Creditable Bonds' Multifunctional Roles during the COVID-19 Pandemic

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A B S T R A C T

The study examines the multiple roles of investment-grade corporate bonds (rated by Moody's as DAAA and DBAA) in the pandemic. Firstly, they outperformed stock indices (such as SPX and other market indices), delivering the highest daily returns and Sharpe ratios across sub-periods of the pandemic. We uncover the patterns of return changes. Secondly, either Pearson's correlation or dynamic conditional correlation (DCC) confirms their function as a safe haven after gold. Thirdly, at the onset of the outbreak in 2020, relief policies worldwide boosted stock index returns. However, this uplift was short-lived. Even with a decline in yields, investment-grade bonds consistently outperformed stock indices. From March 2022, the Federal Reserve initiated a series of federal funds rate increases, positively affecting bond yields. Furthermore, we delved into the effects of the time lags of relief policies and interest rate hikes. Our findings revealed these policies' nuanced and asymmetric impacts, which help explain the observed price dynamics. In conclusion, our research addressed the roles of creditable bonds during the COVID-19 crisis. However, high-credit bonds consistently yielded higher daily risk-adjusted returns and held unique positions during the pandemic.

1. Introduction

The COVID-19 outbreak profoundly impacted global dynamics (Kissler et al., 2020). In early 2020, at the outset of the pandemic, financial markets worldwide took a severe hit. Before the development of the vaccine, daily infection rates in Europe, the US, Asia, and Pacific nations were alarming. Widespread commercial shutdowns, quarantine, lockdowns of public spaces, and subsequent mass immunizations were implemented globally. Not until May 2023, following a regular World Health Organization (WHO) meeting, did officials announce the end of COVID-19, paving the way for full economic normalization.

During the COVID-19 pandemic, many researchers have paid attention to bonds. Naeem et al. (2021) compare the green and the conventional bonds, demonstrating the positive impact of ESG characteristics during a health crisis. He et al. (2022) indirectly confirm the role of the Treasuries as a safe haven, upon considering its yield from the unique position. Kargar et al. (2020) discuss how COVID-19 influences corporate bond liquidity. O'Hara and Zhou (2021) further dissect the corporate bonds' liquidity in the COVID-19 crisis. Boubaker and Nguyen (2022) quantitatively show that low-risk bonds have higher returns than other assets.

Several perplexing issues have been widely recognized in the research on COVID-19. The first is asset performance. It is reported that only 7% of stocks outperformed bonds during the COVID-19. The second issue is which asset could be a safe haven. Gold, as a traditional safe haven during crises, has been investigated by many researchers. It played the role of a safe haven during the outbreak phase (Akhtaruzzaman et al., 2021), but lost this function shortly afterward. However, the duration of this pandemic is long. It is needed to seek a safe-haven asset after gold lost this function. The third issue is the influence of policy shocks. Research has already pointed out that the quantitative ease of the crisis might lead to a contraction (Khemraj & Yu, 2023). During the COVID-19 crisis, the bailout policy is like every rescue operation. However, raising the federal funds rate to meet the 2% inflation rate target is unprecedented, and needs examination. We elaborate on these issues in the following paragraphs and fill the gaps in the literature by investigating the multifunctional roles of bonds during the COVID-19 pandemic.

The juxtaposition of low-risk bond yields and stock performance has long been a point of contention among researchers. For instance, Bessembinder (2018) revealed that only 4% of stocks outperformed treasury bonds from 1928 to 2016. Yet, diversified stock indices serve as benchmarks for numerous passive investors, and are often perceived as low-risk. How did they fare against bonds?

Mutual funds widely advocate stock index-based investment strategies, having grown in prominence over recent decades. Vanguard Fund's founder, John Bogle, a mutual fund industry trailblazer, asserted in his monographs that stock indices, over the long run, can weather volatility and yield higher returns than bonds. Many seasoned investors bolster their strategies with stock indices, underscoring their diversification benefits.

Pastor and Vorsatz (2020), for example, evaluated the merits of active versus passive investment strategies during the pandemic. Their findings surprisingly showed passive strategies outpacing their active counterparts. Building on this, our first research hypothesis contrasts passive investment benchmark stock indices with reputable bonds.

In this paper, we employ a series of quantitative measures, including daily yield and volatility, to empirically demonstrate that bonds with credit ratings above the investable level exhibit higher daily returns than stock indices. We observed that both stocks and bonds were impacted during the COVID-19 period, with yields being lower than the average daily yield of the year preceding the outbreak. Nonetheless, other asset classes were primarily affected in the first year post-outbreak when a majority of European and American nations underwent lockdowns. Subsequently, the returns on these assets surpassed their pre-COVID-19 levels. Even though bonds with high credit ratings were influenced by COVID-19, their daily returns consistently outperformed other asset categories.

Both stocks and bonds are the most commonplace financial instruments in corporate finance to manage liquidity. Therefore, they are the most often-used instrument, which is even used by financial institutions as major investment tools outside their daily market-making business. Bao et al. (2023) infer that recession-induced default risk predicts the returns of both stocks and bonds, underlining the unfavorable investment climate created by COVID-19 for both asset classes.

Therefore, our paper posits that during the COVID-19 crisis, investment-grade bonds outperformed stock indices. This stance holds even upon finer asset class categorizations as noted in Chapter 27 of Boubaker and Nguyen (2022).

Concurrently, scholars are debating the safe-haven status of Treasury bonds amidst the COVID-19 tumult.[1] Investment-grade bonds, akin to Treasuries in terms of their low-risk nature but offering superior returns, prompt the question: As gold is regarded as a safe haven asset during the outbreak (Akhtaruzzaman et al., 2021), could low-risk bonds replace gold as a safe haven asset?

There are four widely investigated safe haven assets: gold, currencies, long-dated Treasury bonds, and cryptocurrencies. Numerous studies in the literature have confirmed that gold (Sokhanvar and Hammoudeh (2024), Ryan et al. (2024), Bei et al. (2024)), US dollars (Sokhanvar & Hammoudeh, 2024), and Yen (Sokhanvar and Hammoudeh (2024), Feder-Sempach et al. (2024), Kopyl and Lee (2016)) often behave like safe havens. US Treasuries are the strongest safe haven investments (Kopyl & Lee, 2016). Cryptocurrencies such as Bitcoin(Sokhanvar and Hammoudeh (2024), Feder-Sempach et al. (2024)), and Ethereum are not safe haven assets in major equity markets, except Tether due to its peg to the US dollar (Conlon et al., 2020).

Gold and the dollar even work during higher VIX values (Sokhanvar & Hammoudeh, 2024). Gold had diversification benefits before March 11, 2020, but exacerbated contagion due to pandemic fear (Bei et al., 2024), thus losing its safe haven status. Moreover, gold is a strong safe-haven asset against the S&P 500 for macroeconomic news but not for other reasons (Ryan et al., 2024), such as the COVID-19 pandemic crisis. Yield curve inversions have changed the VIX-US dollar relationship, along with investor behavior, since the global financial crisis in 2008 (Sokhanvar & Hammoudeh, 2024), so the US dollar is no longer a safe haven asset.

Investors buy gold when confronted with a choice between US government bonds and gold amid ambiguity signals. In contrast, they buy US government bonds in the case of unambiguous signals. With a certain rate hike signal, it is an unambiguous signal. Therefore, creditable bonds are more likely to be safe haven assets (Baur & McDermott, 2012).

On the other hand, instruments like gold, oil, and foreign exchange are considered inflation factors (Nygaard & Sørensen, 2024) and often depend on the situation of monopoly gaming. Historically avid U.S. Treasury buyers, such as oil-producing nations, deviated from their buying patterns observed during the global financial crisis, when confronted by geopolitical risks (as noted by Sweidan and Elbargathi (2023)). Additionally, the oil market witnessed price volatility.

The enactment of significant liquidity measures, such as the CARES (Coronavirus Aid, Relief, and Economic Security) Act in the U.S. and the European Central Bank's initiatives (loan provisions, bond purchasing, interest rate reductions), resulted in a surge of emergency liquidity, particularly in bonds, as highlighted by Kargar et al. (2020). These interventions arguably represent the most expansive global liquidity influx ever, subsequently fueling inflation. With a 2% inflation target, the Federal Reserve commenced successive interest rate hikes in March 2022, aiming to curb excessive inflation. Research postulates that this blend of monetary easing and rate increases could instigate a financial constriction crisis, diminishing societal welfare (referenced by Jasova et al. (2023), Anderson et al. (2023)). We utilized the economic policy uncertainty (EPU) index to underscore the early crisis liquidity easing's impact.

[1] https://www.nber.org/reporter/2020number3/are-us-treasury-bonds-still-safe-haven

Upon regressing the asset returns against the EPU index, we discerned its notable impact on the stock index only during the outbreak phase. While the S&P 500 (SPX) stock index initially ascended under the relief policies, it began its descent after the first year. Concurrently, a significant shift in government bond yields caused equity returns to lag behind those with the least change, as delineated by Zaremba et al. (2023). The expansive credit relief initiated in response to COVID-19 may thus have indirect repercussions on equities.

After March 2022, the Federal Reserve inaugurated a rate hike cycle. Using subsequent data, our regression against the federal funds' interest rate time series suggests that these hikes can account for the surge in the yields of high credit-rated bonds but minimally impact the SPX stock index. The federal funds rates did not significantly sway either stocks or bonds.

We also employed the nonlinear cointegration autoregressive distributed lag (NARDL) model to probe asymmetric error correction, testing the time-lagged impacts of economic policy uncertainty (EPU) and federal funds rates on asset returns. The impact of the time lags of price or those of price differences concentrates on the outbreak phase.

Our first contribution builds upon the work of Pastor and Vorsatz (2020) to attest to the superior performance of low-risk bonds over passive stock indices during the pandemic. Furthermore, we elucidate how asset return patterns evolve amid the pandemic with relaxed liquidity conditions and subsequent rate increases.

Considering the volatility in asset returns and inconclusive stationarity results, we utilized these statistics to assess the asset characteristics and confirm bonds' conservative nature even when compared to equity indices during the COVID-19 crisis.

The second contribution relies on the findings that creditable bonds could act as a safe haven after gold lost its status as a safe haven shortly after the outbreak phase. The covariances of bonds with other assets are either negative or weaker than before. Regressions indicate that DCC could explain the lower extremes of the asset returns. The findings are consistent with the discussion in the literature on the usual safe haven assets safety, the change in investors' risk appetite after the global financial crisis, and their comprehensive effects.

The third notable contribution involves analyzing the repercussions of the COVID-19 outbreak and the ensuing robust mitigation strategies on asset yields. Major relief policies, such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act by the U.S. Congress, boost the struggling economy at the outbreak of COVID-19. The pandemic emergency purchase programme (PPEP) by the European Central Bank substantially injected liquidity into the bond market. After the emergence of post-COVID-19 inflation, the rise in federal funds rate has had a significant positive effect on bonds, underscoring why investment-grade bond yields outstrip returns of the stock index. Using the regression model and the asymmetric time series model (referenced in Sickles and Horrace (2014)), we empirically evaluate the effects on asset returns. The result implies that neither of the two major policy adjustments has favored the stock index.

The paper is structured as follows: Section 2 elucidates the methodologies for examining bonds' performance, the safe haven role, and the influence of the economic policy uncertainty (EPU) index alongside the raising of federal funds rate. Section 3 introduces the datasets, the COVID-19 sub-period classification, and empirical analysis of our hypotheses. Section 4 presents our conclusions.

2. Methodology

In this section, we delineate the methodologies employed to assess the multifunctional roles that bonds rated investment grade or higher played during the COVID-19 pandemic. We explore the causal relationships and mechanisms resulting from the economic policy uncertainty that arose after the relief packages were introduced at the onset of the pandemic and the impact of the federal funds rate increase after March 2022.

2.1. Stock indices or creditable bonds from the perspective of performance

Our **first hypothesis** is that creditable bonds performed better than passive stock indices during the COVID-19 pandemic. We adopt multiple evaluative criteria, which encompass return metrics, risk considerations, and the Sharpe ratio (SR). Our hypothesis posits that high credit-rated bonds deliver the most substantial risk-adjusted returns, which we seek to verify using the following methods.

2.1.1. Return and risk

For a holistic performance comparison across different asset classes, we employ a suite of return measures. The benchmark comparison covers periods before COVID-19, various stages during the COVID-19 crisis, and the subprime crisis for a parallel examination. Our return measures include the mean, maximum, minimum, and mid-point of daily returns. Notably, the mid-point is calculated as the average of the peak and trough returns. By analyzing the extremes – the maximum and minimum – we can deduce the maximum drop-down. This serves dual purposes: gauging risk and discerning the most significant price differential for market timing.

Our risk assessment tools encompass volatility, skewness, Value-at-Risk (VaR), and expected shortfall (ES). Volatility is represented by the standard deviation of returns over a specific duration. Skewness captures the third moment of returns, offering insights into the asymmetry of the distribution. Value-at-Risk (VaR) is a concept introduced by Duffie and Pan (1997). It outlines the potential loss an investment might encounter, measured at a predetermined confidence level. Expected shortfall (ES) is a more refined risk measure than VaR, and is the average of the worst expected losses.

