When safe-haven asset is less than a safe-haven play

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ABSTRACT

We propose a four-state regime-switching model that pairs low volatility (LV) and high volatility (HV) states to test the risk properties of eight stock-safe haven asset portfolios. We find the correlations between gold, U.S. T-bond, and Swiss Franc, and stock markets are negative or zero in all states, including the HV-HV state, while between Bitcoin and stock markets are positive in the HV-HV state, implying that gold, T-bond, and Swiss Franc are full-safe havens and Bitcoin is a partial-safe haven asset. Moreover, our model is effective in portfolio construction, which performs better than the conventional time-varying GARCH-based models.

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1. Introduction

Portfolio theory postulates that the risk reduction effect from diversification depends on the correlations among the assets in the portfolio. To maximize the effect, investors include negatively correlated assets in their portfolios (Jackwerth & Slavutskaya, 2016). The literature (e.g., Baur & Lucey, 2010; Ratner & Chiu, 2013) employs the magnitude and sign of the cross-asset correlation to classify assets into three levels: a diversifier, a hedge, and a safe-haven. A diversifier has a small but positive correlation with another asset; a hedge is an asset that has a zero (or negative) correlation with another asset, and a hedge asset levels up to a safe-haven if a zero (or negative) correlation persists during chaotic times. Accordingly, a diversifier and a safe-haven are assets with the lowest and highest level of risk reduction capability respectively, while a hedge lies between them.

The literature has researched several safe-haven assets for stock investors, including gold (e.g. Hillier et al., 2006; Baur & Lucey, 2010; Pullen et al., 2014; Bekiros et al., 2017), US government bonds (e.g. Fleming et al., 1998; Hartmann et al., 2004; Baur & Lucey, 2010; Noeth & Sengupta, 2010; Chan et al., 2011;) and Swiss Franc (e.g. Kaul & Sapp, 2006; Ranaldo & Söderlind, 2010; Grisse & Nitschka, 2015). In addition to these traditional safe-haven assets, some recent studies (e.g. Bouri et al., 2017; Stensås et al., 2019; Urquhart & Zhang, 2019; Garcia-Jorcanoa & Benito, 2020; Hafner, 2020; Mariana et al., 2021) include Bitcoin. Indeed, several US companies hold a large quantity of Bitcoin (e.g., Microstrategy and Tesla). The critical character of safe-haven assets is their zero or negative correlation with stocks, hence acting as an instrument against stock asset risk. The research of safe-haven assets has renewed attention because of the 2008 Global Financial Crisis (e.g., Cheema et al., 2020) and the COVID-19 pandemic (e.g., Baker et al., 2020 and Mariana et al., 2021).

This study contributes to the safe-haven assets literature in three directions. First, we develop a theoretical perspective to distinguish two types of safe-haven assets: partial-safe and full-safe. Considering a portfolio consisting of stocks and a safe-haven asset with two turmoil circumstances: (1) only one market (either stock or safe-haven asset) experiences a chaotic condition, and (2) both stock and safe-haven asset markets experience a chaotic condition. We define a safe-haven asset as partial-safe if its correlation with the stock market is zero or negative under the first turmoil event but positive under the second event. On the other hand, a safe-haven asset is full-safe if its correlation with stock markets is zero or negative under both turmoil events. While literature lacks this distinction, addressing the difference between these two turmoil events is meaningful. If the risk-benefit of the safe-haven asset is partial, it may protect stock investors when only the stock market encounters turmoil. However, when both stock and safe-haven asset markets are in a turbulent state, the partial-safe haven asset is unable to effectively reduce portfolio risk because of its positive correlation with stocks. The most recent evidence occurred in March 2020 when Covid-19 hit the world hard, both stock market and Bitcoin market crumbled, e.g., the S&P 500 and BTC returned -7.90% and -14.08%, respectively on March 9; -9.99% and -46.47%, respectively on March 12; and -12.77% and -10.39%, respectively on March 16. To the best of our knowledge, the literature has not distinguished these two types of safe-haven assets because they only consider the stock market condition.

Second, to differentiate a partial-safe from a full-safe haven asset and empirically test our argument, we develop a regime-switching approach to identity various volatility state combinations in the stock and safe-haven asset markets and jointly analyze their correlation dynamics. While the existing studies have addressed and tested the dynamic correlations between stock and safe-haven assets (e.g., Cappiello et al., 2006; Hood & Malik, 2013; Ciner et al., 2013; Pullen et al., 2014; Bouri et al., 2017a and 2017b; Wu et al., 2019; Mariana et al., 2021; Mokni et al., 2021), we argue that their two-step methodologies suffer from limitations and yield compromised empirical results due to sample selection bias (see Heckman, 1979).

Third, we conduct a practical portfolio construction test employing our regime-switching model. As evidenced in our empirical results, the magnitude and the sign of the stock-safe haven correlations are non-uniform across various volatility state combinations. As volatilities and correlations are the critical factors for effective portfolio construction, a follow-up question is if our proposed state-varying volatilities and correlations help investors achieve a more efficient stock-safe haven asset portfolio. To the best of our knowledge, few, if any, prior studies have conducted this practical test since they are constrained by the usage of a two-step estimation method in which the sample segmentation and the use of dummy variables are not decided by the data.

The rest of our study proceeds as follows. First, we review related studies and develop research questions in Section 2. In Section 3, we present the models used in this study, including the conventional GARCH (Generalized Autoregressive Conditional Heteroskedasticity), DCC (Dynamic Conditional Correlations) models, and the proposed regime-switching model. We further demonstrate why our regime-switching approach is more appropriate than the conventional DCC model to measure the correlation dynamics in the stock-safe haven asset markets. In Section 4, we report the estimation results. We then discuss our results and conduct the practical portfolio construction test in Section 5. Finally, Section 6 concludes.

2. Literature review and research development

2.1 Studies on safe-haven assets

The recurring financial and economic crises in the past decades reinforce researchers' interest in risk management, one of the most critical issues in finance research. While stock markets provide investors with a significant capital gain over the long run, rare but unanticipated disasters cause a severe short-term loss. There are two commonly used practices to manage risk: hedge by financial derivatives and diversification by portfolio. This study focuses on the second method. The concept of diversification (investing in two or more assets) rests on the notion that asset values do not always move in the same direction at the same time. Therefore, an investor can reduce risk via investing in a portfolio. For effective diversification, the less-than-perfect linkage between assets is essential, particularly during periods of financial chaos. This is because when these unlikely and rare disasters occur, different markets do not crash jointly, or they may move in an opposite direction, i.e., the loss in one market can be offset by the gain in another market.

Whether other assets can be used to control stock risk relies on their correlations with stocks. The literature (e.g., Baur & Lucey, 2010; Ratner & Chiu, 2013) defines three types of assets against stock risk: (1) a diversifier (an asset with a slight positive correlation with stocks), (2) a hedge (an asset with a zero or negative correlation with stocks), and (3) a safe-haven (an asset with a zero or negative correlation with stocks during chaotic events). By definition, including a safe-haven asset in the portfolio is an ideal tool to offset stock risk, particularly during periods of financial and economic distresses.

Certain safe-haven assets have been well documented in the literature, including gold (e.g., Hillier et al., 2006; Baur & Lucey, 2010; Pullen et al., 2014), government bonds (Fleming et al., 1998; Hartmann et al., 2004; Noeth and Sengupta, 2010; Chan et al., 2011;), currencies such as Swiss Franc and the US dollar (e.g. Grisse and Nitschka, 2015; Kaul and Sapp, 2006; Ranaldo and Söderlind, 2010). In addition to these traditional safe-haven assets, recent studies endorse digital currencies such as Bitcoin as a safe-haven asset against stock risk because factors driving cryptocurrency prices are different from those affecting stock markets (e.g. Stensås et al., 2019; Urquhart & Zhang, 2019; Garcia-Jorcanoa & Benito, 2020; Hafner, 2020; Mariana et al., 2021).

Although numerous studies have examined these safe-haven assets, the evidence is inconclusive. Capie et al. (2005), Hammoudeh et al. (2009), and Ciner et al. (2013) highlight the characteristics of gold as a safe-haven asset. Baur and Lucey (2010) and Chan et al. (2011) argue that government bonds outperform gold to diversify stock risk during chaotic times. Grisse & Nitschka (2015) demonstrate the Swiss Franc's safe-haven characteristics against other currencies. While some studies (Kliber et al., 2019; Gil-Alana et al., 2020; Bouri et al., 2020; Mariana et al., 2021) suggest that cryptocurrencies are qualified as a safe haven for stocks, others argue that cryptocurrencies are a poor hedge (Isah & Raheem, 2019; Conlon & McGee,2020; Corbet et al., 2020). In the following section, we advance a new perspective that distinguishes a partial-safe haven from a full-safe haven. To this end, we develop a regime-switching system where combinations of four volatility states are implemented to test our argument.

2.2 Research development

Our research aims to shed light on the debate of safe-haven assets in the literature. We develop combinations of market volatility states in the stock-safe haven asset markets and differentiate two types of safe-haven assets: partial-safe and full-safe. Our conjectures are explained as follows. First, prior studies have well documented the linkage between financial crises and market volatilities, i.e., high market volatility serves as a signal of financial crises (Engle et al., 2013; Baker et al., 2016; Gulen & Ion, 2016; Danielsson et al., 2018). Considering a portfolio consisting of stocks and safe-haven assets, both the stock volatility and safe-haven asset volatility should be taken into account when constructing a portfolio. Therefore, with a regime-switching between a low volatility (LV) and a high volatility (HV) regime for each asset, we develop a four-state system for the stock-safe haven asset portfolios, i.e., LV-LV, HV-LV, LV-HV, and HV-HV.

