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

Afees A. Salisu [a,*], Rangan Gupta[b], Sayar,Karmakar[c], Sonali Das[d]

[a]Centre for Econometrics & Applied Research, Ibadan, Nigeria, Department of Economics, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa
[b]Department of Economics, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa
[c]Department of Statistics, University of Florida, 230 Newell Drive, Gainesville, FL, 32601, USA
[d]Department of Business Management, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa

Corresponding author. Email: adebare1@yahoo.com

Highlights

- A proxy for global uncertainty based on the volatility of gold market over the annual period of 1311–2019, is developed.
- This proxy metric is used to forecast historical growth-rates for eight advanced economies.
- Uncertainty measured with this proxy produces statistically significant forecasting gains for output growth.
- Findings are robust to an alternative measure of uncertainty (the volatility of changes in long-term sovereign real-rates).
- Some important implications of findings for investors and policymakers are highlighted.

Abstract

In this paper, we develop a proxy for global uncertainty based on the volatility of gold market over the annual periods from 1311 to 2019, and then use this proxy metric to forecast historical growth-rates for eight advanced 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 also robust to an alternative measure of uncertainty based on the volatility of the changes in long-term sovereign real-rates over the period 1315-2019. These historical results have important implications for investors and policymakers in the current context in which high frequency gold-price data are available.

Keywords: Historical output growth, advanced economies, gold market volatility, forecasting

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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 with 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 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 as out-of-sample exercises (see for example, Karnizova and Li (2014), Balcilar et al., (2016), Junttila and Vataja (2018), Segnon et al., (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

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

performance (Campbell, 2008), the role of uncertainty in forecasting economic activity 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), using eight centuries of annual data. Note, the choice of these eight countries is driven purely by the availability of historical data, and also for the fact that they cover on an average 78% of Gross Domestic Product (GDP) of the advanced economies (Schmelzing, 2018, 2020). Specifically, the data 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 historical annual data observations, and hence does not suffer from possible sample selection bias. Additionally, our study also provides a picture of uncertainty-based predictability over the entire evolution timespan for these economies, which has indeed witnessed multiple episodes of major uncertainty.

At this stage, it must be realized that uncertainty is a latent concept, and hence one requires tangible ways to measure it. 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 space of uncertainty-output growth rely on sample periods that cover the last 30 or more years.

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[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.

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], because of the well-established role gold plays as a safe-haven (see Boubaker et al., (2020) and Salisu et al., (2021a) for detailed reviews of this literature). This results in higher levels of various estimates of uncertainties due to geopolitical risks, risk aversion, macroeconomic and financial volatility, and results in weak investor sentiment which further leads to more trading in gold, and consequently translates into higher volatility within the gold market. In other words, latent uncertainty is positively related to gold volatility, and can thus be used in our forecasting exercise.

To the best of our knowledge, this is the first attempt to forecast output growth covering eight centuries, 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., (2021)). 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.

[3] See also Piffer and Podstawski (2018) and Çepni et al., (2021) 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.

2. Data and Methodology

2.1. Dataset

Data on real GDP in millions of 1990 International Geary-Khamis dollars, which we convert into growth-rate, are 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[5], which was the latest available data on real GDP at the time of writing of this paper. As far as nominal gold prices are concerned, we obtain the data in British pound from MeasuringWorth[6], which is then 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 till 2016[7], and beyond that, i.e., for the period 2017-2019, from the WDI. We next compute log-returns of the real price of gold[8], 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 the period 1315 to 1487, which involved a series of events in the fourteenth and fifteenth centuries that ended protracted periods of instability in Europe. Three major crises namely, the Great Famine of 1315–1317, the devastating global epidemic of bubonic plague called the 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. Some of these uncertainties are likely to have also emerged from the process of severe colonization by the European powers. At the same time, the heightened

