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A Flight to Quality

A study of how uncertainty and recessions relate to currency valuations

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Abstract

This empirical study analyzes the relationship between real currency returns and US Economic Policy Uncertainty (EPU) with a distinction between low/high-yielding currencies. By employing a DCC-GARCH model, the paper examines the dynamic correlation between the variables. Additionally, a VAR model is implemented to determine how the correlation is impacted by a US recession. The research is based on the gold price and a collection of 26 floating/free-floating currencies from 1999 to 2024.

Key findings indicate that low-yielding (high-yielding) currencies exhibit a positive (negative) correlation with US EPU implying a "flight to quality" phenomenon during periods of heightened uncertainty. The results for the low-yielding currencies are similar to gold, implying that similar safe-haven characteristics are shared between them. Additionally, results from the VAR model indicate tendencies of a strengthened dynamic correlation during recessions. These results are nevertheless statistically insignificant for the majority of currencies examined and the lack of significance is attributed to the limited recessionary data used.

Keywords: Economic Policy Uncertainty, Dynamic conditional correlation, Real effective exchange rate

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1 Introduction

Uncertainty and its impact on global markets have been studied for a long time. The starting point in 1983 established a theoretical link between uncertainty and investment decisions. Uncertainty was determined as the causal factor to explain the cyclical fluctuations observed in investments by Bernanke (1983). The paper concludes that a higher (lower) uncertainty results in a decrease (increase) in irreversible investments. This causal relationship stems from an uncertainty of future probabilities, causing uncertainty in estimated investment returns. Owing to the aforementioned causality, irreversible investments are deferred to the future when probabilities are more certain (Bernanke 1983).

Upon the grounds of Bernanke, research in the area of uncertainty has expanded through the inclusion of a broader array of economic variables. Among these, growth stands out as a crucial variable affected by policy uncertainty, a relationship that depends on the tax regime and the persistence of policy decisions. Through the usage of an OLS regression, with an autoregressive component, Aizenman and Marion (1991) could determine that the gap between tax regimes is of explanatory importance, where a larger gap induces a greater impact from policy uncertainty on growth level. The effect is based upon the assumption of persistence in policy decisions. With persistence, the growth level in a country with a low-tax regime is shown to be stimulated by increased uncertainty while the opposite is true for a country with a high-tax regime. On the other hand, in the absence of persistence, policy uncertainty could not be shown to impact the long-run growth rate. This implies an interactive relationship between a tax regime and the persistence of policy decisions (Aizenman and Marion 1991).

It was later concluded by Bloom (2009), both theoretically and empirically, that spikes in uncertainty are associated with a drop and rebound in output and employment. The theoretical effect was studied through simulating the methods of moments while the empirical data was studied through a vector autoregression (VAR). The research found it important to differentiate between first- and second-moment shocks as they exhibit different characteristics. Notably, a key difference lies in the sharpness of a recession. A second-moment shock creates a sharp drop and recovery in economic variables, whereas a first-moment shock exerts a prolonged influence over the economic variables.

Consequently, a recession does not necessarily require a first-moment shock to occur but increased uncertainty is sufficient (Bloom 2009).

Pastor and Vernesi (2012) conducted further research into how policy uncertainty affects stock prices and predicted a negative stock market response upon the announcement of policy change. Their findings imply that an expected policy change, on average, results in an increase in stock prices whereas an unexpected policy change results in a decrease. This prediction is made under the assumption of a benevolent government (Pastor and Veronesi 2012).

Throughout most earlier studies, the effect of uncertainty has been assumed linear. However, in recent years it has been hypothesized that uncertainty could have a non-linear effect on economic variables. One study suggesting a non-linear approach is Morley and Piger (2012) who empirically modeled the business cycle and found that recessions are characterized by large swings in outputs. Moreover, their research concludes that expansionary periods follow a trend, implying that volatility in output is greater in recessions and thereby time-varying over the business cycle. Thus, output is proposed to possess a non-linear relationship with respect to uncertainty (Morley and Piger 2012).

A multitude of methods have historically been employed when studying uncertainty, with one of the more prevalent being mean models analyzing the first moment. Hamilton (2008) pointed out that disregarding to correctly specify the second moment creates estimation bias. A model that correctly estimates the second moment is therefore needed for unbiased estimates of the first moment, as outliers from periods characterized by heteroscedasticity will have a disproportional impact on first-moment estimates. Specifying the second moment correctly is therefore crucial as economic variables exhibit time-varying volatility over the business cycle, as shown by Morley and Piger (2012). GARCH is proposed as an alternative model since it models the second moment and thereby generates unbiased first moment estimates without assuming homogeneous volatility (Hamilton 2008).

The adoption of a non-linear approach as proposed by Morley and Piger (2012) and the usage of GARCH proposed by Hamilton (2008) led to Jones and Olson (2013) using a DCC-GARCH. Through the implementation of this model, they investigated the time-varying correlation between uncertainty and output/inflation. The research concluded empirically that there is an overall negative correlation between output and uncertainty. However, there were periods where the overall negative correlation did not hold, mainly from the late 1990s to early 2000s (Jones and Olson 2013).

Brogaard and Detzel (2015) continued to expand upon the work of Pastor and Veronesi (2012) by including additional control variables and the uncertainty measurement Economic Policy Uncertainty (EPU) measurement introduced by Baker, Bloom, and Davis (Baker, Bloom, and Davis 2016). Brogaard and Detzel investigated the impact of EPU on asset prices and found that US equity returns exhibit a negative correlation with US EPU. Additionally, they observed a positive correlation between US EPU and the volatility of stock market returns (Brogaard and Detzel 2015).

Other studies in the uncertainty field have been conducted with the application on exchange rates. Brunnermeier, Nagel, and Pedersen (2009) analyzed currency carry trade and the crash risk of currencies. The paper used the stock market volatility measurement VIX as an uncertainty measurement and conducted the study by employing predictive regressions and a smooth transition vector autoregressive (VAR) model. Their research concludes that there is a significant positive correlation between currency crashes of high-yielding currencies and implied stock market volatility (Brunnermeier, Nagel, and Pedersen 2009).

The research on uncertainty and its application to exchange rates is further studied by Kido (2016) who analyzed the time-varying correlation between high/low-yielding currencies and US EPU during recessions. Contrary to Brunnermeier et al (2009), Kido used the policy uncertainty measurement EPU similar to Brogaard and Detzel (2015). Furthermore, when analyzing the correlation between uncertainty and exchange rate valuation, Kido used returns of real effective exchange rates (REER) as they determine a country's trade competitiveness.

Kido bases his methodology on the work of Jones and Olsson (2013) by employing a DCC-GARCH model to analyze the time-varying correlation. Additionally, he employed a smooth transition VAR model to determine if the correlations were affected by a recession. The result was that the low-yielding currencies have a significantly strengthened positive correlation to uncertainty during recessions while high-yielding currencies have a strengthened negative correlation. It was therefore concluded that there is a strengthened appreciation (depreciation) in low-yielding (high-yielding) currencies in a recession (Kido 2016).

The purpose of our research is to describe the relationship between real currency valuations and uncertainty as well as to determine how the relationship is impacted by a recession. Our research is based on Kido's methodology to analyze the aforementioned relationship. Thus, a DCC-GARCH is used to retrieve an estimate for dynamic correlations which then are incorporated into a VAR. The VAR is used to determine if the dynamic correlations are significantly impacted by a recession. The novelty of this paper is that it introduces a larger pool of data than used previously by expanding both the time horizon as well as the number of currencies included. Additionally, the relationship between gold and uncertainty is included to enhance the analysis on safe-haven assets. By achieving our research objectives, this paper aims to provide valuable insights for investors operating in the foreign exchange market and policymakers by supporting their decision-making processes.

The remaining part of the paper is organized as follows: Section 2, *Model*, motivates the choice of methodology. Section 3, *Data*, presents the datasets over REER, gold, EPU, and NBER as well as descriptive statistics over the datasets. Section 4, *Results*, presents the outcomes of the methodology with interpretations. Section 5, *Conclusion*, provides an overall summary of the report.

2 Model

The central model of this paper is a DCC-GARCH which is implemented to describe the time-varying relationship between real currency returns and US EPU. In addition to the DCC-GARCH, a VAR model is employed to determine how the relationship is affected by a recession. The VAR uses the dynamic correlations obtained through the DCC-GARCH and a recession dummy to test a recession's effect on the dynamic correlations.

The usage of a GARCH model is supported by Hamilton as estimating the second moment correctly is integral for unbiased estimates of a time series with a heterogenous volatility (Hamilton 2008). GARCH is also supported by the results from an univariate GARCH where the coefficients (presented as α and β in *Appendix A*) were significant for the majority of currencies. This implies that the variables used to predict future volatility have an explanatory power for most currencies.

2.1 DCC-GARCH

The Auto-Regressive Conditional Heteroscedasticity (ARCH) model captures conditional volatility that depends on the past squared residuals (Engle 2001). The Generalized ARCH (GARCH), extends this model by including the previous period's volatility. This addition results in that past squared residuals are included with an exponentially diminishing weight. Thus, it generates a model with smaller fluctuations in estimated volatility (Engle 2001). Within financial econometrics, GARCH has become a common method due to this property. An extension of GARCH is the Dynamic Conditional Correlation (DCC)-GARCH (Engle 2002). This version possesses the property of allowing for time-varying correlation between the variables within the model. The implication is that the assumption of constant correlation becomes redundant, thereby leading to a lower bias in the estimating process when a constant correlation can not be assumed.

The included variables (*REER returns, gold*, and *US EPU*), are denoted $r_{i,t}$, where i is the respective variable and t is time. $r_{i,t}$ can be divided into two parts, the mean, μ_i, and the variation from the mean, $a_{i,t}$. The division of these two components is carried out as GARCH assumes a mean of zero (Engle 2002).

$$r_{i,t} = \mu_i + a_{i,t} \tag{1}$$

A vector including all assets, $\mathbf{a}_t$ can be divided in two factors, the conditional variance $\mathbf{H}_t$ and a random component $\mathbf{z}_t$. The random component is assumed to be independent and identically distributed (IID).

$$\mathbf{a}_t = \mathbf{H}_t^{1/2}\mathbf{z}_t, \quad \mathbf{z}_t \overset{iid}{\sim} N(0,1) \tag{2}$$

The conditional variance $\mathbf{H}_t$ is itself dependent on the conditional standard deviations, $\mathbf{D}_t$, and the correlations between the variables, $\mathbf{P}_t$. The returns are conditioned on information from past observations and are multiplied as shown in Equation 3 (Engle 2002).

$$\mathbf{H}_t = \mathbf{D}_t\mathbf{P}_t\mathbf{D}_t \tag{3}$$

$\mathbf{D}_t$ is a diagonal matrix over the conditional standard deviations of $\mathbf{a}_t$ (see Equation 4) and $\mathbf{P}_t$ is a matrix of the conditional correlations of $\mathbf{a}_t$. In our dataset, $\mathbf{D}_t$ and $\mathbf{P}_t$ have the structure shown in Figure 1.

