Stockholm School of Economics
Department of Finance
Master Thesis
Spring 2015

Safe Haven Assets

A long-term and short-term analysis of commodities, currencies and bonds

Daniel Hniopek
22108@student.hhs.se

Ilya Kiselev
40541@student.hhs.se

Abstract

This paper examines a broad range of assets including commodities, currencies and bonds, to test whether they could be classified as *safe haven assets*, that is, assets which are uncorrelated or negatively correlated with stocks during crisis periods. Using two different methodologies – a VAR-GARCH study focusing on the correlation between the tested assets and stocks, and a negative shock analysis focusing on the performance before and after shocks to the stock market – we find evidence of potential safe haven assets in all tested asset classes. Three assets in particular stand out – silver, the Swiss franc and global government bonds, all of which demonstrated negative correlation with the S&P 500 during each and every contraction and bear market for which data was available. We also find that switching from stocks to safe haven assets in response to a stock market shock is unprofitable on average, despite previous research suggesting that this behavior is common among investors. Consequently, we recommend that investors who want to use safe haven assets include them in the portfolio for longer periods of time, rather than buying them as a panic response to sudden volatility spikes and selling them shortly thereafter.

Keywords: Safe Haven Assets, VAR-GARCH, Stock Market Shocks, Contractions, Bear Markets

Tutor: Michael Halling

Acknowledgements

We would like to thank our tutor Michael Halling (Associate Professor, Department of Finance at Stockholm School of Economics) for providing us with valuable guidance and insights throughout our work on this thesis. We also wish to thank Markus Lithell for his assistance in proofreading this thesis.

Table of Contents

Acknowledgements **2**

1. Introduction **4**

2. Literature Review **5**
2.1 Commodities ... 5
2.2 Bonds ... 6
2.3 Currencies ... 6

3. Definitions and Data **7**
3.1 Definitions ... 7
3.2 Data ... 8

4. VAR-GARCH Analysis **11**
4.1 VAR-GARCH Methodology ... 11
4.1.1 Usual methodology and its restrictions ... 11
4.1.2 Tests for safe haven assets in a bivariate VAR(k)-GARCH(p,q) model ... 12
4.2 VAR-GARCH Results ... 14
4.2.1 VAR component results ... 14
4.2.2 GARCH component results ... 15
4.2.3 Conditional correlation during aggregated contractions and bear markets ... 17
4.2.4 Evolution of correlations through contractions and bear markets ... 18
4.2.5 Correlation during overlap of contractions and bear markets ... 21
4.2.6 Summary of the VAR-GARCH analysis ... 21
4.3 Limitations of the VAR-GARCH Study ... 22

5. Negative Shock Analysis **23**
5.1 Negative Shock Methodology ... 23
5.2 Negative Shock Results ... 25
5.2.1 Safe haven asset is held from t=-50 to t=50 ... 25
5.2.2 Safe haven asset is held from t=1 to t=50 ... 26
5.3 Limitations of the Negative Shock Analysis ... 30

6. Conclusion **31**

7. Further Research **32**

8. References **34**

9. Appendix **37**

1. Introduction

A safe haven is generally defined as a place of refuge. In the financial literature, this term designates an asset that is uncorrelated or negatively correlated with some other reference asset during a particularly challenging period of time. Given the severity of the recent financial crisis, it is no surprise that this area of study has received much more attention lately by researchers as well as practitioners. Investors might use safe haven assets for varying purposes, from longer-term risk reduction through permanent inclusion in the portfolio to finding short-term protection against sudden volatility spikes. In a similar fashion, researchers have used different definitions of safe haven assets, and applied different methods to investigate them; some studies use a portfolio theory perspective, some look at the correlation of safe haven assets with other assets, and others examine their behavior when negative shocks hit the equity or bond markets.

However, many previous papers focus only on a single asset, such as gold, or an asset class such as currencies. Few papers have applied the same methodological framework to compare a broader range of assets against each other. We expand on previous research by thoroughly examining and comparing the safe haven qualities of commodities, currencies and bonds. We achieve this through two different types of analyses: (i) a VAR-GARCH study of the behavior of safe haven assets during longer crisis periods, which in this paper are separated into *contractions* and *bear markets*, and (ii) a negative shock analysis which investigates the performance of safe haven assets from 50 trading days before a negative shock to the stock market to 50 trading days after, and tests whether profits can be made by switching from stocks to safer assets after a shock has occurred.

In the VAR-GARCH study, we find that there are assets from all tested asset classes – commodities, currencies and bonds – that can be considered *hedges* for U.S. equities in the long run. We also find potential *safe haven* assets in all asset classes – gold futures, silver, a precious metals index, the Swiss franc, the Japanese yen, global government bonds, and short-term U.S. Government bonds all exhibit safe haven qualities for contractions and bear markets. Looking at individual crisis periods, three assets in particular stand out – silver, the Swiss franc and global government bonds, all of which demonstrated negative correlation with the S&P 500 during each and every contraction and bear market for which data was available.

The results of the negative shock analysis show that all safe haven assets outperform stocks prior to a shock and, of course, also on the day of a negative shock to the

stock market. However, very few assets consistently deliver higher returns than stocks *after* a shock. This implies that switching from stocks to, for example, gold in response to a shock is unprofitable on average, even though exactly this behavior is found in practice according to Baur and McDermott (2010) and Baur and Lucey (2010). If the intention of these investors is to reduce risk rather than maximize profits, we show that bond assets generally are both less risky and more profitable than the commodities and currencies tested in this paper.

The rest of the paper is organized as follows: Section 2 provides a review of the safe haven literature by asset class, Section 3 explains the terminology and briefly documents our data sources, Section 4 presents the methodology and results of the VAR-GARCH analysis, Section 5 presents the methodology and results of the negative shock analysis, and Section 6 concludes.

2. Literature Review

2.1 Commodities

When it comes to commodities, gold has received most of the attention in previous research and the consensus appears to be that gold does indeed possess the characteristics of a safe haven asset. Its popularity may be attributed to the historical role of gold in international monetary exchange, where gold in some monetary systems has served as a nominal anchor of currency through the convertibility of currency into gold. Lawrence (2003) highlights several other important properties of gold, for example that it is highly liquid, homogenous, indestructible, and the fact that the inventory of above-ground stocks of gold is large relative to the supply flow. The authors conclude that these characteristics may help explain the apparent lack of correlation between gold and the business cycle, in contrast to what is observed for other commodities.

Baur and McDermott (2010), in one of the earlier studies focusing explicitly on the role of gold as a safe haven asset, find that gold is a hedge and a safe haven for European and American stock markets. They also suggest that investors tend to buy gold in panic immediately after an extreme negative shock to the stock market. Baur and Lucey (2010) also confirm that gold is a hedge against stocks on average and a safe haven during periods of extreme stock market conditions. Furthermore, they show that investors who hold gold for more than 15 trading days after an extreme negative shock to the stock market lose money, which is again interpreted as evidence that investors buy gold in response to such shocks and sell it shortly thereafter. Coudert and Raymond (2011) find that gold on average, but not for

every crisis period, is uncorrelated with stocks during recessions and negatively correlated with stocks during bear markets.

There are few papers that test commodities other than gold in isolation. However, Gorton and Rouwenhorst (2006) construct an index of commodity futures and find that this index generally has negative correlation with stocks.

2.2 Bonds

The relationship between stocks and bonds has been thoroughly investigated in the past, although earlier research was less focused on the performance during crises periods specifically. Several studies have for example documented a general decline in the correlation between stocks and bonds over time (see, e.g., Steeley, 2006; Kim et al., 2006) although Baele et al. (2010), more recently, notes that this trend has not persisted.

Other papers focus on the performance of bonds in response to stock market shocks. Scruggs and Glabadanidis (2003) for example find that bond market variance is relatively unaffected by shocks to the stock market. Baur and McDermott (2012) analyze the response of both bonds and gold to idiosyncratic crisis events, and find that both assets have safe haven qualities although gold actually appears to provide better protection against the most extreme shocks. Flavin et al. (2014) employ a regime-switching framework where common and idiosyncratic shocks are separated, and find evidence suggesting that 10-year U.S. Treasury bonds are better suited as a safe haven asset compared to 1-year bonds.

Finally, Connolly et al. (2005) find evidence of two distinct regimes – the first being a low uncertainty regime with a positive stock-bond relation, and the second being a high uncertainty regime with a modestly negative stock-bond relation. Similarly, Chan et al. (2011) note the existence of a "tranquil" regime, characterized by economic expansion, and a "crisis" regime, characterized by economic decline, where the crisis regime exhibits negative stock returns and a general flight to quality from stocks to bonds.

2.3 Currencies

In the financial literature related to the carry trade, it is fairly well-established that low-interest rate currencies perform well when risk aversion and volatility is high, while high-interest rate currencies often crash during these episodes (see Brunnermeier et al., 2008; Menkhoff et al., 2009). Research on currencies as safe haven assets generally confirms these results, and suggests that certain currencies do exhibit safe haven qualities. Ranaldo and Söderlind (2010) find evidence that the Swiss franc and the Japanese yen appreciate when US stock prices decline. The euro is found to have similar, but weaker, properties, while

currencies with higher interest rates are found to move in the opposite direction of the currencies with safe haven qualities. De Bock and de Carvalho Filho (2013) examine the behavior of currencies after spikes in the option-implied volatility of stock prices (VIX), and note that the U.S. dollar, the Swiss franc and the Japanese yen appreciate against most other currencies. The Swiss franc and the Japanese yen are the only currencies that appreciate relative to the U.S. dollar.

Habib et al. (2012) use a slightly different approach and focus on the underlying fundamentals of currencies, including policy, economic, financial and institutional factors. The authors find that it is difficult to predict what currencies will perform well when global risk aversion is high, and that caution should be exercised when interpreting exchange rate movements during financial crises.

3. Definitions and Data

3.1 Definitions

We follow the definitions used by Baur and McDermott (2010) and Baur and Lucey (2010) in order to classify the behavior of different types of assets.

Hedge: a hedge asset is defined as an asset that is uncorrelated or negatively correlated with stocks on average.

Diversifier: a diversifier is defined as an asset that is positively, but not perfectly, correlated with stocks on average.

Safe Haven: a safe haven is defined as an asset that is uncorrelated or negatively correlated with stocks during *bear markets* or *recessions*. This is a more detailed specification than that of a hedge asset since (i) it *excludes* assets which are uncorrelated or negatively correlated on average, but still have positive correlation during bear markets or recessions, and (ii) it *includes* assets which have positive correlation on average, but still are uncorrelated or negatively correlated during bear markets or recessions.

Contractions: contractions are identified using dates established by the National Bureau of Economic Research (NBER). These contractions last from peak to trough of a business cycle and reflect periods of significant decline in economic activity, normally impacting real GDP, real income, employment, industrial production and wholesale-retail sales. A list of all contraction periods is provided in Table A1 in the Appendix.

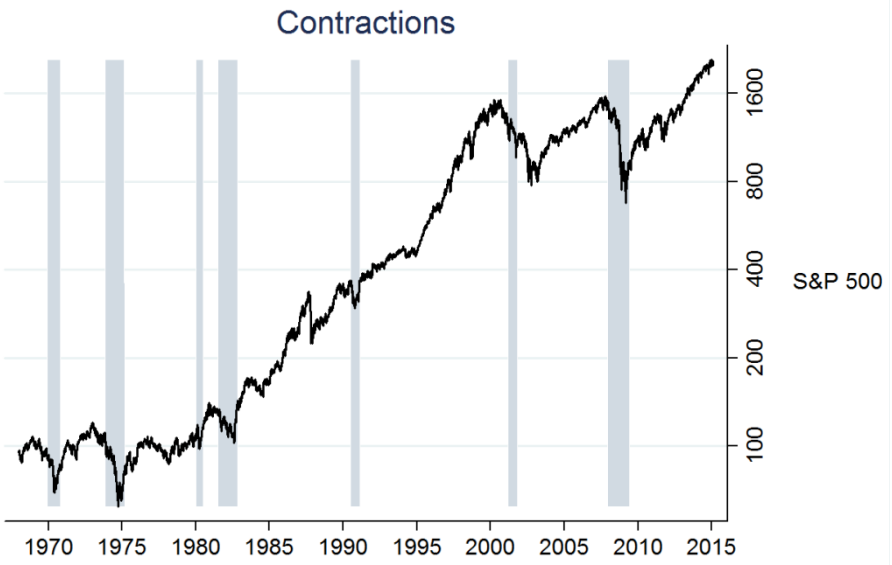


Figure 1

Bear Markets: bear markets are defined using an algorithm proposed by Pagan and Sossounov (2003). This approach identifies peaks and troughs of stock prices and denotes the period as a bear market if, put simply, the stock market decline was long and/or severe enough. A list of all bear market periods is provided in Table A1 in the Appendix.

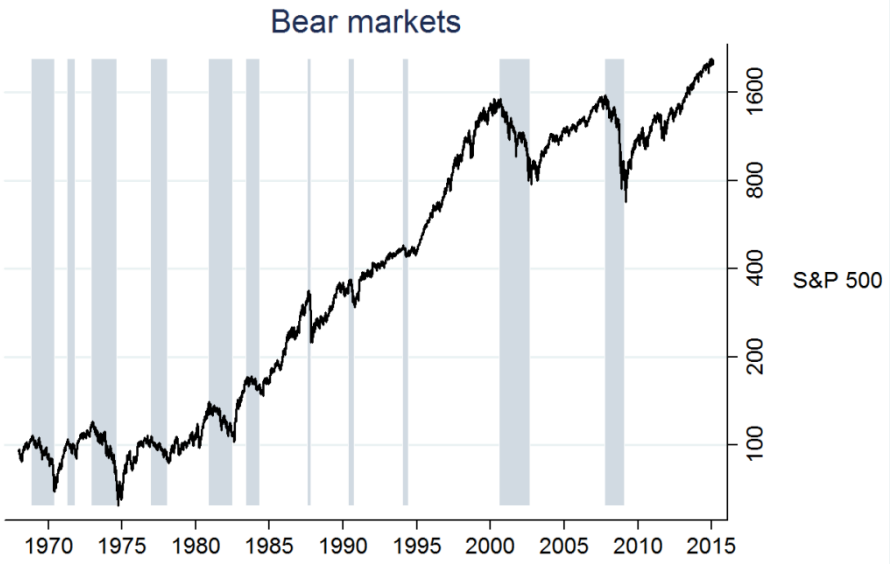


Figure 2

3.2 Data

Our study uses daily data spanning a period of time from 1964 to the beginning of 2015. Each safe haven candidate is tested for safe haven qualities with respect to U.S. equity returns, i.e.

we take the perspective of a U.S. equity investor who wants to protect his or her portfolio during market downturns. All returns are measured in real terms, that is, in excess of inflation. This ensures that we focus on real purchasing power, with which the investor should be concerned, and also adjusts for the difference in nominal returns over time due to different historical inflation regimes.