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 This data is available in US dollars, which has an implied purchasing power parity (PPP) conversion rate of 1 with the International Geary-Khamis dollars.
6 See: https://www.measuringworth.com/datasets/gold/.
7 The data is available at: https://www.bankofengland.co.uk/statistics/research-datasets.
8 The implied PPP conversion rate of the British pound with the International Geary-Khamis dollars in 1990 was 0.67, which we multiplied with the real gold price. But since, we work with log-returns, understandably, such a transformation makes no difference to our computation, and the associated measure of uncertainty.

uncertainty in the early part of the 19th century was possibly as a result of a series of 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, 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.[9] These events of heightened volatility can thus be considered as historical proxy for periods of both economic and financial global uncertainty.[10]

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 the 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.

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.

[9] 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.

[10] 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. To distinctly assess the predictive power of uncertainty in the growth forecasts, we consider two models: first, baseline (restricted) growth model which excludes the uncertainty metric; and second, 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.[11] 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; α is the intercept; β_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 (ε_t) (see Appendix B for the derivation of equation (1)).[12]

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.[13] Furthermore, we account for plausible time-dependence in parameters by adopting a rolling- (using the in-sample as the window size) rather than a fixed-window approach to forecast the growth rate. To determine the time periods to be considered as in-sample and as out-of-sample

[11] 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.

[12] The original model is given as: $Growth_t = \mu + \beta UNC_{t-1} + \nu_t$, 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).

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

intervals, we apply the Bayesian change-point analysis, as originally proposed by Barry and 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.[14]

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

In the final set-up of the methodology, we compare our 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:

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

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 (ε_{uct} and ε_{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

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

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 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. Results and Implications

3.1. Evidence of predictability

Following from the method presented in the previous section, we evaluate the in-sample performance of our predictive model, i.e., by analyzing the sign and statistical significance of β_1, which is the coefficient corresponding to our metric of uncertainty (UNC_gold_t). The results for the individual full-samples[15] of the eight countries are presented in Table 3. In line with the real option theory, barring the case of France, we observe that 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. Recall, decision-making is expected to be affected by uncertainty because it raises the option value of waiting. Put differently, given that the cost associated with wrong investment decisions can be very high, uncertainty makes firms and, in the case of durable goods, also consumers, more cautious. As a result, economic agents tend to defer investment, hiring, and consumption decisions, to periods of lower uncertainty whence such uncertainty is expected to negatively impact overall output due to lower consumption and investment.

At this stage it must be pointed out, that the statistically insignificant results for France, Germany and the US is indicative of the fact that the effect of uncertainty though positive in the first case, and negative in the latter two, the impact is not significantly different from zero in the statistical sense. But from an economic perspective, while the negative sign for Germany and US align with theory, the positive sign for France needs to be delved into a bit further. France is known to have acquired substantial gold holdings historically, which in turn grew significantly during the inter-war period (Eichengreen, 1992). This period is also the phase when our metric of uncertainty is

[15] 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.

shown to gain momentum associated with the sharp increases in the price of gold (Boubaker, 2020; Gupta et al., 2021), which in turn could possibly have had a positive impact economically, though not statistically, on the growth of France. In fact, just before the Great Depression, France stabilized the franc at an undervalued rate after enduring a traumatic bout of inflation, whereby it chose to hold gold alone as part of its central bank reserves and decided to prevent any return of inflation by sterilizing gold inflows to prevent them from increasing domestic prices. The undervaluation of the franc played a major role in generating the balance of payments surpluses due to capital inflows, and possibly growth, driven by gold inflows (Irwin, 2010). Overall, the negative influence of uncertainty based on the real options theory is likely to have cancelled out the positive effect of uncertainty on growth for France, in the statistical sense. A similar story also possibly holds for the US and Germany, which too have over the years, especially following World War II, accumulated gold reserves, causing the effect to be statistically insignificant, though negative from the theoretical perspective.