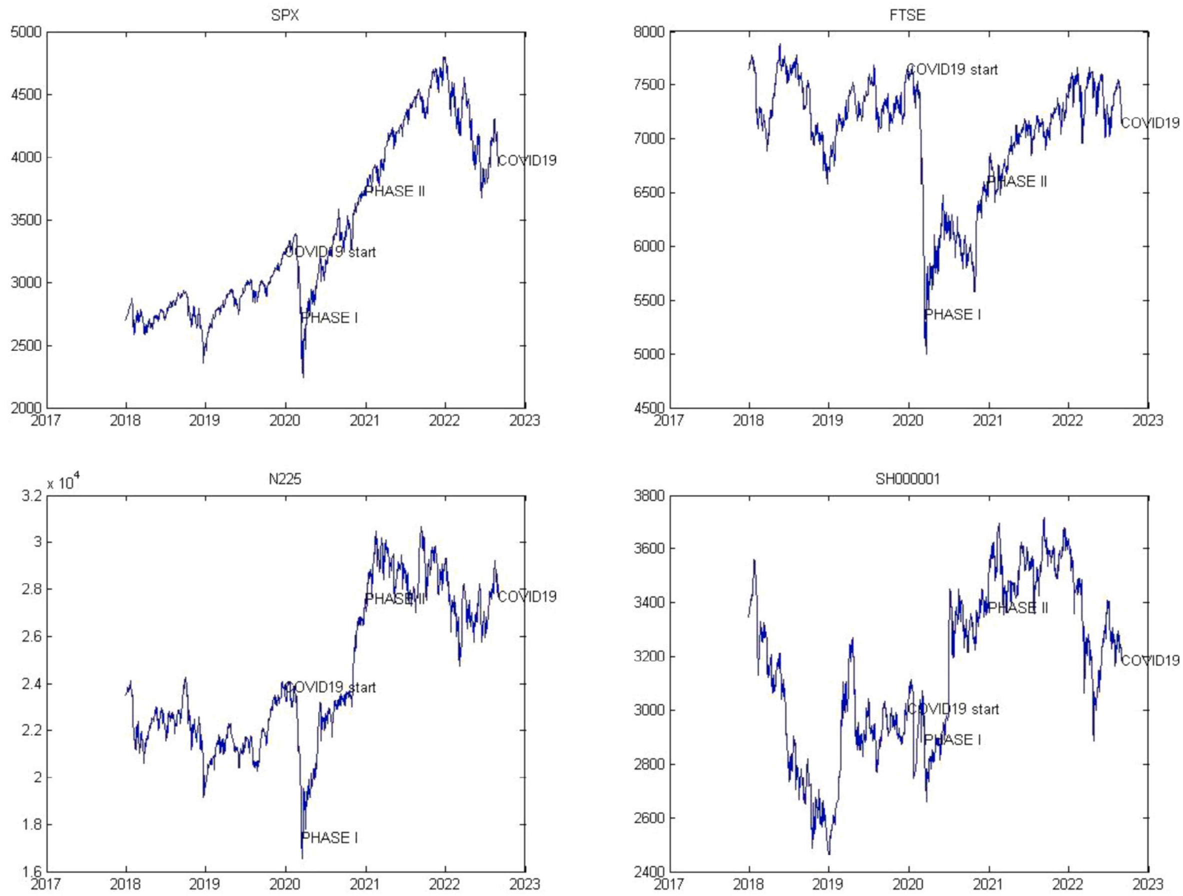

Fig. 1. Equity Asset Price Trend (2018–2022). Note: This chart depicts the SPX's tumultuous journey through the COVID-19 crisis. Initiated by a sharp drop in December 2019, it reached its nadir at the close of Phase I. Following the implementation of CARES and other Fed relief measures, a robust recovery commenced during Phase II, marked by a triangle-shaped pattern of ascents and descents post-lockdown. By September 2022, despite the persisting pandemic, SPX surpassed its pre-COVID-19 levels.

2.1.2. Risk-adjusted performance measures

Sharpe ratio is defined as the unit risk of return over a certain period of time,

$$SR_i = \frac{E(r_i) - r_f}{\sigma_i}, \tag{1}$$

where r_i is the return of the stock i, r_f is the risk-free rate, and σ_i is the standard deviation of stock i's returns. It is widely used to measure the performance (Ledoit and Wolf (2008), Gregoriou and Gueyie (2003)).

2.1.3. Distribution stationarity

When we study the return time series of assets, it is necessary to test whether conditional means and conditional covariances are stationary. The test results could help decide which model to use for correlation modeling.

conditional mean test

The stationary tests show if the conditional means of time series are stationary from the perspective of unit root inference. The method we use to test the stationary property of conditional mean is the Dickey and Fuller (1979) test. The null hypothesis is $H_0 : \phi_1 = 1$ (the series is stationary), while the alternative hypothesis is $H_a : \phi_1 < 1$, indicating non-stationarity.

conditional variance test

Lagrange multiplier tests assess the conditional variance for homoscedasticity in a univariate stationary process. The null hypothesis, H_0: the process is homoscedastic. The alternative, H_a, is that the process is not stationary, with heterogeneous shocks.

2.2. Bond or gold as a safe haven asset

Pearson correlations show the increasing market connectedness during the COVID-19 crisis as a sign of rising systematic risk. Stationarity tests further confirm the deformation of assets' distribution. We conduct stationarity tests, and use dynamic conditional

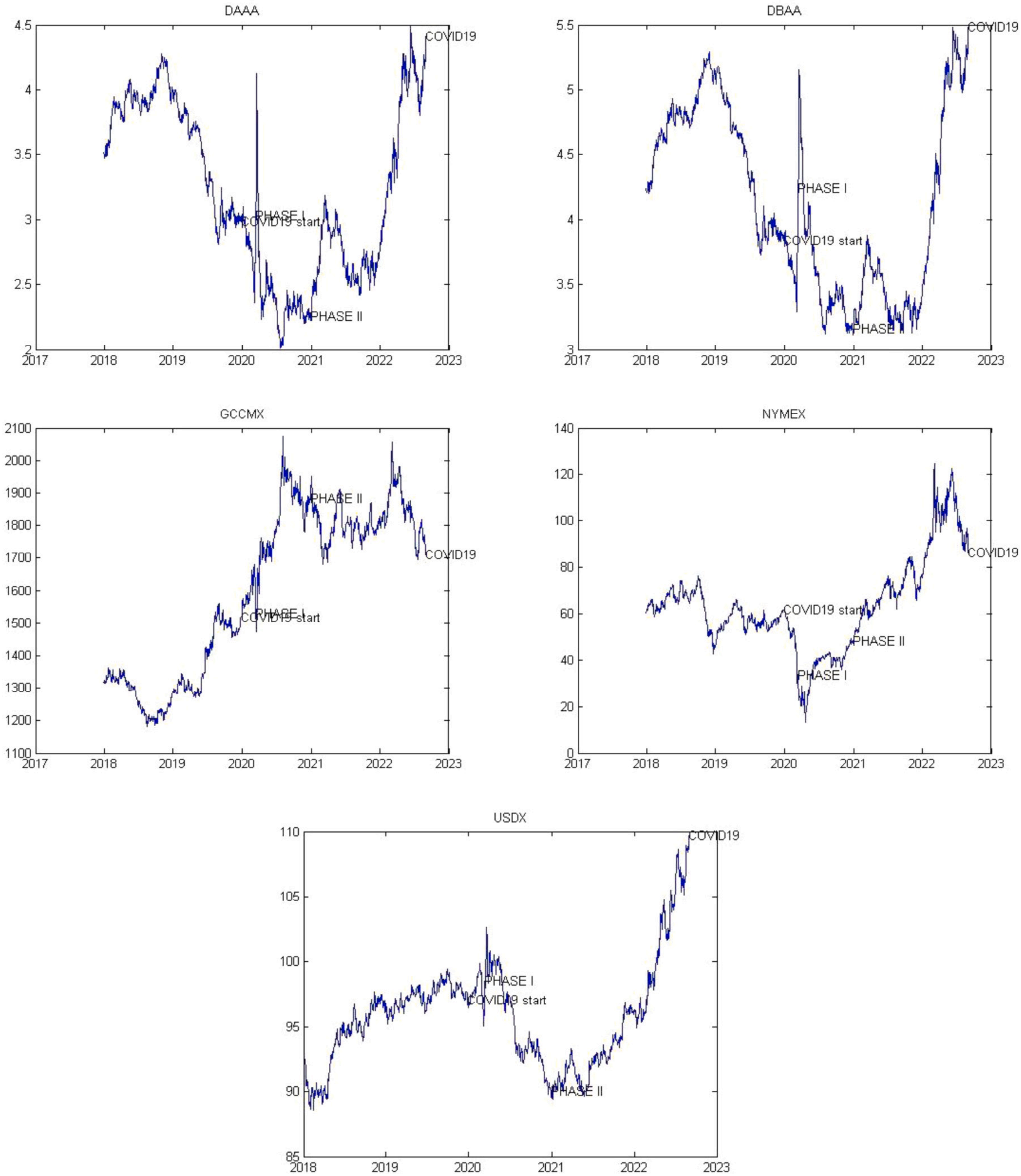

Fig. 2. Inflation-related Asset Price (DAAA,DBAA,GCCMX,NYMEX,USDX) Trend (2018–2022). Note: This figure displaces the yield dynamics for DAAA, which, alongside DBAA, showed congruent trends. Both saw decreased yields in Phase II. In 2021, yields initially rose but then declined. Significantly, DAAA, being the lower-risk bond is plotted with a *y*-axis starting at 2 percent, whereas DBAA started from 3 percent.

correlations (DCC) to test the safe haven role in **hypothesis two** by showing that creditable bonds are negatively correlated or decreasingly correlated with other assets after Phase I, thus resume gold's safe haven role.

2.2.1. Cross-asset correlations

Pearson correlations across asset classes strengthened from the pre-COVID-19 period to the first phase (Phase I) but slightly fell in Phase II and in the aftermath. But falling correlations are still higher than that during the pre-COVID-19 period. We have computed but not presented correlations within every particular asset class here (Boubaker & Nguyen, 2022), which have also strengthened

Table 1
Daily return and risk of asset classes in the subperiods of COVID-19.

	SPX	FTSE	N225	SCI	**DAAA**	**DBAA**	GC.CMX	CL.NYM	USDX.FX
				Pre-COVID-19 (normal)					
mean	0.00036	−0.00002	0.00001	−0.00020	0.01002	**0.01257**	0.00028	0.00004	0.00010
max	0.04840	0.02325	0.03810	0.05449	0.01173	0.01449	0.02457	0.11813	0.01442
min	−0.04184	−0.03284	−0.05141	−0.05745	0.00770	0.01022	−0.02234	−0.08079	−0.01154
mid	0.00328	−0.00479	−0.00665	−0.00148	0.00971	0.01236	0.00111	0.01867	0.00144
std dev	0.00945	0.00773	0.01055	0.01197	0.00107	0.00116	0.00688	**0.01992**	0.00327
skew	−0.61024	−0.38417	−0.80254	−0.36119	−0.66110	−0.48078	0.11827	−0.05853	0.00518
VaR	−0.00528	−0.00565	−0.00647	−0.00843	0.00868	0.01107	−0.00500	−0.01394	−0.00248
ES	−0.01311	−0.01099	−0.01486	−0.01648	0.00824	0.01068	−0.00914	−0.02844	−0.00448
				COVID-19 pandemic crisis Outbreak (Phase I)					
mean	−0.00577	−0.00717	−0.00688	−0.00179	0.00775	**0.01014**	−0.00005	−0.01451	0.00023
max	0.08881	0.02426	0.02348	0.03098	0.00849	0.01162	0.03181	0.14189	0.01563
min	−0.12765	−0.11512	−0.06274	−0.08039	0.00647	0.00901	−0.03676	−0.31821	−0.01103
mid	−0.01942	−0.04543	−0.01963	−0.02471	0.00748	0.01032	−0.00247	−0.08816	0.00230
std dev	0.03302	0.02277	0.01829	0.01823	0.00044	0.00048	0.01242	**0.05768**	0.00435
skew	−1.09098	−2.69212	−1.00807	−1.84563	−0.64699	0.60477	−0.92132	−2.65691	0.50983
VaR	−0.01786	−0.01414	−0.02154	−0.01229	0.00740	0.00970	−0.00946	−0.03388	−0.00317
ES	−0.05476	−0.04072	−0.03646	−0.02949	0.00708	0.00953	−0.01936	−0.08644	−0.00578
				The first year remainder,lockdown (Phase II)					
mean	0.00223	0.00121	0.00246	0.00104	0.00655	**0.00983**	0.00112	0.00254	−0.00043
max	0.08968	0.08667	0.07731	0.05554	0.01129	0.01411	0.06255	0.23745	0.01775
min	−0.06075	−0.05394	−0.04617	−0.04603	0.00551	0.00855	−0.05836	−0.48081	−0.01526
mid	0.01447	0.01636	0.01557	0.00476	0.00840	0.01133	0.00209	−0.12168	0.00125
std dev	0.01761	0.01689	0.01526	0.01151	0.00081	0.00125	0.01356	**0.05810**	0.00428
skew	0.44321	0.31760	0.89042	0.11863	3.23464	1.56307	−0.15556	−2.44437	0.55922
VaR	−0.00798	−0.00904	−0.00748	−0.00611	0.00616	0.00877	−0.00720	−0.02086	−0.00363
ES	−0.02101	−0.02172	−0.01568	−0.01378	0.00587	0.00867	−0.01752	−0.06356	−0.00592
				Afterwards, after the lockdown					
mean	0.00012	0.00025	0.00002	−0.00017	0.00856	**0.01071**	−0.00022	0.00137	0.00046
max	0.03011	0.03839	0.03860	0.03424	0.01233	0.01501	0.02783	0.10417	0.01270
min	−0.04123	−0.03955	−0.04067	−0.05268	0.00608	0.00852	−0.03448	−0.13509	−0.01186
mid	−0.00556	−0.00058	−0.00103	−0.00922	0.00921	0.01177	−0.00332	−0.01546	0.00042
std dev	0.01147	0.00954	0.01238	0.01022	0.00168	0.00207	0.00880	**0.02702**	0.00392
skew	−0.46952	−0.45778	−0.12682	−0.77479	0.74661	0.85761	−0.46856	−0.81024	0.11337
VaR	−0.00775	−0.00548	−0.00963	−0.00804	0.00710	0.00896	−0.00627	−0.01659	−0.00273
ES	−0.01641	−0.01328	−0.01774	−0.01513	0.00685	0.00881	−0.01309	−0.03698	−0.00493
				Full COVID-19 cycle					
mean	0.00029	−0.00006	0.00024	0.00007	0.00790	**0.01041**	0.00018	0.00051	0.00018
max	0.08968	0.08667	0.07731	0.05554	0.01233	0.01501	0.06255	0.23745	0.01775
min	−0.12765	−0.11512	−0.06274	−0.08039	0.00551	0.00852	−0.05836	−0.48081	−0.01526
mid	−0.01898	−0.01423	0.00729	−0.01242	0.00892	0.01177	0.00209	−0.12168	0.00125
std dev	0.01615	0.01364	0.01396	0.01139	0.00167	0.00182	0.01068	**0.04140**	0.00407
skew	−0.87840	−1.10190	0.07619	−0.90372	1.04324	1.20111	−0.29534	−2.70402	0.27754
VaR	−0.00798	−0.00703	−0.00943	−0.00776	0.00655	0.00899	−0.00664	−0.01974	−0.00302
ES	−0.02071	−0.01835	−0.01887	−0.01576	0.00621	0.00878	−0.01481	−0.04870	−0.00532
				Global Financial Crisis (GFC, Subprime)					
mean	−0.00074	−0.00060	−0.00107	−0.00007	0.01523	**0.01977**	0.00066	0.00024	−0.00011
max	0.10957	0.09384	0.13235	0.09034	0.01795	0.02614	0.08589	0.18444	0.01984
min	−0.09470	−0.09266	−0.12111	−0.09256	0.01266	0.01668	−0.06054	−0.13065	−0.03252
mid	0.00744	0.00059	0.00562	−0.00111	0.01530	0.02141	0.01267	0.02689	−0.00634
std dev	0.02083	0.01891	0.02274	0.02497	0.00080	0.00236	0.01612	**0.03264**	0.00625
skew	−0.10284	0.00426	−0.31252	−0.27140	0.43372	0.93724	0.25384	0.15134	−0.42918
VaR	−0.01329	−0.01179	−0.01466	−0.01954	0.01468	0.01778	−0.01083	−0.02059	−0.00434
ES	−0.02899	−0.02572	−0.03174	−0.03685	0.01423	0.01742	−0.02193	−0.04398	−0.00858

Note: The daily average return of DBAA is the highest among these assets. CL.NYM is the most volatile. Overall, the order of the volatility levels of these asset classes is CL.NYM>STOCKS>GC.CMX>USDX.FX>BONDS.

