0.025		0.033
		(0.036)		(0.116)		(0.062)		(0.053)		(0.074)		(0.075)
$\boldsymbol{D_t}$	0.162***	0.141***	-0.020	-0.027	-0.019	-0.016	-0.106	-0.106	-0.069	-0.075	-0.159*	-0.176*
	(0.042)	(0.045)	(0.040)	(0.054)	(0.129)	(0.111)	(0.099)	(0.098)	(0.060)	(0.066)	(0.096)	(0.104)
$\boldsymbol{D_t^{After}}$		-0.018		0.037		-0.017		0.030		0.032		0.034
		(0.049)		(0.061)		(0.067)		(0.050)		(0.046)		(0.068)
$\boldsymbol{I_{1,t}}$		-0.072		0.055		-0.108		0.012		0.050		-0.069
		(0.056)		(0.207)		(0.106)		(0.097)		(0.159)		(0.139)
$\boldsymbol{I_{2,t}}$	-0.190***	-0.157**	0.014	0.019	-0.014	-0.025	0.135	0.135	0.062	0.064	0.254	0.287
	(0.041)	(0.066)	(0.082)	(0.102)	(0.228)	(0.196)	(0.186)	(0.181)	(0.128)	(0.135)	(0.193)	(0.201)
$\boldsymbol{I_{3,t}}$		0.035		-0.016		0.061		-0.012		-0.021		-0.053
		(0.047)		(0.089)		(0.118)		(0.081)		(0.086)		(0.111)
Constant	0.085***	0.084***	0.105***	0.103***	0.096***	0.093***	0.102***	0.101***	0.091***	0.089***	0.107***	0.106***
	(0.017)	(0.021)	(0.020)	(0.020)	(0.020)	(0.020)	(0.017)	(0.017)	(0.014)	(0.014)	(0.021)	(0.025)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.412	0.412	0.410	0.410	0.405	0.405	0.424	0.425	0.430	0.430	0.386	0.386

Table 4.7: Testing for the effect of the Brexit related news categories on the volatilities of UK and Eurozone government bond markets. The table presents the coefficient estimates from the following regressions:

(1) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \gamma_j D_{j,t} + \sum_{j=1}^{5} \mu_j I_{j,t} + \varepsilon_t$

(2) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5}\left(\gamma_{1,j} D_{j,t}^{Before} + \gamma_{2,j} D_{j,t} + \gamma_{3,j} D_{j,t}^{After}\right) + \sum_{j=1}^{5}\sum_{\tau=1}^{3} \mu_{j,\tau} I_{j,\tau.t} + \varepsilon_t$

The equations are estimated for the 01/04/2010 – 28/02/2020 sample period for our government bond sample. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The volatility RV_t at day t is approximated by Parkinson's (1980) high-low volatility estimator. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. The subscript j ($j = 1, 2, 3, 4, 5$) denotes the Brexit news category in the following order: UK Brexit, EU Brexit, UK votes, UK political and industry response. $D_{j,t}$=1 if there is a Brexit category j news announcement on day t and zero otherwise and $\mathrm{I}_{j,t} = \mathrm{D}_{j,t} \times RV_{t-1}$. Similarly, in (2) $D_{j,t}^{Before}$ ($D_{j,t}^{After}$)=1 if t is a day before (after) the announcement of a Brexit news category j and zero otherwise; and $I_{j,\tau.t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Government (sovereign) bonds											
Independent variable	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
	(1)	(1)	(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(2)	(2)
$\boldsymbol{RV_{t-1}}$	0.055*	0.532***	0.532***	0.332***	0.396***	0.477***	0.046	0.583***	0.583***	0.369***	0.400***	0.496***
	(0.033)	(0.066)	(0.066)	(0.093)	(0.069)	(0.087)	(0.032)	(0.083)	(0.083)	(0.093)	(0.065)	(0.078)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.228**	0.467***	0.467***	0.554***	0.374***	0.278***	0.233**	0.299***	0.299***	0.497***	0.428***	0.323***
	(0.095)	(0.096)	(0.096)	(0.067)	(0.046)	(0.085)	(0.100)	(0.086)	(0.086)	(0.090)	(0.039)	(0.082)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.606***	0.047	0.047	0.050	0.143**	0.167**	0.591***	0.060*	0.060*	0.084	0.095	0.132
	(0.090)	(0.035)	(0.035)	(0.051)	(0.066)	(0.077)	(0.092)	(0.034)	(0.034)	(0.061)	(0.058)	(0.083)
UK Brexit:												
$\boldsymbol{D_{1,t}^{Before}}$							-0.763***	1.192***	1.192***	0.765***	0.588**	0.885**
							(0.275)	(0.350)	(0.350)	(0.239)	(0.268)	(0.354)
$\boldsymbol{D_{1,t}}$	0.109	1.606**	1.606**	0.531*	1.040	1.321	0.237	0.732	0.732	0.434	0.846	1.176
	(0.280)	(0.709)	(0.709)	(0.285)	(0.712)	(0.975)	(0.280)	(0.732)	(0.732)	(0.291)	(0.737)	(0.984)
$\boldsymbol{D_{1,t}^{After}}$							0.049	1.597**	1.597**	1.284**	1.155**	1.435**
							(0.330)	(0.793)	(0.793)	(0.648)	(0.515)	(0.674)
EU Brexit:												
$\boldsymbol{D_{2,t}^{Before}}$							-0.081	1.050**	1.050**	0.716*	0.680**	0.607
							(0.540)	(0.438)	(0.438)	(0.401)	(0.346)	(0.390)