Second, among the four states, we highlight the "HV-HV" state. This state reflects extreme economic and/or financial distresses (e.g., COVID-19 pandemic) causing both the stock and safe-haven asset markets to experience excessive price movements concurrently. If the safe-haven asset is positively correlated with stocks in the HV-HV state, then the safe-haven asset and stock will move in tandem and thus the loss in the stock position will meet another loss in the safe-haven asset position. Accordingly, the safe-haven asset position is unable to offset the stock position under this situation, and its protective function is limited during this chaotic condition. Based on this logic, we define two types of safe-haven assets: (1) a full-safe haven asset if its correlation with stocks continues to be zero or negative under the HV-HV state, and (2) a partial-safe haven asset if its correlation with stocks is zero or negative under all states except the HV-HV state.

Our views relate to the literature on the contagion effect. A number of researchers have documented that global equity markets are more strongly correlated during turbulent times (see King & Wadhwani, 1990; Erb et al., 1994; Longin & Solnik, 1995, 2001; Karolyi & Stulz, 1996; Jacquier & Marcus, 2001; Ang & Bekaert, 2002; Forbes & Rigobon, 2002; Bae et al., 2003; Das & Uppal, 2004). However, the contagion effect among international stock markets is not very helpful in explaining the correlation between stocks and safe-haven assets since different fundamentals drive them. Nevertheless, we argue that stocks and safe-haven assets could still be positively correlated. The following two theories help to elucidate our argument. The first theory is the cross-market rebalancing channel of financial contagion as modeled by Kodres & Pritsker (2002). In their model, shocks are transmitted across markets as investors respond to shocks in one market by optimally readjusting their portfolios. This model setting can generate contagion across various markets that do not share common macroeconomic fundamentals. The second theory is the social learning channel proposed by Trevino (2020). In the model, Trevino (2020) demonstrates that contagion occurs when investors are fearful of a crisis in one market after observing a crisis in the other market albeit these two markets are not fundamentally linked. We contend that these two contagion channels exacerbate the cross-market correlations between stocks and safe-haven assets, particularly when both are experiencing chaotic times (i.e., the HV-HV state).

To test the dynamic cross-market correlations between stocks and safe-haven assets, the majority of prior studies (e.g., Hood & Malik, 2013; Ciner et al., 2013; Pullen et al., 2014; Bouri et al., 2017a, and 2017b; Wu et al., 2019; Mariana et al., 2021; Mokni et al., 2021) employ one of the two econometric methods. The first method is the dynamic conditional correlation (DCC) model proposed by Engle (2002). Prior researches use the DCC model to estimate the time-varying correlations between stock and safe-haven assets. They first partition the whole testing period into sub-periods, e.g., crisis versus non-crisis period, followed by a comparative analysis between the two sub-periods (e.g., Cappiello et al., 2006; Ciner et al., 2013; Urquhart & Zhang, 2019; Mariana et al., 2021). The second method is the quantile regression approach employed by Baur and Lucey (2010) and Baur and McDermott (2010). These researches use the 1%, 2.5%, or 5% lower percentiles of stock returns (i.e., stressed or extreme stock returns) to define several quantile dummy variables. They include these dummy variables in the conventional regression analyses of safe-haven asset returns on stock returns and use the estimated results of these dummy variables to infer whether the stocks and safe-haven asset correlations change in chaotic times.

We notice caveats in these two econometric methods adopted by prior studies. First, while Engle's DCC model is the most popular method to estimate the dynamic correlations among assets (Goeij & Marquering, 2004), it uses a two-step approach to estimate the model parameters, hence fails to take into account the linkage between variances and correlations (e.g., Bae et al., 2003; Das & Uppal, 2004). Further, the sample partitioning process (i.e., crisis versus non-crisis periods) is subjective, which may yield compromised empirical results due to sample selection bias (Heckman, 1979). Second, the approach that uses quantile threshold variables to diagnose and examine the impact of turmoil market conditions on the relationship between stock and safe-haven asset markets also bears the limitation of a two-step process and the use of subjective dummy variables. By contrast, our proposed regime-switching approach has two key advantages and thus effectively mitigates these limitations. First, in our regime-switching approach, all the parameters for volatilities and correlations are jointly estimated. Second, the partition of various volatility regimes (i.e., a high or a low volatility regime) is endogenously determined by the data, thus mitigating the bias due to the subjective sample partitioning and the usage of dummy variables.

3. Research methodologies

3.1 Bivariate GARCH model

Following prior studies (e.g., Baur & Lucey, 2010; Ciner et al., 2013), we first present the conventional GARCH model for dynamic volatilities in this section. Considering a two-asset portfolio, stock (STK) and safe-haven asset (SAF), we construct the bivariate GARCH model as follows:

$$r_t^{STK} = \mu^{STK} + \varphi^{STK} \cdot r_{t-1}^{STK} + e_t^{STK} \qquad (1)$$

$$r_t^{SAF} = \mu^{SAF} + \varphi^{SAF} \cdot r_{t-1}^{SAF} + e_t^{SAF} \qquad (2)$$

$$e_t|\Phi_{t-1} = \begin{bmatrix} e_t^{STK} \\ e_t^{SAF} \end{bmatrix} \sim BN\ (0, H_t) \qquad (3)$$

$$H_t = \begin{bmatrix} h_t^{STK} & h_t^{STK,SAF} \\ h_t^{STK,SAF} & h_t^{SAF} \end{bmatrix} \qquad (4)$$

where r_t^{STK} and r_t^{SAF} denote returns on stock and safe-haven assets at time *t*, respectively. We adopt a simple autoregressive process with order one, AR(1), to describe the return generating process (see Equations (1) and (2)) because our focus is the second moment (including variances, covariances, and correlations) instead of the first moment (return mean).

Below we present the time-varying variances (h_t^{STK} and h_t^{HAV}) and covariances ($h_t^{STK,HAV}$) in the bivariate GARCH model:

$$h_t^{STK} = \omega^{STK} + \alpha^{STK} \cdot (e_{t-1}^{STK})^2 + \beta^{STK} \cdot h_{t-1}^{STK} \quad (5)$$

$$h_t^{SAF} = \omega^{SAF} + \alpha^{SAF} \cdot (e_{t-1}^{SAF})^2 + \beta^{SAF} \cdot h_{t-1}^{SAF} \quad (6)$$

$$h_t^{STK,SAF} = \rho \times (h_t^{STK} \cdot h_t^{SAF})^{1/2} \quad (7)$$

Notably, the above setting suffers from a constant conditional correlation (CCC) assumption, i.e., ρ in Equation (7).[1] In the next section, we introduce the dynamic conditional correlations (DCC) proposed by Engle (2002) and incorporate the DCC setting into the bivariate GARH model.

3.2 DCC model

In this section, we present the DCC model by Engle (2002) as follows:

$$q_t = \tau + \pi \cdot q_{t-1} + \lambda \cdot e_{t-1}^{STK} \cdot e_{t-1}^{SAF} / \sqrt{h_{t-1}^{STK} \cdot h_{t-1}^{SAF}} \quad (8)$$

$$\rho_t = q_t \,/\, \sqrt{1 + q_t^2} \quad (9)$$

$$h_t^{STK,SAF} = \rho_t \times (h_t^{STK} \cdot h_t^{SAF})^{1/2} \quad (10)$$

Comparing Equations (10) and (7) clearly shows the difference between the DCC and CCC models: ρ_t versus ρ. Moreover, Equations (8) shows three components in the DCC setting: (1) the unconditional correlation (τ), (2) the lagged conditional correlation (q_{t-1}), and (3) the cross-product term of the lagged standardized residuals. Since the correlation coefficient should range from -1 to +1, we develop Equation (9) to meet the requirement. Specifically, when q_t is negative, ρ_t is close to -1, while ρ_t is close to 1 when q_t is a positive number. Notably, we may convert the DCC model to the CCC model by implementing the restriction of $\pi = \lambda = 0$ to Equation (8). This study uses a one-step estimation method to determine all the model parameters for variances and correlations. Our one-step estimation method may

[1] See Bollerslev (1990) and Baillie and Bollerslev (1990).

effectively mitigate the unrealistic assumptions involved in the two-step estimation process (see Section 2.2).[2]

3.3 Bivariate Markov-switching autoregressive conditional heteroskedasticity model

The critical character of the GARCH and DCC models is to use the past variances and correlations to predict future variances and correlations (see Equations (5), (6), and (8)). The literature (e.g., Schmitt & Westerhoff, 2017; Akhtaruzzaman et al., 2020; Corbet et al., 2020; Mariana et al., 2021) has well documented the clustering phenomena of volatilities and correlations, i.e., a high variance/correlation followed by a high variance/correlation. However, these simple and pure time-dependent settings fail to control discrete volatility jumps and are unable to capture the relation between volatilities and correlations (Nelson, 1991; Engle & Mustafa, 1992). To mitigate these limitations, we extend Hamilton and Susmel's (1994) Markov-switching Autoregressive Conditional Heteroskedasticity (SWARCH) model to investigate the regime-switching pattern for market volatility (i.e., switching between a low- and high-volatility regime) and the regime-switching volatility-correlation relation. Considering the two asset positions in the stock-safe haven portfolio, we develop a bivariate SWARCH model as follows:

$$h_t^{STK} = g_{s_t^{STK}}^{STK} \times [\omega^{STK} + \alpha^{STK} \cdot (e_{t-1}^{STK})^2] \tag{11}$$

$$h_t^{SAF} = g_{s_t^{HAV}}^{SAF} \times [\omega^{SAF} + \alpha^{SAF} \cdot (e_{t-1}^{SAF})^2] \tag{12}$$

Equations (11) and (12) denote the conditional variance for STK and SAF, respectively. The key variables in the SWARCH model are s_t^{STK} and s_t^{SAF}, a discrete state variable with two possible outcomes: 1 or 2. When the state variable is 1 (i.e., regime I), the conditional variances for STK and SAF are g_1^{STK} and g_1^{SAF} times the respective conventional ARCH (1) process. When the state variable is 2 (i.e., regime II), the conditional variances for

[2] Broyden–Fletcher–Goldfarb–Shanno algebra in GAUSS is employed to estimate the model parameters. In particular, we search for the values of the parameters (including both variances and correlations) that maximize the log-likelihood function. The program codes are available upon request.

