When Gold Meets Copper:

A Comprehensive Look at the Relative Value of Gold on Global Stock Markets

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October 2022

Abstract

We comprehensively examine the information content of the relative value of gold on global stock markets. Among gold prices relative to commodity prices (silver, oil, platinum, copper, and soybeans), consumer price (CPI), and stock price (Dow Jones Industrial Average), we find that the gold–copper ratio significantly predicts intermediate horizon stock returns for most developed countries, whereas other measures fail. Furthermore, the return predictability of the gold–copper ratio is mainly driven during bad economic periods classified by investor sentiment of Baker and Wurgler. Only the gold–copper ratio predicts 6-month excess stock returns for all 23 countries in our sample at the 5% significance level during low-sentiment periods, whereas other measures do not. During economic downturns, the overvaluation of gold compared to copper for seeking safe assets with low demand on industrial metals can considerably coincide with the increase of financial uncertainty level; thus, combined with the uncertainty–return tradeoff framework of Yu and Yuan (2011), gold–copper ratio predicts the future returns. Moreover, the role of copper as a signal economic recovery during these bad economic periods in the short-term affects the strong intermediate horizon predictive power of the gold–copper ratio. Additionally, the predictive power of the gold–copper ratio is valid out-of-sample and economically significant.

JEL classification: G12; G14

Keywords: Gold; return predictability; Gold-Copper ratio; global economic conditions; uncertainty level

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1. Introduction

It is well documented that aggregate stock markets are predictable. Such a return predictability pattern is observed in the U.S. market, which serves a leading role in the global stock market, and other major industrialized countries. Studies in international stock return predictability have mainly concentrated on testing the return predictability of traditional predictors, such as the short rate or dividend–price ratio, by constructing localized ones (e.g., Bekaert and Hodrick 1992; Ferson and Harvey 1993; Ang and Bekaert 2007; Hjalmarsson 2010). In line with this, recent studies suggesting a new return predictor in the U.S. market also conduct localized robustness checks on other industrialized countries (e.g., Cooper and Priestley 2009). Meanwhile, another strand of the literature has focused on uncovering a single indicator that simultaneously forecasts each country's market excess returns. For example, Rapach *et al.* (2013) and Chen *et al.* (2019) show that U.S. market variables [1] predict strongly for most industrialized countries. Møller and Rangvid (2018) provide evidence that global industrial production growth at the end of the year predicts 1-year returns ahead of the stock markets of individual countries.

Gold is a globally traded asset and is invested by major financial institutions as well as individual investors. Historically, gold is regarded as a safe haven, and its price reflects the fear level in the global economy. Although the gold price is a natural candidate for a global stock market predictor, it has not been studied as such.

In this paper, we examine the informative value of gold on the global stock market. Importantly, rather than the dollar value of gold, we analyze the relative value of gold to various assets since it has more suitable properties as a global market predictor. First, the time series of

[1] Rapach *et al.* (2013) use 1-month lagged U.S market returns, and Chen *et al.* (2019) rely on implied market skewness from the S&P500 option market.

the relative value of gold holds stationarity, which is suitable as a return predictor,[2] under a simple assumption that relative asset prices will mean revert in the long run as overvaluation or undervaluation persist. In addition, in contrast to the pro-cyclical pattern of dollar value over time, the relative value of gold to commodity prices or stock index is counter-cyclical, which is consistent with the general economic intuition that gold can be a helpful hedging vehicle and it is especially relevant under poor economic conditions, a so-called “safe haven”.

To test the return predictability of gold, we consider gold prices relative to commodity prices (silver, oil, platinum, copper, soybeans), consumer prices (CPI), and stock prices (Dow Jones Industrial Average) as global market predictors. We find that only the logarithm of the gold–copper ratio (gold–copper ratio, hereafter) strongly predicts 6-month and 1-year stock returns for most developed countries (17 out of 23 countries) and global aggregated stock market level returns. One notable result is that the gold–copper ratio strongly predicts returns of the Japanese and U.S. stock markets together at 1% statistical significance. Additionally, the return predictability of the gold–copper ratio is more pronounced in highly industrialized countries such as Sweden, South Korea, Taiwan, and Finland, than in countries with abundant natural resources (e.g., Canada and Australia).

Furthermore, we find that the return predictability of the gold–copper ratio is stronger during economic downturns. The overvaluation level of gold compared to copper corresponds to high expected stock returns and low current stock prices only during bad economic times. Specifically, we find a striking pattern: during bad times, the gold–copper ratio positively predicts 6-month excess stock returns for all 23 of our sample countries at the 5% significance level,

[2] It avoids spurious regressions and biased estimates using variables with a nearly unit root process.

whereas other measures do not. In other words, the strong return predictability of the gold–copper ratio for the un-conditioning case is mainly driven by its forecasting power during economic downturns. This result implies that the gold–copper ratio—the relative value of gold to copper—confirms a safe haven property of gold compared to copper. This property is behind the strong return predictability of the gold–copper ratio.

Why does only the gold–copper ratio strongly predict global stock market returns? Both gold and copper prices are both strongly related to economic conditions.[3] Indeed, we find a positive contemporaneous relationship between the gold–copper ratio and financial uncertainty measures, representing a “fear gauge” (e.g., VIX) during bad economic times. Therefore, we hypothesize that the overvaluation of gold compared to copper for seeking safe assets with low demand on industrial metals (e.g., copper) for production purposes can considerably coincide with the increase in financial uncertainty level, especially during bad economic times. Combined with the finding of Yu and Yuan (2011) that *ex-ante* risk–return (uncertainty–return) tradeoff is observed only during bad economic times, such a coincidence can lead to the strong return predictability of the gold–copper ratio. Moreover, an increase in copper price signals the macroeconomy to recover during the economic downturns. This role of copper, also known as “Dr. Copper,” affects the gold–copper ratio's predictive power during bad economic times.

Next, we conduct a battery of robustness checks regarding the return predictability of the gold–copper ratio. The results are robust under the presence of local and other global predictors suggested by the previous studies. In addition, the return predictability of the gold–copper ratio is valid out-of-sample and economically significant for most cases (16 out of 23 countries). Trading

[3] Several studies have shown that copper price is closely related to macroeconomic conditions. In this paper, we empirically show that copper price changes predict future GDP growth (up to four quarters).

strategies based on the gold–copper ratio can generate sizable economic gains for most countries, even considering transaction costs. Specifically, forecasts based on the gold–copper ratio lead to positive annualized certainty equivalent return (CER) gains for 17 of the 23 countries, and the CER gain associated with the global portfolios is approximately 3%.

This paper contributes to the well-established body of literature on the linkage between the gold market and other significant assets such as stocks, bonds, and currencies. For instance, Nguyen *et al.* (2019) examine the co-movements of expected gold returns with expected returns of stocks and bonds. In addition, numerous studies have investigated the relationship between the gold price and the value of major currencies (e.g., Sjaastad and Scacciavillani 1996; Pukthuanthong and Roll 2011). This paper adds new empirical evidence to the literature on the return predictability of gold for global stock markets, which has been rarely focused on in previous literature.

Our paper is also related to several other studies examining international stock return predictability (e.g., Rapach *et al.* 2013; Møller and Rangvid 2018; Chen *et al.* 2019; Chen *et al.* 2022). The novelty of our study is that we suggest a global return predictor that predicts stock returns for an extensive set of industrialized countries at intermediate horizons (6-months and 1-year), and its explanatory power is comparable to well-known powerful stock return predictors reported in the literature.

Finally, the solid contemporaneous relationship between the gold–copper ratio and financial uncertainty measures is in line with Baur *et al.* (2020) reporting the linkage between the gold–copper ratio and macroeconomic uncertainty. The strong return predictability of the gold–copper ratio only during low sentiments is also aligned with the findings of Yu and Yuan (2011).

The remainder of this paper proceeds as follows: Section 2 provides background on the relative value of gold as a return predictor. Section 3 describes the data and explains the variables of primary interest. Section 4 documents the return predictability of various measures associated with the relative value of gold in an international setting at various horizons and discusses the economic interpretation of the predictive pattern. Section 5 provides various robustness checks, including out-of-sample analysis. Section 6 concludes.

2. Relative Value of Gold as a Potential Return Predictor

The literature studying the linkage between the gold market and the stock market mainly focuses on the role of gold as a safe haven. A commonly accepted view is that the gold price tends to increase during market crashes (e.g., Baur and Lucey 2010; Baur and McDermott 2010; Reboredo 2013). However, as shown by Huang and Kilic (2019), the actual gold price fell during market crashes such as the recession of the early 1980s and the 2008–2009 Global Financial Crisis. This inability to observe the safe haven property of gold empirically might be a reason for mixed evidence about the role of gold as a safe haven in the extant literature.

Baur *et al.* (2020) suggest a new approach of analyzing the relative value of gold rather than the absolute value. This approach is motivated by an empirically observed fact that other commodity prices or asset prices substantially drop when compared to gold price during market crash periods, whereas the gold price falls only slightly. In other words, the relative value of gold substantially increases in bad economic times, and this pattern is consistent with the idea that gold serves as a safe haven. Baur *et al.* (2020) formally investigate the source of time-variation of the relative price of gold and show that heightened uncertainty increases the relative price of gold, confirming the role of gold as a safe haven.

Usage of the relative value of gold, which shows a pronounced counter-cyclical variation, can uncover a clear linkage between stock markets and gold price. We argue that this measure has a strong potential as a global stock market indicator due to its unique safe haven feature worldwide. To test it, we mainly rely on several key gold ratios using other commodity prices and stock indexes, as Baur *et al.* (2020) suggests. Note that we analyze with the logarithm of the gold ratios. The gold ratios utilized in this paper are as follows:

Gold–Silver Ratio: Similar to gold, silver also widely served as a currency and was historically used as a substitute for gold. Therefore, in academia, much research has been conducted to investigate their relationship, especially for co-integration issues (e.g., Chan and Mountain 1988; Wahab *et al.* 1994; Escribano and Granger 1998).

Gold–Platinum Ratio: Platinum is known as "white gold" and is regarded as a scarce resource. Together with silver, it is also used for industrial purposes, especially for autocatalysts of diesel vehicles. Huang and Kilic (2019) show that the gold–platinum ratio significantly predicts U.S. excess returns of the U.S. stock index. It should be noted that the platinum price substantially decreased after the Dieselgate scandal while palladium, which is used for autocatalysts of gasoline vehicles, increased, meaning that the platinum price is exposed mainly to industry-specific shocks. [4]

Gold–Copper Ratio: Copper is an essential raw material used as an input in many products in various industries (e.g., construction, automotive, and electronics). The well-known "Dr. Copper" concept explains price trends in copper's ability to predict the overall health of an economy.

[4] For more detail about the usage of autocatalysts and the price of platinum, see a report published by the CME group (https://www.cmegroup.com/education/articles-and-reports/is-automotive-demand-for-platinum-increasing-or-decreasing.html#)

Throughout the media, an increase in copper price has been referred to as a signal for recovery of the real economy.

Gold–Oil (Crude Oil) Ratio: Oil is an essential commodity used everywhere. Although the exposure of the oil price to business cycle risk due to its vast industrial usage is somewhat similar to industrial metal, the oil price is primarily affected by geopolitical events. A substantial body of literature has been established to explain oil price movements and price co-movement between oil and other assets.

Gold–Soybean Ratio: Soybean can be regarded as a representative grain commodity. Soybeans are consumed mainly in two major countries, the United States and China. Thus, the futures price of soybeans has been widely used as a barometer of the global economy in recent years (Cheng and Xiong 2014).

Gold–CPI (Consumer Price Index) Ratio: An inflation hedge is another significant role of gold from the asset allocation perspective. Thus, the gold–CPI ratio itself is an inflation-neutral measure. We obtain CPI data from Federal Reserve Economic Data (FRED).

Gold–DJIA (Dow Jones Industrial Average) Ratio: We use this proxy to measure the relative performance between gold and the stock markets. Compared to other metals such as platinum and copper, the stock index sometimes drops substantially, and the literature models this phenomenon as negative jumps. We select the Dow Jones Industrial Average (DJIA) as the representative stock index.

All historical commodity price data (gold, silver, platinum, copper, crude oil, soybean, corn, wheat, and aluminum) and S&P GSCI spot index data are from Datastream. Figure 1 plots the time series of the gold ratios from 1990 to 2019. Panel A displays the time-variation of the gold–silver ratio, gold–platinum ratio, gold–copper ratio, and gold–oil ratio and Panel B reports the gold–

soybean, gold–CPI, and gold–DJIA ratios. The shaded area is associated with recession periods determined by the National Bureau of Economic Research (NBER). All of the gold ratios increase substantially during economic recessions. Except for the gold–DJIA ratio, the gold ratios are relatively high after the Global Financial Crisis compared to the period before the Global Financial Crisis or the 1990s.

[Figure 1 about here]

Panel A of Table 1 documents the mean, standard deviation, skewness, kurtosis, minimum value, maximum value, and first-order autocorrelation of the monthly time series of the logarithm of the gold ratio. It should be noted that kurtosis is relatively low for most cases, meaning that the relative values of gold are stable, as their extreme movements are rare.[5] However, the first-order autocorrelation coefficients of the gold ratios are close to 1, indicating a near unit-root process, similar to that of output gap or capacity utilization which is a well-known macro-based return predictor. We calculate the augmented Dickey–Fuller statistics to formally test whether the gold ratios are a unit-root process. We find that the gold–silver ratio, gold–copper ratio, and gold–oil ratio are not unit-root variables at the 5% significance level, whereas other gold ratios are. This finding contrasts the results reported by Baur *et al.* (2020), showing that the augmented Dickey–Fuller test is rejected for most gold ratios. The main reason for such a discrepancy is that Baur *et al.* (2020) additionally use observations from 1960 to 1989, which show more dramatic and mean-reverting patterns.

[Table 1 about here]

[5] Low kurtosis in a data set indicates that data has light tails or lacks outliers.

3. Global Stock Market Data

To test the predictive power of the gold ratios for international market excess returns, we first investigate 23 industrialized countries: 1) G7 countries: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States; 2) developed countries in Europe: Australia, Belgium, Denmark, Finland, Ireland, Netherlands, Spain, Sweden, and Switzerland; and 3) developed countries in Asia-Pacific: Australia, Hong Kong, New Zealand, Singapore, South Korea, Taiwan, and Thailand. We obtain the monthly market returns in dollar terms for these 23 countries for January 1990 to June 2019 from Datastream. [6] Specifically, we use the Thompson Reuters Datastream market index. [7]We also analyze global aggregate stock market portfolios constructed based on both the equally weighted (EW) scheme and the value-weighted (VW) scheme. For the VW scheme, we use market capitalization in U.S. dollars as the combined weight to compute the value-weighted global aggregate stock market portfolios. We define market excess returns as the difference between the log returns and risk-free rates.

Panel B of Table 1 provides the statistical descriptions of the excess returns of the global aggregate stock market portfolios (EW and VW) and the excess returns of the individual countries. For all cases, the excess returns are leptokurtic (negative skewness and high kurtosis).

4. Main Results

[6] We set year 1990 as a starting point of our sample due to availability of international stock index data.
[7] For the robustness check of our results, we also analyze with international stock index data from Morgan Stanley Capital International (MSCI). The results based on MSCI are presented in the online appendix A.

This section examines whether the monthly gold–copper ratio predicts future international excess stock returns. We first estimate the baseline predictive regression of international excess stock returns for the global equal- and value-weighted aggregate portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific. Moreover, we explain our empirical results during economic expansions and recessions within various economic measures.

4.1. Predictive Regression of Gold Ratios to Excess Stock Returns

First, we run the following regression for 23 countries in our sample:

$$R^i_{t,t+h} = \alpha^i + \beta^i GR_t + \epsilon^i_{t+h} \tag{1}$$

where $R^i_{t,t+h}$ is the cumulative log excess return of each stock market (or portfolio) i for the horizon h. The cumulative log excess return $R^i_{t,t+h}$ is calculated over 1-month, 3-month, 6-month, 1-year, 2-year, and 3-year periods by using the monthly overlapping observations. GR_t represents the logarithm of a gold ratio. As described in Section 2, seven gold ratios (silver, platinum, copper, oil, soybeans, CPI, and DJIA) are considered. The null hypothesis is that a gold ratio has no predictability. In other words, the regression coefficient β^i is zero. In this baseline predictive regression, the in-sample predictability is tested by the Hodrick (1992) *t*-statistics corresponding to the regression estimated coefficient, β^i. Since the baseline predictive regression is based on overlapping observations, we use the Hodrick (1992) *t*-statistics because it is adjusted for predictive models with overlapping observations of the dependent variable side. If a gold ratio has predictive power, β^i should be different from zero, and we reject the null hypothesis, which states that the gold ratio contains valuable information in forecasting global stock markets. However, if the Hodrick (1992) *t*-statistics is insignificant, the baseline regression model reduces to the constant model, implying that the gold ratio does not have any predictive power. We also present the adjusted R-square statistic (R^2_{adj}) in order to display the explanatory power of the predictive regression model.

4.2. Short-Horizon Return Predictability: 1-Month and 3-Month

[Table 2 about here]

Table 2 reports the estimation results of the baseline regression model at the short forecasting horizons of 1 month and 3 months. Panel A and Panel B show the results for the 1-month and 3-month forecasting horizons, respectively. Panel A indicates that excluding the gold–copper ratio and gold–oil ratio, the 1-month horizon β^i values associated with gold ratios are statistically insignificant at the 10% significance level for more than 80% of the 23 countries. In the case of the gold–copper (gold–oil) ratio, we find that 1-month horizon β^i values are statistically significant at the 10% significance level for 9 (10) out of the 23 countries. When we analyze with global aggregate portfolios, only the 1-month horizon β^is associated with the gold–oil ratio are significant at the 10% significance level for both EW (*t*-stat = 1.94) and VW (*t*-stat = 2.35) global aggregate market portfolios, whereas the 1-month ahead return predictability of other gold ratios on the aggregate portfolios are non-existent. In sum, we cannot find any gold ratios showing a strong 1-month ahead return predictability on global stock markets.

The predictive pattern for the 3-month horizon is similar to that of the 1-month. Panel B shows that only the gold–copper and gold–oil ratios show weak cross-country return predictability patterns, while other gold ratios do not. Specifically, the gold–copper ratio strongly predicts for 10 (14) out of 23 countries at the 5% (10%) significance level and gold–oil ratio strongly predicts for 5 (9) out of 23 individual countries at the 5% (10%) significance level, indicating that the gold–oil ratio shows a weaker cross-country predictive power for a 3-month horizon than for a 1-month horizon. In the case of the global aggregate portfolios, both the gold–copper ratio and gold–oil ratios predict 3-month ahead excess returns of EW and VW global aggregate market portfolios significantly, whereas other measures do not. In terms of the explanatory power, the R^2_{adj} statistics associated with 1-month ahead predictability of the gold–oil ratios for EW and VW global aggregate market portfolios are 0.98% (0.64%) and 1.71% (0.18%), respectively. Even though the R^2_{adj} values are small, they are still economically sizable in magnitude.[8]

In summary, none of the gold ratios we consider in this study show a strong cross-country predictive pattern for short horizons. However, at aggregate portfolio level, gold–copper and gold–oil ratios matter for short-run return forecasting.

