A Safe Haven Index*

Dirk G. Baur†[1] and Thomas Dimpfl[2]

[1]University of Western Australia
[2]University of Hohenheim

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Abstract

There are several assets that are frequently labelled a safe haven, in particular gold, and, more recently, Bitcoin. This paper proposes a safe haven index to benchmark safe haven assets and identify some stylized facts. The analysis shows that (i) safe haven assets are risky despite their "safe" label, (ii) the crisis-specific riskiness is a necessary condition to function as a strong safe haven, and (iii) safe haven asset risk can be diversified. An analysis of the COVID-19 shock in March 2020 reveals that the safe haven index briefly fell with the market contrasting previous crises over the last years.

Keywords: safe haven, volatility, gold, government bonds, Bitcoin, COVID-19, safe assets

JEL: C43, G01, G11, G12, G15

*The Safe Haven Index is available for download from https://datascience.uni-hohenheim.de/en/applications.

†Corresponding author. UWA Business School, The University of Western Australia, 35 Stirling Highway, Crawley WA 6009, Australia, e-mail: *dirk.baur@uwa.edu.au*

1 Introduction

An index is an efficient way to communicate the state and evolution of a market and is useful as a benchmark. In fact, there are indices for a broad range of assets including stocks, bonds, commodities, cryptocurrencies, and even volatility, but there is no safe haven index. Indeed, one may wonder why there are indices for almost everything but not one safe haven index. Of course, there is only a handful of safe haven assets and it is relatively easy to follow them individually. However, there is no single safe haven asset benchmark and thus no "stylized facts" of safe haven assets. In this paper, we provide such stylized facts, e.g., that safe haven assets are volatile and risky in both normal periods and in crisis periods. We demonstrate that a safe haven index can substantially enhance our understanding of safe haven assets, in particular to identify similarities and distinctive features of such assets. The index can also reveal which safe haven asset is best in terms of its raw return and which safe haven asset is best in terms of its risk-adjusted return. More specifically we ask whether gold is the best safe haven asset, or rather U.S. Treasuries or the Swiss franc.

We also analyze whether a portfolio of safe haven assets represented by the index outperforms single (one-asset) safe haven portfolios in normal periods and in crisis periods. This setting further allows a test whether Markowitz' "free lunch of diversification" also holds in crisis periods for a specific set of assets.[1]

Among those assets which are regularly cited as safe haven assets are gold, U.S. government bonds, German government bonds, the Swiss franc and the Japanese yen. Whether they share common safe haven features is an open question we aim to answer in this article. In addition, there are further assets such as silver, the euro, and even Bitcoin which are not (as) regularly regarded as safe haven assets, but share some features of the former and, thus, may also be safe haven assets. We also analyze the exposure of large technology stocks, the so-called FANGs – Facebook, Amazon, Netflix and Google –, motivated by recent articles in the financial media that they act as safe havens.[2]

[1] https://www.barrons.com/articles/the-importance-of-diversification-51552738215

[2] FANGs have recently been labelled "safe havens" (Plender, FT 2020, www.ft.com/content/6f79044a-3615-11ea-a6d3-9a26f8c3cba4) and "safe haven plays" (e.g., see www.bloombergquint.com/technology/for-the-other-fangs-it-s-like-apple-s-warning-never-happened).

The empirical safe haven literature dates back to articles by Kaul and Sapp (2006) for government bonds, Baur and Lucey (2010) and Baur and McDermott (2010) for gold, and Ranaldo and Söderlind (2010) for currencies.[3] Despite the fact that safe haven events are linked to flights to quality or safety, studies on flight to quality appear largely disconnected from the safe haven literature. Examples of articles on flight to quality from stocks to bonds are Gulko (2002), Connolly, Stivers, and Sun (2005), Baur and Lucey (2009), Adrian, Crump, and Vogt (2019) and Baele, Bekaert, Inghelbrecht, and Wei (2019). While safe haven assets are, obviously, related to safe assets, the safe asset literature (e.g., Caballero and Simsek, 2013; Caballero, Farhi, and Gourinchas, 2017; Gorton, 2016; Gorton and Ordoñez, 2020; He, Krishnamurthy, and Milbradt, 2016) does generally not discuss safe haven assets and also appears to be segmented from the safe haven literature.

The difference between safe haven assets and safe assets is potentially rooted in their risk exposure or volatility. However, the volatility or risk of safe haven assets is rarely analyzed; notable exceptions are Baur (2012) and Piffer and Podstawski (2018). More recently, some authors search for safe haven assets among commodities and real estate (e.g., Chan, Treepongkaruna, Brooks, and Gray, 2011; Ciner, Gurdgiev, and Lucey, 2013; Creti, Joëts, and Mignon, 2013) and focus on the role of safe haven assets during the COVID-19 pandemic (e.g., Akhtaruzzaman, Boubaker, Lucey, and Sensoy, 2020; Cheema and Szulczuk, 2020; Conlon and McGee, 2020; Corbet, Hou, Hu, Larkin, and Oxley, 2020; Ji, Zhang, and Zhao, 2020).

Our basic safe haven index is comprised of seven assets – gold, the Swiss franc, the Japanese yen, U.S. 2-year, 10-year and 30-year and German 10-year government bonds – and reflects the average price reaction of safe haven assets in normal and in crisis times. The choice of these particular index constituents is motivated by prior literature which identifies (usually only one of) these assets as safe haven assets. Since there are no studies that systematically analyze a large set of safe haven assets, we perform such an analysis and propose a safe haven index to benchmark actual and potential safe haven assets against this index. The index is designed as an unweighted performance index to mitigate issues of different asset classes of its constituents and different currencies in which these assets are traded.

In line with other indices, it can be used as a benchmark to investigate the relative performance

[3] Erb and Harvey (2013) also discuss the safe haven feature of gold in their broader analysis of gold prices.

of an asset compared to the index (alpha) and its co-movement with the index (beta). The results reveal substantial differences in betas with high betas for gold and relatively low betas for 2-year U.S. Treasuries, for example. The index further shows that safe haven assets exhibit the strongest increase in volatility in crises relative to normal periods leading to an inverted volatility asymmetry.

The use of our proposed safe haven index as a benchmark is also highlighted when applied to Bitcoin. The results show that Bitcoin is not a safe haven. The high excess returns represented by alpha suggest that Bitcoin often appears to be a safe haven because of its large positive returns and performance since its inception, but less so because of its beta, showing no synchronicity with other safe haven assets.

The finding that safe haven assets are risky may be surprising given their "safe" labels, but the riskiness is a necessary condition for an asset to act as a safe haven: A price increase in reaction to a safe haven event or extreme shock is followed by a price decrease once the shock dissipates. If the price did not go up and did not fall afterwards (resulting in increased volatility) the safe haven asset would not function as a safe haven asset.

Finally, the COVID-19 pandemic presents a very recent case of a safe haven event. It provides the unique finding that some safe haven assets did not perform as in previous major crisis periods, but were pulled down by the market and lost some of their value at the beginning of the crisis. This may be surprising but also lends to the possibility that safe haven assets were used to cover losses and to obtain cash illustrating the benefits of holding safe haven assets as an insurance in contrast to a flight to quality which implies the buying of safe haven assets in reaction to a large shock.

The paper is structured as follows: Section 2 introduces the Safe Haven Index (SHI), followed by an analysis of typical features of safe haven assets based on the SHI as a benchmark in Section 3. Section 4 investigates the volatility of the SHI and its components in crisis periods and in normal times with GARCH and Quantile Autoregressive models. Section 5 summarizes the main results and provides concluding remarks.

2 The Safe Haven Index

To enhance our understanding of typical safe haven properties of individual assets we use a benchmark. While gold is often identified as a safe haven asset, it is not the only safe haven asset that exists. There are many more safe haven assets such as U.S. government bonds, the U.S. dollar, or the Swiss franc. An index combines features of different asset types and allows to compare all assets, including gold, with the index, similar to the comparison of individual stocks to a market-based index. We therefore compose an index based on a basket of typical safe haven assets merging information contained in multiple assets into a single time series, thus, reducing the necessary dimensionality of the analysis (cp. Carreira-Perpiñán, 1997). As a consequence, the index is expected to be less noisy, less volatile, and less prone to outliers than individual safe haven asset time series (Velliangiri, Alagumuthukrishnan, and Joseph, 2019). This feature may be useful to identify and distill stylized facts of safe haven assets.