STK and SAF are g_2^{STK} and g_2^{SAF} times the respective ARCH (1) process. We normalize g_1^{STK} and g_1^{SAF}, the volatility degree parameter for regime I, to be unity (i.e., g_1^{STK} = g_1^{SAF} = 1). Accordingly, the variance under regime II is g_2^{STK} multiples of regime I for STK returns, and for SAF returns, the variance under regime II is g_2^{SAF} multiples of regime I. As shown in Tables 6 and 7, the estimated g_2^{STK} and g_2^{SAF} coefficients are significantly higher than the value of one. Based on the results, we define regime II and regime I as a high volatility (HV) and a low volatility (LV) regime, respectively.

Next, we model the conditional correlations for the STK-SAF portfolio. Given a two-state setting for the conditional variance of each asset in the portfolio, we define a four-state conditional correlation as follows:

$$h_t^{STK,SAF} = \rho_{s_t^{STK},s_t^{SAF}} \times (h_t^{STK} \cdot h_t^{SAF})^{1/2} \tag{13}$$

As shown in Equation (13), the STK-SAF correlation is $\rho_{1,1}$ when both the STK and SAF markets are in an LV state (i.e., s_t^{STK} = 1 and s_t^{SAF} = 1). The correlation is $\rho_{2,2}$ when both the STK and SAF markets are experiencing an HV state. If the two markets are in opposite state (i.e., one is an HV and the other one is an LV), the cross-market correlations are $\rho_{2,1}$ (s_t^{STK} = 2 and s_t^{SAF} = 1) or $\rho_{1,2}$ (s_t^{STK} = 1 and s_t^{SAF} = 2). The four-state correlations in Equation (13) depict the relationship between market volatilities and correlations; hence it is suitable for testing our argument of partial-safe versus full-safe haven assets (see Section 2.2). In short, we establish a one-step estimation method to jointly determine volatilities and correlations, which effectively mitigates the biased results obtained from the two-step estimation method seen in the extant studies.

Last but not least, we use a first-order Markov chain process to control the regime-switching pattern for the discrete state variables, as proposed by Hamilton and Susmel (1994):

$$P\left(s_t^{STK} = 1 \middle| s_{t-1}^{STK} = 1\right) = p_{11}^{STK},\ p\left(s_t^{STK} = 2 \middle| s_{t-1}^{STK} = 2\right) = p_{22}^{STK} \tag{14}$$

$$P\left(s_t^{SAF} = 1 \middle| s_{t-1}^{SAF} = 1\right) = p_{11}^{SAF},\ p\left(s_t^{SAF} = 2 \middle| s_{t-1}^{SAF} = 2\right) = p_{22}^{SAF} \tag{15}$$

4. Data and model estimation results

4.1 Data

There are two positions in the stock-safe haven asset portfolio – stock and safe-haven. For the stock position, we employ two international stock indexes: S&P500 and FTSE100. For the safe-haven asset position, we consider gold, U.S. Treasury bond (T-Bond), Swiss Franc (CHF), and Bitcoin (BTC). Based on these two stock indexes and four safe-haven assets, we thus construct up to eight (4 x 2) portfolios for our empirical tests. The testing period is between April 30, 2003, and January 18, 2021, for a total of 2,015 daily observations. To ensure that the data used for the empirical analysis are stationary, we use the return series rather than the price level series. The data are collected from the DataStream database except for Swiss Franc and Bitcoin, which are obtained from the online database of the Swiss National Bank and https://coinmarketcap.com/, respectively.

Table 1 presents the descriptive statistics for the two stock indexes and the four safe-haven assets. As shown in Panel B, the correlation between S&P500 and FTSE100 is 0.5922 (*p-value* < 0.001), which is much larger than the correlations between stocks and safe-haven assets (range between -0.4116 and 0.1109). We further examine the correlations between two stock indexes and four safe-haven assets. First, the correlations between stock indexes and Bitcoin are positive and significant (e.g., the S&P500-BTC correlation = 0.1109 with *p-value* < 0.01). Second, the correlations with gold are positive but insignificant (e.g., the S&P500-Gold correlation = 0.0048 with *p-value* > 0.05). Third, the correlations with T-Bond and CHF are negative and significant (e.g., the S&P500-TBond correlation = -0.4116 with *p-value* < 0.01). These preliminary results imply that T-Bond and CHF outperform gold in diversifying stock risk and that Bitcoin might be less qualified as a safe-haven asset.

(Insert Table 1 about here)

4.2 Illustration of volatility regimes

To illustrate volatility regimes in the stock and cryptocurrency markets, we calculate the volatilities of their daily returns over one month (i.e., 21 trading days) rolling windows. Figure 1 graphs the daily return series, and Figure 2 graphs the return volatilities. As shown in Figure 2, the volatilities of stocks and safe-haven assets are non-constant. Moreover, frequent prominent moves (i.e., several peaks) are observed in Figure 2. These peaks provide evidence of volatility regimes in the markets. For instance, peaks are identified in mid-March 2020, which correspond to the economic and financial distresses due to the COVID-19 pandemic.

(Insert Figures 1 and 2 about here)

4.3 Results of bivariate GARCH-CCC and -DCC models

In this section, we apply the conventional GARCH models to the eight stock-safe haven asset portfolios. First, the results of the bivariate GARCH-CCC model are presented in Tables 2 and 3. As shown in these two tables, the two GARCH parameter estimates, α^{STK} , and β^{STK} for the stock position and α^{SAF} and β^{SAF} for the safe-have asset position, are positive and significant (*p-value* < 0.01) for all the portfolios. Moreover, the sums of the two GARCH parameter estimates are close to unity. These results indicate that the volatilities of the stock-safe haven asset markets are not constant, and the GARCH-based volatilities exhibit persistence (i.e., high volatility is followed by high volatility). Last but not least, the correlations between stock indexes (S&P500 and FTSE100) and the traditional safe-haven assets (gold, T-Bond, and CHF) are negative and significant (e.g., the FTSE100-TBond correlation = -0.2718 with *p-value* < 0.01). However, their correlations with Bitcoin are positive, with the FTSE100-BTC correlation significant at the 5% level.

(Insert Tables 2 and 3 about here)

Tables 4 and 5 present the estimation results of the bivariate GARCH-DCC model.

Consistent with Tables 2 and 3, the two GARCH parameter estimates are significantly positive, and the sums of the two estimates are close to unity, implying a volatility clustering property. Furthermore, the DCC parameter estimates are positive and significant for all portfolios (e.g., S&P500-Gold portfolio: $\pi = 0.9174$ with *p-value* < 0.01 and $\lambda = 0.0130$ with *p-value* < 0.05), which support a correlation clustering property (i.e., high correlation associates with high correlation).

(Insert Tables 4 and 5 about here)

4.4 Results of bivariate SWARCH model

While the results of the bivariate GARCH-DCC model support the notion of time-varying volatilities and correlations in the stock-safe haven assets markets, the relationship between their volatilities and correlations warrants further investigation per our discussions in Section 2.2. Accordingly, we develop the bivariate SWARCH model with four volatility regime combinations to further examine the relationship. Table 6 reports the estimation results for the portfolios consisting of S&P500 and four safe-haven assets, while the results for the portfolios combining FTE100 and four safe-haven assets are presented in Table 7.

(Insert Tables 6 and 7 about here)

First, as shown in Tables 6 and 7, the scale of regime II volatility (i.e., g_2^{STK} for the stock market and g_2^{SAF} for the safe-haven asset market) is significantly higher than one for all eight portfolios. Using the S&P500-Gold portfolio as an example, the g_2^{STK} estimate is 8.8615 with a standard deviation of 0.7729 and the g_2^{SAF} estimate is 6.3906 with a standard deviation of 0.5559. Notably, their 99% confidence intervals do not overlap with the value of one, the scale of regime I volatility. We thus define regime II as a high volatility (HV) regime and regime I as a low volatility (LV) regime. In addition, the ARCH parameter estimates (i.e.,

α^{STK} and α^{SAF}) are positive and significant for all portfolios, indicating a time-varying volatility property. To sum up, both time-varying and regime-varying properties are observed in the conditional volatilities of the stock-safe haven asset markets.

Next, we turn our attention to conditional correlations. Based on the setting of the two discrete volatility regimes (HV versus LV) for each asset in the portfolios, we investigate the dynamic conditional correlations under four (2 X 2) volatility regime combinations (i.e., LV-LV, HV-LV, LV-HV, and HV-HV). As shown in Tables 6 and 7, while these correlation estimates are significantly negative or insignificant for most cases, the estimated correlations between the two stock indexes (S&P500 and FTSE100) and Bitcoin are positive and significant under the HV-HV state. To be sure, the S&P500-BTC and FTSE100-BTC correlation estimates under the HV-HV state (i.e., $\rho_{2,2}$) are 0.2173 and 0.3324 respectively, with *p-value* < 0.01.

