# ESSAYS IN EMPIRICAL FINANCE: NEWS SENTIMENT IN CRYPTOCURRENCY, THE VALUE OF NOISE TIMING, AND THE PRICING OF CLIMATE CHANGE RISKS

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# Contents

This thesis contains 36,148 words including title page, tables, and footnotes.

# List of figures

# List of tables

# List of publications

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# Abstract

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Essays in empirical finance: News sentiment in cryptocurrency, the value of noise timing, and the pricing of climate change risks

This thesis improves the understanding of cryptocurrencies as financial assets by examining the Bitcoin reaction to high-frequency news compared to Forex, explores the role of news within financial markets, quantifies the economic value of a novel investment strategy which times financial noise able to manage price noise-risk, and assesses the extent to which climate change physical and transition risks are incorporated into asset prices. The thesis consists of three essays.

The first essay "News sentiment in the cryptocurrency market: An empirical comparison with Forex" considers high frequency intra-day data to investigate the influence of unscheduled currency and Bitcoin news on the returns, volume and volatility of the cryptocurrency Bitcoin and traditional currencies over the period from January 2012 to November 2018. Results show that Bitcoin behaves differently to traditional currencies. Fiat currencies typically experience a decrease in returns after negative news arrivals and an increase in returns following positive news whereas Bitcoin reacts positively to both positive and negative news. This suggests investor enthusiasm for Bitcoin irrespective of the sentiment of the news. This phenomenon exacerbates during bubble periods. Conversely, cryptocurrency cyber-attack news and fraud news dampen this effect, decreasing Bitcoin returns and volatility.

The second essay "The economic value of financial noise timing" proposes a dynamic noise-timing strategy which exploits the temporary dependence in noise traders' beliefs. Decomposing prices of the portfolio assets (stocks, bonds, gold, and cryptocurrencies) into permanent and noise components, we assess the economic value of a dynamic investment strategy which times the noise component. Our results show that risk averse and short horizon investors would be willing to pay a positive annual performance fee of between 314 and 940 basis points to switch from an ex-ante static investment strategy to a noise timing strategy. Our findings are robust to comparisons with other benchmark strategies, such as the volatility timing, and different periods of heightened volatility, including the Covid-19 period.

The third essay "Transition versus physical climate risk pricing in euro area financial markets: A text-based approach" prices climate change risks in equity markets within a Fama-French five factor model. We build two novel vocabularies on physical and transition climate risks, and we construct a Physical Risk Index and a Transition Risk Index comparing them to a corpus of news over the period 2015-2019 using the cosine-similarity approach. Climate news are found to carry relevant information especially for brown firms, with transition risk appearing to be more concerning for investors. Returns of low environmental and ESG scores firms negatively relate to both shocks to physical and transition risk, whereas returns of high Greenhouse Gas emissions levels and intensity firms further decline with transition risk news. While investors appear to penalise high climate risk exposure, there is no evidence of an increase in returns of less exposed firms.

# Declaration of originality

I, Lavinia Rognone, declare that no portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institute of learning.

# Copyright statement

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*I dedicate this thesis to my father, Fabrizio Rognone, and to my mother, Cristina Campagna.*

# Chapter 1

# Introduction

## 1.1 Research objectives and motivation

Over the past decade, there have been a number of developments in terms of financial technology, our understanding of the role of financial market participants and in the wider economic and global environment. As the financial environment evolves, it is important to gain a thorough understanding of how these developments impact markets and market participants, and any potential implications for regulators and policy makers. This thesis seeks to further our understanding in three key areas. In each area, the thesis develops an innovative empirical study that answers a unique set of questions and makes an original contribution to the literature.

First, there has been rapid development in financial technology and the growth in the adoption and issuance of cryptocurrencies. The rapid growth in the cryptocurrency market has attracted much attention from researchers, investors and regulators keen to understand how digital currencies have influenced the broad financial system and how they connect to other financial products. Consequently, there is a need to understand the characteristics of these cryptocurrencies: how they behave, how they are priced, the similarities and differences to other assets, etc. Specifically, the first essay in the thesis contributes to our understanding of how the cryptocurrency Bitcoin behaves compared to traditional currencies in its reaction to high frequency news.

Second, alongside greater focus on behavioural aspects of finance there is greater awareness of the role of noise and noise trading. The second essay in the thesis develops a model of financial noise and explores the asset allocation implications of seeking to exploit this noise. Assessing the economic value of financial noise timing quantifies how much investors would be willing to pay to either stop bearing the noise risk, i.e. assets price fluctuations not due to changes in fundamental values, or to take advantage of it. This research question is particularly relevant for institutional investors and our understanding of market behaviour as it investigates the impact of noise trading within financial markets considering the noise risk as a source of price risk. The proposal of a noise-timing strategy may be attractive especially if it yields significant gains and if investors are found to prefer it to alternative investment strategies. Further, this thesis paves the way for future research aimed at developing and improving the study of the noise risk within the context of risk and portfolio management.

Third, the increased global focus on issues of climate change has fuelled a growth in 'green' finance. The role of climate-related risks within financial markets is attracting large attention from financial participants following the increasingly frequent actions adopted by governments to curb global warming. Investors want to know how sensitive asset prices are to shocks to climate change risks and regulators are concerned about the consequences from a potential incorrect pricing of climate-related risks. The final essay of the thesis seeks to explore whether risks associated with climate change, namely, physical and transition risks are incorporated into asset prices. Investigating to what extent asset prices incorporate climate change risks is relevant to understand whether climate risks are perceived as a source of financial risk, whether investors consider some firms or activities as more exposed to climate risks than others, and whether the financial sector can function as a vehicle to transmit climate mitigation policies. The study further provides climate risks indices with the potential of several applications of interest of both academics (e.g. for future research), regulators (e.g. for policy analyses), and investors (e.g. for risk and portfolio management).

## 1.2 Thesis overview

In the first essay, I investigate the influence of unscheduled currency and Bitcoin news on the returns, volume and volatility of the cryptocurrency Bitcoin and traditional currencies. At the time of the writing, the growing cryptocurrencies literature went through a debate on the nature of Bitcoin aimed to determine whether the cryptocurrency should be considered as a financial asset or as a medium of exchange. Proponents of the financial assets view argued that Bitcoin does not hold the usual characteristics of money, especially due to its high volatility. Opponents claimed that Bitcoin neither adheres to characteristics depicting financial assets, as it does not mature or pay any dividends for instance. Corbet et al. (2019), while providing a technical review of the literature related to the debate, highlight the need to classify cryptocurrencies by studying the characteristics they may share with other well-known financial products. In this essay I then study the intradaily relationship between Bitcoin and the major traditional currencies to assess whether there exists a similar reaction to news sentiment and to provide further evidence on cryptocurrency characteristics.

Using 15-minute data from January 1, 2012 to November 1, 2018, this essay explores the high-frequency characteristics of Bitcoin with respect to traditional currencies. I consider six major currencies against the U.S. Dollar (USD), namely the Australian Dollar (AUD), the Canadian Dollar(CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY) alongside Bitcoin (BTC). Using Ravenpack News Analytics 4.0 I construct a sentiment index for each currency and Bitcoin and I examine how currency returns, volume and volatility are affected by the news sentiment using exogenous vector autoregressive model (VAR-X). The main findings suggest that while Forex comoves and reacts homogeneously to news demonstrating the strong inter-linkage of this market, Bitcoin behaves differently. The main results suggest that Bitcoin does not share many characteristics with traditional currencies and it is mostly unrelated to Forex news sentiment during the entire sample. On one side, there is evidence of a contemporaneous statistically significant relationship between foreign exchange and news sentiment such that traditional currencies typically experience a decrease in returns after negative news arrivals and an increase in returns following positive news. On the other hand, I find that both positive and negative news increase Bitcoin returns. This finding is exacerbated during the Bitcoin bubble periods suggesting the strong investors' enthusiasm toward the digital currency irrespective of the sentiment of the news. I then investigate the Bitcoin reaction to intraday cryptocurrency cyber-attacks and fraud news sentiments and find that such news dampen enthusiasm, decreasing Bitcoin returns and volatility upon arrival of negative cyber-attack news. The main results are robust to tests for commonality and multicollinearity.

This analysis contributes to the discussion on the nature of Bitcoin as a currency or as an asset. The main findings further inform practitioners about the characteristics of cryptocurrencies and inform regulators about the influence of news on Bitcoin volatility, particularly during bubble periods. Practitioners are generally concerned about risks and other characteristics of a potential investment into cryptocurrencies, and understanding how they react to news sentiment can help them to better assess the volatility and riskiness of their investments, also during different market conditions. On the other hand, policy-makers aim to better understand possible systemic risks posed by cryptocurrencies as well as other issues such as cyber-criminality and fraud. The results of this essay further contribute to the more general body of literature on Forex suggesting that trading strategies and standard models of exchange-rate determination could benefit from the inclusion of non-scheduled news sentiment on the exchange rate.

In the second essay, I assess the economic value of financial noise timing for short-horizon and risk-averse investors. Noise traders with stochastic beliefs play an important role in financial markets as they affect asset prices generating the so-called noise risk, usually referred to as price variation without changes in fundamental value (Black, 1986; De Long et al., 1990; Mendel & Shleifer, 2012; Shleifer & Vishny, 1997). While speculators and informed traders are expected to absorb the noise risk helping prices to converge toward fundamental values, they fail or intentionally do not entirely counteract it mainly due to arbitrage limits, market frictions, and other limitations (see for instance De Long et al. (1990), Gemmill and Thomas (2002), Hu et al. (2013), Stambaugh (2014), and Wang (2010)). It follows that the noise risk is not fully eliminated from the market and affects investors holdings (Gemmill & Thomas, 2002; Kondor et al., 2007). It is therefore vital for investors to take into account noise risk when managing their portfolios. Traders are keen to know and learn about other traders' beliefs that can influence the market, even when these expectations are wrong (Marmora & Rytchkov, 2018). However, due to the unpredictability of noise traders' future beliefs, it is difficult to create hedging and speculative strategies based on next period noise traders' expectations (Asparouhova et al., 2013; Blume & Stambaugh, 1983; Brennan & Wang, 2010; Shleifer & Summers, 1990).

I propose to model next period traders beliefs by exploiting the noise component of price time series. In particular, I estimate the noise price component via a Kalman filter which decomposes the original price time series into a permanent (fundamental) component and the temporary (noise) component similarly to Brogaard et al. (2014) and Hendershott and Menkveld (2014), and in line with the noise-trader theory approach by De Long et al. (1990) and Shleifer and Summers (1990). I then use its predictions to model the next period noise traders' expectation based on past and present prices. In this fashion the noise represents any temporary price deviation from fundamental value further in line with Asparouhova et al. (2013) and Hu et al. (2013). I then create a dynamic noise-timing strategy considering stocks, bonds, gold, and cryptocurrencies under a Markowitz (1952) mean-variance optimization problem, in the spirit of Fleming et al. (2001). The economic value of the noise-timing strategy is calculated according to a utility-based approach as maximum annual performance fee that makes an investors indifferent between two investments alternatives (Fleming et al., 2001; Jondeau & Rockinger, 2007; Karstanje et al., 2013). The main findings provide evidence that the noise timing strategy has statistically positive value such that a risk-averse and short-horizon investor is willing to pay a positive annual performance fee of between 314 and 940 basis points, depending on his risk aversion parameter and target return, to switch from a static strategy to the noise-timing strategy. The noise timing strategy performs better than alternative benchmark strategies such as the volatility timing, naïve, and random walk strategies. It further provides significant gains in presence of transaction costs and during periods of heightened volatility, including the initial Covid-19 period.

This essay contributes to the literature on the role of noise in financial markets originally proposed by Black (1986) by assessing the economic value of noise-timing to short-horizon and risk-averse investors. I propose a model that allows to estimate next period traders beliefs, previously considered unpredictable, which enables the creation of noise timing strategies able to hedge and speculate on the noise risk. This study sheds light on the role of noise risk for portfolio selection, a type of price-risk which despite its importance for financial markets has been largely neglected in that context. Therefore, this essay also contributes to the general body of literature on risk and portfolio management as it investigates noise as source of price-risk proposing a method to manage it. Finally, including cryptocurrencies as an additional asset into the common portfolio of stocks, bonds and gold, the study further contributes the more recent strand of literature on cryptocurrencies and their investment characteristics.

In the third essay, I study the sensitivity of asset prices to climate-related risks to examine to which extent they are priced by financial markets. Investors may tend toward a negative valuation of exposed firms as climate change risk increases. While this theoretical assumption might seem rational as also supported by the credited beliefs that climate risks represent a source of financial risk, its empirical evidence is not as trivial as demonstrated by the conflicting results from the existent green finance literature. There are several challenges which might impede a responsible allocation of capital from the market such as the lack of agreed and common metrics to evaluate firms' exposure to climate risks. It follows that investors might not be able to easily identify exposed firms failing to detect climate risky investments. On the other hand, there is the possibility that the market is insensitive to shocks to climate change news suggesting the failure to perceive these risks as a source of financial risk. Both scenarios lead to a mispricing of climate risks which pose critical consequences on the functioning of the financial sector as a vehicle to transmit climate mitigation policies.

Considering that climate change can affect the financial system differently through two main channels, namely physical risk (i.e. loss of value or increased costs due to the disruptive impact of physical hazards like heat waves and rising sea levels on exposed and vulnerable financial participants) and transition risk (set of financial risks arising from the process of adjustment toward a low carbon economy), I use a textual analysis approach in line with Engle et al. (2020) to document their impact on asset prices separately. I examine scientific texts on climate change to build two novel vocabularies on physical and transition risk. I compare the vocabularies with newspapers obtaining a Physical Risk Index and a Transition Risk Index, based on the idea that investors use newspapers as a source of information to update subjective beliefs about climate risks. I add the risk indices into a Fama-French five factor model to test the daily sensitivity of the returns of brown and green portfolios constructed according to firms GHG emissions level, GHG emissions intensity, Environmental (E) scores, and Environmental, Social, and Governance (ESG) scores. I consider EuroStoxx 600 Index historical constituents over the period 2015-2019. Results show that the excess returns of brown portfolios are negatively and significantly related to unexpected changes in transition risk. This suggests that investors consider firms with poor environmental and ESG performances, as well as firms with high GHG emissions level and intensity (i.e. GHG emissions scaled by net-revenue), exposed to transition risk and tend toward a negative valuation of them. In addition, firms with poor E and ESG ratings are also negatively related with rises in physical risk suggesting that investors use E and ESG scores to screen firms exposed to this risk. Overall, financial markets appear to price climate related risks and investors perceive these risks as financial risks. I also conduct a sectoral analysis which suggests that investors combine sectoral information with detailed firm-level characteristics to identify firms exposed to climate risks.

These findings inform both investors, policy makers, and financial institutions on the extent to which financial markets price climate-related risks and react to stimuli from the process of adjustments toward a carbon neutral economy. This study further contributes to the green finance literature by proposing a method to distinguish between physical and transition risk, providing two vocabularies and two risk indices with several application for future research. The novel vocabularies can be used to understand the relative importance of each component of climate risks and possibly apply additional decomposition of risks. The risk indices find applications for risk management and portfolio management issues, such as the implementation of physical and transition risk climate hedging investment strategies, the assessment of the portfolios sensitivity to climate risks, the detection of climate risky investments, and the possibility to carry stress tests and scenario analyses.

## 1.3 Thesis structure

The thesis structure follows the journal format that allows chapters to be incorporated into a format suitable for submission and publication in peer-reviewed academic journals. Therefore, this thesis is structured around three essays containing original research in chapters 2, 3, and 4. The chapters are self-contained, i.e., each chapter has a separate literature review, answers unique and original questions, and employs distinct analysis with different datasets. Page numbers, titles, and subtitles have a sequential order throughout the thesis.

The remainder of the thesis is organised as follows. Chapter 2 examines the effects of high-frequency unscheduled news sentiment on the returns, volume, and volatility of the cryptocurrency Bitcoin compared to traditional currencies. Chapter 3 explores the noise risk and proposes a strategy to time financial noise. Chapter 4 studies to which extent financial markets price climate change physical and transition risks in equity market. Chapter 5 concludes.

In chapters 2, 3, and 4, I use the first person plural (we, our) rather than the singular (I, my), as these chapters are in the form of co-authored papers.

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# Chapter 2

# News sentiment in the cryptocurrency market: An empirical comparison with Forex

**Preface**

This paper represents the first research output of my doctoral studies at AMBS, and is a co-authored work with my supervisors, Professor Stuart Hyde and Dr. Sarah S. Zhang. It has been published in the *International Review of Financial Analysis* in May 2020.

The paper has been presented at the *Cryptocurrency Research Conference 2019* held at the University of Southampton, UK, where it was awarded the *Best Ph.D. Paper Award*. It was also presented at the *INFINITI Conference on International Finance 2019* at the University of Glasgow, UK, and at the *IFABS 2019 conference Angers* (International Finance and Banking Society) held at the ESSCA School of Management in Angers, France. I further presented the paper in a seminar at the National University of Singapore (NUS) at the Risk Management Institute in 2019. In addition, the paper was awarded the *Best Paper – 1st Runner Up* at the *Best Doctoral Paper Competition* during the Alliance Manchester Business School AMBS Doctoral Conference 2020 at the University of Manchester, UK.

The paper also benefited from previous presentations at the *International Summer School on "Empirical Methods in Market Microstructure Research"* organised by the University of Molise, in collaboration with ECMCRC (European Capital Markets Cooperative Research Centre) and CMCRC (Capital Markets Cooperative Research Centre) at Agnone, Italy, in 2018, and at the *SoFiE Financial Econometrics School on Big Data in Macroeconomics and Finance* held at National Bank of Belgium, Belgium, in 2018.

As a co-authored work, my individual contribution to this paper was substantial. I developed the original research question and hypotheses, searched sources from relevant existent literature, managed data collection and cleaning, implemented the empirical analysis both analytical and computational coding, worked at the writing, and acted as presenter at conferences. The contribution of my supervisors was pivotal to develop the paper. The discussion, exchange of opinions, guidance, supervision on both theoretical and empirical issues, and effort in editing the paper draft from supervisors were essential to the completion and publication of this piece of work.

**Abstract**

We use high frequency intra-day data to investigate the influence of unscheduled currency and Bitcoin news on the returns, volume and volatility of the cryptocurrency Bitcoin and traditional currencies over the period from January 2012 to November 2018. Results show that Bitcoin behaves differently to traditional currencies. Traditional currencies typically experience a decrease in returns after negative news arrivals and an increase in returns following positive news whereas Bitcoin reacts positively to both positive and negative news. This suggests investor enthusiasm for Bitcoin irrespective of the sentiment of the news. This phenomenon is exacerbated during bubble periods. Conversely, cryptocurrency cyber-attack news and fraud news dampen this effect, decreasing Bitcoin returns and volatility. Our results contribute to the discussion on the nature of Bitcoin as a currency or an asset. They further inform practitioners about the characteristics of cryptocurrencies as a financial asset and inform regulators about the influence of news on Bitcoin volatility, particularly during bubble periods.

## 2.1 Introduction

In recent years, Bitcoin has attracted much attention from policy-makers, investors, academics and regulators due to its rapid price appreciation. The price of Bitcoin increased markedly over the 12 months from $788 on December 17, 2016 to $19,650 one year later, experiencing an increase of 2,394%. The current debate on the nature of Bitcoin tries to determine whether the digital currency should be considered a financial asset or a medium of exchange, bringing out the need to classify cryptocurrencies as financial instruments and to study the shared characteristics they may have with other well-known financial products. This paper contributes to the literature investigating the intradaily relationship between Bitcoin and the major traditional currencies to assess whether there exists a similar reaction to news sentiment and to provide further evidence on cryptocurrency characteristics to help the debate. Particularly, we investigate how high-frequency unscheduled news releases related to Forex and Bitcoin affect returns, volume and volatility of Forex and whether Bitcoin exhibits similar responses. We provide a comprehensive study for Bitcoin including a sample period of almost seven years of 15-minute data from January 1, 2012 to November 1, 2018. We consider six major currencies against the U.S. Dollar (USD) (counter), namely the Australian Dollar (AUD), the Canadian Dollar (CAD), the Swiss Franc (CHF), the Euro (EUR), the British Pound (GBP), the Japanese Yen (JPY) alongside Bitcoin (BTC). Using *Ravenpack News Analytics 4.0* we construct a sentiment index for each currency and Bitcoin and we examine how currency returns, volume and volatility are affected by the news sentiment using exogenous vector autoregressive model (VAR-X).

Our key results suggest that while Forex comoves and reacts homogeneously to news, Bitcoin behaves differently. There is evidence of a contemporaneous statistically significant relationship between foreign exchange and news sentiment such that positive (negative) news on the base appreciate (depreciate) the exchange rate, while positive (negative) news on the counter decrease (increase) the exchange rate returns. Overall news on the base increase Forex volume. These findings do not hold for Bitcoin, where an overall low level of significance is found while testing for the contemporaneous news sentiment impact, such that only positive Bitcoin news are informative for Bitcoin returns. We then consider the impact that news sentiment have on Bitcoin one period after due to the existence of potential delays and technological advancements issues in the Bitcoin market, and find that both positive and negative news increase Bitcoin returns. This finding is exacerbated during the Bitcoin bubble periods suggesting the strong investors' enthusiasm toward the digital currency. We then focus on intra-day cryptocurrency cyber-attacks and fraud news sentiments and find that such news dampen enthusiasm, reducing volatility in conjunction with negative Bitcoin returns upon arrival of negative cyber-attack news. Results are robust to tests for commonality and multicollinearity.

Our results are particularly relevant for practitioners and regulators. On one side, practitioners are generally concerned about risks and other characteristics of a potential investment into cryptocurrencies. On the other side, regulators aim to better understand possible systemic risks of cryptocurrencies as well as other issues, such as cyber-criminality and fraud. Our results provide insight for both groups of stakeholders to better understand the characteristics of cryptocurrencies.

The remainder of this paper is organized as follows: Section 2.2 provides a short background on Bitcoin and the related literature on the topic. Section 2.3 describes the data collection. Section 2.4 presents the sentiment index construction and the empirical model, while Section 2.5 presents a discussion of the main results. Section 2.6 focuses with a numbers of robustness tests. Finally, Section 2.7 concludes the study summarizing the findings and proposing further analyses.

## 2.2 Background and related literature

Introduced in 2008, Bitcoin is a digital currency, namely an electronic cash system without a physical counter value and is infinitely divisible. There is no unique market or a central authority, rather cryptocurrencies such as Bitcoin are decentralized and characterized by a peer-to-peer network fragmented over more than fifteen thousand exchanges. Each transaction must be approved by other users, or nodes, to be validated and recorded on the public ledger, namely the blockchain. Bitcoin is the leading digital currency relative to Litecoin, Ripple, Bitcoin Cash, Ethereum and other cryptocurrencies with a market capitalization of around $217 billion and covering 63.4% of the entire cryptocurrency market[1].

Regarding the debate on the nature of Bitcoin, Bitcoin is originally considered money according to its developer, Satoshi Nakamoto. Money should generally serve as a medium of exchange, as a store of value, and as a unit of account. Proponents of the financial asset perspective challenge this view as not all of these properties seem to hold for Bitcoin, for example due to its high volatility. However, Bitcoin does not adhere to characteristics of traditional financial assets, as it does not mature or pay any dividend for instance. With our study, we aim to find Bitcoin characteristics which can

[1]Coinmarketcap.com on July 8, 2019 at 22:42 GMT +0100.

help the understanding of this new financial product. Related literature includes Baur et al. (2018) who claim that Bitcoin is mainly used as speculative investment but that its behavior is unrelated to that of stocks, bonds and commodities. Dyhrberg (2016) further highlights the risk management advantages of using Bitcoin as a medium of exchange. She concludes that the digital currency can be classified as something in between a traditional currency, such as the U.S. Dollar, and a store of value, such as gold.

This paper compares Bitcoin and traditional currencies with respect to the reaction to financial sentiment using non-scheduled non-fundamental news. Previous studies have focused on the relationship between Bitcoin and foreign exchange with respect to the hedging properties of Bitcoin. Urquhart and Zhang (2019) base their study on the Baur and Lucey (2010) hedge, diversifier and safe-haven definitions and find that Bitcoin acts as a hedge for the Swiss Franc, the Euro and the British Pound and as a diversifier for the Australian Dollar and the Canadian Dollar and the Japanese Yen at the intraday level with an hourly frequency. Baumöhl (2019) explores the interconnectedness between six cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin, Stellar Lumens, and NEM) and six traditional currencies (Euro, Japanese Yen, British Pound, Swiss Franc, Canadian Dollar, and Chinese Renminbi), finding that investors benefit from diversifying across the two groups. Other papers explore the volatility connectedness between Bitcoin and precious metal markets (Mensi et al., 2019) and the dynamic relationship between cryptocurrencies and other financial assets (Corbet et al., 2018c).

Other studies look at the connection between cryptocurrencies and news through macroeconomics news announcements. For instance, Corbet et al. (2018a) create a sentiment index for four macroeconomics variables, namely Gross Domestic Product, Consumer Price Index, unemployment and durable goods and find that only stories related to the last two macroeconomic variables appear to be relevant for Bitcoin returns. In contrast to this study, we use unscheduled news for different currencies and compare the effects on Bitcoin to other traditional currencies. Abraham et al. (2018) collect information from Twitter Data and Google Trend Data to forecast the price direction of Bitcoin and Ethereum, finding that only tweet volume and not the sentiment is significant for the forecast. Furthermore, Urquhart (2018) uses Google Trends data and finds that volatility and volume are important drivers of next day attention of Bitcoin.

Similarly, the literature on foreign exchange provides evidence that macroeconomic news influence both returns and volatility. However, macroeconomic news cannot completely explain the majority of foreign exchange-rate movements due to the low frequency of the announcements and because the information they bring is not as surprising as that of non-scheduled news (Andersen et al., 2003). Evans and Lyons (2005) conclude that exchange rates do not instantaneously react to macro news, while Evans and Lyons (2008) show that only the 30% of the daily price variation of FX is due to macro announcements. Omrane and Savaşer (2017) show that the exchange rate volatility response differs for different types of macroeconomic news during the financial crisis period. Also, Love and Payne (2007) find that not all the information included in scheduled news announcements is impounded in the Forex price. Other papers, such as Lahaye (2016), Chatrath et al. (2014), and Lahaye et al. (2011), find evidence of cojumps around news for different traditional currency pairs.

Our study is further related to papers on specific high-frequency non-scheduled news related to traditional currencies and Bitcoin. Dominguez and Panthaki (2006) study the importance that scheduled macroeconomic surprises, non-scheduled fundamental news and non-scheduled non-fundamental news have on foreign exchange. They find that non-scheduled non-fundamental news influence the USD/GBP and the USD/EUR intraday returns, volatility and transaction intensity. Ederington and Lee (2001) also examine non-scheduled news announcements and find evidence that high volatility persists more after non-scheduled shocks than after scheduled news due to the surprise component.

This paper further contributes to the cryptocurrency literature which studies the investor sentiment and attention toward digital currencies (Baig et al., 2019; Ibikunle et al., 2020; López-Cabarcos et al., 2021; Oad Rajput et al., 2020; Shen et al., 2019; Urquhart, 2018), the behaviour of the Bitcoin returns (Atsalakis et al., 2019; Corbet et al., 2018b; Katsiampa, 2017; Phillip et al., 2018; Urquhart, 2017) and volatility (Catania et al., 2019; Chaim & Laurini, 2018; Katsiampa, 2017; Katsiampa et al., 2019; Shen et al., 2020), the existence of bubbles (Cheah & Fry, 2015; Corbet et al., 2018b), the cyber-criminality of cryptocurrencies (Corbet et al., 2020; Gandal et al., 2018), and further relates to the literature that studies the cryptocurrency markets using high frequency data (Aslan & Sensoy, 2020; Chu et al., 2019; Katsiampa et al., 2019; Ma et al., 2020; Manahov, 2021; Zargar & Kumar, 2019; Zhang et al., 2019; Zhang et al., 2020).

## 2.3 Data

### 2.3.1 Bitcoin data

We collect data[2] for Bitcoin for the sample period January 1, 2012 – November 1, 2018 from *bitcoincharts.com*, a website providing transaction data for most of the Bitcoin exchanges around the world (see, for example, Corbet et al. (2019)). We consider single trade prices and volume data from Bitstamp[3], one of the oldest and most active Bitcoin exchanges (Brandvold et al., 2015) providing reliable data.[4] We focus on Bitcoin over U.S. Dollar due to its high liquidity. Data are aggregated into 15-minute intervals to construct log-returns.[5] The original sample consists of 239,616

[2] All data are in Universal Time Coordinated (UTC).

[3] Bitstamp is a cryptocurrency marketplace based in Luxembourg since 2011 with more than 3 million of users which allows to trade Bitcoin, Ethereum, Litecoin, Bitcoin Cash and Ripple along with U.S. Dollar and Euro. It utilizes advanced security technologies to guarantee secure and transparent transactions by storing offline the 98% of the digital funds. It is subject to annual audit by one of the Big Four accountancy firms (EY, Deloitte, KPMG, PwC).

[4] One main issue with cryptocurrency data relates to fake reported volumes. Many digital currency exchanges modify and increase their reported volume to climb in the rankings to appear more attractive to investors. The data provider company Bitwise examined exchanges for fake volumes by monitoring real time trading data from the top 80 cryptocurrency exchanges. Bitwise found that the 95% of reported volume is fake. Only Binance, Bitfinex, Coinbase, Kraken, Bitstamp, bitFlyer, Gemini, itBit, Bittrex, and Poloniex exchanges report reliable volume data. Among these exchanges, we select Bitstamp to collect reliable long time series data being it the oldest exchanage together with Kraken. Bitstamp also belongs to the top five exchanges in terms of monthly volume for the entire sample, ranking third at the end of the sample period. Further information can be found at "Meeting with Bitwise Asset Management, Inc., NYSE Arca, Inc., and Vedder Price P.C", U.S. Securities and Exchange Commission held in March 19, 2019, and at data.bitcoinity.org

[5] Shen et al. (2020) plot the Bitcoin volatility signature and show that it stabilizes around the 5-minute sampling frequency suggesting that the microstructure noise may bias the digital currency variance estimator for higher frequencies. Additionally, considering that on average the median confirmation time to accept Bitcoin transactions is around 10-minute (see blockchain.com), we choose 15-minute as sampling frequency to further control for potential delays to validate transactions.

observations, but we filter the Bitcoin sample to match the Forex opening time[6] reducing the sample to 171,605 observations. For any 15-minute interval with no transaction record, we assume the last recorded price generating a zero return. Volume is measured in logarithms and volatility is the conditional variance from a GARCH(1,1) model.

Table 2.1 presents the summary statistics for Bitcoin to U.S. Dollar data over the sample period. Historically, Bitcoin returns have been positive and close to zero with a high intraday volatility of about 58.4%. Bitcoin returns are positively skewed, and kurtosis far exceeds the Gaussian distribution kurtosis, suggesting that they are not normal. The null hypothesis of non-stationarity is clearly rejected according to the Phillips-Perron test results conducted with trend and drift. Bitcoin log-volume mean is about 3.425, showing the historical presence of high-frequency transaction and confirming the intraday liquidity of Bitstamp. Furthermore, average volatility has been high, around 37.6%.

Figure 2.1, panel a plots the sample period Bitcoin price evolution and it shows the rapid price appreciation which peaks on December 17, 2017 at 12:15:00 when the price of one Bitcoin reached 19,650 U.S. Dollars. Subsequently, Bitcoin suffered a rapid drop, probably due to the burst of the bubble (Corbet et al., 2018b). Trading volume is plotted in figure 2.1, panel b and reveals insight on the liquidity of Bitstamp at the intraday level. The highest volume is registered during the burst of the first Bitcoin bubble (July 2013 – December 2013, Gerlach et al. (2019)), particularly on February 10, 2014 at 11:00 AM, when 11,167 Bitcoins were traded within 15-minute. Among the other volume peaks, 10,000 Bitcoins were exchanged on January 14, 2015 at 07:15 AM around (but not necessarily linked to) the high turmoil for the Swiss Franc exchange rate. There is also evidence of high transaction activity during the second bubble (January 2016 – December 2017, Gerlach et al. (2019)) which peaks on March 10, 2017 at 09:00 PM with 9,066 Bitcoins traded.

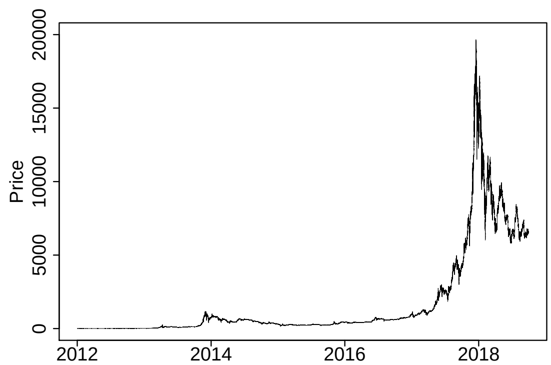
[6]FXCM opens on Sunday 10 pm UTC and closes on Friday 10 pm UTC. It is also closed on Christmas day, December 25, and new year's day, January 1.

**Table 2.1:** Summary statistics Bitcoin data

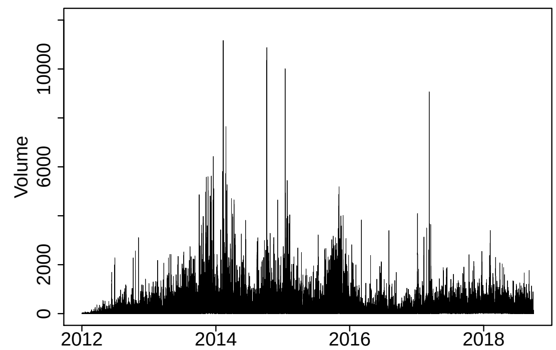
| | | | | | PACF | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | Skew | Kurtosis | 1 | 2 | 3 | 4 | PP Test |
| Log-returns (%) | 0.003 | 0.584 | 6.798 | 1,101.497 | 0.043 | -0.054 | -0.032 | -0.016 | -398.890* |
| Log-volume | 3.425 | 1.848 | -0.449 | 2.472 | 0.720 | 0.320 | 0.219 | 0.168 | -287.350* |
| Volatility | 0.376 | 0.430 | 10.663 | 264.822 | 0.991 | -0.115 | -0.034 | -0.051 | -33.366* |

Note: Mean, standard deviation (SD), skewness (Skew), Kurtosis, partial autocorrelation (PACF) and Phillips-Perron stationarity test with drift and trend (PP test) for 15-minute percentage log-returns, log-volume and GARCH(1,1) volatility for Bitcoin to U.S. Dollar for the period Jan 2012 - Nov 2018. * indicates p-value<0.01.

**Figure 2.1:** Bitcoin price and volume




(**a**) Price




(**b**) Volume

Note: 15-minute Bitcoin to U.S. Dollar (BTCUSD) price (a) and trading volume (b) for Bitstamp over the sample period Jan 2012 - Nov 2018.

### 2.3.2 News sentiment data

News sentiment data for the currencies and Bitcoin are drawn from *RavenPack*, a company that provides real-time news analysis services to institutional investors and financial professionals. *RavenPack News Analytics* is a leading global news database affiliated with *Dow Jones News*, which analyses relevant information from *Dow Jones Newswires*, regional editions of the *Wall Street Journal*, *Barron's* and *MarketWatch* and has been used in a number of prior studies (e.g. Dai et al. (2015), Kolasinski et al. (2013), and Shroff et al. (2014)). *RavenPack* continuously collects and automatically processes hundreds of thousands of articles a day delivering news timestamped to the millisecond from leading publishers and web aggregators, including national and local news, blog sites, industry and business publishers, government and regulatory updates and trustworthy financial websites (see RavenPack News Analytics – 2015 User Guide v.4.0.). *RavenPack News Analytics* is comprised of two main editions: the *Dow Jones* edition and the *Web* edition. In this paper, we use both of these editions to exploit all the information provided by this dataset, similarly to Sabherwal et al. (2011) and more recently Bushman et al. (2017), Ho et al. (2018), and Chinco et al. (2019).

RPNA4 (*RavenPack News Analytics 4.0*) provides news items which are tagged for each currency as well as timestamp, and most importantly, includes separate scores for relevance, novelty and sentiment[7]. While other studies, such as Birz and Lott (2011), Lott and Hassett (2014), Caporale et al. (2017) and Corbet et al. (2018a), focus on newspaper coverage of scheduled macroeconomic announcements and classify news sentiment by their headlines, RPNA4 also analyzes the news body and provides a sentiment measure on a granular scale. In particular, RPNA4 provides 32 fields for each record, such as timestamp, reference identifiers, scores for relevance, novelty and sentiment, and a unique identifier for each news story analysed. The principal fields of interest are (RPNA4 code in brackets):

– *Timestamp* (TIMESTAMP_UTC): the date and time (YYYY-MM-DD hh:mm:ss.sss) at which *RavenPack* receives the news item with millisecond precision;

– *Identifier* (RP_ENTITY_ID): a permanent and unique 6 alphanumeric character assigned by *RavenPack* to each entity[8];

– *Relevance*: a score between 0–100 that indicates how strongly the news story is related to the entity, higher values mean greater relevance. It follows a brief score interpretation:

    – 100: highly relevant score and context-aware. Entities which receive this relevance score are prominent in the news story and play a key role. RavenPack's relevance analysis goes further the only interpretation of key words or mentions. In fact, its automated classifiers can detect the roles entities play in events like legal disputes and acquisitions or during

[7]Other studies that use similar Reuters data include Groß-Klußmann and Hautsch (2011) and Riordan et al. (2013).

[8]RPNA4 Identifiers for AUD, CAD, CHF, EUR, GBP, JPY, USD and BTC are 5A72C2, D74D70, 74086E, 3E823F, DF632D, A753BA, FE1757 and A25816 respectively.

announcing corporate actions and other categories, understanding the meaning (context awareness). Thus, a score of 100 is given if and only if the news is highly relevant and context-aware.

– 0–99: score context-unaware, the score is assigned by a proprietary text positioning algorithm based on where the entity is first mentioned, the number of references in the text and the overall number of entities mentioned in the story. However, a score between 90 and 99 is considered significantly relevant. In this case, the entity is mentioned directly in the main title or in the headline. A score ranging from 75 to 89 still represents a relevant score, the entity reference is further in the story body. Scores below 75 are not relevant scores.

– *Sentiment*: a score between 0–100 representing the sentiment and financial perception of facts. The score is determined by systematically matching stories categorized by financial experts according to the short-term positive or negative financial impact.[9] The financial expert consensus is then combined with traditional language analysis and sophisticated proprietary algorithms dynamically assign an Event Sentiment Score (ESS) considering an emotional factor[10], a weather and a climate factor[11], an analyst rating factor[12], a credit rating factor, a fundamental comparison factor[13] and a causalities factor[14]. Positive (or negative) sentiments are associated with scores above (or below) 50 and neutral sentiments are linked to sentiment scores of 50.

– *Novelty*: an integer number between 0–100 representing how novel a story is within a 24-hour time window across all news stories. The first story reporting a categorized event is the most novel and important and receives a score of 100. The Event Novelty Score (ENS) represents the order in which entity records are

[9]The proprietary algorithm is trained to match stories with a collection of surveys where experts rated entity-specific events as conveying positive or negative sentiment and to what extent.

[10]There are 5 sales containing groups of words and phrases with different emotional magnitude: *Low Magnitude*, *Moderate Magnitude*, *Substantial Magnitude*, *Severe Magnitude* and *Critical Magnitude*.

[11]Measure extreme weather according to official measure like Richter scale or the Volcanic Eruption Index.

[12]Over 150 different broker and analysts scales for stocks, strong buy, buy, hold, sell, strong sell.

[13]Compares actual versus estimated figures about earning, revenues or dividend and gives a score.

[14]Used as sentiment strength factor for natural disasters and industrial accidents based on the number of dead people.

published per news story by attaching scores following a decay function (100 75 56 42 32 24 18 13 10 8 6 4 3 2 2 1 1 1 1 0 ...) to each repeated news within 24-hours. Hence, the second story of the day matching the first with the same entity and referring to the same event receives a score of 75, the third similar story receives an ENS of 56, and so on. We interpret the second similar story to be only 75% novel, the third one 56% novel, up to the twentieth that has no more novelty power, 0%.

Hafez (2009) provides evidence that only 20% of news stories are relevant and including the remainder mostly adds noise. Following Groß-Klußmann and Hautsch (2011) and Smales (2014b) who find that market prices are affected only by highly relevant news, we sample only news with a relevance score above 90 which in fact results in a sample where all news have maximum relevance score of 100. The sample is further filtered according to one-day novelty to eliminate redundancy among the data. Within the day news are weighted by novelty in order to keep information from related news but place greater emphasis on new stories.

Table 2.2 presents the descriptive statistics for the 15-minute sample news sentiment data. On average, Bitcoin news items mostly have a neutral average sentiment (mean 0.041%), with the lowest standard deviation of 4.7% compared to the other currencies. Negative average sentiment is linked to the currencies CAD, CHF and JPY. JPY has on average the lowest sentiment of about -0.376%. The two leading currencies in terms of number of news are the U.S. Dollar and the Euro with 84,694 and 51,140 news items respectively. The lowest number of news items is that of Bitcoin. The sample data set includes only 3,108 positive and negative stories for the digital currency. Phillips-Perron unit-root test statistics with drift and trend always reject the null.

**Table 2.2:** Summary statistics news sentiment data

| | Mean x 100 | SD | Skew | Kurtosis | PP test | No. Obs. |
|---|---|---|---|---|---|---|
| News AUD | 0.037 | 0.117 | -0.090 | 22.374 | -392.060* | 29,956 |
| News CAD | -0.278 | 0.117 | -0.223 | 21.785 | -389.510* | 28,496 |
| News CHF | -0.292 | 0.085 | -0.759 | 43.187 | -396.690* | 20,530 |
| News EUR | 0.178 | 0.143 | -0.059 | 14.696 | -393.910* | 51,140 |
| News GBP | 0.106 | 0.125 | -0.020 | 19.687 | -395.500* | 36,664 |
| News JPY | -0.376 | 0.140 | -0.195 | 16.170 | -394.870* | 37,702 |
| News USD | 0.046 | 0.202 | -0.084 | 7.235 | -402.140* | 84,694 |
| News BTC | 0.041 | 0.047 | 1.446 | 147.476 | -382.230* | 3,108 |

Note: Mean (%), standard deviation (SD), skewness (Skew), Kurtosis, Phillips-Perron stationarity test with drift and trend (PP test) and number of observation (No. Obs.) for 15-minute news sentiment data for Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) for the period Jan 2012 - Nov 2018. * indicates p-value$<$0.01.

