Resources Policy 74 (2021) 102306

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Detecting speculative bubbles in metal prices: Evidence from GSADF test and machine learning approaches

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A R T I C L E I N F O

Keywords:
Metal prices
Multiple bubbles
Random forest algorithm
Macroeconomic factors

A B S T R A C T

The importance of metal prices to real economic activity and financial markets has increased the focus on detecting price bubbles in precious and industrial metals. Several studies looked at the influence of macroeconomic factors in the formation of a single metal bubble and tried to identify bubble dates. Our study extends the literature and analyzes monthly gold, platinum, palladium, rhodium, silver, and aluminum, copper, lead, nickel, steel, tin prices over 1980M1-2019M12, and contributes to the literature in two ways: First, the analysis incorporates the Generalized Supremum Augmented Dickey-Fuller (GSADF) test to detect potential bubbles. Second, the study evaluates the impact of potential financial, real, and speculative factors in the likelihood of price bubbles using the random forest method. Our findings indicate that financial factors are more critical in predicting precious metal price bubbles. The monetary policy rate and the production index are important to predict bubbles in industrial metal prices. However, our findings suggest that speculative activity may not adequately predict metal price bubbles.

1. Introduction

The behavior of commodity prices has long been discussed, as they have real and significant consequences for individual consumers and countries that are dependent on imports and exports of these materials (Enders and Halt, 2011). Commodity price changes have been providing many implications in real and financial terms. On the real side, the rise in the prices of nonferrous metals leads to decelerate economic growth in commodity-dependent emerging countries since they are employed as raw material in industrial activity (Chen et al., 2019). The rise in commodity prices also puts inflationary pressures (Byrne et al., 2011) and directly adverse effects on social welfare in commodity-dependent economies (Brooks et al., 2015). Commodity exporters also suffer from fluctuations in commodity prices, as fluctuations in export earnings may create current account imbalances (Byrne et al., 2011).

On the financial side, the price changes in precious and industrial metals are attributed to market inefficiency and provide a signal for arbitrageurs and speculators to reap abnormal returns in the short run (Narayan and Liu, 2011). Commodities are regarded as investible assets due to their distinct benefits in portfolio diversification and hedging against inflation, which led to the financialization of the commodity markets in the early 2000s (Brooks et al., 2015). Beyond hedging, the rise in commodity-based financial derivatives in financial markets increased the volume of speculating activities. Therefore, financial institutions might have become one of the critical forces in commodity markets. Such financialization increased the awareness of economic agents and scholars to financial factors in examining significant fluctuations of commodity prices (Chen et al., 2019).

The literature suggests that various factors may have contributed to the rise in metal prices (Vansteenkiste, 2009). The first group of factors is regarded as the macroeconomic fundamentals. They include commodity-specific geopolitical conditions, the rising demand of fast-growing emerging countries, the rise of oil prices, the depreciation of the US dollar, and the low-interest rates. However, speculative activity is also labeled as a factor that accelerates the metal prices beyond these macroeconomic fundamentals.

The mechanism through which the macroeconomic fundamentals and speculative factors might affect the metal price fluctuations is well discussed in the literature. According to Vansteenkiste (2009), rapid industrialization and commodity-intensive growth in emerging countries increased commodity demand, pushing global metal prices. Frankel (2006) argued that low-interest rates (i) decrease the desire to extract for

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https://doi.org/10.1016/j.resourpol.2021.102306
Received 2 June 2021; Accepted 15 August 2021
Available online 23 August 2021

producers and reduce the supply, (ii) might trigger economic activity and exacerbate the demand for metals, and (iii) discourage speculators from buying some future contracts that also cause spot prices to rise. Since the US dollar is a unit of account in the transaction of these commodities, Lombardi et al. (2012) argue that fluctuations in the real value of the US dollar will influence investor decisions and cause fluctuations in demand for these commodities. Narayan and Liu (2011) attribute the volatility of commodity prices to the changes in interest rates, exchange rates, and the business cycle phase. Therefore, it is reasonable to assume that both real and financial factors can influence metal prices. According to Zhu et al. (2015), oil prices affect metal prices via production costs, imported inflation, and the pace of economic activity. As a result, oil prices may be used as a proxy for global commodity demand. Finally, Chen et al. (2019) show how non-commercial transactions and speculative activity will affect metal prices theoretically.

