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Gold and the US dollar: Hedge or haven?

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ABSTRACT

Using a model of dynamic conditional correlations covering 23 years of weekly data for 16 major dollar-paired exchange rates, this paper addresses a practical investment question: Does gold act as a hedge against the US dollar, as a safe haven, or neither? Key findings are as follows. (i) During the past 23 years gold has behaved as a hedge against the US dollar. (ii) Gold has been a poor safe haven. (iii) In recent years gold has acted, increasingly, as an effective hedge against currency risk associated with the US dollar.

1. Introduction

For many years gold as a tradable financial asset has had a reputation as a safe haven from market turbulence. Market reports often refer to gold as a *safe-haven asset*. But very few academic studies have addressed the role of gold as a safe-haven asset and even fewer have examined gold's safe-haven status with respect, specifically, to currency movements. Further, to date, the work that has addressed this issue suffers from shortcomings that offer scope for improvement. This paper examines gold's ability to act as a financial safe haven and improves on other work by addressing correlation rather than dependence, allowing for system feedback and by focusing on the link between changes in the price of gold and the US dollar. Specifically, this paper asks, Does gold act as a safe haven against the US dollar, as a hedge, or neither? Movements in the price of gold and the US dollar are analysed

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using a model of dynamic conditional correlations covering 23 years of weekly data for 16 major US dollar-paired exchange rates.

Studies relevant to this paper are few. Perhaps most relevant is the work of Capie et al. (2005) which assesses the role of gold as a *hedge* against the US dollar by estimating elasticities for a model of the responsiveness of gold to changes in the exchange rate. Capie et al. (2005) find that gold has in the past acted as an effective hedge. But their approach takes the form of a single-equation model in which the independent variable, the exchange rate, is assumed to be unaffected by the time path of the dependent variable, the price of gold. That is, the authors assume no feedback.[1] Improving over the work of Capie et al. (2005), this paper focuses on correlation, employing a dynamic model of conditional correlations in which all variables are treated symmetrically.

Baur and Lucey (2006) address the specific question of gold's role as a *safe-haven asset*. They find evidence in support of gold providing a haven from losses incurred in the bond and stock markets. However, their approach includes generated regressors, neglects interactions with the currency market and, like Capie et al. (2005), permits no explicit role for feedback in its model of returns. The work of Baur and McDermott (2010), similarly, neglects feedback in its principal regression model even after allowing for it in a number of constructed parameters.[2]

A handful of studies investigate the financial concept of a *safe-haven asset* without reference to gold. Ranaldo and Soderlind (2010) and Kaul and Sapp (2006) examine safe-haven currencies while Upper (2000) examines German government bonds as safe-haven investments. Other studies look at the wider financial properties of gold without focusing on its role as a safe haven.[3] None of these examine gold's ability to act as a safe haven with respect to the US dollar.

In addressing the question of gold's use as a safe haven from currency risk, it is instructive to ask, is currency risk large enough, in general, to elicit the pursuit of safe-haven assets? Existing research suggests that it is. Santis and Gerard (1998), for instance, show that currency risk is economically significant and represents a large fraction of the total risk faced when investing overseas. Andersen et al. (2007) show that exchange-rate volatility outstrips bond-market volatility in their sample of futures prices for US, British and German markets while Hau and Rey (2006) find that the ratio of exchange-rate volatility to equity return volatility is close, but less than one, in line with their equilibrium model of exchange rates, stock prices and capital flows.

There are of course various ways to hedge against currency risk. Hedging mechanisms can be financial or operational.[4] Given the options available, why might gold be used as a hedge or safe haven? The reasons are many. Gold, as a financial asset, is liquid, available, priced in US dollars and can be traded on a futures market. Further, while gold as a hedge cannot be designed for purpose in the same way as foreign-exchange derivatives, even bespoke hedging techniques are less than perfect in their effectiveness (Huffman and Makar, 2004). Gold, as a *natural* hedge or haven, may be useful if effective. It is the effectiveness of gold as a hedge and safe haven that this paper aims to examine.

Any discussion of investment safe havens and hedges requires clear definitions. What, exactly, is a haven? What is a hedge? This study adopts the definitional approach of Baur and Lucey (2006) and Kaul and Sapp (2006): If an investor holds a given asset, γ, then a haven is defined as any other asset that does not co-move with γ in times of stress. That is, a haven is uncorrelated or correlated negatively with γ if γ experiences sharp changes in value. A hedge, meanwhile, is an asset that is uncorrelated or correlated negatively with γ not just in times of stress, but *on average*. The definitional difference between a hedge and a haven is subtle but important: an asset that functions as a haven is uncorrelated or correlated negatively with γ in times of stress only, and not necessarily on average.

The contribution of this study to the existing literature is two-fold. First, this study assesses the role of gold as both a hedge and a safe haven with respect to the US dollar. While other work has

[1] Chen and Rogoff (2003), Clements and Fry (2008) and Swift (2004) among others highlight the importance of allowing for feedback and co-determination in the analysis of currency and commodity markets.

