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On the efficiency of the gold market: Results of a real-time forecasting approach

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ABSTRACT

Using a real-time forecasting approach, we study whether publicly available information on a large set of financial and macroeconomic variables help in forecasting out-of-sample monthly excess returns on investing in gold. The real-time forecasting approach accounts for the fact that an investor must reach an investment decision in real time under uncertainty concerning the optimal forecasting model. The real-time forecasting approach also accounts for the possibility that the optimal forecasting model may change over time. We account for transaction costs and show that using forecasts implied by the real-time forecasting approach to set up a simple trading rule does not necessarily lead to a superior performance relative to a buy-and-hold strategy, implying that the gold market is informationally efficient with respect to the predictor variables that we study in this research.

1. Introduction

Much research has been done to deepen our understanding of the links between movements of the price of gold and important financial and macroeconomic variables. Some researchers have studied the link between the dynamics of the price of gold and the inflation rate (Blose, 2010; Fortune, 1987; Gosh, Levin, Macmillan, & Wright, 2004; Levin & Wright, 2006; Mahdavi & Zhou, 1997; among others). Other financial and macroeconomic variables that researchers have considered as determinants of gold-price fluctuations include interest rates, measures of the stance of the business cycle, and commodity prices (see, among others, Cai, Cheung, & Wong, 2001; Christie-David, Chaudhry, & Koch, 2000; Diba & Grossman, 1984; Fortune, 1987; Koutsoyiannis, 1983; Melvin & Sultan, 1990). The link between movements in the price of gold and exchange rates has also been under scrutiny (Capie, Mills, & Wood, 2005; Pukthuanthong & Roll, 2011; Reboredo,2013; Sjaastad, 2008; Tully & Lucey, 2007; to name just a few). Other researchers have analyzed whether gold is a "safe haven" investment against stocks in times of economic and financial crises (Baur & Lucey, 2010; Baur & McDermott, 2010; Hillier, Draper, & Faff, 2006).

Given the wide variety of financial and macroeconomic variables considered in earlier research as determinants or predictors of movements of the price of gold, we study the out-of-sample predictability of monthly excess returns of the price of gold by means of the real-time forecasting approach developed by Pesaran & Timmermann (1995, 2000). In earlier studies, several researchers have used the real-time forecasting approach to forecast stock returns (Alcock & Gray, 2005; Bohl, Döpke, & Pierdzioch, 2008; Bossaerts & Hillion, 1999; Hartmann, Kempa, & Pierdzioch, 2008), exchange rates (Sarno & Valente, 2009), and commodities (Vrugt, Bauer, Molenaar, & Steenkamp, 2007). Vrugt et al. (2007) use a variant of the real-time forecasting approach to study whether financial and macroeconomic variables help to forecast the excess returns on the Goldman Sachs Commodity Index (GSCI), which reflects investments in agricultural, energy, industrial metals, livestock, and precious metal (gold and silver) commodity futures. Unlike our research, their study focuses on commodities rather than on the price of gold. Precious metals make only a rather tiny contribution to the GSCI index. Moreover, their sample ends in 2004, implying that their study does not cover the recent period of rapid increases in the price of gold.

The recursive real-time forecasting approach rests on the insight that, when reaching an investment decision, an investor can only use the then available information on financial and macroeconomic variables to forecast excess returns. In addition, forecasting excess returns is complicated by the problem that an investor, in real time, must reach an investment decision under uncertainty concerning the "optimal" forecasting model. The real-time forecasting approach resolves this problem by assuming that an investor uses a search-and-updating technique to predict changes in the price of gold. The search part requires that an investor, in every period of time when an investment

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Table 1
Information criteria — thin modeling.