4.3. Intermediate-Horizon Return Predictability: 6-Month and 1-Year

Table 3 reports the results associated with intermediate forecasting horizons of 6 months and 1 year. Panel A and B show the results for the 6-month and 1-year forecasting horizons, respectively. We find that only the gold–copper ratio shows strong cross-country predictive patterns at 6-month and 1-year horizons, whereas other measures do not. Specifically, the gold–copper ratio strongly predicts 6-month excess stock returns for 14 (18) out of 23 individual countries at the 5% (10%) significance level and forecasts significantly 1-year ahead excess stock returns for 12 (15) out of 23 individual countries at the 5% (10%) significance level. The 6-month horizon β^i values are all positive for all countries, indicating that higher gold–copper ratio is associated with larger market risk premium for most well-developed countries.

[Table 3 about here]

[8] According to Campbell and Thompson (2008), monthly R^2_{adj} statistics near 0.5% can signal economically significant predictability.

Such a cross-country predictive pattern is not only limited to the specific country groups. According to Panel A, the 6-month horizon β^i values are statistically significant at the 5% significance level for five out of seven G7 countries, five out of nine European countries, and seven out of nine Asia-Pacific countries. One striking finding is that the 6-month ahead return predictability of the gold–copper ratio is pronounced in both the U.S. (t-stat = 2.71) and Japanese markets (t-stat = 3.26), and also it is clearly evident in manufacturing countries such as South Korea (t-stat = 2.44), Sweden (t-stat = 2.16), and Taiwan (t-stat = 2.88). The strong cross-country return predictability of gold–copper ratio for intermediate horizons is also confirmed at the aggregate portfolio level. The gold–copper ratio strongly predicts the excess returns of EW and VW global aggregate market portfolios at a 5% significance level for both 6-month horizon. The similar pattern can be found for the return predictability of gold-copper ratio for return of 1-year horizon. In terms of explanatory power, the R^2_{adj} statistics associated with the 1-year ahead predictability of the gold–copper ratio for VW (EW) global aggregate market portfolio is 10.99% (10.24%). In the case of the individual countries, the R^2_{adj} statistics for the gold–copper ratio range from 2.85% to 15.57% and they are more pronounced for major countries such as Japan (15.57%) and the United States. (12.80%). The explanatory power of the gold–copper ratio is comparable to well-known powerful return predictors in the literature, as Rapach *et al.* (2016) argue that annual R^2_{adj} statistics of 12.89%, the value they report, is arguably the strongest for forecasting returns of aggregate stock markets.

Overall, we find strong evidence that the gold–copper ratio positively predicts future market excess returns for most developed countries for intermediate horizons, and its explanatory power is sizable.

4.4. Long-Horizon Return Predictability: 2-Year and 3-Year

Finally, we investigate the long-horizon return predictability of the gold ratios. Table 4 shows the 2-year (Panel A) and 3-year (Panel B) horizons. When we investigate through our variable of interest, gold–copper ratio, whereas its 3-year ahead return predictability almost disappears, it predicts 2-year returns for six (12) out of 23 countries at the 5% (10%) significance level, indicating that the long-run predictability of the gold–copper ratio is weak or non-existent. For the other gold ratios, the cross-country return predictability is non-existent. One result is that there is a tendency for the long-horizon return predictability of the gold–silver ratio to exist for some countries. The gold–silver ratio significantly predicts 2-year and 3-year returns for seven of the 23 countries.

[Table 4 about here]

Regarding the explanatory power, R^2_{adj} statistics for VW global aggregate market portfolios are 22.42% for the 2-year horizon and 19.24% for the 3-year horizon, showing that for long horizons, its explanatory power decreases as the forecasting horizon increases. This pattern also indicates that the long-run predictability of the gold–copper ratio is weak or non-existent.

To summarize, no gold ratios show strong cross-country return predictability for forecasting horizons longer than 1 year.

4.5. Can the Gold–Copper Ratio Show a Safe Haven Property?

So far, we have shown that among various gold ratios and forecasting horizons, only the gold–copper ratio significantly predicts stock returns for most countries for intermediate horizons. The next logical step is to test whether the gold–copper ratio is a safe haven, as expected from the selection of the relative valuation of gold rather than its absolute value (dollar term). Under the existence of the safe haven property, a high gold–copper ratio corresponds to a low current stock price and high expected stock returns only during bad economic times. We hypothesize that the return predictability of the gold–copper ratio is only valid during economic downturns if the gold–copper ratio acts as a safe haven.

Before testing the hypothesis associated with the asymmetric effect, we need to define the classification standard of good and bad economic states. Even though numerous studies have relied on business cycle (e.g., NBER, ECRI) classification in studying the asymmetry in the predictability of economic variables, we utilize the classification based on the investment sentiment suggested by Baker and Wurgler (2006). The main reason for using the investment sentiment is our small sample size issue. Recession periods classified by NBER or ECRI are too scarce for our sample (1990–2018),[9] so the statistical inference on the coefficients associated with recession periods might be problematic. Additionally, most recession periods classified by NBER or ECRI in our sample are highly related to the Global Financial Crisis; thus, the return predictability evidence might be driven by one short episode. Such a concern is well documented in Priestley (2019). He shows that the return predictability of aggregate short interest, reported by Rapach *et al.* (2016), disappears when excluding data for 2008 when the Global Financial Crisis had its most immense impact on stock markets. However, we can solve this problem by guaranteeing enough samples for both good and bad economic periods when classified by the investor sentiment index from Baker and Wurgler (2006), as most papers in the literature on behavioral studies define high and low investor sentiment states by splitting a data sample based on its median value.

[9] Based on the NBER indicator, only 10.6% of monthly observations (total 37 months) are classified as recession months.

There is a concern that using investment sentiment is not appropriate for defining economic states because several papers treat Baker and Wurgler's (2006) sentiment index as a behavioral variable that might be unrelated to economic conditions. However, as stated by Sibley *et al.* (2016), most of the six proxies used for constructing the sentiment index of Baker and Wurgler (2006) are closely related to risk factors, stock market conditions, and the overall business environment. Sibley *et al.* (2016) also document that Baker and Wurgler's (2006) investor sentiment index is strongly correlated with business cycle variables such as the short interest rate and liquidity factors. Therefore, the choice of investment sentiment can be justified.[10]

We test the asymmetry in the return predictability associated with gold ratios by employing the state-switching model based on the investment sentiment. The model is specified below:

$$R^i_{t,t+6} = \alpha^i_1 \cdot D_{1,t} + \alpha^i_2 \cdot D_{2,t} + \beta^i_1 \cdot GR_t \cdot D_{1,t} + \beta^i_2 \cdot GR_t \cdot D_{2,t} + \epsilon^i_{t,t+6} \qquad (2)$$

where $R^i_{t,t+6}$ is the 6-month[11] cumulative excess return of each stock market (or portfolio) i, GR_t represents the logarithm of gold ratios, $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods. Low- and high-sentiment samples are split based on the median[12] of the investment sentiment index of Baker and Wurgler (2006).

Table 5 documents the results of the return predictability conditioning on the investment sentiment for 6-month horizons. Panel A reports the results for the gold–silver ratio, gold–platinum ratio, gold–copper, and gold–oil ratio, and Panel B shows the results for the gold–soybean ratio, gold–CPI ratio, and gold–DJIA ratio. We find a striking pattern; during low-sentiment periods

[10] Most observations during GFC periods are classified as bad sentiment states.

[11] We only report the 6-month ahead (intermediate horizons) prediction case that is associated with the outstanding performance of gold–copper ratio. Even though not reported, we also find qualitatively similar results when we examine with 1-year forecasting horizon.

[12] The median value is based on the sample period from 1990 to 2018.

only the gold–copper ratio predicts 6-month excess stock returns for all 23 countries at the 5% significance level.

[Table 5 about here]

In sum, the gold–copper ratio, the relative value of gold compared to copper, shows a safe haven property. This property mainly drives the strong return predictability of gold–copper for the un-conditioning case.

4.6. Economic Explanation: Why Does Only the Gold–Copper Ratio Matter?

The most striking pattern throughout our analysis is that only the gold–copper ratio significantly predicts stock returns for most countries while other gold ratios fail to do so. Additionally, only the gold–copper ratio shows the asymmetric predictive relationship consistent with the concept of "safe haven." The next natural question is why only the gold–copper ratio matters for return prediction worldwide. In this section, we further investigate its driving source.

4.6.1 Linkage Between Gold–Copper Ratio and Uncertainty

One possible channel is that only the gold–copper ratio captures the global market uncertainty level well during bad economic times. This linkage can generate the safe haven property of the gold–copper ratio. Relevant studies that link the gold–copper ratio with uncertainty are scarce; however, Baur *et al.* (2020) document that macroeconomic uncertainty explains the time-variation of the gold–copper ratio. The gold price has been regarded as a proxy for safe haven demand that captures the overall fear level in the market. The copper price has also been suggested to reflect the overall economic conditions of a market. Copper is a critical industrial metal globally used in a wide range of industrial applications. Historically, its price has garnered a substantial amount of attention during economic recessions. Whereas other commodities are primarily exposed to geopolitical risk (e.g., oil) or climate risk (e.g., grain), copper price is mainly exposed to business cycle risk because it is primarily driven by demand shocks rather than supply shocks (Stuermer 2018). Therefore, we argue that during economic downturns, the overvaluation of gold compared to copper for seeking safe assets with low demand on copper, the industrial metal, for production purposes can considerably coincide with the increase of financial uncertainty level.

Based on this argument, we establish a hypothesis that explains the unique pattern associated with the return predictability of the gold–copper ratio during bad economic times in comparison to other gold ratios. Suppose the channel associated with the strong relationship between the gold–copper ratio and aggregate uncertainty level is only valid during periods of low investor sentiment. In this case, we expect the contemporaneous relation between the gold–copper ratio and the uncertainty measures is strong while other gold ratios are not. Moreover, combined with the argument that a positive return–uncertainty relationship is present only during bad economic times,[13] the pattern will lead to the strong return predictability of the gold–copper ratio during periods of low investor sentiment, as shown in Section 4.5.

In order to test this argument, the relevant model for detecting the contemporaneous relationship is specified as

$$U_t = \alpha_1^i \cdot D_{1,t} + \alpha_2^i \cdot D_{2,t} + \beta_1^i \cdot GR_t^i \cdot D_{1,t} + \beta_2^i \cdot GR_t^i \cdot D_{2,t} + \epsilon_t^i \tag{3}$$

where U_t is the uncertainty measure, GR_t^i represents the logarithm of each gold ratio i, $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-

[13] Yu and Yuan (2011) demonstrate that market volatility predicts stock market returns only during low market sentiment periods and argue that this is due to the strong influence of sentiment investors during high-sentiment periods. Therefore, we investigate whether the uncertainty channel and the return predictability pattern of gold ratios are only valid under specific economic conditions.

sentiment periods. We consider two groups of monthly aggregate uncertainty proxies. One group consists of aggregate uncertainty measures in the U.S. stock market: stock market variance (SVAR), implied volatility (IV) and variance risk premium (VRP).[14] The other group comprises uncertainty measures presented by Jurado *et al.* (2015), which are constructed from an extensive set of financial and macroeconomic variables: macroeconomic uncertainty (MU), real uncertainty (RU), and financial uncertainty (FU).[15] If a gold ratio strongly moves in the same direction with uncertainty measures only during low-sentiment periods, we expect that β_2 is significantly positive and β_1 is statistically insignificant.

Table 6 shows the second test's corresponding equation (3) results. Panel A shows the results for aggregate stock market uncertainty measures and Panel B is associated with the uncertainty measures of Jurado *et al.* (2015). Panel A indicates that only the gold–copper ratio positively moves with stock market uncertainty measures during low-sentiment periods at the 5% significance level, regardless of various uncertainty measures. However, we cannot find any cases with a positive β_2 value except for a combination of the gold–oil ratio and VRP. Panel B indicates that the gold–copper ratio positively moves only with FU. In contrast, the gold–copper ratio is negatively correlated with MU and RU. The positive β_2 value for the gold–copper ratio and FU seems more striking as the negative correlation or insignificant relationship between gold ratios, and the uncertainty measures of Jurado *et al.* (2015) is observed for most cases. Overall, during low-sentiment periods, the gold–copper ratio can be an indicator that reflects uncertainty levels in

[14] SVAR is from Amit Goyal's website. IV and VRP are from Hao Zhou's website (https://sites.google.com/site/haozhouspersonalhomepage/).

[15] We obtain the uncertainty measures of Jurado *et al.* (2015) from Sydney Ludvigson's website (https://www.sydneyludvigson.com/data-and-appendixes). For more details about the construction of the uncertainty measures, see Jurado *et al.* (2015).

the global financial markets, rather than the macroeconomy, as it is positively correlated with stock market uncertainty or financial market uncertainty.

[Table 6 about here]

In summary, the contemporaneous relationship between the gold–copper ratio and uncertainty measures in the financial markets is strong only during low-sentiment periods. Among various gold ratios, this pattern is only observed for the gold–copper ratio. The result suggests that we can treat the gold–copper ratio as a proxy for FU under specific economic conditions, in line with Baur *et al.* (2020) reporting the linkage between the gold–copper ratio and MU.

Thus, during bad economic times, the gold–copper ratio can be regarded as a valuable and powerful indicator reflecting the uncertainty level in the global financial markets. The gold–copper ratio is informative in predicting future stock returns for most developed countries. Our result aligns with the findings of Yu and Yuan (2011).

4.6.2 Discussion: The Role of Copper

Using the gold price and copper price together and utilizing the relative ratio of gold is quite effective in uncovering the safe haven property of gold. More importantly, the use of the copper price is crucial. Our explanation mainly relies on the unique feature that copper is widely used in the real economy. Furthermore, in comparison to other commodities, the copper price is mainly sensitive from the demand side. An increase in the copper price can signal that future economic conditions will improve. Several studies focus on the relationship between the copper price and the macroeconomy. Barsky and Kilian (2001) first report that increases in industrial commodity prices are related to economic booms. Stuermer (2017) shows that an increase in manufacturing output leads to an increase in copper demand, which mainly drives the change in the copper price, as shown by Stuermer (2018). The relation also affects the asset prices in the market. For instance, Jacobsen *et al.* (2019) show that increased prices of industrial metals such as copper and aluminum are welcome news for equity markets in recessions and unwanted news in expansions. Therefore, as evidenced by the findings in the previous studies, it is worthwhile to thoroughly explore the role of copper from the perspective of international stock return predictability.

In this section, we further investigate the role of copper in explaining the return predictability pattern associated with the gold–copper ratio by formally testing its relationship with the global economy and stock prices in the global stock market.

We first examine whether copper price changes affect future economic conditions, conditioning the investment sentiment. It is worth noting that we utilize the logged commodity price change since the logged commodity price itself fails to pass the unit-root test. For measuring global (mainly developed countries) future economic conditions, we use the GDP growth of the U.S. economy. We run the following regression model:

$$\ln(GDP)_{t,t+h} = \alpha_1 \cdot D_{1,t} + \alpha_2 \cdot D_{2,t} + \beta_1 \cdot \Delta\ln(Comm)_{t,} \cdot D_{1,t} + \beta_2 \cdot \Delta\ln(Comm)_{t,} \cdot D_{2,t} + \epsilon^{i}_{t+h}, \quad (4)$$

where $\ln(GDP)_{t,t+h}$ is the next year's growth, $\Delta\ln(Comm)_t$ represents the logarithm change of commodity prices, $D_{1,t}$ is the dummy variable for high-sentiment periods, and $D_{2,t}$ is the dummy variable for low-sentiment periods. We focus on five commodities (silver, platinum, copper, crude oil, and soybeans) that are used for our primary analysis with gold ratios. We consider the following forecasting horizons: 1-, 2-, 4-, and 8-quarter. As GDP growth data are available quarterly, the regression is quarterly based.

According to the results of the market conditioning analysis in Table 7, only copper has information on near future GDP growth (up to 4 quarters) during bad economic times, whereas other commodities do not. The predictive relationship between future GDP growth and the copper price does not hold for the 8-quarter ahead forecast. The results indicate that during economic downturns, a decrease (an increase) in copper price uniquely signals that economic conditions will worsen (improve) shortly. This finding is consistent with the widely accepted view related to the role of commodities in predicting economic condition. Furthermore, the pattern that the strong predictive relationship holds up to the 4-quarter horizon but not the 8-quarter horizon provides some explanation for why the return predictability of the gold–copper ratio is mainly valid at the intermediate horizon (6-month ahead or 1-year ahead).

[Table 7 about here]

Next, we examine how global stock markets incorporate the information embedded in the copper price, which is relevant for economic conditions in the near future. We conjecture that global stock markets quickly react to the information embedded in the copper price as a signal, especially when the market situation is poor. The regression model is specified as follows:

$$R_t^i = \alpha_1^i \cdot D_{1,t} + \alpha_2^i \cdot D_{2,t} + \beta_1^i \cdot \Delta\ln(Copper)_{t,} \cdot D_{1,t} + \beta_2^i \cdot \Delta\ln(Copper)_{t,} \cdot D_{2,t} + \epsilon_{t+h}^i, \tag{5}$$

where R_t^i is the monthly stock return for each developed country i, $\Delta\ln(Copper)_t$ represents the logarithm change in the copper price, $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods.

The relevant results from Table 8 indicate that most countries have a positive contemporaneous relationship between stock returns and the copper price. This relationship is amplified during periods of low sentiment. Specifically, β_2^i, the sensitivity during bad economic times, is greater than β_1^i (the sensitivity for good economic times) for all countries except South Korea. We interpret this to mean that the change in copper price is a signal that the economic situation could worsen (improve) and thus, the market participants react to that signal pessimistically (optimistically) and instantly, which leads to the decrease (increase) of current asset prices.

[Table 8 about here]

Overall, the drivers behind the return predictability of the gold–copper ratio under bad economic conditions can be summarized as follows: (i) the gold price decreases slightly or is relatively flat; (ii) the copper price decreases as future economic output is expected to be low; (iii) the current stock price decreases substantially in response to the copper price decrease, which contains information about near future (up to the 4-quarter horizon) economic conditions; and (iv) the gold–copper ratio shows a strong counter-cyclical pattern and coincides with other financial uncertainty measures considerably.

5. Robustness Checks

In this section, we conduct a battery of robustness checks for the strong return predictability of the gold–copper ratio. Section 5.1 shows the return predictability of the gold–copper ratio after controlling for alternative U.S. market-based predictors. Section 5.2 investigates the robustness of the return predictability in the presence of alternative local market predictors. Section 5.3 examines its out-of-sample performance, and Section 5.4 presents an asset allocation analysis based on the out-of-sample forecasting power.

5.1. Controlling Alternative U.S Market-Based Predictors

The extant literature reports the role of the U.S. predictors in predicting international excess stock returns. Ang and Bekaert (2007) and Rapach *et al.* (2013) show that dividend yield is one of the most prominent economic predictors that enter directly into international return predictability studies. Bollerslev *et al.* (2014) and Londono (2015) highlight the predictive power of the U.S. variance risk premium (VRP) for international excess stock market returns. Following the spirit of literature, we add two alternative U.S. variables to the baseline regression from Section 4.2: the dividend–price ratio in Ang and Bekaert (2007) and the U.S. VRP in Bollerslev *et al.* (2009). We follow Bollerslev *et al.* (2009) and define the monthly VRP as the difference between the squared monthly VIX and the monthly realized variance, the sum of the squared daily returns within a month. In this section, the predictive regression model becomes

$$R^i_{t,t+h} = \alpha^i + \beta^i_1 DP^{US}_t + \beta^i_2 VRP^{US}_t + \beta^i_3 \log GC_t + \epsilon^i_{t+h} \quad (6)$$

where $R^i_{t,t+h}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of gold–copper ratio. DP^{US}_t is a dividend–price ratio of the U.S. stock market, and VRP^{US}_t is the U.S. variance risk premium as in Bollerslev *et al.* (2009). The cumulative excess return $R^i_{t,t+h}$ is calculated over 3-month, 6-month, and 1-year periods by using the monthly overlapping observations. The international stock market data are from Datastream.