5. Discussion and portfolio construction

5.1 Explanation and discussion

By definition, a safe-haven asset for stock investors should be negatively correlated (or zero correlation) with stocks during chaotic times (e.g., Baur & Lucey, 2010; Ratner & Chiu, 2013). This study reexamines the issue on the four representative safe-haven assets commonly seen in the literature: gold, government bond, Swiss Franc and Bitcoin. First, we consider four volatility regime combinations in the stock-safe haven asset portfolios and classify safe-haven assets into partial-safe and full-safe havens. Our theoretical arguments are based on the cross-market rebalancing channel by Kodres and Pritsker (2002) and the social learning channel by Trevino (2020). We argue that the correlation between stocks and safe-haven assets might be heightened under high volatility conditions through these two channels.

As shown in Tables 6 and 7, the correlations between stocks (S&P500 and FTSE100) and three traditional safe-haven assets (gold, T-Bond, and CHF) are significantly negative or insignificant in all states, including the HV-HV state. These results support the notion that these assets are full-safe haven assets for stock investors. However, the correlations between stocks and Bitcoin are positive and significant under the HV-HV state (i.e., $\rho_{2,2}$), although the correlations are either insignificant or negative under other volatility states (i.e., $\rho_{1,1}$, $\rho_{2,1}$ and $\rho_{1,2}$). This result implies that Bitcoin is a partial-safe haven asset, falls short of a full-safe haven against stocks.

These findings require further discussion and elucidations. First, using the S&P500-Gold portfolio as an example, Figure 3 graphs the probabilities of various volatility state combinations estimated from our bivariate SWARCH model. We then adopt a maximum value criterion to define the state for each time point. For example, if the estimated probability of the "HV-HV" state is higher than that of the other three states, an "HV-HV" state is defined at this time point. Table 8 lists the percentage of different volatility state combinations observed for the eight stock-safe haven asset portfolios. The percentage of the "HV-HV" state ranges between 1.94% for the FTSE100-TBond portfolio and 9.55% for the S&P500-Gold portfolio. Therefore, the percentage of realizing any of the other three states (i.e., LV-LV, LV-HV, and HV-LV) ranges from 90.45% and 98.06%. Among the four-state combinations, the LV-LV is consistently the most commonly realized state (with a percentage ranging from 49.08% to 77.97%) across all eight stock-safe haven asset pairs. Since $\rho_{1,1}$ estimates reported in Tables 6 and 7 are either negative or zero in the LV-LV state, all of these four non-stock assets examined live up to their generally expected role as a diversifying or hedging asset for stock investors for a majority of the time.

However, it is less certain if these non-stock assets can serve as safe-haven assets for stock investors when both markets are in distress. Figure 4 graphs the HV-HV probabilities for the four S&P500-safe haven asset portfolios. Consistent with the statistics shown in Table

8, the HV-HV state occurs less often compared with the LV-LV state. The HV-HV state corresponds to periods during which both stocks and safe-haven assets experience volatile movements. For instance, in mid-March 2020, the coronavirus pandemic triggered the concern of global recession. As a result, the stock markets experienced some worst days in early mid-March, 2020, e.g., S&P500 = -7.90% and FTSE100 = -7.99% on the 9th of March; S&P500 = -9.99% and FTSE100 = -11.51% on the 12th of March; S&P500 = -12.77% and FTSE100 = -4.09% on the 16th of March. The Bitcoin market also suffered from a huge negative return on the same days, i.e., BTC = -14.09% (March 9), -46.47% (March 12), and -10.39% (March 16). By contrast, the three traditional safe-haven assets fared better with either a small loss or a positive gain on the same days, e.g., Gold = -0.14%, T-Bond = 0.73% and CHF = 0.79% on the 9th of March; Gold = -4.88%, T-Bond = -0.27% and CHF = 0.54% on the 12th of March; Gold = -1.89%, T-Bond = 1.53% and CHF = 0.66% on the 16th of March. These observations corroborate our findings that gold, U.S. Treasury bond, and Swiss Franc play a better role as a full-safe haven asset against stock market risk because their prices do not move in the same direction with stocks under the HV-HV state. However, with prices move in the same direction as stocks, Bitcoin is a partial-safe haven asset as it cannot protect stock investors well under the “HV-HV” state.

Stock markets mainly reflect investors’ expectations on the future corporate profits and macroeconomic conditions, such as economic growth, inflation, interest rate, and unemployment. By contrast, the Bitcoin market is unregulated, and its prices are mainly driven by media coverage, speculative activities, and market sentiment (e.g., Dastgir et al., 2019; Lyócsa et al., 2020). Since different factors drive stock and Bitcoin markets, a weak and negative correlation between them is possible; hence Bitcoin may provide diversification benefit against the risk of stocks. However, we conjecture that two contagion channels, the cross-market rebalancing channel (Kodres and Pritsker, 2002) and the social learning channel

(Trevino, 2020), may explain the possibility of a positive correlation between stock and Bitcoin markets under the "HV-HV" state.

It should be highlighted that our empirical findings show that the cross-market correlations between stocks and the three traditional safe-haven assets (Gold, T-Bond, and CHF) are either insignificant or significantly negative even under the most strict "HV-HV" state. These results imply that the financial contagion does not occur between stocks and these three traditional safe-haven assets. It is plausible that these traditional safe-haven assets are influenced by risk factors fundamentally different from stocks. For example, as fixed-income securities, bonds are much more sensitive to interest rate risk than stocks. Sovereign risk in a nation's government bonds is different from corporate default risks in stocks. During periods of crisis, Federal Reserve purchases or sells government bonds to influence interest rates and bond prices, whereas Federal Reserve does not directly trade stocks in markets. The most recent evidence occurred in March 2020 when Covid-19 hit the nation hard, both stock and government bond markets crumbled. However, the near-meltdown in the government bond markets prompted the U.S. Fed to buy a massive $1 trillion Treasuries in less than one month.

5.2 Portfolio construction: A beauty contest

As is well known, effective portfolio construction relies on the estimation quality of variances and correlations. Accordingly, a related question is whether the state-varying variances and correlations addressed in this study may help an investor construct a more efficient stock-safe haven asset portfolio. Since the use of safe-haven assets is to reduce portfolio risk, we employ a minimum variance portfolio construction strategy to conduct this test (e.g., French and Poterba, 1991; Tesar and Werner, 1992; Ramchand and Susmel, 1998). Considering the portfolio consisting of stock (STK) and safe-haven asset (SAF), the weight given to each position is presented as follows:

$$w_t^{STK} = [h_t^{SAF} - \rho_t(h_t^{SAF} \cdot h_t^{STK})^{1/2}]/[h_t^{STK} + h_t^{SAF} - 2 \cdot \rho_t(h_t^{SAF} \cdot h_t^{STK})^{1/2}] \quad (16)$$

$$w_t^{SAF} = 1 - w_t^{STK} \quad (17)$$

where w_t^{STK} and w_t^{SAF} represent the weight given to stock (STK) and safe-haven asset position (SAF), respectively. h_t^{STK} and h_t^{SAF} denote the conditional variances of STK and SAF respectively, and ρ_t is the correlation between them.

Given the weights, we then calculate the return of the stock-safe haven asset portfolio at time t (r_t^{POT}):

$$r_t^{POT} = w_t^{STK} \cdot r_t^{STK} + w_t^{SAF} \cdot r_t^{SAF} \quad (18)$$

Next, we calculate the STK-SAF portfolio's return mean and volatility over the testing period to examine whether the state-varying bivariate SWARCH model outperforms the time-varying bivariate GARCH-CCC and -DCC models.

First, we compare the performance of different models using the bivariable GARCH-CCC model as a benchmark. We examine the four portfolios consisting of S&P500 and safe-haven assets and present the results in Table 9, in which Panels A and B show portfolio mean return and volatility, respectively. As shown in Table 9, comparing with the bivariate GARCH-CCC and -DCC models, the bivariate SWARCH model produces portfolios of stock and safe-haven assets with higher mean returns and lower return volatilities. Moreover, the return and volatility differences between the bivariate SWARCH model and the bivariate GARCH-CCC model are significant at the 1% level for most cases, except for the return mean of the S&P500-TBond portfolio. Table 10 presents the results of the portfolios consisting of FTSE100 and four safe-haven assets. Similarly, the portfolios constructed by the bivariate SWARCH model have higher return means and lower return volatilities comparing with the bivariate GARCH-CCC and -DCC models. The differences in volatilities between the bivariate SWARCH model and the bivariate GARCH-CCC model are significant at the

1% level for all cases. In short, the state-varying volatilities and correlations in our proposed bivariate SWARCH model enhance the performance of stock-safe haven asset portfolios constructed.

Next, we compare the differences in performances among various stock-safe haven portfolios. As shown in Panel B of Table 9, given the model, i.e., bivariate SWARCH model, the return volatilities of S&P500-TBond and S&P500-CHF portfolios (0.1676 and 0.2363) are lower than those of S&P500-Gold and S&P500-BTC (0.5511 and 0.9669). These results echo our four-state correlation system presented earlier. Recall the results in Table 6, the correlations under the HV-HV state (i.e., $\rho_{2,2}$) for S&P500-TBond and S&P500-CHF pairs are negative and significant (-0.2618 with *p-value* < 0.01 and -0.1317 with *p-value* < 0.01), while the same statistic for S&P500-Gold pair is positive but insignificant (0.0345 with *p-value* > 0.05) and the estimate of $\rho_{2,2}$ for S&P500-BTC pair is positive and significant (0.2173 with *p-value* <0.01). Overall, this is consistent with our notion that T-Bond and CHF are better safe-havens than gold, while Bitcoin, at best, is a partial-safe haven asset. While gold is the most legendary safe-haven asset and its safe-haven characteristics during the previous crises such as the 1987 stock market crash and the 2008 Global Financial Crisis have been well documented in the literature (see Baur and McDermott, 2010), recent experiences cast doubt on its credibility. Gold prices reached a historical high of $1898.25 on September 5, 2011, but lost their peak value by 45% by December 17, 2015. Over four years, the 45% value depreciation causes investors to lose trust in gold and question its effectiveness as a safe-haven asset (The Business Times, 2021).[3] Our empirical results resonate with this concern. Lastly, as shown in Panel A of Table 9, the mean returns of S&P500-BTC and S&P500-Gold portfolios (0.0609 and 0.0435) are higher than those of S&P500-TBond and S&P500-CHF portfolios (0.0090 and 0.0121). This result is consistent with the risk-return

[3] See https://www.businesstimes.com.sg/companies-markets/recent-events-prove-gold-is-no-longer-a-safe-haven: Recent events prove gold is no longer a safe haven by Neil Behrmann.

trade-off principle. In Table 10, similar findings apply to the portfolios consisting of FTSE100 and safe-have assets.