### 2.3.3 Foreign Exchange data

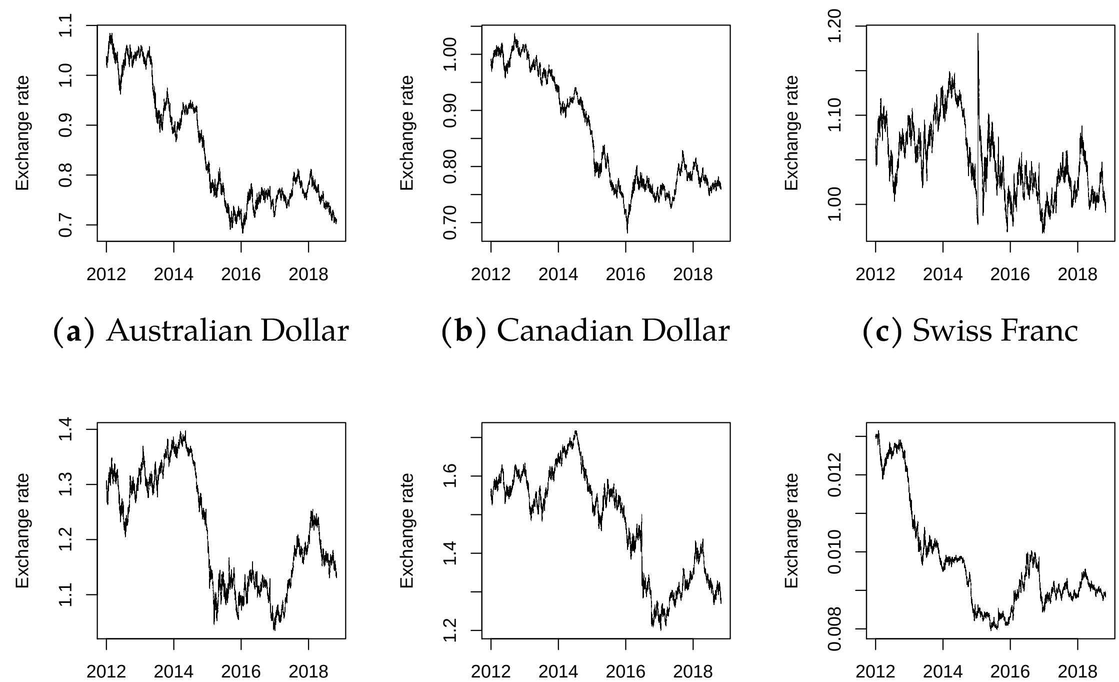
The lack of a central foreign exchange market presents a major challenge to obtain an aggregate and valid measure of trading volume. While some foreign exchange brokers provide data on historical intraday exchange rates, they only present a portion of the total FX volume. Some practitioners have systematically overcome this limitation by using tick-volume, namely the number of price updates over a certain time interval, as proxy for currency trading volume. Marney (2010, 2011) provides evidence that price updates have a high positive correlation with the actual traded volume in FX at the hourly level, which is also the basis for the Marney Volume Indicator (MVI). 15-minute UTC exchange rates[15] and tick-volumes for the pairs AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD and JPY/USD are collected from Forex Capital Markets[16] (FXCM) for the period 1 January 2012 – 1 November 2018. Figure 2.2 shows the exchange rates evolution over the sample period for each pair. Despite the different scale, FX 15-minute exchange rates depict a similar development over the sample period.

Table 2.3 presents the descriptive statistics for foreign exchange data. Panel a shows traditional currencies returns summary statistics. All the currencies have zero percentage return, for three decimal results, and low volatility consistent with the

[15] Mid-quote prices.

[16] FXCM is a Forex retail broker since 1999 based in London. It is a leading Forex provider around the world that trades 24-hours, five days a week on the major and the commodity pairs. It allows to trade 39 currency pairs covering most of the trading in FX market.

**Figure 2.2:** Foreign Exchange evolution.




(**a**) Australian Dollar (**b**) Canadian Dollar (**c**) Swiss Franc

(**d**) Euro (**e**) British Pound (**f**) Japanese Yen

Note: Australian Dollar (a), Canadian Dollar (b), Swiss Franc (c), Euro (d), British Pound (e), Japanese Yen (f) 15-minute exchange rates to US Dollar for the period Jan 2012 - Nov 2018.

existing Forex microstructure literature (Dominguez & Panthaki, 2006). Panel b shows summary statistics for volume. On average, the 15-minute log-volume ranges from 6.608 for CAD/USD to a maximum of about 6.975 for EUR/USD. Panel c reports the GARCH(1,1) volatility statistics and overall FX volatility is similar with a average intraday variability ranging between 0.046 and 0.063.

**Table 2.3:** Summary statistics Forex data

| | Panel a: Log-returns (%) | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | PACF at lag | | | | |
| | Mean | SD | Skew | Kurtosis | 1 | 2 | 3 | 4 | PP test |
| AUDUSD | 0.000 | 0.066 | -0.452 | 30.237 | -0.026 | -0.008 | -0.001 | 0.004 | -425.600* |
| CADUSD | 0.000 | 0.050 | 0.048 | 39.348 | -0.021 | -0.004 | -0.006 | -0.002 | -423.430* |
| CHFUSD | 0.000 | 0.063 | 26.693 | 4254.355 | -0.033 | 0.000 | 0.059 | 0.012 | -427.820* |
| EURUSD | 0.000 | 0.054 | 0.316 | 53.982 | -0.021 | 0.000 | 0.003 | 0.006 | -422.900* |
| GBPUSD | 0.000 | 0.055 | -3.117 | 209.595 | -0.030 | 0.001 | 0.010 | 0.010 | -426.800* |
| JPYUSD | 0.000 | 0.059 | 1.533 | 94.404 | -0.010 | -0.003 | 0.000 | 0.003 | -418.640* |
| | Panel b: Log-tick-volume | | | | | | | | |
| | | | | | PACF at lag | | | | |
| | Mean | SD | Skew | Kurtosis | 1 | 2 | 3 | 4 | PP test |
| AUDUSD | 6.821 | 1.462 | -2.872 | 13.68 | 0.893 | 0.185 | 0.063 | 0.017 | -105.630* |
| CADUSD | 6.608 | 1.705 | -1.789 | 7.831 | 0.909 | 0.218 | 0.080 | 0.030 | -103.280* |
| CHFUSD | 6.650 | 1.533 | -2.277 | 10.400 | 0.890 | 0.200 | 0.078 | 0.021 | -108.100* |
| EURUSD | 6.975 | 1.559 | -2.339 | 11.178 | 0.905 | 0.180 | 0.062 | 0.012 | -100.580* |
| GBPUSD | 6.969 | 1.635 | -2.239 | 10.193 | 0.909 | 0.183 | 0.074 | 0.018 | -101.150* |
| JPYUSD | 6.973 | 1.578 | -2.343 | 10.863 | 0.904 | 0.186 | 0.069 | 0.022 | -106.520* |
| | Panel c: Volatility | | | | | | | | |
| | | | | | PACF at lag | | | | |
| | Mean | SD | Skew | Kurtosis | 1 | 2 | 3 | 4 | PP test |
| AUDUSD | 0.063 | 0.016 | 1.247 | 6.379 | 0.999 | -0.059 | -0.040 | -0.024 | -11.201* |
| CADUSD | 0.046 | 0.026 | 3.894 | 38.544 | 0.923 | -0.011 | 0.002 | 0.005 | -83.122* |
| CHFUSD | 0.052 | 0.041 | 33.493 | 2716.493 | 0.943 | 0.002 | 0.029 | -0.153 | -69.958* |
| EURUSD | 0.048 | 0.028 | 3.856 | 38.917 | 0.963 | -0.049 | -0.012 | -0.020 | -60.130* |
| GBPUSD | 0.049 | 0.033 | 10.791 | 325.152 | 0.933 | -0.011 | 0.017 | 0.018 | -77.517* |
| JPYUSD | 0.055 | 0.026 | 6.450 | 115.671 | 0.959 | -0.036 | -0.011 | 0.001 | -25.399* |

Note: Mean, standard deviation (SD), skewness (Skew), Kurtosis, partial autocorrelation function (PACF) and Phillips-Perron stationarity test with trend and intercept (PP test) for 15-minute Australian Dollar (AUDUSD), Canadian Dollar (CADUSD), Swiss Franc (CHFUSD), Euro (EURUSD), British Pound (GBPUSD), Japanese Yen (JPYUSD) to U.S. Dollar percentage log-returns (a), log-tick-volume (b) and GARCH(1,1) volatility (c) for the period Jan 2012 - Nov 2018. * indicates p-value<0.01.

## 2.4 Methodology

### 2.4.1 Sentiment Indices

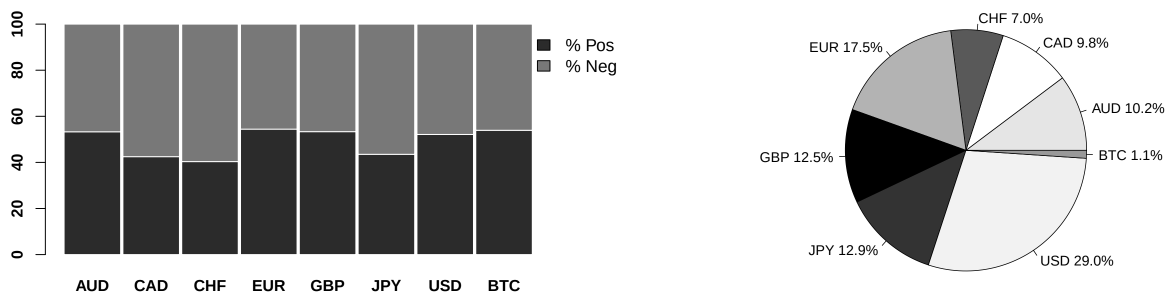
We construct sentiment indices for AUD, CAD, CHF, EUR, GBP, JPY, USD and BTC news using only relevant news. Each Event Sentiment Score (ESS) is scaled on a range from [-1, 1], with -1 representing negative and 1 representing positive sentiment news: (ESS-50)/50. The score is further multiplied by a novelty weight factor $w_{j,t,s} = ENS_{j,t,s}/100$, where ENS is the individual news novelty score and 100 represents the maximum novelty score assigned to the first news of the day for a specific entity and event. $w_{j,t,s}$ represents the novelty weight for instrument *j*={*AUD, CAD, CHF, EUR, GBP, JPY, USD, BTC*} at time interval *t* for the series of similar news of the day *s* and it follows a decay function according to the percentage of novelty of the news. $w_{j,t,s} \in [0,\ 1]$ such that the closer to 1 the more novel the news in a series of similar news is, within one day. The closer to 0 the lower the novelty, meaning that the news has been repeated many times during the current day.

The resulting novelty weighted sentiment score, WESS (Weighted Event Sentiment Score) keeps the ESS sign without alteration, positive or negative sentiment, but it lowers the ESS magnitude if the specific news has a low ENS (poor novelty power). Each WESS index for the eight instruments is aggregated and simple averaged in 15-minute buckets creating the Average Weighted Event Sentiment Score $AWESS = \sum_{k=1}^{N} WESS_k/N$ which takes a value between [-1, 1]. Values above (below) 0 are considered positive (negative) sentiment and values equal 0 are treated as neutral. $N$ represents the number of news within a time bucket and it may vary across intervals because non-scheduled news time arrival is stochastic and not equally spaced.

The bar-plot in figure 2.3 (a) shows the percentage of negative (grey bars) and positive (black bars) news of the currencies, with most currencies having a similar proportion of positive and negative news. The pie-chart in figure 2.3 (b) presents the overall number of news per currency in percentage. The U.S. Dollar has the highest number of stories covering the 29% of the entire sample, followed by the Euro which covers the 17.5%, the Japanese Yen (12.9%) and the British Pound (12.5%). Bitcoin news only account for the 1.1% of the sample.

Figure 2.4 presents the cumulative number of news for the seven currencies and Bitcoin at the 15-minute level for the period Jan 2012 – Nov 2018. The lines' slope determine the rate at which the number of news grows. Forex news grew constantly until mid-2017, as suggested by the absence of changes in the slope in figure 2.4 (a). Subsequently, the lines flatten revealing a lower news intensity. The evolution of Bitcoin news is not discernible from figure 2.4 (a), because of the scale. Figure 2.4 (b)

**Figure 2.3:** Sample news

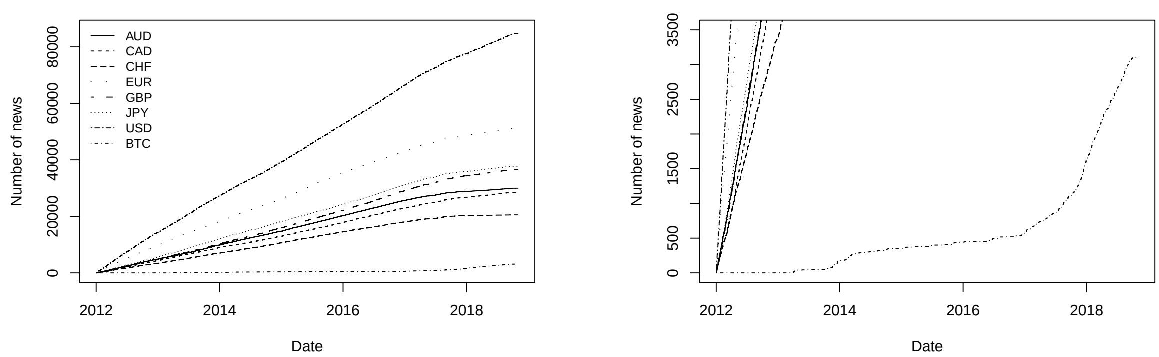



(a) (b)

Note: (a) presents the relative percentage of 15-minute positive (black) and negative (grey) news for Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) during Jan 2012 - Nov 2018. (b) shows the overall sample news proportion for the same period.

replicates figure 2.4 (a) but it uses a different scale allowing a more detailed picture of the Bitcoin news growth rate. There is evidence of an increase in the Bitcoin number of news in 2014 and a sharp increase from 2017, indicating that Bitcoin has received greater investor and media attention during these periods, most likely due to the two biggest Bitcoin bubbles. Starting from 2017, Bitcoin news have grown at a similar rate to that of FX, suggesting the continuous importance of the cryptocurrency.

**Figure 2.4:** Cumulative sample news




(a) (b)

Note: Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) cumulative sample 15-minute news for the period Jan 2012 - Nov 2018. Big scale (a), small scale (b).

### 2.4.2 The VAR-X model and hypotheses. Impact of sentiment on currencies and Bitcoin

We study the relationship between intraday Forex and Bitcoin returns, volume and volatility and news sentiment by testing whether the Bitcoin reaction to exogenous high-frequency non-scheduled news sentiment is similar to traditional currencies. We use a vector autoregressive exogenous model VAR-X($p$, 0) of the form:

$$\begin{bmatrix} r_{i,t} \\ v_{i,t} \\ \sigma_{i,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ c_3 \end{bmatrix} + \begin{bmatrix} a^1_{rr} & a^1_{rv} & a^1_{r\sigma} \\ a^1_{vr} & a^1_{vv} & a^1_{v\sigma} \\ a^1_{\sigma r} & a^1_{\sigma v} & a^1_{\sigma\sigma} \end{bmatrix} \begin{bmatrix} r_{i,t-1} \\ v_{i,t-1} \\ \sigma_{i,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} a^p_{rr} & a^p_{rv} & a^p_{r\sigma} \\ a^p_{vr} & a^p_{vv} & a^p_{v\sigma} \\ a^p_{\sigma r} & a^p_{\sigma v} & a^p_{\sigma\sigma} \end{bmatrix} \begin{bmatrix} r_{i,t-p} \\ v_{i,t-p} \\ \sigma_{i,t-p} \end{bmatrix} + \begin{bmatrix} b^0_{rAUD} & b^0_{rCAD} & \cdots & b^0_{rBTC} \\ b^0_{vAUD} & b^0_{vCAD} & \cdots & b^0_{vBTC} \\ b^0_{\sigma AUD} & b^0_{\sigma CAD} & \cdots & b^0_{\sigma BTC} \end{bmatrix} \begin{bmatrix} AWESS_{AUD,t} \\ AWESS_{CAD,t} \\ \vdots \\ AWESS_{BTC,t} \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix}, \tag{2.1}$$

where $i$={*AUD*/*USD*, *CAD*/*USD*, *CHF*/*USD*, *EUR*/*USD*, *GBP*/*USD*, *JPY*/*USD*, *BTC*/*USD*}, the dependent variables $r_t$, $v_t$ and $\sigma_t$ are log-returns in percentage, log-volume and volatility respectively. $AWESS_i$ are the sentiment indices for each of the currencies which are treated as exogenous variables. In utilizing contemporaneous specifications, we are implicitly assuming that news sentiments are not influenced by contemporaneous returns (Smales, 2014a). We choose the optimal lag-length for our VAR-X($p$, $s$) according to the Akaike Information Criterion (AIC) setting as maximum lags for the dependent variables $p$ equal 4 and for the exogenous $s$ equal 0. One hour of past lags ensures elimination of serial correlation and we are interested in contemporaneous effects of exogenous news. After model comparison simulations, AIC determines as best model the VAR-X(4, 0). We correct for serial correlation and heteroskedasticity in the error term by using Newey West standard errors (Newey & West, 1987).

We separate positive and negative sentiment using dummy variables to test the following main hypotheses:

– $H_1$: Positive (negative) news on the base increase (decrease) the exchange rate return, meanwhile positive (negative) news on the counter reduce (increase) the exchange rate return;

– $H_2$: Both negative and positive news on the base and counter increase volume and volatility of the pair;

– $H_3$: Negative news for the pair (negative news for base, positive news for counter) are expected to be more significant and have a bigger impact on the dependent variables;

where, for instance, we refer to EUR as base and to USD as counter for the exchange rate EUR/USD. $H_1$ is an extension of standard models of exchange rate behaviour which state that when positive news arrives for a currency, demand for that currency rises, causing exchange rate appreciation (Dominguez & Panthaki, 2006). $H_1$ claims that negative news for USD, the counter, are considered positive for the pair since the exchange rate denomination is in USD. Therefore, a negative news on USD appreciates the base over USD and *vice-versa*. Positive (negative) news on the counter are negatively (positively) related with exchange rate returns, the reverse idea holds for sentiment on the base. $H_2$ considers that both positive and negative sentiment attached to news contain some information that shocks the Forex and Bitcoin markets increasing the price variability and transaction volume. $H_3$ relates to the asymmetric impact of positive (gains) and negative (losses) environments, first introduced by Kahneman and Tversky (1979) in their prospect theory. We hypothesize that investors dislike bad news more than how much they like good news. Negative news for the pair, namely negative for the base and positive for the counter, have a bigger or equal effect in magnitude on the dependent variables than positive news on the pair implying the existence of an asymmetric instantaneous response for returns, volume and volatility to news according to the news investors' financial perception.

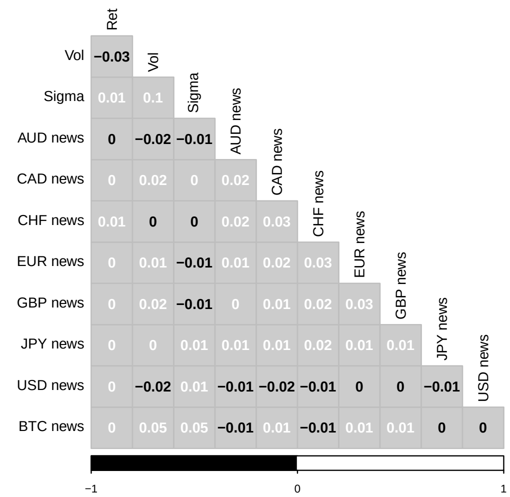
The 15-minute intervals are considered a sufficient time to test for contemporaneous Bitcoin reaction to news, because the average median confirmation time to accept transactions is 10 minutes.[17] However, there could be delays in the Bitcoin reaction due to Bitcoin market frictions and technological advancement issues and/or to the low number of high-frequency traders at least during the first part of the sample. To capture these, we also consider VAR-X(4, 1) for Bitcoin.

## 2.5 Empirical results

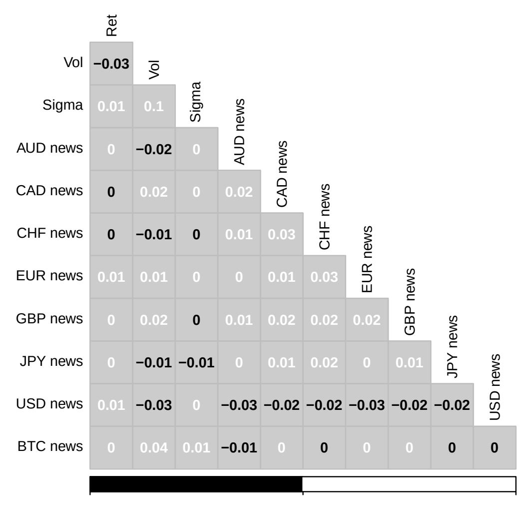
To gain an initial understanding of the influence of and potential links between news sentiment related to different currencies, figure 2.5 presents the Pearson correlation coefficients between negative (a) and positive (b) news sentiment for the various currencies in addition to Bitcoin returns, volume and volatility. Correlations between the news sentiments are typically low, never exceeding 0.03. Given this evidence that the news sentiment in each currency is largely uncorrelated with that of other currencies, we proceed with the VAR-X regressions.

[17] Time for a transaction to be accepted into a mined block and added to the public ledger (see blockchain.com).

**Figure 2.5:** Pearson correlation




**(a)** Negative sentiment




**(b)** Positive sentiment

Note: Negative (a) and positive (b) Pearson correlations between Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD), Bitcoin (BTC) sentiments alongside Bitcoin log-returns (%) (Ret), log-trading-volume (Vol) and volatility (Sigma) for the period Jan 2012 - Nov 2018.

### 2.5.1 Relationship between news sentiment and Forex

Tables 2.4-2.9 report the results for the VAR-X in (2.1), separated into positive and negative news for each currency pair. Each table has six columns corresponding to returns, volume and volatility for negative and positive news. Due to our focus on news sentiment and for brevity, lagged values on the dependent variables are not reported.

We find that $H_1$ holds for all the six currency pairs AUD/USD, CAD/USD, CHF/USD, EUR/USD, GBP/USD and JPY/USD. These currency pairs have a positive (negative) and highly relevant contemporaneous relationship between positive (negative) news sentiment on the base and the exchange rate returns. This finding is in line with prior literature. Dominguez and Panthaki (2006) find that non-scheduled non-fundamental news influence intraday foreign exchange returns, although they use an aggregate measure for sentiment indices and do not disentangle negative and positive news.

Columns 1-2 of Table 2.4 demonstrate that an increase in the measure for negative and positive base AUD news sentiment induces a 1.2% decrease and a 1.2% increase for AUD/USD returns respectively. Table 2.5 columns 1-2 show a similar reaction for CAD/USD such that an increase in negative news sentiment on CAD induces an instantaneous drop of the 0.7% in returns, while a more positive surrounding generates an immediate appreciation of about 0.8%. The same logic for the base sentiment coefficient sign is also verified for the Swiss Franc, the Euro, the British Pound and the Japanese Yen. Tables 2.7, 2.8 and 2.9 columns 1-2 report that EUR/USD, GBP/USD and JPY/USD returns experience statistically significant increases of about 0.6%, 0.7% and 1.2% following a more positive sentiment on the base and conversely, they experience a decrease of about 0.7%, 1% and 1% after an increase in negative news sentiment. CHF/USD supports $H_1$ on the sign but negative news on the base are not significantly affecting returns. All pairs present a negative relationship between returns and news on the counter (USD) supporting $H_1$. There is a reverse-cross-response in Forex for news on the base and counter and this holds for all the currencies adopted in this study.

**Table 2.4:** Sentiment impact on AUD/USD

| | AUDUSD $\text{Return}_t$ | | AUDUSD $\text{Volume}_t$ | | AUDUSD $\text{Volatility}_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD $\text{News}_t$ | −0.012*** | 0.012*** | −0.055** | −0.007 | 0.00002 | 0.00003* |
| | (0.002) | (0.002) | (0.023) | (0.022) | (0.00002) | (0.00002) |
| CAD $\text{News}_t$ | −0.004* | 0.007*** | 0.054*** | 0.070*** | −0.00002 | 0.00000 |
| | (0.002) | (0.002) | (0.012) | (0.014) | (0.00002) | (0.00002) |
| CHF $\text{News}_t$ | 0.003 | 0.002 | 0.052** | 0.050** | 0.00003 | −0.00001 |
| | (0.003) | (0.003) | (0.022) | (0.024) | (0.00004) | (0.00003) |
| EUR $\text{News}_t$ | −0.003** | 0.002 | 0.025* | 0.003 | −0.00003** | −0.00003* |
| | (0.002) | (0.002) | (0.015) | (0.014) | (0.00001) | (0.00001) |
| GBP $\text{News}_t$ | −0.002 | 0.007*** | 0.060*** | 0.066*** | 0.00001 | −0.00004*** |
| | (0.002) | (0.002) | (0.016) | (0.014) | (0.00002) | (0.00001) |
| JPY $\text{News}_t$ | 0.001 | 0.00004 | 0.042*** | 0.050*** | 0.00001 | −0.00000 |
| | (0.002) | (0.002) | (0.015) | (0.016) | (0.00002) | (0.00002) |
| USD $\text{News}_t$ | 0.006*** | −0.005*** | −0.010 | −0.010 | −0.00002** | −0.00000 |
| | (0.001) | (0.001) | (0.013) | (0.013) | (0.00001) | (0.00001) |
| BTC $\text{News}_t$ | −0.003 | −0.008 | 0.134*** | 0.087* | −0.00001 | −0.00000 |
| | (0.004) | (0.005) | (0.046) | (0.046) | (0.00004) | (0.00004) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.001 | 0.001 | 0.806 | 0.806 | 0.998 | 0.998 |
| F Statistic | 11.453*** | 12.275*** | 35,705.150*** | 35,703.490*** | 4,131,539.000*** | 4,131,522.000*** |

Note: VAR-X(4,0) with the Australian Dollar to U.S. Dollar (AUDUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. * p<0.1; ** p<0.05; *** p<0.01.

**Table 2.5:** Sentiment impact on CAD/USD

| | CADUSD $\text{Return}_t$ | | CADUSD $\text{Volume}_t$ | | CADUSD $\text{Volatility}_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD $\text{News}_t$ | −0.005*** | 0.002* | −0.049** | −0.029 | −0.00003 | −0.0003 |
| | (0.001) | (0.001) | (0.024) | (0.023) | (0.0003) | (0.0002) |
| CAD $\text{News}_t$ | −0.007*** | 0.008*** | 0.099*** | 0.101*** | 0.00004 | 0.001** |
| | (0.002) | (0.002) | (0.014) | (0.016) | (0.0002) | (0.0004) |
| CHF $\text{News}_t$ | 0.004 | 0.004 | 0.051** | 0.065** | −0.0001 | −0.001** |
| | (0.002) | (0.002) | (0.022) | (0.027) | (0.0003) | (0.0004) |
| EUR $\text{News}_t$ | −0.003** | 0.0003 | 0.024 | 0.021 | −0.001*** | −0.0003 |
| | (0.001) | (0.001) | (0.016) | (0.015) | (0.0002) | (0.0002) |
| GBP $\text{News}_t$ | −0.002 | 0.004*** | 0.071*** | 0.093*** | −0.0004 | −0.001** |
| | (0.001) | (0.001) | (0.018) | (0.017) | (0.0002) | (0.0002) |
| JPY $\text{News}_t$ | 0.0001 | −0.0004 | 0.042*** | 0.034* | −0.0001 | 0.0001 |
| | (0.001) | (0.001) | (0.015) | (0.018) | (0.0002) | (0.0003) |
| USD $\text{News}_t$ | 0.004*** | −0.004*** | −0.021 | −0.025* | −0.0005*** | −0.0004*** |
| | (0.001) | (0.001) | (0.013) | (0.014) | (0.0002) | (0.0001) |
| BTC $\text{News}_t$ | −0.003 | −0.005 | 0.154*** | 0.153*** | −0.0003 | −0.001 |
| | (0.004) | (0.004) | (0.039) | (0.037) | (0.001) | (0.001) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.001 | 0.001 | 0.837 | 0.837 | 0.860 | 0.860 |
| F Statistic | 8.348*** | 8.360*** | 43,901.080*** | 43,902.840*** | 52,900.350*** | 52,902.270*** |

Note: VAR-X(4,0) with the Canadian Dollar to U.S. Dollar (CADUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

**Table 2.6:** Sentiment impact on CHF/USD

| | CHFUSD Return$_t$ | | CHFUSD Volume$_t$ | | CHFUSD Volatility$_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD News$_t$ | −0.004** | 0.003** | −0.070*** | −0.057** | 0.0005 | −0.001** |
| | (0.002) | (0.001) | (0.024) | (0.023) | (0.0004) | (0.0004) |
| CAD News$_t$ | −0.003 | 0.003 | 0.097*** | 0.103*** | 0.001*** | 0.001* |
| | (0.002) | (0.004) | (0.014) | (0.014) | (0.0003) | (0.001) |
| CHF News$_t$ | −0.003 | 0.006** | 0.071*** | 0.067*** | 0.001 | −0.001 |
| | (0.002) | (0.003) | (0.022) | (0.023) | (0.0005) | (0.001) |
| EUR News$_t$ | −0.006*** | 0.005*** | 0.051*** | 0.039** | 0.00003 | −0.0002 |
| | (0.001) | (0.001) | (0.016) | (0.015) | (0.0002) | (0.0003) |
| GBP News$_t$ | −0.001 | −0.001 | 0.051*** | 0.098*** | −0.00001 | −0.0003 |
| | (0.001) | (0.002) | (0.018) | (0.015) | (0.0003) | (0.0004) |
| JPY News$_t$ | −0.002 | 0.001 | 0.014 | 0.031* | −0.0002 | −0.0002 |
| | (0.001) | (0.001) | (0.016) | (0.018) | (0.0002) | (0.0003) |
| USD News$_t$ | 0.006*** | −0.004*** | −0.002 | −0.009 | −0.001* | 0.0002 |
| | (0.001) | (0.001) | (0.014) | (0.013) | (0.0003) | (0.0002) |
| BTC News$_t$ | 0.001 | −0.005 | 0.221*** | 0.094** | −0.001 | 0.001 |
| | (0.004) | (0.004) | (0.044) | (0.044) | (0.001) | (0.001) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.016 | 0.016 | 0.803 | 0.803 | 0.904 | 0.904 |
| F Statistic | 142.754*** | 141.824*** | 34,872.450*** | 34,872.220*** | 80,977.330*** | 80,976.600*** |

Note: VAR-X(4,0) with the Swiss Franc to U.S. Dollar (CHFUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

**Table 2.7:** Sentiment impact on EUR/USD

| | EURUSD Return$_t$ | | EURUSD Volume$_t$ | | EURUSD Volatility$_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD News$_t$ | −0.003* | 0.002 | −0.062*** | −0.051** | −0.00003 | −0.0003* |
| | (0.001) | (0.001) | (0.024) | (0.022) | (0.0002) | (0.0002) |
| CAD News$_t$ | −0.002 | −0.002 | 0.120*** | 0.098*** | 0.001*** | 0.0004** |
| | (0.002) | (0.002) | (0.015) | (0.014) | (0.0002) | (0.0002) |
| CHF News$_t$ | −0.002 | 0.006** | 0.072*** | 0.063** | 0.0003 | 0.0001 |
| | (0.002) | (0.002) | (0.022) | (0.025) | (0.0004) | (0.0003) |
| EUR News$_t$ | −0.007*** | 0.006*** | 0.038** | 0.052*** | 0.0001 | −0.00003 |
| | (0.001) | (0.001) | (0.016) | (0.014) | (0.0002) | (0.0002) |
| GBP News$_t$ | −0.001 | 0.0005 | 0.066*** | 0.094*** | −0.0001 | 0.00001 |
| | (0.001) | (0.002) | (0.017) | (0.013) | (0.0002) | (0.0002) |
| JPY News$_t$ | −0.001 | 0.00004 | 0.017 | 0.041** | −0.0002 | −0.0001 |
| | (0.001) | (0.001) | (0.015) | (0.016) | (0.0002) | (0.0002) |
| USD News$_t$ | 0.006*** | −0.004*** | 0.001 | 0.001 | −0.0002 | 0.0001 |
| | (0.001) | (0.001) | (0.013) | (0.013) | (0.0001) | (0.0001) |
| BTC News$_t$ | 0.001 | −0.008 | 0.189*** | 0.145*** | −0.0001 | 0.0001 |
| | (0.004) | (0.006) | (0.046) | (0.040) | (0.0004) | (0.0004) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.001 | 0.001 | 0.825 | 0.825 | 0.930 | 0.930 |
| F Statistic | 10.617*** | 9.489*** | 40,552.870*** | 40,551.730*** | 114,221.600*** | 114,215.800*** |

Note: VAR-X(4,0) with the Euro to U.S. Dollar (EURUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

**Table 2.8:** Sentiment impact on GBP/USD

| | GBPUSD $\text{Return}_t$ | | GBPUSD $\text{Volume}_t$ | | GBPUSD $\text{Volatility}_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD $\text{News}_t$ | −0.005*** | 0.003* | −0.075*** | −0.033 | −0.001*** | 0.0005 |
| | (0.001) | (0.002) | (0.024) | (0.023) | (0.0003) | (0.001) |
| CAD $\text{News}_t$ | −0.003 | 0.003 | 0.107*** | 0.118*** | 0.001** | 0.001*** |
| | (0.002) | (0.002) | (0.013) | (0.014) | (0.0004) | (0.0004) |
| CHF $\text{News}_t$ | −0.0001 | 0.002 | 0.078*** | 0.080*** | −0.0001 | −0.0004 |
| | (0.002) | (0.002) | (0.023) | (0.025) | (0.0004) | (0.0004) |
| EUR $\text{News}_t$ | −0.003*** | 0.001 | 0.042*** | 0.034** | −0.0001 | −0.0002 |
| | (0.001) | (0.001) | (0.016) | (0.015) | (0.0002) | (0.0002) |
| GBP $\text{News}_t$ | −0.010*** | 0.007*** | 0.076*** | 0.096*** | −0.0001 | 0.0003 |
| | (0.001) | (0.001) | (0.017) | (0.014) | (0.0003) | (0.0003) |
| JPY $\text{News}_t$ | −0.001 | −0.0002 | 0.049*** | 0.049*** | −0.001*** | −0.0002 |
| | (0.001) | (0.001) | (0.014) | (0.017) | (0.0002) | (0.0002) |
| USD $\text{News}_t$ | 0.004*** | −0.004*** | 0.011 | 0.003 | −0.0002 | −0.0001 |
| | (0.001) | (0.001) | (0.013) | (0.013) | (0.0002) | (0.0002) |
| BTC $\text{News}_t$ | 0.002 | −0.012 | 0.219*** | 0.142*** | 0.002** | −0.00002 |
| | (0.004) | (0.013) | (0.054) | (0.037) | (0.001) | (0.001) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| F Statistic | 21.887*** | 20.877*** | 42,621.400*** | 42,617.400*** | 61,336.840*** | 61,334.460*** |

Note: VAR-X(4,0) with the British Pound to U.S. Dollar (GBPUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

**Table 2.9:** Sentiment impact on JPY/USD

| | JPYUSD $\text{Return}_t$ | | JPYUSD $\text{Volume}_t$ | | JPYUSD $\text{Volatility}_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD $\text{News}_t$ | −0.0004 | 0.0001 | −0.050** | −0.023 | −0.0001 | −0.00004 |
| | (0.002) | (0.002) | (0.023) | (0.021) | (0.0001) | (0.00005) |
| CAD $\text{News}_t$ | 0.001 | −0.002 | 0.050*** | 0.066*** | −0.0001 | −0.00004 |
| | (0.002) | (0.002) | (0.014) | (0.015) | (0.0001) | (0.0001) |
| CHF $\text{News}_t$ | 0.002 | 0.001 | 0.055*** | 0.073*** | 0.0001 | 0.00003 |
| | (0.002) | (0.003) | (0.020) | (0.023) | (0.0001) | (0.0001) |
| EUR $\text{News}_t$ | −0.002 | 0.003** | 0.038** | 0.013 | −0.0001** | −0.0001* |
| | (0.001) | (0.001) | (0.016) | (0.015) | (0.0001) | (0.00004) |
| GBP $\text{News}_t$ | −0.0004 | −0.003* | 0.060*** | 0.098*** | −0.00001 | −0.0001** |
| | (0.002) | (0.002) | (0.017) | (0.015) | (0.0001) | (0.0001) |
| JPY $\text{News}_t$ | −0.010*** | 0.012*** | 0.051*** | 0.068*** | 0.00002 | −0.0001 |
| | (0.001) | (0.002) | (0.015) | (0.018) | (0.0001) | (0.0001) |
| USD $\text{News}_t$ | 0.003*** | −0.004*** | 0.010 | −0.004 | −0.0001*** | −0.00002 |
| | (0.001) | (0.001) | (0.013) | (0.014) | (0.00003) | (0.00004) |
| BTC $\text{News}_t$ | −0.003 | 0.004 | 0.158*** | 0.109*** | −0.0001 | −0.0001 |
| | (0.004) | (0.006) | (0.038) | (0.038) | (0.0001) | (0.0001) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.0005 | 0.001 | 0.825 | 0.825 | 0.990 | 0.990 |
| F Statistic | 5.286*** | 6.211*** | 40,416.730*** | 40,420.940*** | 828,767.400*** | 828,741.400*** |

Note: VAR-X(4,0) with the Japanese Yen to U.S. Dollar (JPYUSD) log-returns (%), log-tick-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, 5) and positive (2, 4, 6) sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

The traditional currencies used in this study exhibit a common feature which supports $H_2$ as shown in tables 2.4-2.9 columns 3-6. Volume for the Canadian Dollar, the Swiss Franc, the Euro, the British Pound and the Japanese Yen over USD all exhibit a positive and significant reaction to positive and negative news on the base. The arrival of a non-scheduled news in the Forex market determines a surprise and causes a contemporaneous shock which intensifies the currency trading activity at the 15-minute frequency. Independently of the sentiment of the news, volume rises in conjunction with the news arrival. For instance, the Japanese Yen to U.S. Dollar volume rises of about +5.1% for negative and +6.8% for positive sentiment on the base. The British Pound and the Euro transaction volume is positively related to positive news on the base of about 0.096 and 0.052 respectively, and to negative news of about 0.076 and 0.038 respectively. Similar results are found for the Swiss Franc and the Canadian Dollar. These results are consistent with those of Dominguez and Panthaki (2006) such that non-scheduled non-fundamental news lead to an increase in the transaction frequency.

Mixed results are found for foreign exchange volatility response to intra-day news sentiment, and the behavioural bias presented in $H_3$ is not systematically verifiable from the empirical results in tables 2.4-2.9.

Overall, despite the presence of some heterogeneous effects within the Forex results, traditional currencies comove and share homogeneous reactions to news sentiment suggesting the strong inter-linkage of this market. Non-scheduled news create a contemporaneous statistically significant impact on FX returns and volume.

### 2.5.2 News sentiment relationship with Bitcoin - Comparison with FX

Having documented the behaviour of Forex with respect to non-scheduled news sentiment, we study whether Bitcoin behaves in a similar manner. The odd columns in Table 2.10 present the results of the estimations of the VAR-X(4, 0) for BTC/USD returns (columns 1, 3), volume (columns 5, 7) and volatility (columns 9, 11).