$D_{2,t}$	-1.006***	-1.910*	-1.910*	-1.481	-1.470**	-0.956	-0.816*	-1.841**	-1.841**	-1.272	-1.338**	-0.642
	(0.379)	(1.059)	(1.059)	(1.100)	(0.696)	(0.832)	(0.461)	(0.754)	(0.754)	(0.983)	(0.650)	(0.642)
$D_{2,t}^{After}$							1.316	7.070**	7.070**	0.846*	1.905	1.512***
							(0.848)	(3.496)	(3.496)	(0.488)	(1.201)	(0.540)
UK votes:												
$D_{3,t}^{Before}$							-0.063	-22.091***	-22.091***	-2.702***	-7.006***	-4.048***
							(1.137)	(3.736)	(3.736)	(0.660)	(1.522)	(1.026)
$D_{3,t}$	-0.000	2.190***	2.190***	2.186***	1.440***	1.847***	0.297	2.907**	2.907**	2.112***	1.559**	1.867***
	(0.777)	(0.500)	(0.500)	(0.615)	(0.422)	(0.587)	(0.815)	(1.133)	(1.133)	(0.567)	(0.635)	(0.633)
$D_{3,t}^{After}$							-2.738*	0.508	0.508	-0.314	-0.074	-1.810***
							(1.415)	(1.424)	(1.424)	(0.701)	(0.812)	(0.614)
UK political:												
$D_{4,t}^{Before}$							-0.597	1.990*	1.990*	3.298***	2.870***	3.668***
							(0.556)	(1.087)	(1.087)	(1.011)	(1.003)	(1.261)
$D_{4,t}$	2.450***	2.126***	2.126***	2.628**	1.780***	2.620***	2.726***	2.093**	2.093**	2.394**	1.848***	2.670***
	(0.756)	(0.804)	(0.804)	(1.196)	(0.641)	(0.942)	(0.768)	(1.045)	(1.045)	(1.108)	(0.691)	(0.902)
$D_{4,t}^{After}$							0.638	0.196	0.196	-0.715	0.656	-0.618
							(0.843)	(0.620)	(0.620)	(0.638)	(0.629)	(0.737)
Industry response:												
$D_{5,t}^{Before}$							0.240	-0.989	-0.989	-0.103	0.712	0.990
							(0.944)	(0.922)	(0.922)	(0.699)	(0.701)	(0.828)
$D_{5,t}$	-0.795	2.622***	2.622***	2.618**	5.545**	6.553*	-0.916	2.780***	2.780***	2.744***	6.327**	7.309*
	(0.659)	(0.977)	(0.977)	(1.092)	(2.448)	(3.680)	(0.703)	(0.960)	(0.960)	(1.031)	(2.539)	(3.796)
$D_{5,t}^{After}$							0.987*	-1.446	-1.446	-1.768**	-0.144	-0.732
							(0.599)	(0.968)	(0.968)	(0.883)	(0.735)	(1.142)
Constant	0.267*	-0.044	-0.044	0.214*	0.254**	0.219*	0.302**	0.165	0.165	0.186	0.240*	0.171
	(0.138)	(0.159)	(0.159)	(0.123)	(0.117)	(0.114)	(0.136)	(0.156)	(0.156)	(0.150)	(0.129)	(0.129)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.362	0.494	0.494	0.529	0.462	0.520	0.373	0.799	0.799	0.548	0.489	0.543

Table 4.8: Testing for the effect of the Brexit related news categories on the volatilities of UK and Eurozone equity (stock) markets. The table presents the coefficient estimates from the following regressions:

(1) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \gamma_j D_{j,t} + \sum_{j=1}^{5} \mu_j I_{j,t} + \varepsilon_t$

(2) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \left(\gamma_{1,j} D_{j,t}^{Before} + \gamma_{2,j} D_{j,t} + \gamma_{3,j} D_{j,t}^{After}\right) + \sum_{j=1}^{5} \sum_{\tau=1}^{3} \mu_{j,\tau} I_{j,\tau.t} + \varepsilon_t$

The equations are estimated for the 01/04/2010 – 28/02/2020 sample period for our equity (stock) sample. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The volatility RV_t at day t is approximated by Parkinson's (1980) high-low volatility estimator. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. The subscript j ($j = 1, 2, 3, 4, 5$) denotes the Brexit news category in the following order: UK Brexit, EU Brexit, UK votes, UK political and industry response. $D_{j,t}$=1 if there is a Brexit category j news announcement on day t and zero otherwise and $\mathrm{I}_{j,t} = \mathrm{D}_{j,t} \times RV_{t-1}$. Similarly, in (2) $D_{j,t}^{Before}$ ($D_{j,t}^{After}$)=1 if t is a day before (after) the announcement of a Brexit news category j and zero otherwise; and $I_{j,\tau.t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Equity (stocks)											
Independent variable	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
	(1)	(1)	(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(2)	(2)
$\boldsymbol{RV_{t-1}}$	0.187***	0.231***	0.199***	0.253***	0.254***	0.238***	0.188***	0.235***	0.204***	0.256***	0.256***	0.246***
	(0.050)	(0.057)	(0.064)	(0.054)	(0.056)	(0.049)	(0.050)	(0.058)	(0.065)	(0.054)	(0.059)	(0.045)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.408***	0.360***	0.357***	0.354***	0.373***	0.382***	0.401***	0.361***	0.358***	0.355***	0.376***	0.387***
	(0.054)	(0.050)	(0.054)	(0.051)	(0.045)	(0.052)	(0.060)	(0.051)	(0.054)	(0.052)	(0.044)	(0.068)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.266***	0.288***	0.331***	0.270***	0.247***	0.231***	0.268***	0.284***	0.327***	0.267***	0.246***	0.221***
	(0.059)	(0.042)	(0.067)	(0.056)	(0.051)	(0.052)	(0.065)	(0.043)	(0.068)	(0.058)	(0.050)	(0.065)
UK Brexit:												
$\boldsymbol{D_{1,t}^{Before}}$							-0.034	0.066	0.059	-0.053	0.017	0.008
							(0.064)	(0.072)	(0.088)	(0.062)	(0.065)	(0.085)
$\boldsymbol{D_{1,t}}$	0.100	-0.240	-0.017	-0.051	-0.121	-0.087	0.125	-0.060	0.039	0.040	-0.009	-0.029
	(0.150)	(0.328)	(0.182)	(0.155)	(0.177)	(0.162)	(0.115)	(0.141)	(0.136)	(0.103)	(0.092)	(0.111)
$\boldsymbol{D_{1,t}^{After}}$							-0.035	-0.061	-0.059	-0.018	-0.001	-0.048
							(0.062)	(0.087)	(0.090)	(0.067)	(0.056)	(0.068)
EU Brexit:												
$\boldsymbol{D_{2,t}^{Before}}$							0.170**	0.199	0.195*	0.149	0.181**	0.186
							(0.084)	(0.128)	(0.116)	(0.110)	(0.085)	(0.159)
$\boldsymbol{D_{2,t}}$	-0.052	0.187*	0.321***	0.145	0.110	0.133**	-0.057	0.207*	0.310**	0.123	0.104	0.192

