UNIVERSIDADE CATÓLICA PORTUGUESA

Gold returns dynamics and forecast

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Resumo

O foco principal deste estudo centra-se na utilização de métodos de domínio de frequências na previsão de retornos do ouro. Considerando para cada variável macroeconómica a respetiva alta frequência, a frequência do ciclo económico e a baixa frequência. A componente de baixa frequência do Equity Risk Premium, extraída através da filtragem wavelet, surge como a variável com o maior poder preditivo sobre os retornos do ouro, superando as restantes variáveis e mantendo-se estável ao longo de um período fora de amostra de 24 anos. O poder preditivo de diferentes variáveis para os retornos do ouro durante ciclos económicos expansivos e recessivos também é explorado. A componente de baixa frequência do Equity Risk Premium surge como o fator com maior poder preditivo durante expansões económicas. Em contraste, a componente de alta frequência do Default Yield Spread apresenta um maior poder preditivo durante períodos económicos recessivos. Estas conclusões demonstram como diferentes frequências de indicadores macroeconómicos conseguem captar informações relevantes sobre a dinâmica futura dos retornos do ouro.

Palavras-Chave: Domínio de Frequências, Previsão, Ouro, Matérias-Primas, Wavelets

Número de Palavras: 7063

Abstract

This study uses frequency-domain approaches to forecast gold returns, considering the high-frequency, business cycle-frequency, and low-frequency of each variable. The low-frequency component of the Equity Risk Premium, extracted using wavelet filtering, emerges as a strong predictor of gold returns, outperforming the other variables, and remaining stable over a 24-year out-of-sample period. The predictive power of different variables for gold returns during expansive and recessive business cycles is also explored. The low-frequency component of the Equity Risk Premium emerges as the most significant predictor during economic expansions. In contrast, the high-frequency component of the Default Yield Spread exhibits greater predictive power during recessions. These findings demonstrate how different frequencies of macroeconomic predictors can individually capture important information regarding the future dynamics of gold returns.

Keywords: Frequency domain, Predictability, Gold returns, Commodities, Frequency domain, Wavelets

Number: 7063

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Introduction

Given the importance of gold in today's society, it is self-evident that being able to forecast the price of gold accurately is crucial. Therefore, finding the model that predicts the price of gold more precisely than others is of key importance. Out-of-sample (OSS) forecasting can provide monetary policy makers, hedge fund managers, and global portfolio managers with an advantage in terms of information availability. These forecasts can be used to gauge future inflation, estimate jewellery demand, choose which commodities to invest in, and predict the future movement of the dollar exchange rate. In-sample prediction was the primary technique used to identify the most accurate predictors prior to 2008. If the objective is to determine the economic relationship between variables, then this approach is the right one. The most important information is, however, which predictor, considering the information now available, is the best and most capable of making accurate future predictions. The pivotal moment came in 2008 when Goyal and Welch evaluated the top in-sample and found that they were indeed poor predictors. This discovery marked a significant turning point in the forecasting literature, prompting study into additional determinants and other strategies for forecasting equity returns. Literature on the out-of-sample predictability is vast and is dominated by time-series analysis. By evaluating the OOS predictive ability of these new predictors, new essential information is uncovered that is concealed in a time-series study, such as the optimal frequencies to be used as predictors.

This study forecasts gold returns using frequency-domain approaches that include creating a new predictor and getting data from each original variable for a number of time series, each of which corresponds to a different predictor of the original variable. Improvements in statistical and economic forecasting are the ultimate objective. The information in the original set of data is always retained, even though we deconstruct the original variables into new frequency-distinct variables. Observing several frequencies allows to separate those frequencies with the highest predictive power from others that bring noise to the exercise and confirms the importance of using frequency-domain information of the original predictive variables. In this paper three economically motivated frequency components of each variable are considered as potential gold returns predictors: the high-frequency component, the business cycle-frequency component, and the low-frequency component. The main focus is to evaluate the out-of-sample forecasting performance of these frequency components.

I found that the low-frequency component of the Equity Risk Premium, extracted using wavelet filtering methods, is a strong and robust out-of-sample predictor of the gold returns (both from a statistical and an economic point of view) for forecasting horizons ranging from one month to two years. Its outperformance versus the historical mean benchmark is remarkably good for the one-month horizon, increases with the forecasting horizon, and is consistently stable throughout an out-of-sample period comprising 24 years of monthly data. It also outperforms several variables that have recently been proposed as good gold returns forecasts, including Ditch (2020). Apart from this predictor, only the high frequency component of the Default Return spread exhibited a positive and statistically significance over the historical average forecast benchmark. Differently, the remaining frequency components of the remaining variables are poor gold returns out-of-sample predictors.

Throughout this analysis, an intriguing dichotomy emerges regarding the predictive power of two key variables for forecasting future gold returns, depending on the prevailing business cycle conditions, demonstrating different uses of the gold commodity as an asset. Specifically, the low frequency component of the Equity Risk Premium proves to be the most pertinent predictor during expansions business cycles, whereas the high frequency component of the Default Yield Spread exhibits greater predictive efficacy during business recessions cycles.

This finding shed light on the dynamic relationship between these variables and the business cycle, offering valuable insights for forecasting gold returns. Expansions business cycles, characterized by economic growth and investor optimism, are associated with elevated stock prices and a correspondingly increased Equity Risk Premium. As investors display a preference for higher-risk assets like equities in search of greater returns, the demand for safe-haven assets such as gold tends to diminish. Consequently, the link between gold returns and the factors traditionally associated with its safe-haven status weakens during these periods.

Conversely, recessions marked by economic contraction and heightened uncertainty, amplify the predictive accuracy of the Default Yield Spread in forecasting gold returns. During recessions, default risk escalates, prompting investors to adopt a more risk-averse stance and redirect their investments toward safer assets. This flight to quality and risk-averse behaviour stimulates the demand for gold as a safe-haven asset. Consequently, the relationship between gold returns and the Default Yield Spread gains strength during recessions.

1. Related Literature and my contribution

1.1 Frequency domain asset pricing

Asset pricing is a fundamental area of analysis in finance and economics, which aims to discern the drivers underpinning the prices of multiple financial assets such as equities, bonds, and commodities. The conventional approach to asset pricing has predominantly relied upon time series data in the time domain. However, recently, the frequency domain approach has been the subject of increasing attention mainly because it offers a distinct perspective on asset pricing by dissecting the frequency components of asset returns, thus allowing for the opportunity to explore the dynamic behaviour of asset prices across diverse time horizons.

This research is situated within the context of the literature on the spectral properties of financial asset returns. The utilization of frequency domain techniques in economics has a long history, as evidenced by seminal works such as Granger and Hatanaka (1964) and Engle (1974). Hodrick and Prescott (1997) who were pioneers in applying frequency domain analysis to asset pricing, by using a rudimental version of a band-pass filter to decompose economic time series into different frequency components. By finding that the high-frequency component of asset prices was strongly correlated with trading volume, they were able to provide evidence of short-term speculation in financial markets. This research has since been further expanded upon, with subsequent studies examining the relationship between different frequency components of economic variables and asset returns.

Over the past decade, this methodology has gained popularity, with wavelets being employed in various noteworthy applications, including the analysis of stocks (Fernandez, 2006; In and Kim, 2006; Rua and Nunes, 2009), commodities (Vacha and Barunik, 2012; Graham et al., 2013) exchange rates (Nekhili et al., 2002; Karuppiah and Los, 2005; Nikkinen et al., 2011), as well as other financial and economic variables or their interactions (Kim and In, 2005; Faÿ et al., 2009; Rua, 2010; Aguiar-Conraria and Soares, 2012; Gallegati et al., 2011; Aguiar-Conraria et al., 2012).

Chaudhuri and Lo (2016) employed spectral analysis techniques to quantify stock-return dynamics over multiple time horizons so to propose a new a spectral portfolio theory. Faria and Verona (2018) and Bandi et al. (2019) applied models in which returns and predictors are linear aggregates of components which operate at different frequencies. Additionally, Faria and Verona (2020) concluded that the term spread is a useful and robust out-of-sample predictor of stock market returns, after properly purging the time series from its short-term noise and medium-term fluctuations.

In this study, the goal is to investigate whether and how different frequencies of macroeconomic predictors individually capture important information regarding the future dynamics of gold returns.