In contrast to traditional currencies, news sentiment appears to have little or no

**Table 2.10:** Sentiment impact on BTC/USD

| | BTCUSD $\text{Return}_t$ | | | | BTCUSD $\text{Volume}_t$ | | | | BTCUSD $\text{Volatility}_t$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Negative | | Positive | | Negative | | Positive | | Negative | | Positive | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| AUD $\text{News}_t$ | −0.003 | −0.006 | 0.012 | 0.014 | −0.050 | −0.047 | −0.039 | −0.037 | −0.002 | −0.002 | 0.001 | 0.002 |
| | (0.016) | (0.016) | (0.016) | (0.015) | (0.034) | (0.034) | (0.034) | (0.034) | (0.001) | (0.001) | (0.002) | (0.002) |
| CAD $\text{News}_t$ | 0.010 | 0.012 | −0.009 | −0.009 | −0.011 | −0.019 | 0.043 | 0.033 | −0.003*** | −0.003*** | −0.001 | −0.001 |
| | (0.018) | (0.018) | (0.019) | (0.019) | (0.032) | (0.033) | (0.033) | (0.033) | (0.001) | (0.001) | (0.002) | (0.002) |
| CHF $\text{News}_t$ | 0.060* | 0.058* | −0.005 | −0.005 | 0.023 | 0.017 | −0.010 | −0.019 | 0.0003 | 0.0002 | −0.001 | −0.002 |
| | (0.032) | (0.032) | (0.023) | (0.024) | (0.044) | (0.044) | (0.046) | (0.046) | (0.002) | (0.002) | (0.002) | (0.002) |
| EUR $\text{News}_t$ | 0.024* | 0.026** | 0.034** | 0.032** | 0.062** | 0.054** | 0.083*** | 0.071** | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.013) | (0.013) | (0.016) | (0.016) | (0.027) | (0.027) | (0.028) | (0.028) | (0.001) | (0.001) | (0.002) | (0.001) |
| GBP $\text{News}_t$ | 0.023* | 0.019 | 0.030* | 0.030* | 0.068** | 0.056* | 0.061** | 0.054* | −0.003*** | −0.003*** | 0.001 | 0.0002 |
| | (0.014) | (0.014) | (0.018) | (0.018) | (0.030) | (0.030) | (0.030) | (0.031) | (0.001) | (0.001) | (0.001) | (0.001) |
| JPY $\text{News}_t$ | 0.022 | 0.023 | 0.009 | 0.007 | −0.009 | −0.009 | 0.003 | 0.005 | 0.0003 | 0.0001 | 0.0005 | 0.001 |
| | (0.022) | (0.023) | (0.013) | (0.013) | (0.028) | (0.028) | (0.031) | (0.032) | (0.001) | (0.001) | (0.001) | (0.001) |
| USD $\text{News}_t$ | 0.008 | 0.007 | 0.024* | 0.023* | 0.008 | 0.003 | −0.019 | −0.016 | −0.0005 | −0.001 | −0.002 | −0.002* |
| | (0.011) | (0.010) | (0.013) | (0.013) | (0.020) | (0.020) | (0.021) | (0.021) | (0.001) | (0.001) | (0.001) | (0.001) |
| BTC $\text{News}_t$ | 0.033 | −0.007 | 0.077** | 0.069* | 0.487*** | 0.449*** | 0.153*** | 0.122** | 0.025 | 0.025 | 0.003 | 0.003 |
| | (0.129) | (0.115) | (0.039) | (0.040) | (0.061) | (0.061) | (0.058) | (0.058) | (0.016) | (0.016) | (0.003) | (0.003) |
| AUD $\text{News}_{t-1}$ | | 0.035** | | −0.020 | | −0.030 | | −0.033 | | 0.001 | | −0.003* |
| | | (0.017) | | (0.017) | | (0.034) | | (0.034) | | (0.001) | | (0.001) |
| CAD $\text{News}_{t-1}$ | | −0.017 | | −0.004 | | 0.057* | | 0.061* | | 0.001 | | 0.002 |
| | | (0.016) | | (0.022) | | (0.031) | | (0.033) | | (0.002) | | (0.003) |
| CHF $\text{News}_{t-1}$ | | 0.039 | | −0.003 | | 0.052 | | 0.084 | | 0.002 | | 0.001 |
| | | (0.026) | | (0.027) | | (0.045) | | (0.055) | | (0.003) | | (0.002) |
| EUR $\text{News}_{t-1}$ | | −0.021 | | 0.016 | | 0.049* | | 0.080*** | | −0.001 | | 0.002 |
| | | (0.014) | | (0.015) | | (0.029) | | (0.028) | | (0.001) | | (0.002) |
| GBP $\text{News}_{t-1}$ | | 0.029 | | −0.008 | | 0.080*** | | 0.034 | | −0.002* | | 0.003 |
| | | (0.019) | | (0.016) | | (0.030) | | (0.031) | | (0.001) | | (0.002) |
| JPY $\text{News}_{t-1}$ | | −0.014 | | 0.013 | | 0.004 | | −0.014 | | 0.003 | | −0.002* |
| | | (0.019) | | (0.014) | | (0.028) | | (0.031) | | (0.002) | | (0.001) |
| USD $\text{News}_{t-1}$ | | 0.011 | | 0.001 | | 0.051** | | −0.020 | | 0.001 | | 0.001 |
| | | (0.010) | | (0.012) | | (0.021) | | (0.021) | | (0.001) | | (0.001) |
| BTC $\text{News}_{t-1}$ | | 0.294** | | 0.074* | | 0.252*** | | 0.294*** | | 0.0004 | | −0.0004 |
| | | (0.148) | | (0.040) | | (0.060) | | (0.059) | | (0.009) | | (0.002) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.009 | 0.009 | 0.009 | 0.009 | 0.597 | 0.597 | 0.597 | 0.597 | 0.983 | 0.983 | 0.983 | 0.983 |
| F Statistic | 79.936*** | 58.87*** | 79.99*** | 57.36*** | 12,734.09*** | 9,097.87*** | 12,731.38*** | 9,096.15*** | 498,682.00*** | 356,198.10*** | 498,586.90*** | 356,139.10*** |

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 2, 5, 6, 9, and 10) and positive (3, 4, 7, 8, 11, and 12) sentiments as and exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

significant impact on Bitcoin returns, such that only positive Bitcoin news increase Bitcoin returns of about 7.7%. Contrary to $H_3$, contemporaneous negative Bitcoin news are therefore less important than positive news providing some intuition of Bitcoin users' enthusiasm. In addition, contrary to $H_1$, positive news on the counter USD appreciates BTC/USD of about 2.4%. Negative and positive news on BTC are significant at the one percent level for the contemporaneous trading volume with exogenous coefficients of +0.487 and +0.153 respectively, while sentiment on the counter does not significantly affect volume. Independently from their sentiment score, only news on the base induces a contemporaneous increase in the Bitcoin trading volume. The larger coefficient compared to the FX reaction is explained by the use of two different measures for volume, trading volume for BTC/USD (which considers the size of each trade) and tick-volume for FX. The findings partially support $H_2$ with regard to Bitcoin volume. However, coefficients for volatility are found to be not statistically significant indicating that news sentiment does not seem to affect Bitcoin price variability.

In summary, Bitcoin results deviate from the FX findings during the period January 2012 – November 2018, implying that Bitcoin does not share many characteristics with traditional currencies. Particularly, the contemporaneous impact of news sentiment is not as strong and significant as in the foreign exchange market where currencies promptly react to news.

However, the 15-minute time window might not be enough to capture an immediate Bitcoin response to news sentiment due to market frictions, technological advancement issues and a potential low high-frequency traders' activity. The average median confirmation time for Bitcoin transaction is 10 minutes. Bitcoin sell and buy orders need on average 10 minutes to be executed and registered in the public ledger. Within the sample period there could be a number of times in which this delay is longer than 10/15 minutes hence the Bitcoin market might not be able to absorb the effects of contemporaneous news because of this inefficiency. There might be other frictions that do not allow the news sentiment information to be incorporated into Bitcoin prices as fast as it happens in the more efficient Forex market. Therefore, we increase the time window allowing the news sentiment to have sufficient time to generate a potential impact. We control for 1 lag in the exogenous variable increasing our time window to 30-minutes to check and capture potential effects that unscheduled news arriving at *t-1* can have on Bitcoin at time *t*. Table 2.10 (even columns) reports the coefficient estimates omitting the lag dependent variables and intercept for the VAR-X(4, 1) regressions. The contemporaneous impact is almost unchanged with respect to the VAR-X(4, 0) case. Positive Bitcoin news are positively related to returns with a coefficient of about 0.069, and negative contemporaneous news sentiment again have no power in explaining Bitcoin returns, rejecting $H_3$. Again positive news at time *t* on the counter increase the returns, rejecting $H_1$. Findings are further consistent with the previous ones for the volume and volatility. Looking at columns 2 and 4 we can observe that negative and positive news on Bitcoin at *t-1* have an impact on Bitcoin returns at time *t* suggesting that this market needs more time to digest information because of delays and frictions. Surprisingly, a positive relation between returns and news is found independently of whether the news sentiment is classified as positive or negative. Negative news one period before are positively related to returns of about 0.294, while positive news generate a smaller impact of about 0.074. This further represents an insight of the investors' enthusiasm towards the digital currency. This behavior is very different from that of Forex, confirming the different nature of Bitcoin to traditional currencies.

### 2.5.3 Cross results

Tables 2.4-2.10 provide more insights for similarities between Forex and Bitcoin news sentiment. In short, negative and positive news sentiment on BTC are significantly and positively related to all traditional currencies volume. Negative Bitcoin news coefficients are higher than the positive ones, suggesting that they influence more Forex volume. The largest effects highlight that negative financial BTC news are positively related to the CHF/USD, GBP/USD and EUR/USD contemporaneous volume of about 0.221, 0.219 and 0.189 respectively. This cross dependency shows part of the interconnectedness between cryptocurrencies and traditional currencies. The results might imply that foreign exchange investors care about high-frequency news on BTC such that negative perceptions on BTC stories lead investors to very quickly adjust their financial positions in the FX market. On the other hand, apart from some evidence of the influence of the Euro and the British Pound on Bitcoin, such that news on these currencies increase the cryptocurrency contemporaneous returns and volume, Bitcoin is mostly unrelated to Forex news sentiment during the entire sample.

### 2.5.4 Isolating the Bitcoin Bubble

The impact of good and bad news can depend on the state of the economy in which the news occurs. Andersen et al. (2003) find evidence that bad news in good times have bigger impact than good news in good times because they incorporate more information about the current state of the economy. Positive news are considered to confirm investors beliefs, while negative news surprise them. During the sample period under examination, the nascent Bitcoin market has experienced potential bubbles. We therefore isolate the late 2013 and 2017 bubbles as Gerlach et al. (2019), particularly July 2013 – December 2013 and January 2016 – December 2017, with a dummy variable in order to investigate whether the reaction of Bitcoin to news during bubble periods differs compared to the whole sample period. Table 2.11 summarizes the results for the VAR-X(4,0) in the odd columns and VAR-X(4,1) in the even columns. In contrast to Andersen et al. (2003), there is no evidence of a contemporaneous relationship between Bitcoin returns and negative news on Bitcoin (columns 1, 2). While negative news at time $t$ do not surprise the Bitcoin market during the bubble periods, negative news occurring at time *t-1* have a significant impact. Contrary to standard expectations, rather than causing a decrease in returns, lagged negative news increase returns confirming the irreversible enthusiasm of Bitcoin investors during the bubbles. As additional evidence of this phenomenon, contemporaneous positive sentiment registered during the bubble periods immediately positively affects returns. These results are in line with the Dominguez and Panthaki (2006) findings such that non-scheduled non-fundamental news have a higher impact when many news hit the market and during periods of high volatility.

**Table 2.11:** Sentiment impact on BTC/USD during the bubbles

| | BTCUSD Return$_t$ | | | | BTCUSD Volume$_t$ | | | | BTCUSD Volatility$_t$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Negative | | Positive | | Negative | | Positive | | Negative | | Positive | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| AUD News$_t$ x Bubble | 0.012 | 0.006 | 0.022 | 0.021 | 0.030 | 0.015 | 0.015 | −0.003 | −0.002 | −0.002 | 0.001 | 0.002 |
| | (0.024) | (0.025) | (0.021) | (0.021) | (0.052) | (0.052) | (0.049) | (0.050) | (0.002) | (0.002) | (0.004) | (0.004) |
| CAD News$_t$ x Bubble | 0.039* | 0.041* | 0.008 | 0.004 | 0.092** | 0.055 | 0.152*** | 0.122*** | −0.006*** | −0.005*** | −0.006*** | −0.005*** |
| | (0.023) | (0.022) | (0.021) | (0.021) | (0.046) | (0.047) | (0.046) | (0.047) | (0.001) | (0.001) | (0.002) | (0.001) |
| CHF News$_t$ x Bubble | 0.038 | 0.043 | −0.019 | −0.015 | 0.165*** | 0.133** | 0.205*** | 0.166*** | −0.003** | −0.003 | −0.0004 | 0.0002 |
| | (0.028) | (0.028) | (0.027) | (0.027) | (0.064) | (0.064) | (0.062) | (0.063) | (0.002) | (0.002) | (0.002) | (0.002) |
| EUR News$_t$ x Bubble | 0.023 | 0.027 | 0.030 | 0.030 | 0.119*** | 0.083** | 0.197*** | 0.152*** | −0.001 | −0.001 | −0.002 | −0.002 |
| | (0.017) | (0.017) | (0.021) | (0.021) | (0.039) | (0.040) | (0.040) | (0.041) | (0.002) | (0.002) | (0.002) | (0.002) |
| GBP News$_t$ x Bubble | 0.034 | 0.029 | 0.026 | 0.026 | 0.104** | 0.071 | 0.163*** | 0.126*** | −0.005*** | −0.004*** | −0.002 | −0.001 |
| | (0.022) | (0.021) | (0.019) | (0.019) | (0.046) | (0.048) | (0.043) | (0.045) | (0.001) | (0.001) | (0.002) | (0.002) |
| JPY News$_t$ x Bubble | −0.033 | −0.032 | 0.029 | 0.030 | 0.113*** | 0.093** | 0.068 | 0.039 | −0.004*** | −0.004*** | −0.002 | −0.001 |
| | (0.022) | (0.021) | (0.019) | (0.019) | (0.040) | (0.041) | (0.046) | (0.047) | (0.001) | (0.001) | (0.001) | (0.001) |
| USD News$_t$ x Bubble | −0.002 | −0.002 | 0.028* | 0.028* | 0.129*** | 0.101*** | 0.133*** | 0.103*** | −0.003* | −0.002 | −0.004*** | −0.003*** |
| | (0.012) | (0.012) | (0.015) | (0.014) | (0.029) | (0.029) | (0.031) | (0.031) | (0.001) | (0.001) | (0.001) | (0.001) |
| BTC News$_t$ x Bubble | 0.072 | 0.011 | 0.143*** | 0.134*** | 0.543*** | 0.478*** | 0.238*** | 0.185** | 0.047 | 0.050 | 0.003 | 0.004 |
| | (0.150) | (0.146) | (0.046) | (0.046) | (0.090) | (0.089) | (0.080) | (0.081) | (0.037) | (0.039) | (0.004) | (0.004) |
| AUD News$_{t-1}$ x Bubble | | 0.051** | | 0.010 | | −0.014 | | −0.011 | | 0.001 | | −0.003 |
| | | (0.025) | | (0.021) | | (0.053) | | (0.051) | | (0.003) | | (0.002) |
| CAD News$_{t-1}$ x Bubble | | −0.037* | | 0.031 | | 0.163*** | | 0.086* | | −0.003** | | −0.004*** |
| | | (0.022) | | (0.020) | | (0.045) | | (0.047) | | (0.001) | | (0.001) |
| CHF News$_{t-1}$ x Bubble | | −0.036 | | −0.039 | | 0.067 | | 0.153** | | −0.004*** | | −0.002 |
| | | (0.027) | | (0.030) | | (0.065) | | (0.070) | | (0.001) | | (0.002) |
| EUR News$_{t-1}$ x Bubble | | −0.030* | | −0.003 | | 0.151*** | | 0.198*** | | −0.003** | | 0.0001 |
| | | (0.017) | | (0.019) | | (0.041) | | (0.039) | | (0.001) | | (0.002) |
| GBP News$_{t-1}$ x Bubble | | 0.041** | | −0.003 | | 0.076* | | 0.085* | | −0.002* | | −0.003** |
| | | (0.019) | | (0.018) | | (0.044) | | (0.047) | | (0.001) | | (0.001) |
| JPY News$_{t-1}$ x Bubble | | −0.009 | | −0.005 | | 0.047 | | 0.071 | | 0.001 | | −0.002* |
| | | (0.020) | | (0.018) | | (0.041) | | (0.045) | | (0.001) | | (0.001) |
| USD News$_{t-1}$ x Bubble | | −0.009 | | 0.004 | | 0.117*** | | 0.104*** | | −0.002*** | | −0.003*** |
| | | (0.012) | | (0.014) | | (0.030) | | (0.034) | | (0.001) | | (0.001) |
| BTC News$_{t-1}$ x Bubble | | 0.415** | | 0.060 | | 0.272*** | | 0.283*** | | −0.019 | | −0.003 |
| | | (0.201) | | (0.055) | | (0.097) | | (0.082) | | (0.017) | | (0.002) |
| Observations | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 | 171,601 |
| Adjusted $R^2$ | 0.009 | 0.009 | 0.009 | 0.009 | 0.597 | 0.598 | 0.598 | 0.598 | 0.983 | 0.983 | 0.983 | 0.983 |
| F Statistic | 79.599*** | 58.120*** | 79.831*** | 57.122*** | 12,736.890*** | 9,101.219*** | 12,738.010*** | 9,102.244*** | 498,723.000*** | 356,239.500*** | 498,607.900*** | 356,147.500*** |

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 2, 5, 6, 9, and 10) and positive (3, 4, 7, 8, 11, and 12) sentiments interaction with bubble periods Jul 2013 – Dec 2013 and Jan 2016 – Dec 2017 dummy as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

Further comments relate to the significance of contemporaneous positive stories on USD for Bitcoin returns in an opposite direction to $H_1$. Both negative and positive news on the base and the counter during the bubble periods generate an immediate increase in the trading volume for Bitcoin to USD which is also persistent one period after providing evidence for $H_2$. Volatility during this turmoil period is not affected by base news contrary to $H_2$, and only a volatility decrease following negative counter news is found. The behavioural bias presented in $H_3$ is reversed during Bitcoin bubble periods, such that Bitcoin returns are more affected by contemporaneous positive Bitcoin news than negative news. This is in line with the high enthusiasm finding and shows that investors either downplay or reverse negative news during bubbles. Again BTC/USD seems not to behave in a similar manner to traditional currencies but a higher level of connection with FX news is registered by a higher significance in the BTC/USD volume reaction.

### 2.5.5 Relationship of news on cyber-attacks and fraud with Bitcoin

In addition to bubble periods, a further differentiating feature of the nascent Bitcoin market relative to the established Forex market is the concern around criminality. In fact, one key issue related to digital currencies concerns cyber-criminality which forms part of the cryptocurrency trilemma described by Corbet et al. (2019) together with bubbles and regulatory alignments. Further, according to Gandal et al. (2018), user anonymity characterizes the major problem with technological advances of cryptocurrencies which links them to criminality. While both Forex news and negative news on Bitcoin itself fail to reduce Bitcoin returns as demonstrated in tables 2.10 and 2.11 this may not be the case for news directly related to cyber-criminality. Such news may be anticipated to have a negative relationship with Bitcoin returns, namely able to generate instability among Bitcoin users' and investors' beliefs and potentially mitigate the general enthusiasm toward the digital currency. We test whether news sentiment related to cryptocurrency cyber-attacks and fraud can generate drops in the Bitcoin returns[18]. Results for VAR-X(4,0) and VAR-X(4,1) are reported in table 2.12. Contemporaneous news sentiment on cyber-attacks are negatively related with Bitcoin returns of about -0.200, and -0.198 (when including 1 lag for the exogenous variable). The arrival of a news about fraud related to Bitcoin is not affecting Bitcoin returns, but it lowers the Bitcoin trading volume one period after. Bitcoin volatility is negatively affected by both news on fraud and cyber-attacks, suggesting that once these news occur, there is a dampening effect on the Bitcoin market. We conjecture that investors have more heterogeneous beliefs on the value of Bitcoin, which deprecates due to the fraud and cyber-attack news.

**Table 2.12:** Crime sentiment impact on BTC/USD

| | $\text{Return}_t$ | | $\text{Volume}_t$ | | $\text{Volatility}_t$ | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Cyber Attacks $\text{News}_t$ | $-0.200^{**}$ | $-0.198^{**}$ | 0.193 | 0.164 | $-0.008^{*}$ | $-0.007^{*}$ |
| | (0.096) | (0.095) | (0.194) | (0.193) | (0.004) | (0.004) |
| Fraud $\text{News}_t$ | $-0.029$ | $-0.045$ | $-0.185$ | 0.538 | $-0.040^{***}$ | $-0.038^{***}$ |
| | (0.116) | (0.187) | (0.455) | (0.735) | (0.007) | (0.007) |
| Cyber Attacks $\text{News}_{t-1}$ | | $-0.019$ | | 0.249 | | $-0.006$ |
| | | (0.119) | | (0.197) | | (0.005) |
| Fraud $\text{News}_{t-1}$ | | 0.041 | | $-1.859^{***}$ | | $-0.005^{**}$ |
| | | (0.256) | | (0.609) | | (0.002) |
| Observations | 239,612 | 239,611 | 239,612 | 239,611 | 239,612 | 239,611 |
| Adjusted $R^2$ | 0.008 | 0.008 | 0.601 | 0.601 | 0.984 | 0.984 |
| F Statistic | $132^{***}$ | $115^{***}$ | $25{,}787^{***}$ | $22{,}563^{***}$ | $1{,}033{,}223^{***}$ | $904{,}059^{***}$ |

Note: VAR-X(4,0) and VAR-X(4,1) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Cryptocurrencies cyber-attacks and fraud news sentiments as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

## 2.6 Robustness tests

Although the Pearson correlation coefficients for news sentiments are close to zero motivating our initial analysis, we perform a number of robustness checks to account for the possibility of commonality in news sentiment and potential multicollinearity

[18] *Ravenpack* identifies and labels news as fraud or cyber-attacks. We filter this news for relevance to cryptocurrencies and Bitcoin.

that may bias the main findings. We also check the robustness of the results at the daily level.

### 2.6.1 Commonality in news - $R^2$

Following Dang et al. (2015), we identify the commonality in news as the $R^2$ coming from the regression of a news sentiment index on a set of regressors composed by other news sentiment indices. The resulting $R^2$ measures the level of commonality between the dependent variable news sentiment and the remainder of the news sample. Each sentiment index is regressed on all the other sentiment indices except for itself. For instance, to test how much of the news sentiment for AUD is already explained by all the others news sentiment indices excluding the index for AUD, we regress the AUD sentiment index on the matrix of indices for CAD, CHF, EUR, GBP, JPY, USD and BTC. On the one hand, a very high $R^2$ would represent a high level of commonality among news and thus imply that AUD sentiment is superfluous for the analysis. On the other hand, a low $R^2$ would imply that AUD sentiment index is not already explained by the remaining indices and that its inclusion will add value to the study bringing the desired new information on AUD. Table 2.13 reports the $R^2$ commonality of each sentiment index with all the other indices (column 1), and with the USD counter only (column 2). Although there is not a clear threshold to determine whether commonality can be considered low or high, we believe that $R^2$ results reported in the table are all sufficiently small to overcome commonality. In fact, only 3.01% of the Australian Dollar sentiment is explained by the other sentiment indices and around the 70% of this is explained by its counter USD, as shown in column 2 where the $R^2$ from the regression of AUD sentiment on USD sentiment is 2.07%. Moreover, only 2.05% of the Canadian Dollar is redundant with a counter commonality of 1.80%. Popular currencies such as the Euro, the Japanese Yen and the U.S. Dollar, which serve as counter for many traditional currencies, share a higher level of commonality in news of about 7.47%, 6.52% and 15.21% respectively. They still bring 92.53%, 93.48% and 84.79% of useful and additional information to the study respectively. Bitcoin reveals a very low $R^2$ of 0.04% both for its counter and the other news sentiment indices, suggesting an individual informative power of about 99.96% but a potential detachment from the Forex news.

**Table 2.13:** Commonality in news sentiment

| | With: | |
|---|---|---|
| | The others News (1) | USD News (Counter) (2) |
| AUD News | 3.01%*** | 2.07%*** |
| CAD News | 2.05%*** | 1.80%*** |
| CHF News | 2.01%*** | 1.39%*** |
| EUR News | 7.47%*** | 2.92%*** |
| GBP News | 5.68%*** | 1.88%*** |
| JPY News | 6.52%*** | 2.85%*** |
| USD News | 15.21%*** | 100.00%*** |
| BTC News | 0.04%*** | 0.04%*** |

Note: $R^2$ from regressing each sentiment index for Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) on the reminder sentiment indices (1) and U.S. Dollar (2). *** p-value<0.01.

### 2.6.2 Multicollinearity in news - residuals sentiment analysis

We further study potential biases stemming from multicollinearity in the news sentiment variables. We use the residuals of the commonality regressions between each sentiment index and the remaining indices presented in the previous paragraph as residual sentiment indices. In this way, the residual individual information from each new sentiment index orthogonal to the other news is used as an exogenous variable and exclude the commonality component. We separate residuals into positive and negative news for each index and absolute values are considered. We repeat the VAR-Xs for each pair using the matrix composed by the residual news sentiment. Results are omitted for brevity. However, findings are consistent since the magnitude, sign and statistical significance of the coefficients remain similar to the previous results. Therefore, our results are robust after taking potential multicollinearity into account.

### 2.6.3 Lower frequency study

We repeat the analysis at a lower frequency level to check if the main conclusions we find for Bitcoin for the high-frequency case hold. We consider daily frequency and we look how the average daily sentiment on currencies and Bitcoin affect Bitcoin during the entire sample and during bubbles. Table 2.14 reports the VAR-X(4,0) results for the daily analysis.

**Table 2.14:** Sentiment impact on BTC/USD daily level

| | BTCUSD Return$_t$ | | BTCUSD Volume$_t$ | | BTCUSD Volatility$_t$ | |
|---|---|---|---|---|---|---|
| | Negative | Positive | Negative | Positive | Negative | Positive |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| AUD News$_t$ | −0.063 | −0.184* | −681.263*** | −420.496* | 0.007 | 0.431 |
| | (0.242) | (0.111) | (189.501) | (246.064) | (0.392) | (0.512) |
| CAD News$_t$ | 0.107 | −0.079 | 1,988.716*** | 3,250.650*** | 0.534 | 1.036* |
| | (0.154) | (0.170) | (552.832) | (449.754) | (0.459) | (0.606) |
| CHF News$_t$ | 0.277 | −0.120 | −1,017.497** | −1,985.474*** | 0.875* | −0.621 |
| | (0.254) | (0.201) | (422.168) | (484.191) | (0.525) | (0.550) |
| EUR News$_t$ | 0.002 | 0.207** | 241.653 | 323.197 | −0.191 | −0.089 |
| | (0.127) | (0.091) | (184.987) | (227.286) | (0.244) | (0.286) |
| GBP News$_t$ | −0.187 | 0.100 | 743.865* | 764.472** | −0.330 | 0.150 |
| | (0.125) | (0.136) | (439.361) | (376.852) | (0.270) | (0.371) |
| JPY News$_t$ | −0.034 | 0.133 | −141.462 | 90.322 | 0.698** | −0.242 |
| | (0.131) | (0.103) | (273.014) | (200.298) | (0.328) | (0.274) |
| USD News$_t$ | 0.246** | −0.121* | 704.007** | 22.659 | 0.287 | 0.243 |
| | (0.110) | (0.063) | (312.265) | (141.130) | (0.302) | (0.201) |
| BTC News$_t$ | −2.040*** | 0.232 | 5,240.723*** | 6,264.506*** | 5.844*** | 1.007 |
| | (0.472) | (0.398) | (863.004) | (1,942.045) | (1.711) | (0.990) |
| AUD News$_t$ x Bubble | 0.303 | 0.256 | −209.063 | −462.954 | 0.175 | 0.993 |
| | (0.283) | (0.181) | (413.796) | (388.192) | (0.474) | (1.335) |
| CAD News$_t$ x Bubble | 0.125 | −0.024 | 702.367 | −873.466 | −0.541 | −1.976** |
| | (0.267) | (0.261) | (652.729) | (775.423) | (0.603) | (0.883) |
| CHF News$_t$ x Bubble | −0.192 | −0.269 | −412.766 | 2,387.469*** | −0.730 | −1.959* |
| | (0.356) | (0.388) | (881.904) | (839.683) | (0.820) | (1.190) |
| EUR News$_t$ x Bubble | −0.0004 | −0.177 | 793.726* | 547.331 | −0.470 | 0.531 |
| | (0.256) | (0.164) | (474.763) | (395.787) | (0.489) | (0.436) |
| GBP News$_t$ x Bubble | −0.004 | −0.088 | −754.219 | 716.844 | 0.315 | 0.016 |
| | (0.212) | (0.218) | (570.135) | (611.855) | (0.479) | (0.601) |
| JPY News$_t$ x Bubble | 0.308 | −0.299* | 444.133 | −659.062** | −0.259 | 0.307 |
| | (0.219) | (0.153) | (402.754) | (309.462) | (0.501) | (0.380) |
| USD News$_t$ x Bubble | −0.302** | 0.304*** | 124.860 | 296.275 | 0.078 | −0.191 |
| | (0.136) | (0.096) | (326.007) | (318.290) | (0.327) | (0.281) |
| BTC News$_t$ x Bubble | 2.394*** | 0.924* | −2,069.679 | −4,370.782* | 5.016 | −0.258 |
| | (0.898) | (0.503) | (1,612.286) | (2,286.354) | (3.482) | (1.353) |
| Observations | 2,134 | 2,134 | 2,134 | 2,134 | 2,134 | 2,134 |
| Adjusted $R^2$ | 0.027 | 0.016 | 0.266 | 0.260 | 0.528 | 0.513 |
| F Statistic | 3.092*** | 2.216*** | 28.580*** | 27.721*** | 86.121*** | 81.265*** |

Note: Daily VAR-X(4,0) with Bitcoin to U.S. Dollar (BTCUSD) log-returns (%), log-trading-volume and volatility as dependent variables (omitted). Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Euro (EUR), British Pound (GBP), Japanese Yen (JPY), U.S. Dollar (USD) and Bitcoin (BTC) negative (1, 3, and 5) and positive (2, 4, and 6) sentiments and sentiments interaction with bubble periods Jul 2013 – Dec 2013 and Jan 2016 – Dec 2017 dummy as exogenous variable. *p<0.1; **p<0.05; ***p<0.01.

In this case, Bitcoin negative news decrease Bitcoin returns providing a more intuitive relation between sentiment and returns, similar to that of Forex. Also sentiment on the counter seems to be coherent with $H_1$ at the daily level. However, when the news sentiment interact with the bubble periods dummy variable, results confirm the paper main findings and there is strong evidence of Bitcoin investors' enthusiasm also at the daily level. Negative and positive news for Bitcoin arriving during bubble periods increase Bitcoin returns, with coefficient of about 2.394 and 0.924 respectively. Albeit a daily analysis addresses the technological advancements issue, what a low frequency measurement of sentiment on a daily level captures is different from that of a 15-minute window, object of this paper. A daily news is a summary feeling on the news of the day. Considering the entire sample, the Bitcoin investors' enthusiasm is not sufficiently strong to counteract the entire-day-negative sentiment, but during bubble periods the extreme positive surrounding around the digital currency dominates negative news impact and the paper results are confirmed, and further demonstrates the Bitcoin investors' enthusiasm also at the daily level. In this case, negative sentiments during bubbles have a reversed outcome which increase returns.

## 2.7 Conclusions

In this paper, we investigate whether Bitcoin and foreign exchange returns, volume and volatility share similar characteristics and comove in terms of reaction to high-frequency non-scheduled news sentiment at the 15-minute level for the period January 2012 – November 2018. We test three main hypotheses to check for similarities between foreign exchange market and Bitcoin. $H_1$ concerns the different impact that negative and positive news have on the pairs returns. $H_2$ focusses on the impact of both negative and positive news on volatility and volume, and $H_3$ relates to the concept of asymmetric impact of negative and positive news. We use VAR-X(4, 0) models to test the assumptions and the results report an almost homogeneous behaviour of Forex. We provide evidence that traditional currencies immediately and significantly react to news wire messages coming from the economy. Particularly, negative (positive) news on the pair decrease (increase) the exchange rate returns, and volume rises when both negative and positive news on the base arrive. Conversely, the results for Bitcoin are different from those on Forex, suggesting that Bitcoin does not react similarly to news arrivals compared to traditional currencies.

Using a VAR-X(4, 1), we find evidence of Bitcoin users' enthusiasm such that only positive news on Bitcoin affect Bitcoin returns, while intra-day negative Bitcoin news are ignored by investors. When isolating the Bitcoin bubbles, positive news are found to lead to an immediate increase in Bitcoin returns, reinforcing the Bitcoin investors' enthusiasm effect. Contrary to traditional currencies, negative news sentiment are found to have a delayed positive relationship with Bitcoin returns, against $H_1$. Bitcoin volume increases in conjunction of news arrivals, but Bitcoin volatility seems invariant to news on the base. We provide further insight that particularly cryptocurrency cyber-attack news are negatively related to Bitcoin returns and thus seem to dampen the Bitcoin users' enthusiasm. Together with cryptocurrency fraud news, they also lead to a decrease in volatility of Bitcoin reducing the exuberance in the market.

To further test the robustness of our findings, we take into account potential biases due to multicollinearity in news sentiment indices. We calculate commonality in news as the $R^2$ from regressing each sentiment index on a matrix composed by all the remaining sentiment indices and we conclude that all the $R^2$ can be considered sufficiently low to overcome this issue. We calculate the residuals news sentiment by regressing from the commonality regressions and we use them as new sentiment indices for the VAR-X models. Again, results are found to be extremely close to the original ones suggesting that results are robust to multicollinearity tests. In conclusion, we do not find evidence that Bitcoin to U.S. Dollar reacts to non-scheduled news sentiment similarly to traditional currencies.

Our analysis contributes to the general debate on the nature of Bitcoin as to whether it can be considered as an asset or a currency. Our results highlight the differences of Bitcoin to other traditional currencies, since the reaction of Bitcoin to non-scheduled news related to Bitcoin and other currencies differs from other traditional currencies.

We further provide insight into differences in the effects during bubble periods.

Our results are further relevant for practitioners and regulators. Investors are concerned about the characteristics of their investment in Bitcoin, such as their risk-return profile. By understanding the reaction of digital currencies to news sentiment in different market conditions, they are better able to assess the volatility and possible risks of their investment. Furthermore, policy-makers have been concerned about systemic risks posed by cryptocurrencies, some issues related to their volatility. We show that Bitcoin volatility is mostly unrelated to currency news, but that news impact increases during bubble periods.

Future research might further test for non-linear reaction of Bitcoin to high frequency news sentiment. Trading strategies could be implemented and standard models of exchange-rate determination could benefit from the inclusion of non-scheduled news sentiment on the base and counter.

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# Chapter 3

# The economic value of financial noise timing

**Preface**

I developed this paper during my PhD Exchange at the National University of Singapore (NUS). The Faculty of Humanities Strategy Investment Fund from the University of Manchester grants two successful applicants per year a bursary aimed to initiate and lead international research collaborations with selected foreign universities. This paper is the output of the research carried during my Post-Graduate Research (PGR) Programme where I was hosted by the Department of Mathematics and by the Risk Management Institute at NUS for the period September-December 2019. The paper was then finalised at Alliance Manchester Business School and it is a co-authored work with my supervisors, Professor Stuart Hyde and Dr. Sarah S. Zhang, and my host supervisor at NUS, Professor Ying Chen.

The paper has been presented at the *Southwestern Finance Association 2021 Annual Meeting* conference, and accepted for presentation at the *10th International Conference of the Financial Engineering and Banking Society* (FEBS) that will be held at Lille University - School of Management, France, in 2021.

As a co-authored work, my individual contribution to this paper was substantial. I developed the original research question, searched sources from relevant existent literature, managed data collection and cleaning, implemented the empirical analysis both analytical, theoretical, and computational coding, worked at the writing, and acted as presenter at research conference. My supervisors contribution was essential to make progresses and improve the paper. They provide exhaustive discussion, exchange of opinions, guidance, supervision on both theoretical and empirical issues, and supported the editing of the paper draft.

**Abstract**

We propose a dynamic noise-timing strategy which exploits the temporary dependence in noise traders' beliefs. Decomposing prices of the portfolio assets (stocks, bonds, gold, and cryptocurrencies) into permanent and noise components, we assess the economic value of a dynamic investment strategy which times the noise component. Our results show that investors would be willing to pay a positive annual performance fee of between 314 and 940 basis points to switch from an ex-ante static investment strategy to a noise timing strategy. Our findings are robust to comparisons with other benchmark strategies and different periods of heightened volatility, including the Covid-19 period.

## 3.1 Introduction

Noise traders play an important role in financial markets. Within a trading day, most of an asset's price variation can be attributed to the impact of noise trading rather than to changes in fundamental value (Black, 1986; De Long et al., 1990; Shleifer & Vishny, 1997). Noise traders with stochastic beliefs affect prices generating so-called noise risk, commonly referred to as the variation of prices without changes in fundamental values (Black, 1986; De Long et al., 1990; Shleifer & Summers, 1990). This paper sheds light on the role of noise risk for portfolio selection, a type of price risk which, despite its importance for financial markets, has been largely neglected in that context.

In the absence of arbitrage limits, speculators and informed traders absorb any risk due to noise trading helping asset prices to converge towards fundamental values. However, due to trading constraints and other limitations in financial markets, the impact of noise traders still persists (Gemmill & Thomas, 2002). As a result, noise risk cannot be ruled out by speculators and consequently investors' holdings are exposed to such noise risk as prices can diverge significantly from fundamental values even in absence of fundamental risk.[1] Kondor et al. (2007) provide evidence of exposure to

[1] It can also occur because of the so-called *bandwagon effect*, such that speculators at first simulate uninformed traders to feed

this risk finding that simulated portfolios optimized under various risk measures are all strongly sensitive to noise. It is therefore vital for investors to take into account noise risk when managing their portfolios. However, due to the unpredictability of noise traders' future beliefs, it is difficult to create hedging and speculative strategies based on noise trading.

In this paper, we propose a model for next period noise traders' beliefs and expectations about the "value" of assets.[2] This allows us to create *ex-ante* dynamic strategies which, by anticipating uninformed traders' moves, are able to hedge and speculate on the noise risk. Our purpose is not to completely rule noise traders out from the economy.[3] Rather, our aim is to quantify how much investors value noise price risk and how much investors are willing to pay in terms of performance fee to adopt a noise timing strategy able to anticipate noise trading. Traders are keen to know and learn about other traders' beliefs that can influence the market, even when these expectations are wrong (Marmora & Rytchkov, 2018). Marmora and Rytchkov (2018) claim that investors who acquire information on noise to assess mispricing make markets more informationally efficient, and that prices tend to be more informative when more investors choose to learn only about noise. Investors may also have incentives to acquire non-fundamental information because it helps them to predict future noise trading and speculate on it (Marmora & Rytchkov, 2018). We construct a model which uses the noise component of asset prices to generate a dynamic strategy that anticipate mispricing and turns out to provide significant gains supporting an evidence to this theory.

This paper contributes to the literature on the role of noise in financial markets, by assessing the economic value of noise-timing to short-horizon and risk-averse investors in a mean-variance framework in the spirit of Fleming et al. (2001).

the bubble and make the deviation from fundamental larger to then take opposite positions that ensure a higher profit (Alfano et al., 2015; De Long et al., 1987; Shleifer & Vishny, 1997).

[2]We adopt the notation "value" (in quotes) when we refer to the noise traders expectations. Quotation marks are added to contrast with *fundamental value*, information that the noise trader does not hold/ignores by definition.

[3]In fact, noise traders have also positive impact on the markets as issuer of liquidity increasing market volume and depth (Bloomfield et al., 2009). Noise is therefore pivotal in explaining high volume in financial markets (Black, 1986; Wang, 2010) and noise in prices contains important information about the overall amount of liquidity in the market (Hu et al., 2013). Noise is further informative for fundamental prices (Marmora & Rytchkov, 2018) and it improves price informativeness (Kyle et al., 2011; Marmora & Rytchkov, 2018)

Additionally, mean-variance analysis is considered a natural framework for assessing the economic value of strategies which exploit predictability in the mean and variance as demonstrated by its wide use within the existing literature (Della Corte et al., 2008; Della Corte et al., 2009; Fleming et al., 2001, 2003; Han, 2006; Jondeau & Rockinger, 2007; Karstanje et al., 2013; Marquering & Verbeek, 2004; Rime et al., 2010; Thornton & Valente, 2012; West et al., 1993). We further investigate noise as source of risk from a portfolio management view proposing a model to predict noise traders' beliefs. Our main findings provide evidence that the economic value of noise-timing strategies is positive and statistical significant. Specifically, we propose to model the noise following the noise-trader approach such that the price time series is disaggregated into a fundamental price and a noise price component (De Long et al., 1990; Shleifer & Summers, 1990). Hendershott and Menkveld (2014) use a Kalman Filter to decompose prices into a permanent and a temporary component, where the fundamental value is represented by the permanent price component which is interpreted as *information* and changes in fundamental value are due to information. Brogaard et al. (2014) add to Hendershott and Menkveld (2014) that the transitory component of price is interpreted as price noise. According to this rationale, the transitory component represents the price component for which changes are not related to changes in fundamentals and information, making it appealing as a price noise risk estimate. Hence, similarly to Brogaard et al. (2014), we estimate the noise price component via a Kalman filter which decomposes the original price time series into a permanent (fundamental) component and the temporary (noise) component. We use its predictions to model the next period noise traders' expectation about future asset "values" based on past and present prices. In this fashion, the noise represents any temporary price deviation from the fundamental value further in line with Hu et al. (2013) and Asparouhova et al. (2013).

Using the temporary component of price time series as a measure of noise, we create the noise-timing strategy as the dynamic strategy under a Markowitz (1952) mean-variance optimization (MVO) problem which minimises the portfolio risk given a target level of portfolio return, similarly to Fleming et al. (2001). The economic value of the noise-timing strategy is then calculated according to a utility-based approach as maximum performance fee an investor is willing to pay to switch from the benchmark strategy, the optimal *ex-ante* static strategy with same target return, to the noise-timing strategy (Fleming et al., 2001; Jondeau & Rockinger, 2007). The main findings suggest that the noise-timing strategy yields statistically significant gains and risk-averse investors are willing to pay a positive annual performance fee of between 314 and 940 basis points, depending on their risk-aversion parameter and target return, to switch from a static strategy to a dynamic noise-timing strategy. We include cryptocurrencies as an additional fourth asset into the common portfolio of stocks, bonds and gold. Thereby, we contribute to the general body of literature on noise trading and portfolio management, but also the more recent strand of literature on cryptoassets and their investment characteristics (see Platanakis and Urquhart (2020)).

The noise timing strategy is found to perform better than a number of simulated portfolios and a set of additional benchmark portfolios, such as the volatility timing portfolio, Random Walk portfolio, and the naïve equally weighted portfolio, among others. This supports the robustness of findings against a wide range of benchmarks and ensures that the economic valuation does not depend on the choice of a unique benchmark. The noise timing strategy provides significant gains even in presence of high transaction costs ranging from 7 to 17 basis points per transaction. The sample used for the main analysis considers the period from September 2014 to December 2019 for four asset classes, namely stock, bond, gold and cryptocurrency. We further extend the analysis to the initial Covid-19 period, identified from January 2020 to April 2020, to seek for noise timing strategy characteristics and abilities during a period of high market turmoil. Albeit the pandemic negatively affects the noise timing strategy, the strategy continues to deliver a good performance during the initial Covid-19 period.

The reminder of this paper is organised as follows: Section 3.2 presents the role of noise traders within financial markets providing a background of the theory and related literature; Section 3.3 explains the methodology adopted; Section 3.4 reports the data used to develop the analysis; Section 3.5 reports the main results; Section 3.6 considers robustness tests; Section 3.7 concludes the paper.

## 3.2 The role of noise traders and related literature

Previous literature has explored the role of noise traders and its impact on financial markets. Under the noise trader theory, originally introduced by Black (1986), investors in the economy can be divided into two groups, informed and uninformed traders. The informed traders, also called speculators, have information about the fundamental value of the asset, while uninformed traders, also called noise traders, do not have any information on the fundamental asset value (Kyle, 1985; Shleifer & Summers, 1990). The importance of noise within financial markets is well established in the existing literature. Roll (1988) demonstrates that changes in price are not solely driven by public, fundamental, news, Cutler et al. (1991) provide evidence that largest market price movements are not registered during fundamental news release days and Shleifer and Summers (1990) conclude that it is uninformed changes in demand as well as changes in the fundamental value of asset that moves prices. Additionally, Gemmill and Thomas (2002) provide evidence that noise generated by small investors affect prices and Harris (2002) argues that cumulative orders imbalances and large orders by uninformed traders cause prices move away from their fundamental values while Mendel and Shleifer (2012) find that noise traders affect asset prices increasing the distance between prices and fundamental values. Further they show that rational but uninformed traders occasionally chase noise as if it were information, enhancing the price deviation and the noise risk.

