The Usage of Safe Haven Currencies in Mitigating Portfolio Risk during Market Turmoil Periods

Paper examines the capability of currencies to reduce portfolio risk during market turmoil periods by comparing the effect of active and naïve portfolio management strategies. Naïve strategy outperforms active in all cases, while diversification to CAD and GBP produce the lowest value at risk (VaR) and expected shortfall (ES).

Keywords: safe-haven currencies, portfolio diversification, market turmoil, conditional correlations, VIX index.

Introduction

Recent Global financial crisis has demonstrated deficiency of traditional portfolio diversification strategies and failure of traditional asset classes to reduce investment risk due to increase in cross-asset correlations in market turmoil periods. However, albeit vast empirical evidence of existent dynamics in cross-asset correlations, constant correlation assumption is still governing the research in portfolio management. This is no surprise given that classical paradigmatic portfolio theories (Markowitz, 1952; Sharpe, 1964; Lintner, 1965) are based on the assumption of constant cross-asset correlation parameters. Yet, empirical evidence suggests that correlations have a tendency to change over time (Durai, Bhaduri, 2011; Aslandis, Martinez, 2012; Chadwick et al., 2012). In particular, they tend to increase or “cluster” in market turmoil periods (Engle, 1999; Di Maggio, 2013) with large negative returns in one security being related with large negative returns in another – the phenomenon commonly referred to as “correlation breakdown” (Pfaff, 2013). Nawroth et al.
(2015) finds that an upsurge in cross-asset correlations during market turmoil periods significantly reduces benefits of portfolio diversification and increases portfolio downside risk as measured by VaR. Colloquially, portfolio diversification does not provide efficient risk mitigation when it is needed the most, i.e., during market turmoil periods.

Correlation clustering phenomenon prompted portfolio managers and researchers alike to explore alternative portfolio management strategies aimed at mitigating portfolio risk during financial market turmoil periods. One stream of research analyzes the effect of increasing portfolio allocation towards the so-called “safe haven” investable securities (Upper, 2000; Kaul, Sapp, 2006; Caballero, Krishnamurthy, 2007). Historically, this to a large extent was limited to changing portfolio composition between “risky” stocks and “risk-free” bonds. However, proliferation of the number of alternative investable securities (commodities, real estate, currencies etc.) and better access to multiple financial markets significantly increased portfolio diversification opportunities. Particular attention is given to the so-called alternative safe-haven assets, which are characterized by negative correlation with risky assets during market turmoil periods e.g., gold (Baur, Lucey, 2009).

Another stream of research analyzes the predictability of market turmoil periods, which would allow a timely rebalancing of investment portfolio away from risky assets. Examples of the models include Markov chain regime-switching models with constant (Hamilton, 1989) or dynamic (Diebold et al., 1993) transitional probabilities as well as Threshold Auto-regressive models (Tong, Lim, 1980). The latter uses exogenous threshold variable such as specific business cycle change indicators e.g., NBER (Brocato, Sted, 1998) or diffusion index (Stock, Watson, 2002), financial distress factors e.g., Value at Risk measure (Wang et al., 2012), volatility index (Sarwar, 2012), exchange rate index (Chadwick et al., 2012) or inter-bank marked distress indicators (e.g., OIS spread) or forward-looking indicators such as implied volatility index (VIX). Habib and Stracca (2012) found that implied-VIX index performs better compared to alternative business cycle indicators or the realized volatility.

Paper endeavors to reconcile the two aforementioned streams of research with an aim to test whether the usage of safe-haven currencies helps mitigating portfolio risk during market turmoil periods. Specifically, the research aims to answer the following questions:

1. Do currencies exhibit safe-haven properties relative to the underlying portfolio;
2. Does diversification towards safe-haven currencies help mitigating portfolio risk during market turmoil periods (naïve diversification);
3. Does active portfolio allocation towards and away from safe-haven currencies, based on changes in VIX implied volatility index, helps mitigating portfolio risk during market turmoil periods (active diversification).

Paper contributes to ongoing debates between supporters and opponents of active portfolio management in several respects. First, we aim at filling the gap in literature contributed to safe-haven currencies estimation by threshold-based dynamic models. The previous stream of research investigates the correlation between asset returns using regime-switching models (Aslanidis, Martinez, 2012) as well as
the feature of VIX as transition variable in smooth transition conditional correlation (DSTCC-GARCH) models of changes in correlation between stocks, bonds and commodity futures returns (Silvennuinen, Thorp, 2010). However, still little credit is granted to safe-haven currencies estimation by dynamic threshold-based models.

Second, we propose a new attitude toward currencies as a separate asset class and powerful tool for portfolio risk mitigation during market turmoil periods. Third, we evaluate the effectiveness of active portfolio diversification strategy compared to naïve diversification alternative.

The paper continues as follows. Next section provides a concise literature review describing the passive vs. active portfolio management debate followed by the description of the concept of alternative safe-haven assets and market turmoil indicators. It is followed by methodology describing the rationale of the usage of DCC(1,1)-GARCH(1,1)-TAR model. After that, methodology on assessment of diversification strategies is explained, followed by empirical results for the different frameworks mentioned above. Conclusions are discussed in the last section.