Specifically, I use wavelet analysis to decompose each predictor into different frequency components and analyse the relationship between these components and future gold dynamics. This study adds to the literature by providing further evidence on the usefulness of frequency domain tools in finance, and by exploring new applications of these tools in asset pricing research.

1.2 Wavelet filtering methods

This research also contributes to the literature that uses wavelets methods to forecast (out-of-sample) economic and financial time series. The use of wavelet filtering methods is a very popular approach in the fields of signal processing and data analysis. In the world of finance, they are commonly more used to analyse the relationship between economic variables and asset returns, as their ability to decompose signals into their frequency and time components makes them a powerful tool for identifying underlying patterns and relationships in data sets, allowing for the development of models that can capture these patterns and relationships. Their unique ability to provide a complete picture of data from both time and frequency angles at the same time is what distinguishes them. This means they help break down what's happening in the market into different parts based on how often things happen, and we can look at each part separately. They don't have some of the problems that regular methods have when looking at frequency, making them well-suited for the examination of financial variables whose temporal evolution is shaped by the interaction of a diverse array of frequency components**.** Some examples that illustrate the advantages of wavelet-based techniques over traditional econometric techniques in finance, include Huang and Wu (2004) wavelet analysis on the volatility of exchange rates, Jiang et al. (2020) wavelet analysis on the relationship between oil prices and stock prices and Faria and Verona (2020) analysis on the relationship between different frequencies of the term spread and the dynamics of equity markets. These papers find that wavelet-based measures outperform traditional measures in their respective studies.

1.3 Gold Forecasting Literature Review

In the field of finance, predicting market returns has always been a considerable challenging task. While numerous studies have been conducted to examine the predictability of the stock market, few have focused on predicting the returns of the gold market. There are two major strands of literature on gold market predictions: predictions based on publicly available fundamental and macroeconomic data, and predictions based solely on historical gold prices.

1.3.1 Predictions with macroeconomic variables

Pierdzioch et al. (2014a) conducted a thorough study on the predictability of monthly excess gold market returns based on publicly available information about fundamental and macroeconomic variables. They used a real-time forecasting approach that accounted for the possibility of the optimal forecasting model changing over time. The authors used both "thin" and "thick" modelling approaches, selecting the most promising forecast model for each monthly prediction, and combining all forecasts based on different combination methods. They also set up a simple trading rule to judge the forecast quality of their prediction models for the 1997–2012 out-of-sample period and compared the results with a buy-and-hold strategy. The study concluded that the gold market is informationally efficient with respect to the predictor variables considered in their study.

Building on the positive results of Cooper and Priestley (2009) in terms of stock and bond market predictions, Pierdzioch et al. (2014b) investigated the predictive power of the international business cycle for excess gold returns. Their study found some evidence of predictive power for gold price fluctuations, but a simple trading rule built on real-time out-of-sample forecasts did not lead to superior performance over a buy-and-hold strategy after accounting for transaction costs.

Baur et al. (2016) applied the dynamic model averaging framework proposed by Raftery et al. (2010) along with a dynamic model selection approach to predict gold returns over one, three, and twelve months. The gold price used in their study was the 3PM London fixing price, denominated in U.S. dollars. The authors' findings showed that the dynamic model averaging framework improved forecasts compared to other frameworks and provided evidence for the time variation of gold price predictors.

Aye et al. (2015) used a similar prediction approach to forecast gold prices. However, unlike Baur et al. (2016), they did not use the potential predictors variables directly, instead aggregating them using a recursive principal component analysis to six global factors (business cycle, inflation rate, interest rate, commodity, exchange rate, and stock price). The dynamic model selection approach provided the highest prediction quality across all forecast horizons, while the exchange rate factor exhibited the strongest predictive power. However, the authors only measured prediction quality with the mean squared forecast error and the sum of log predictive likelihoods, and do not provide any economic evaluation criteria, so it remains unclear whether the higher prediction quality in terms of statistical criteria can be profitably exploited within an active investment strategy.

1.3.2 Predictions based on historical gold prices.

In contrast to the fundamental and macroeconomic variables-based predictions, a number of studies have explored the predictability of gold market returns based solely on historical gold prices. Lucey (2011) examined the predictability of daily gold returns over a long-term horizon (1792-2010) and found that there was evidence of predictability in the long run but not in the short run. However, the author did not specify the methodologies used for the predictions. Sari et al. (2010) used artificial neural networks (ANNs) to predict daily gold returns based on past gold prices, past returns, and past volatility. The authors found that ANNs outperformed traditional linear models in predicting gold returns, but the outperformance was not statistically significant. The study suggested that the use of ANNs may provide a promising alternative to traditional linear models in predicting gold market returns.

In a more recent study, Al-Yahyaee et al. (2019) investigated the predictability of gold returns based on past gold prices using machine learning techniques. The authors used a variety of models, including linear regression, decision trees, and random forests, to predict monthly gold returns over the period of 1990 to 2018. Their findings suggested that machine learning models, particularly random forests, outperformed the traditional linear regression model in predicting gold returns. The study highlighted the potential of machine learning techniques in improving the accuracy of gold return predictions.

1.3.3 Correlations of Gold with Macroeconomic Variables

In sum, much research has been done to deepen our understanding of the links between movements of the price of gold and important financial and macroeconomic variables. With more research done, studying the link between the dynamics of the price of gold and the inflation rate (Fortune, 1987; Mahdavi & Zhou, 1997; Gosh, Levin, Macmillan, & Wright, 2004; Levin & Wright, 2006; Blose, 2010; among others). Other financial and macroeconomic variables that researchers have considered as determinants of gold-price fluctuations include interest rates, measures of the stance of the business cycle, and commodity prices (see, among others, Koutsoyiannis, 1983; Diba & Grossman, 1984; Fortune, 1987; Melvin & Sultan, 1990; Cai, Cheung, & Wong, 2001; Christie-David, Chaudhry,

& Koch, 2000). The link between movements in the price of gold and exchange rates has also been under scrutiny (Capie, Mills, & Wood, 2005; Pukthuanthong & Roll, 2011; Reboredo,2013; Sjaastad, 2008; Tully & Lucey, 2007; to name just a few). In earlier studies, several researchers have used the real-time forecasting approach to forecast stock returns (Alcock & Gray, 2005; Bohl, Döpke, & Pierdzioch, 2008; Bossaerts & Hillion, 1999; Hartmann, Kempa, & Pierdzioch, 2008), exchange rates (Sarno & Valente, 2009), and commodities (Vrugt, Bauer, Molenaar, & Steenkamp, 2007). However, given the wide variety of financial and macroeconomic variables considered in earlier research as determinants or predictors of movements of the price of gold, this study will focus on the out-of-sample predictability of monthly excess returns of the price of gold by means of the real time forecasting approach developed by Pesaran and Timmermann (1995)

Throughout the literature it is observed that gold exhibits varying correlations with different fundamental variables, and studying these correlations is crucial for understanding gold price forecasts and its role as a predictor. The historical relationship between gold and these variables has been the subject of extensive research, shedding light on their predictive power and their implications for financial markets. Here, I delve into the correlations of gold with each fundamental variable and highlight the importance of studying them as potential predictors of gold price forecasts, supported by relevant literature examples.

Macroeconomic predictor variables[1]

Variabl e	Description	Publication Lag
INFL	Inflation calculated from the Consumer Price Index for all urban consumers	1 month
USD	Exchange rate as the continuously compounded year-on-year change in the trade-weighted effective nominal U.S. exchange rate	1 month
TBL	Interest rate on a three-month Treasury bill	no
LTY	Long-term government bond yield	no
LTR	Return on long-term government bonds	no
TMS	Term spread computed as long-term yield minus Treasury bill rate	no
DFY	Default yield spread, computed as the difference between Moody's BAA- and AAA-rated corporate bond yields	no
DFR	Default return spread, computed as the long-term corporate bond return minus the long-term government bond return	no
ERP	Equity risk premium, calculated as the difference between the log return on the S&P 500 index and the log return on a risk-free bill	no
DY	Dividend yield (log), calculated as the log of a twelve-month moving sum of dividends paid on the S&P 500 index, minus the log of lagged stock prices (S&P 500 index)	no

Table 1: Variable Description

1.3.4 Gold and Inflation

Inflation is an important macroeconomic indicator that affects the purchasing power of currencies and investors' perception of gold as a store of value. Research by Baur and McDermott (2010) found a positive relationship between gold and inflation, suggesting that gold can serve as an inflation hedge. Similarly, Baur and Lucey (2010) showed that gold returns are positively correlated with inflation uncertainty. Studying the correlation between gold and inflation is crucial for understanding gold's potential as a hedge against inflationary pressures and its role in preserving wealth.

