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## Forecasting Output Growth of Advanced Economies Over Eight Centuries: The Role of Gold Market Volatility as a Proxy of Global Uncertainty

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**Forecasting Output Growth of Advanced Economies Over Eight Centuries: The Role of Gold Market Volatility as a Proxy of Global Uncertainty**

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**Abstract**

In this paper we develop a proxy for global uncertainty based on the volatility of gold market over the annual period of 1311 to 2019, and then use this proxy metric to forecast historical growth-rates for eight advance economies namely, France, Germany, Holland, Italy, Japan, Spain, the United Kingdom (UK), and the United States (US). We find that for the within-sample period, uncertainty negatively impacts output growth, but more importantly, over the out-of-sample period, gold market volatility produces statistically significant forecasting gains. Our findings are robust to an alternative measure of uncertainty based on the volatility of the changes in long-term sovereign real-rates over 1315 to 2019. These historical results have important implications for investors and policymakers in the current context in which high frequency gold price data is available.

**Keywords:** Historical output growth, advance economies, gold market volatility, forecasting

**JEL Codes:** C22, C53, E32, Q02

## 1. Introduction

In the wake of the global financial crisis of 2007-2009, which led to the "Great Recession", followed by the European sovereign debt crisis, and more recently following the outbreak of the COVID-19 pandemic, a large international empirical literature has emerged to highlight the negative impact of uncertainty on output (see Bloom (2014, 2017), Castelnuovo et al., (2017), Gupta et al., (2018, 2019, 2020a, 2020b), Al-Thaqeb and Algharabali (2019), Caggiano et al., (2020), for detailed reviews). The fact that uncertainty has a recessionary impact corroborates the predictions of the real option theory which suggests that decision-making is affected by uncertainty because it raises the option value of waiting (see for example, Bernanke (1983), Pindyck (1991), Dixit and Pindyck (1994), and more recently, Bloom (2009)). In other words, given that the cost associated with wrong investment decisions are very high, uncertainty makes firms and, in the case

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of durable goods, also consumers, more cautious. As a result, economic agents tend to postpone investment, hiring, and consumption decisions to periods of lower uncertainty, which results in cyclical fluctuations in macroeconomic aggregates. This implies that uncertainty is expected to negatively impact overall output due to lower consumption and investment.

While the literature dealing with the influence of uncertainty on output is primarily based on in-sample structural analyses, more recently, quite a few studies have also analyzed the role of uncertainty in forecasting output growth and recessions in out-of-sample exercises (see for example, Karnizova and Li (2014), Balcilar et al., (2016), Junttila and Vataja (2018), Aye et al., (2019a, 2019b), Gupta et al., (2020c), Erconali and Natoli (2020), Pierdzioch and Gupta (2020), Claveria (2021)).[1] This is an important line of research since policymakers in general, and central banks in particular, would need accurate real-time predictions of the future path of the economy following periods of heightened uncertainty while making their policy decisions. At the same time, it is understandable that precise forecasting of the macroeconomy is also important for investors. Finally, since in-sample predictability might not translate into forecasting gains, and the ultimate test of any predictive model (in terms of econometric methodologies and the predictors being used) is primarily considered to be in its out-of-sample performance (Campbell, 2008), the role of uncertainty in forecasting economic activity area also forms a pertinent question for academicians.

Against this backdrop, our paper takes a historical perspective in testing the role of uncertainty in predicting (in- and out-of-sample) the growth of eight advanced economies namely, France, Germany, Holland, Italy, Japan, Spain, the United Kingdom (UK), and the United States (US), over eight centuries of annual data. Note that the choice of these countries are purely due to the availability of historical data, and for the fact that they cover on average 78% of Gross Domestic Product (GDP) of the advanced economies. Specifically speaking, the data samples for France, Germany, Holland, Italy, Japan, Spain, the UK, and the US start at 1388, 1327, 1401, 1311, 1871, 1419, 1311, and 1787 respectively, with all of them ending in 2019. Unlike the above-mentioned existing studies that deal with forecasting output growth or recession due to uncertainty, primarily over the last three and half decades[2], our study analyzes over 700 years of available data, and hence does not suffer from possible sample selection bias. Additionally, our study also provides a picture

[1] See also a working paper by Balcilar et al., (2021), which unlike these single or multiple country studies, highlights the role of uncertainty in forecasting regional growth rates of the United Kingdom (UK).

