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Understanding the stock-bond correlation: the evidence from COVID-19 period.

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Table of Contents

ABSTRACT **2**

1 INTRODUCTION **3**

2 LITERATURE REVIEW **6**

2.1 Stock-Bond Nexus 6
2.2 Economic Uncertainty 8
2.3 COVID-19 Effect on Economics 10
2.3.1 COVID-induced Economic Uncertainty *11*

3 AN OVERVIEW OF THE U.S. FINANCIAL MARKET **12**

3.1 An Overview of the U.S. Stock Market 12
3.2 An Overview of the U.S. Bond Market 13

4 DATA **15**

4.1 Time Frame 15
4.2. Uncertainty 15
4.3 Bond Returns 16
4.4 Stock Returns 17

5 EMPIRICAL RESULTS **18**

5.1 Data Analysis 18
5.2 Unconditional Correlation 20
5.3 Conditional Correlation 20

CONCLUSION **22**

BIBLIOGRAPHY **24**

APPENDIX **28**

I Tables and Figures 28
II Calculations 40
A Log Returns *40*
B Significance of Correlation *40*
III Implementation of analysis 41

SUMMARY **45**

Abstract

Understanding the connection between stock and bond returns helps investors to create a better portfolio. This paper examines the stock-bond nexus focusing on economic uncertainty effect. First, we provide a review of different perspectives on the stock-bond correlation and cover economic variables that have been commonly used in the literature as underlying factors of the stock-bond relation. Then we investigate in detail the economic uncertainty as a driving force of the correlation. Finally, we conduct empirical research on the stock-bond correlation during the pandemic period of 2020 in the U.S. and provide a discussion on results.

1 Introduction

It is important to acknowledge what drives the relation between stock and bond returns in order to have a better perspective on financial market performance. By allocating investments among capital stocks (riskier but more profitable financial instruments) and government bonds (safer assets but with less significant rewards), investors may diversify portfolio – reach the target return, reducing the risk. When diversification is not enough, investors may suffer from realized risks, but even when a portfolio is properly constructed with risk minimized, the benefits from diversification depend on the level of correlation between its assets. Like this, in periods of negative stock-bond correlation, benefits from stock-bond diversification increase while the positive stock-bond correlation moves assets in the same direction reducing benefits from diversification. Therefore, it is important to figure out what exactly drives the stock-bond nexus and which way, as well as determine factors that have good explanatory power to the correlation.

The periods of shocks are of particular interest since they have a tremendous effect both on the real economy and financial system, and as a consequence on investors' decisions as well. At the time of writing, the world is in the middle of the crisis caused by a respiratory infection COVID-19. According to the World Health Organization (WHO) Report, 2020 there are 216 countries, areas or territories with cases of Coronavirus: within 3-4 months the disease spread from China to all over the world (see Li, Pei, Chen, Song, Zhang, Yang, and Shaman, 2020 for a possible explanation of the incredible infection rate). There are no specific vaccines or treatments for this disease, according to Wang et al., 2020, at least publicly available ones, and the earliest access to vaccines is forecasted by early 2021 by Le et al., 2020. Considering the fact that the epidemic is developing rapidly and the lack of global access to necessary special medical equipment, it is essential to keep monitoring the situation constantly and take relevant precautionary measures (see policy recommendations by Budish, Kashyap, Koijen, and Neiman, 2020). At different points, many authorities following the WHO recommendations announced the lockdown: the first lockdown in the U.S. was announced in California on 19 March 2020, the U.K. entered the quarantine on Monday 23 March 2020. The precautions necessary to take, including world-wide shutdown, have exposed the world economy to the inevitable shock and have caused severe economic costs (Atkeson, 2020; Coibion, Gorodnichenko, and Weber, 2020; Gormsen and Koijen, 2020). Opinions were divided among economists about the future state of the economy: while Paul Krugman forecasts a fast recovery[1], Nouriel Roubini[2] and Kenneth S. Rogoff[3] see a poor recovery and predict a depression after COVID-19.

Bloom et al. 2020 analyze the recent period up until March 2020 and show the effect of COVID-19 on economic uncertainty. At the time of writing, two more months have passed under the world-wide crisis. We follow Bloom et al. 2020 in their understanding of the uncertainty and go further adjusting their analysis to the new data became available.

The level of uncertainty definitely has its impact on the economy, including financial market performance, since it reflects and affects the expectations of market participants. Though it is challenging to establish any causalities because uncertainty, in turn, arises from certain economic and real conditions, we can detect correlations and try and predict the future behavior of the market. Like this, Connoly et al., 2005 find a negative relation between the uncertainty measures and the future correlation of stock and bond returns.

Examination of assets' behavior and stock-bond correlation in different economic conditions has a broad scope of application since it helps build more accurate financial forecasts. Discovering macroeconomic channels, financial intermediaries' actions, and other structural kinds of explanations that tend to have a certain level of predictions, allows us to estimate the response of variables of interest to the shocks that are going to move the market. This paper provides a better perspective on the linkage of economic uncertainty caused by a world-wide breakdown and financial market performance. In turn, accurate prognosis allows investors to adjust their market expectations to the shocks.

[1] See Krugman's interview on the Princeton Economics Webinar, 2020.
[2] See Roubini's interview on the Bloomberg Markets podcast, 2020.
[3] See Rogoff's interview on the Fox News release, 2020.

Along with the practical value of this paper to capital market participants, our analysis might be interesting to authorities that would like to have a better understanding of the effect that the real news and policies such as an infectious disease and a lockdown may have on the economic and financial systems.

The remainder of this paper is organized as follows. Chapter 2 covers the literature on relevant topics: Section 2.1 is devoted to stock-bond relation, Section 2.2 discusses the concept of economic uncertainty; the discussion on the COVID-19 pandemic and its effect on the world economy is provided in Section 2.3. Chapter 3 contains an overview of the U.S. and the U.K. capital markets at the moment of writing this paper: both the stock market and bond market. Chapter 4 describes the data used in the analysis. The experimental framework used to evaluate the impact of the resulting uncertainty on the stock-bond correlation, as well as the empirical results, is reported in Chapter 5. Finally, we close the paper with Conclusion. The Summary of the paper is also attached. All relevant attachments (graphs, calculations, and code) are presented in Appendix.

2 Literature Review

2.1 Stock-Bond Nexus

This paper contributes to the literature in many ways. First, it further integrates to the literature with asset pricing by focusing on the driven force of uncertainty. Second, it further investigates the empirics of bond-stock co-movements using the most recent data and analyzing the market under the unique macroeconomic circumstances.

Most papers choose long-term bond yields, e.g., 10-year U.S. Treasury notes, while we focus on the short-term returns in order to focus on short-horizon effects.

There is a massive amount of papers that try to explain the correlation between stock and bond returns by their common exposure to macroeconomic factors. One such factor is an interest rate. Indeed, since the fundamental value of a bond is defined as the sum of all discounted future cash-flows, bond returns are inversely correlated with discounting rates: when rates go up, bond returns fall, and vice-versa. Bunda, Hamann, and Lall, 2009; Lin, Yang, March, and Cheng, 2018; Skintzi, 2019; Viceira, 2012 et al. consider interest rate as one of the primary reasons for changes in bond returns, therefore in stock-bond relation. Rigobon and Sack, 2004 also notice that surprise changes in interest rate have an impact on stock performance as well, resulting in a decline in stock prices.

Campbell and Ammer, 1993 use a VAR model to investigate what moves the stock and bond markets and argue that long-term bond returns are mostly driven by inflation while real interest rates have little impact on returns. Inflation is considered to be a major driven force of bond returns and as a consequence of a stock-bond correlation in many papers: Andersson, Krylova, and Vähämaa, 2008; Campbell and Ammer, 1993; Dimich, Kiviaho, Piljak, and Äijö, 2016; Yang, Zhou, and Wang, 2009 and others.

Another possible way to detect the stock-bond correlation is to track the information coming to the market. With a high-frequency approach, Cieslak and Pang, 2020 tries and identify economic shocks from stock and government bonds using the national news as a source of time-varying stock-bond correlation.

Some papers assumed the constant stock-bond correlation during the entire period of examination. Most studies, though, observe time-varying correlation in stock and bond returns. Lin et al., 2018, in their recent paper, adopt continuous wavelet analysis to capture the dynamics of stock-bond correlation across different frequencies. They note that the macroeconomic factors that drive the stock-bond nexus do not vary across the time frequencies, while the impacts of crises do vary across frequencies.

It is also a stylized fact that the stock-bond correlation turned from mostly positive to mostly negative in the mid-1990-s [see Campbell, Pflueger, and Viceira, 2020 for the possible explanation]. Campbell and Ammer, 1993 used monthly data and showed a small positive correlation driven positively by variation in real rates and negatively by variation in expected inflation. Connolly et al., 2005 show the significant time variation in correlation observed in the 1986–2000 sample period and argue that a negative sign cannot be explained simply by expected inflation. They examine whether the stock-bond nexus varied with two measures of stock market uncertainty: implied volatility from the Chicago Board Options Exchange's Volatility Index and stock turnover (following Kodres and Pritsker, 2002, they associate the higher value of turnover with a higher level of uncertainty).

A common way to look at the time variation in the stock-bond nexus is to introduce the concept of flights: *flight-from-quality* (FFQ) and *flight-to-quality* (FTQ), also referred to as *flight-to-safety*. The idea behind the flights is that if investors choose bonds over stocks, i.e., they buy bonds and sell stocks, they cause, what is called, FTQ. Similarly, if investors choose stocks over bonds, i.e., they buy stocks and sell bonds, they cause an FFQ. Baur and Lucey, 2009 suggest that such flights may cause negative stock-bond returns correlation. Meanwhile, it is natural to assume that the negative correlation itself causes investors to diversify their portfolios in order to minimize losses. Empirical research shows that flights happen a lot in crises, which are associated with a negative correlation (see Connolly et al., 2005; Gonzalo and Olmo, 2015; Baele, Bekaert, and Inghelbrecht, 2010; Dimic et al., 2016). FTQ and FFQ happen during the stock and bond crisis correspondingly. As a contrary to flights which are characterized by a significant decrease in the stock-bond return correlation resulting in a negative correlation coefficient[4] (i.e., stocks and bonds moving in the opposite direction), Baur and Lucey, 2009 define the contagion effect as a significant increase in the correlation resulting in positive correlation coefficient (i.e., co-movement of assets).

It is also a common practice to link the economic uncertainty to the stock-bond relation. There is a significant part of the related literature that discovers the driving force of the financial market uncertainty for their correlation: Andersson et al., 2008; Bunda et al., 2009; Chiang, Li, and Yang, 2015; Connolly, Stivers and Sun, 2005; Dimich et al., 2016; Lin et al., 2018.

The empirical investigation of Connolly et al., 2005 shows that the time-series variation of the uncertainty proxied by VIX is indeed informative about the time-series behavior of the stock market. They find a negative correlation between uncertainty and future stock-bond nexus.

2.2 Economic Uncertainty

There are many ways to define and estimate economic uncertainty in academic literature. Taking into account that uncertainty always implies unpredictability of future outcomes, its actual value depends on the expectations, i.e., beliefs, which may vary through individuals: consumers, managers, financial market participants, policymakers, government authorities, and others. Therefore, depending on the goal, one may use the proxy for economic uncertainty that most fully reflects their purposes. Here we are interested in those kinds of uncertainty that could potentially affect the variation of stock-bond nexus.

The role of uncertainty is tremendous. It allows us to estimate the level of an individual's confidence in future economic conditions, which in turn determines the individual behavior and decisions regarding investments, employment, consumption, and others. As follows, there is a kind of simultaneous relation between uncertainty and economic conditions. Bloom, 2014 mentions four channels for uncertainty to influence economic growth: real options, risk premia, growth options, and so-called Oi-Hartman-

[4] If a decrease in the stock-bond return correlation results still in a positive correlation coefficient, *decoupling* effect takes place.

Abel effect. The predictive power of uncertainty might help to build a better prognosis of fundamental economic variables. Bloom, 2009 and Baker and Bloom, 2013 show that uncertainty tends to jump up after major shocks with a subsequent slowdown in investment, hiring, and productivity growth.

In particular, Dimich et al., 2016 examine the impact of financial market uncertainty on the stock-bond correlation in emerging markets. They analyze the effect of stock and bond market uncertainty in both global and local economies. We follow them and use both the stock and bond market implied volatilities. Since we focus on the developed U.S. market, the global and local economies coincide in our research.

There is a common practice (see Andersson et al., 2008; Baker, Bloom, Davis, and Terry, 2020; Barrero, Bloom, and Wright, 2017; Connolly et al., 2005; Dimich et al., 2016; Lin et al., 2018; Skintzi, 2019) to proxy a global short-run stock market uncertainty with the CBOE Volatility Index (VIX), which estimates expected volatility by aggregating the weighted prices of S&P 500 Index. Barrero, Bloom, and Wright, 2017 go further and estimate the long-run uncertainty up to a five-year horizon with the generalized VIX index, using the stylized fact that the volatility curve is approximately linear.