Table 9 reports the estimation results of the regression model. The coefficient of VRP^{US}_t is multiplied by 100 for readability. Panels A, B, C, and D show the results for the global aggregate portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. The table shows the results for the annualized excess return of the market portfolio, $R^i_{t,t+h}$ calculated within each country's stock market return on horizon for the 3-month, 6-month, and 1-year periods. After controlling for the two U.S. forecasting variables, all β_3^i coefficients remain positive, which is consistent with our results in Table 2.

[Table 9 about here]

When we analyze global aggregate portfolios, five out of six of the 3-month, 6-month, and 1-year horizon β^i values of the gold–copper ratio are significant are at the 10% significance level for both EW and VW global aggregate market portfolios. Specifically, for the 1-year horizon, the β^i values are 0.245 (*t*-stat = 2.09) with EW portfolios and 0.209 (*t*-stat = 2.09) with VW global aggregate market portfolios. Moreover, according to Panel B, for the 6-month horizon β_3^i values, five are statistically significant out of seven G7 countries at the 10% level or better. Moreover, Panels C and D show similar results to Panel B. For the developed countries in Europe (Panel C), six out of nine β_3^i values are statistically significant at the 10% level or better. Similarly, for the developed countries in Asia-Pacific (Panel D), four out of seven β_3^i values are statistically significant at the 10% level or better. The results suggest incremental forecasting information in the gold–copper ratio. The R_{adj}^2 values of regression (3) for 1-year ahead excess market returns are economically significant, ranging from 3.87% (Canada) to 24.80% (United States) for Panel A, 4.12% (Finland) to 8.33% (Netherlands) for Panel B, 5.05% (Republic of Korea) to 9.38% (Hong Kong) for Panel D. This indicates that incorporating the gold–copper ratio into existing predictive models from prior studies can further improve the predictability of international excess stock returns.

Table 9 also presents the forecasting results for DP_t^{US} and VRP_t^{US}. According to the previous literature, VRP_t^{US} has strong predictive power for international stock markets; however, when the gold–copper ratio is included in the regression, only three out of 23 β_2^i coefficients are statistically significant at least the 10% level. Similar patterns also occur in the case of DP_t^{US}. DP_t^{US} significantly predicts only three markets when we include the gold–copper ratio as the control variable.[16]

Overall, we confirm that the predictive power of variables that are well known to predict the excess return of the international stock market weaken when the gold–copper ratio is included in the regression. In other words, we can say that the predictability of the gold–copper ratio is robust to some extent.

5.2. Controlling Alternative Local Market Predictors

Ang and Bekaert (2007), Rapach *et al.* (2013), and other studies about the return predictability among international or domestic stock market returns show the effect of dividend yields on domestic excess stock returns. Furthermore, the local stock market risk, such as expected market variance, can explain the local stock market excess return. Therefore, we control for these two local economic variables. We construct the expected market variance based on the realized historical data instead of the option-implied measures because of lack of data availability for the international markets. Following Paye (2012) and other methodologies of computing the monthly realized variance, we sum the squared daily returns within a month. We then estimate a first-order autoregressive model for the monthly realized variance and use the estimated parameters along with the information observable at the end of each month. The calculated variable is denoted as the expected realized variance of the country for the next month (ERV_t^i). We obtain the local

[16] We also check the return predictability of the gold–copper ratio in the presence of well-known macroeconomic predictors. We consider output gap and capacity utilization as a single control variable. The results are qualitatively similar to those associated with Table 9. The relevant results are reported in the online appendix B.

dividend yields from Datastream. Then, we incorporate the estimated expected variance into the regression; thus, the specified predictive regression is

$$R_{t,t+h}^{i} = \alpha^{i} + \beta_{1}^{i} ERV_{t}^{i} + \beta_{2}^{i} DY_{t}^{i} + \beta_{3}^{i} \log GC_{t} + \epsilon_{t+h}^{i} \tag{7}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i for horizon h, and $\log GC_t$ represents the log of the gold–copper ratio. ERV_t^i denotes the expected realized variance of country i at time t. DY_t^i is the dividend yield of country i at time t. The cumulative excess return $R_{t,t+h}^{i}$ is calculated over 3-month, 6-month, and 1-year periods based on monthly overlapping observations. The international stock market data are from Datastream.

Table 10 reports the estimation results of the regression model. The coefficient of VRP_t^{US} is multiplied by 100 for readability. Panels A, B, and C show the results for the G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. The table shows the results for the annualized excess return of market portfolio, $R_{t,t+h}^{i}$ calculated within each country's stock market return on the 3-month, 6-month, and 1-year horizons. After controlling for the two U.S. forecasting variables, all β_3^i coefficients remain positive, which is consistent with our results in Table 2. According to Panel A, for the 6-month horizon β^i values, four out of seven G7 countries are statistically significant at the 10% level or better. Moreover, Panels B and C show similar results to Panel A. For the developed countries in Europe (Panel B), six out of nine β^i values are statistically significant at the 10% level or better. Similarly, for the developed countries in Asia-Pacific (Panel C), four out of seven β^i values are statistically significant at the 10% level or better. The results are in line with our previous findings. The R_{adj}^2 values of regression (3) of 1-year time horizon excess stock market return are economically large, ranging from 2.16% (Canada) to 12.02% (United States) for Panel A, 1.20% (Spain) to 9.04%

(Belgium) for Panel B, and 5.26% (Republic of Korea) to 21.79% (Hong Kong) for Panel C. This suggests that the gold–copper ratio contains additional information beyond the local economic variables or local risk measures.

[Table 10 about here]

In contrast to the gold–copper ratio, the local economy and market risk measures, DY_t^i and ERV_t^i show limited predictive abilities. ERV_t^i does not significantly predict the excess stock returns for any country at the 10% significance level, while DY_t^i has significant predictive power for only Hong Kong, Singapore, Taiwan and Thailand. The significant results appear only for some developed countries in Asia-Pacific, and there is no predictive power for the G7 countries or developed countries in Europe. One possible reason for the low predictive power of local market risk or economic measures might be the usage of ERV based on historically realized variance rather than option-implied variance. In other words, neither the local stock market risk nor dividend yields can explain the predictive power of the gold–copper ratio. The results suggest that the forecasting information of the gold–copper ratio is still significant whether the local variables are controlled.

5.3. Out-of-Sample Performance

Given the solid in-sample international market return predictability of the gold–copper ratio, we now assess the out-of-sample performance. Welch and Goyal (2008) point out that in studying real-time return predictability, out-of-sample tests seem more relevant since the out-of-sample test can examine the data-generating process's stability and avoid the over-fitting problem in the in-sample predictability regression.

To analyze out-of-sample stock return predictability, the accuracy of the predictive regression forecast is compared to the historical average benchmark forecast, which assumes constant expected excess returns. Following the out-of-sample methodology of Campbell and Thompson (2008) and Welch and Goyal (2008), we start with an initialization period from January 1990 to December 1999 and estimate the predictive regression (5) for the international stock equity excess returns. First, we produce the out-of-sample forecast for January 2000. Then, we repeat the out-of-sample forecasting step after expanding the estimation window and obtain the out-of-sample forecast estimates until we reach the end of the sample period. The out-of-sample forecast evaluation period ranges from January 2000 to June 2019. In order to have sufficient observations for precise estimation of the initial parameters and have a relatively long out-of-sample period to evaluate the forecast, we set the initialization period and out-of-sample period as 10 years. Following the methodology of well-known Campbell and Thompson (2008) R_{os}^2 statistic and Clark and West (2007) mean squared forecasting errors (MSFEs), MSFE-adjusted statistics are calculated to evaluate the out-of-sample regression suitability.

The R_{os}^2 statistic is

$$R_{os}^2 = 1 - \frac{SS_{res}}{SS_{tot}} = 1 - \frac{MSFE_i}{MSFE_0} = 1 - \frac{\sum_{t=n}^{T-1}\left(R_{t+1}^i - \hat{R}_{t+1}^i\right)^2}{\sum_{t=n}^{T-1}\left(R_{t+1}^i - \bar{R}_{t+1}^i\right)^2} \tag{8}$$

where SS_{res} is the residual sum of squares, SS_{res} is the total sum of squares, R_{t+1}^i is the actual monthly stock market excess return for country I, $\hat{R}_{t+1}^i$ is the forecasted excess stock return based on the regression, and $\bar{R}_{t+1}^i$ is the historical average benchmark. The R_{os}^2 can range from a negative value to 1; A positive R_{os}^2 implies that the predictive regression forecast $\hat{R}_{t+1}^i$ outperforms the historical benchmark $\bar{R}_{t+1}^i$ in terms of the out-of-sample MSFEs. The R_{os}^2 from Campbell and Thompson (2008) is a convenient statistic for comparing MSFEs. It is analogous to the conventional in-sample R^2_{adj} and measures the proportional reduction in MSFE for the predictive regression forecast relative to the historical average. While R^2_{os} measures the improvement in MSFE, we want to test whether the improvement is statistically significant; we want to test the null hypothesis that the historical average MSFE is less than or equal to that of the predictive regression forecast against the one-sided (upper-tail) alternative hypothesis that the historical average MSFE is greater than that of the predictive regression forecast. Therefore, we are interested in the following hypothesis: H_0: $MSFE_0 \leq MSFE_i$ against H_A: $MSFE_0 > MSFE_i$; in other words, H_0: $R^2_{os} \leq 0$ against H_A: $R^2_{os} > 0$.

[Table 11 about here]

Table 11 presents the out-of-sample forecasting results for the 23 industrialized countries for the forecast evaluation period from January 2000 to June 2019. The MSFE-adjusted statistics are reported in parentheses. When we analyze with global aggregate portfolios, the 3-month, 6-month, 1-year, and 2-year horizon R^2_{os} values associated with the gold–copper ratio are significant are at the 10% significance level for both EW and VW global aggregate market portfolios. Specifically, according to Panel A, for the 1-year horizon, the R^2_{os} values are 11.190 (MSFE-adjusted statistics = 1.65) with EW portfolios and 12.025 (MSFE-adjusted statistics = 1.84) with VW global aggregate market portfolios. For the individual countries, the R^2_{os} values of regression (3) of the 1-year time horizon excess stock market return are economically large, ranging from 2.812% (Canada) to 18.57% (Japan) for Panel B, 2.58% (Spain) to 13.26% (Austria) for Panel C excluding Finland, 3.18% (Hong Kong) to 16.717% (New Zealand) for Panel D excluding Republic of Korea. Positive R^2_{os} values can be confirmed in all samples except two, and 16 out of 23 R^2_{os} values of developed countries are economically sizable and statistically significant at the 10% level or better according to the MSFE-adjusted statistics. Our results indicate that predictive regression forecasts based on the gold–copper ratio produce a substantially smaller MSFEs than the historical average benchmark does. Therefore, the results in Table 11 demonstrate that the gold–copper ratio also has a strong out-of-sample predictive power for international stock market excess returns, which is in line with our in-sample findings in Table 2.

5.4. Asset Allocation Analysis

Prior literature such as Campbell and Thompson (2008), Rapach *et al.* (2010), and Ferreira and Santa-Clara (2011) frequently analyze stock return forecasts with profit- or utility-based metrics, which provide more direct measures of the value of forecasts to economic agents. In this section, stock return forecasts of the gold–copper ratio serve as inputs for asset allocation decisions derived from expected utility maximization problems. A leading utility-based metric for analyzing U.S. equity premium forecasts is the average utility gain for a mean-variance risk-averse investor. Consider a mean-variance investor with relative risk aversion γ who allocates her portfolio between risky stocks and risk-free bills based on the predictive regression forecast within the gold–copper ratio of the equity premium. At the end of month *t*, the investor predicts the next month's out-of-sample excess return for a specific country and makes asset allocation decisions. The investor allocates the following share or the weight of the equities in her portfolio to equities during *t*+1:

$$a_{1,i,t} = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{r}_{1,i,t+1}}{\hat{\sigma}^2_{i,t+1}}\right) \tag{9}$$

where γ is the risk aversion coefficient, $\hat{r}_{1,i,t+1}$ is the out-of-sample forecast of excess stock returns for country *i*, and $\hat{\sigma}^2_{i,t+1}$ is the forecast of the variance of stock returns.

Over the forecast evaluation period, the investor notices the average utility as

$$\hat{\pi}_{1,i} = \hat{\mu}_{1,i} - 0.5\hat{\sigma}_{1,i}^2 \tag{10}$$

where $\hat{\mu}_{1,i}$ is the sample mean and $\hat{\sigma}_{1,i}^2$ is the sample variance of the portfolio formed based on $\hat{r}_{1,i,t+1}$ and $\hat{\sigma}_{i,t+1}^2$ over the forecast evaluation period.

When the investor relies on the historical average forecast of the equity premium based on the gold–copper ratio using the same variance forecast, she allocates the portfolio share as

$$a_{0,i,t} = (\frac{1}{\gamma})(\frac{\bar{r}_{i,t+1}}{\hat{\sigma}_{i,t+1}^2}) \tag{11}$$

to assets during *t*+1 and similarly in this case, during the forecast evaluation period, the investor notices the average utility

$$\hat{\pi}_{0,i} = \hat{\mu}_{0,i} - 0.5\hat{\sigma}_{0,i}^2 \tag{12}$$

where $\hat{\mu}_{0,i}$ is the sample mean and $\hat{\sigma}_{0,i}^2$ is the sample variance of the portfolio formed based on $\bar{r}_{i,t+1}$ and $\hat{\sigma}_{i,t+1}^2$. The difference between the two certainty equivalent returns (CERs) above is the difference between the CER for an investor who uses a predictive regression forecast of monthly returns and the CER for an investor who uses the historical average forecast. In other words, it is the utility gain accrued to use the predictive regression forecast of the equity premium in place of the historical average forecast in the asset allocation decision. The CER gain, can be interpreted as the portfolio management fee that an investor would be willing to pay to have access to the information in the predictive regression forecast instead of the baseline information from the historical average alone.

Based on the weight $a_{k,i,t(k=0,1)}$, the investor allocates her portfolio by $a_{k,i,t(k=0,1)}$ to equities and $1 - a_{k,i,t(k=0,1)}$ to risk-free bills. Consequently, the realized portfolio return ($R_{k,i,t+1(k=0,1)}$) for country *i* at time *t*+1 is

$$R_{k,i,t+1} = a_{k,i,t} R^{s}_{k,i,t+1} + (1 - a_{k,i,t}) R^{f}_{k,i,t+1} = a_{k,i,t}(R^{s}_{k,i,t+1} - R^{f}_{k,i,t+1}) + R^{f}_{k,i,t+1} \ (k = 0,1)$$

(13)

where $R^{s}_{k,i,t+1}(k = 0,1)$ is the raw return of stocks for country i at time t+1, and $R^{f}_{i,t+1}(k = 0, i)$ is the gross risk-free bill rate for country i at time t+1.

Following Campbell and Thompson (2008), we assume that the investor uses a 5-year moving window of past returns to estimate the variance of future excess stock returns. To examine the effect of risk aversion, we consider portfolio rules based on the risk aversion coefficients γ of 3 and 5. We multiply the CER gain difference by 12 so that we can interpret it as the annual risk-free return that an investor would be willing to pay to have access to the predictive regression forecast instead of the historical average forecast. By asset allocation analysis, we can evaluate the economic value of the predictability.

[Table 12 about here]

[Table 13 about here]

Tables 12 an 13 report the asset allocation performance. In these tables, we compute the annualized CER gain when the holding period is 3 months, 6 months, and 1 year after considering the transaction cost for the portfolio of a mean-variance investor who optimally allocates across equities and risk-free bills using the predictive regression forecasts. Table 12 shows the results when we consider the cost as zero; the table shows that forecasts based on the gold–copper ratio lead to positive CER gains for most international equity markets.

When we analyze global aggregate portfolios, the annualized CER gains of the 6-month holding period are positive for both EW and VW global aggregate market portfolios when the risk aversion parameter (γ) is either 3 or 5. The results indicate that an investor with a risk aversion level of 3 would be willing to pay an annual portfolio management fee of up to 320bp to access the predictive regression forecast based on the gold–copper ratio instead of using the historically EW average forecast. Moreover, according to Panel B, the annualized CER gains of a 6-month holding period are positive for 17 of the 23 countries, ranging from 0.48% (France) to 7.85% (Austria) when the risk aversion parameter (γ) is 3. Similar patterns occur in the case when the risk aversion parameter is 5. The CER gains of the 6-month holding period are positive for 17 of the 23 countries, ranging from 0.28% (France) to 4.69% (Austria). After considering the transaction cost of 50 bp (Table 13), the net-CER gains are still primarily positive and sizable among aggregate portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific.

To summarize, our results highlight the strong predictive power of the gold–copper ratio for out-of-sample market excess returns in a broad range of international equity markets. Given the strong in-sample and out-of-sample predictability, portfolios based on these forecasts produce considerable investment profits or economic values across countries.

6. Conclusion

In this paper, we examine the informative value of the relative value of gold on the global stock market. To explore this hypothesis, we first estimate the gold–copper ratio by dividing the monthly gold price by the monthly copper ratio from Datastream from January 1990 to August 2019. To test that the gold–copper ratio is superior to other gold ratio measures, we consider gold prices relative to seven commodity prices (silver, platinum, copper, aluminum, wheat, soybeans, and corn), consumer prices (CPI), and stock index (Dow Jones Industrial Average). The results show that only an increase in the gold–copper ratio significantly predicts high future excess returns of developed international equity market for 6-month and 1-year periods, as well as worldwide aggregate stock market returns. In contrast, other gold ratio measures do not show strong return predictability patterns for various forecasting horizons. Our findings are robust when we obtain international stock return data from an alternative database setting—Morgan Stanley Capital International.

To support our results, we examine the return predictability of the gold ratios conditioned on market sentiment. Under bad market conditions classified by the investor sentiment index of Baker and Wurgler (2006), the gold–copper ratio predicts stock returns for all 23 countries, whereas other gold ratios do not. We explain our results by suggesting that the gold–copper ratio can be regarded as a valuable and powerful indicator reflecting the uncertainty level in the international stock markets. It is informative in predicting future stock returns for most developed countries. Combined with the uncertainty–return framework, the gold–copper ratio has strong return predictability, especially during bad economic times. Moreover, since copper signals the overall macroeconomy will recover in the short term during these economic downturns, this affects the strong intermediate horizon return predictability of the gold–copper ratio.

Our findings appear remarkably robust across different model specifications and when including a set of U.S. or local control economic variables. In addition, the out-of-sample tests show that the gold–copper ratio generates superior results, and the asset allocation analysis shows that the gold–copper ratio has high economic significance.