Table 2
Alpha and SR of asset classes through these subperiods of COVID-19 and subprime crisis.

	SPX	FTSE	N225	SCI	DAAA	DBAA	GC.CMX	CL.NYM	USDX.FX
					Pre-COVID-19				
SR	0.04462	0.02541	0.03113	0.01496	3.59743	**3.88386**	0.04230	0.04543	−0.02950
					Outbreak (Phase I)				
SR	0.00715	−0.01856	−0.00175	0.00826	3.59743	**3.69217**	0.04226	−0.01396	−0.01084
					First year remainder, Lockdown (Phase II)				
SR	0.08525	0.05684	0.08739	0.07444	**3.59743**	3.06482	0.07908	0.04285	−0.06971
					Full COVID-19				
SR	0.02319	0.00403	0.01690	0.00006	3.38752	**6.05761**	0.02555	0.02772	0.03409
					Global Financial Crisis (GFC, Subprime)				
SR	−0.03522	−0.03801	−0.04658	0.00446	**16.58506**	8.38479	0.04149	0.00719	−0.02999

Note: DBAA and DAAA interchangeably act as the highest SR assets through these subperiods. For alphas with significant t-statistics, CL.NYM's alphas are very high, excluding Fama French's five factors' risk. However, we have seen from the last table that CL.NYM's volatility is the highest. In Phase I and the subprime crisis, among the significant t-statistics alpha coefficients, DBAA's alphas are the highest.

during the crisis.

2.2.2. *Examination of creditable bonds as a safe haven asset class using DCC*

A safe haven asset[2] is an asset that is expected to hold or increase value during periods of economic uncertainty and market turbulence. Investors seek safe haven assets in such times in order to limit their exposure to possible downturns in the market.

A diversifier is an asset that only has a weak positive correlation with another asset (Baur and Lucey (2010), Bouri et al. (2017), Ratner and Chiu (2013)). A weak (or strong) hedge is an asset that is uncorrelated (or even negatively correlated) with another asset. Finally, a weak (or strong) safe haven is an asset that is uncorrelated (or even negatively correlated) with another asset during turbulence. So we have the null hypothesis H_0: creditable bond is a safe haven asset, which has negative correlations with other assets. The alternative hypothesis, H_a: creditable bond is not a safe haven asset.

As the return distribution is not stationary during the COVID-19 crisis, we use a dynamic conditional correlation (DCC) model to compute the correlations between the safe haven asset and other asset classes. In this paper, for the proposed safe haven asset, investment-grade or above bonds, we use, the highest yield and lowest grade among creditable bonds, DBAA, for examination.

The estimation of the DCC model entails three steps (Engle, 2002). Firstly, we need to estimate volatility to construct standard errors. This is the de-GARCH procedure. Secondly, based on the standard errors, we estimate the correlations in the dynamic form. Thirdly, we adjust estimated correlations to obtain the true correlation matrix.

2.2.3. *Regressions of DCC effects with dummy variables representing extremes*

To further investigate how seriously the crisis influenced the asset correlations and how safe haven assets protected investment from extremes, we regress the DCC time series of the investment-grade bond DBAA and other assets with dummy variables $D_t(r_{q10})$, $D_t(r_{q5})$, $D_t(r_{q1})$ that represent the 10%, 5% and 1% quantiles of the most negative returns of the asset classes:

$$DCC_t = m_0 + m_1 D_t(r_{q10}) + m_2 D_t(r_{q5}) + m_3 D_t(r_{q1}) + \epsilon_t, \tag{2}$$

where dummy variables are,

$$D_t(r_{q10}) = \begin{cases} 1 & r_{it} < r_{q10} \\ 0 & otherwise, \end{cases} \tag{3}$$

$$D_t(r_{q5}) = \begin{cases} 1 & r_{it} < r_{q5} \\ 0 & otherwise, \end{cases} \tag{4}$$

$$D_t(r_{q1}) = \begin{cases} 1 & r_{it} < r_{q1} \\ 0 & otherwise, \end{cases} \tag{5}$$

r_{it} is asset i's return at time t; r_{q10}, r_{q5}, and r_{q1} are the thresholds at 10%, 5%, and 1% quantiles respectively.

Similarly, we demonstrate the effects of Phase I and Phase II on asset correlations using dummies of these two deep crisis phases, $D_t(r_{p1})$ and $D_t(r_{p2})$:

$$DCC_t = m_{p0} + m_{p1} D_t(r_{p1}) + m_{p2} D_t(r_{p2}) + \epsilon_t, \tag{6}$$

[2] https://admiralmarkets.com/education/articles/general-trading/safe-haven-assets.

Table 3
Stationarity tests of conditional means and conditional variances.

Target	Item	SPX	FTSE	N225	SCI	DAAA	DBAA	GC.CMX	CL.NYM	USDX.FX
					Pre-COVID-19 (normal)					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.4071	0.4670	0.0010	0.0010	0.0010
	Stat	−22.8126	−22.2386	−22.3603	−21.9834	−0.6674	−0.5037	−23.3644	−24.0108	−22.3045
	c-value	−1.9411	−1.9411	−1.9412	−1.9412	−1.9411	−1.9411	−1.9411	−1.9411	−1.9411
cond var	h	1	1	1	0	1	1	0	1	0
	p-value	0.0000	0.0010	0.0007	0.6205	0.0000	0.0000	0.9904	0.0024	0.7144
	Stat	25.7910	10.7694	11.5654	0.2451	480.7640	483.1914	0.0001	9.2045	0.1340
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415
					Outbreak (Phase I)					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.5114	0.7941	0.0010	0.0010	0.0010
	Stat	−12.0307	−6.7182	−4.8451	−6.3263	−0.3713	0.4024	−5.5777	−7.5334	−6.9749
	c-value	−1.9464	−1.9464	−1.9470	−1.9470	−1.9464	−1.9464	−1.9464	−1.9464	−1.9464
cond var	h	1	0	0	0	1	1	0	1	1
	p-value	0.0000	0.7833	0.1045	0.6271	0.0000	0.0000	0.5285	0.0372	0.0234
	Stat	21.9342	0.0756	2.6358	0.2360	26.4020	24.0775	0.3972	4.3402	5.1374
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415
					Lockdown (Phase II)					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.3531	0.2194	0.0010	0.0010	0.0010
	Stat	−17.6271	−14.8725	−13.6891	−13.1590	−0.8130	−1.1782	−13.9803	−12.8448	−11.7066
	c-value	−1.9423	−1.9423	−1.9424	−1.9424	−1.9423	−1.9423	−1.9423	−1.9423	−1.9423
cond var	h	0	1	1	0	1	1	0	1	1
	p-value	0.0571	0.0010	0.0000	0.6380	0.0000	0.0000	0.1548	0.0438	0.0000
	Stat	3.6182	10.7417	58.8295	0.2214	150.5183	185.1631	2.0244	4.0646	39.2446
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415
					After-lockdown time					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.9816	0.9942	0.0010	0.0010	0.0010
	Stat	−20.2294	−21.5036	−20.7391	−20.5410	1.7680	2.2471	−19.4062	−20.5259	−21.1060
	c-value	−1.9413	−1.9414	−1.9414	−1.9414	−1.9413	−1.9413	−1.9413	−1.9413	−1.9413
cond var	h	1	1	1	1	1	1	1	0	0
	p-value	0.0253	0.0000	0.0266	0.0000	0.0000	0.0000	0.0141	0.1318	0.0585
	Stat	5.0059	21.3708	4.9145	17.9577	402.3559	411.0607	6.0237	2.2709	3.5780
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415
					Full COVID-19					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.8562	0.9251	0.0010	0.0010	0.0010
	Stat	−32.7715	−26.4615	−24.4862	−24.9377	0.6511	1.0628	−24.6144	−24.7487	−24.7182
	c-value	−1.9413	−1.9413	−1.9412	−1.9412	−1.9413	−1.9413	−1.9413	−1.9413	−1.9413
cond var	h	1	1	1	1	1	1	1	1	1
	p-value	0.0000	0.0004	0.0000	0.0008	0.0000	0.0000	0.0003	0.0000	0.0000
	Stat	162.8859	12.5475	122.8311	11.3074	647.1948	657.7210	12.9666	19.7087	51.9795
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415
					Global Financial Crisis (GFC, Subprime)					
cond mean	h	1	1	1	1	0	0	1	1	1
	p-value	0.0010	0.0010	0.0010	0.0010	0.6375	0.8818	0.0010	0.0010	0.0010
	Stat	−28.9347	−26.0805	−24.7495	−23.9911	−0.0384	0.7842	−22.5640	−26.9875	−22.4840
	c-value	−1.9412	−1.9412	−1.9411	−1.9411	−1.9412	−1.9412	−1.9412	−1.9412	−1.9412
cond var	h	1	1	1	0	1	1	1	1	1
	p-value	0.0000	0.0000	0.0000	0.1066	0.0000	0.0000	0.0001	0.0013	0.0001
	Stat	46.9084	32.2794	47.3785	2.6037	516.0873	560.2713	16.2331	10.2929	14.8622
	c-value	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415	3.8415

Note: Most of the test results show that conditional means and variances are not stationary, so we use dynamic conditional correlations as the measures.

Table 4
The asset return dynamics in the COVID-19 pandemic.

Dynamics	Phase I of Lockdown	Phase II of Lockdown	Aftermath
SPX	↓	↑	↓
FTSE	↓	↑	↓
NIKKEI	↓	↑	↓
SCI	↓	↑	↓
DAAA	↓	↓	↑
DBAA	↓	↓	↑
gold	↓	↑	↓
crude oil	↓	↑	↓
USDX	↑	↓	↑

Note: The upward arrow stands for increasing return compared to the previous subperiod. The downward arrow stands for falling return compared to the previous subperiod. The shaded cells mean that the asset returns are higher than those in the pre-COVID-19 period. We could observe that stock indices all follow the same pattern: They plummeted during the outbreak, rose up subsequently due to the relief policies, and then fell down. The regional difference existed when Western countries' stock indices were still in the COVID-19 crisis. But eastern markets were higher than the pre-COVID-19 return after the first phase of lockdown. The pulse length of the COVID-19 shock on the bonds is longer, probably due to creditable bonds' low elasticity from the low-risk characteristics. The bonds were falling even in the second Phase of the lockdown. The slope is relatively flat, so their daily returns were still higher than that of the stocks. Gold and crude oil followed the common pattern of reaction to COVID-19, but crude had risen higher than that of the pre-COVID-19 return earlier in the second phase of the first year. Gold lost its safe haven status shortly after phase I due to its falling returns. The hit of the pulse to the USDX had an initial phase as late as the second subperiod of the COVID-19 crisis. It recovered very soon, higher than the condition in the pre-COVID-19. The volatilities of assets magnify or shrink with the rise and fall of the returns.

where dummy variables for Phase I and Phase II are,

$$D_t(r_{p1}) = \begin{cases} 1 & t \in p1 \\ 0 & otherwise, \end{cases} \tag{7}$$

and

$$D_t(r_{p2}) = \begin{cases} 1 & t \in p2 \\ 0 & otherwise, \end{cases} \tag{8}$$

where $p1$ and $p2$ stand for Phase I and Phase II.

2.3. *Bonds or alternative assets' prices and difference in prices under the policy shocks*

2.3.1. *Regression of relief policies and federal funds rate increase with asset returns*

To examine the significant events during the COVID-19 crisis, we employ regression analysis. In the initial stages of the pandemic, global economies launched a myriad of relief policies. To evaluate their impact, we regress the Economic Policy Uncertainty (EPU) index against asset returns, as detailed in **hypothesis three**.

Furthermore, to understand the ramifications of the increase in federal funds rate after March 2022, we also run the regression of federal funds rates with returns in **hypothesis four**, which tests the impact of rate rise on the stock index return and bond yields.

2.3.2. *Asymmetric impact of economic policy uncertainty and federal funds rate increase on time lags*

We employ the nonlinear cointegration autoregressive distributed lag (NARDL) model to capture the asymmetric and time-lagged responses underlined in our **fifth and sixth hypotheses**, for economic policy uncertainty (EPU) and federal funds rate (FFR) increase on assets respectively. These pertain to the effects of the EPU following relief package announcements and the federal funds rate adjustments.

The NARDL, leveraging automatic AIC and BIC selection for independent variables, reveals the asymmetrical influence of these shocks on the time lags of various asset classes. Our primary focus is on understanding the disparate reactions of assets in the wake of the introduction of relief policy and federal funds rate adjustments.

We have the following models:

$$EPU_t^+ = \sum_{j=1}^{t} \Delta EPU_j^+ = \sum_{j=1}^{t} \max(\Delta EPU_j, 0), \tag{9}$$

Table 5
Pearson correlations among asset classes through the subperiods.