[2] Baur and McDermott (2010) and Baur and Lucey (2006) also construct GARCH models that include dummy variables, causing standard inference on their estimated coefficients to be potentially invalid (Doornik and Ooms, 2003).

[3] See for instance Cheung and Lai (1993), Faugere and Van Erlach (2004), Sherman (1982), Sjaastad (2008) and Worthington and Pahlavani (2007).

[4] See Allayannis and Ofek (2001), Allayannis et al. (2001), Elliot et al. (2003) and Habib and Joy (2010).

investigated the role of gold as a hedge and a haven for bonds and equities, no study has tackled the same subject with a specific focus on exchange rates.[5] Second, using the correlation modelling techniques of Engle (2002), this study offers an empirical analysis of a 17-variable system of returns, considering a larger number of currencies than Capie et al. (2005).

This study's key findings are as follows. (i) During the past 23 years gold has behaved as a hedge against the US dollar—that is, gold-price returns have, on average, been correlated negatively with US dollar returns. (ii) There is no evidence to suggest that gold has acted as a consistent and effective safe haven. (iii) In recent years gold has become an increasingly effective hedge against the US dollar, with conditional correlations more negative now than they have been at any point during the past two and a half decades.

2. Empirical methodology

Key to the empirical approach is a multivariate GARCH model of dynamic conditional correlations (also known as the DCC–GARCH model) first proposed by Engle (2002). The DCC–GARCH model can be best understood by recalling that the conditional correlation between two random variables r_1 and r_2 (where r_1 and r_1 represent, here, asset-price returns), each with mean zero, can be defined as

$$\rho_{r_1 r_2,t} = \frac{E_{t-1}(r_{1t} r_{2t})}{\sqrt{E_{t-1}(r_{1t}^2) E_{t-1}(r_{2t}^2)}} \tag{1}$$

The relation between the conditional correlations, $\rho_{r_i r_j t}$, and the conditional variances, h_{it}, can be clarified by expressing each returns series, r_{it}, as the product of the conditional standard deviation, $\sqrt{h_{it}}$, and the standardised error term, ϵ_{it}, such that $r_{it} = \sqrt{h_{it}}\epsilon_{it}$ and $h_{it} = E_{t-1}(r_{it}^2)$ for $i = 1, 2$ where ϵ is a standardised error term that has mean zero and variance one for each series. Substituting $r_{it} = \sqrt{h_{it}}\epsilon_{it}$ into Eq. (1) gives $\rho_{r_1 r_2,t} = E_{t-1}(\epsilon_{1t}\epsilon_{2t})$. That is, the conditional correlation, $\rho_{r_1 r_2,t}$, is equal to the conditional covariance between the standardised error terms, $E_{t-1}(\epsilon_{1t}\epsilon_{2t})$. The conditional variance–covariance matrix of returns can be defined as $H_t \equiv E_{t-1}(r_t r_t')$.

In the multivariate GARCH model of *constant* conditional correlations proposed by Bollerslev (1990), the conditional variance–covariance matrix of returns, H_t, can be partitioned as $H_t = D_t \Gamma D_t$ where $D_t = \text{diag}\{\sqrt{h_t}\}$ and where Γ is a correlation matrix containing the conditional correlations, which do not vary over time. In both the model of dynamic conditional correlations and constant conditional correlations the elements of D_t are modelled as univariate GARCH processes. That is, all time-varying conditional volatilities are assumed to be represented adequately well by GARCH processes such that

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} r_{i(t-p)}^2 + \sum_{q=1}^{Q_i} \beta_{iq} h_{i(t-q)} \tag{2}$$

for $i = 1, 2, \ldots, k$ with the usual GARCH restrictions for non-negativity of variances and stationarity.[6] Lag lengths for P and Q need not be the same. In this way, with all time-varying conditional volatilities modelled as GARCH processes, D_t becomes a time-varying diagonal matrix of standard deviations from univariate GARCH models.

Engle (2002) builds on the model of constant conditional correlations by proposing the DCC–GARCH model in which correlations are not constant, but are instead *dynamic*. That is, $H_t = D_t \Gamma_t D_t$ where Γ_t is, as before, the correlation matrix, but where this correlation matrix is now allowed to vary over time. The conditional variances of Γ_t must be equal to one. Other than this, requirements for the parameterisation of Γ_t are the same as for H_t. Typical elements of Γ_t will be of the form

$$\rho_{ijt} = \frac{q_{ijt}}{\sqrt{q_{iit} q_{jjt}}} \tag{3}$$

[5] For a discussion of gold's relationship with bonds and equities, see Baur and Lucey (2006).

[6] For stationarity, $\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1$.

with the aim being to define q_{ijt} in such a way as to provide a dynamic correlation structure (provide a parameterisation of Γ_t) that is both useful and tractable.