Figure 1: The matrices $\mathbf{D}_t$ and $\mathbf{P}_t$, where $d_{i,t}$ is the conditional standard deviation and ρ_t is the estimated correlation.

$$\mathbf{D}_t = \begin{bmatrix} \sqrt{d_{1,t}} & 0 \\ 0 & \sqrt{d_{2,t}} \end{bmatrix} \qquad \mathbf{P}_t = \begin{bmatrix} 1 & \rho_t \\ \rho_t & 1 \end{bmatrix}$$

The equation for estimating the conditional standard deviations, $d_{i,t}$, is described in Equation 4 (Engle 2002). Applied to this dataset, $\alpha_{i,t}$ is the coefficient for the previous period's $a_{i,t}$ value and β_i is the coefficient for the previous period's conditional variance.

$$d_{i,t} = \alpha_{i,0} + \alpha_{i,1}a_{i,t-1}^2 + \beta_i d_{i,t-1} \tag{4}$$

Furthermore, Figure 1 shows that $\mathbf{P}_t$ is a matrix containing the correlation, ρ_t, between the used variables (*REER returns*, *gold*, and *US EPU*). When estimating the correlation matrix, $\mathbf{P}_t$, the errors from the univariate GARCH, $\boldsymbol{\epsilon}_t$, are used. Since $\boldsymbol{\epsilon}_t = \mathbf{D}_t^{-1}\mathbf{a}_t$, Equation 3 can be rewritten to Equation 5 to retrieve the time-varying correlation $\mathbf{P}_t$ (Engle 2002).

$$E_{t-1}(\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t^T) = \mathbf{D}_t^{-1}\mathbf{H}_t\mathbf{D}_t^{-1} = \mathbf{P}_t \tag{5}$$

Since $\mathbf{P}_t$ is a time-varying correlation matrix, two requirements need to be considered when used in the DCC-GARCH model (Engle 2002):

1. The conditional covariance matrix, $\mathbf{H}_t$, must by definition be positive definite since it is a covariance matrix and it is ensured by $\mathbf{P}_t$ being positive definite.

2. The absolute value of each element in $\mathbf{P}_t$ is equal to or less than one by definition.

To satisfy the two requirements above, the correlation matrix, $\mathbf{P}_t$, is constructed from $\mathbf{Q}_t$ and the inverse of $\mathbf{Q}_t^*$ as in Equation 6.

$$\mathbf{P}_t = \mathbf{Q}_t^{*-1}\mathbf{Q}_t\mathbf{Q}_t^{*-1} \tag{6}$$

$\mathbf{Q}_t^*$ is representative of a diagonal matrix seen in Figure 2.

Figure 2: Visualisation of the matrix $\mathbf{Q}_t^*$

$$\mathbf{Q}_t^* = \begin{bmatrix} \sqrt{q_{1,1,t}} & 0 \\ 0 & \sqrt{q_{2,2,t}} \end{bmatrix}$$

The diagonal elements in the $\mathbf{Q}_t^*$ matrix are estimated using Equation 7 where, $\rho_{i,j,t}$ is the conditional correlation estimator located in the correlation matrix, $\mathbf{P}_t$, in Figure 1 (Engle 2002).

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \tag{7}$$

The $\mathbf{Q}_t$ matrix in Equation 6 is defined as in Equation 8 to ensure the assumption of H_t being positive definite.

$$\mathbf{Q}_t = (1-a-b)\bar{\mathbf{Q}} + a\boldsymbol{\epsilon}_{t-1}\boldsymbol{\epsilon}_{t-1}^T + b\mathbf{Q}_{t-1} \tag{8}$$

where a and b are scalars and $\bar{\mathbf{Q}}$ is the unconditional covariance matrix of standardized errors, $\boldsymbol{\epsilon}_t$.

To ensure that the covariance matrix, $\mathbf{H}_t$ is positive definite, the covariance matrix for $\boldsymbol{\epsilon}_t$ is required to be positive definite as it assures the correlation matrix $\mathbf{P}_t$ being positive definite. Moreover, to ensure a positive unconditional variance, the scalars a and b must satisfy the following conditions; $a \geq 0$, $b \geq 0$, and $a + b < 1$.

A normal distribution is assumed when estimating the parameters in the DCC-GARCH. This is motivated by the residuals following this distribution (see *Appendix B*). Moreover, the estimation process is conducted through the usage of a maximum likelihood estimation (Engle 2002).

The estimated parameters, θ, are divided into two subsets $\theta = (\eta, \omega)$, where $\eta = (\alpha_1, \beta_1)$ and $\omega = (a, b)$. The former describes the parameters of the univariate GARCH model and the latter describes the correlation structure between the assets. The maximum likelihood estimation is performed twice, once for estimating the parameters of η and once for the parameters of ω. The estimation process of the DCC-GARCH is presented in Equation 9 (Orskaug 2009).

$$L(\theta) = \prod_{t-1}^{T} \frac{1}{(2\pi)^{n/2}|\mathbf{H}_t|^{-1/2}} e^{-\frac{1}{2}\mathbf{a}_t^T\mathbf{H}^{-1}\mathbf{a}_t} \tag{9}$$

This equation is simplified to Equation 10.

$$\begin{aligned} log(L(\theta)) &= -\frac{1}{2}\sum_{t-1}^{T}(nlog(2\pi) + log(|\mathbf{H}_t|) + \mathbf{a}_t^T\mathbf{H}_t^{-1}\mathbf{a}_t) = \\ &= -\frac{1}{2}\sum_{t-1}^{T}(nlog(2\pi) + 2log(|\mathbf{D}_t|) + log(|\mathbf{P}_t|) + \mathbf{a}_t^T\mathbf{D}_t^{-1}\mathbf{P}_t^{-1}\mathbf{D}_t^{-1}\mathbf{a}_t) \end{aligned} \tag{10}$$

In the first iteration of the estimation, the correlation matrix, $\mathbf{P}_t$, is replaced with an identity matrix, $\mathbf{I}$. This replacement provides the possibility for further simplification to Equation 11.

$$\begin{aligned} log(L_1(\eta)) = -\frac{1}{2}\sum_{t-1}^{T}(nlog(2\pi) + 2log(|\mathbf{D}_t|) + log(|\mathbf{P}_t|) + \mathbf{a}_t^T\mathbf{D}_t^{-1}I^{-1}\mathbf{D}_t^{-1}\mathbf{a}_t) = \\ = \sum_{i=1}^{n}(-\frac{1}{2}\sum_{t-1}^{T}[log(d_{i,t}) + \frac{a_{i,t}^2}{d_{i,t}}] + constant) \end{aligned} \tag{11}$$

As seen in Equation 11, the loglikelihood function is the sum of all the univariate GARCH for the n assets included. This function will estimate the parameters of η which in turn is needed to estimate the conditional variance, $d_{i,t}$, the diagonal of the $\mathbf{D}_t$ matrix (see Figure 1). The correlation matrix, $\mathbf{P}_t$, and the residuals, ϵ_t are the essential output needed from the first iteration of the estimation. As previously stated, ϵ_t can be defined as $\epsilon_t = \mathbf{D}_t^{-1/2}\mathbf{a}_t$ where $\mathbf{a}_t$ is retrieved from Equation 1. As seen in Equation 6, $\mathbf{P}_t$ is estimated based on the three variables $\bar{\mathbf{Q}}$, $\mathbf{Q}_t$, and $\mathbf{Q_t^*}$ which all are based on ϵ_t (Orskaug 2009).

The parameters included in ω are estimated in the subsequent iteration of the estimation process. As the variables $\mathbf{P}_t$ and ϵ_t are returned from the first step, they can be incorporated into Equation 10. A simplification through the equality presented previously, $\epsilon_t = \mathbf{D}_t^{-1/2}\mathbf{a}_t$, is also made resulting in the simplification in Equation 12.

$$log(L_2(\omega)) = -\frac{1}{2}\sum_{t-1}^{T}(nlog(2\pi) + 2log(|\mathbf{D}_t|) + log(|\mathbf{P}_t|) + \epsilon_t^T\mathbf{P}_t^{-1}\epsilon_t) \tag{12}$$

Lastly, by excluding the constants, the second step of the estimation process can be simplified further into Equation 13.

$$log(L_2(\omega)) = -\frac{1}{2}\sum_{t-1}^{T} log(|\mathbf{P}_t|) + \epsilon_t^T\mathbf{P}_t^{-1}\epsilon_t) \tag{13}$$

2.2 Vector Autoregression

A Vector Autoregression (VAR) model is employed to test how the correlations are affected by a recession. A VAR is a linear stochastic model used for prediction. The model is based on lagged values on all time series variables considered and is an extension of the univariate Auto Regression (AR) model through the inclusion of multiple time series variables. The VAR is constructed by a set of time series regressions where the number of time series variables used decides the number of equations the VAR is composed of. The VAR equations are estimated with Ordinary Least Squares (OLS) estimation and the regressors are lagged values of all used variables (Stock and Watson 2020).

Furthermore, the VAR is based upon the least squares assumptions for forecasting with time series data. It is therefore assumed that (Stock and Watson 2020):

- Error term's conditional mean is zero
- Distribution of the random variables is stationary
- Large outliers are unlikely
- No perfect multicollinearity

To determine the behavior of the correlation between US EPU and the REER returns during recessions, the VAR model is using the dynamic conditional correlation obtained through the DCC-GARCH model and a recession dummy. The VAR equation is constructed in the following way:

$$\mathbf{P}_{i,t} = \alpha_i + \beta_i \mathbf{P}_{i,t-1} + \gamma_i NBER_{t-1} + \epsilon_{i,t} \tag{14}$$

where $\mathbf{P}_t$ is the term for the dynamic conditional correlation, β is the coefficient of the $\mathbf{P}_t$ term, $NBER_t$ is the dummy variable for recession periods defined by National Bureau of Economic Research (NBER), γ is the coefficient of the $NBER_t$ term, and $\epsilon_{i,t}$ denotes the error term.

Equation 14 is the central equation of this model as it determines if the correlations between US EPU and the REER returns change during recessions. The equation is based on the work by the

DCC-GARCH model since the P_t parameter is used with the addition of the recession variable, $NBER_t$. It is the γ parameter that indicates if there are any significant changes in the correlation between US EPU and REER returns during recessions.

3 Data

Four datasets are used in this study and are all measured monthly. First, data for Real Effective Exchange Rates (REER) is obtained from the Bank of International Settlements (BIS) (Bank for International Settlements 2024). Second, data on the gold price is obtained from the World Bank Commodity Price Data (World bank 2024). Third, the US EPU news-based measurement, which is retrieved from the founders' website (Baker, Bloom, and Davis 2016). Fourth, a binary measurement for when there is a recession or not. This data is retrieved from NBER (National Bureau of Economic Research 2024b).

3.1 REER AND GOLD

Real effective exchange rate (REER) is an exchange rate measurement describing the changes in trade competitiveness of a country over time. REER uses both exchange rates and inflation levels to compare the value of a country's currency to its trading partners' currencies. A decrease (increase) in REER implies an increase (decrease) in trade competitiveness (OECD 2013).

The formula for the real exchange rate:

$$s_j = e_j \times \frac{P^f}{P} \tag{15}$$

where s_j is the real exchange rate, e_j is the nominal exchange rate, P^f is the price level in a foreign country and P is the price level in a domestic country (Takáts, E 2012).

The formula for REER:

$$REER_i = \sum_{j=1}^{N} w_j \times s_j \tag{16}$$

where w_j is the trade weight between country i and j, and s_j is the real exchange rate for country j (Takáts, E 2012). The equation utilized to derive the REER return ($r_{i,t}$) is displayed in Equation 17. In this equation, a calculation for the return of the gold price is also presented. The gold price (*Gold_i,t*) is measured as a mean of daily rates, in dollars per troy ounce and the equation returns the monthly return equally to the REER equation (World bank 2024).

$$r_{i,t} = \frac{REER_{i,t}}{REER_{i,t-1}} \qquad\qquad r_{i,t} = \frac{Gold_{i,t}}{Gold_{i,t-1}} \tag{17}$$

The different REERs are sorted into two groups, low-yielding and high-yielding currencies. Low-yielding currencies are characterized by low interest rates and are generally considered safe havens during times of financial distress (Habib and Stracca 2011). This group of currencies possess the qualities associated with a safe haven currency and are namely the US Dollar, the Japanese Yen, and to a lesser extent the Euro (Ranaldo and Söderlind 2010).