[2] It must be pointed out that Karnizova and Li (2014) and Pierdzioch and Gupta (2020) did analyze the role of uncertainty in predicting US recessions from 1900 and 1889 respectively to recent dates.

of uncertainty-based predictability over the entire evolution timespan for these economies, which has indeed witnessed multiple episodes of fluctuation levels of uncertainty.

At this stage, it must be realized that uncertainty is a latent concept, and hence one requires tangible ways to measure it. In this regard, besides the various alternative metrics of uncertainty associated with financial markets (such as the implied-volatility indices, realized volatility, idiosyncratic volatility of equity returns, corporate spreads), there are primarily three broad approaches to quantify uncertainty (Christou et al., 2020): (1) A news-based approach, in which the main idea is to perform word-searches in major newspapers for terms related to economic and policy uncertainty, and then to use the results to construct indices of uncertainty; (2) Measures of uncertainty derived from stochastic-volatility estimates of various types of small- and large-scale structural models related to macroeconomics and finance; and, (3) Measures of uncertainty obtained from dispersion of professional forecaster disagreements. Given these three newspapers-based or macroeconomic and financial data-driven methods, it is understandable why most studies in the area of uncertainty-output growth rely on sample periods that cover the last 30 or more years. In the process of providing a forecasting analysis covering eight centuries of historical data on output growth for the first time, we also contribute to this literature by developing a new metric of historical uncertainty associated with the variability of gold prices, data for which is available since 1257. In particular, for our purpose of measuring uncertainty, we use the (conditional) volatility of real gold returns, which in turn has been shown to be positively associated with uncertainty (see for example, Balcilar et al., (2016, 2017), Demirer et al., (2019, 2020), Asai et al., (2020), Baur and Smales (2020), Gkillas et al., (2020), Bonato et al., (2021), Bouri et al., (2021)).[3] This is because of the well-established role of gold as a safe-haven (see Boubaker et al., (2020) and Salisu et al., (2021a) for detailed reviews of this literature), due to which, higher levels of various estimates of uncertainties due to geopolitical risks, risk aversion, macroeconomic and financial volatility, and weak investor sentiment leads to more trading in gold, which translates into higher volatility in the gold market. In other words, latent uncertainty is positively related to gold volatility, and can be used for our forecasting exercise.

[3] See also Piffer and Podstawski (2018) and Çepni et al., (forthcoming) who use the sudden variation in intraday gold price over a month around specific events of economic and financial crises as an instrumental variable for uncertainty in in-sample structural analyses involving the macroeconomy and financial markets.

To the best of our knowledge, this is the first attempt to forecast eight centuries of output growth based on gold market volatility as a proxy of uncertainty for eight advanced economies and its aggregate, based on a distributed lag predictive model of Westerlund and Narayan (2012, 2015; WN). This econometric framework simultaneously accommodates for salient features of the variables of interest such as persistence and endogeneity bias, with both these features well-established in the literature (see for example, Mumtaz and Theodoridis (2019), Salisu and Gupta (2020), Ludvigson et al., (forthcoming)). The remainder of the paper is organized as follows: Section 2 outlines the data and the methodologies used; Section 3 presents the empirical results with robustness checks, and finally Section 4 presents the concluding remarks based on the study outcomes and findings.

## 2. Data and Methodology

### *2.1. Dataset*

Data on real GDP, which we convert into growth-rate, is derived from the work of Schmelzing (2020) till 2018,[4] and then updated to 2019 using the data from the World Development Indicators (WDI) of the World Bank , which was the latest available data on real GDP at the time of writing this paper. As far as nominal gold prices are concerned, we obtain the data in British Pound from MeasuringWorth[5], which then is deflated by Consumer Price Index (CPI) of the UK derived from *A Millennium of Macroeconomic Data for the UK*, maintained by the Bank of England up till 2016,[6] and beyond that, i.e., for the period 2017-2019, from the WDI. We then compute log-returns of the real price of gold, and derive the conditional volatility of real gold returns, which is our metric of uncertainty, from a Generalized Autoregressive Conditional Heteroskedasticity (GARCH (1,1)) model. This developed metric produced a better fit relative to asymmetric versions of the GARCH model (like Exponential-GARCH (EGARCH, Nelson, 1991) and GJR-GARCH due to Glosten et al., (1993)). The volatility of real gold returns is plotted in Figure A1 in the Appendix, and reveals that volatility of the gold market clearly increases during the early part of the sample period associated with the Crisis of the Late Middle Ages covering 1315 to 1487, which involved a series of events in the fourteenth and fifteenth centuries that ended protracted periods

