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Fluctuations of the Real Exchange Rate, Real Interest Rates, and the Dynamics of the Price of Gold in a Small Open Economy

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Fluctuations of the Real Exchange Rate, Real Interest Rates, and the Dynamics of the Price of Gold in a Small Open Economy

February 2014

Abstract

Economic theory predicts that, in a small open economy, the dynamics of the real price of gold should be linked to real interest rates and the rate of change of the real exchange rate. Using data for Australia, we use a real-time forecasting approach to analyze whether real interest rates and the rate of change of the real exchange rate help to forecast out-of-sample the rate of change of the real price of gold. We study the economic value-added of out-of-sample forecasts using a behavioral-finance approach that takes into account that a forecaster may have an asymmetric loss function.

JEL classification: C53; E44; G02

Keywords: Gold price; Real-time forecasting; Real exchange rate; Real interest rates; Behavioral-finance approach

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1 Introduction

Against the background of the U.S. subprime mortgage crisis, the European sovereign debt crisis, global financial-market jitters, and historically low interest rates in major industrialized countries, research on the dynamics of a rallying price of gold has mushroomed in recent years. Some researchers have studied the link between the dynamics of the price of gold and the inflation rate (Gosh *et al.*, 2004; Capie *et al.*, 2005; Blose, 2010). Other researchers have focused on the link between the dynamics of the price of gold and exchange rates (Sjaastad, 2008; Pukthuanthong and Roll, 2011; Reboredo, 2013). Still other researchers have studied the “safe” haven property of investments in gold (Baur and McDermott, 2010; Baur and Lucey, 2010). Our contribution to this significant research is threefold.

First, like Frankel (1986, 2008) and Frankel and Rose (2010), we draw on a set of fundamental no-arbitrage conditions to set up a simple model that links the dynamics of the price of gold to the rate of change of the real exchange rate and the real interest rate. The model implies that, in a small open economy, the rate of change of the real price of gold can be expressed as a linear combination of the rate of change of the real exchange rate and a set of large-country foreign real interest rates (for earlier research on the real interest rate as a determinant of the price of gold, see Diba and Grossman, 1984; Barsky and Summers, 1988; Pindyck and Rotemberg, 1990). Frankel (2008) reports strong evidence for various commodity prices and for various countries that the real interest rate is negatively correlated with commodity prices. Frankel and Rose (2010) apply the model to study the determinants of agricultural and mineral commodity prices. Chen *et al.* (2010) show that, for major commodity-exporting countries, exchange-rate movements help to forecast fluctuations of commodity prices. We use data for Australia, a small open economy, to study the predictive power of the rate of change of the real exchange rate and G6 real interest rates for the rate of change of the price of gold.¹

Second, like Pierdzioch *et al.* (2014a, 2014b), we use the real-time forecasting approach developed by Pesaran and Timmermann (1995, 2000) to study whether real interest rates and the rate of change of the real exchange rate help to predict out-of-sample the rate of change of the price of gold. The real-time forecasting approach is a natural choice for studying the

¹Interest rates for Japan are available only from 2002 onwards from the datasource that we use. For this reason, we exclude Japan from our empirical analysis.

out-of-sample predictability because it accounts for the fact that a forecaster, in real-time, can only use the then available data on real interest rates and the rate of change of the real exchange rate to compute a forecast. Moreover, the real-time forecasting approach accounts for the fact that a forecaster, in real-time, must form a forecast under model uncertainty. Even if a forecaster believes that only real interest rates and the rate of change of the real exchange rate are relevant predictors of the rate of change of the price of gold, these predictors can be combined in several alternative ways to yield a large number of forecasting models. A forecaster does not know which of these models is the “optimal” forecasting model. The real-time forecasting approach resolves this problem by assuming that, in a first step, a forecaster estimates a large number of competing forecasting models. Then, in a second step, a forecaster either selects a forecasting model by means of some model-selection criterion or uses some forecast-averaging scheme to combine the information from the various forecasting models. Because this model-selection and model-averaging processes are restarted in every period of time as new information on real interest rates and the rate of change of the real exchange rate becomes available, the real-time forecasting approach also accounts for the possibility that the forecasting model may change over time. Recent applications of the real-time forecasting approach include Bossaerts and Hillion (1999), Alcock and Gray (2005), Hartmann *et al.* (2008), and Sarno and Valente (2009), while Chen *et al.* (2010) discuss the issue of model instability in the context of forecasting commodity prices.

Third, we use a flexible behavioral-finance approach to evaluate the economic value-added of forecasts. It has long been common practice in applied research to evaluate forecasts by assuming that forecasters have a symmetric (that means, a quadratic) loss function. Results of significant recent research, however, show that invoking symmetry of the loss function may be too restrictive (Elliott *et al.*, 2005; Christodoulakis and Mamatzakis, 2008, 2013; Fritsche *et al.*, 2014; among others). Pierdzioch *et al.* (2014b), using a loss function studied by Elliott *et al.* (2005, 2008), show how a behavioral-finance approach can be applied to evaluate out-of-sample forecasts under an asymmetric loss function. Their criterion nests an out-of-sample forecasting criterion recently advocated by Campbell and Thompson (2008) in the case that the loss function is assumed to be symmetric. We apply the behavioral-finance approach proposed by Pierdzioch *et al.* (2014b) to study the predictive power of real interest rates and the rate of change of the real exchange rate for the rate of change of the real price of gold under both a symmetric and an asymmetric loss function.

We briefly sketch some theoretical considerations in Section 2. We lay out the empirical model in Section 3, and we describe our empirical analysis in Section 4. We conclude in Section 5.