The sample of currencies used in this study are the currencies fulfilling two properties. First, they are free-floating or floating as defined by the IMF (International Monetary Fund 2023). Second, data on the REER values are available from BIS. The IMF defined 48 currencies to be either floating or free-floating. Out of these, BIS store data for 26 of the countries, three of which are categorized as low-yielding and 23 categorized as high-yielding. Thus, for the purpose of this report, the US Dollar, Japanese Yen, and Euro are considered to be low-yielding currencies and the remaining 23 currencies are high-yielding currencies.

3.2 EPU

EPU indices capture short- and long term economic policy uncertainty (Baker, Bloom, and Davis 2016). The US EPU index is a news-based uncertainty measurement derived from counting the frequency of words related to economy, policy, and uncertainty in the top ten industry-leading newspapers (Baker, Bloom, and Davis 2016). In addition to the word frequency, data from different governmental organizations such as data on tax code expirations from the Congressional Budget Office is used to enhance the measurement (Baker, Bloom, and Davis 2024).

There are similarities between stock market volatility measurements and EPU as they both influence each other (Pastor and Veronesi 2017). One similarity is that uncertainty spreads across the entire economy leading to a high correlation between the measurements. However, the correlation is not perfect and the impact of EPU on stock market volatility is determined by two factors: First, a higher EPU leads to higher stock market volatility. Second, a lower precision of a policy signal leads to a lower correlation between stock market volatility and EPU (Pastor and Veronesi 2017). The difference between the uncertainty measurements lies in what type of uncertainty they are measuring. EPU measures mainly economic and policy uncertainty while stock market volatility measures market uncertainty (Baker, Bloom, and Davis 2016).

Both EPU and stock market volatility measurements are equally valid as a measurement of uncertainty. The final verdict for which measure to use comes down to comparability. Within the field of studying the relationship between currencies and uncertainty, the main uncertainty measurement has been EPU as exemplified by Kido (Kido 2016). Thus, EPU is the measurement used in this paper.

The US EPU index is chosen over the global EPU index due to three main reasons. First, there is a high correlation between the two EPU measurements, meaning that the difference between the two is marginal. Second, the choice of US EPU increases the comparability to previous literature. Third, it is reasonable to use the US EPU in conjunction with US recessionary data. However, a counterargument for using the US EPU is that the index may not affect different countries equally. For instance, a close trading partner to the US may be affected more by the US EPU than a country with little trade.

The EPU data is transformed to fulfill the assumption of stationarity. Equation 18 shows how the trend and intercept are subtracted, leaving u_t as the value representing a stationary EPU.

$$EPU_t = a + b \cdot EPU_{t-1} + u_t \tag{18}$$

3.3 NBER

NBER is a binary variable over US recession periods. The Business Cycle Dating Committee at National Bureau of Economic Research (NBER) determines the US recession periods with key economic activity factors including employment, industrial production, and real personal consumption expenditures (National Bureau of Economic Research 2024a).

3.4 Descriptive Statistics

An Augmented Dickey-Fuller (ADF) test is implemented to determine if the data is stationary as it is an underlying assumption of the GARCH model. Table 1 displays a summary of the descriptive statistics and a detailed version can be found in *Appendix C*. In Table 1 it is observed that all of the variables have a significant ADF term implying that the data is stationary and thereby fulfilling this assumption. Furthermore, it is observed that the average standard deviation is 2.09, 1.61, and 3.25 for high/low-yielding currencies and gold respectively. This indicates that the low-yielding currencies have a smaller dispersion than the high-yielding currencies. Finally, the average correlation for the high-yielding currencies is -8.71%. Noteworthy, in *Appendix C* it is observed that New Zealand, Peru, and Sweden are all having positive correlations even though they are high-yielding currencies. The low-yielding currencies have an average correlation to US EPU of 9.58% and gold correlates approximately 6%.

Table 1: Summary of descriptive statistics

	High	Low	Gold
Std	2.09	1.61	3.25
Min corr.	-0.00076	0.0775	0.0599
Mean corr.	-0.0871	0.0958	0.0599
Max corr.	-0.168	0.112	0.0599
ADF.	100%	100%	100%

4 Results

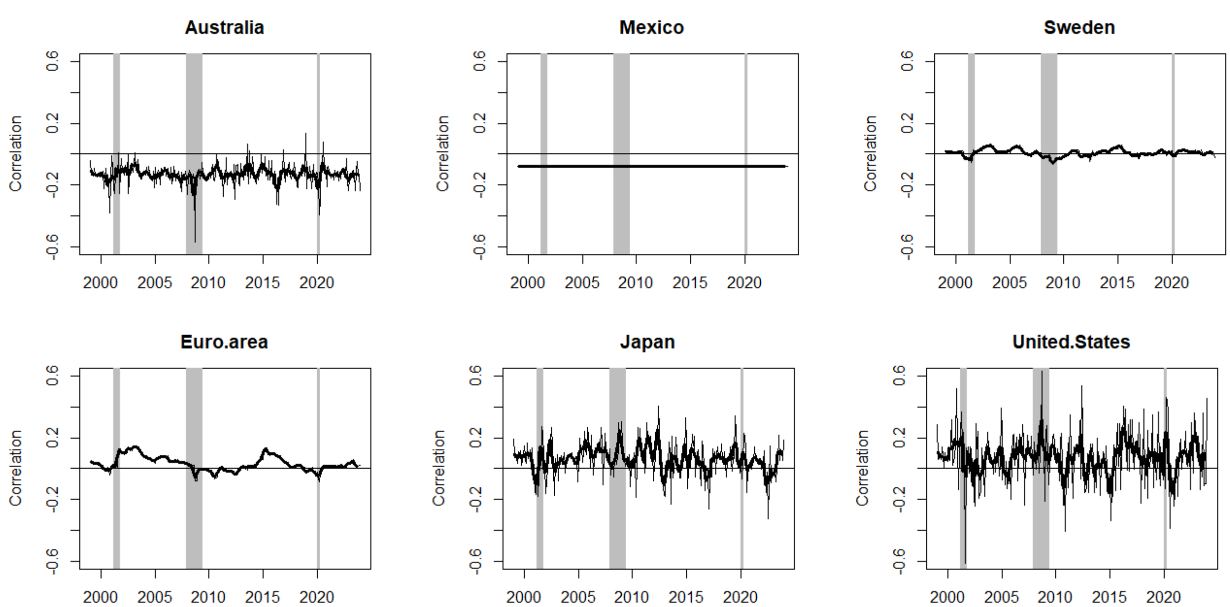
R is the main statistical tool utilized to perform the statistical tests employed within this article. Within *R*, the packages *"rmgarch"* and *"vars"* are used to perform the DCC-GARCH and VAR model respectively.

Table 2: Proportion of currencies having a positive/negative correlation of the high/low-yielding currencies.

	High	Low
Positive	13.0%	100%
Negative	87.0%	0%

From the descriptive statistics in *Appendix C*, it can, assuming a constant correlation, be determined that high-yielding currencies tend to be negatively correlated with the US EPU while low-yielding currencies are positively correlated. There are three outliers: the New Zealand Dollar, the Peruvian Sol, and the Swedish Krona, which all show a positive constant correlation to the US EPU. Contrary to high-yielding currencies, low-yielding currencies act similarly to gold through its positive correlation to US EPU.

Figure 3: A selection of the correlation between different currencies and US EPU.



The assumption of a constant correlation is made redundant when applying a DCC-GARCH. The dynamic correlations reveal a similar pattern to the constant correlations; that high-yielding (low-yielding) currencies tend to be negatively (positively) correlated to US EPU. (The dynamic correlations, given by Equation 6, are graphed in *Appendix E*, and a selection of currencies is presented in Figure 3.)

Table 3: Table over a selection of the sample.

	Australia	Mexico	Sweden	Euro area	Japan	United States	Gold
Intercept	86.6	1.01	29.0	0	308***	56.6	257**
	(62.3)	(4.00)	(19.6)	(~0)	(92.7)	(79.2)	(118)
α	0.178	0	0.119**	0.00872***	0.256**	0.133	0.0985**
	(0.110)	(0.00632)	(0.0491)	(0.00193)	(0.122)	(0.188)	(0.0464)
β	0.630***	0.999***	0.724***	0.989***	0.111	0.492	0.0715***
	(0.208)	(0.000402)	(0.130)	(0.00223)	(0.192)	(0.663)	(0.0929)
a	0.0821	0	0.0115	0.0141	0.134*	0.224***	0
	(0.318)	(~0)	(0.0265)	(0.0171)	(0.0784)	(0.0825)	(0.000767)
b	0	0.918***	0.860***	0.926***	0.277	0	0.876**
	(2.02)	(0.0658)	(0.0841)	(0.0337)	(0.371)	(0.230)	(0.385)
a+b	0.0821	0.918	0.871	0.940	0.411	0.224	0.876

α is the coefficient for ARCH, β is the coefficient for GARCH. *a* denotes the degree of volatility and *b* represents the trend in the data.
Standard deviations are in parentheses.
In the table.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

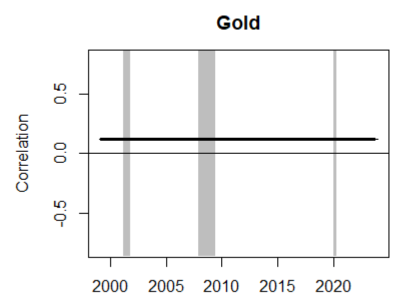
When examining the dynamic correlations, different patterns are observed as exemplified in Figure 3. These patterns stem from the estimation of the two parameters *a* and *b* in the DCC-GARCH seen in Table 3. More intuitively, it is shown in Equation 8 that a high value in *a* indicates that the previous period, the short term, will have a large impact on the estimation of the current period's correlation. Additionally, a high value in *b* implies that the long-term trend in the data will have an increased impact on the correlation.

One extreme pattern is observed in the Mexican Peso where the currency is characterized by a constant dynamic correlation. Conversely, currencies such as the Japanese Yen and US Dollar display a highly volatile dynamic correlation. Between these extremes lies currencies like the Swedish Krona and the Euro exhibiting a stable yet varied correlation with the US EPU.

Starting with the Australian Dollar, the currency displays a low degree of volatility amid an otherwise stable level dynamic correlation which is supported both by the correlation plots and the estimated parameters of a and b. Since b is approximately equal to zero, it indicates that the most recent observations are dominating Q_t and thus also dominating the estimated dynamic correlation between the Australian Dollar and the US EPU. On the contrary, the Mexican peso exhibits constant dynamic correlation which is explained by a being estimated to 0. The Swedish Krona and the Euro show similar characteristics, with a comparable value for both a and b resulting in both having a smooth and stable dynamic correlation. In contrast, the Japanese yen and the US Dollar have an a estimated to be approximately 10-20x greater than that of the Swedish Krona and the Euro, resulting in the high volatility observed in the correlation plots. Furthermore, the b value for the US Dollar is approximately equal to zero, implying that the most recent observations dominate Q_t and also the dynamic correlation between the currency and the US EPU.

The results of low-yielding (high-yielding) currencies having a positive (negative) correlation to US EPU can be compared to the result of gold. Gold shows a constant positive dynamic correlation resulting from an increased demand when uncertainty increases. This is similar to the resulting correlation for the low-yielding currencies implying similar characteristics in the assets. Therefore, the safe-haven properties seen in gold can also be seen in the low-yielding currencies. It implicates a "flight to quality" effect where demand for safer (low-yielding) currencies increases at the cost of high-yielding currencies' demand.

Figure 4: The correlation between gold and US EPU.