[4] The data is available for download from: https://www.bankofengland.co.uk/working-paper/2020/eight-centuries-of-global-real-interest-rates-r-g-and-the-suprasecular-decline-1311-2018.
[5] See: https://www.measuringworth.com/datasets/gold/.
[6] The data is available at: https://www.bankofengland.co.uk/statistics/research-datasets.

of instability in Europe. Three major crises namely, the Great Famine of 1315–1317, the devastating global epidemic of bubonic plague called Black Death of 1347-1351, and the Hundred Years' War between the two leading European powers of the day, namely, France and England, led to demographic collapse, political instabilities, and religious upheavals. The uncertainty peak during the 16th century can be associated with discoveries of precious metals, and numerous wars in Europe, which in turn led to a host of financial crises. At the same time, the heightened uncertainty in the early part of the 19th century was possibly a result of series of bank panics in the UK, and in the US, resulting in bank failures and recessions. The increases in uncertainty in the 20th and in the 21st centuries are of course due to the two World Wars, with the Spanish flu and the "Great Depression" in between the two oil price shocks (causing inflation fears and the peak in real gold returns volatility in 1982). The more recent uncertainty is of course attributed to the global financial crisis, and to the European sovereign debt crisis.[7] These events of heightened volatility can thus be considered as historical proxy for periods of both economic and financial global uncertainty.[8]

The data characteristics are presented in Table 1 for the growth rates, as well as for conditional volatility of gold ($UNC\_gold_t$), the latter being the proxy for uncertainty. As mentioned earlier, the data frequency is annual, with the start dates differing across selected eight countries, while the end date of 2019 is common for all the variables, as presented later in Table 2. While the selected growth rates seem to be mostly negatively skewed (except for France and Holland) and leptokurtic, the predictor variable is positively skewed and leptokurtic. Moreover, all the growth rates and $UNC\_gold_t$ are stationary. Finally, the presence of statistically significant persistence effect particularly for the predictor of interest (i.e., $UNC\_gold_t$), which is the source of endogeneity bias in the WN-type predictive model, further lends support to the choice of the methodology discussed in detail below.

**[Insert Table 1]**

[7] Though our sample period does not cover 2020, and hence the outbreak of the Coronavirus pandemic, gold market showed evidence of tremendous volatility when the plot is extended to cover 2020, and hence confirming the suitability of this metric of uncertainty. Further details are available upon request from the authors.

[8] The above historical discussion is derived from Galbraith (1990), Reinhart and Reinhart (2010), Reihart and Rogoff (2009, 2011), and Boubaker et al., (2020).

## 2.2. Econometric model

We set out to forecast the individual growth rate of eight advanced economies where uncertainty serves as a predictor. In order to distinctly assess the predictive power of uncertainty in growth forecasts, we consider two models: baseline (restricted) growth model which excludes the uncertainty metric, and the extended (unrestricted) growth model that accounts for it. Our predictive model follows the WN-type distributed lag model as it can simultaneously accommodate certain salient features of the variables of interest, such as persistence and endogeneity bias which are known to improve forecast outcomes of economic variables.[9] Thus, any inherent endogeneity bias that may result from restricting the growth predictors to the variables of interest is resolved in the estimation process. Consequently, the uncertainty-based growth predictive model is specified in equation (1) as:

$$Growth_t = \alpha + \beta_1 UNC_{t-1} + \beta_2 \left(UNC_t - \rho UNC_{t-1}\right) + \varepsilon_t \tag{1}$$

where $Growth_t$ is the country's growth rate at time $t$; $UNC_t$ is the generic term for our uncertainty measure, i.e., $UNC\_gold_t$ in our case; $\alpha$ is the intercept; $\beta_1$ is the slope coefficient that measures the predictability of uncertainty. The additional term $\beta_2\left(UNC_t - \rho UNC_{t-1}\right)$ is incorporated to correct for any resultant endogeneity bias (and by extension, persistence effect) that may be occasioned by the correlation between $UNC_t$ and the error term ( $\varepsilon_t$ ).[10]