We conceive our safe haven index (SHI) as a performance index, reflecting the average price development of a basket of n safe haven assets. Denote by $R_{i,t}$ the logarithmic return of the i-th asset in the basket from $t-1$ to t based on daily closing prices of the asset, then the equally weighted return of the basket R_t^b is

$$R_t^b = \frac{1}{n}\sum_{i=1}^{n} R_{i,t}. \tag{1}$$

The SHI is then defined using the basket return in Equation (1) and an initial value of $SHI_0 = 100$ as

$$SHI_t = \exp\left(\ln(SHI_{t-1}) + R_t^b\right). \tag{2}$$

Our safe haven index is comprised of seven assets which have been identified in the literature as safe haven assets: gold (see Baur and Lucey, 2010; Reboredo, 2013), the Swiss franc, the Japanese yen (Grisse and Nitschka, 2015; Ranaldo and Söderlind, 2010), U.S. 2-year, 10-year and 30-year and German 10-year government bonds (Hager, 2017; Liu, 2020). In contrast to stock market indices where each company receives a weighting based on market capitalization, we design the safe haven index as an equally weighted index. The SHI comprises assets from different asset classes which are not directly comparable in terms of market capitalization. A stock market index comprises a homogeneous set of assets, namely stocks, while the safe haven index is composed of precious metals, currencies, and government bonds. The weights for currencies, for example, would be disputable as it could be based on daily turnover or any of the definitions M1 to M4. To circumvent such issues the SHI is based on equally weighted returns of the basket assets.

To calculate the index, we obtain daily data from Thomson Reuters Datastream for the period January 1, 1985, until May 31, 2020. Figure 1 presents the index for this time period, together with the S&P 500 index. We highlight four key safe haven events in gray: the October 1987 stock price crash, the September 11, 2001 terrorist attacks, the Lehman collapse in September 2008 leading to the Global Financial Crisis (GFC), and the COVID-19 pandemic induced market crash in March 2020. There is a general tendency that the SHI goes up when the S&P 500 goes down. This holds in particular for the 9/11 terrorist attacks and around the Lehman crash, but also for the dot-com crisis at the beginning of the 2000s. In contrast, the 1987 stock market crash seems to have been so strong that the safe haven index turned negative as well. Similarly, the current COVID-19 pandemic, another truly global crisis, also led to a shock in the stock market and a slight downturn of the SHI. Still, the SHI has been on a substantial rise since the 2000s. At the beginning of the COVID-19 crisis, the index reached its highest value, higher than during previous crises and higher than during the European debt crisis which started in 2009. If safe haven assets were highly valued prior to the COVID-19 shock it would at least partially explain why safe assets performed differently in that crisis compared to most other crises.

[Figure 1 about here.]

Figure 2 presents the time series of log-returns of the index including grey vertical bars that highlight the key safe haven events. The graph shows that the volatility of the SHI increases during the safe haven events. Hence, a safe haven asset is a safe haven in terms of the returns of the asset, but not in terms of the risk which is prevalent in crisis periods.

[Figure 2 about here.]

Figure 3 zooms in on the safe haven events and shows how the SHI returns evolve during these periods. The plots show a relatively stable SHI compared with the evolution of the S&P500 over these periods, but also negative returns particularly in March 2020.

[Figure 3 about here.]

To further characterize the SHI, we calculate a few key statistics of the SHI log returns which are presented in Table 1. Compared to gold or the S&P 500, the SHI has a lower average return, but also a decisively lower standard deviation. The averaging of the returns of the basket assets (Equation (1)) takes away the extreme movements which are observed, for example, for gold with a minimum return of -10.16%. The low standard deviation coupled with the volatility clustering which becomes evident from Figure 2 suggests that in tranquil times, the volatility of the SHI is low and considerably lower than the volatility of a stock market index such as the S&P 500. This is what we expect from a safe haven asset: when there is no safe haven event, the asset's volatility is relatively low.

[Table 1 about here.]

3 Performance of the Safe Haven Index

This section analyzes the performance of the Safe Haven Index relative to its constituents, the market and other no-safe-haven assets. We first analyze the returns in normal periods and in crisis periods, assess the diversification benefits from the SHI and, in a third step, use the SHI as a benchmark against all other assets.

We expand the data in this section and include risky assets to better understand the relative performance of safe haven assets and the SHI against these no-safe-haven risky assets. The additional data used is also obtained from Thomson Reuters Datastream for the period January 1, 1985, until May 31, 2020. This yields 9,251 observations per asset if the data is available from 1985. For example, the data for Bitcoin are only available from August 2011 which reduces the number of observations to 2,304, making it the shortest time series in our sample. Similarly, the VIX, the FANG stocks, and the exchange rates are also not available for the entire period. For all time series, we calculate log-returns which are then tested for stationarity using an augmented Dickey-Fuller test. The null hypothesis of a unit root is always rejected.

3.1 Average and crisis-specific returns

Table 2 presents the crisis-specific returns for all assets, the SHI, and all constituents. The estimates are based on regressions of each asset's returns on a constant and four crisis dummy variables which cover the October 1987 stock price crash, the September 11, 2001 terrorist attacks, the Lehman collapse in September 2008 during the global financial crisis, and the COVID-19 pandemic which led to a market crisis in March 2020. We use October 15, 1987, September 11, 2011, September 15, 2008, and February 24, 2020, respectively as starting dates for the crisis periods. The following results are based on an assumed crisis length of 20 business days.[4]

[Table 2 about here.]

The estimates show that safe haven assets generally exhibit positive returns in a crisis period with some exceptions, particularly in the COVID-19 crisis. The average effect of safe haven assets as represented by the SHI is positive in all crisis periods. The positive returns in the COVID period appear to be driven by U.S. government bonds. The non-crisis estimates captured by the constant c are lower for safe haven assets and the constituents of the SHI than for the risky assets. This result is expected as safe haven assets cannot outperform risky assets in crisis periods and in normal times. If safe haven assets outperformed other assets in all periods or conditions, they would yield utopian returns.

3.2 Diversification opportunities

Investing in financial assets is risky, but some risk, the non-systematic part, can be diversified by holding a portfolio of assets. In the context of safe haven assets which are also risky, it is unclear whether a diversification strategy is useful as they are needed in crisis times only and a single safe haven asset might be sufficient. We therefore investigate whether holding the index portfolio of safe haven assets is better than holding only one safe haven asset like gold for example. To answer this question, we compare the returns, the volatility, and the return/risk ratio of the index with its constituents and other assets which are generally regarded as safe.

The results are summarized in Table 3. We differentiate the full sample results from the crisis

[4] We analyze variations of the crisis length in the Robustness section.

periods to highlight how diversification is particularly useful during such periods. The estimates show that the SHI has a higher return per unit of risk than the individual constituents with the exception of U.S. 2-year and 10-year government bonds. The return/risk ratio of the SHI is positive and larger during the crisis period than over the full sample period which is expected from a safe haven asset. In contrast, the ratio turns negative for most other assets during the crises. Bitcoin stands out with very high negative returns and high volatility in the crisis period, respectively. But even in the full sample, the volatility of Bitcoin is twice as high as the one of the FANG stocks, for example.

The full sample and crisis period mean and standard deviation comparisons highlight the uncertainty inherent in the market as a whole during crisis periods. The volatility of volatility, as expressed by the standard deviation of the VIX, also more than doubles during crises.

[Table 3 about here.]

3.3 Over- and Underperformance of Safe Haven Assets

With the proposed Safe Haven Index, we can now evaluate the performance of the composing assets as well as any other asset in terms of their safe haven ability. We draw on a CAPM-style regression and estimate the excess return α and the exposure to the index β. As our assets are safe haven assets, we do not subtract a risk-free rate as these assets should be what is considered risk-free in the CAPM context. The results are summarized in Table 4. A first observation is that the SHI and the S&P 500 are negatively related in terms of β which was to be expected. Also, the S&P 500 yields a higher return on investment during the entire sample period, indicated by the significant $\hat{\alpha}$. During a crisis period, the S&P 500's $\hat{\alpha}$ turns negative, albeit not statistically significant. The estimated β almost quadruples (to -2.255) , indicating that the safe haven assets in the index provide a safe haven in times of financial distress.