**Literature Review**

Paper contributes to ongoing passive vs. active portfolio management debate (Fama, French, 2010). Supporters of the passive portfolio management strategy find theoretical support for Efficient Market Hypothesis (Fama, 1970), which states that it is not possible to “beat the market” on a consistent basis since all the available information is already included in today’s asset prices. As a result, future returns are unpredictable, making any attempt to beat the market akin to a pure gambling. Proponents of the active portfolio management strategy, on the contrary, argue that by utilizing security selection and/or market timing it is possible to improve risk-return properties of the investment portfolio and outperform passively managed portfolios on a consistent basis. Active portfolio management finds support in behavioral finance theories, which challenge the underlying assumption of rational investor behavior (Kahneman, Tversky, 1979; Shiller, 2005). Irrational investors’ behavior creates numerous market inefficiencies and/or anomalies (e.g., price bubbles, flight to quality, correlation breakdown etc.), which can be utilized to generate superior returns on a consistent basis.

Opponents of active portfolio management strategies quote studies that suggest active portfolio management strategies on aggregate being unable to outperform the passive ones (Fama, French, 2010) with as much as 80% of actively managed funds reportedly having underperformed the passive benchmarks over the last decade (Soe, 2016). However, there is a wide body of research, concluding that active portfolio management strategies can outperform passive alternative. Factor models is a good example of free factor model by Fama and French (1992), four factor model by Carhart (1997) or five factor model by Fama and French (2015) all demonstrate the ability to outperform benchmark stock market portfolios. Fama and French (1993) presents a five-factor model, which includes three factors explaining stock returns (market risk premium, size and value) and two factors explaining bond returns (maturity and default risk) and conclude that all the aforementioned factors have predictable power in explaining return dynamics. Increasing popularity of alternative...
asset classes prompted researchers to look for global factors, explaining joint return dynamics of different asset classes. The notable example is a three-factor model originated by Asness et al. (2013), who found that two global factors (value and momentum) explain return dynamics of five asset classes namely, stock indices, individual stocks, commodity futures, currencies and government bonds. The latter finding is of particular interest as it is closely related with behavioral finance theories. Momentum factor can be explained by herd-behavior bias, while the existence of value factor is explained by over and under-reaction bias. Good overview of other factor models is provided by Podkaminer (2013).

More specifically, another stream of research argues that inclusion of safe-haven assets into traditional portfolios improves overall risk-adjusted performance and decreases the frequency and extent of extreme negative returns e.g., commodities (Engle, 2011; Dupoyet et al., 2016) or currencies (Campbell et al., 2002). Hence, contemporary dynamic portfolio management strategies do not limit themselves to traditional asset classes (stocks and bonds) and instead dynamically rebalance investment portfolios to include alternative safe-haven assets (commodities, currencies, high-yield bonds, real estate funds, emerging market indices etc.).

Approach to foreign exchange currencies as a separate asset class has received increasing attention from portfolio managers during the last decade, owing to their low correlation with traditional asset classes, such as equities and fixed income (Leitner et al., 2007). Currencies open up new portfolio diversification opportunities which go beyond traditional long-only stock and bond portfolios. The usage of currencies as a source for effective risk management is discussed by Ronaldo and Soderlind (2007), and Campbell et al. (2009). Conventional wisdom, which suggests risk-averse investors avoid exposure to foreign currency risk, is challenged by findings similar to Campbell et al. (2002), Schmittmann (2010), which demonstrate the capability of foreign exchange currencies improve portfolio risk/return properties.

The benefit of employing safe-haven currencies as a tool for portfolio diversification is their capability to provide investors access to different types of risks within a single investment portfolio. In other words, investments in foreign exchange currencies may serve as a tool to diversify portfolio towards specific countries’ economic development. Reflecting the trends in economies’ GDP, industrial production, interest rates, trade balance, political stability and other factors, foreign exchange currencies offer investors wider opportunities of effective risk-spreading among different economies and regions. Moreover, foreign exchange markets are easily accessible to individual and corporate investors, whereas investment horizon may vary from long-term to intra-day trading, satisfying the needs of different investors’ types and strategies. Finally, including currencies in the internationally diversified portfolio may serve as a tool for hedging foreign exchange risks.

The concept of safe-haven currencies, however, is still in its adolescent stage and does not have a strict definition yet. Some economists like Upper (2000) assign safe-haven properties to assets with low risk in a time of crisis. Kaul and Sapp (2006) argue that safe-haven assets distinguish themselves by increased demand by investors when markets are uncertain. Alternatively,
Ronald and Soderlind (2007) claim that safe-havens are any assets performing well as opposed to reference portfolio. In a broader sense, as it has been concluded by Caballero and Krishnamurthy (2007), perceived riskiness triggers investors’ “flight to quality” and subsequently increases demand for safe-haven assets in times of overall risk aversion. Grisse and Nitschka (2013) refer to safe-haven currencies as the ones capable of hedging the global risks on average and during market turmoil periods particularly. In the scope of our research, safe-haven currencies are estimated by their capability to reduce SPDR S&P 500 ETF (further in the text: SPY) portfolio value at risk (further in the text: VaR) and expected shortfall (further in the text: ES) during market turmoil periods. 