2 Theoretical Foundation

As in the theoretical models studied by Frankel (1986, 2008), the main building block of the model is a no-arbitrage condition that stipulates that the total return on holdings in gold must be equal to the return an investor earns upon depositing money in the bank. This no-arbitrage condition can be written as follows²

$$i_t = \dot{g}_t - sc_t, \quad (1)$$

where i_t denotes the nominal interest rate in period of time t , \dot{g}_t denotes the rate of change of the price of gold, and sc_t denotes storage costs. Upon subtracting the inflation rate, π_t , from both sides of Equation (1), we get

$$r_t = \dot{g}_{r,t} - sc_t, \quad (2)$$

where, by the Fisher parity condition, $r_t = i_t - \pi_t$ denotes the real interest rate, and $\dot{g}_{r,t}$ denotes the real rate of change of the price of gold.

Another building block of the model is the no-arbitrage condition of uncovered interest-rate parity:

$$\dot{s}_t = i_t - i_t^*, \quad (3)$$

where \dot{s}_t denotes the rate of change of the nominal exchange rate and an asterisk denotes a foreign variable. For a small open economy, the foreign interest rate, i_t^* , is exogenously given. Using the domestic and foreign Fisher parity conditions, we can rewrite Equation (3) as a real-interest-rate-parity condition of the format $\dot{s}_{r,t} = r_t - r_t^*$, where $\dot{s}_{r,t}$ denotes the rate of change of the real exchange rate.

²For notational simplicity, we assume that the convenience yield of investing in gold and a risk premium can be subsumed in the storage costs (see also Frankel 1986, Page 345, Equation (1)). This assumption does not rule out the possibility that the convenience yield and the risk premium have a time-varying component. See Equations (5) and (6).

Next, we rearrange Equation (2) and we add and subtract the foreign real interest rate, r_t^* . We arrive at the equation $\dot{g}_{r,t} = (r_t - r_t^*) + r_t^* + sc_t$ (see also Frankel, 2008). Upon substituting the real-interest-rate-parity condition into this result, we get

$$\dot{g}_{r,t} = \dot{s}_{r,t} + r_t^* + sc_t, \quad (4)$$

Decomposing the storage costs into a constant and a stochastic disturbance term, $sc_t = \beta_0 + \epsilon_t$, the empirical counterpart of Equation (4) yields³

$$\dot{g}_{r,t} = \beta_0 + \beta_1 \dot{s}_{r,t} + \beta_2 r_t^* + \epsilon_t, \quad (5)$$

where β_j , $j = 0, 1, 2$ are coefficients to be estimated. Next, we define $\dot{g}_{r,t} = r_{g,t}$ and $\dot{s}_{r,t} = r_{s,t}$ for notational convenience, and we take into account that a small open economy that is integrated into international financial markets may face several foreign real-interest rates. Similarly, a small open economy may trade with various other countries. For this reason, we interpret $r_{s,t}$ as the rate of change of a real effective (that is, trade-weighted) real exchange rate. Finally, upon leading in Equation (5) the rate of change of the real price of gold and the stochastic disturbance term by one period to set up a forecasting model, we arrive at our empirical model:

$$r_{g,t+1} = \beta_0 + \beta_1 r_{s,t} + \sum_{j=2}^n \beta_j r_{j-1,t}^* + \epsilon_{t+1}. \quad (6)$$

3 The Empirical Model

3.1 The Real-Time Forecasting Approach

Equation (6) shows that the rate of change of the real price of gold can be predicted by means of a constant and up to n predictor variables (the real interest rates and the change of the real exchange rate). However, a forecasting model that features all n predictor variables is perhaps not the best forecasting model. In principle, a forecaster can choose, in every period of time t , among all 2^n forecasting models that feature alternative combinations of the

³In the “overshooting” model studied by Frankel (1986, 2008), households expect that the real price of gold reverts to its steady-state value, implying that the formation of rational expectations can be expressed as $\dot{g}_{r,t} = -(g_{r,t} - \bar{g}_r)$, where \bar{g}_r denotes the steady-state value. As a result, the coefficients, β_1 and β_2 , in Equation (5) should have a negative sign.

predictor variables on the right-hand-side of Equation (6).⁴ Accordingly, we account for model uncertainty by estimating in every period of time, t , by the ordinary least squares technique all 2^n forecasting models that can be derived as special cases of Equation (6). The estimated versions of Equation (6) can then be used, in every period of time, to compute 2^n real-time forecasts of the change of the real price of gold.

Model-selection criteria can be used to select from the 2^n forecasts an “optimal” forecast. We analyze the following widely studied model-selection criteria: The Adjusted Coefficient of Determination (ACD, Theil, 1966), the Akaike Information Criterion (AIC, Akaike, 1973), the Schwarz Information Criterion (SIC, Schwarz, 1978), and the Direction of Change Criterion (DCC, Pesaran and Timmermann, 1995). The ACD model-selection criterion is perhaps the most widely studied model-selection criterion in applied research. The AIC and SIC model-selection criteria select relatively parsimonious forecasting models. The DCC model-selection criterion selects a model that maximizes the proportion of correct in-sample sign forecasts.⁵

Alternatively, we use a “thick” modeling approach (Granger and Jeon, 2004; Aiolfi and Favero, 2005; Rapach, *et al.* 2010) to combine the 2^n different forecasts to a single “optimal” forecast. Like Pierdzioch *et al.* (2014b), we study a Simple Averaging Criterion (SAV), a Median-Based Averaging Criterion (MAV), a Weighted-Mean Averaging Criterion (AAV), and a Truncated-Mean Averaging Criterion (TAV). The SAV model-averaging criterion computes a forecast as the simple unweighted mean of all 2^n forecasts. The MAV model-averaging criterion uses the median of the 2^n as the forecast. The AAV model-averaging criterion uses the ACD model-selection criterion as a weighting factor to compute a weighted average of the 2^n forecasts.⁶ Finally, the TAV model-averaging criterion uses only the forecasts in the interval plus/minus one standard deviation around the mean of the 2^n forecasts to form a forecast.