[1] Variable data comes from the Welch and Goyal's (2008) dataset. The data can be retrieved from Amit Goyal's webpage at http://www.hec.unil.ch/agoyal/.

1.3.5 Gold and the U.S. Dollar

The exchange rate of the U.S. dollar can impact the attractiveness of gold as an investment. A strong negative correlation between gold and the USD exchange rate implies that a weaker dollar tends to lead to higher gold prices. This relationship is explored in studies such as Lucey and Li (2015), where they find evidence of a negative correlation between gold and the USD exchange rate. Understanding the correlation between gold and the USD exchange rate is essential for assessing the impact of currency movements on gold price dynamics.

1.3.6 Gold and Interest Rates

Interest rates, particularly those on Treasury bills and long-term government bonds, can influence the opportunity cost of holding gold. Research by Baur and Lucey (2013) found a negative correlation between gold and short-term interest rates, suggesting that lower interest rates make gold more attractive. In contrast, long-term government bond yields may exhibit a positive correlation with gold due to their role as safe-haven assets during periods of economic uncertainty. The correlation between gold and interest rates highlights the importance of studying the relationship between these variables to gauge the attractiveness of gold as an investment in relation to other fixed-income instruments.

1.3.7 Gold and Corporate Bonds

The default yield spread, which represents the difference between corporate bond yields of different credit ratings, can reflect market sentiment and risk perceptions. Gold has shown a positive correlation with the default yield spread, as it tends to rise during times of increased financial stress and market volatility. Research by Daskalaki, Skiadopoulos, and Topaloglou (2018) found a positive correlation between gold and the default yield spread, suggesting that gold can act as a safe-haven asset during periods of credit risk. Studying the correlation between gold and the default yield spread provides insights into gold's role as a hedge against credit-related market turbulence.

1.3.8 Gold and the Stock Market

The equity risk premium represents the excess return required by investors to hold equities instead of risk-free assets. Gold has demonstrated a negative correlation with the equity risk premium, as it tends to rise during periods of heightened market uncertainty and negative sentiment towards equities. Research by Arouri, Lahiani, and Nguyen (2015) found evidence of a negative correlation between gold and the equity risk premium, highlighting gold's role as a safe-haven asset during times of equity market stress. Understanding the correlation between gold and the equity risk premium contributes to the understanding of gold's dynamics as a risk-averse investment.

2.Methodology

2.1 Predictability and Forecasting.

Let r_t be the gold excess returns for month t and h the forecasting horizon. For each predictor x_t, the predictive regression is:

(1) $r_{t:\mathrm{t+h}} = \alpha + \beta x_t + \varepsilon_{\mathrm{t:t+h}} \quad \forall\, \mathrm{t} = 1, \ldots, \mathrm{T} - \mathrm{h},$

where $r_{t:\mathrm{t+h}} = (1/\mathrm{h})\,(r_{t+1} + \cdots + r_{t+h})$.

Then, OLS is used in order to test the significance of estimated β coefficients.

The OOS forecasts are produced using a sequence of expanding windows. The h-step-ahead OOS forecast of the excess returns, $\hat{r}_{t:t+h}$, is computed as:

(2) $\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β in the predictive regression previously mentioned, respectively, using data from the beginning of the sample until month t. The time-frequency series components of each variable are then recomputed recursively at each iteration of the OOS forecasting process by using data from the start of the available sample through the month of forecast formation.

2.2 Time-frequency decomposition of time series using wavelet filtering methods.

Wavelet multiresolution analysis (MRA) is a mathematical technique that allows for the decomposition of any variable, regardless of its time series properties, into different levels of detail, such as a trend, a cycle, or a noise component that can each be studied and examined individually.

To perform a wavelet multiresolution analysis, the variable is first decomposed into a series of sub-signals or approximation coefficients at different levels of resolution, by applying a series of high-pass and low-pass filters to the signal, which separate it into different frequency bands. The low-pass filter is used to extract the coarsest approximation of the signal, while the high-pass filter extracts the details at finer scales.

Using a wavelet filter, any time series y_t can be decomposed as follows:

(3) $y_t = \sum_{j=1}^{J} y_t^{D_j} + y_t^{S_j}$

where $y_t^{D_j}$, j = 1, 2, …, J, are the J wavelet detail components and $y_t^{S_j}$ is the wavelet smooth component.

This equation shows that the original series y_t, which is solely defined in the time domain, can be decomposed into different time series components, each of which is defined in the time domain and represents the fluctuation of the original time series in a specific frequency band. For small j, the j wavelet detail components represent the time series' higher frequency characteristics (i.e., its short-term dynamics). As j increases, the j wavelet detail components represent the series' lower frequency movements. Finally, the smooth component of the wavelet captures the lowest frequency dynamics (i.e., its long-term behaviour).

Each wavelet filter at frequency j approximates an ideal high-pass filter with passband f ∈ [1⁄2j+1, 1⁄2j], while the smooth component is associated with frequencies f ∈ [0, 1⁄2j+1]. The level j wavelet components are thus associated to fluctuations with periodicity [2j, 2j+1] (months).

In my study, three different frequency components are computed. The first captures the high-frequency fluctuations of the series (HF). The second broadly corresponds to business cycle fluctuations (BCF). The third captures the low-frequency fluctuations of the series (LF).

This is done by running a J = 6 level MODWT MRA to each variable using the Haar waveletfilter (as done by, Faria and Verona et al., 2020, Manchaldore et al., 2010 and Malagon et al., 2015). Because the data used is in a monthly length, the first component will capture oscillations of the variables between 2 and 4 months, while the next components will capture between the period of 4-8, 8-16, 16-32, 32-64, and 64-128 months, sequentially. While the smooth component of the variable will capture the oscillations of the variables with a period exceeding 128 months.

The high-frequency component is computed as the sum of the discrete wavelet transform coefficient of the variable from J=1 to J =3, similarly, the business-cycle-frequency component is computed by summing up the values from J=4 to J=6 and finally, the low-frequency component corresponds to the smoothing coefficient at the highest scale of the wavelet decomposition, which is the variable coefficient at scale 6.

Moreover, the maximal overlap discrete wavelet transform (MODWT) MRA is used to perform wavelet decomposition analysis, as this methodology is not limited to a specific sample size, is translation-invariant, which means it is not affected by the starting point of the time series under consideration and does not introduce phase shifts in the wavelet coefficients. It addresses the limitations of traditional econometric techniques by capturing both low-frequency and high-frequency components of the data simultaneously, making them useful for analysing non-stationary and non-linear data and providing multiscale analysis of financial time series data, allowing for the identification of patterns and trends at different time scales.[2]

2.3 Data and Predictors

I follow Ditch (2020) footsteps and forecast the continuously compounded monthly excess returns of gold over the risk-free rate, using a dataset comprising data from December 1975 through December 2014. The data used for the fundamental and macroeconomic factors is observed on a monthly basis. The in-sample analysis is performed for the period spanning from January 1976 (1976:01) to December 2014 (2014:12), with an initial estimation period for the fundamental predictive regression models. The out-of-sample period starts from January 1991 (1991:01) and extends until December 2014 (2014:12), allowing for an assessment of forecasting ability across different market environments.

The study focuses on the predictability of gold excess returns, measured as the end-of-month spot gold fixing prices from the London Bullion Market[3], recorded at 3:00 p.m. London time and denominated in USD minus the log return on a one-month Treasury bill. The study forecasts monthly excess returns of gold over the risk-free rate, with the Treasury bill rate provided in Welch and Goyal's (2008) dataset serving as the risk-free rate.

In order to assess forecasting ability in different market environments, I also employ NBER-dated business cycle expansions and recessions data.

For each macroeconomic variable three frequency components are evaluated as individual excess gold returns predictors. The high-frequency fluctuations of

[2] A more detailed analysis of wavelets methods can be found in the Appendix.
[3] Gold fixing prices can be found at https://www.lbma.org.uk/prices-and-data/precious-metal-prices#/.

the series (HF), the business cycle fluctuations (BCF) and the low-frequency fluctuations of the series (LF).