Through the usage of a VAR, it is tested if a US recession has a significant impact on the correlations. The result is that 60-70% of the correlations are not significantly impacted by a US recession. An interesting result is that of the correlations significantly impacted, the low-yielding currencies showed an increased positive correlation while high-yielding showed an increased negative correlation. This direction of strengthened correlation during a US recession supports the "flight to quality" theory since there is a sign that the positive/negative correlation strengthens during a US recession. However, it is important to reiterate that the results are insignificant for most currencies.

When analyzing the result of the VAR, it is evident that all high-yielding (low-yielding) currencies, except the currencies experiencing a constant dynamic correlation and Indonesia (see *Appendix F*), have a negative (positive) coefficient. From the dynamic correlation, it can be determined that Indonesia's positive coefficient can be attributed to an increase in the currency value during the 2002 recession. The coefficient will although not be further analyzed due to the insignificance of its coefficient and it being an exception to an otherwise homogeneous group. The homogeneous direction in the group response suggests that a recession might be impacting the dynamic correlations. Given this, the lack of significance could be explained by the small sample size of periods categorized as recessions.

Table 4: The signage for the coefficient (γ) of NBER in the VAR-model from *Appendix F*

	High	Low
Positive	0%	33.3%
Negative	36.4%	0%
Non-significant	63.6%	66.7%

5 Conclusion

This empirical study analyzes the relationship between real currency returns and US Economic Policy Uncertainty with a distinction between low/high-yielding currencies. The models implemented to conduct this research are a DCC-GARCH and a VAR where the former captures the time-varying correlation between the variables and the latter incorporates this correlation to determine if a US recession affects the aforementioned relationship.

The estimated dynamic correlation obtained from the DCC-GARCH shows a similar division of characteristics between high/low-yielding currencies as in previous studies. The conclusion from the results is that low-yielding currencies tend to be positively correlated to US EPU and the opposite is true for high-yielding currencies. Comparing the result to the dynamic correlation for gold it is determined that low-yielding currencies and gold share a similar pattern regarding to the correlation with US EPU. It is found that both act as a safe-haven when uncertainty increases, supporting a "flight to quality" effect in the market.

The results from the VAR model are partially aligned with previous studies. The model shows that there is a tendency for strengthened dynamic correlations during US recessions. However, for the majority of the currencies, these results are statistically insignificant and a conclusion about the influence of US recessions can therefore not be drawn.

There are various opportunities to expand the research within the field of uncertainty and real currency valuation. One is to expand the timeline studied to increase the sample size of recession periods. Another interesting approach for expanding the field is to include currencies of other exchange rate arrangements to test if they act similarly to floating/free-floating currencies.

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A Appendix: Estimated parameters

Appendix A shows the estimated coefficients from the usage of a DCC-GARCH. An interpretation of the coefficients is found in the *Results* section.

Table 5: Table over countries A-E

	Australia	Brazil	Canada	Chile	Colombia	Czechia	Euro.area
Intercept	86.6	402***	20.1	32.9	63.8**	12.8	0
	(62.3)	(117)	(16.2)	(22.1)	(30.1)	(9.48)	(~0)
α	0.178	0.448***	0.127	0.0342	0.130***	0.0416	0.00872***
	(0.110)	(0.139)	(0.0782)	(0.0243)	(0.0461)	(0.0260)	(0.00193)
β	0.630***	0.240*	0.798***	0.895***	0.785***	0.907***	0.989***
	(0.208)	(0.128)	(0.117)	(0.0472)	(0.0510)	(0.0395)	(0.00223)
a	0.0821	0.105	0.201	0.00358	0.144**	0.0713	0.0141
	(0.318)	(0.113)	(0.123)	(0.0166)	(0.0611)	(0.0570)	(0.0171)
b	0	0	0.0643	0.955***	0	0.655	0.926***
	(2.02)	(1.42)	(0.0741)	(0.0314)	(0.164)	(0.486)	(0.0337)
a+b	0.0821	0.105	0.265	0.959	0.144	0.726	0.940

α is the coefficient for ARCH, β is the coefficient for GARCH. *a* denotes the degree of volatility and *b* represents the trend in the data.
Standard deviations are in parentheses.
In the table.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 6: Table over countries H-K

	Hungary	Iceland	India	Indonesia	Israel	Japan	Korea
Intercept	16.2	68.8**	7.20	154***	17.5**	308***	32.7*
	(12.3)	(32.6)	(5.50)	(43.0)	(7.17)	(92.7)	(18.2)
α	0.146**	0.371***	0.0268	0.886***	0.0787**	0.256**	0.203**
	(0.0689)	(0.118)	(0.0163)	(0.257)	(0.0345)	(0.122)	(0.0862)
β	0.818***	0.544***	0.942***	0.113	0.847***	0.111	0.693***
	(0.0821)	(0.128)	(0.0278)	(0.0933)	(0.0312)	(0.192)	(0.110)
a	0.0409*	0.115*	0	0.0758	0	0.134*	0.214**
	(0.0240)	(0.0632)	(0.000109)	(0.101)	(~0)	(0.0784)	(0.0864)
b	0.873***	0.0119	0.914***	0	0.923***	0.277	0.114
	(0.102)	(0.308)	(0.250)	(0.953)	(0.214)	(0.371)	(0.174)
a+b	0.914	0.127	0.914	0.0758	0.923	0.411	0.329

α is the coefficient for ARCH, β is the coefficient for GARCH. *a* denotes the degree of volatility and *b* represents the trend in the data.
Standard deviations are in parentheses.
In the table.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 7: Table over countries M-R

	Malaysia	Mexico	New.Zealand	Norway	Peru	Poland	Russia
Intercept	26.0**	1.01	101***	126***	25.1	8.50	106*
	(11.4)	(4.00)	(32.3)	(26.4)	(17.2)	(5.70)	(59.4)
α	0.194***	0	0.178***	0.511**	0.0779	0.137***	0.560***
	(0.0727)	(0.006320)	(0.0617)	(0.245)	(0.0476)	(0.0492)	(0.201)
β	0.599***	0.999***	0.575***	0.107	0.764***	0.847***	0.439***
	(0.120)	(0.000402)	(0.0958)	(0.144)	(0.114)	80.0483)	(0.124)
a	0	0	0.0177	0.00320	0	0.209	0.0921
	(~0)	(~0)	(0.0257)	(0.0163)	(0.000246)	(0.426)	(0.0700)
b	0.923***	0.918***	0.916***	0.944***	0.952***	0	0.282
	(0.164)	(0.0658)	(0.153)	(0.0763)	(0.254)	(1.74)	(0.255)
a+b	0.923	0.918	0.934	0.947	0.952	0.209	0.374

α is the coefficient for ARCH, β is the coefficient for GARCH. *a* denotes the degree of volatility and *b* represents the trend in the data.
Standard deviations are in parentheses.
In the table.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

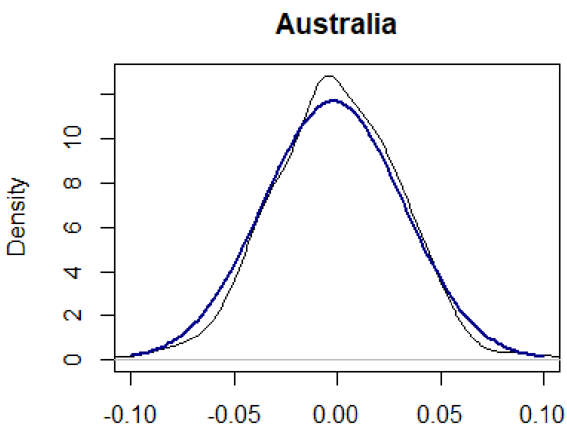
Table 8: Table over countries S-U + Gold

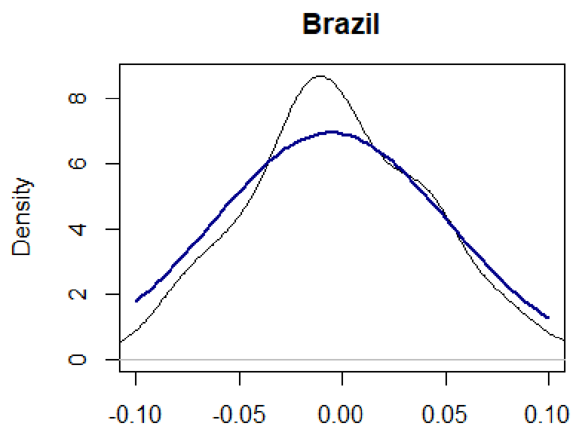
	South.Africa	Sweden	Thailand	United.Kingdom	United.States	Gold
Intercept	90.6*	29.0	24.2	27.9***	56.6	257**
	(50.0)	(19.6)	(15.2)	(10.6)	(79.2)	(118)
α	0.182**	0.119**	0.278**	0.150***	0.133	0.0985**
	(0.0841)	(0.0491)	(0.111)	(0.0555)	(0.188)	(0.0464)
β	0.747***	0.724***	0.602***	0.726***	0.492	0.715***
	(0.0781)	(0.130)	(0.152)	(0.0754)	(0.663)	(0.0929)
a	0.139	0.0115	0.191***	0	0.224***	0
	(0.199)	(0.0265)	(0.0691)	(0.0000620)	(0.0825)	(0.000767)
b	0.372	0.860***	0.0733	0.913***	0	0.876**
	(1.35)	(0.0841)	(0.308)	(0.141)	(0.230)	(0.385)
a+b	0.512	0.871	0.264	0.913	0.224	0.876

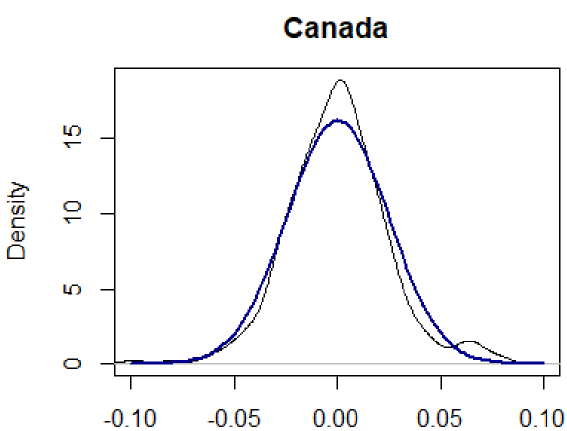
α is the coefficient for ARCH, β is the coefficient for GARCH. *a* denotes the degree of volatility and *b* represents the trend in the data.
Standard deviations are in parentheses.
In the table.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

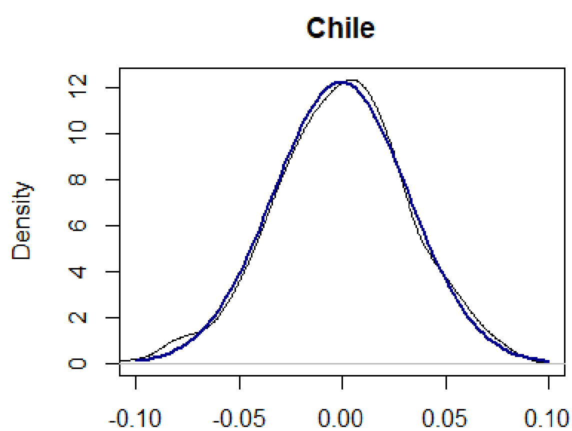
B Appendix: Residuals

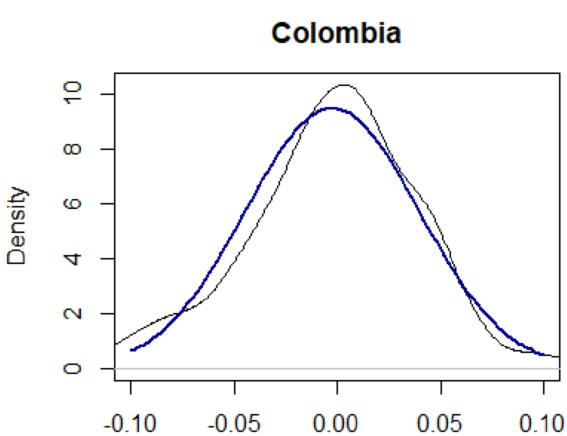
Appendix B shows plots of residuals from a linear regression for every currency. The dark black line is a normal distribution and the lighter black line is the actual. These plots are used to determine the distribution of the parameters in the DCC-GARCH model.