6. Conclusion

In this paper, we examine the dynamic conditional correlations between stocks (S&P500 and FTSE100) and safe-have assets (gold, U.S. government bond, Swiss Franc and Bitcoin). Our contributions to the literature are in three facades. First, we provide theoretical grounds to address the difference between partial-safe haven assets and full-safe haven assets, which is overlooked by the extant literature. Second, we develop a bivariate SWARCH model with four-state volatility combinations and employ the realized data to test the model empirically. Last but not least, we conduct portfolio construction, a practical test, to validate our proposed regime-switching approach.

Based on the two discrete volatility regimes (HV versus LV) for each position in the stock-safe haven asset portfolios, we develop a novel system with four volatility regime combinations (i.e., LV-LV, HV-LV, LV-HV, and HV-HV) and examine the dynamic conditional correlations under these volatility regimes. While existing studies have tested the dynamic conditional correlations in the stock-safe haven asset markets (the majority of the studies use the conventional DCC models), to the best of our knowledge, they have neither explicitly addressed the correlation dynamics under various volatility regimes, nor developed a theoretical foundation to explain the dynamic correlations. This study fills these gaps in the literature and offers several contributions, including developing a theoretical hypothesis, constructing a specific econometric method, and conducting two practical risk management tests. Our hypothesis and tests are meaningful and bring the statistical estimation results closer to practices.

Our empirical results are consistent with the following notions. First, the correlations between the three traditional safe-haven assets (gold, U.S. Treasury bond, and Swiss Franc) and the two stock markets (S&P500 and FTSE100) are significantly negative or zero under all volatility states, including the most strict HV-HV state (i.e., both stock and safe-haven asset markets experience high volatility). These results imply that gold, U.S. Treasury bonds, and Swiss Franc are full-safe haven assets. Second, the correlations between Bitcoin and the two major stock markets are positive and significant in the HV-HV state, although insignificant or negative in other volatility states. Our results imply that contagion occurs between stocks and Bitcoin markets when both of them experience chaotic conditions, rendering Bitcoin a less than a full-safe haven asset. Third, the regime-switching model proposed in this study proves to be more effective than the conventional GARCH-based models in portfolio construction. Fourth, comparing three traditional safe-haven assets, our results indicate that U.S. Treasury bonds and Swiss Franc are stronger safe havens than gold, which echos the press opinions, including Russ Koesterich of the BlackRock Global Allocation Fund, that gold's role as a safe haven has been exaggerated and waned.[4]

[4] For example, MacDonald and Shumsky, Wall Street Journal: https://www.wsj.com/articles/golds-role-as-safe-haven-investment-wanes-1445250762.

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Table 1. Descriptive statistics

Panel A: Basic statistic of individual return on stock indexes and safe haven assets

	S&P500	FTSE100	Gold	T-Bond	CHF	BTC
Mean	0.0432	0.0011	0.0099	0.0010	0.0021	0.2667
SD.	1.0740	1.0169	0.9069	0.2037	0.2892	4.9603
Q1	-0.3016	-0.4546	-0.4400	-0.1133	-0.1534	-1.4798
Medium	0.0394	0.0189	0.0127	0.0000	-0.0012	0.1950
Q3	0.4973	0.4878	0.4782	0.1145	0.1617	2.1883
Skewness	-1.0759	-0.9177	-0.1350	0.1872	-0.2459	-0.0533
Kurtosis	26.3658	17.5786	7.4216	12.3537	6.9277	16.5488

Panel B: Correlation matrix

	S&P500	FTSE100	Gold	T-Bond	CHF	BTC
S&P500	1.0000					
FTSE100	0.5922***	1.0000				
Gold	0.0048	-0.0396	1.0000			
T-Bond	-0.4116***	-0.2933***	0.2498***	1.0000		
CHF	-0.1288***	-0.2196***	0.1609***	0.1296***	1.0000	
BTC	0.1109***	0.0914***	0.0610***	-0.0144	-0.0067	1.0000

Notes: This table reports the basic statistics (Panel A) and correlation matrix (Panel B) for the two stock indexes (S&P500 and FTSE100) and the four safe-haven assets (Gold, T-Bond, Swiss France, and Bitcoin). The testing period ranges from April 30, 2003, to January 18, 2021 (2,015 daily observations). To ensure that the data are stationary, return series are used rather than the price level series. The data are collected from the DataStream database except for Swiss France and Bitcoin. In addition, we obtain the data of the Swiss Franc index from the online database of the Swiss National Bank and the data of Bitcoin is obtained with https://coinmarketcap.com/.

Table 2. Bivariate GARCH-CCC model: S&P 500 and safe-haven assets

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
S&P500 equation				
μ^{STK}	0.0881 (0.0147)***	0.0832 (0.0147)***	0.0899 (0.0146)***	0.0876 (0.0180)***
φ^{STK}	-0.0537 (0.0314)*	-0.0420 (0.0240)*	-0.0822 (0.0252)***	-0.0555 (0.0352)
ω^{STK}	0.0413 (0.0061)***	0.0454 (0.0064)***	0.0414 (0.0060)***	0.0421 (0.0064)***
α^{STK}	0.2245 (0.0243)***	0.2037 (0.0225)***	0.2213 (0.0240)***	0.2254 (0.0246)***
β^{STK}	0.7391 (0.0225)***	0.7458 (0.0225)***	0.7413 (0.0223)***	0.7369 (0.0236)***
Safe haven asset equation				
μ^{SAF}	-0.0034 (0.0325)	-0.0042 (0.0040)	-0.0015 (0.0058)	0.1951 (0.0921)***
φ^{SAF}	-0.0044 (0.0178)	-0.0317 (0.0227)	0.0249 (0.0279)	0.0070 (0.0484)
ω^{SAF}	0.0127 (0.0044)***	0.0051 (0.0011)***	0.0109 (0.0024)***	1.2642 (0.2299)***
α^{SAF}	0.0642 (0.0080)***	0.1009 (0.0171)***	0.1221 (0.0186)***	0.1582 (0.0198)***
β^{SAF}	0.9247 (0.0101)***	0.7582 (0.0433)***	0.7470 (0.0404)***	0.8086 (0.0214)***
Correlation				
ρ	-0.0881 (0.0240)***	-0.3534 (0.0196)***	-0.1451 (0.0223)***	0.0190 (0.0474)
Lik.	-4884.86	-1664.78	-2582.02	-8175.44

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 3. Bivariate GARCH-CCC model: FTSE 100 and safe-haven assets

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
FTSE100 equation				
μ^{STK}	0.0295 (0.0173)*	0.0287 (0.0167)*	0.0284 (0.0175)	0.0286 (0.0153)*
φ^{STK}	0.0200 (0.0242)	0.0207 (0.0266)	-0.0111 (0.0349)	0.0168 (0.0209)
ω^{STK}	0.0461 (0.0078)***	0.0465 (0.0081)***	0.0448 (0.0074)***	0.0467 (0.0078)***
α^{STK}	0.1524 (0.0192)***	0.1419 (0.0185)***	0.1428 (0.0180)***	0.1546 (0.0194)***
β^{STK}	0.7981 (0.0222)***	0.8055 (0.0227)***	0.8075 (0.0210)***	0.7954 (0.0222)***
Safe-haven asset equation				
μ^{SAF}	-0.0018 (0.0283)	-0.0029 (0.0040)	-0.0009 (0.0060)	0.1960 (0.0856)***
φ^{SAF}	-0.0043 (0.0282)	-0.0504 (0.0244)*	0.0216 (0.0331)	0.0071 (0.0037)*
ω^{SAF}	0.0122 (0.0042)***	0.0051 (0.0012)***	0.0110 (0.0025)***	1.2647 (0.2178)***
α^{SAF}	0.0639 (0.0079)***	0.1042 (0.0181)***	0.1218 (0.0194)***	0.1585 (0.0198)***
β^{SAF}	0.9257 (0.0096)***	0.7541 (0.0454)***	0.7468 (0.0428)***	0.8084 (0.0208)***
Correlation				
ρ	-0.0986 (0.0225)***	-0.2718 (0.0208)***	-0.2042 (0.0217)***	0.0295 (0.0136)**
Lik.	-5054.10	-1891.97	-2732.11	-8346.17

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 4. Bivariate GARCH-DCC model: S&P 500 and safe-haven assets