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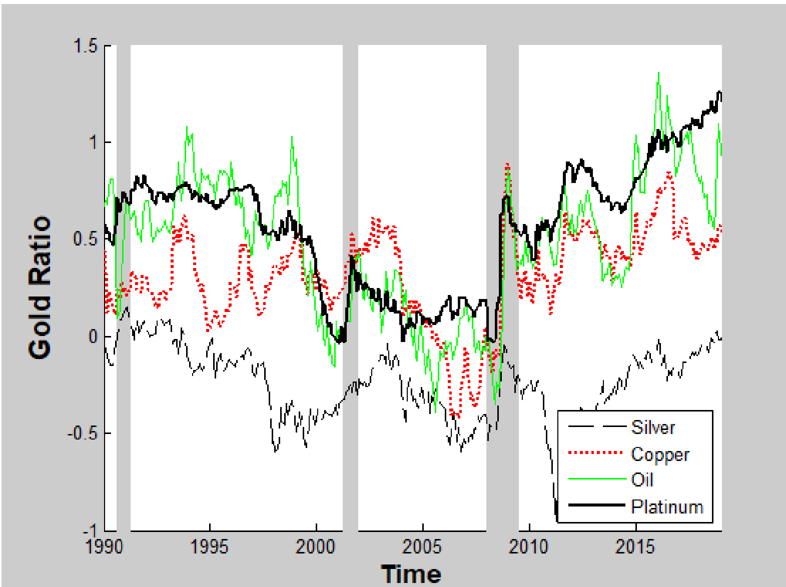
Figure 1
Time-Variation of the Relative Value of Gold
This figure plots the time series of the gold ratios from 1990 to 2019. Panel A displays the time-variation of the Gold-Silver ratio, Gold-Platinum ratio, Gold-Copper ratio, and Gold-Oil ratio. Panel B is for the Gold-Soybean ratio, Gold-CPI ratio, and Gold-DJIA ratio. Shaded area is associated with NBER recession periods.

Panel A: Silver, Copper, Oil, and Platinum



Panel B: Soybean, CPI, and Dow-Jones Industrial Average

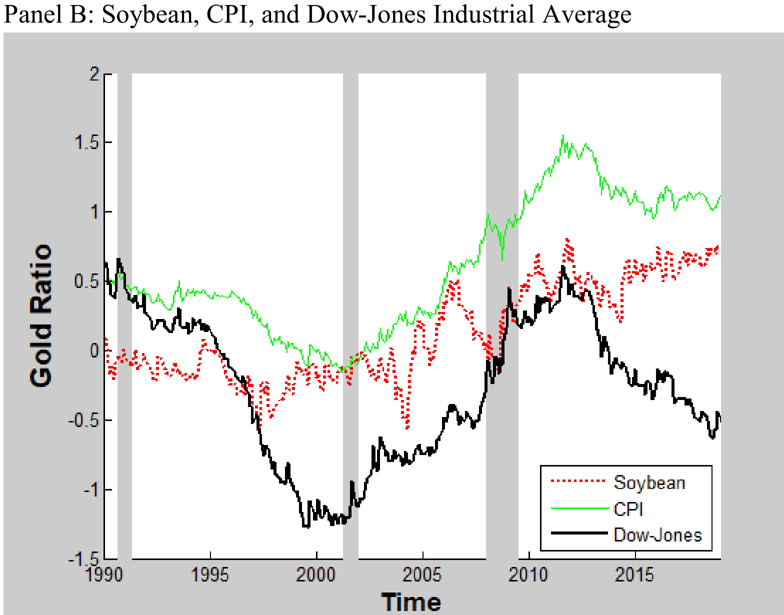


Table 1
Summary Statistics of the Relative Value of Gold and International Stock Returns
This table presents summary statistics for the variables. Panel A documents the mean, standard deviation, skewness, kurtosis, minimum value, maximum value, and first-order autocorrelation of the monthly time series of the logarithm of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA). Panel B provides the statistical description of the excess returns of the global aggregate stock market portfolios based on equal-weighted and value-weighted schemes, and the excess returns of individual countries. The sample period is January 1990 to June 2019.

Panel A: Gold ratios								
	mean	STD	skew	kurt	min	max	ar(1)	DF stat
Gold-Silver ratio	-0.236	0.191	-0.378	2.872	-0.963	0.154	0.957	-2.890
Gold-Platinum ratio	0.573	0.330	-0.139	2.172	-0.039	1.303	0.988	-0.608
Gold-Copper ratio	0.316	0.245	-0.667	3.686	-0.421	0.888	0.958	-2.929
Gold-Oil ratio	0.483	0.359	-0.221	2.272	-0.393	1.357	0.965	-2.879
Gold-Soybean ratio	0.137	0.358	0.254	1.744	-0.578	0.819	0.976	-1.558
Gold-CPI ratio	0.613	0.473	0.196	1.748	-0.154	1.551	0.996	-0.472
Gold-DJIA ratio	-3.279	0.516	-0.185	1.941	-4.281	-2.334	0.993	-1.808
Panel B: International stock returns								
	mean	STD	skew	kurt	min	max	ar(1)	
EW	0.39%	4.93%	-0.98	6.35	-27.07%	13.57%	0.12	
VW	0.39%	4.46%	-0.75	4.73	-21.31%	11.07%	0.06	
Canada	0.46%	5.31%	-1.02	7.55	-30.87%	18.51%	0.10	
France	0.47%	5.60%	-0.63	4.21	-24.32%	13.82%	0.06	
Germany	0.32%	5.86%	-0.78	4.82	-23.27%	17.57%	0.03	
Italy	0.11%	6.81%	-0.28	3.61	-26.36%	18.96%	-0.01	
Japan	-0.16%	5.74%	-0.01	4.24	-19.84%	23.22%	0.08	
U.K.	0.38%	4.70%	-0.49	4.77	-22.56%	13.77%	0.08	
U.S.	0.66%	4.26%	-0.67	4.22	-17.23%	11.35%	0.05	
Austria	0.21%	6.60%	-1.30	9.67	-42.01%	20.03%	0.17	
Belgium	0.38%	5.47%	-1.46	11.04	-39.13%	14.76%	0.17	
Denmark	0.59%	5.44%	-0.96	6.91	-30.72%	17.15%	0.12	
Finland	0.54%	7.96%	-0.33	4.69	-34.20%	25.71%	0.18	
Ireland	0.35%	6.07%	-0.89	5.97	-27.69%	18.03%	0.15	
Netherlands	0.45%	5.62%	-1.52	10.06	-37.06%	15.07%	0.10	
Spain	0.38%	6.47%	-0.42	4.21	-25.60%	19.31%	0.03	
Sweden	0.53%	6.99%	-0.57	4.76	-30.35%	20.22%	0.08	
Switzerland	0.62%	4.59%	-0.67	4.32	-17.38%	14.14%	0.07	
Australia	0.53%	5.84%	-0.77	5.75	-31.48%	16.16%	0.06	
Hong Kong	0.70%	6.94%	-0.35	5.86	-34.80%	25.36%	0.07	
South Korea	0.54%	5.78%	-0.52	3.70	-20.64%	14.78%	0.02	
New Zealand	0.34%	6.40%	-0.56	6.08	-30.41%	23.01%	0.10	
Singapore	0.15%	9.89%	0.09	5.76	-37.89%	50.65%	0.03	
Taiwan	0.04%	9.03%	0.15	6.69	-41.21%	44.99%	0.12	
Thailand	0.39%	9.74%	-0.43	5.72	-39.44%	33.93%	0.08	

Table 2

International Stock Return Predictability of the Relative Value of Gold: Short-Horizons

This table shows the return predictability of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA) associated with short forecasting horizons: 1-month and 3-month for the international stock market. The regression is a univariate predictive regression:

$$R^{i}_{t,t+h} = \alpha^{i} + \beta^{i} \log GR_{t} + \epsilon^{i}_{t+h}$$

where $R^{i}_{t,t+h}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and and $\log GR_{t}$ represents the log of seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA). Cumulative excess return $R^{i}_{t,t+h}$ is calculated over 1-month and 3-month, based on the monthly overlapping observations. The international stock market data is from DataStream. Panel A and B show the results for 1-month and 3-month estimation periods, respectively. In each panel, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific. Hodrick (1992) t-values are reported in parentheses. The t-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R^{2}_{adj}) in percentages. The sample period is from January 1990 to June 2019.

	Gold-Silver ratio			Gold-Platinum ratio			Gold-Copper ratio			Gold-Crude Oil ratio			Gold-Soybean ratio			Gold-CPI ratio			Gold-DJIA ratio		
	Coef.	(t).	$^{2}_{adj}$	Coef.	(t).	R^{2}_{adj}	Coef.	(t).	R^{2}_{adj}	Coef.	(t).	R^{2}_{adj}	Coef.	(t)	R^{2}_{adj}	Coef.	(t).	R^{2}_{adj}	Coef.	(t)	R^{2}_{adj}
Panel A: 1-month horizon																					
Aggregate Portfolios																					
EW	0.009	0.64	-0.18	0.007	1.02	-0.05	0.019	**1.83**	0.64	0.016	**1.94**	0.98	0.007	0.97	-0.06	0.001	0.23	-0.27	0.004	0.68	-0.13
VW	0.013	1.03	-0.02	0.011	1.61	0.41	0.012	1.32	0.18	0.017	**2.35**	1.71	0.005	0.69	-0.17	0.003	0.56	-0.21	0.008	1.49	0.56
G7 Countries																					
Canada	0.021	1.14	0.06	-0.002	-0.26	-0.31	0.007	0.62	-0.22	0.007	0.78	-0.08	-0.001	-0.16	-0.32	-0.004	-0.57	-0.23	0.003	0.36	-0.28
France	0.003	0.17	-0.28	0.008	0.98	-0.07	0.012	1.07	0.00	0.013	1.62	0.45	0.002	0.23	-0.28	0.000	-0.05	-0.29	0.002	0.27	-0.26
Germany	-0.001	-0.05	-0.29	0.006	0.72	-0.17	0.009	0.69	-0.16	0.013	1.46	0.31	0.005	0.64	-0.18	0.003	0.44	-0.22	0.005	0.71	-0.10
Italy	-0.008	-0.40	-0.24	0.004	0.46	-0.25	0.016	1.23	0.05	0.017	**1.71**	0.48	-0.001	-0.08	-0.29	-0.002	-0.26	-0.27	-0.004	-0.51	-0.20
Japan	0.002	0.13	-0.34	0.010	1.24	0.10	0.018	**1.87**	0.56	0.014	**1.81**	0.73	0.014	**1.71**	0.70	0.007	1.18	0.16	0.005	0.73	-0.12
U.K.	0.010	0.74	-0.14	0.007	1.02	-0.05	0.011	1.12	0.03	0.014	**1.87**	0.83	0.002	0.24	-0.27	0.001	0.13	-0.28	0.006	1.20	0.19
U.S.	0.016	1.40	0.19	0.015	**2.27**	1.08	0.014	**1.68**	0.40	0.017	**2.58**	1.77	0.007	1.10	0.05	0.006	1.09	0.10	0.009	**1.75**	0.89
Developed countries in Europe																					
Austria	0.021	0.98	-0.03	-0.007	-0.70	-0.22	0.020	1.43	0.35	0.012	1.01	0.12	0.006	0.62	-0.24	-0.004	-0.51	-0.26	-0.001	-0.13	-0.33
Belgium	0.003	0.18	-0.28	0.001	0.17	-0.28	0.017	1.52	0.30	0.014	1.51	0.60	0.001	0.18	-0.28	0.000	0.05	-0.29	0.004	0.74	-0.13
Denmark	0.003	0.17	-0.28	0.000	-0.01	-0.29	0.011	0.96	-0.04	0.009	0.97	0.04	0.004	0.57	-0.21	0.001	0.19	-0.28	0.001	0.15	-0.28
Finland	0.002	0.10	-0.29	0.018	1.42	0.26	0.026	**1.75**	0.35	0.026	**2.22**	1.11	0.002	0.18	-0.28	-0.005	-0.50	-0.20	-0.004	-0.42	-0.21
Ireland	0.010	0.56	-0.20	0.011	1.18	0.03	0.023	**1.72**	0.60	0.020	**1.94**	1.04	0.002	0.26	-0.27	-0.001	-0.20	-0.28	0.003	0.49	-0.21
Netherlands	0.015	1.01	-0.05	0.011	1.27	0.08	0.011	0.91	-0.06	0.021	**2.12**	1.44	0.002	0.25	-0.27	0.000	0.07	-0.29	0.007	1.14	0.09

Spain	0.001	0.08	-0.29	0.004	0.42	-0.25	0.008	0.65	-0.19	0.010	1.12	0.02	-0.005	-0.51	-0.22	-0.002	-0.30	-0.26	0.001	0.17	-0.28
Sweden	0.004	0.20	-0.28	0.012	1.14	0.03	0.025	**1.77**	0.48	0.023	**2.10**	1.12	0.007	0.74	-0.16	0.003	0.34	-0.25	0.007	0.83	-0.02
Switzerland	0.007	0.54	-0.20	0.007	1.10	-0.03	0.004	0.44	-0.24	0.009	1.31	0.16	0.001	0.16	-0.29	0.002	0.39	-0.24	0.007	1.26	0.29
Developed countries in Asia-Pacific																					
Australia	0.011	0.69	-0.17	0.000	0.05	-0.29	0.017	1.25	0.20	0.015	1.54	0.52	0.005	0.57	-0.21	-0.002	-0.27	-0.27	0.003	0.52	-0.20
Hong Kong	0.037	1.58	0.51	0.011	1.08	-0.07	0.018	1.32	0.09	0.015	1.41	0.27	0.011	0.96	-0.02	0.002	0.25	-0.30	0.010	1.11	0.14
South Korea	0.018	1.08	0.05	0.008	0.96	-0.09	0.029	**2.19**	1.21	0.017	**1.84**	0.79	0.010	1.27	0.11	0.003	0.49	-0.22	0.004	0.56	-0.18
New Zealand	0.014	0.77	-0.13	0.005	0.59	-0.22	0.019	1.55	0.26	0.013	1.41	0.26	0.016	**1.73**	0.52	0.004	0.56	-0.19	0.008	1.09	0.17
Singapore	-0.009	-0.31	-0.26	0.003	0.26	-0.28	0.038	**2.18**	0.60	0.022	1.57	0.31	0.020	1.27	0.22	-0.001	-0.06	-0.29	-0.002	-0.18	-0.28
Taiwan	0.016	0.60	-0.17	0.024	**2.05**	0.46	0.043	**2.65**	1.11	0.018	1.47	0.24	0.019	1.56	0.24	0.009	0.97	-0.08	0.003	0.25	-0.26
Thailand	0.030	1.08	0.05	0.009	0.72	-0.20	0.044	**2.68**	0.95	0.023	**1.74**	0.40	0.032	**2.11**	1.01	0.012	1.04	0.04	0.018	1.56	0.67
Panel B: 3-months horizon																					
Aggregate Portfolios																					
EW	0.046	1.16	0.61	0.031	1.37	0.87	0.072	**2.17**	3.32	0.045	**1.84**	2.75	0.021	1.01	0.37	0.004	0.21	-0.26	0.012	0.75	0.18
VW	0.054	1.39	1.13	0.041	**1.94**	2.58	0.051	**1.84**	2.36	0.054	**2.55**	5.95	0.014	0.73	0.10	0.009	0.55	-0.04	0.025	1.55	2.11
G7 Countries																					
Canada	0.069	1.32	0.93	0.006	0.24	-0.29	0.041	1.11	0.72	0.031	1.10	0.93	-0.001	-0.05	-0.33	-0.010	-0.55	-0.09	0.008	0.38	-0.19
France	0.027	0.56	-0.03	0.032	1.26	0.79	0.057	**1.67**	1.72	0.041	**1.65**	1.95	0.009	0.38	-0.18	-0.001	-0.03	-0.29	0.005	0.28	-0.21
Germany	0.010	0.20	-0.25	0.026	0.99	0.38	0.040	1.11	0.62	0.037	1.43	1.39	0.019	0.75	0.14	0.009	0.44	-0.10	0.015	0.73	0.27
Italy	0.017	0.27	-0.21	0.022	0.77	0.09	0.070	**1.76**	1.91	0.043	1.47	1.44	0.002	0.05	-0.29	-0.006	-0.27	-0.22	-0.011	-0.48	-0.06
Japan	0.014	0.29	-0.28	0.034	1.44	1.13	0.069	**2.45**	3.22	0.047	**2.10**	3.10	0.042	**1.72**	2.24	0.020	1.14	0.85	0.015	0.78	0.29
U.K.	0.047	1.18	0.78	0.028	1.33	0.84	0.046	1.53	1.47	0.044	**1.98**	3.14	0.007	0.33	-0.22	0.002	0.15	-0.27	0.020	1.32	1.21
U.S.	0.050	1.50	1.28	0.054	**2.64**	4.91	0.055	**2.17**	2.86	0.052	**2.69**	5.71	0.022	1.16	0.76	0.018	1.17	0.94	0.027	**1.79**	3.06
Developed countries in Europe																					
Austria	0.117	**1.84**	2.01	-0.004	-0.14	-0.33	0.090	**1.95**	2.98	0.043	1.20	1.17	0.019	0.71	-0.05	-0.012	-0.59	-0.11	-0.003	-0.12	-0.33
Belgium	0.042	0.99	0.28	0.017	0.65	-0.02	0.071	**1.89**	2.37	0.040	1.37	1.57	0.009	0.40	-0.20	0.000	0.02	-0.29	0.014	0.86	0.20
Denmark	0.034	0.73	0.11	0.013	0.49	-0.12	0.055	1.46	1.45	0.029	1.04	0.76	0.021	0.91	0.23	0.004	0.23	-0.25	0.004	0.23	-0.25
Finland	0.019	0.28	-0.23	0.064	1.59	1.52	0.088	**1.99**	1.73	0.070	**1.97**	2.45	0.003	0.07	-0.29	-0.015	-0.51	-0.06	-0.012	-0.41	-0.11
Ireland	0.056	1.09	0.54	0.044	1.56	1.16	0.093	**2.17**	3.47	0.060	**1.94**	3.06	0.007	0.30	-0.24	-0.004	-0.18	-0.27	0.012	0.59	-0.02
Netherlands	0.068	1.53	1.23	0.045	**1.71**	1.66	0.053	1.38	1.28	0.062	**2.06**	4.20	0.010	0.42	-0.18	0.001	0.07	-0.29	0.021	1.17	0.74
Spain	0.031	0.59	0.00	0.014	0.51	-0.13	0.037	0.96	0.37	0.025	0.95	0.37	-0.011	-0.37	-0.17	-0.008	-0.35	-0.17	0.004	0.20	-0.25
Sweden	0.047	0.81	0.21	0.048	1.44	1.17	0.090	**2.04**	2.73	0.060	**1.82**	2.59	0.022	0.76	0.08	0.008	0.33	-0.20	0.022	0.87	0.52
Switzerland	0.043	1.08	0.67	0.027	1.41	0.87	0.023	0.87	0.19	0.027	1.39	1.07	0.007	0.37	-0.19	0.007	0.41	-0.15	0.021	1.30	1.37
Developed countries in Asia-Pacific																					

Australia	0.054	1.12	0.64	0.012	0.46	-0.15	0.067	1.63	2.08	0.046	1.57	2.07	0.014	0.58	-0.06	-0.005	-0.26	-0.23	0.011	0.61	0.03
Hong Kong	0.103	1.48	1.58	0.040	1.33	0.73	0.061	1.45	1.17	0.051	1.62	1.83	0.029	0.84	0.33	0.006	0.25	-0.27	0.027	1.02	0.72
New Zealand	0.075	1.56	1.73	0.032	1.24	0.74	0.091	**2.30**	4.64	0.048	**1.79**	2.69	0.034	1.38	1.11	0.009	0.46	-0.12	0.013	0.68	0.18
Singapore	0.053	1.00	0.39	0.025	0.93	0.13	0.069	**1.70**	1.63	0.041	1.40	1.17	0.051	**1.78**	1.90	0.012	0.52	-0.09	0.025	1.10	0.84
South Korea	-0.001	-0.01	-0.29	0.015	0.38	-0.22	0.112	**2.11**	2.19	0.053	1.29	0.88	0.046	1.01	0.58	-0.005	-0.16	-0.27	-0.007	-0.21	-0.24
Taiwan	0.073	0.93	0.36	0.080	**2.28**	2.00	0.142	**2.90**	3.85	0.052	1.44	0.91	0.054	1.50	0.93	0.026	0.99	0.24	0.011	0.33	-0.17
Thailand	0.099	1.21	0.77	0.034	0.88	0.07	0.133	**2.58**	2.91	0.050	1.23	0.68	0.093	**2.04**	2.90	0.034	0.99	0.47	0.055	1.58	2.22

Table 3

International Stock Return Predictability of the Relative Value of Gold: Intermediate-Horizons

This table shows the return predictability of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA) associated with intermediate forecasting horizons: 6-month and 12-month(1-year) for the international stock market. The regression is a univariate predictive regression:

$$R_{t,t+h}^{i} = \alpha^{i} + \beta^{i} \log GR_{t} + \epsilon_{t+h}^{i}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GR_t$ represents the log of seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA). Cumulative excess return $R_{t,t+h}^{i}$ is calculated over 6-month and 1-year based on the monthly overlapping observations. The international stock market data is from DataStream. Panel A and B show the results for 6-month and 12-month estimation period, respectively. In each panel, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific. Hodrick (1992) *t*-values are reported in parentheses. The *t*-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R_{adj}^2) in percentages. The sample period is from January 1990 to June 2019.