	(0.157)	(0.100)	(0.123)	(0.101)	(0.100)	(0.059)	(0.144)	(0.106)	(0.129)	(0.110)	(0.110)	(0.119)
$D_{2,t}^{After}$							0.052	0.143	0.388***	0.259*	0.073	0.396*
							(0.286)	(0.159)	(0.117)	(0.149)	(0.099)	(0.208)
UK votes:												
$D_{3,t}^{Before}$							0.057	-0.145	0.007	-0.145**	-0.088**	0.020
							(0.096)	(0.098)	(0.070)	(0.057)	(0.044)	(0.095)
$D_{3,t}$	-0.150	0.171*	0.158	0.092	-0.010	-0.068	-0.002	0.511***	0.269	0.223	0.133	-0.023
	(0.148)	(0.098)	(0.147)	(0.122)	(0.097)	(0.131)	(0.226)	(0.164)	(0.224)	(0.145)	(0.108)	(0.152)
$D_{3,t}^{After}$							-0.594	-1.635**	-0.586	-0.588*	-0.780***	-0.477*
							(0.487)	(0.801)	(0.370)	(0.342)	(0.277)	(0.288)
UK political:												
$D_{4,t}^{Before}$							-0.235	-0.282	0.042	-0.119	-0.077	-0.156
							(0.159)	(0.186)	(0.209)	(0.178)	(0.142)	(0.241)
$D_{4,t}$	0.085	-0.038	-0.222	-0.209*	-0.023	-0.237***	0.048	-0.084	-0.226	-0.243**	-0.073	-0.219**
	(0.089)	(0.078)	(0.139)	(0.116)	(0.078)	(0.086)	(0.119)	(0.098)	(0.150)	(0.123)	(0.089)	(0.106)
$D_{4,t}^{After}$							0.119	0.346**	0.282*	0.291**	0.285***	0.285***
							(0.099)	(0.151)	(0.145)	(0.122)	(0.102)	(0.086)
Industry response:												
$D_{5,t}^{Before}$							0.102	0.127	0.031	0.130	-0.063	0.206
							(0.129)	(0.131)	(0.168)	(0.177)	(0.135)	(0.143)
$D_{5,t}$	0.256	0.036	0.188*	-0.149**	-0.048	-0.115	0.229	-0.040	0.179	-0.165**	0.015	-0.117
	(0.162)	(0.097)	(0.098)	(0.059)	(0.085)	(0.108)	(0.151)	(0.098)	(0.125)	(0.072)	(0.069)	(0.117)
$D_{5,t}^{After}$							0.148	0.286	0.236	0.229	0.292*	0.188
							(0.189)	(0.186)	(0.259)	(0.160)	(0.175)	(0.215)
Constant	0.096***	0.105***	0.094***	0.101***	0.091***	0.106***	0.100***	0.107***	0.093***	0.101***	0.088***	0.105***
	(0.019)	(0.020)	(0.020)	(0.017)	(0.014)	(0.021)	(0.020)	(0.021)	(0.020)	(0.017)	(0.013)	(0.026)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.348	0.412	0.407	0.425	0.431	0.388	0.362	0.432	0.412	0.431	0.443	0.397

Table 4.9: Contribution and proportion of Brexit news announcements by Brexit news category. The table shows the impact of the news announcements on the daily volatilities of our government bond and equity samples by Brexit news classification (category). Where the contribution per news category $j = \gamma_{1,j} + \gamma_{2,j} + \gamma_{3,j}$, proportion per new category j $= \frac{|\gamma_{1,j}|+|\gamma_{2,j}|+|\gamma_{3,j}|}{\sum_{j=1}^{5}|\gamma_{1,j}|+|\gamma_{2,j}|+|\gamma_{3,j}|}$ and , $\gamma_{1,j}$, $\gamma_{2,j}$ and $\gamma_{3,j}$ are the coefficients of the jth category dummies from Eq. (4.7). The contribution figures indicate the direction and magnitude of the shift in the volatility by the Brexit news category during the 3-day event window, whereas the proportion figures weigh the impact of each Brexit news category relative to the total Brexit news volatility response.

News (event) category	**Contribution**						**Proportion (%)**					
	UK	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
Government (sovereign) bonds												
UK Brexit	-0.477	3.521	3.521	2.483	2.589	3.496	8.415%	7.263%	7.263%	11.566%	9.343%	11.664%
EU Brexit	0.419	6.279	6.279	0.290	1.247	1.477	17.758%	20.547%	20.547%	13.205%	14.160%	9.213%
UK Votes	-2.504	-18.676	-18.676	-0.904	-5.521	-3.991	24.849%	52.608%	52.608%	23.884%	31.181%	25.776%
UK Political	2.767	4.279	4.279	4.977	5.374	5.720	31.784%	8.825%	8.825%	29.847%	19.396%	23.213%
Industry Response	0.312	0.345	0.345	0.873	6.895	7.567	17.194%	10.757%	10.757%	21.497%	25.920%	30.134%
Total	0.517	-4.252	-4.252	7.720	10.584	14.269	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%
Equity (stocks)												
UK Brexit	0.057	-0.055	0.039	-0.031	0.007	-0.069	9.627%	4.458%	5.431%	4.007%	1.269%	3.353%
EU Brexit	0.165	0.549	0.894	0.531	0.358	0.775	13.881%	13.106%	30.710%	19.136%	16.320%	30.371%
UK Votes	-0.540	-1.268	-0.309	-0.510	-0.735	-0.481	32.556%	54.658%	29.651%	34.430%	45.669%	20.390%
UK Political	-0.068	-0.019	0.098	-0.072	0.135	-0.090	20.019%	16.979%	18.897%	23.528%	19.861%	25.863%
Industry Response	0.480	0.373	0.446	0.195	0.243	0.277	23.917%	10.799%	15.311%	18.899%	16.881%	20.023%
Total	0.094	-0.420	1.167	0.113	0.008	0.412	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%