Market turmoil is not directly observable variable, necessitating the usage of proxies instead. Among them, implied volatility index (VIX) is a widely employed measure of market turmoil in existing literature. Other proxies for market turmoil include Global Index of Financial Turbulence (GIFT), Risk Aversion indicator developed by Merill Lynch and the realized, rather than the implied, volatility of the Datastream benchmark world stock index. However, empirical evidence suggests that alternative measures fail to outperform implied volatility index as market turmoil proxies (Habib, Stracca, 2010). According to Weber (2012), VIX index proved to outperform Brocato and Stted’s (1998) NBER turning points which indicate changes in business cycle regimes. Finally, as outlined by Carr and Wu (2009), VIX index combines two components – the quantity and price of anticipated risk, amplifying its recognition as a proxy for market turmoil. 

Being a forward-looking indicator of market risk sentiment, VIX index has proven its relevance in regime-switching, threshold and transition models (Whaley, 2009) aimed at modeling return, volatility or correlation dynamics in different market regimes. Specifically, VIX index is used as exogenous variable determining the state of the world in Threshold autoregressive (TAR) models (Tong, Lim, 1980), which is easier to interpret compared to Markov-Switching (Chen, 2008) or hidden Markov-Switching (Wu, 2010) models. Hansen (1997) explains the popularity of TAR model by its advantage over other nonlinear models in relative simplicity to specify, estimate and interpret. Di Maggio (2013) found the significance of exogenous threshold in explaining stock market movement with negative shocks exceeding threshold level resulting in further decline in equities prices, whereas shocks below threshold level resulting in subsequent equity price return to fundamental levels. Likewise, Aslandis and Martinez (2012) have found that conditional correlation model, conditioned on a number of threshold variables, significantly reduces portfolio downside risk as opposed to the model using constant correlation estimate. Duran and Bonmarito (2010), Kirby and Ostdiek (2012) found that market-timing strategies based on dynamic threshold-based rebalancing outperform traditional buy-and-hold approach even despite the presence of high transaction costs.

**Methodology**

The central question in portfolio management is whether it is possible to design alternative portfolio management strategy that would allow achieving superior performance compared to the benchmark. As it was described in the theoretical background part, there is an ongoing active vs. passive debate in academia as well as among practitioners as to whether
active portfolio management strategies can improve portfolio performance vis-à-vis passive benchmark. This paper aims at contributing to this debate by comparing the performance of the three strategies:

1. Baseline – buy and hold, tracking a broad-based stock market index (SPY).
2. Naïve diversification – buy and hold, tracking a broad-based stock market index (SPY) with stable proportion invested in one of the safe-haven currencies.
3. Active diversification – buy and hold, tracking a broad-based stock market index (SPY) with varying proportion invested in one of the safe-haven currencies. Proportion invested is being determined by the changes in VIX implied volatility index (proxy for market turmoil).

The performance of the aforementioned strategies is evaluated by estimating the underlying data generating processes of broad-based stock market index returns, safe-haven currency returns and implied volatility (VIX) index. The univariate time-series are modeled using GARCH (1,1) model (Bollerslev, 1986), while dependence structure is modeled using DCC(1,1)-GARCH(1,1) model of Engle (1999), which allows capturing time-varying correlation i.e., correlation clustering phenomenon (Jondeau, Rockinger, 2006). Finally, correlation series are modeled using threshold autoregressive model (TAR) proposed by Tong and Lim (1980) with daily changes in CBOE Volatility index (further in text: VIX) level set as a threshold. VIX daily changes above estimated threshold are treated as market turmoil indicators and imply when SPY portfolio should be diversified towards the position in corresponding currency under active diversification approach. The following Figure 1 provides a concise illustration of the research method employed.

Estimated models are then used in Monte Carlo simulation to simulate a large number (100,000) of random realizations under the baseline and alternative portfolio investment strategies. Obtained portfolio profit/loss distributions are then compared using non-parametric performance measures: Value at Risk (VaR) and Expected Shortfall (ES). The choice of performance measures is motivated by

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**Fig. 1. Employed research method**
increasing evidence (Kahneman, Tversky, 1979) that investors are not overly sensitive to volatility as such (which is considered to be a standard risk metrics in classical portfolio theories), but rather to downside risks. VaR and ES are thus more suitable measures as they measure potential portfolio loss over the chosen time period with pre-defined probability.

Data

Our sample consists of daily log-returns of currencies, SPY and daily changes of VIX index during the period 1999.01.01–2013.12.31, which gives us 3774 observations. The period starts with an introduction of euro and represents both bull and bear markets, together with occasional turbulence periods. Specifically, the period includes September 11 terrorist attack (2001), Internet bubble burst (2002, July), the financial crisis of 2008, Greek sovereign debt crisis (2010, May), US credit rating downgrade in August, 2011, Cypriot financial crisis, 2013 March. Spikes in VIX illustrating the latter shocks are displayed in Error: Reference source not found. During the period under study, VIX has deviated from its minimum value of 9.89 (2007/01/23) to maximum of 80.86 (2008/11/19) with an average of 22.15. The study is conducted from the standpoint of US investor, therefore currency series are expressed in US dollars (AUD, CAD, CHF, EUR, GBP and JPY). Data is obtained from Macrobond.

Summary statistics is presented in Appendix 1. All series are defined by excess kurtosis, while only CHF and EUR are positively skewed, alongside with VIX, indicating that the frequency of positive returns in these series exceeds that of negative returns. As expected, Ljung-Box test results strongly reject the null hypothesis of no serial autocorrelation among residuals for all-time series except EUR. ADF test rejected the null hypothesis of unit root presence in data. Finally, we obtained sample correlation coefficients over the full sample. It can be observed that SPY and CAD returns are mostly negatively correlated (-0.2347) when compared to other currencies under study, while AUD, EUR and GBP correlation estimates with SPY are estimated positive.