	SPX	FTSE	N225	SCI	DAAA	DBAA	GC.CMX	CL.NYM	USDX.FX
Pre-COVID-19 (normal)									
SPX									
FTSE	0.407593								
N225	0.198596	0.320503							
SH	0.146290	0.304992	0.428207						
DAAA	−0.054703	−0.025265	−0.036691	−0.032273					
DBAA	**−0.042480**	**−0.000741**	**−0.022780**	**−0.002347**	**0.955942**				
GC.CMX	−0.153569	−0.104486	−0.100084	0.025064	−0.028047	**−0.010332**			
CL.NYM	0.361172	0.286721	0.124292	0.156076	−0.042790	**−0.038594**	−0.048126		
USDX.FX	−0.066512	0.115604	0.028707	−0.055096	0.046934	**0.044166**	−0.534219	−0.058866	
Outbreak (Phase I)									
SPX									
FTSE	0.789438								
N225	0.331126	0.574545							
SH	0.353112	0.322011	0.474286						
DAAA	0.194082	0.392897	0.305756	−0.015420					
DBAA	**0.079000**	**0.215821**	**0.008965**	**−0.144546**	**0.823938**				
GC.CMX	−0.019677	0.295234	0.433721	0.233270	0.043908	**−0.148289**			
CL.NYM	0.648985	0.603017	0.459242	0.447775	0.251722	**0.105912**	−0.055834		
USDX.FX	0.505620	0.301757	0.073960	0.051685	0.173586	**0.386339**	−0.351181	0.461511	
Lockdown (Phase II)									
SPX									
FTSE	0.633260								
N225	0.296620	0.464530							
SH	0.256030	0.255892	0.369857						
DAAA	0.014882	0.090624	0.159378	−0.030038					
DBAA	**0.083102**	**0.107171**	**0.160089**	**0.018783**	**0.842755**				
GC.CMX	0.236243	0.045288	0.046279	0.138932	0.158572	**0.141143**			
CL.NYM	0.195265	0.118774	0.078525	0.055313	−0.061258	**−0.017679**	0.013851		
USDX.FX	−0.209870	−0.157505	−0.247057	−0.224719	0.103475	**0.044721**	−0.313480	0.000556	
Full COVID-19 cycle									
SPX									
FTSE	0.595256								
N225	0.275538	0.425300							
SH	0.205045	0.244742	0.368544						
DAAA	−0.060535	0.000741	−0.014093	−0.034371					
DBAA	**−0.028575**	**0.016502**	**0.022818**	**−0.015900**	**0.915944**				
GC.CMX	0.109922	0.063873	0.093674	0.121457	−0.009355	**0.006986**			
CL.NYM	0.280161	0.252929	0.158858	0.155015	−0.032445	**−0.026298**	0.089246		
USDX.FX	−0.146806	−0.130922	−0.166635	−0.134171	0.101348	**0.069761**	−0.362308	0.037149	

Note: As a gigantic crisis, COVID-19 made the correlations among the financial assets increase, which forced investors to find a safe haven asset to avoid connected risk. It is obvious that most correlations increased dramatically from pre-COVID-19 to Phase I. Correlations slightly fell down in Phase II. The full COVID-19 cycle correlations are still higher than those from pre-COVID-19.

$$EPU_t^- = \sum_{j=1}^{t} \Delta EPU_j^- = \sum_{j=1}^{t} \min(\Delta EPU_j, 0), \tag{10}$$

where EPU represents the Economic Policy Uncertainty index.

Hence, we could obtain the NARDL (Sickles & Horrace, 2014),

$$\begin{aligned} \Delta r_t =& const + \sum_{i=1}^{y_{lr}} \alpha_i r_{t-i} + \sum_{i=1}^{z_{lr}^+} \beta_i^+ EPU_{t-i}^+ + \sum_{i=1}^{z_{lr}^-} \beta_i^- EPU_{t-i}^- \\ &+ \sum_{i=1}^{y_{sr}} \gamma_i \Delta r_{t-i} + \sum_{i=1}^{z_{sr}^+} \delta_i^+ \Delta EPU_{t-i}^+ + \sum_{i=1}^{z_{sr}^-} \delta_i^- \Delta EPU_{t-i}^- + \mu_t, \end{aligned} \tag{11}$$

where r_t represents the returns of financial assets, α_i stands for asset i's long-run coefficients. y_{lr} stands for long-run effects' number of lags. z_{lr}^+ stands for positive long-run effects' number of lags for the variable economic policy uncertainty. The same logic applies to the notation for short-run effects coefficients. If $\delta_i^+ = \delta_i^-$, the short-term economic stability has a symmetric impact on asset prices. If $\beta_i^+ = \beta_i^-$, the long-term economic stability has a symmetric impact on asset prices. The model for the federal funds rate is similar, so we omit it here. Long-run effects are on the time lags of prices. Short-run effects are on the time lags of difference in prices.

Table 6
DBAA safe haven property and DCC regressions.

	SPX	FTSE	N225	SCI	DAAA	GCCMX	NYMEX	USDX
				DCC mean				
subprime	5.73E−05	2.51E−04	8.15E−04	5.76E−04	4.25E−06	2.00E−06	2.50E−04	−1.01E−04
pre	−7.53E−07	2.36E−05	2.47E−04	1.24E−04	1.64E−06	−1.42E−05	1.04E−04	3.30E−05
phase1	1.46E−03	8.06E−04	−1.13E−03	−2.00E−05	6.74E−06	−3.68E−04	2.78E−03	2.97E−04
phase2	5.32E−04	5.65E−04	1.12E−04	−1.01E−04	1.65E−06	−4.91E−05	−1.07E−03	2.90E−04
later	−4.06E−05	−1.10E−04	3.05E−06	−7.81E−06	3.45E−07	7.66E−07	−2.09E−04	5.92E−05
whole	\	2.29E−05	−9.74E−05	−1.02E−04	\	−7.48E−05	6.44E−05	4.43E−05
				Outbreak(Phase I)				
constant	0.00002	0.00002	0.00012	0.00000	0.00000	−0.00001	−0.00008	0.00002
	0.71702	0.95442	1.01597	1.25681	1.25521	−0.67501	−1.13782	2.17978
one time-lag	0.71346	0.74425	0.06743	0.87868	0.43940	0.65709	0.63399	0.75076
	35.80635	38.80690	2.29036	62.86475	17.18989	30.65427	28.82323	39.94714
Phase I dummy	0.00040	0.00019	−0.00117	−0.00001	0.00000	−0.00012	0.00110	0.00005
	4.27283	3.52780	−3.28305	−0.79928	2.10697	−5.36603	5.38048	1.82420
R^2	55.12%	58.42%	1.35%	77.65%	19.92%	49.44%	46.33%	57.11%
				The first year remainder (Phase II)				
constant	0.00005	0.00002	−0.00003	0.00001	0.00000	−0.00002	0.00013	0.00002
	1.59717	1.13802	−0.26427	1.96784	1.95750	−2.32484	1.82672	1.99288
one time-lag	0.73677	0.75334	0.07718	0.87044	0.44456	0.69527	0.66198	0.74975
	38.28817	39.87571	2.62280	60.33666	17.44113	33.99464	31.04492	39.81632
Phase II dummy	0.00009	0.00012	0.00014	−0.00002	0.00000	0.00000	−0.00049	0.00005
	1.07382	2.43926	0.43465	−2.37012	−0.08475	0.18046	−2.74779	1.99671
R^2	54.47%	58.20%	0.44%	77.75%	19.63%	48.26%	45.41%	57.13%
				Quantiles				
constant	0.00008	0.00004	−0.00003	0.00000	\	−0.00002	0.00005	0.00003
	2.45149	2.07365	−0.28853	0.93653	\	−2.35783	0.74350	2.93705
one time-lag	0.73916	0.76179	0.07684	0.87952	\	0.69515	0.67189	0.75525
	38.48136	40.88034	2.60864	63.06137	\	33.95646	31.82513	40.47056
Q10 dummy	−0.00005	0.00005	0.00025	0.00000	\	−0.00001	−0.00001	−0.00002
	−0.41435	0.58213	0.50645	−0.09670	\	−0.23069	−0.05142	−0.56672
Q5 dummy	−0.00016	−0.00009	−0.00010	0.00001	\	0.00002	0.00005	0.00002
	−0.82672	−0.83112	−0.14513	0.26981	\	0.42766	0.10838	0.25272
Q1 dummy	0.00014	0.00000	0.00017	0.00000	\	0.00000	−0.00010	−0.00002
	0.38432	0.02503	0.11979	0.09841	\	0.03102	−0.13622	−0.17335
R^2	54.47%	57.95%	0.28%	77.61%	\	48.19%	44.98%	56.94%

3. Empirical analysis

In this section, we employ the previously outlined methods to test our hypotheses and delineate the empirical results. We begin with a description of the data. Our findings demonstrate that investment-grade bonds exhibit superior risk-adjusted performance. Particularly after Phase I, these bonds underscored their role as a safe haven, as evidenced by their diminishing correlations with other asset classes. Moreover, they displayed swift positive assimilation in the face of economic uncertainty following the introduction of relief policies and after the federal funds rate increase, all within the broader comparative framework for asset class performance.

3.1. Data

3.1.1. Datasets of asset classes

Major global stock market indices include the S&P 500 (Standard & Poor's 500), FTSE (Financial Times Stock Exchange), SH000001 (Shanghai Composite Index), and NIKKEI 225 (Japan). We sourced these from the professional Wind database. The S&P 500 tracks large-cap US stocks; FTSE covers British stocks; NIKKEI 225 gauges the Japanese stock market; and SH000001 is China's premier composite index. Our study period encompasses the COVID-19 market fluctuations from December 2019 to September 2022, contrasting it with the pre-COVID-19 subperiod from January 2018 to December 2019. We also include the subprime crisis period from February 2007 to June 2009 as a reference.

For fixed income assets, our data originates from the Federal Reserve Bank of St. Louis. We focus on Moody's seasoned DAAA and DBAA corporate bond yields, which represent credible bonds. The Baa corporate bond occupies the lower echelon of investment-grade bonds, characterized by moderate risk.[3] While we have also analyzed DBT3, a near-cash 3-month Treasury, and DGS10, a

[3] https://www.investopedia.com/terms/b/b1-b.asp

Table 7
US and Europe COVID-19 relief policies.

Time	Institution	Action
		US
2020	Federal Funding	$2.59 trillion in fiscal year 2020[a]
2020.3.27	Congress	Coronavirus Aid, Relief, and Economic Security Act[b]
2020.3.19	Federal Reserve System, the Federal Deposit Insurance Corporation and the Office of the Comptroller of the Currency	Community Reinvestment Act (CRA)[c]
		Europe
2020.3	European Central Bank	asset purchase program (APP) pandemic emergency purchase program (PEPP) landing programs Targeted longer-term refinancing operations (TLTROs)[d] pandemic emergency longer-term refinancing operations (PELTROs)[e]
		Pan-European support measures
2020.4	European Investment Bank	a loan guarantee scheme
2020.5	European Stability Mechanism	a new credit line
2020.7	European Council	next generation EU fund multiannual financial framework (MFF)

[a] https://www.stlouisfed.org/open-vault/2021/april/federal-covid-funding.

[b] https://www.congress.gov/116/plaws/publ136/PLAW-116publ136.pdf.

[c] https://www.stlouisfed.org/publications/bridges/volume-1-2020/covid19-community-reinvestment-act-assessment-area-responsiveness.

[d] https://www.ecb.europa.eu/mopo/implement/omo/tltro/html/index.en.html.

[e] https://www.ecb.europa.eu/home/search/html/pandemic_emergency_longer-term_refinancing_operations_peltros.en.html.

Table 8
Federal funds rate increase.

Time	Action	Target range
2022.3.15–16	raise 25BP	0.25%–0.5%
2022.5.3–4	raise 50BP	0.75%–1.0%
2022.6.14–15	raise 75BP(first time in 27 years)	1.5%–1.75%
2022.7.26–2022.7.27	raise 75BP	2.25%–2.5%
2022.9.20–21	raise 75BP	3%–3.25%
2022.11.1–2	raise 75BP	3.75%–4%
2023.1.31–2.1	raise 25BP	4.5%–4.75%
2023.3.21–22	raise 25BP	4.75%–5%
2023.5.4	raise 25BP	5%–5.25%
2023.7.26	raise 25BP	5.25%–5.5%
2023.9.19–20	preserve	5.25%–5.5%

Note: It is said to be a historically large scale of rate increases after historical fiscal and monetary ease. We can see from this table that the Fed started a historically large-scale interest rate rise from the later stage of COVID-19.

10-year Treasury (Boubaker & Nguyen, 2022), the findings are not detailed here due to their relatively conservative nature and lesser yields compared to Aaa and Baa bonds.

Additionally, our study incorporates gold (GC.CMX), energy (CL.NYM), and foreign exchange (USDX index) data, also procured from the Wind database, which is related to inflation. These products are representative financial instruments in corresponding asset classes.

3.1.2. Plots of asset returns for performance assessment

We plot the asset prices in Figs. 1 and 2. COVID-19, especially during Phase I, exhibited pronounced volatility. After Phase I, most stocks began their upward trajectory, reverting to their pre-COVID-19 values. Commodities like GC.CMX and CL.NYM experienced downturns at the onset of COVID-19. While gold initially served as a Phase I safe haven asset, its subsequent performance faltered. Gold and oil, overall, displayed greater volatility compared to bonds.

3.1.3. COVID-19 subperiod division

We divide the COVID-19 pandemic timeline into three subperiods and use the pre-COVID-19 subperiod (from January 2, 2018 to December 30, 2019) as the benchmark for normal-time performance. The COVID-19 eruption (Phase I) spanned from December 30, 2019 to March 16, 2020. The lockdown during the remaining part of the first year, termed Phase II, was from March 16, 2020 to December 30, 2020. The period after the first year leading up to stabilization is the third phase, from December 30, 2020 to

Table 9
Regression analysis.