All time series are extracted from Datastream, and a brief overview of the assets that are included in this study is presented in Table 1.

Table 1: Data overview

Variable	Type	Data availability	Description
S&P500	Equity	1964-2015	S&P 500
GOLD	Commodity	1978-2015	Gold futures
SILVER	Commodity	1968-2015	LBMA Silver
PRECIOUSMET	Commodity	1973-2015	S&P GSCI Precious Metals Index
USD/JPY	Currency	1986-2015	USD/JPY
USD/CHF	Currency	1986-2015	USD/CHF
USD/EUR	Currency	1999-2015	USD/EUR
USGOVBOND2	Bond	1989-2015	2-year U.S. Government Bonds
USGOVBOND5	Bond	1989-2015	5-year U.S. Government Bonds
USGOVBOND10	Bond	1989-2015	10-year U.S. Government Bonds
USGOVBOND30	Bond	1989-2015	30-year U.S. Government Bonds
USCORPIG	Bond	1989-2015	Barclays U.S. Corporate Bonds - Investment Grade
GOVBONDXUS	Bond	1986-2015	JPM Global Government Bonds excl. U.S.

These particular assets were selected from a broader range of assets, based on what has been tested in previous research and based on descriptive statistics of how the assets behave throughout the business cycle and during bear and bull markets. Descriptive statistics of all the assets are presented below in Table 2 (contractions and expansions) and Table 3 (bear and bull markets). The descriptive statistics are based on monthly data and converted into yearly figures. All other tests in this paper are however conducted using daily data, as previously mentioned.

Table 2: Descriptive statistics during contractions and expansions

	Total				Contraction				Expansion			
Variable	n	Mean	St.dev.	Skewness	n	Mean	St.dev.	Skewness	n	Mean	St.dev.	Skewness
S&P500	565	3.7%	15.5%	-0.40	83	-20.7%	22.6%	0.36	482	8.5%	13.5%	-0.44
GOLD	445	3.7%	19.7%	0.58	56	6.1%	29.6%	0.33	389	3.3%	17.9%	0.64
SILVER	565	5.7%	33.0%	0.82	83	-5.3%	47.6%	0.67	482	7.8%	29.7%	0.92
PRECIOUSMET	504	5.2%	22.9%	0.84	72	7.3%	35.8%	0.58	432	4.9%	20.0%	0.90
USD/JPY	348	-0.3%	11.6%	0.57	34	7.9%	12.6%	-0.20	314	-1.1%	11.5%	0.67
USD/CHF	348	0.8%	11.9%	0.00	34	4.7%	12.9%	0.51	314	0.4%	11.8%	-0.08
USD/EUR	192	-1.6%	10.5%	-0.02	26	-4.9%	14.7%	0.10	166	-1.1%	9.7%	-0.02
USGOVBOND2	313	2.2%	2.1%	0.67	34	6.1%	3.3%	0.44	279	1.8%	1.9%	0.38
USGOVBOND5	313	3.7%	4.7%	0.16	34	9.8%	6.0%	0.68	279	3.0%	4.5%	-0.10
USGOVBOND10	313	4.6%	7.6%	0.33	34	9.6%	10.2%	1.50	279	4.0%	7.2%	-0.12
USGOVBOND30	313	6.5%	13.1%	0.62	34	9.6%	19.2%	0.97	279	6.2%	12.1%	0.37
USCORPIG	313	6.1%	5.9%	-0.28	34	2.4%	8.8%	-0.41	279	6.6%	5.5%	-0.10
GOVBONDXUS	349	5.0%	9.5%	0.21	34	8.6%	10.3%	0.00	315	4.6%	9.5%	0.24

Table 3: Descriptive statistics during bear markets and bull markets

	Total				Bear market				Bull market			
Variable	n	Mean	St.dev.	Skewness	n	Mean	St.dev.	Skewness	n	Mean	St.dev	Skewness
S&P500	565	3.7%	15.5%	-0.40	146	-17.1%	15.2%	-0.27	419	12.0%	14.9%	-0.46
GOLD	445	3.7%	19.7%	0.58	85	-9.1%	20.7%	-0.27	360	6.9%	19.4%	0.84
SILVER	565	5.7%	33.0%	0.82	146	-6.4%	31.1%	0.66	419	10.3%	33.5%	0.85
PRECIOUSMET	504	5.2%	22.9%	0.84	117	1.3%	28.1%	1.14	387	6.4%	21.1%	0.63
USD/JPY	348	-0.3%	11.6%	0.57	54	4.8%	11.2%	0.20	294	-1.2%	11.7%	0.64
USD/CHF	348	0.8%	11.9%	0.00	54	8.1%	11.0%	0.83	294	-0.5%	12.0%	-0.10
USD/EUR	192	-1.6%	10.5%	-0.02	41	0.9%	12.3%	0.28	151	-2.3%	9.9%	-0.20
USGOVBOND2	313	2.2%	2.1%	0.67	51	5.2%	3.1%	0.40	262	1.7%	1.9%	0.42
USGOVBOND5	313	3.7%	4.7%	0.16	51	7.5%	5.9%	0.46	262	3.0%	4.4%	-0.10
USGOVBOND10	313	4.6%	7.6%	0.33	51	7.4%	9.3%	1.38	262	4.1%	7.2%	-0.15
USGOVBOND30	313	6.5%	13.1%	0.62	51	10.9%	15.7%	1.90	262	5.7%	12.5%	0.10
USCORPIG	313	6.1%	5.9%	-0.28	51	2.0%	8.1%	-0.25	262	6.9%	5.4%	-0.14
GOVBONDXUS	349	5.0%	9.5%	0.21	54	6.7%	9.3%	0.13	295	4.7%	9.6%	0.23

Note: the descriptive statistics in Table 2 and Table 3 are based monthly data and converted into yearly figures.

As demonstrated above, most of the assets except gold and silver have positive returns during bear markets and contractions, which might be expected from a safe haven asset. The bond assets show positive returns during bull markets and expansions as well, and appear to be relatively stable overall. Gold and silver, despite showing unstable performance during bear markets and contractions, were included because they have received a lot of attention in previous research on safe haven assets.

The surprisingly low return on the S&P 500, 3.7% per annum after inflation, can be explained by the fairly poor performance of stocks during the first 20 years of our sample period.

4. VAR-GARCH Analysis

4.1 VAR-GARCH Methodology

4.1.1 Usual methodology and its restrictions

As Coudert and Raymond (2011) note, the majority of the empirical literature on gold as a safe haven asset is based on univariate regressions between gold returns and the returns of the asset being hedged. Using this approach, the return on gold is simply regressed on the return of the initial investment, e.g. stocks:

$$r_t^G = \alpha + \beta * r_t^S + \varepsilon_t^G \quad (1)$$

where r_t^G is the return on gold and r_t^S is the return on stocks. If β is negative or equal to zero, the assets are assumed to be uncorrelated or inversely correlated and gold is considered a hedge. In a safe haven context, the usual extension to this type of methodology is to test if the value of β changes during crises (Baur and Lucey, 2010) in order to check if the tested asset acts as a safe haven during such periods.

This type of approach has one important limitation, however; such a linear model assumes that stock returns are exogenous from the returns of the tested asset, i.e that $E(\varepsilon_t^G | r_t^S) = 0$ holds. This condition requires the error term ε_t^G to be uncorrelated with the explanatory variable r_t^S. A more realistic assumption would be to have time varying covariance between ε_t^G and r_t^S, since autoregressive heteroskedasticity in stock and gold returns is well documented, as noted by Coudert and Raymond (2011). It is reasonable to assume that the same characteristic might be problematic for several other assets tested in this paper as well.

Furthermore, as noted by Roach and Rossi (2009), when asset return volatilities show time-variation and clustering, a VAR(k)-GARCH(p,q) model might be more appropriate simply because it models price returns and volatility jointly. Considering the limitations of a univariate methodology mentioned above and the advantages of a bivariate GARCH(p,q) framework, we use a VAR(k)-GARCH(p,q) approach, with which we are able to examine if any significant conditional mean or volatility spillovers exist between the stock market and the candidate asset.

4.1.2 Tests for safe haven assets in a bivariate VAR(k)-GARCH(p,q) model

To summarize the entire procedure, we apply a bivariate VAR(k) process on the returns of the S&P 500 and each candidate asset, respectively. The VAR component of our model allows us to see if there are any significant mean spillovers from the S&P 500 to the candidate asset. The residuals from this estimation are then fed into a GARCH(p,q) process, which lets us detect any conditional volatility spillover from the S&P 500 to the candidate asset. Estimated parameters of the GARCH(p,q) model are then used to calculate the correlation between the S&P 500 and each tested asset for every day in the sample, which allows us to find the average correlation either for the full sample of data, or for a subsample such as a specific contraction or bear market. This will help us understand how the safe haven qualities of the tested assets have evolved through time – for each and every historical contraction and bear market in our sample, and for the short periods of time where both of these indicators overlap.

The Vector Autoregressive Models (VAR), popularized by Sims (see Sims, 1980), is a natural generalization of autoregressive models. Tedongap (2014) notes that the biggest advantages of VAR models are:

- They are more general than Autoregressive Moving Average (ARMA) models, allowing the returns of an asset to depend on another variable, and not just on its own lags or combinations of white noise terms.
- The Ordinary Least Squares method can be separately used on each equation due to the absence of contemporaneous terms on the right hand side of the equations.

A bivariate VAR(k) model for a candidate asset and the S&P 500 can be written in the following form:

$$\begin{cases} Asset_t = a_{10} + \sum_{i=1}^{k} b_{1i}\, Asset_{t-i} + \sum_{i=1}^{k} c_{1i}\, S\&P500_{t-i} + \sum_{i=1}^{k} d_{1i}\, Asset_{t-i} I_{Asset,t-i} + \sum_{i=1}^{k} g_{1i}\, S\&P500_{t-i} I_{S\&P500,t-i} + \varepsilon_{Asset,t} \\ S\&P500_t = a_{20} + \sum_{i=1}^{k} b_{2i}\, S\&P500_{t-i} + \sum_{i=1}^{k} c_{2i}\, Asset_{t-i} + \sum_{i=1}^{k} d_{2i}\, S\&P500_{t-i} I_{S\&P500,t-i} + \sum_{i=1}^{k} g_{2i}\, Asset_{t-i}\, I_{Asset,t-i} + \varepsilon_{S\&P500,t} \end{cases} \quad (2)$$

where the log return of the tested asset, $Asset_t$, is conditional both on $Asset_{t-i}$ and $S\&P500_{t-i}$ and the same is true for $S\&P500_t$.

This type of model allows us to test if any shock to the stock market might be transmitted to the returns of the tested asset. The dummy variables $I_{Asset,t-i}$ and $I_{S\&P,t-i}$ are equal to *1* when the corresponding lagged return is negative and *0* otherwise. These asymmetric terms are included in both VAR(k) equations as a way of distinguishing between the effects of positive and negative shocks, since there is often reason to believe that negative shocks might have a different impact on a series than positive shocks.

The number of lags used in the VAR(k) model is selected by minimizing the multivariate version of the Bayesian information criterion (MBIC):

$$MBIC = ln(|\Sigma_e|) + \frac{ln(T)}{T} \cdot m^2 k \tag{3}$$

where Σ_e is the variance-covariance matrix of the residuals from the VAR(k) estimation, *m* is the number of series we are estimating, *k* is the order of the VAR process, and *T* is the length of time series. Since the financial (and statistical) literature does not really provide any guidance in terms of selecting one information criterion over another, we prefer BIC due to its strong consistency compared to the Akaike information criterion (AIC), despite its lower efficiency (Tedongap, 2014).

For ten out of twelve candidate assets, MBIC was minimized with a *k* equal to 1, i.e. with one day's lagged return. In order to significantly simplify the implementation of the entire routine, we assume that all twelve assets follow the same process with a lag of one.

As mentioned above, univariate volatility models test the conditional variance of an asset return independently of all other financial assets. This is not a completely realistic assumption – there may be volatility spillovers, that is, a tendency for volatility to change in one market or asset following a change in the volatility of another, which leads to potential misspecification of a univariate model. Furthermore, covariances between financial assets as well as the variances of the individual assets are of interest themselves, especially when we are concerned with diversification and portfolio hedging issues. This is why a multivariate GARCH(p,q) model might be a better approach to use, since it provides estimates for the conditional variance as well as conditional covariances between assets.

In a multivariate GARCH(p,q) model, the conditional variance can be separated into an ARCH and a GARCH component. The ARCH component represents the squared

residuals of the previous period, while the GARCH component is associated with the persistence of shocks (Morley, 2012). Thus, for any two assets it is possible to form a diagonal GARCH(1,1) model using the following set of three equations:

$$\begin{cases} \sigma_{A,t}^2 = c_A + \alpha_A \varepsilon_{A,t-1}^2 + \beta_A \sigma_{A,t-1}^2 \\ \sigma_{S,t}^2 = c_S + \alpha_S \varepsilon_{S,t-1}^2 + \beta_S \sigma_{S,t-1}^2 \\ \sigma_{AS,t}^2 = c_{AS} + \alpha_{AS} \varepsilon_{A,t-1} \varepsilon_{S,t-1} + \beta_{AS} \sigma_{AS,t-1}^2 \end{cases} \quad (4)$$

where $\sigma_{A,t}^2$ is the conditional variance of the candidate asset, $\sigma_{S,t}^2$ is the conditional variance of stocks, and $\sigma_{AS,t}^2$ is the conditional covariance between the candidate asset and stocks.

Volatility spillovers are identified through the ARCH parameter α_{AS}, which represents the spillover from a shock to the stock market to the candidate asset. The GARCH parameter β_{AS} represents the persistence in variance transmitted from the stock market to the candidate asset. An estimate of the long-run relationship between the two assets is made through the constant term c_{AS}. The coefficients in the GARCH(1,1) model are estimated using maximum likelihood estimation over the full samples of daily data.

When we have estimates of the conditional covariances and variances, we are able to compute conditional correlations between the S&P 500 and all tested assets respectively for each day in the sample:

$$\rho_{AS,t} = \frac{\sigma_{AS,t}^2}{\sigma_{A,t}\sigma_{S,t}} \quad (5)$$

Finally, we can compute the average conditional correlation for the full sample as well as for any specific subsample in which we are interested. This enables us to see the "evolution" of correlations over time, which in turn allows us to investigate whether or not a tested asset has acted as a safe haven, and how reliable this property has been throughout the different historical crises in our sample.

4.2 VAR-GARCH Results

4.2.1 VAR component results

The conditional mean VAR(1) results estimated on the full sample of data are provided in Table 4 below, with p-values for every estimated coefficient provided in brackets.