The model estimation ensues in two main steps: First, we ascertain the most appropriate model structure following the observed data characteristics; and second, we specify our predictive model that incorporates one-period lag of the predictor, and also accounts simultaneously for observed data features.[11] Furthermore, we account for plausible time-dependence in parameters by adopting a rolling- (using the in-sample as the window size) rather than fixed-window approach to forecast the growth rate. To determine the time periods to be considered as in-sample and as out-of-sample intervals, we apply the Bayesian change-point analysis, as originally proposed by Barry and

[9] In this regard, the reader is refereed to: Narayan and Gupta (2015), Phan et al., (2015), Narayan et al., (2018); Salisu et al., (2018a, b, 2019a, b, c, d, 2021b), Tule et al., (2019, 2020), and references cited therein.

[10] The original model is given as: $Growth_t=\phi_0+\phi_1 UNC_{t-1}+\eta_t$, and some computational procedures are required to account for persistence effect in the predictor series and by implication endogeneity bias in the predictive model, as documented in WN, to produce the predictive model specified in Equation (1).

[11] The technical-minded reader is referred to Westerlund and Narayan (2012, 2015) for the details of the computational procedure of the adopted methodology.

Hartigan (1993), on the growth rates, so that the parts of the data before the first identified change point (based on a cut-off of 95% posterior probability) are considered as the in-sample periods, while the intervals from the change-point to the end-date is considered as our out-of-sample, over which our models are estimated recursively to produce the forecasts. The advantages of the change-point detection method, unlike the classical Bai and Perron (2003) tests of structural breaks, are that we do not need to specify the maximum number of breaks, and trim the end points of the data (and hence miss the breaks in that part of the sample). The date summary and the sample intervals are presented in Table 2.[12]

**[Insert Table 2]**

In the final set-up of the methodology, we compare out-of-sample forecast performance of the uncertainty-based predictive model with the benchmark (driftless random-walk) model over multiple forecast horizons (1-, 2-, 5- and 10-year forecasts), and since the two competing models are non-nested, we employ the modified Diebold and Mariano (1995; DM) as per Harvey, et al., (1997) to calculate the *p*-value and address the issue with the assumption of zero covariance at 'unobserved' lags. Specifically, the test statistic is formulated as:

$$DM\ Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \qquad (2)$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean of the loss differential $d_t \equiv l(\varepsilon_{uct}) - l(\varepsilon_{rwt})$; $l(\varepsilon_{uct})$ and $l(\varepsilon_{rwt})$ are the loss functions of the forecast errors ($\varepsilon_{uct}$ and $\varepsilon_{rwt}$, respectively) that are associated with the growth forecasts of the uncertainty-based and random-walk models, respectively; and $V(d_t)$ is the unconditional variance of the loss differential $d_t$. The null hypothesis of relative equality of the forecast precision of the contending model pairs is tested by examining $E[d_t] = 0$; with statistical significance implying a statistically significant difference in the forecast precision of the contending model pairs. Based on the *p*-value of Harvey et al., (1997) for the DM statistic, a statistically significant negative DM statistic implies the adoption of the uncertainty-based model, while the benchmark model is chosen if the test statistic is positive and significant. However, if

[12] Details on all the break dates of output growth are available upon request from the authors.

the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be similar.

## 3. Discussion of results

Following from the method presented in the previous section, we evaluate the in-sample perfromance of our predictive model, i.e., by analyzing the sign and statistical significance of $\beta_1$, which is the coefficient corresponding to our metric of uncertainty ($UNC\_gold_t$). The results for the individual full-samples[13] of the eight countries are presented in Table 3, and in line with theory, barring the case of France, the response of growth to uncertainty is negative for the remaining seven countries. However, the positive relationship for France is statistically insignificant, as are the negative impacts on the growth rates of Germany and the US. But, as indicated at the onset, a stronger test of predictability is based on the out-of-sample forecasting, to which we turn next.