However, in general, there are two potential channels through which uncertainty can also have a positive effect on the economy. The first is the theory of "growth options" which refers to a mechanism in which uncertainty can encourage investment, because the upside when the uncertainty is resolved can be high, while there is a limited downside (Segal et al., 2015; Kraft et al., 2018). The second channel is called the "Oi-Hartman-Abel" effect(Oi, 1961; Hartman, 1972; Abel, 1983), and in this case, an increase in uncertainty is an increase in both potential good outcomes and bad outcomes, with firms being able to easily contract works as an insurance against bad outcomes, and increased risk is looked upon positively. As such, the "Oi-Hartman-Abel" effect mechanism makes firms invest in large capacity since it enables them to take advantage of potential positive news, but if the news is bad, they will, with low effort, be able to scale back. In other words, there exists competing effects of uncertainty on economic activity, and the final effect would be contingent on the strength of these effects, though it is generally expected that the real-options theory will dominate and have a negative influence on output. But these opposite effects can indeed affect the statistical significance of the impact of uncertainty on economic growth. But, as indicated at the onset, a stronger test of predictability is based on the out-of-sample forecasting, to which we turn next.

Table 3. In-sample predictability

	β_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.

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 performance of the benchmark driftless random-walk model without the uncertainty series, using 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 (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, beyond the in-sample period (barring the case of Italy and Japan at h=2 and h=5, respectively). In general, the overarching finding from 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.

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.

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 the period of 1315 to 2019 is obtained from Schmelzing (2020), whereby the author relies on a collection of evidence from 14th century European municipal and imperial registers over the Habsburg, British and Dutch crown documents, and from available earlier secondary sources, and then finally using 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. However, it can be noted that Japan now shows statistically significant forecastability of output growth only at h=1.[16] 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 the results for Japan seem to be weak, especially for the longer forecasting horizons. One reason behind this could be the fact that, most of the gold market volatility are associated with crises in Europe, in the UK and in the US. Further, the relevance of gold as a strategic asset in Japan is more of a recent phenomenon.[17]

3.2. *Implications for academics, investors, and policymakers*

Our results have important implications from the perspective of an academician in the sense that, we confirm that in-sample tests should not necessarily be relied upon to gauge predictability in the context of models and predictors, but instead, one must conduct out-of-sample forecasting experiment – a finding in line with the proposal of Campbell (2008). From the perspective of policymakers, it is evident that volatility of gold prices can be used to predict the future path of output, and in the process, can be used to design policies, in particular expansionary ones, if the economy is headed for a recession. For this, we draw on the robust finding based on the longest possible sample of data available for major economies of the world. Going forward, policymakers can use metrics of daily realized volatility of gold, based on recently available intra-day data, to arrive at a more accurate measure of uncertainty (McAleer and Medeiros, 2008). And once this is achieved, the future path of low frequency economic activity variables can be nowcasted to make timely policy decisions. At the same time, since gold volatility seems to capture global uncertainty aptly, this information can also be used by investors in making portfolio allocation decisions. In this regard, high-frequency estimate of uncertainty associated with gold volatility is high importance from the perspective of Value-at-Risk calculations required for the design of investment portfolios (Ghysels and Valkanov, 2012). In other words, studying how the gold price fluctuates has now been historically shown to be important for various economic agents in the economy, and based on the finding in this paper, going forward, academics, investors and

[16] 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.
[17] See: https://www.gold.org/goldhub/research/relevance-of-gold-as-a-strategic-asset-in-japan.

policymakers can use recently available higher-frequency estimates of gold volatility to undertake their respective decisions in an optimal fashion.