Table 4: Estimated VAR parameters

Variable	Constant	$Asset_{t-1}$	$S\&P500_{t-1}$	$I_{Asset, t-1}$	$I_{S\&P500, t-1}$
GOLD	0.0003	-0.0091 (0.7799)	0.0289 (0.2704)	0.0075 (0.8836)	0.0218 (0.6251)
SILVER	0.0010	-0.1472 (0.0001)	0.1284 (0.1213)	0.0923 (0.1651)	0.0269 (0.6883)
PRECIOUSMET	0.0005	-0.0125 (0.6412)	0.0429 (0.1129)	0.0384 (0.3582)	0.0271 (0.5590)
USD/JPY	0.0001	-0.0502 (0.1658)	0.0192 (0.1925)	0.0629 (0.2288)	-0.0087 (0.7411)
USD/CHF	0.0000	-0.0224 (0.3517)	0.0148 (0.3581)	-0.0100 (0.8163)	-0.0037 (0.8945)
USD/EUR	0.0000	-0.0788 (0.0195)	0.0414 (0.0277)	0.0759 (0.1788)	-0.0292 (0.3415)
USGOVBOND2	0.0001	0.0554 (0.0296)	0.0019 (0.5250)	-0.0313 (0.4894)	0.0002 (0.9743)
USGOVBOND5	0.0002	0.0028 (0.9149)	0.0035 (0.6774)	0.0513 (0.2486)	0.0035 (0.7847)
USGOVBOND10	0.0003	0.0024 (0.9274)	0.0089 (0.5159)	0.0564 (0.2207)	0.0016 (0.9402)
USGOVBOND30	0.0003	0.0232 (0.4705)	-0.0015 (0.9452)	-0.0023 (0.9632)	0.0204 (0.5658)
USCORPIG	0.0004	0.0065 (0.7920)	0.0187 (0.0235)	0.0341 (0.4498)	0.0316 (0.0302)
GOVBONDXUS	0.0002	0.0099 (0.6617)	0.0102 (0.3899)	0.0310 (0.4425)	-0.0282 (0.1390)

These results demonstrate that for the majority of the candidate assets (excluding USD/EUR and U.S. corporate investment grade bonds) we are unable to find any evidence that disturbances in the stock market would be transmittable to the candidate assets, since there are no significant mean spillovers at the 5% level or even at the 10% level. This is positive for the potential safe haven abilities of these assets.

Silver, USD/EUR and 2-year U.S. Government bonds demonstrate autocorrelation, showing statistically significant coefficients for lag with themselves. More importantly, USD/EUR has a significant positive lag component from the returns of the S&P 500. This means that for USD/EUR, there might be statistically significant transmission of disturbances from the previous day's stock market return to the current period of candidate asset return, which might negatively affect its ability to serve as a safe haven asset.

For U.S Corporate Investment Grade bonds, a statistically significant positive asymmetric component is detected, as well as a significant positive lag component from the returns of the S&P 500. This implies that the current period return might be affected by the previous period's S&P 500 return, especially in the case of negative returns.

4.2.2 GARCH component results

The results of the GARCH(1,1) model estimations are presented in Table 5. The rightmost column, which provides the mean conditional correlation for each asset for the full sample of data, is perhaps the most interesting. We see that all assets except USD/EUR are considered hedge assets for equity investors in the long-run, i.e. they are uncorrelated or negatively correlated with stocks on average.

Table 5: Estimated GARCH parameters

	Conditional Variance of Asset			Conditional Variance of Stocks			Conditional Covariance between Asset and Stocks (significant at 10% level)				
Variable	c_A	α_A	β_A	c_S	α_S	β_S	c_{AS}	α_{AS}	β_{AS}	Mean variance	Mean conditional correlation
GOLD	0,0000	0,0406	0,9592	0,0000	0,0698	0,9195	0,0000	0,0205	0,9669	0,000150	-0,0183
SILVER	0,0000	0,0822	0,9129	0,0000	0,0671	0,9249	0,0000	-0,0300	-0,4500	0,000488	-0,0178
PRECIOUSMET	0,0000	0,0411	0,9554	0,0000	0,0670	0,9232	0,0000	0,0385	0,9096	0,000180	-0,0027
USD/JPY	0,0000	0,0438	0,9414	0,0000	0,0814	0,9082	0,0000	0,0671	0,9141	0,000050	-0,1637
USD/CHF	0,0000	0,0235	0,9557	0,0000	0,0812	0,9084	0,0000	0,0173	0,9715	0,000059	-0,1150
USD/EUR	0,0000	0,0339	0,9635	0,0000	0,0799	0,9102	0,0002	0,0650	0,9172	0,000041	0,0931
USGOVBOND2	0,0000	0,0331	0,9667	0,0000	0,0664	0,9239	0,0000	0,0622	0,9159	0,000001	-0,1204
USGOVBOND5	0,0000	0,0355	0,9590	0,0000	0,0665	0,9238	0,0000	0,0335	-0,9600	0,000007	-0,0951
USGOVBOND10	0,0000	0,0370	0,9541	0,0000	0,0667	0,9235	0,0000	0,0326	0,9611	0,000020	-0,0918
USGOVBOND30	0,0000	0,0372	0,9560	0,0000	0,9325	0,0610	0,0000	0,0278	0,9688	0,000059	-0,0698
USCORPIG	0,0000	0,0328	0,9598	0,0000	0,0669	0,9235	0,0000	0,0427	0,9283	0,000013	-0,0342
GOVBONDXUS	0,0000	0,0350	0,9597	0,0000	0,0813	0,9082	0,0000	-0,0040	-0,2000	0,000030	-0,0978

4.2.3 Conditional correlation during aggregated contractions and bear markets

Using the GARCH parameters estimated over the full sample of data, we calculate conditional variances, covariances and correlations for each trading day of the sample. These time series are illustrated for gold in Figure 3 below. In the bottom graph, we can see how the conditional correlation varies around zero, with slightly larger fluctuations in the beginning and in the end of the sample period.

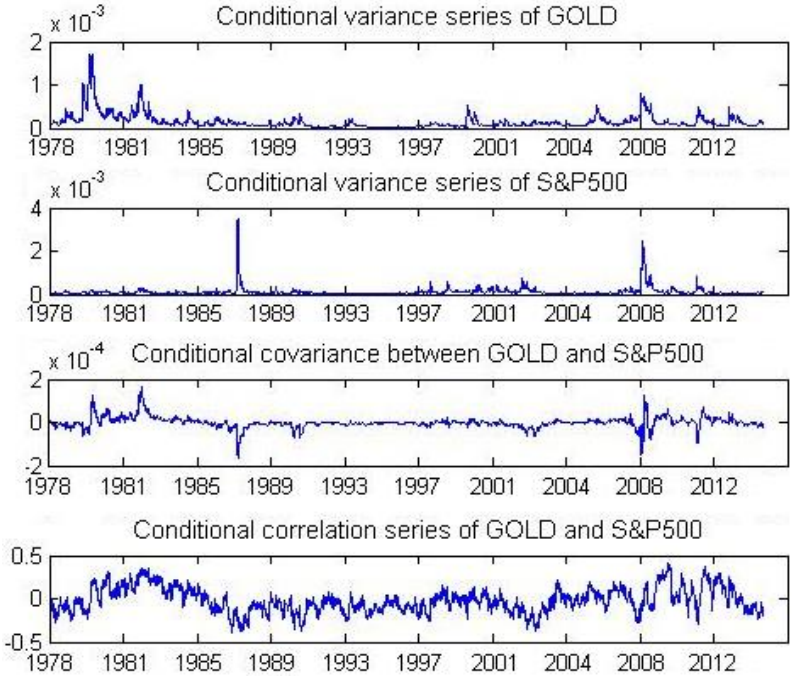


Figure 3

Table 6 demonstrates the average conditional correlation between the S&P 500 and every tested asset for the full sample of data and over aggregated contractions and aggregated bear markets.

Table 6: Mean correlations during full sample, contractions and bear markets

Variable	Full sample	Contractions aggregated	Bear markets aggregated
GOLD	-0,018	-0,009	-0,001
SILVER	-0,018	-0,012	-0,018
PRECIOUSMET	-0,003	-0,025	-0,013
USD/JPY	-0,164	-0,133	-0,220
USD/CHF	-0,115	-0,145	-0,160
USD/EUR	0,093	0,024	-0,015
USGOVBOND2	-0,120	-0,150	-0,049
USGOVBOND5	-0,095	-0,137	-0,024
USGOVBOND10	-0,092	-0,099	0,007
USGOVBOND30	-0,070	-0,062	0,030
USCORPIG	-0,034	-0,028	0,061
GOVBONDXUS	-0,098	-0,061	-0,085

As was demonstrated already in Table 5, all candidate assets except USD/EUR can be considered hedge assets for U.S. equity investors since the conditional correlation with the S&P 500 is negative when averaged over the full sample. Furthermore, we see that average conditional correlation varies depending on the asset class. The commodities are almost completely uncorrelated with stocks over the full sample, while bonds show negative correlations in the -3% to -12% range, with government bonds exhibiting larger negative correlations than corporate bonds.

Looking at the conditional correlation averaged over all aggregated contraction periods, we see again that all candidate assets except USD/EUR show negative correlations with stocks. This is a clear indication of safe haven qualities and a potential to protect the value of a portfolio of stocks during contractions. Commodities are again almost uncorrelated with stocks, while bonds demonstrate larger negative correlations.

The results for the aggregated bear markets are slightly different, indicating that longer-term U.S. Government bonds and U.S. Corporate Investment Grade bonds are positively correlated with the S&P 500. Remaining assets exhibit safe haven qualities during bear markets, with the currency pairs USD/JPY and USD/CHF standing out as particularly strong safe havens.

4.2.4 Evolution of correlations through contractions and bear markets

Table 7 demonstrates average conditional correlations for every candidate asset during different historical contractions. The number of contractions for which we have results is different for each candidate asset, depending on the length of that particular time series. The time frame of each contraction and bear market is presented in Table A1 in the Appendix.

Table 7: Mean correlations during contractions

Variable	Contractions aggregated	Contraction 1	Contraction 2	Contraction 3	Contraction 4	Contraction 5	Contraction 6	Contraction 7
GOLD	-0,018			0,069	0,175	-0,198	-0,034	-0,057
SILVER	-0,018	-0,024	-0,007	-0,003	-0,014	-0,017	-0,013	-0,004
PRECIOUSMET	-0,003		-0,010	0,065	-0,002	-0,135	-0,024	-0,044
USD/JPY	-0,164					0,118	-0,028	-0,491
USD/CHF	-0,115					-0,124	-0,166	-0,146
USD/EUR	0,093						-0,061	0,108
USGOVBOND2	-0,120					0,132	-0,214	-0,369
USGOVBOND5	-0,095					0,309	-0,246	-0,474
USGOVBOND10	-0,092					0,372	-0,227	-0,443
USGOVBOND30	-0,070					0,413	-0,174	-0,424
USCORPIG	-0,034					0,258	-0,118	-0,225
GOVBONDXUS	-0,098					-0,078	-0,064	-0,040

The correlation of gold seems to have changed over time from somewhat positive to negative, which coincides with what Coudert and Raymond (2011) finds, i.e. that gold is uncorrelated on average but not for every contraction. The Precious Metals Index demonstrated correlations that were slightly negative or around zero but with some fluctuations over time. Silver however appears to be a very stable safe haven asset, showing slightly negative correlation with the S&P 500 during all seven contractions. Throughout the entire sample period (1968-2015), investors in U.S. equities could have used silver as a safe haven during recessions.

Currencies demonstrate significant potential as well, although we have less data on which to base our judgment. USD/JPY shows large negative correlation on average, but also very large fluctuations. USD/CHF on the other hand exhibits strong, persistent negative correlation during every contraction.

The bond assets can be divided into two different groups. Both U.S. Corporate Investment Grade bonds and U.S. Government bonds of different maturities demonstrate a similar pattern of correlation with very large fluctuations, from strong positive correlation to strong negative. Global government bonds on the other hand exhibit stable negative correlation throughout all three contractions, which suggests that they add another dimension of diversification compared to U.S. Government bonds.

Table 8, which is displayed on the next page, demonstrates average conditional correlations for every candidate asset during different historical bear markets. As we can see, the results for bear markets are very similar to those seen for contractions, for most of the candidate assets.

Gold and precious metals demonstrate a similar pattern with higher correlations during the earlier bear markets and negative correlations during the later, while silver again exhibits weak but stable negative correlation with the S&P 500 during all eleven bear markets.

Among the currencies, USD/CHF and USD/JPY display persistent negative correlation throughout all bear markets, except for one period where USD/JPY shows slightly positive correlation. It is interesting to note that USD/JPY appears to be a slightly more stable safe haven asset during bear markets than during contraction periods.

Bonds demonstrate similar properties as during contractions, i.e. global government bonds show stable negative correlation during all bear markets, while the correlations of U.S. Corporate Investment Grade bonds and U.S. Government bonds are positive during the earlier bear markets and negative during the later.

Table 8: Mean correlations during bear markets

Variable	Bear markets aggregated	Bear market 1	Bear market 2	Bear market 3	Bear market 4	Bear market 5	Bear market 6	Bear market 7	Bear market 8	Bear market 9	Bear market 10	Bear market 11	Bear market 12
GOLD	-0,001					0,151	0,145	0,151	-0,173	-0,125	-0,055	-0,068	-0,031
SILVER	-0,018		-0,026	-0,028	-0,010	-0,032	-0,015	-0,013	-0,005	-0,024	-0,019	-0,016	-0,005
PRECIOUSMET	-0,013				-0,029	0,013	0,103	0,106	-0,109	-0,101	-0,038	-0,040	-0,022
USD/JPY	-0,220								-0,274	0,036	-0,121	-0,191	-0,550
USD/CHF	-0,160								-0,189	-0,147	-0,078	-0,183	-0,202
USD/EUR	-0,015											-0,083	0,054
USGOVBOND2	-0,049									0,155	0,320	-0,259	-0,412
USGOVBOND5	-0,024									0,284	0,398	-0,266	-0,510
USGOVBOND10	0,007									0,328	0,415	-0,237	-0,478
USGOVBOND30	0,030									0,344	0,390	-0,176	-0,437
USCORPIG	0,061									0,276	0,360	-0,139	-0,254
GOVBONDXUS	-0,085								-0,060	-0,102	-0,141	-0,070	-0,050

4.2.5 Correlation during overlap of contractions and bear markets

For equity investors, it is crucial to be protected during the most difficult of times. A particularly troubling time for investors might be when there are problems both in the economy (contractions) and in the financial markets (bear markets). These periods, when both crisis indicators used in this paper overlap, are presented in the Appendix (Table A1). The average conditional correlations for these periods are shown in Table 9.