Descriptive statistics

Period	Mean	Std.	Min	Max	Skewness	Kurtosis
1976:01–2014:12	0.05	5.58	-2,53	23.53	-0.02	6.41
1991:01-2014:12	0.16	4.58	15.61	-19.18	-0.07	1.53

Table 2: Descriptive Statistics of excess gold returns

Table 2 provides descriptive statistics for the monthly gold excess returns; The corresponding values are reported for the entire data sample (1976:01-2014:12) and the out-of-sample period (1991:01-2014:12). Splitting data sample is essential for rigorous empirical research and predictive modelling. Relying solely on the in-sample period for evaluation can lead to overfitting, where the model performs well on the training data but fails to generalize to unseen data. To overcome this limitation, the out-of-sample period for model validation and testing is used, assessing how well the model predicts gold excess returns on data it has not been trained on. This out-of-sample evaluation ensures the model's reliability, robustness, and generalizability, providing more credible and realistic predictions for real-world applications beyond the historical data period.

3. Empirical Results

3.1 Out-of-sample analysis

The OOS forecasts are produced using a sequence of expanding windows, meaning that the initial estimation period from 1976:01 to 1990:12 (to predict the gold excess return in 1991:01) is expanded each month with new available data until the end of the sample. The full OOS period runs from 1991:01 to 2014:12.

The out-of-sample (OOS) forecasting performance of different predictors is evaluated using the Campbell and Thompson (2008) R^2_{OS} statistic. Also, the historical mean (HM) forecast $\overline{r_t}$ (average excess return up to time t) is used as the benchmark model. This approach is standard in the literature and allows for a comparison of the forecasting accuracy of different models.

The R^2_{OS} is given by:

(4) $R^2_{OS} = 1 - \frac{\sum_{t=s}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=s}^{T}(r_t - \overline{r}_t)^2}$

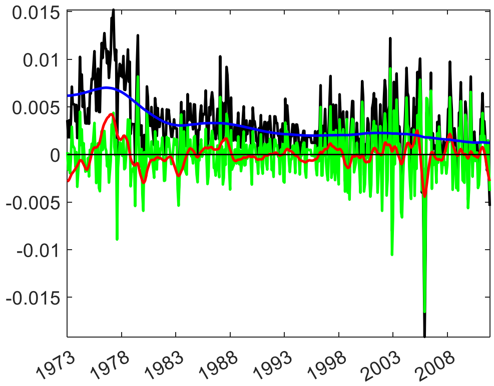
(5) $R^2_{OS} = 1 - \frac{MSFE_i}{MSFE_0}$

The R^2_{OS} statistic provides a measure of the proportion of the variance of the excess returns that is explained by each predictor, relative to the benchmark model. Looking at the R^2_{OS} allows to identify which predictors are most useful in forecasting excess returns and can inform investment decisions.

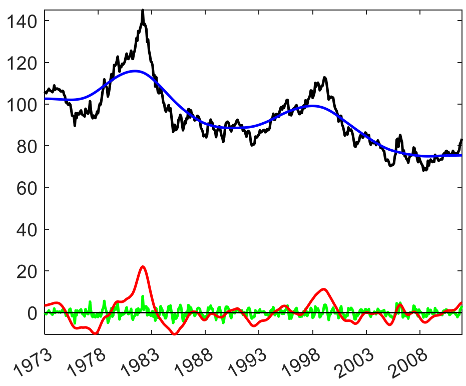
Predictor	R^2_{OS}	R^2_{OS} T-STAT	CER Gains
INFL	-2.13	-1.21	-1.05
$INFL_{HF}$	0.00	0.27	-0.33
$INFL_{BCF}$	-1.90	-1.03	-1.28
$INFL_{LF}$	-1.70	-0.54	-0.93
USD	-0.27	0.08	-0.65
USD_{HF}	-3.76	-0.15	-3.02
USD_{BCF}	0.19	0.88	0.50
USD_{LF}	-0.85	0.24	-1.68
TBL	-0.83	1.08	-1.02
TBL_{HF}	-0.13	0.28	0.34
TBL_{BCF}	-0.56	1.12	1.12
TBL_{LF}	-0.28	0.43	-0.13
LTY	-2.74	0.18	-4.35
LTY_{HF}	-9.89	-0.59	-1.48
LTY_{BCF}	-3.50	0.40	-1.70
LTY_{LF}	-1.83	0.43	-1.29
LTR	-0.43	-0.98	-0.31
LTR_{HF}	-0.47	-0.53	0.08
LTR_{BCF}	-0.57	-1.95	-0.80
LTR_{LF}	0.11	1.12	1.52
TMS	-0.08	-0.11	0.04
TMS_{HF}	-0.10	-0.16	-0.05
TMS_{BCF}	-0.06	0.07	0.23
TMS_{LF}	-0.94	-0.46	-0.82
DFY	-1.15	-1.22	-2.02
DFY_{HF}	-0.91	0.83	0.27
DFY_{BCF}	-3.08	-0.98	-0.10
DFY_{LF}	-0.60	-0.64	-0.10
DFR	0.97**	1.85	0.60
DFR_{HF}	1.11*	1.54	1.20
DFR_{BCF}	-1.78	0.82	-1.37
DFR_{LF}	-0.42	0.31	-0.29
ERP	-1.05	-1.35	-0.98
ERP_{HF}	-0.50	-0.82	-0.33
ERP_{BCF}	-2.28	-0.92	-0.79
ERP_{LF}	2.01***	2.45	3.31
DY	-2.74	0.18	-1.36
DY_{HF}	-9.89	-0.59	0.23
DY_{BCF}	-3.50	0.40	0.91
DY_{LF}	-1.83	0.43	-0.45