**[Insert Table 3]**

Using the data split presented in Table 2 as obtained from the Bayesian change point analysis, we provide the out-of-sample forecast evaluation results in Table 4(a)-(b), whereby we report the ratio of root mean square errors (RMSEs) of the unrestricted model relative to the restricted model, i.e., (RRMSE), and the modified DM statistics with their corresponding *p*-values, respectively. Specifically speaking the out-of-sample performance of the uncertainty-based predictive model is compared with the same of the benchmark driftless random-walk model without the uncertainty series in terms of the RRMSE and the modified DM test. As can be seen from Table 4(a), the RRMSEs are less than one for all the countries and across all the four forecast horizons of one-, two-, five-, and ten-year-ahead, suggesting that including *UNC_gold* in the model produces lower RMSEs associated with the forecast of output growth, compared to the case, when we do not consider this metric of uncertainty.

While including uncertainty indeed reduces the forecast errors of output growth, it is of paramount importance that we evaluate whether the forecasting gains are statistically significant, and for which we turn to Table 4(b), where we report the modified DM statistics. The negative and statistically significant modified DM statistics at the conventional levels of significance

[13] Unlike the partitioned data into in-sample and out-of-sample periods, the long range data for the full sample requires pre-weighting Equation (1) with the inverted standard deviation of the regression residuals as suggested by Westerlund and Narayan (2012, 2015) in order to account for any inherent variations occasioned by the data range.

(prominently at 1% level), across the multiple forecast horizons and for the various countries, validates the out-of-sample predictive power of uncertainty in improving the growth forecasts in a statistically significant fashion beyond the in-sample period (barring the case of Italy and Japan at h=2 and h=5, respectively).

In general, the overarching finding in this study further complements the in-sample and out-of-sample predictive prowess of uncertainty as discussed in the literature presented in the introduction, but now from a historical perspective.

**[Insert Table 4]**

To check for robustness of our results, contingent on the metric of uncertainty, we also provide below results derived from an alternative measure of the same. In this regard, we use the GARCH(1,1)-based conditional volatility estimate of the change in the real capital cost for the "safe" sovereign debt issuer ($UNC_2$), with the data also derived from Schmelzing (2020) and the WDI. Note, the "safe asset provider" long-term sovereign real rates over 1315 to 2019 is obtained by Schmelzing (2020) by relying on a collection of evidence from 14th century European municipal and imperial registers, over Habsburg, British, Dutch, crown documents, to earlier secondary sources, and to current Federal Reserve data. As observed from Table A1(a)-(b) in the Appendix of the paper, our basic conclusions of Table 4(a)-(b) remain the same over the same out-of-sample periods, i.e., RRMSEs are consistently less than one for all countries and across the four forecast horizons, with these gains being dominantly significant statistically at conventional levels based on the modified DM test. But note, Japan now shows statistically significant forecastability of output growth only at $h$=1.[14] In other words, regardless of the choice of measure of uncertainty, accounting for uncertainty in the predictive model of growth improves its historical out-of-sample forecasts in a statistically significant manner, though results for Japan seems to be weak, especially at longer forecasting horizons. One reason behind this could be the fact that, most of the gold market volatility is associated with crises in Europe, the UK and the US. Further, the relevance of gold as a strategic asset in Japan is more of a recent phenomenon.[15]

[14] The in-sample effect of $UNC_2$ on the growth rate of the US confirmed a statistically significant (at the 1% level) negative effect on the growth rates of the US, as widely documented in the literature. Complete details of the in-sample predictability results for all the countries are available upon request from the authors.

[15] See: https://www.gold.org/goldhub/research/relevance-of-gold-as-a-strategic-asset-in-japan.

## 5. Conclusion

Due to a series of global macroeconomic events which resulted in tremendous volatility in financial markets and the economies of the world over the last decade and half, a burgeoning literature on measuring uncertainty, an otherwise latent variable, and analyzing its impact on output growth has emerged. Studies in the regard have primarily focused on in-sample structural analysis, highlighting the negative impact of uncertainty on output. More recently, research has started to delve into out-of-sample forecasting, to show that metrics of uncertainty can indeed produce out-of-sample predictive gains. Given that, existing studies have primarily concentrated on the last three-and-half decades. We add to this literature by: (i) Conducting both in-sample and out-of-sample forecasting of eight advanced economies (France, Germany, Holland, Italy, Japan, Spain, the UK, and the US), covering over 700 years of historical data (starting at 1388, 1327, 1401, 1311, 1871, 1419, 1311, and 1787 respectively), thereby characterizing the evolution of their entire historical growth rates in terms of uncertainty, and; (ii) in the process, we also develop a metric of historical global uncertainty captured by the conditional volatility of the gold market, which is shown to depict heightened variability in the wake of historical crises as a consequence of higher trading, given that gold is known to be a well-established safe-haven.