Although VIX is a well-recognized index, implied volatility is not the only way to measure the uncertainty. Ahir, Bloom, and Furceri, 2019 develop a new index of uncertainty – the World Uncertainty Index (WUI), based on the frequency of the words 'uncertainty' in the quarterly Economist Intelligence Unit country reports. A similar approach to the construction of uncertainty index, based on newspaper coverage frequency, had been taken by Baker, Bloom, and Davis, 2016 in developing of Economic Policy Uncertainty Index (EPU). Both indices were created to capture economic changes, with the second one focusing on political developments like the withdrawal of the U.K. from the European Union in 2020, the failure of Lehman Brothers in 2007, or the U.S. gubernatorial elections 2020. Like this, they are expected to reflect the world-wide instability related to the COVID-19 pandemic: from medical concerns to policy responses. Baker et al., 2020 document a significant increase in economic uncertainty in April 2020 using VIX and EPU indices.

The bond market uncertainty is widely estimated by the Merrill Lynch Option Volatility Estimate (MOVE) index, developed by Bank of America Merrill Lynch. The MOVE index measures the U.S. interest rate expected volatility (by calculating the weighted average of over-the-counter volatilities on the two-, five-, ten-, and thirty-year Treasuries) and captures the realized volatility in bond market sentiment. The inventor of the index himself, Harley Bassman, in his interview "Insight in Volatile Markets", 2020, compares the MOVE index to the VIX index, saying that although "The MOVE and the VIX are very similar in that they basically measure short-dated one-month volatility…the MOVE…tends to signal things ahead` of the equity market, because the underlying plumbing of finance happens in the bond market". Empirical data supports the fact that the MOVE index anticipates the VIX signals: the bond market response to the COVID-19 policies is a week ahead from the stock market reaction (see Figure I1).

2.3 COVID-19 Effect on Economics

Quarantine measures caused by the COVID-19 pandemic, started in 2019 and still ongoing at the time of writing (the second quarter of 2020), undoubtedly had a crucial effect on world economics. Almost every aspect of life was affected by the outbreak. We are in a unique kind of situation now with a lack of comparable historical periods.

A significant number of employees in the U.K. were forced to leave their jobs that cannot be done remotely: the Office for National Statistics report, 2020 noted that "in the reference period 23 March[5] to 5 April 2020, 78% of the workforce had been furloughed in businesses that had temporarily closed or had paused trading"; according to the data on U.S. civilian unemployment rate[6] from the U.S. Bureau of Labor Statistics, 2020 the rate was equal to 3.5% in February 2020, increased by 0.9% to 4.4% in March 2020 and reached its pick at 14.7% in April 2020 (see Appendix Figure I2); moreover, the U.S. Bureau of Labor Statistics Report, 2020 noted that the

[5] The Prime Minister of the U.K., Boris Johnson, announced the lockdown amid coronavirus pandemic on Monday 23 March 2020 (see the New York Times article, 2020).

[6] The U.S. Bureau of Labor Statistics uses the seasonally adjusted unemployment rate. For further details on concepts and adjustment technics used, consult the BLS Handbook of Methods.

unemployment rate 14.7% in April 2020 was “the highest rate and the largest over-the-month increase in the history of the series” since January 1948.

In an attempt to help distressed workers and firms cope with the situation, central banks attempted easing monetary policies, governments postponed tax payments, and companies made an incredibly rapid transition into remote work in order to slow down the spread of the virus. Gormsen & Koijen, 2020 explore how the coronavirus outbreak and corresponding policy responses affect the investors’ expectations about economic growth. They show that fiscal stimulus boosts long-term market expectation but have little effect on a short horizon.

2.3.1 COVID-induced Economic Uncertainty

In particular, Baker et al., 2020 study the impact of COVID-19 pandemic on economic uncertainty. They consider five types of uncertainty measures and find the enormous increase in economic uncertainty triggered by the pandemic and associated measures. Following Baker et al., 2020, we include in our analysis stock market volatility VIX and newspaper-based measure EPU.

Empirical data confirms the unusual variation in uncertainty level during the inter-pandemic period. Panel A of Figure I3 shows that due to the COVID-19 shock VIX implied volatility index rocketed from 13.68 on 14 February 2020 to 82.69 on 16 March 2020 — in a month, the proxy of short-run stock market uncertainty increased by more than 500% and reached its highest value since 1990 (see Figure I4). The last comparable record was observed more than 12 years ago: VIX was equal to 80.86 on 20 November 2008 when the financial crisis of 2007-2009 hit the world. While the index shows a steady decline in the two past months and market stability is generally bouncing back now, the volatility still did not reach its pre-COVID-19 shock value, almost two times exceeding it.

3 An Overview of the U.S. Financial Market

A capital market provides a spectrum of financial assets and includes both the stock market and bond markets. A stock market is a financial market where market participants such as investors and speculators trade shares of corporations. A bond market allows participants to issue, buy, and sell debt securities like bonds, notes, bills, and others, playing an essential role in the debt market.

3.1 An Overview of the U.S. Stock Market

The U.S. major stock market exchanges are the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotation (NASDAQ). The NYSE, founded in 1792[7], trades both stocks and bonds of more than 3000 companies and is now the world's largest stock exchange by market capitalization, i.e., the total value of all shares issued on the exchange, equal to $28.2 trillion. According to the NYSE Internal Database and Consolidated Tape Statistics, Q1 2020, the NYSE has the largest market share equal to 24.3% with more than two times more liquidity than the next largest exchange (see Figure I5). The AMEX was started back in the 1800s, acquired by NYSE in 2008 and known since then as NYSE American. It is a smaller still competitive stock exchange designed for growing companies, trading over 8000 NMS securities in a fully electronic manner nowadays. The NASDAQ began trading in 1971 and is trading about 5000 common stocks now. Unlike NYSE, which actually has a physical trading floor, NASDAQ operates online and bills itself as the world's first electronic stock market. It is the second-largest stock exchange after NYSE, with market capitalization equal to $12.95 trillion and a market share of 11.5% in Q1 2020 (see Figure I5).

In this paper, we consider the S&P 500 portfolio, constructed by common stocks issued by 500 companies with the highest market capitalization and traded on American stock exchanges: S&P 500 companies represent around 80% of the total American capital market capitalization (see Figure I6).

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[7] Consult the Library of Congress on the history of U.S. stock exchanges.

3.2 An Overview of the U.S. Bond Market

Bonds might be issued both by government and corporations, both financial and non-financial. In this paper, we focus on the government bond market. With government bonds, also known as sovereign bonds, a national government borrows money to fund its operations. Government bonds are considered low-risk investments compared to stocks because the government backs them, and returns on bonds are pre-fixed given that sovereign default is unlikely[8]. Historically, the interest rate paid by the U.S. government to its lenders is considered to be the risk-free rate that settles the benchmark for the risk-premia of other securities.

The U.S. government bond market is the largest in the world, grown to more than \$19 trillion during the past decade, with average daily trading volume varying between \$500 billion and \$1 trillion in the past year (see Figure I7) and roughly 600 outstanding bond issues according to Cbonds. With the U.S. GDP worth roughly \$21.3 trillion and the U.S. Government Debt-to-GDP ratio equivalent to 135% in 2019[9], the U.S. government bonds cover over 66% of the debt[10].

U.S. government bonds are referred to as *treasuries*. A bond value is determined by its coupon rate and maturity. The treasury interest rate statistics are published on a daily basis by the U.S. Department of Treasury[11]. The range of maturities in the U.S. bond

[8] Though the likelihood of a sovereign defaulting on its loan payment tends to be low, the world economic history has examples of the failure of the government to pay back its debt: a series of defaults in the U.S., including the default of Arkansas state in 1933; Russian financial crisis of 1998; Greece default to the International Monetary Fund in 2015 and others – Tomz and Wright, 2013 in their empirical research on sovereign debt detect 248 external defaults by 107 distinct entities from 1820 to 2013.

[9] The GDP per capita, Government Debt-to-GDP ratio, and population data are available at the Organisation for Economic Co-operation and Development (OECD) Data. The GDP is calculated as GDP per capita multiplied by the population. Retrieved 17 June 2020 from https://data.oecd.org/united-states.htm.

[10] In comparison, according to the article of Analytical Credit Rating Agency (ACRA) the total bond market in Russia accounted for around 21% of the GDP and the government bond market constitutes around the 50% of the overall government debt equal to roughly \$200 billion, which makes the total government bond market volume equal to only \$100 billion.

[11] Statistics is available at the Data Center of the U.S. Department of the Treasury.

market is from 1 month (1M) to 30 years (30Y). Depending on a bond's maturity treasuries can be classified as:

- Treasury bill (T-bill) if the bond expires in less than a year;
- Treasury note (T-note) if the bond expires in one to ten years;
- Treasury bond (T-bond) if the bond expires in more than ten years.

The price of government bonds reflects what the market thinks will happen to interest rates in the future since bond returns are inversely correlated with discounting rates: when rates go up, bond returns fall.

Since our analysis is conducted within a short horizon, we focus on short-term maturity bonds (see section Data). Treasury bills volume falls in the range of roughly \$100 billion to \$200 billion in the past year constituting around 20% of the total treasury market (see Figure I7).

4 Data

4.1 Time Frame

Connoly et al., 2005 note that constant long-term unconditional stock-bond relation may be accompanied by time-varying high-frequency correlation. In our analysis, we use daily data where it is available in order to capture those variations. Daily data is especially beneficial when the time interval in focus is not so long: in our case, it has been only five months since the first official announcement of the pandemic. Besides, the economic uncertainty may change significantly in a day without any considerable change in a month.

Campbell et al., 2020 and others report the change from nominal Treasury bonds being risky in the 1980-s to safe in the 2000-s as well as the change in a sign of stock-bond correlation from positive to negative. Taking this into account and also the fact that the 1M Treasury yields are available since 2001 we calculation correlations using daily data on zero-coupon Treasury bonds and the stock market from Wednesday 1 August 2001 to Friday 29 May 2020, with a focus on the recent data: from Monday 2 December 2020 to Friday 29 May 2020. This way, we make sure we include the data since the pandemic was announced in China and even one month before. This way, we also can compare the numbers for an extended period (with shocks smoothed over the sample) and a short subsample with a shock caused by COVID-19.

4.2. Uncertainty

We follow the literature and proxy short-run stock market uncertainty with the VIX index[12], designed to measure the 30-day market's expectation of future volatility implied by U.S. S&P 500 options prices. VIX is a well-recognized daily market indicator, widely used by market participants and reporting authorities. It is calculated by averaging the implied volatilities of S&P 500 index options (SPX) out-of-the-money calls and out-of-the-money puts at the strike price closest to the at-the-money strike

[12] Available at www.cboe.com. For further details on CBOE's approach to VIX calculation, consult the CBOE Exchange Inc. report, 2019.

price K_0 with two expiration dates around the 30-day target. Each of the individual implied volatility can be derived from the market price of the related option and calculated through the formula provided by CBOE.

Next, we follow Dimich et al., 2016 and estimate the bond market uncertainty with Merrill Lynch MOVE index. Figure I1 plots the time series of the MOVE in the COVID-19 pandemic period. Like the VIX, the MOVE catches the uncertainty inflow caused by the COVID-19 pandemic announcement along with the following policies. In a month, the MOVE volatility level rocketed from 61.24 (6 February 2020) to 163.70 (9 March 2020). However, unlike the VIX, the MOVE fully recovered to the value at the moment of writing.

The third uncertainty index we use in this paper is newspaper-based. The EPU index[13], developed by Baker et al., 2016 is defined by three factors: the frequency of policy-related uncertainty mentions in large newspapers, the uncertainty behind the federal tax code path measured by the dollar-weighted number of federal tax code provisions set to expire in 10 years, and the level of disagreement among economic forecasters about policy-related macroeconomic variables.

4.3 Bond Returns

U.S. Department of the Treasury publishes daily data on Treasury yield curve rates (commonly referred to as 'constant maturity treasury' rates, or CMTs) from 1-month to 30-years[14]. The Treasury yield curve is estimated daily using a cubic spline model with a floor of zero (reset negative yields to zero)[15]. We use the 3-months CMTs as short-term bond returns and the 10-years CMTs as long-term bond returns. Though we do not directly use the long-term rates in analysis, we consider the term spread defined as a difference between 10Y and 3M Treasury yields. The data is given in percentage.

[13] Available at https://policyuncertainty.com/index.html on a daily and monthly basis.

[14] Extracted from the Resource Center of the U.S. Department of the Treasury on 7 June 2020. The data for daily Treasury yield curve rates is available from 2 January 1990 till now. See

[15] See report on Treasury Yield Curve Methodology for details on derivations.

4.4 Stock Returns

There are two popular choices of stock portfolio in the literature. Campbell et al., 2020, uses daily value-weighted stock returns[16] of CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ to analyze the U.S. stock market. These returns are calculated for the portfolio constructed from the six value-weight portfolios formed on size and book-to-market, the six value-weight portfolios formed on size and operating profitability, and the six value-weight portfolios formed on size and investment. The other popular choice of a stock portfolio in papers is the S&P 500 portfolio. In our analysis, we use the S&P 500 Stock market index computed from the prices of those common stocks, which is widely used by investors to estimate the overall performance of the market. During 2019 the market capitalization of S&P 500 companies was stable around 80% of the total American capital market capitalization (see Figure I6). In the past quarter, the share value rocketed to the 96.39% in April 2020: even though there was a significant drop in both the overall U.S. market and the S&P 500 market caps by roughly $5.42 T and $3.05 T correspondingly, the latter mostly recovered in a month. Since the correlation between the differentiated logarithmic daily returns from the Kenneth French's Data Library and daily S&P500 returns is 0.990, the analysis is robust to both portfolio choices.