Table 4.10: Testing for the effect of the Brexit news announcements on the realised volatilities of UK and Eurozone equity markets. The table presents the coefficient estimates from the following regressions:

(1) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma D_t + \mu I_t + \varepsilon_t$

(2) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \gamma_1 D_t^{Before} + \gamma_2 D_t + \gamma_3 D_t^{After} + \sum_{\tau=1}^{3} \mu_\tau I_{\tau,t} + \varepsilon_t$

The equation are estimated for the 01/04/2010 – 28/02/2020 sample period for our equity (stock) sample. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. RV_t is the realised volatility at day t based on 5-min high frequency returns. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. D_t=1 if there is a Brexit news announcement on day t and zero otherwise and $I_t = D_t \times RV_{t-1}$. Similarly, in (2) D_t^{Before}(D_t^{After})=1 if t is a day before (after) the announcement of a Brexit news and zero otherwise; and $I_{\tau,t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Realised volatility of equity (stocks)												
Independent variable	**UK**		**Eurozone**		**Germany**		**France**		**Netherlands**		**Belgium**	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
$\boldsymbol{RV_{t-1}}$	0.252***	0.249***	0.380***	0.380***	0.319***	0.317***	0.408***	0.407***	0.416***	0.414***	0.415***	0.419***
	(0.042)	(0.049)	(0.062)	(0.064)	(0.068)	(0.069)	(0.061)	(0.062)	(0.059)	(0.048)	(0.068)	(0.069)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.384***	0.380***	0.369***	0.365***	0.420***	0.420***	0.355***	0.355***	0.364***	0.363***	0.363***	0.362***
	(0.054)	(0.076)	(0.054)	(0.053)	(0.044)	(0.044)	(0.050)	(0.050)	(0.048)	(0.066)	(0.052)	(0.052)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.254***	0.259***	0.171***	0.174***	0.187***	0.187***	0.160***	0.161***	0.139***	0.139**	0.133***	0.132***
	(0.051)	(0.064)	(0.035)	(0.036)	(0.045)	(0.046)	(0.035)	(0.036)	(0.037)	(0.057)	(0.035)	(0.038)
$\boldsymbol{D_t^{Before}}$		-0.079		-0.151		-0.108		-0.117		-0.119		0.011
		(0.144)		(0.167)		(0.139)		(0.140)		(0.189)		(0.131)
$\boldsymbol{D_t}$	0.162***	0.166***	0.150***	0.129**	0.017	0.039	0.035	0.036	0.060*	0.063*	0.089**	0.069
	(0.042)	(0.058)	(0.050)	(0.054)	(0.058)	(0.046)	(0.046)	(0.046)	(0.036)	(0.038)	(0.040)	(0.052)
$\boldsymbol{D_t^{After}}$		-0.004		0.053		-0.012		0.024		0.023		0.045
		(0.053)		(0.050)		(0.039)		(0.047)		(0.050)		(0.064)
$\boldsymbol{I_{1,t}}$		0.142		0.193		0.147		0.161		0.178		-0.040
		(0.257)		(0.253)		(0.214)		(0.224)		(0.340)		(0.215)
$\boldsymbol{I_{2,t}}$	-0.190***	-0.200***	-0.214***	-0.180**	-0.053	-0.085	-0.073	-0.072	-0.104*	-0.106	-0.125	-0.089
	(0.041)	(0.072)	(0.055)	(0.071)	(0.101)	(0.073)	(0.084)	(0.088)	(0.062)	(0.066)	(0.078)	(0.099)
$\boldsymbol{I_{3,t}}$		0.007		-0.054		0.027		-0.024		-0.024		-0.052

		(0.079)		(0.064)		(0.059)		(0.064)		(0.088)		(0.090)
Constant	0.085***	0.085***	0.075***	0.077***	0.066***	0.067***	0.067***	0.068***	0.061***	0.063***	0.066***	0.065***
	(0.017)	(0.024)	(0.015)	(0.016)	(0.014)	(0.014)	(0.013)	(0.013)	(0.011)	(0.016)	(0.012)	(0.012)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.412	0.412	0.568	0.569	0.605	0.605	0.627	0.627	0.612	0.613	0.580	0.580

Table 4.11: Testing for the effect of the Brexit related news categories on the realised volatilities of UK and Eurozone equity (stock) markets. The table presents the coefficient estimates from the following regressions:

(1) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \gamma_j D_{j,t} + \sum_{j=1}^{5} \mu_j I_{j,t} + \varepsilon_t$

(2) $RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5} \left(\gamma_{1,j} D_{j,t}^{Before} + \gamma_{2,j} D_{j,t} + \gamma_{3,j} D_{j,t}^{After}\right) + \sum_{j=1}^{5} \sum_{\tau=1}^{3} \mu_{j,\tau} I_{j,\tau.t} + \varepsilon_t$

The equations are estimated for the 01/04/2010 – 28/02/2020 sample period for our equity (stock) sample. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. RV_t is the realised volatility at day t based on 5-min high frequency returns. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. The subscript j ($j = 1, 2, 3, 4, 5$) denotes the Brexit news category in the following order: UK Brexit, EU Brexit, UK votes, UK political and industry response. $D_{j,t}$=1 if there is a Brexit category j news announcement on day t and zero otherwise and $\mathrm{I_{j,t}} = \mathrm{D_{j,t}} \times RV_{t-1}$. Similarly, in (2) $D_{j,t}^{Before}$ ($D_{j,t}^{After}$)=1 if t is a day before (after) the announcement of a Brexit news category j and zero otherwise; and $I_{j,\tau.t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