Criterion	Abbreviation	Formula	Decision rule
Adjusted coefficient of determination	*ACD*	$ACD_{t,i} = 1-\frac{(1-R^2_{t,i})(T_t-1)}{T_t-k_{t,i}}$	$\max_i\ ACD_{t,i}$
Akaike information criterion	*AIC*	$AIC_{t,i} = \ln\left(\frac{RSS_{t,i}}{T_t}\right) + \frac{2k_{t,i}}{T_t}$	$\min_i\ AIC_{t,i}$
Schwarz information criterion	SIC	$SIC_{t,i} = \ln\left(\frac{RSS_{t,i}}{T_t}\right) + \frac{k_{t,i}ln(T_t)}{T_t}$	$\min_i\ SIC_{t,i}$
Direction of change criterion	*DCC*	$DCC_{t,i} = \frac{1}{T_t}\sum_{s=t-T_t+1}^{t}\left[I(\hat{r}_{s,i})I(r_s)-(1-I(\hat{r}_{s,i})(1-I(r_s))\right]$	$\max_i\ DCC_{t,i}$
Amemiya prediction criterion	*APC*	$APC_{t,i} = RSS_{t,i}\frac{1+\frac{k_{t,i}}{T_t}}{(T_t-k_{t,i})}$	$\min_i\ APC_{t,i}$
Hannan–Quinn criterion	*HQC*	$HQC_{t,i} = \ln\left(\frac{RSS_{t,i}}{T_t}\right) + \frac{k_{t,i}ln(ln(T_t))}{T_t}$	$\min_i\ HQC_{t,i}$
Fisher information criterion	*FIC*	$FIC_{t,i} = RSS_{t,i}\frac{T_t}{T_t-k_{t,i}} + \ln\left(\left\lvert X'_{t,i}X_{t,i}\right\rvert / \frac{RSS_{t,i}}{T_t-k_{t,i}}\right)\frac{RSS_{t,k}}{T_t-k}$	$\min_i\ FIC_{t,i}$
Posterior information criterion	*PIC*	$PIC_{t,i} = RSS_{t,k}\left(\frac{RSS_{t,i}}{RSS_{t,k}}-1\right) + \ln\left(\left\lvert X'_{t,i}X_{t,i}\right\rvert / \frac{RSS_{t,k}}{T_t-k}\right)\frac{RSS_{t,k}}{T_t-k}$	$\min_i\ PIC_{t,i}$

Note: For the ACD model-selection criterion, see Theil (1966). For the AIC and SIC model-selection criteria, see Akaike (1973) and Schwarz (1978). For the DCC model-selection criterion, see also Pesaran & Timmermann (1995). For the APC and HQC model-selection criteria, see Amemiya (1980) and Hannan & Quinn (1979). For the FIC and PIC model-selection criteria, see Wei (1992) and Phillips & Ploberger (1992). See also Bossaerts & Hillion (1999). Notation: The index i denotes model i. The index k denotes a model that contains all predictor variable. R^2 denotes the coefficient of determination, T_t denotes the number of observations available in period of time t (or the length of the rolling window), k_i denotes the number of predictor variables included in model i in period of time t, k (without an index) denotes the number of predictor variables in a model that contains all predictor variables, $I(\cdot)$ denotes an indicator function that assumes the value one when its argument is positive, and zero otherwise, $X_{t,i}$ denotes the matrix of predictor variables used in period of time t under model i, and $(\hat{r}_{t+1,i})$ denotes the forecast of excess gold returns under model i. RSS denotes the residual sum of squares. If two or more models satisfy $\max_i DCC_{t,i}$, then an investor chooses among these models by using the ACD model-selection criterion.

decision must be reached, estimates a large number of forecasting models and then identifies an "optimal" model by means of some model-selection or model-averaging criterion. The updating part, in turn, requires, that an investor re-estimates the forecasting models whenever new information on financial and macroeconomic variables becomes available. The real-time forecasting approach, thereby, does not only account for model uncertainty but also for the possibility that the optimal forecasting model may change over time. Changes in the optimal forecasting model may arise due to structural breaks and regime shifts, as has been well-documented for common stocks in the extensive literature on return-prediction models (Hartmann et al., 2008; Paye & Timmermann, 2006; Perez-Quiros & Timmerman, 2000; Pesaran & Timmermann, 2002; Rapach & Wohar, 2006; Timmermann, 2001). Furthermore, empirical evidence shows that the sensitivity of gold-price fluctuations to macroeconomic news may have changed over time, not at least due to increasing financialization (Roache & Rossi, 2010).