The DCC–GARCH model allows for GARCH(m,n) processes in the dynamics of q_{ijt}, such that,

$$
\begin{aligned}
Q_t &= \overline{Q}\left(1 - \sum_{m=1}^{M}\alpha_m - \sum_{n=1}^{N}\beta_n\right) + \sum_{m=1}^{M}\alpha_m\left(\epsilon_{t-m}\epsilon'_{t-m}\right) + \sum_{n=1}^{N}\beta_n Q_{t-n} \\
\Gamma_t &= \mathrm{diag}\{Q_t\}^{-1} Q_t \mathrm{diag}\{Q_t\}^{-1}
\end{aligned}
\tag{4}
$$

where $Q_t \equiv \{q_{ijt}\}$ is the conditional variance–covariance matrix of residuals and where $\overline{Q}$ is the time-invariant (unconditional) variance–covariance matrix found by estimating Eq. (2) in what is the *first stage* of the estimation process. Meanwhile, diag$\{Q_t\}$ is a diagonal matrix composed of the square root of the diagonal elements of Q_t, implying that a typical element of Γ_t will take the form $\rho_{ijt} = q_{ijt}/\sqrt{q_{iit}q_{jjt}}$. Eq. (4) tells us that Q_t can be thought of as an autoregressive, moving-average process capturing deviations in the correlations around their unconditional values ($\overline{Q}$).

For the purposes of this study, the focus of interest is $\rho_{1jt} = q_{1jt}/\sqrt{q_{11t}q_{jjt}}$, which represents the conditional correlation between the price of gold and each exchange-rate pair, j, in the dataset.

3. Data

The dataset consists of the price of gold (US dollars per Troy ounce) and 16 US dollar exchange-rate pairings (expressed in terms of home currency per US dollar). The frequency of the data is weekly. The sample period extends from 10 January 1986 to 29 August 2008, comprising t = 1182 observations per variable. Exchange rates are from Datastream. Gold prices are from Bloomberg.

The 16 currencies included in the sample, all expressed in terms of home currency per US dollar, are the euro, yen, Indian rupee, Taiwan dollar, Australian dollar, Canadian dollar, Danish krone, Israeli Shekel, Maltese lira, New Zealand dollar, Norwegian krone, Singapore dollar, South African rand, Swedish krona, Swiss franc, and the UK pound. Demeaned continuously compounded percentage returns of the exchange rates are calculated by taking the weekly difference of the natural logarithm of each exchange rate, subtracting the sample mean, then multiplying by 100. Demeaned returns for gold are calculated similarly.

Table 1 suggests that gold-price returns, like other commodity-price returns, are more variable than exchange-rate returns, mirroring the standard findings of other studies.[7] Variance for the price of gold (2.8) is more than double the average variance of the 16 nominal exchange rates in the sample (which have mean variance of 1.3). All series seem to exhibit two common features of financial time series: excess kurtosis and volatility clustering. Indeed, Table 1 shows that in Jarque–Bera tests of normality, the null hypothesis of normality can be rejected in all cases for both exchange-rate returns and gold-price returns.

Financial time series, and in particular exchange rates, often exhibit little correlation in the mean processes (the returns) but significant correlation in the variance processes (the square of the returns).[8] Under such conditions, GARCH modelling is particularly appropriate. Quantifying the degree of correlation present in the returns and the square of the returns is done by employing the Ljung and Box (1978) portmanteau test for serial correlation. Under the null hypothesis of no serial correlation, the test statistic is asymptotically chi-square distributed. Testing for serial correlation in the *square* of the returns, Table 2 shows that the Ljung and Box (1978) portmanteau test for up to twentieth-order correlation breaches the relevant critical value (31.401) for the 95% fractile in the asymptotic chi-square distribution for nearly all the currencies and the commodities in the dataset. That is, the null of no serial correlation is, for nearly all of the series, rejected.

These features are typical of the empirical characteristics, first formalised by Mussa (1979), of many financial series, and the model best able to capture this pattern of time dependence is the ARCH(q) model developed by Engle (1982), or more parsimoniously, the GARCH(p, q) model developed

[7] See for instance Clements and Fry (2008).
[8] See for instance Baillie and Bollerslev (1989) and Diebold and Nerlove (1989).

Table 1
Descriptive statistics.