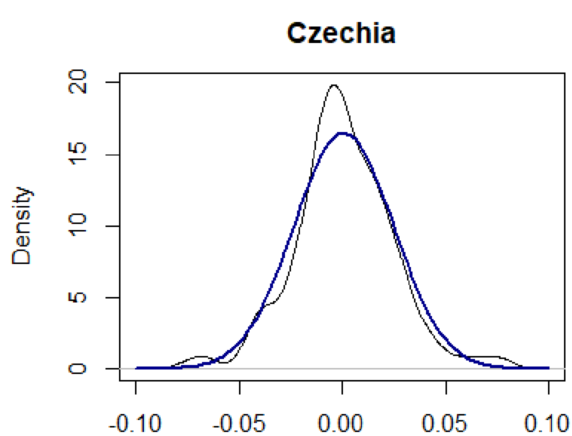


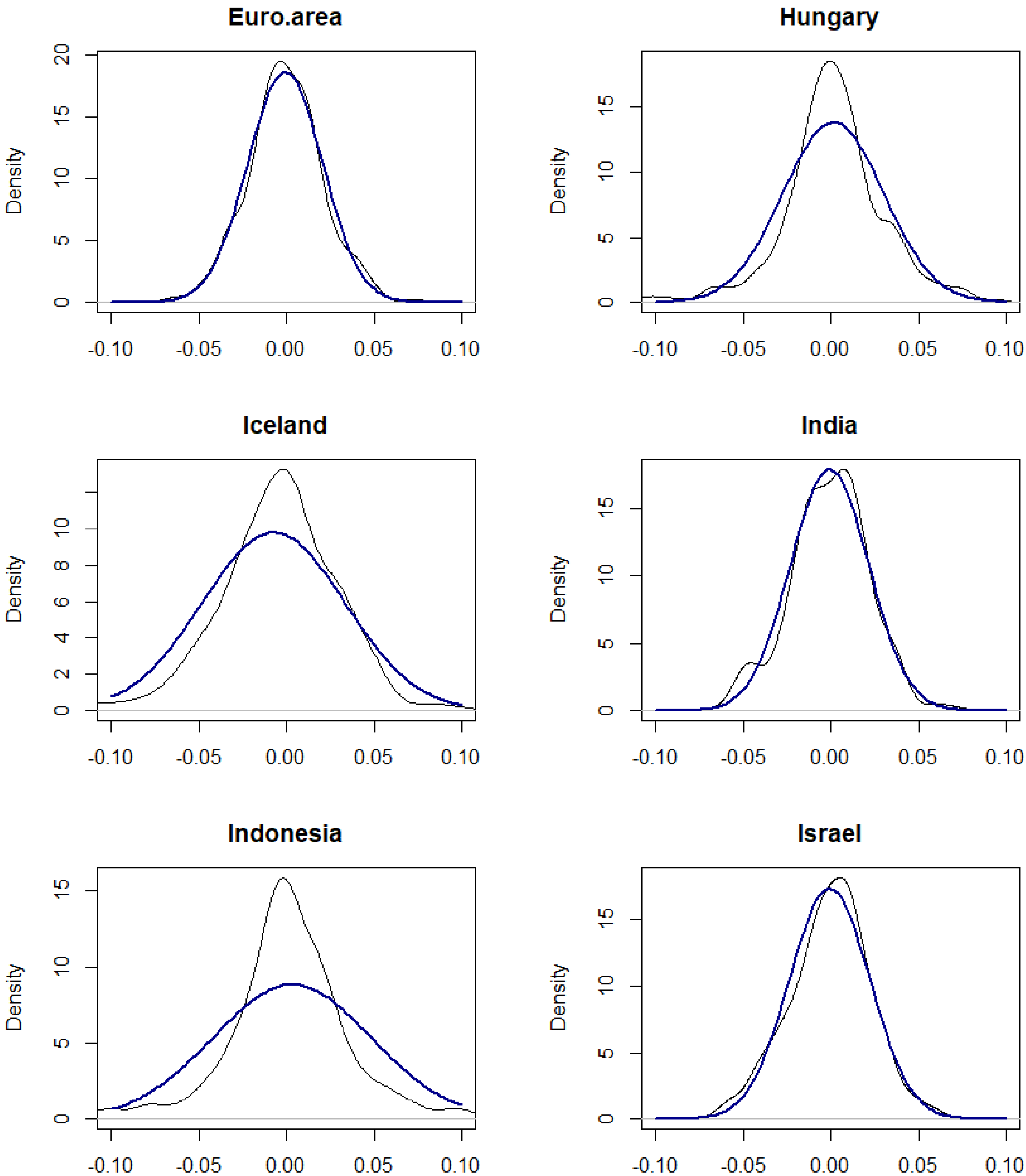








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Israel
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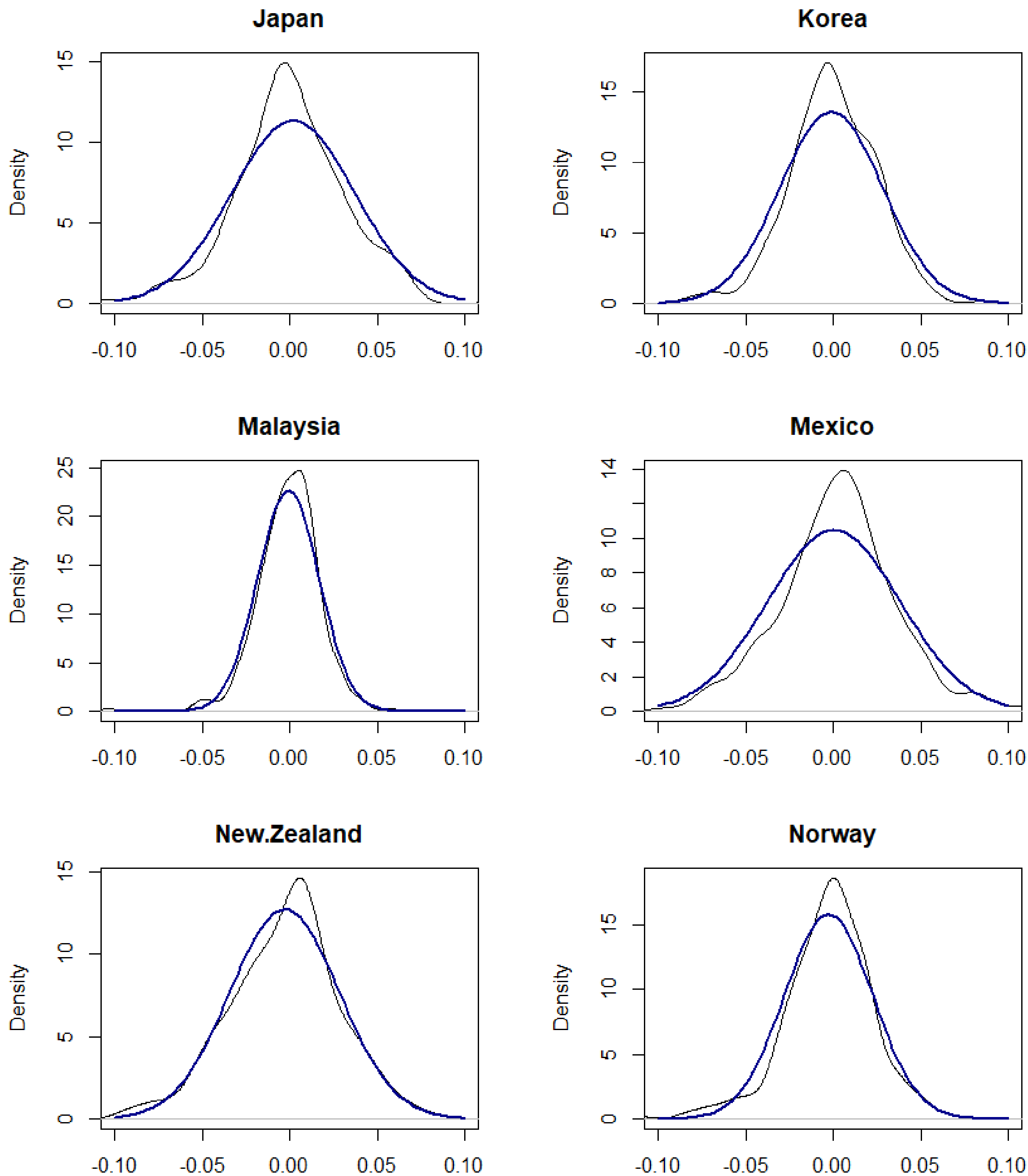
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Korea
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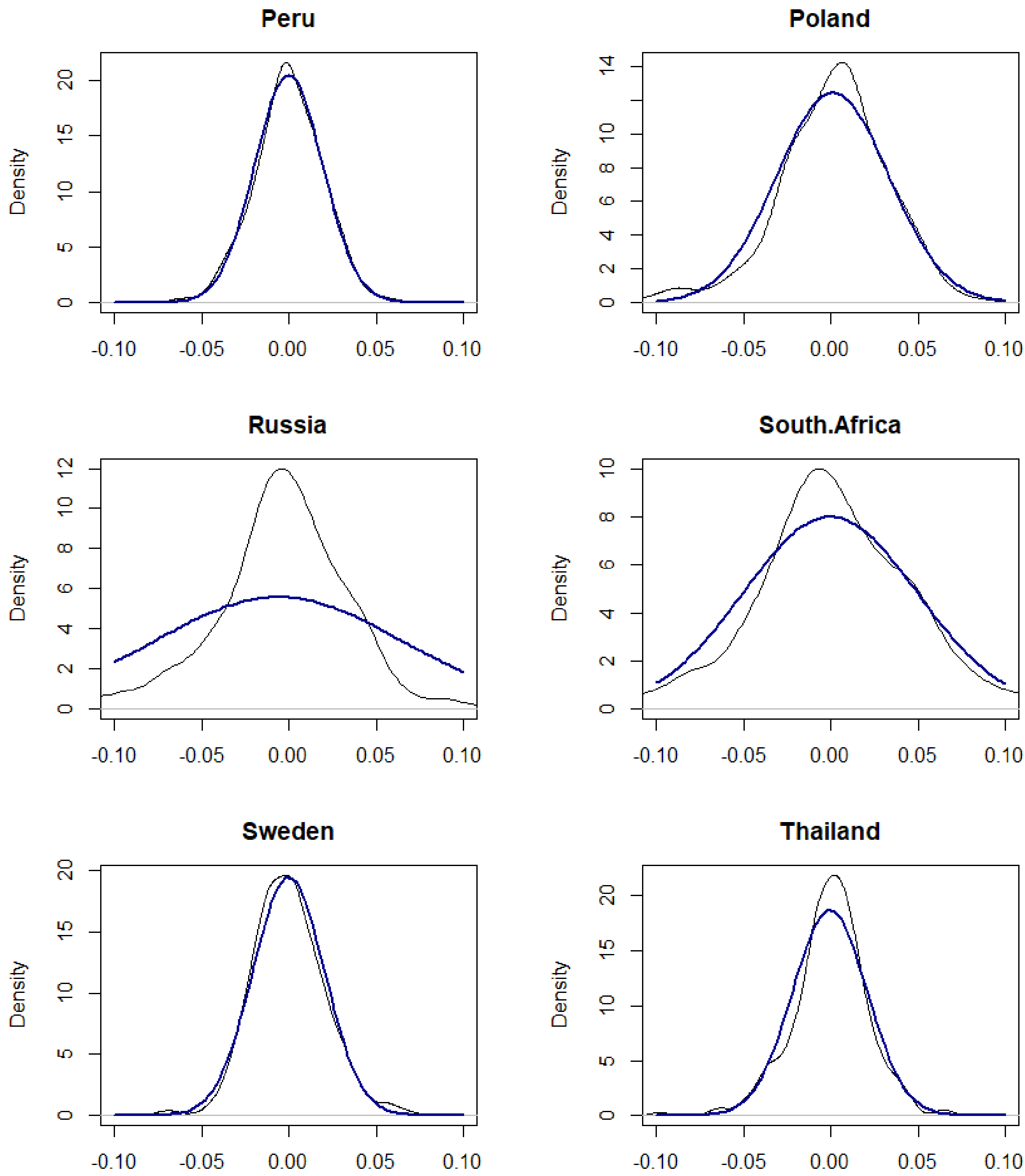
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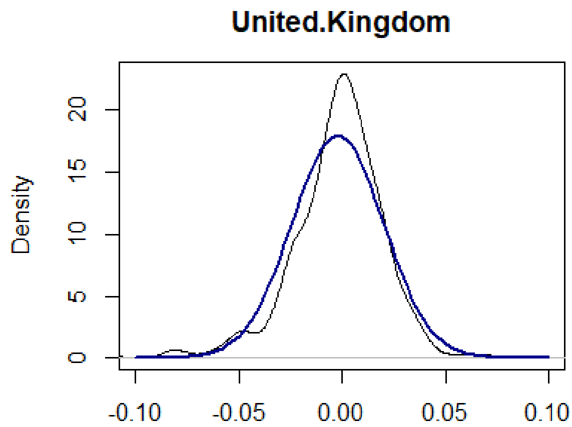
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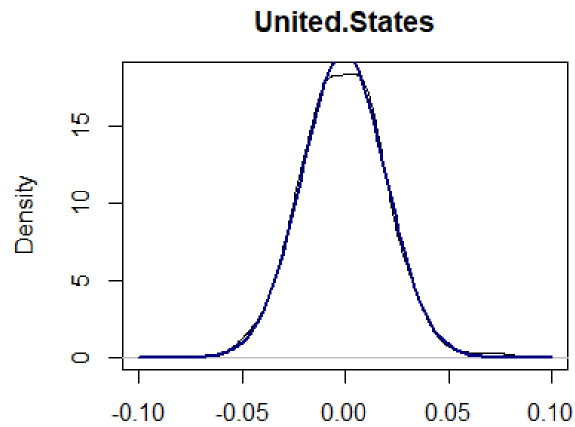
United.States
Density
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C Appendix: Descriptive Statistics