Hu et al. (2013) argue that during normal times, informed and institutional investors have abundant arbitrage capital sufficient to eliminate big price deviations from fundamental values. Speculators and informed traders therefore help asset prices to converge to fundamental values when there are gaps between actual prices and fundamental values, ruling out market inefficiencies absorbing any risk due to noise trading, so-called noise risk, leading asset prices to converge towards fundamental values. However, due to trading constraints and other limitations, the impact of noise traders still persists (Gemmill & Thomas, 2002). Additionally during liquidity crises, the lack of arbitrage capital limits arbitrage forces and assets are traded at prices significantly away from their fundamental values (Hu et al., 2013). Informed traders are risk-averse and do not always take positions against noise traders (De Long et al., 1990; Kyle, 1985; Shleifer & Summers, 1990) and while Wang (2010) concludes informed traders take aggressive and large opposite positions against noise traders, he notes that informed investors may choose not to entirely eliminate the influence of noise trading on prices. Stambaugh (2014) finds that active managers can correct the majority of the mispricing induced by noise traders, however they are impeded by both idiosyncratic risk and trading costs and a fraction of mispricing remains therefore uncorrected. Shleifer and Summers (1990), Shleifer and Vishny (1997) and Jegadeesh and Thaler (1995) agree that arbitrage for informed traders is limited and De Long et al. (1990) add that betting against noise traders is risky because noise traders' beliefs and impact on asset prices might not revert even in the long run. As result, speculators or informed traders such institutional investors, are not able to entirely counteract the impact that uninformed traders have on market prices due to the existence of trading constraints, limitations and risks (De Long et al., 1987; Gemmill & Thomas, 2002; Hu et al., 2013; Stambaugh, 2014). This phenomenon is due to the unpredictability of noise traders' beliefs (Shleifer & Summers, 1990). Blume and Stambaugh (1983) state that noise in prices is independent across time periods however Brennan and Wang (2010) and Asparouhova et al. (2013) allow for dependence and model noise as an autoregressive process of order 1, AR(1). Therefore, noise creates a price-risk which deters informed traders from aggressively betting against noise traders De Long et al. (1990). The unpredictability of noise traders' beliefs about the "value" of assets makes difficult for speculators and investors to hedge the noise risk or create profitable optimal strategies based on next period noise traders' expectations. Speculators can only counteract and not anticipate the noise traders' actions, such that speculators trade occurs in reaction of noise traders' impact on prices.

This paper proposes to model next period traders beliefs exploiting the noise component of price time series with aim to evaluate noise-timing strategies according to a utility-based approach.

## 3.3 Methodology

To assess the economic value of the noise-timing strategy we mainly follow Fleming et al. (2001) and Karstanje et al. (2013). We construct a dynamic portfolio which allows weights to vary over time according to noise only. We compare the dynamic portfolio with a benchmark portfolio.[4] Finally, we calculate the maximum performance fee a risk averse investor is willing to pay to switch from the benchmark portfolio to the noise-timing portfolio. This fee determines the economic value of noise-timing.

Building on previous research (Della Corte et al., 2008; Della Corte et al., 2009; Fleming et al., 2001, 2003; Karstanje et al., 2013; Thornton & Valente, 2012; West et al., 1993), we employ mean-variance analysis as a standard measure of portfolio performance and apply quadratic utility to examine and to compare the economic gains of the different strategies.[5] While the asset-allocation under a mean-variance framework can only be considered optimal if the first two moments fully characterise the joint distribution of returns and investors have logarithmic utility, it remains a reasonable benchmark for this study since if noise-timing has economic value using a suboptimal strategy, then more sophisticated strategies are likely to yield even better outcomes (Fleming et al., 2001).[6] In addition, the MVO facilitates the assessment of the significance and robustness of results through the use of easy simulation approach, and, if related to quadratic utility, it enables to quantify the extent to which the value of noise timing is affected by risk aversion (e.g. Fleming et al. (2001)).

[4]Following Fleming et al. (2001), the benchmark portfolio is represented by the optimal *ex-ante* static strategy with same targets of the dynamic strategy within a MVO framework. The static strategy is used as benchmark strategy also in Fleming et al. (2003), Han (2006), Jondeau and Rockinger (2007), and Marquering and Verbeek (2004). In the robustness test section of this paper, we consider alternative benchmark strategies to check the validity of our results.

[5]Other studies consider the mean-variance framework to calculate the economic value of specific strategies (Han, 2006; Jondeau & Rockinger, 2007; Marquering & Verbeek, 2004).

[6]Future research may consider more sophisticated strategies such as Black and Litterman (1992) among others.

### 3.3.1 Noise measure

To obtain a noise estimate, we follow the methodology adopted by Brogaard et al. (2014), based on the noise-trader theory approach by De Long et al. (1990) and Shleifer and Summers (1990).[7] The price of an asset is decomposed into a permanent component and a temporary (noise) component through a state space model. According to Hendershott and Menkveld (2014), changes in the temporary component are not attributable to changes in information as opposed to changes in the permanent component, also referred to as the efficient price or fundamental value. Brogaard et al. (2014) further link the transitory component to price noise. It follows that only changes in the permanent component denote changes in the fundamental value of the asset, while changes in the temporary (noise) price component represent price variation in absence of changes in fundamental value and information, suitably relating to the noise-risk originated by noise-traders, and further in line with the theoretical framework of Hu et al. (2013) and Asparouhova et al. (2013). We then consider a state space model estimated with maximum likelihood, where the likelihood is calculated using the Kalman filter. The appendix 3.7 presents details on the model implementation and estimation. The Kalman filter has been widely used in the financial literature as technique to decompose price time series (see Hendershott and Menkveld (2014); Menkveld et al. (2007); Hannemann et al. (2018); Alfano et al. (2020); Brown and Cliff (2004); Haleh et al. (2011), Johnson and Sakoulis (2008), and Schwartz and Smith (2000)) and it provides estimates of the unobserved states and estimates of their uncertainty. The noise estimate is then provided by the Kalman smoother which represents a backward recursion after the Kalman filter estimates. The Kalman smoother delivers new state estimates conditional on all the past, present and future observations facilitating the series decomposition (Brogaard et al., 2014). However, to ensure the feasibility of the proposed strategy, we consider a Kalman smoother which updates the estimates on a rolling basis considering the available historic and present information only. The state space model describes the asset

[7] Hautsch et al. (2011) use a Kalman filter to decompose bid and ask returns into a common ("efficient") component and two market-side-specific components which again capture deviations of observed and efficient return.

log-price, $y_t$, as the sum of a permanent component, $m_t$, modeled as a martingale, and a stationary noise component, $s_t$, modelled as an AR(1) process similarly to Brennan and Wang (2010) and Asparouhova et al. (2013), as follows

$$y_t = m_t + s_t \tag{3.1a}$$

$$m_t = m_{t-1} + w_t, \tag{3.1b}$$

$$s_t = \phi s_{t-1} + v_t. \tag{3.1c}$$

Both $m_t$ and $s_t$ are unobserved state variables with mutually independent and identical distributed error terms $w_t \sim i.i.d.N(0, \sigma_w^2)$, $v_t \sim i.i.d.N(0, \sigma_v^2)$, and $E(\sigma_{w_t}^2, \sigma_{v_k}^2) = 0$ for all $t$ and $k$.

The Kalman filter measurement, or observed, equation can be rewritten as

$$y_t = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} m_t \\ s_t \end{bmatrix} \tag{3.2a}$$

and the transition equations as

$$\begin{bmatrix} m_t \\ s_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \phi \end{bmatrix} \begin{bmatrix} m_{t-1} \\ s_{t-1} \end{bmatrix} + \begin{bmatrix} w_t \\ v_t \end{bmatrix}. \tag{3.2b}$$

In a more familiar state space model notation, they reduce to

$$y_t = H z_t, \tag{3.3a}$$

$$z_t = F z_{t-1} + \epsilon_t, \tag{3.3b}$$

with $H = \begin{bmatrix} 1 & 1 \end{bmatrix}$, $z_t = \begin{bmatrix} m_t \\ s_t \end{bmatrix}$, $\epsilon_t = \begin{bmatrix} w_t \\ v_t \end{bmatrix}$ and $\epsilon_t \sim i.i.d.N(0, Q)$.

### 3.3.2 Noise traders expectations

In order to generate a noise-timing strategy in a mean-variance Markowitz framework, we require an estimate of the next period expected return and variance. Here we present the calculation for the noise traders' expectations about the future asset "value" which will represent the expected return predictions within the asset allocation optimization.

Following Karstanje et al. (2013), we adopt a model for conditional expected excess returns that is solely driven by noise. Though inclusion of the fundamental price component in the model would likely enhance expected excess return predictions, our focus is to look at the noise component only and to investigate whether it can be used to generate a profitable strategy. If instead noise is just a random variable with no beneficial value for forecasting expected returns, it cannot be used to optimally allocate assets and the model would not generate a profitable strategy. Moreover, adding the fundamental value into a model that aims to predict the next period noise traders' belief would assume that noise traders have or act on fundamental information, which is incorrect by definition. We therefore model the next period noise traders' belief as

$$\begin{aligned} \mu_t^{\text{Noise Traders}} = E_t[r_{i,t+1} - r_f] &= \delta_0 + \delta_1 E_t[s_{i,t+1}] \\ &= \delta_0 + \delta_1[\phi s_{i,t}] \\ &= \beta_0 + \beta_1 s_{i,t}, \end{aligned} \tag{3.4}$$

where $s_t$ is the price noise component estimated from the model as in equation (3.1) with $\beta_0 = \delta_0$, and $\beta_1 = \delta_1\phi_1$. In this set-up, the noise is assumed to be the sole driver of expected return changes over time. If we assume the variance-covariance matrix as constant, this strategy is equivalent to following a noise-timing strategy in a mean-variance framework as the optimal portfolio weights ignore any time variation in the variance-covariance matrix. The sole source of time variation comes from changes in the expected returns, which, in turn, depends on noise. This approach closely follows that used by Fleming et al. (2001) to assess the value of volatility timing. This further mitigates the concern that the economic value of noise-timing is driven by variation in the variance-covariance matrix. In fact, if we instead admit the variance to change over time, it would be difficult to identify whether any potential gains of the strategy are driven by changes in the variance or by changes in the noise.

We estimate the parameters in equation (3.4) using a rolling window with a window length of three years. The first return prediction is made for September 1, 2017. Therefore, for the three years moving window, we estimate equation (3.4) using data from September 1, 2014 to August 31, 2017. We shift the window one day ahead and the estimation window runs from September 2, 2014 to September 1, 2017 and we make the prediction for September 2, 2017. This procedure is repeated for all days t={September 1, 2017; September 2, 2017; ...; December 30, 2019; December 31, 2019} and for each asset class.

### 3.3.3 Optimization problem

To construct the noise-timing strategy, the investor dynamically rebalances the portfolio weights in order to minimise the portfolio variance given a target expected portfolio return at each time $t$, as follows

$$\begin{aligned} \min_{w_t} \quad & \boldsymbol{w}_t' \hat{\boldsymbol{\Sigma}} \boldsymbol{w}_t \\ \text{s.t.} \quad & 1)\ \boldsymbol{w}_t' \boldsymbol{\mu}_t^{\text{Noise Traders}} = \boldsymbol{\mu}_p \\ & 2)\ \boldsymbol{w}_t' \mathbf{1} = 1 \\ & 3)\ \boldsymbol{w}_{t,i} \geq 0, \quad (i = \textit{Stock, Bond, Gold, Cryptocurrency}) \\ & 4)\ \boldsymbol{w}_{t,Cryptocurrency} \leq \alpha W_t \end{aligned} \tag{3.5}$$

where $\hat{\Sigma}$ denotes the next period estimate of the variance-covariance matrix calculated as the sample variance and assumed to be constant over time, and $\mu_t^{\text{Noise Traders}}$ denotes the vector of expected returns estimated from equation $(3.4)$. Constraint $1)$ refers to the classic Markowitz portfolio choice. We choose as the target daily return the equivalent of an annual return of 8% and conduct a sensitivity analysis for a wider range of target expected returns. We consider unleveraged portfolios applying constraint 2), which requires that all the wealth at time *t* is invested, and constraint 3), which prevents short-selling. Constraint 4) limits the investment in the cryptocurrency market to a maximum portion $\alpha$ of the total investor' wealth, $W_t$. Cryptocurrencies are highly volatile and a risk-averse investor would probably diversify his or her resources, rather than invest the totality of his or her wealth into this class. More likely he or she prefers to set a limit on investment on cryptocurrencies to avoid both extra volatility and severe liquidity problems otherwise induced by too much weight on cryptocurrency (Trimborn et al., 2019). In addition, the investment limit may mitigate potential losses due to inaccurate predictions. When the target return is not achievable, the return is maximised as much as possible.

Similarly to Jondeau and Rockinger (2007) and Fleming et al. (2001), the benchmark portfolio is the *ex-ante* optimal static portfolio with same target expected return as the dynamic portfolio. The investor solves at time $t$ a unique optimization problem of the form:

$$
\begin{aligned}
\min_{w} \quad & \boldsymbol{w}'\hat{\boldsymbol{\Sigma}}\boldsymbol{w} \\
\text{s.t.} \quad & 1)\ \ \boldsymbol{w}'\hat{\boldsymbol{\mu}} = \boldsymbol{\mu}_p \\
& 2)\ \ \boldsymbol{w}'\mathbf{1} = 1 \\
& 3)\ \ \boldsymbol{w}_i \geq 0, \quad (i = \textit{Stock, Bond, Gold, Cryptocurrency}) \\
& 4)\ \ \boldsymbol{w}_{Cryptocurrency} \leq \alpha W_t
\end{aligned}
\tag{3.6}
$$

where $\hat{\Sigma}$ and $\hat{\mu}$ are the sample variance and sample mean, respectively, and they remain constant over time.

The optimal weights for the dynamic and static strategies are then applied to the actual returns to obtain the portfolios realised performances. This allows us to compare the strategies and evaluate the potential gains of the noise-timing strategy over the benchmark strategy.

### 3.3.4 Economic value of noise-timing

The Sharpe ratio, or return-to-variability, is a popular economic criterion to evaluate investments and portfolios performances. However, performances of dynamic portfolios can be underestimated using this metric as explained by Han (2006) and Marquering and Verbeek (2004). In line with previous studies (Fleming et al., 2001, 2003; Jondeau & Rockinger, 2007; Karstanje et al., 2013), we assess the economic value of noise-timing using a utility-based approach to obtain a more robust valuation. Particularly, the economic value is calculated as maximum performance fee a risk averse investor with quadratic utility is willing to pay to switch from the benchmark strategy to the noise-timing strategy. The difference between the noise-timing and static strategies would be indistinguishable if the dynamic portfolio has zero value. On the other hand, one strategy would outperform the other when the noise-timing has non-zero value. The performance fee measure is based on mean-variance analysis with quadratic utility (Della Corte et al., 2008; Della Corte et al., 2009; Fleming et al., 2001; Karstanje et al., 2013; Rime et al., 2010; Thornton & Valente, 2012; West et al., 1993).[8] The quadratic utility can be seen as the second order approximation of the true investor' utility function. We have that the realised utility at time *t+1* can be written as

$$U(W_{t+1}) = W_t R_{p,t+1} - \frac{aW_t^2}{2} R_{p,t+1}^2, \tag{3.7}$$

where $W_{t+1}$ is the investor's wealth at time *t+1*, *a* is his or her absolute risk aversion, and $R_p$ indicates the return on the generic portfolio *p*. Similarly to Fleming et al. (2001) we hold $aW_t$ constant to ease comparisons across portfolios. It follows we consider the relative risk aversion (RRA) as $\gamma_t = aW_t/(1 - aW_t)$ equal to some fixed value $\gamma$. Under these conditions, West et al. (1993) demonstrate that the average realised utility $\bar{U}(\cdot)$ can be used to consistently estimate the expected utility generated by a given level of initial

[8]The use of quadratic utility is not strictly necessary to justify mean–variance optimization as, for instance, other utility functions belonging to the constant relative risk aversion (CRRA) class, such as power or log utility, can be instead considered. However, as underlined by Della Corte et al. (2008) and Della Corte et al. (2009), quadratic utility is an attractive assumption because it allows to use the Fleming et al. (2001) framework, provides a high degree of analytical tractability, can be viewed as a second-order Taylor series approximation to expected utility, and provides a highly satisfactory approximation to a wide range of more sophisticated utility functions (Hlawitschka, 1994).

wealth $W_0$ as

$$\bar{U}(\cdot) = W_0 \left( \sum_{t=0}^{T-1} R_{p,t+1} - \frac{\gamma}{2(1+\gamma)} R_{p,t+1}^2 \right). \tag{3.8}$$

Following the literature, fixing the degree of RRA, $\gamma$, implies that expected utility is linearly homogeneous in wealth and allows us to standardize the investor problem by assuming $W_0 = 1$.[9]

We estimate noise-timing by equating the averaged utilities for the two alternative strategies. The performance fee, denoted $\Delta$, represents the average return that when added to the return of the static strategy makes the investor indifferent between the two alternatives, thereby quantifying the economic value of noise-timing. We find numerically the value of $\Delta$ that satisfies:

$$\sum_{t=0}^{T-1} R_{d,t+1} - \frac{\gamma}{2(1+\gamma)} R_{d,t+1}^2 = \sum_{t=0}^{T-1} (R_{s,t+1} + \Delta) - \frac{\gamma}{2(1+\gamma)} (R_{s,t+1}^2 + \Delta) \tag{3.9}$$

where $R_{d,t+1}$ and $R_{s,t+1}$ denote the optimal portfolio return of the noise-timing strategy and the optimal portfolio return obtained by the static strategy respectively.

### 3.3.5 Transaction costs

An important consideration with portfolio management is related to transaction costs. Transaction costs may considerably affect the portfolio performances especially when portfolios are frequently rebalanced and high transaction costs could make dynamic strategies less desirable than static strategies. However, it is difficult to properly estimate the exact level of transaction costs because this information it is not readily available in most cases (Han, 2006).[10] We therefore prefer to consider break-even transaction costs, $\tau^{be}$, that renders an investors indifferent between two strategies, similarly to previous

[9] Della Corte et al. (2008), Della Corte et al. (2009), Fleming et al. (2001), Karstanje et al. (2013), Rime et al. (2010), Thornton and Valente (2012), and West et al. (1993).

[10] Empirical studies use a wide range of estimates to determine the size of transaction costs, for instance Marquering and Verbeek (2004) identify three levels of transaction costs as low, 0.1%, medium, 0.5%, and high, 1%.

research (Della Corte et al., 2009; Han, 2006; Jondeau & Rockinger, 2007; Karstanje et al., 2013; Marquering & Verbeek, 2004; Rime et al., 2010; Thornton & Valente, 2012). The proportional break-even transaction costs, $\tau^{be}$, is applied ex-post to the optimal portfolio performances (Della Corte, 2020; Jondeau & Rockinger, 2007; Marquering & Verbeek, 2004). If we assume that transaction costs are equal to a fixed fraction $\tau$ of the value traded for all assets in the portfolio, the average daily transaction cost of this strategy is $\tau \cdot tc$, where[11]

$$tc = \frac{1}{T}\sum_{t=1}^{T}\sum_{i=1}^{n}\left| w_{i,t} \cdot \frac{w_{i,t-1}(1+r_{i,t})}{1+r_{p,t}} \right| \tag{3.10}$$

where $w_{i,t}$ denotes the weight of asset *i* at date *t*, $r_{p,t}$ is the portfolio *p* return in *t*. $\tau^{be}$ is the maximum level of transaction costs which makes an investor indifferent between the dynamic noise-timing strategy *d* and the benchmark static strategy $s$, such that the investor prefers the noise-timing strategy for a level of transaction costs lower than $\tau^{be}$. $\tau^{be}$ satisfies the following equation

$$\sum_{t=0}^{T-1}\left[\left(R_{d,t+1} - \tau^{be}tc\right) - \frac{\gamma}{2(1+\gamma)}\left(R_{d,t+1} - \tau^{be}tc\right)^2\right] = \sum_{t=0}^{T-1} R_{s,t+1} - \frac{\gamma}{2(1+\gamma)}R_{s,t+1}^2 \tag{3.11}$$

We report $\tau^{be}$ in daily basis point because $\tau^{be}$ is a proportional cost paid every day when the dynamic portfolio is rebalanced.

## 3.4 Data

We consider four asset classes: stocks, bonds, gold, and cryptocurrency.[12] Specifically, we use the S&P 500 index for the stock market, the iShares core US aggregate bond ETF for the bond market, the gold spot to US Dollar price, and the CRypto IndeX CRIX by Trimborn and Härdle (2018) for the cryptocurrency market. The sample period consists of an estimation period, from September 2014 to October 2017, and an allocation period, from September 2017 to December 2019.[13] Similar to

[11] We also check results where we relax this assumption for the cryptocurrency class considering a 50 basis points $\tau$ per transaction in line with Platanakis and Urquhart (2019) and Lintilhac and Tourin (2017).

[12] Gold is included instead of a generic commodity index because of better diversification abilities.

[13] The start of our sample period is restricted by data for CRIX.

Fleming et al, we focus on the US economy at the daily frequency and the prices are the closing prices expressed in US Dollars.[14] Due to different opening hours of these markets, we filter the sample to create a consistent data-set keeping the days in which the markets are jointly open.

**Table 3.1:** Summary statistics

| | | Stock | | Bond | | Gold | | Cryptocurrency | |
|---|---|---|---|---|---|---|---|---|---|
| Period | Obs. | $\mu\%$ | $\sigma\%$ | $\mu\%$ | $\sigma\%$ | $\mu\%$ | $\sigma\%$ | $\mu\%$ | $\sigma\%$ |
| Entire sample (*Sep 2014 - Dec 2019*) | 1,343 | 9.38 | 13.43 | 0.40 | 3.22 | 3.13 | 12.90 | 72.15 | 72.28 |
| Estimation sample (*Sep 2014 - Oct 2017*) | 757 | 7.24 | 12.95 | 0.14 | 3.41 | 0.89 | 14.40 | 148.43 | 63.60 |
| Allocation sample (*Sep 2017 - Dec 2019*) | 586 | 12.20 | 14.04 | 0.74 | 2.97 | 6.11 | 10.67 | 7.11 | 82.10 |

Note: Annualised realised mean return in percentage ($\mu\%$), standard deviation in percentage ($\sigma\%$) for stock, bond, gold and cryptocurrency asset classes during the entire sample (Sep 2014 - Dec 2019), the estimation sample (Sep 2014 - Oct 2017), and the allocation sample (Sep 2017 - Dec 2019) with their respective number of observation (Obs.).

Table 3.1 reports the summary statistics for the four asset classes during the full sample, estimation period, and allocation period. The table presents the number of observations for each sample and reports the realised annualised mean and standard deviation of returns expressed in percentages. Stocks report a higher mean return and larger standard deviation with respect to bonds, as expected from traditional finance literature. The mean return of gold during the estimation sample is 0.89%, much lower than that during the allocation period of about 6.11%, suggesting that static strategies which use sample means as an estimate of expected returns could allocate lesser weight to this class if other more profitable classes are available with the same volatility. The cryptocurrency asset class exhibits the highest mean return during all three samples together with the highest volatility. This market is highly volatile and the Bitcoin bubble in late 2017 is included in the sample resulting in a very high mean returns especially during the estimation period where the bubble was still growing. The summary statistics for cryptocurrency further foresees an increase in volatility

[14] Gemmill and Thomas (2002) argue that noise may have both a low frequency and a high frequency influence on asset prices. Asparouhova et al. (2013) find that noise in prices is important for daily or higher frequency returns and not for monthly returns. We adopt daily frequency because this frequency better captures and incorporates the noise risk effect with respect to lower frequency data, such as weekly or monthly, where prices are more likely to change because of changes in fundamental values. Further, rebalancing the portfolio daily is more feasible than on an intraday basis and avoiding higher frequencies avoids potential intraday issues with cryptocurrencies.

when this class is included into a portfolio, anticipating the need to limit its investment.

## 3.5 Results

### 3.5.1 State space model estimates

The space model presented in equation (3.1) dissects the price time series into a fundamental price component and a noise component through a Kalman filter estimation. The measurement equation, or imperfect information, is the process which models the log-prices $y_t$, including the error component $s_t$ (the "noise"). The Kalman filter acts as a filter which provides a decomposition by filtering the fundamental information component $m_t$ and keeping the noise component $s_t$. The state space model estimates of the permanent and noise price components are reported in table 3.2. The model parameter $\phi$ represents the persistence of past noise on the noise component. The four asset class noise price components show high persistence with $\phi$ ranging from 0.93 to 0.95. The model also provides estimates for both the noise component estimate uncertainty, denoted by $\sigma_v^2$, and the permanent component estimate uncertainty, denoted by $\sigma_w^2$. The state space model commits low estimation error as depicted by the small values for $\sigma_v^2$ and $\sigma_w^2$ expressed in 100 basis points, suggesting particular small uncertainty around the noise and permanent estimates for stock, bond and gold prices. Larger estimation errors are incurred for cryptocurrency prices, probably due to the very high volatility of the asset class.

Figure 3.1 illustrates the observed historical log-prices $y_t$ (orange lines) against the Kalman smoother state space model estimates of the permanent price component $m_t$ (black lines) on the upper part of the plots and the evolution of the noise price components $s_t$ (grey lines) on the bottom, for stocks (a), bonds (b), gold (c), and cryptocurrency (d) for the full sample period. Although the permanent component follows the observed price evolution overall, it filters the majority of variation out resulting in a smoother path which reflects fundamental changes in asset prices.

Deviation from the fundamental price can be large as visible from a number of spikes. The noise component reveals the size of this gap and it is found to be stationary.

**Table 3.2:** Kalman-Filter estimates

Panel A: Permanent price component $m_t$

| | Units | Stock | Bond | Gold | Cryptocurrency |
|---|---|---|---|---|---|
| $\sigma_w^2$ | bps×100 | 7.18 | 0.43 | 6.99 | 261.10 |

Panel B: Noise price component $s_t$

| | Units | Stock | Gold | Bond | Cryptocurrency |
|---|---|---|---|---|---|
| $\phi$ | | 0.93 | 0.94 | 0.95 | 0.95 |
| (t-stat.) | | (95.49) | (98.21) | (107.69) | (117.36) |
| $\sigma_v^2$ | bps×100 | 6.60 | 0.36 | 5.82 | 190.13 |

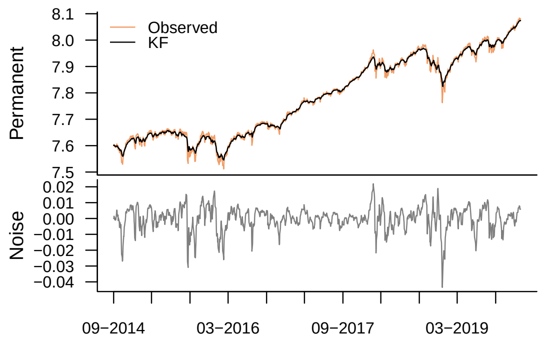
Note: State space model from equations 3.1 estimates of permanent component and noise component. $\phi$ represents the persistence of past noise on the noise component, $\sigma_v^2$ and $\sigma_w^2$ are the estimates of the estimates uncertainties for the noise component and permanent component of price respectively expressed in 100 basis points (bpsx100). The model is estimated through maximum likelihood calculated from a Kalman filter and smoother for stock, bond, gold and cryptocurrency asset classes.

The noise price component as calculated in this paper exhibits properties in line with those documented in the prior literature. The magnitude of the noise and the relative importance of noise traders' role are larger during financial market turmoils and crashes characterised by either abnormal volatility or scarcity of liquidity, similar to Aabo et al. (2017) and Hu et al. (2013). The largest noise values are registered during severe market drop days for the stock market[15] and during the high turbulence bubble period for the cryptocurrency market.[16] This is consistent with Rognone et al. (2020) who note that cryptocurrencies are more influenced by non-fundamental news during bubble periods. On January 22, 2015, the gold price jumped above $1,300 per ounce determining higher volatility and a subsequent increase of noise traders' role importance, as the gold noise magnitude reached its peak. Beside this event, noise for gold has few spikes. On the other hand, there are no key events which lead to extreme noise values in the bond market. This is in line with the idea that the bond value is not as exposed as other classes to the noise risk, and that its price is less likely to considerably deviate from its fundamental value, resulting in a smaller impact of noise traders.

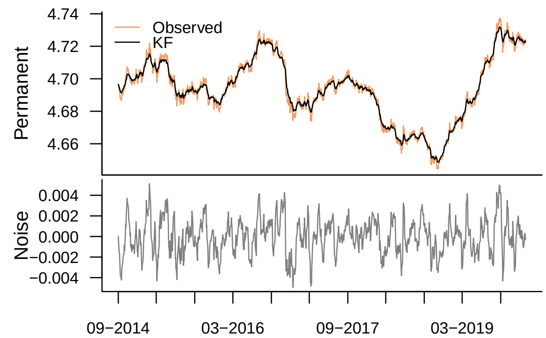
[15]Some of the key events which triggered a high level of stock market noise were substantial crash market days, such as on Monday, August 24, 2015 when world stock markets were overall down; during February 2016 due to the Brexit announcement; on June 27, 2016 when US market lost 3 trillion; among others.

[16]Higher noise traders' role occurred during the Bitcoin bubble between end of 2017 and beginning of 2018.

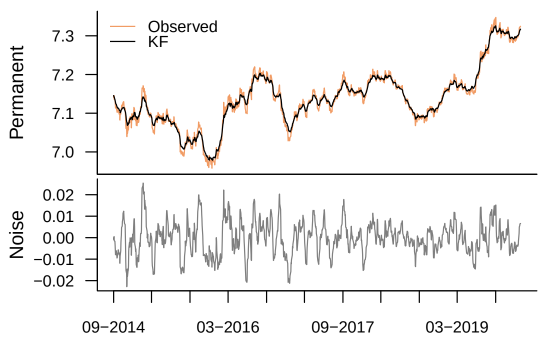
**Figure 3.1:** Historical log-prices (Observed), Kalman smoother permanent and noise components



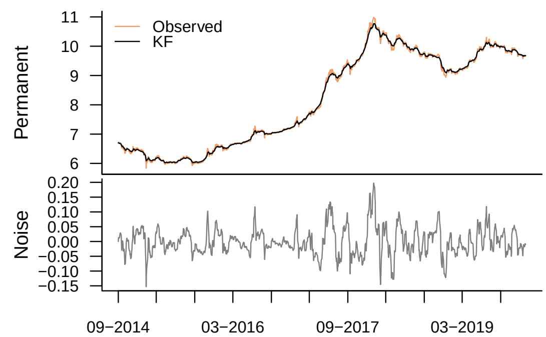

(**a**) Stock




(**b**) Bond




(**c**) Gold



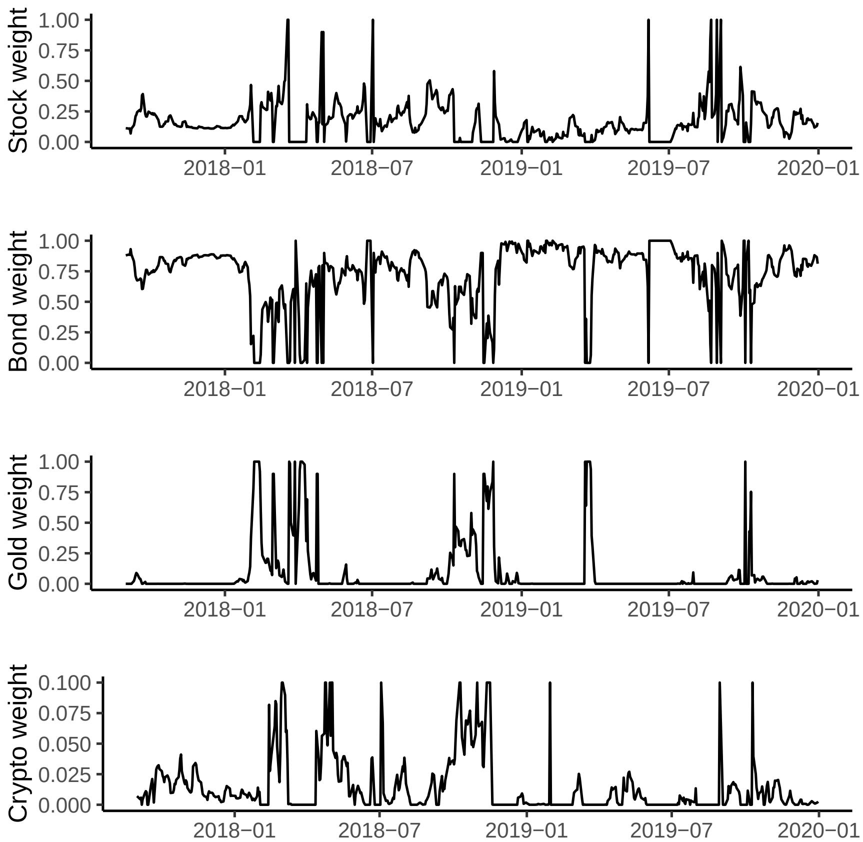

(**d**) Cryptocurrency

Note: This plot shows the evolution of the permanent component and noise component of stock price (a), bond price (b), gold price (c), and cryptocurrency price (d) from the state space model in equations 3.1 estimates for the period September 2014 - December 2019. Each subplot presents on the top the path of the permanent component (black line) against the observed log-price (orange line), and on the bottom the path of the noise price component (grey line).

### 3.5.2 Main results

The noise-timing strategy solves at each time $t$ a mean-variance optimization problem that minimises the portfolio variance given a target portfolio return. Equation (3.5) expresses how the dynamic optimal weights are calculated. The sample variance-covariance matrix is used as an estimate for the one-step-ahead portfolio variance and assumed to be constant over time, while the expected returns come from a model for noise-traders' future beliefs solely driven by noise. The benchmark portfolio is obtained by the optimal *ex-ante* static portfolio that solves the same optimization problem of the dynamic portfolio but with sample means as estimate for future returns.

**Figure 3.2:** Dynamic portfolio weights allocation over time




Note: The figure illustrates the noise-timing strategy from the optimization problem in 3.5 optimal allocation over time.

Figure 3.2 provides a graphical representation of the dynamic, noise-timing, strategy portfolio weights during the allocation period, and table 3.3 reports the portfolio composition of the dynamic, average weights, and static portfolios. The noise-timing portfolio is mainly composed by bonds with an average investment of 72.46% of the wealth. It further allocates on average 16.64%, 9.42%, and 1.48% of the wealth in stocks, gold, and cryptocurrency respectively. The static portfolio is 72.83% composed by bonds, 20.37% by stocks, 0.03% by gold, and 6.77% by cryptocurrency. Both the strategies allocate a high percentage of wealth into bonds as the safest asset class, in line with optimization problem objective to generate the minimum variance portfolio. On the other hand, to achieve the target portfolio return set equal to 8%, the two portfolios invest in the other asset classes accordingly to their estimated expected returns and risk levels. The noise-timing strategy is dynamically rebalanced and the portfolio weights are optimally adjusted every day based on the upcoming information.

**Table 3.3:** Dynamic and static portfolios compositions

| | Average Investment dynamic | Investment static |
|---|---|---|
| Stock | 16.64% | 20.37% |
| Bond | 72.46% | 72.83% |
| Gold | 9.42% | 0.03% |
| Cryptocurrency | 1.48% | 6.77% |

Note: This table reports the average portfolio composition of the dynamic noise-timing strategy calculated from equation 3.5 and the portfolio weights for the benchmark static optimal *ex-ante* portfolio from equation 3.6. The portfolio weights are expressed in percentage of investor' wealth.

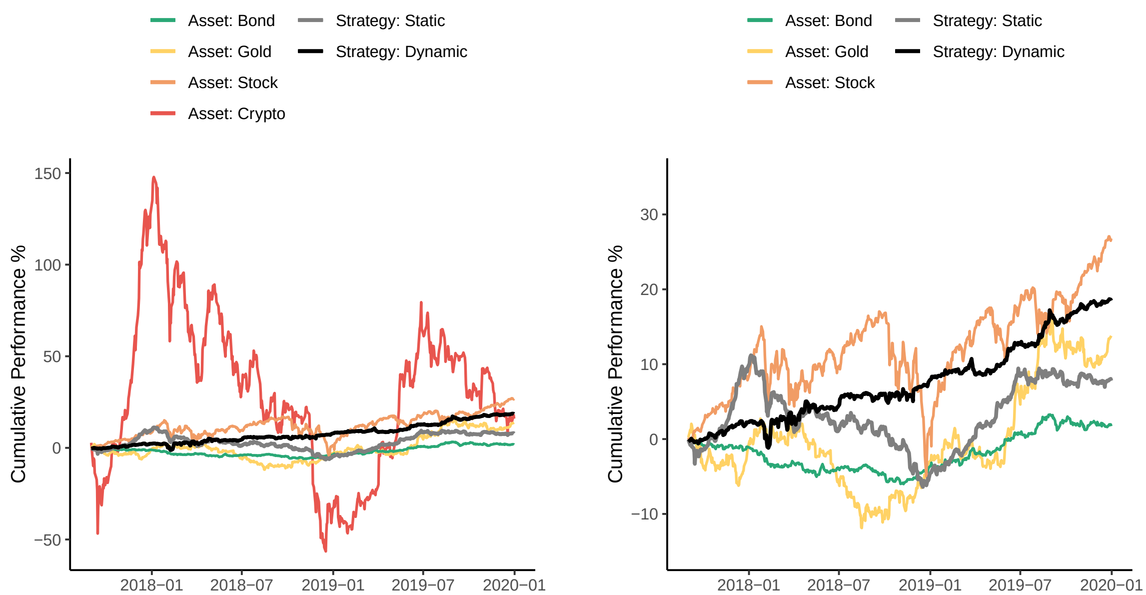
**Table 3.4:** Comparison of the noise-timing and *ex-ante* optimal static strategies using different target expected returns - Portfolio composition

| | Dynamic portfolio Average investment | | | | Static portfolio Investment | | | |
|---|---|---|---|---|---|---|---|---|
| Target Return | Stock | Bond | Gold | Crypto | Stock | Bond | Gold | Crypto |
| 6 % | 14.72 | 75.97 | 8.06 | 1.25 | 17.71 | 77.37 | 0.01 | 4.91 |
| 7 % | 15.68 | 74.33 | 8.64 | 1.35 | 19.05 | 75.11 | 0.00 | 5.84 |
| 8 % | 16.64 | 72.46 | 9.42 | 1.48 | 20.37 | 72.83 | 0.03 | 6.77 |
| 9 % | 17.60 | 70.82 | 10.00 | 1.59 | 21.72 | 70.34 | 0.27 | 7.68 |
| 10 % | 18.56 | 69.32 | 10.39 | 1.73 | 23.06 | 67.78 | 0.59 | 8.58 |
| 11 % | 19.50 | 67.64 | 10.99 | 1.86 | 24.39 | 65.22 | 0.92 | 9.47 |

Note: This table reports the average portfolio composition of the dynamic noise-timing strategy calculated from equation 3.5 and the portfolio weights for the benchmark static optimal *ex-ante* portfolio from equation 3.6 for different levels of target returns. The portfolio weights are expressed in percentage of investor' wealth.

Table 3.4 reports the portfolio weights composition on average for the noise timing and static strategies for different levels of target returns. As the target return increases, the portfolios become more risky, investing a larger portion of wealth into the riskier asset classes and reducing the exposure on the lower risk classes. In this way, the portfolios try to match the increasing desired level of target return asked by the investor.

**Figure 3.3:** Cumulative portfolio performances




(**a**) Large scale (**b**) Small scale

Note: The figure illustrates the realised cumulative performances expressed in percentage of the dynamic portfolio (black line), static portfolio (grey line), bond (green line), gold (yellow line), stock (orange line), and cryptocurrency (red line) over the allocation period Sept 2017 - Oct 2019.

We apply the optimal portfolio weights to the actual returns to get the realised strategies performances. Figure 3.3 shows the noise-timing strategy cumulative realised percentage performance, black line, against that of the static strategy, grey line, and of the other asset classes. Overall, the noise-timing strategy outperforms the benchmark strategy as the cumulative dynamic performances plotted above the static performances during the majority of the allocation period. The dynamic strategy has quite stable performances suggesting that the optimization problem successfully minimises the portfolio variance. The realised static performances are characterised by higher volatility depicted by large ups and downs during the allocation period which ultimately expose investors to larger risk. The dynamic portfolio appears to provide good hedge during turbulence times, such as December 2018 when the US stock market suffered a dramatic drop. The noise-timing strategy demonstrates abilities to anticipate market crashes and to rebalance the portfolio weights optimally to hedge these phenomena. This ability is not verifiable for the static strategy which fails to foresee crises and does not efficiently respond to negative exogenous shocks.

Table 3.5 considers different target returns and it shows the noise-timing strategy and the optimal *ex-ante* static strategy annualised performance means, standard deviations, Sharpe ratios, the economic value of the noise-timing, $\Delta$, and the break-even proportional transaction costs, $\tau^{be}$, for two levels of investors' risk aversion, $\gamma = 1$ and $\gamma = 10$. As the target expected return increases, the portfolio means, volatilities and Sharpe ratios increase. The dynamic noise-timing strategy portfolio always has better results than the *ex-ante* optimal static portfolio, in terms of higher means, lower volatilities, and larger Sharpe ratios. Most important, the economic value of noise-timing, calculated as maximum annualised performance fees that a risk averse investor with quadratic utility is willing to pay to switch from the benchmark static strategy to the noise-timing strategy, is always positive ranging from 313.71 to 940.41 basis point per year depending on both the investor's level of risk aversion and his or her target expected return. The performance fee the short-horizon investor is willing to pay to invest into the dynamic strategy increases with the target return, such that the noise-timing strategy is more valuable for higher target return. For instance, if the target return is 8%, the investor with risk aversion of 1 (10) is willing to pay every year a performance fee of about 481.56 (584.54) basis points to switch to the noise-timing strategy. However, if the target return is higher, *i.e.* 11%, then the investor with risk aversion of 1 (10) would pay a higher annual fee up to 697.93 (940.41) basis point to switch to the noise-timing strategy. While some economic values for noise-timing could seem unfeasibly high, the circumstances in which these high values occur are unlikely to happen in real economies. For instance, the highest economic value of 940.41 corresponds to the improbable scenario in which the investor is very risk averse, $\gamma = 10$, but requires a very high rate of return, $\bar{\mu} = 11\%$. Therefore, the economic value $\Delta_{10} = 940.41$ is technically correct but unlikely to happen in real financial markets where high risk averse investors target lower expected returns to contain risk. As result, although all the results for the economic value of noise-timing are correct and meaningful for a deeper theoretical understanding of the relationship between noise-timing and risk averse investors, the more likely values belong to the more feasible $(\gamma, \bar{\mu})$ pairs.