Outbreak	Constant	EPU		Adj R^2
SPX	−1.8087	578.8184		6.37%
	(−2.7760)	(3.4078)		
DAAA	0.0283	−0.0105		−0.58%
	(216.1609)	(−0.3065)		
DBAA	0.0370	−0.0302		−0.15%
	(277.9244)	(−0.8710)		
After March 2022	**Constant**	**Federal funds rate**		**Adj R^2**
SPX	−0.0006	0.0000		−0.85%
	(−0.2161)	(0.0259)		
DAAA	3.8881	0.1688		41.56%
	(−101.1538)	(14.2962)		
DBAA	5.1456	0.1307		23.74%
	(101.6987)	(8.8778)		
Full crisis	**Constant**	**Federal funds rate**	**Infectdisemv**	**Adj R^2**
SPX	0.0013	−0.0006	0.0000	−0.07%
	(1.3354)	(−1.0800)	(−0.8145)	
DAAA	2.8096	0.4234	−0.0039	70.27%
	(121.7013)	(54.1675)	(−3.1210)	
DBAA	3.5562	0.4909	0.0061	72.22%
	(145.8465)	(59.4555)	(4.5777)	

Note: Our first panel shows the effects of relief policy indicator EPU on the BAAA, DBAA and SPX returns at the outbreak. The return of creditable bonds and stock index regressing with EPU shows that only stock was relieved seriously. It is reflected in the asset returns that stock indices bounced up instantly, but bonds bounced up later. Our second panel shows the regression results of the impact of federal funds rate increase on the asset return change. After the federal funds rate rose, DAAA and DBAA were greatly positively impacted. SPX's return is not influenced by the federal funds rate rise. We also use infectious disease and equity market volatility (infectdisemv) as a controlling variable to test the funds rate raise effects. The results are similar to that of using the federal funds rate only. The two regressions demonstrate that federal funds rates greatly boost the creditable bond yields.

September 2, 2022. Together, these subperiods – the eruption (Phase I), the rest of the first year/lockdown (Phase II), and the post-first year leading to stabilization – encompass the entire course of the COVID-19 pandemic. As a reference in our crisis study, we use the Global Financial Crisis (GFC or subprime crisis[4]) period, from February 13, 2007 to June 1, 2009.

It is worth noting that the global financial crisis stemmed from the subprime crisis, whereas COVID-19 is primarily a health crisis that had a profound impact on the real economy. The financial market, which reflects the real economy, plummeted soon after the onset of COVID-19. This swift decline indicates that the financing of listed companies, which relies on investors' future expectations, can be easily and rapidly influenced by a black swan event.

3.1.4. Macro variable data

The EPU index data is sourced from Federal Reserve Economic Data (FRED) St. Louis. To illustrate the policy impact of the crisis, we use the daily US EPU, as the GDP of the US was $23 trillion among the global GDP of $94.94 trillion in 2021. EPU data is available in daily frequency exclusively for the US. Fred does offer EPU data for global and other countries, but this data is provided on a monthly frequency.

The data on the federal funds rate is also retrieved from the FRED St. Louis. Furthermore, we have gathered information about federal funds rate increase announcements from the Federal Reserve (Fed) website, which is presented in Table 8. The control variable, an infectious disease impact tracker, is also formulated by the Fed.

We conduct regression analysis to understand the influence of EPU and FFR on asset returns during the initial outbreak and the later stages of federal funds rate hikes during the COVID-19 pandemic. Moreover, we employed NARDL analysis to study time lag effects on the SPX, DAAA, DBAA, USDX, GCCMX, and NYMEX using the daily EPU index and federal funds rates. This was to discern the asymmetrical effects of time lags throughout the outbreak, first-year remainder, and the post-first-year subperiods.

3.2. Empirical results of the hypotheses verification

In this section, we verify six hypotheses in the empirical analysis. Our findings reveal that investment-grade bonds are the top daily performers, through daily rebalancing.

4 https://www.rba.gov.au/education/resources/explainers/the-global-financial-crisis.html

Table 10
NARDL model long-term and short-term coefficients and statistical test results of EPU on SPX.

Economic policy uncertainty (EPU) on SPX NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards			
	Estimate	t-value			Estimate	t-value			Estimate	t-value	
Short run effects on price difference time lags											
Const	−2.70E+00	(−1.503)		Const	1.6672	(2.515)	*	Const	0.3561	(1.139)	
γ_{spx1}	−1.42E+00	(−17.085)	***	γ_{spx1}	−1.2156	(−17.842)	***	γ_{spx1}	−1.0027	(−20.41)	***
γ_{spx2}	2.80E−01	(3.27)	**	γ_{spx2}	0.1012	(1.503)		δ^{+}_{epu}	43.5470	(1.213)	
γ_{spx3}	4.66E−01	(5.485)	***	γ_{spx3}	−0.1572	(−2.36)	*	δ^{+}_{epu1}	−24.9236	(−0.545)	
δ^{+}_{epu}	7.67E+02	(2.962)	**	γ_{spx4}	−0.3101	(−4.79)	***	δ^{-}_{epu}	19.2947	0.456	
δ^{+}_{epu1}	−1.16E+03	(−2.565)	*	δ^{+}_{epu}	−20.1172	(−0.132)					
δ^{+}_{epu2}	1.16E+03	(2.533)	*	δ^{-}_{epu}	49.8448	(0.421)					
δ^{+}_{epu3}	3.44E+02	(0.763)		δ^{-}_{epu1}	−239.2957	(−1.338)					
δ^{+}_{epu4}	−9.09E+02	(−2.732)	**	δ^{-}_{epu2}	55.2267	(0.376)					
δ^{-}_{epu}	−3.06E+02	(−1.106)		δ^{-}_{epu3}	44.8059	(0.328)					
δ^{-}_{epu1}	1.49E+03	(4.18)	***	δ^{-}_{epu4}	77.0520	(0.658)					
δ^{-}_{epu2}	−5.41E+02	(−1.366)									
δ^{-}_{epu3}	−8.98E+02	(−2.356)	*								
δ^{-}_{epu4}	4.67E+02	(2.258)	*								
Long run effects on price time lags											
α_{spx2}	0.1972	(3.0506)	**	α_{spx2}	0.0832	(1.4792)		β^{+}_{epu}	43.429	(1.2044)	
α_{spx3}	0.3281	(5.4539)	***	α_{spx3}	−0.1293	(−2.3165)	*	β^{+}_{epu1}	−24.856	(−0.5444)	
β^{+}_{epu}	539.8748	(2.8117)	**	α_{spx4}	−0.2551	(−4.7112)	***	β^{-}_{epu}	19.242	(0.4558)	
β^{+}_{epu1}	−813.4655	(−2.4797)	*	β^{+}_{epu}	−16.5491	(−0.132)					
β^{+}_{epu2}	815.1944	(2.3999)	*	β^{-}_{epu}	41.0040	(0.42)					
β^{+}_{epu3}	242.3828	(0.7729)		β^{-}_{epu1}	−196.8526	(−1.3282)					
β^{+}_{epu4}	−639.9153	(−2.7763)	**	β^{-}_{epu2}	45.4313	(0.3752)					
β^{-}_{epu}	−215.6405	(−1.1216)		β^{-}_{epu3}	36.8588	(0.328)					
β^{-}_{epu1}	1048.0536	(3.9735)	***	β^{-}_{epu4}	63.3855	(0.6594)					
β^{-}_{epu2}	−381.0723	(−1.3251)									
β^{-}_{epu3}	−632.1515	(−2.4354)	*								
β^{-}_{epu4}	328.5877	(2.2712)	*								
Adj R^2:	79.00%			Adj R^2:	65.77%			Adj R^2:	50.20%		
	Stat	p-value			Stat	p-value			Stat	p-value	
JB	0.9280	0.0000		JB	0.9484	0.0000		JB	0.9782	0.0000	
LM	3.9174	0.3518		LM	17.1335	0.1790		LM	0.2244	0.7184	
ARCH	25.2467	0.0000		ARCH	10.5895	0.0316		ARCH	5.7286	0.0167	
W_{sr}:	6.3417	0.0420		W_{sr}:	0.1691	0.9189		W_{sr}:	0.2813	0.8688	
W_{lr}:	3.1457	0.2074		W_{lr}:	0.1144	0.9444		W_{lr}:	0.2797	0.8695	

Note: For SPX, the negative asymmetry deepened in Phase II, while the asymmetric impact turned positive after the lockdown. *** indicates 1% significance. ** indicates 5% significance. * indicates 10% significance.

3.2.1. *Investment-grade bond as a superior high risk-adjusted return asset*

We have **hypothesis one**: High-credit bonds outperformed stocks and other major assets in terms of daily returns. This hypothesis confirms that investment-grade bonds performed best during the COVID-19 pandemic as measured by daily return and risk. We further examine asset performance throughout the pandemic and describe how each asset reacted differently over various phases.

To validate our findings, we employed several measures: the mean, maximum, minimum, midpoint, standard deviation, skewness, Value-at-Risk (VaR), and expected shortfall (ES). The computed statistics of return and risk measures throughout the COVID-19 subperiods can be found in Table 1. Significant figures in Table 1 are highlighted in bold type. The DBAA consistently reported the highest average daily return during every subperiod of COVID-19.

Stock markets, being the most liquid and accessible trading venues, mirrored the crisis's effects through stock price fluctuations. For instance, the S&P 500 index (GSPC), a widely recognized stock market performance indicator, experienced a sharp decline when the pandemic escalated in March 2020. The lowest stock price of the Nikkei 225 index in Japan occurred slightly after the S&P 500 reached the bottom. For bonds with a grade higher than DBAA, yields peaked in March 2020, evincing the undeniable impact of

Table 11
NARDL model long-term and short-term coefficients and statistical test results of EPU on DAAA.

Economic policy uncertainty **(EPU)** on DAAA NARDL short-run, long-run coefficients and statistics										
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards		
	Estimate	t-value			Estimate	t-value			Estimate	t-value
Short run effects on price difference time lags										
Const	0.0030	(2.863)	**	Const	4.62E−03	(9.467)	***	Const	0.0002	(1.289)
γ_{daaa1}	0.1970	(2.277)	*	γ_{daaa1}	−3.57E−01	(−5.831)	***	γ_{daaa1}	−0.0088	(−1.242)
γ_{daaa2}	−0.3045	(−3.515)	***	γ_{daaa2}	1.63E−01	(2.893)	**	δ^{+}_{epu}	0.0060	(1.003)
δ^{+}_{epu}	0.0729	(2.948)	**	δ^{+}_{epu}	−7.68E−05	(−0.004)		δ^{-}_{epu}	0.0059	(0.976)
δ^{+}_{epu1}	−0.1486	(−3.477)	***	δ^{+}_{epu1}	6.04E−03	(0.256)				
δ^{+}_{epu2}	0.0820	(2.162)	*	δ^{+}_{epu2}	−8.88E−03	(−0.432)				
δ^{-}_{epu}	−0.0577	(−2.203)	*	δ^{+}_{epu3}	−2.82E−03	(−0.146)				
δ^{-}_{epu1}	0.1158	(3.293)	**	δ^{-}_{epu4}	1.09E−02	(0.652)				
δ^{-}_{epu2}	−0.0860	(−3.341)	**	δ^{-}_{epu}	5.58E−03	(0.278)				
δ^{-}_{epu3}	0.0250	(1.149)								
δ^{-}_{epu4}	0.0093	(0.585)								
Long run effects on price time lags										
α_{daaa2}	1.5461	(4.7432)	***	α_{daaa2}	0.4567	(5.2701)	***	β^{+}_{epu}	0.6807	(0.7896)
β^{+}_{epu}	−0.3700	(−2.2157)	*	β^{+}_{epu}	−0.0002	(−0.0044)		β^{-}_{epu}	0.6625	(0.7704)
β^{+}_{epu1}	0.7547	(2.1686)	*	β^{+}_{epu1}	0.0169	(0.256)				
β^{+}_{epu2}	−0.4165	(−1.8607)	.	β^{+}_{epu2}	−0.0249	(−0.4304)				
β^{-}_{epu}	0.2930	(1.592)		β^{+}_{epu3}	−0.0079	(−0.1457)				
β^{-}_{epu1}	−0.5881	(−2.223)	*	β^{-}_{epu4}	0.0304	(0.6507)				
β^{-}_{epu2}	0.4365	(2.1982)	*	β^{-}_{epu}	0.0156	(0.2786)				
β^{-}_{epu3}	−0.1269	(−1.1359)								
β^{-}_{epu4}	−0.0472	(−0.5737)								
Adj R^2:	11.66%			Adj R^2:	37.43%			Adj R^2:	−00.04%	
	Stat	p-value			Stat	p-value			Stat	p-value
JB	0.9709	0.0026		JB	0.9771	0.0029		JB	0.9911	0.0128
LM	1.5366	0.4955		LM	14.7351	0.1812		LM	0.6798	0.5611
ARCH	33.8224	0.0000		ARCH	0.7352	0.6924		ARCH	2.3512	0.1252
W_{sr}:	10.3304	0.0057		W_{sr}:	0.0668	0.9672		W_{sr}:	1.7010	0.4272
W_{lr}:	266.3165	0.0000		W_{lr}:	0.5236	0.7696		W_{lr}:	21 719.6400	0.0000

Note: For DAAA, negative asymmetry in the outbreak (Phase I) turned positive after the outbreak (Phase II), and kept neutral after the lockdown.

the COVID-19 crisis on the bond market, even though the yield curves stabilized shortly after.

To summarize observations from Table 1, we utilized upward and downward arrows to depict asset return patterns in Table 4. The return and risk of assets varied across subperiods, exhibiting distinct characteristics. Global stock indices touched their lowest points during the outbreak (Phase I) and largely recovered due to relief policies in the subsequent subperiod (Phase II). However, this rapid recovery, attributed mostly to the relief packages, was not sustained, indicating that the real economy had not recovered due to the prolonged pandemic.

For comparative analysis, we also reviewed the global financial crisis in 2008, a significant financial upheaval in recent times. According to the World Health Organization (WHO), COVID-19 spanned from the start of 2020 to May 2023, a duration time surpassing that of the subprime crisis. While the subprime crisis was attributed to global leverage on asset-backed securities (ABS) and collateral-backed obligations (CBO) with real foreclosures concentrated in the United States, COVID-19 was a worldwide health pandemic. During the subprime crisis, DBAA boasted the highest average return among assets, with DAAA trailing close behind. In contrast, Japan's N225 recorded the lowest average return. CL.NYM attained both the maximal and minimal returns and exhibited the highest volatility. In terms of skewness, DBAA leaned most towards the right, while USDX was the most left skewed, indicating softened US currency during the crisis. CL.NYM ranked the highest in terms of VaR and ES, indicating creditable fixed income's anti-crisis revenue, with SCI (000001) coming next. This suggests that, excluding the crisis, the US and Chinese markets effectively flipped their performance standings from approximately 2010 to 2020.