Considering the assets which are used to construct the index, we find that none of these exhibits a significant $\hat{\alpha}$ in any situation (with the exception of 2-year U.S. government bonds, but the estimate is economically negligible). In contrast, the βs are all statistically significant and vary considerably across the safe haven assets for the crisis period. For example, the U.S. dollar beta is negative, the U.S. 2-year Treasury beta is 0.237, whereas the 30-year Treasury beta is 2.246.

Shorter maturities have a lower beta than long maturities for both U.S. and German bonds. Gold's safe haven beta is 1.492 and closest to 10-year and 30-year government bonds. Silver, Bitcoin, oil and several exchange rates have insignificant crisis betas meaning that they do not move with the safe haven index. The VIX exhibits the strongest positive SHI beta (above 7) and the FANG stocks exhibit the strongest negative betas consistent with the SHI beta of the S&P500.

Assets which belong to the same asset class as the safe haven assets (but are not included in the SHI) are silver, exchange rates, and bonds. In general, these assets are positively related to the SHI. Only U.S. T-bills exhibit a significant α and thus excess returns. During the crisis, the average yield over the holding period is statistically significant, but economically the result is negligible. To distinguish short maturity T-bills from longer maturity Treasury bonds we use the daily (coupon) yield in contrast to the returns based on the prices of Treasury bonds. The use of the yields presents a case where an investor will receive the average yield over the holding period. Since this return will always be positive the T-bills represent a safe asset at each point in time and not only if held until maturity. We make this strong assumption only to be able to distinguish safe assets from more risky safe haven assets.

Bitcoin, in contrast, does not qualify as a safe haven asset. While the excess α which we find over the entire sample period would not inhibit this property, the performance during crises does. In such periods, Bitcoin's $\hat{\alpha}$ is even more negative than the one we found for the S&P 500 (albeit also not being statistically significant). The estimate for β turns out negative as well. This indicates that Bitcoin does not behave like the average safe haven asset in our index. It seems that previous studies that identified Bitcoin as a safe haven asset base their conclusion mainly on the high returns. However, there was no severe crisis since the introduction of Bitcoin which might blur these results. Now, with the COVID-19 outbreak, the picture looks different. But even when benchmarking Bitcoin against our index, one might be inclined to qualify Bitcoin as a safe haven as the $\hat{\beta}$ is positive during the full sample. But when it matters, during crises, that does not hold. In addition, the regression R^2 is zero which indicates that Bitcoin is detached from the SHI and the other safe haven assets.

The FANG stocks which received a lot of attention during the COVID-19 pandemic as their business soared during the lockdown do not qualify as a safe haven asset during the crisis either. While they exhibit excess returns compared to the SHI over the full sample, this does not hold for the crisis periods. In addition, the estimated β is always significantly negative which indicates that they go down when the SHI goes up, just like the average asset contained in the S&P 500.

For the assets which are part of the index, we observe that the R^2 rises during crisis periods. This indicates that in general, these assets are linked, but their idiosyncratic component is very important during non-crisis periods, probably rooted in their different use. During the crisis, all of them show their safe haven potential and move stronger in sync with the index, with the only exception of gold. As gold is a dominating constituent in the index, the R^2 does not change much, it even goes down by 0.02. For the remaining assets, the picture is not clear. In the case of silver, for example, the R^2 is reduced which indicates that idiosyncratic risk increases in a crisis period. On the other hand, the R^2 rises substantially for the FANG stocks. Coupled with the larger negative $\hat{\beta}$ during a crisis, this indicates that they are systematically exposed to crisis risk.

[Table 4 about here.]

4 Volatility of the Safe Haven Index

In the following section, we examine the volatility of the safe haven index and the sample of assets to illustrate that despite being labeled "safe haven", these assets are still risky. We then look at index properties in more detail using an asymmetric GARCH and a QAR model.

4.1 Volatility during crisis periods

In a first step, we investigate the volatility of the SHI, the composite assets, and the comparison assets used in Section 3. Motivated by the work of Forsberg and Ghysels (2007), we use absolute returns $\mid r_{i,t} \mid$ as a measure of volatility. To distinguish crises from other periods, we conduct a linear regression using dummy variables as defined in Section 3.1.

Table 5 presents the regression results. The estimates show that the volatility increases for all assets and all crisis periods. There are only two exceptions: During the 1987 stock market crash, oil volatility decreased, and during the 9/11 terrorist attacks, long-term U.S. government bonds also exhibited a slightly lower volatility. Again, the ongoing COVID-19 pandemic stands out as the increase in volatility has never been as high during any of the other crisis. This holds for almost all assets except for silver and gold. In these cases volatility increased by more during the Lehman crisis period than during the COVID-19 pandemic.

[Table 5 about here.]

It may be surprising that safe haven assets are volatile and that the volatility of these assets also increases in crises. However, if an asset is increasing in value during a crisis because investors perceive it as a safe haven and buy the asset, it is intuitive that investors will sell the asset once the severity and uncertainty of a crisis dissipates. The increase and subsequent decrease or reversal of the price of safe haven assets implies increased volatility. Nevertheless, other assets like the FANGs or the S&P500 exhibit a much greater increase of volatility in the crisis periods.

4.2 Asymmetric volatility effects in the indices

In this section we analyze the volatility of the SHI in more detail. The mean and standard deviation of the index returns changed during the four crises periods from 0.007 to 0.092 (mean) and from 0.402 to 0.614 (standard deviation). These numbers point to a special "inverted" volatility asymmetry with positive shocks increasing the volatility by more than negative shocks. To analyze this feature in greater detail, we estimate an asymmetric GARCH(1,1) model (Glosten, Jagannathan, and Runkle, 1993) of the SHI returns. The model is implemented as follows:

$$\begin{aligned} R_t &= \mu + \theta R_{t-1} + \varepsilon_t \\ h_t &= \omega + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 \mathbb{1}(\varepsilon_{t-1} < 0) + \beta h_{t-1} \\ \varepsilon_t &\sim i.i.d.\, N(0, h_t), \end{aligned} \tag{3}$$

where $\mathbb{1}(\cdot)$ is the indicator function that takes on a value of 1 if $\varepsilon_{t-1} < 0$ and 0 otherwise. We refer to this specification as Model (1). The variance model parameters α and β are restricted to be positive while γ can take any value between -1 and 1. In addition, the restriction $1 - \alpha - \beta - \frac{1}{2}\gamma > 0$ is imposed such that the parameter estimates will restricted to be compatible with a stationary variance process.

Table 6 presents the coefficient estimates of Model (1) and shows that the volatility asymmetry is inverted for the sample including the crises: Positive shocks increase the volatility by more than negative shocks ($\hat{\gamma} < 0$) which is in contrast to the "classical" asymmetry identified for the S&P500 ($\hat{\gamma} > 0$).

[Table 6 about here.]

Figure 4 presents the estimated conditional volatility of the SHI. The graph illustrates the increased volatility in the four crises and safe haven events, in line with the pattern observed for returns (see Figure 2).

[Figure 4 about here.]

To distinguish the behaviour of the SHI volatility during crisis times and normal times, we take out the effect of the four crisis periods. To this end, we modify the return equation in Equation (3) and include a dummy variable D_t which captures all the crisis periods defined in Section 3.1 jointly. The new return model becomes

$$R_t = \mu + \theta R_{t-1} + \delta D_t + \varepsilon_t,$$

where ε_t is specified as in Equation (3). The variance model is not altered. We refer to this specification as Model (2). The estimation results are presented in Table 6, columns 4-5. Comparing them to the estimates reported in columns 2-3 of Table 6 shows that the safe haven events have a clear influence on the estimates as they seem to reduce the asymmetric volatility effect (γ) as the filtered "ex-crisis" estimates have no significant volatility asymmetry. The estimates based on the sample accounting for the four major crisis periods suggest that the crisis periods play a major role for the inverted asymmetric effect of volatility. In other words, safe haven events do not only increase the volatility of non-safe haven assets but even the volatility of the safe haven assets itself.