The break-even transaction costs are sufficiently high and increase with the target return, suggesting that investors prefer the dynamic strategy in terms of utility. $\tau^{be}$ in table 3.5 ranges from a minimum of 6.68 basis point per transaction to a maximum of 17.30 basis point supporting the advantages of the dynamic portfolio.[17]

We observe another interesting finding as evidenced by the higher economic value of noise-timing for more risk-averse investors, $\Delta_{10} > \Delta_1$ for all target returns. This supports the assumption that investors care about noise-risk and wish to hedge against it accepting to pay higher fees according to their risk-aversion. Also the break-even transaction costs are higher for more risk-averse investors, $\tau^{be}_{10} > \tau^{be}_{1}$ for all target returns, as insight that these investors prefer the noise-timing strategy more strongly than less risk averse investors.

In summary, we find that the noise-timing has positive, non zero, economic value to short-horizon and risk averse investors. The following section examines a number of robustness tests to check the validity of these results.

**Table 3.5:** Comparison of the noise-timing and *ex-ante* optimal static strategies using different target expected returns

| Target Return | Dynamic portfolio | | | Static portfolio | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu$% | $\sigma$% | SR | $\mu$% | $\sigma$% | SR | $\Delta_1$(bp) | $\Delta_{10}$(bp) | $\tau^{be}_1$(bp) | $\tau^{be}_{10}$(bp) |
| 6% | 6.19 | 4.47 | 0.92 | 3.00 | 4.99 | 0.20 | 313.71 | 348.31 | 6.68 | 7.25 |
| 7% | 7.39 | 4.55 | 1.16 | 3.20 | 5.68 | 0.21 | 412.89 | 479.06 | 8.67 | 9.89 |
| 8% | 8.27 | 4.64 | 1.32 | 3.41 | 6.39 | 0.22 | 481.56 | 584.54 | 9.36 | 11.20 |
| 9% | 9.01 | 4.81 | 1.43 | 3.63 | 7.11 | 0.22 | 534.62 | 677.48 | 10.27 | 12.38 |
| 10% | 10.20 | 4.99 | 1.61 | 3.85 | 7.84 | 0.23 | 631.65 | 819.96 | 11.92 | 15.25 |
| 11% | 11.06 | 5.10 | 1.74 | 4.08 | 8.57 | 0.24 | 697.93 | 940.41 | 13.04 | 17.30 |

Note: The table shows how the performance of the noise-timing strategy varies with the target expected return. The table reports the annualized mean realized returns in percentage ($\mu$%), annualised realised volatilities in percentage ($\sigma$%), and realised Sharpe ratios in basis points (SR) for each strategy, and the average annualised basis point fees ($\Delta_\gamma$) that an investor with quadratic utility and constant relative risk aversion of $\gamma = 1$ or $\gamma = 10$ would be willing to pay to switch from the static portfolios to the noise-timing strategy. Break-even proportional transaction costs per transaction in basis point are reported distinguishing from investors with risk aversion $\gamma = 1$ ($\tau^{be}_1$) and $\gamma = 10$ ($\tau^{be}_{10}$).

[17] We get similar results for $\tau^{be}$ including only stocks, bonds, and gold, and considering $\tau$ for cryptocurrency equal to 50 basis points (Lintilhac & Tourin, 2017; Platanakis & Urquhart, 2019), most likely due to the small value traded per day for the cryptocurrency class, e.g. for a $\bar{\mu} = 8\%$ the daily average transaction in cryptocurrency is 0.6% of the wealth.

## 3.6 Robustness tests

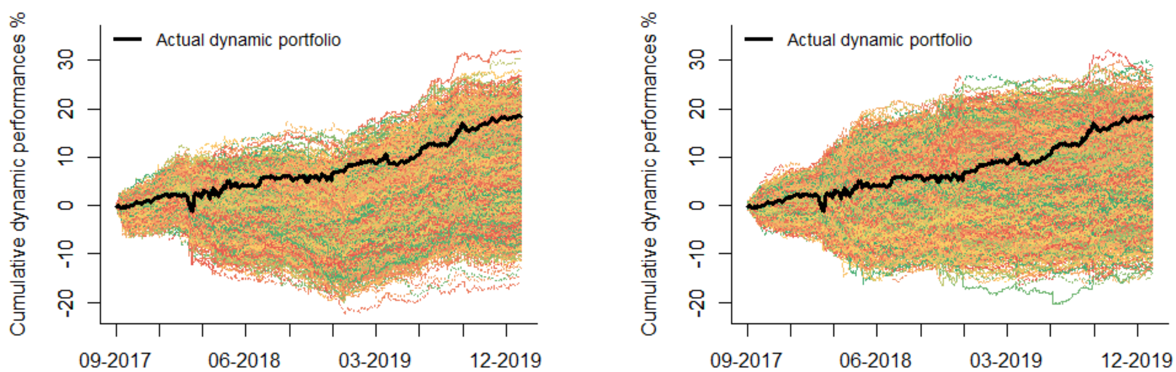
This section aims to test the validity of the paper results investigating a number of robustness checks. We test the statistical significance of the economic value of noise timing strategy, we consider a broader set of benchmark portfolios, we relax the cryptocurrency limit investment assumption, we manage outliers in the data, we address the possible effects of structural breaks in the data, and we look at results during the Covid-19 period. The main paper results are verified and the noise-timing strategy is found to bring robust and valuable gains to risk-averse and short-horizon investors.

### 3.6.1 Statistical significance of noise-timing strategy

It is unlikely that any fixed-weight portfolio choice *ex-ante* turns out to be efficient or that it outperforms a dynamic portfolio. Therefore following Fleming et al. (2001), we assess the statistical significance of the noise-timing results through random permutation tests. We create portfolio simulations where weights are generated independently of the asset returns. We form 10,000 random permutations of the optimal portfolio weights and we apply them to the actual returns. As alternative, we also randomise the actual returns 10,000 times and we apply them to the actual optimal noise-timing weights. If the noise-timing strategy gains are significant, then the actual dynamic portfolio created with the combination of actual weights and actual returns should perform better than the simulations.

Figure 3.4 illustrates the 10,000 simulated portfolios that randomise the portfolio weights (a) and actual returns (b). The actual noise timing strategy, depicted by the black line, seems to perform well against the simulations suggesting that its gains are not merely due to luck. Table 3.6 shows the proportion of trials in which the noise-timing strategy has higher realised performance mean, lower volatility, and larger Sharpe ratio than the simulations of the two random permutation tests. It is clear the advantage of the noise timing strategy as, for instance, its realised mean is greater than the simulation the 96.95% of the times. On the 98.65% of the times, the noise timing strategy has lower volatility than simulations, and on the 98.46% of the times, it has larger Sharpe ratio. Similar results hold for the permutation of portfolio weights.

**Figure 3.4:** Random permutation tests




**(a)** Permutation weights **(b)** Permutation returns

Note: This figure illustrates the random permutation of weights simulations (a) and the random permutation of returns simulations (b) against the actual noise timing dynamic portfolio cumulative performances expressed in percentage (thick black line) during the allocation period.

**Table 3.6:** Actual dynamic portfolio against random permutation performances

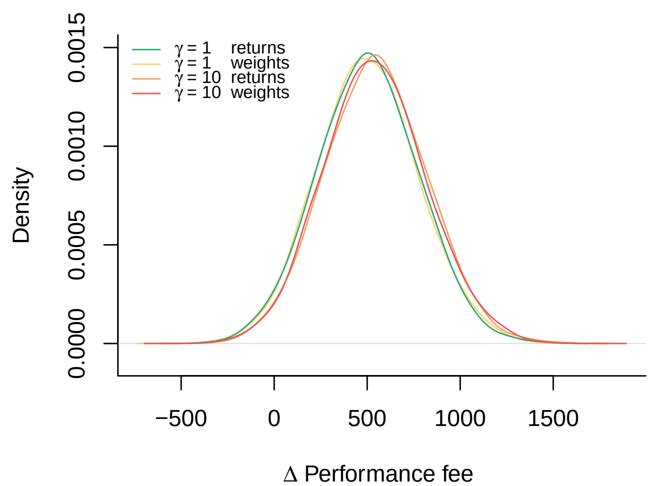
| | Proportion of trials | |
|---|---|---|
| | Permutation returns | Permutation weights |
| $\text{Mean}_d > \text{Mean}_{simulation}$ | 96.95% | 97.08% |
| $\text{SD}_d < \text{SD}_{simulation}$ | 98.65% | 96.43% |
| $\text{SR}_d > \text{SR}_{simulation}$ | 98.46% | 98.31% |

Note: This table presents the proportion of trials the dynamic noise timing strategy outperforms the random permutation of weights simulations and the random permutation of returns simulations in terms of higher mean, lower volatility and larger Sharpe ratio.

On average the annualised performance fee in basis point that an investor is willing to pay to switch from a permutation returns simulation to the noise timing strategy is 505.07 (547.55) for a risk aversion of 1 (10). While the investor wants to pay an annual fee of about 503.99 (541.62) to switch the permutation weights strategy to the noise timing strategy for a risk aversion of 1 (10). These results consider a target return $\bar{\mu} = 8\%$, and are robust with the paper findings for similar target return. Figure 3.5 plots the distribution of performance fees for the simulations with different level of risk-aversion

$\gamma$.

**Figure 3.5:** Permutation tests noise-timing economic value densities




Note: This plot shows the performance fees distribution that the risk averse investor is willing to pay to switch from the random permutation simulations to the noise timing strategy for different levels of risk aversion $\gamma$.

### 3.6.2 Benchmarks

In this paragraph we consider different benchmarks in addition to the optimal *ex-ante* static portfolio. Specifically, an equally weighted portfolio[18], an equally weighted portfolio with cryptocurrency class constrained to 10% investment, and a portfolio which allocates weights according to random walk predictions. We further consider as an alternative strategy a volatility-timing strategy, similarly to Jondeau and Rockinger (2007), where the investor follows the mean-variance criterion, but assumes a time-varying conditional covariance matrix estimated with a DCC model under the assumption of a joint normal distribution. We also consider the optimal *ex-ante* static portfolio when the estimation risk is negligible since the estimates of the sample mean and sample variance-covariance can affect the predictions and the mean-variance optimal weights selection especially when we consider a static portfolio. In addition, the estimation risk is particularly relevant for portfolios of cryptocurrencies given the higher potential estimation errors in their parameters due to their high volatility

[18]DeMiguel et al. (2009) show that sample-based mean-variance models difficultly outperform naive $1/N$ portfolios.

(Platanakis & Urquhart, 2019). To mimic a static portfolio with negligible estimation risk we consider as estimate of mean and variance the full sample mean and variance.

**Table 3.7:** Noise-timing against benchmarks

| Strategy | $\mu$% | $\sigma$% | SR | $\Delta_1$(bp) | $\Delta_{10}$(bp) | $\tau_1^{be}$(bp) | $\tau_{10}^{be}$(bp) |
|---|---|---|---|---|---|---|---|
| Dynamic | 8.27 | 4.64 | 1.32 | - | - | - | - |
| *Benchmark* | | | | | | | |
| Static | 3.41 | 6.39 | 0.22 | 481.56 | 584.54 | 9.36 | 11.20 |
| Static No Est Risk | 6.10 | 7.84 | 0.51 | 225.87 | 422.70 | 4.38 | 8.08 |
| Equally Weighted | 6.46 | 21.04 | 0.21 | 387.22 | 2570.12 | 7.54 | 45.69 |
| Equally Weighted Constr. | 6.34 | 9.74 | 0.44 | 220.72 | 575.76 | 4.28 | 11.02 |
| RW | 5.12 | 5.39 | 0.57 | 304.68 | 351.21 | - | - |
| Volatility Timing | 5.67 | 7.28 | 0.49 | 263.80 | 422.08 | - | - |

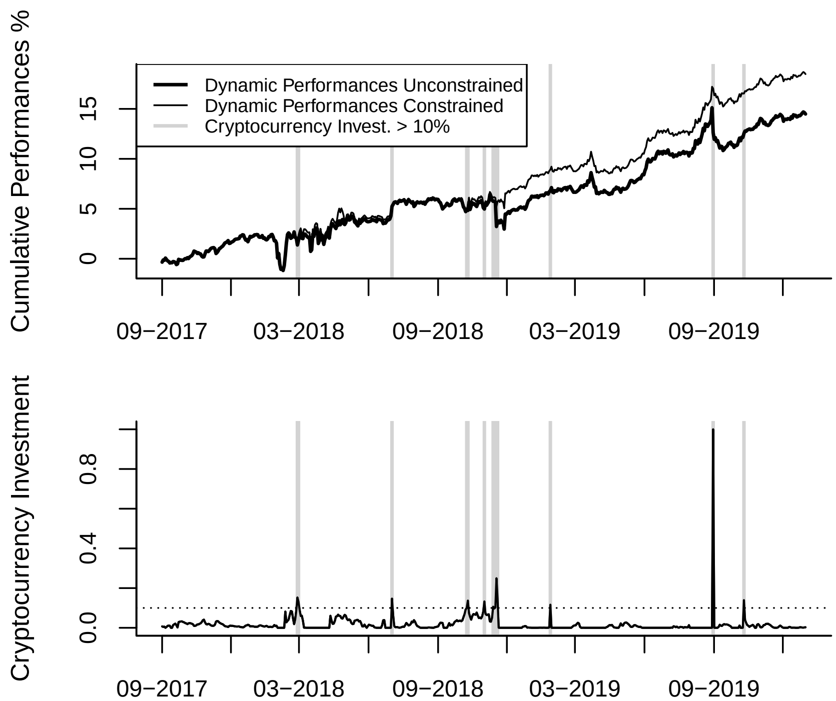
Note: The table reports the annualized mean realized returns in percentage ($\mu$%), annualized realised volatilities in percentage ($\sigma$%), and realised Sharpe ratios in basis points (SR) for the noise timing strategy (Dynamic), optimal *ex-ante* static strategy (Static), optimal *ex-ante* static strategy (Static No Est Risk) with negligible estimation risk, the equally weighted portfolio (25% invested in each class), the equally weighted constrained portfolio (10% maximum portfolio weight on cryptocurrency), the random walk predictions portfolio (RW), and a volatility timing portfolio. The table also reports the average annualised basis point fees ($\Delta_\gamma$) that an investor with quadratic utility and constant relative risk aversion of $\gamma = 1$ or $\gamma = 10$ would be willing to pay to switch from the static portfolios to the noise-timing strategy. Break-even proportional transaction costs per transaction in basis point are reported distinguishing from investors with risk aversion $\gamma = 1$ ($\tau_1^{be}$) and $\gamma = 10$ ($\tau_{10}^{be}$).

Table 3.7 reports the annualised means, volatilities, and Sharpe ratios of each strategy alongside with the economic value of the noise timing strategy and the break-even transaction costs. The noise-timing strategy has highest annualised realised return, lowest standard deviation, and larger Sharpe ratio with respect to the benchmark strategies. The paper main findings are verified as the noise-timing strategy has positive values against all the benchmarks. The economic value of noise-timing against the equally weighted portfolio for high risk-averse investors, $\gamma = 10$, represents a special case. To explain the resulting high fee of about 2,570.12 basis point it is sufficient to consider that the naïve portfolio allocates a fixed weight of 25% of the wealth in the cryptocurrency asset class, generating very high volatility - annualised standard deviation of 21.04% - which is largely disliked by high risk-averse investors.

### 3.6.3 Cryptocurrency investment

In the noise timing optimization problem we impose a cryptocurrency investment threshold above which the investor can not invest. We set the cryptocurrency investment limit equal to 10%. We now present the optimal portfolio weights when this limit is relaxed and we allow our model to allocate wealth into the riskier class in absence of any constraint. Figure 3.6 upper part shows the cumulative noise timing performances for the two alternatives. The constrained realised performance is represented by the thin black line, while the unconstrained one is plotted with the thick black line. The grey bars correspond to those days in which the model proposes an optimal cryptocurrency allocation higher than the 10% of investor wealth. The bottom part of the plot shows the unconstrained portfolio weights over time. It is found that a higher cryptocurrency weight is chosen only a few times and mainly when the other classes all have expected returns lower than the target returns, or lower than zero. This suggests that, unconstrained, the model does not allocate too high weight to cryptocurrency, only rarely at points when other classes provide poor or negative expected returns. Results do not significantly change if we assume the constraint on the cryptocurrency investment, and performance trends are similar. However, there is an insight that the unconstrained portfolio has higher variability than the constrained one, possibly resulting in structural breaks. Figure 3.6 performances have as target return 8%, but if the target return increases then the unconstrained portfolio might allocate too high weight to cryptocurrency trying to match the target return. This would result in very high volatility and severe losses in case of inaccurate prediction. Therefore, we maintain that it is reasonable to impose a limit to the allocation optimization for the cryptocurrency class.

**Figure 3.6:** Dynamic performances constrained and unconstrained cryptocurrency investment




Note: The figure shows the constrained (thin black line) and unconstrained (thick black line) cryptocurrency investment noise timing realised cumulative performances expressed in percentage. The grey bars represent those days in which the unconstrained model suggest cryptocurrency portfolio weights higher than the 10% threshold. The bottom part plots the evolution over time of the unconstrained optimal cryptocurrency portfolio weights where the horizontal dotted line represent the 10% threshold.

### 3.6.4 Outliers and structural breaks

Outliers can influence the estimation procedure and determine structural breaks, and ultimately affect the paper main findings. We check how results change when filtering the returns time series for outliers. We define an outlier as an observation that lies outside four times the Inter-Quartile Range (IQR) measured from the median. On detection, an outlier is replaced with the highest, or lowest in the case of a negative outlier, value in the sample that lies within the set IQR limit. Results are robust and the economic valuation of the noise-timing strategy against the static strategy is positive.

Table 3.8 panel a presents a comparison of portfolio weights for the case when outliers are removed and replaced in the sample (No-Outliers) and the case in which the outliers

**Table 3.8:** Comparison between removed outliers case and not removed outliers case

Panel a)

| | Dynamic portfolio Average investment | | | | Static portfolio Investment | | | |
|---|---|---|---|---|---|---|---|---|
| | Stock | Bond | Gold | Crypto | Stock | Bond | Gold | Crypto |
| No-Outliers | 16.65 | 72.94 | 8.84 | 1.57 | 20.10 | 73.25 | 0.00 | 6.64 |
| Outliers | 16.64 | 72.46 | 9.42 | 1.48 | 20.37 | 72.83 | 0.03 | 6.77 |

Panel b)

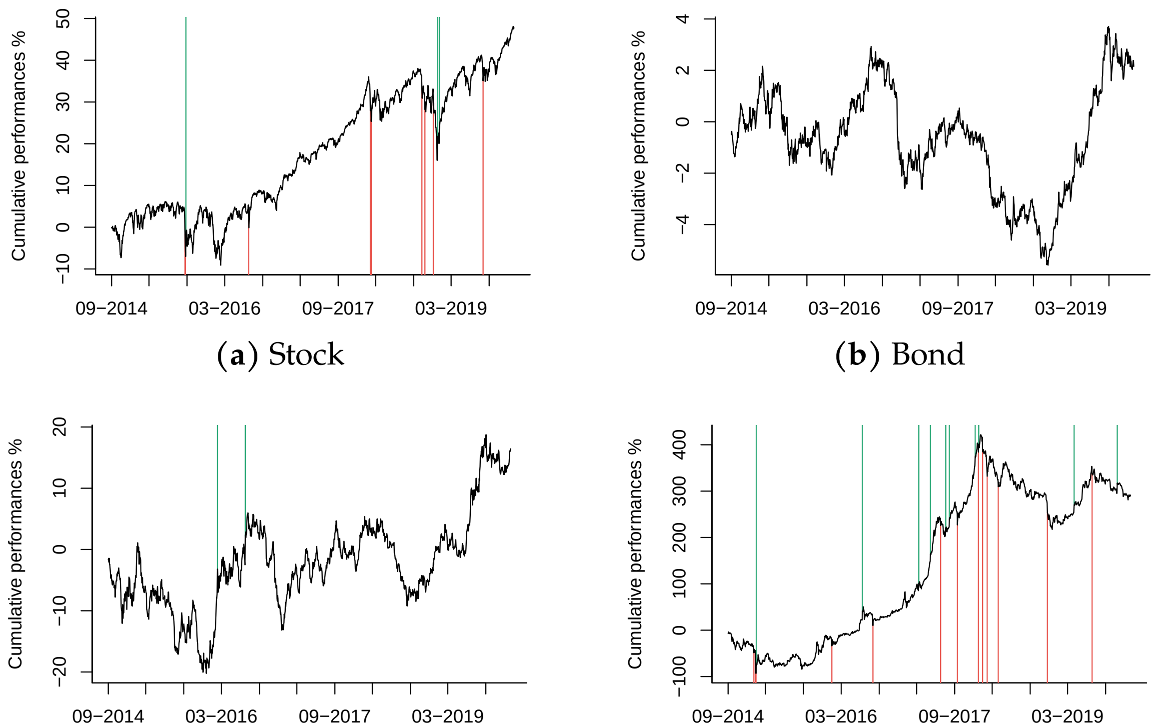
| | Dynamic portfolio | | | Static portfolio | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $\mu\%$ | $\sigma\%$ | SR | $\mu\%$ | $\sigma\%$ | SR | $\Delta_1$(bp) | $\Delta_{10}$(bp) | $\tau_1^{be}$(bp) | $\tau_{10}^{be}$(bp) |
| No-Outliers | 6.68 | 5.88 | 0.94 | 4.19 | 4.88 | 0.37 | 246.19 | 307.56 | 4.94 | 6.03 |
| Outliers | 8.27 | 4.64 | 1.32 | 3.41 | 6.39 | 0.22 | 481.56 | 584.54 | 9.36 | 11.20 |

Note: Portfolio weights allocation comparison between sample with outliers replaced as in section 5.4 (No-Outliers) and sample with outliers (Outliers) for the noise timing strategy and the static strategy (panel a). Comparison of portfolio performances (panel b), particularly annualized mean realized returns in percentage ($\mu\%$), annualised realised volatilities in percentage ($\sigma\%$), and realised Sharpe ratios in basis points (SR) for each strategy, and the average annualised basis point fees ($\Delta_\gamma$) that an investor with quadratic utility and constant relative risk aversion of $\gamma = 1$ or $\gamma = 10$ would be willing to pay to switch from the static portfolios to the noise-timing strategy. Break-even proportional transaction costs per transaction in basis point are reported distinguishing from investors with risk aversion $\gamma = 1$ ($\tau_1^{be}$) and $\gamma = 10$ ($\tau_{10}^{be}$).

data are retained in the sample (Outliers). The portfolio weights are similar for both the dynamic noise-timing strategy and the static strategy when including or excluding outliers. Panel b of the table presents the paper analysis results, where outliers are kept, and in the case in which the outliers are removed. The results refer to a target return of 8% and, overall, the two cases present similar conclusions.

Figure 3.7 illustrates the cumulative returns in percentage of the four asset classes overlapped with green bars and red bars representing the positive returns outliers and negative returns outliers respectively. The stock market registers a low number of outliers during the entire sample, with fewer outliers of the gold price, and none in the bond market. On the contrary, the cryptocurrency market is characterised by a relatively higher number of outliers in line with its higher volatility.

**Figure 3.7:** Outliers on cumulative returns



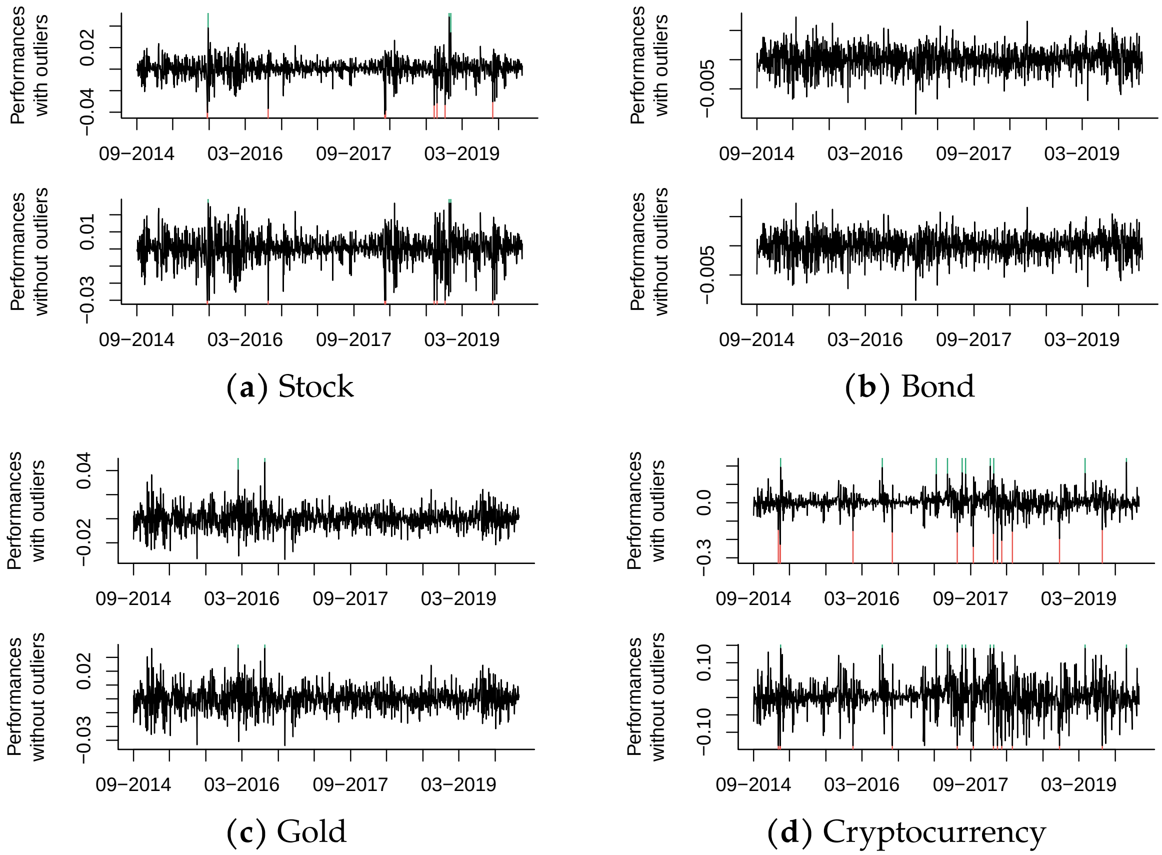

(**a**) Stock (**b**) Bond (**c**) Gold (**d**) Cryptocurrency

Note: This figure illustrates the cumulative percentage returns for stock (a), bond (b), gold (c), and cryptocurrency (d) over the period Aug 2014 - Dec 2019, together with positive outliers in green, negative outliers in red calculated from returns time series.

Figure 3.8 presents the returns for stock, bond, gold, and cryptocurrency overlapped with the outliers bars. This figure provides a better understanding of the outliers location in time as each green or red bar indicates the days in which the positive or negative outliers occur, denoted by spikes in the return time series. We confirm that outliers does not represent an issue for the robustness of the main results.

As the presence of outliers can further indicate the existence of structural breaks in the data, we investigate whether this influences our main findings. Originally, we calculate the noise traders' predictions in equation 3.4 using a 3-year rolling window. The adoption of a three year window may be sensitive to or influenced by the presence of structural breaks, hence we follow Karstanje et al. (2013) and Pesaran and Pick (2011), and we average predictions generated using different rolling window lengths

**Figure 3.8:** Outliers returns




Note: This figure illustrates the returns for stock (a), bond (b), gold (c), and cryptocurrency (d) over the period Aug 2014 - Dec 2019, together with positive outliers in green, negative outliers in red calculated from returns time series.

to minimise the impact of structural breaks on results. Table 3.9 compares the paper results with those obtained taking the average of four different predictions based on 6 months, 1, 2, and 3 years window lengths. The dynamic timing strategy using the average predictions outperforms the static strategy and the economic valuation of noise timing is confirmed positive and increasing in traders' risk-aversion and target return.

**Table 3.9:** Rolling Window Size

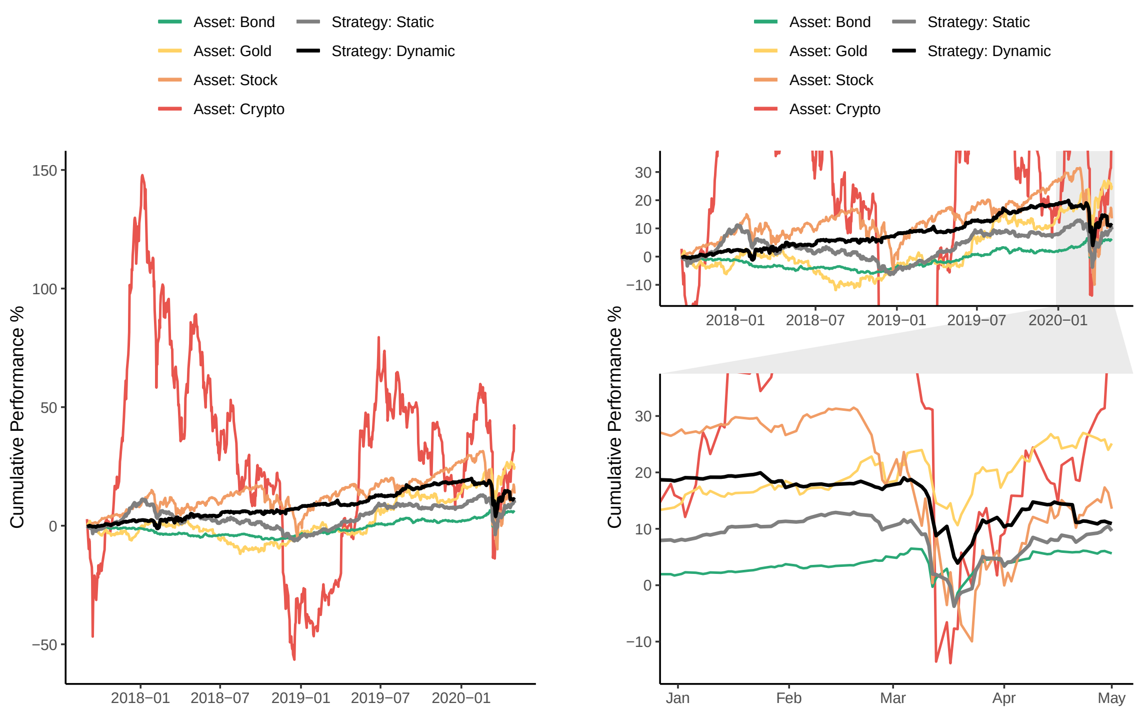
| | | Dynamic portfolio | | | Static portfolio | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\bar{\mu}$ | Rolling Window | $\mu$% | $\sigma$% | SR | $\mu$% | $\sigma$% | SR | $\Delta_1$(bp) | $\Delta_{10}$(bp) | $\tau_1^{be}$(bp) | $\tau_{10}^{be}$(bp) |
| 6% | 3-Year | 6.19 | 4.47 | 0.92 | 3.00 | 4.99 | 0.20 | 313.71 | 348.31 | 6.68 | 7.25 |
| | Average | 7.32 | 4.78 | 1.09 | 3.00 | 4.99 | 0.20 | 422.78 | 443.87 | 8.00 | 8.27 |
| 7% | 3-Year | 7.39 | 4.55 | 1.16 | 3.20 | 5.68 | 0.21 | 412.89 | 479.06 | 8.67 | 9.89 |
| | Average | 7.38 | 4.81 | 1.10 | 3.20 | 5.68 | 0.21 | 411.11 | 465.55 | 7.76 | 8.66 |
| 8% | 3-Year | 8.27 | 4.64 | 1.32 | 3.41 | 6.39 | 0.22 | 481.56 | 584.54 | 9.36 | 11.20 |
| | Average | 7.46 | 4.85 | 1.10 | 3.41 | 6.39 | 0.22 | 402.32 | 495.38 | 7.73 | 9.37 |
| 9% | 3-Year | 9.01 | 4.81 | 1.43 | 3.63 | 7.11 | 0.22 | 534.62 | 677.48 | 10.27 | 12.38 |
| | Average | 7.66 | 5.00 | 1.11 | 3.63 | 7.11 | 0.22 | 404.04 | 536.45 | 7.45 | 9.75 |
| 10% | 3-Year | 10.20 | 4.99 | 1.61 | 3.85 | 7.84 | 0.23 | 631.65 | 819.96 | 11.92 | 15.25 |
| | Average | 8.63 | 5.14 | 1.27 | 3.85 | 7.84 | 0.23 | 479.95 | 658.46 | 8.60 | 11.64 |
| 11% | 3-Year | 11.06 | 5.10 | 1.74 | 4.08 | 8.57 | 0.24 | 697.93 | 940.41 | 13.04 | 17.30 |
| | Average | 9.68 | 5.30 | 1.42 | 4.08 | 8.57 | 0.24 | 563.43 | 792.92 | 9.42 | 13.08 |

Note: The table shows how the performance of the noise-timing strategy varies with the target expected return ($\bar{\mu}$) and using the predictions from the 3-Year rolling window and the averaged predictions using 3-Year, 2-Year, 1-Year, and 6-Month rolling windows for equation 3.4. The table reports the annualized mean realized returns in percentage ($\mu$%), annualised realised volatilities in percentage ($\sigma$%), and realised Sharpe ratios in basis points (SR) for each strategy, and the average annualised basis point fees ($\Delta_\gamma$) that an investor with quadratic utility and constant relative risk aversion of $\gamma = 1$ or $\gamma = 10$ would be willing to pay to switch from the static portfolios to the noise-timing strategy. Break-even proportional transaction costs per transaction in basis point are reported distinguishing from investors with risk aversion $\gamma = 1$ ($\tau_1^{be}$) and $\gamma = 10$ ($\tau_{10}^{be}$).

### 3.6.5 Covid-19 period extension

We extend the sample period to include the Covid-19 period from December 31, 2020 to beginning of May 2020. We consider the day on which China first announces and alerts the World Health Organization (WHO) about the existence of the new disease as the Covid-19 period start date. We look at this period to seek for noise timing strategy characteristics and abilities during high turmoil market times. This period is known to have strongly and negatively impacted the economies of several countries. In our data, it is visible how all the asset classes, except for the safe haven gold, experienced a severe loss. Figure 3.9 shows the entire sample extended with the Covid-19 period cumulative performances for the stock, gold, bond, cryptocurrency, noise timing dynamic strategy, and static strategy. The noise timing strategy, albeit suffering a negative impact comparable to the other classes during the pandemic, is found to sufficiently provide good performances. The minimum cumulative noise-timing return is positive 3.9%, while the static portfolio drops to negative 3.7% and even more dramatic drops are registered individually in the stock, bond, and cryptocurrency markets. The noise timing strategy is able to generate sufficient returns during the entire sample to counteract the losses caused by the pandemic and very turbulent market times in general.

**Figure 3.9:** Covid-19 period extension




(**a**) Large scale (**b**) Small scale and zoom

Note: The figure illustrates the cumulative return performances in percentage for the noise timing strategy (black line), benchmark optimal *ex-ante* static portfolio (grey line), and the four asset classes bond (green line), gold (yellow line), stock (orange line), and cryptocurrency (red line) for the period Aug 2014 - Apr 2020. The large scale ensures the cryptocurrency path is entirely visible and the small scale allows a better understanding of results by shrinking the y-axis limits. The small scale further zooms in on the Covid-19 period from December 31, 2019 to beginning of May 2020.

## 3.7 Conclusions

This paper assesses the economic value of noise-timing for short-horizon and risk averse investors. The noise timing strategy solves a dynamic optimization problem under the mean-variance framework with the objective of minimising the portfolio variance given a target portfolio return. To conduct the allocation optimization we need an estimate of both the next period expected return and variance-covariance matrix. We propose a model for the next-period expected returns that is solely driven by noise. We then use the forecasts as an estimate of future returns in the mean-variance optimization alongside with the assumption of constant sample variance-covariance matrix. The assumption is in line with the approach adopted by Fleming et al. (2001) and ensures the results of the economic value depend only on the noise component excluding any uncertainty that may arise if we allow time variation in the portfolio weights coming from the variance-covariance matrix. The price noise is estimated using a Kalman filter which decomposes the price time series based on a state space model. The state space model assumes the price is given by the sum of a permanent, efficient, component and a noise component. The model is estimated with maximum likelihood calculated with the Kalman smoother. The economic value of noise-timing is finally calculated in terms of performance fee following Fleming et al. (2001), Jondeau and Rockinger (2007), and Karstanje et al. (2013). Particularly, the economic value of noise timing is the maximum performance fee a risk averse investor is willing to pay every year to switch from a benchmark strategy, the optimal *ex-ante* static portfolio with same target return of the dynamic portfolio, to the noise-timing strategy. Our main findings provide evidence that the noise timing strategy has statistically positive value. Risk averse investors are willing to pay an annual performance fee of about 314/940 basis point to switch from the benchmark strategy to the noise timing strategy.

This paper provides interesting contributions to the noise-trader theory proposed by Black (1986) and to the finance literature more broadly. We propose a model that allows to estimate next period traders beliefs, previously considered unpredictable, exploiting a Kalman filter to extract the unobserved price noise component. We exploit this forecasts to create optimal *ex-ante* strategies that are able to hedge and speculate on the noise risk, namely that risk such that price deviates from fundamental in absence of fundamental change. This paper therefore proposes a method to manage this source of price-risk that has been neglected by the portfolio and risk management literature. The positivity of the economic value of noise timing is robust to a series of robustness tests which consider the estimation risk and multiple benchmark strategies. The economic value of noise timing is higher for more risk averse investors suggesting that different type of investors can perceive a different degree of sensitivity to the noise risk.

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# Appendix

## 3.A State space model implementation

The likelihood of the state space model in equations 3.2a-3.2b is implemented in R and calculated using the Kalman filter which provides state estimates and estimates of their uncertainty (see Durbin and Koopman (2012)). Tusell (2011) summarises a variety of optimization routines. Among these, we use the Kalman filter and smoother from KFAS package by Helske (2017). KFAS contains the Kalman smoother which is a backward recursion after the Kalman filter forward recursion. The Kalman smoother facilitates the price series decomposition into the unobserved permanent and noise components as, at each time $t$, it provides new state estimates based on all current and past observations. The likelihood is then optimized using the quasi-Newton BFGS algorithm proposed by Broyden, Fletcher, Goldfarb, and Shanno. Following Brogaard et al. (2014) and Hendershott and Menkveld (2014), we run the optimization for the parameters $\phi$, $\sigma_w$ and $\sigma_w$. To prevent instability in the quasi-Newton optimization such that routines often lead to very persistent $\phi$ if all the parameters are let free, $\phi$ is fixed on a 10-point grid from 0 to 0.9. For each $\phi$, $\sigma_w$ and $\sigma_w$ range from 0 to an asset-specific upper bound assumed to be the 80% of the asset's unconditional variance. We keep the parameterisation that yields highest likelihood.

# Chapter 4

# Transition versus physical climate risk pricing in euro area financial markets: A text-based approach

## Preface

I developed this paper during my visiting at the European Central Bank (ECB). I joined the Directorate General of Monetary Policy at the ECB, and in particular the Capital Markets and Financial Structure Division, as a PhD Trainee in September 2020. The paper concerns green finance issues and represents a research collaboration between the ECB and the University of Manchester.

This paper contributed to the internal ECB Strategy Review on Climate Change issues, and to the forthcoming report publication by the Organisation for Economic Co-operation and Development (OECD) on ”Financial Markets and Climate Transition”.

I presented the paper during the conference meeting of *Committee on Financial Markets* held by the OECD in February 2021. The paper was also presented in a seminar at the Central Bank of Ireland in May 2021, and internally to the ECB at the Directorate of Financial Stability.

This paper is a joint work with Dr. Giovanna Bua, Dr. Daniel Kapp, and Mr. Federico Ramella. As a co-authored work, my individual contribution to this paper was substantial. I conducted the whole empirical analysis, including the textual analysis (infrastructure now used by the division), data analysis, data cleaning, coding, study and application of empirical models etc. I actively contributed to the development of the original research question and searched sources from relevant existent literature. I exhaustively worked at the writing and drafting of the paper. The discussion, exchange of opinions, guidance, and effort in editing the paper draft from co-authors were essential to the development and improvement of this research.

Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect the views of the European Central Bank. Any errors and omissions are the sole responsibility of the authors.

**Abstract**

This paper analyses the pricing of climate risk in equity markets. We collect scientific texts on the topic of physical risk and transition risk and build two novel vocabularies. We apply the cosine-similarity approach suggested by Engle et al. (2020) to compare the vocabularies with a corpus of European daily news and construct a physical risk index and a transition risk index. The risk indices are integrated into a Fama-French five factor asset pricing model to test the sensitivity of daily equity returns to climate shocks, controlling for several exposure metrics. News on physical risk and transition risk are found to carry relevant information which is reflected in asset prices – with transition risk appearing to be the predominant climate related concern for investors. Firms with poor environmental (E) and ESG performances, and firms with high Greenhouse Gas emissions level and intensity are negatively related to rises in transition risk. Excess returns of firms with low E and ESG scores decline in the event of physical risk news. While investors appear to penalise high climate risk exposure, there is not significant evidence of a positive valuation of less exposed firms.

## 4.1 Introduction

Since 1980 there has been a three-fold increase in the number of catastrophes caused by natural hazards, with 820 such events recorded in 2019. The summer of 2019 witnessed the hottest July on record globally and the repeated breaking of high temperature records across Europe and parts of the US.[1] The associated economic costs have also increased from around USD 60 billion in 1980, to USD 150 billion in 2019, with a peak of USD 350 billion in 2018.[2] There is high consensus among scientists that changes in climate and global warming are attributable to anthropogenic greenhouse gas (GHG) emissions. Accordingly, the Paris Agreement

[1] Law (2019).
[2] Munich Re NatCatSERVICE.

goal to limit global warming below 2°C, compared to pre-industrial temperature level set specific timelines to reach net-zero emissions.[3] The financial sector can help to reach these goals through a sustainable allocation of resources, inter alia through identifying companies which are most/least apt to react to climate risk and impact their relative financing costs.