Table 9: Mean correlations during overlapping periods

Variable	Overlap 1	Overlap 2	Overlap 3	Overlap 4	Overlap 5
GOLD			-0,171	-0,034	-0,051
SILVER	-0,028	-0,007	-0,019	-0,013	-0,004
PRECIOUSMET		-0,017	-0,129	-0,023	-0,036
USD/JPY			0,028	-0,027	-0,545
USD/CHF			-0,215	-0,166	-0,213
USD/EUR				-0,061	0,034
USGOVBOND2			0,179	-0,214	-0,406
USGOVBOND5			0,336	-0,246	-0,511
USGOVBOND10			0,394	-0,227	-0,480
USGOVBOND30			0,410	-0,174	-0,447
USCORPIG			0,308	-0,118	-0,252
GOVBONDXUS			-0,082	-0,064	-0,044

This demonstrates that there are several assets which had negative average correlation during all overlapping periods. All commodities, USD/CHF and global government bonds functioned as safe haven assets during all periods for which we have data. The remaining bond assets and USD/JPY displayed highly fluctuating correlations, generally replicating the results we saw for separate contractions and bear markets.

It should however be noted that the sample sizes are very limited for these particular periods.

4.2.6 Summary of the VAR-GARCH analysis

The main results of the VAR-GARCH analysis can be summarized as following:

- All tested assets except USD/EUR can be considered hedges for U.S. stocks in the long run.
- We find potential safe haven assets in all asset classes. Gold futures, the Precious Metals Index, silver, USD/CHF, USD/JPY, global government bonds, 2-year U.S. Government bonds and 5-year U.S. Government bonds all exhibit safe haven qualities for aggregated contractions and bear markets.

- Looking at individual crisis periods, three assets in particular stand out – silver, USD/CHF and global government bonds, which demonstrated negative correlation with the S&P 500 during each and every contraction and bear market, and during the periods when both of these crisis indicators overlap.
- In general, we see similar patterns of correlation regardless of whether we look at contractions, bear markets or overlapping periods. This suggests that the choice of how to define a crisis period is not crucial, or at least that our three indicators capture periods which are relatively similar in terms of how different assets behave.

4.3 Limitations of the VAR-GARCH Study

A general restriction with an analysis that is focused mainly on crisis periods is the limited amount of data that is available. Even when going back 25-30 years, which is about the length of eight of our twelve time series, we still only cover three contractions and four or five bear markets. For these assets, that effectively sums up only to a couple of years of data spread out over a long period of time, which might make it difficult to discern any trends in the behavior of these assets over time or make any predictions about what the performance will be in the future.

Another issue relates to how these crisis periods are identified. Both the contractions (which are dated by the NBER) and the bear markets (which are identified using an algorithm) are dated after the fact. In other words, our study implicitly assumes that the investor is able to determine exactly when a contraction or a bear market has begun or ended. Therefore it might be difficult for a real investor to apply the results of our study in practice, since a real investor would not be able to know when these turning points have occurred until afterwards.

Finally, even though our methodology is relatively sophisticated, average correlations might not provide a measure of how safe an asset is that coincides with the experience that a real investor in the asset would have. For example, during the recent financial crisis, the price of silver changed from about $14/oz to nearly $13/oz, maintaining its value relatively well and demonstrating slightly negative average correlation in our VAR-GARCH approach. However, examining the underlying data, we see that the price of silver first moved in the opposite direction of stocks during the main part of the crisis, surging from $14/oz to $18-20/oz, only to then crash completely down to a low of about $9/oz before recovering to $13/oz. In other words, even though we can see with hindsight that its value was maintained overall, an investor at the time would probably have perceived this asset as very

risky. In this particular case, using weekly or monthly data might have provided a different picture of how of correlated this asset really was with stocks during the financial crisis.

5. Negative Shock Analysis

5.1 Negative Shock Methodology

Whereas the regression model in the VAR-GARCH analysis serves to test how the safe haven candidates behave during longer periods of time, the negative shock analysis instead tests the resilience of these assets in the face of an extreme negative shock to the stock market. This is accomplished by examining the average cumulative returns of stocks and the safe haven candidates, respectively, during a period of time spanning from 50 trading days before a shock to 50 trading days after.[1]

As far as we are aware, this type of analysis was first conducted in a safe haven context by Baur and Lucey (2010), who tested only gold. Although their analysis was interesting, it gave little guidance to investors regarding when they should buy and when they should sell gold. In essence, their data suggests that it is only profitable to hold gold instead of stocks on the actual day when a negative shock to the stock market occurs. However, since we cannot know in advance when these shocks will occur, their finding implies that investors should perhaps not even buy gold in the first place. Thus, the short-lived safe haven property of gold that they find is actually non-existent, or rather, existent but impossible to profitably utilize for investors.

With these limitations in mind, we extend the analysis conducted by Baur and Lucey (2010) in a way that we believe should provide investors with better guidance on how to utilize safe haven assets in practice. This is achieved by (i) analyzing the performance both before and after the shock as opposed to just examining the performance after the shock, and (ii) explicitly analyzing both the case when the safe haven candidate is held during the entire period surrounding the shock (Section 5.2.1), and the case where the safe haven candidate is bought on the day after the shock has already occurred (Section 5.2.2).

To identify negative shocks to the stock market, we look at the 5% and the 1% worst stock market days in our sample. The distribution of these shocks over time is presented in Figure 4 and Figure 5.

[1] The selection of time period to examine is an arbitrary choice and difficult to motivate. It can be interpreted as a measure of the outcome to an investor who holds the asset exactly during this time period. Using a shorter or longer holding period might of course affect the results and thus the conclusions that we draw from this experiment. However, by looking at Figure A13-A18 in the Appendix, we can see the results for any holding period within t=-50 and t=50.

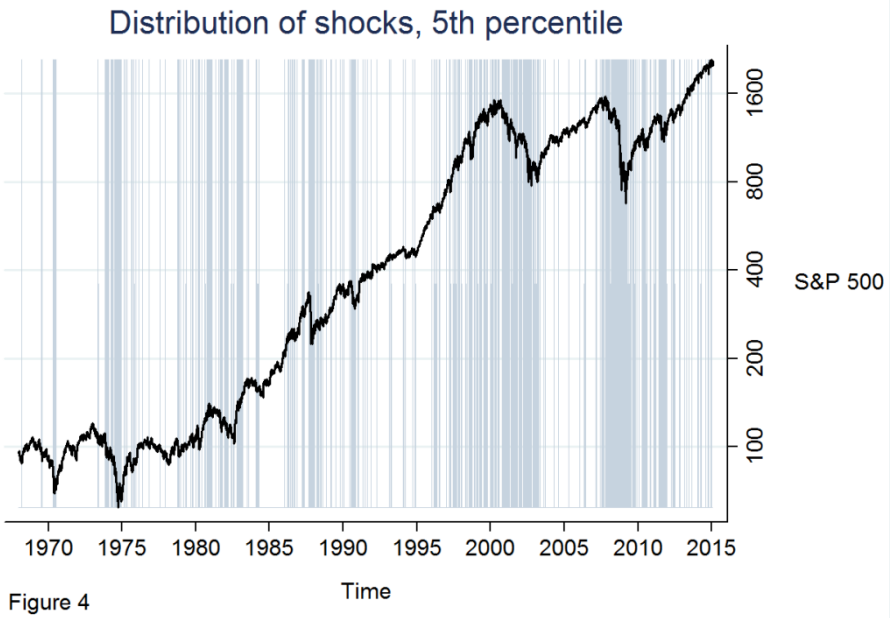


Figure 4

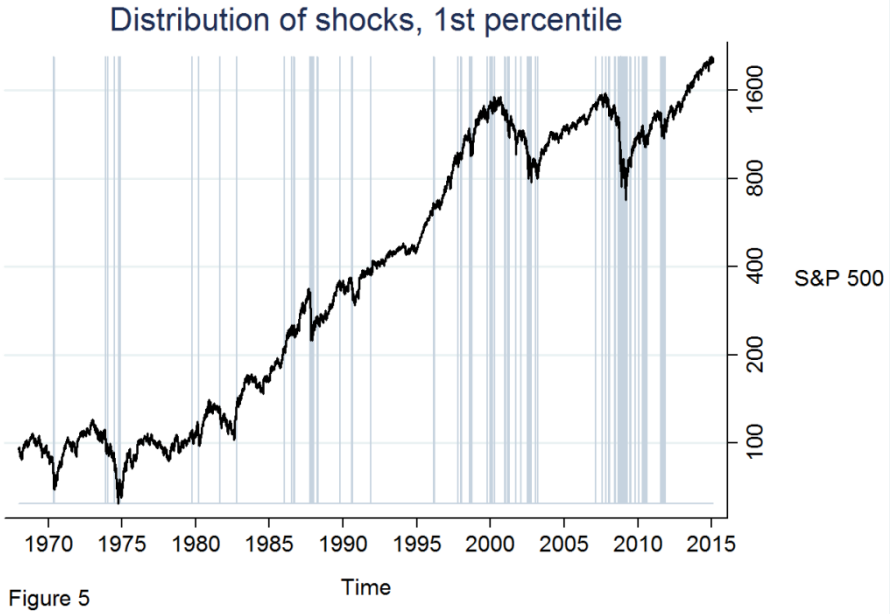


Figure 5

Depending on which asset we are concerned with, the average cumulative returns are calculated over about 400-600 shocks in the 5th percentile case, and 100-120 shocks for the 1st percentile.

5.2 Negative Shock Results

5.2.1 Safe haven asset is held from t=-50 to t=50

The main results from the tests where the safe haven candidate is held both before and after a shock are presented in the Appendix (Figure A13-A18). We can see that all the safe haven candidates easily outperform the S&P 500 during the period from t=-50 to t=50, which is not surprising since the data is constructed around negative shocks to the S&P 500. Some other general patterns that we note are:

- Stocks generally decline during the days leading up to a shock, and then recover after the shock.
- Some safe haven candidates exhibit a small price increase on the day of an actual shock, which may stem from increased demand as investors switch from stocks to other assets in response to the shock.[2] The assets that display this behavior include the Japanese yen, the Swiss franc, and all bond assets. For all of these assets, the price increase on the day of the shock is larger in response to a more severe shock (i.e. when comparing 5th percentile shocks against 1st percentile shocks). This is demonstrated below in Figure 6 (5th percentile) and Figure 7 (1st percentile).
- The longer-term U.S. Treasury bonds and the global government bonds are generally among the top performers over the entire period. The Japanese yen also performs exceptionally well around the most extreme negative shocks.

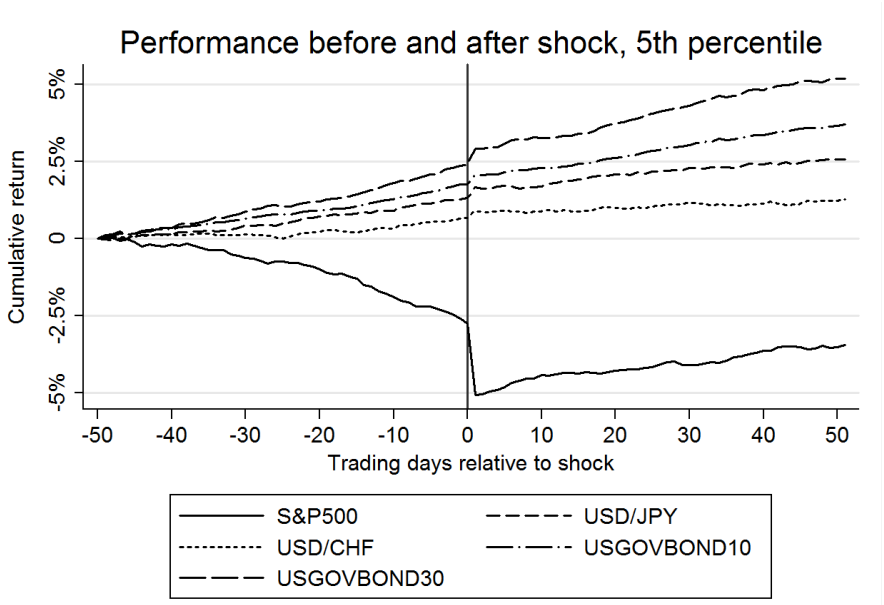


Figure 6

[2] Another explanation might be that a shock to the stock market is correlated with some other factor which in turn has an impact on the return of the safe haven candidate.

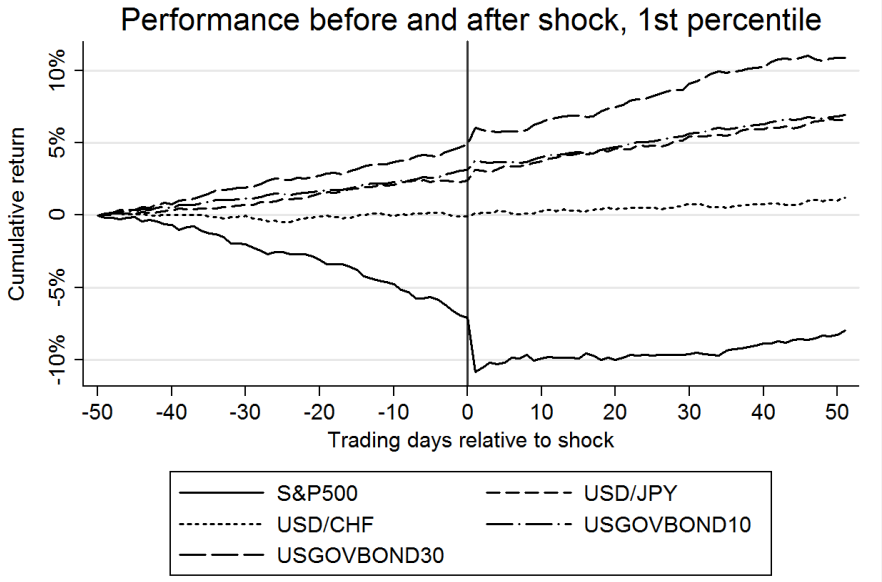


Figure 7

5.2.2 Safe haven asset is held from t=1 to t=50

The more interesting case is perhaps when the safe haven candidate is bought on the day after the shock has already occurred. This test enables us to comment on the real world practice noted by Baur and McDermott (2010) and Baur and Lucey (2010), where a safe haven asset is bought by investors in response to a negative shock. Finding an asset which actually outperforms the S&P 500 would imply that there is a trading opportunity which could be utilized by selling the S&P 500 and buying this other asset. The results are presented in Table 10, with graphical representations being presented in the Appendix (Figure A19-A24).