	Gold-Silver ratio			Gold-Platinum ratio			Gold-Copper ratio			Gold-Crude Oil ratio			Gold-Soybean ratio			Gold-CPI ratio			Gold-DJIA ratio		
	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2	Coef.	(*t*).	R_{adj}^2
Panel A: 6-months horizon																					
Aggregate Portfolios																					
EW	0.131	1.55	2.90	0.072	1.50	2.50	0.160	**2.46**	7.70	0.088	**1.82**	4.86	0.045	1.07	0.98	0.005	0.14	-0.26	0.024	0.73	0.48
VW	0.157	**1.90**	5.01	0.095	**2.17**	6.49	0.125	**2.33**	6.66	0.110	**2.65**	10.98	0.033	0.84	0.63	0.016	0.50	0.08	0.050	1.56	3.87
G7 Countries																					
Canada	0.188	1.64	4.06	0.034	0.62	0.23	0.094	1.25	2.23	0.060	1.09	1.85	0.001	0.03	-0.33	-0.024	-0.65	0.28	0.010	0.25	-0.23
France	0.104	1.07	1.57	0.077	1.49	2.68	0.136	**2.07**	5.06	0.088	**1.78**	4.51	0.025	0.52	0.07	-0.002	-0.06	-0.28	0.008	0.22	-0.20
Germany	0.076	0.72	0.62	0.064	1.17	1.58	0.107	1.59	2.77	0.076	1.48	3.01	0.043	0.88	0.74	0.016	0.37	-0.04	0.028	0.70	0.67
Italy	0.095	0.78	0.79	0.061	1.04	1.01	0.162	**2.10**	4.97	0.075	1.32	2.14	0.007	0.12	-0.27	-0.015	-0.31	-0.12	-0.023	-0.53	0.20
Japan	0.076	0.83	0.44	0.075	1.62	2.73	0.172	**3.26**	9.03	0.099	**2.27**	6.09	0.084	**1.75**	4.07	0.038	1.07	1.39	0.034	0.87	0.94
U.K.	0.141	**1.70**	4.02	0.071	1.59	2.88	0.118	**1.98**	4.79	0.093	**2.12**	6.37	0.017	0.43	-0.08	0.003	0.10	-0.27	0.041	1.39	2.45
U.S.	0.124	**1.76**	4.35	0.118	**2.84**	11.76	0.127	**2.71**	7.84	0.106	**2.84**	11.90	0.046	1.22	1.86	0.035	1.16	1.99	0.051	**1.76**	5.71
Developed countries in Europe																					
Austria	0.345	**2.51**	8.12	0.018	0.28	-0.25	0.210	**2.26**	7.08	0.083	1.19	2.05	0.042	0.78	0.24	-0.030	-0.73	0.22	-0.006	-0.14	-0.32
Belgium	0.123	1.40	1.81	0.048	0.84	0.64	0.157	**2.04**	5.44	0.075	1.28	2.51	0.020	0.46	-0.09	0.000	-0.01	-0.29	0.027	0.83	0.48
Denmark	0.111	1.14	1.55	0.048	0.85	0.69	0.138	**1.80**	4.51	0.062	1.13	1.79	0.048	1.06	0.88	0.008	0.21	-0.23	0.011	0.32	-0.16
Finland	0.078	0.57	0.15	0.130	1.62	3.21	0.188	**2.27**	3.93	0.137	**1.96**	4.51	-0.006	-0.08	-0.28	-0.036	-0.60	0.28	-0.023	-0.38	-0.01
Ireland	0.169	1.62	2.79	0.102	**1.74**	2.95	0.205	**2.49**	7.27	0.119	**1.99**	5.21	0.015	0.31	-0.21	-0.009	-0.22	-0.24	0.026	0.66	0.26
Netherlands	0.190	**1.98**	4.90	0.110	**1.91**	4.72	0.138	**1.75**	4.32	0.125	**2.10**	7.72	0.027	0.60	0.08	0.001	0.03	-0.29	0.041	1.19	1.53
Spain	0.120	1.13	1.74	0.035	0.63	0.21	0.095	1.28	1.86	0.051	0.97	1.04	-0.012	-0.21	-0.22	-0.018	-0.37	-0.02	0.005	0.13	-0.26

Sweden	0.135	1.12	1.51	0.104	1.54	2.82	0.187	**2.16**	5.52	0.108	**1.67**	3.84	0.045	0.80	0.41	0.013	0.26	-0.19	0.038	0.77	0.80
Switzerland	0.144	**1.80**	4.91	0.068	**1.73**	3.13	0.078	1.59	2.29	0.064	**1.68**	3.39	0.022	0.54	0.11	0.013	0.41	-0.03	0.047	1.59	3.90
Developed countries in Asia-Pacific																					
Australia	0.151	1.47	3.15	0.038	0.68	0.34	0.144	**1.80**	4.94	0.079	1.38	3.05	0.036	0.72	0.36	-0.013	-0.32	-0.13	0.022	0.61	0.27
Hong Kong	0.200	1.42	3.39	0.084	1.39	2.12	0.137	1.61	3.54	0.097	1.61	3.79	0.064	0.93	1.32	0.011	0.24	-0.22	0.049	0.97	1.51
New Zealand	0.175	**1.77**	4.45	0.075	1.43	2.21	0.189	**2.54**	9.02	0.086	**1.65**	3.86	0.077	1.57	2.91	0.017	0.44	-0.02	0.027	0.71	0.55
Singapore	0.136	1.24	1.77	0.056	1.01	0.73	0.150	**1.83**	3.94	0.078	1.33	2.14	0.096	**1.67**	3.26	0.020	0.45	-0.01	0.047	1.05	1.54
South Korea	-0.002	-0.02	-0.29	0.020	0.26	-0.22	0.243	**2.44**	5.30	0.101	1.27	1.77	0.083	0.91	1.04	-0.017	-0.26	-0.19	-0.016	-0.24	-0.18
Taiwan	0.157	1.05	1.18	0.152	**2.14**	3.73	0.265	**2.88**	6.76	0.106	1.53	2.13	0.097	1.39	1.63	0.047	0.90	0.54	0.027	0.43	0.04
Thailand	0.197	1.21	1.85	0.062	0.78	0.33	0.253	**2.46**	5.67	0.087	1.08	1.21	0.177	**1.92**	5.65	0.062	0.93	1.03	0.096	1.39	3.53
Panel B: 12-months horizon																					
Aggregate Portfolios																					
EW	0.237	1.49	4.92	0.115	1.21	3.09	0.259	**2.20**	10.24	0.124	1.41	4.83	0.055	0.69	0.64	0.006	0.09	-0.27	0.049	0.83	1.43
VW	0.285	**1.89**	7.69	0.181	**2.18**	10.65	0.232	**2.36**	10.99	0.176	**2.31**	13.33	0.055	0.74	0.89	0.035	0.58	0.64	0.097	1.58	7.31
G7 Countries																					
Canada	0.333	1.63	6.69	0.051	0.50	0.30	0.147	1.08	2.96	0.088	0.90	2.16	-0.016	-0.18	-0.26	-0.053	-0.74	1.28	0.017	0.22	-0.18
France	0.239	1.32	4.55	0.152	1.46	5.13	0.243	**1.98**	8.25	0.141	1.53	5.82	0.027	0.29	-0.09	-0.003	-0.03	-0.29	0.026	0.36	0.15
Germany	0.183	0.96	2.39	0.120	1.10	2.92	0.185	1.49	4.38	0.111	1.16	3.29	0.068	0.72	0.96	0.032	0.38	0.23	0.063	0.83	2.12
Italy	0.189	0.83	1.88	0.116	0.97	1.95	0.293	**2.10**	8.54	0.107	1.01	2.23	-0.011	-0.09	-0.27	-0.026	-0.28	-0.03	-0.036	-0.43	0.31
Japan	0.124	0.72	0.49	0.136	1.53	3.71	0.342	**3.63**	15.57	0.166	**2.03**	7.22	0.144	1.52	4.96	0.074	1.06	2.48	0.071	0.96	2.13
U.K.	0.277	**1.76**	7.74	0.134	1.53	4.89	0.198	**1.98**	6.73	0.130	**1.64**	6.12	0.006	0.09	-0.28	0.006	0.10	-0.27	0.082	1.44	5.08
U.S.	0.227	**1.75**	7.16	0.234	**3.01**	21.60	0.231	**2.67**	12.80	0.198	**2.85**	20.10	0.070	1.00	2.10	0.071	1.20	4.25	0.110	**1.97**	13.09
Developed countries in Europe																					
Austria	0.666	**2.62**	15.12	0.009	0.07	-0.34	0.374	**2.16**	11.68	0.076	0.61	0.68	0.056	0.54	0.17	-0.062	-0.78	0.91	-0.025	-0.30	-0.14
Belgium	0.261	1.57	4.14	0.074	0.66	0.70	0.255	**1.74**	6.95	0.068	0.64	0.81	0.006	0.07	-0.29	0.003	0.05	-0.29	0.060	0.98	1.53
Denmark	0.181	0.99	2.18	0.091	0.83	1.44	0.242	**1.72**	7.22	0.068	0.68	0.95	0.071	0.82	0.97	0.018	0.24	-0.14	0.028	0.43	0.15
Finland	0.190	0.71	0.82	0.256	1.63	5.33	0.326	**2.21**	5.32	0.282	**2.14**	8.64	-0.052	-0.39	-0.02	-0.066	-0.57	0.56	-0.026	-0.22	-0.13
Ireland	0.351	**1.81**	5.81	0.203	**1.74**	5.37	0.372	**2.44**	11.42	0.173	1.58	5.05	-0.005	-0.06	-0.29	-0.010	-0.13	-0.26	0.067	0.92	1.41
Netherlands	0.390	**2.14**	10.74	0.210	**1.82**	8.58	0.237	1.59	6.66	0.191	**1.77**	9.30	0.028	0.32	-0.10	0.005	0.07	-0.28	0.090	1.35	4.26
Spain	0.271	1.28	4.72	0.068	0.60	0.59	0.169	1.23	3.02	0.071	0.73	0.96	-0.034	-0.29	-0.03	-0.032	-0.34	0.16	0.014	0.18	-0.19
Sweden	0.277	1.20	3.28	0.171	1.27	3.50	0.304	**1.98**	7.10	0.181	1.54	5.26	0.049	0.44	0.07	0.020	0.21	-0.17	0.081	0.87	2.05
Switzerland	0.316	**2.12**	12.04	0.140	**1.76**	6.50	0.146	1.62	4.24	0.090	1.25	3.34	0.023	0.29	-0.07	0.025	0.39	0.18	0.102	**1.77**	9.45
Developed countries in Asia-Pacific																					
Australia	0.238	1.18	4.27	0.028	0.25	-0.11	0.186	1.26	4.47	0.077	0.73	1.43	0.033	0.34	0.00	-0.034	-0.43	0.30	0.034	0.49	0.41

Hong Kong	0.206	0.82	1.54	0.110	0.96	1.61	0.201	1.34	3.75	0.124	1.15	2.95	0.106	0.80	1.85	0.022	0.24	-0.15	0.078	0.85	2.00
New Zealand	0.299	1.59	6.23	0.109	1.03	2.12	0.316	**2.32**	12.12	0.111	1.14	2.96	0.121	1.24	3.30	0.026	0.34	0.01	0.053	0.76	1.31
Singapore	0.169	0.83	1.22	0.042	0.38	-0.03	0.186	1.33	2.85	0.077	0.73	0.85	0.130	1.14	2.72	0.025	0.29	-0.08	0.083	1.02	2.53
South Korea	-0.074	-0.25	-0.16	-0.054	-0.34	-0.09	0.369	**2.05**	5.53	0.092	0.62	0.47	0.101	0.54	0.56	-0.043	-0.34	0.00	-0.037	-0.30	-0.02
Taiwan	0.257	0.92	2.34	0.206	1.45	4.39	0.367	**2.38**	8.84	0.190	1.51	4.90	0.126	0.95	1.81	0.081	0.80	1.37	0.081	0.73	1.74
Thailand	0.234	0.76	1.06	0.021	0.13	-0.26	0.337	**1.82**	4.50	0.064	0.44	0.07	0.277	1.50	6.11	0.099	0.76	1.24	0.156	1.23	4.36

Table 4

International Stock Return Predictability of the Relative Value of Gold: Long-Horizons

This table shows the return predictability of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA) associated with long forecasting horizons: 24-month (2-year) and 36-month (3-year) for the international stock market. The regression is a univariate predictive regression:

$$R_{t,t+h}^{i} = \alpha^{i} + \beta^{i} \log GR_{t} + \epsilon_{t+h}^{i}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GR_t$ represents the log of seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA). Cumulative excess return $R_{t,t+h}^{i}$ is calculated over 24-month and 36-month, based on the monthly overlapping observations. The international stock market data is from DataStream. Panel A and B show the results for 24-month and 36-month estimation periods, respectively. In each panel, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific. Hodrick (1992) t-values are reported in parentheses. The t-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R_{adj}^{2}) in percentages. The sample period is from January 1990 to June 2019.

	Gold-Silver ratio			Gold-Platinum ratio			Gold-Copper ratio			Gold-Crude Oil ratio			Gold-Soybean ratio			Gold-CPI ratio			Gold-DJIA ratio		
	Coef.	(*t*).	R_{adj}^{2}	Coef.	(*t*).	R_{adj}^{2}	Coef.	(*t*).	R_{adj}^{2}	Coef.	(*t*)	R_{adj}^{2}	Coef.	(*t*).	R_{adj}^{2}	Coef.	(*t*).	R_{adj}^{2}	Coef.	(*t*).	R_{adj}^{2}
Panel A: 24-months horizon																					
Aggregate Portfolios																					
EW	0.504	**1.72**	13.04	0.190	0.97	4.48	0.483	**1.85**	20.97	0.177	1.11	5.55	0.038	0.24	-0.06	0.027	0.21	-0.07	0.093	0.84	3.34
VW	0.602	**2.28**	17.53	0.336	**2.01**	17.13	0.457	**2.10**	22.42	0.299	**2.21**	19.34	0.068	0.47	0.57	0.094	0.80	3.15	0.189	1.63	14.69
G7 Countries																					
Canada	0.717	**1.99**	18.84	0.044	0.21	-0.09	0.299	1.01	8.18	0.155	0.89	4.26	-0.124	-0.66	2.22	-0.103	-0.75	3.31	0.027	0.20	-0.08
France	0.490	1.53	10.72	0.296	1.38	9.87	0.509	**1.95**	20.35	0.269	1.58	11.57	-0.010	-0.06	-0.29	0.019	0.12	-0.21	0.076	0.56	1.80
Germany	0.465	1.44	9.10	0.252	1.11	6.64	0.411	1.57	12.44	0.205	1.16	6.21	0.089	0.45	0.77	0.081	0.48	1.46	0.138	0.95	6.27
Italy	0.419	0.94	5.22	0.255	1.05	4.87	0.582	**2.06**	18.21	0.228	1.18	5.53	-0.069	-0.29	0.17	-0.027	-0.15	-0.16	-0.033	-0.21	-0.03
Japan	0.239	0.72	1.09	0.219	1.20	4.17	0.604	**3.08**	24.32	0.233	1.62	6.77	0.211	1.11	4.88	0.160	1.17	6.00	0.125	0.90	3.48
U.K.	0.579	**2.03**	17.27	0.254	1.43	8.24	0.419	**1.80**	15.67	0.234	**1.64**	9.94	-0.032	-0.22	-0.13	0.031	0.26	0.02	0.158	1.49	10.07
U.S.	0.459	**2.06**	13.44	0.460	**2.94**	34.40	0.469	**2.51**	24.61	0.370	**2.96**	31.49	0.108	0.77	2.09	0.167	1.46	11.08	0.231	**2.22**	27.26
Developed countries in Europe																					
Austria	1.253	**2.68**	23.82	-0.051	-0.20	-0.22	0.787	**1.99**	24.85	0.058	0.26	-0.10	0.011	0.05	-0.36	-0.122	-0.80	1.89	-0.099	-0.64	1.09
Belgium	0.597	**1.84**	12.19	0.162	0.70	2.03	0.539	1.64	17.40	0.088	0.46	0.67	-0.023	-0.14	-0.25	0.041	0.30	0.05	0.128	1.09	4.23
Denmark	0.326	0.94	4.29	0.179	0.79	3.19	0.550	**1.81**	22.33	0.146	0.80	2.99	0.081	0.46	0.58	0.051	0.35	0.39	0.059	0.47	0.88
Finland	0.692	1.36	6.95	0.537	**1.79**	10.73	0.579	**1.91**	8.53	0.474	**2.01**	11.85	-0.238	-0.88	2.41	-0.093	-0.41	0.52	0.039	0.17	-0.12
Ireland	0.774	**2.13**	13.72	0.462	**1.87**	12.28	0.827	**2.49**	27.48	0.351	**1.75**	10.00	-0.054	-0.29	-0.09	0.026	0.17	-0.21	0.165	1.24	4.76
Netherlands	0.800	**2.31**	24.62	0.408	**1.68**	16.10	0.495	1.48	16.31	0.333	**1.68**	15.11	-0.010	-0.06	-0.29	0.045	0.30	0.19	0.199	1.53	11.85
Spain	0.484	1.18	7.75	0.155	0.67	1.77	0.389	1.38	8.71	0.155	0.87	2.65	-0.081	-0.35	0.41	-0.041	-0.22	0.06	0.034	0.22	0.01