Although the economic theory highlights the role of supply and demand forces in price determination, it is unclear to attribute a role to fundamental factors to explain drastic rises in commodity prices (Brooks et al., 2015). Such extreme up and down movements in the economic cycle is regarded as economic bubbles, which are either the product of an economic cycle or the result of investor behavior (Girdzijauskas et al., 2009).

Identifying commodity price bubbles has been attracting scholars' attention, and the literature has grown recently due to some obvious reasons. First, investors or those who engage in the trade of these commodities will benefit during such upswing periods of commodity prices. However, they will suffer from dramatic losses when the price bubbles burst (Brooks et al., 2015). Second, beyond investors, politicians and policymakers also need to be aware of the commodity bubbles since fluctuations in commodity prices have detrimental effects on economic activity, the balance of payment deficits, price stability, exchange rates, and other macroeconomic indicators. Third, the rapid industrialization and higher economic growth rates in emerging economies led by China seem to increase their demand for such commodities, which in turn maintains to provoke the commodity prices (Chen et al., 2019).

However, although scholars have to care about commodity price bubbles recently, factors that create price bubbles and bursts are still scarce and deserve more attention. Therefore, the purpose of this study is to provide whether there were explosive bubbles in both precious and industrial metals that are critical in global and domestic policy settings. The study further aims to find potential factors that conduce the formation of price bubbles in these metals.

To this end, the study analyzes monthly gold, platinum, palladium, rhodium, silver, and aluminum, copper, lead, nickel, steel, tin prices over 1980M1-2019M12. This study contributes to the literature in two ways: First, the analysis incorporates the Generalized Supremum Augmented Dickey-Fuller (GSADF) test that achieves estimation efficiency and offers a better way of detecting potential bubbles in any frequency and irrespective of subjective judgments (Su et al., 2017). Second, the study goes one step further and concentrates on the role of financial, real, and speculative factors in the occurrence of price bubbles in various metal prices. The study uses the random forest algorithm to determine the most critical factors in creating price bubbles. To our understanding, this is the first research in the literature to use a machine learning algorithm for metal price bubble analysis. The study takes advantage of the methodological benefits of a random forest model, which does not require an a priori functional form or precise variable distribution and provides out-of-sample predictive power for the described model.

The remainder of the study is as follows: The next section reviews the literature. The third section introduces empirical strategy, data, and methodology. The fourth section provides empirical findings, and the last section concludes the study.

2. Theoretical framework and literature review

2.1. Theoretical framework of bubbles

According to Brunnermeier (2016), bubbles emerge if an asset's price is greater than its fundamental value. The determinants of the fundamentals include estimated returns, the estimated terminal value of the asset, and the discount rate. Thus, when the current price of an asset is high and fundamental factors do not support that price, a bubble is said to exist (Stiglitz, 1990).

Studies of bubbles with micro-theoretic foundations can be grouped into four different strands of the literature, according to Brunnermeier (2016), rational bubbles under symmetric information, asymmetric information bubbles, bubbles due to limited arbitrage, and heterogeneous beliefs bubbles. Empirical literature, on the other hand, focuses on testing the presence of bubbles in price series. While testing for the existence of a bubble is not an easy task (Stiglitz, 1990), extensive literature on econometrically testing the presence of bubbles has emerged (Gürkaynak, 2008).

Testing for the presence of a bubble starts with a conceptual asset pricing model. According to the basic asset pricing relationship with the standard "no arbitrage" and "rational expectations" assumptions in economics and finance, the asset price consists of two parts: a "market fundamental" part and a "bubble" part, which does not arise from mispricing rather is a component of the asset price (Gürkaynak, 2008). Under certain assumptions, the "market fundamental" part of the price equation converges while the "bubble" part is non-stationary. Thus, absent any bubble, price is equal to market fundamentals that are stationary. A way to test for the presence of a bubble in the price of any asset is to test the stationarity of the price data. To this end, various time-series methods have been employed in the related literature to detect bubbles in asset prices. These econometric techniques have also been applied to commodity prices to detect the presence of bubbles.