[16] Extracted from the Kenneth French's Data Library on 7 June 2020.

5 Empirical Results

5.1 Data Analysis

After cleaning for missing values in data, we select the period of interest and then merge data of stock returns, bond returns and uncertainty indices). The extended period includes 4697 observations from 1 August 2001 to 29 May 2020. The crisis subsample includes 124 observations from 2 December 2019 (three months before the official start of the pandemic[17]) to 31 May 2020. For convenience, in the final analysis we use natural logarithmic returns rather than prices or raw returns[18].

News-based indices quite differ in their response to the pandemic shock. All indices show a spike around the WHO announcement, however, VIX and MOVE slowly level out and recover since then, while the U.S. EPU index after-shock fluctuations stay at a sufficiently high level (see Figure I1 and Figure I3).

Stock market reacts to the shock with a crucial drop in returns. During the crisis VIX and S&P 500 indices seem to have almost opposite movement with VIX anticipating changes in S&P 500 approximately by a week (see Figure I3). As the literature on stock-bond correlation suggests, bond market answers to the shock with an increase in term spread yield, while the short-term yield falls and reach their pick right after the announcement (see Figure I8).

Correlation as well as many other time-series analyses requires input data to be stationary (i.e., have constant variation and be mean reverting). We check data for stationarity with the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. We use the whole sample (from 2001 to 2020) to in order to conduct tests on sufficient amount of observations while not including the stylized change in the end of 20th century. The results of the tests are presented in Table I1. For 1M CMT yield, the ADF statistic is equal to −1.244, which is higher than the critical

[17] The WHO officially announced COVID-19 outbreak a pandemic on 12 March 2020. See https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic.

[18] See Appendix II for a discussion on benefits of using returns over prices and logarithmic returns over arithmetic returns.

value with a 5% significance level, equal to −2.862. Same for 10Y CMT yield: the ADF statistics, equal to −1.278, is higher than the critical value (5%) equal to −2.862. Therefore, we fail to reject the Null hypothesis that the series have a unit root, i.e., non-stationarity for both 1M CMT and 10Y CMT yields. KPSS test confirms ADF test results. For both maturities, the KPSS statistic is greater than the corresponding critical value with a 1% significance level, meaning we strongly reject the Null hypothesis that the series is trend stationary. The KPSS statistics for 1M CMT yield is equal to 3.552, which is higher than the critical value (1%) 0.739, and the KPSS statistic for 10Y CMT yield is equal to 18.600, which is higher than the critical value (1%) 0.739. The tests do not confirm stationarity of the time series; however, they show stationarity for the first difference of both series. The argumentation is similar to that presented above.

Tests results for daily S&P 500 log returns confirm stationarity (see Table I2). Since there is no need to differentiate the series, we could use raw logarithmic values for the further analysis. However, in order to keep the same order of magnitude for all variables, we take the first difference of S&P 500 log returns as well.

Another way to check for stationarity is look at the plots. Log yield time series have strong trends while stock log returns time series look more like a random walk and has an almost zero linear trend (see Figure I8).

Table I4 and Table I5 summarize statistics on the data used in analysis: number of observations, mean, standard deviation, minimum and maximum, the 25%, 50% and 75% percentiles, skewness and kurtosis of stock and bond returns. For the 2001 to 2000 period, the unconditional daily variance of the stock returns is about forty times as large as the unconditional daily variance of the 3-months bond returns. In the period of shock the stock daily variance increases in more than 2 times, while the bond volatility remains approximately the same (see Table I4). The average of the VIX grew by more than 1.5 times and the mean of the EPU index raised even more, from 105.05 to 281 (see Table I5).

5.2 Unconditional Correlation

First, we estimate the unconditional Pearson correlation between bond and stock returns: Table I6 shows the results. The daily correlation between the 1st differenced logarithmic short-term Treasury yields and the 1st differenced logarithmic stock returns is roughly equal to 0.067 for the whole sample August 2001 – May 2020 and 0.154 for the subsample December 2019 – May 2020 which is more than two times higher than the whole sample correlation. The daily correlation of the same stock returns with term spread is negative and equal to −0.53. The numbers support past research by negative sign of the correlation between stock returns and long-tern bond yields and show that the short-term bond returns move in the same direction as stocks in average.

Second, we measure the rolling correlation choosing the rolling windows equal to 22 days which is an average number of working days in a month. Figure I9, shows the time series of 22-trading-day correlations between stock and bond returns, formed from days t to t+21. Panel A exhibits the correlation between S&P 500 and T-bills 3M log yields, and Panel B presents the correlation between S&P 500 and term spread log yields. Both time series share seasonality with a negative spike in February 2020. The correlation with long-term yields also show the second, more significant spike in March 2020.

5.3 Conditional Correlation

Finally, we follow Connoly et al., 2005 and build a distribution of forward-looking correlations formed from daily returns over days t to t+21 following a given uncertainty level at the end of the day t−1. This way we capture the forward-looking relationship of uncertainty indices and stock-bond correlation. Here we focus on S&P 500 – short-term bond returns correlation.

Panel A of Table I7 reports the stock-bond correlation conditional on VIX values divided into 9 groups[19]. The mean of the 22-trading day correlation coefficients over the whole sample is 0.267 and the probability of a negative correlation is 26%. For high

[19] Connoly et al., 2005 consider 5 groups based on conditions: VIX>40%, VIX>35%, VIX>30%, VIX>25%, VIX<20%. At the moment of their writing VIX did not raise more than 45%, while we analyze the unique situation where the VIX reached its highest pick at more than 80%. We extend the analysis with four more conditions: VIX>50%, VIX>45%, VIX<15%, VIX<10%.

VIX t-1 values of greater than 50%, the mean correlation is high at 0.313 and the probability of subsequent negative correlation is 0%. With decreasing VIX t-1 values the probability of subsequent negative correlation is increasing and the mean correlation is decreasing with negative mean at -0.007 for VIX values < 15%. For the very low VIX values the mean is positive again at 0.074 and comparable to the mean for the very high VIX values.

Similar results are obtained for controlling variable MOVE. Average correlation for a high-level uncertainty MOVE>160 is positive and equal to 0.297 which is greater than the total average value 0.237. With the level of uncertainty decreasing, the mean of correlation also falls.

The highest averaged correlation is observed for medium-level implied volatility uncertainty: both, VIX and MOVE indices. This result might be a support for non-linear dependency of stock-bond relation on uncertainty level.

Finally, Panel C of Table 7 reports the stock-bond correlation conditional on EPU values divided into 8 groups. EPU's effect on the correlation differs from the one we saw earlier. For high MOVE t-1 values of greater than 800, the mean correlation is negative and equal to -0.024 and the probability of subsequent negative correlation is 67% (i.e., two of three observations have negative correlation). With decreasing MOVE t-1 values the probability of subsequent negative correlation is decreasing at first, and then increasing again, for the medium values of uncertainty. The proportion of negative correlations for high values of uncertainty level exceeds such proportion for low values (< 200 and <100), as one would expect.

Conclusion

We study daily stock and bond returns from 2001 to 2020 and examine the uncertainty linkage to the stock-bond relation. We are particularly interested in the COVID-19 pandemic period (and a month pre-period) associated with a high economic uncertainty measured by VIX, EPU, and MOVE indices and a significant drop in stock returns.

As we have shown, the COVID-19 pandemic caused an enormous boost in economic uncertainty: all uncertainty indices show a huge increase in value after the WHO announcement, however, while VIX and MOVE slowly level out and recover since then, the U.S. EPU index after-shock volatiles at a sufficiently high level with a slightly negative trend.

With an increased level of uncertainty, we would expect a strengthening of negative correlation between stock and bond returns soon. We detect a significant drop in February resulting in negative value for both stock-bill and stock-spread 22-trading-day correlation. The result supports the past research. However, the constant correlation and averaged rolling correlation both show a slight increase during the shock period. One possible explanation is a timely monetary policy response by Central Banks.

The results on conditional correlation questions the ability to attribute the current crisis to the 'classical' crisis with the flight-to-safety effect. One would expect the stock-bond correlation to decrease resulting in negative value once uncertainty level increases. However, the conditional correlation on VIX and MOVE do not confirm this hypothesis. The news-based EPU index, in turn, shows quite interesting results. First, we detect that the index anticipates the other indices reactions to the shock with a significant boost. Second, from a forward-looking perspective, we find a negative relation between the uncertainty level and the future correlation of stock and bond returns. As we can see, the newspapers and reports capture have more predictive power about the future market behaviour that volatility extracted from assets themselves.

Our results extend the empirical research on stock-bond nexus and have a practical value for investors willing to diversify their portfolio. The relevance of results is supported by using the up-to-date data related to the unique circumstances: the world-wide pandemic. We also compare the results of the analysis conducted on the current data and the historical one, which gives a better prospect on the comparison of financial market behavior during crisis times and normal times.

As we finish the paper, the world slowly comes to its 'normal' pace. The world-wide breakdown comes to an end in most countries and states. According to the Business Insider article, 2020 in the U.S., five states had no stay-at-home order issued, 37 states have lockdown lifted, seven states have partial lockdown lifted, and the lockdown in New Jersey was extended as at 3 June 2020. The COVID-19 death statistics are believed to on the wane; people go back to work. In other words, there is a positive outlook that reflects on the financial market performance, individuals' expectations, level of uncertainty. Still, it is important to keep tracking the situation and repeat the presented analysis continuously in order to be able to predict the deviations in the economy at this fragile time.

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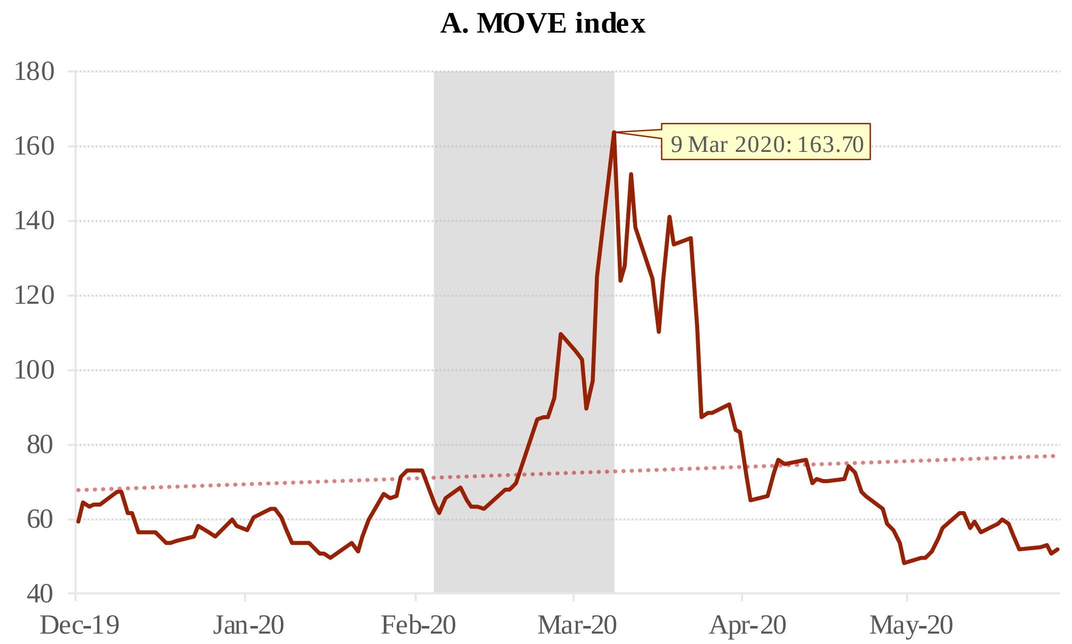
Appendix

I Tables and Figures



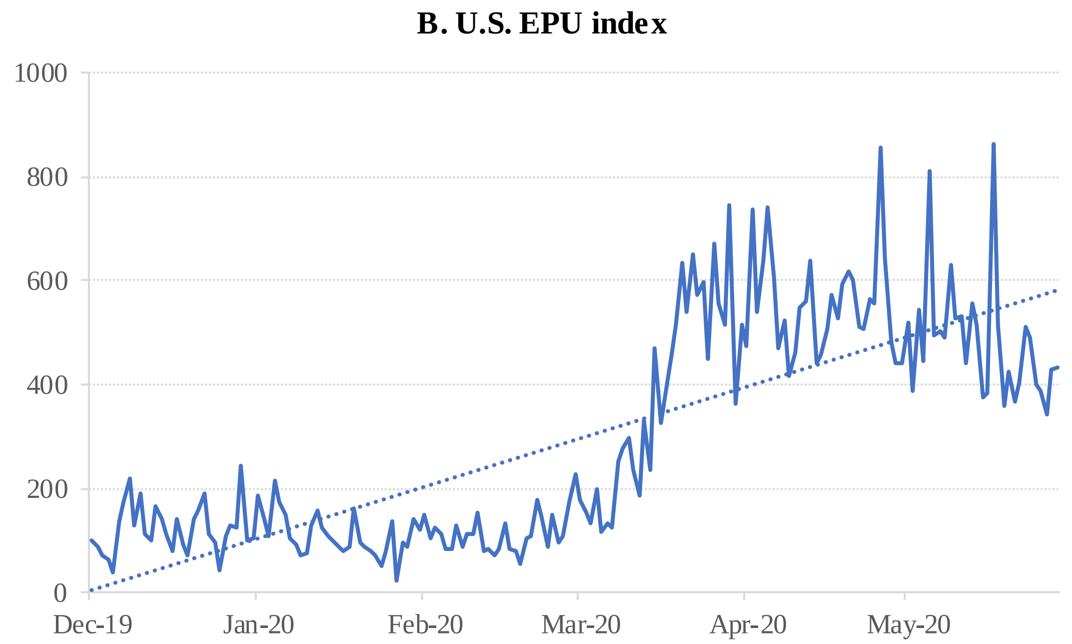


Figure I1. *Time Series of Uncertainty indices: December 2019 – May 2020.* Panel A – graph of the daily MOVE volatility index. Data retrieved 1 June 2020 from Google Finance. Panel B – graph of the daily EPU volatility index. Data retrieved 1 June 2020 from https://policyuncertainty.com/index.html.