Finally, excluding the COVID-19 crisis from the sample leads to a switch of the sign of the SHI's $\hat{\gamma}$ in Model (2) to a positive value. Still, the coefficient estimate remains not statistically significant. In contrast, the estimate $\hat{\gamma}$ in the model for the S&P500 remains positive and statistically significant in this case. This leads us to conclude that the results are not driven by the COVID-19 pandemic which stands out in particular in terms of the performance of the SHI constituents (compare Table 2).

4.3 Quantile persistence of the safe haven index

In this section we have a closer look at the dynamics of the safe haven index returns and derive implications for the SHI volatility. We use a Quantile Autoregressive Model (QAR; Koenker and Xiao, 2006) to evaluate the persistence of the returns in the quantiles of the return distribution. This is motivated by the fact that safe haven assets are generally not in the focus of investors and the media when the market is in a normal or tranquil state, but receive a lot of attention when markets exhibit extreme losses, i.e., the lower tail of the return distribution. A comparison with the S&P 500 index can further highlight specific differences between safe haven assets and other stocks. We implement a linear QAR(1) model

$$Q_{R_t}(\tau|R_{t-1}) = \theta_0(\tau) + \theta_1(\tau)R_{t-1} \tag{4}$$

for $\tau \in (0,1)$ in steps of 0.01.

The estimates of θ_1 are graphically depicted in Figure 5 and show a u-shaped pattern for the SHI (black line) with increased persistence in upper quantiles and slightly increased persistence in lower quantiles. The u-shaped pattern of the autoregressive coefficients is in stark contrast to what is found for the S&P500 (blue line) and stock markets in general (see Baur, Dimpfl, and Jung, 2012). The strong negative autoregressive coefficient estimates in upper quantiles for the S&P500 are due to large positive shocks preceded by large negative shocks consistent with return dynamics in a crisis or a high volatility period.[5]

Since the returns of the SHI and the S&P500 are negatively correlated (with a correlation coefficient of approximately -0.16), it is likely and intuitive that large positive return realizations of the SHI (upper quantiles) coincide with large negative return realizations of the S&P500 (lower quantiles). Since both lower conditional stock return quantiles and upper conditional safe haven index return quantiles exhibit persistence our results are compatible with phases of safe haven events which are marked by persistent losses in the stock market and persistent gains in safe haven assets.

[Figure 5 about here.]

[5] Simulations show that only two such subsequent shock combinations suffice to produce the observed pattern for a simulated time-series with 1,000 observations.

In addition to the insights presented above, the difference between the extreme quantile estimates based on Equation (4) can be used to identify volatility asymmetry. Baur and Dimpfl (2019) suggest to calculate the difference δ between high and low quantile (τ) estimates

$$\delta(\tau, 1-\tau) = \hat{\theta}_1(\tau) - \hat{\theta}_1(1-\tau). \quad (5)$$

If $\delta(\tau, 1-\tau)$ is different from zero, there is an asymmetric reaction of volatility to positive and negative innovations. A positive value would indicate that negative past returns increase the variance by more than positive ones, a pattern typically found for stocks. When applied to the SHI returns and calculated using a range of 10 quantiles instead of only the very extremes, we obtain $\hat{\delta} = -0.070$, which supports the findings obtained with the GARCH model that volatility asymmetry is inverted. Since the high quantile estimates are positive and larger than the low quantile tail estimates, positive shocks are associated with a higher volatility than negative shocks. In contrast, we obtain a value of $\hat{\delta} = 0.221$ for the S&P 500 during the same time period which indicates "normal" asymmetric volatility.

The strong dispersion of the parameter estimates in the tails of the return distribution is, to a large extent, driven by the four crisis periods. When we augment the model in Equation (4) by a dummy variable for the crisis periods, the dispersion of the estimates is reduced to $\hat{\delta} = -0.055$ indicating a weaker asymmetric effect. For the S&P 500, the crises seem to affect the asymmetry less as we only observe a slight decrease of $\hat{\delta}$ to 0.215.

4.4 Robustness

This section investigates the robustness of the index and the estimation results. One alternative to calculate the SHI is to use standardized returns. We have implemented such an index calculation and found that it yields very similar results. However, there is one argument why standardized returns are inferior to the raw returns implemented above. An index based on standardized returns is not robust to updates leading to a longer sample period because the entire sample period is used to estimate the means and standard deviations which are used to calculate the standardized returns. Since an index should be easy to update and be time-consistent, standardized returns are not the best alternative to calculate an index. In contrast, the proposed index based on raw returns can be updated and extended without changing the index values of shorter samples.

Another concern may be the sensitivity of the index to the exclusion or inclusion of safe haven assets. We analyze this question by (i) excluding gold from the index and (ii) excluding all safe haven assets except gold. The results are reported in Tables 7 and 8 in the appendix and show that the composition of the index matters while the key findings remain evident and valid if gold is excluded from the index. If only gold is used as the index the betas fall significantly for most assets except for silver and Bitcoin.

Lastly, we vary the length of the crisis period. Using a short window of 5 days increases the effect of the crisis on the return of the index: The difference between calm periods and crises is found to be greater. This observation holds for up to 10 days. Afterwards, the return difference decreases again and somewhat levels off after 20 days which is the reason why we chose 20 days for our main results above. Detailed results are presented in Table 9 in the Appendix. Similarly, the risk/return ratio also remains high for roughly 10-20 days before it starts to fall again, indicating that a strong safe haven effect is rather short-lived and dies out quickly (see Figure 6 in the Appendix).

5 Summary and Conclusion

This paper proposes a safe haven index as a benchmark to enhance our understanding of safe haven assets and to distinguish them from both safe assets and risky assets. The paper is motivated by the lack of a clear safe haven benchmark, a lack of stylized facts about safe haven assets, the extreme stock price changes due to the COVID-19 induced market crash in March 2020, and recurring claims that Bitcoin or other assets are safe havens or have lost their safe haven status. This paper aims to clarify what a safe haven asset is and what it is not and how it differs from risky assets such as stocks.

Our analysis of more than 20 assets over 35 years including the usual safe haven asset suspects such as gold, U.S. and German government bonds and major currencies, but also recent additions such as Bitcoin, shows that all safe haven assets are volatile and thus risky both in normal times and in crisis times. This also applies to the so-called risk-free or safe U.S. government bonds.

The riskiness of safe haven assets may be surprising but is plausible given that safe haven asset prices increase in crisis periods (safe haven events) and fall afterwards. Further analysis of the volatility of safe haven assets demonstrates that they exhibit an inverted asymmetric volatility effect (positive shocks increase volatility by more than negative shocks) which disappears if safe haven events are controlled for. Our benchmark also reveals that Bitcoin has an insignificant safe haven beta (exposure to the safe haven index) and thus is very different to the more traditional safe haven assets that form the index.

In addition to being risky, safe haven assets are all different in terms of their risk-adjusted returns and their relationship to the safe haven index. The differences are also reflected in the lower risk of the safe haven index compared to its constituents. This finding implies that diversification pays off even for safe haven assets and even in crisis periods contrasting claims that diversification does not work when it is needed the most.

Despite the fact that the safe haven index and its underlying portfolio provides diversification benefits investors may not want to hold a diversified portfolio of safe haven assets but only one. Whilst gold stands out as a physical asset with a long history as a store of value, the best safe haven asset in terms of its raw and risk-adjusted returns are 2-year U.S. government bonds. This may be good news for U.S. investors that are not exposed to U.S. dollar depreciation risk in contrast to non-U.S. international investors. However, the outperformance of U.S. government bonds can also be explained with central bank bond purchases in crisis periods, especially in response to the COVID outbreak.[6] Without such intervention government bonds may be less advantageous in crisis periods.

Finally, the results demonstrate that the COVID crisis is fundamentally different to previous crises. The safe haven index briefly fell with the market at the start of the pandemic and did perform very differently compared with the preceding 35 years since 1985. Whilst this finding may suggest that safe haven assets did not work and lost their safe haven status the opposite may also be true. Safe haven assets worked and lost value exactly because they were a safe haven and had been held as an insurance to cover losses or to obtain cash.

[6] e.g., see https://www.nytimes.com/2020/03/15/us/politics/coronavirus-economy-dodd-frank.html.