In addition to studying the original model-selection-based "thin" modeling approach advocated by Pesaran & Timmermann (1995), we study an extension of the real-time forecasting approach known as "thick" modeling (Granger & Jeon, 2004). The "thick" modeling approach has become quite popular recently because it uses forecast combinations and model-averaging techniques rather than model-selection techniques to forecast excess returns (Aiolfi & Favero, 2005; Rapach, Strauss, & Zhou, 2010; among others). Furthermore, we compare a variant of the real-time forecasting approach that uses an expanding recursive data window to forecast excess returns on the price of gold with a variant that uses a rolling data window. We study the forecasts

Table 2
Information criteria — thick modeling.

Criterion	Abbreviation	Formula
Simple combination criterion	*SAV*	$\hat{r}_{t+1,SAV} = \frac{1}{2^k}\sum_{i=1}^{2^k}\hat{r}_{t+1,i}$
Median-based combination criterion	*MAV*	$\hat{r}_{t+1,MAV} = \text{median}(\hat{r}_{t+1,i})$
ACD-based combination criterion	*AAV*	$\hat{r}_{t+1,AAV} = \left(1/\sum_{i=1}^{2^k}ACD_{t,i}\right)\sum_{i=1}^{2^k}ACD_{t,i}\hat{r}_{t+1,i}$
Truncated combination criterion	*TAV*	$\hat{r}_{t+1,TAV} = \frac{1}{k_\sigma}\sum_{i=1}^{k_\sigma}\hat{r}_{t+1,i}$

Note: For similar model-averaging criteria, see, for example, Aiolfi & Favero (2005). For an explanation of notational conventions, see the note of Table 1. We use the notation k_σ to express that only forecasts enter into the computation of the TCC model-selection criterion that are within a plus/minus one standard deviation range around the mean value of all 2^k forecasts. 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.

implied by the various variants of the real-time forecasting approach using both statistical and economic criteria. As for the statistical criteria, we study market-timing tests (Cumby & Modest, 1987; Pesaran & Timmermann, 1992). Because a pure statistical analysis of forecasts may give misleading results as to the economic value-added of forecasts (Leitch & Tanner, 1991), we also treat gold as an investment asset and use economic criteria to assess the quality of forecasts. To this end, we study a simple trading rule by assuming that, depending on the sign of the real-time out-of-sample forecast of excess returns on holdings in gold, an investor invests either in gold or in a riskless alternative investment. We measure the performance of a simple trading rule in terms of terminal wealth and in terms of Sharpe's ratio (Sharpe, 1966), and we use White's (2000) bootstrap reality check to study the robustness of our results.

Our results show that the variant of the real-time forecasting approach that uses a rolling data window in many cases performs well, and that "thick" modeling yields in general more stable (but not necessarily superior) results than "thin" modeling. Given our trading rule, the performance of the various variants of real-time forecasting as compared to the performance of a buy-and-hold strategy, however, depends on the magnitude of transaction costs. Once we factor in transaction costs, the trading rule that uses the forecasts implied by the real-time forecasting approach hardly outperforms a buy-and-hold strategy. The results of the bootstrap reality check also demonstrate that the trading rule does not perform better than a buy-and-hold strategy, irrespective of whether we study a recursive or a rolling data window. In sum, our results confirm results of earlier research (Ho, 1985; Smith, 2002; Solt & Swanson, 1981; Tschoegl, 1980; see, however, Basu & Clouse, 1993) and suggest that, from the viewpoint of a U.S.-based investor, the gold market is reasonably efficient with respect to our financial and macroeconomic predictor variables. Vrugt et al. (2007), in contrast, report that their forecasting experiment yields returns that dominate the returns on a buy-and-hold strategy, even after accounting for the presence of transaction costs. The good performance of their trading strategy also holds, although to a lesser extent than in the cases of, for example, energy and industrial metals, for a precious metals GSCI subindex. Our results, in contrast, suggest that, if one confines the analysis to the price of gold, informational efficiency of the gold market with respect to the predictor variables being studied in this research cannot be rejected.[1]

[1] This efficiency result also complements results of recent research on the profitability of technical and momentum trading in commodity futures markets. For example, Fuertes, Miffre, & Rallis (2010) study technical trading strategies using data on futures contracts on a broad set of commodities and find that they yield positive abnormal returns. In another recent study, Marshall, Cahan, & Cahan (2008) study a large universe of trading rules involving commodity futures contracts and find that such trading rules are not profitable.