U.S. Civilian Unemployment Rate

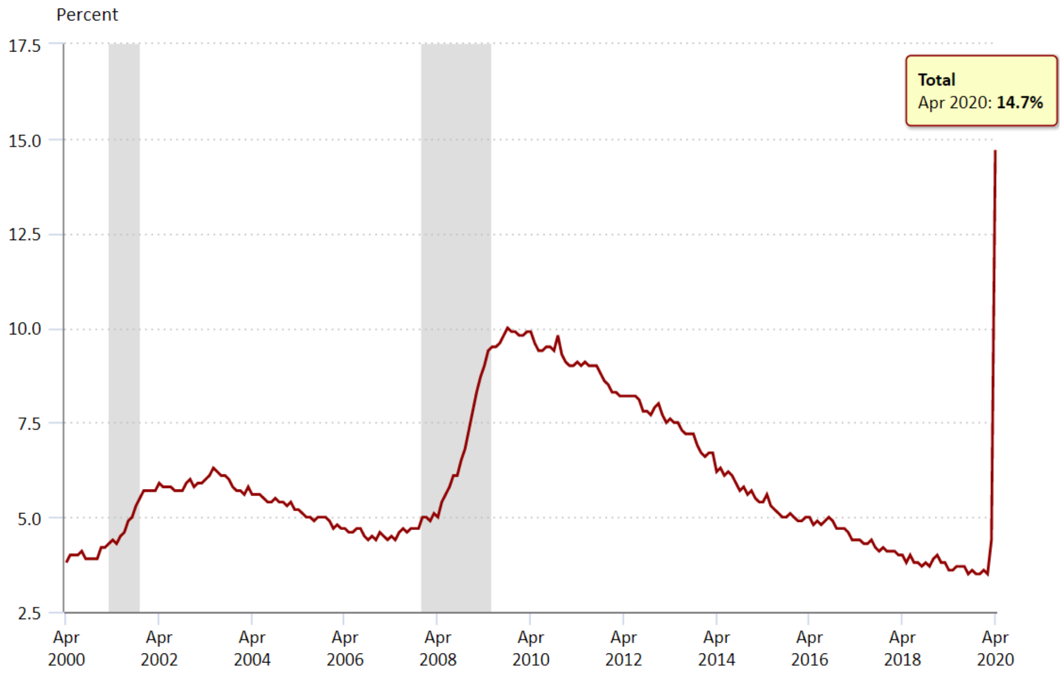


Figure I2. *U.S. Civilian Unemployment Rate*. Graph of the monthly civilian unemployment rate, seasonally adjusted: April 2000 – April 2020. Reprinted 1 June 2020 from the U.S. Bureau of Labor Statistics, 2020.

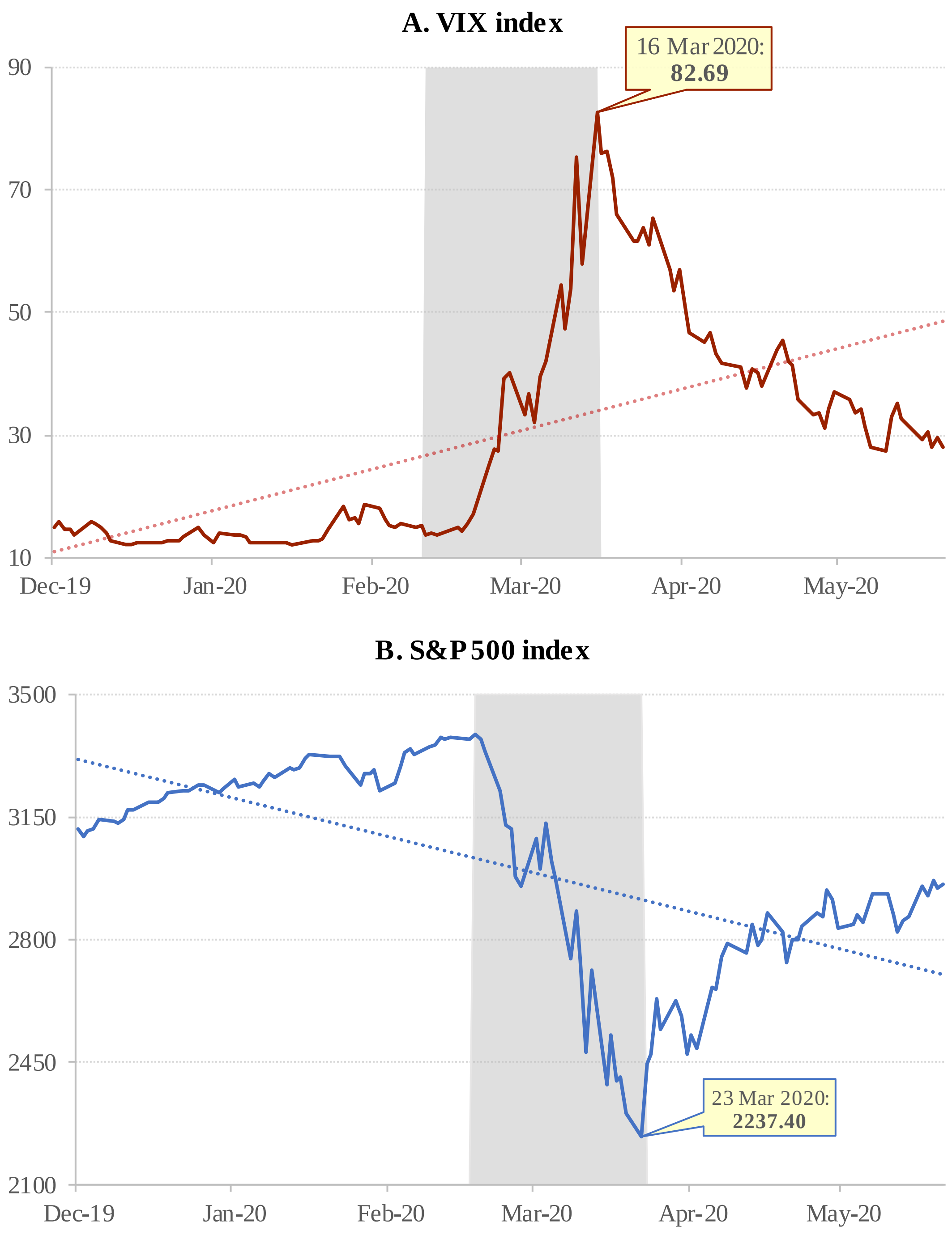


Figure I3. *Time Series of S&P 500 Index and VIX Index.* Panel A – graph of the daily CBOE volatility index: December 2019 – May 2020. Data retrieved 1 June 2020 from www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data. Panel B – graph of the daily S&P 500 index: December 2019 – May 2020. Data retrieved 1 June 2020 from finance.yahoo.com/quote/%5EGSPC/. Trend lines are dotted.

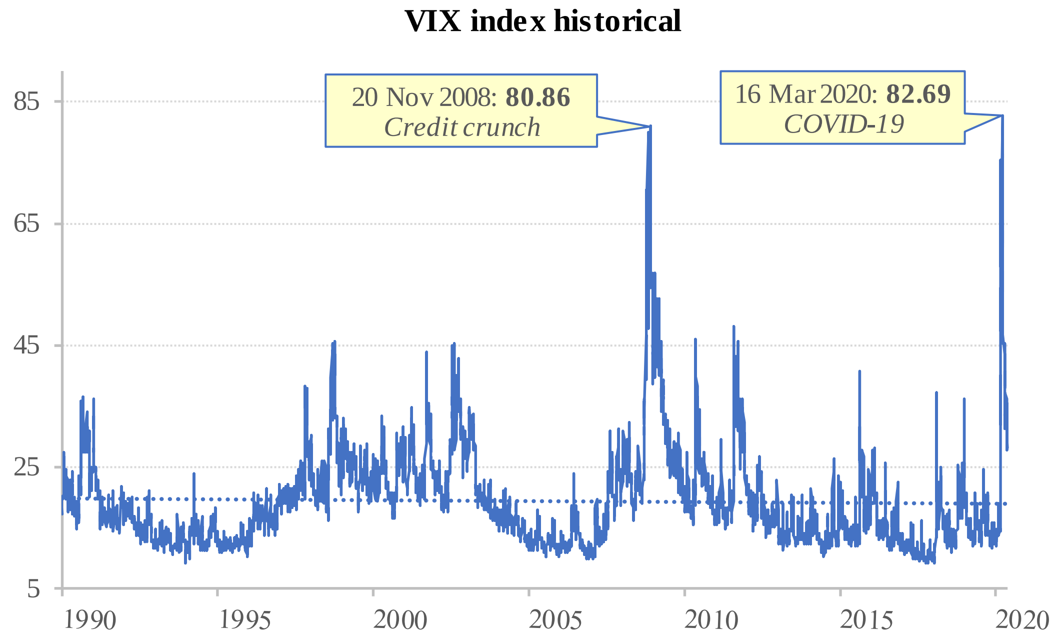


Figure I4. *Historical Time Series of VIX Index.* Time series of the daily CBOE volatility index: January 1990 – May 2020 and its highest values of the index. Data retrieved 1 June 2020 from www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index/vix-historical-data.

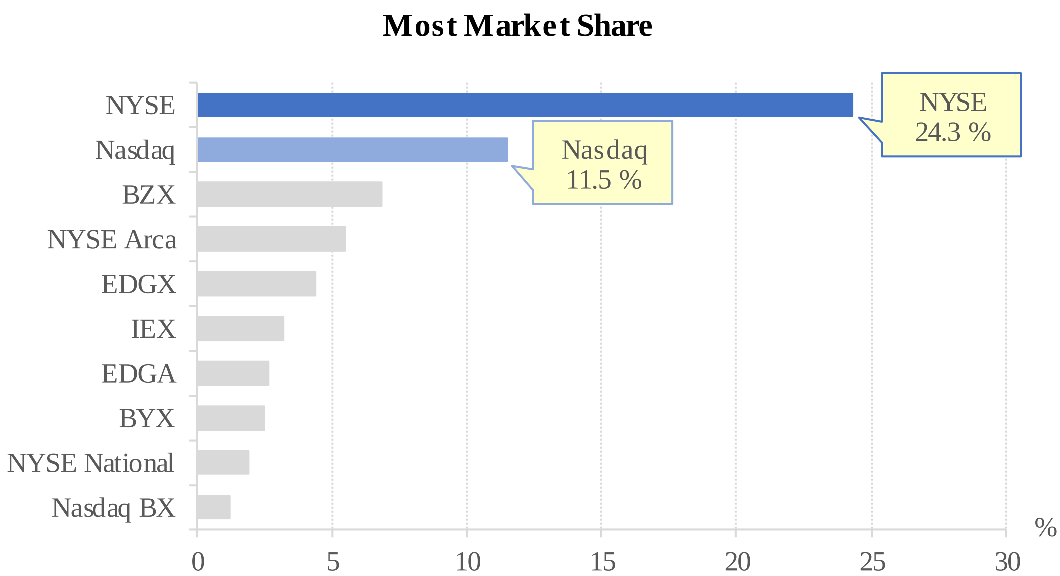


Figure I5. *Most Market Share in the U.S.* Bar plot of the top-10 U.S. stock exchanges by market share. The two largest market shares belong to NYSE (24.3%) and NASDAQ (11.5%) in Q1 2020. Data retrieved from https://www.nyse.com/markets/nyse-american.