DCC(1,1)-GARCH(1,1) Model Estimation

Model is estimated in two steps. First, DCC(1,1)-GARCH(1,1) part is estimated and time-varying currency-SPY variance-covariance matrix is obtained as model output. Second, cross-asset correlation time series are obtained from variance-covariance matrix from the first step. Estimated cross-asset correlation time series are modeled by TAR model with a lagged daily change in VIX level standing as a state-determining threshold variable. Delay parameter is set to be \( t-1 \), which means that change in uncertainty index at time \( t-1 \) in magnitude above or below estimated threshold implies a switch in currency-SPY correlation dynamics. Independent variable in TAR regressions is also set to be lagged daily change in VIX level. Significance and sign of the latter are interpreted as an indicator of particular currency-SPY correlation’s dependence upon the change in VIX index and indicates either corresponding currency should be considered as a safe-haven or risky investment when VIX level increases. The threshold level is determined by model optimization.
Conditional correlation between two assets returns, expressed by \( r_i \) and \( r_j \) at time \( t \) is defined as:

\[
\rho_{i,j,t} = \frac{E_{t-1}(r_{i,t} - \bar{r}_i)(r_{j,t} - \bar{r}_j)}{\sqrt{E_{t-1}(r_{i,t} - \bar{r}_i)^2}E_{t-1}(r_{j,t} - \bar{r}_j)^2} (1)
\]

With the following expression clarifying relation between conditional correlation and conditional variance:

\[
h_t = E_{t-1}(r_t - \bar{r})^2, \quad (r_t - \bar{r}) = \sqrt{h_t} \varepsilon_t \tag{2},
\]

where \( \varepsilon_t \) are standardized residuals; \( \varepsilon_t \sim (0,1) \).

Substituting (1) into (2) gives conditional correlation being also the conditional covariance between standardized residuals:

\[
\rho_{i,j,t} = \frac{E_{t-1}(\varepsilon_{i,t}\varepsilon_{j,t})}{\sqrt{E_{t-1}(\varepsilon_{i,t})^2}E_{t-1}(\varepsilon_{j,t})^2} = E_{t-1}(\varepsilon_{i,t}\varepsilon_{j,t}) \tag{3}
\]

DCC-GARCH model is expressed by following definition:

\[
R_t | \Omega_{t-1} \sim N(0,H_t)
\]

\[
H_t = D_t \Sigma_t D_t
\]

\[
\Sigma_t = Q_t^{-1} Q_t Q_t^{-1}
\]

\[
Q_t = (1 - \varphi - \omega)\bar{Q} + \varphi(\varepsilon_{t-1}\varepsilon_{t-1}') + \omega Q_{t-1}
\]

\[
\varepsilon_t = D_t^{-1} u_t \tag{4}.
\]

In our study, we follow methodology proposed by Engle and Sheppard (2001). The DCC(1,1)-GARCH(1,1) model is estimated in 2 steps. First, univariate GARCH models for all \( i \) assets (currency pairs and SPY) return time series are estimated and each time series residuals are standardized by standard deviation obtained from corresponding univariate GARCH model. Second, DCC matrix is estimated.

Univariate GARCH model with restrictions for non-negativity and stationarity is estimated as proposed by Bollerslev (1986) and Taylor (1986) for all \( i \) return time series as follows:

\[
\begin{align*}
Y_{i,t} &= \mu_i + u_{i,t} \\
u_{i,t} &= \sqrt{h_{i,t}}\varepsilon_{i,t}; \quad u_{i,t} \sim N(0,h_{i,t}); \quad h_{i,t} - IID(0,1) \\
h_{i,t} &= \alpha_{i,0} + \alpha_{i,1} u_{i,t-1}^2 + \beta_i h_{i,t-1}
\end{align*}
\]

A required condition for non-negativity and stationarity imply constraints:

\[
(\alpha_{i,1} + \beta_i) < 1; \quad \alpha_{i,0} \geq 0, \alpha_{i,1} \geq 0, \text{and } \beta_i \geq 0 \tag{6}
\]

Jointly minimizing the terms of the \( LLF^2 \) implies minimizing the error variance. The values of the parameters that maximize the \( LLF \) are estimated.

Before estimating DCC model, \( n \times n \times t \) diagonal matrix \( D_t \) is derived with \( \sqrt{h_{i,t}} \) on \( i^{th} \) diagonal and 0 outside the main diagonal from the first step (GARCH(1,1) estimation). Residuals of the model are standardized and the matrix of standardized residuals \( \varepsilon_t \) are obtained. DCC matrix is derived accordingly to Engle and Sheppard (2001):

\[
Q_{t,t} = \left( 1 - \sum_{i=1}^{p} \varphi_i - \sum_{j=1}^{q} \omega_j \right) \bar{Q} + \sum_{i=1}^{p} \varphi(\varepsilon_{t-1}\varepsilon_{t-1}') + \sum_{j=1}^{q} \omega Q_{t-1}
\]

\[
C_t = Q_t^{-1} Q_t Q_t^{-1} \tag{7}.
\]

The assumption of normality in (4) gives rise to log-likelihood function (LLF), which is maximized through parameters of the model\(^1\). Jointly minimizing the terms of the imply minimizing the error variance. The values of the parameters that maximize the \( LLF \) are estimated.