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
S&P500 equation				
μ^{STK}	0.0890 (0.0146)***	0.0923 (0.0145)***	0.0913 (0.0147)***	0.0876 (0.0148)
φ^{STK}	-0.0581 (0.0254)**	-0.0447 (0.0237)*	-0.0907 (0.0254)***	-0.0595 (0.0261)**
ω^{STK}	0.0413 (0.0061)***	0.0431 (0.0062)***	0.0416 (0.0061)***	0.0422 (0.0062)***
α^{STK}	0.2260 (0.0246)***	0.2223 (0.0236)***	0.2214 (0.0243)***	0.2210 (0.0247)***
β^{STK}	0.7373 (0.0228)***	0.7347 (0.0224)***	0.7402 (0.0227)***	0.7394 (0.0233)***
Safe-haven asset equation				
μ^{SAF}	0.0012 (0.0114)	-0.0035 (0.0038)	-0.0003 (0.0057)	0.1806 (0.0917)**
φ^{SAF}	-0.0164 (0.0221)	-0.0242 (0.0216)	0.0376 (0.0234)	0.0143 (0.0161)
ω^{SAF}	0.0056 (0.0023)***	0.0014 (0.0005)***	0.0024 (0.0008)***	1.2532 (0.2159)***
α^{SAF}	0.0387 (0.0069)***	0.0788 (0.0131)***	0.0589 (0.0113)***	0.1556 (0.0198)***
β^{SAF}	0.9554 (0.0079)***	0.8845 (0.0234)***	0.9117 (0.0193)***	0.8103 (0.0208)***
Time-varying correlations				
τ	-0.0057 (0.0051)	-0.0554 (0.0294)*	-0.0447 (0.0461)	0.0005 (0.0008)
π	0.9174 (0.0624)***	0.8041 (0.0883)***	0.6674 (0.3274)***	0.9656 (0.0146)***
λ	0.0130 (0.0076)*	0.0553 (0.0167)***	0.0274 (0.0169)	0.0162 (0.0059)***
Lik.	-4864.42	-1624.99	-2564.52	-8165.09

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 5. Bivariate GARCH-DCC model: FTSE 100 and safe-haven assets

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
FTSE100 equation				
μ^{STK}	0.0261 (0.0213)	0.0268 (0.0166)	0.0267 (0.0181)	0.0226 (0.0185)
φ^{STK}	0.0236 (0.0205)	0.0215 (0.0219)	-0.0107 (0.0226)	0.0195 (0.0429)
ω^{STK}	0.0329 (0.0094)***	0.0355 (0.0080)***	0.0329 (0.0073)***	0.0328 (0.0078)***
α^{STK}	0.1352 (0.0227)***	0.1335 (0.0189)***	0.1295 (0.0178)***	0.1323 (0.0193)***
β^{STK}	0.8300 (0.0293)***	0.8269 (0.0239)***	0.8347 (0.0218)***	0.8326 (0.0238)***
Save haven asset equation				
μ^{SAF}	0.0028 (0.1225)	-0.0024 (0.0039)	-0.0003 (0.0056)	0.1964 (0.0934)**
φ^{SAF}	-0.0144 (0.0925)	-0.0484 (0.0228)**	0.0300 (0.0271)	0.0101 (0.0162)
ω^{SAF}	0.0050 (0.0026)*	0.0014 (0.0005)***	0.0026 (0.0009)***	1.2525 (0.2180)***
α^{SAF}	0.0371 (0.0068)***	0.0690 (0.0126)***	0.0596 (0.0116)***	0.1553 (0.0200)***
β^{SAF}	0.9577 (0.0082)***	0.8907 (0.0242)***	0.9084 (0.0205)***	0.8106 (0.0210)***
Time-varying correlations				
τ	-0.0091 (0.0126)	-0.0226 (0.0176)	-0.0387 (0.0187)**	0.0015 (0.0017)
π	0.8901 (0.1220)***	0.9007 (0.0719)***	0.7800 (0.0956)***	0.9349 (0.0384)***
λ	0.0149 (0.0097)	0.0136 (0.0080)*	0.0330 (0.0126)***	0.0180 (0.0068)***
Lik.	-5026.83	-1870.11	-2707.20	-8333.94

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 6. Bivariate SWARCH model with state-dependent correlations: S&P 500 and safe-haven assets

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
S&P500 equation				
p_{11}^{STK}	0.9728 (0.0064)***	0.9744 (0.0070)***	0.9744 (0.0060)***	0.9743 (0.0058)***
p_{22}^{STK}	0.9411 (0.0129)***	0.9431 (0.0131)***	0.9428 (0.0126)***	0.9424 (0.0125)***
μ^{STK}	0.1039 (0.0141)***	0.0983 (0.0143)***	0.1057 (0.0142)***	0.1044 (0.0149)***
φ^{STK}	-0.0694 (0.0258)***	-0.0550 (0.0257)**	-0.0969 (0.0272)***	-0.0690 (0.0293)***
ω^{STK}	0.2165 (0.0165)***	0.2275 (0.0212)***	0.2228 (0.0155)***	0.2225 (0.0161)***
α^{STK}	0.2066 (0.0355)***	0.1917 (0.0353)***	0.1970 (0.0343)***	0.1881 (0.0341)***
g_2^{STK}	8.8615 (0.7729)#	8.0573 (0.6734) #	8.8447 (0.7698) #	9.0750 (0.7832) #
Save-haven asset equation				
p_{11}^{SAF}	0.6457 (0.0562)***	0.9795 (0.0087)***	0.9549 (0.0137)***	0.8352 (0.0280)***
p_{22}^{SAF}	0.1125 (0.0617)*	0.7647 (0.0639)***	0.8902 (0.0382)***	0.7426 (0.0455)***
μ^{SAF}	0.0228 (0.0182)	0.0005 (0.0039)	-0.0005 (0.0057)	0.2618 (0.0625)***
φ^{SAF}	-0.0206 (0.0224)	-0.0410 (0.0222)*	0.0328 (0.0247)	-0.0398 (0.0245)
ω^{SAF}	0.2776 (0.0272)***	0.0258 (0.0015)***	0.0384 (0.0029)***	3.3595 (0.3749)***
α^{SAF}	0.1399 (0.0441)***	0.0864 (0.0275)***	0.0510 (0.0277)*	0.0424 (0.0341)
g_2^{SAF}	6.3906 (0.5559)#	5.9373 (1.3600) #	4.5987 (0.4786) #	16.1550 (1.5565) #
State-varying correlations				
$\rho_{1,1}$	-0.0995 (0.0499)**	-0.3297 (0.0512)***	-0.1218 (0.0397)***	-0.0234 (0.0462)
$\rho_{2,1}$	-0.1318 (0.0662)**	-0.5379 (0.0390)***	-0.1446 (0.0646)**	0.1543 (0.0727)**
$\rho_{1,2}$	0.0255 (0.0392)	-0.1021 (0.2683)	-0.1915 (0.0624)***	-0.0645 (0.0560)
$\rho_{2,2}$	0.0345 (0.0380)	-0.2618 (0.0674)***	-0.1317 (0.0559)***	0.2173 (0.0616)***
Lik.	-4845.38	-1664.91	-2534.55	-7955.22

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. # represents the estimate that significantly deviates from the value of one at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 7. Bivariate SWARCH model with state-dependent correlations: FTSE 100 and safe-haven assets

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
FTSE100 equation				
p_{11}^{STK}	0.9798 (0.0062)***	0.9824 (0.0055)***	0.9803 (0.0061)***	0.9842 (0.0054)***
p_{22}^{STK}	0.9327 (0.0185)***	0.9412 (0.0165)***	0.9326 (0.0182)***	0.9413 (0.0178)
μ^{STK}	0.0316 (0.0169)*	0.0320 (0.0159)**	0.0336 (0.0174)*	0.0310 (0.0151)**
φ^{STK}	0.0299 (0.0385)	0.0236 (0.0261)	-0.0114 (0.0182)	0.0218 (0.0196)
ω^{STK}	0.3356 (0.0227)***	0.3365 (0.0219)***	0.3433 (0.0229)***	0.3609 (0.0236)***
α^{STK}	0.1914 (0.0392)***	0.2135 (0.0361)***	0.1722 (0.0364)***	0.1594 (0.0379)***
g_2^{STK}	7.0646 (0.7061) #	6.4071 (0.6038) #	7.1551 (0.7005) #	7.3665 (0.7550) #
Safe-haven asset equation				
p_{11}^{SAF}	0.6311 (0.0636)***	0.9898 (0.0051)***	0.9556 (0.0145)***	0.8272 (0.0298)***
p_{22}^{SAF}	0.1133 (0.0568)**	0.7853 (0.0811)***	0.8932 (0.0422)***	0.7317 (0.0463)***
μ^{SAF}	0.0236 (0.0243)	0.0014 (0.0039)	-0.0006 (0.0056)	0.2571 (0.0607)***
φ^{SAF}	-0.0210 (0.0183)	-0.0562 (0.0231)***	0.0294 (0.0259)	-0.0397 (0.0177)**
ω^{SAF}	0.2677 (0.0272)***	0.0273 (0.0016)***	0.0387 (0.0031)***	3.2670 (0.3882)***
α^{SAF}	0.1546 (0.0446)***	0.0794 (0.0271)***	0.0527 (0.028)*	0.0511 (0.0358)
g_2^{SAF}	6.4284 (0.5789) #	8.7631 (2.9290) #	4.4594 (0.4841) #	16.3942 (1.6408) #
State-varying correlations				
$\rho_{1,1}$	-0.1271 (0.0436)***	-0.2098 (0.0309)***	-0.1773 (0.0408)***	0.0193 (0.0193)
$\rho_{2,1}$	-0.1610 (0.0773)***	-0.4841 (0.0512)***	-0.2827 (0.0886)***	0.1093 (0.0672)
$\rho_{1,2}$	-0.0142 (0.0284)	-0.1672 (0.1911)	-0.1078 (0.0604)*	-0.0636 (0.0384)*
$\rho_{2,2}$	-0.0418 (0.0865)	-0.1863 (0.0885)**	-0.3389 (0.0720)***	0.3324 (0.0740)***
Lik.	-4998.78	-1879.83	-2670.32	-8111.76

Notes: * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. # represents the estimate that significantly deviates from the value of one at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 8. Percentage of various volatility states

Panel A: S&P 500 and safe-haven assets

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
LV-LV	60.47%	68.37%	56.64%	49.08%
HV-LV	24.17%	27.40%	20.44%	20.59%
LV-HV	9.55%	1.19%	13.48%	21.43%
HV-HV	9.55%	3.03%	9.45%	8.90%
Total	100%	100%	100%	100%

Panel B: FTSE 100 and safe-haven assets

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
LV-LV	67.93%	77.97%	63.60%	55.64%
HV-LV	16.11%	19.19%	12.68%	14.32%
LV-HV	10.79%	0.90%	15.51%	24.96%
HV-HV	5.17%	1.94%	8.20%	5.07%
Total	100%	100%	100%	100%

Notes: One key feature of the bivariate SWARCH model employed in this study is to provide the estimated probabilities of a specific state for each time point (Please refer to Figure 3 for the S&P500-Gold portfolio example). We use these estimated probabilities and a maximum value criterion to define the volatility state. For example, if the estimated probability of the "HV-HV" state is higher than that of the other three states, we identify this time point as an "HV-HV" state.