The literature agrees that climate change poses challenges for companies, and in turn for the financial system, mainly through two distinct risk channels: physical risk and transition risk. Physical risk materialises in the form of financial losses resulting from extreme weather events (e.g., floods, hurricanes, droughts, wildfires, extreme temperatures) and gradual shift in climate patterns (e.g., sea level changes, glacial melting, and ocean temperatures). Companies are often affected through damaged assets, disruption of business operations and/or changes in consumer preferences. Physical risk can also translate into credit risk for banks - if climate change impacts the creditworthiness of counterparties, market risks - in case of abrupt repricing of assets, and liquidity risks. Transition risk, on the other hand, arises from a costly adjustment towards a carbon neutral economy and is usually of most concern for companies with large dependencies on energy and fossil fuels. It can be prompted, for example, by changes in climate and environmental policy, technological advances, and shift in public preferences (ECB, 2019; NGFS, 2020). Depending on how fast and orderly the process of decarbonisation occurs, the impact of transition risk may worsen causing large swings in asset prices and stranded assets.

This paper studies the pricing of climate risk in equity markets both in the form of transition and physical risk. Building on the assumption that events covered in newspapers can carry relevant information on both of these risks, we exploit textual analysis to build a physical risk index and a transition risk index with the aim to capture the multifaceted characteristics of each risk type. As a first step, we collect authoritative and scientific texts on the topic of physical risk and transition risk and compare them with the corpus of European daily news from *Reuters News*. Relying on two novel vocabularies, we apply the cosine-similarity approach and estimate two

[3]Climate neutrality, or net-zero emissions, is achieved when GHG emissions caused by human-related activities are compensated by removing the same GHG amount out of the atmosphere.

time series that roughly represent the portion of daily news dedicated to either the physical risk or transition risk, denoted as *concern*. We then construct a *Physical Risk Index* (PRI) and a *Transition Risk Index* (TRI) to capture climate-related risk shocks as residuals from autoregressive processes. Since *Reuters News* is widely consumed by European market participants, we believe that the resulting indices may contain relevant information which is digested by financial market participants. We include the time series of risk shocks in a Fama-French five factor asset pricing model (Fama & French, 2015) to test the sensitivity of daily equity price returns of EuroStoxx 600 Index constituents for the period 2015-2019. Equity excess returns are sorted according to several metrics of climate exposure (GHG emissions level; GHG emissions intensity; Environmental (E) score; Environmental, Social and Government (ESG) score) and aggregated into *green* and *brown* portfolios. We further conduct a sectoral analysis by aggregating returns of firms belonging to the same industry sector (NACE Rev. 2).[4]

Our results suggest that news on physical risk and transition risk carry relevant information which is reflected in asset prices – with transition risk appearing to be the predominant climate related concern for investors. Firms with poor environmental and ESG performances, as well as firms with high GHG emissions level and emissions intensity are significantly and negatively related to transition risk shocks. Additionally, excess returns of low E and low ESG scores portfolios decline as the market is surprised by physical risk news. While investors appear to penalise high climate risk exposure, we find no significant evidence in favour of a more positive valuation of less exposed firms, suggesting negative screening as a predominant investment strategy. The sectoral analysis suggests that investors combine sectoral classification information with detailed firm-level characteristics within their investment decision process, such as the firms' commitment in reducing carbon emissions.

This study contributes to the evolving and growing strand of literature which focuses on understanding the impact of climate change on financial markets. Most studies on the consequences of physical risk for asset prices have mainly focused on specific events (Addoum et al., 2020; Hong et al., 2019; Kruttli et al., 2019). Hong et al.

[4]Eurostat (2008).

(2019), for example, focus on drought indices showing that they are predictive of food company stock returns. Addoum et al. (2020) consider high temperature events and find limited impact on companies' sales, productivity, or earnings. Even if the literature on transition risks is more developed, results concerning the potential presence of risk premia for companies most exposed to climate change are overall not conclusive. While some studies find that investors require additional compensation for holding brown assets, especially following the Paris Agreement, others provide no evidence of price differentials between green and other securities (Alessi et al., 2019; Bolton & Kacperczyk, 2019; In et al., 2019).

Researchers identify as critical challenges for conflicting empirical results the absence of agreed metrics of firms' climate risks exposure and the difficulty in identifying proper climate risk measures. Recently, some studies have resorted to textual analysis in order to refine the identification of climate risks (Ardia et al., 2020; Batten et al., 2016; Engle et al., 2020; Faccini et al., 2021; Meinerding et al., 2020). While they improve on the previous literature, these studies do not distinguish between the two types of risks (Engle et al., 2020), or they focus on only transition risks (Batten et al., 2016; Meinerding et al., 2020), or they identify sub-topics of physical and transition risks (Ardia et al., 2020; Faccini et al., 2021).[5]

The methodology proposed by this paper, which combines the cosine-similarity approach suggested by Engle et al. (2020) with the screening of texts on the topic of physical and transition risks, allows us to distinguish between the two type of risks considering the multifaceted characteristics of each type of risk. The physical risk index, for instance, includes both extreme and chronic hazards directly caused by climate change. The transition risk index includes different aspects of climate risk such as technological advances and environmental policies. We also consider the fact that

[5] Using a textual analysis approach, Ardia et al. (2020) identify eight climate change sub-categories, labelled by the authors as "Financial and Regulation", "Agreement and Summit", "Public Impact", "Research", "Disaster", "Environmental Impact", "Agricultural Impact", and "Other". Faccini et al. (2021) filter news by "climate change" and "global warming" to then employ a Latent Dirichlet Allocation approach to cluster news topics. The authors label the resulting topics into a "Natural Disasters", "Global Warming", "International Summit", and "U.S. Climate Policy" factors. Our paper differs from previous studies as we separate climate change risks into physical and transition risk capturing the entire multifaceted characteristics and multiple dimensions of the two climate risks without discarding relevant categories, e.g. chronical hazard for physical risk or technological advances for transition risk. Our climate risk indices also differ from recent studies which exploit textual analysis to build firm-level climate factors (Li et al., 2020; Sautner et al., 2020) as we capture market-wide climate risks

the two risks are intertwined, creating two vocabularies where common terms are *context-scaled*.

We consider multiple variables as potential proxies of firms' exposure to climate risks (E score, ESG, GHG emissions level, GHG emissions intensity, and sectors) to address the limit of data reliability identified in the literature and to provide interesting insights on the informational content of each metric. In particular, we can infer the information enclosed within each exposure metric by looking at the relationship between physical (transition) risk and the excess returns of portfolios constructed according to each metric, such that if a significant relation is found this would imply the exposure metric contains information to proxy firms' exposure to the physical (transition) risk.

Our results are informative for investors, policy makers, and financial institutions to understand to what extent the financial market reacts to stimuli from the process of adjustments toward a carbon neutral economy. They further inform investors on the equity sensitivity to physical and transition risk shocks for a better management of climate risks.

The remainder of this paper is organised as follows: Section 4.2 provide the background information on physical and transition risk together with their associated financial risks; Section 4.3 presents a technical review of the multiple metrics of firms' climate risk exposures; Section 4.4 provides a detailed methodology of the textual analysis adopted in this paper and describes the constructed physical and transition risk vocabularies and risk measures; Section 4.5 introduces the asset pricing model; Section 4.6 describes the data; Section 4.7 discusses the results; Section 4.8 concludes.

## 4.2 Physical and transition risks: description and source of financial risk

To gain an initial understanding of the physical and transition risk characteristics as well as their link with the financial system, this paragraph briefly describes these climate-related risks and provides an overview of the associated financial risks. Climate-related risks represent a source of financial risk with repercussions for companies, banks, financial stability, and thus the wider macro-economy (NGFS, 2018) and they can affect the financial system through two main channels, namely physical risk and transition risk. Despite physical and transition risks belonging to the same risk class, they present self-characteristics that are unique which make them differ and possibly move independently in reaction to climate events (Engle et al., 2020). As result, they have the potential to impact financial markets differently (ECB, 2019), necessitating the need to assess the transmission of these risks separately.

### 4.2.1 Physical risk

*Physical risk refers to the adverse effects of physical hazards caused by global warming and climate change on exposed and vulnerable elements, including societies and ecosystems*. In particular, the hazard is represented by the occurrence, or probability of occurrence, of a physical event or trend with potential unfavourable effects. It can be classified as acute, if related to extreme weather or climate events such as heat or cold waves, floods, wildfires, storms, landslides; or chronic, if associated to incremental shifts in climate parameters (like temperature, precipitation, and wind) and longer-term changes in climate patterns involving phenomena such as sea-level rise, permafrost thawing, rising temperatures, drought, and oceans acidification. Exposure refers to the inventory of elements - people, livelihoods, species or ecosystems, services, and resources, infrastructure, or assets - in areas and settings that could be adversely affected. Vulnerability refers to the propensity or predisposition of exposed elements to suffer damages due to the hazardous event. It in turn depends on the sensitivity to harm, meant as the degree to which a social or natural system respond to a change in climate, and on the lack of capacity to cope and adapt, meant as the failure to anticipate and transform structure, functioning, or organization to better survive hazards. Physical risk therefore rises from the interaction of hazard, exposure, and vulnerability which combined represents the main factors driving the risk.

*From a financial perspective, physical risk represents the loss of value or the increased costs due the disruptive impact of chronic and acute physical events on exposed and vulnerable financial participants*. For instance, resource-intensive companies whose production requires high consumption of energy and water might be adversely affected by heat waves and water scarcity experiencing higher resource costs. Extreme weather events might also cause business interruptions, damage or permanent loss of infrastructures and facilities giving rise to reparation and reconstruction costs, lowering the collateral value of firms, and reducing their financing ability. In addition to the hazard occurrence, also its probability of occurrence harms financial participants. For instance, firms whose value chain or production plants are located in risky areas like floodplains or fire-prone areas might experience relocation costs to move facilities to less vulnerable and less exposed places. Physical risk might also have unfavourable consequences on specific sectors which rely on stable weather conditions, such as logistics and transportation, as well as on good resource availability and biodiverse ecosystems, such as fishery and agriculture. It further indirectly threatens investors, credit institutions, and banks with portfolios composed of risky assets of exposed firms and sectors. Besides, as climate change tightens, hazards become more frequent and intense resulting in a rise of vulnerable areas and enhancing the severity of physical risk impacts. From here, the need arises for exposed and vulnerable firms to undertake a number of adaptive measures aimed at increasing their resilience to hazards. The adaptation process can be costly and require new investments to innovate or build resilient infrastructures to cope with physical events. Companies and financial institutions should therefore consider physical risk in their strategy and risk management, run stress tests and scenario analyses, and closely monitor the potential adverse impacts. They can further consider new investment opportunities -

such as consulting services for the selection of production locations and for the construction of infrastructure resistant to extreme weather conditions - to increase competitiveness and protect reputation. Physical risk induces also socio-economic effects such as migration and social unrest, changes in the availability of resources and increase in the volatility of commodity prices. Additionally, it compromises food security, impacts human health, and reduces labour work raising the need for a macro climate action by governments.

### 4.2.2 Transition risk

*Transition risk refers to the process of adjustments toward a climate neutral world with the aim to reduce the rate of climate change and mitigate its adverse effects.* Climate neutrality, or net-zero emissions, is achieved when GHG emissions caused by human-related activities are compensated by removing the same GHG amount out of the atmosphere. To this end, human-caused emissions must rapidly reach their peak and be reduced to enable the offset of the remaining GHGs with an equivalent amount of carbon removal. There is high consensus among scientists that changes in climate and global warming are attributable to anthropogenic emissions of GHGs. Under the legally binding international treaty on climate change known as Paris Agreement, involved countries agreed to undertake a 5-year cycle climate action to limit global warming below 2°C, preferably 1.5°C, compared to pre-industrial temperature levels. To achieve this temperature goal, the world needs to follow specific timelines to reach net-zero emissions according to the target scenario, limiting to 2°C or 1.5°C, and according to the type of GHG, CO2 and non-CO2. Particularly, model pathways with no overshoot of 1.5°C (2°C) project global anthropogenic CO2 emissions to decline by 45% (25%) from 2010 levels by 2030 (2050) and reach net-zero around 2050 (2070) (IPCC, 2018). Non-CO2 emissions projections are similar across scenarios and typically follow a more relaxed timeline to reach net-zero. In order to realise the transition process, it is vital that the economy evolves as well moving toward carbon neutrality.

*Transition risk represents therefore the set of financial risks associated with the process of* *adjustments toward a low carbon economy, typically triggered by the introduction of climate mitigation policies, technology advances, and shift in public preferences.* The severity of transition risk impact on the financial system depends on the speed to which the adjustments required to decarbonise the economy are implemented. Particularly, an abrupt transition would cause a large structural break and a substantial effect on the financial system. Despite the significant economic and financial impact, a disorderly transition is expected to lead to a better overall outcome in the long run than the scenario where the transition is not occurring at all. Additionally, financial risks can be contained by implementing an orderly transition which respects the climate target deadlines and that advances at a speed which enables the exposed subjects, such as carbon intensive firms, to have sufficient time and incentives to manage the risk and implement strategies to be aligned with the transition. Climate mitigation policies aim to reduce GHG emissions and promote activities to remove GHG from the atmosphere. However, the introduction of carbon taxes or regulations to cut GHG emissions can affect the value of financial assets. Riskier assets are likely to belong to the class of firms often referred to as brown, such as assets of firms with high level of GHG emissions, or assets of firms with poor performance ability in managing environmental risks. The process of reducing GHG can further penalise the business of firms which revenues highly rely on GHG emissions, i.e. high GHG emissions intensity firms. For instance, the expected value of future cash flows for carbon-intensive assets might fall as the market awareness of transition risk rises. Transition risk might generate stranded assets for exposed firms or downgrades of credit rating for firms with a lack of transparency in disclosing emissions levels or without a solid climate action plan. The cost of energies such as fossil fuels, like coal or oil, can increase to disincentivise the use of brown energy and make way for the use of renewable energies such as solar and wind. New opportunities can also arise and investments into new technologies can help firms in the energy transition and to reach the net-zero emissions target by offering carbon removal solutions, such as the direct air capture and storage (DACS) technology. Additionally, the shift in public sentiment or preferences can occur as investors perceive the rise in climate change related risks, and start moving wealth and capital away from brownest assets and companies who are not committed to reduce, i.e., their environmental impact.

## 4.3 Climate change risks and firms' climate risk exposures

In order to test whether financial market prices react to shocks to physical and transition climate risks we need to identify firms that are exposed to these shocks. In this section we provide an overview of measures of firms' climate risk exposures that have been used by the climate finance literature. We focus on GHG emissions levels, GHG emissions intensity, Environmental (E) score, Environmental, Social and Government (ESG) score, and NACE2 1-digit sectors classification. Our aim is to underline their informational content and different results reached in the literature. We identify measures of both transition and physical risk exposure.

In order to quantify exposure to transition risks, investors need to identify the climate policy sensitivity of a firm, such as the firm's reaction to changes in the regulatory framework related to the adjustment toward a low carbon economy (NGFS, 2020). Practitioners and supervisors have typically taken GHG emissions level or GHG emissions scaled by the firm's revenue (emissions intensity) as a proxy to assess the sensitivity to transition risk. The rationale is that carbon-intensive activities are more likely to be affected by policies aimed at reducing carbon emissions (Ardia et al., 2020; Bolton & Kacperczyk, 2019; In et al., 2019). However, empirical findings based on these measures are not conclusive. Bolton and Kacperczyk (2019), for instance, find that carbon premium is related to the level and to changes in emissions, but not on carbon intensity. In et al. (2019), on the other hand, by using carbon intensity, find that green firms outperform brown firms. Hsu et al. (2020) show that a long-short portfolio constructed from firms with high versus low toxic emission intensity within industry generates positive average excess return According to Bolton and Kacperczyk (2019) one reason why the premium is tied to total emissions is that regulations limiting emissions are more likely to target activities where the level of emissions is highest.

Other studies implement more sophisticated screening methodologies to test whether investors consider other metrics than GHG emissions to identify climate policy sensitive firms (Alessi et al., 2019; Engle et al., 2020; Görgen et al., 2020). Görgen et al. (2020), for instance, build an ad-hoc green-brown score based on carbon intensity, ESG scores, and adaptability score. ESG scores are intended to capture public perception as they are readily available for investors. Adaptability is added to capture the ability of firms to transition to a greener economy that can limit exposure. Alessi et al. (2019) build a greenness indicator combining ESG disclosure score (as a measure of transparency) with quantitative measures on emissions. Engle et al. (2020) focus only on the environmental dimension of the ESG score trying to identify the best proxy of climate change exposure.

Finally, some have also relied on sectoral analysis identifying the most climate sensitive activities such as the sectors with highest GHG emissions (see for example, Batten et al. (2016) and Choi et al. (2020)). This approach is particularly relevant in contexts where the lack of transparency in the calculation of other measures (i.e. ESG ratings) limits the ability of investors to interpret their content, and to steer their investment toward climate-hedged portfolios. In this context, investors may identify risky firms and simply pigeonhole firms into the industry they operate in, rather than using firm level information (Bolton & Kacperczyk, 2019). One limit of this methodology may result from the use of statistical classifications not originally designed to consider climate impact and that might neglect differences within sectors.[6] Batten et al. (2016), for instance, when studying the impact of transition risk on the energy sector find that it only impacts the abnormal returns of renewable energy companies. On the other hand, Choi et al. (2020) looking at the impact of google search volume for "global warming", find that sectors identified as major emissions sources by the Intergovernmental Panel on Climate Change (IPCC) earn lower stock returns than other firms.

While the designing of carbon benchmarks is complex, developing measures of climate physical exposure is also challenging for financial institutions and supervisors.

[6] In order to overcome this limitation, other studies have moved beyond this classification and remap all the sectors at NACE Rev. 2 4-digit level into new climate policy-sensitive sectors, combining criteria including carbon emissions, the role of the sector in the supply chain, and the existence of traditional policy institutions for the sector (Battiston et al., 2017)

Physical risk, in fact, depends on the interaction between the likelihood of the hazard (acute or chronic), the exposure of the system (the presence in a place that could be adversely affected by a hazard), and its vulnerability (the interaction between sensitivity and adaptation capacity) which captures the propensity to suffer adverse consequences from the exposure to the hazard. Most of these dimensions are determined by both local and specific factors, as well as the macro-context. The exposure depends on the location of the physical assets along the entire value chain. The sensitivity depends on sectoral aspects such as the dependence to natural resources or infrastructure assets. The adaptive capacity also involves specific behaviour of a company (such as insurance coverage or innovation), and broader scale elements such as the macro environment (e.g. the capacity of a country to adapt to climate hazards such as dykes reducing the exposure to flooding episodes).

Currently, most of the information on physical risk exposure is provided by some public sources (e.g. EC JRC Risk Data Hub) and private providers.[7] These databases, however, are not fully comparable as they focus on different risk aspects, types of hazard, and types of entity. Due to these limitations, most studies that explore the consequences of physical risks on asset prices have focused on specific events, limiting the number of dimensions that define exposure (see for example, Addoum et al. (2020), Hong et al. (2019), and Kruttli et al. (2019)). More recently, supervisors have started building indices of exposure considering both macro factors, such as countries resilience to climate change (DNB, 2017) and more granular factors like firms' climate-related information (ECB, 2021).

Alternatively, sectors can also be used to proxy physical exposure. While all economic sectors can suffer from climate natural disasters (EIB, 2021), those that include systems that are vulnerable to hazards are clearly more subjected to climate physical risks. In this framework, energy, transportation, telecommunications and water are highly exposed to physical hazard through their infrastructure assets. Primary economic activities (e.g., agriculture, forestry, fishing, mining and quarrying), are also exposed through the natural and food systems on which they depend directly.

[7] Four Twenty Seven, Carbone 4, MSCI Carbon Delta, Mercer, Trucost.

While most of the metrics described in this section have been used to capture exposure to transition rather than physical risks, their distinction is not always clear and their potential to capture physical exposure has been largely unexplored. E pillar and overall ESG scores, for example, may capture further aspects of climate risk than GHG production and transition exposure. Broadly speaking, ESG scores measure a company's environmental performance, social and governance performance (ESG). However, their exact information content depends largely on the methodology applied and the rationale of what constitutes good environmental performance for each credit provider. In general, to arrive at the final scores, most providers look at standard set of categories (such as emission, natural resources, and waste) and combine them with forward looking information (such as commitment to find eco-efficient solutions along the entire supply chain, emissions reduction targets, and water use reduction targets). These categories are then reweighted and (sometimes) normalised by the company's industry. Therefore, ESG scores may provide good ratings to high polluting companies, as they are recalibrated upwards by methodologies like best-in-practise, and also because they are more likely to engage in adaptation activities reducing their exposure.

In this study, we decided to use the same measures of exposure for both types of risk, in order to explore their information content and to tackle the ability of investors to distinguish physical and transition risks.

## 4.4 Measuring climate risk through text analysis: *tf-idf* and cosine similarity

To test whether financial markets are sensitive to shocks to physical and transition climate risks we need proxies to measure risks. We exploit newspaper content to identify shocks to physical and transition risks following the textual analysis approach used by Engle et al. (2020) to proxy innovations to climate change news. We compare authoritative texts on climate risk with a large amount of news with European regional focus from *Reuters News*[8] based on the assumption that events covered in newspapers can carry relevant information on climate change. We construct two risk indices and two time series about climate change concern taking into account information that is used by European financial investors to update beliefs for their investment decisions. As a methodological contribution to the previous literature, we create two separate vocabularies on physical and transition risk that embody the multifaceted characteristics of the two risk types. A key feature of our vocabularies is the ability to rank terms by relevance. This allows for a deeper understanding of each risk nature examining which term, also referred to as dimension or aspect or characteristic, turns out to be the most important in contributing to the overall risk description.[9]

### 4.4.1 The physical risk and transition risk vocabularies

As a first step, we select a number of scientific and authoritative texts on the topic of climate change published by governmental authorities and other institutions starting with the collection already adopted by Engle et al. (2020). In particular, we screen the textual content and we keep texts which can be easily associated with either physical risk or transition risk topics. In this way, we are able to have a set of texts that relates to either physical risk or transition risk. We further add financial texts related to both risk types as a genuine attempt to construct risk measures built on multiple perspectives. The complete list of texts is summarised in table 4.A1 in Appendix 4.A and it includes texts published by authorities such as the IPCC, among others. As a result, the list of texts is split between the two risk types as each text either belongs to the physical risk document or to the transition risk document. We aggregate 13 (10) texts on physical (transition) risk to create a single document on physical (transition) risk.

Before processing the two documents, we filter out the so-called stop words typically considered as noise terms including the most common words used in a

[8]Reuters provides business, financial, national and international news to professionals via desktop terminals, the world's media organizations, industry events and directly to consumers. *Reuters News* also includes the Breakingviews.com content and provides news delivered instantly in multiple languages (Source reuters.com and reutersagency.com, accessed on 16/06/2021). We use English language news.

[9]A summary of the methodology is presented in the Appendix 4.C.

language such as *the*, *that*, *is*, *which*, and so on.[10] We then create two lists of unique stemmed[11] unigrams and bigrams, jointly referred to as terms, with the associated *term-frequency* scores (*tf*) from the physical risk and transition risk documents. The resulting list represents the terms constituting the physical (transition) risk vocabulary. To start, each term of the physical (transition) risk document is associated to a *tf* score calculated as $tf_i = \text{count}(term_i)/N$, namely as the ratio between the $term_i$ count in the document and the total number of terms $N$ in the document. It follows that the more frequent a term is, the higher its *tf* score. The *tf* scores need however to be multiplied by the respective *inverse document frequency* (*idf*) scores to be able to rank the vocabulary by term relevance, indicated by *term frequency-inverse document frequency* (*tf-idf*) scores. The *idf* score for the $i^{th}$ physical (transition) risk term is computed as the logarithm of the ratio between the total number of documents, $T$, of a given collection, $k$, and the total number of documents, $M$, containing $term_i$, as $idf_{(i,k)} = log(T_k/M_k)$ where $M_k \in [1, T_k]$ as $term_i$ appears at least in the physical (transition) risk document, $M = 1$, or at most in all the $T$ documents, $M = T$. In this way, terms mentioned in many documents of a given collection are considered common terms and earn low $idf$ scores. Conversely, the rarest terms, namely those mentioned by only few documents across the entire collection, earn high $idf$ scores. In order to get objective $idf$ scores, we need to consider a sufficiently large collection of documents of varied content besides the physical (transition) document. In fact, an adequate number of documents covering different topics is likely to provide better $idf$ score estimates which more closely reveal how rare a term is with respect to either a large number of documents about the same topic (potential issue of underestimation) or a limited number of documents (potential issue of overestimation).

We believe that a set of news which spans a sufficiently long period of time holds the desired characteristics to calculate robust $idf$ scores for the physical (transition) risk vocabulary terms. In addition, as our goal is to obtain a risk measure for both

[10]Removing stop words is a common pre-processing step within the text analysis literature and Natural Language Processing (NLP) analyses as stop words mostly ensure the structure of sentences without however adding much to the meaning of a text such that if removed the text keeps its sense.

[11]The stemming is a text normalisation technique widely used in the NLP field consisting of the process of reducing inflection in words to their root forms. Stemmed words can result in words which are not actually words. For instance, the words climate and climatic reduce to the same stemmed word climat which however does not represent a real word.

physical risk and transition risk by exploiting newspaper content, comparing news corpus content with the physical (transition) risk document content is a necessary step. We therefore gather a total of 611,504 of real time news from the *Factiva* database for the *Refinitiv Reuters News* over the period 2015-2019.[12] We then apply a one-day novelty filter to the sample to eliminate redundancy among the data.[13] In particular, only the first news of the day is kept from a series of similar news published on the same day. Additionally, only news published during days on which the European equity markets are open are considered. The final sample accounts for 296,287 news. We select *Reuters News* with European regional focus[14] due to its extensive news coverage, with nearly 240 news per day on average, and because it is largely consumed by investors, thereby helping us to better capture shocks to physical (transition) risk within a financial environment.

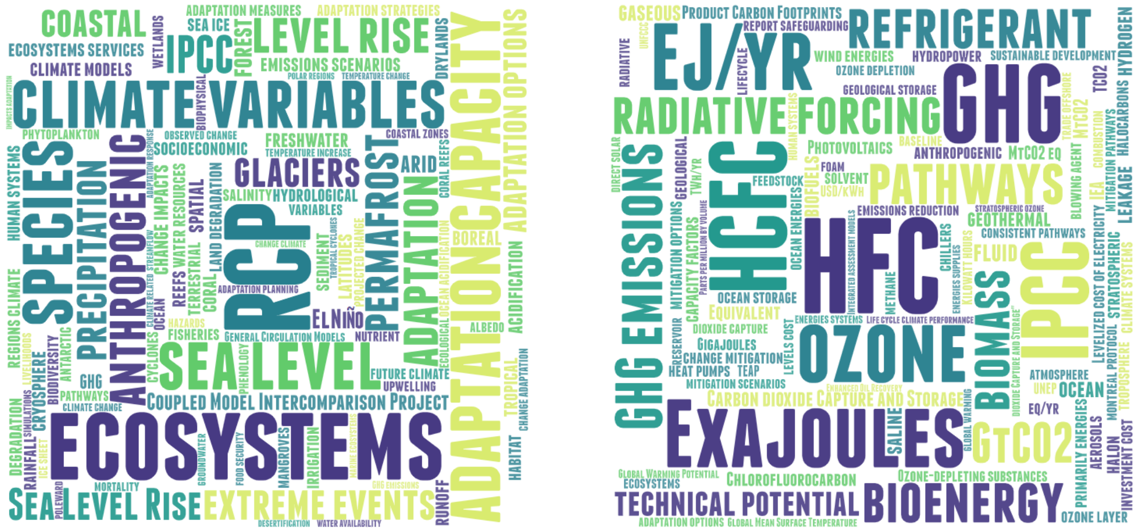
We then aggregate the corpus of real-time news occurring within the same day creating a *Reuters News* daily edition. Each daily news is treated as a document for which we create a list of unique stemmed unigrams and bigrams with relative $tf$ scores, similarly to our previous step. The resulting lists are all composed of different terms, depending on each daily news corpus, and of different lengths, depending on each daily news total unique terms. To facilitate the comparison, we only consider the physical (transition) risk vocabulary terms from each daily news list keeping the relative *tf* scores, if the terms appear in the original daily news corpus, or with zero *tf*, if the terms do not appear in the original daily news corpus (Engle et al., 2020). This allows us to work on a well-shaped set of lists with the same length and terms, where *tf* scores vary according to each individual document corpus. While this approach is equivalent to the baseline method, i.e. without limiting lists length, it provides the advantage of reduced dimensionality, thereby easing computation. The final collection, $k$, is then composed of $T$ documents, a total of $T-1$ daily news documents and $1$ physical (transition) risk document, which enables us to calculate the *idf* scores. As a final step of converting document text into numerical vectors, we calculate the

[12]News which corpus length exceeds 5,000 words are not included in our analysis for both computational reasons and because they can be considered as outliers due to their great length and very marginal occurrence.
[13]See Dang et al. (2015) and Rognone et al. (2020)
[14]The European regional focus delivers news which content relates to any of the EU countries plus UK.

*tf-idf* score matrix, generally called the 'document-term' matrix in the field of natural language processing and computational text analysis. The document-term matrix is a sparse matrix where every column corresponds to a document, every row to a word, and a cell stores the weighting of a term in a document by the *tf-idf*. Particularly, the *tf-idf* score for the $i^{th}$ term of the $j^{th}$ document is computed as $\textit{tf-idf}_{(i,j,k)} = tf_{(i,j,k)} \cdot \textit{idf}_{(i,k)}$, where $k$ denotes the collection composed by the $T-1$ daily news and the physical (transition) risk documents, i=$\{\textit{term}_1, \textit{term}_2, \cdots, \textit{term}_{(S-1)}, \textit{term}_S\}$ with $S$ representing the total number of terms of the physical (transition) risk vocabulary, and $j = \{\textit{daily news document}_1, \textit{daily news document}_2, \cdots, \textit{daily news document}_{(T-2)}, \textit{daily news document}_{(T-1)}, \textit{physical (transition) risk document}\}$. Terms with high *tf-idf* bring relevant information to describe the individual document content as they are frequent within the document (high *tf*) and infrequent among other documents (high *idf*). On the other hand, low *tf-idf* score terms are common to many documents (low *idf*) or very infrequent within the document (low *tf*) and therefore have poor ability in representing the content of the individual text (Engle et al., 2020; Gentzkow et al., 2019).

By sorting the physical risk and transition risk vocabularies according to term *tf-idf* scores, we are able to obtain vocabularies ranked by term relevance. We can detect the terms, or aspects, which are more representative the two climate risks and unveil information which allow a deeper understanding of these risks. Figure 4.1 shows the most relevant terms of the transition risk vocabulary, on the right, and the physical risk vocabulary, on the left, as word clouds where each term size is proportional to its *tf-idf* score. Each vocabulary is found to capture the multifaceted characteristics of each climate risk. The physical risk dictionary includes, for instance, both extreme and chronic hazards directly caused by climate change. On the other hand, the transition risk vocabulary includes different aspects of climate risk such as technological advances and environmental policies. Terms such as *ecosystems*, *sea level*, and *precipitation* are found to be highly representative of the physical risk topic, while terms such as *hydrofluorocarbon* (HFC), *bioenergy*, and *greenhouse gas* (GHG) are representative of the transition risk topic.

**Figure 4.1:** Word clouds summary for physical and transition risk vocabularies



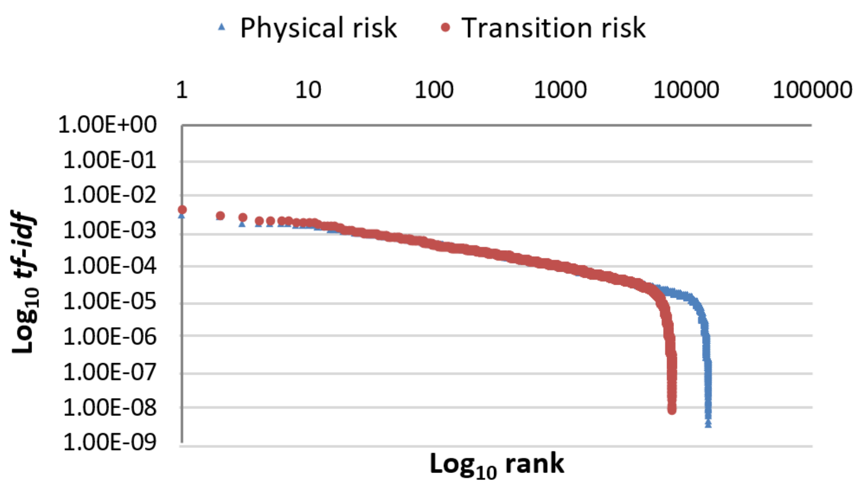

(**a**) Physical risk (**b**) Transition risk

Note: Word cloud summaries for the physical risk (a) and transition risk (b) vocabularies. Term sizes depend on the relative importance of terms for the topic according to their individual *tf-idf* score. Reported terms are the reconstructed stemmed terms. Major acronyms: Representative Concentration Pathways (RCP), hydrofluorocarbon (HFC), hydrochlorofluorocarbon (HCFC). Appendix 4.B table 4.B1 reports the full acronyms.

The estimation technique allows to both discern between physical and transition risks and to address the issue of overlapping concepts between these two risk types. For instance, the term *GHG* appears in both vocabularies, but to a different extent, playing a primary role in explaining the transition risk and a minor one for physical risk. The term *adaptation*, on the other hand, represents a common concept between physical or transition risk and appears in both vocabularies. However, its semantic is different whether it is considered within the context of physical or transition risk and thus depends on the other terms in the vocabulary. These examples suggest that the constructed vocabularies are also likely to capture interconnections between the two complex concepts of physical and transition risks, and to contextualise common terms.

By applying the test proposed by Dang et al. (2015), we evaluate the actual degree of commonality between the two vocabularies as the $R^2$ from regressing the physical risk vocabulary on the transition risk one, or vice-versa. Despite there not being a clear threshold level (Rognone et al., 2020), the resulting $R^2 < 5\%$ is considered sufficiently small to support a reliable separation of the two risks. The $R^2$ suggests that transition risk vocabulary is able to explain less than the 5% of the physical risk one which in turns carries about 95% of individual information, and vice-versa. Both distributions of physical risk and transition risk vocabularies, as ranked, roughly obey a power law known as Zipf's law (Zipf, 1936). The Zipf's law describes many human-related fields and especially languages suggesting that the vocabularies are likely to hold the original texts characteristics. Figure 4.2 provides a log-log plot of the *tf-idf* vocabularies and helps to visualise this property as the vocabularies' terms linearly decrease. In addition, we can detect a break point from which the patterns sharply change slopes meaning that the terms in the tails, i.e. after the break point, approach the zero *tf-idf*. The break point can be then interpreted as a cut-off useful to reduce vocabularies length and dimensionality as terms in the tails cease to obey the rank rule and can be easily dropped without loss of vocabulary information.

**Figure 4.2:** Physical and transition risk vocabularies log-log scale




Note: The figure plots the physical risk vocabulary *tf-idf* terms (red) and the transition risk vocabulary *tf-idf* terms (blue) in a log-log scale. The scale of a plot which reports the *tf-idf* scores on the y-axis and the rank position on the x-axis is changed to log-log with base 10. The break point of physical risk vocabulary occurs at a later rank position with respect to that of the transition risk vocabulary likely due to the different lengths of the two vocabularies, i.e. physical risk has a longer vocabulary than the transition risk.

### 4.4.2 The physical risk and transition risk indices

The physical (transition) risk document can be interpreted as an artificial daily news entirely dedicated to the physical (transition) risk topic which can be used as a benchmark to compare how the actual daily news discuss the physical (transition) risk. To evaluate the level of media concern toward the physical (transition) risk, we adopt the cosine similarity approach, in line with Engle et al. (2020). Albeit this approach is widely used for text comparisons, it works with numerical vectors, thus requiring a conversion of texts into vectors. In particular, the cosine similarity expresses the angular distance between two vectors such that if the vectors point in exactly the same direction forming a 0 degree angle, their cosine equals 1 denoting perfect similarity; if instead the two vectors point in the exact opposite direction forming a 180 degree angle, they have lowest cosine equal to -1 which denotes perfect dissimilarity. Therefore, the closer two vectors point, the smaller their angular distance, the greater the cosine, and the greater their similarity. We consider the *tf-idf* scores numerical transformation of documents to implement this methodology. Additionally, as the *tf-idf* scores are positive by construction, the cosine similarity scores $\in[0,1]$.[15] In fact, the daily news is at least unrelated to the physical (transition) risk news earning 0 similarity score. We then compute the news concern toward the physical (transition) risk topic on day $t$ as the cosine similarity between the *tf-idf* vector of the daily news document$_t$, denoted for simplicity by $News_t$, and that of the physical (transition) risk document, denoted by $PR$ ($TR$). The physical risk concern time series index is therefore obtained as

$$\begin{aligned}\text{Concern}_{t,PR} &= \text{CosineSimilarity}_t(News_t, PR)\\ &= \frac{News_t \cdot PR}{|News_t| \cdot |PR|} = \frac{\sum_{i=1}^{S_{PR}}(News_{t,i} \cdot PR_i)}{\sqrt{\sum_{i=1}^{S_{PR}} News_{t,i}^2} \cdot \sqrt{\sum_{i=1}^{S_{PR}} PR_i^2}}\end{aligned} \tag{4.1a}$$

[15] If instead of the positive *tf-idf* scores we would have implemented a numerical representation of texts which, for instance, associates numerical scores of opposite sign according to synonyms and antonyms, we could have potentially had negative cosine similarity scores.

and we are able to construct an analogous index for the transition risk as

$$\begin{aligned}\text{Concern}_{t,TR} &= \text{CosineSimilarity}_t(News_t, TR) \\ &= \frac{News_t \cdot TR}{|News_t| \cdot |TR|} = \frac{\sum_{i=1}^{S_{TR}}(News_{t,i} \cdot TR_i)}{\sqrt{\sum_{i=1}^{S_{TR}} News_{t,i}^2} \cdot \sqrt{\sum_{i=1}^{S_{TR}} TR_i^2}}\end{aligned} \tag{4.1b}$$

where $S_{PR}$ and $S_{TR}$ represent the physical risk and transition risk vocabularies lengths respectively. We therefore consider the physical (transition) risk as a vector, the direction of which depends on the intensity of each element, as the *tf-idf* of vocabulary terms. High *tf-idf* terms are, for instance, both the most relevant terms in describing the risk and the most influential elements in determining the vector direction. Furthermore, the final direction resulting from the combination of each *tf-idf* score, with relative attraction ability according to their magnitude, is unique and can be interpreted as the physical (transition) risk topic. In this fashion, other texts, such as daily news corpus, which are pointing in the same direction of the physical (transition) risk vector are meant to discuss the physical (transition) risk topic.[16] The concern indices roughly represent the portion of daily news corpus dedicated to either the topic of physical risk or transition risk measuring their media coverage. In line with Engle et al. (2020), the level of concerns are modelled as autoregressive processes of order 1, AR(1), where the residuals represent either the shocks to the physical risk or transition risk generating the *Physical Risk Index* (PRI) and the *Transition Risk Index* (TRI) as follow

$$\text{Concern}_{t,PR} = c_{PR} + \phi_{PR}\text{Concern}_{t-1,PR} + PRI_{t,PR} \tag{4.2a}$$

$$\text{Concern}_{t,TR} = c_{TR} + \phi_{TR}\text{Concern}_{t-1,TR} + TRI_{t,TR} \tag{4.2b}$$

Table 4.1 reports the dates of highest physical risk shock together with the topic of high relevant news. We are able to retrieve which intraday news have particularly caused a rise in PRI by repeating the cosine similarity *tf-idf* approach considering

[16] Therefore, the vocabularies represent the set of terms associated with either the physical risk or transition risk discourse, and the tf-idf scores as their usage intensity used to identify news discussing the topic of physical risk or transition risk.

intraday news during each high shock day as single documents.[17] For instance, the peak for PRI is registered on 19/09/2018 with a shock of 12.78% coinciding with a high unexpected discussion on physical risk. In particular, we detect an intraday news concerning an unprecedented loss of Artic Sea ice as a driver of risk. This news is related with the physical chronic risk of permafrost thawing, and the corpus further discusses other critical aspects of the physical risk such as the rise of sea levels and changes in the salinity of oceans. In general, high shock days might cover a multiplicity of physical risk topics further suggesting that the constructed index is able to capture the multifaceted characteristics of this climate risk. Therefore, PRI is able to identify chronic risks such as permafrost thawing, heat stress, sea level rise, and acute risk such as heat waves and floods, as well as the adverse impact on the ecosystem such as biodiversity loss risk and ocean acidification, and socio-economic risks such as migration and food security.

**Table 4.1:** Physical risk most relevant days and news articles

| Date | Shock | Topic | Relevant title |
|---|---|---|---|
| 19/09/2018 | 12.78% | Artic Sea Minimum | Greenland and the hunt for better climate science |
| 08/08/2019 | 8.57% | Food Security | Farming and eating need to change to curb global warming – UN report |
| 25/11/2019 | 8.46% | Glacier Retreat Cop25 | New photos vs old: comparisons show dramatic Swiss glacier retreat |
| 21/08/2017 | 7.82% | Flood Resilience | Europe's authorities must do more to prepare for climate disasters |
| 06/12/2019 | 7.68% | Biodiversity Loss | Europe must do more to protect its rivers and lakes – scientists |
| 13/06/2016 | 6.56% | Heat Stress | At ground zero of warming, Greenland seeks to unlock frozen assets |
| 08/10/2018 | 6.50% | Chronic Heat Risks | Temperatures to rise 1.5$^o$ by 2030-2052 without rapid steps-UN |
| 26/10/2018 | 6.03% | Biodiversity Loss | As warming threatens reefs, fragile Fiji explores inland tourism |
| 25/09/2019 | 5.85% | Glacier Retreat | Mont Blanc glacier at risk of collapse, PM calls for climate action |
| 19/07/2018 | 5.80% | Biodiversity Loss | Deep reefs won't be "twilight zone" refuge for fish, corals – study |
| 13/06/2018 | 5.56% | Sea Level Rise | Antarctic thaw quickens, trillions of tonnes of ice raise sea levels |
| 15/03/2018 | 5.47% | Heat Stress | None like it hot - warmer winters worry Arctic |
| 15/01/2019 | 5.44% | Sea Level Rise | Antarctica's melt quickens, risks meters of sea level rise – study |

Note: Most relevant news article titles on top physical risk shock days. We report the highest shock date, the level of shock (residuals of AR(1) on cosine similarity time series), and one of the daily most relevant article's title.