2.2. Literature review

Since the price of precious and industrial metals are critical for both investors and policymakers in designing their investment decisions and macroeconomic policymaking, scholars examined bubbles in metal prices, and the literature has grown. Studies that have dealt with bubbles in metal prices can be assigned into two groups. The first category includes studies that rely on the mean-reverting behavior of metal prices or on determining the dates of metal price bubbles. These studies focus on whether metal prices revert towards their trend values or behave explosively. Studies focusing on finding the bubble dates in metal prices analyze the unit root behavior of the series against explosive alternatives (Zhao et al., 2015). The second group of studies go a step further and deals with the potential causes of movements in metal prices.

Of the first group of studies, Bialkowski et al. (2011) used a Markow-regime switching Augmented Dickey-Fuller (ADF) test during November 1978 and March 2010 to examine gold prices. However, they reported that they failed to find speculative bubbles in gold prices during this period. Also, Lucey and O'Connor (2013) used the Markow-regime switching ADF test and analyzed the occurrence of explosive bubbles in gold prices from 1989 to 2013. They found that the constant variance model is more robust so that they concluded that gold prices exhibit some bubble periods. Baur and Tran (2014) found that gold and silver prices have a long-run cointegration relationship. However, they argued that the financial crises and potential bubble episodes might break up the link between gold and silver prices. Zhao et al. (2015) found that gold prices exhibit explosive bubbles during financial crises since investors assign a hedging role to the gold during the economic and financial downturns.

Narayan and Liu (2011) proposed several unit root tests and examined the mean-reverting behavior of metal prices from the 1970s to 2010. They concluded that shocks to gold, silver, platinum, palladium, and copper are persistent, whereas remaining industrial metal prices are subject to transitory effects. Gil-Alana and Triphaty (2014) used daily data over January 2009–June 2012 and examined the volatility in industrial metal prices. They handled various models and concluded that the volatility in metal prices is highly persistent.

Ahmed et al. (2014) examined the prices of 17 commodities, including precious and industrial metal, over 1991–2012. Although they argued that their findings do not support the same speculative bubbles in metal prices, they exhibit excess volatility and unexplained trends. Recently, Adewuyi et al. (2020) used various unit root tests to analyze the mean-reverting behavior of four precious and seven industrial metals over 1960–2017. They found that when nonlinearity and structural changes are taken into account, metal prices exhibit stationarity. Therefore, they concluded that shocks to metal prices would not create permanent effects, and it is a signal for the subsistence of abnormal returns for arbitrageurs.

The second group of studies concentrates on the factors that have a significant impact on metal prices. In one of the earlier studies, Borensztein and Reinhart (1994) analyzed the factors explaining the variation in commodity prices over 1970–1992. Their variance decomposition analysis demonstrated that supply shocks explain the significant share of commodity price variation. The industrial production of developed countries and the US real exchange rate are other important factors in explaining commodity price changes. Hammoudeh and Yuan (2008) used daily gold, silver, and copper price data over January 1990 and May 2006. They concentrated on the impact of crude oil and interest rate shocks on metal prices and found that gold and silver prices have more volatility persistence than copper prices.

Vansteenkiste (2009) analyzed the factors driving non-oil commodity prices, including industrial metals over 1957Q1-2008Q1. They found that commodity prices are guided by the common factor highly correlated with oil prices, US dollar effective exchange rate, short-term interest rate, and global industrial production. Batten et al. (2010) analyzed the impact of monetary and financial factors on the volatility of precious metal returns over January 1986 and May 2006. They found that the variability of precious metal prices is not explained fully by common factors. Instead, they demonstrated that monetary and financial variables partly explain the return volatilities in gold, platinum, and palladium. However, they lack to explain the volatility in silver returns. Similarly, Bastourre et al. (2012) found evidence favoring the role of US dollar depreciation, the fall of interest rates, and the decrease in global risk appetite strengthen commodity prices. Also, Baffes and Savescu (2012) concluded that industrial production, changes in the value of the US dollar, physical metal stocks, and input prices are significant on metal prices. However, Lombardi et al. (2012) failed to find a strong correlation between interest rate and the common factor driving metal prices during 1975–2008.