Appendix C reviews the descriptive statistics for all currencies. It shows tables over means, standard deviations, min/max values, ADF test and finally the correlation to US EPU. The most important components are the ADF test, that shows if the data is stationary, and the correlation to US EPU.

Table 9: Descriptive statistics over countries A-E

	Australia	Brazil	Canada	Chile	Colombia	Czechia	Euro area
Mean	0.110	0.0494	0.0433	-0.0393	-0.0126	0.208	-0.0165
Std	2.15	3.69	1.58	2.14	2.68	1.63	1.39
Min.	-13.4	-19.8	-8.53	-8.73	-8.81	-6.21	-4.99
Max.	5.50	12.41	6.07	6.59	8.45	7.10	5.26
ADF.	-11.9***	-13.9***	-13.9***	-14.4***	-13.4***	-4.65***	-12.1***
Corr.	-0.0925	-0.168	-0.103	-0.0194	-0.154	-0.121	0.112

For each country, data are returns of REER.
In the table.
*** Denote 1% significant level.

Table 10: Descriptive statistics over countries H-K

	Hungary	Iceland	India	Indonesia	Israel	Japan	Korea
Mean	0.114	0.0470	0.0718	0.159	0.00718	-0.230	0.0319
Std	1.87	2.56	1.50	2.93	1.50	2.22	1.81
Min.	-8.37	-12.7	-4.68	-13.3	-4.91	-6.59	-12.3
Max.	6.41	11.9	4.50	18.7	5.00	11.3	8.07
ADF.	-6.03***	-11.7***	-15.5***	-14.9***	-5.45***	-9.54***	-11.6***
Corr.	-0.144	-0.0738	-0.125	-0.00076	-0.0665	0.0979	-0.135

For each country, data are returns of REER.
In the table.
*** Denote 1% significant level.

Table 11: Descriptive statistics over countries M-R

	Malaysia	Mexico	New Zealand	Norway	Peru	Poland	Russia
Mean	-0.0522	0.0613	0.0913	-0.0639	0.0487	0.101	0.273
Std	1.14	2.47	2.01	1.61	1.27	1.99	4.23
Min.	-5.45	-15.1	-7.00	-8.50	-3.81	-8.66	-18.4
Max.	3.34	8.23	5.84	5.13	5.29	5.36	36.4
ADF.	-11.7***	-13.1***	-13.8***	-13.3***	-14.3***	-11.4***	-10.9***
Corr.	-0.129	-0.163	0.00493	-0.0621	0.0534	-0.186	-0.0643

For each country, data are returns of REER.
In the table.
*** Denote 1% significant level.

Table 12: Descriptive statistics over countries S-U and US EPU

	South Africa	Sweden	Thailand	United Kingdom	United States	Gold	EPU
Mean	-0.0436	-0.0956	0.0393	-0.0465	0.0474	0.710	0.0303
Std	3.22	1.32	1.35	1.51	1.22	3.75	57.0
Min.	-15.8	-4.27	-6.20	-6.38	-3.57	-11.7	-111
Max.	9.23	5.81	4.83	4.47	5.64	17.4	329
ADF.	-8.93***	-6.49***	-7.28***	-15.7***	-7.24***	-15.1***	-4.45***
Corr.	-0.111	0.0355	-0.105	-0.0739	0.0775	0.0559	1

For each country, data are returns of REER.
In the table.
*** Denote 1% significant level.

D Appendix: Linear Regression

Appendix D reviews the results from the linear regression. A Breusch-Pagan test is conducted to determine if the currencies are heteroscedastic. VIF is used to test for multicollinearity.

Table 13: Table over countries A-E

	Australia	Brazil	Canada	Chile	Colombia	Czechia	Euro area
R_{t-1}	0.251***	0.302***	0.210***	0.166***	0.241***	0.127**	0.176***
	(0.0566)	(0.0559)	(0.0570)	(0.0582)	(0.0569)	(0.0582)	(0.0574)
U_{t-1}	0.00632**	0.00104	0.00263	0.00201	0.00101	0.00110	0.00387*
	(0.00308)	(0.00488)	(0.00228)	(0.00315)	(0.00385)	(0.00234)	(0.00202)
R^2	0.0872	0.0915	0.0503	0.0296	0.0589	0.0173	0.0462
Breusch-Pagan	0.0520	0	0.235	0.230	0.0713	0.131	0.442
VIF	1.03	1.00	1.00	1.00	1.00	1.00	1.01

Dependent variables are corresponding countries' REER returns or US EPU expressed in equations. Standard deviations are in parentheses. The Breusch-Pagan term represents the p-value of the Breusch-Pagan test. VIF is the Variance Inflation Factor and represents a measurement of multi-collinearity.
In the table,
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 14: Table over countries H-K

	Hungary	Iceland	India	Indonesia	Israel	Japan	Korea
R_{t-1}	0.195***	0.307***	0.0962	0.178***	0.164***	0.258***	0.353***
	(0.0576)	(0.0559)	(0.0584)	(0.0569)	(0.0582)	(0.0565)	(0.0550)
U_{t-1}	0.000757	-0.000668	-0.00238	-0.000864	-0.00129	-0.00307	0.00186
	(0.00274)	(0.00363)	(0.00222)	(0.00424)	(0.00220)	(0.00318)	(0.00252)
R^2	0.0382	0.0946	0.0141	0.0328	0.0275	0.0707	0.125
Breusch-Pagan	0.285	0.000127	0.970	0.466	0.858	0.442	0.00863
VIF	1.00	1.00	1.01	1.00	1.00	1.00	1.00

Dependent variables are corresponding countries' REER returns or US EPU expressed in equations. Standard deviations are in parentheses. The Breusch-Pagan term represents the p-value of the Breusch-Pagan test. VIF is the Variance Inflation Factor and represents a measurement of multi-collinearity.
In the table,
*** Denote 1% significant level.

Table 15: Table over countries M-R

	Malaysia	Mexico	New Zealand	Norway	Peru	Poland	Russia
R_{t-1}	0.213***	0.180***	0.216***	0.232***	0.192***	0.313***	0.333***
	(0.0573)	(0.0576)	(0.0574)	(0.0573)	(0.0573)	(0.0557)	(0.0555)
U_{t-1}	0.000773	0.00770**	0.00266	0.00160	-0.00217	0.000221	-0.00120
	(0.00165)	(0.00356)	(0.00292)	(0.00234)	(0.00184)	(0.00280)	(0.00592)
R^2	0.0468	0.0514	0.0515	0.0573	0.0416	0.0975	0.110
Breusch-Pagan	0.169	0.138	0.311	0.527	0.232	0.000929	0.000285
VIF	1.00	1.01	1.01	1.01	1.00	1.00	1.00

Dependent variables are corresponding countries' REER returns or US EPU expressed in equations. Standard deviations are in parentheses. The Breusch-Pagan term represents the p-value of the Breusch-Pagan test. VIF is the Variance Inflation Factor and represents a measurement of multi-collinearity.
In the table,
** Denote 5% significant level.
*** Denote 1% significant level.

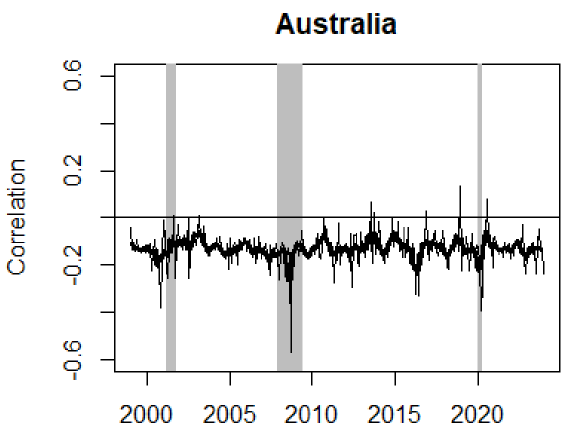
Table 16: Table over countries S-U

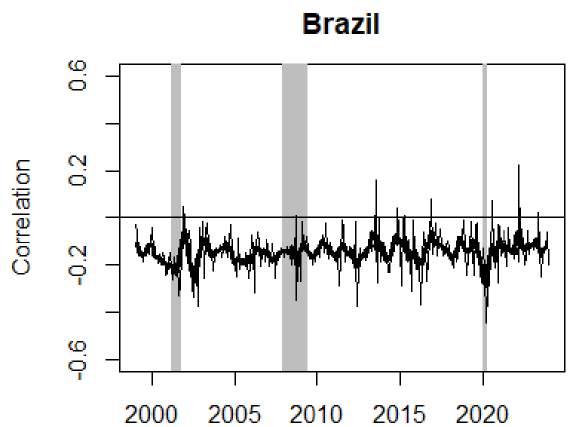
	South Africa	Sweden	Thailand	United Kingdom	United States	Gold
R_{t-1}	0.202***	0.171***	0.254***	0.0875	0.352***	0.126**
	(0.0574)	(0.0582)	(0.0568)	(0.0583)	(0.0549)	(0.0583)
U_{t-1}	0.000572	0.00302	-0.000599	-0.00178	-0.00335**	-0.00181
	(0.00471)	(0.00195)	(0.00195)	(0.00224)	(0.00170)	(0.00559)
R^2	0.0408	0.0418	0.0644	0.0101	0.147	0.0158
Breusch-Pagan	0.0205	0.275	0.519	0.00754	0.810	0.0196
VIF	1.00	1.02	1.00	1.00	1.01	1.00

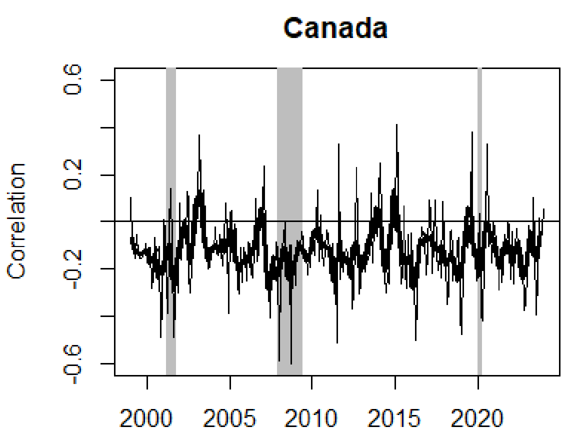
Dependent variables are corresponding countries' REER returns or US EPU expressed in equations. Standard deviations are in parentheses. The Breusch-Pagan term represents the p-value of the Breusch-Pagan test. VIF is the Variance Inflation Factor and represents a measurement of multi-collinearity.
In the table,
** Denote 5% significant level.
*** Denote 1% significant level.