	GLD	SXEU	SJP	SINDIA	STW	SAU
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Std. dev.	1.660	1.147	1.229	0.755	0.580	1.135
Variance	2.757	1.317	1.511	0.571	0.336	1.288
Jarque–Bera	1184	190	628	101,813	32,552	178
Probability	0.000	0.000	0.000	0.000	0.000	0.000
	SCA	SDK	SIS	SMA	SNZ	SNO
Mean	0.000	0.000	0.000	0.000	0.000	0.000
Std. dev.	0.672	1.167	1.154	1.164	1.205	1.182
Variance	0.452	1.363	1.332	1.355	1.451	1.397
Jarque–Bera	209	37	65,142	19,984	502	280
Probability	0.000	0.000	0.000	0.000	0.000	0.000
	SSG	SSA	SSK	SSF	SGB	
Mean	0.000	0.000	0.000	0.000	0.000	
Std. dev.	0.551	1.503	1.169	1.299	1.105	
Variance	0.304	2.259	1.368	1.686	1.221	
Jarque–Bera	2899	1284	375	17	1056	
Probability	0.000	0.000	0.000	0.000	0.000	

Notes: All returns are demeaned. *Abbreviations*: Gold (GLD), Euro (SXEU), Yen (SJP), Indian rupee (SINDIA), Taiwan dollar (STW), Australian dollar (SAU), Canadian dollar (SCA), Danish krone (SDK), Israeli Shekel (SIS), Maltese lira (SMA), New Zealand dollar (SNZ), Norwegian krone (SNO), Singapore dollar (SSG), South African rand (SSA), Swedish krona (SSK), Swiss franc (SSF), UK pound (SGB). Sample period: 10 January 1986 to 29 August 2008.

Table 2
Ljung–Box–Pierce *Q*-test for serial correlation.

	GLD	SXEU	SJP	SINDIA	STW	SAU
Ljung–Box (Mean)	120.043	81.245	122.472	86.258	134.654	94.589
Probability	0.000	0.000	0.000	0.000	0.000	0.000
Ljung–Box (Variance)	204.314	106.438	154.668	133.749	77.560	61.482
Probability	0.000	0.000	0.000	0.000	0.000	0.000
	SCA	SDK	SIS	SMA	SNZ	SNO
Ljung–Box (Mean)	86.529	81.228	31.255	25.161	81.812	59.321
Probability	0.000	0.000	0.052	0.195	0.000	0.000
Ljung–Box (Variance)	503.304	149.507	57.006	129.643	108.678	80.187
Probability	0.000	0.000	0.000	0.000	0.000	0.000
	SSG	SSA	SSK	SSF	SGB	
Ljung–Box (Mean)	110.883	132.219	88.959	75.842	97.630	
Probability	0.000	0.000	0.000	0.000	0.000	
Ljung–Box (Variance)	739.293	450.492	344.206	65.062	235.119	
Probability	0.000	0.000	0.000	0.000	0.000	

Notes: All returns are demeaned. *Abbreviations*: Gold (GLD), Euro (SXEU), Yen (SJP), Indian rupee (SINDIA), Taiwan dollar (STW), Australian dollar (SAU), Canadian dollar (SCA), Danish krone (SDK), Israeli Shekel (SIS), Maltese lira (SMA), New Zealand dollar (SNZ), Norwegian krone (SNO), Singapore dollar (SSG), South African rand (SSA), Swedish krona (SSK), Swiss franc (SSF), UK pound (SGB).

by Bollerslev (1986). In the empirical analysis that follows, all conditional variances are assumed to behave in a manner consistent with GARCH(p, q) processes.

4. Results

Evidence of conditional heteroscedasticity lends support to the use of ARCH-type models and, in particular, to the use of GARCH(p, q) models to capture the volatility behaviour of the data series. Tests

Table 3
DCC–GARCH model estimation results, 1986-08.

i	GLD	SXEU	SJP	SINDIA	STW	SAU
GARCH parameters						
ω_i	0.063	0.038	0.138	0.020	0.059	0.044
	(0.039)	(0.023)	(0.055)	(0.015)	(0.026)	(0.044)
α_{i1}	0.127	0.058	0.101	0.351	0.545	0.060
	(0.050)	(0.021)	(0.037)	(0.049)	(0.231)	(0.033)
β_{i1}	0.863	0.913	0.807	0.649	0.455	0.907
	(0.039)	(0.033)	(0.057)	(0.090)	(0.141)	(0.062)
	SCA	SDK	SIS	SMA	SNZ	SNO
GARCH parameters						
ω_i	0.008	0.041	0.023	0.014	0.003	0.078
	(0.003)	(0.025)	(0.013)	(0.013)	(0.003)	(0.035)
α_{i1}	0.121	0.062	0.039	0.041	0.039	0.111
	(0.027)	(0.021)	(0.024)	(0.025)	(0.012)	(0.033)
β_{i1}	0.867	0.907	0.945	0.951	0.960	0.837
	(0.025)	(0.035)	(0.024)	(0.029)	(0.012)	(0.044)
	SSG	SSA	SSK	SSF	SGB	
GARCH parameters						
ω_i	0.009	0.063	0.042	0.020	0.015	
	(0.005)	(0.033)	(0.019)	(0.019)	(0.035)	
α_{i1}	0.104	0.211	0.067	0.023	0.039	
	(0.034)	(0.068)	(0.021)	(0.021)	(0.024)	
β_{i1}	0.864	0.776	0.902	0.965	0.949	
	(0.043)	(0.059)	(0.028)	(0.044)	(0.032)	
DCC parameters						
a_1	0.010					
	(0.000)					
b_1	0.988					
	(0.013)					
Diagnostics						
χ^2-test: $R_t = R$	317.085					
	(0.000)					
Log-likelihood	−13,108					