Sweden	0.566	1.28	7.80	0.275	1.02	4.53	0.541	**1.70**	12.55	0.288	1.34	7.18	-0.019	-0.09	-0.28	0.045	0.24	0.02	0.156	0.86	4.52
Switzerland	0.633	**2.40**	25.16	0.278	**1.68**	12.21	0.334	**1.76**	12.04	0.194	1.46	8.26	0.005	0.03	-0.30	0.066	0.55	1.44	0.215	**1.97**	22.42
Developed countries in Asia-Pacific																					
Australia	0.446	1.19	11.00	-0.040	-0.17	-0.08	0.316	1.00	9.55	0.045	0.23	0.10	-0.025	-0.13	-0.20	-0.069	-0.44	1.37	0.023	0.18	-0.07
Hong Kong	0.388	0.89	4.56	0.127	0.54	1.45	0.314	1.03	7.42	0.175	0.91	4.53	0.149	0.56	2.75	0.049	0.29	0.34	0.106	0.66	3.00
New Zealand	0.532	1.51	10.54	0.113	0.52	0.94	0.546	**2.00**	19.50	0.094	0.53	0.91	0.168	0.84	3.09	0.042	0.28	0.11	0.092	0.70	2.25
Singapore	0.317	0.88	2.96	-0.059	-0.25	-0.02	0.259	0.87	3.48	-0.017	-0.09	-0.27	0.136	0.59	1.58	0.042	0.26	0.05	0.099	0.68	2.24
South Korea	0.110	0.20	-0.12	-0.202	-0.61	1.31	0.546	1.48	7.82	-0.071	-0.26	-0.02	0.025	0.07	-0.28	-0.077	-0.33	0.28	-0.122	-0.54	1.55
Taiwan	0.512	0.95	7.75	0.304	1.05	6.84	0.417	1.42	8.98	0.235	1.02	5.72	0.228	0.88	4.73	0.168	0.86	5.10	0.167	0.81	6.51
Thailand	0.467	0.83	2.12	-0.136	-0.42	0.22	0.504	1.36	4.60	-0.167	-0.63	0.81	0.438	1.19	6.42	0.170	0.70	1.69	0.203	0.88	3.34
Panel B: 36-months horizon																					
Aggregate Portfolios																					
EW	0.659	**1.64**	19.77	0.138	0.45	1.68	0.541	1.29	21.48	0.142	0.56	2.70	-0.005	-0.02	-0.31	0.029	0.16	-0.08	0.116	0.74	4.68
VW	0.803	**2.31**	25.59	0.346	1.32	13.17	0.484	1.38	19.24	0.317	1.51	16.23	0.061	0.27	0.18	0.133	0.77	5.18	0.250	1.54	21.61
G7 Countries																					
Canada	0.945	**1.98**	29.42	-0.092	-0.27	0.54	0.301	0.64	6.93	0.085	0.30	0.78	-0.262	-0.90	9.21	-0.173	-0.86	8.70	-0.021	-0.11	-0.22
France	0.649	1.49	15.93	0.271	0.81	6.13	0.543	1.31	18.03	0.286	1.08	9.96	-0.078	-0.28	0.35	0.021	0.09	-0.21	0.102	0.53	2.90
Germany	0.646	1.49	14.29	0.182	0.52	2.33	0.399	0.95	8.69	0.165	0.60	2.78	0.066	0.22	0.13	0.104	0.43	1.94	0.183	0.87	9.01
Italy	0.508	0.89	6.38	0.227	0.61	2.71	0.609	1.38	15.19	0.265	0.89	5.61	-0.153	-0.43	1.43	-0.047	-0.18	0.03	-0.019	-0.09	-0.24
Japan	0.463	1.15	4.06	0.210	0.75	2.65	0.746	**2.42**	28.61	0.153	0.71	1.88	0.262	0.92	5.82	0.233	1.17	10.49	0.174	0.90	5.91
U.K.	0.755	**2.04**	23.33	0.256	0.91	5.86	0.471	1.27	14.55	0.284	1.27	10.60	-0.084	-0.37	0.52	0.036	0.20	0.00	0.205	1.39	13.60
U.S.	0.614	**1.99**	16.74	0.575	**2.36**	33.61	0.513	**1.70**	18.91	0.456	**2.31**	30.30	0.155	0.71	2.78	0.259	1.55	17.83	0.335	**2.29**	40.32
Developed countries in Europe																					
Austria	1.222	**2.11**	15.67	-0.330	-0.79	3.51	0.941	1.48	23.37	-0.078	-0.22	-0.07	-0.124	-0.41	0.33	-0.232	-1.05	5.20	-0.250	-1.17	6.34
Belgium	0.642	1.48	10.81	0.151	0.41	1.08	0.664	1.28	18.90	0.153	0.51	1.75	-0.019	-0.07	-0.29	0.059	0.30	0.25	0.159	0.95	5.15
Denmark	0.310	0.70	3.33	0.108	0.31	0.69	0.606	1.28	22.22	0.135	0.48	1.94	0.059	0.22	0.06	0.063	0.30	0.59	0.072	0.41	1.26
Finland	1.301	**1.92**	21.53	0.734	**1.66**	15.50	0.579	1.20	6.66	0.595	**1.74**	14.58	-0.435	-1.05	6.68	-0.099	-0.30	0.43	0.175	0.56	2.85
Ireland	1.014	**2.05**	15.68	0.655	**1.69**	14.82	1.156	**2.18**	33.21	0.587	**1.86**	17.16	-0.111	-0.39	0.24	0.058	0.26	0.00	0.266	1.41	8.46
Netherlands	1.062	**2.29**	33.65	0.480	1.26	15.49	0.591	1.10	16.66	0.425	1.35	17.41	-0.066	-0.24	0.06	0.072	0.33	0.61	0.282	1.52	18.76
Spain	0.623	1.16	9.90	0.102	0.29	0.31	0.440	1.01	7.92	0.171	0.61	2.20	-0.154	-0.44	1.46	-0.074	-0.28	0.54	0.046	0.22	0.13
Sweden	0.891	1.51	17.04	0.240	0.58	2.55	0.496	0.99	8.40	0.264	0.81	4.68	-0.087	-0.25	0.15	0.057	0.21	0.11	0.222	0.87	8.22
Switzerland	0.840	**2.45**	31.83	0.281	1.09	7.93	0.327	1.06	7.58	0.217	1.04	6.66	-0.001	-0.01	-0.32	0.091	0.52	1.95	0.289	**1.92**	29.53
Developed countries in Asia-Pacific																					
Australia	0.541	1.06	14.25	-0.187	-0.51	3.65	0.355	0.70	9.77	-0.048	-0.16	0.06	-0.117	-0.38	1.63	-0.131	-0.57	4.76	-0.024	-0.13	-0.09

Hong Kong	0.528	0.93	10.32	0.013	0.03	-0.34	0.384	0.82	12.53	0.075	0.24	0.62	0.108	0.28	1.39	0.053	0.22	0.56	0.099	0.46	3.16
New Zealand	0.575	1.19	8.44	0.059	0.17	-0.11	0.718	**1.72**	21.67	0.034	0.12	-0.22	0.186	0.62	2.31	0.046	0.21	0.02	0.094	0.51	1.55
Singapore	0.414	0.84	4.56	-0.270	-0.73	4.41	0.261	0.55	2.81	-0.224	-0.72	4.35	0.108	0.31	0.64	0.035	0.15	-0.11	0.069	0.35	0.76
South Korea	0.209	0.30	0.34	-0.387	-0.73	4.78	0.661	1.11	10.26	-0.297	-0.66	3.99	-0.082	-0.15	-0.03	-0.123	-0.37	1.04	-0.206	-0.71	4.75
Taiwan	0.686	0.89	13.64	0.301	0.67	5.79	0.428	0.95	8.43	0.161	0.45	2.19	0.286	0.73	6.59	0.245	0.87	10.28	0.247	0.84	14.16
Thailand	0.419	0.54	0.95	-0.513	-0.97	3.98	0.495	0.87	2.53	-0.581	-1.33	7.60	0.548	1.00	5.86	0.197	0.57	1.36	0.141	0.45	0.82

Table 5

International Stock Return Predictability of the Relative Value of Gold at 6-Months Horizons across Market Sentiment States

This table shows the return predictability of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA) for the international stock market. The regression is a univariate predictive regression:

$$R^i_{t,t+h} = \alpha^i_1 \cdot D_{1,t} + \alpha^i_2 \cdot D_{2,t} + \beta^i_1 \cdot \log GR_t \cdot D_{1,t} + \beta^i_2 \cdot \log GR_t \cdot D_{2,t} + \epsilon^i_{t+h}$$

where $R^i_{t,t+h}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, $\log GR_t$ represents the log of seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA), $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods. We split our full sample, for each month, into low- and high-sentiment periods based on median investment sentiment index of Baker and Wurgler (2006). Cumulative excess return $R^i_{t,t+h}$ is calculated over 6-month based on the monthly overlapping observations. The international stock market data is from DataStream. Panel A shows results for the Gold-Silver ratio, Gold-Platinum ratio, Gold-Copper ratio, and Gold-Oil ratio. Panel B shows results for the Gold-Soybean ratio, Gold-CPI ratio, and Gold-DJIA ratio. In each panel, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific. Hodrick (1992) t-values are reported in parentheses. The t-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R^2_{adj}) in percentages. The sample period is from January 1990 to June 2019.

Panel A: Silver, Platinum, Copper, and Crude Oil

	Gold-Silver ratio					Gold-Platinum ratio					Gold-Copper ratio					Gold-Crude Oil ratio				
	β_1.	(t).	β_2.	(t)	R^2_{adj}	β_1.	(t)	β_2.	(t)	R^2_{adj}	β_1.	(t)	β_2.	(t).	R^2_{adj}	β_1.	(t).	β_2.	(t)	R^2_{adj}
Aggregate Portfolios																				
EW	0.115	1.19	0.144	1.15	2.97	0.069	1.14	0.065	0.84	2.17	-0.037	-0.52	0.440	**2.74**	21.82	0.039	0.77	0.135	1.52	6.02
VW	0.102	1.19	0.103	0.95	3.14	0.107	**1.91**	0.067	1.02	5.79	-0.037	-0.63	0.346	**2.68**	19.17	0.063	1.43	0.126	**1.75**	9.03
G7 Countries																				
Canada	0.068	0.61	0.179	1.45	2.66	0.035	0.49	0.011	0.13	0.20	-0.103	-1.19	0.353	**2.13**	14.09	-0.005	-0.08	0.100	1.08	2.75
France	0.112	0.97	0.084	0.62	1.60	0.086	1.20	0.061	0.79	2.37	-0.062	-0.82	0.407	**2.70**	17.66	0.044	0.77	0.129	1.52	5.24
Germany	0.077	0.63	0.069	0.47	0.26	0.083	1.14	0.044	0.53	1.20	-0.104	-1.32	0.402	**2.61**	16.34	0.040	0.71	0.112	1.25	3.21
Italy	0.081	0.53	0.111	0.65	0.28	0.061	0.73	0.062	0.70	0.44	-0.016	-0.17	0.452	**2.61**	14.00	0.038	0.54	0.116	1.21	2.21
Japan	0.117	0.97	-0.060	-0.46	7.16	0.082	1.08	0.014	0.20	7.04	-0.021	-0.29	0.311	**2.53**	14.72	0.047	0.78	0.085	1.33	8.18
U.K.	0.117	1.20	0.173	1.42	3.63	0.100	**1.72**	0.052	0.73	2.72	-0.021	-0.32	0.347	**2.41**	15.03	0.061	1.29	0.131	**1.66**	6.85
U.S.	0.105	1.27	0.137	1.41	6.00	0.151	**2.61**	0.077	1.32	12.91	-0.005	-0.09	0.281	**2.62**	16.06	0.095	**2.15**	0.107	**1.75**	12.38
Developed countries in Europe																				
Austria	0.066	0.53	0.318	**1.81**	3.70	-0.091	-1.39	0.089	0.78	1.39	-0.058	-0.73	0.680	**2.77**	26.95	-0.074	-1.39	0.219	1.63	8.08
Belgium	0.063	0.74	0.210	1.36	2.10	0.047	0.83	0.062	0.60	0.36	-0.010	-0.15	0.472	**2.26**	17.77	0.036	0.80	0.128	1.07	3.30
Denmark	0.070	0.62	0.163	1.15	1.40	0.044	0.64	0.047	0.50	0.14	-0.064	-0.80	0.442	**2.35**	17.46	0.010	0.18	0.117	1.12	2.73
Finland	0.217	1.25	-0.103	-0.54	1.45	0.216	1.62	0.084	0.81	4.09	0.007	0.07	0.543	**2.92**	11.90	0.158	1.61	0.132	1.29	4.47
Ireland	0.154	1.32	0.205	1.26	3.21	0.137	**2.03**	0.109	1.12	4.23	0.055	0.66	0.567	**2.73**	21.00	0.095	**1.77**	0.171	1.51	6.87

Netherlands	0.154	1.43	0.246	**1.66**	4.85	0.108	**1.68**	0.132	1.31	4.99	-0.068	-0.89	0.498	**2.37**	21.28	0.062	1.23	0.207	**1.75**	10.47
Spain	0.095	0.76	0.154	0.96	1.29	0.043	0.56	0.031	0.37	-0.35	-0.098	-1.09	0.391	**2.41**	13.21	0.019	0.31	0.089	0.99	1.07
Sweden	0.162	1.07	0.080	0.49	2.73	0.175	**1.68**	0.018	0.19	4.78	-0.042	-0.38	0.462	**2.38**	13.89	0.113	1.40	0.083	0.80	4.37
Switzerland	0.180	**1.82**	0.095	0.89	4.91	0.105	**1.81**	0.052	0.90	3.70	-0.033	-0.54	0.285	**2.56**	11.82	0.053	1.13	0.083	1.31	3.37
Developed countries in Asia-Pacific																				
Australia	0.043	0.32	0.293	**2.10**	5.14	-0.008	-0.10	0.066	0.77	0.52	-0.069	-0.69	0.450	**2.49**	18.45	-0.006	-0.09	0.166	1.62	6.41
Hong Kong	0.238	1.51	0.243	**1.70**	7.53	0.107	1.10	0.076	0.93	3.58	-0.079	-0.64	0.352	**2.27**	10.09	0.038	0.44	0.142	1.64	5.10
New Zealand	0.190	1.55	0.148	1.08	4.26	0.063	0.81	0.078	1.06	1.76	0.023	0.22	0.449	**3.04**	18.60	0.041	0.62	0.130	1.56	4.48
Singapore	0.086	0.65	0.178	1.20	4.37	-0.019	-0.23	0.077	0.96	3.43	-0.134	-1.33	0.451	**2.49**	17.73	-0.029	-0.42	0.163	**1.68**	7.54
South Korea	-0.029	-0.15	0.009	0.04	0.60	-0.066	-0.53	0.049	0.46	1.07	0.049	0.39	0.475	**2.34**	8.36	-0.026	-0.24	0.212	**1.78**	4.86
Taiwan	0.161	0.83	0.123	0.61	2.55	0.155	1.19	0.114	1.33	4.21	0.033	0.23	0.532	**2.83**	11.56	0.068	0.63	0.116	1.31	3.12
Thailand	0.131	0.63	0.249	1.21	4.54	-0.031	-0.23	0.076	0.70	3.09	-0.026	-0.17	0.526	**2.49**	11.82	0.005	0.04	0.131	1.09	4.13

Panel B: Soybean, CPI, and DJIA

	Gold-Soybean ratio					Gold-CPI ratio					Gold-DJIA ratio				
	β_1.	(t)	β_2.	(t).	R^2_{adj}	β_1.	(t).	β_2.	(t)	R^2_{adj}	β_1.	(t).	β_2.	(t)	R^2_{adj}
Aggregate Portfolios															
EW	0.028	0.40	0.041	0.72	0.65	0.021	0.33	-0.026	-0.67	0.49	0.054	1.30	-0.017	-0.40	2.15
VW	0.004	0.07	0.042	0.80	1.24	0.039	0.69	-0.014	-0.39	1.33	0.060	1.58	-0.004	-0.12	4.01
G7 Countries															
Canada	-0.008	-0.10	-0.011	-0.18	-0.04	0.014	0.21	-0.076	-1.94	3.03	0.028	0.61	-0.038	-0.93	1.25
France	-0.018	-0.23	0.031	0.49	0.20	0.007	0.09	-0.031	-0.68	0.39	0.040	0.82	-0.034	-0.71	1.58
Germany	0.021	0.25	0.053	0.78	0.29	0.050	0.61	-0.013	-0.26	0.25	0.066	1.29	-0.017	-0.32	2.23
Italy	-0.062	-0.65	0.041	0.55	0.07	-0.021	-0.28	-0.025	-0.44	-0.45	-0.006	-0.11	-0.047	-0.79	0.15
Japan	0.086	1.28	0.002	0.03	6.96	0.072	1.40	-0.050	-1.03	8.47	0.080	1.56	-0.080	-1.51	12.96
U.K.	-0.011	-0.17	0.034	0.62	-0.37	0.025	0.45	-0.013	-0.35	-0.45	0.058	1.53	0.023	0.58	2.39
U.S.	-0.002	-0.03	0.050	1.05	3.06	0.054	0.94	0.004	0.13	3.38	0.067	**1.70**	0.025	0.72	7.57
Developed countries in Europe															
Austria	0.004	0.05	0.086	1.06	0.53	-0.068	-0.92	-0.016	-0.32	0.17	-0.037	-0.84	-0.015	-0.27	-0.18
Belgium	-0.044	-0.76	0.076	1.06	0.90	-0.031	-0.59	0.026	0.54	-0.25	0.015	0.41	0.046	0.94	0.33
Denmark	0.044	0.63	0.051	0.78	0.31	0.045	0.70	-0.023	-0.52	0.12	0.033	0.76	-0.017	-0.39	0.08
Finland	-0.056	-0.51	0.037	0.40	-0.38	0.033	0.30	-0.080	-1.07	0.78	0.096	1.10	-0.150	-1.99	7.39
Ireland	-0.020	-0.27	0.075	1.07	0.96	0.002	0.02	0.009	0.20	-0.14	0.043	0.92	0.019	0.37	0.75
Netherlands	-0.027	-0.36	0.079	1.19	0.93	0.021	0.30	-0.002	-0.05	-0.67	0.069	1.59	0.016	0.35	1.99
Spain	-0.041	-0.49	-0.002	-0.03	-0.60	-0.015	-0.23	-0.028	-0.49	-0.44	0.014	0.29	-0.005	-0.09	-0.74
Sweden	0.038	0.40	0.007	0.09	1.12	0.083	0.92	-0.073	-1.28	3.93	0.107	1.57	-0.051	-0.84	6.22
Switzerland	-0.033	-0.49	0.072	1.44	1.87	0.002	0.03	0.032	0.88	0.06	0.059	1.47	0.036	0.95	3.75

Developed countries in Asia-Pacific															
Australia	0.038	0.42	0.024	0.37	-0.09	-0.009	-0.11	-0.039	-0.87	0.25	0.021	0.42	0.018	0.40	-0.04
Hong Kong	0.082	0.68	-0.019	-0.27	1.89	0.053	0.62	-0.072	-1.34	3.46	0.121	**1.87**	-0.009	-0.16	7.46
New Zealand	0.058	0.74	0.090	1.41	2.45	-0.005	-0.08	0.017	0.37	-0.24	0.056	1.12	-0.011	-0.22	1.56
Singapore	0.150	1.39	0.022	0.32	5.23	0.039	0.47	-0.044	-0.87	3.40	0.071	1.23	0.000	-0.01	4.57
South Korea	0.157	0.95	-0.003	-0.04	2.08	-0.016	-0.14	-0.080	-1.00	1.74	0.017	0.19	-0.074	-0.90	1.72
Taiwan	0.038	0.32	0.083	0.90	2.11	0.079	0.82	-0.020	-0.30	2.06	0.078	0.89	-0.052	-0.64	3.22
Thailand	0.253	1.48	0.081	0.81	7.08	0.065	0.57	-0.003	-0.04	3.00	0.129	1.40	0.031	0.37	6.31

Table 6

Contemporaneous Relationship Between of the Relative Value of Gold and Aggregate Uncertainty Measures Conditioning on Market Sentiment States

This table shows the return predictability of the seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA) for the international stock market. The regression is a univariate predictive regression:

$$U_t = \alpha_1 \cdot D_{1,t} + \alpha_2 \cdot D_{2,t} + \beta_1 \cdot \log GR_t \cdot D_{1,t} + \beta_2 \cdot \log GR_t \cdot D_{2,t} + \epsilon_t$$

where U_t is the uncertainty measure, $\log GR_t$ represents the log of seven gold ratios (against silver, platinum, copper, oil, soybeans, CPI, and DJIA), $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods. Low- and high-sentiment samples are split based on based on median investment sentiment index of Baker and Wurgler (2006). Panel A shows the results for aggregate uncertainty measures in U.S. stock market: Stock market variance (SVAR), Implied Volatility (IV) and Variance Risk Premium (VRP). Panel B documents the results for the uncertainty measures of Jurado et al. (2015), which are constructed from an extensive set of financial and macroeconomic variables: Macroeconomic Uncertainty (MU), Real Uncertainty (RU), and Financial Uncertainty (FU). Hodrick (1992) *t*-values are reported in parentheses. The *t*-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R^2_{adj}) in percentages. The sample period is from January 1990 to June 2019.