Byrne et al. (2011) used 24 commodity prices, including industrial and precious metals, between 1900 and 2008. They constructed a factor augmented VAR model and found that real interest rate and stock market uncertainty are negatively related to commodity prices. They also discovered that supply and demand shocks have a significant positive impact on commodity prices. Arango et al. (2012) examined the determinants of commodity prices during 1960–2006. Their dataset includes prices of precious and industrial metals. They concluded a significant and negative relationship between interest rates and commodity prices, but the impact of productivity on commodity prices is relatively weak.

Jain and Ghosh (2013) provided evidence for the dynamic cointegration relationship between gold prices, oil prices, and the Rupee-USD exchange rate. Zhu et al. (2015) analyzed the impact of some macroeconomic indicators on Chinese precious metal prices over October 2006 and July 2013. Their findings demonstrated that international oil prices significantly impact metal prices over the short- and long-run. They also found that the exchange rate plays a vital role in the short run. However, they revealed that the interest rate is insignificant in predicting precious metal prices.

Bosch and Pradkhan (2015) examined the precious metal prices in futures markets over 2006–2013. Their findings proposed an insignificant role of speculative activity to create instabilities in future prices of precious metals. Similarly, Brooks et al. (2015) argued that the substantial rises and subsequent falls in commodity prices mainly depend on fundamental factors instead of the result of speculative activities. Mayer et al. (2017) analyzed the volatility in metal prices during 1993–2013 and concluded that speculative trading activity plays an insignificant role in explaining the metal price volatility. However, Figuerola-Ferretti and McCrorie (2016) demonstrated the increasing importance of speculative activity in precious metal prices after the global financial crisis.

Furthermore, Chen et al. (2019) analyzed the volatility in copper futures prices from August 2004 to October 2016. Their findings proposed that financial factors fully explain the copper price volatility. They further argued that financial speculators affect the copper future prices by their non-commercial trading positions.

Kucher and McCoskey (2017) used data from 1975 to 2015 and concentrated on the long-run relationship between precious metal prices and the role of macroeconomic factors on the relationship among metal prices. They found that business cycle fluctuations and macroeconomic factors significantly influence the long-run cointegration relationship among precious metals. Dutta (2018) analyzed the volatility in industrial and precious metal prices daily over May 2007 and June 2016 and found that oil price volatility is highly significant over fluctuations in industrial metal prices. However, gold and silver prices seem to be insensitive to oil price shocks. Liao et al. (2018) analyzed the factors affecting the prices of several metals during July 2005 and December 2015. They mainly concentrated on the role of the Chinese stock market and exchange rate on commodity prices. Their findings pointed out that the impact of the Chinese stock market and exchange rate on commodity prices increased after the global financial crisis. Recently, Su et al. (2020) found four bubble periods in copper prices from 1980 to 2019. Their findings proposed that the likelihood of bubbles is attributed to speculative activity, the US dollar exchange rate, supply-demand imbalances, and financial crises.

The summary of these studies is illustrated in Table 1.

Overall, empirical research on metal prices focuses on the occurrence of explosive price bubbles and examines macroeconomic factors that directly impact metal prices over time. Although several studies are concentrating on the bubbles in metal prices, our study differs from the existing literature and benefits from the methodological advantages of the GSADF test in detecting bubbles in metal prices and benefits from the use of machine learning algorithms to provide insights for the early warning indicators of price bubbles in these markets.

3. Empirical framework, data, and methodology

3.1. Empirical framework

This analysis concentrates on price bubbles in precious and industrial metals to determine the potential causes of metal price bubbles. In this respect, the empirical framework of the study involves two stages. In the first step, the analysis uses the GSADF test to see whether metal prices are prone to explosive bubbles and pinpoint these bubbles' dates in precious and industrial metal prices. In the second step, the study employs a random forest algorithm and creates a bubble classification model to deal with the potential causes of explosive bubbles in metal prices.

3.2. Data

This study uses monthly data to detect price bubbles in five precious metals and six industrial metals over 1980M1-2019M12. Our precious metals dataset includes gold, palladium, platinum, rhodium, and steel,

Table 1
Summary of literature on metal prices.