**TAR Model Estimation**

TAR model proposed by Tong and Lim (1980) allows determining the state of the world by exogenous lagged observable threshold variable. Hansen (1997) explains the popularity of TAR model by its advantage over other nonlinear models in relative simplicity to specify, estimate and interpret. In our research, we employ TAR
model to estimate correlation dynamics between currencies and SPY portfolio dependent upon lagged VIX level. DCC estimates time series are obtained from dynamic conditional correlation matrix which is the output of DCC(1,1)-GARCH(1,1) model specified in (4)–(7).

As long as we aim at estimating safe-haven currencies for SPY portfolio risk mitigation during market turmoil periods, we focus only on high VIX regime periods, i.e., periods denoted by the change in VIX above estimated threshold. Threshold estimation is important as it signals about a shift in currency/SPY dynamic correlations and indicates market turmoil periods, when the application of active portfolio diversification strategy is plausible. Therefore, daily change in VIX level with delay parameter \( t-1 \) is set as the exogenous threshold in our model.

TAR model is specified by:

\[
\rho_{i,SPY,t} = \begin{cases} 
\mu_1 + \gamma_1 \Delta VIX_{t-1} + u_{1,t}, & \Delta VIX_{t-d} \leq c \\
\mu_2 + \gamma_2 \Delta VIX_{t-1} + u_{2,t}, & \Delta VIX_{t-d} > c 
\end{cases}
\]  

Prior to model estimation, correlation time series are tested for stationarity. ADF test for all 6 currency-SPY correlation time series derived from DCC(1,1)-GARCH(1,1) model is performed. TAR model coefficients are estimated by least squares procedure as proposed by Hensen (1999).

The number of regimes identified differs across studies with most researchers assuming two regimes (e.g., Chesnay, Jondeau, 2001; Maheu, McCurdy, 2000) while others assuming three (e.g., Hauptmann et al., 2012) and four (e.g., Guidolin, Timmermann, 2006), which include crash, recovery, slow growth and bull. However, the existence of regimes is necessary, but not sufficient condition to justify the existence of dynamic strategies. Changes in the regimes need to be predictive so that dynamic investment strategy can be employed to utilize them. Hence, for the sake of parsimony, we choose the two-regime framework, which implies estimation of 1 threshold.

**Evaluation of Diversification Strategies**

Assessment of alternative diversification strategies is based on VaR and ES analysis, which are estimated by Monte Carlo simulation. We aim at comparing the effectiveness of two SPY portfolio allocation strategies: naïve diversification (currency buy and hold through the whole period), and active diversification (buying / short-selling currency in market turmoil only). We also estimate VaR and ES for a non-diversified SPY portfolio for comparison purposes. As noted previously, market turmoils are determined by periods when VIX daily change values exceed threshold estimated by TAR model. VaR and ES are estimated with 95% confidence level for 30 days investment period.

Simulations are performed for different weights of currencies in investment portfolio relative to SPY (0%, 20%, 40%, 60%, 80%, and 100%). In our study, 0% currency weight refers to non-diversified SPY portfolio, while 100% refers to equally weighted currency/SPY portfolio. Type of currency transaction (either long or short) depends upon its unconditional correlation estimate with SPY provided in Appendix 2.

We assess the effect of diversification strategies by computing the difference \( \Delta_u \) between VaR and ES of non-diversified SPY portfolio and that of corresponding diversification strategy for each currency weight by:

\[
\Delta_u = VaR_{naive/active} - VaR_{non-diversified}
\]  

(9)
Empirical Results

Estimation of Model Parameters

DCC-GARCH model is estimated in two steps. First, univariate GARCH models are estimated for SPY and all currencies time series. Second, DCC matrix is estimated and time-varying correlation time series are obtained. Statistically significant univariate GARCH coefficients are summarized in Appendix 3. DCC matrix is estimated with model coefficients provided in Table 1.

<table>
<thead>
<tr>
<th>( \varphi )</th>
<th>( \omega )</th>
</tr>
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<tbody>
<tr>
<td>0.00329</td>
<td>0.9479</td>
</tr>
</tbody>
</table>

Correlation time series obtained from DCC(1,1)-GARCH(1,1) are modeled by TAR with daily change in VIX set as threshold variable. Threshold values, as well as TAR coefficients, are presented in Table 2.

Model results confirm regime-switching currency/SPY correlation behavior for all dynamic correlation series except for AUD/SPY series. The threshold level is estimated for each correlation series by applying likelihood ratio test as explained in the Methodology section. A sample of likelihood ratio sequence plots is presented in Appendix 4. Coefficients for each correlation series in both regimes are obtained. Alongside, OLS regression coefficients without threshold are obtained for comparative analysis.

As reported in the last column of Table 2, when simple OLS without threshold is applied, none of currency/SPY correlation dynamics can be explained by changes in VIX level for the whole sample. This would lead to a conclusion that none of the currencies under study could be used for SPY portfolio risk mitigation purposes. However, when threshold model is applied,
currency/SPY correlation behavior is split into 2 states: higher and lower regimes of VIX. Regime switching point is indicated by the threshold value which is estimated individually for all currency/SPY series by applying Likelihood Ratio test with confidence intervals.

Model results report significant regressor coefficients for CAD, CHF, GBP and JPY correlation series in high regime and CAD, EUR, GBP and JPY correlation with SPY in the lower regime.