Declaration of interest statement

No conflict of interest exists. No funding was received for this work.

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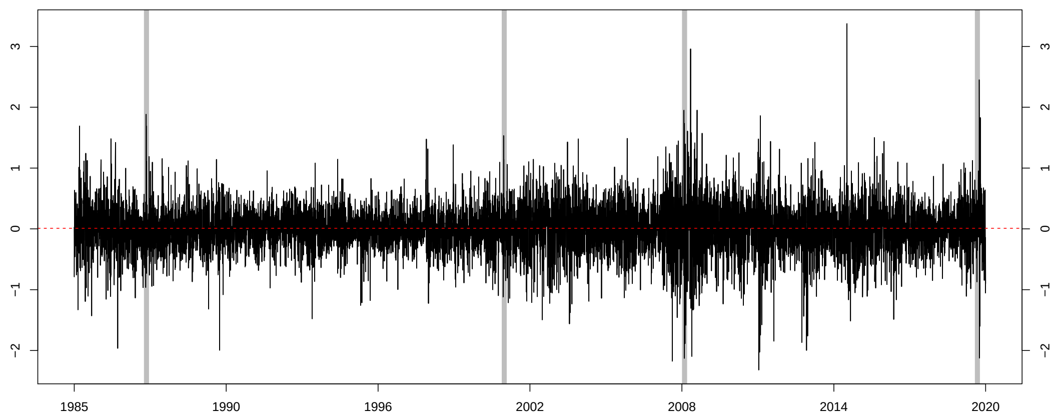
Figure 1: The safe haven index and the S&P 500

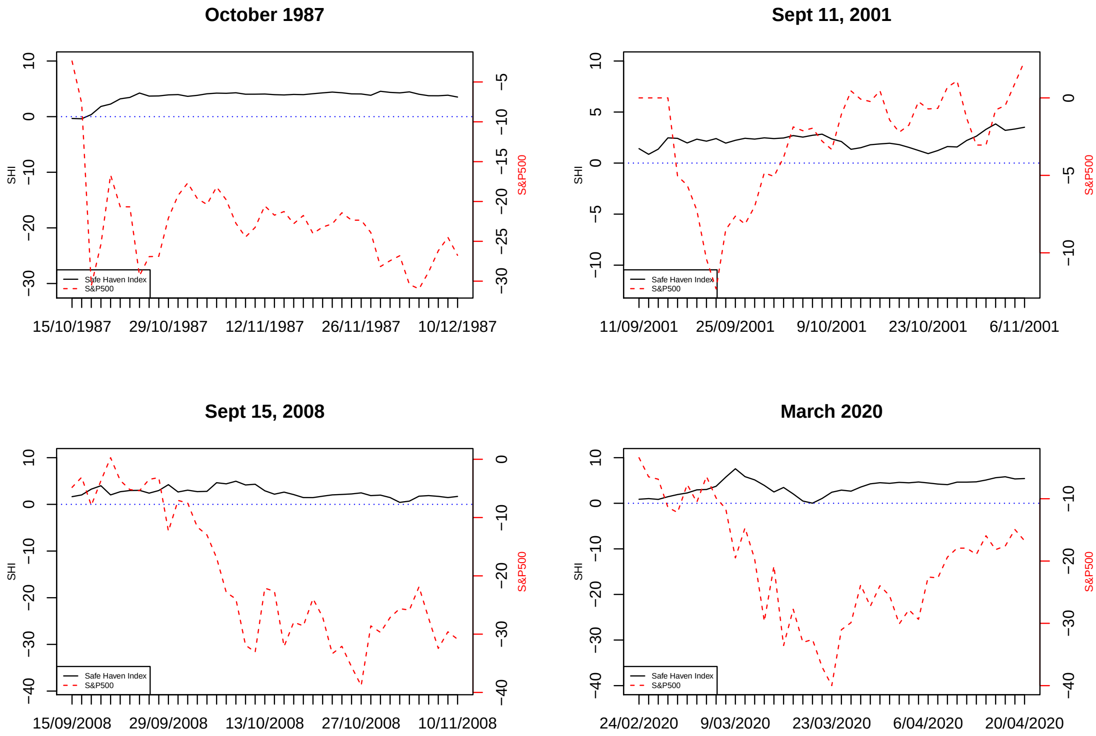
Note. The figure presents the safe haven index (SHI, black line, left axis) and the S&P 500 (blue, right axis) from 1985 to 2020. The October 1987 stock price crash, the September 11, 2001 terrorist attacks crisis, the Lehman collapse in September 2008, and the COVID-19 pandemic induced crash in March 2020 are highlighted in gray.

Figure 2: Safe haven index returns



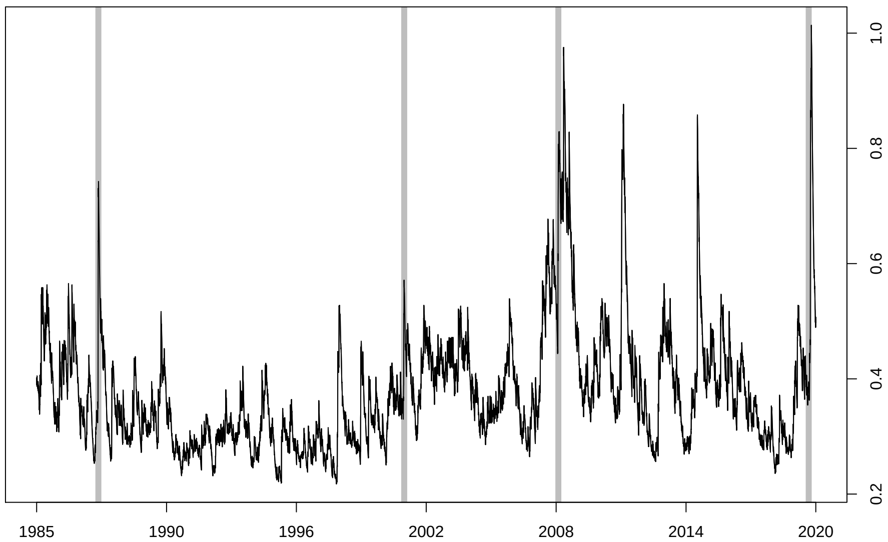
Note. The figure presents the safe haven index returns from 1985 to 2020. The October 1987 stock price crash, the September 11, 2001 terrorist attacks crisis, the Lehman collapse in September 2008, and the COVID-19 pandemic induced crash in March 2020 are highlighted in gray.

Figure 3: The safe haven index and financial crises



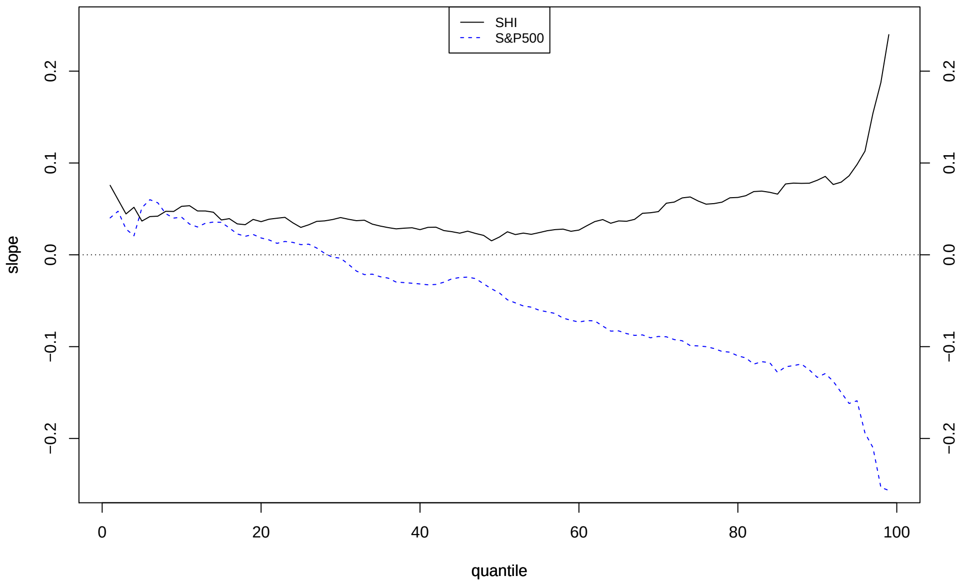
Note. The figure presents log returns of the safe haven index (black) and the S&P500 (red) from 1985 to 2020. The October 1987 stock price crash, the September 11, 2001 terrorist attacks crisis, the Lehman collapse in September 2008, and the COVID-19 pandemic induced crash in March 2020 are highlighted in gray.