Independent variable	***Equity (stocks)***											
	UK	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
	(1)	(1)	(1)	(1)	(1)	(1)	(2)	(2)	(2)	(2)	(2)	(2)
$\boldsymbol{RV_{t-1}}$	0.255***	0.385***	0.320***	0.410***	0.422***	0.417***	0.257***	0.390***	0.318***	0.407***	0.421***	0.419***
	(0.042)	(0.062)	(0.068)	(0.061)	(0.058)	(0.069)	(0.044)	(0.063)	(0.069)	(0.062)	(0.057)	(0.070)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.379***	0.366***	0.421***	0.354***	0.359***	0.361***	0.377***	0.365***	0.424***	0.361***	0.365***	0.369***
	(0.053)	(0.053)	(0.044)	(0.050)	(0.052)	(0.052)	(0.057)	(0.055)	(0.044)	(0.051)	(0.054)	(0.053)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.252***	0.166***	0.184***	0.159***	0.135***	0.131***	0.252***	0.161***	0.182***	0.155***	0.131***	0.126***
	(0.053)	(0.036)	(0.044)	(0.035)	(0.038)	(0.035)	(0.057)	(0.037)	(0.045)	(0.035)	(0.041)	(0.035)
UK Brexit:												
$\boldsymbol{D_{1,t}^{Before}}$							0.129	0.110	-0.036	-0.078	0.012	0.001
							(0.109)	(0.146)	(0.083)	(0.059)	(0.043)	(0.058)
$\boldsymbol{D_{1,t}}$	-0.295	-0.404	-0.237	-0.242	-0.380	-0.284	-0.156	-0.145	-0.061	-0.075	-0.104	-0.150
	(0.451)	(0.524)	(0.268)	(0.283)	(0.348)	(0.332)	(0.241)	(0.220)	(0.121)	(0.127)	(0.107)	(0.183)
$\boldsymbol{D_{1,t}^{After}}$							-0.175***	-0.074	-0.032	-0.064	-0.077*	0.010
							(0.066)	(0.067)	(0.060)	(0.042)	(0.046)	(0.042)
EU Brexit:												
$\boldsymbol{D_{2,t}^{Before}}$							-0.116	0.059	0.057	0.117	0.167*	0.020
							(0.136)	(0.105)	(0.090)	(0.107)	(0.094)	(0.083)
$\boldsymbol{D_{2,t}}$	-0.024	0.084	0.207*	0.087	-0.005	0.279***	0.012	0.148	0.258**	0.093	0.087	0.380***

	(0.194)	(0.124)	(0.113)	(0.111)	(0.102)	(0.086)	(0.170)	(0.093)	(0.112)	(0.109)	(0.090)	(0.107)
$\boldsymbol{D_{2.t}^{After}}$							0.592	0.559*	0.322	0.483**	0.417**	0.168
							(0.443)	(0.318)	(0.200)	(0.224)	(0.165)	(0.218)
UK votes:												
$\boldsymbol{D_{3,t}^{Before}}$							0.005	0.060	0.067	0.099	0.051	0.184**
							(0.172)	(0.137)	(0.130)	(0.102)	(0.106)	(0.076)
$\boldsymbol{D_{3,t}}$	0.274*	0.004	-0.145	0.275*	0.137	0.315**	0.804**	0.579*	0.028	0.455***	0.275**	0.565**
	(0.165)	(0.147)	(0.106)	(0.153)	(0.094)	(0.149)	(0.330)	(0.299)	(0.167)	(0.160)	(0.111)	(0.236)
$\boldsymbol{D_{3,t}^{After}}$							-1.879*	-2.069**	-0.648**	-0.764*	-0.977**	-0.814
							(1.101)	(0.997)	(0.328)	(0.449)	(0.399)	(0.550)
UK political:												
$\boldsymbol{D_{4,t}^{Before}}$							-0.417**	-0.559***	-0.159	-0.399**	-0.352**	-0.054
							(0.183)	(0.172)	(0.206)	(0.172)	(0.152)	(0.111)
$\boldsymbol{D_{4,t}}$	0.140**	0.202***	0.108*	0.110*	0.149***	0.180***	0.246**	0.217**	0.111	0.162**	0.215***	0.157**
	(0.071)	(0.062)	(0.060)	(0.065)	(0.046)	(0.061)	(0.106)	(0.093)	(0.086)	(0.082)	(0.073)	(0.067)
$\boldsymbol{D_{4,t}^{After}}$							0.298**	0.390***	0.296**	0.310**	0.266***	0.293*
							(0.123)	(0.134)	(0.117)	(0.148)	(0.101)	(0.150)
Industry response:												
$\boldsymbol{D_{5,t}^{Before}}$							0.191*	0.241***	-0.026	0.166	0.181	0.239**
							(0.112)	(0.092)	(0.199)	(0.193)	(0.163)	(0.122)
$\boldsymbol{D_{5,t}}$	0.062	0.127	0.208***	0.075	0.266	0.022	0.038	0.116	0.198***	0.072	0.167	0.028
	(0.130)	(0.095)	(0.067)	(0.086)	(0.219)	(0.185)	(0.137)	(0.095)	(0.067)	(0.067)	(0.102)	(0.182)
$\boldsymbol{D_{5,t}^{After}}$							0.692*	0.391**	-0.169	-0.014	0.084	0.186
							(0.418)	(0.195)	(0.176)	(0.197)	(0.116)	(0.137)
Constant	0.087***	0.078***	0.066***	0.067***	0.063***	0.067***	0.089***	0.082***	0.068***	0.068***	0.064***	0.065***
	(0.019)	(0.016)	(0.014)	(0.013)	(0.012)	(0.013)	(0.018)	(0.016)	(0.014)	(0.013)	(0.013)	(0.012)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.418	0.575	0.606	0.628	0.618	0.586	0.451	0.609	0.612	0.637	0.634	0.597

Table 4.12: Contribution and proportion of Brexit news announcements by news category. The table shows the impact of the news announcements on the realised volatilities of our equity (stock) sample bond by Brexit news classification (category). Where the contribution per news category $j = \gamma_{1,j} + \gamma_{2,j} + \gamma_{3,j}$, proportion per new category j $= \frac{|\gamma_{1,j}|+|\gamma_{2,j}|+|\gamma_{3,j}|}{\sum_{j=1}^{5}|\gamma_{1,j}|+|\gamma_{2,j}|+|\gamma_{3,j}|}$ and , $\gamma_{1,j}$, $\gamma_{2,j}$ and $\gamma_{3,j}$ are the coefficients of the jth category dummies from Eq. (4.7). The contribution figures indicate the direction and magnitude of the shift in the volatility by the Brexit news category during the 3-day event window, whereas the proportion figures weigh the impact of each Brexit news category relative to the total Brexit news volatility response.