The process of forecast selection and forecast averaging is repeated in every new period of time based on new estimates of the 2^n forecasting models. As we move forward in time, we

⁴The forecasting models always include a constant.

⁵If more than one model maximizes the proportion of correct in-sample forecasts, we use the ACD model-selection criterion to select a single forecasting model.

⁶When computing the ACC criterion, we use a logistic function to transform the ACD model-selection criterion so as to decrease (increase) the weight attached to forecasts implied by forecasting models with a low (high) ACD model-selection criterion.

use both an expanding recursive estimation window and a rolling estimation window. The former implies that the number of observations that we use to estimate the 2^n forecasting models increases over time, while the latter implies that the number of observations being used for estimating the forecasting models is constant over time. Using a rolling estimation window implies that the effect of structural changes on the forecasting models fade away as the rolling estimation window moves forward in time. A rolling estimation window, however, also implies that the number of data used for estimation is restricted by construction. As a result, forecasts may be less robust to outliers in the data than under the recursive modeling scheme.

3.2 Evaluating Out-of-Sample Forecasts

We use the behavioral-finance approach recently proposed by Pierdzioch *et al.* (2014b) to assess the economic value-added of forecasts. The starting point of their behavioral-finance approach is an asymmetric loss function of the type studied by Elliott *et al.* (2005, 2008). A forecaster may have an asymmetric loss function due to psychological effects as described in the behavioral-finance literature (for a survey, see Shiller, 1999). Risk management considerations also may give rise to an asymmetric loss function. Whatever is the reason that motivates the asymmetry, the loss function of a forecaster is of the format $\mathcal{L} = [\alpha + (1 - 2\alpha)I(r_{g,t} - \hat{r}_{g,t,m} < 0)]|r_{g,t} - \hat{r}_{g,t,m}|^p$, where $\hat{r}_{g,t}$ denotes the forecast of the real price of gold, m denotes the forecast-selection or forecast-averaging criterion being studied, and $r_{g,t} - \hat{r}_{g,t,m}$ denotes the forecast error. A so-called lin-lin loss function obtains for $p = 1$, and a so-called quad-quad loss function obtains for $p = 2$. The asymmetry parameter can assume values in the interval $\alpha \in (0, 1)$. A symmetric loss function results in the case of $\alpha = 0.5$, and a standard symmetric quadratic loss function results if we additionally set $p = 2$. For $\alpha = 0.5$ and $p = 1$, the loss increases in the absolute forecast error, where it does not matter for the magnitude of the loss whether a forecaster under- or overpredicts the rate of change of the real price of gold (**where the forecaster is indifferent between under- and overprediction of the rate of change of the real price of gold**).

Figure 2 shows examples of quad-quad loss functions for alternative parameters (**values**) of the shape parameter, α . If a forecaster has a loss function with shape parameter $\alpha > 0.5$ ($\alpha < 0.5$), the loss from underpredicting (overpredicting) the rate of change of the real price

of gold exceeds the loss from an overprediction (underprediction) of the same size. For example, an underprediction, $r_{g,t} - \hat{r}_{g,t,m} > 0$, arises if $r_{g,t} > 0$ and $\hat{r}_{g,t,m} > 0$ and $r_{g,t} > \hat{r}_{g,t,m}$, but also if, for example, $r_{g,t} < 0$ and $\hat{r}_{g,t,m} < 0$ and $|r_{g,t}| < |\hat{r}_{g,t,m}|$, and if $r_{g,t} > 0$ and $\hat{r}_{g,t,m} < 0$. An overprediction arises if $r_{g,t} - \hat{r}_{g,t,m} < 0$.

– Please include Figure 2 about here. –

Pierdzioch *et al.* (2014b) propose the following out-of-sample relative loss criterion for evaluating the economic value-added of a sequence of forecasts under asymmetric loss:

$$\mathcal{L}_o(\alpha, p, r_{g,t}, m) = 1 - \frac{\sum_{t=\tau}^T [\alpha + (1 - 2\alpha)I(r_{g,t} - \hat{r}_{g,t,m} < 0)] |r_{g,t} - \hat{r}_{g,t,m}|^p}{\sum_{t=\tau}^T [\alpha + (1 - 2\alpha)I(r_{g,t} - \bar{r}_{g,t} < 0)] |r_{g,t} - \bar{r}_{g,t}|^p}, \quad (7)$$

where $\bar{r}_{g,t}$ denotes the historical mean of the rate of change of the real price of gold estimated by means of a recursive/rolling estimation window, and τ is the first period for which a forecast is available. Equation (7) shows that the out-of-sample relative loss criterion evaluates a sequence of forecasts (that is, the implied sequence of forecast errors) by comparing it with the naive historical mean forecast, given the functional form, p , and the shape, α , of the loss function and given a forecast-selection or forecast-averaging criterion, m . If $\mathcal{L}_o(\alpha, p, r_{g,t}, m) > 0$, a sequence of forecasts implied by a forecast-selection or forecast-averaging criterion, m , gives rise to a lower loss than a sequence of forecasts implied by the historical mean. Similarly, if $\mathcal{L}_o(\alpha, p, r_{g,t}, m) < 0$, a sequence of forecasts implied by the historical mean dominates the sequence of forecasts implied by the forecast-selection or forecast-averaging criterion, m . The out-of-sample relative loss criterion nests the out-of-sample R^2 studied by Campbell and Thompson (2008) for the special case of $\alpha = 0.5$ and $p = 2$.