Based on a predictive regression model which controls for persistence and endogeneity, we show that uncertainty, as captured by gold market volatility, has negatively impacted output growth historically, but more importantly, this measure of global volatility, has led to significant out-of-sample forecasting gains over the period of 1311 to 2019. Our forecasting results are found to be robust to an alternative metric of uncertainty obtained from the conditional volatility of the changes in long-term sovereign real rates over 1315 to 2019.

Given that gold data is available at daily frequency from the late 1960's, and more recently at the intraday-level from the late 1990s, which in turn can be used to produce (model-free) estimates of of gold market (realized) volatility at daily frequency, our finding of statistical forecasting gains for output growth due to historical gold market volatility should be of compelling value to both policymakers and investors. The information contained within high-frequency movements of gold returns variability as a proxy for global uncertainty can be used by investors to make optimal portfolio allocations. Also, policy authorities can use such daily volatility of gold to forecast low-frequency (monthly and quarterly) movements of real macroeconomic aggregates, based on nowcasting approaches using mixed-frequency data sampling (MIDAS) models (Banbura et al., 2011), which can indeed serve as an interesting area of future research. Moreover, contingent on historical data availability, it would also be worthwhile to analyze the predictability of historical output growth of developing economies.

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**Table 1. Summary statistics**

| | Mean | Std. Dev. | Skewness | Kurtosis | N | ADF | Persistence |
|---|---|---|---|---|---|---|---|
| **Growth Rate** | | | | | | | |
| **France** | 0.823 | 3.653 | 1.315 | 38.103 | 632 | -12.300$^{***b}$ | 0.180$^{***}$ |
| **Germany** | 0.844 | 3.929 | -10.791 | 208.556 | 693 | -18.165$^{***b}$ | 0.363$^{***}$ |
| **Holland** | 1.081 | 3.498 | 3.040 | 109.105 | 619 | -12.877$^{***b}$ | 0.250$^{***}$ |
| **Italy** | 0.694 | 3.340 | -3.481 | 67.606 | 709 | -22.515$^{***b}$ | 0.220$^{***}$ |
| **Japan** | 3.223 | 7.593 | -5.792 | 57.129 | 149 | -10.975$^{***a}$ | 0.096 |
| **Spain** | 0.889 | 2.600 | -0.625 | 23.883 | 601 | -18.719$^{***b}$ | 0.334$^{***}$ |
| **UK** | 0.882 | 2.473 | -8.843 | 174.317 | 709 | -21.507$^{***a}$ | 0.208$^{***}$ |
| **US** | 2.913 | 4.335 | -0.704 | 10.372 | 233 | -11.249$^{***b}$ | 0.292$^{***}$ |
| **Uncertainty Proxy** | | | | | | | |
| ***UNC_gold*** | 82.974 | 76.264 | 2.543 | 11.386 | 710 | -3.512$^{***a}$ | 0.978$^{***}$ |

**Note:** Std. Dev. is the standard deviation. *** imply statistical significance at 1% level. The superscripts "a" and "b" respectively denote Augmented Dickey-Fuller (ADF) test regressions with constant only and constant and trend. The uncertainty index, $UNC\_gold_t$ is obtained as GARCH-based conditional volatility of real gold returns.