Table 3: Out-of-sample R-squares

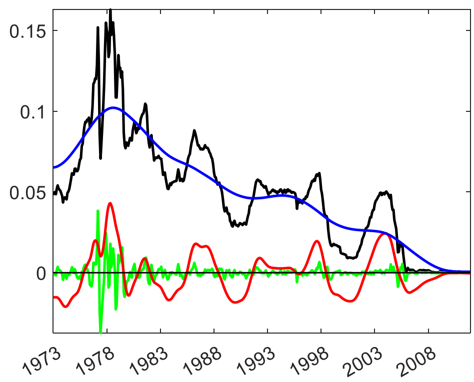
Panel A: Inflation



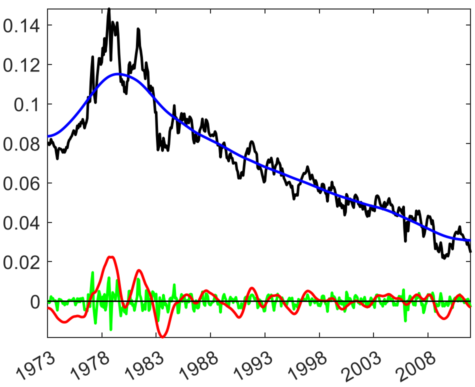
Panel B: USD



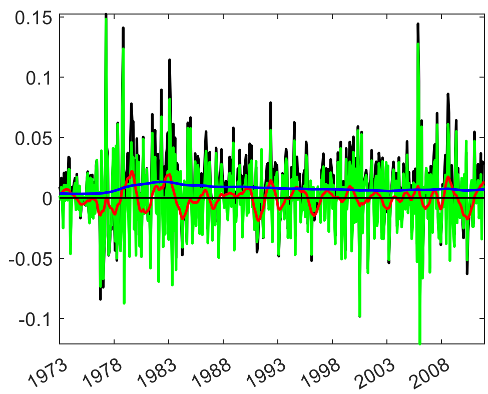
Panel C: TBL



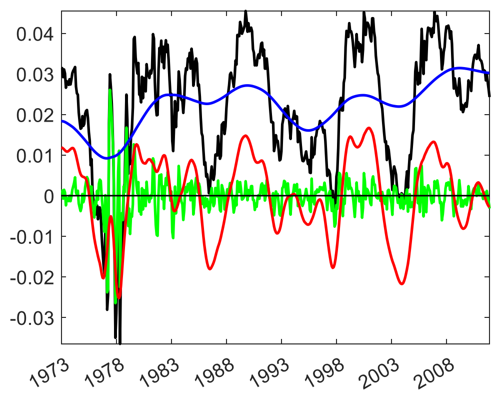
Panel D: LTY



Panel E: LTR



Panel F: TMS



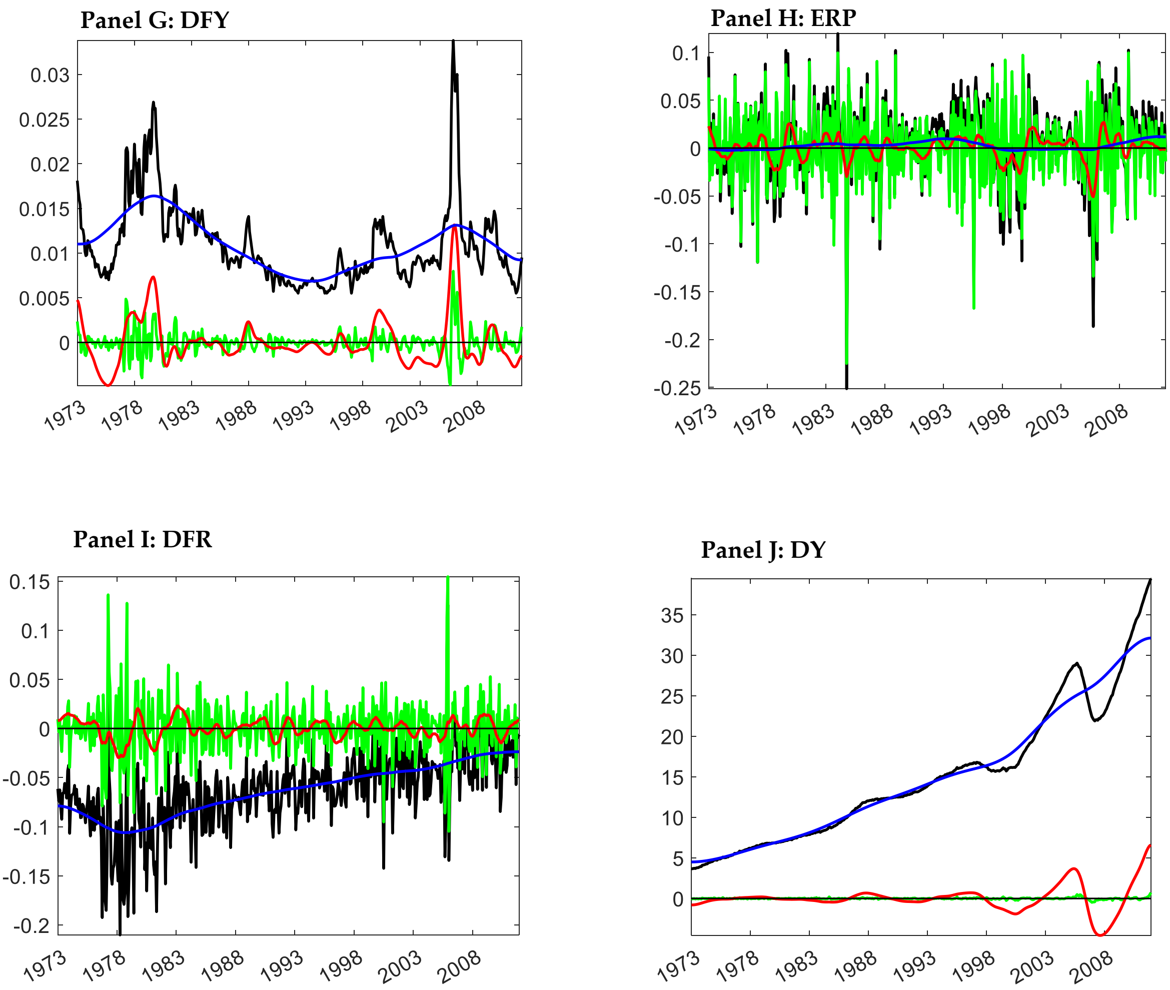


Fig. 1: Time series of the variables. Each panel shows original time series of the respective variable (black line) and of its three frequency components High Frequency (green line), Business Cycle Frequency (red line), and Low Frequency (blue line) obtained through wavelets decomposition capturing oscillations of the variable less than 16 months, between 16 and 128 months and greater than 128 months, respectively. Sample period runs from 1991:01 to 2014:12, monthly frequency.

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Table 3 reports the out-of-sample forecasting results obtained using the statistical evaluation criteria just discussed of each macroeconomic variable and their respective different frequency components, while the panels in Figure 1 provide a graphical overview of the values.

As already shown by Ditch (2020) the default return spread is the only statistically significant predictor, exhibiting the lowest MSFE of all the fundamental regression models and a statistically significant R_{OS}^2 of 0.97 over the historical average forecast benchmark. All other regressions exhibit negative R^2s, indicating lower predictive accuracy than the historical average in terms of the MSFE.

However, by exploring the different frequency components of each variable, promising results were uncovered related to ERP_{LF} variable. It exhibits a statistically significance R_{OS}^2 of 2.02 over the historical average forecast benchmark. Its high- and business-cycle frequencies (ERP_{HF} and ERP_{BCF}) perform, however, rather poorly as OOS gold forecast predictors. Apart from this, only the DFR_{HF} presented a positive and statistically significance R^2 of 1.11 over the historical average forecast benchmark, which is in line with the original DFR in terms of predictive power. The remaining different frequency components of the predictors deliver negative R^2s.

3.2 Asset allocation analysis

To examine the economic value of this predictive model from an asset allocation perspective, the distribution between gold and risk-free bills in an investor portfolio is considered. A mean variance investor will optimally allocate a certain amount of its portfolio to gold, at the end of month t, through the following way:

$$(6) \quad w_t = \frac{1}{\gamma} \frac{\hat{R}_{t+h}}{\widehat{\sigma^2}_{t+h}}$$

Considering the period from t to t + h, γ equals to the investor's relative risk aversion coefficient, $\hat{R}_{t+h}$ the out-of-sample forecasts of gold returns and $\widehat{\sigma^2}_{t+h}$ the out-of-sample forecasts of the variance of the gold returns. To estimate the variance of the gold excess returns a relative risk aversion coefficient of three, and a ten-year moving window of past excess returns are used. The weights w_t are constrained to a range between −0.5 and 1.5.

The certainty equivalent returns (CER) of an investor that uses this method, is calculated using the formula CER = $\overline{RP} - 0.5\gamma\sigma 2\ \overline{RP}$, with $\overline{RP}$ being the sample mean and $\sigma 2\overline{RP}$ the variance of the portfolio return.

Considering the utility gain as the difference between the CER for an investor that uses this predictive model to forecast excess returns and the CER for an investor who uses the HM benchmark for forecasting, in Table 3 the annualized utility gain from using the predictive models associated with different predictors can be observed.

The results in Table 3 show that the performance of the ERP_{LF} is also strong from an economic point of view, meaning its information may be useful to investors with different profiles for forecasting purposes. Apart from this, the rest of the CER gains obtained are not remarkable.

3.3 Robustness test

To gain deeper understanding of the relative effectiveness of gold returns during periods characterized by economic expansion and recession, Neely et al. (2014) alternative interpretations of the conventional R^2 statistic, are calculated aiming to provide intuitive insights into the relationship between gold returns and the status of the business cycle.

Consistent with the approaches of Rapach and Zhou (2013) and Neely et al. (2014), the identification of business cycle expansions and recessions is based on the National Bureau of Economic Research (NBER) dating methodology.

In a next step, the effects of different market environments on the performance of fundamental-based predictive regressions are analysed.