In order to assess the significance (or lack thereof) of the economic value-added of forecasts under the out-of-sample relative loss criterion, we use a bootstrap simulation. To this end, we resample from the data using the block bootstrap described by Politis and Romano (1994). The simulations for the various model-selection/model-averaging criteria and recursive/rolling estimation windows are based on the same seed of random numbers.

4 Empirical Analysis

4.1 The Data

We study quarterly data on the price of gold downloaded from the web site of the Federal Reserve Bank of St. Louis.⁷ We use the nominal exchange rate (also taken from this web site) to convert the gold price into Australian dollars. We then compute the annualized continuously compounded quarterly rate of change of the gold price, where we subtract the annualized quarterly change in the Australian consumer price index to compute the rate of change of the real price of gold. The upper row of Figure 1 shows the real price of gold (1979/Q1=100) and its rate of change.⁸ The real price of gold experienced a clear upward trend from 2000 onwards. This upward trend reflects both increases in the nominal price of gold and low inflation rates. The upward trend accelerated in recent years and only lost momentum at the very end of the sample period. The unconditional mean of the rate of change of the real price of gold is 2.22% (standard deviation: 33.47%). The density functions shown in the lower row of Figure 1 indicate that normality of the rate of change of the real price of gold can soundly be rejected at conventional significance levels. There are also signs of short-lived autocorrelation, where the coefficient of first-order autocorrelation is 0.22.

— Please include Figure 1 about here. —

The data on the Australian consumer price index and the consumer prices and nominal short-term interest rates for the G6 countries are from the web site of the OECD.⁹ The sample period ranges from 1979/Q1 to 2013/Q3. Table 1 shows summary statistics of the real interest rates of the G6 countries and the rate of change of the real effective exchange rate. Data on the real effective exchange rate (narrow definition) are from the web site of the Bank for International Settlements.¹⁰ The summary statistics show that, in line with economic theory (see Footnote

⁷See <http://research.stlouisfed.org/fred2/>.

⁸All graphs and computations were coded up using the free R programming environment (R Development Core Team, 2013).

⁹See <http://www.oecd.org>.

¹⁰See <http://www.bis.org>

2), the rate of change of the period- $(t + 1)$ real price of gold is negatively correlated with the period- t real interest rates and the rate of change of the real exchange rate.

– Please include Table 1 about here. –

4.2 Composition of the Selected Forecasting Models

Table 2 shows how often (in percent) the forecasting models under the model-selection approach feature the rate of change of the real exchange rate and the real interest rates of the G6 countries as predictor variables. A number smaller than 100% indicates that a predictor variable is not always included in the selected forecasting model. We compute the results given in Table 2 using a “training” period of 10 years to start the real-time forecasting approach. Because the choice of the training period is somewhat arbitrary, we shall present in Section 4.3 also results for training periods of 15 and 20 years. We use the length of the training period to fix the length of the rolling estimation window when studying the rolling real-time forecasting approach.

– Please include Table 2 about here. –

Results show that none of the individual predictor variables is always included in the selected forecasting models. As one would have expected, the importance of the predictor variables differs depending on whether we assume a recursive or a rolling estimation window. The AIC and SIC model-selection criteria select parsimonious forecasting models. The SIC model-selection criterion even drops all predictor variables all the time from the selected forecasting models under the recursive forecasting scheme, implying that only a time-varying intercept is being used to form forecasts under the SIC model-selection criterion. Across all model-selection criteria, the rate of change of the real exchange rate and the U.S. real interest rate are the most important predictor variables under the recursive forecasting scheme. If we use a rolling-window forecasting scheme, European real interest rates become important also under the ACD and AIC model-selection criteria.

4.3 Forecast Evaluation Under Asymmetric Loss

Tables 3 (recursive real-time forecasting approach) and 4 (rolling real-time forecasting approach) summarize the results for the out-of-sample relative loss criterion. We present, as a robustness check, the results for three different training periods (10, 15, and 20 years). Panel A contains the results for a lin-lin loss function, while Panel B contains the results for a quad-quad loss function. We present results for a two-sided test. The null hypothesis is that the economic value-added of forecasts computed by means of the real-time forecasting approach is not different from the economic value-added of naive forecasts derived from the historical mean of the rate of change of the real price of gold.¹¹

– Please include Tables 3 and 4 about here. –

The general message conveyed by the results is that using the real interest rates and the rate of change of the real exchange rate as predictors of the rate of change of the real price of gold leads to an inferior forecasting performance in terms of the out-of-sample relative loss criterion if the loss function of a forecaster can be characterized by setting $\alpha < 0.5$. Similarly, for a symmetric loss function ($\alpha = 0.5$), the out-of-sample relative loss criterion attains negative values in the majority of cases. In contrast the out-of-sample relative loss criterion tends to become positive for $\alpha > 0.5$. In other words, if a forecaster deems an overprediction more costly than an underprediction of the same size, then this forecaster should use the naive historical mean to forecast the rate of change of the real price of gold. By the same token, if a forecaster deems an underprediction more costly than an overprediction of the same size, then this forecaster benefits from using the real-time forecasting approach.