	Equity (stocks)											
News (event) category	**Contribution**						**Proportion (%)**					
	UK	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
UK Brexit	-0.203	-0.110	-0.129	-0.217	-0.169	-0.139	8.004%	5.751%	5.213%	6.478%	5.628%	4.967%
EU Brexit	0.488	0.767	0.637	0.693	0.671	0.568	12.521%	13.413%	25.833%	20.675%	19.550%	17.484%
UK Votes	-1.070	-1.430	-0.553	-0.210	-0.651	-0.065	46.756%	47.358%	30.090%	39.310%	37.939%	48.077%
UK Political	0.127	0.049	0.248	0.074	0.129	0.396	16.710%	20.402%	22.930%	26.022%	24.292%	15.515%
Industry Response	0.921	0.748	0.003	0.224	0.432	0.454	16.010%	13.075%	15.934%	7.514%	12.591%	13.957%
Total	0.262	0.024	0.206	0.564	0.413	1.214	100.000%	100.000%	100.000%	100.000%	100.000%	100.000%

Table 4.13: Robustness checks: Testing for the effect of the Brexit related news categories. The table presents the coefficient estimates from the following regression:

$$RV_t = c + \beta_1 RV_{t-1} + \beta_2^{(w)} RV_{t-1}^{(w)} + \beta_3^{(m)} RV_{t-1}^{(m)} + \sum_{j=1}^{5}\left(\gamma_{1,j} D_{j,t}^{Before} + \gamma_{2,j} D_{j,t} + \gamma_{3,j} D_{j,t}^{After}\right) + \sum_{j=1}^{5}\sum_{\tau=1}^{3} \mu_{j,\tau} I_{j,\tau.t} + \varepsilon_t$$

The equations are estimated for the 01/04/2010 – 28/02/2020 sample period for our government bond and equity samples. Numbers in parentheses are the estimates' Newey and West (1994) heteroscedasticity and autocorrelation consistent standard errors. The volatility RV_t at day t is approximated by Parkinson's (1980) high-low volatility estimator for government bonds; whereas it is the realised volatility based on 5-min high frequency returns for the equity indices. RV_{t-1} is the lagged daily volatility on day t and $RV_{t-1}^{(w)}$ and $RV_{t-1}^{(m)}$ are the lagged weekly and monthly volatilities, respectively. The subscript j ($j = 1, 2, 3, 4, 5$) denotes the Brexit news category in the following order: UK Brexit, EU Brexit, UK votes, UK political and industry response. $D_{j,t}$=1 if there is a Brexit category j news announcement on day t and zero otherwise and $I_{j,t} = D_{j,t} \times RV_{t-1}$. Similarly, $D_{j,t}^{Before}$ ($D_{j,t}^{After}$)=1 if t belongs to three (one) day(s) window before (after) the announcement of a Brexit news category j and zero otherwise; and $I_{j,\tau.t}$ their corresponding interaction terms with RV_{t-1}.*, **, and *** represent the statistical significance at the 10 %, 5 %, and 1 % levels, respectively.

	Government (sovereign) bonds						***Equity (stocks)***					
Independent variable	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**	**UK**	**Eurozone**	**Germany**	**France**	**Netherlands**	**Belgium**
$\boldsymbol{RV_{t-1}}$	0.039	0.202	0.202	0.166**	0.434**	0.424***	0.252***	0.390***	0.325***	0.413***	0.427***	0.421***
	(0.030)	(0.156)	(0.156)	(0.077)	(0.189)	(0.145)	(0.045)	(0.063)	(0.070)	(0.063)	(0.055)	(0.069)
$\boldsymbol{RV_{t-1}^{(w)}}$	0.219**	0.687***	0.687***	0.815***	0.465***	0.353***	0.391***	0.374***	0.422***	0.361***	0.367***	0.372***
	(0.097)	(0.209)	(0.209)	(0.164)	(0.069)	(0.124)	(0.059)	(0.057)	(0.045)	(0.052)	(0.058)	(0.054)
$\boldsymbol{RV_{t-1}^{(m)}}$	0.586***	0.102**	0.102**	0.075	0.111**	0.210**	0.246***	0.156***	0.180***	0.152***	0.127***	0.124***
	(0.089)	(0.050)	(0.050)	(0.090)	(0.054)	(0.091)	(0.058)	(0.037)	(0.045)	(0.035)	(0.048)	(0.036)
UK Brexit:												
$\boldsymbol{D_{1,t}^{Before}}$	-0.525*	1.675**	1.675**	0.932**	0.537	0.624	0.115	0.136	0.090*	0.047	0.031	0.055
	(0.275)	(0.772)	(0.772)	(0.370)	(0.375)	(0.387)	(0.086)	(0.086)	(0.053)	(0.045)	(0.037)	(0.045)
$\boldsymbol{D_{1,t}}$	0.217	1.879	1.879	0.979**	1.299*	1.604	-0.166	-0.176	-0.094	-0.118	-0.140	-0.155
	(0.271)	(1.188)	(1.188)	(0.479)	(0.784)	(1.048)	(0.246)	(0.222)	(0.129)	(0.146)	(0.114)	(0.182)
$\boldsymbol{D_{1,t}^{After}}$	0.056	2.022	2.022	1.423	1.547**	1.737**	-0.053	0.025	-0.032	-0.054	-0.050	0.025
	(0.327)	(1.340)	(1.340)	(0.943)	(0.776)	(0.885)	(0.081)	(0.059)	(0.053)	(0.045)	(0.055)	(0.049)
EU Brexit:												
$\boldsymbol{D_{2,t}^{Before}}$	0.202	1.234**	1.234**	0.354	0.602**	0.204	-0.049	0.057	0.024	0.084	0.104	0.047
	(0.316)	(0.502)	(0.502)	(0.365)	(0.287)	(0.271)	(0.051)	(0.060)	(0.054)	(0.066)	(0.070)	(0.041)
$\boldsymbol{D_{2,t}}$	-0.463	-1.441	-1.441	-2.212**	-1.239**	-0.845	-0.024	0.107	0.239**	0.085	0.073	0.323***