Notes: Parameter estimates are based on the DCC–GARCH model: $h_{it} = \omega_i + \alpha_{i1}\epsilon^2_{i(t-1)} + \beta_{i1}h_{i(t-1)}$ and $Q_t = (1 - a_1 - b_1)\overline{Q} + a_1(\varepsilon_{t-1}\varepsilon'_{t-1}) + b_1 Q_{t-1}$. Probability values ($p$-values) are in parenthases. All estimation is undertaken in MATLAB. *Abbreviations*: Gold (GLD), Euro (SXEU), Yen (SJP), Indian rupee (SINDIA), Taiwan dollar (STW), Australian dollar (SAU), Canadian dollar (SCA), Danish krone (SDK), Israeli Shekel (SIS), Maltese lira (SMA), New Zealand dollar (SNZ), Norwegian krone (SNO), Singapore dollar (SSG), South African rand (SSA), Swedish krona (SSK), Swiss franc (SSF), UK pound (SGB).

of model adequacy (see Appendix A) suggest that the most appropriate form of GARCH(p, q) model is the GARCH(1, 1) model.[9]

The multivariate GARCH model of dynamic conditional correlations is to be estimated using maximum likelihood. However, since the series in our dataset show some evidence of non-normality, the remedy here is to use the quasi maximum likelihood method (Bollerslev et al., 1988) in order to generate consistent standard errors that are robust to non-normality. A comparison of the loglikelihood

[9] Higher-order variants are estimated up to and including GARCH(26, 26). While fit is reasonable in some of the higher-order variants, the GARCH(1, 1) model provides best fit in the estimation of univariate GARCH(p, q) models for the observed data. Model adequacy is confirmed after testing for serial correlation in the standardised residuals from each univariate GARCH(1, 1) process, and calculating Ljung–Box test statistics for the squared standardised residuals.