The only exception is the SIC model-selection criterion in the case of the recursive real-time forecasting approach because the real interest rates and the rate of change of the real exchange rate are never included in the selected forecasting models under this model-selection criterion. In consequence, the forecast of the rate of change of the real price of gold computed by the

¹¹It is straightforward to set up a one-sided test based on the null hypothesis that the real-time forecasting approach gives rise to forecasts that perform not better than the naive forecasts derived from the historical mean.

real-time forecasting approach exactly matches the naive historical mean forecast, implying that the out-of-sample relative loss criterion always assumes the value zero.

In terms of statistical significance, the results show that the forecasts implied by the real-time forecasting approach often give significantly worse results in terms of the out-of-sample relative loss criterion than the naive historical mean forecast if we set $\alpha < 0.5$. The null hypothesis of equal economic-value added of forecasts can never be rejected only if we combine the rolling real-time forecasting approach (i) with a quad-quad loss function, and, (ii) with a lin-lin loss function when the model-averaging criteria are being used to form forecasts. The real-time forecasting approach often implies forecasts that are significantly better in terms of the out-of-sample relative loss criterion than the naive historical mean forecast if we set $\alpha > 0.5$ and, at the same time, combine a lin-lin loss function with (i) the model-averaging criteria and a recursive estimation window, and, (ii) the model-selection criteria with a rolling estimation window. The dominance of the forecasts computed by means of the real-time forecasting approach tends to strengthen in these two cases as the training period gets longer.

4.4 Volatility

It is well-known from research on asymmetric loss functions (Christoffersen and Diebold, 1997) that optimal prediction in the presence of an asymmetric (linex) loss function can be done by using the conditional prediction-error variance as an additional regressor.¹² Batchelor and Peel (1998) capture this idea by estimating an ARCH-in-mean model. We account for the potential effects of volatility on the forecasting models by adding the monthly volatility of the rate of change of the real price of gold as an additional potential predictor variable to the forecasting model given in Equation (6).

While the significance of the results (not reported, but available from the authors upon request) somewhat weakens in case of a lin-lin loss function, the general picture that emerges is qualitatively similar to the picture conveyed by Panel A of Tables 3 and 4. Hence, for $\alpha < 0.5$, the out-of-sample relative loss criterion implies that the forecasts derived from the

¹²The out-of-sample relative loss criterion could easily be framed in terms of a linex loss function. We specify the out-of-sample relative loss criterion given in Equation (7) in terms of the loss function studied by Elliott *et al.* (2005, 2008) because Pierdzioch *et al.* (2014b) report results for such a specification.

real-time forecasting approach often perform significantly worse than the naive forecasts. In contrast, for $\alpha > 0.5$, the out-of-sample relative loss criterion attains positive values, which are significant in some (but not in all) cases.

Assuming a quad-quad loss function, the coefficients are no longer significant in the case of the recursive real-time forecasting approach. We still observe a negative out-of-sample relative loss criterion for $\alpha < 0.5$, but the recursive real-time forecasting approach no longer performs significantly worse than the historical mean in terms of the out-of-sample relative loss criterion if a forecaster evaluates forecasts in terms of a quad-quad loss function. At the same time, for $\alpha > 0.5$, the real-time forecasting approach does not perform significantly better than the historical mean, resembling the results summarized in Panel B of Table 3. For the rolling window real-time forecasting approach, the out-of-sample relative loss criterion is never significant, corroborating the results documented in Panel B of Table 4.

5 Concluding Remarks

Our results for Australia, a major gold producing country, show that the economic value-added of forecasts of the rate of change of the real price of gold depends on the shape of a forecaster's loss function. In many cases, a forecaster who attaches a larger cost to an overestimation error relative to an underestimation error of the same size would have fared worse using the real-time forecasting approach than using the forecasts derived from the historical mean of price changes. At the same time, assuming a lin-lin loss function, a forecaster who attaches a larger weight to an underestimation error relative to an overestimation error of the same size would have fared better in some cases using the real-time forecasting approach than using the forecasts derived from the historical mean of price changes. Depending on the shape of a forecaster's loss function, the rate of change of the real exchange rate and the real interest rates of the G6 countries, thus, may have a positive economic-value added for a forecaster as predictors of fluctuations of the real price of gold.

Our results are silent with respect to the question of whether the gold market is informationally inefficient with respect to the predictor variables being studied in this research. In earlier literature, several authors have found that the gold market is informationally efficient with respect to the predictor variables being focused on in the various empirical studies

(Tschoegl, 1980; Solt and Swanson, 1981; Ho, 1985; Pierdzioch *et al.*, 2014a, 2014b). A positive economic value-added, when measured in terms of a forecaster’s loss function and the out-of-sample relative loss criterion, is not necessarily inconsistent with market efficiency because our behavioral-finance approach does not measure the economic value-added of forecasts in terms of excess profits derived from using forecasts to set up a trading rule. Depending on the trading rule being studied and on the magnitude of transaction costs, forecasts may yield nonpositive excess profits when used to set up a trading rule and, at the same time, a positive economic value-added as measured by the behavioral-finance approach.

An alternative to using an asymmetric loss function as a means to evaluate forecasts is to take explicitly into account, for example, potential nonlinearities in the data-generating process that may be the source of the asymmetries that the loss function captures. Accounting for such nonlinearities or other specific features of the data-generating process, however, requires estimation of increasingly sophisticated econometric models.¹³ While such complex econometric models certainly will deepen our understanding of the determinants of the gold price, they may be of limited use to a forecaster simply because the costs of estimating such models under real-time conditions of model instability and model uncertainty may be prohibitively high. In real-time, an economically more efficient strategy may be to evaluate the economic value-added of forecasts by combining a simple econometric model of the type we have studied in our research with a flexible asymmetric loss function.