Predictor	R^2 REC	R^2 EXP	R2OS T-stat REC	R2OS T-stat EXP
INFL	-2,98	-1,92	-0.92	-2.66
*INFL*HF	-0,24	0,06	0.09	-0.13
*INFL*BCF	-7,63	-0,47	-0.84	-2.32
*INFL*LF	-0,85	-1,91	0.42	-1.3
USD	-1,21	-0,04	-1.21	-0.69
*USD*HF	2,79	-5,39	-0.10	-3.72
*USD*BCF	-1,03	0,49	0.45	0.04
*USD*LF	-2,12	-0,53	-0.79	-1.12
TBL	-1,31	-0,71	-0.33	-1.56
*TBL*HF	0,05	-0,17	-0.10	-0.30
*TBL*BCF	-1,27	-0,38	0.23	-1.17
*TBL*LF	-0,63	-0,19	-0.78	-0.76
LTY	-1,72	-3,93	-0.56	-4.09
*LTY*HF	0,01	-1,37	-0.17	-1.26
*LTY*BCF	0,33	-2,62	-0.32	-3.23
*LTY*LF	-1,52	-0,59	-1.14	-1.29
LTR	-0,72	-0,36	-1.24	-0.48
*LTR*HF	-1,22	-0,28	-0.69	-0.51
*LTR*BCF	-0,88	-0,49	-2.20	-0.66
*LTR*LF	-0,95	0,38	0.73	-0.39
TMS	-0,16	-0,06	-1.28	-0.48
*TMS*HF	-0,05	-0,11	-0.71	-0.15
*TMS*BCF	-0,62	0,08	-2.23	-0.48
*TMS*LF	0,07	-1,19	-0.14	-1.30
DFY	-2,04	-0,92	-1.46	-0.82
*DFY*HF	10,89	-3,84	0.90	-0.69
*DFY*BCF	-9,24	-1,55	-1.06	-3.03
*DFY*LF	-1,39	-0,41	-0.24	-0.34
DFR	5,54	-0,17	0.93	-0.35
*DFR*HF	3,72	0,46	1.49	1.02
*DFR*BCF	2,96	-2,95	0.30	-2.13
*DFR*LF	-0,99	-0,28	-0.82	-0.89
ERP	-1,93	-0,83	-1.60	-1.07
*ERP*HF	-0,50	-0,50	-1.06	-0.57
*ERP*BCF	-7,77	-0,91	-1.15	-2.34
*ERP*LF	-1,64	2,92	2.45	1.60
DY	-0,67	-3,26	0.55	-2.82
*DY*HF	-2,97	-11,61	-0.11	-7.27
*DY*BCF	-2,86	-3,66	1.07	-1.40
*DY*LF	-0,58	-2,15	0.57	-2.12

Table 4: Expansive/Recessive business cycle: Impact on out-of-sample R^2 s.

The out-of-sample results documented in table 4 suggest that some fundamental predictor variables provide better forecast results during expansive business cycles, while others are better in recessive business environments.

On recessive business cycles, the DFR model provides a statistically significance R^2 of 5.54 over the historical average forecast, while underperforming the benchmark on expansive periods. The same applies for the USD_{HF} model which displays a statistically significance R^2 of 2.79 over the benchmark on recessive periods, but a R^2 of -5.38 underperformance on expansive periods.

However, DFY_{HF} stands out in recessions with a higher predictive power than any of the other studied variables. It exhibits a statistically significance R^2 of 10.89 over the historical average forecast benchmark.

In expansive business cycles, the results are different. The only predictor which displays a statistical significance over the historical average forecast benchmark is the ERP_{LF}, with a R^2 of 2,92. All other fundamental predictive regressions exhibit negative R^2s, indicating lower predictive accuracy than the historical average in terms of the MSFE.

3.4 Interpretation of Results

The empirical results of this study show that decomposing fundamental predictor variables into different levels of detail provides superior forecasts of gold excess returns over the historical level benchmark. Through a wavelet multiresolution analysis, variables with a higher predictive power were found with statistical significance, specifically when studied in different business cycles.

3.4.1 Comparison with different methodologies

A Wavelet Multiresolution Analysis (MRA) may achieve higher predictive power than normal regression models when analysing gold forecast returns for several reasons specific to the characteristics of gold and the nature of its price movements.

Nonlinear Relationships: Gold price movements often exhibit nonlinear patterns, which may not be adequately captured by linear regression models. MRA, with its ability to capture nonlinearity through the decomposition of data into different frequency components, can better identify and model these nonlinear relationships. This flexibility allows MRA to capture complex and non-trivial dynamics in gold prices that regression models may overlook.

Time-Frequency Localization: Gold prices are influenced by various factors that can operate at different time scales. MRA's time-frequency localization properties enable the analysis of gold price data at multiple resolutions, capturing both short-term fluctuations and long-term trends. This multi-scale approach allows MRA to capture the inherent complexity and dynamics of gold price movements, leading to improved predictive power compared to regression models that assume constant relationships over time.

Noise Reduction: Gold price data often contain various sources of noise and short-term fluctuations that can obscure the underlying trends. MRA's ability to decompose the data into different frequency components allows for effective noise reduction, separating the signal from the noise. By focusing on the relevant frequency bands, MRA can reduce the impact of noise on the analysis and improve the accuracy of the predictions.

Adaptability to Market Conditions: Gold prices can be influenced by changing market conditions, such as periods of high volatility or shifts in investor sentiment. MRA's adaptability to non-stationary patterns enables it to capture and model these changing dynamics effectively. By adjusting the resolution and focus of analysis based on market conditions, MRA can provide more accurate predictions of gold price movements compared to regression models that assume constant relationships.

Overall, the superior predictive power of MRA in analysing gold forecast returns can be attributed to its ability to capture nonlinear relationships, handle multivariate analysis, localize time-frequency information, reduce noise, and adapt to changing market conditions. These features make MRA a valuable tool for understanding and forecasting the complex dynamics of gold prices.

3.4.2 Usefulness

The finding that different fundamental variables exhibit varying predictive power for gold returns during expansive and recessive business cycles has significant implications for investors, portfolio managers, and policymakers. This is speciality important for an asset such as gold, which is commonly used as a way to hedge against future recession periods. Understanding the usefulness of this finding can help inform investment strategies, risk management decisions, and policy interventions. Here, it is expanded on why and how this finding is useful:

Investment Strategy: The identification of predictors that are more suitable for forecasting gold returns in specific business cycles allows investors to tailor their investment strategies accordingly. According to their beliefs and views of where the current economic cycle is and where it is heading, investors can follow different indicators to forecast gold prices. During expansive cycles, when the Equity Risk Premium demonstrates higher predictive power, investors may consider adjusting their asset allocation to capture the potential benefits of economic growth and positive market sentiment. They can allocate a larger proportion of their portfolio to equities and riskier assets, potentially reducing exposure to gold. Conversely, during recessive cycles, when the Default Yield Spread exhibits higher predictive accuracy, investors may increase their allocation to gold as a safe-haven asset to hedge against economic downturns and market volatility. This information empowers investors to optimize their portfolio construction and enhance risk-adjusted returns.

Risk Management: The differential predictive power of fundamental variables in different business cycles provides insights into risk management strategies. By considering the specific economic environment, investors can better gauge the risk associated with their portfolios and adjust their risk exposure accordingly. As gold is considered a safe-haven asset, it can be used as way for investors to hedge their portfolios against recessive cycles. This information can be especially useful in determining the amount of exposure investors should allocate to gold in their portfolios and the returns they should expect in doing so.

Academic Contribution: The finding of differential predictive power for gold returns in expansive and recessive business cycles contributes to the existing academic literature on safe-haven assets and their dynamics. It enriches our understanding of gold's behaviour as a safe-haven asset during periods of market turbulence and economic uncertainty. The identification of specific predictors in different business cycles provides empirical evidence and supports theoretical frameworks that explain the role of gold as a store of value and a hedge against market downturns. This finding adds to the body of knowledge on safe-haven assets and their implications for financial markets.

4. Concluding Remarks

The low-frequency component of the Equity Risk Premium, effectively extracted through wavelet filtering methods, emerges as a strong out-of-sample predictor of gold returns, not only in terms of predictive power, but also from an economic point of view. Among the other variables analysed, only the high-frequency component of the Default Return spread exhibited positive and statistically significant predictive power over the historical average forecast benchmark. In contrast, the remaining frequency components of the other variables proved to be poor predictors of gold returns in the out-of-sample context and in an economic point of view.

The identification of different predictors for gold returns in expansive and recessive business cycles also proves have practical implications for investment strategies, risk management, policy interventions, and academic research.

During periods of economic expansion, characterized by optimistic market sentiment and rising stock prices, the low-frequency component of the Equity Risk Premium emerges as the most pertinent predictor of gold returns. This finding suggests that as economic growth and investor confidence lead to higher stock valuations, investors exhibit a preference for riskier assets, causing a reduced demand for safe-haven assets like gold. Consequently, the safe-haven characteristics of gold weaken during these expansionary phases.

Conversely, in times of business recessions marked by economic contraction and heightened uncertainty, the high-frequency component of the Default Yield Spread exhibits greater predictive efficacy for gold returns. As economic conditions deteriorate, default risk rises, prompting investors to adopt a more risk-averse stance and seek safer assets like gold. This shift in investor behaviour stimulates demand for gold as a safe-haven asset, resulting in a strengthened predictive relationship between gold returns and the Default Yield Spread during recessionary cycles.