In our study we focus on market turmoil periods only, therefore discussion covers only TAR model output for modeling currency/SPY correlation estimates time series in high VIX regime. Significant VIX daily changes coefficients in high regime are estimated for CAD, CHF, GBP and JPY dynamic conditional correlation series. Coefficients of negative sign indicate the negative relation between VIX and currency/SPY correlation dynamics in high VIX regime. By way of interpretation, if VIX daily change at \( t-1 \) is above estimated threshold, the correlation between currency and SPY at time \( t \) is further increased in absolute value by times lagged VIX daily change value additionally to negative constant term (in case of CAD, CHF, and JPY). On the contrary, in case of GBP lagged VIX daily change above threshold triggers increase in positive GBP/SPY correlation adding to the positive constant. TAR model results suggest the opportunity of SPY portfolio risk mitigation through diversification towards long positions in CAD, CHF and JPY and short positions in GBP in high VIX regimes.

Another distinguishable feature is reported for CHF/SPY correlation series. In lower regime TAR model estimates non-significant coefficient. However, in high regime is estimated statistically significant (-0.013385). A plausible explanation of this result suggests that CHF and SPY are non-significantly correlated in periods when VIX changes are below threshold. However, in periods when VIX daily changes at time \( t-1 \) exceeded threshold value, CHF converted to safe-haven asset relative to SPY portfolio.

Interestingly, AUD/SPY dynamic conditional correlation time series did not prove to follow regime-switching behavior. Independent variable coefficients are estimated to be non-significant for both regimes and OLS regression without threshold.

**Assessment of Diversification Strategies**

*Naïve Diversification VaR and ES*

Figure 2 illustrates the effect of naïve diversification approach on SPY portfolio VaR by plotting difference (\( \Delta u \)) between VaR of a non-diversified SPY portfolio and that of naïve diversification for each currency weight. Positive results infer improvement in VaR under naïve diversification approach comparing to non-diversified SPY portfolio. X axis refers to the weight of corresponding currency relative to SPY portfolio.

Long positions in CAD (100%), JPY (40%) and short positions in EUR (60%), GBP (80%) prove to reduce non-diversified SPY portfolio VaR under naïve diversification approach, while AUD and CHF fail to improve portfolio VaR. CAD is reported to mostly effectively reduce portfolio VaR when the equally-weighted CAD-SPY portfolio is considered. ES results are the same as VaR, indicating improvement in expected shortfall when the equally-weighted CAD-SPY portfolio is considered.
Active Diversification VaR and ES

Under active diversification approach, SPY portfolio is diversified towards corresponding currency only during market turmoil periods. Benefits of active approach are evaluated similarly to those of naïve diversification. The effect of active diversification approach is illustrated in Figure 3.

SPY portfolio 95% VaR is mitigated when active diversification to long positions in CAD (100%) and JPY (40%), and short positions in GBP (100%) and EUR (80%). Lowest VaR and ES are achieved when the equally-weighted CAD-SPY portfolio is considered.
Summary of Naïve and Active Diversification Strategies

Both naïve and active diversification strategies report long positions in CAD and JPY and short positions in GBP and EUR help improving SPY portfolio VaR and ES. In all cases, the equally-weighted CAD-SPY portfolio is reported to be the most effective diversification alternative. Table 3 provides a summary on currencies which proved to reduce SPY portfolio VaR and ES as well as corresponding weights in parentheses.

SPY portfolio VaR is greatly mitigated when naïve equally-weighted CAD-SPY portfolio allocation strategy is considered, i.e., equally-weighted long position in CAD is open during all investment period. ES is the least under naïve diversification to equally-weighted short position in GBP. Furthermore, naïve diversification strategy has proven to outperform active strategy in all cases.

Limitations

We acknowledge certain limitations of our study, which we five-fold. First, the definition of market turmoil by TAR model can be more effective by employing a higher number of thresholds (e.g., distinguishing between bull, bear and consolidating market risk sentiment). Using more thresholds would allow to achieve more precise results and obtain better recommendations. Second, the study could combine S&P500 VIX index (employed in our study) with other local volatility indices (e.g., EUROSTOXX volatility index for EUR) in order to distinguish between global and local turmoil. For example, local turmoil linked with local political events does not necessarily translate into deviations in S&P500 VIX index, which is referred as a global proxy for market risk sentiment. However, such events may be well captured by local volatility indices. Third, we do not account for trading costs and carry trade. However, we aimed at minimizing the effect of this limitation by selecting most liquid major foreign exchange currencies, which are characterized by low bid-ask spreads. Omission of carry trade is minimized by current low-interest rates environment. Last two limitations are rather exogenous and apply to all studies in the field. Specifically, it is hardly possible to control for direct interventions in foreign exchange markets and capital controls. Therefore, we admit the presence of such risk, but cannot control it in our study.