An interesting avenue for future research is to apply the behavioral-finance approach used in this research to study the economic value-added of forecasts of fluctuations of stocks, exchange rates, and other asset prices. In the case of exchange rates, it has been known at least since the by-now classic work by Meese and Rogoff (1983) that it is notoriously difficult to forecast fluctuations of exchange rates by means of economic “fundamentals”. Results recently reported by Sarno and Valente (2009) show that the real-time forecasting approach may be a useful modeling device to study the potentially time-varying link between exchange rates and

¹³The real-time forecasting approach accounts for such nonlinearities in a rudimentary way because the predictor variables and their coefficients can change over time. Notwithstanding, one can imagine extensions that strengthen the ability of the real-time forecasting approach to capture nonlinearities. For such an extension that accounts for the effects of financial crises, see Hartmann *et al.* (2008). See Minford and Srinivasan (2008) for an analysis of the observational equivalence of nonlinearities in the data-generating process and an asymmetric loss function in the context of monetary policy.

fundamentals. Combining their real-time forecasting approach with the behavioral-finance approach studied in this research may yield further insights into how the predictive value of fundamentals for exchange rates depends on the shape of a forecaster's loss function.

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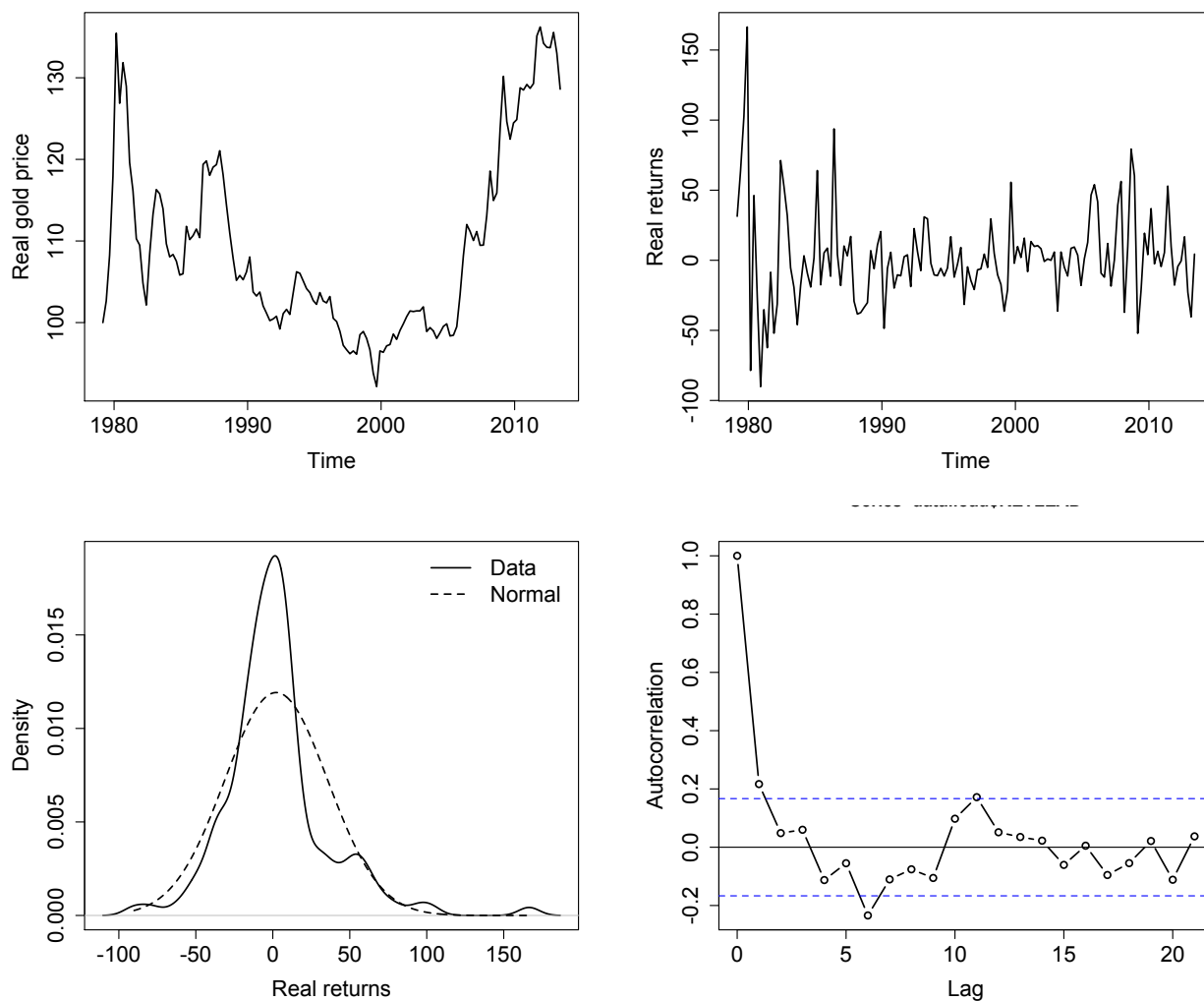
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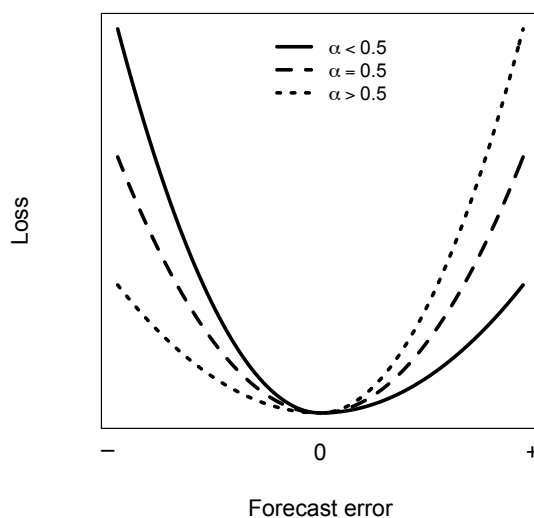
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Figure 1: Gold Price in Levels and Returns



Note: The real price of gold starts in 1979/Q1 at 100. Continuously compounded quarterly returns are expressed per year. The dashed vertical lines in the lower panels denote the 95% boundaries of the confidence intervals of the (partial) autocorrelation function.