[17] Intraday news which are responsible to increase PRI (TRI) are the intraday news with higher similarity with the physical (transition) risk document.

**Table 4.2:** Transition risk most relevant days and news articles

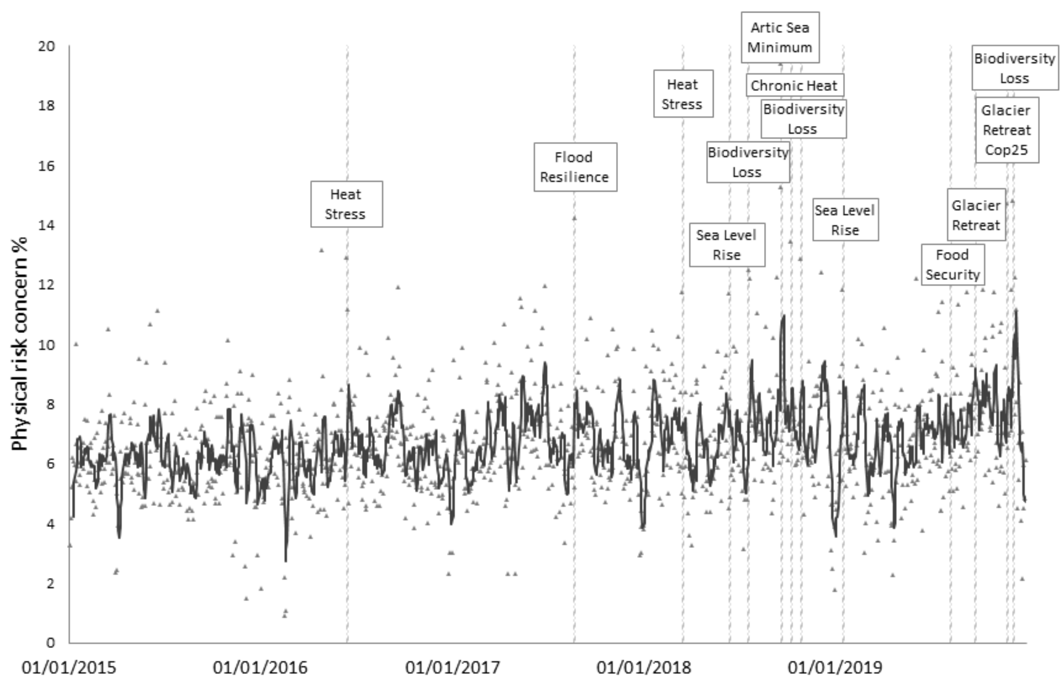
| Date | Shock | Topic | Relevant title |
|---|---|---|---|
| 15/10/2015 | 13.88% | Emissions Regulation | U.S. announces new moves to limit super greenhouse gases |
| 08/10/2018 | 10.87% | Speed Transition Up | U.N. report on keeping global warming down to 1.5 degrees Celsius |
| 28/02/2017 | 9.93% | Carbon Reform Deal | Nineteen EU nations back common position on carbon market reform |
| 29/03/2018 | 9.39% | Emissions Target | Britain's greenhouse gas emissions fall again as coal use plummets |
| 22/07/2016 | 8.32% | Montreal Protocol | U.S. calls for rapid progress on greenhouse-gas pact |
| 08/08/2019 | 7.43% | "Meat Free" | Farming and eating need to change to curb global warming UN report |
| 23/08/2018 | 6.76% | Technological Innov. | Imitate Vaxjo? As heat rises, Swedish city goes green - and thrives |
| 02/11/2017 | 6.41% | Oil Refineries at Risk | Quarter of oil refineries risk closure under climate goals |
| 13/03/2018 | 6.29% | Emissions Target | Anglo American launches new sustainability goals |
| 27/03/2015 | 5.75% | Renewable Energy | Cuadrilla, geothermal firm eye renewable heat from oil, gas wells |
| 19/09/2018 | 5.49% | CO2 Removal Tech. | Taking back carbon 'imperative' to stop planet overheating |
| 23/10/2019 | 5.45% | Transition Taxonomy | Climate targets – the devil's in the detail |
| 11/06/2019 | 5.34% | Net Zero Emissions | Britain to become first G7 country with net zero emissions target |

Note: This table reports the most relevant news article titles on top transition risk shock days. We report the highest shock date, the level of shock (residuals of AR(1) on cosine similarity time series), and one of the daily most relevant article's title.

Table 4.2 represents the equivalent of table 4.1 for transition risk. The largest shock for TRI of 13.88% concurs with a news published on 15/10/2015 regarding the US announcement to limit the emissions of greenhouse gases. The table shows additional evidence that news discussing about regulations and measures to curb the GHG emissions generate large spikes in TRI, e.g. news regarding the EU carbon reform deal or the Montreal Protocol, as well as news concerning the urgency to speed the transition up with the help of technological innovation and renewable energies. TRI also increases when media discusses approaches and implications to reach the net zero emissions target. News which lead to a rise in TRI are likely to disseminate information which can increase the public perception of the risks associated to the transition toward a low carbon economy. Again, TRI demonstrates to have the ability to capture multiple aspects related with the transition to climate neutrality highlighting the complexity of the constructed risk index.

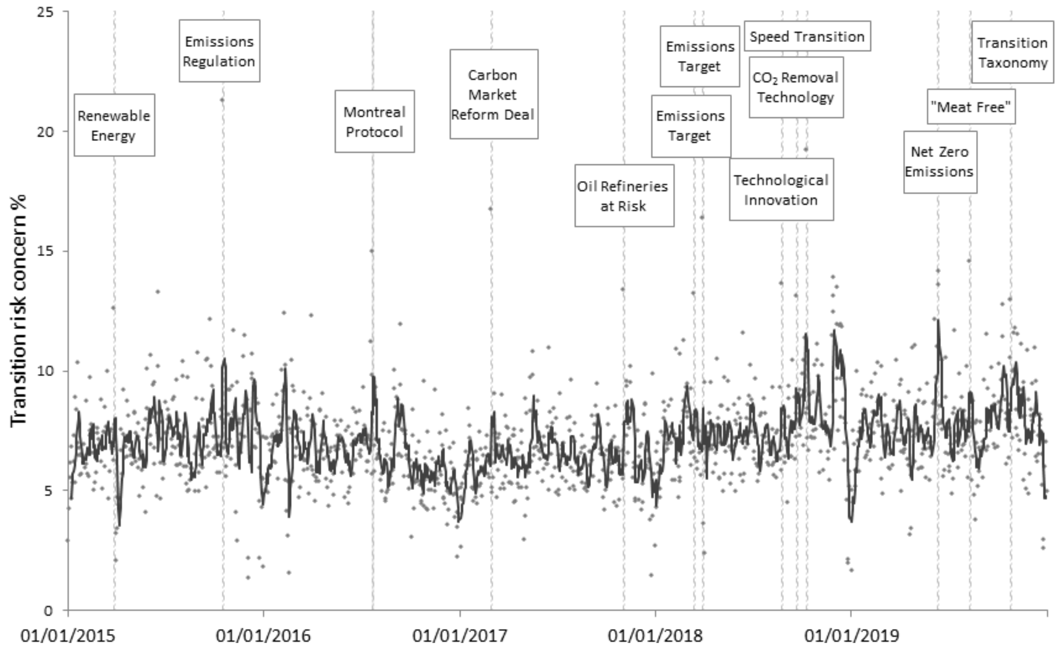
We overlap the topic of high shock news for physical (transition) risk with the physical (transition) risk concern time series to get a deeper understanding of the dynamics over time of the physical (transition) risk media concern along with the PRI (TRI) peaks. Figures 4.3 and 4.4 report the scatter plots of daily physical risk and transition media concerns, respectively, together with their one-week moving average and the relative timelines of high shock topics as in tables 4.1 and 4.2. The larger shocks to transition risk are more equally distributed during the full sample period, while largest shocks to physical risk mostly occur during the end of the sample period suggesting a recent growth of such risk.

**Figure 4.3:** Physical risk concern time series




Note: Daily physical risk concern in percentage (grey upper triangles), its one-week moving average (black solid line), and the major physical risk shock topics, over the period 2015-2019.

**Figure 4.4:** Transition risk concern time series




Note: Daily transition risk concern in percentage (grey dots), its one-week moving average (black solid line), and the major transition risk shock topics, over the period 2015-2019.

Table 4.3 summarises the AR1 estimates from equations 4.2a and 4.2b. Both physical risk and transition risk concern time series show positive drifts ($c_{TR} = 0.071$ and $c_{PR} = 0.067$) denoting that the news coverage toward these climate risks tends to increase over time. The media concern on transition risk seems to be more persistent than that on physical risk with $\phi_{PR} = 0.25$ and $\phi_{TR} = 0.30$.

**Table 4.3:** AR1 estimates of physical risk and transition risk concern

| | Concern$_{t,PR}$ | Concern$_{t,TR}$ |
|---|---|---|
| Intercept $c$ | 0.067 | 0.071 |
| | (-0.001) | (-0.001) |
| $\phi$ | 0.25 | 0.30 |
| | (-0.027) | (-0.026) |

Note: Estimates of Autoregressive of order 1 (AR1) concern time series on physical risk, as in equation 4.2a, and transition risk as in equations 4.2b. Standard error in parenthesis.

## 4.5 Pricing physical and transition risks

To test whether financial markets price physical (transition) risk, we add the constructed *Physical Risk Index* (PRI) or *Transition Risk Index* (TRI) into the Fama-French five factor (FF5) asset pricing model (Fama & French, 2015). We measure the sensitivity of equity prices to shocks to either physical risk or transition risk for different portfolios. In particular, we consider E score, ESG score, GHG emissions level, and GHG emissions intensity as exposure metrics to sort firms and create green or brown portfolios as follows

- *E score and ESG score metrics.* Firms whose E score is above (below) the 75th (25th) percentile on a given day are defined as green (brown) firms. The green (brown) portfolio is then created as an equally weighted portfolio composed of green (brown) firms. The same approach is applied to the ESG score metric. Portfolios are annually rebalanced;
- *GHG emissions level and GHG emissions intensity metrics.* GHG emissions level ($\text{GHG}_E$) is calculated as the sum of Scope 1 and 2, while GHG emissions intensity ($\text{GHG}_{EI}$) is calculated as GHG emissions level scaled by firms' net revenue. Firms whose GHG emissions level is below (above) the 25th (75th) percentile on a given day are defined as green (brown) firms. The green (brown) portfolio is the naıve portfolio composed by green (brown) firms. The same approach is applied to GHG emissions intensity metric. Portfolios are annually rebalanced.

While this section focuses on the econometric model adopted in the analysis, the data section provides exhaustive description of these metrics.

We therefore plug our *Physical Risk Index* (PRI) and *Transition Risk Index* (TRI) innovations time series into the models for equity excess returns:

$$\begin{aligned} r^{exc}_{p_i,t} = c_{p_i} + \beta^{MKT}_{p_i} MKT_t + \beta^{SMB}_{p_i} SMB_t + \beta^{HML}_{p_i} HML_t + \beta^{RMW}_{p_i} RMW_t + \\ \beta^{CMA}_{p_i} CMA_t + \beta^{TRI}_{p_i} TRI_t \end{aligned} \tag{4.3a}$$

to price transition risk, and

$$r^{exc}_{p_i,t} = c_{p_i} + \beta^{MKT}_{p_i} MKT_t + \beta^{SMB}_{p_i} SMB_t + \beta^{HML}_{p_i} HML_t + \beta^{RMW}_{p_i} RMW_t + \beta^{CMA}_{p_i} CMA_t + \beta^{PRI}_{p_i} PRI_t \tag{4.3b}$$

to price physical risk. $r^{exc}_{p_i}$ denotes the excess return at time $t$ for green or brown portfolios where $p$ ={green portfolio, brown portfolio} and $i = \{\text{GHG}_E, \text{GHG}_{EI}, \text{E}, \text{ESG}\}$. $c_{p_i}$ is the constant term, $MKT_t$ denotes the market excess return, $SMB_t$ is the return spread between small capitalisation stocks and large capitalisation stocks, $HML_t$ denotes the return spread between high book-to-market companies and low book-to-market companies, $RMW_t$ represents the return spread between most profitable, i.e. robust, minus least profitable, i.e. weak, companies, and $CMA_t$ indicates the return spread between firms that invest conservatively and firms that invest aggressively.[18] The coefficients $\beta^{PRI}$ and $\beta^{TRI}$ measure the contemporaneous relationship between an unexpected change in the physical and transition risk, and the excess returns of portfolios constructed according the different exposure metrics. Statistically significant $\beta^{PRI}$ and $\beta^{TRI}$ would indicate that financial markets price, at least to some extent, these climate risks. In the case of brown portfolio analysis, for instance, if the coefficients are also large, this would denote high sensitivity of brown stocks toward climate risks suggesting investors perceive them as source of financial risk and would possibly require premia to hold the risky assets. An increase in physical (transition) risk identified as shocks to physical (transition) risk concern potentially represent new information which is expected to be reflected into asset prices within the trading day on which the news occurs. We therefore look at the daily contemporaneous relationship between climate risks and equity to study to which extent the new information is incorporated into closing prices. Additionally, a correct pricing of climate risks would suggest the financial market can act as a vehicle to transmit climate mitigation policies helping an effective transition toward climate

[18] The Fama-French 5 factors are constructed considering the EuroStoxx 600 Index constituents over 2015-2019 for which we calculate the 6 value-weight portfolios formed on size (market capitalisation) and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment (change in total assets). Data are collected from *Eikon*. More details on the methodology can be found in the Fama-French data library where the breakpoint for size are 60% and 40% percentile of the market capitalisation of all companies in year *t*, while for the other variable are 70% and 30%.

neutrality.

As additional output of this analysis, we are able to investigate the informational content of each exposure metric used. In particular, by testing the physical (transition) risk on portfolios constructed according to each metric we can infer the information enclosed within each exposure such that if a significant relation is found this would imply the exposure metric contains information to proxy firms exposure to the physical (transition) risk.

We further conduct a sectoral analysis by aggregating the excess returns of firms belonging to same sector to test the response of different sectors to physical and transition risks. In this way, we are also able to verify where investors simply consider a rough sectoral classification to react to physical and transition news, for instance by divesting from the carbon intensive sector assets if transition risk rises.

## 4.6 Data

### 4.6.1 Equity data

The augmented FF5 model (equations 4.3a and 4.3b) uses the 1-month Overnight Index Swap (OIS) rate as the risk-free rate, and returns of the EuroStoxx 600 Index as the proxy for the market return. We collect daily price time series for the historical constituents of the EuroStoxx 600 Index from the *Thomson Reuters Datastream* database over the period 2015-2019, resulting in a total of 793 companies. The sample period is in line with recent studies which assume stronger importance of climate risks during the past few years, especially from the period surrounding the Paris Agreement (e.g. Bolton and Kacperczyk (2019)). We further prefer to exclude the Covid-19 period to avoid high turmoil market times.

### 4.6.2 GHG emissions level, GHG emissions intensity, E score, ESG score, and sector data

Data on firms GHG emissions level, GHG emissions intensity, E score, and ESG score are downloaded from *Refinitiv Eikon*. The level of GHG emissions of a company are the thousands of metric tonnes of carbon dioxide equivalent (tCO2e) it produces.[19] The GHG Protocol Accounting and Reporting Standard[20] distinguishes GHG emissions into three Scopes according to the emissions source: direct emissions from operations (Scope 1), indirect emissions from purchased electricity by the owned or controlled equipment or operations of the firm (Scope 2), and other supply chain emissions (Scope 3). We measure the level of GHG emissions as the sum of Scope 1 and 2 because including Scope 3 would reduce the data coverage. We take only information reported by the company and exclude any estimated by the provider. GHG emissions intensity is calculated as the level of GHG emissions scaled by the firm's net-revenue and it measures the thousands of metric tCO2e necessary for a firm to generate a one million net-revenue.

ESG scores measure the environmental, social, and governance performance of a company. The *Refinitiv* methodology relies on backward- and forward-looking variables grouped into categories that reformulate the E, S, and G pillars. The E pillar focusses on the commitment and effectiveness of the company to tackle issues related to the use of resources, emission, and innovation.[21] Notably, scores are normalised by industry as performances are relative to sector peers and pillar scores are aggregated based on weights that vary across industries. Another important feature is that the scores consider the level of disclosure penalising firms that do not disclose data. E and ESG scores range from 0 to 100, with higher values indicating better performances.

Table 4.4 provides the data coverage for each of the exposure metrics for each year in

[19]Greenhouse Gases are defined as those gases which contribution the trapping of heat in the Earth's atmosphere and they include Carbon Dioxide (CO2), Methane, and Nitrous Oxide.

[20]WBCSD & WRI (2004)

[21]The use of resources reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management. The emissions reduction score measures a company's commitment and effectiveness towards reducing environmental emissions in its production and operational processes. The innovation score reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products (Refinitiv, 2020).

the sample, highlighting a general increase in coverage over time. It further reports the thresholds data ($25^{th}$ and $75^{th}$ percentiles) for constructing brown and green portfolios.

Finally, we define sectors using the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2).[22] Even though it was not originally designed to capture climate impact, this statistical classification has been adopted in the climate literature. Following Dafermos et al. (2020), we rely on the NACE Rev. 2 level-1 classification.

**Table 4.4:** Exposure data

| Panel a) % of firms with data | | | | |
|---|---|---|---|---|
| Year | $GHG_E$ | $GHG_{EI}$ | E | ESG |
| 2015 | 74.91 | 73.77 | 87.39 | 87.39 |
| 2016 | 79.82 | 77.30 | 89.66 | 89.66 |
| 2017 | 83.73 | 79.95 | 94.58 | 94.83 |
| 2018 | 86.76 | 81.34 | 97.10 | 97.10 |
| 2019 | 87.52 | 80.08 | 97.98 | 97.86 |
| Panel b) Threshold | | | | |
| 25th Percentile | 26,215 | 7,720 | 39.69 | 49.63 |
| 75th Percentile | 808,601 | 89,659 | 80.01 | 75.83 |

Note: Exposure data % coverage over time (from 2015 to 2019) for the EuroStoxx 600 Index constituents (panel a) and the threshold levels to construct green and brown portfolios (panel b) for GHG emissions levels ($GHG_E$), GHG emissions intensity ($GHG_{EI}$), Environmental score (E), and Environmental, Social, and Governance score (ESG).

### 4.6.3 Data description

In order to give a deeper overview of the composition and characteristics of the EuroStoxx 600 Index at the sectoral level, table 4.5, reports the number of firms in our sample (No.), the average of the exposure metrics (E, ESG, $GHG_{EI}$ , $GHG_E$ ) and the annual contribution of each sector to EuroStoxx 600 Index GHG emissions. In the last column, we also add the overall sector contribution to EU GHG emissions (EU contribution), for comparison reasons.[23] The table is sorted according to descendent E score, where higher E values correspond to "greener" sectors. Green and brown sectors according to each metric are also identified by the colour scale, such as green

[22] Eurostat (2008). Dafermos et al. (2020) for example identifies high-carbon intensive activities taking NACE 1-digit sectors that mostly contribute to EU emissions.

[23] EU27, Data source: Eurostat.

(red) colour is associated to green (brown) sectors. As expected, *D-Electricity, gas, steam and air conditioning supply* (D- Electricity), *C-Manufacturing*, and *H-Transportation and storage* (H-Transportation) are among the most polluting sectors contributing to 70% of total EU emissions and 62% of total EuroStoxx 600 Index emissions, respectively. On the other hand, the *A-Agriculture, forestry and fishing* (A-Agriculture) is a high emissions contributor at the European level (16%), but not for our sample (0%), most likely due to the underrepresentation of this sector within the EuroStoxx 600 Index (one company). *B-Mining and quarrying* (B-Mining) and *M-Professional, scientific and technical activities* (M-Professional)[24] are small contributors at European level but show high level of GHG emissions in our sample.[25] D-Electricity, C-Manufacturing, and H-Transportation are the sectors receiving the highest E scores, on average.

The cross-correlations of the variables show that the level of emissions has 0.65 correlation coefficient with emissions intensity. Recalling GHG emissions intensity as the ratio between GHG emissions and net-revenues, a high ratio is either associated with high emissions or low net-revenues. The positive, not perfect, correlation suggests that high emissions intensity companies have usually also high emissions. Table 4.5 shows that sectors with average good E (and ESG) ratings also have high GHG emissions levels (and intensity), suggesting E and ESG scores correlate positively with GHG emissions in line with Boffo et al. (2020). This may imply that companies with high GHG emissions can receive positive environmental scores, and vice versa. In other words, highly positive environmental, or ESG, ratings are not necessarily associated with low carbon emissions, aligned with the assumption that E, and ESG, informational content capture aspects of climate risk further to GHG production.

Figure 4.5 presents the distribution of the metrics. E and ESG scores are quite homogeneous across sectors, while GHG emissions differ largely within and across sectors. This is in line with ESG scoring industry-specific methodology which

[24]The broad characterisation of this sector makes its interpretation challenging. In our sample 70 percent are activities carried on by head offices.

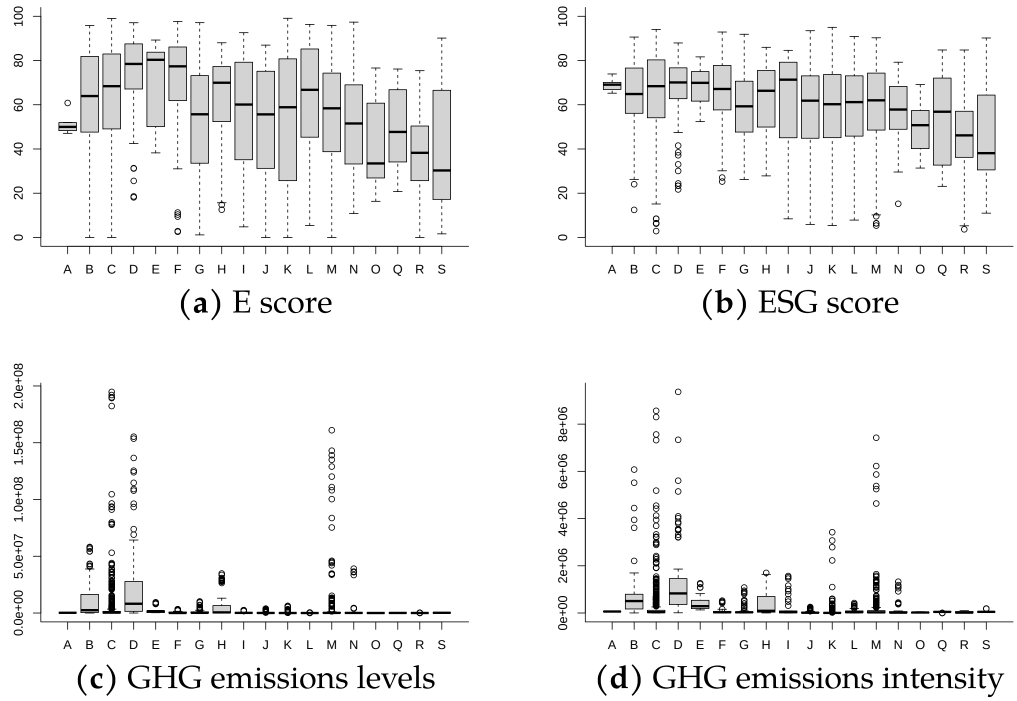
[25]This might be due to dislocation of operating activity of these companies, e.g. extraction of crude oil petroleum areas and sites outside EU.

**Table 4.5:** EuroStoxx 600 Index – Historical constituents' sectoral composition

| | NACE Rev. 2 | No. | E | ESG | $GHG_{EI}$ | $GHG_E$ | $GHG_E$ contribution Index | $GHG_E$ contribution EU |
|---|---|---|---|---|---|---|---|---|
| D | Electricity, gas, steam and air conditioning supply | 23 | 74.01 | 67.26 | 1,272,120.00 | 24,594,111.00 | 23% | 28% |
| F | Construction | 26 | 71.97 | 66.91 | 61,086.24 | 626,127.37 | 1% | 2% |
| E | Water supply; sewerage, waste management and remediation activities | 5 | 70.2 | 67.95 | 458,882.00 | 2,569,643.60 | 1% | 5% |
| C | Manufacturing | 193 | 64.22 | 65.92 | 261,189.10 | 4,613,442.30 | 34% | 26% |
| H | Transportation and storage | 22 | 63.57 | 61.51 | 380,005.70 | 5,603,418.10 | 5% | 14% |
| L | Real estate activities | 26 | 62.91 | 57.49 | 73,819.96 | 41,112.83 | 0% | 0% |
| B | Mining and quarrying | 30 | 62.4 | 64.8 | 687,768.30 | 9,984,332.40 | 13% | 2% |
| I | Accommodation and food service activities | 9 | 56.48 | 60.92 | 248,978.80 | 561,204.76 | 0% | 1% |
| G | Wholesale and retail trade; repair of motor vehicles and motorcycles | 48 | 54.37 | 58.97 | 72,743.90 | 938,823.32 | 2% | 3% |
| M | Professional, scientific and technical activities | 99 | 54.17 | 59.66 | 228,009.00 | 5,374,059.90 | 19% | 1% |
| K | Financial and insurance activities | 167 | 53.55 | 58.36 | 40,147.67 | 194,794.88 | 1% | 0% |
| A | Agriculture, forestry and fishing | 1 | 51.63 | 69.05 | 61,456.91 | 218,137.00 | 0% | 16% |
| J | Information and communication | 63 | 51.6 | 58.51 | 27,501.42 | 291,675.46 | 1% | 0% |
| N | Administrative and support service activities | 19 | 51.33 | 57.8 | 120,377.40 | 2,683,802.70 | 2% | 1% |
| Q | Human health and social work activities | 7 | 48.94 | 52.88 | 44,734.65 | 104,573.64 | 0% | 1% |
| S | Other service activities | 5 | 42.23 | 48.2 | 62,472.40 | 197,392.27 | 0% | 0% |
| O | Public administration and defence; compulsory social security | 4 | 41.36 | 49.19 | 22,069.64 | 89,008.20 | 0% | 1% |
| R | Arts, entertainment and recreation | 8 | 38.84 | 46.31 | 29,241.48 | 45,376.90 | 0% | 0% |
| NA | | 38 | | | | | | |
| Tot | | 793 | | | | | | |

Note: EuroStoxx 600 Index historical constituents sectoral (NACE Rev. 2) composition over the period 2015-2019, number of companies per sector (No.), average Environmental score (E score), Environmental, Social, and Governance score (ESG score), for GHG emissions levels ($GHG_E$), GHG emissions intensity ($GHG_{EI}$). The greener the colour the 'greener' the sector, the more red the colour, the 'browner' the sector according to each metric (E score, ESG score, $GHG_{EI}$, $GHG_E$). EuroStoxx 600 Index sector average per year GHG emissions contribution ($GHG_E$ contribution Index). Full sector average per year GHG emissions contribution ($GHG_E$ contribution EU) to European Union GHG emissions total.

**Figure 4.5:** Distribution of exposure metrics



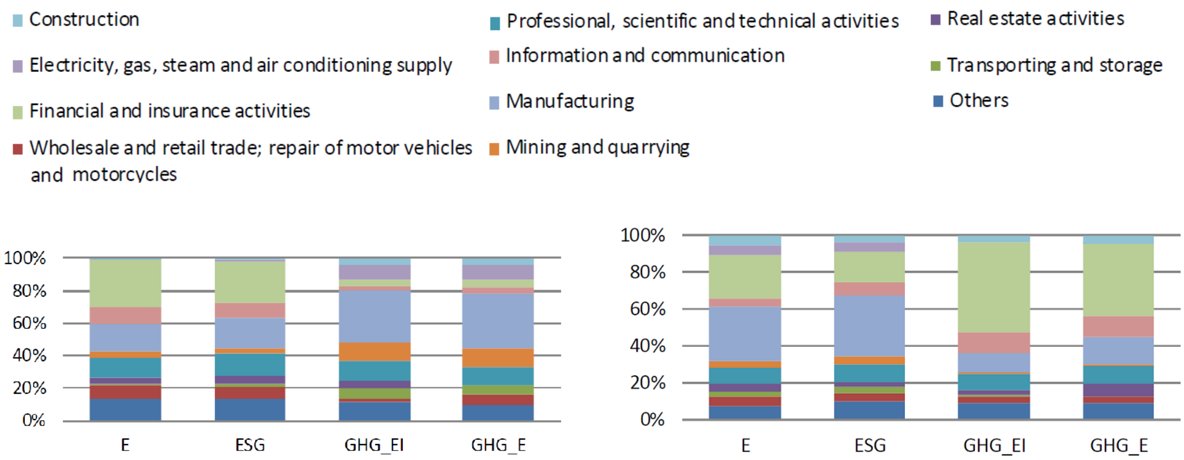

(**a**) E score (**b**) ESG score (**c**) GHG emissions levels (**d**) GHG emissions intensity

Note: E score (a), ESG score (b), GHG emissions levels (c) and intensity (d) NACE Rev. 2 sectors boxplots.

recalibrates upwards the rating of high pollution companies. The distribution of GHG emissions by sectors also confirms that the NACE classification discards important climate-policy relevant differences.

Figure 4.6 shows the sectoral composition of brown (a) and green (b) portfolios according to the different exposure metrics. We can observe that the composition of brown (green) E and ESG portfolios is similar, as well as the composition of brown (green) GHG emissions and GHG emissions intensity portfolios. Additionally, in line with the positive correlation between high (low) GHG emissions and good (bad) environmental performance scores as pointed in table 4.5 (such that sectors which on average are polluting, i.e. high GHG emissions, also receive on average good E and ESG scores), we can expect some degree of similarity between the composition of brown GHG emissions portfolio and the green E (ESG) portfolio, and vice versa.

**Figure 4.6:** Brown and green portfolios sectoral composition




(**a**) Brown portfolios (**b**) Green portfolios

Note: sectoral (NACE Rev. 2) composition of brown (a) and green portoflios (b) according to Environmental score (E), Environmental, Social, and Governance score (ESG), GHG emissions level (GHG_E), and GHG emissions intensity (GHG_EI).

Considering as high polluting those firms with higher GHG emissions levels, we in fact notice that the brown GHG portfolio (which pulls together the most polluting firms by construction) is mainly represented by the C-Manufacturing sector and C-Manufacturing further most represents both the E and ESG green portfolios, suggesting that many firms belonging to this sector also receive positive environmental and ESG scores. Accordingly, sectors that on average are characterised by low GHG emissions, such as *K-Financial and insurance activities* (K-Financial) and *J-Information and communication* (J-Information), most represent the GHG green portfolio (namely that portfolio which groups the lowest emissions firms) and also the brown E (ESG) portfolio (namely that portfolio which groups firms with worst environmental (ESG) performances).

It may be surprising to acknowledge that green portfolios can include stocks of companies operating into sectors considered brown like C-Manufacturing. Recalling that E and ESG scores are industry specific, very polluting sectors firms can earn E and ESG scores as positive as firms operating in less polluting sectors, because they compete with sector pairs. In other words, if a company is performing better than sector pairs earn high E and ESG ratings regardless the sector it operates in. Therefore, the industry specific nature of E and ESG scores, possibly combined with an uneven sectoral representation of the EuroStoxx 600 Index, make the green E and ESG portfolios including firms from polluting sectors.

It follows that there might be different interpretations on what is considered *green* or *brown*. For instance, under this framework one can state that the *green* firm is either that firm with low level of GHG emissions, because less polluting, or that with high E score, because more committed to improve its environmental performances. If we imagine a similar logic in interpreting what is *brown*, it might be not clear whether investors convey on one of the two interpretations, or both, or if they even are aware of the potential positive correlation between E score and GHG emissions. We then study how sensitive to climate risks are portfolios constructed under different exposure metrics individually.

Further details on the brown and green portfolios are in tables 4.C1 and 4.C2, Appendix 4.D.

## 4.7 Results

We begin our analysis by testing whether unexpected increases in transition risk concerns lower (increase) brown (green) firms' stock returns. Table 4.6 reports results for portfolios created according the four metrics (E score, E; ESG score, ESG; GHG emissions intensity, $\text{GHG}_{EI}$; and GHG emissions level, $\text{GHG}_{E}$). Table 4.7 shows the results at the sectoral level. We report the corresponding results in tables 4.8 and 4.9 for the physical risk analysis.

### 4.7.1 Pricing of transition risk

Table 4.6 reports the results from the augmented FF5 model as presented in equation 4.3a with the relative sensitivity estimates of the excess returns of brown portfolios (panel a) and green portfolios (panel b) to the *Transition Risk Index* (TRI), and Newey-West robust standard errors in parentheses (Newey & West, 1987).[26] We find

[26]We use Newey-West standard errors throughout.

evidence of a statistically significant decrease in the excess returns of brown portfolios as the market is surprised by transition risk concerns. A one percent increase in TRI is associated to a decrease of -1.077, -0.894, -0.974, and -0.708% in the excess returns using E score, ESG score, GHG emissions intensity, and GHG emissions level portfolios, respectively. The result suggests that investors recognise multiple aspects of carbon risks and use different metrics to identify firms exposed to transition risks. Additionally, while investors may divest the brown assets as TRI rises to reduce their exposure into the risky assets, we do not find statistically significant results of increase in returns of the ideal opposite green class (as showed in panel b). The lack of significance may be due to the fact that investors combine multiple metrics to identify green portfolios, or need more time to identify the green class. Results might also imply that investors tend towards a negative valuation of brown firms, but do not consider green firms as an alternative investment.

Our conclusions are aligned with multiple studies on climate finance. We confirm the results of Ardia et al. (2020) for an European sample. Using GHG emissions intensity for US companies, they find that when climate change concerns increase unexpectedly, stock returns of brown firms earn lower returns. We also find that E and ESG scores contain important additional information to carbon emissions, which investors use to penalise companies. This is consistent with Görgen et al. (2020) who build a composite index of exposure and find that brown firms provide a negative return when they shock the markets with negative climate-related news.

**Table 4.6:** Pricing Transition Risk Index (TRI) – Brown and green portfolios

| Panel a) Brown portfolios | | | | |
|---|---|---|---|---|
| | E | ESG | $GHG_{EI}$ | $GHG_E$ |
| **TRI** | **-1.077**** | **-0.894**** | **-0.974**** | **-0.708**** |
| | **(0.365)** | **(0.388)** | **(0.398)** | **(0.340)** |
| MKT | 0.946*** | 0.928*** | 0.950*** | 0.973*** |
| | (0.014) | (0.012) | (0.011) | (0.010) |
| SMB | 0.617*** | 0.562*** | 0.154*** | 0.082*** |
| | (0.029) | (0.023) | (0.023) | (0.023) |
| HML | -0.061** | -0.079*** | 0.307*** | 0.317*** |
| | (0.025) | (0.023) | (0.033) | (0.030) |
| RMW | 0.077*** | 0.017 | 0.137*** | 0.136*** |
| | (0.029) | (0.026) | (0.023) | (0.019) |
| CMA | 0.052 | 0.075* | 0.026 | -0.018 |
| | (0.043) | (0.040) | (0.049) | (0.039) |
| Intercept | -0.025*** | -0.016** | -0.013 | -0.018** |
| | (0.007) | (0.007) | (0.009) | (0.007) |
| Panel b) Green portfolios | | | | |
| | E | ESG | $GHG_{EI}$ | $GHG_E$ |
| **TRI** | **-0.120** | **-0.172** | **-0.224** | **-0.553** |
| | **(0.244)** | **(0.216)** | **(0.431)** | **(0.396)** |
| MKT | 0.983*** | 1.004*** | 1.007*** | 0.947*** |
| | (0.008) | (0.008) | (0.018) | (0.015) |
| SMB | 0.178*** | 0.123*** | 0.524*** | 0.607*** |
| | (0.020) | (0.018) | (0.061) | (0.050) |
| HML | 0.236*** | 0.192*** | 0.195*** | 0.038 |
| | (0.016) | (0.016) | (0.031) | (0.024) |
| RMW | 0.007 | 0.006 | 0.053 | 0.050* |
| | (0.014) | (0.013) | (0.032) | (0.028) |
| CMA | 0.066*** | 0.035** | 0.117*** | 0.123*** |
| | (0.021) | (0.018) | (0.033) | (0.032) |
| Intercept | -0.014*** | -0.011*** | -0.016** | -0.013* |
| | (0.022) | (0.004) | (0.007) | (0.007) |

Note: FF5 augmented by Transition Risk Index (TRI) as in equation 4.3a. Reported the daily E, ESG, $GHG_{EI}$, $GHG_E$ portfolios sensitivity to TRI, $\beta^{TRI}$, with Newey-West standard errors in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Moving to the sectoral analysis presented in table 4.7, we find that transition risk has a negative impact on the returns of B-Mining (-3.242%) and C-Manufacturing (-0.803%). We also find that *E-Water supply; sewerage; waste management and remediation activities* is positively related to increase in transition risks (2.718%). Results for B-Mining and C-Manufacturing are expected. Both sectors contribute directly or indirectly to high level of GHG emissions and are usually considered climate-sensitive sectors. The positive impact on *E-Water supply; sewerage; waste management and*

**Table 4.7:** Pricing Transition Risk Index (TRI) – sectors NACE Rev. 2 Level 1

| | D<br>Electricity, gas, steam and air conditioning supply | F<br>Construction | E<br>Water supply; sewerage, waste management and remediation activities | C<br>Manufacturing | H<br>Transportation and storage | L<br>Real estate activities |
|---|---|---|---|---|---|---|
| **TRI** | **0.624** | **0.089** | **2.718**** | **-0.803**** | **-1.051** | **0.190** |
| | **(0.857)** | **(0.737)** | **(1.232)** | **(0.351)** | **(0.795)** | **(0.908)** |
| MKT | 0.770*** | 0.999*** | 0.790*** | 0.970*** | 0.878*** | 0.727*** |
| | (0.023) | (0.043) | (0.033) | (0.017) | (0.021) | (0.026) |
| SMB | -0.043 | 1.299*** | 0.337*** | 0.138*** | 0.708*** | 0.412*** |
| | (0.055) | (0.165) | (0.083) | (0.040) | (0.044) | (0.044) |
| HML | 0.016 | 0.357*** | -0.250*** | -0.129*** | 0.163*** | -0.047 |
| | (0.066) | (0.087) | (0.075) | (0.040) | (0.040) | (0.047) |
| RMW | -0.039 | 0.450*** | 0.186** | -0.002 | 0.206*** | -0.102** |
| | (0.045) | (0.064) | (0.076) | (0.024) | (0.039) | (0.047) |
| CMA | -0.100 | 0.291*** | -0.169* | 0.092* | 0.037 | 0.457*** |
| | (0.079) | (0.089) | (0.094) | (0.047) | (0.059) | (0.071) |
| Intercept | -0.005 | -0.023* | -0.018 | -0.002 | -0.021* | 0.005 |
| | (0.017) | (0.014) | (0.024) | (0.007) | (0.012) | (0.015) |

| | B<br>Mining and quarrying | I<br>Accommodation and food service activities | G<br>Wholesale and retail trade; repair of motor vehicles and motorcycles | M<br>Professional, scientific and technical activities | K<br>Financial and insurance activities | A<br>Agriculture, forestry and fishing |
|---|---|---|---|---|---|---|
| **TRI** | **-3.242**** | **-2.213**** | **-0.797** | **-0.815**** | **-0.001** | **-1.201** |
| | **(1.538)** | **(1.052)** | **(0.643)** | **(0.411)** | **(0.437)** | **(2.225)** |
| MKT | 1.039*** | 0.966*** | 0.942*** | 0.943*** | 0.989*** | 0.798*** |
| | (0.040) | (0.025) | (0.016) | (0.016) | (0.019) | (0.057) |
| SMB | -0.279*** | 0.967*** | 0.758*** | 0.196*** | 0.484*** | -0.314*** |
| | (0.088) | (0.048) | (0.046) | (0.035) | (0.059) | (0.094) |
| HML | 1.340*** | -0.284*** | -0.053* | -0.178*** | 0.373*** | -0.365*** |
| | (0.110) | (0.055) | (0.029) | (0.036) | (0.034) | (0.115) |
| RMW | 0.472*** | 0.234*** | 0.240*** | -0.049** | -0.184*** | -0.086 |
| | (0.084) | (0.048) | (0.033) | (0.024) | (0.034) | (0.094) |
| CMA | -0.233 | -0.085 | 0.064 | 0.075 | 0.096*** | 0.109 |
| | (0.158) | (0.075) | (0.050) | (0.056) | (0.035) | (0.156) |
| Intercept | -0.018 | -0.024 | -0.027** | 0.002 | -0.031*** | 0.024 |
| | (0.030) | (0.017) | (0.011) | (0.007) | (0.009) | (0.036) |

| | J<br>Information and communication | N<br>Administrative and support service activities | Q<br>Human health and social work activities | S<br>Other service activities | O<br>Public administration and defence; compulsory social security | R<br>Arts, entertainment and recreation |
|---|---|---|---|---|---|---|
| **TRI** | **-0.443** | **-1.071** | **-0.507** | **-0.635** | **-0.100** | **-2.056*** |
| | **(0.498)** | **(0.755)** | **(1.250)** | **(1.183)** | **(0.983)** | **(1.233)** |
| MKT | 0.888*** | 1.019*** | 0.752*** | 0.914*** | 1.028*** | 0.824*** |
| | (0.013) | (0.020) | (0.028) | (0.023) | (0.029) | (0.025) |
| SMB | 0.400*** | 0.624*** | 0.603*** | 0.672*** | 0.885*** | 0.902*** |
| | (0.024) | (0.053) | (0.103) | (0.055) | (0.083) | (0.059) |
| HML | -0.308*** | -0.276*** | -0.178** | 0.003 | 0.045 | -0.234*** |
| | (0.028) | (0.059) | (0.086) | (0.076) | (0.070) | (0.077) |
| RMW | -0.054** | 0.071 | 0.192** | 0.156** | 0.273*** | -0.030 |
| | (0.025) | (0.057) | (0.075) | (0.066) | (0.058) | (0.066) |
| CMA | 0.010 | -0.084 | 0.083 | 0.102 | 0.010 | 0.129 |
| | (0.037) | (0.066) | (0.102) | (0.089) | (0.088) | (0.093) |
| Intercept | -0.015* | -0.039** | -0.027 | -0.073*** | -0.031 | -0.014 |
| | (0.008) | (0.015) | (0.024) | (0.024) | (0.019) | (0.022) |

Note: Regression results from FF5 (SMB, HML, RMW, and CMA) and TRI on EuroStoxx 600 Index NACE 1-digit sectors excess returns. The columns are ordered according sectors descending environmental score. Newey-West standard error in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

*remediation activities* might suggest that investors perceive waste management and remediation activities as benefitting from the transition, for instance by contributing to achieve a more circular economy.[27] The increase in returns shows that investors update their beliefs about the future value of these firms positively on days on which transition risk rises. Additionally, albeit there is only small representation (5 firms) in our sample, these companies receive very high E scores (in particular, in the E sub-categories *use of resources* and *innovation*), suggesting that investors may screen companies using also firm level information about company' commitment and ability to find eco-efficient solutions. A similar mechanism is observed for the D-Electricity, *I-Accommodation, food and services sector* (I-Accommodation) and *R-Arts, entertainment and recreation* (R-Arts). The unexpected insignificant results for D-Electricity may be driven by the combination of high E scores and high GHG emissions that characterizes this sector in our sample. Also, the negative and significant results for the low emissions I-Accommodation and R-Arts may be driven by the low E and ESG scores that these sectors receive. We also find a negative result for M-Professional. Given the broad characterisation of this sector there is no obvious interpretation why the sector responds to transition risk.