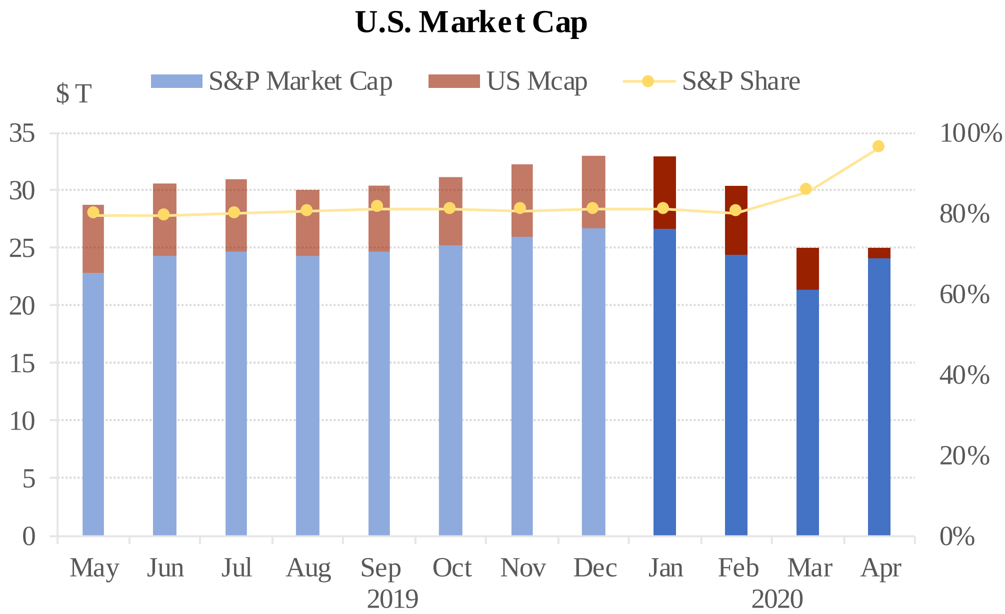


Figure I6. *U.S. Market Capitalization.* Bar plot of the U.S. total market capitalization and S&P 500 market capitalization (market cap). Capitalization is given in $ trillion (T). Line graph shows the percentage share of S&P500 market cap to the total market cap. Data retrieved 1 June 2020 from https://ycharts.com/indicators.

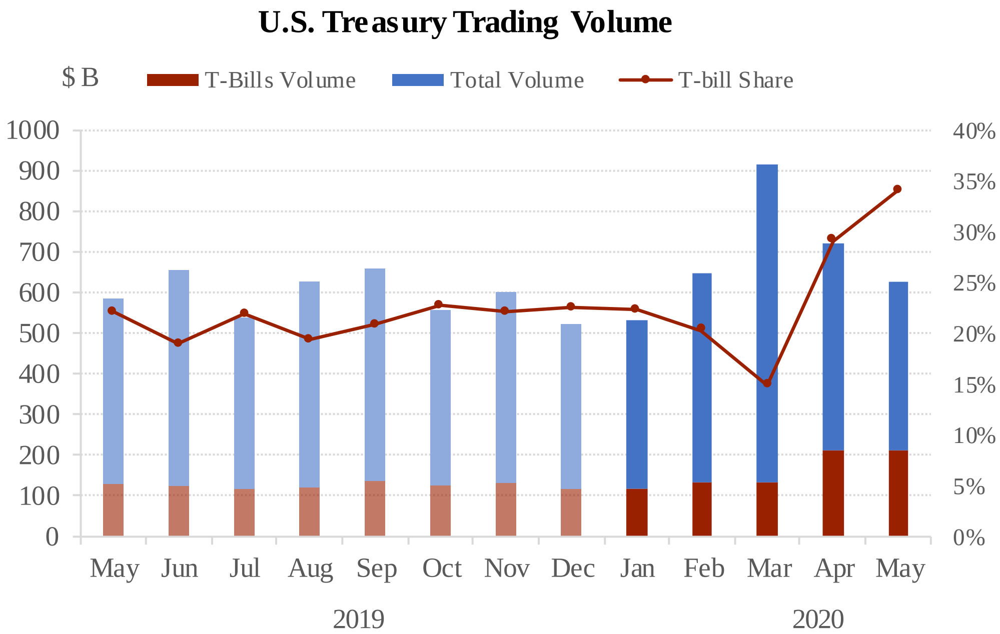


Figure I7. *U.S. Treasury Average Daily Trading Volume*. Bar plot of the total U.S. Treasury Averaged Daily Trading Volume by month (blue) and the Averaged Daily Trading Volume of Treasury bills (red): May 2019 – May 2020. Volume is given in $ billion (B). Total volume ranges in roughly $500 B – $1 T, Treasury bills volume ranges in roughly $100 B – $200 B. Line graph shows the percentage share of Treasury bill volume to the total trading volume. Data retrieved 1 June 2020 from https://www.sifma.org/resources/research/us-treasury-trading-volume/.

ADF test results. CMT yields

	1M	10Y	1M 1st diff	10Y 1st diff
Test Statistic	-1.244	-1.278	-12.113	-22.237
p-value	0.654	0.639	0.000	0.000
Critical Value (1%)	-3.432	-3.431	-3.432	-3.431
Critical Value (5%)	-2.862	-2.862	-2.862	-2.862
Critical Value (10%)	-2.567	-2.567	-2.567	-2.567
Number of Lags Used	32	14	32	13
Number of Observations Used	4676	7593	4675	7593
H0	Can not reject	Can not reject	Reject	Reject

Table I1. *ADF test results: CMT yields*. The table reports the ADF test results for the log 1M Treasury yield time series (August 2001 – May 2020) and log 10Y Treasury yield time series (January 1990 – May 2020) and for the differenced time series. Numbers are rounded to three significant digits. The tests imply the stationarity of the 1st-differenced times series of CMT yields.

KPSS test results. CMT yields

	1M	10Y	1M 1st diff	10Y 1st diff
Test Statistic	3.552	18.600	0.173	0.021
p-value	0.010	0.010	0.100	0.100
Critical Value (1%)	0.739	0.739	0.739	0.739
Critical Value (5%)	0.463	0.463	0.463	0.463
Critical Value (10%)	0.347	0.347	0.347	0.347
Number of Lags Used	32	36	32	36
H0	Reject	Reject	Can not reject	Can not reject

Table I2. *KPSS test results: CMT yields.* The table reports the KPSS test results for the 1M Treasury yield Time Series (August 2001 – May 2020) and 10Y Treasury yields time series (January 1990 – May 2020) and for the differenced time series. Numbers are rounded to three significant digits. The tests imply the stationarity of the 1st-differenced times series of CMT yields.

Stationarity test results. Daily value-weighted returns

	ADF	KPSS
Test Statistic	-16.072	0.160
p-value	0.000	0.100
Critical Value (1%)	-3.432	0.739
Critical Value (5%)	-2.862	0.463
Critical Value (10%)	-2.567	0.347
Number of Lags Used	18	32
Number of Observations Used	4697	
H0	Reject	Can not reject

Table I3. *ADF and KPSS results: S&P 500 log returns.* The table reports the ADF and KPSS test results for the daily value-weighted combined NYSE/AMEX/Nasdaq stock log returns time series (August 2001 – April 2020). Numbers are rounded to three significant digits. The tests imply the stationarity of the times series.

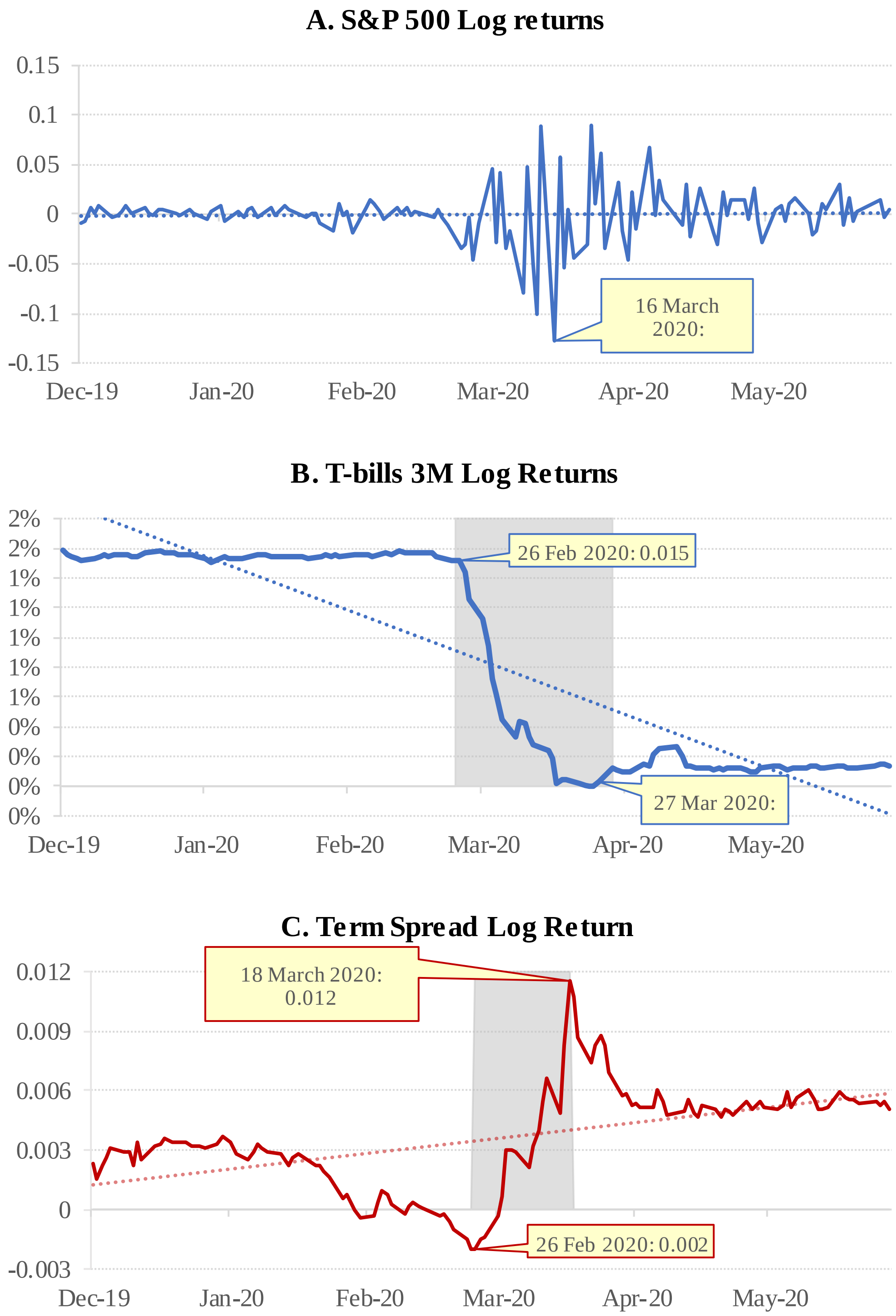


Figure I8. *Time Series of stock and bond log returns.* Panel A: time series of the daily S&P 500 log returns: December 2019 – May 2020 and its lowest value on 16 March 2020. Panel B: Time series of the daily T-bills 3-months log returns: December 2019 – May 2020 and its lowest value on 27 March 2020 at almost zero. Panel C: Time series of the daily term spread log returns: December 2019 – May 2020 and its highest value on 18 March 2020 at 0.012. Trend lines are dotted.

Summary statistics for 3M T-bills, Term spread & SP500 returns.

	Returns 2001-2020			Returns 2019-2020		
Statistics	Bonds 3M	Term spread	Stocks SP500	Bonds 3M	Term spread	Stocks SP500
Mean	-0.00001	-0.00000	-0.00002	-0.00012	0.00003	0.00007
Minimum	-0.00806	-0.00505	-0.21646	-0.00228	-0.00208	-0.21646
25%	-0.00010	-0.00039	-0.00814	-0.00010	-0.00040	-0.01557
Median	0.00000	0.00000	-0.00070	0.00000	-0.00010	0.00082
75%	0.00010	0.00030	0.00800	0.00010	0.00040	0.01114
Maximum	0.00755	0.00718	0.18875	0.00110	0.00338	0.18875
# of Obs	4697	4697	4697	124	124	124
Std	0.00045	0.00065	0.01861	0.00047	0.00075	0.04747
Skewness	-0.96939	0.39045	0.46853	-2.15926	1.37137	0.24778
Kurtosis	80.21906	11.67888	16.15298	7.04192	5.79250	6.6617

Table I4. *Summary statistics for 3M T-bills, Term spread & SP500 returns.* The table describes the first-difference of log returns on 3M Treasury bills time series for the extended period (August 2001 – May 2020) and a subsample (December 2019 – May 2020). Decimal numbers are rounded to five significant digits. The table statistics include mean, standard deviation (Std), minimum and maximum, 25%, 50% (Median) and 75% percentiles, skewness, kurtosis, and number of observations (# of Obs).

Summary statistics for returns on uncertainty indices: VIX, EPU, and MOVE.