Figure 2: Examples of a Quad-Quad Loss Function



Note: The figure shows examples of quad-quad loss functions for alternative values of the parameter α . A positive (negative) forecast error implies an underprediction (overprediction) of the actual rate of change of the real price of gold.

Table 1: Descriptive Statistics

Variable	Mean	Max	Min	SD	Cor
Rate of change of the real price of gold	2.22	166.44	-90.12	33.47	1.00
Rate of change of the real exchange rate	0.16	42.42	-81.35	16.37	-0.10
<i>Real interest rates</i>					
Canada	3.22	9.66	-4.94	3.16	-0.07
France	2.89	10.55	-3.31	2.96	-0.04
Germany	2.54	7.89	-2.47	2.41	-0.05
Italy	3.1	13.23	-9.28	3.79	-0.12
United Kingdom	3.5	11.88	-12.86	4.34	-0.11
United States	2.09	14.52	-6.41	3.37	-0.07

Note: *SD* = standard deviation. *Cor* = coefficient of correlation.

Table 2: Inclusion of the Predictor Variables in the Forecasting Models

Estimation window Criterion	Recursive Forecasting				Rolling-Window Forecasting			
	ACD	AIC	SIC	DCC	ACD	AIC	SIC	DCC
Rate of change of the real exchange rate	98.98	21.43	0.00	10.20	25.51	15.31	3.06	20.41
<i>Real interest rates</i>								
Canada	0.00	0.00	0.00	39.80	9.18	0.00	0.00	35.71
France	19.39	0.00	0.00	54.08	48.98	18.37	1.02	45.92
Germany	0.00	0.00	0.00	50.00	37.76	9.18	0.00	54.08
Italy	36.74	19.39	0.00	53.06	58.16	39.80	9.18	66.33
United Kingdom	19.39	9.18	0.00	0.00	12.25	1.02	0.00	35.71
United States	63.27	26.53	0.00	52.04	46.94	20.41	1.02	25.51

Note: We use a training period of 10 years to start the recursive real-time forecasting approach. The numbers given in this table are in percent. The length of the rolling window is equal to the training period.

Table 3: Forecast Evaluation Using the Out-Of-Sample Relative Loss Criterion (Recursive Real-Time Forecasting)

Panel A: Lin-lin Loss Function ($p = 1$)

		ACD	AIC	SIC	DCC	SCC	MCC	ACC	TCC
<i>10 year training period</i>									
α	0.10	-0.30***	-0.20**	0.00	-0.28***	-0.22***	-0.23**	-0.22***	-0.23***
	0.25	-0.23***	-0.16***	0.00	-0.21***	-0.17***	-0.17***	-0.17***	-0.17***
	0.50	-0.12***	-0.09**	0.00	-0.10**	-0.08*	-0.08*	-0.08*	-0.08*
	0.75	-0.03	-0.03	0.00	0.01	0.00	0.00	0.00	0.00
	0.90	0.03	0.00	0.00	0.06*	0.04	0.04	0.04	0.04
<i>15 year training period</i>									
α	0.10	-0.26***	-0.20**	0.00	-0.21***	-0.22***	-0.23***	-0.22***	-0.23***
	0.25	-0.18***	-0.15***	0.00	-0.14***	-0.15***	-0.16***	-0.15***	-0.16***
	0.50	-0.08**	-0.08**	0.00	-0.04	-0.05	-0.06	-0.05	-0.06
	0.75	0.01	-0.02	0.00	0.05*	0.04	0.03	0.04	0.03
	0.90	0.06	0.02	0.00	0.10**	0.08**	0.08**	0.08**	0.08**
<i>20 year training period</i>									
α	0.10	-0.30**	-0.23**	0.00	-0.26**	-0.26**	-0.26**	-0.26**	-0.26**
	0.25	-0.20***	-0.16**	0.00	-0.16**	-0.16**	-0.06**	-0.06**	-0.06**
	0.50	-0.06	-0.08**	0.00	-0.04	-0.04	-0.04	-0.04	-0.04
	0.75	0.04	-0.01	0.00	0.06*	0.06*	0.06*	0.06*	0.06*
	0.90	0.09	0.02	0.00	0.11**	0.10**	0.10**	0.10**	0.10**

Panel B: Quad-quad Loss Function ($p = 2$)