In conjunction with the return pattern analysis, we extracted several characteristics of these asset classes. Firstly, a shared trough appeared for these assets around April 2020 during Phase I. Secondly, there was a noticeable increase in volatility throughout the lockdown periods (Phase I and Phase II). Thirdly, both intra- and inter-asset class correlations saw an uptick after the outbreak

Table 12
NARDL model long-term and short-term coefficients and statistical test results of EPU on DBAA.

Economic policy uncertainty **(EPU)** on DBAA NARDL short-run, long-run coefficients and statistics										
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards		
	Estimate	t-value			Estimate	t-value			Estimate	t-value
Short run effects on price difference time lags										
Const	0.0073	(4.176)	***	Const	0.0018	(3.63)	***	Const	0.0001	(0.748)
γ_{dbaa1}	0.1500	(1.854)	.	γ_{dbaa1}	0.0638	(0.881)		γ_{dbaa1}	−0.0043	(−0.828)
γ_{dbaa2}	−0.3369	(−2.731)	**	γ_{dbaa2}	−0.0538	(−0.519)		δ^{+}_{epu}	0.0047	(0.869)
γ_{dbaa3}	0.1751	(1.432)		γ_{dbaa3}	−0.0187	(−0.188)		δ^{-}_{epu}	0.0046	(0.839)
γ_{dbaa4}	−0.1806	(−2.159)	*	γ_{dbaa4}	−0.0409	(−0.728)				
δ^{+}_{epu}	0.0454	(1.72)	.	δ^{+}_{epu}	−0.0029	(−0.219)				
δ^{+}_{epu1}	−0.1492	(−3.304)	**	δ^{+}_{epu1}	−0.0060	(−0.362)				
δ^{+}_{epu2}	0.0734	(2.104)	*	δ^{-}_{epu}	−0.0080	(−0.495)				
δ^{-}_{epu}	−0.0695	(−2.285)	*							
δ^{-}_{epu1}	0.1239	(3.26)	**							
δ^{-}_{epu2}	−0.0847	(−3.735)	***							
Long run effects on price time lags										
α_{dbaa2}	2.2453	(2.7186)	**	α_{dbaa2}	0.8433	(0.8153)		β^{+}_{epu}	1.0961	(0.6059)
α_{dbaa3}	−1.1667	(−1.2181)		α_{dbaa3}	0.2941	(0.1812)		β^{-}_{epu}	1.0582	(0.5909)
α_{dbaa4}	1.2039	(1.3559)		α_{dbaa4}	0.6414	(0.5287)				
β^{+}_{epu}	−0.3027	(−1.4077)		β^{+}_{epu}	0.0450	(0.2139)				
β^{+}_{epu1}	0.9946	(1.6522)	.	β^{+}_{epu1}	0.0942	(0.3366)				
β^{+}_{epu2}	−0.4890	(−1.4648)		β^{-}_{epu}	0.1248	(0.4399)				
β^{-}_{epu}	0.4635	(1.3797)								
β^{-}_{epu1}	−0.8256	(−1.7447)	.							
β^{-}_{epu2}	0.5648	(1.7488)	.							
Adj R^2:	20.80%			Adj R^2:	11.54%			Adj R^2:	00.04%	
	Stat	p-value			Stat	p-value			Stat	p-value
JB	0.9405	0.0000		JB	0.9900	0.1901		JB	0.9926	0.0372
LM	14.4457	0.1945		LM	3.8080	0.3647		LM	0.1375	0.7739
ARCH	17.3108	0.0017		ARCH	8.3551	0.0794		ARCH	1.7481	0.1861
W_{sr}:	6.5693	0.0375		W_{sr}:	0.0953	0.9535		W_{sr}:	2.1478	0.3417
W_{lr}:	291.8295	0.0000		W_{lr}:	23.4514	0.0000		W_{lr}:	114 545.9	0.0000

Note: The symmetric impact of shock lags in the outbreak (Phase I) turned positive in the first year remainder (Phase II) and became symmetric lags after lockdown.

(Phase I). Fourthly, creditworthy bonds consistently outperformed other asset classes like stocks and alternatives in terms of daily returns. Fifthly, assets that encountered disruptions later tended to perform better, suggesting inherent resilience to crises.

To delve deeper into different bond grades within the bond asset class, we referenced the bond return and risk analysis by Boubaker and Nguyen (2022). Among various grades, including DBT3 (3-month Treasury), DAAA, DBAA, and DGS10 (10-year Treasury), the creditworthy corporate bond DBAA boasted the highest performance ratio, as reflected by its daily return. The superior performance of DBAA can be attributed to the fact that it is the latest disrupted bond. Furthermore, DBAA also recorded the highest Sharpe Ratio (SR).

Continuation of **hypothesis one**: The investment-grade bond is posited as the best-performing financial asset in terms of the Sharpe ratio. In Table 2, we present the SRs (Sharpe Ratios) of these asset classes during the subperiods of COVID-19, pre-COVID-19, and the subprime crisis.

In Table 2, significant results are highlighted. DAAA and DBAA exhibit high SR ratios. We analyze the information from Table 2 regarding assets and subperiods. Generally, although the Sharpe ratios of bonds are higher than those of stocks, their ratios continue to decline from the outbreak to the lockdown phase. This suggests that when considering return and risk together, bonds hold a significant advantage.

We conduct SR comparison across asset classes in the subperiods of COVID-19, normal time in the pre-COVID-19 period, and the comparative subprime crisis. DBAA has the highest SR of 3.88386 in the pre-COVID-19 period. It rose to 6.05761 during COVID-19. The USDX.FX has the lowest SR of −0.02950 in the pre-COVID-19 subperiod. SH000001 has the lowest SR of 0.00006 in the COVID-19 crisis.

Table 13
NARDL model long-term and short-term coefficients and statistical test results of EPU on USDX.

Economic policy uncertainty **(EPU)** on USDX NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards			
	Estimate	t-value			Estimate	t-value			Estimate	t-value	
				Short run effects on price difference time lags							
Const	0.2366	(0.944)		Const	−0.2293	(−1.672)	.	Const	0.0191	(0.161)	
γ_{usdx1}	−0.9956	(−11.834)	***	γ_{usdx1}	−0.8857	(−12.489)	***	γ_{usdx1}	−1.0222	(−21.13)	***
γ_{usdx2}	0.1926	(2.458)	*	γ_{usdx2}	0.0584	(0.851)		δ^+_{epu}	9.9596	(0.617)	
δ^+_{epu}	36.3070	(1.146)		γ_{usdx3}	−0.0407	(−0.608)		δ^+_{epu1}	−38.7476	(−2.202)	*
δ^+_{epu1}	−203.6762	(−3.46)	***	γ_{usdx4}	−0.1350	(−2.1)	*	δ^+_{epu2}	21.7291	(1.355)	
δ^+_{epu2}	180.5619	(3.074)	**	δ^+_{epu}	−35.9362	(−1.093)		δ^-_{epu}	−11.2564	(−0.747)	
δ^+_{epu3}	−48.1361	(−0.8)		δ^-_{epu}	−33.7580	(−1.292)		δ^-_{epu1}	4.0240	(0.194)	
δ^+_{epu4}	−99.1506	(−1.962)	.	δ^-_{epu1}	−2.2514	(−0.063)					
δ^-_{epu}	−27.0249	(−0.634)									
δ^-_{epu1}	129.9749	(2.701)	**								
δ^-_{epu2}	−128.6810	(−2.69)	**								
δ^-_{epu3}	−152.4706	(−3.101)	**								
δ^-_{epu4}	44.2130	(1.575)									
				Long run effects on price time lags							
α_{usdx2}	0.1934	(2.4073)	*	α_{usdx2}	0.0660	(0.8549)		β^+_{epu}	9.7431	(0.6185)	
β^+_{epu}	36.4658	(1.1457)		α_{usdx3}	−0.0460	(−0.6061)		β^+_{epu1}	−37.9051	(−2.1832)	*
β^+_{epu1}	−204.5673	(−3.4988)	***	α_{usdx4}	−0.1525	(−2.0981)	*	β^+_{epu2}	21.2567	(1.3469)	
β^+_{epu2}	181.3519	(2.8134)	**	β^+_{epu}	−40.5758	(−1.0816)		β^-_{epu}	−11.0117	(−0.7452)	
β^+_{epu3}	−48.3467	(−0.784)		β^-_{epu}	−38.1165	(−1.2727)		β^-_{epu1}	3.9365	(0.1941)	
β^+_{epu4}	−99.5844	(−2.0362)	*	β^-_{epu1}	−2.5421	(−0.0629)					
β^-_{epu}	−27.1431	(−0.6434)									
β^-_{epu1}	130.5435	(2.6668)	**								
β^-_{epu2}	−129.2439	(−2.5504)	*								
β^-_{epu3}	−153.1377	(−3.2088)	**								
β^-_{epu4}	44.4064	(1.5167)									
Adj R^2:	60.63%			Adj R^2:	44.31%			Adj R^2:	51.45%		
	Stat	p-value			Stat	p-value			Stat	p-value	
JB	0.9539	0.0000		JB	0.9957	0.8371		JB	0.9920	0.0204	
LM	6.7060	0.2634		LM	13.2404	0.2029		LM	0.4850	0.6127	
ARCH	13.7050	0.0011		ARCH	7.0782	0.1318		ARCH	1.8660	0.1719	
W_{sr}:	1.1294	0.5685		W_{sr}:	0.0037	0.9981		W_{sr}:	0.9552	0.6203	
W_{lr}:	1.1393	0.5657		W_{lr}:	0.0048	0.9976		W_{lr}:	0.9141	0.6332	

Note: The EPU impact turned more negative in the first year remainder (Phase II) and had more positive lags after the lockdown. The R^2 in three subperiods are explanatory. The short-run and long-run results show no asymmetric impact.

In Table 3, the stationarity tests statistics for conditional mean and variance of these assets show that bonds, DAAA, and DBAA, have stationary mean, but are not significant, supporting its conservative and less-volatile style characteristics. All the other assets' conditional mean test results reject the null hypothesis. SH000001 has stationary variance in four subperiods: subprime, pre-COVID-19, and Phase I and II. GC.CMX has three stationary subperiods, including pre-COVID-19, Phase I, and Phase II. SPX becomes stationary in Phase II. FTSE and N225 become stationary in Phase I. CL.NYM and USDX.FX become stationary in the phase after lockdown. All the other cases reject the null hypothesis and have conditional heteroscedasticity.

3.2.2. Bond as the safe haven asset after gold

It is reported that gold served as the safe haven asset during the outbreak. Thus we have **hypothesis two**: Creditable bonds could resume the safe haven role after gold. Table 5 presents the Pearson correlations among different asset classes. Overall, there was a substantial increase in correlations among assets from the pre-COVID-19 period to Phase I. However, a slight reduction was observed from the outbreak to the remainder of the first year, hinting at a softening shock volatility after introducing the CARES Act and other liquidity-providing policies.

Table 14
NARDL model long-term and short-term coefficients and statistical test results of EPU on GCCMX.

Economic policy uncertainty **(EPU)** on GC CMX NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards			
	Estimate	*t*-value			Estimate	*t*-value			Estimate	*t*-value	
Short run effects on price difference time lags											
Const	−0.1311	(−0.183)		Const	−0.0781	(−0.127)		Const	−0.1975	(−0.711)	
γ_{gccmx1}	−0.6092	(−7.208)	***	γ_{gccmx1}	−1.0165	(−14.28)		γ_{gccmx1}	−0.9376	(−19.62)	***
γ_{gccmx2}	−0.0670	(−0.731)		δ^+_{epu}	159.4842	(1.557)		γ_{gccmx2}	−0.0981	(−2.055)	*
γ_{gccmx3}	0.0625	(0.632)		δ^+_{epu1}	−207.4354	(−1.462)		δ^+_{epu}	32.3475	(0.973)	
γ_{gccmx4}	−0.1980	(−2.136)	*	δ^+_{epu2}	109.4506	(0.904)		δ^-_{epu}	−1.6599	(−0.062)	
δ^+_{epu}	−65.4145	(−0.613)		δ^+_{epu3}	−152.5075	(−1.342)		δ^-_{epu1}	49.9652	(1.372)	
δ^+_{epu1}	−296.7102	(−1.593)		δ^-_{epu4}	−14.6670	(−0.15)		δ^-_{epu2}	−16.0105	(−0.625)	
δ^+_{epu2}	414.1760	(2.182)	*	δ^-_{epu}	−101.0087	(−0.842)					
δ^+_{epu3}	−196.2747	(−1.216)									
δ^-_{epu}	−455.4364	(−3.91)	***								
δ^-_{epu1}	447.3914	(2.852)	**								
δ^-_{epu2}	−166.1727	(−0.976)									
δ^-_{epu3}	108.3623	(0.88)									
δ^-_{epu4}	−77.2272	(−0.863)									
Long run effects on price time lags											
α_{gccmx2}	−0.1099	(−0.7043)		β^+_{epu}	156.893	(1.5472)		α_{gccmx2}	−0.1047	(−2.0321)	*
α_{gccmx3}	0.1025	(0.6296)		β^+_{epu1}	−204.066	(−1.446)		β^+_{epu}	34.5023	(0.9707)	
α_{gccmx4}	−0.3251	(−2.0695)	*	β^+_{epu2}	107.673	(0.8968)		β^-_{epu}	−1.7704	(−0.0618)	
β^+_{epu}	−107.3736	(−0.608)		β^+_{epu3}	−150.03	(−1.3263)		β^-_{epu1}	53.2936	(1.3659)	
β^+_{epu1}	−487.0303	(−1.5529)		β^-_{epu4}	−14.429	(−0.1497)		β^-_{epu2}	−17.0770	(−0.624)	
β^+_{epu2}	679.8425	(2.037)	*	β^-_{epu}	−99.368	(−0.8424)					
β^+_{epu3}	−322.1720	(−1.1749)									
β^-_{epu}	−747.5688	(−3.2608)	**								
β^-_{epu1}	734.3634	(2.4389)	*								
β^-_{epu2}	−272.7615	(−0.9419)									
β^-_{epu3}	177.8696	(0.8781)									
β^-_{epu4}	−126.7633	(−0.8617)									
Adj R^2:	48.34%			Adj R^2:	52.65%			Adj R^2:	47.71%		
	Stat	*p*-value			Stat	*p*-value			Stat	*p*-value	
JB	0.9478	0.0000		JB	0.9396	0.0000		JB	9.77E−01	2.66E−06	
LM	21.9483	0.1586		LM	22.5799	0.1320		LM	0.3213	0.7802	
ARCH	16.6291	0.0023		ARCH	0.4372	0.5085		ARCH	6.3542	0.0417	
W_{sr}:	4.9356	0.0848		W_{sr}:	4.0586	0.1314		W_{sr}:	0.9104	0.6343	
W_{lr}:	13.2980	0.0013		W_{lr}:	3.9278	0.1403		W_{lr}:	1.0357	0.5958	

Note: The EPU impact is asymmetrically more negative in the outbreak (Phase I), and much more positive in the first year remainder (Phase II). It turned negative after the lockdown, which reaffirms that gold lost its safe-haven function since the first year remainder (Phase II).