**Table 2. Sample period description**

| Period | France | Germany | Holland | Italy | Japan | Spain | UK | US |
|---|---|---|---|---|---|---|---|---|
| **In-Sample** | 1388-1819 | 1327-1912 | 1401-1878 | 1311-1865 | 1871-1943 | 1419-1798 | 1311-1699 | 1787-1877 |
| **Out-of-Sample** | 1820-2019 | 1913-2019 | 1879-2019 | 1866-2019 | 1944-2019 | 1799-2019 | 1700-2019 | 1878-2019 |

**Table 3. In-sample predictability**

| | $\beta_1$ |
|---|---|
| **France** | 0.0446 [0.0288] |
| **Germany** | -0.0007 [0.0085] |
| **Holland** | -0.0552$^{**}$ [0.0272] |
| **Italy** | -0.1512$^{***}$ [0.0090] |
| **Japan** | -0.1471$^{***}$ [0.0437] |
| **Spain** | -0.0344$^{***}$ [0.0051] |
| **UK** | -0.1723$^{***}$ [0.0075] |
| **US** | -0.0024 [0.0164] |

**Note:** In this table, reported estimates are the first lag slope (predictability) coefficients of the predictor series, i.e., *UNC_gold* in equation (1). The values in square brackets are the corresponding standard errors of the slope coefficients. *** and ** imply statistical significance at the 1% and 5% levels, respectively.

**Table 4(a). Relative RMSE (RRMSE) for the out-of-sample predictability of *UNC_gold***

| | h=1 | h=2 | h=5 | h=10 |
|---|---|---|---|---|
| **France** | 0.9073 | 0.9175 | 0.9224 | 0.9298 |
| **Germany** | 0.8287 | 0.8824 | 0.8919 | 0.8944 |
| **Holland** | 0.8844 | 0.8911 | 0.8901 | 0.8863 |
| **Italy** | 0.9840 | 0.9869 | 0.9854 | 0.9844 |
| **Japan** | 0.8232 | 0.9679 | 0.9599 | 0.9429 |
| **Spain** | 0.6127 | 0.9316 | 0.9307 | 0.9291 |
| **UK** | 0.9844 | 0.9838 | 0.9820 | 0.9792 |
| **US** | 0.5635 | 0.5798 | 0.5831 | 0.5858 |

**Note:** *UNC_gold* is the uncertainty due to the gold market. The relative RMSE (RRMSE) is computed as the ratio of RMSE of the uncertainty-based model to that of the benchmark model, such that a value less (greater) than one is considered to indicate superior (inferior) performance of the former over the latter.

**Table 4(b). Statistical significance of out-of-sample predictability of *UNC_gold* relative to the random walk model**

| | h=1 | h=2 | h=5 | h=10 |
|---|---|---|---|---|
| **France** | -5.0242 [0.0000] | -4.7955 [0.0000] | -4.6864 [0.0000] | -4.3582 [0.0000] |
| **Germany** | -5.5374 [0.0000] | -3.6172 [0.0003] | -3.3169 [0.0009] | -3.3240 [0.0009] |
| **Holland** | -5.5540 [0.0000] | -5.5551 [0.0000] | -5.7645 [0.0000] | -6.0809 [0.0000] |
| **Italy** | -1.9843 [0.0472] | -1.5962 [0.1104] | -1.7782 [0.0754] | -1.8934 [0.0583] |
| **Japan** | -2.6526 [ 0.0080] | -2.6526 [0.0080] | -1.2853 [0.1987] | -1.8334 [0.0668] |
| **Spain** | -12.0646 [0.0000] | -4.6316 [0.0000] | -4.7021 [0.0000] | -4.8158 [0.0000] |
| **UK** | -2.2712 [ 0.0231] | -2.3616 [0.0182] | -2.6031 [ 0.0092] | -6.8501 [0.0000] |
| **US** | -5.9238 [0.0000] | -5.6763 [0.0000] | -5.8649 [0.0000] | -5.9315 [0.0000] |

**Note:** *UNC_gold* is the uncertainty due to the gold market. We employ the modified Diebold and Mariano (1995) test as per Harvey, et al., (1997) to calculate the *p*-value and address the issue with the assumption of zero covariance at 'unobserved' lags. Thus, we report both the test statistics and the corresponding *p*-values reported in square brackets – [ ]. If the statistic is negative and significant, the uncertainty-based model is favoured, while the benchmark model is chosen if the test statistic is positive and significant. However, if the test statistic is not significant (implying a non-rejection of the null hypothesis), the forecast performance of the two competing models is assumed to be identical.