	(0.495)	(1.092)	(1.092)	(0.903)	(0.606)	(0.567)	(0.185)	(0.107)	(0.117)	(0.110)	(0.091)	(0.090)
$D_{2.t}^{After}$	1.245	0.635	0.635	-0.176	0.453	0.852	0.620	0.578*	0.301	0.493**	0.434**	0.200
	(0.811)	(1.050)	(1.050)	(0.896)	(0.459)	(0.680)	(0.418)	(0.310)	(0.195)	(0.218)	(0.174)	(0.200)
UK votes:												
$D_{3,t}^{Before}$	0.161	-1.042	-1.042	1.701***	-0.358	0.337	-0.047	0.010	0.094	0.128*	0.121**	0.050
	(0.641)	(1.693)	(1.693)	(0.435)	(0.652)	(0.492)	(0.076)	(0.077)	(0.081)	(0.069)	(0.053)	(0.061)
$D_{3,t}$	0.609	-1.080	-1.080	1.058	0.600	0.873	0.864***	0.589**	-0.004	0.426***	0.227**	0.577***
	(0.799)	(1.465)	(1.465)	(0.670)	(0.567)	(0.606)	(0.324)	(0.281)	(0.150)	(0.149)	(0.088)	(0.223)
$D_{3,t}^{After}$	-2.418**	0.361	0.361	-0.705	-0.414	-2.313***	-2.007*	-2.285**	-0.732**	-0.893*	-1.128**	-0.850
	(1.224)	(0.886)	(0.886)	(0.593)	(0.669)	(0.696)	(1.163)	(1.030)	(0.368)	(0.523)	(0.441)	(0.571)
UK political:												
$D_{4,t}^{Before}$	-0.229	0.805*	0.805*	2.321***	1.838***	1.782**	-0.229**	-0.246**	-0.028	-0.048	-0.091	0.004
	(0.294)	(0.424)	(0.424)	(0.773)	(0.666)	(0.723)	(0.116)	(0.097)	(0.062)	(0.071)	(0.075)	(0.075)
$D_{4,t}$	2.584***	1.872	1.872	3.177*	2.109*	2.998**	0.407***	0.388***	0.164*	0.222**	0.300***	0.186**
	(0.715)	(1.341)	(1.341)	(1.883)	(1.081)	(1.199)	(0.115)	(0.135)	(0.093)	(0.108)	(0.104)	(0.093)
$D_{4,t}^{After}$	0.918	0.516	0.516	-0.200	0.870	-0.314	0.373**	0.440***	0.270**	0.283**	0.280***	0.261*
	(0.785)	(1.099)	(1.099)	(0.729)	(0.786)	(0.764)	(0.174)	(0.143)	(0.111)	(0.138)	(0.102)	(0.143)
Industry response:												
$D_{5,t}^{Before}$	-0.257	0.678	0.678	-0.119	3.811	2.453	0.009	0.031	0.087	0.095	0.092	0.120*
	(0.373)	(1.125)	(1.125)	(0.504)	(3.307)	(2.185)	(0.076)	(0.063)	(0.071)	(0.059)	(0.065)	(0.064)
$D_{5,t}$	-0.892	1.899**	1.899**	0.669	4.435*	5.195	0.112	0.179	0.185**	0.077	0.189*	0.025
	(0.770)	(0.813)	(0.813)	(0.696)	(2.539)	(3.835)	(0.153)	(0.119)	(0.074)	(0.075)	(0.115)	(0.184)
$D_{5,t}^{After}$	0.596	-0.929	-0.929	-1.996**	-1.067	-1.870	0.701*	0.440**	-0.166	-0.002	0.116	0.130
	(0.454)	(0.833)	(0.833)	(0.948)	(1.048)	(1.481)	(0.410)	(0.199)	(0.172)	(0.196)	(0.113)	(0.132)
Constant	0.344**	0.042	0.042	-0.047	0.018	0.073	0.087***	0.080***	0.066***	0.066***	0.063***	0.063***
	(0.143)	(0.292)	(0.292)	(0.181)	(0.254)	(0.177)	(0.018)	(0.017)	(0.015)	(0.014)	(0.013)	(0.012)
Observations	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514	2,514
R-squared	0.378	0.545	0.545	0.575	0.477	0.539	0.448	0.606	0.612	0.636	0.633	0.596

5 Concluding remarks

This thesis consists of three comparative essays on bonds, which explore three diverse areas in bond literature: credit rating prediction, herding behaviour towards the market consensus, and the impact of Brexit news announcements on volatility. In the first empirical chapter, we investigate and contrast the credit rating determinants of a sample of Malaysian Islamic and conventional bonds and find the most effective model to forecast their ratings. To conduct our analysis, we follow the literature and employ a statistical and artificial intelligence method: ordered probit regressions and support vector machines, respectively. Our first stage results show that both Islamic and conventional bond ratings are determined by their issuers' financial variables; nevertheless, we detect several distinctions in their sensitivities to them. In addition, the Islamic bond ratings depend on a wider set of variables, including non-financial ones, where their Islamic structure plays a significant role in determining their credit quality. The second stage results clearly point out that a single model is insufficient to accurately predict the ratings of both types of bonds and adding a single Islamic binary variable (or interaction terms with it) to the model is insufficient to fully capture the difference in them. Dividing the rating assignments to individual Islamic and conventional 'tailor-made' models improve the forecasting accuracy in as well as out-of-sample. Furthermore, we find evidence that sukuk structure variables significantly enhance (by more than 7-14%) the Islamic bond rating prediction accuracy. Our results are consistent throughout all our samples using both rating methods, nonetheless the SVM persistently outperforms the ordered probit forecasts by more than 20%. As a result, to attain the most accurate bond rating predictions we recommend adopting the SVM approach and splitting the rating assignments of Islamic and conventional bonds.