		ACD	AIC	SIC	DCC	SCC	MCC	ACC	TCC
<i>10 year training period</i>									
α	0.10	-0.37***	-0.29**	0.00	-0.44***	-0.26*	-0.26*	-0.26*	-0.26*
	0.25	-0.26***	-0.21**	0.00	-0.32***	-0.18*	-0.18**	-0.18*	-0.18*
	0.50	-0.13***	-0.11*	0.00	-0.17***	-0.08	-0.08	-0.08	-0.08
	0.75	-0.03	-0.03	0.00	-0.05	-0.01	0.00	-0.01	0.00
	0.90	0.01	0.00	0.00	0.01	0.03	0.04	0.03	0.03
<i>15 year training period</i>									
α	0.10	-0.30**	-0.27*	0.00	-0.27*	-0.25	-0.25*	-0.25	-0.25
	0.25	-0.20*	-0.19**	0.00	-0.18*	-0.16	-0.16*	-0.16	-0.16
	0.50	-0.08	-0.09	0.00	-0.08	-0.06	-0.06	-0.05	-0.06
	0.75	0.01	-0.02	0.00	-0.01	0.02	0.02	0.02	0.02
	0.90	0.05	0.01	0.00	0.03	0.05	0.06	0.05	0.05
<i>20 year training period</i>									
α	0.10	-0.28*	-0.26*	0.00	-0.28*	-0.24	-0.24*	-0.24	-0.24*
	0.25	-0.16*	-0.17*	0.00	-0.18*	-0.14	-0.14*	-0.14	-0.14
	0.50	-0.04	-0.08	0.00	-0.07	-0.03	-0.03	-0.03	-0.03
	0.75	0.04	-0.01	0.00	0.00	0.04	0.04	0.04	0.04
	0.90	0.08	0.02	0.00	0.03	0.07	0.07	0.07	0.07

Note: *** (**, *) denotes significance at the 1% (5%, 10%) level. A bootstrap simulation is used to assess the significance of the out-of-sample relative loss criterion. Bootstrap simulations are based on a block bootstrap (smoothing parameter 1/12, 250 simulation runs) as described by Politis and Romano (1994).

Table 4: Forecast Evaluation Using the Out-Of-Sample Relative Loss Criterion (Rolling Window Real-Time Forecasting)

Panel A: Lin-lin Loss Function ($p = 1$)

		ACD	AIC	SIC	DCC	SCC	MCC	ACC	TCC
<i>10 year rolling window</i>									
α	0.10	-0.34***	-0.24**	-0.03	-0.33***	0.03	0.05	0.03	0.05
	0.25	-0.26***	-0.18**	-0.02	-0.24***	-0.01	0.01	-0.01	0.01
	0.50	-0.13**	-0.10*	-0.01	-0.11**	-0.06	-0.05	-0.06	-0.06
	0.75	-0.02	-0.03	0.00	0.01	-0.11	-0.11	-0.11	-0.11
	0.90	0.04*	0.01	0.01	0.07**	-0.14	-0.14	-0.14	-0.14
<i>15 year rolling window</i>									
α	0.10	-0.28***	-0.23***	-0.02	-0.24***	0.00	0.00	0.00	0.00
	0.25	-0.19***	-0.16**	0.00	-0.15**	-0.02	-0.02	-0.02	-0.02
	0.50	-0.06	-0.09	0.02	-0.03	-0.05	-0.05	-0.05	-0.05
	0.75	0.04*	0.02	0.03*	0.08**	-0.07	-0.07	-0.07	-0.08
	0.90	0.10**	0.06*	0.04	0.13***	-0.08	-0.09	-0.08	-0.09
<i>20 year rolling window</i>									
α	0.10	-0.31***	-0.24***	-0.01	-0.27***	-0.06	-0.06	-0.06	-0.06
	0.25	-0.19***	-0.15***	0.01	-0.15***	-0.07	-0.06	-0.07	-0.06
	0.50	-0.03	-0.05	0.03	-0.01	-0.07	-0.07	-0.07	-0.07
	0.75	0.09**	0.03	0.04	0.10***	-0.08	-0.08	-0.08	-0.08
	0.90	0.14**	0.07*	0.05	0.15**	-0.08	-0.08	-0.08	-0.08

Panel B: Quad-quad Loss Function ($p = 2$)

		ACD	AIC	SIC	DCC	SCC	MCC	ACC	TCC
<i>10 year rolling window</i>									
α	0.10	-0.34	-0.27	0.02	-0.42	-0.08	-0.06	-0.09	-0.06
	0.25	-0.25	-0.20	0.01	-0.31	-0.11	-0.09	-0.11	-0.09
	0.50	-0.14	-0.11	0.00	-0.17	-0.14	-0.13	-0.14	-0.13
	0.75	-0.05	-0.05	-0.01	-0.06	-0.16	-0.16	-0.16	-0.16
	0.90	0.00	-0.01	-0.02	-0.01	-0.18	-0.18	-0.17	-0.18
<i>15 year rolling window</i>									
α	0.10	-0.29	-0.26	0.01	-0.26	-0.04	-0.03	-0.04	-0.03
	0.25	-0.19	-0.17	0.01	-0.17	-0.06	-0.05	-0.06	-0.05
	0.50	-0.06	-0.07	0.02	-0.06	-0.08	-0.08	-0.08	-0.08
	0.75	0.03	0.00	0.02	0.01	-0.09	-0.10	-0.09	-0.10
	0.90	0.07	0.03	0.02	0.05	-0.10	-0.11	-0.10	-0.11
<i>20 year rolling window</i>									
α	0.10	-0.27	-0.26	0.00	-0.27	-0.10	-0.10	-0.10	-0.10
	0.25	-0.14	-0.15	0.02	-0.16	-0.08	-0.08	-0.08	-0.08
	0.50	0.00	-0.04	0.03	-0.04	-0.07	-0.07	-0.07	-0.07
	0.75	0.09	0.03	0.04	0.04	-0.06	-0.06	-0.06	-0.06
	0.90	0.13	0.07	0.05	0.08	-0.05	-0.06	-0.05	-0.06

Note: *** (**, *) denotes significance at the 1% (5%, 10%) level. A bootstrap simulation is used to assess the significance of the out-of-sample relative loss criterion. Bootstrap simulations are based on a block bootstrap (smoothing parameter $1/12$, 250 simulation runs) as described by Politis and Romano (1994).