These findings contribute to the understanding of gold's role as an asset class and its performance during different economic phases. By acknowledging the divergent predictive power of these two components depending on the business cycle, investors and policymakers can make more informed decisions to optimize their portfolios and mitigate risks during economic fluctuations.

5.Bibliography

Aguiar-Conraria, L., Martins, M. M. F., & Soares, M. J. (2012). The yield curve and the macro-economy across time and frequencies. *Journal of Economic Dynamics and Control*, *36*(12). https://doi.org/10.1016/j.jedc.2012.05.008

Alcock, J., & Gray, P. (2005). Forecasting stock returns using model-selection criteria. *Economic Record*, *81*(253). https://doi.org/10.1111/j.1475-4932.2005.00239.x

Al-Yahyaee, K. H., Mensi, W., & Yoon, S. M. (2018). Efficiency, multifractality, and the long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters*, *27*. https://doi.org/10.1016/j.frl.2018.03.017

Aye, G., Gupta, R., Hammoudeh, S., & Kim, W. J. (2015). Forecasting the price of gold using dynamic model averaging. *International Review of Financial Analysis*, *41*. https://doi.org/10.1016/j.irfa.2015.03.010

Bandi, F. M., Perron, B., Tamoni, A., & Tebaldi, C. (2019). The scale of predictability. *Journal of Econometrics*, *208*(1). https://doi.org/10.1016/j.jeconom.2018.09.008

Baur, D. G., Beckmann, J., & Czudaj, R. (2016). A melting pot — Gold price forecasts under model and parameter uncertainty. *International Review of Financial Analysis*, *48*. https://doi.org/10.1016/j.irfa.2016.10.010

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2). https://doi.org/10.1111/j.1540-6288.2010.00244.x

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking and Finance*, *34*(8). https://doi.org/10.1016/j.jbankfin.2009.12.008

Blose, L. E. (2010). Gold prices, cost of carry, and expected inflation. *Journal of Economics and Business*, *62*(1). https://doi.org/10.1016/j.jeconbus.2009.07.001

Bohl, M. T., Döpke, J., & Pierdzioch, C. (2008). Real-time forecasting and political stock market anomalies: Evidence for the United States. *Financial Review*, *43*(3). https://doi.org/10.1111/j.1540-6288.2008.00196.x

Bossaerts, P., & Hillion, P. (1999). Implementing statistical criteria to select return forecasting models: What do we learn? *Review of Financial Studies*, *12*(2). https://doi.org/10.1093/rfs/12.2.405

Cai, J., Cheung, Y. L., & Wong, M. C. S. (2001). What moves the gold market? *Journal of Futures Markets*, *21*(3). https://doi.org/10.1002/1096-9934(200103)21:3<257::AID-FUT4>3.0.CO;2-W

Campbell, J. Y., & Thompson, S. B. (2008). Predicting excess stock returns out of sample: Can anything beat the historical average? *Review of Financial Studies*, *21*(4). https://doi.org/10.1093/rfs/hhm055

Capie, F., Mills, T. C., & Wood, G. (2005). Gold as a hedge against the dollar. *Journal of International Financial Markets, Institutions and Money*, *15*(4). https://doi.org/10.1016/j.intfin.2004.07.002

Chaudhuri, S. E., & Lo, A. W. (2017). Spectral Portfolio Theory. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2788999

Christie-David, R., Chaudhry, M., & Koch, T. W. (2000). Do macroeconomics news releases affect gold and silver prices? *Journal of Economics and Business*, *52*(5). https://doi.org/10.1016/s0148-6195(00)00029-1

Cooper, I., & Priestley, R. (2009). Time-varying risk premiums and the output Gap. *Review of Financial Studies*, *22*(7). https://doi.org/10.1093/rfs/hhn087

C.W.J. Granger Spectral Analysis of Economic Time Series. In Association with M. Hatanaka. Princeton Studies in Mathematical Economics, number 1. Princeton, N.J., Princeton University Press, 1964, XVIII p. 299 p., $8.50. (1967). *Recherches Économiques de Louvain*, *33*(2). https://doi.org/10.1017/s0770451800022570

Daskalaki, C., Skiadopoulos, G., & Topaloglou, N. (2017). Diversification benefits of commodities: A stochastic dominance efficiency approach. *Journal of Empirical Finance*, *44*. https://doi.org/10.1016/j.jempfin.2017.07.004

Diba, B. T., & Grossman, H. I. (1984). Rational Bubbles in the Price of Gold. *NBER Working Paper*, *March*.

Dichtl, H. (2020). Forecasting excess returns of the gold market: Can we learn from stock market predictions? *Journal of Commodity Markets*, *19*. https://doi.org/10.1016/j.jcomm.2019.100106

El Hedi Arouri, M., Lahiani, A., & Nguyen, D. K. (2015). World gold prices and stock returns in China: Insights for hedging and diversification strategies. *Economic Modelling*, *44*. https://doi.org/10.1016/j.econmod.2014.10.030

Engle, R. F. (1974). Band Spectrum Regression. *International Economic Review*, *15*(1). https://doi.org/10.2307/2526084

Eric J. Levin, R. E. W. (2006). Short-Run And Long-Run Determinants Of The Price Of Gold. *Psychotherapy Research*, *22*(32).

Faria, G., & Verona, F. (2018). Forecasting stock market returns by summing the frequency-decomposed parts. *Journal of Empirical Finance*, *45*. https://doi.org/10.1016/j.jempfin.2017.11.009

Faria, G., & Verona, F. (2020). The yield curve and the stock market: Mind the long run. *Journal of Financial Markets*, *50*. https://doi.org/10.1016/j.finmar.2019.100508

Faÿ, G., Moulines, E., Roueff, F., & Taqqu, M. S. (2009). Estimators of long-memory: Fourier versus wavelets. *Journal of Econometrics*, *151*(2). https://doi.org/10.1016/j.jeconom.2009.03.005

Fernandez, V. (2006). The impact of major global events on volatility shifts: Evidence from the Asian crisis and 9/11. *Economic Systems*, *30*(1). https://doi.org/10.1016/j.ecosys.2005.09.004

Gallegati, M., Gallegati, M., Ramsey, J. B., & Semmler, W. (2011). The US Wage Phillips Curve across Frequencies and over Time. *Oxford Bulletin of Economics and Statistics*, *73*(4). https://doi.org/10.1111/j.1468-0084.2010.00624.x

Gao, J., Sultan, H., Hu, J., & Tung, W. W. (2010). Denoising nonlinear time series by adaptive filtering and wavelet shrinkage: A comparison. *IEEE Signal Processing Letters*, *17*(3). https://doi.org/10.1109/LSP.2009.2037773

Ghosh, D., Levin, E. J., Macmillan, P., & Wright, R. E. (2004). Gold as an Inflation Hedge? In *Studies in Economics and Finance* (Vol. 22, Issue 1). https://doi.org/10.1108/eb043380

Graham, M., Kiviaho, J., & Nikkinen, J. (2013). Short-term and long-term dependencies of the S&P 500 index and commodity prices. *Quantitative Finance*, *13*(4). https://doi.org/10.1080/14697688.2013.768773

Hartmann, D., Kempa, B., & Pierdzioch, C. (2008). Economic and financial crises and the predictability of U.S. stock returns. *Journal of Empirical Finance*, *15*(3). https://doi.org/10.1016/j.jempfin.2007.07.003

Hodrick, R. J., & Prescott, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*, *29*(1). https://doi.org/10.2307/2953682

Huang, D., Jiang, F., Tu, J., & Zhou, G. (2015). Investor sentiment aligned: A powerful predictor of stock returns. *Review of Financial Studies*, *28*(3). https://doi.org/10.1093/rfs/hhu080

In, F., & Kim, S. (2006). The hedge ratio and the empirical relationship between the stock and futures markets: A new approach using wavelet analysis. In *Journal of Business* (Vol. 79, Issue 2). https://doi.org/10.1086/499138

Jiang, Z., & Yoon, S. M. (2020). Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. *Energy Economics*, *90*. https://doi.org/10.1016/j.eneco.2020.104835

Karuppiah, J., & Los, C. A. (2005). Wavelet multiresolution analysis of high-frequency Asian FX rates, Summer 1997. *International Review of Financial Analysis*, *14*(2). https://doi.org/10.1016/j.irfa.2004.06.014

Kim, S., & In, F. (2005). The relationship between stock returns and inflation: New evidence from wavelet analysis. *Journal of Empirical Finance*, *12*(3). https://doi.org/10.1016/j.jempfin.2004.04.008

Koutsoyiannis, A. (1983). A short-run pricing model for a speculative asset, tested with data from the gold bullion market. *Applied Economics*, *15*(5). https://doi.org/10.1080/00036848300000037

Lucey, B. M. (2011). What do Academics Think They Know About Gold? *The Alchemist*, *62*.