	Index values 2001-2020		Index values 2019-2020		
Statistics	VIX	EPU	VIX	EPU	MOVE
Mean	19.395	105.046	29.946	280.999	72.298
Minimum	9.140	3.320	12.100	22.250	48.110
25%	13.310	56.340	14.323	100.930	56.995
Median	16.620	84.940	27.915	158.965	64.070
75%	22.360	129.400	40.293	469.762	74.428
Maximum	82.690	809.590	82.69	809.590	163.700
# of Obs	4697	4697	124	124	124
Std	9.156	79.356	17.914	205.731	24.203
Skewness	2.359	2.838	0.959	0.519	1.811
Kurtosis	7.973	12.645	0.161	-1.166	2.808

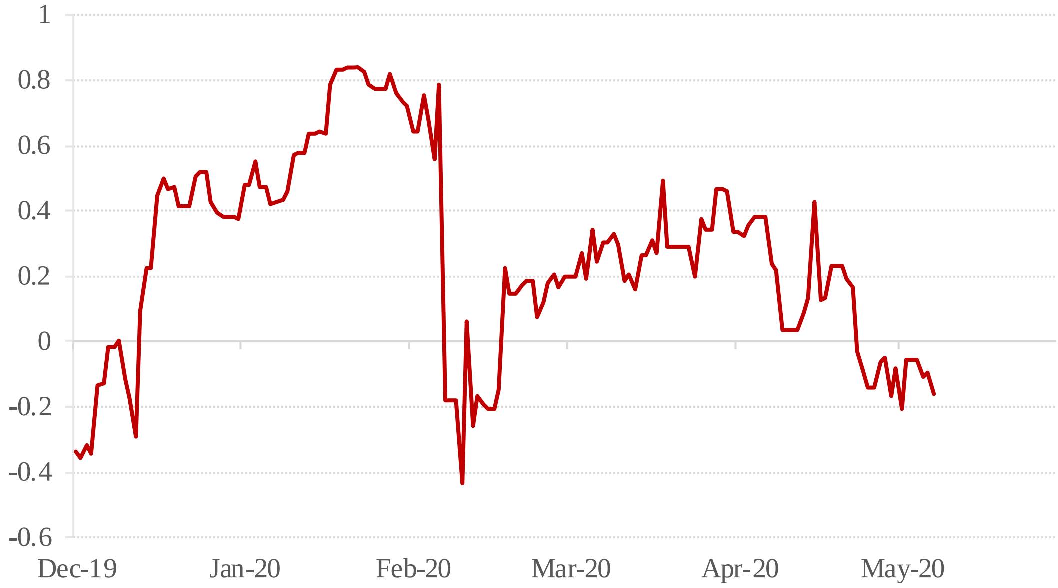
Table I5. *Summary statistics for returns on uncertainty indices: VIX, EPU, and MOVE.* The table describes uncertainty indices for the extended period (August 2001 – May 2020) and a subsample (December 2019 – May 2020). Numbers are rounded to three significant digits. The table statistics include mean, standard deviation (Std), minimum and maximum, 25%, 50% (Median) and 75% percentiles, skewness, kurtosis, and number of observations (# of Obs).

Correlation matrix.

		S&P 500	T-bills 3M	Term Spread
	S& P500	1.000	(0.067)	(0.190)
	T-bills 3M	0.154	1.000	(-0.527)
Correlation	Term Spread	0.297	-0.401	1.000
	S& P500		(4.601)	(13.260)
	T-bills 3M	1.722		(-42.489)
t-Statistics	Term Spread	3.435	-4.835	
	S& P500	0.000	(0.000)	(0.000)
	T-bills 3M	0.089	0.000	(0.000)
p-value	Term Spread	0.001	0.000	0.000

Table I6. *Correlation matrix.* The table reports the correlation coefficients with corresponding *t*-Statistics and *p*-values for the 2001–2020 sample period in brackets and on the upper triangle. The correlation coefficient, *t*-Statistics, and p-values for the 2019–2020 subsample period are on the lower triangle.

A. Stock-bond Correlation: short term.



Stock-bond Correlation: term spread.

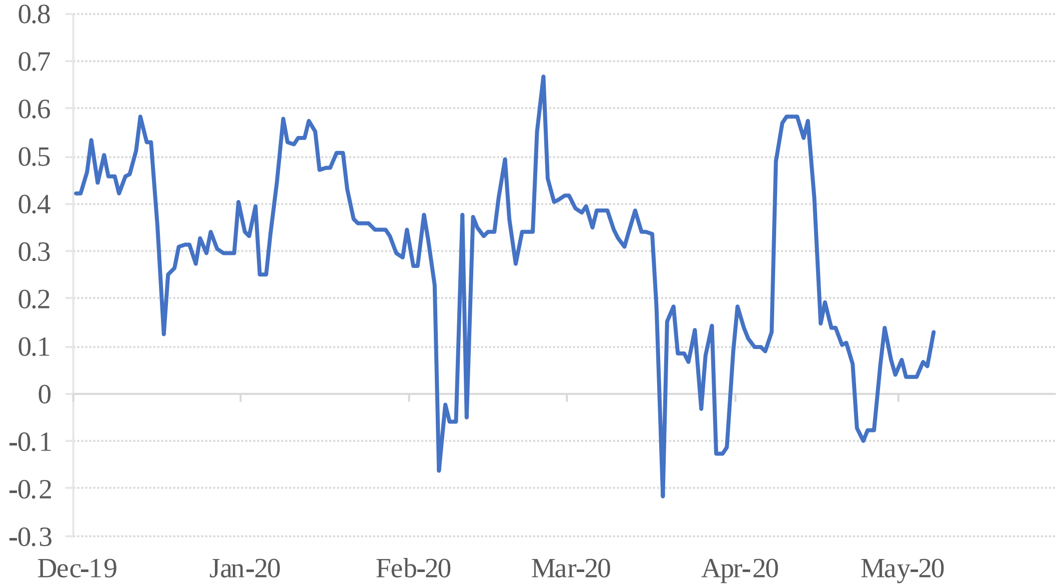


Figure I9. *22-Trading-Day Stock-Bond Correlations*. Graph of the daily 22-trading-day correlation coefficients between stock and bond differenced log returns. Panel A: correlation between S&P 500 and T-bills 3M log yields. Panel B: correlation between S&P 500 and term spread log yields.

Correlation matrix conditional on VIX, MOVE, & EPU.

A. Stock-Bond Correlations Conditional on VIX: 2019–2020

VIX group	# of Obs.	Proportion of Corr. < 0	Correlations Avg.	25%	50%	75%
All	n=179	0.263	0.237	-0.019	0.240	0.440
VIX>50%	n=18	0	0.313	0.276	0.310	0.342
VIX>45%	n=23	0	0.296	0.229	0.290	0.342
VIX>40%	n=33	0.061	0.238	0.167	0.266	0.334
VIX>35%	n=42	0.143	0.208	0.139	0.225	0.317
VIX>30%	n=55	0.273	0.153	-0.038	0.195	0.293
VIX>25%	n=66	0.303	0.124	-0.059	0.187	0.288
VIX<20%	n=56	0.25	0.343	0.041	0.445	0.636
VIX<15%	n=40	0.225	0.353	0.131	0.445	0.570

B. Stock-Bond Correlations Conditional on MOVE: 2019–2020

MOVE group	# of Obs.	Proportion of Corr. < 0	Correlations Avg.	25%	50%	75%
All	n=179	0.263	0.237	-0.019	0.240	0.440
MOVE>160	n=1	0	0.297	0.297	0.297	0.297
MOVE>140	n=3	0	0.247	0.222	0.222	0.292
MOVE>120	n=11	0	0.250	0.202	0.202	0.289
MOVE>100	n=16	0	0.267	0.200	0.200	0.292
MOVE<80	n=121	0.28	0.224	-0.055	-0.055	0.432

C. Stock-Bond Correlations Conditional on EPU: 2019–2020

VIX group	# of Obs.	Proportion of Corr. < 0	Correlations Avg.	25%	50%	75%
All	n=179	0.371	0.237	-0.019	0.240	0.440
EPU>800	n=3	0.667	-0.024	-0.077	-0.060	0.093
EPU>700	n=6	0.333	0.188	-0.024	0.221	0.070
EPU>600	n=15	0.267	0.187	0.018	0.240	0.069
EPU>500	n=44	0.341	0.139	-0.060	0.150	0.099
EPU>400	n=64	0.344	0.132	-0.064	0.150	0.177
EPU>300	n=75	0.347	0.117	-0.067	0.133	0.191
EPU<200	n=95	0.211	0.328	0.131	0.393	0.303
EPU<100	n=39	0.282	0.345	-0.132	0.459	0.174

Table I7. *Correlation matrix conditional on VIX, MOVE, & EPU.* The table report S&P 500 – 3M T-bills correlation coefficients conditional on uncertainty level and summary statistics: number of observations (# of Obs.), proportion of negative correlation, average and 25%, 50%, 75% percentiles.

II Calculations

A Log Returns

The reason we use the logarithm of returns (log returns) rather than price or raw returns is that log returns have several useful properties. The log return at time t r_{t+1} is calculated as $log(\frac{r_{t+1}-r_t}{r_t})$. First, returns are preferred to prices due to the normalization. Second, log returns share *log-normality*: if we assume the prices are distributed log-normally, which is usually done in asset pricing models, then log returns are also normally distributed. Log returns are also preferable due to *approximate raw-log equality:* $\log(1+\mathrm{r}) \approx \mathrm{r}, \mathrm{r} \ll 1$. Finally, log returns share *time-additivity*: the calculation of compounding return over n periods turns from multiplication of n returns to a simple operation: $\log(\mathrm{p}_{\mathrm{t+n}} - \mathrm{p}_{\mathrm{n}})$), which itself reduces the algorithmic complexity of analysis.

B Significance of Correlation

Once we calculate the unconditional correlation of two samples, it is unclear whether the correlation coefficient is significantly different from zero. In order to confirm the significance of result, we calculate t-statistics based on number of observations in sample *n* and correlation coefficient *r*.

Formula for t-statistics is as follows: $t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$. The *p-value* is calculated using a *t*-distribution with *n-2* degrees of freedom.

III Implementation of analysis

```
''' import packages'''
import numpy as np
import pandas as pd
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.stattools import kpss
```

```
'''Define functions for stationary tests: ADF abd KPSS.'''


def adf_test(timeseries, name=''):
    # Perform Dickey-Fuller test:
    print('Results of Dickey-Fuller Test: ' + name)
    dftest = adfuller(timeseries, autolag='AIC')
    dfoutput = pd.Series(dftest[0:4],
                         index=[
                             'Test Statistic', 'p-value', '#Lags
Used',
                             'Number of Observations Used'
                         ])
    for key, value in dftest[4].items():
        dfoutput['Critical Value (%s)' % key] = value
    print(dfoutput)
    print()


def kpss_test(timeseries, name=''):
    print('Results of KPSS Test: ' + name)
    kpsstest = kpss(timeseries, regression='c', nlags='legacy')
    kpss_output = pd.Series(kpsstest[0:3],
                            index=['Test Statistic', 'p-value', '
Lags Used'])
    for key, value in kpsstest[3].items():
        kpss_output['Critical Value (%s)' % key] = value
    print(kpss_output)
    print()
```

```
''' Set time frames '''
start_date, end_date = '8/1/2001', '5/29/2020'
start_date_covid, end_date_covid = '12/2/2019', '5/29/2020'
```

```
''' Read S&P 500 data '''
file_loc_sp500_archive = 'Data/Stocks/SP500_Yahoo_30Dec1927_30May
2020.xlsx'
SP500 = pd.read_excel(file_loc_sp500_archive, index_col='Date')
SP500 = SP500.rename(columns={"Close": "SP Close"})
SP500_p = SP500['SP Close']
SP500_r = SP500_p.pct_change()
SP500_lr = np.log(SP500_r + 1)
SP500_lr_diff = SP500_lr.diff()
```

```
''' Test stationarity of S&P 500 log returns '''
col = 'SP500 log returns'
adf_test(SP500_lr.loc[start_date:end_date], col)
kpss_test(SP500_lr.loc[start_date:end_date], col)

''' Read VIX data '''
file_loc_vix_archive_p1 = 'Data/Uncertainty/VIX_cboe_2Jan1990_31D
ec2003.xlsx'
file_loc_vix_archive_p2 = 'Data/Uncertainty/VIX_cboe_2Jan2004_30M
ay2020.xlsx'
VIX_p1 = pd.read_excel(file_loc_vix_archive_p1,
                       index_col='Date').dropna(thresh=1)
VIX_p2 = pd.read_excel(file_loc_vix_archive_p2, index_col='Date')
VIX = pd.concat([VIX_p1, VIX_p2])
VIX_p = VIX['VIX Close']

''' Read MOVE data '''
file_loc_move_archive = 'Data/Uncertainty/MOVE_GoogleFinance_10No
v2019_30May2020.xlsx'
MOVE = pd.read_excel(file_loc_move_archive, index_col='Date')
MOVE = MOVE.rename(columns={"Close": "MOVE Close"})
MOVE_p = MOVE['MOVE Close']

''' Read EPU data '''
file_loc_epu_archive = 'Data/Uncertainty/EPU_US_Daily_Policy_Data
_1Jan1985_30May2020.xlsx'
EPU = pd.read_excel(file_loc_epu_archive, index_col='Date')
EPU_i = EPU['daily_policy_index']

''' Read Treasury yield data '''
file_loc_TreasuryYieldCurve = 'Data/Bonds/DailyTreasuryYieldCurve
US_TreasuryGov_2Jan1990_29May2020.xlsx'
TreasuryYTM = pd.read_excel(file_loc_TreasuryYieldCurve,
                            index_col='Date')
TreasuryYTM['Term spread'] = TreasuryYTM['10 Yr'] - TreasuryYTM['
3 Mo']
TreasuryYTM = TreasuryYTM[['3 Mo', 'Term spread']].dropna()
TreasuryYTM_lr = np.log(TreasuryYTM/100 + 1)
TreasuryYTM_lr_diff = TreasuryYTM_lr.diff()

''' Test stationarity of Treasury log returns '''
cols = ['3 Mo', 'Term spread']
for col in cols:
    adf_test(TreasuryYTM_lr.loc[start_date:end_date, col], col)
    kpss_test(TreasuryYTM_lr.loc[start_date:end_date, col], col)

''' Test stationarity of Treasury log returns first difference'''
cols = ['3 Mo', 'Term spread']
for col in cols:
    adf_test(TreasuryYTM_lr_diff.loc[start_date:end_date, col], c
ol+'diff')
    kpss_test(TreasuryYTM_lr_diff.loc[start_date:end_date, col],
col+'diff')
```

```
''' Create dataframe '''
Data = pd.concat([TreasuryYTM_lr_diff, SP500_lr_diff, VIX_p, EPU_
i], axis=1)

''' Select 2001-2020 sample '''
Data_2001_20 = Data.loc[start_date:end_date].dropna()
Data_2019_20 = Data.loc[start_date_covid:end_date_covid].dropna()

''' Calculate Kurtosis and Skewness '''
for col in Data_2001_20.columns:
    print('Kurtosis ', col+'\t', np.round(Data_2001_20[col].kurto
sis(), 5))
    print('Skewness ', col+'\t', np.round(Data_2001_20[col].skew(
), 5))

''' Summary statistics'''
Data_2001_20.describe().round(5)

''' Calculate Unconditional correlation '''

Data_2001_20.corr()
Data_2019_20.corr()
```

```
# Calculate 22-Trading-Day Stock-Bond Correlations
window = 21
coeffs_SP_3M = pd.Series(index=Data.index, dtype='float64')
coffs_SP_Spread = pd.Series(index=Data.index, dtype='float64')
for start_window in Data.index:
    end_window = start_window + pd.Timedelta(window, 'D')
    x = Data.loc[start_window:end_window, 'SP Close']
    y = Data.loc[start_window:end_window, '3 Mo']
    z = Data.loc[start_window:end_window, 'Term spread']
    coeffs_SP_3M.loc[start_window] = x.corr(y)
    coffs_SP_Spread.loc[start_window] = x.corr(z)
Data['rolling corr Sp-3Mo'] = coeffs_SP_3M
Data['rolling corr Sp-spread'] = coffs_SP_Spread

''' Calculate Correlation Conditional on VIX '''
Data = pd.concat([Data, MOVE_p], axis=1)
cond_corr_Sp_3M = pd.DataFrame(Data['rolling corr Sp-spread'])
for i in [25, 30, 35, 40, 45, 50]:
    cond_corr_Sp_3M['VIX>'+str(i)] = Data[Data.shift(1)['VIX Clos
e']>i]['rolling corr Sp-3Mo']
for i in [15, 25]:
    cond_corr_Sp_3M['VIX<'+str(i)] = Data[Data.shift(1)['VIX Clos
e']<i]['rolling corr Sp-3Mo']
for j in [300, 400, 500, 600, 700, 800]:
    cond_corr_Sp_3M['EPU>'+str(j)] = Data[Data.shift(1)['daily_po
licy_index']>j]['rolling corr Sp-3Mo']
for i in [100, 200]:
    cond_corr_Sp_3M['EPU<'+str(i)] = Data[Data.shift(1)['daily_po
licy_index']<i]['rolling corr Sp-3Mo']
for k in [100, 120, 140, 160]:
```

```
    cond_corr_Sp_3M['MOVE>'+str(k)] = Data[Data.shift(1)['MOVE Cl
ose']>k]['rolling corr Sp-3Mo']
for i in [60, 80]:
    cond_corr_Sp_3M['MOVE<'+str(i)] = Data[Data.shift(1)['MOVE Cl
ose']<k]['rolling corr Sp-3Mo']
cond_corr_Sp_3M.loc[start_date_covid:end_date_covid].describe()
```