Figure 4: Volatility of the safe haven index



Note. The figure presents the conditional daily volatility of the Safe Haven Index returns, based on a GARCH(1,1) model. The October 1987 stock price crash, the September 11, 2001 terrorist attacks crisis, the Lehman collapse in September 2008, and the COVID-19 pandemic induced crash in March 2020 are highlighted in gray.

Figure 5: QAR(1) parameter estimates of SHI and S&P500 returns



Note. The figure presents the quantile autoregression (QAR) estimates $\theta_1(\tau)$ of the SHI and the S&P500 across 99 quantiles.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	Skewness	Kurtosis	Ljung-Box	p-value
SHI	0.007	0.328	-2.025	2.668	0.053	6.804	31.277	<0.001
Gold (USD)	0.019	0.964	- 10.162	7.382	-0.305	10.563	5.135	0.400
Swiss franc to USD	0.006	0.660	-8.475	11.419	0.763	23.533	4.272	0.511
Japanese yen to USD	0.001	0.660	-3.710	6.582	0.456	8.237	3.123	0.681
U.S. bonds 2-year	0.003	0.104	-0.991	0.977	0.250	10.959	13.680	0.018
U.S. bonds 10-year	0.007	0.457	-2.876	4.061	-0.040	6.576	8.272	0.142
U.S. bonds 30-year	0.011	0.816	-6.904	8.201	0.009	8.106	11.472	0.043
German bonds 10-year	0.007	0.338	-2.526	2.657	-0.267	6.494	41.168	<0.001
S&P500	0.032	1.143	-22.900	10.957	-1.274	31.285	52.443	<0.001

Note. The table presents descriptive statistics of the safe haven index and its constitutents. It reports the time series average of returns (mean), the standard deviation of returns (SD), the minimum (Min) and maximum (Max) return, skewness (Skew) and kurtosis (Kurt). The column labelled "LB" presents the test statistic of a Ljung-Box test for no autocorrelation. The associated p-value is given in the last column.

Table 2: Crisis effects: Returns

	c	1987	9/11	Lehman	COVID-19	R^2
Gold (USD)	0.017	0.159	0.555	1.564	-0.312	0.004
Swiss franc to USD	0.005		0.548	0.316	-0.025	0.001
Japanese yen to USD	-0.0002		0.268	0.207	0.015	0.000
U.S. bonds 2-year	0.002	0.222	0.109	0.094	0.097	0.010
U.S. bonds 10-year	0.005	0.737	0.087	0.070	0.346	0.004
U.S. bonds 30-year	0.008	0.943	-0.192	0.255	0.677	0.003
German bonds 10-year	0.007	0.389	0.0003	0.138	-0.036	0.002
SHI	0.006	0.349	0.197	0.378	0.109	0.004
S&P500	0.041	-2.047	-0.734	-1.162	-1.945	0.012
Bitcoin (USD)	0.313				-2.222	0.001
U.S. dollar	0.001		-0.207	-0.174	0.131	0.001
German bonds 30-year	0.017		-0.199	0.155	0.098	0.000
Silver (USD)	0.013	-1.091	0.778	1.789	-1.743	0.004
Crude Oil (WTI, USD)	0.026	0.061	-2.168	-0.467	-4.654	0.008
CBOE VIX	-0.016		1.085	5.464	6.124	0.003
AUD to USD	0.003		-0.322	-0.035	-0.677	0.003
EURO to USD	0.003	0.354	0.237	0.162	-0.044	0.001
GBP to USD	0.001	0.360	0.070	0.118	-0.574	0.002
U.S. T-bill 3-months	0.013	0.010	-0.003	-0.010	-0.011	0.005
U.S. T-bill 4-weeks	0.005		0.005	-0.004	-0.002	0.003
Facebook	0.104				-1.771	0.006
Amazon	0.129		-1.916	-2.055	-0.589	0.001
Netflix	0.126			0.514	-0.381	0.000
Alphabet (Google)	0.093			-1.354	-1.720	0.006

Note. The table presents the long-run average return c and differences from c during the October 1987 stock price crash (1987), the September 11, 2001 terrorist attacks (9/11), the Lehman collapse in September 2008 (Lehman), and the COVID-19 pandemic induced crash in March 2020 (COVID-19). The results are based on daily data. Missing entries arise when data are not available for the respective crisis period.

Table 3: Full sample and crisis period risk adjusted returns

	Full Sample			Crisis Sample		
	Mean	SD	return/risk	Mean	SD	return/risk
Gold (USD)	0.019	0.964	0.019	0.120	2.189	0.055
Swiss franc to USD	0.006	0.660	0.010	0.063	0.896	0.070
Japanese yen to USD	0.001	0.660	0.001	0.115	1.145	0.100
U.S. bonds 2-year	0.003	0.104	0.026	0.086	0.286	0.300
U.S. bonds 10-year	0.007	0.457	0.016	0.203	1.120	0.181
U.S. bonds 30-year	0.011	0.816	0.014	0.369	2.228	0.166
German bonds 10-year	0.007	0.338	0.022	0.070	0.745	0.094
SHI	0.007	0.328	0.023	0.140	0.812	0.172
S&P500	0.032	1.143	0.028	-1.024	4.814	-0.213
Bitcoin (USD)	0.293	5.851	0.050	-1.909	12.687	-0.150
U.S. dollar	0.0005	0.501	0.001	0.082	0.861	0.095
German bonds 30-year	0.017	0.765	0.022	0.091	1.951	0.046
Silver (USD)	0.011	1.701	0.007	-0.559	3.663	-0.152
Crude Oil (WTI, USD)	0.012	2.677	0.004	-1.818	7.511	-0.242
CBOE VIX	0.009	6.537	0.001	3.388	14.005	0.242
AUD to USD	0.0002	0.743	0.0002	-0.565	2.282	-0.247
EURO to USD	0.004	0.611	0.007	0.028	0.893	0.032
GBP to USD	0.001	0.614	0.001	-0.093	0.986	-0.095
U.S. T-bill 3-months	0.013	0.010	1.283	0.009	0.008	1.112
U.S. T-bill 4-weeks	0.005	0.006	0.870	0.005	0.004	1.147
Facebook	0.087	2.287	0.038	-1.667	5.440	-0.306
Amazon	0.120	3.607	0.033	-0.876	5.335	-0.164
Netflix	0.126	3.593	0.035	-0.480	5.318	-0.090
Alphabet (Google)	0.081	1.881	0.043	-1.143	5.183	-0.221

Note. The table presents average returns of the named assets (Mean) over the full sample period and the crisis sub-samples, their standard deviation (SD), and the return/risk ratio. The crisis period figures are calculated over 20 days.