Lucey, B. M., & Li, S. (2015). What precious metals act as safe havens, and when? Some US evidence. *Applied Economics Letters*, *22*(1). https://doi.org/10.1080/13504851.2014.920471

Mahdavi, S., & Zhou, S. (1997). Gold and commodity prices as leading indicators of inflation: Tests of long-run relationship and predictive performance. *Journal of Economics and Business*, *49*(5). https://doi.org/10.1016/s0148-6195(97)00034-9

Malagon, J., Moreno, D., & Rodríguez, R. (2015). Time horizon trading and the idiosyncratic risk puzzle. *Quantitative Finance*, *15*(2). https://doi.org/10.1080/14697688.2012.755560

Manchaldore, J., Palit, I., & Soloviev, O. (2010). Wavelet decomposition for intra-day volume dynamics. *Quantitative Finance*, *10*(8). https://doi.org/10.1080/14697680903369484

Melvin, M., & Sultan, J. (1990). South African political unrest, oil prices, and the time varying risk premium in the gold futures market. *Journal of Futures Markets*, *10*(2). https://doi.org/10.1002/fut.3990100202

Mittal, P. (2023). Wavelet transformation and predictability of Gold Price Index Series with ARMA model. *International Journal of Experimental Research and Review*, *30*, 127–133. https://doi.org/10.52756/ijerr.2023.v30.014

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the equity risk premium: The role of technical indicators. *Management Science*, *60*(7). https://doi.org/10.1287/mnsc.2013.1838

Neill Fortune, J. (1987). The inflation rate of the price of gold, expected prices and interest rates. *Journal of Macroeconomics*, *9*(1). https://doi.org/10.1016/S0164-0704(87)80007-1

Nekhili, R., Altay-Salih, A., & Gençay, R. (2002). Exploring exchange rate returns at different time horizons. *Physica A: Statistical Mechanics and Its Applications*, *313*(3–4). https://doi.org/10.1016/S0378-4371(02)00986-X

Nikkinen, J., Pynnönen, S., Ranta, M., & Vähämaa, S. (2011). Cross-dynamics of exchange rate expectations: A wavelet analysis. *International Journal of Finance and Economics*, *16*(3). https://doi.org/10.1002/ijfe.423

PESARAN, M. H., & TIMMERMANN, A. (1995). Predictability of Stock Returns: Robustness and Economic Significance. *The Journal of Finance*, *50*(4). https://doi.org/10.1111/j.1540-6261.1995.tb04055.x

Pierdzioch, C., Risse, M., & Rohloff, S. (2014a). On the efficiency of the gold market: Results of a real-time forecasting approach. *International Review of Financial Analysis*, *32*. https://doi.org/10.1016/j.irfa.2014.01.012

Pierdzioch, C., Risse, M., & Rohloff, S. (2014b). The international business cycle and gold-price fluctuations. *Quarterly Review of Economics and Finance*, *54*(2). https://doi.org/10.1016/j.qref.2014.01.002

Pukthuanthong, K., & Roll, R. (2011). Gold and the Dollar (and the Euro, Pound, and Yen). *Journal of Banking and Finance*, *35*(8). https://doi.org/10.1016/j.jbankfin.2011.01.014

Raftery, A. E., Kárný, M., & Ettler, P. (2010). Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill. *Technometrics*, *52*(1). https://doi.org/10.1198/TECH.2009.08104

Rapach, D. E., Strauss, J. K., & Zhou, G. (2013). International stock return predictability: What is the role of the united states? *Journal of Finance*, *68*(4). https://doi.org/10.1111/jofi.12041

Reboredo, J. C. (2013). Is gold a safe haven or a hedge for the US dollar? Implications for risk management. *Journal of Banking and Finance*, *37*(8). https://doi.org/10.1016/j.jbankfin.2013.03.020

Rua, A. (2010). Measuring comovement in the time-frequency space. *Journal of Macroeconomics*, *32*(2). https://doi.org/10.1016/j.jmacro.2009.12.005

Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, *16*(4). https://doi.org/10.1016/j.jempfin.2009.02.002

Sari, R., Hammoudeh, S., & Soytas, U. (2010). Dynamics of oil price, precious metal prices, and exchange rate. *Energy Economics*, *32*(2). https://doi.org/10.1016/j.eneco.2009.08.010

Sarno, L., & Valente, G. (2009). Exchange rates and fundamentals: Footloose or evolving relationship? *Journal of the European Economic Association*, *7*(4). https://doi.org/10.1162/JEEA.2009.7.4.786

Sjaastad, L. A. (2008). The price of gold and the exchange rates: Once again. *Resources Policy*, *33*(2). https://doi.org/10.1016/j.resourpol.2007.10.002

Tully, E., & Lucey, B. M. (2007). A power GARCH examination of the gold market. *Research in International Business and Finance*, *21*(2). https://doi.org/10.1016/j.ribaf.2006.07.001

Vacha, L., & Barunik, J. (2012). Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. *Energy Economics*, *34*(1). https://doi.org/10.1016/j.eneco.2011.10.007

Vrugt, E. B., Bauer, R., Molenaar, R., & Steenkamp, T. (2011). Dynamic Commodity Timing Strategies. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.581423

Welch, I., & Goyal, A. (2008). A comprehensive look at the empirical performance of equity premium prediction. *Review of Financial Studies*, *21*(4). https://doi.org/10.1093/rfs/hhm014

Wu, Z., & Huang, N. E. (2004). A study of the characteristics of white noise. *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, *460*.

6.Appendix

The multiresolution analysis (MRA) of the discrete wavelet transform (DWT) enables the decomposition of a time series into its constituent components at various frequencies. This analysis involves two distinct types of wavelets: father wavelets (ϕ) responsible for capturing the smooth and low-frequency portion of the series, and mother wavelets (ψ) designed to capture the high-frequency components. The father wavelets serve the purpose of integrating to unity and effectively represent the exceedingly smooth and elongated components within a signal. On the other hand, the mother wavelets integrate to zero and capture the deviations or fluctuations from these smooth components. The father wavelets are responsible for generating the so-called "scaling coefficients," while the mother wavelets generate the differencing coefficients. These wavelets satisfy the conditions $\int \phi(t)\,dt = 1$ and $\int \psi(t)\,dt = 0$.

Given a time series y_t comprising N observations, its representation in the wavelet multiresolution domain can be expressed as follows:

$$y_t = \sum_k s_{j,k}\ \phi_{j,k}(t) + \sum_k d_{j,k}\ \psi_{j,k}(t) + \sum_k d_{j-1,k}\ \psi_{j-1,k}(t) + \dots + \sum_k d_{1,k}\ \psi_{1,k}(t),$$

where J represents the number of multiresolution levels (or frequencies), k defines the length of the filter, $\phi_{J,k}$ (t) and $\psi_{j,k}$ (t) are the wavelet functions, and $s_{J,K}$, $d_{J,K}$, $d_{J-1,K}$, …, $d_{1,k}$ are the wavelet coefficients.

The wavelet functions are generated from the father and mother wavelets through scaling and translation as follows:

$\phi_{J,k}(t) = 2^{-J/2}\phi(2^{-J}t-k)$

$\psi_{J,k}(t) = 2^{-J/2}\psi(2^{-J}t-k)$

while the wavelet coefficients are given by:

$S_{j,k} = \int y_t \, \phi_{J,k} (t) \, dt$

$d_{j,k} = \int y_t \, \psi_{j,k} (t) \, dt$,

where $j = 1, 2, \ldots, J$.

In empirical applications, the practical constraints associated with the discrete wavelet transform (DWT) necessitate the utilization of an alternative approach known as the maximal overlap discrete wavelet transform (MODWT) for wavelet decomposition analysis. Unlike DWT, the MODWT is not constrained by a specific sample size, exhibits translation invariance, thereby avoiding sensitivity to the selection of the initial time series point, and preserves the alignment of peaks or troughs in the original time series with corresponding events in the MODWT multiresolution analysis (MRA) without introducing phase shifts in the wavelet coefficients. This property is particularly significant when conducting forecasting exercises.