4. Conclusion

Due to a series of global macroeconomic events which resulted in substantial volatility in financial markets and in 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 this regard have primarily focused on in-sample structural analysis, highlighting the negative impact of uncertainty on output. More recently, research has delved into out-of-sample forecasting to support that metrics of uncertainty can indeed produce out-of-sample predictive gains. As such, existing studies have primarily concentrated on the last three-and-half decades, and through this paper 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 for the eight countries), 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 the period 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 the 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 (Bańbura 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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APPENDIX A

Figure A1. Conditional volatility of real gold returns

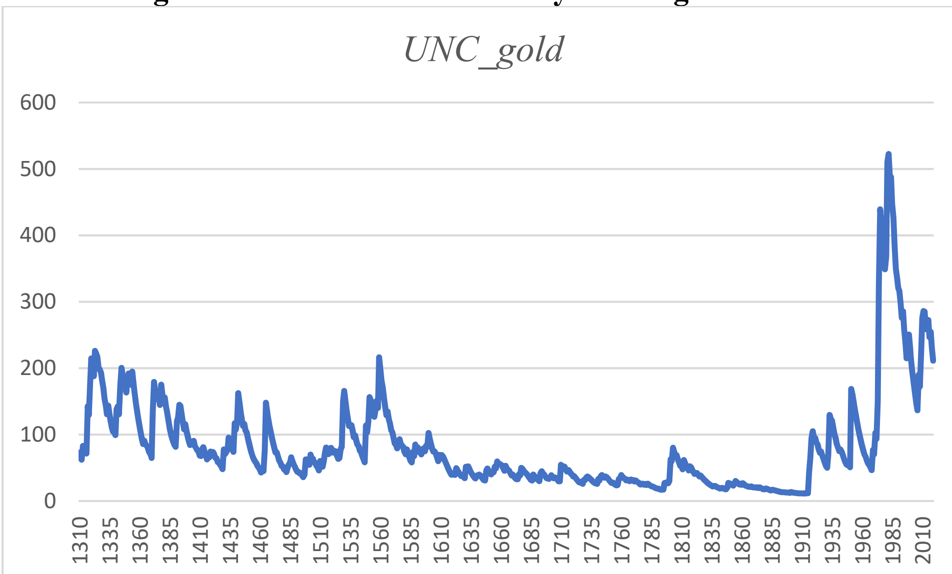

Table A1(a). Relative RMSE (RRMSE) for the out-of-sample predictability of UNC_2

	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)

APPENDIX B

Derivation of Equation (1) in the Main Text

We begin the exercise with a standard predictive model written as:

$$Growth_t = \mu + \beta UNC_{t-1} + \nu_t ; \qquad \nu_t \sim N\left(0, \sigma_\nu^2\right) \tag{B1}$$

where $Growth_t$ and UNC_t are as previously defined. We further assume the presence of persistence effect in the predictor series, UNC_t (see also, Plakandaras et al., (2019) for the case of uncertainty in general, and Asai et al., (2019, 2020) for the case of gold in particular):

$$UNC_t = \phi + \rho UNC_{t-1} + \xi_t ; \qquad \xi_t \sim N\left(0, \sigma_\xi^2\right) \tag{B2}$$

Given the way equations (B1) and (B2) are specified, we expect the two disturbances (ν_t and ξ_t) to be correlated and therefore the issue of endogeneity bias becomes relevant. To capture any inherent endogeneity bias as well as persistence effect due to equation (B2), we can write an equation for the two disturbances as:

$$\nu_t = \gamma \xi_t + \varepsilon_t \tag{B3}$$

Note that $\nu_t = Growth_t - \mu - \beta UNC_{t-1}$ from equation (B1) and $\xi_t = UNC_t - \phi - \rho UNC_{t-1}$ from equation (B2). By way of substitution and re-arrangement, we can rewrite equation (B3) as:

$$Growth_t = \alpha + \beta UNC_{t-1} + \gamma\left(UNC_t - \rho UNC_{t-1}\right) + \varepsilon_t \tag{B4}$$

where $\alpha = \mu - \phi\gamma$. Note that equation (B4) is the same as equation (1) in the main text. The additional term in (B4) relative to (B1) captures the inherent endogeneity bias as well persistence effect in the predictive model.