Panel A: Stock Market Uncertainty Measures

	Gold-Silver ratio			Gold-Platinum ratio			Gold-Copper ratio			Gold-Crude Oil ratio			Gold-Soybean ratio			Gold-CPI ratio			Gold-DJIA ratio		
	SVAR.	IV.	VRP	SVAR.	IV.	VRP	SVAR.	IV.	VRP	SVAR.	IV.	VRP	SVAR.	IV.	VRP	SVAR.	IV.	VRP	SVAR.	IV.	VRP
β_1	3.25	0.04	-0.04	-4.79	-0.16	-0.25	3.51	0.07	-0.01	-8.63	-0.16	-0.08	-8.29	-0.20	-0.27	-6.85	-0.17	-0.27	4.13	0.13	0.11
(*t*-stat)	**2.68**	1.18	-0.60	-0.93	-1.34	-1.45	1.10	1.14	-0.17	**-2.06**	-1.49	-0.38	-1.48	-1.51	-1.09	-1.06	-1.01	-0.88	0.76	1.12	0.53
β_2	-25.11	-0.22	-0.02	-15.38	-0.11	0.14	18.55	0.26	0.41	-12.47	-0.02	0.37	-4.95	-0.20	-0.56	6.53	-0.09	-0.46	-58.49	-0.70	-0.72
(*t*-stat)	**-3.82**	**-2.80**	-0.20	-0.81	-0.65	0.92	**2.11**	**2.46**	**2.66**	-0.58	-0.08	**2.02**	-0.29	-1.15	**-2.49**	0.22	-0.34	**-2.20**	-1.17	**-1.83**	**-2.54**
R^2_{adj}	5.0%	4.1%	-0.3%	6.6%	7.9%	7.6%	17.5%	19.5%	18.9%	3.9%	4.2%	4.0%	19.2%	21.4%	22.5%	29.5%	30.1%	30.9%	5.7%	8.1%	4.6%

Panel B: Uncertainty Measures of Jurado et al. (2015)

	Gold-Silver ratio			Gold-Platinum ratio			Gold-Copper ratio			Gold-Crude Oil ratio			Gold-Soybean ratio			Gold-CPI ratio			Gold-DJIA ratio		
	MU.	RU.	FU	MU.	RU.	FU	MU.	RU.	FU	MU.	RU.	FU	MU.	RU.	FU	MU.	RU.	FU	MU.	RU.	FU
β_1	0.15	0.34	0.02	-0.71	-0.25	-0.52	-0.17	-0.28	-0.07	-0.73	-0.73	-0.52	-0.33	0.65	-0.60	-0.19	1.28	-0.59	1.19	3.35	0.28
(*t*-stat)	1.05	1.39	0.20	**-1.76**	-0.45	**-1.97**	-0.42	-0.41	-0.34	-1.44	-0.95	-1.75	-0.92	0.86	**-1.94**	-0.38	1.26	-1.38	**2.83**	**2.91**	0.83
β_2	-1.68	-1.84	-0.35	-3.66	-3.52	-0.53	-1.08	-0.50	0.49	-4.09	-4.03	-0.47	1.30	1.65	-0.48	-0.87	0.07	-0.50	-4.66	-4.92	-1.85
(*t*-stat)	**-4.11**	**-3.31**	**-2.36**	**-7.09**	**-3.90**	**-2.01**	-1.57	-0.57	**2.33**	**-5.76**	**-3.20**	-1.39	**1.66**	1.56	**-2.55**	-1.17	0.06	-1.75	**-4.32**	**-2.45**	**-4.99**
R^2_{adj}	13.6%	6.0%	4.4%	30.9%	13.0%	13.6%	19.2%	16.1%	21.3%	27.6%	11.2%	8.4%	20.9%	20.1%	24.8%	29.7%	30.4%	32.6%	19.2%	16.1%	20.5%

Table 7

Predictability of Commodity Price Changes on Future GDP Growth Conditioning on Market Sentiment

This table shows the predictability of the commodity price change on future GDP growth, conditioning on market sentiment. The regression is specified as:

$$\ln(GDP)_{t,t+h} = \alpha_1^i \cdot D_{1,t} + \alpha_2^i \cdot D_{2,t} + \beta_1^i \cdot \Delta\ln(Commodity)_t \cdot D_{1,t} + \beta_2^i \cdot \Delta\ln(Commodity)_t \cdot D_{2,t} + \epsilon_{t+h}^i$$

We consider forecasting horizon $h = 1, 2, ,4, 8$ quarters. Cumulative log changes of real GDP per capita, $\ln(GDP)_{t,t+h}$ is calculated over h-quarter based on the quarterly overlapping observations. $\Delta\ln(Commodity)_t$ is change of log of the five commodities prices (Silver, Platinum, Copper, Crude Oil, and Soybean). We take the change in order to avoid the possibility of unit-root of commodity price. $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods. Note that we split our full sample, for every month into low- and high-sentiment periods based on median investment sentiment index of Baker and Wurgler (2006). Hodrick (1992) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. This table also reports the adjusted R-square (R^2_{adj}) in percentages. The sample period is from 1990 Q1 to 2019 Q2.

	h = 1q.					h = 2q				
	β_1	(t)	β_2	(t)	R^2_{adj}	β_1	(t)	β_2	(t)	R^2_{adj}
Silver	0.010	1.079	-0.001	-0.377	0.033	0.012	0.852	-0.006	-0.569	0.008
Platinum	0.025	3.081***	-0.001	-0.242	0.151	0.041	3.251***	-0.014	-1.149	0.139
Copper	-0.001	-0.260	0.015	2.405**	0.089	-0.007	-1.322	0.025	2.640***	0.072
Crude Oil	0.003	0.529	-0.005	-1.425	0.019	0.003	0.299	-0.007	-1.081	-0.004
Soybean	0.007	0.784	-0.007	-1.311	0.024	0.003	0.288	-0.007	-1.071	-0.006
	h = 4q.					h = 8q				
	β_1	(t)	β_2	(t)	R^2_{adj}	β_1	(t)	β_2	(t)	R^2_{adj}
Silver	0.021	1.267	-0.010	-0.392	-0.005	-0.036	-0.946	0.008	0.499	-0.017
Platinum	0.054	3.875***	-0.073	-1.774*	0.140	-0.113	-1.953*	0.038	2.191**	0.070
Copper	-0.025	-2.526**	0.028	2.583***	0.028	-0.033	-1.800*	0.013	0.992	-0.011
Crude Oil	0.004	0.541	-0.023	-1.356	-0.006	-0.040	-1.282	0.000	0.048	-0.005
Soybean	0.001	0.115	-0.018	-0.987	-0.017	-0.069	-1.359	0.002	0.160	0.024

Table 8
Contemporaneous Relationship between Copper Price Changes and Stock Returns: Conditioning on Market Sentiment

This table shows the contemporaneous relationship between copper price change and stock returns for each country, conditioning on market sentiment or NBER business cycle. The regression is specified as:

$$R_t^i = \alpha_1^i \cdot D_{1,t} + \alpha_2^i \cdot D_{2,t} + \beta_1^i \cdot \Delta\ln(Copper)_t \cdot D_{1,t} + \beta_2^i \cdot \Delta\ln(Copper)_t \cdot D_{2,t} + \epsilon_{t+h}^i$$

where R_t^i is the monthly excess return of each stock market (or portfolio) i. $\Delta\ln(Copper)_t$ is change of log of the copper price. We take the change in order to avoid the possibility of unit-root of commodity price. $D_{1,t}$ is the dummy variable for the high-sentiment periods, and $D_{2,t}$ is the dummy variable for the low-sentiment periods. Note that we split our full sample, for every month into low- and high-sentiment periods based on median investment sentiment index of Baker and Wurgler (2006). The international stock market data is from DataStream. In Panel A, B, C, and D, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. Hodrick (1992) t-values are reported. The t-values in bold indicate the significance at the 10% level. This table also reports the adjusted R-square (R_{adj}^2) in percentages. The sample period is from January 1990 to June 2019.

	β_1.	(t).	β_2.	(t).	R_{adj}^2
Panel A: Aggregate Portfolios					
EW	0.204	**3.341**	0.395	**6.271**	0.205
VW	0.144	**2.731**	0.328	**6.806**	0.165
Panel B: G7 countries					
Canada	0.277	**4.616**	0.469	**7.733**	0.266
France	0.151	**2.073**	0.365	**5.756**	0.123
Germany	0.169	**2.118**	0.378	**6.036**	0.123
Italy	0.105	1.208	0.376	**4.672**	0.079
Japan	0.087	1.507	0.209	**3.997**	0.044
U.K.	0.180	**3.607**	0.365	**5.906**	0.189
U.S.	0.117	**2.263**	0.277	**6.448**	0.128
Panel C: developed countries in Europe					
Austria	0.242	**3.045**	0.551	**4.697**	0.211
Belgium	0.139	**3.184**	0.411	**3.592**	0.161
Denmark	0.134	**2.018**	0.363	**3.589**	0.125
Finland	0.200	**2.102**	0.407	**5.440**	0.076
Ireland	0.135	**2.323**	0.389	**3.948**	0.116
Netherlands	0.192	**3.116**	0.447	**4.302**	0.190
Spain	0.110	**1.831**	0.333	**4.322**	0.070
Sweden	0.190	**2.055**	0.466	**6.067**	0.129
Switzerland	0.148	**2.536**	0.240	**5.448**	0.091
Panel D: developed countries in Asia-Pacific					
Australia	0.309	**4.642**	0.474	**6.373**	0.233
Hong Kong	0.210	**2.333**	0.422	**8.387**	0.112
New Zealand	0.190	**2.850**	0.329	**6.367**	0.103
Singapore	0.200	**2.394**	0.442	**6.690**	0.146
South Korea	0.518	**3.916**	0.475	**6.460**	0.118
Taiwan	0.283	**3.052**	0.392	**5.117**	0.064
Thailand	0.412	**3.571**	0.486	**5.538**	0.100

Table 9
Results after Controlling for Alternative U.S. Predictors
This table shows the return predictability of the gold-copper ratio for the international stock market after controlling for alternative U.S. predictive variables. The regression model is following:

$$R^i_{t,t+h} = \alpha^i + \beta^i_1 DP^{US}_t + \beta^i_2 VRP^{US}_t + \beta^i_3 \log GC_t + \epsilon^i_{t+h}$$

where $R^i_{t,t+h}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of the gold-copper ratio. DP^{US}_t is a dividend-price ratio of the U.S. stock market, and VRP^{US}_t is the U.S. Variance Risk Premium as in Bollerslev *et al.* (2009). Cumulative excess return $R^i_{t,t+h}$ is calculated over 3-month, 6-month, and 1-year, based on the monthly overlapping observations. The international stock market data is from DataStream. In Panel A, B, C, and D, we report the results for aggregate portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. We present the estimates of the regression slope coefficients. The coefficient of VRP^{US}_t is multiplied by 100 for readability. Hodrick (1992) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. This table also reports the adjusted R-square (R^2_{adj}) in percentages. The sample period is from January 1990 to June 2019.

	3-month				6-month				1-year			
	DP	VRP	Gold-Copper ratio	R^2_{adj}	DP	VRP	Gold-Copper ratio	R^2_{adj}	DP	VRP	Gold-Copper ratio	R^2_{adj}
Panel A: Aggregate Portfolios												
EW	0.030	0.081**	0.063*	6.47	0.062	0.078	0.149**	9.76	0.131	0.020	0.245**	13.09
	(0.96)	(2.05)	(1.91)		(1.01)	(1.41)	(2.27)		(1.26)	(0.25)	(2.09)	
VW	0.034	0.087**	0.044	7.71	0.071	0.098*	0.115**	11.37	0.156	0.062	0.209**	16.67
	(1.12)	(2.53)	(1.56)		(1.22)	(1.95)	(2.11)		(1.58)	(0.88)	(2.16)	
Panel B: G7 countries												
Canada	0.017	0.091***	0.041	4.02	0.039	0.107**	0.087	4.44	0.081	0.081	0.126	3.87
	(0.51)	(2.74)	(1.10)		(0.60)	(2.06)	(1.18)		(0.70)	(0.99)	(0.94)	
France	0.020	0.090*	0.052	4.95	0.039	0.091	0.127*	6.56	0.096	0.047	0.232*	9.42
	(0.56)	(1.93)	(1.51)		(0.57)	(1.40)	(1.89)		(0.77)	(0.52)	(1.84)	
Germany	0.029	0.089*	0.033	3.64	0.059	0.083	0.096	4.43	0.133	0.020	0.172	6.74
	(0.76)	(1.69)	(0.90)		(0.80)	(1.18)	(1.38)		(1.04)	(0.21)	(1.35)	
Italy	-0.011	0.089*	0.070*	4.17	-0.021	0.086	0.159**	5.58	-0.035	-0.010	0.299**	8.11
	(-0.27)	(1.90)	(1.72)		(-0.26)	(1.20)	(2.00)		(-0.23)	(-0.09)	(2.06)	

Japan	0.003	0.008	0.070**	1.99	0.018	0.039	0.164***	6.61	0.059	0.030	0.315***	11.79
	(0.06)	(0.20)	(2.27)		(0.21)	(0.63)	(2.81)		(0.41)	(0.34)	(3.21)	
U.K.	0.046	0.097***	0.039	8.05	0.094	0.105**	0.104*	10.64	0.190*	0.063	0.178	14.45
	(1.47)	(3.10)	(1.27)		(1.63)	(2.29)	(1.68)		(1.80)	(0.90)	(1.59)	
U.S.	0.055*	0.113***	0.037	13.15	0.109**	0.131***	0.099*	16.66	0.233**	0.114	0.195**	24.80
	(1.91)	(3.39)	(1.39)		(1.97)	(2.67)	(1.94)		(2.29)	(1.56)	(2.04)	
Panel C: Developed countries in Europe												
Austria	-0.006	0.057	0.103**	4.31	-0.008	0.032	0.225**	7.57	-0.045	-0.115	0.395**	12.22
	(-0.15)	(1.30)	(2.18)		(-0.09)	(0.47)	(2.41)		(-0.37)	(-1.21)	(2.31)	
Belgium	0.032	0.051	0.069*	3.62	0.064	0.037	0.151*	6.22	0.134	-0.047	0.247	8.95
	(1.00)	(1.19)	(1.74)		(1.02)	(0.63)	(1.88)		(1.23)	(-0.56)	(1.63)	
Denmark	0.006	0.053	0.057	2.37	0.020	0.043	0.138*	4.59	0.053	-0.006	0.242*	7.21
	(0.17)	(1.55)	(1.47)		(0.30)	(0.81)	(1.75)		(0.46)	(-0.07)	(1.67)	
Finland	-0.008	0.117**	0.079*	3.57	-0.003	0.117	0.173**	4.12	0.027	0.089	0.309**	4.72
	(-0.14)	(2.24)	(1.80)		(-0.02)	(1.46)	(2.07)		(0.12)	(0.74)	(2.04)	
Ireland	0.023	0.096**	0.089**	6.14	0.052	0.083	0.195**	8.00	0.117	-0.008	0.369**	12.54
	(0.56)	(1.98)	(2.03)		(0.66)	(1.20)	(2.33)		(0.86)	(-0.08)	(2.36)	
Netherlands	0.052*	0.066*	0.049	4.25	0.113*	0.071	0.127	8.33	0.238**	-0.015	0.219	14.93
	(1.67)	(1.73)	(1.21)		(1.86)	(1.25)	(1.56)		(2.13)	(-0.18)	(1.43)	
Spain	0.031	0.090*	0.030	2.95	0.055	0.099	0.082	3.47	0.098	-0.007	0.159	3.74
	(0.79)	(1.79)	(0.75)		(0.72)	(1.41)	(1.07)		(0.74)	(-0.07)	(1.12)	
Sweden	0.043	0.099**	0.080*	5.40	0.089	0.090	0.169*	7.08	0.188	0.026	0.280*	9.62
	(0.88)	(2.07)	(1.79)		(0.91)	(1.31)	(1.92)		(1.07)	(0.26)	(1.78)	
Switzerland	0.046	0.061	0.016	3.97	0.096	0.068	0.069	7.89	0.212**	0.002	0.130	15.56
	(1.49)	(1.39)	(0.59)		(1.62)	(1.13)	(1.37)		(2.06)	(0.02)	(1.40)	
Panel D: Developed countries in Asia-Pacific												
Australia	0.039	0.100**	0.061	6.24	0.082	0.102	0.126	7.65	0.146	0.038	0.161	7.07
	(1.11)	(2.16)	(1.46)		(1.22)	(1.62)	(1.54)		(1.19)	(0.41)	(1.07)	
Hong Kong	0.091**	0.075	0.044	5.23	0.172*	0.073	0.102	9.38	0.347**	0.068	0.118	14.73
	(2.00)	(1.53)	(1.03)		(1.94)	(1.00)	(1.21)		(2.15)	(0.56)	(0.79)	
New Zealand	0.027	0.029	0.088**	4.93	0.056	0.018	0.180**	9.06	0.103	-0.083	0.307**	13.17
	(0.68)	(0.62)	(2.20)		(0.74)	(0.27)	(2.39)		(0.78)	(-0.82)	(2.20)	
Singapore	0.055	0.083*	0.060	4.30	0.106	0.091	0.129	6.46	0.215	0.072	0.152	7.32
	(1.19)	(1.67)	(1.44)		(1.20)	(1.24)	(1.56)		(1.43)	(0.61)	(1.06)	

South Korea	-0.003	0.106	0.105**	2.99	-0.013	0.109	0.230**	5.05	-0.023	0.147	0.343*	4.92
	(-0.05)	(1.16)	(2.02)		(-0.10)	(0.83)	(2.28)		(-0.10)	(0.74)	(1.85)	
Taiwan	0.016	0.104*	0.129**	4.55	0.050	0.048	0.241**	5.70	0.170	-0.032	0.336**	9.78
	(0.22)	(1.74)	(2.58)		(0.35)	(0.53)	(2.55)		(0.73)	(-0.24)	(2.13)	
Thailand	0.107	0.100	0.111**	5.62	0.181	0.094	0.219**	8.62	0.310	0.030	0.290	8.47
	(1.54)	(1.32)	(2.07)		(1.35)	(0.90)	(2.07)		(1.32)	(0.17)	(1.54)	

Table 10
Results after Controlling for Local Economic Variables

This table shows the return predictability of the gold-copper ratio for the international stock market after controlling for alternative local predictive variables. The regression model is following:

$$R_{t,t+h}^{i} = \alpha^{i} + \beta_1^{i} ERV_t^{i} + \beta_2^{i} DY_t^{i} + \beta_3^{i} \log GC_t + \epsilon_{t+h}^{i}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of the gold-copper ratio. ERV_t^{i} denotes the expected realized variance of country i at time t. DY_t^{i} is a dividend yield of country i at time t. Cumulative excess return $R_{t,t+h}^{i}$ is calculated over 3-month, 6-month, and 1-year, based on the monthly overlapping observations. The international stock market data is from DataStream. Panel A, B and C shows results for G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. In this table, we present the estimates of the regression slope coefficients. Hodrick (1992) t-values are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. This table also reports the adjusted R-square (R_{adj}^2) in percentages. The sample period is from January 1990 to June 2019.