Author(s)	Year	Data Span	Commodities	Methodology
Arango et al.	2012	1960–2006	50 commodities	Generalized Method of Moments (GMM)
Batten et al.	2010	January 1986–May 2006	gold, silver, platinum, and palladium	Block exogeneity tests for the conditional volatilities
Borensztein and Reinhart	1994	1970Q1-1992Q3	all-commodity index	OLS-variance decomposition
Bosch and Pradkhan	2015	June 2006–June 2013	gold, silver, platinum, palladium	Regression and VAR models
Brooks et al.	2015	February 1967–December 2011	18 commodities (grains, softs, animals and woods, precious metals, and energy)	Switching Regression Approach
Byrne et al.	2011	1900–2008	24 commodities	FAVAR
Chen et al.	2019	August 2004–October 2016	Copper	MS-VAR model
Dutta	2018	10 May 2007–30 June 2016	industrial and precious metals	GARCH-jump specification
Figuerola-Ferretti and McCrorie	2016	2000–2013	gold, silver, platinum and palladium	PSY test
Hammoudeh and Yuan	2008	January 2, 1990–May 1, 2006.	gold, silver and copper	A group of GARCH models
Jain and Ghosh	2013	2nd January 2009–30th December 2011	gold, silver and platinum	Cointegration and Granger causality
Kucher and McCoskey	2017	January 1975–February 2015	gold, silver, platinum	Cointegration tests
Liao et al.	2018	July 19, 2005–December 31, 2015	crude oil, copper, aluminum, lead, zinc, nickel, gold, silver	ARDL and SVAR models
Mayer et al.	2017	January 1993–December 2013	copper, gold, palladium, platinum, and silver	Granger Causality and EGARCH Model
Su et al.	2020	January 1980–May 2019	Copper	GSADF approach
Zhu et al.	2015	October 30, 2006–July 5, 2013,	Brent crude oil, spot prices of domestic gold, silver and platinum prices	TY causality and Impulse-response analysis
Vansteenkiste	2009	January 1957–May 2008	32 non-fuel commodity price series	The Linear State-Space Model
Lombardi et al.	2012	2003Q1-2008Q2	Seven metals and seven other commodities	FAVAR model
Bastourre et al.	2012	December 1997–March 2011.	A group of metal and other commodity prices	FAVAR model
Baffes and Savescu	2014	1991Q1–2012Q4	aluminum, copper, lead, nickel, tin and zinc	OLS and panel regression model

and the industrial metals dataset comprises aluminum, copper, lead, nickel, steel, and tin. Fig. 1 demonstrates the behavior of metal prices over 1980 and 2019.

Details on data span, data source, and descriptive statistics for metal prices are illustrated in Table 2.

Our primary data source for precious and industrial metals is the World Bank Commodity Price Data. We also used Kitco historical database (https://www.kitco.com/charts) to obtain palladium, platinum, and rhodium price series. The unit of measure for gold, palladium, platinum, rhodium, and silver prices is the US dollar per troy ounce ($/troy oz). The measure for aluminum, copper, lead, nickel, steel, and tin prices is the US dollar per metric ton ($/mt).

In the second step of our empirical analysis, we handle financial, real, and speculative factors. Table 3 introduces the definition of these variables, their data source, time span and provides their descriptive statistics.

To examine the potential causes of bubbles in precious and industrial metals, we handle real, financial, and speculative factors. These variables are gathered through the literature. We can group these variables into three main categories. The first group consists of us_industrial_prod_index, china_prod_index, and oil price and stands for the real factors. Arango et al. (2012) argued that the commodity price booms are directly related to economic activity dynamics in China and other emerging economies. Also, Su et al. (2020) mentioned Chinese industrial development in metal price hikes. Lombardi et al. (2012) also employed global industrial production as a proxy for the global economic activity and the demand for metals to examine the metal price movements. The oil_price variable is the average of the crude oil price (Brent, Dubai, and WTI) in nominal US dollars. Oil price is related to the metal prices since the changes in oil prices affect the real economic activity via production and transportation costs in the metal industry and metal-related industries throughout the economy (Dutta, 2018).

The second group includes us_policy_rate and usd_index and are regarded as financial factors. In this setting, us_policy_rate is the FED's discount rate, and the usd_index is the real effective exchange rate index of the US dollar. As Frankel (2006) argues, the interest rate can affect economic activity and the demand for industrial and precious metals. The dominance of the US dollar in metal trades points to the role of fluctuations in the real value of the US dollar on metal price movements. Therefore, Su et al. (2020) and Hammoudeh et al. (2013) highlighted the impact of US dollar depreciation in portfolio allocation and decisions and their implications on commodity prices.