**APPENDIX**

**Figure A1. Conditional volatility of real gold returns**

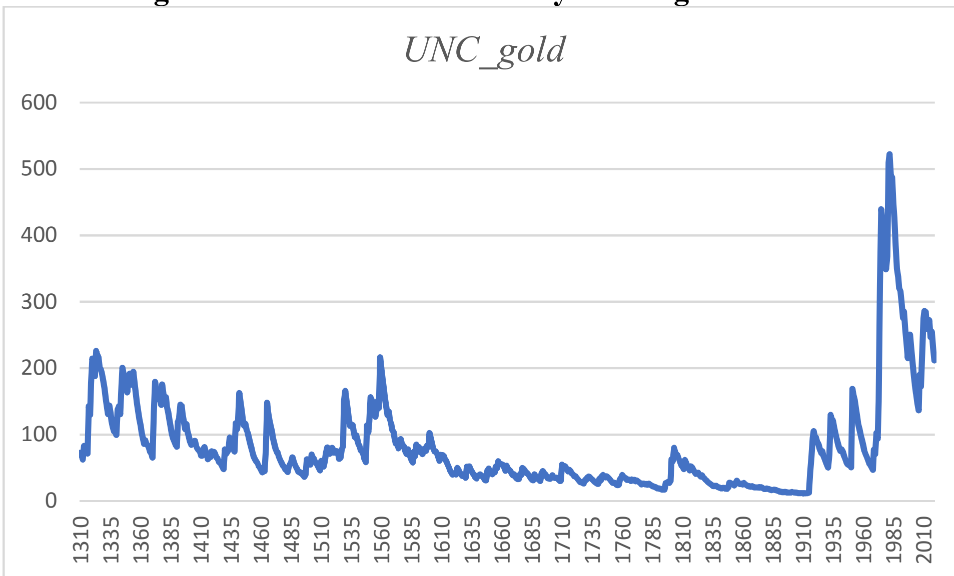

**Table A1(a). Relative RMSE (RRMSE) for the out-of-sample predictability of $UNC_2$**

| | h=1 | h=2 | h=5 | h=10 |
|---|---|---|---|---|
| **France** | 0.9110 | 0.9218 | 0.9267 | 0.9335 |
| **Germany** | 0.8663 | 0.9080 | 0.9155 | 0.9158 |
| **Holland** | 0.8849 | 0.8909 | 0.8898 | 0.8857 |
| **Italy** | 0.9962 | 0.9973 | 0.9966 | 0.9962 |
| **Japan** | 0.8673 | 0.9890 | 0.9819 | 0.9680 |
| **Spain** | 0.6294 | 0.9301 | 0.9292 | 0.9277 |
| **UK** | 0.9943 | 0.9941 | 0.9939 | 0.9937 |
| **US** | 0.6160 | 0.6234 | 0.6198 | 0.6211 |

**Note:** $UNC_2$ is the uncertainty due to the risk free assets. See Notes to Table 4(a).

**Table A1(b). Statistical significance of out-of-sample predictability of $UNC_2$ relative to the random walk model**

| | h=1 | h=2 | h=5 | h=10 |
|---|---|---|---|---|
| **France** | -5.0766 [0.0000] | -4.9215 [0.0000] | -4.7962 [0.0000] | -4.5310 [0.0000] |
| **Germany** | -5.5407 [0.0000] | -3.5656 [0.0004] | -3.2679 [0.0011] | -3.3238 [0.0009] |
| **Holland** | -5.7942 [0.0000] | -5.7222 [0.0000] | -5.9257 [0.0000] | -6.2523 [0.0000] |
| **Italy** | -2.4265 [0.0152] | -1.7714 [0.0765] | -2.0306 [0.0423] | -2.1986 [0.0279] |
| **Japan** | -2.4320 [0.0150] | -0.3051 [0.7603] | -0.5180 [0.6044] | -0.9451 [0.3446] |
| **Spain** | -11.8716 [0.0000] | -3.9075 [0.0001] | -3.9641 [0.0001] | -4.0584 [0.0001] |
| **UK** | -3.2250 [0.0013] | -3.3303 [0.0009] | -3.5383 [0.0004] | -3.8615 [0.0001] |
| **US** | -5.8517 [0.0000] | -5.4897 [0.0000] | -5.6385 [0.0000] | -5.7143 [0.0000] |

**Note:** See Notes to Table 4(b).