Table 10: Performance of assets from t=1 to t=50

	5th percentile						1st percentile					
Variable	n	Average return[1]	St.dev.[2]	Average return/St.dev	Outperformed S&P?[3]	Maintained value?[4]	n	Average return[1]	St.dev.[2]	Average return/St.dev	Outperformed S&P?[3]	Maintained value?[4]
S&P500	611	1.72%	8.99%	0.19	n/a	61.9%	122	3.25%	11.18%	0.29	n/a	60.7%
GOLD	531	0.86%	8.48%	0.10	40.9%	49.0%	115	2.50%	8.91%	0.28	46.1%	53.9%
SILVER	611	0.81%	16.00%	0.05	42.1%	45.3%	122	1.08%	17.23%	0.06	40.2%	44.3%
PRECIOUSMET	598	1.37%	12.09%	0.11	43.5%	50.2%	121	2.67%	12.38%	0.22	46.3%	50.4%
USD/JPY	466	0.90%	6.00%	0.15	38.2%	52.6%	110	3.38%	7.41%	0.46	40.9%	62.7%
USD/CHF	466	0.37%	5.51%	0.07	38.6%	51.3%	110	1.08%	6.69%	0.16	41.8%	53.6%
USD/EUR	332	-0.08%	5.12%	-0.02	43.7%	50.6%	85	0.65%	5.73%	0.11	44.7%	54.1%
USGOVBOND2	410	0.78%	1.19%	0.66	40.7%	75.1%	97	1.10%	1.52%	0.73	40.2%	78.4%
USGOVBOND5	410	1.31%	2.59%	0.51	42.7%	68.3%	97	2.13%	3.29%	0.65	43.3%	70.1%
USGOVBOND10	410	1.60%	4.40%	0.36	43.2%	62.4%	97	3.05%	6.00%	0.51	43.3%	63.9%
USGOVBOND30	410	2.21%	7.91%	0.28	45.4%	59.5%	97	4.57%	11.34%	0.40	44.3%	61.9%
USCORPIG	410	1.42%	3.47%	0.41	43.9%	72.2%	97	1.92%	4.89%	0.39	41.2%	69.1%
GOVBONDXUS	466	1.53%	4.79%	0.32	42.7%	59.7%	110	3.33%	5.78%	0.58	47.3%	67.3%

[1] Average increase in wealth from investing in the asset from t=1 to t=50.
[2] Standard deviation in the end-of-period (t=50) wealth over all relevant shocks.
[3] Percentage of shocks where the safe haven candidate outperformed the S&P 500 during t=1 to t=50.
[4] Percentage of shocks where the safe haven candidate had non-negative cumulative return during t=1 to t=50.

The most important column is perhaps the one of average returns throughout the holding period, and the first thing we note is that few assets actually beat the S&P 500 (and this is measured before any eventual transaction costs). This implies that switching from stocks to a safe haven asset generally comes with a cost in terms of forgone profits. Why some investors would choose to incur this cost is unknown to us, but we can think of two reasons in general: (i) investors want to reduce risk temporarily, and/or (ii) investors believe, although being incorrect on average, that stocks will continue to plummet and seek to profit from selling stocks and buying safer assets. In the first case, that of risk reduction, we will soon show that some assets achieve this goal better and more cheaply than others. In the second case, that of trying to profit from a negative shock to the stock market, we will show that only one or two of the tested assets are able to achieve this.

Many of the safe haven assets are able to reduce risk, where risk in this case is measured as the dispersion of end-of-period (t=50) wealth over all shocks. Almost all safe haven candidates except silver and precious metals have lower risk than the S&P 500. Furthermore, since many assets also have higher return than silver and precious metals, we can quickly conclude that these two assets are not optimal for post-shock investing. Looking at gold we can see that, despite its popularity, it is not the best choice out there either. Investing in gold after a 1st percentile shock to the S&P 500 yields on average a 2.50% cumulative return over 50 trading days. However, there are assets such as the Japanese yen, 10-year U.S. Treasury bonds, and global government bonds which produce even higher returns at an even lower risk. When it comes to risk reduction, the performance of shorter-term (2-5 year) government bonds is unmatched. They produce decent returns at very low levels of risk, and they are also the assets which most often are able to maintain their value throughout the entire period (i.e. produce at least a positive return). More generally, we also note that the bond assets have higher returns per unit of risk compared to most other assets.

The only asset that is able to comfortably produce a higher return than the S&P 500 is the 30-year U.S. Treasury bond, and this is done at a risk level similar to that of the S&P. For example, after a 1st percentile shock 30-year U.S. Treasury bonds produce on average a cumulative return of 4.57% over 50 trading days, corresponding to a 25% return annualized. The Japanese yen and global government bonds also outperform the S&P 500, just barely, after 1st percentile shocks, although they do so at a lower risk level than the S&P and might therefore also be considered worthwhile investments.

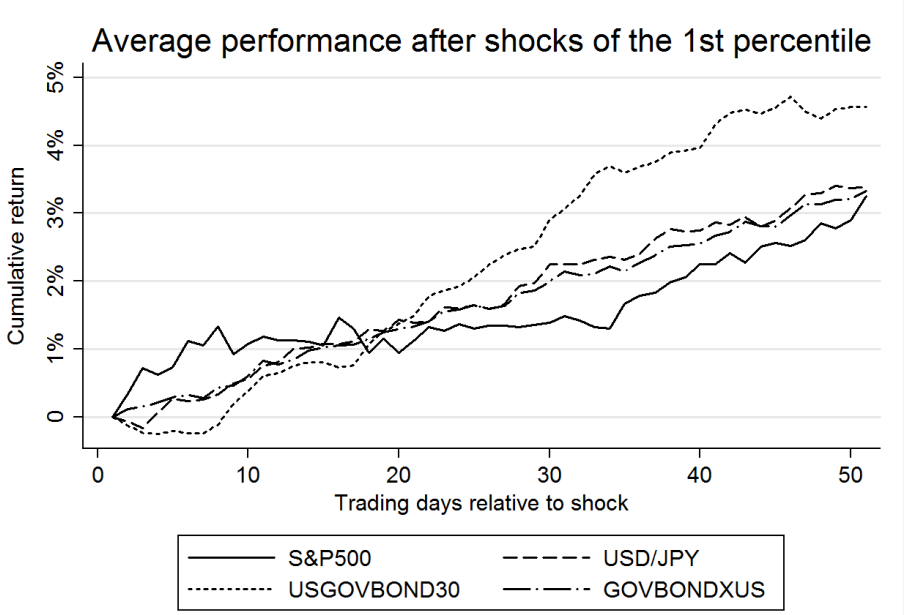


Figure 8

Finally, we note that the post-shock performance of many of the safe haven candidates is slightly positively skewed. For example, 2-year U.S. Treasury bonds seldom lose more than 1% of their value over the 50 trading days following a stock market shock. However, they record gains in the 2-5% region relatively often, as demonstrated in Figure 9 below.

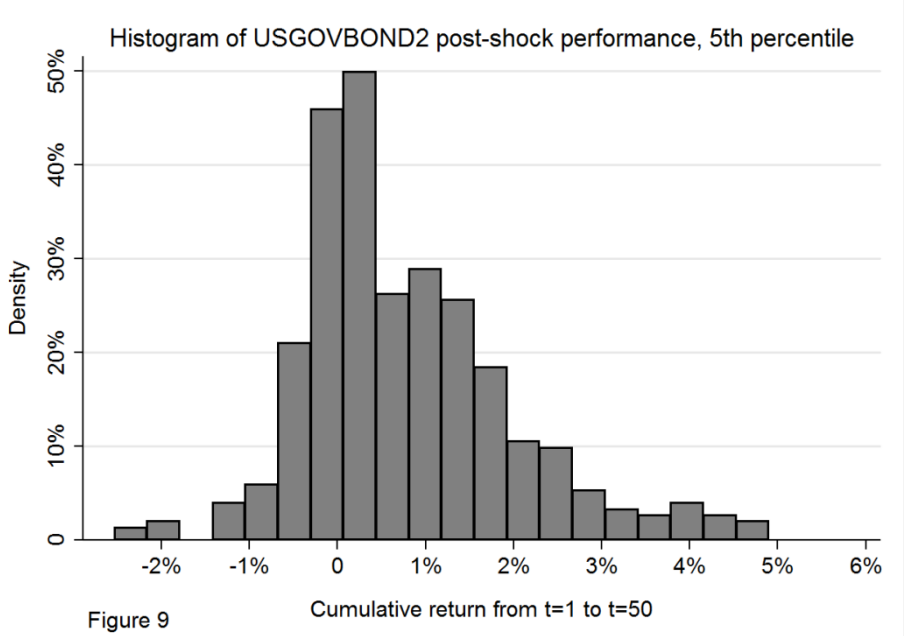


Figure 9

Looking at the performance of a riskier asset, such as 30-year U.S. Treasury bonds, we see the same pattern but with a larger spread in cumulative returns. The distribution of post-shock

cumulative returns for shocks of the 1st percentile is visualized in Figure 10, and shows that the cumulative return rarely falls below -10%, although a significant portion of the observations fall within the 20-35% range in the positive spectrum.

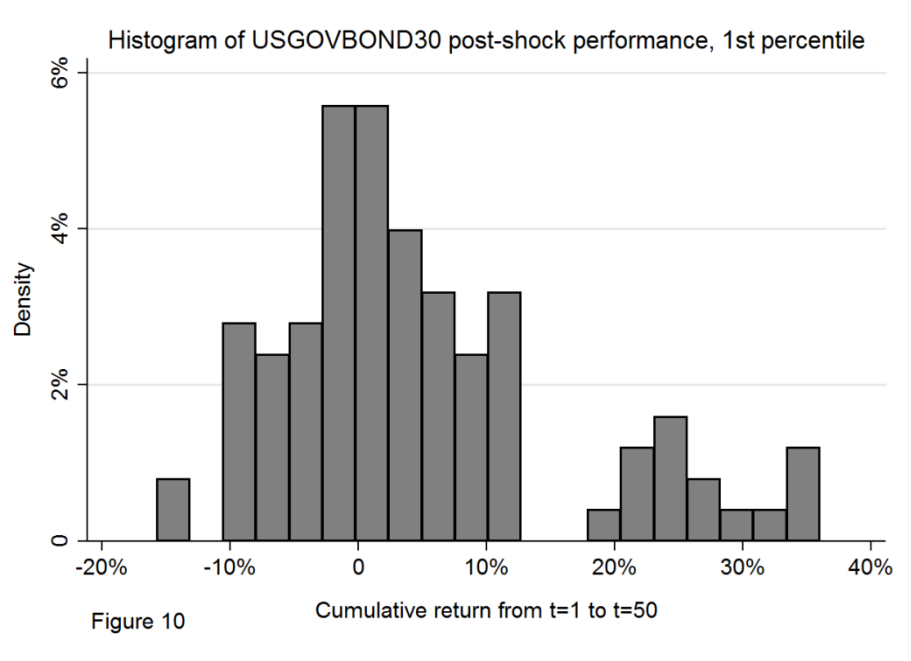


Figure 10

On one hand, positive skew is generally something desirable, at least compared to negative skew. On the other hand, it also implies that the high average returns that we see for 30-year U.S. Treasury bonds are somewhat driven by a few outliers, and that one might need to invest in many of these shocks over a long period of time to ensure that the end result really is a return higher than that of the S&P 500.

5.3 Limitations of the Negative Shock Analysis

Even though our results suggest that there might be profits to make by buying long-term bonds after the most extreme shocks, we would exercise caution in interpreting this as a statistical truth. The sample size for shocks of the 1st percentile is only about 100-120 observations, depending on which asset we examine, and there is a period during 2008 with a particularly high concentration of negative shocks during which bonds generally performed very well. On one hand, this might have provided an exaggerated view on the performance of bonds. On the other hand, this particular period was one of the most challenging times in the history of stock markets, and bonds turned out to deliver high returns precisely at the time when it was needed the most. This is very much related to the issue of skewness, and the histogram presented in Figure 10 might give investors a better view of what to expect

compared to the average numbers presented in Table 10. This issue should however not be a concern when looking at the 5th percentile shocks, since the sample size is much larger and the distribution of shocks over time is more even.

Investing in long-term bonds is also relatively risky compared to investing in shorter-term bonds because of their sensitivity to interest rate changes. This is however captured implicitly in our study, i.e. if negative shocks are correlated with changes in expectations of interest rates it will also impact bond returns which are measured in our study.

In the discussion of whether gold or bonds should be used as a safe haven asset in relation to stock market shocks, an investor might also be concerned with protecting the portfolio against a surge in inflation. Since higher inflation is somewhat associated with higher future policy rates and higher yield requirements by bond investors who desire a positive real return, gold might provide better protection against higher inflation. This is an aspect that is not covered in the negative shock analysis. However, it should not be a major concern since the main purpose of this particular exercise is to evaluate the performance during shorter time frames for which inflation should not be an issue.

Finally, an analysis like this, which focuses only on negative shocks, will never provide a conclusive answer on which safe haven assets to use and how to use them. However, it does provide more information and guidance to investors on a small piece of the puzzle. Combined with the VAR-GARCH analysis, we believe that we have made a contribution to the topic of how to use safe haven assets both for short-term and for long-term purposes.

6. Conclusion

In this paper, we set out to test the safe haven qualities of a broad range of assets including commodities, currencies and bonds. Using two different types of analyses – a VAR-GARCH study focusing on the average correlations between the safe haven candidates and stocks during longer crisis periods, and a negative shock analysis focusing on the performance before and after shocks to the stock market – we find plenty of evidence of assets with safe haven qualities.

Global government bonds perform decently in both analyses, i.e. they seem to be negatively correlated with stocks during contractions and bear markets, and also perform relatively well both before and after negative stock market shocks. U.S. Government bonds and U.S. Corporate Investment Grade bonds are the best performing assets against stock market shocks, though the results are skewed. They also perform well *on average* during

aggregate contractions (and are uncorrelated during bear markets), but the results are unstable over time. An investor using these assets might get very good protection in some cases, but not in others.

The Japanese yen appears to be better suited for dealing with stock market turbulence than for periods of general economic decline, since it shows better performance during bear markets than during contractions. Furthermore, the results are strong but uneven over time, and it seems to deliver the best protection only against the most extreme shocks to the stock market.

The Swiss franc and silver show the best and most stable results in the entire VAR-GARCH analysis, but they provide poor protection against stock market shocks. They might be suitable to include in the portfolio during longer periods of uncertainty or turbulence, but should probably not be used for shorter-term trading.

Finally, for gold, one of the more commonly used safe haven assets, we find that it does perform decently in both analyses – however, it should not be automatically considered the go-to safe haven asset, since there are other assets which perform better in both of our analyses.

We also find that switching from stocks to safe haven assets after a shock to the stock market [which is the type of behavior that investors seem to have according to Baur and McDermott (2010) and Baur and Lucey (2010)] is generally not profitable. For that reason, we recommend that investors who want to use safe haven assets include them in the portfolio for longer periods of time, rather than buying them as a panic response to sudden volatility spikes and selling them shortly thereafter.