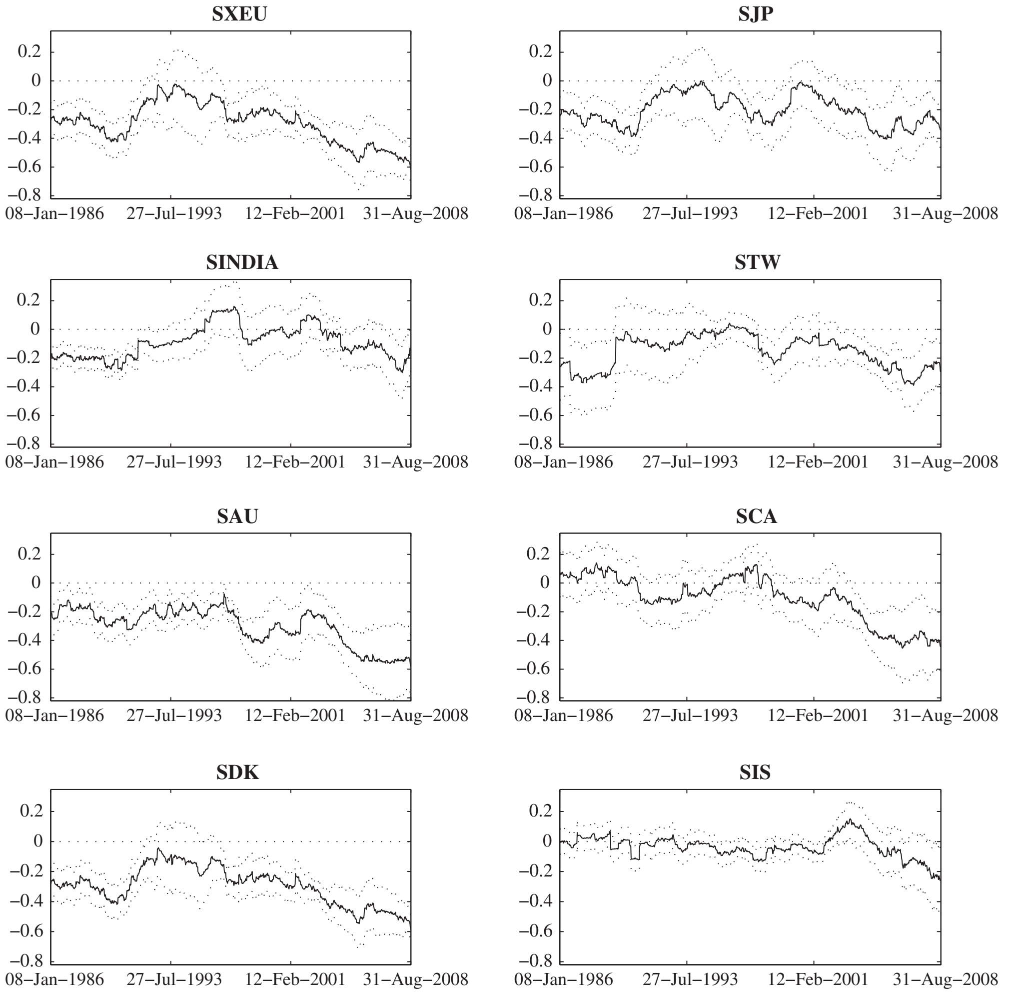

Fig. 1. Dynamic conditional correlation: gold and exchange-rate returns. *Notes*: Figure shows the dynamic conditional correlation between innovations in the price of gold and eight major exchange rate pairs: US dollar against the euro (SXEU), the yen (SJP), the Indian rupee (SINDIA), the Taiwan dollar (STW), the Australian dollar (SAU), the Canadian dollar (SCA), the Danish krone (SDK) and the Israeli shekel (SIS). The dashed lines are the confidence bands (bootstrapped) for the estimated dynamic conditional correlations. Returns are percentage demeaned nominal currency returns. Exchange rates expressed as home currency per US dollar. Frequency is weekly.

values among alternative lag specifications suggests that data behaviour is best captured by a DCC(1, 1) with each of the conditional variances captured by a univariate GARCH(1, 1) model. Table 3 displays estimation results for the DCC(1, 1)–GARCH(1, 1) model for the 17 asset prices under analysis. Probability values reflect *t*-stats calculated with robust standard errors.

All univariate GARCH processes show a high degree of persistence. That is, the sums of α_i and β_i are all close to one. The estimated DCC parameters, a_1 and b_1, imply a persistent correlation.[10] However, results of a test of parameter constancy indicate strong evidence against the assumption of constant

[10] Half-life innovation is 6 years. Half-life is defined as the time it takes for a shock to correlation to reduce by half. Half-life is computed as $\ln(0.5) + \ln(a_1 + b_1)$.