Table 4: Index exposure

	Full Sample			Crisis Periods		
	$\hat{\alpha}$	$\hat{\beta}$	R^2	$\hat{\alpha}$	$\hat{\beta}$	R^2
S&P500	0.036***	-0.627***	0.03	-0.006	-2.255***	0.14
	(0.012)	(0.063)		(0.012)	(0.063)	
Gold (USD)	0.006	1.694***	0.33	-0.001	1.492***	0.31
	(0.008)	(0.041)		(0.008)	(0.041)	
Bitcoin (USD)	0.291**	0.537	0.00	-0.017	-0.185	0.00
	(0.122)	(0.442)		(0.122)	(0.442)	
U.S. dollar	0.004	-0.53***	0.13	0.001	-0.366**	0.15
	(0.005)	(0.021)		(0.005)	(0.021)	
Swiss franc to USD	-0.002	1.05***	0.33	0.000	0.587***	0.35
	(0.006)	(0.037)		(0.006)	(0.037)	
Japanese yen to USD	-0.008	1.104***	0.36	0.000	0.935***	0.54
	(0.006)	(0.025)		(0.006)	(0.025)	
U.S. bonds 2-year	0.001	0.172***	0.30	<0.001**	0.237***	0.43
	(0.001)	(0.005)		(0.001)	(0.005)	
U.S. bonds 10-year	0.000	0.974***	0.49	0.000	1.081***	0.61
	(0.003)	(0.017)		(0.003)	(0.017)	
U.S. bonds 30-year	-0.002	1.731***	0.48	0.000	2.246***	0.67
	(0.006)	(0.033)		(0.006)	(0.033)	
German bonds 10-year	0.004	0.498***	0.23	0.000	0.563***	0.38
	(0.003)	(0.012)		(0.003)	(0.012)	
German bonds 30-year	0.009	1.053***	0.24	-0.001	1.249***	0.34
	(0.008)	(0.033)		(0.008)	(0.033)	
Silver (USD)	-0.002	1.729***	0.11	-0.006*	0.666	0.02
	(0.017)	(0.074)		(0.017)	(0.074)	
Crude Oil (WTI, USD)	0.015	-0.376***	0.00	-0.014*	-1.865	0.04
	(0.028)	(0.139)		(0.028)	(0.139)	
CBOE VIX	-0.018	3.641***	0.04	0.020	7.108***	0.20
	(0.072)	(0.293)		(0.072)	(0.293)	
AUD to USD	-0.003	0.348***	0.03	-0.005*	-0.232	0.01
	(0.009)	(0.042)		(0.009)	(0.042)	
EURO to USD	-0.001	0.716***	0.15	0.000	0.318**	0.09
	(0.006)	(0.027)		(0.006)	(0.027)	
GBP to USD	-0.002	0.426***	0.05	-0.001	0.152	0.02
	(0.006)	(0.030)		(0.006)	(0.030)	
U.S. T-bill 3-months	0.013***	0.000	0.00	<0.001***	0.002**	0.03
	(0.000)	(0.000)		(0.000)	(0.000)	
U.S. T-bill 4-weeks	0.005***	0.000	0.00	<0.001***	0.001	0.02
	(0.000)	(0.000)		(0.000)	(0.000)	
Facebook	0.090*	-0.879***	0.02	-0.014	-2.240**	0.20
	(0.049)	(0.159)		(0.049)	(0.159)	
Amazon	0.131***	-1.169***	0.01	-0.006	-2.205***	0.14
	(0.046)	(0.125)		(0.046)	(0.125)	
Netflix	0.139***	-1.001***	0.01	-0.003	-1.360*	0.07
	(0.052)	(0.147)		(0.052)	(0.147)	
Alphabet (Google)	0.092***	-0.951***	0.04	-0.008	-2.432***	0.24
	(0.029)	(0.101)		(0.029)	(0.101)	

Note. The table reports excess returns ($\hat{\alpha}$) and co-movement ($\hat{\beta}$) of the named assets with the Safe Haven Index. The crisis periods contain 20 trading days each. Robust standard errors are presented in parentheses.

Table 5: Crisis effects: Volatility

	c	1987	9/11	Lehman	COVID-19	R^2
Gold (USD)	0.634	0.210	0.281	1.760	0.988	0.023
Swiss franc to USD	0.465		0.199	0.267	0.162	0.002
Japanese yen to USD	0.464		0.056	0.527	0.449	0.008
U.S. bonds 2-year	0.067	0.116	0.050	0.233	0.078	0.035
U.S. bonds 10-year	0.328	0.352	0.027	0.477	0.724	0.025
U.S. bonds 30-year	0.577	0.412	-0.059	0.691	1.838	0.035
German bonds 10-year	0.239	0.431	-0.011	0.260	0.398	0.021
SHI	0.233	0.060	0.107	0.500	0.630	0.036
S&P500	0.699	2.773	0.502	3.086	3.922	0.118
Bitcoin (USD)	3.402				2.346	0.003
U.S. dollar	0.368		0.042	0.368	0.347	0.007
German bonds 30-year	0.535		-0.049	0.660	1.629	0.040
Silver (USD)	1.101	1.059	0.175	2.695	1.752	0.019
Crude Oil (WTI, USD)	1.655	-0.819	0.990	3.063	6.282	0.033
CBOE VIX	4.522		0.236	5.750	9.564	0.019
AUD to USD	0.501		0.307	2.113	0.688	0.065
EURO to USD	0.442	0.227	0.054	0.320	0.223	0.003
GBP to USD	0.434	0.244	-0.030	0.530	0.661	0.012
U.S. T-bill 3-months	0.013	0.010	-0.004	-0.010	-0.011	0.009
U.S. T-bill 4-weeks	0.005		0.004	-0.004	-0.003	0.007
Facebook	1.430				3.051	0.037
Amazon	2.210		1.532	3.431	1.217	0.008
Netflix	2.233			1.388	1.975	0.004
Alphabet (Google)	1.192			2.905	3.180	0.057

Note. The table presents the long-run average daily volatility c and differences from c during the October 1987 stock price crash (1987), the September 11, 2001 terrorist attacks (9/11), the Lehman collapse in September 2008 (Lehman), and the COVID-19 pandemic induced crash in March 2020 (COVID-19). The results are based on monthly data. Missing entries arise when data are not available for the respective crisis period.

Table 6: GARCH model estimates

	(1)		(2)	
	SHI	S&P 500	SHI	S&P 500
μ	0.0061*	0.0343***	0.0055	0.0441***
	(0.0036)	(0.0078)	(0.0036)	(0.0118)
θ	0.0631***	-0.0086	0.0619***	-0.0802***
	(0.0109)	(0.0110)	(0.0108)	(0.0104)
δ			0.2790***	-1.6805***
			(0.1041)	(0.1555)
ω	0.0009***	0.0204***	0.0001	0.0015
	(0.0002)	(0.0056)	(0.0067)	(0.0011)
α	0.0520***	0.0133	0.0632***	0.0520***
	(0.0046)	(0.0081)	(0.6355)	(0.0128)
β	0.9535***	0.8954***	0.9391***	0.9029***
	(0.0010)	(0.0207)	(0.8211)	(0.0231)
γ	-0.0254***	0.1425***	-0.0200	0.0739***
	(0.0069)	(0.0284)	(0.1119)	(0.0278)

Note. The table presents the estimation results of the asymmetric GARCH model for the Safe Haven Index and the S&P 500. Model (1) is specified as in Equation (3), Model (2) includes a dummy variable for the crisis periods in the mean equation. Robust standard errors are given in parentheses.

Appendix

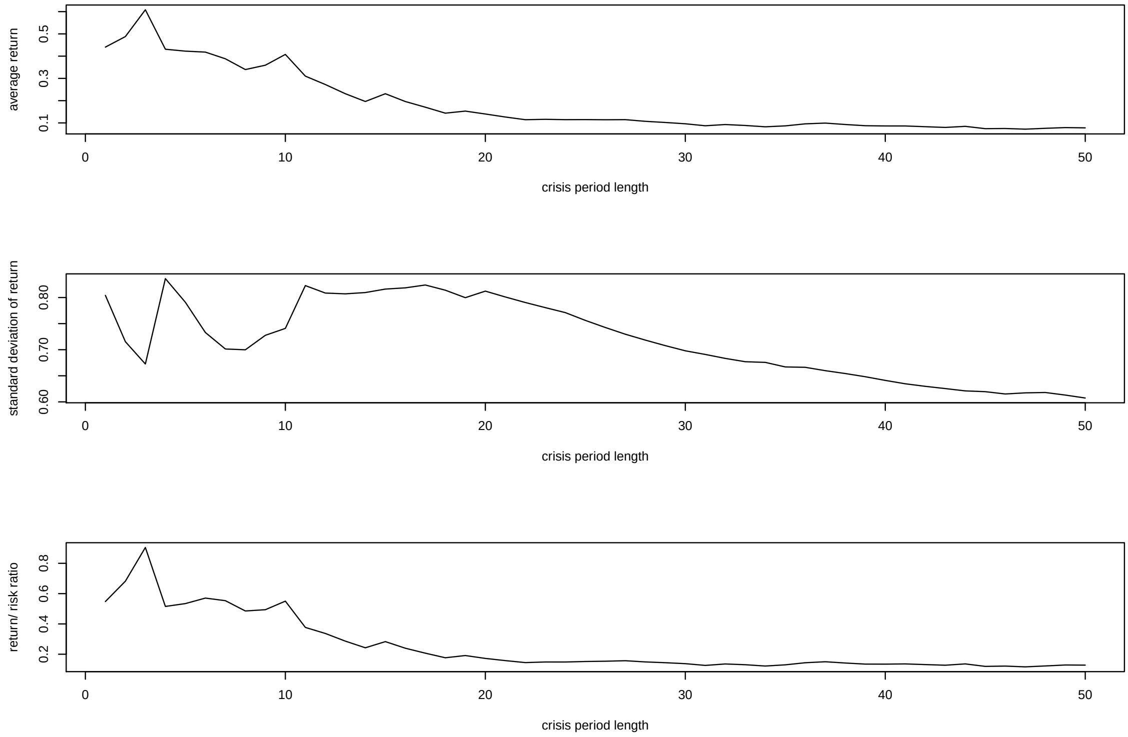
[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

[Figure 6 about here.]