7. Further Research

Since this is a fairly new research topic, we can think of several possible extensions to our study which might provide more knowledge on the topic or overcome some of the limitations that we bring up in this paper.

An obvious suggestion is to test the broad range of assets that we have examined in this paper on other markets. Do European investors or investors in Emerging and Frontier markets have similar opportunities when it comes to safe haven assets?

An extension of the VAR-GARCH analysis could be to replicate our results in a framework where contractions and bear markets are identified in "real-time". For example, the investor could continuously estimate a probability of being in a particular regime, using only information that was available at the time when the estimation was made.

Alternatively, a different methodology, such as the Engle-Granger two-step approach, could be used to test if an asset is a potential hedge or safe haven for the S&P 500 in the long run.

An extension to the negative shock analysis could be to investigate if assets perform differently before and after shocks that occur during different states of the economy, e.g. if a shock is perceived differently if it occurs during a contraction compared to an expansion.

In general, more research on how to use safe haven assets in practice is also needed. For example, a portfolio theory perspective, which not only deals with volatility and correlations but also takes expected returns into account, might be applied with a focus on safe haven assets and crisis periods in particular. Cenedese (2012) employs such a framework in a Markov regime-switching model where a portfolio of currency assets is optimized, but similar work is required for other asset classes as well.

Finally, even though we have a fairly long data sample, there are still very few contractions and bear markets to analyze. More data or more efficient methodologies might simply be needed to provide some conclusive answers on how several of these assets behave during crisis periods.

8. References

Baele, L., Bekaert, G. and Inghelbrecht, K. (2010) "The determinants of stock and bond return comovements", *Review of Financial Studies*, 23(6), pp. 2374-2428.

Baur, D.G. and Lucey, B.M. (2010) "Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold", *Financial Review*, 45(2), pp. 217-229.

Baur, D.G. and McDermott, T.K. (2010) "Is gold a safe haven? International evidence", *Journal of Banking and Finance*, 34, pp. 1886-1898.

Baur, D.G. and McDermott, T.K. (2012) *"Safe haven assets and investor behavior under uncertainty"*, Working Paper, UTS Business School – University of Technology Sydney, No 173.

Brunnermeier, M.K., Nagel S. and Pedersen, L.H. (2008) "Carry Trades and Currency Crashes", *NBER Macroeconomics Annual 2008*, 23, pp. 313-347.

Cenedese, G. (2012) *"Safe Haven Currencies: A Portfolio Perspective"*, Working Paper, Bank of England.

Chan, K.F., Treepongkaruna, S., Brooks, R. and Gray, S. (2011) "Asset market linkages: evidence from financial, commodity and real estate assets", *Journal of Banking and Finance*, 35, pp. 1415-1426.

Cheung, Y.W and Kon S. Lai (1995) "Lag Order and Critical Values of A Modified Dickey-Fuller Test", *Oxford Bulletin of Economics and Statistics*, 57, pp. 411-419.

Connolly, R., Stivers, C. and Sun, L. (2005) "Stock market uncertainty and the relation between stock and bond returns", *Journal of Financial and Quantitative Analysis*, 40, pp. 161-194.

Coudert, V. and Raymond, H. (2011) "Gold and financial assets: are there any safe havens in bear markets?", *Economic Bulletin*, 31(2), pp. 1613-1622.

Degennaro, R.P., Kunkel, R.A. and Lee, J. (1994) "Modeling international long-term interest rates", *The Financial Review*, 29(4), pp. 577-597.

Flavin, T.J., Panopoulou, E. and Unalmis, D. (2008) "On the stability of domestic financial market linkages in the presence of time-varying volatility", *Emerging Markets Review*, 9(4), pp. 280-301.

Gorton, G. and Rouwenhorst, G. (2006) "Facts and fantasies about commodity futures", *Financial Analysts Journal*, 62, pp. 47-68.

Habib, M.M. and Stracca, L. (2012) "Getting beyond carry trade: What makes a safe haven currency?", *Journal of International Economics*, 87(1), pp. 50-64.

Kim, S.J., Moshirian, F. and Wu, E. (2006) "Evolution of international stock and bond market integration: influence of the European Monetary Union", *Journal of Banking and Finance*, 30, pp. 1507-1534.

Lawrence, C. (2003) *"Why is gold different from other assets? An empirical investigation"*, Research Paper, World Gold Council, March 2003.

Menkhoff, L., Sarno, L., Schmeling, M. and Schrimpf, A. (2009) "Carry Trades and Global Foreign Exchange Volatility", *Journal of Finance*, 67(2), pp. 681-718.

Morley, C (2012) *"Is Gold a Safe Haven for Equity Investors? A VAR-GARCH analysis"*, Working Paper, National University of Ireland.

Pagan, A.R. and Sossounov K.A. (2003) "A simple framework for analyzing bull and bear markets", *Journal of Applied Econometrics*, 18, pp. 23-46.

Roach, S. K. and Rossi, M. (2009) *"The effects of economic news on commodity prices: Is gold just another commodity?"*, Working Paper, IMF, 09/140.

Scruggs, J.T. and Glabadanidis, P. (2003) "Risk premia and the dynamic covariance between stock and bond returns", *Journal of Financial and Quantitative Analysis*, 38(2), pp. 295-316.

Sims, C.A. (1980) "Macroeconomics and Reality," *Econometrica*, 48, pp. 1-48.

Steeley, J.M. (2006) "Volatility transmission between stock and bond markets", *Journal of International Financial Markets, Institutions and Money*, 16, pp. 71-86.

Tedongap, R. (2014) “Multivariate Time Series Modeling”, *Quantitative Modeling of Asset Prices*, lecture materials, Semester 2, 2014, Stockholm School of Economics.

9. Appendix

Table A1: Overview of contractions and bear markets, and periods when these indicators overlap

Contractions				Bear markets				Overlapping periods			
Name	Peak	Trough	Length (months)	Name	Peak	Trough	Length (months)	Name	Start	End	Length (months)
Contraction 1	1969:12	1970:11	11	Bear market 1	1966:01	1966:09	8	Overlap 1	1969:12	1970:05	5
Contraction 2	1973:11	1975:03	16	Bear market 2	1968:11	1970:06	19	Overlap 2	1973:11	1974:08	9
Contraction 3	1980:01	1980:07	6	Bear market 3	1971:04	1971:11	7	Overlap 3	1990:07	1990:10	3
Contraction 4	1981:07	1982:11	16	Bear market 4	1972:12	1974:09	21	Overlap 4	2001:03	2001:10	7
Contraction 5	1990:07	1991:03	8	Bear market 5	1976:12	1978:02	14	Overlap 5	2007:12	2009:01	13
Contraction 6	2001:03	2001:11	8	Bear market 6	1980:11	1982:07	20				
Contraction 7	2007:12	2009:06	18	Bear market 7	1983:06	1984:05	11				
				Bear market 8	1987:08	1987:11	3				
				Bear market 9	1990:05	1990:10	5				
				Bear market 10	1994:01	1994:06	5				
				Bear market 11	2000:08	2002:09	25				
				Bear market 12	2007:10	2009:02	16				