Table 9. Performance of portfolio construction: S&P500 and safe-haven assets

Panel A: Portfolio mean return

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
Bivariate GARCH-CCC	0.0301	0.0054	0.0068	0.0391
Bivariate GARCH-DCC	0.0297	0.0060	0.0066	0.0364
	(-0.4680)	(0.9893)	(-0.4364)	(-1.1446)
Bivariate SWARCH	0.0435	0.0090	0.0121	0.0609
	(2.6375)***	(4.4458)***	(3.6147)***	(2.1735)**

Panel B: Portfolio return volatility

	S&P500-Gold	S&P500-TBond	S&P500-CHF	S&P500-BTC
Bivariate GARCH-CCC	0.6089	0.1717	0.2545	1.1594
Bivariate GARCH-DCC	0.6064	0.1690	0.2549	1.1573
	(-1.4316)	-1.4823	0.5220	-0.1939
Bivariate SWARCH	0.5511	0.1676	0.2363	0.9669
	(-4.8909)***	(-1.5399)	(-6.7247)***	(-1.7805)*

Notes: This table examines the performance of portfolio construction via various models, including the time-varying bivariate GARCH-CCC and bivariate GARCH-DCC models, as well as the state-varying bivariate SWARCH model. Two performance measures are portfolio return mean (see Panel A) and portfolio return volatility (see Panel B). Two stock indexes (S&P500 and FTSE100) and four safe-haven assets (Gold, T-Bond, CHF, and BTC) are employed to develop eight (2 X 4) portfolios for the empirical tests. We use the bivariate GARCH-CCC model as a benchmark to calculate the statistics for the difference across various models. * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

Table 10. Performance of portfolio construction: FTSE100 and safe-have assets

Panel A: Portfolio mean return

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
Bivariate GARCH-CCC	0.0071	-0.0006	0.0004	0.0065
Bivariate GARCH-DCC	0.0066	-0.0006	-0.0002	0.0062
	(-0.4751)	(-0.1512)	(-1.3402)	(-0.1321)
Bivariate SWARCH	0.0128	-0.0004	0.0017	0.0286
	(1.1049)	(0.2650)	(1.0695)	(2.6299)***

Panel B: Portfolio return volatility

	FTSE100-Gold	FTSE100-TBond	FTSE100-CHF	FTSE100-BTC
Bivariate GARCH-CCC	0.6249	0.1829	0.2510	1.0551
Bivariate GARCH-DCC	0.6215	0.1825	0.2518	1.0369
	(-1.2480)	-0.4013	0.9899	-0.8329
Bivariate SWARCH	0.5521	0.1758	0.2349	0.8979
	(-8.8161)***	(-3.1571)***	(-8.4714)***	(-2.5436)***

Notes: This table examines the performance of portfolio construction via various models, including the time-varying bivariate GARCH-CCC and bivariate GARCH-DCC models, as well as the state-varying bivariate SWARCH model. Two performance measures are portfolio return mean (see Panel A) and portfolio return volatility (see Panel B). Two stock indexes (S&P500 and FTSE100) and four safe-haven assets (Gold, T-Bond, CHF, and BTC) are employed to develop eight (2 X 4) portfolios for the empirical tests. We use the bivariate GARCH-CCC model as a benchmark to calculate the statistics for the difference across various models. * denotes significance at the 5% level, ** denotes significance at the 2.5% level, and *** denotes significance at the 1% level. For sample descriptions and data sources, please refer to Table 1.