Summary

It is important to acknowledge what drives the relation between stock and bond returns in order to have a better perspective on financial market performance. By allocating investments among capital stocks (riskier but more profitable financial instruments) and government bonds (safer assets but with less significant rewards), investors may diversify portfolio – reach the target return, reducing the risk. When diversification is not enough, investors may suffer from realized risks, but even when a portfolio is properly constructed with risk minimized, the benefits from diversification depend on the level of correlation between its assets. Like this, in periods of negative stock-bond correlation, benefits from stock-bond diversification increase while the positive stock-bond correlation moves assets in the same direction reducing benefits from diversification. Therefore, it is important to figure out what exactly drives the stock-bond nexus and which way, as well as determine factors that have good explanatory power to the correlation.

The periods of shocks are of particular interest since they have a tremendous effect both on the real economy and financial system, and as a consequence on investors' decisions as well. At the time of writing, the world is in the middle of the crisis caused by a respiratory infection COVID-19. There are no specific vaccines or treatments for this disease, at least publicly available ones, and the earliest access to vaccines is forecasted by early 2021 by Le et al., 2020. Considering the fact that the epidemic is developing rapidly and the lack of global access to necessary special medical equipment, it is essential to keep monitoring the situation constantly and take relevant precautionary measures. At different points, many authorities following the WHO recommendations announced the lockdown. The precautions necessary to take, including world-wide shutdown, have exposed the world economy to the inevitable shock and have caused severe economic costs. Opinions were divided among economists about the future state of the economy.

Bloom et al. 2020 analyze the recent period up until March 2020 and show the effect of COVID-19 on economic uncertainty. At the time of writing, two more months have passed under the world-wide crisis. We follow Bloom et al. 2020 in their understanding

of the uncertainty and go further adjusting their analysis to the new data became available.

The level of uncertainty definitely has its impact on the economy, including financial market performance, since it reflects and affects the expectations of market participants. Though it is challenging to establish any causalities because uncertainty, in turn, arises from certain economic and real conditions, we can detect correlations and try and predict the future behavior of the market. Like this, Connoly et al., 2005 find a negative relation between the uncertainty measures and the future correlation of stock and bond returns.

Examination of assets' behavior and stock-bond correlation in different economic conditions has a broad scope of application since it helps build more accurate financial forecasts. Discovering macroeconomic channels, financial intermediaries' actions, and other structural kinds of explanations that tend to have a certain level of predictions, allows us to estimate the response of variables of interest to the shocks that are going to move the market. This paper provides a better perspective on the linkage of economic uncertainty caused by a world-wide breakdown and financial market performance. In turn, accurate prognosis allows investors to adjust their market expectations to the shocks.

Along with the practical value of this paper to capital market participants, our analysis might be interesting to authorities that would like to have a better understanding of the effect that the real news and policies such as an infectious disease and a lockdown may have on the economic and financial systems.

There is a massive amount of papers that try to explain the correlation between stock and bond returns by their common exposure to macroeconomic factors. One such factor is an interest rate. Indeed, since the fundamental value of a bond is defined as the sum of all discounted future cash-flows, bond returns are inversely correlated with discounting rates: when rates go up, bond returns fall, and vice-versa.

Inflation is also considered to be a major driven force of bond returns and as a consequence of a stock-bond correlation in many papers.

Another possible way to detect the stock-bond correlation is to track the information coming to the market. With a high-frequency approach, Cieslak and Pang, 2020 tries and identify economic shocks from stock and government bonds using the national news as a source of time-varying stock-bond correlation.

Some papers assumed the constant stock-bond correlation during the entire period of examination. Most studies, though, observe time-varying correlation in stock and bond returns. Lin et al., 2018, in their recent paper, adopt continuous wavelet analysis to capture the dynamics of stock-bond correlation across different frequencies. They note that the macroeconomic factors that drive the stock-bond nexus do not vary across the time frequencies, while the impacts of crises do vary across frequencies.

It is also a stylized fact that the stock-bond correlation turned from mostly positive to mostly negative in the mid-1990-s. Campbell and Ammer, 1993 used monthly data and showed a small positive correlation driven positively by variation in real rates and negatively by variation in expected inflation. Connolly et al., 2005 show the significant time variation in correlation observed in the 1986–2000 sample period and argue that a negative sign cannot be explained simply by expected inflation.

A common way to look at the time variation in the stock-bond nexus is to introduce the concept of flights: *flight-from-quality* (FFQ) and *flight-to-quality* (FTQ), also referred to as *flight-to-safety*. The idea behind the flights is that if investors choose bonds over stocks, i.e., they buy bonds and sell stocks, they cause, what is called, FTQ. Similarly, if investors choose stocks over bonds, i.e., they buy stocks and sell bonds, they cause an FFQ. Baur and Lucey, 2009 suggest that such flights may cause negative stock-bond returns correlation. Meanwhile, it is natural to assume that the negative correlation itself causes investors to diversify their portfolios in order to minimize losses. Empirical research shows that flights happen a lot in crises, which are associated with a negative correlation. FTQ and FFQ happen during the stock and bond crisis correspondingly. As a contrary to flights which are characterized by a significant decrease in the stock-bond return correlation resulting in a negative correlation coefficient[20] (i.e., stocks and bonds moving in the opposite direction), Baur and Lucey, 2009 define the contagion effect as

[20] If a decrease in the stock-bond return correlation results still in a positive correlation coefficient, *decoupling* effect takes place.

a significant increase in the correlation resulting in positive correlation coefficient (i.e., co-movement of assets).

It is also a common practice to link the economic uncertainty to the stock-bond relation. The empirical investigation of Connolly et al., 2005 shows that the time-series variation of the uncertainty proxied by VIX is indeed informative about the time-series behavior of the stock market. They find a negative correlation between uncertainty and future stock-bond nexus.

There are many ways to define and estimate economic uncertainty in academic literature. Taking into account that uncertainty always implies unpredictability of future outcomes, its actual value depends on the expectations, which may vary through individuals.

The role of uncertainty is tremendous. It allows us to estimate the level of an individual's confidence in future economic conditions, which in turn determines the individual behavior and decisions regarding investments, employment, consumption, and others. As follows, there is a kind of simultaneous relation between uncertainty and economic conditions. Bloom, 2014 mentions four channels for uncertainty to influence economic growth: real options, risk premia, growth options, and so-called Oi-Hartman-Abel effect. The predictive power of uncertainty might help to build a better prognosis of fundamental economic variables. Bloom, 2009 and Baker and Bloom, 2013 show that uncertainty tends to jump up after major shocks with a subsequent slowdown in investment, hiring, and productivity growth.

In particular, Dimich et al., 2016 examine the impact of financial market uncertainty on the stock-bond correlation in emerging markets. They analyze the effect of stock and bond market uncertainty in both global and local economies. We follow them and use both the stock and bond market implied volatilities. Since we focus on the developed U.S. market, the global and local economies coincide in our research.

There is a common practice to proxy a global short-run stock market uncertainty with the CBOE Volatility Index (VIX), which estimates expected volatility by aggregating the weighted prices of S&P 500 Index.

Although VIX is a well-recognized index, implied volatility is not the only way to measure the uncertainty. Ahir, Bloom, and Furceri, 2019 develop a new index of uncertainty – the World Uncertainty Index (WUI), based on the frequency of the words 'uncertainty' in the quarterly Economist Intelligence Unit country reports. A similar approach to the construction of uncertainty index, based on newspaper coverage frequency, had been taken by Baker, Bloom, and Davis, 2016 in developing of Economic Policy Uncertainty Index (EPU). Both indices are expected to reflect the world-wide instability related to the COVID-19 pandemic: from medical concerns to policy responses. Baker et al., 2020 document a significant increase in economic uncertainty in April 2020 using VIX and EPU indices.

The bond market uncertainty is widely estimated by the Merrill Lynch Option Volatility Estimate (MOVE) index, developed by Bank of America Merrill Lynch. The MOVE index measures the U.S. interest rate expected volatility (by calculating the weighted average of over-the-counter volatilities on the two-, five-, ten-, and thirty-year Treasuries) and captures the realized volatility in bond market sentiment.

Quarantine measures caused by the COVID-19 pandemic, started in 2019 and still ongoing at the time of writing (the second quarter of 2020), undoubtedly had a crucial effect on world economics. Almost every aspect of life was affected by the outbreak. We are in a unique kind of situation now with a lack of comparable historical periods.

A significant number of employees in the U.K. were forced to leave their jobs that cannot be done remotely. In an attempt to help distressed workers and firms cope with the situation, central banks attempted easing monetary policies, governments postponed tax payments, and companies made an incredibly rapid transition into remote work in order to slow down the spread of the virus. Gormsen & Koijen, 2020 explore how the coronavirus outbreak and corresponding policy responses affect the investors' expectations about economic growth. They show that fiscal stimulus boosts long-term market expectation but have little effect on a short horizon.

In particular, Baker et al., 2020 study the impact of COVID-19 pandemic on economic uncertainty. They consider five types of uncertainty measures and find the enormous increase in economic uncertainty triggered by the pandemic and associated measures.

Following Baker et al., 2020, we include in our analysis stock market volatility VIX and newspaper-based measure EPU.

Empirical data confirms the unusual variation in uncertainty level during the inter-pandemic period. Panel A of Figure I3 shows that due to the COVID-19 shock VIX implied volatility index rocketed from 13.68 on 14 February 2020 to 82.69 on 16 March 2020 — in a month, the proxy of short-run stock market uncertainty increased by more than 500% and reached its highest value since 1990 (see Figure I4). The last comparable record was observed more than 12 years ago: VIX was equal to 80.86 on 20 November 2008 when the financial crisis of 2007-2009 hit the world. While the index shows a steady decline in the two past months and market stability is generally bouncing back now, the volatility still did not reach its pre-COVID-19 shock value, almost two times exceeding it.

A capital market provides a spectrum of financial assets and includes both the stock market and bond markets. A stock market is a financial market where market participants such as investors and speculators trade shares of corporations. A bond market allows participants to issue, buy, and sell debt securities like bonds, notes, bills, and others, playing an essential role in the debt market.