Our results provide new formal evidence of the distinction between sukuk and conventional bonds, in terms of their credit quality. In addition to the empirical contribution to literature, our findings have practical implications. They signify that credit raters must acknowledge the difference between the bonds and accordingly distinguish between their rating methodologies. Moreover, the findings are useful for issuers, investors, portfolio managers and analysts that do not want to rely on or wait for external credit ratings in their decision-making. It enables them to predict the credit ratings of Islamic as well as conventional bonds of their choice with a relatively small set of variables that are accessible. This way issuers can predict the potential external ratings they might receive on their new issues and investors can assess the credit risk of unrated bonds or anticipate their changes to inform their asset allocation decisions. Moreover, we encourage investors to take advantage of the difference between the types of bonds and explore the benefits they can gain from them.

In the second comparative essay we apply Chang, Cheng and Khorana (2000) model to examine the existence of herding behaviour in US corporate bonds and equities. Our initial unconditional tests detect limited herding effects; restricted to speculative grade bonds. However, when allowing for herding asymmetries (up/down markets, high/low liquidity and high/low volatility), herding behaviour is observed in both markets. Our corporate bond and equity samples produce consistent results, indicating that investors are inclined to herd towards the market average during more stable market periods charactarised by high liqiuidity and low volatility. The strongest and most persistent herding effects are observed in high liquidity and low volatility market days. Unexpectedly, we observe a substantially higher level of investor herding in corporate bonds in comparison to equities. The results are consistent through our three credit rating portfolios (investment grade, high yield and non-rated), but we document more intense herding in investment grade (speculative grade) bonds during during extremely liquid (low volatility) market days. Moreover, we find herding to be positvely related to liquidity, with market volatility acting as a catalyst to the herding effect.

More importantly, in the second essay we provide new empirical evidence of the existence of cross-asset herding spillovers, where the trading dynamics in one market can induce herding in the other. Specifically, we detect cross-herding from US corporate bonds to US equities, which may be in part attributed to the different profile of investors. We conclude that the direction of the cross-herding is not constant; as it shifts in the post-crisis period from equities to corporate bonds. Our findings are of value to investors since herding behaviour can affect asset allocation in varying degrees, especially during liquid and less volatile market periods. The closer clustering of asset prices around the market consensus during these periods and cross-herding spillover could reduce the benefits of diversification.

The last empirical essay examines the impact of a large number of Brexit news announcements (151 news) on the volatility of government bond and equity markets. Applying an extension of Corsi (2009) Heterogeneous Autoregressive model, we analyse the effect of the news on UK as well as a Eurozone benchmark and four Eurozone countries. The initial HAR regressions that incorporate all Brexit news together show that the volatility of Eurozone's government bonds and UK stock market substantially increase on the day of the announcement of Brexit news. The findings further suggest that half of the bond markets anticipate the arrival of the news one day ahead. Moreover, we show that the markets' responses vary depending on the type (category) of Brexit news; the strongest reactions are observed with the release of UK votes and political news and least to UK Brexit news. In fact, our contribution and proportion analysis reveal that UK votes and political news explain more than 55% (on average) of the markets' volatility responses to Brexit news.

Overall, most Brexit news induces greater market uncertainty over the 3-day event window and its impact often lasts more than a day; yet the leading and lagging effects vary across news categories. The notable exception is UK votes news category which has negative total contributions, suggesting that they generally stabilise market volatilities possibly because they often offer some degree of clarity to the direction of the Brexit. What is more, government bond markets appear to be more sensitive to Brexit news than equity markets. To our surprise, both samples indicate the impact of the news is more pronounced in the Eurozone as opposed to the UK, affirming the close links between the UK and EU countries. Lastly, the additional equity analysis based on intraday (5-min) realised volatility are mostly consistent with the original results employing Parkinson's range-based volatility (high-low range) estimator. However, it provides a better-fit model and demonstrate greater volatility responses to the Brexit news. To conclude, this chapter presents novel evidence of the significance of Brexit news that carry valuable information for national as well as international government bond and equity markets. It also unveils that the effect of Brexit is not restricted to the EU referendum, but extends to various events including the UK Parliamentary votes on Brexit and key political news. As a result, it is essential that investors and portfolio managers anticipate the potential impact of new Brexit news or other political events on capital market volatilities, which should inform their investment decisions and portfolio optimisation.

Despite the contributions and practical implications of this thesis, it is still subject to a few limitations and constraints that should be addressed in future work. For example, the first empirical essay is based on a single country's bonds, Malaysia in this instance, which has a significantly smaller number of conventional bonds. Hence, we recommend that future research expands this comparison, providing multi-country results and studying the difference in the credit risk of different types of Islamic bonds (for example, asset-based and asset-backed). With a larger sample, a more balanced comparison can be achieved and robustness checks can be made employing a matched sample to reduce any possible confounding and self-selection biases. Similarly, for the second essay's findings to be generalised it would be worth examining whether stronger herding effects are also detected in other major bond markets (non-US). Future research could also investigate the reasons why investors consistently and intensively herd in corporate bond markets and assess whether is it based on fundamentals. More importantly, considering the potential destabilising effects of herding and consequences of cross-herding, it is critical to examine the existence and nature of cross-herding spillovers between other asset classes domestically and internationally. The last empirical essay sheds light on the importance of political news to financial markets, which we believe is worth exploring in a wider context with other political events. Similarly, it would be interesting to study the impact of other major events, such as the COVID-19 pandemic and the related government announcements on market volatilities. Lastly, our government bond analysis could have been improved by adopting realised volatility measures based on 5-minute returns that we could not obtain due to data unavailability. We encourage further research to use realised volatilities in their news announcement studies to boost the estimation accuracy and Bikhchandani and Sharma (2001) restrict the negative effects of market microstructure frictions.

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