Figure 6: Risk/return characteristics for increasing crisis period length



Note. The graph shows the evolution of the average return, the standard deviation and the return/risk ratio of the SHI for crisis period lengths of 1 to 50.

Table 7: Robustness Analysis: Gold excluded from SHI (daily data)

	$\hat{\alpha}$	s.e.	$\hat{\beta}$	s.e.	R^2
A: SHI constitutents					
Swiss franc to USD	0.001	0.01	1.006	0.04	0.28
Japanese yen to USD	-0.006	0.01	1.159	0.03	0.37
U.S. bonds 2-year	0.001	0.00	0.204	0.00	0.44
U.S. bonds 10-year	0.000	0.00	1.139	0.01	0.72
U.S. bonds 30-year	-0.002	0.00	1.998	0.02	0.69
German bonds 10-year	0.004	0.00	0.531	0.01	0.29
B: other assets					
S&P500	0.035	0.01	-0.534	0.06	0.03
Gold (USD)	0.016	0.01	0.468	0.04	0.03
Bitcoin (USD	0.292	0.12	0.081	0.41	0.00
U.S. dollar	0.003	0.01	-0.466	0.02	0.10
German bonds 30-year	0.010	0.01	1.212	0.04	0.30
Silver (USD)	0.009	0.02	0.249	0.08	0.00
Crude Oil WTI, USD)	0.018	0.03	-0.943	0.14	0.01
CBOE VIX	-0.015	0.07	3.879	0.29	0.04
AUD to USD	0.000	0.01	0.090	0.04	0.00
EURO to USD	0.001	0.01	0.525	0.03	0.09
GBP to USD	-0.001	0.01	0.263	0.03	0.02
U.S. T-bill 3-months	0.006	0.00	0.000	0.00	0.00
U.S. T-bill 4-weeks	0.013	0.00	0.000	0.00	0.00
Facebook	0.090	0.05	-1.140	0.17	0.03
Amazon	0.129	0.05	-1.392	0.13	0.02
Netflix	0.137	0.05	-1.227	0.15	0.02
Alphabet (Google)	0.089	0.03	-1.147	0.11	0.05

Note. The table presents the exposure of the assets listed in column 1 to the safe haven index which is calculated excluding gold. Estimates are based on daily data. Columns 3 and 5 present robust standard errors.

Table 8: Robustness Analysis: Only Gold constituent of SHI (daily data)

	$\hat{\alpha}$	s.e.	$\hat{\beta}$	s.e.	R^2
A: SHI constitutents					
Gold USD	0.000	–	1.000	–	1.00
B: other assets					
S&P500	0.033	0.01	-0.052	0.02	0.00
Bitcoin (USD)	0.294	0.12	0.483	0.24	0.01
U.S. dollar	0.003	0.01	-0.129	0.01	0.06
Swiss franc to USD	0.002	0.01	0.227	0.01	0.12
Japanese yen to USD	-0.003	0.01	0.164	0.01	0.06
U.S. bonds 2-year	0.003	0.00	0.004	0.00	0.00
U.S. bonds 10-year	0.007	0.00	0.012	0.01	0.00
U.S. bonds 30-year	0.011	0.01	0.017	0.01	0.00
German bonds 10-year	0.007	0.00	0.029	0.01	0.01
German bonds 30-year	0.015	0.01	0.079	0.01	0.01
Silver (USD)	-0.011	0.01	1.163	0.02	0.43
Crude Oil (WTI, USD)	0.005	0.03	0.344	0.05	0.02
CBOE VIX	0.004	0.07	0.254	0.11	0.00
AUD to USD	-0.005	0.01	0.254	0.02	0.11
EURO to USD	0.000	0.01	0.198	0.01	0.10
GBP to USD	-0.002	0.01	0.158	0.01	0.06
U.S. T-bill 3-months	0.006	0.00	0.000	0.00	0.00
U.S. T-bill 4-weeks	0.013	0.00	0.000	0.00	0.00
Facebook	0.087	0.05	-0.013	0.07	0.00
Amazon	0.122	0.05	-0.073	0.05	0.00
Netflix	0.128	0.05	-0.050	0.05	0.00
Alphabet (Google)	0.083	0.03	-0.059	0.04	0.00

Note. The table presents the exposure of the assets listed in column 1 to the safe haven index which is calculated based on gold only. Estimates are based on daily data. Columns 3 and 5 present robust standard errors.

Table 9: SHI returns for different crisis period lengths

Length	c	1987	9/11	Lehman	COVID-19	R^2
5	0.006	0.527	0.322	0.444	0.371	0.004
6	0.006	0.488	0.329	0.418	0.414	0.005
7	0.006	0.525	0.262	0.369	0.372	0.005
8	0.006	0.404	0.261	0.261	0.408	0.004
9	0.006	0.366	0.190	0.290	0.567	0.006
10	0.006	0.350	0.197	0.378	0.683	0.009
11	0.006	0.325	0.197	0.215	0.481	0.005
12	0.006	0.275	0.175	0.228	0.389	0.004
13	0.006	0.267	0.171	0.189	0.274	0.003
14	0.006	0.268	0.154	0.180	0.159	0.002
15	0.006	0.258	0.148	0.284	0.211	0.003
16	0.006	0.240	0.152	0.253	0.115	0.003
17	0.006	0.232	0.135	0.269	0.021	0.003
18	0.006	0.206	0.137	0.212	-0.005	0.002
19	0.006	0.196	0.135	0.209	0.047	0.002
20	0.006	0.187	0.106	0.132	0.109	0.002
21	0.006	0.173	0.090	0.093	0.125	0.001
22	0.006	0.163	0.052	0.108	0.109	0.001
23	0.006	0.160	0.056	0.081	0.142	0.001
24	0.006	0.152	0.065	0.052	0.164	0.001
25	0.006	0.152	0.066	0.049	0.167	0.002
26	0.006	0.152	0.066	0.059	0.156	0.001
27	0.006	0.152	0.058	0.066	0.158	0.002
28	0.006	0.142	0.047	0.067	0.148	0.001
29	0.006	0.130	0.035	0.068	0.149	0.001
30	0.006	0.125	0.024	0.073	0.137	0.001
31	0.006	0.114	0.032	0.052	0.125	0.001
32	0.006	0.132	0.043	0.054	0.117	0.001
33	0.006	0.122	0.040	0.037	0.130	0.001
34	0.006	0.116	0.057	0.006	0.126	0.001
35	0.006	0.117	0.067	0.013	0.124	0.001
36	0.006	0.103	0.083	0.041	0.132	0.001
37	0.006	0.093	0.095	0.043	0.142	0.001
38	0.006	0.090	0.076	0.038	0.143	0.001
39	0.006	0.090	0.077	0.030	0.127	0.001
40	0.006	0.080	0.080	0.035	0.126	0.001

Note. The table presents the long-run average return c of the SHI and differences from c during the October 1987 stock price crash (1987), the September 11, 2001 terrorist attacks (9/11), the Lehman collapse in September 2008 (Lehman), and the COVID-19 pandemic induced crash in March 2020 (COVID-19). The results are based on daily data and the length of days included in the crisis definition is varied from 5 to 40 as indicated in the first column.