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<tr>
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<th>Naive diversification</th>
<th>Active diversification</th>
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<tr>
<td></td>
<td>VaR</td>
<td>ES</td>
</tr>
<tr>
<td>CAD</td>
<td>95%</td>
<td>-6.3054 (100%)</td>
</tr>
<tr>
<td>EUR</td>
<td>95%</td>
<td>-6.836 (60%)</td>
</tr>
<tr>
<td>GBP</td>
<td>95%</td>
<td>-6.5741 (80%)</td>
</tr>
<tr>
<td>JPY</td>
<td>95%</td>
<td>-7.1377 (20%)</td>
</tr>
</tbody>
</table>

*weight of investment in currency in parentheses
Conclusions

The aim of our paper was to test whether the usage of safe-haven currencies helps mitigating portfolio risk during market turmoil periods. Specifically, we estimate the capability of major currencies (AUD, CAD, CHF, EUR, GBP and JPY) to reduce SPY portfolio risk through the lens of different diversification strategies. Research results challenge conventional wisdom suggesting risk-averse investors avoid exposure to foreign currencies. Research findings have demonstrated that SPY portfolio diversification towards certain currencies helps mitigating portfolio downside risk measured by VaR and ES metrics. Specifically, long positions in CAD and JPY, and short positions in EUR and GBP have proven to improve portfolio VaR and expected shortfall under both diversification strategies.

Yet, naïve, i.e., buy-and-hold diversification strategy outperforms active strategy in all cases. Additional portfolio reallocation costs incurred due to portfolio management costs, bid/ask spreads, carry trade and other, would further diminish the benefits of active SPY portfolio reallocation compared to the buy-and-hold alternative. This suggests that VIX implied volatility index has low predictive power.

Research findings challenge results reported by previous studies in several spectrums. First, research results suggest that active portfolio diversification strategy based on threshold autoregressive model fails to improve SPY portfolio VaR and ES when compared to naïve strategy. This contradicts to findings obtained by Ang and Bekaert (1999) who reported benefits of the dynamic regime-switching approach to equities portfolio allocation. Similarly, Aslanidis and Martinez (2012) have estimated a statistically significant reduction in stocks, bonds and major exchange currencies portfolio variance when threshold model was applied against the alternative.

Second, our study reports safe-haven properties in currencies considering short positions in EUR and GBP and long positions in JPY and CAD. Contradicting to conventional wisdom, CHF did not prove to carry safe-haven properties when SPY portfolio is considered as reference portfolio. Contrary to our results, the study by Campbell et al. (2009) reports safe-haven properties of long positions in EUR and CHF and short positions in JPY, CAD, AUD and GBP when the portfolio of European stocks is concerned. Even though both European and US stocks are referred to as risky assets, their correlation dynamics report to follow different behavior with foreign exchange currencies, therefore diversification strategies should be selected cautiously and precisely.

Finally, we argue that the usage of safe-haven currencies may serve as a tool to mitigate portfolio downside risk in market turmoil periods.
References


THE USAGE OF SAFE HAVEN CURRENCIES IN MITIGATING PORTFOLIO RISK DURING MARKET TURMOIL PERIODS

Notes

1 Constraints for scalars are applied to ensure covariance matrix is positive definite: \( \varphi \geq 0 \) and \( \omega \geq 0 \);
\( \varphi + \omega < 1 \).

2 Time-varying correlation matrix \( C_t \) in its multivariate form is estimated, which takes form of \( \rho_{i,j,t} = \frac{\sigma_{i,t}\sigma_{j,t}}{\sigma_{i,t}\sigma_{j,t}} \).

3 The paper submitted April 9, 2017
Prepared for publication June 1, 2017

Tamara MARINIČEVAITĖ, Žygimantas MAURICAS

SAUGUS PRIEGLOBŠČIO VALIUTŲ NAUDOJIMAS MAŽINANT PORTFELIO RIZIKĄ RINKOS NEAPIBRĖŽTUMO LAIKOTARPIAIS

Santrauka

Praėjusi didžioji finansų krizė privertė investuotojus ieškoti alternatyvių portfelio rizikos mažinimo būdų. Stebima vis didėjančios koreliacijos tarp tradicinių turto klasų tendenciją skatina tirti naujus investicinės rizikos mažinimo šaltinius ir analizuoti alternatyvias investavimo strategijas. Šiame darbe autoriai tiria pagrindinių valiutų naudojimo efektyvumą mažinant portfelio riziką rinkos neapibrėžtumo laikotariais. Tyrimo duomenys apima kintamumo (VIX) indeksą (naudojamą kaip rinkos sentimento rodiklį), S&P 500 biržoje prekiaujamą fondą (naudojamą kapitalo permainos atraskės modeli), ir pagrindines valiutas: Australijos dolerį, Kanados dolerį, Šveicarijos franką, eurą, Didžiosios Britanijos svarą ir Japonijos yeną. Dienos dažnio duomenys apima laikotarpį nuo 1999 m. sausio 1 d. iki 2015 m. gruodžio 31 d. Tyrimas atliekamas dviem etapais. Pirmame etape yra nustatomos saugaus prieglobščio valiutų, sumažinančių investicinio portfelio riziką rinkos neapibrėžtumo laikotariai. Antrame etape autoriai palygina primityvius ir aktyvius portfelio valdymo strategijos įtaką investicinio portfelio rizikų mažinimui. Taikant primityvią portfelio valdymo strategiją, investicinis portfelis perskirstomas investavimo laikotarpui atsižvelgiant į VIX indekso lygį, kuris naudojamas kaip rinkos neapibrėžtumo laikotarpio rodiklis. 


Tyrimo rezultatai rodo, kad saugaus prieglobščio valiuto naudojimas mažina investavimo riziką rinkos neapibrėžtumo laikotariais. Atsiranda atvejų, kai investavimo strategija būtų efektyvesnė kaip investavimo strategija, naudojantis VIX indekso lygį kaip slenkstinį rodiklį. 