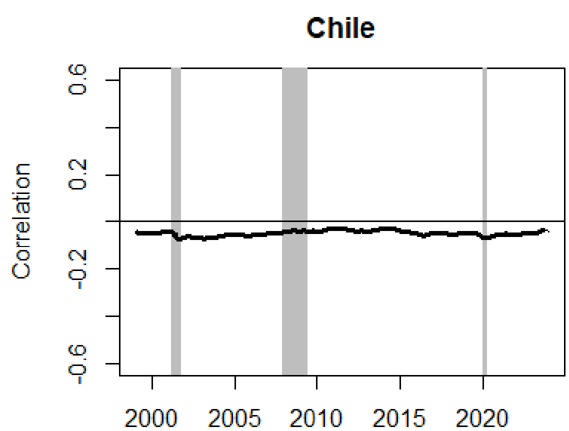
E Appendix: Correlation plots

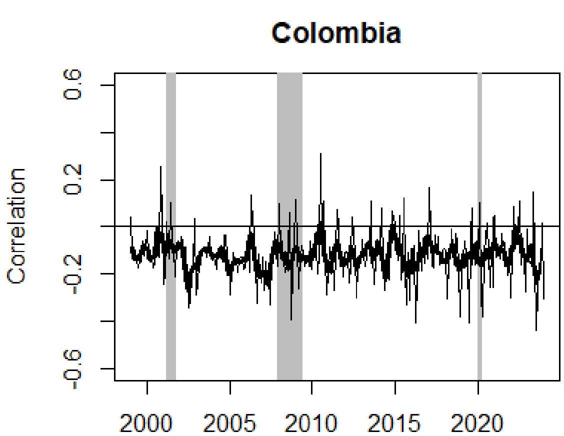
Appendix E consists of correlation plots for all currencies and gold. The plots show the dynamic correlation between US EPU and the respective currency over the time period 1999 to 2024. The darker gray areas represent periods of US recession as determined by NBER.