The sectoral analysis suggests that investors – while screening brown companies – do not treat sectors as a homogeneous group and combine the information with detailed firm-level characteristics. They seem to consider the firms' commitment in reducing carbon emissions and adapting to climate risks in their investment decisions. These results contribute to the Bolton and Kacperczyk (2019) analysis aimed to understand whether investors who identify risky firms just pigeonhole firms into the industry they operate in, rather than using firm level information (i.e. GHG emission). It also adds to the work by Batten et al. (2016) who suggest that transition risk events do not impact the returns of the energy sector, as investors may be uncertain about the future course of climate-related policies. We add to this, suggesting that sectoral analysis may hide important heterogeneity across firms and does not account for firm-level commitment to reduce exposure – which are likely to be relevant in climate-sensitive sectors.

[27] A circular economy is based on the principles of designing out waste and pollution, keeping products and materials in use, and regenerating natural systems.

### 4.7.2 Pricing of physical risk

Table 4.8 reports the Physical Risk Index (PRI) sensitivities of the brown portfolios (panel a) and green portfolios (panel b) as presented by the augmented FF5 in equation 4.3b.

First, we find that the excess returns for low E score and ESG score portfolios significantly decrease by -0.698 and -0.830% respectively on days when PRI rises. The result suggests that the financial market is surprised by physical risk news and asset prices respond to the new information. It also reflects that E and ESG scores contain information which investors use to detect firms exposed to physical risk. E score, in fact, includes measures of firm' adaptive capacity, e.g. innovation and use of resources, that can be relevant to identify, for instance, exposed firms characterised by high dependency on water and energy and without a resource use reduction plan.[28] In addition, the largest impact on ESG score implies that social and governance pillars also matter. The social pillar is found to be predominant as it measures a company's effectiveness in providing safe and healthy working conditions, defining the sensitivity of worker productivity to physical hazards. While these results confirm that investors tend to a negative valuation of firms exposed to physical risk or require higher premia to hold the risky assets, panel b shows no evidence of significant increase in returns for green portfolios.

Second, we find that portfolios constructed according GHG emissions levels and intensity are not sensitive to unexpected changes in physical risk supporting evidence that our PRI clearly captures aspects of climate change risk different to TRI. This result further confirms that carbon emissions are better suited for screening companies exposed to transition risks and that investors recognise the different sources of risk (transition and physical).

[28] As climate change fastens, these firms might suffer losses due to increased cost of energy or water scarcity during, for instance, heat waves.

**Table 4.8:** Pricing Physical Risk Index (PRI) – Brown and green portfolios

| Panel a) Brown portfolios | | | | |
|---|---|---|---|---|
| | E | ESG | $GHG_{EI}$ | $GHG_{E}$ |
| **PRI** | **-0.698*** | **-0.830**** | **-0.761** | **-0.592** |
| | **(0.358)** | **(0.364)** | **(0.492)** | **(0.445)** |
| MKT | 0.947*** | 0.928*** | 0.950*** | 0.947*** |
| | (0.014) | (0.012) | (0.011) | (0.010) |
| SMB | 0.616*** | 0.561*** | 0.153*** | 0.082*** |
| | (0.028) | (0.023) | (0.023) | (0.024) |
| HML | -0.060** | -0.078*** | 0.308*** | 0.317*** |
| | (0.025) | (0.023) | (0.032) | (0.030) |
| RMW | 0.077*** | 0.017 | 0.137*** | 0.136*** |
| | (0.028) | (0.026) | (0.023) | (0.019) |
| CMA | 0.052 | 0.074* | 0.025 | -0.018 |
| | (0.043) | (0.040) | (0.047) | (0.039) |
| Intercept | -0.025*** | -0.016** | -0.013 | -0.018** |
| | (0.007) | (0.007) | (0.009) | (0.007) |
| Panel b) Green portfolios | | | | |
| | E | ESG | $GHG_{EI}$ | $GHG_{E}$ |
| **PRI** | **0.092** | **-0.253** | **-0.237** | **-0.182** |
| | **(0.209)** | **(0.196)** | **(0.341)** | **(0.363)** |
| MKT | 0.983*** | 1.004*** | 1.007*** | 0.948*** |
| | (0.007) | (0.008) | (0.018) | (0.015) |
| SMB | 0.178*** | 0.122*** | 0.524*** | 0.607*** |
| | (0.020) | (0.018) | (0.061) | (0.050) |
| HML | 0.236*** | 0.192*** | 0.195*** | 0.038 |
| | (0.016) | (0.016) | (0.031) | (0.025) |
| RMW | 0.007 | 0.006 | 0.053 | 0.050* |
| | (0.014) | (0.013) | (0.032) | (0.029) |
| CMA | 0.066*** | 0.035* | 0.117*** | 0.123*** |
| | (0.021) | (0.018) | (0.032) | (0.031) |
| Intercept | 0.014*** | -0.011*** | -0.016** | -0.013* |
| | (0.004) | (0.004) | (0.007) | (0.007) |

Note: FF5 augmented by Physical Risk Index (PRI) as in equation 4.3b. Reported the daily E, ESG, $GHG_{EI}$, $GHG_{E}$ portfolios sensitivity to PRI, $\beta^{PRI}$, with Newey-West standard errors in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Moving to the sectoral analysis presented in table 4.9, while there are some sectors exposed to the weather and potentially directly affected by climate change, other economic activities take place in controlled environments (such manufacturing and services). Sectors, however, are connected through markets so that the impact of climate change can spillover between activities (IPCC, 2014).

In this framework, energy, transportation, telecommunications, and water are expected to be exposed to physical hazard through their infrastructure assets. Primary

**Table 4.9:** Pricing Physical Risk Index (PRI) – sectors NACE Rev. 2 Level 1

| | D<br>Electricity, gas, steam and air conditioning supply | F<br>Construction | E<br>Water supply; sewerage, waste management and remediation activities | C<br>Manufacturing | H<br>Transportation and storage | L<br>Real estate activities |
|---|---|---|---|---|---|---|
| **PRI** | **0.327** | **0.351** | **2.043** | **-0.278** | **-1.692**** | **-0.627** |
| | **(0.984)** | **(0.694)** | **(1.255)** | **(0.379)** | **(0.697)** | **(0.799)** |
| MKT | 0.770*** | 0.999*** | 0.790*** | 0.970*** | 0.887*** | 0.726*** |
| | (0.023) | (0.043) | (0.033) | (0.017) | (0.021) | (0.026) |
| SMB | -0.043 | 1.300*** | 0.339*** | 0.138*** | 0.706*** | 0.411*** |
| | (0.055) | (0.165) | (0.084) | (0.040) | (0.044) | (0.044) |
| HML | 0.015 | 0.357*** | -0.251*** | -0.129*** | 0.164*** | -0.047 |
| | (0.066) | (0.087) | (0.077) | (0.040) | (0.040) | (0.047) |
| RMW | -0.039 | 0.450*** | 0.187** | -0.002 | 0.205*** | -0.102** |
| | (0.045) | (0.064) | (0.077) | (0.024) | (0.039) | (0.047) |
| CMA | -0.100 | 0.291*** | -0.168* | 0.092* | 0.036 | 0.457*** |
| | (0.079) | (0.089) | (0.093) | (0.047) | (0.059) | (0.071) |
| Intercept | -0.005 | -0.023* | -0.018 | -0.002 | -0.021* | 0.005 |
| | (0.017) | (0.014) | (0.024) | (0.007) | (0.012) | (0.015) |

| | B<br>Mining and quarrying | I<br>Accommodation and food service activities | G<br>Wholesale and retail trade; repair of motor vehicles and motorcycles | M<br>Professional, scientific and technical activities | K<br>Financial and insurance activities | A<br>Agriculture, forestry and fishing |
|---|---|---|---|---|---|---|
| **PRI** | **-1.740** | **-1.069** | **-0.772** | **-0.826**** | **0.131** | **-1.043** |
| | **(1.452)** | **(1.000)** | **(0.601)** | **(0.405)** | **(0.351)** | **(2.167)** |
| MKT | 1.040*** | 0.967*** | 0.942*** | 0.944*** | 0.989*** | 0.798*** |
| | (0.040) | (0.025) | (0.016) | (0.016) | (0.019) | (0.057) |
| SMB | -0.280*** | 0.967*** | 0.758*** | 0.196*** | 0.484*** | -0.315*** |
| | (0.088) | (0.048) | (0.047) | (0.035) | (0.059) | (0.094) |
| HML | 1.342*** | -0.283*** | -0.052* | -0.177*** | 0.373*** | -0.365*** |
| | (0.113) | (0.055) | (0.030) | (0.036) | (0.034) | (0.115) |
| RMW | 0.472*** | 0.234*** | 0.240*** | -0.049** | -0.184*** | -0.086 |
| | (0.085) | (0.048) | (0.033) | (0.024) | (0.034) | (0.094) |
| CMA | -0.224 | -0.085 | 0.064 | 0.074 | 0.096*** | 0.109 |
| | (0.158) | (0.074) | (0.050) | (0.056) | (0.035) | (0.157) |
| Intercept | -0.018 | -0.024 | -0.027** | 0.002 | -0.031*** | 0.024 |
| | (0.030) | (0.017) | (0.010) | (0.007) | (0.009) | (0.036) |

| | J<br>Information and communication | N<br>Administrative and support service activities | Q<br>Human health and social work activities | S<br>Other service activities | O<br>Public administration and defence; compulsory social security | R<br>Arts, entertainment and recreation |
|---|---|---|---|---|---|---|
| **PRI** | **-0.716** | **-1.194** | **-1.795** | **-1.471** | **-0.536** | **-0.804** |
| | **(0.497)** | **(0.975)** | **(1.462)** | **(1.277)** | **(1.280)** | **(1.379)** |
| MKT | 0.888*** | 1.019*** | 0.751*** | 0.914*** | 1.028*** | 0.825*** |
| | (0.013) | (0.020) | (0.028) | (0.023) | (0.029) | (0.025) |
| SMB | 0.399*** | 0.623*** | 0.600*** | 0.671*** | 0.884*** | 0.901*** |
| | (0.025) | (0.054) | (0.102) | (0.056) | (0.083) | (0.060) |
| HML | -0.308*** | -0.275*** | -0.178** | 0.003 | 0.045 | -0.233*** |
| | (0.028) | (0.061) | (0.085) | (0.076) | (0.070) | (0.077) |
| RMW | -0.054** | 0.070 | 0.191*** | 0.155** | 0.273*** | -0.030 |
| | (0.025) | (0.058) | (0.074) | (0.066) | (0.058) | (0.066) |
| CMA | 0.010 | -0.084 | 0.081 | 0.101 | 0.010 | 0.129 |
| | (0.036) | (0.065) | (0.101) | (0.089) | (0.088) | (0.092) |
| Intercept | -0.015* | -0.039** | -0.027 | -0.073*** | 0.031 | -0.014 |
| | (0.008) | (0.016) | (0.024) | (0.024) | (0.019) | (0.022) |

Note: Regression results from FF5 (SMB, HML, RMW, and CMA) and PRI on EuroStoxx 600 Index NACE 1-digit sectors excess returns. The columns are ordered according sectors descending environmental score. Newey-West standard error in parenthesis. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

economic activities (e.g., agriculture, forestry, fishing, mining and quarrying), are also expected to be exposed through the natural and food systems on which they depend directly.

Among the sectors potentially exposed to physical hazards, we find that physical risk has a negative relationship only with H-Transportation (-1.692%). One possible explanation is that firms operating in sectors that are potentially exposed through their infrastructure assets and natural systems (i.e. D-Electricity, E-Water, F-Construction and A-Agriculture) receive very high ESG scores, suggesting their commitment to adapt and to provide, for example, safe working conditions. We also find a negative but not statistically significant relationship between physical risk and the excess returns of *L-Real Estate Activities*. This result appears to confirm the Murfin and Spiegel (2020) belief of optimism about the physical chronic hazard of rises in sea levels or the possibilities of mitigation and bailouts, and contrasts with Bernstein et al. (2019) and Baldauf et al. (2020).[29]

These results show that investors, as with transition risk, do not treat sectors as a homogeneous group and combine the information with detailed firm-level characteristics to identify firms exposed to physical risk. They seem to take into account for the firms' commitment in reducing carbon emissions and adapting to climate risks in their investment decisions.[30] They appear to be further in line with the Krueger et al. (2020) statement such that institutional investors believe that equity valuations in some sectors do not fully reflect climate risks.

## 4.8 Conclusions

As climate change risk increases, investors may tend toward a negative valuation of exposed firms. While this theoretical assumption might seem rational, its empirical evidence is not trivial as demonstrated by the conflicting results from the existent

[29] Hong et al. (2020) and Giglio et al. (2021) provide a technical climate finance review and further details on the literature about climate risks.

[30] We also find negative results for M-Professional. Given the broad characterisation of this sector there is no obvious interpretation why this sector responds to physical risk shocks.

green finance literature. There are several challenges which might impede a responsible allocation of capital from the market such as the lack of agreed and common metrics to evaluate firms' exposure to climate-related risks. It follows that investors might not be able to easily screen exposed firms failing to detect climate risky investments. On the other hand, there is the possibility that the market is insensitive to shocks to climate change news suggesting the failure to perceive these risks as source of financial risk. Both scenarios lead to a mispricing of climate change risks which pose critical consequences on the functioning of the financial sector as a vehicle to transmit climate mitigation policies.

In this paper, we test whether financial markets price climate-related risks analysing the physical risk and transition risk channels separately. This allows us to also test the existence of price differentials between the two risks as a possible consequence of their different transmission to the financial system. Additionally, we adopt a wide range of exposure metrics in order study their informational content and to identify the type of information use by investments in their investment decisions.

As a methodological contribution, we propose to distinguish between physical and transition risk using a textual analysis approach in the spirit of Engle et al. (2020). Starting from a list of authoritative texts on climate change, we build two novel vocabularies on the topic of physical risk and transition risk able to capture the multifaceted characteristics of the two risks as well as their interconnections. We then use *Reuters News* (with European regional focus) to calculate the proportion of daily news dedicated to the topic of physical risk and transition risk as the cosine-similarity with our vocabularies. This allows us to create a Physical Risk Index (PRI) and a Transition Risk Index (TRI) time series indicating the daily unexpected changes in these climate risks. The proposed risk indices reflect the climate-related information contained within the *Reuters News* which European investors might use to make their investment decisions. PRI and TRI are found to spike during days where the discussion on physical risk and transition risk were substantial. The PRI captures multiple aspects of physical risk detecting, for instance, news concerning rising sea levels, heat waves, and permafrost thawing. The TRI is able to detect news regarding the introduction of new regulation to curb the emissions of GHG, as well as news discussing the importance of the technological advances to help the transition.

We use our risk indices within the Fama-French five factor asset pricing model (Fama & French, 2015) to test the portfolios sensitivity to physical risk and transition risk. We collect closing daily prices from the EuroStoxx 600 Index historical constituents over the period 2015-2019 and we sort firms according to E score, ESG score, GHG emissions level, and GHG emissions intensity. We then aggregate firms' returns according to the so-called "greenness" or "brownness" under each metric creating eight naïve portfolios. We also conduct a sectoral analysis aggregating returns of firms belonging to the same sector considering the NACE Rev. 2 classification.

Our main findings suggest that the market, at least to some extent, prices transition risk and physical risk. There is evidence that returns of firms with poor environmental and ESG performances, as well as firms with high GHG emissions levels and intensity decrease as transition risk rise. We also find that returns of low E and ESG portfolios decline as the market is surprised by physical risk news. Our results show that both news on physical risk and transition risk carry relevant information which is reflected in asset prices. Investors perceive climate-related risks as financial risk and negatively update their expectations on future performances of exposed firms on days surrounded by higher risk. Our results also show that E and ESG exposure metrics contain information that goes beyond carbon emissions and provide information on firms' physical risk exposure. Overall, while these results show that investors identify risky assets from exposed firms possibly requiring higher premia to hold them, we find no evidence of significant increase in the returns of portfolios with positive E and ESG scores or low GHG emissions and intensity.

Overall, the sectoral analysis suggests that investors – while screening companies exposed to physical or transition risks – do not treat sectors as a homogeneous group and combine the information with detailed firm-level characteristics to detect firms exposed to climate related risks. They seem to take into account for firms' commitment in reducing carbon emissions and adapting to climate risks in their investment decisions. The transition risk sectoral analysis results provide some evidence supporting that the returns of carbon intensive sectors reduce with a rise in transition risk, i.e. C-Manufacturing and B-Mining. However, other sectors for which a negative relationship was expected, i.e. D-Electricity, are instead found to be insensitive to unexpected changes in transition risk. From a deeper analysis of our data, we highlight a positive correlation between the ESG scores and the GHG emissions, such that companies with high emissions are also found to receive higher E and ESG scores. While this fact might sound controversial, one explanation can come from the way data provides calculate E and ESG scores, typically normalising by industry. In addition, high emissions sectors might also include more firms highly committed in reducing their environmental impact with respect to sectors *per se* less polluting. This may lead to insignificant results for some high polluting sectors for which we ex ante expect a negative relationship with TRI. The physical analysis also confirms these results. Unexpected increase in physical risk concerns negatively impact only H-Transportation. We do not find significant results for any other sectors that we would ex ante considered exposed to physical hazards. This is possibly due to the high E and ESG score these sectors receive.

Our results inform both investors, policy makers, and financial institutions on the extent to which financial markets price climate-related risks and react to stimuli from the process of adjustments toward a carbon neutral economy. Our paper further technically reviews the most used metrics to identify firms' exposure to climate change and provides interesting results about the informational content of each metric.

Future studies can use the proposed vocabularies to understand the relative importance of each component of climate risks. Using the proposed risk indices, further research can be done to find physical and transition risk climate hedging investment strategies, or to assess the sensitivity of investors holdings to climate risks, or to make more responsible investments, or also to carry stress tests analyses of climate-risks.

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# Appendices

## 4.A List of climate change texts

**Table 4.A1:** List of climate change white papers for transition and physical risk

| Source | Title | Transition | Physical | Year |
|---|---|---|---|---|
| IPCC | IPCC Synthesis Report 1990 | 115-148p | | 1990 |
| IPCC | Climate change: The IPCC Impacts Assessment | | Entire | 1990 |
| IPCC | Climate change: The IPCC 1990 and 1992 Assessments | | 87-113p | 1992 |
| IPCC | IPCC Special Report: Aviation and the Global Atmosphere | Entire | | 1999 |
| IPCC | IPCC Special Report: Methodological and Technological Issues in Technology Transfer | Entire | | 2000 |
| IPCC | IPCC Synthesis Report 2001 | 302-354p | | 2001 |
| IPCC | Climate change 2001: Impacts, Adaptation and Vulnerability | | Entire | 2001 |
| IPCC | IPCC Special Report: Carbon Dioxide Capture and Storage | Entire | | 2005 |
| IPCC | IPCC Special Report: Safeguarding the Ozone Layer and the Global Climate System: Issues Related to Hydrofluorocarbons and Perfluorocarbons | Entire | | 2005 |
| IPCC | IPCC Synthesis Report 2007 | 55-70p | | 2007 |
| IPCC | Climate change 2007: Impacts, Adaptation and Vulnerability | | Entire | 2007 |
| IPCC | IPCC Special Report: Renewable Energy Sources and Climate Change Mitigation | Entire | | 2011 |
| IPCC | IPCC Special Report: Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation | | Ch. 2-4 | 2012 |
| IPCC | IPCC Synthesis Report 2014 | 75-112p | | 2014 |
| IPCC | Climate change 2014: Impacts, Adaptation and Vulnerability | | Part A & B | 2014 |

| Source | Title | Transition | Physical | Year |
|---|---|---|---|---|
| UNEP FI - Acclimatise | Navigating a new climate. Part 2: Physical risks and opportunities | | Entire | 2018 |
| IPCC | IPCC Special Report: Global warming of 1.5C | Ch. 2 & 4 | Ch. 3 | 2018 |
| IPCC | IPCC Special Report: Climate Change and land | | Ch. 1-5 | 2019 |
| IPCC | IPCC Special Report: The Ocean and Cryosphere in a changing climate | | Entire | 2019 |
| IMF – Journal of Macroeconomics | The Effects of Weather Shocks on Economic Activity: What are the Channels of Impact? | | Entire | 2020 |
| McKinsey Global Institute | Climate risk and response: Physical hazards and socioeconomic impacts | | Entire | 2020 |
| Swiss Re Institute | Natural catastrophes in times of economic accumulation and climate change | | Entire | 2020 |

Note: IPCC, Intergovernmental Panel on Climate Change; IMF, International Monetary Fund; UNEP FI, United Nations Environment Programme Finance Initiative.

## 4.B List of transition and physical risk vocabularies acronyms

**Table 4.B1:** Physical risk and transition risk vocabularies list of acronyms

| Physical risk vocabulary acronyms | | | |
|---|---|---|---|
| GHG | Greenhouse gas | RCP | Representative Concentration Pathway |
| IPCC | Intergovernmental Panel on Climate Change | | |

| Transition risk vocabulary acronyms | | | |
|---|---|---|---|
| EJ/yr | Exajoules per year | MtCO2 | Megatonne of carbon |
| eq/yr | Equivalent per year | MtCO2 eq | Megatonne of carbon equivalent |
| GHG | Greenhouse gas | TCO2 | Tonne of carbon |
| GtCO2 | Gigatonne of carbon | TEAP | Technology and Economic Assessment Panel |
| HFC | Hydrofluorocarbon | TWh/yr | Terawatt hours/year |
| HCFC | Hydrochlorofluorocarbon | UNEP | United Nations Environment Programme |
| IPCC | Intergovernmental Panel on Climate Change | UNFCCC | United Nations Framework Convention on Climate Change |
| IEA | International Energy Agency | USD/kWh | United States Dollar/Kilowatt hour |

Note: Physical risk and transition risk summary vocabulary as in figure 4.1 list of acronyms.

## 4.C Methodology summary

Main steps to create the *Transition Risk Index* (TRI) and the *Physical Risk Index* (PRI)

1. Create documents

   - Collect climate change texts (full list in table 4.A)
   - Screen texts content
   - Separate transition risk and physical risk texts
     - **Transition risk document**
     - **Physical risk document**
   - Collect real time news for the sample period
     - Aggregate news into **daily news documents**

2. Create the Transition Risk *tf-idf* Matrix (TRM) and the Physical Risk *tf-idf* Matrix (PRM)

   (a) Transition risk case

   - Consider the collection of documents composed by all daily news plus the transition risk document
   - For each document of the collection
     - Remove the *stopwords*
     - Create a list of unique stemmed unigrams & bigrams (terms) with the relative count
     - Keep only transition risk document terms
     - Calculate the *tf* of each term
   - Compute the *idf* for each term
   - Create the Transition Risk *tf-idf* Matrix (TRM)

    - Obtain the **ranked transition risk vocabulary** (column *TR* of the TRM)

(b) Physical risk case

- Consider the collection of documents composed by all daily news plus the physical risk document
- For each document of the collection
    - Remove the *stopwords*
    - Create a list of unique stemmed unigrams & bigrams (terms) with the relative count
    - Keep only physical risk document terms
    - Calculate the *tf* of each term
- Compute the *idf* for each term
- Create the Physical Risk *tf-idf* Matrix (PRM)
    - Obtain the **ranked physical risk vocabulary** (column *PR* of the PRM)

3. Compare each daily news to the transition risk vocabulary and physical risk vocabulary

(a) Transition risk case

- Compute the cosine similarity between the *tf-idf* of each daily news and the *tf-idf* of the transition risk document
- Model the cosine similarity time series (transition risk media concern) as an AR1
- Extract the residuals which determine the shocks to the transition risk, namely the ***Transition Risk Index*** (**TRI**)

(b) Physical risk case

- Compute the cosine similarity between the *tf-idf* of each daily news and the *tf-idf* of the physical risk document

- Model the cosine similarity time series (physical risk media concern) as an AR1
- Extract the residuals which determine the shocks to the physical risk, namely the ***Physical Risk Index*** (**PRI**)

Transition Risk *tf-idf* Matrix (TRM) and Physical Risk *tf-idf* Matrix (PRM)

$$\mathrm{TRM} = \begin{array}{c} \begin{array}{cccccc} \mathrm{News}_1 & \mathrm{News}_2 & & \mathrm{News}_{T-1} & \mathrm{News}_T & \mathrm{TR} \end{array} \\ \begin{bmatrix} a_{News_1}(term_1^{TR}) & a_{News_2}(term_1^{TR}) & \cdots & a_{News_{T-1}}(term_1^{TR}) & a_{News_T}(term_1^{TR}) & a_{TR}(term_1^{TR}) \\ a_{News_1}(term_2^{TR}) & a_{News_2}(term_2^{TR}) & \cdots & a_{News_{T-1}}(term_2^{TR}) & a_{News_T}(term_2^{TR}) & a_{TR}(term_2^{TR}) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ a_{News_1}(term_{M-1}^{TR}) & a_{News_2}(term_{M-1}^{TR}) & \cdots & a_{News_{T-1}}(term_{M-1}^{TR}) & a_{News_T}(term_{M-1}^{TR}) & a_{TR}(term_{M-1}^{TR}) \\ a_{News_1}(term_M^{TR}) & a_{News_2}(term_M^{TR}) & \cdots & a_{News_{T-1}}(term_M^{TR}) & a_{News_T}(term_M^{TR}) & a_{TR}(term_M^{TR}) \end{bmatrix} \end{array} \begin{array}{l} \\ term_1^{TR} \\ term_2^{TR} \\ \\ term_{M-1}^{TR} \\ term_M^{TR} \end{array}$$

$$\mathrm{PRM} = \begin{array}{c} \begin{array}{cccccc} \mathrm{News}_1 & \mathrm{News}_2 & & \mathrm{News}_{T-1} & \mathrm{News}_T & \mathrm{PR} \end{array} \\ \begin{bmatrix} a_{News_1}(term_1^{PR}) & a_{News_2}(term_1^{PR}) & \cdots & a_{News_{T-1}}(term_1^{PR}) & a_{News_T}(term_1^{PR}) & a_{PR}(term_1^{PR}) \\ a_{News_1}(term_2^{PR}) & a_{News_2}(term_2^{PR}) & \cdots & a_{News_{T-1}}(term_2^{PR}) & a_{News_T}(term_2^{PR}) & a_{PR}(term_2^{PR}) \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ a_{News_1}(term_{N-1}^{PR}) & a_{News_2}(term_{N-1}^{PR}) & \cdots & a_{News_{T-1}}(term_{N-1}^{PR}) & a_{News_T}(term_{N-1}^{PR}) & a_{PR}(term_{N-1}^{PR}) \\ a_{News_1}(term_N^{PR}) & a_{News_2}(term_N^{PR}) & \cdots & a_{News_{T-1}}(term_N^{PR}) & a_{News_T}(term_N^{PR}) & a_{PR}(term_N^{PR}) \end{bmatrix} \end{array} \begin{array}{l} \\ term_1^{PR} \\ term_2^{PR} \\ \\ term_{N-1}^{PR} \\ term_N^{PR} \end{array}$$

Note: $a$ denotes the *tf-idf* score, $News_1$ denotes the daily news document for day 1, $T$ denotes the total number of days in the sample period, $term_1^{TR}$ denotes the $1^{st}$ alphabetical vocabulary term of the transition risk document (TR), $term_1^{PR}$ denotes the $1^{st}$ alphabetical vocabulary term of the physical risk document (PR), $M(N)$ denotes the total number of terms of the transition (physical) risk vocabulary.

## 4.D Brown and green portfolios details

**Table 4.C1:** Brown portfolios details

| Panel a) Brown portfolios | | E | ESG | $GHG_{EI}$ | $GHG_E$ |
|---|---|---|---|---|---|
| Metric Average | | 22.01 | 36.23 | 783,345 | 14,261,210 |
| Number of assets | | 273 | 304 | 190 | 182 |
| **Panel b) Composition** | | | | | |
| NACE Code | NACE Sector | E | ESG | $GHG_{EI}$ | $GHG_E$ |
| A | Agriculture, forestry and fishing | 0.00% | 0.00% | 0.00% | 0.00% |
| B | Mining and quarrying | 3.30% | 2.63% | 12.11% | 11.54% |
| C | Manufacturing | 17.58% | 19.41% | 32.11% | 34.07% |
| D | Electricity, gas, steam and air conditioning supply | 0.73% | 1.64% | 10.00% | 9.89% |
| E | Water supply; sewerage; waste management and remediation activities | 0.37% | 0.00% | 2.63% | 1.65% |
| F | Construction | 0.73% | 0.66% | 3.68% | 3.85% |
| G | Wholesale and retail trade; repair of motor vehicles and motorcycles | 8.06% | 6.91% | 2.11% | 6.59% |
| H | Transporting and storage | 1.83% | 2.63% | 6.84% | 5.49% |
| I | Accommodation and food service activities | 1.10% | 0.99% | 1.58% | 1.10% |
| J | Information and communication | 9.89% | 8.88% | 2.63% | 3.30% |
| K | Financial and insurance activities | 28.94% | 25.33% | 3.16% | 4.40% |
| L | Real estate activities | 2.93% | 4.61% | 4.21% | 0.00% |
| M | Professional, scientific and technical activities | 12.82% | 13.82% | 12.11% | 11.54% |
| N | Administrative and support service activities | 2.93% | 2.96% | 1.05% | 1.10% |
| O | Public administration and defence; compulsory social security | 1.10% | 0.66% | 0.00% | 0.00% |
| Q | Human health and social work activities | 1.10% | 0.99% | 0.00% | 0.00% |
| R | Arts, entertainment and recreation | 1.83% | 2.30% | 0.53% | 0.00% |
| S | Other services activities | 1.10% | 1.32% | 0.53% | 0.00% |
| N/A | | 3.66% | 4.28% | 4.74% | 5.49% |

Note: Brown portfolios metric averages, number of assets, and % sectoral (NACE Rev. 2) composition according to Environmental score (E), Environmental, Social, and Governance score (ESG), GHG emissions level ($GHG_E$), and GHG emissions intensity ($GHG_{EI}$).

**Table 4.C2:** Green portfolios details

| Panel a) Green portfolios | | E | ESG | $GHG_{EI}$ | $GHG_E$ |
|---|---|---|---|---|---|
| Metric Average | | 87.60 | 82.56 | 3,251 | 8,937.90 |
| Number of assets | | 251 | 279 | 220 | 222 |
| **Panel b) Composition** | | | | | |
| NACE Code | NACE Sector | E | ESG | $GHG_{EI}$ | $GHG_E$ |
| A | Agriculture, forestry and fishing | 0.00% | 0.00% | 0.00% | 0.00% |
| B | Mining and quarrying | 3.98% | 4.66% | 0.91% | 1.35% |
| C | Manufacturing | 29.88% | 32.62% | 10.45% | 14.41% |
| D | Electricity, gas, steam and air conditioning supply | 5.18% | 4.66% | 0.00% | 0.45% |
| E | Water supply; sewerage; waste management and remediation activities | 1.20% | 0.72% | 0.00% | 0.00% |
| F | Construction | 5.58% | 3.94% | 3.18% | 4.05% |
| G | Wholesale and retail trade; repair of motor vehicles and motorcycles | 5.18% | 3.94% | 3.64% | 3.15% |
| H | Transporting and storage | 2.39% | 3.58% | 0.91% | 0.00% |
| I | Accommodation and food service activities | 1.20% | 1.79% | 1.36% | 0.90% |
| J | Information and communication | 4.38% | 6.81% | 11.36% | 11.26% |
| K | Financial and insurance activities | 23.11% | 17.20% | 49.55% | 39.64% |
| L | Real estate activities | 4.78% | 2.51% | 2.27% | 7.21% |
| M | Professional, scientific and technical activities | 7.97% | 10.04% | 8.64% | 9.01% |
| N | Administrative and support service activities | 1.20% | 1.08% | 2.27% | 1.35% |
| O | Public administration and defence; compulsory social security | 0.00% | 0.00% | 0.45% | 0.90% |
| Q | Human health and social work activities | 0.00% | 0.72% | 0.45% | 0.45% |
| R | Arts, entertainment and recreation | 0.00% | 0.36% | 0.91% | 1.80% |
| S | Other services activities | 0.40% | 0.36% | 0.00% | 0.00% |
| N/A | | 3.59% | 5.02% | 3.64% | 4.05% |

Note: Green portfolios metric averages, number of assets, and % sectoral (NACE Rev. 2) composition according to Environmental score (E), Environmental, Social, and Governance score (ESG), GHG emissions level ($GHG_E$), and GHG emissions intensity ($GHG_{EI}$).

# Chapter 5

# Conclusions

This thesis constitutes three original studies that make contributions to the general finance literature and especially to the cryptocurrency, risk and portfolio management, noise-trader, and green finance strands of literature. Through the thesis, I answer unique research questions and conduct different empirical analyses. This thesis improves the understanding of cryptocurrencies as financial assets by examining the Bitcoin reaction to high-frequency news compared to traditional currencies. It documents the role of news within different markets. It additionally quantifies the economic value of a novel investment strategy which times financial noise, providing a solution to manage price noise-risk and proposing a method to model next period noise traders beliefs. Finally, it tests the sensitivity of equity prices to the climate change physical and transition risks, delivering new climate risk indices with several application for future research and other practical analyses.

Chapter 2 investigates whether Bitcoin and foreign exchange returns, volume and volatility share similar characteristics and comove in terms of reaction to high-frequency non-scheduled news sentiment at the 15-minute level for the period January 2012 – November 2018. I construct a sentiment index for each currency and Bitcoin which I implement into exogenous vector autoregressive models. I find that, while traditional currencies comove and share homogeneous reactions to news sentiment suggesting the strong inter-linkage of this market, the Bitcoin results deviate from the Forex findings. The main results imply that Bitcoin does not share many characteristics with traditional currencies and it is mostly unrelated to Forex news sentiment during the entire sample. I document that the contemporaneous impact of news sentiment on Bitcoin is not as strong and significant as in the foreign exchange market where currencies promptly react to news. Additionally, there is evidence of delayed significant impact of news sentiment on Bitcoin returns suggesting this market needs more time to digest information, most likely due to Bitcoin market frictions and technological advancement issues. Surprisingly, a positive relation between Bitcoin returns and news is found independently of whether the news sentiment is classified as positive or negative, suggesting the strong investors' enthusiasm towards the digital currency. This result exacerbates during Bitcoin bubble periods confirming the high enthusiasm finding and showing that investors either downplay or reverse negative news during bubbles. I further document the Bitcoin reaction to intraday cryptocurrency cyber-attacks and fraud news sentiments. I find that the arrival of negative cyber-attack news dampen the enthusiasm toward the digital currency, decreasing Bitcoin returns and volatility. The main results are robust to tests for commonality and multicollinearity.

This study contributes to the cryptocurrency literature and help the discussion on the nature of Bitcoin as a currency or an asset. Results are informative for both investors and policy-makers as they provide new empirical evidence on the behaviour of the digital currency Bitcoin both in relation to news sentiment and with respect to Forex considering different market conditions. The analysis provides insights about the characteristics of the digital currency that can be in fact exploited by investors to better assess the volatility and riskiness of their investments, and by policy-makers to better understand possible systemic risks posed by cryptocurrencies as well as other issues such as cyber-criminality and fraud. The results of this essay further contribute to the Forex literature suggesting that both trading strategies and standard models of exchange-rate determination could benefit from the inclusion of unscheduled news sentiment about the exchange rate.

Chapter 3 studies the role of noise risk for portfolio selection with aim to assess the economic value of strategies that time financial noise. While the importance of noise trading has been documented by the noise-traders literature since the seminal work of Black (1986), the noise as a source of price-risk remains largely unexplored by the risk and portfolio management literature. The unpredictability of noise-traders future beliefs prevents from creating ex-ante strategies able to hedge or speculate on the noise-risk and limits the investigation of this price-risk.

Chapter 3 proposes a dynamic noise-timing strategy which exploits the temporary dependence in noise traders' beliefs. It assesses the economic value of noise-timing according to a utility-based approach for risk-averse and short-horizon investors. It proposes to estimate noise via a Kalman filter which decomposes price time series into a permanent (fundamental) and temporary (noise) component, similarly to Brogaard et al. (2014) and Hendershott and Menkveld (2014), and to use its prediction to model next period noise traders beliefs. This allows for the creation of a dynamic noise-timing strategy which is able to manage the noise risk based on next period noise traders' expectations, under a mean-variance framework in the spirit of Fleming et al. (2001). The economic value of noise-timing is finally calculated in terms of performance fee that makes an investor indifferent between two investment alternatives, in line with Fleming et al. (2001), Jondeau and Rockinger (2007), and Karstanje et al. (2013). The main findings provide evidence that the noise timing has statistically positive value and risk-averse and short-horizon investors are willing to pay an annual performance fee of between 314 and 940 basis points, according to their level of risk aversion and their target returns, to switch from a static strategy to the noise timing strategy. The noise timing strategy performs better than other benchmark strategies including the random walk and volatility timing strategies, and it yields significant gains also during period of heightened volatility including the initial Covid-19 period. This study offers relevant contribution to the noise-trader literature and more broadly to the risk and portfolio management literature. It proposes a model that allows to estimate next period traders beliefs, previously considered unpredictable, and that grants the possibility to manage the noise price-risk. It further contributes to the more recent strand of literature on cryptocurrencies and their investment characteristics by considering these as additional portfolio asset allocation.

Chapter 4 studies the sensitivity of equity prices to climate change risks. In particular, it proposes a method to assess separately the impact of the two main climate risks, namely physical risk and transition risk. In fact, the literature agrees that the two climate risks have the potential to impact the financial system differently and highlights the need to document their transmission separately. In line with Engle et al. (2020), I adopt a textual analysis approach to build two risk time series on physical risk and transition risk. Specifically, I screen climate change scientific texts and create two novel vocabularies on physical and transition risk. Considering that investors may updated their subjective beliefs on climate risks from newspapers, I compare the vocabularies with a corpus of news obtaining a Physical Risk Index and a Transition Risk Index. The two indices are found to spike during days where news highly discuss topic regarding specific themes about physical risk and transition risk indicating the ability of the indices to capture shocks to climate risks. Integrating the risk indices into a Fama-French five factor model, I group the returns of the historical constituents of the EuroStoxx 600 Index over the period 2015-2019 into green and brown portfolios according to several exposure metrics to test their sensitivity to climate risks. I consider the GHG emissions levels, GHG emissions intensity, environmental scores, and ESG scores of firms to create portfolios. Results suggest that investors perceive climate related risks as a source of financial risk and they appear to negatively value exposed firms as climate risks rise. In particular, firms with low environmental scores and ESG scores, as well as firms with high GHG emissions level and intensity are found to decrease in returns as transition risk rises suggesting investors consider these firms as exposed to this climate risk. In addition, firms with low E and ESG ratings also decrease in returns when physical risk increases. This finding suggests that investors exploit E and ESG scores to screen firms exposed to physical risk. I also conduct a sectoral analysis from which arises that investors combine the sectoral information with detailed firm-level characteristics to identify firms exposed to climate risks. The findings of this study are informative to understand the extent of market price response to shocks to climate change risks and to assess the pricing differential of physical and transition risk. The study further provides two novel vocabularies and risk indices on physical and transition risks that can support future research and contribute to the green finance literature and finance literature more broadly.

## 5.1 Implications and future research

This thesis provides evidence of differences between the cryptocurrency Bitcoin's and the major traditional currencies' responses to high-frequency news. Future research could analyse the reaction to news sentiment of other cryptocurrencies to further investigate the interlinkages of the cryptocurrency market, or extend the study to non-linear models to further investigate the Bitcoin/cryptocurrency sensitivity to news. Future research may also focus on the response of Bitcoin return and volatility to news sentiment considering different Bitcoin denominations to investigate potential asymmetric reactions, or considering lagged effects to gather insights on the persistence of news sentiment impacts.

The finding of a positive economic valuation of strategies that time price noise paves the way for a new strand of literature that focuses on the role of noise risk within the context of portfolio and risk management. Additional research is needed to address some limitations of this thesis, for instance considering more sophisticated asset allocation approaches and assuming different utility functions which can improve the assessment of the noise-timing value. Future analyses can further assess the economic value of noise timing to longer-horizon investors exploring the possibility that noise traders' beliefs will not revert to their mean for a long time. The findings of this thesis also call for new research on the importance of noise traders for asset price formation.

Finally, this thesis documents the financial implications of climate change and finds that financial markets price climate-related risks at least to some extent. More research is required to find agreed and common metrics of firms' climate risk exposure otherwise new mispricings can arise from inaccurate metrics investors might use to detect climate risky investments. Future research can deepen the response to climate risks of sectors combined with granular firms characteristics, or investigate the existence of physical and transition climate risks premia. My current research extends the climate risks indices proposed in this thesis to a wider sample period and studies the time varying physical and transition risks spillover effects on asset prices returns and volatilities to measure the interdependence between climate risks and equity.

## 5.2 Summary

The topics addressed by this thesis are of great interest for both academics, investors and regulators. Additional research is needed to monitor the evolution and growth of digital currencies and their derivatives and their impact on risk and portfolio management. Finally, in the today's changing climate world it is essential to study and explore the financial consequences and implications of the transition to a carbon neutral economy and how this process influences asset prices and financial decision making.

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