Figure A1 & Figure A2

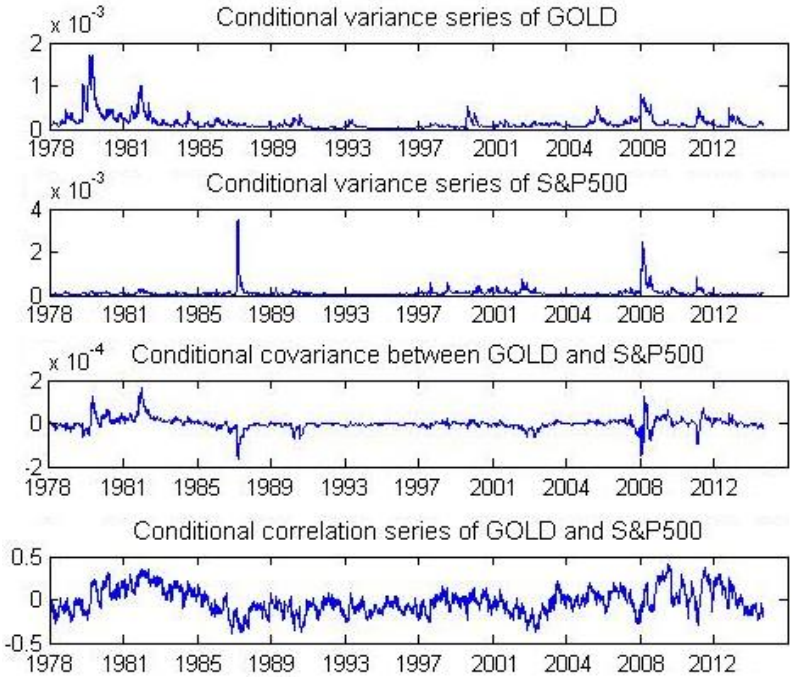


Figure A1

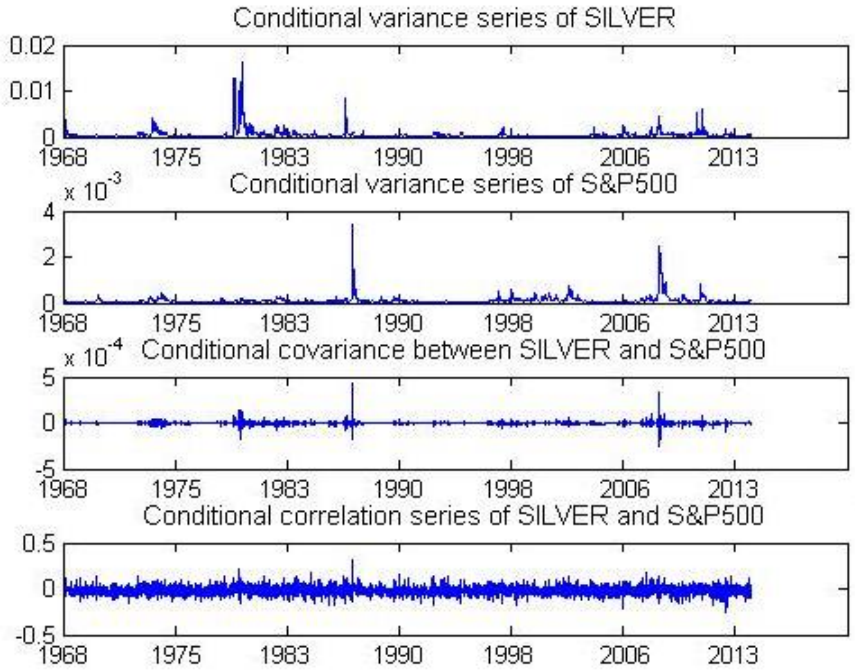


Figure A2

Figure A3 & Figure A4

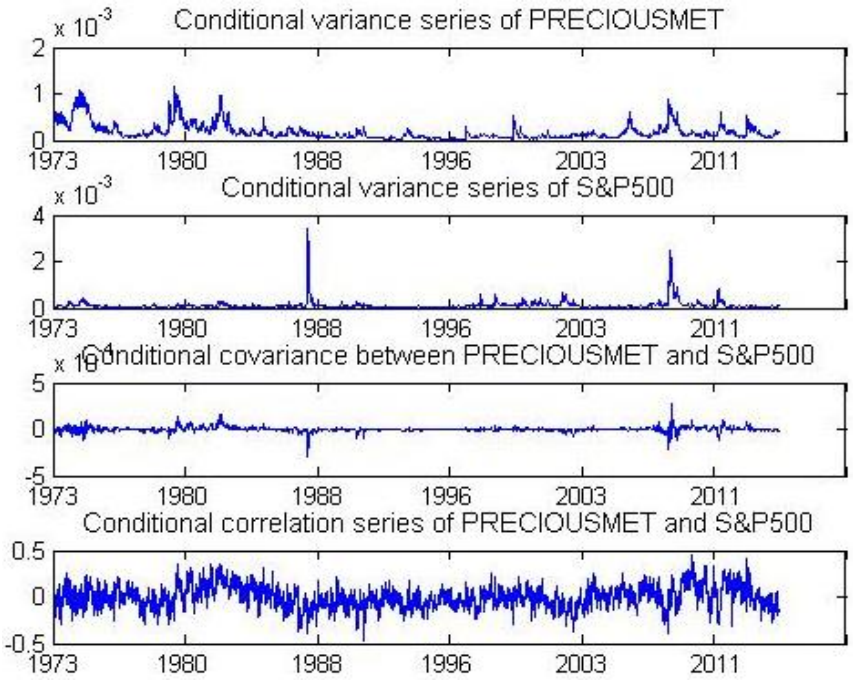


Figure A3

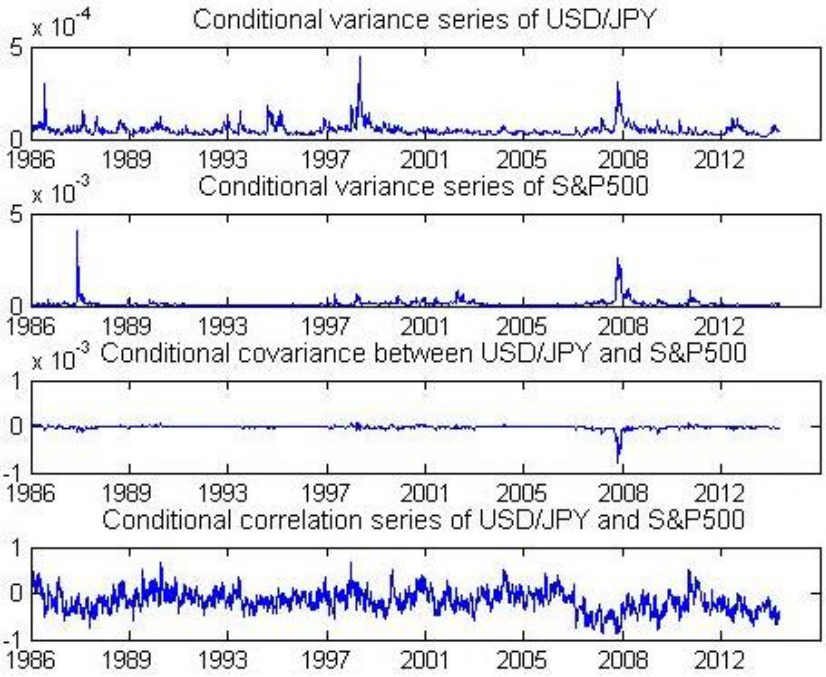


Figure A4

Figure A5 & Figure A6

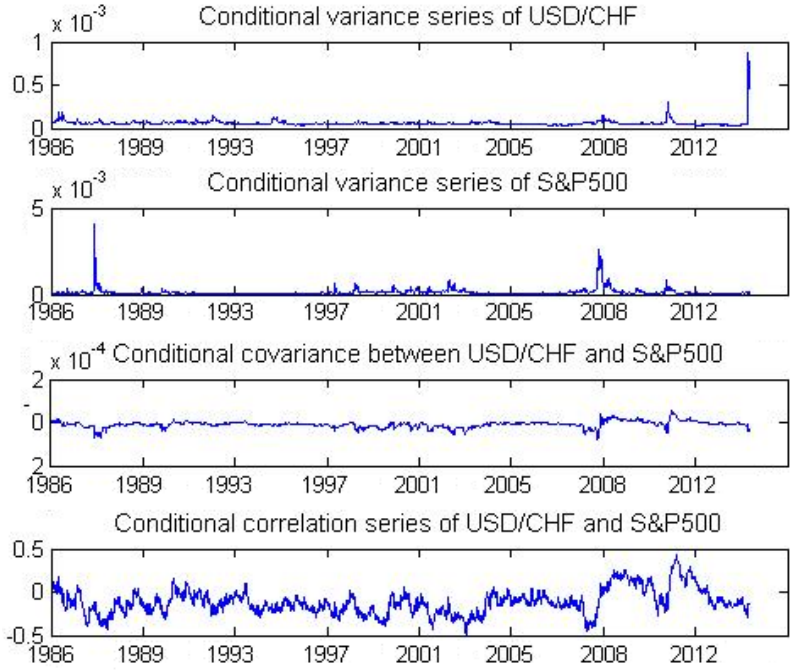


Figure A5

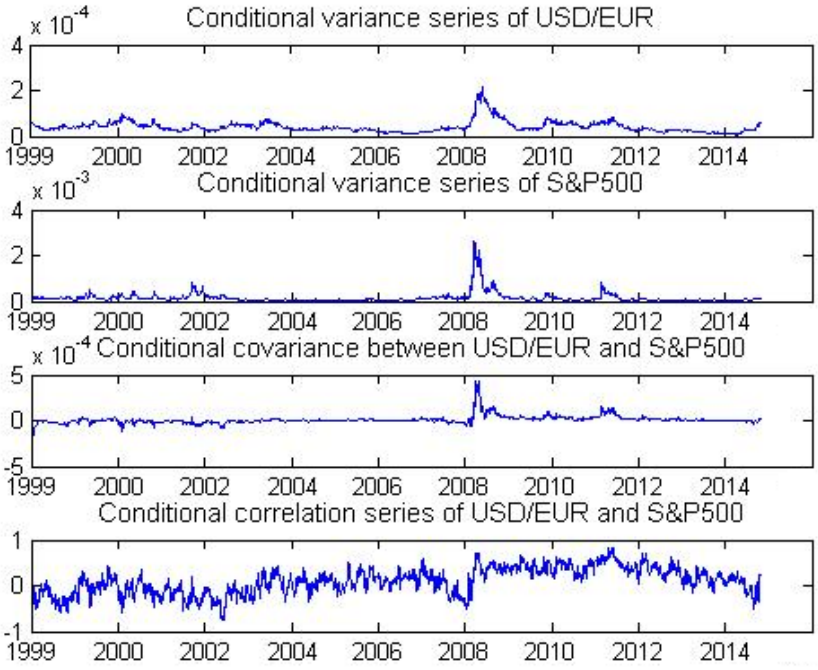


Figure A6

Figure A7 & Figure A8

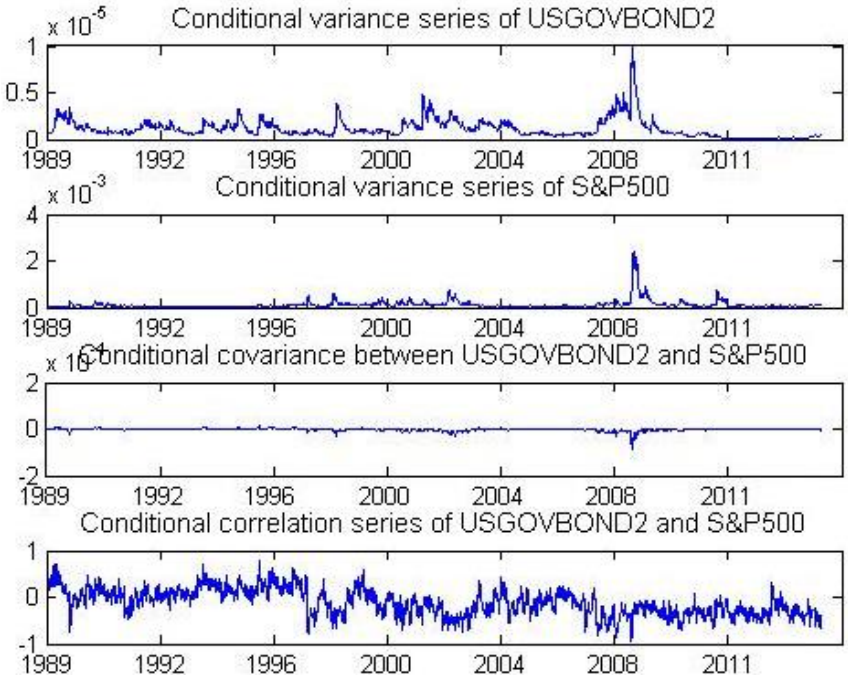


Figure A7

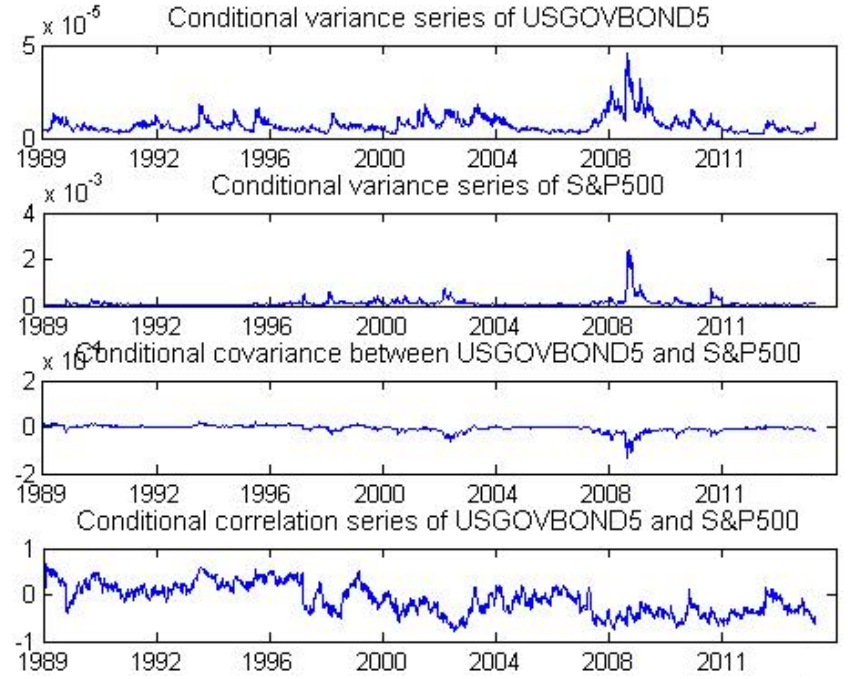


Figure A8

Figure A9 & Figure A10

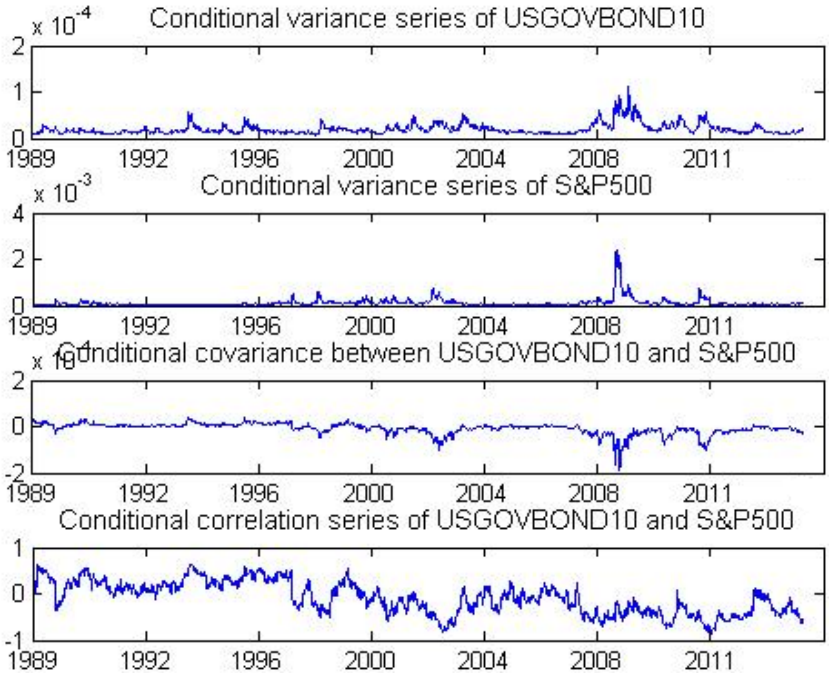


Figure A9

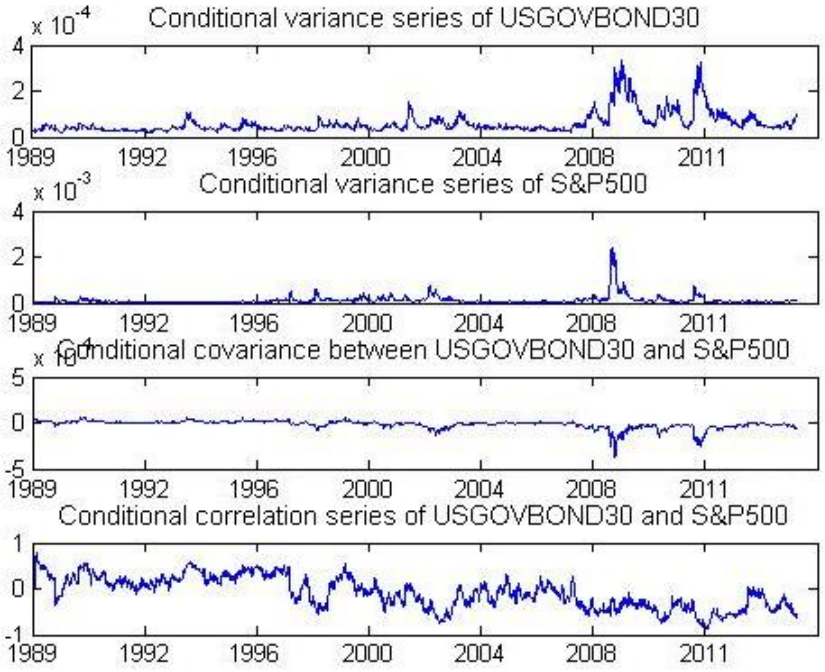


Figure A10

Figure A11 & Figure A12

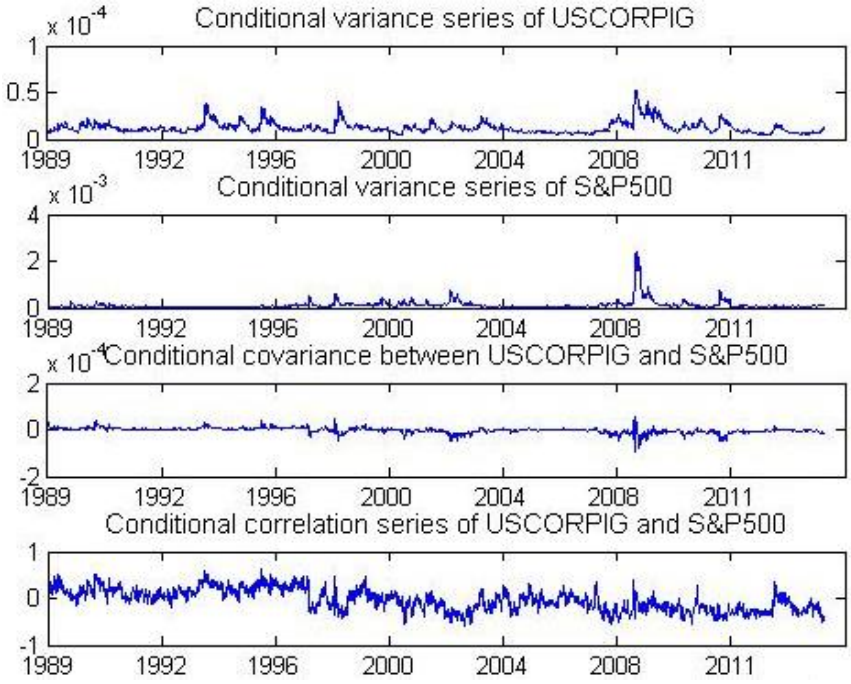


Figure A11

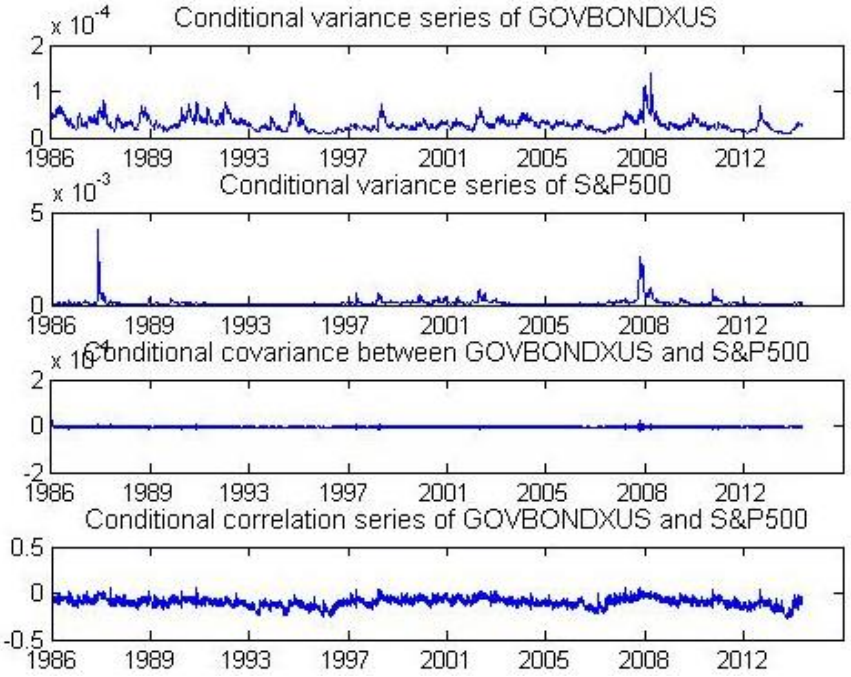


Figure A12

Figure A13 – Figure A15
Shocks of the 5th percentile
t = -50 to t = 50