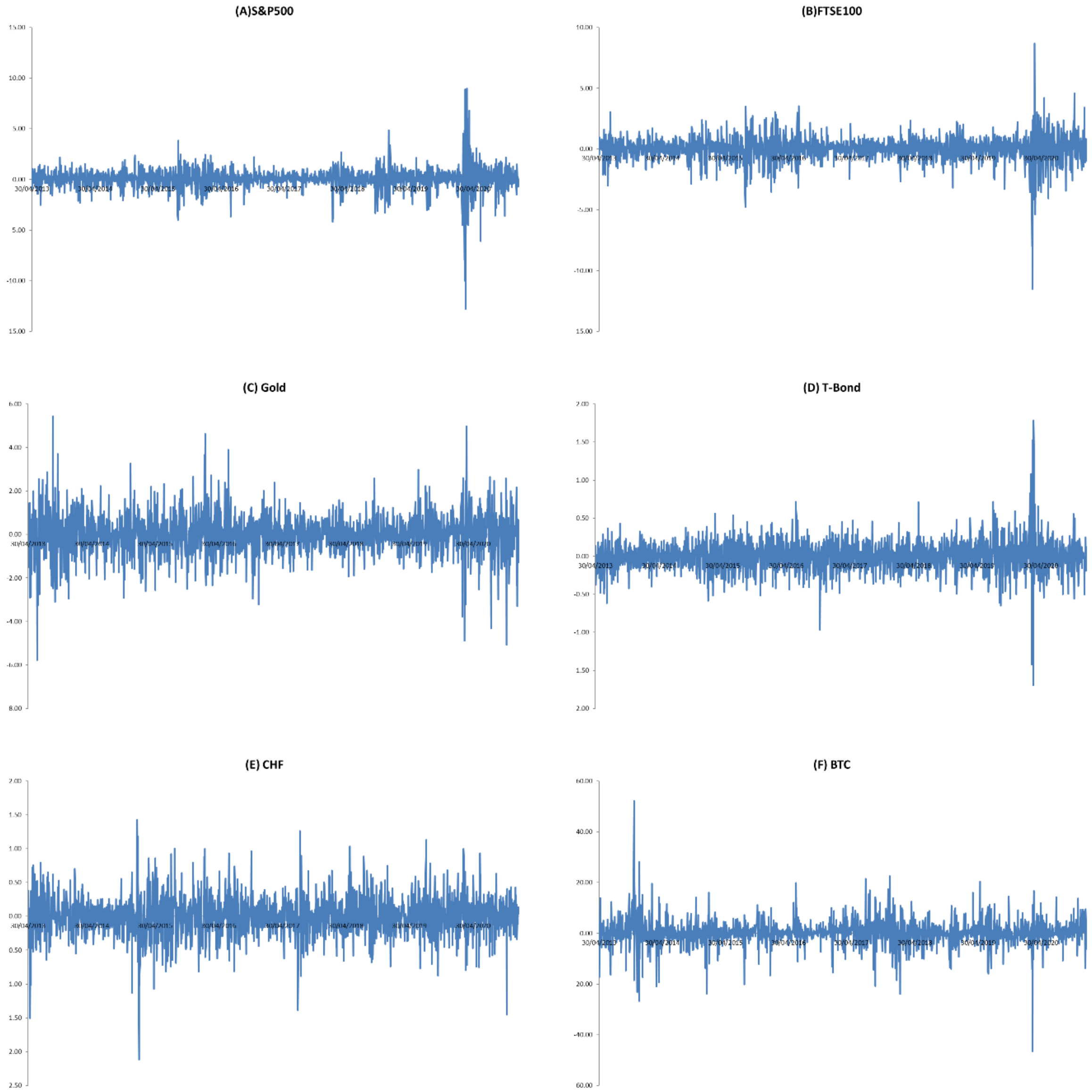

Figure 1 Return rates on a stock index and safe-haven assets

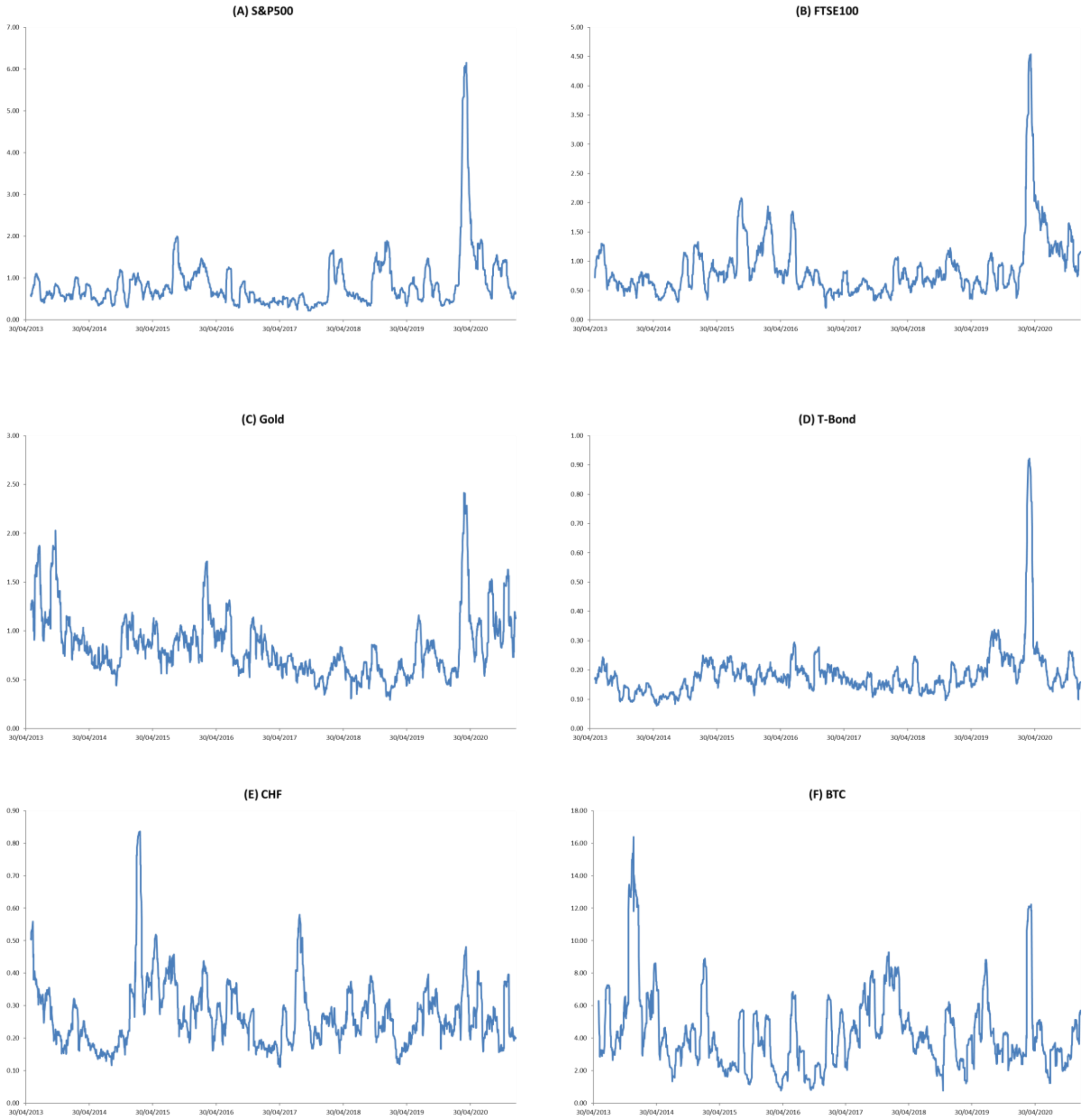

Figure 2 Volatility of return rates on a stock index and safe-haven assets

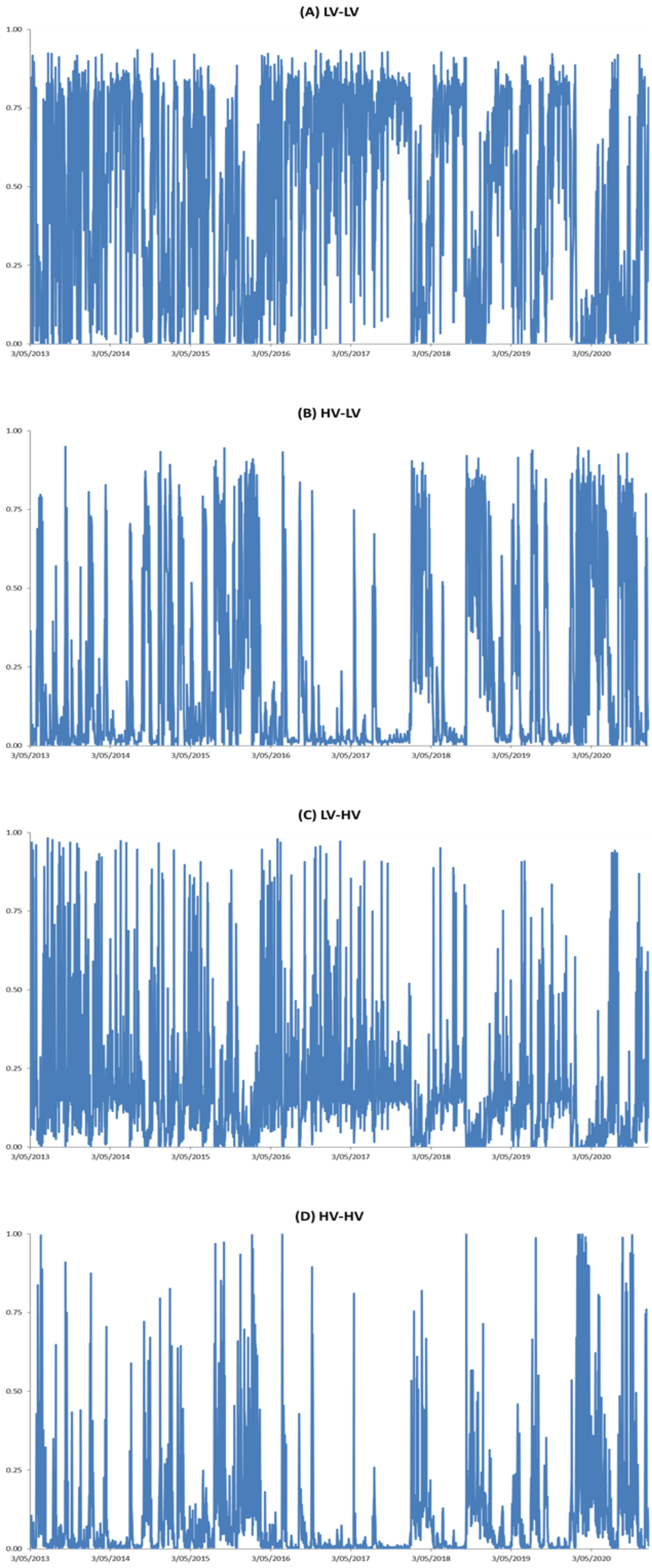

Figure 3 Probabilities of various volatility state combinations: S&P500-Gold portfolio

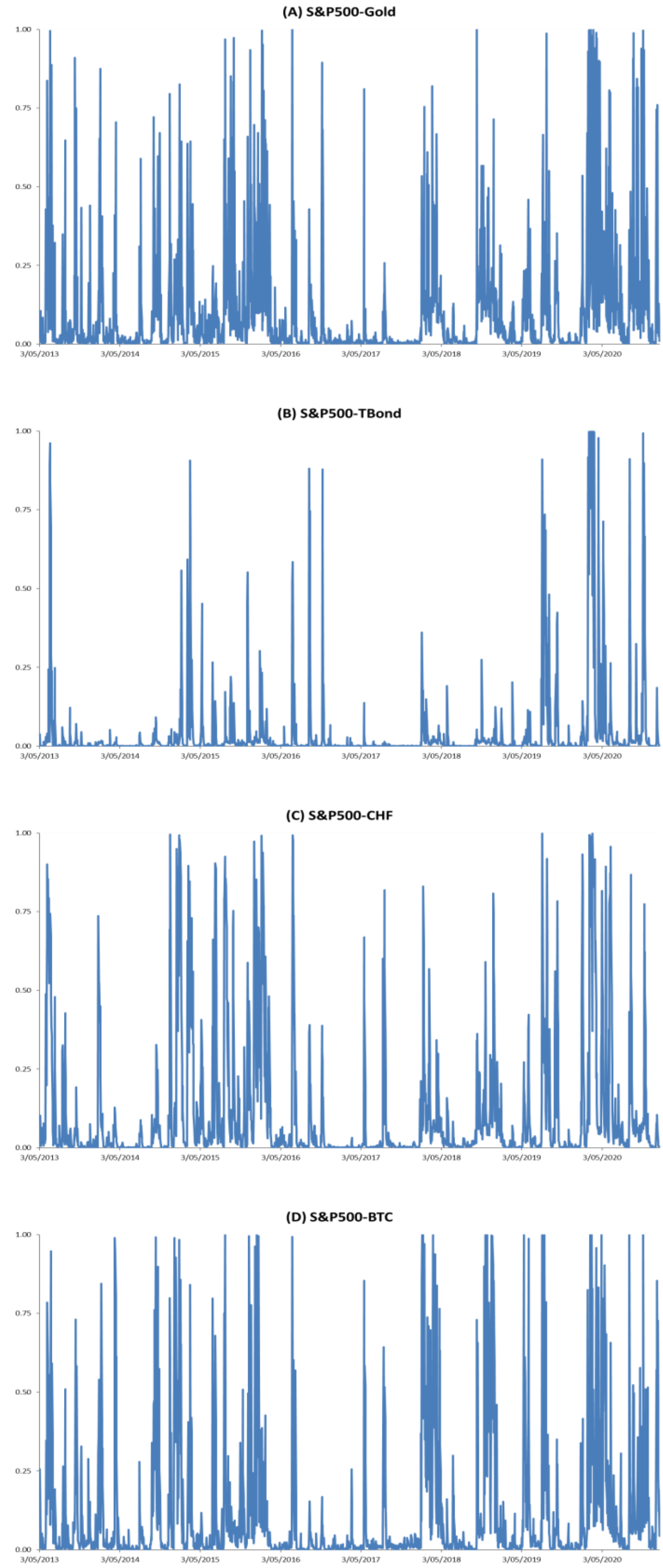

Figure 4 The HV-HV state probabilities: S&P500 and safe-haven asset portfolios