When juxtaposing correlations from the pre-COVID-19 period with those from the entire course of COVID-19, stocks and bonds showed heightened Pearson correlations. However, alternative assets displayed reversed correlation signs. In Table 6, we document the regression of DCC with asset extremes, showing the strong explanatory power of the correlations. It supports hypothesis two that creditable bonds could be a safe haven asset.

3.2.3. Bond or other assets under policy shocks

At the onset of the COVID-19 pandemic, institutions in the US, Europe, and other sovereign nations implemented many relief measures immediately. These actions are detailed in Table 7. In the United States, the CARES Act totaled about $2 trillion. Of that amount, $349 billion was to be spent on small business management and $100 billion on health care provisions. Corporate tax breaks were to be waived; personal and family tax refunds were to be given; unemployment benefits were to be provided to affected employees; federal economic stimulus and relief programs were to be implemented for industries that had been hit hard. All these actions increased job retainment and reduced the labor income risk. Stable workforces shore up economic operations. Economic

Table 15
NARDL model long-term and short-term coefficients and statistical test results of EPU on CL.NYMEX.

Economic policy uncertainty **(EPU)** on CL NYMEX NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				Afterwards			
	Estimate	t-value			Estimate	t-value			Estimate	t-value	
Short run effects on price difference time lags											
Const	3.11E−01	(0.101)		Const	2.0049	(0.997)		Const	1.0925	(1.602)	
γ_{nymex1}	−1.20E+00	(−14.901)	***	γ_{nymex1}	−0.8850	(−12.651)	***	γ_{nymex1}	−1.0248	(−21.154)	***
δ^{+}_{epu}	1.18E+03	(2.491)	*	γ_{nymex2}	−0.1703	(−2.463)	*	γ_{nymex2}	−0.0957	(−1.977)	*
δ^{+}_{epu1}	−2.08E+03	(−2.495)	*	γ_{nymex3}	−0.0516	(−0.765)		γ_{nymex3}	−0.0257	(−0.528)	
δ^{+}_{epu2}	2.46E+03	(3.853)	***	γ_{nymex4}	−0.2201	(−3.279)	**	δ^{+}_{epu}	30.0908	(0.413)	
δ^{-}_{epu}	−2.21E+02	(−0.387)		δ^{+}_{epu}	504.1753	(0.927)		δ^{-}_{epu}	31.2494	(0.429)	
δ^{-}_{epu1}	2.51E+03	(3.655)	***	δ^{-}_{epu}	199.1339	(0.506)					
δ^{-}_{epu2}	−7.21E+02	(−1.785)	.	δ^{-}_{epu1}	308.1015	(0.539)					
Long run effects on price time lags											
β^{+}_{epu}	981.29	(2.5023)	*	α_{nymex2}	−0.1924	(−2.3695)	*	α_{nymex2}	−0.0934	(−1.973)	*
β^{+}_{epu1}	−1729.98	(−2.5214)	*	α_{nymex3}	−0.0583	(−0.7685)		α_{nymex3}	−0.0250	(−0.5293)	
β^{+}_{epu2}	2046.59	(3.7623)	***	α_{nymex4}	−0.2487	(−3.2294)	**	β^{+}_{epu}	29.3614	(0.4129)	
β^{-}_{epu}	−184.15	(−0.3897)		β^{+}_{epu}	569.7233	(0.9286)		β^{-}_{epu}	30.4919	(0.4287)	
β^{-}_{epu1}	2090.29	(3.6773)	***	β^{-}_{epu}	225.0233	(0.5048)					
β^{-}_{epu2}	−599.68	(−1.7787)	.	β^{-}_{epu1}	348.1579	(0.5403)					
Adj R^2:	61.46%			Adj R^2:	46.89%			Adj R^2:	51.13%		
	Stat	p-value			Stat	p-value			Stat	p-value	
JB	0.7630	0.0000		JB	0.7650	0.0000		JB	9.48E−01	3.67E−11	
LM	1.1407	0.4791		LM	5.2759	0.3142		LM	3.8619	0.3541	
ARCH	1.8389	0.1751		ARCH	26.5562	0.0000		ARCH	26.8760	0.0000	
W_{sr}:	2.7806	0.2490		W_{sr}:	0.2853	0.8671		W_{sr}:	1.5844	0.4528	
W_{lr}:	1.9256	0.3818		W_{lr}:	0.3643	0.8335		W_{lr}:	1.5085	0.4704	

Note: In the outbreak (Phase I), the positive and negative lags are balanced in both the long term and short term. In the first year remainder (Phase II), the EPU impact turned more negative in both the long term and short term. In the post-lockdown period, the EPU impact turned symmetric again.

stability ensures low bond default rates, laying the solid groundwork for the bond market to prosper.

In the meantime, the European Central Bank launched a pandemic emergency purchase program (PEPP) under the asset purchase program (APP). It totaled Euro 1850 billion from December 10, 2020. The PEPP bought covered bonds, corporate bonds, and public sector securities, totaling 1637.347 billion at the end of July 2024.[5] Until 14 December 2024, the Governing Council announced that it would keep reinvestment during the first half of 2024 and reduce the PEPP by Euro 7.5 billion per month over the year's second half. Finally, the Governing Council would discontinue reinvestment at the end of 2024. Therefore, the PEPP directly bought bonds during the crisis, which naturally pushed the bond market higher.

Running regression analysis of economic policy uncertainty (EPU) and federal funds rate (FFR) on assets' return, we have **hypothesis three**: Economic policy uncertainty (EPU) has a slight regression impact on the SPX return during the outbreak but no impact on the DAAA and DBAA. Initially, EPU was found to influence SPX positively, but no significant impact was observed thereafter. According to adjusted-R^2 and t-statistics, our regression analysis of EPU and asset return revealed that, at the outbreak's commencement, the effect of EPU on SPX was notable. However, the effects on DAAA and DBAA were not significant.

Empirical findings are presented in the first panel of Table 9. Additionally, we conducted a regression analysis between EPU and SPX, DAAA, and DBAA post-outbreak. EPU did not have a significant effect on SPX then.

We propose **hypothesis four**: From March 2022, the federal funds rate (FFR) hikes positively affected DAAA and DBAA yields but did not affect the SPX return. In the later stages of the COVID-19 pandemic, the Federal Reserve embarked on a series of rapid rate increases that had not been witnessed in recent history. The rate schedules from March 2022 are collated in Table 8.

Our regression analysis, incorporating the federal funds rate and asset yield, infers that after the interest rate elevations, the federal funds rate hikes can elucidate the return trend of high-quality bonds such as DAAA and DBAA. The effects are decidedly positive. For SPX, however, the adjusted R^2 indicated no explanatory power, and the t statistic was found to be insignificant. These empirical results are presented in the second panel of Table 9.

[5] https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html

Table 16
Long-term and short-term coefficients and statistical test results of FFR on SPX captured by NARDL model.

Federal funds rates **(FFR)** on SPX NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				After March 2022			
	Estimate	*t*-value			Estimate	*t*-value			Estimate	*t*-value	
Short run effects on price difference time lags											
Const	0.0025028	(0.541)		Const	0.04573	(2.139)	*	Const	−0.003142	(−1.057)	
γ_{spx1}	−1.0741354	(−7.023)	***	γ_{spx1}	−1.22797	(−18.656)	***	γ_{spx1}	−1.037421	(−11.12)	***
γ_{spx2}	−0.0091803	(−0.067)		γ_{spx2}	0.12958	(1.931)	.	δ^{+}_{ffr}	0.002942	(0.96)	
γ_{spx3}	0.9792678	(5.622)	***	γ_{spx3}	−0.17182	(−2.662)	**	δ^{-}_{ffr}	−1.1082	(−0.68)	
γ_{spx4}	−0.8941589	(−4.423)	***	γ_{spx4}	−0.30953	(−4.93)	***	δ^{-}_{ffr1}	1.667459	(1.045)	
γ_{spx5}	−0.2677003	(−1.257)		δ^{+}_{ffr}	0.31739	(0.693)					
δ^{+}_{ffr}	0.2506457	(0.762)		δ^{+}_{ffr1}	−0.39805	(−0.641)					
δ^{+}_{ffr1}	−0.9187487	(−2.076)	*	δ^{+}_{ffr2}	−0.36295	(−0.592)					
δ^{+}_{ffr2}	0.8811984	(1.931)	.	δ^{+}_{ffr3}	0.86215	(1.399)					
δ^{+}_{ffr3}	0.0196529	(0.044)		δ^{+}_{ffr4}	−1.21204	(−1.954)	.				
δ^{+}_{ffr4}	0.258671	(0.583)		δ^{+}_{ffr5}	0.86005	(1.871)	.				
δ^{+}_{ffr5}	−0.567336	(−1.737)	.	δ^{-}_{ffr}	−0.37402	(−0.94)					
δ^{-}_{ffr}	−0.0002544	(−0.01)		δ^{-}_{ffr1}	0.5651	(1.668)	.				
δ^{-}_{ffr1}	0.1841749	(3.942)	***								
δ^{-}_{ffr2}	−0.2788746	(−3.912)	***								
δ^{-}_{ffr3}	0.3481231	(5.974)	***								
δ^{-}_{ffr4}	−0.4754276	(−7.492)	***								
δ^{-}_{ffr5}	0.3039798	(5.766)	***								
Long run effects on price time lags											
α_{spx2}	−0.0085467	(−0.067)		α_{spx2}	0.105527	(1.8856)	.	β^{+}_{ffr}	0.0028357	(0.965)	
α_{spx3}	0.9116801	(3.7849)	***	α_{spx3}	−0.139926	(−2.6081)	**	β^{-}_{ffr}	−1.0682262	(−0.6806)	
α_{spx4}	−0.8324452	(−3.055)	**	α_{spx4}	−0.252067	(−4.8386)	***	β^{-}_{ffr1}	1.6073118	(1.0484)	
α_{spx5}	−0.249224	(−1.1633)		β^{+}_{ffr}	0.258466	(0.6923)					
β^{+}_{ffr}	0.2333465	(0.7634)		β^{+}_{ffr1}	−0.324151	(−0.6399)					
β^{+}_{ffr1}	−0.8553379	(−1.9188)	.	β^{+}_{ffr2}	−0.295572	(−0.5928)					
β^{+}_{ffr2}	0.8203793	(1.745)	.	β^{+}_{ffr3}	0.702097	(1.3957)					
β^{+}_{ffr3}	0.0182965	(0.0438)		β^{+}_{ffr4}	−0.987034	(−1.9319)	.				
β^{+}_{ffr4}	0.2408178	(0.584)		β^{+}_{ffr5}	0.700383	(1.857)	.				
β^{+}_{ffr5}	−0.5281792	(−1.728)	.	β^{-}_{ffr}	−0.304587	(−0.9331)					
β^{-}_{ffr}	−0.0002368	(−0.0103)		β^{-}_{ffr1}	0.460189	(1.6461)	.				
β^{-}_{ffr1}	0.1714634	(3.0338)	**								
β^{-}_{ffr2}	−0.259627	(−2.7923)	**								
β^{-}_{ffr3}	0.3240961	(4.1347)	***								
β^{-}_{ffr4}	−0.4426142	(−4.2428)	***								
β^{-}_{ffr5}	0.2829995	(3.598)	***								
Adj R^2:	91.58%			Adj R^2:	68.51%			Adj R^2:	50.59%		
	Stat	*p*-value			Stat	*p*-value			Stat	*p*-value	
JB	0.9721321	0.3186287		JB	0.9448148	8.67148E−07		JB	0.97662314	0.03730161	
LM	2.8606687	0.4199273		LM	9.3424059	0.2400535		LM	0.9516618	0.5078846	
ARCH	5.347649	0.374941		ARCH	17.84999959	0.001320238		ARCH	0.1240202	0.7247145	
W sr:	0.5714522	0.7514684		W sr:	1.255808	0.5337092		W sr:	0.4653084	0.7924275	
W lr:	0.4952926	0.780636		W lr:	0.8328196	0.65941		W lr:	0.4323455	0.8055961	

Note: The results are all significant in the outbreak (Phase I), the first year remainder/lockdown (Phase II), and the time after the federal funds rate increase in 2022, which shows FFR has a time lag impact on SPX returns.

Table 17

Long-term and short-term coefficients and statistical test results of FFR on DAAA captured by NARDL model.