Investavimo strategijos testavimo rezultatai rodo, kad saugaus prieglobščio valiutų naudojimas mažina investavimo riziką rinkos neapibrėžtumo laikotariai. 

Dviejų valiutų – Australijos dolerio ir Šveicarijos frankos – naudojimas mažina investavimo riziką rinkos neapibrėžtumo laikotariais.
### Appendix 1. Summary statistics, using observations 1999.01.05–2013.12.31

<table>
<thead>
<tr>
<th></th>
<th>VIX</th>
<th>SPY</th>
<th>AUD</th>
<th>CAD</th>
<th>CHF</th>
<th>EUR</th>
<th>GBP</th>
<th>JPY</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.01714</td>
<td>0.01084</td>
<td>0.00977</td>
<td>-0.00959</td>
<td>-0.01142</td>
<td>0.00412</td>
<td>-0.00006</td>
<td>-0.00184</td>
</tr>
<tr>
<td>Median</td>
<td>-0.42207</td>
<td>0.05334</td>
<td>0.04078</td>
<td>-0.00659</td>
<td>0.010447</td>
<td>0</td>
<td>0.01512</td>
<td>0.006904</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>6.295</td>
<td>1.304</td>
<td>0.848</td>
<td>0.59</td>
<td>0.702</td>
<td>0.645</td>
<td>0.593</td>
<td>0.671</td>
</tr>
<tr>
<td>C.V.</td>
<td>367.80</td>
<td>120.32</td>
<td>86.738</td>
<td>61.592</td>
<td>61.472</td>
<td>156.62</td>
<td>9645.7</td>
<td>364.83</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.587</td>
<td>-0.166</td>
<td>-0.808</td>
<td>-0.012</td>
<td>0.39</td>
<td>0.158</td>
<td>-0.247</td>
<td>-0.204</td>
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</tbody>
</table>

### Appendix 2. Unconditional correlation estimates

<table>
<thead>
<tr>
<th></th>
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<th>SPY</th>
<th>AUD</th>
<th>CAD</th>
<th>CHF</th>
<th>EUR</th>
<th>GBP</th>
<th>JPY</th>
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<tbody>
<tr>
<td>VIX</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>SPY</td>
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<td>1.0000</td>
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<td>AUD</td>
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<td>0.2165</td>
<td>1.0000</td>
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<td></td>
</tr>
<tr>
<td>CAD</td>
<td>0.1772</td>
<td>-0.2347</td>
<td>-0.6228</td>
<td>1.0000</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CHF</td>
<td>0.0489</td>
<td>-0.0586</td>
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<td>1.0000</td>
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<td></td>
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</tr>
<tr>
<td>EUR</td>
<td>-0.0618</td>
<td>0.0719</td>
<td>0.5564</td>
<td>-0.4539</td>
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<tr>
<td>GBP</td>
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<td>-0.5406</td>
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<td>0.6742</td>
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<tr>
<td>JPY</td>
<td>0.154</td>
<td>-0.1670</td>
<td>0.0179</td>
<td>0.0106</td>
<td>0.3681</td>
<td>0.2454</td>
<td>0.1430</td>
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</tr>
</tbody>
</table>

### Appendix 3. Univariate GARCH coefficients

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<thead>
<tr>
<th></th>
<th>$\alpha_0$</th>
<th>Std. error</th>
<th>$\alpha_1$</th>
<th>Std. error</th>
<th>$\beta$</th>
<th>Std. error</th>
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<tbody>
<tr>
<td>SPY</td>
<td>0.0167176**</td>
<td>0.00919297</td>
<td>0.0856416**</td>
<td>0.00919297</td>
<td>0.904250**</td>
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</tr>
<tr>
<td>AUD</td>
<td>0.00686119*</td>
<td>0.00746087</td>
<td>0.0595165**</td>
<td>0.00746087</td>
<td>0.930419**</td>
<td>0.00746087</td>
</tr>
<tr>
<td>CAD</td>
<td>0.0014246**</td>
<td>0.000543447</td>
<td>0.0530125**</td>
<td>0.00603691</td>
<td>0.942792**</td>
<td>0.00638886</td>
</tr>
<tr>
<td>CHF</td>
<td>0.0036275**</td>
<td>0.00136323</td>
<td>0.0445781**</td>
<td>0.00540973</td>
<td>0.949323**</td>
<td>0.00610133</td>
</tr>
<tr>
<td>EUR</td>
<td>0.00141599*</td>
<td>0.000679533</td>
<td>0.0323095**</td>
<td>0.00416192</td>
<td>0.964706**</td>
<td>0.00448660</td>
</tr>
<tr>
<td>GBP</td>
<td>0.00230395**</td>
<td>0.000816600</td>
<td>0.0384757**</td>
<td>0.00533444</td>
<td>0.954232**</td>
<td>0.00650215</td>
</tr>
<tr>
<td>JPY</td>
<td>0.00769760**</td>
<td>0.00219181</td>
<td>0.0415919**</td>
<td>0.00709967</td>
<td>0.940498**</td>
<td>0.0107778</td>
</tr>
</tbody>
</table>

**Statistically significant coefficient with 0.01 confidence interval
* Statistically significant coefficient with 0.05 confidence interval
Appendix 4. TAR model likelihood ratio test confidence intervals for threshold estimation

AUD/SPY

CAD/SPY

CHF/SPY

EUR/SPY

GBP/SPY

JPY/SPY