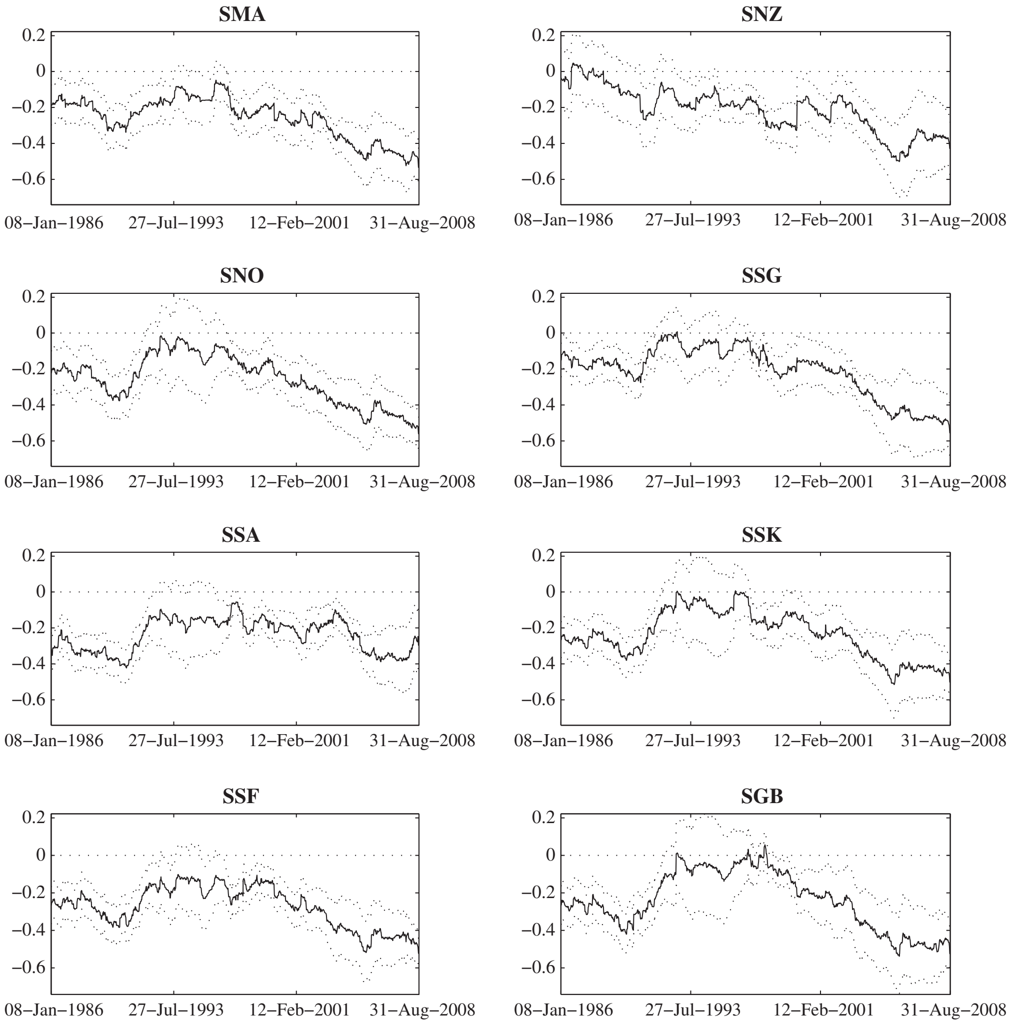

Fig. 2. Dynamic conditional correlation: gold and exchange-rate returns. *Notes*: Figure shows the dynamic conditional correlation between innovations in the price of gold and eight major exchange rate pairs: US dollar against the Maltese lira (SMA), New Zealand dollar (SNZ), the Norwegian krone (SNO), the Singapore dollar (SSG), the South African rand (SSA), the Swedish krona (SSK), the Swiss franc (SSF) and the pound sterling (SGB). The dashed lines are the confidence bands (bootstrapped) for the estimated dynamic conditional correlations. Returns are percentage demeaned nominal currency returns. Exchange rates expressed as home currency per US dollar. Frequency is weekly.

conditional correlations: the test, developed by Engle and Sheppard (2001), uses a χ^2-statistic to test the null of $R_t = R$. The resulting test statistic, 317.1, is highly significant, rejecting the null hypothesis of constant conditional correlations.

Figs. 1 and 2 show the evolution over time of ρ_{1i}, the dynamic conditional correlations between the price of gold and the 16 major exchange rate pairs in the sample. The sign of all correlation coefficients over the sample period is consistently negative. That is, there is a negative relationship between gold-price returns and all US dollar returns. Further, most if not all of the correlation coefficients in the sample grow in magnitude from the early 1990s onwards, becoming increasingly negative, reaching their most negative at the end of 2008. The negative relationship between the price of gold and the dollar's value in terms of euros is particularly well-defined, with ρ_{12} reaching -0.6 in August 2008.

Table 4
Constant conditional correlations and quantiles.

	Const. corr.	10% quantile	5% quantile	1% quantile
US dollar exchange rate				
Euro	−0.309	−0.284	−0.269	−0.252
	(0.010)	(0.125)	(0.110)	(0.113)
Yen	−0.214	−0.210	−0.218	−0.219
	(0.008)	(0.092)	(0.087)	(0.095)
Indian rupee	−0.087	−0.132	−0.123	−0.290
	(0.020)	(0.097)	(0.102)	(0.133)
Taiwan dollar	−0.155	−0.217	−0.230	−0.243
	(0.054)	(0.107)	(0.106)	(0.093)
Australian dollar	−0.341	−0.337	−0.351	−0.364
	(0.020)	(0.127)	(0.125)	(0.111)
Canadian dollar	−0.159	−0.218	−0.246	−0.270
	(0.008)	(0.165)	(0.160)	(0.188)
Danish krone	−0.320	−0.280	−0.266	−0.241
	(0.012)	(0.110)	(0.100)	(0.107)
Israeli shekel	−0.057	−0.056	−0.056	−0.096
	(0.016)	(0.103)	(0.117)	(0.105)
Maltese lira	−0.287	−0.260	−0.242	−0.249
	(0.007)	(0.102)	(0.091)	(0.123)
New Zealand dollar	−0.256	−0.223	−0.202	−0.173
	(0.027)	(0.141)	(0.142)	(0.149)
Norwegian krone	−0.300	−0.281	−0.277	−0.255
	(0.017)	(0.138)	(0.137)	(0.139)
Singapore dollar	−0.261	−0.232	−0.222	−0.204
	(0.020)	(0.139)	(0.121)	(0.062)
South African rand	−0.257	−0.248	−0.240	−0.241
	(0.019)	(0.087)	(0.083)	(0.067)
Swedish krona	−0.268	−0.233	−0.221	−0.182
	(0.021)	(0.135)	(0.125)	(0.130)
Swiss franc	−0.317	−0.258	−0.256	−0.219
	(0.047)	(0.095)	(0.095)	(0.084)
UK pound	−0.262	−0.249	−0.248	−0.280
	(0.026)	(0.144)	(0.121)	(0.112)

Notes: Table shows constant conditional correlations (Const. corr.) for gold returns versus the returns of 16 US dollar exchange rates pairings estimated over the full sample period (10 January 1986 to 29 August 2008); table also shows mean dynamic conditional correlations for selected quantiles (10%, 5%, 1%) of the most negative exchange-rate returns. Asymptotic standard errors are in parentheses for constant conditional correlations. Quantile standard deviations are in parentheses for mean dynamic conditional correlations.

Figs. 1 and 2 also plot the 95% confidence intervals for the estimated dynamic conditional correlations.[11] The confidence intervals are computed using bootstrap methods with 1000 draws from the estimated distribution of the DCC(1, 1)–GARCH(1, 1) coefficients. The confidence intervals show that while for some currencies the negative relationship with gold returns has not, for some periods, been statistically significant (in the early 1990s the relationship broke down for a number of currencies), for most currencies during most of the sample period the negative relationship has been strongly significant.