The U.S. major stock market exchanges are the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers Automated Quotation (NASDAQ). The NYSE trades both stocks and bonds of more than 3000 companies and is now the world's largest stock exchange by market capitalization, i.e., the total value of all shares issued on the exchange, equal to $28.2 trillion. The AMEX is a smaller still competitive stock exchange designed for growing companies, trading over 8000 NMS securities in a fully electronic manner nowadays. The NASDAQ began trading in 1971 and is trading about 5000 common stocks now.

In this paper, we consider S&P 500 portfolio, constructed by common stocks issued by 500 companies with the highest market capitalization and traded on American stock exchanges: S&P 500 companies represent around 80% of the total American capital market capitalization (see Figure I6).

Bonds might be issued both by government and corporations, both financial and non-financial. In this paper, we focus on the government bond market. With government bonds, also known as sovereign bonds, a national government borrows money to fund its operations. Government bonds are considered low-risk investments compared to stocks because the government backs them, and returns on bonds are pre-fixed given that sovereign default is unlikely. Historically, the interest rate paid by the U.S. government to its lenders is considered to be the risk-free rate that settles the benchmark for the risk-premia of other securities.

The U.S. government bond market is the largest in the world, grown to more than $19 trillion during the past decade, with average daily trading volume varying between $500 billion and $1 trillion in the past year (see Figure I7) and roughly 600 outstanding bond issues according to Cbonds. With the U.S. GDP worth roughly $21.3 trillion and the U.S. Government Debt-to-GDP ratio equivalent to 135% in 2019, the U.S. government bonds cover over 66% of the debt.

U.S. government bonds are referred to as *treasuries*. A bond value is determined by its coupon rate and maturity. The treasury interest rate statistics are published on a daily basis by the U.S. Department of Treasury. The range of maturities in the U.S. bond market is from 1 month (1M) to 30 years (30Y).

The price of government bonds reflects what the market thinks will happen to interest rates in the future since bond returns are inversely correlated with discounting rates: when rates go up, bond returns fall.

Since our analysis is conducted within a short horizon, we focus on short-term maturity bonds (see section Data). Treasury bills volume falls in the range of roughly $100 billion to $200 billion in the past year constituting around 20% of the total treasury market (see Figure I7).

Connoly et al., 2005 note that constant long-term unconditional stock-bond relation may be accompanied by time-varying high-frequency correlation. In our analysis, we use daily data where it is available in order to capture those variations. Daily data is especially beneficial when the time interval in focus is not so long: in our case, it has been only five months since the first official announcement of the pandemic. Besides, the economic uncertainty may change significantly in a day without any considerable change in a month.

Campbell et al., 2020 and others report the change from nominal Treasury bonds being risky in the 1980-s to safe in the 2000-s as well as the change in a sign of stock-bond correlation from positive to negative. Taking this into account and also the fact that the 1M Treasury yields are available since 2001 we calculation correlations using daily data on zero-coupon Treasury bonds and the stock market from Wednesday 1 August 2001 to Friday 29 May 2020, with a focus on the recent data: from Monday 2 December 2020 to Friday 29 May 2020. This way, we make sure we include the data since the pandemic was announced in China and even one month before. This way, we also can compare the numbers for an extended period (with shocks smoothed over the sample) and a short subsample with a shock caused by COVID-19.

We follow the literature and proxy short-run stock market uncertainty with the VIX index, designed to measure the 30-day market's expectation of future volatility implied by U.S. S&P 500 options prices.

Next, we follow Dimich et al., 2016 and estimate the bond market uncertainty with Merrill Lynch MOVE index. Figure I1 plots the time series of the MOVE in the COVID-19 pandemic period. Like the VIX, the MOVE catches the uncertainty inflow caused by the COVID-19 pandemic announcement along with the following policies. In a month, the MOVE volatility level rocketed from 61.24 (6 February 2020) to 163.70 (9 March 2020). However, unlike the VIX, the MOVE fully recovered to the value at the moment of writing.

The third uncertainty index we use in this paper is newspaper-based. The EPU index[21], developed by Baker et al., 2016 is defined by three factors: the frequency of policy-related uncertainty mentions in large newspapers, the uncertainty behind the federal tax code path measured by the dollar-weighted number of federal tax code provisions set to expire in 10 years, and the level of disagreement among economic forecasters about policy-related macroeconomic variables.

[21] Available at https://policyuncertainty.com/index.html on a daily and monthly basis.

U.S. Department of the Treasury publishes daily data on Treasury yield curve rates (commonly referred to as 'constant maturity treasury' rates, or CMTs) from 1-month to 30-years. The Treasury yield curve is estimated daily using a cubic spline model with a floor of zero (reset negative yields to zero). We use the 3-months CMTs as short-term bond returns and the 10-years CMTs as long-term bond returns. Though we do not directly use the long-term rates in analysis, we consider the term spread defined as a difference between 10Y and 3M Treasury yields. The data is given in percentage.

In our analysis, we use the S&P 500 Stock market index computed from the prices of those common stocks, which is widely used by investors to estimate the overall performance of the market. During 2019 the market capitalization of S&P 500 companies was stable around 80% of the total American capital market capitalization (see Figure I6). In the past quarter, the share value rocketed to the 96.39% in April 2020: even though there was a significant drop in both the overall U.S. market and the S&P 500 market caps by roughly $5.42 T and $3.05 T correspondingly, the latter mostly recovered in a month.

After cleaning for missing values in data, we select the period of interest and then merge data of stock returns, bond returns and uncertainty indices). The extended period includes 4697 observations from 1 August 2001 to 29 May 2020. The crisis subsample includes 124 observations from 2 December 2019 (three months before the official start of the pandemic[22]) to 31 May 2020. For convenience, in the final analysis we use natural logarithmic returns rather than prices or raw returns[23].

News-based indices quite differ in their response to the pandemic shock. All indices show a spike around the WHO announcement, however, VIX and MOVE slowly level out and recover since then, while the U.S. EPU index after-shock fluctuations stay at a sufficiently high level (see Figure I1 and Figure I3).

[22] The WHO officially announced COVID-19 outbreak a pandemic on 12 March 2020. See https://www.euro.who.int/en/health-topics/health-emergencies/coronavirus-covid-19/news/news/2020/3/who-announces-covid-19-outbreak-a-pandemic.

[23] See Appendix II for a discussion on benefits of using returns over prices and logarithmic returns over arithmetic returns.

Stock market reacts to the shock with a crucial drop in returns. During the crisis VIX and S&P 500 indices seem to have almost opposite movement with VIX anticipating changes in S&P 500 approximately by a week (see Figure I3). As the literature on stock-bond correlation suggests, bond market answers to the shock with an increase in term spread yield, while the short-term yield falls and reach their pick right after the announcement (see Figure I8).

Correlation as well as many other time-series analyses requires input data to be stationary (i.e., have constant variation and be mean reverting). We check data for stationarity with the Augmented Dickey-Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The tests do not confirm stationarity of the time series; however, they show stationarity for the first difference of both series. The argumentation is similar to that presented above.

Tests results for daily S&P 500 log returns confirm stationarity (see Table I2). Since there is no need to differentiate the series, we could use raw logarithmic values for the further analysis. However, in order to keep the same order of magnitude for all variables, we take the first difference of S&P 500 log returns as well.

Table I4 and Table I5 summarize statistics on the data used in analysis: number of observations, mean, standard deviation, minimum and maximum, the 25%, 50% and 75% percentiles, skewness and kurtosis of stock and bond returns. For the 2001 to 2000 period, the unconditional daily variance of the stock returns is about forty times as large as the unconditional daily variance of the 3-months bond returns. In the period of shock the stock daily variance increases in more than 2 times, while the bond volatility remains approximately the same (see Table I4). The average of the VIX grew by more than 1.5 times and the mean of the EPU index raised even more, from 105.05 to 281 (see Table I5).

First, we estimate the unconditional Pearson correlation between bond and stock returns: Table I6 shows the results. The daily correlation between the 1st differenced logarithmic short-term Treasury yields and the 1st differenced logarithmic stock returns is roughly equal to 0.067 for the whole sample August 2001 – May 2020 and 0.154 for the subsample December 2019 – May 2020 which is more than two times higher than the whole sample correlation. The daily correlation of the same stock returns with term spread is negative and equal to −0.53. The numbers support past research by negative sign of the correlation between stock returns and long-tern bond yields and show that the short-term bond returns move in the same direction as stocks in average.

Second, we measure the rolling correlation choosing the rolling windows equal to 22 days which is an average number of working days in a month. Figure I9, shows the time series of 22-trading-day correlations between stock and bond returns, formed from days t to t+21. Panel A exhibits the correlation between S&P 500 and T-bills 3M log yields, and Panel B presents the correlation between S&P 500 and term spread log yields. Both time series share seasonality with a negative spike in February 2020. The correlation with long-term yields also show the second, more significant spike in March 2020.

Finally, we follow Connoly et al., 2005 and build a distribution of forward-looking correlations formed from daily returns over days t to t+21 following a given uncertainty level at the end of the day t−1. This way we capture the forward-looking relationship of uncertainty indices and stock-bond correlation. Here we focus on S&P 500 – short-term bond returns correlation.

Panel A of Table I7 reports the stock-bond correlation conditional on VIX values divided into 9 groups[24]. The mean of the 22-trading day correlation coefficients over the whole sample is 0.267 and the probability of a negative correlation is 26%. For high VIX t-1 values of greater than 50%, the mean correlation is high at 0.313 and the probability of subsequent negative correlation is 0%. With decreasing VIX t-1 values the probability of subsequent negative correlation is increasing and the mean correlation is decreasing with negative mean at -0.007 for VIX values < 15%. For the very low VIX values the mean is positive again at 0.074 and comparable to the mean for the very high VIX values.

Similar results are obtained for controlling variable MOVE. Average correlation for a high-level uncertainty MOVE>160 is positive and equal to 0.297 which is greater than

[24] Connoly et al., 2005 consider 5 groups based on conditions: VIX>40%, VIX>35%, VIX>30%, VIX>25%, VIX<20%. At the moment of their writing VIX did not raise more than 45%, while we analyze the unique situation where the VIX reached its highest pick at more than 80%. We extend the analysis with four more conditions: VIX>50%, VIX>45%, VIX<15%, VIX<10%.

the total average value 0.237. With the level of uncertainty decreasing, the mean of correlation also falls.

The highest averaged correlation is observed for medium-level implied volatility uncertainty: both, VIX and MOVE indices. This result might be a support for non-linear dependency of stock-bond relation on uncertainty level.

Finally, Panel C of Table 7 reports the stock-bond correlation conditional on EPU values divided into 8 groups. EPU's effect on the correlation differs from the one we saw earlier. For high MOVE t-1 values of greater than 800, the mean correlation is negative and equal to -0.024 and the probability of subsequent negative correlation is 67% (i.e., two of three observations have negative correlation). With decreasing MOVE t-1 values the probability of subsequent negative correlation is decreasing at first, and then increasing again, for the medium values of uncertainty. The proportion of negative correlations for high values of uncertainty level exceeds such proportion for low values (< 200 and <100), as one would expect.

We study daily stock and bond returns from 2001 to 2020 and examine the uncertainty linkage to the stock-bond relation. We are particularly interested in the COVID-19 pandemic period (and a month pre-period) associated with a high economic uncertainty measured by VIX, EPU, and MOVE indices and a significant drop in stock returns.

As we have shown, the COVID-19 pandemic caused an enormous boost in economic uncertainty: all uncertainty indices show a huge increase in value after the WHO announcement, however, while VIX and MOVE slowly level out and recover since then, the U.S. EPU index after-shock volatiles at a sufficiently high level with a slightly negative trend.

With an increased level of uncertainty, we would expect a strengthening of negative correlation between stock and bond returns soon. We detect a significant drop in February resulting in negative value for both stock-bill and stock-spread 22-trading-day correlation. The result supports the past research. However, the constant correlation and averaged rolling correlation both show a slight increase during the shock period. One possible explanation is a timely monetary policy response by Central Banks.

The results on conditional correlation questions the ability to attribute the current crisis to the 'classical' crisis with the flight-to-safety effect. One would expect the stock-bond correlation to decrease resulting in negative value once uncertainty level increases. However, the conditional correlation on VIX and MOVE do not confirm this hypothesis. The news-based EPU index, in turn, shows quite interesting results. First, we detect that the index anticipates the other indices reactions to the shock with a significant boost. Second, from a forward-looking perspective, we find a negative relation between the uncertainty level and the future correlation of stock and bond returns.

Our results extend the empirical research on stock-bond nexus and have a practical value for investors willing to diversify their portfolio. The relevance of results is supported by using the up-to-date data related to the unique circumstances: the world-wide pandemic. We also compare the results of the analysis conducted on the current data and the historical one, which gives a better prospect on the comparison of financial market behavior during crisis times and normal times.

As we finish the paper, the world slowly comes to its 'normal' pace. The world-wide breakdown comes to an end in most countries and states. According to the Business Insider article, 2020 in the U.S., five states had no stay-at-home order issued, 37 states have lockdown lifted, seven states have partial lockdown lifted, and the lockdown in New Jersey was extended as at 3 June 2020. The COVID-19 death statistics are believed to on the wane; people go back to work. In other words, there is a positive outlook that reflects on the financial market performance, individuals' expectations, level of uncertainty. Still, it is important to keep tracking the situation and repeat the presented analysis continuously in order to be able to predict the deviations in the economy at this fragile time.