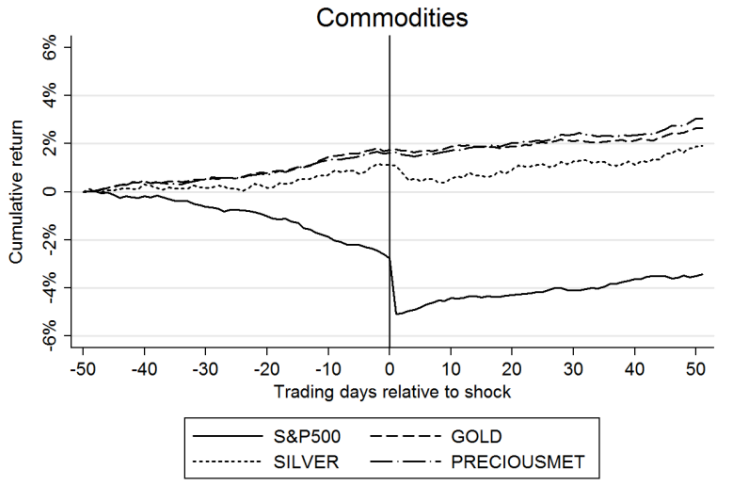


Figure A13

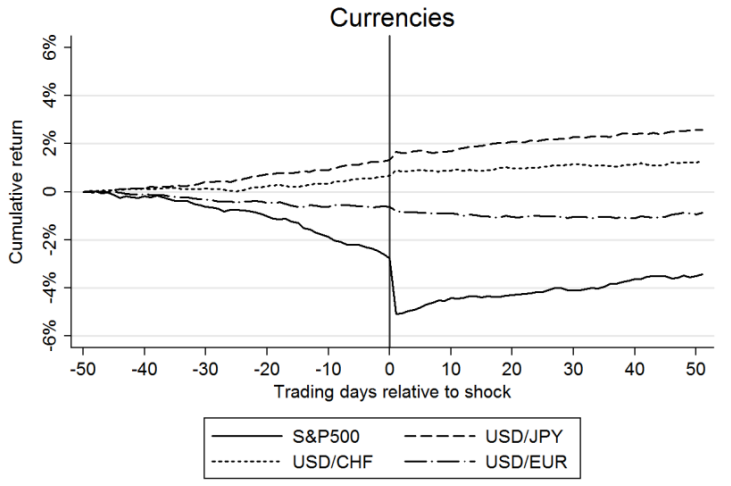


Figure A14

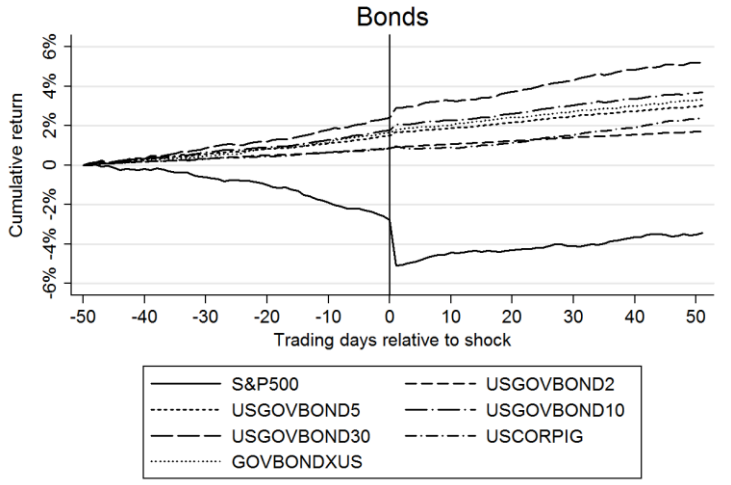


Figure A15

Figure A16 – Figure A18
Shocks of the 1st percentile
t = -50 to t = 50

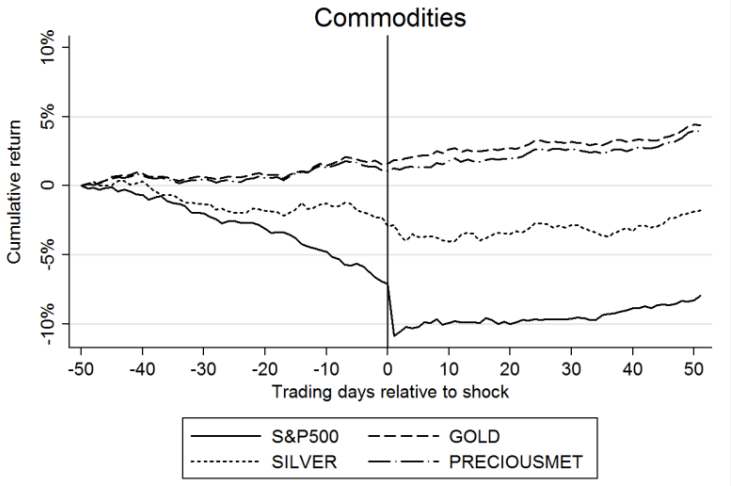


Figure A16

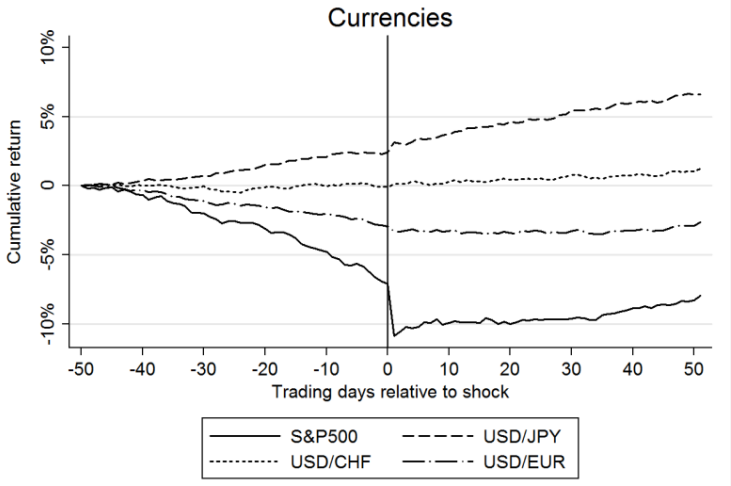


Figure A17

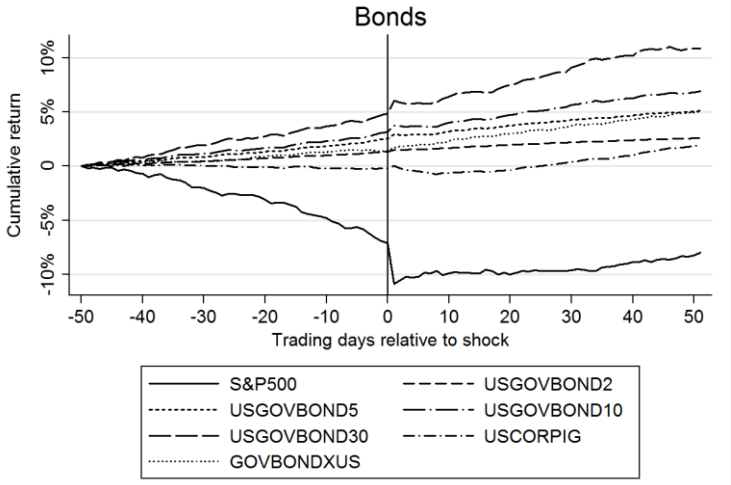


Figure A18

Figure A19 – Figure A21
Shocks of the 5th percentile
t = 1 to t = 50

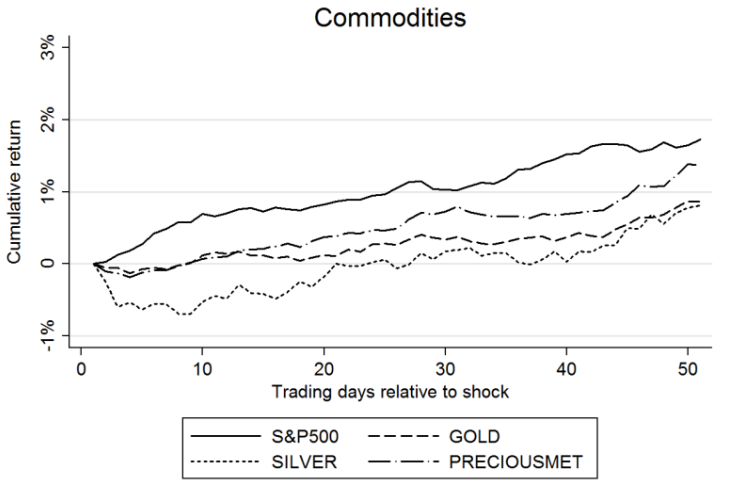


Figure A19

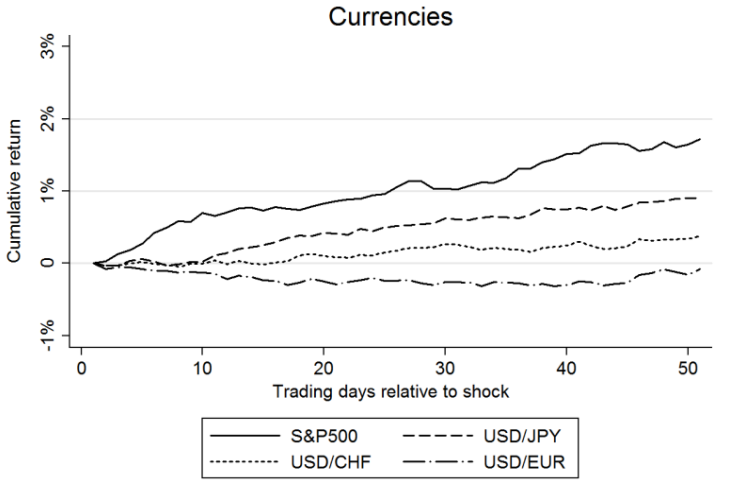


Figure A20

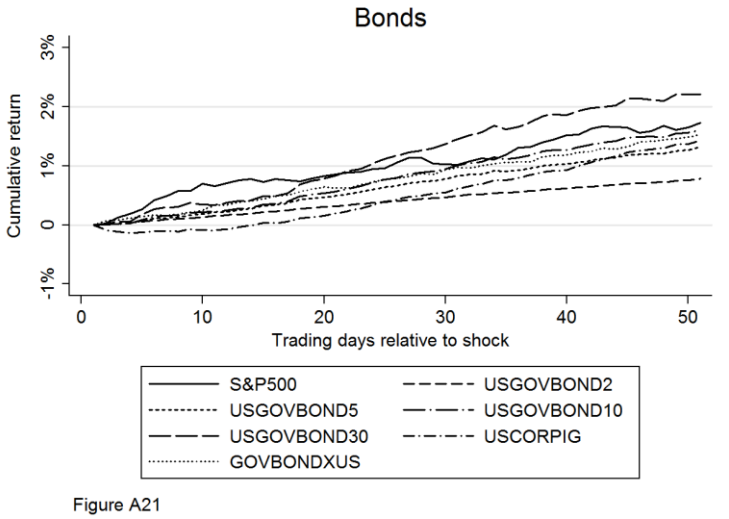


Figure A21

Figure A22 – Figure A24
Shocks of the 1st percentile
t = 1 to t = 50

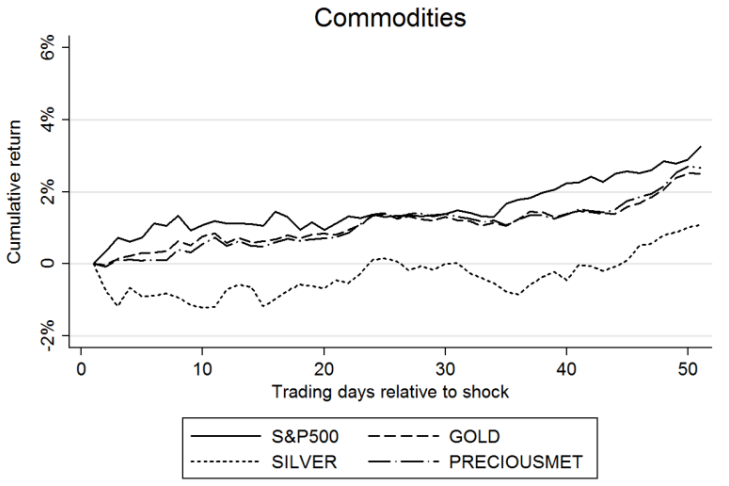


Figure A22

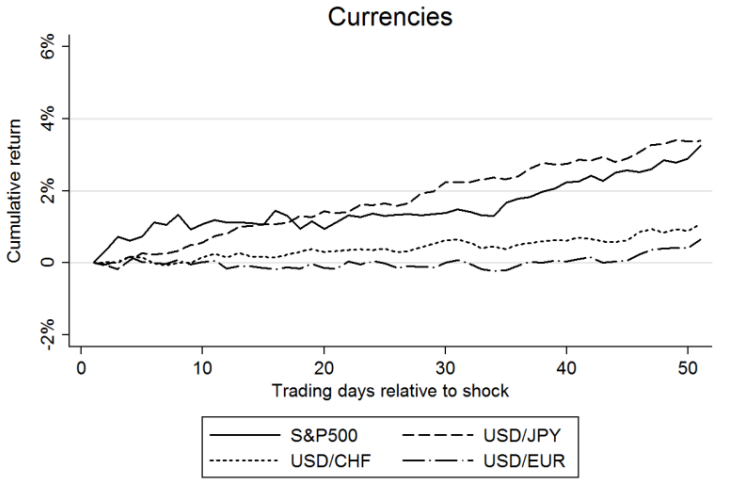


Figure A23

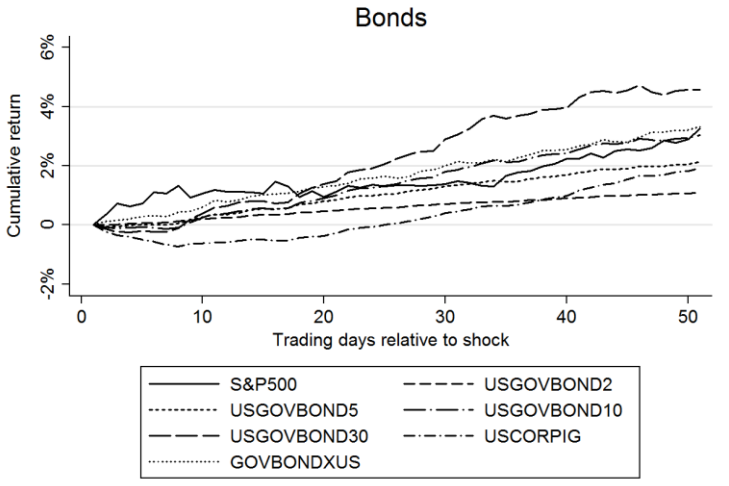


Figure A24