	3-month				6-month				1-year			
	ERV	DY	Gold-Copper ratio	R_{adj}^2	ERV	DY	Gold-Copper ratio	R_{adj}^2	ERV	DY	Gold-Copper ratio	R_{adj}^2
Panel A: G7 countries												
Canada	-1.049	0.005	0.048	1.10	0.639	0.011	0.090	2.16	2.236	0.022	0.122	3.29
	(-1.29)	(0.27)	(1.21)		(0.31)	(0.32)	(1.15)		(0.65)	(0.34)	(0.84)	
France	-4.250	0.025	0.054	4.44	-3.342	0.047	0.116	8.04	-2.255	0.089	0.192	14.81
	(-1.23)	(1.44)	(1.54)		(-0.68)	(1.48)	(1.64)		(-0.36)	(1.57)	(1.39)	
Germany	-4.094	0.016	0.035	1.21	-1.619	0.029	0.085	3.42	-2.358	0.074	0.128	8.09
	(-0.72)	(0.79)	(0.90)		(-0.22)	(0.80)	(1.07)		(-0.29)	(1.11)	(0.85)	
Italy	-1.303	0.002	0.078*	1.75	1.421	0.004	0.155*	4.66	4.327	0.008	0.274*	8.69
	(-0.40)	(0.17)	(1.91)		(0.27)	(0.20)	(1.94)		(0.64)	(0.20)	(1.80)	
Japan	3.527	0.020	0.052	3.67	3.793	0.040	0.130**	8.63	13.320	0.083	0.247**	16.83
	(0.86)	(1.18)	(1.55)		(0.53)	(1.16)	(2.00)		(1.55)	(1.32)	(2.07)	
U.K.	-1.812	0.016	0.048	3.89	-0.967	0.033	0.109*	7.35	0.717	0.078*	0.170	15.39
	(-1.71)	(1.25)	(1.49)		(-0.44)	(1.37)	(1.75)		(0.23)	(1.83)	(1.48)	
U.S.	-3.473	0.028*	0.049*	7.77	-2.379	0.056*	0.107**	12.02	-1.487	0.122**	0.194*	23.03
	(-1.51)	(1.84)	(1.82)		(-0.56)	(1.95)	(2.07)		(-0.28)	(2.35)	(1.94)	
Panel B: Developed countries in Europe												

Austria	-1.329	-0.006	0.118*	3.92	2.523	-0.009	0.237*	7.77	5.053	-0.008	0.387*	12.01
	(-0.59)	(-0.25)	(1.85)		(0.58)	(-0.21)	(1.90)		(0.94)	(-0.13)	(1.69)	
Belgium	-2.447	0.010	0.077*	3.59	-1.158	0.023	0.156*	9.04	4.121	0.036	0.238	13.20
	(-0.68)	(0.99)	(1.87)		(-0.25)	(1.30)	(1.92)		(0.65)	(1.41)	(1.54)	
Denmark	-1.035	0.007	0.060	1.60	0.084	0.041	0.124	5.25	0.990	0.165*	0.176	15.28
	(-0.94)	(0.26)	(1.44)		(0.03)	(0.85)	(1.50)		(0.27)	(1.96)	(1.15)	
Finland	-4.622	-0.011	0.112**	4.98	-6.788	-0.019	0.222**	7.19	-13.271	-0.019	0.372**	10.10
	(-1.58)	(-0.84)	(2.37)		(-1.19)	(-0.75)	(2.43)		(-1.23)	(-0.40)	(2.14)	
Ireland	-5.286	0.009	0.112**	6.86	-4.630	0.022	0.231***	8.54	-4.115	0.048	0.423***	14.40
	(-1.64)	(0.71)	(2.42)		(-0.95)	(1.07)	(2.75)		(-0.55)	(1.43)	(2.71)	
Netherlands	-1.813	0.009	0.062	1.73	-2.323	0.030	0.146*	6.60	-2.273	0.074**	0.239	15.46
	(-0.88)	(0.71)	(1.53)		(-0.69)	(1.35)	(1.80)		(-0.44)	(2.09)	(1.52)	
Spain	0.043	0.000	0.038	-0.16	0.194	0.002	0.089	1.20	5.733	0.002	0.147	3.03
	(0.01)	(0.01)	(0.93)		(0.03)	(0.13)	(1.11)		(0.70)	(0.07)	(0.99)	
Sweden	1.405	-0.010	0.094*	2.68	5.598	-0.008	0.170*	6.50	6.703	0.025	0.254	9.08
	(0.53)	(-0.59)	(1.93)		(1.07)	(-0.25)	(1.79)		(0.91)	(0.43)	(1.44)	
Switzerland	-2.954	-0.004	0.032	0.03	2.348	-0.009	0.093	2.25	15.777	-0.012	0.150	5.54
	(-0.35)	(-0.31)	(0.98)		(0.20)	(-0.37)	(1.42)		(1.01)	(-0.25)	(1.20)	
Panel C: Developed countries in Asia-Pacific												
Australia	-1.290	0.018	0.058	3.95	0.142	0.033	0.112	6.66	2.490	0.061	0.123	10.46
	(-1.06)	(1.15)	(1.32)		(0.08)	(1.20)	(1.29)		(1.12)	(1.36)	(0.76)	
Hong Kong	-7.701	0.058***	0.040	12.37	-10.045	0.108***	0.090	21.79	-16.371	0.227***	0.083	41.65
	(-2.17)	(3.36)	(0.95)		(-1.54)	(3.42)	(1.08)		(-1.47)	(4.55)	(0.56)	
New Zealand	-3.436	-0.006	0.089**	4.80	4.319	-0.012	0.182**	8.37	20.626	-0.026	0.300**	12.16
	(-0.40)	(-0.47)	(2.23)		(0.31)	(-0.53)	(2.44)		(1.12)	(-0.72)	(2.16)	
Singapore	0.868	0.032	0.038	4.34	0.607	0.075**	0.069	11.23	9.424	0.164***	0.018	22.18
	(0.19)	(1.61)	(0.84)		(0.07)	(2.02)	(0.76)		(0.61)	(2.59)	(0.11)	
South Korea	0.442	0.019	0.117**	3.82	0.039	0.050	0.252**	5.26	0.854	0.150	0.399**	10.35
	(0.80)	(0.50)	(2.19)		(0.06)	(0.77)	(2.52)		(0.96)	(1.36)	(2.20)	
Taiwan	-1.562	0.020*	0.123**	6.51	0.893	0.046**	0.226**	12.07	-0.264	0.064	0.317**	16.32
	(-0.36)	(1.68)	(2.58)		(0.13)	(2.06)	(2.49)		(-0.03)	(1.64)	(1.99)	
Thailand	-3.965	0.039**	0.136**	9.25	-6.275	0.073**	0.259**	16.27	-4.682	0.135**	0.361*	19.40
	(-1.42)	(2.33)	(2.57)		(-1.15)	(2.34)	(2.48)		(-0.47)	(2.39)	(1.93)	

Table 11
Out-of-Sample Forecasting Results

This table shows the out-of-sample forecasting power of the gold-copper ratio. The regression is an univariate predictive regression:

$$R_{t,t+h}^{i} = \alpha^{i} + \beta^{i} \log GC_{t} + \epsilon_{t+h}^{i}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of the gold-copper ratio. Cumulative excess return $R_{t,t+h}^{i}$ is calculated over 1-month, 3-month, 6-month, 1-year, and 2-year, based on the monthly overlapping observations. The international stock market data is from DataStream. In Panel A, B, C, and D, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. This table reports the Campbell and Thompson (2008) out-of-sample R^2 in percentage. The Clark and West (2007) MSFE-adjusted statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. The out-of-sample forecasting results are for the initial period from January 1990 to December 1999 within forecast evaluation period from January 2000 to June 2019.

	1-month	3-month	6-month	1-year	2-year
Panel A: Aggregate Portfolios					
EW	-1.215	1.603*	6.369*	11.190**	25.174**
	(0.75)	(1.38)	(1.51)	(1.65)	(1.68)
VW	-0.429	2.386**	7.309**	12.025**	25.211**
	(0.33)	(1.73)	(1.81)	(1.84)	(1.77)
Panel B: G7 Countries					
Canada	-0.644	0.899	2.237	2.812	9.564
	(-0.27)	(0.90)	(0.94)	(0.93)	(1.10)
France	-0.633	1.115	5.158*	9.279**	23.572**
	(-0.23)	(1.11)	(1.51)	(1.78)	(1.75)
Germany	-0.915	-0.098	2.107	4.684*	15.545**
	(-1.02)	(0.53)	(1.17)	(1.43)	(1.72)
Italy	-0.857	0.588	5.459*	11.643**	26.350**
	(0.12)	(1.12)	(1.44)	(1.72)	(1.79)
Japan	0.434	4.070**	10.869**	18.570**	33.000**
	(1.02)	(1.73)	(1.89)	(1.95)	(2.22)
U.K.	-0.396	1.540	4.871	7.025*	17.383*
	(0.11)	(1.17)	(1.27)	(1.37)	(1.30)
U.S.	-0.310	1.857*	4.916*	10.031**	22.737**
	(-0.08)	(1.48)	(1.57)	(1.71)	(1.69)
Panel C: Developed countries in Europe					
Austria	0.498	3.834*	8.079*	13.263**	25.527**
	(1.13)	(1.54)	(1.58)	(1.69)	(1.73)
Belgium	0.161	2.582*	5.813*	7.525*	23.425*
	(0.85)	(1.36)	(1.44)	(1.52)	(1.44)
Denmark	-0.412	1.380	4.620*	8.373**	26.522**
	(0.29)	(1.25)	(1.49)	(1.66)	(1.72)
Finland	-2.168	-1.994	-1.484	-0.567	15.108*
	(0.69)	(1.15)	(1.12)	(1.19)	(1.54)
Ireland	0.517	4.165*	7.893*	13.208**	33.918*
	(1.06)	(1.53)	(1.59)	(1.67)	(1.48)
Netherlands	-0.424	1.112*	4.148*	6.901**	18.874*
	(-0.26)	(1.37)	(1.59)	(1.83)	(1.60)
Spain	-0.699	-0.189	1.662	2.581	11.328*
	(-0.54)	(0.50)	(0.92)	(1.20)	(1.44)

Sweden	-0.312	1.987*	5.236*	7.606*	16.670*
	(0.85)	(1.33)	(1.39)	(1.45)	(1.53)
Switzerland	-0.845	-0.517	2.612	3.902	17.350*
	(-1.19)	(0.29)	(1.21)	(1.27)	(1.43)
Panel D: Developed countries in Asia-Pacific					
Australia	-0.702	1.168	4.071	4.180	9.302
	(0.56)	(1.17)	(1.18)	(1.16)	(1.05)
Hong Kong	-1.617	-0.699	1.621	3.180*	1.021
	(0.10)	(0.75)	(1.05)	(1.35)	(0.75)
New Zealand	0.508*	5.025**	10.779**	16.717**	27.319**
	(1.61)	(1.86)	(1.83)	(1.98)	(1.70)
Singapore	-2.382	-2.065	0.186	1.510	4.993
	(0.26)	(0.77)	(0.95)	(0.85)	(0.98)
South Korea	-3.133	-2.164	-5.765	-7.783	15.278*
	(0.76)	(1.10)	(1.08)	(0.87)	(1.44)
Taiwan	-1.516*	-0.333**	1.679*	3.493*	12.989*
	(1.34)	(1.65)	(1.63)	(1.51)	(1.57)
Thailand	-0.490*	2.195**	5.308*	7.066*	10.732*
	(1.47)	(1.65)	(1.60)	(1.30)	(1.38)

Table 12
Asset Allocation Performance (Zero Cost)
This table shows the economic value of the predictability of the gold-copper ratio from an asset allocation perspective under zero transaction cost. It reports the annualized certainty equivalent return (CER) gain using the predictive regression forecast instead of the historical average benchmark forecast:

$$R_{t,t+h}^{i} = \alpha^{i} + \beta^{i} \log GC_t + \epsilon_{t+h}^{i}$$

where $R_{t,t+h}^{i}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of the gold-copper ratio We assume a mean-variance investor, who rebalances portfolios quarterly, bi-annually, or annually between equities and risk-free bills using the out-of-sample return forecasts for stock market excess return in each country. The relative risk aversion coefficient (γ) is set to be 3 or 5. In Panel A, B, C, and D, we report the results for the gloabal aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. The sample period is from January 1990 to June 2019.

	γ = 3			γ = 5		
	3-month	6-month	12-month	3-month	6-month	12-month
Panel A: Aggregate Portfolios						
EW	2.305	3.201	0.683		1.557	0.410
VW	0.670	1.342	0.778		0.953	0.482
Panel B: G7 Countries						
Canada	-0.172	-2.177	-1.859	-0.103	-1.304	-1.165
France	-0.742	0.477	-0.051	-0.445	0.286	-0.955
Germany	-1.055	-0.668	-1.043	-0.633	-0.401	-0.626
Italy	1.163	2.786	3.448	0.698	1.671	2.069
Japan	1.732	4.836	4.064	1.056	2.978	2.468
U.K.	0.637	1.261	-0.475	0.386	0.715	-1.238
U.S.	1.621	1.385	1.066	0.671	1.238	-0.055
Panel C: Developed countries in Europe						
Austria	7.563	7.852	3.384	4.562	4.699	2.030
Belgium	1.366	1.104	0.162	0.820	0.663	0.097
Denmark	-0.276	-1.285	-1.452	-0.166	-0.770	-0.871
Finland	1.737	2.499	1.600	1.042	1.500	0.960
Ireland	1.842	2.906	1.253	1.105	1.281	0.519
Netherlands	-0.088	-4.392	-3.736	-0.213	-2.383	-2.249
Spain	-1.378	-0.868	-1.406	-0.827	-0.521	-0.843
Sweden	2.351	3.217	1.729	1.411	1.930	1.037
Switzerland	-0.031	-0.211	-0.113	-0.461	-0.351	-1.913
Panel D: Developed countries in Asia-Pacific						
Australia	1.840	1.873	-4.251	1.279	0.721	-2.551
Hong Kong	-0.149	0.471	-5.435	-0.090	0.283	-3.261
New Zealand	5.567	7.071	1.561	3.202	4.353	0.937
Singapore	1.888	2.307	0.471	1.133	1.384	0.282
South Korea	2.056	2.307	2.115	1.234	1.384	1.269
Taiwan	5.282	3.294	2.459	3.215	1.976	1.475
Thailand	3.686	4.919	1.053	2.212	2.951	0.632

Table 13
Asset Allocation Performance (50 bp cost)
This table shows the economic value of the predictability of the gold-copper ratio from an asset allocation perspective. It reports the annualized certainty equivalent return (CER) gain accounting for transaction cost (50 bp) using the predictive regression forecast instead of the historical average benchmark forecast:

$$R^i_{t,t+h} = \alpha^i + \beta^i \log GC_t + \epsilon^i_{t+h}$$

where $R^i_{t,t+h}$ is the annualized excess return of each stock market (or portfolio) i by the horizon h, and $\log GC_t$ represents the log of the gold-copper ratio We assume a mean-variance investor, who rebalances portfolios quarterly, bi-annually, or annually between equities and risk-free bills using the out-of-sample return forecasts for stock market excess return in each country. The relative risk aversion coefficient (γ) is set to be 3 or 5. In Panel A, B, C, and D, we report the results for the global aggregate market portfolios, G7 countries, developed countries in Europe, and developed countries in Asia-Pacific, respectively. The sample period is from January 1990 to June 2019.

	γ = 3			γ = 5		
	3-month	6-month	12-month	3-month	6-month	12-month
Panel A: Aggregate Portfolios						
EW	2.041	3.015	0.598	1.224	1.426	0.358
VW	0.407	1.174	0.675	0.123	0.851	0.421
Panel B: G7 Countries						
Canada	-0.371	-2.275	-1.959	-0.223	-1.362	-1.203
France	-0.931	0.363	-0.119	-0.559	0.218	-1.020
Germany	-1.152	-0.751	-1.082	-0.692	-0.451	-0.648
Italy	1.016	2.681	3.380	0.609	1.608	2.028
Japan	1.612	4.702	3.913	0.975	2.864	2.368
U.K.	0.363	1.115	-0.583	0.220	0.611	-1.332
U.S.	1.411	1.277	0.960	0.552	1.133	-0.153
Panel C: Developed countries in Europe						
Austria	7.402	7.772	3.336	4.452	4.648	2.001
Belgium	1.147	0.959	0.091	0.688	0.575	0.052
Denmark	-0.522	-1.407	-1.517	-0.313	-0.851	-0.904
Finland	1.562	2.351	1.532	0.937	1.410	0.922
Ireland	1.592	2.746	1.080	0.952	1.156	0.425
Netherlands	-0.230	-4.462	-3.822	-0.302	-2.445	-2.297
Spain	-1.534	-0.951	-1.467	-0.920	-0.571	-0.882
Sweden	2.153	3.071	1.677	1.291	1.842	1.006
Switzerland	-0.163	-0.303	-0.208	-0.567	-0.422	-2.017
Panel D: Developed countries in Asia-Pacific						
Australia	1.599	1.701	-4.336	1.117	0.582	-2.601
Hong Kong	-0.297	0.346	-5.502	-0.178	0.207	-3.303
New Zealand	5.259	6.865	1.492	2.997	4.217	0.895
Singapore	1.708	2.179	0.435	1.024	1.307	0.261
South Korea	1.874	2.160	2.062	1.124	1.295	1.236
Taiwan	5.061	3.143	2.400	3.073	1.885	1.439
Thailand	3.531	4.784	1.027	2.118	2.869	0.616