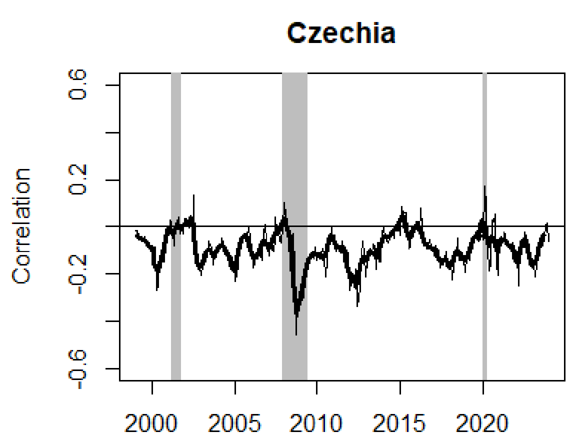


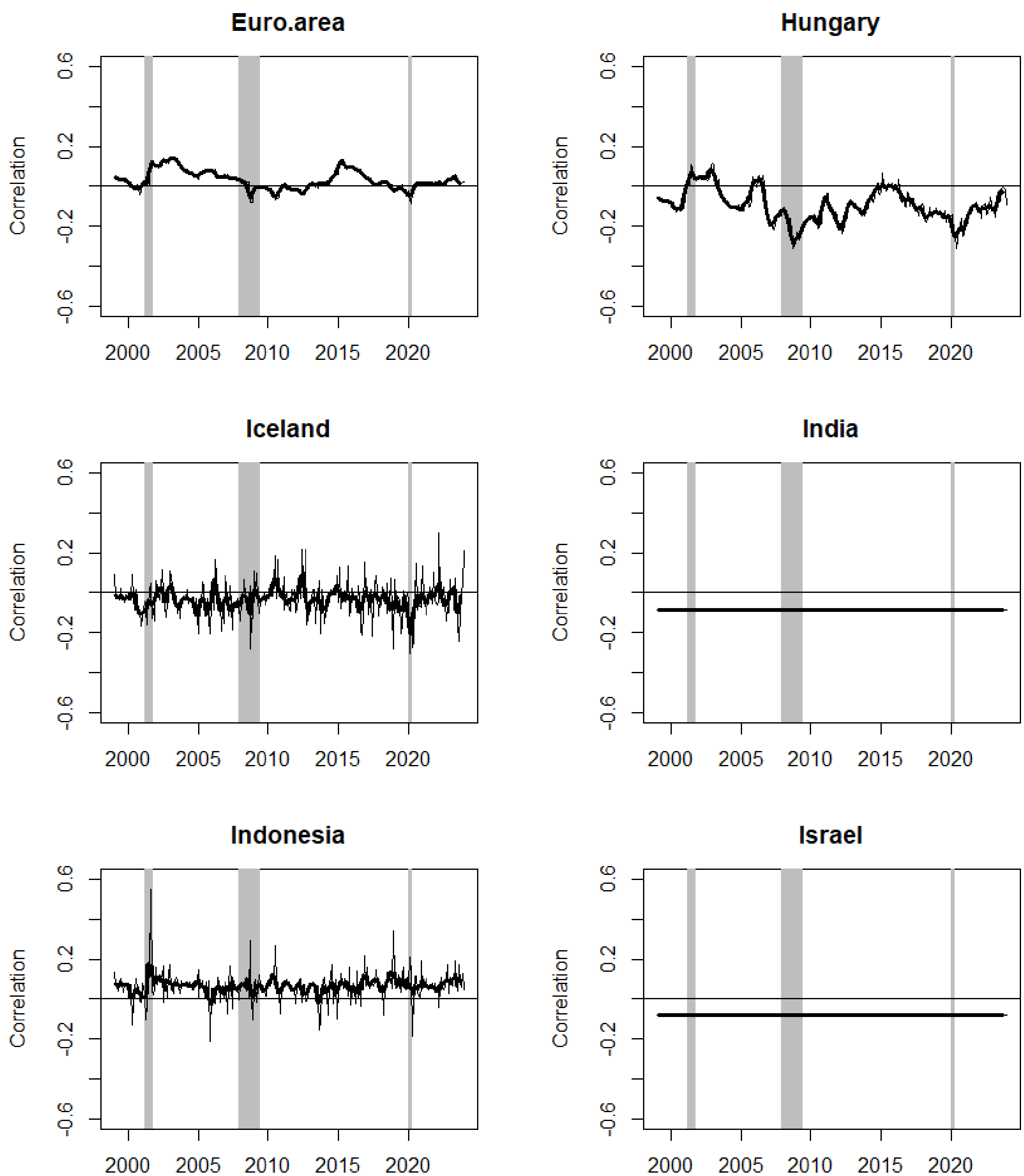


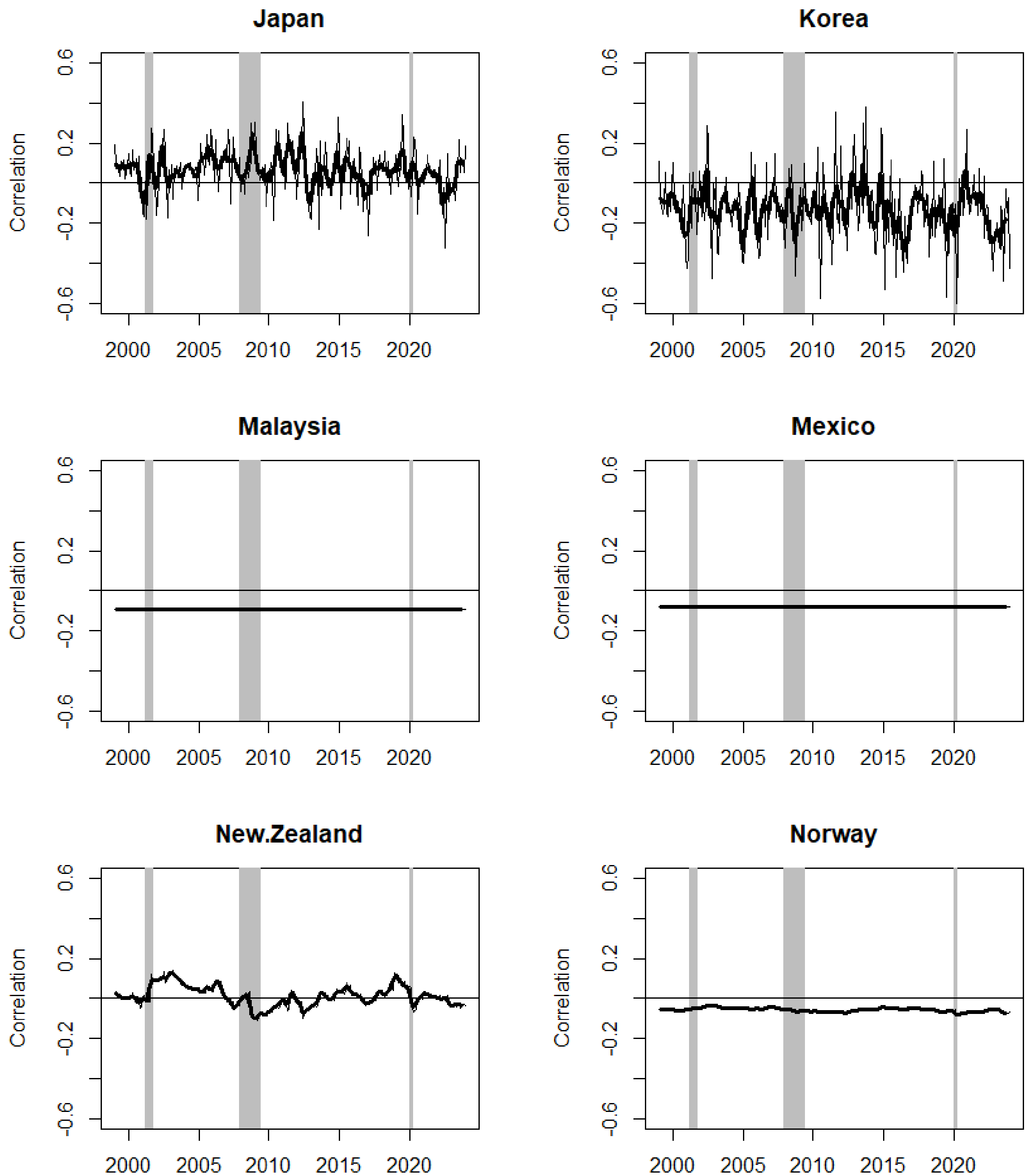


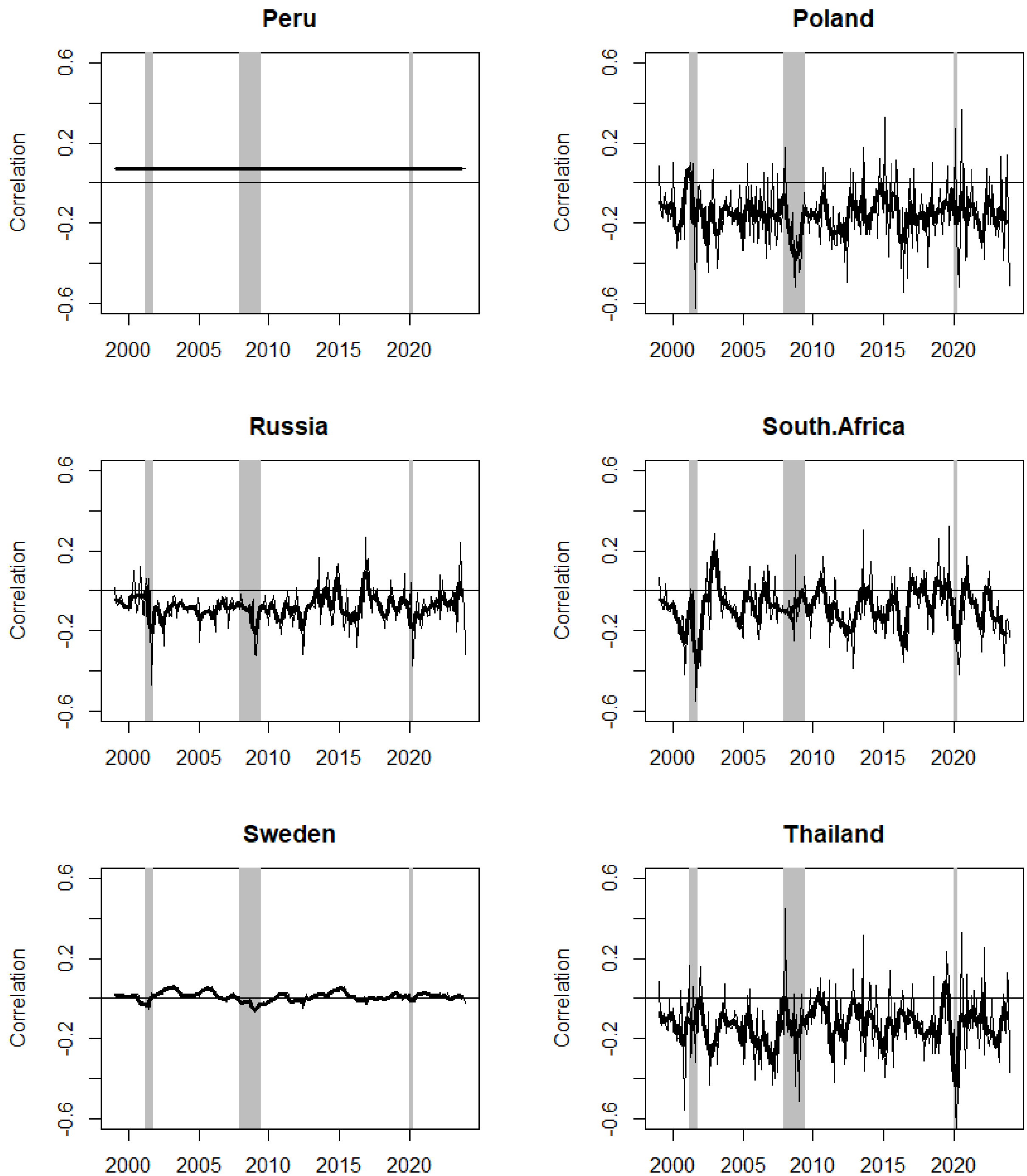


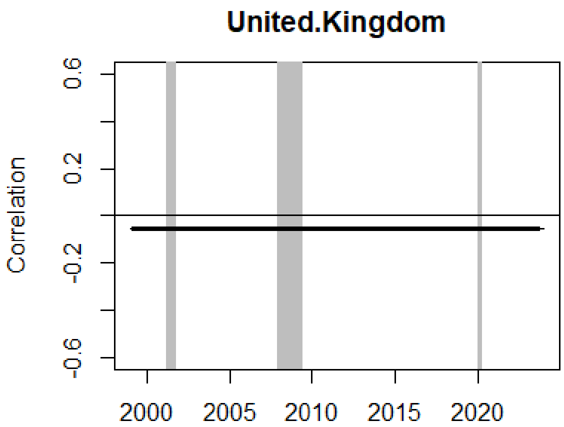


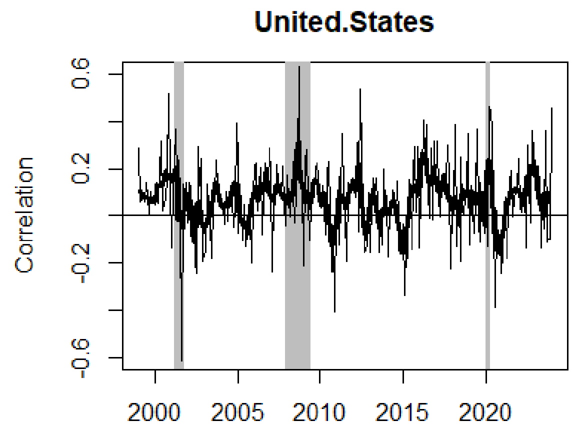


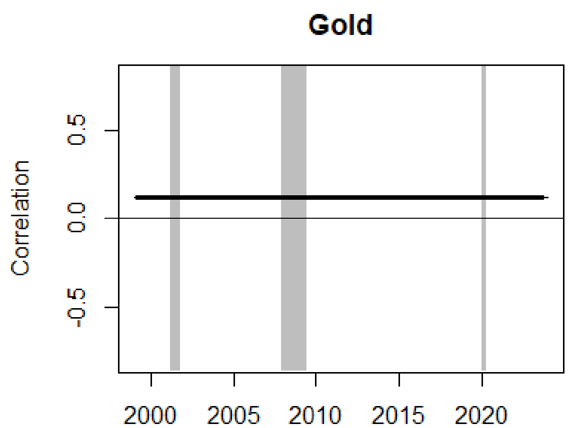

Euro.area
Hungary
Iceland
India
Indonesia
Israel
Correlation
0.6
0.2
-0.2
-0.6
2000
2005
2010
2015
2020


Japan
Korea
Malaysia
Mexico
New.Zealand
Norway
Correlation
0.6
0.2
-0.2
-0.6
2000
2005
2010
2015
2020


Peru
Poland
Russia
South.Africa
Sweden
Thailand
Correlation
0.6
0.2
-0.2
-0.6
2000
2005
2010
2015
2020


United.Kingdom
Correlation
-0.6
-0.2
0.2
0.6
2000
2005
2010
2015
2020


United.States
Correlation
-0.6
-0.2
0.2
0.6
2000
2005
2010
2015
2020


Gold
Correlation
-0.5
0.0
0.5
2000
2005
2010
2015
2020

F Appendix: VAR

Appendix F shows tables over the VAR results. The interesting components are the P_{t-1} and the $NBER_t$ denoting the DCC term and the recession dummy variable, respectively.

Table 17: VAR test for countries A-E

	Australia	Brazil	Canada	Chile	Colombia	Czechia	Euro.area
Constant	-0.117***	-0.124***	-0.0839***	-0.00172**	-0.0996***	-0.0191***	0.00135
	(0.00831)	(0.00930)	(0.0107)	(0.000810)	(0.00940)	(0.00459)	(0.00114)
P_{t-1}	0.0744	0.107*	0.249***	0.961***	0.165***	0.767***	0.949***
	(0.0582)	(0.0577)	(0.0561)	(0.0166)	(0.0575)	(0.0369)	(0.0190)
$NBER_t$	-0.0418***	-0.0405**	-0.0678**	-0.00132**	-0.00599	-0.0202*	0.00226
	(0.0133)	(0.0157)	(0.0285)	(0.000622)	(0.0208)	(0.0106)	(0.00307)
R^2	0.0380	0.0326	0.0835	0.918	0.0205	0.596	0.896

P_{t-1} corresponds to the dynamic conditional correlation term. $NBER_t$ represents the recession dummy variable. Standard deviations are in parentheses.
In the table,.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 18: VAR test for countries H-K

	Hungary	Iceland	India	Indonesia	Israel	Japan	Korea
Constant	-0.00628**	-0.0239***	-0.00860***	0.0606***	-0.00766***	0.0370***	-0.0913***
	(0.00267)	(0.00529)	(0.00223)	(0.00554)	(0.00201)	(0.00673)	(0.0115)
P_{t-1}	0.925***	0.182***	0.900***	0.0702	0.905***	0.404***	0.292***
	(0.0215)	(0.0579)	(0.0259)	(0.0581)	(0.0249)	(0.0531)	(0.0557)
$NBER_t$	-0.00888	-0.0254	0	0.00294	0	0.0210	-0.0235
	(0.00612)	(0.0164)	(~0)	(0.0134)	(~0)	(0.0190)	(0.0294)
R^2	0.866	0.0372	0.806	-0.00151	0.816	0.163	0.0819

P_{t-1} corresponds to the dynamic conditional correlation term. $NBER_t$ represents the recession dummy variable. Standard deviations are in parentheses.
In the table,.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 19: VAR test for countries M-R

	Malaysia	Mexico	New.Zealand	Norway	Peru	Poland	Russia
Constant	-	-0.0110***	0.00121	-0.00286***	0.00443***	-0.122***	-0.0408***
	-	(0.00237)	(0.00118)	(0.00106)	(0.00148)	(0.0123)	(0.00595)
P_{t-1}	-	0.865***	0.930***	0.947***	0.940***	0.195***	0.450***
	-	(0.0293)	(0.0212)	(0.0189)	(0.0202)	(0.0571)	(0.0520)
$NBER_t$	-	0	-0.00486	-0.00116*	0	-0.0580**	-0.0381**
	-	(~0)	(0.00373)	(0.000605)	(~~0)	(0.0283)	(0.0147)
R^2	-	0.753	0.873	0.894	0.879	0.0475	0.226

P_{t-1} corresponds to the dynamic conditional correlation term. $NBER_t$ represents the recession dummy variable. Standard deviations are in parentheses.
In the table,.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.

Table 20: VAR test for countries S-U

	South Africa	Sweden	Thailand	United Kingdom	United States
Constant	-0.0357***	0.00195**	-0.0992***	-0.00663***	0.0526***
	(0.00743)	(0.000792)	(0.0111)	(0.00140)	(0.0104)
P_{t-1}	0.533***	0.837***	0.251***	0.872***	0.179***
	(0.0491)	(0.0323)	(0.0564)	(0.0269)	(0.0574)
$NBER_t$	-0.0278	-0.00604**	-0.0221	0	0.0642**
	(0.0208)	(0.00252)	(0.0271)	(~0)	(0.0317)
R^2	0.288	0.763	0.0596	0.799	0.0427

P_{t-1} corresponds to the dynamic conditional correlation term. $NBER_t$ represents the recession dummy variable. Standard deviations are in parentheses.
In the table,.
* Denote 10% significant level.
** Denote 5% significant level.
*** Denote 1% significant level.