[11] Bootstrapped confidence intervals for *constant* conditional correlations are available from the author upon request. They show that the dynamic correlations vary widely, straying beyond the limits of the estimated constant confidence bounds for long periods, thus highlighting that the conditional correlations cannot be described as constant.

Recall the definitions of hedge and haven. An asset that functions as a safe haven for another asset will not co-move with the other asset *in times of stress*. An asset that acts as a hedge is one that is uncorrelated or correlated negatively with another asset *on average*. Using these definitions, Figs. 1 and 2 show that gold has acted as a hedge against the US dollar throughout the sample period. That is, gold-price returns have been correlated negatively with US dollar returns, for all 16 exchange-rate pairs, not only in times of stress but also on average throughout the 22-year sample period.

Supporting evidence is offered in Table 4. The table gives maximum likelihood estimates of the constant conditional correlations between gold-price returns and returns for the 16 US dollar exchange-rate pairings. All are negative and significant and are consistent with the hypothesis that gold provides an effective *hedge* against the US dollar. The most consistently negative relationships are between gold-price returns and US dollar returns in terms of euros, Swiss francs, Australian dollars and Danish kroner.

The third, fourth and fifth columns in Table 4 show mean dynamic correlations during periods of market stress, defined according to the 10%, 5% and 1% quantiles of most negative exchange-rate returns. The smaller the size of the quantile the more extreme the market stress. The quantile correlations define the extent to which gold acts as a *safe haven* from US dollar volatility. That is, for any given US dollar exchange-rate pair, if gold acts as an effective safe haven, then quantile correlations will be more negative than the corresponding constant correlations. Or they will be uncorrelated. Table 4 shows that, in fact, neither is true. For most of the US dollar exchange-rate pairings the quantile correlations are less negative, not more negative, than the constant conditional correlations. The yen and the UK pound are exceptions at the 1% quantile. However, the difference is not statistically significant: quantile correlations for the yen and UK pound are more negative by less than two asymptotic standard errors. All of this suggests that gold's role as a safe haven from US dollar movements is negligible.[12] Gold's only effective role, in terms of offering investment protection from movements in the US dollar, is as a hedge.

Indeed, Figs. 1 and 2 show that since 2001 gold's efficacy as a hedge has become more pronounced. The negative conditional correlation between gold-price returns and US dollar returns has grown increasingly strong. The reason why is unclear.[13] This period does coincide with a steady downward spiral in the value of the US dollar. But other periods of dollar depreciation have not gone hand in hand with strengthening negative correlations with gold. Figs. 1 and 2 show that between 1985 and 1988, when the US dollar lost 12% of its trade-weighted value, the correlation between gold returns and US dollar returns did not turn increasingly negative.

5. Conclusions

This study investigates the nature of the relationship between the price of gold and the US dollar, how it has changed during the past 25 years, and how these changes cast light upon the role gold plays as an investment hedge and a haven. Empirical results based on a multivariate GARCH model of dynamic conditional correlations show that the conditional correlation between changes in the price of gold and changes in the US dollar's exchange rate is broadly negative. That is, increases in the price of gold tend to be associated with decreases in the value of the US dollar. This correlation has not, however, remained constant over time. During the past 7 years the correlation has turned increasingly negative. In 2008 it was more negative than at any point during the past three decades. The implication is that gold's role as an investment *hedge* against the US dollar is much stronger and more durable than suggested by Capie et al. (2005).

[12] Baur and McDermott (2010) similarly find no consistent role for gold as a safe haven from share-price movements for data of the same frequency, ie, weekly. They do find evidence in favour of gold's role as a safe haven for daily data, but the evidence is partial (supported only at the 1% quantile) and economically trivial (marginal effects are very small). Baur and Lucey (2006) find that gold is not a safe haven for bonds. For stocks, the only economically meaningful role gold plays as a safe haven is, they find, for the UK. For other markets the marginal effects are small.

[13] Potential explanations based on the increasing role of the derivatives market during the 1990s (Kearney and Lombra, 2008) or feedback trading (Campbell and Kyle, 1993; Cutler et al., 1990; Delong et al., 1990; Kirman, 1993; Shleifer, 2000) are beyond the scope of this paper.

Analysis of gold's role as a *safe haven* provides very different conclusions. Quantile correlations show gold does not act as an effective safe haven from market stress. These results chime with those of Baur and McDermott (2010), who find no evidence that gold acts as a consistent safe haven with respect to weekly movements in international share prices. Baur and Lucey (2006) find no evidence that gold acts as a safe haven for bonds.

Given these findings, identifying the factors that have contributed to gold's strengthening role as a hedge against the US dollar offers plenty of scope for further research.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.frl.2011.01.001.

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