Federal fund rates **(FFR)** on DAAA NARDL short-run, long-run coefficients and statistics											
Outbreak (Phase I)				Lockdown (Phase II)				After March 2022 rate raise			
	Estimate	t-value			Estimate	t-value			Estimate	t-value	
Short run effects on price difference time lags											
Const	1.97544	(2.679)	*	Const	0.109612	(0.981)		Const	0.123961	(2.266)	*
γ_{daaa1}	−0.05109	(−0.3)		γ_{daaa1}	−0.270756	(−3.76)	***	γ_{daaa1}	−0.028543	(−2.052)	*
γ_{daaa2}	−0.14243	(−0.584)		γ_{daaa2}	0.139806	(1.882)	.	δ^{+}_{ffr}	0.001893	(0.36)	
γ_{daaa3}	0.12547	(0.449)		γ_{daaa3}	0.099411	(1.38)		δ^{-}_{ffr}	0.133925	(0.036)	
γ_{daaa4}	−0.45712	(−1.555)		γ_{daaa4}	−0.098497	(−1.415)		δ^{-}_{ffr1}	1.912575	(0.369)	
γ_{daaa5}	−0.13593	(−0.463)		γ_{daaa5}	−0.002751	(−0.058)		δ^{-}_{ffr2}	−3.949576	(−0.776)	
δ^{+}_{ffr}	−0.93922	(−0.59)		δ^{+}_{ffr}	−0.814693	(−3.059)	**	δ^{-}_{ffr3}	0.652296	(0.126)	
δ^{+}_{ffr1}	−1.18815	(−0.604)		δ^{-}_{ffr}	−1.053434	(−2.584)	*	δ^{-}_{ffr4}	1.296398	(0.344)	
δ^{+}_{ffr2}	0.24941	(0.126)									
δ^{+}_{ffr3}	1.01679	(0.521)									
δ^{+}_{ffr4}	−1.30538	(−0.933)									
δ^{-}_{ffr}	0.09425	(1.333)									
Long run effects on price time lags											
α_{daaa2}	−2.7878	(−0.2115)		α_{daaa2}	0.516353	(2.3352)	*	β^{+}_{ffr}	0.066312	(0.3938)	
α_{daaa3}	2.4558	(0.2339)		α_{daaa3}	0.367159	(1.3732)		β^{-}_{ffr}	4.692012	(0.0356)	
α_{daaa4}	−8.9473	(−0.2894)		α_{daaa4}	−0.363784	(−1.2931)		β^{-}_{ffr1}	67.006283	(0.3635)	
α_{daaa5}	−2.6607	(−0.3066)		α_{daaa5}	−0.010162	(−0.0577)		β^{-}_{ffr2}	−138.37176	(−0.7243)	
β^{+}_{ffr}	−18.3835	(−0.3082)		β^{+}_{ffr}	−3.008955	(−2.9135)	**	β^{-}_{ffr3}	22.852935	(0.1256)	
β^{+}_{ffr1}	−23.2558	(−0.2558)		β^{-}_{ffr}	−3.890712	(−2.5257)	*	β^{-}_{ffr4}	45.418754	(0.3394)	
β^{+}_{ffr2}	4.8817	(0.1125)									
β^{+}_{ffr3}	19.9018	(0.2638)									
β^{+}_{ffr4}	−25.5504	(−0.2889)									
β^{-}_{ffr}	1.8448	(0.3035)									
Adj R^2:	11.83%			Adj R^2:	23.61%			Adj R^2:	−0.2517%		
	Stat	p-value			Stat	p-value			Stat	p-value	
JB	0.9707763	0.2714992		JB	0.976297451	0.002250951		JB	0.9925568	0.1708393	
LM	4.334233	0.348732		LM	3.869634	0.367166		LM	0.4119858	0.6367241	
ARCH	12.95583447	0.02379618		ARCH	10.79234734	0.05565616		ARCH	0.5970873	0.4396915	
W sr:	0.4088158	0.8151298		W sr:	1.457806	0.482438		W sr:	0.001231561	0.9993844	
W lr:	156.6208	9.77747E−35		W lr:	19.88578	4.80681E−05		W lr:	1.511645	0.4696242	

Note: The results are significant in the outbreak (Phase I) and the first year after the outbreak (Phase II), but not significant after rate raise.

To reinforce our findings, we introduced a control variable in addition to the federal funds rate to gauge its impact throughout the entirety of the COVID-19 crisis. This control variable is the equity market volatility (infectdisemv), termed as the infectious disease tracker.[6] This tracker encompasses three metrics: stock market volatility, newspaper-sourced economic uncertainty, and subjective uncertainty discerned from business expectation surveys. The outcomes bolster the conclusion that federal funds rate increases boosted yields of credible bonds, yet had no bearing on stock index returns throughout the entire COVID-19 pandemic.

Economic policy uncertainty (EPU) influenced the SPX during the outbreak. After the federal funds rate hikes, the federal funds rate (FFR) exhibited a pronounced positive effect on DAAA-grade and DBAA-grade bonds. Throughout the crisis, both the FFR and the infectious disease equity market volatility had a positive influence on creditable bonds.

Considering the asymmetric time lag impact of the economic policy uncertainty (EPU) index and the federal funds rate (FFR) increase, we have **hypothesis five**: The impact of economic policy uncertainty (EPU) on the stock is all over the entire COVID-19 crisis. Its impact on time lags of bond yields and time lags of yield difference existed during the outbreak and exhibited positive asymmetry, especially on the most conservative grade bond DAAA—a hidden driver of asset performance. This hypothesis aims to confirm that the force behind this, namely the delayed absorption of policy relief, bolstered the return performance and risk-hedging role of these bonds.

6 https://fred.stlouisfed.org/series/INFECTDISEMVTRACKD

Table 18
Long-term and short-term coefficients and statistical test results of FFR on DBAA captured by NARDL model.

Federal funds rates **(FFR)** on DBAA NARDL short-run, long-run coefficients and statistics									
Outbreak (Phase I)			Lockdown (Phase II)			After March 2022 rate raise			
	Estimate	t-value		Estimate	t-value		Estimate	t-value	
Short run effects on price difference time lags									
dbaa1	−0.03019	(−0.331)	γ_{dbaa1}	0.05716	(0.794)	Const	0.1223	(2.093)	*
δ^{+}_{ffr}	0.93317	(0.606)	γ_{dbaa2}	−0.04254	(−0.411)	γ_{dbaa1}	−0.02162	(−1.807)	.
δ^{+}_{ffr1}	−0.90869	(−0.436)	γ_{dbaa3}	0.00002812	(0)	δ^{+}_{ffr}	−0.00003215	(−0.006)	
δ^{+}_{ffr2}	−0.87227	(−0.415)	γ_{dbaa4}	−0.07302	(−1.226)	δ^{-}_{ffr}	0.0301	(0.009)	
δ^{+}_{ffr3}	1.10565	(0.719)	δ^{+}_{ffr}	−1.233	(−0.884)	δ^{-}_{ffr1}	2.245	(0.464)	
δ^{-}_{ffr}	−0.03945	(−0.66)	δ^{+}_{ffr1}	0.7934	(0.58)	δ^{-}_{ffr2}	−3.707	(−0.766)	
			δ^{-}_{ffr}	−0.2055	(−0.745)	δ^{-}_{ffr3}	1.38	(0.398)	
Long run effects on price time lags									
β^{+}_{ffr}	30.9136	(0.2787)	α_{dbaa2}	0.74433	(0.6145)	β^{+}_{ffr}	−0.0014871	(−0.0061)	
β^{+}_{ffr1}	−30.1026	(−0.2586)	α_{dbaa3}	−0.00049195	(−0.0003)	β^{-}_{ffr}	1.3921	(0.0087)	
β^{+}_{ffr2}	−28.8962	(−0.2678)	α_{dbaa4}	1.2775	(0.6271)	β^{-}_{ffr1}	103.81	(0.4494)	
β^{+}_{ffr3}	36.6272	(0.2915)	β^{+}_{ffr}	21.566	(0.5966)	β^{-}_{ffr2}	−171.44	(−0.7043)	
β^{-}_{ffr}	−1.307	(−0.3882)	β^{+}_{ffr1}	−13.881	(−0.4769)	β^{-}_{ffr3}	63.845	(0.3859)	
			β^{-}_{ffr}	3.5958	(0.5392)				
Adj R^2:	−6.591%		Adj R^2:	12.38%		Adj R^2:	0.238%		
	Stat	p-value		Stat	p-value		Stat	p-value	
JB	0.927774143	0.005072413	JB	0.9905362	0.2259162	JB	0.9921303	0.1381311	
LM	9.8232159	0.1966204	LM	4.6193676	0.3340629	LM	0.6780805	0.5614448	
ARCH	11.40324	0.000733161	ARCH	7.1753156	0.1269086	ARCH	0.0005327	0.981586227	
W sr:	0.4002833	0.8186148	W sr:	0.5183073	0.7717044	W sr:	7.52983E−05	0.9999624	
W lr:	439.2822	4.08407E−96	W lr:	158.6511	3.54279E−35	W lr:	0.1610673	0.9226238	

Note: The results are significant only in Phase II, not in Phase I or after the rate increase.

The finding that NARDL tests suggest that EPU exhibits a delayed effect on DAAA and DBAA aligns with the asset price trends observed in the verification results of our first hypothesis, wherein the relief policy momentarily drove up the SPX before causing a decline. In contrast, the returns of DAAA and DBAA were declining, albeit remaining superior to the daily returns of SPX.

Tables 10 to 15 present the NARDL model results of the EPU index's asymmetric impact on the time lags of SPX, DAAA, DBAA, USDX, GCCMX, and NYMEX, respectively. We observe that bonds with investment grades and above responded swiftly and with a positive asymmetry to economic policy uncertainties during the lockdown. Conversely, stocks and other assets displayed a negatively skewed response to these uncertainties. Furthermore, the bond grade is directly proportional to its speed of reaction to the EPU index. Notably, DAAA-grade bonds displaced a quicker positive asymmetry than DBAA-grade bonds.

These results further substantiate the asymmetry in the lagged response of different asset classes as well as the apparent shift of the safe haven role from gold to bonds at the end of the outbreak. Initially, both gold and bonds recovered rapidly in Phase II of the lockdown since the positive effects outweighed the negative ones. Subsequent NARDL results after the first lockdown year suggest the diminished safe haven status of gold after the outbreak (Phase I), given its increasing negative asymmetry. The positive asymmetric NARDL outcome for DBAA in the first year corroborates its potential as a safe haven asset class, following gold, due to uplifting relief policies. Positive asymmetric responses of bonds to the EPU index can counterbalance assets exhibiting negative reactions in the relevant subperiods. However, for assets that also exhibited positive asymmetry, bonds did not retain their safe haven status, explaining why DBAA was not viewed as a safe haven asset for USDX.

Importantly, the NARDL model results enhance our understanding of the inter-asset relationships and explain the return dynamics of various assets. For the stock index, SPX (Table 10), the EPU index demonstrates significant asymmetric coefficients only during the initial phase of the lockdown. The EPU index notably influenced the DAAA-grade and DBAA-grade bonds (see Table 11, Table 12) exclusively during the lockdown subperiods (Phase I and II). As for the remaining three asset classes – crude oil, US dollar foreign exchange, and gold – their primary influence lingered in the COVID-19 lockdown. Detailed lag and parameter specifications for these assets are available in their respective tables (Tables 13 to 15).

We propose **hypothesis six**: The impact of federal funds rate (FFR) on stock return time lags and return difference time lags is negative and decreases; the impact on the DAAA increases but is slight, and the impact on the DBAA is not as obvious as that on the DAAA from the outbreak onwards.

Initially, strategies such as asset purchases and relaxing lending policies bolstered asset prices, as detailed in Table 7. However, from March 2022, with evident inflation, inflation control took precedence over economic stimulation. The Federal Reserve strived for a soft economic landing through interest rate increases. The empirical outcomes of the NARDL model, using FFR as an independent variable to discern the asymmetric time lag effects on DAAA, DBAA, and SPX, are consolidated in Tables 16 through 18.

During the inaugural year of COVID-19, FFR influenced DAAA and DBAA, with a more pronounced effect on DAAA, which boasts higher credit ratings as compared to DBAA. The adjusted R^2 indicates that FFR's time lags during both Phase I and II effectively explain the behavior of DAAA's yield, but only the Phase II lag has an explanatory effect on DBAA. Following the interest rate hikes in March 2022, FFR ceased to have a notable time lag effect on either DAAA or DBAA.

Regarding SPX, FFR exhibited a significant asymmetric time lag during Phase I, Phase II of the first outbreak year, and post-interest rate hikes. The onset of COVID-19 marked a negative asymmetric lag in Phase I, which persisted during the interest rate hikes. Only in Phase II was a short-term negative effect counterbalanced by a weak long-term positive influence.

Various statistical tests (JB, LM, and ARCH) then shed light on R^2. Short-run and long-run W-stats indicate if the models possess short- or long-term asymmetric effects. Both EPU and FFR influenced SPX across all crisis phases. The primary impact on bonds occurred during the lockdown year. While EPU demonstrated an asymmetric effect on the three assets, FFR did not.

4. Conclusion

Firstly, the risk-adjusted return of investment-grade bonds performs more conservatively and more stably than stock indices. Particularly, grade DBAA bonds boast the highest value, persistently rising after the immediate response to relief packages. Moreover, the Sharpe ratio of creditable bonds, albeit declining, still ranks the highest among assets.

Secondly, given that risk measure value comparison demonstrates that bonds are a risk-averse asset class, this study further attests to safe haven role of investment-grade bonds using covariance measures and DCC regression analysis in our second hypothesis test.

Thirdly, at the outset of the COVID-19 pandemic, both the US Federal Reserve and the European Central Bank (ECB) rolled out some of the most generous relief policies ever witnessed. However, inflation spiraled out of control in the US. From March 2022 onwards, the Federal Reserve began incrementing interest rates, catalyzing a global trend in rate hikes. Regression analyses indicate that these policy decisions deeply influenced asset prices, buttressing the outstanding performance of premium bonds during these tumultuous times.

Drawing from the NARDL model outcomes, it becomes evident that the impact of the EPU is confined to the initial lockdown phase for assets like bonds, but the impact on stocks occurred throughout the full course of the COVID-19 pandemic. This EPU-centric study successfully segregates policy-driven impacts from those arising due to real economic circumstances. The findings resonate with the observed return trajectories of these assets and their evolving correlations.

Lastly, we examined the effects of the FFR on the SPX, DAAA, and DBAA time lags. After the lockdown, the FFR hikes were initiated in March 2022. The influence of the FFR, considering the delayed impact on the SPX following these rate hikes, aligns with intuitive expectations and appears to have no negative asymmetric effect.

As the Federal Reserve shifts its policy stance and reduces in September 2024, the asset class allocation should change with the policy. Against the background of this new policy, the returns of more risky asset classes, such as stocks, may shift. Gold rises again. Environmental, social, and governance (ESG) regulations have raised global attention and action. ESG assets manifest their sustainable characteristics in the COVID-19 crisis, thus becoming even more noticeable assets. In future research, it is worthwhile to explore the shifting performance of traditional asset classes such as equities, and bonds as well as assets with new characteristics such as digital assets, and sustainable assets in the new policy and macroeconomic regime.

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