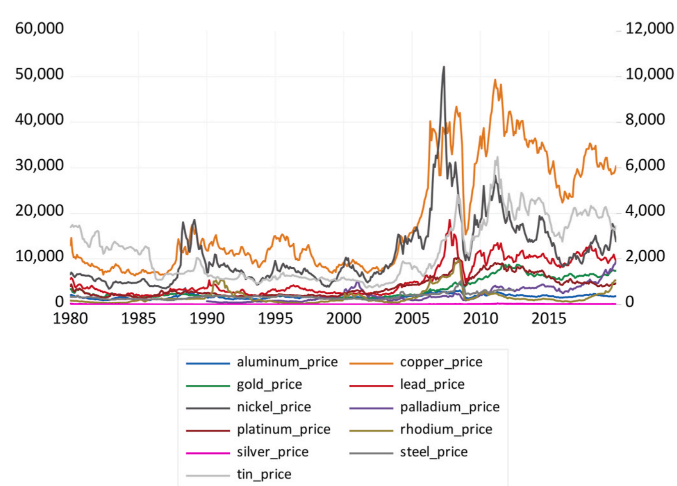


Fig. 1. Metal prices over the period 1980–2019.
Note: Copper, nickel, rhodium, and tin prices are illustrated on the left axis, whereas aluminum, gold, lead, palladium, platinum, silver, and steel prices are represented on the right axis.
Source: World Bank and kitco.com.

Table 2
Descriptive statistics for metal prices.

Prices ($)	Mean	Median	Max	Min	St. Dev.	Data Source	Time Span
Gold Price	659.60	412.32	1,772.14	256.08	431.69	World Bank	1980–2019
Palladium Price	445.87	335.68	1,900.59	80.64	341.34	kitco.com	1990–2019
Platinum Price	757.36	566.08	2,052.45	260.76	436.57	kitco.com	1980–2019
Rhodium Price	1,608.82	1,122.50	9,745.71	182.89	1,602.97	kitco.com	1980–2019
Silver Price	10.91	7.11	42.70	3.65	7.83	World Bank	1980–2019
Aluminum Price	1,692.44	1,609.23	3,578.10	918.85	460.60	World Bank	1980–2019
Copper Price	3,686.50	2,520.98	9,867.60	1,272.07	2,390.92	World Bank	1980–2019
Lead Price	1,104.52	700.50	3,719.72	351.64	756.40	World Bank	1980–2019
Nickel Price	11,158.14	8,578.10	52,179.05	3,433.66	7,367.16	World Bank	1980–2019
Steel Price	349.97	330.00	1,030.00	190.00	139.85	World Bank	1980–2012*
Tin Price	11,528.08	9,041.80	32,363.31	3,694.50	6,494.64	World Bank	1980–2019

Note: *Steel prices ends at 2012M6 due to data availability.

Table 3
Descriptive statistics for macroeconomic variables.

Variables	Mean	Median	Max	Min	St. Dev.	Data Source	Time Period*
us_industrial_prod_index	96.94	100.73	119.04	65.75	14.79	IMF-IFS	
china_prod_index	111.89	111.80	129.40	78.90	5.38	IMF-IFS	
oil_price ($/bbl)	47.94	39.90	132.83	10.41	31.41	WB-CPD	1995M3-2019M12
us_policy_rate (%)	3.10	3.00	7.00	0.50	2.00	IMF-IFS	1990M1-2019M12
usd_index	105.81	106.82	130.75	69.34	15.65	IMF-PGI	1990M1-2012M6
base_metals_price_index	66.08	57.89	127.17	31.25	27.05	WB-CPD	
precious_metals_price_index	70.92	69.10	127.17	32.42	27.16	WB-CPD	
speculative_activity (SPEC)							
Gold	0.12	0.17	0.39	−0.32	0.16	Thomson Reuters	1995M3-2019M12
Palladium	0.30	0.38	0.67	−0.33	0.25	Thomson Reuters	1995M3-2019M12
Platinum	0.37	0.40	0.71	−0.31	0.21	Thomson Reuters	1995M3-2019M12
Copper	0.02	0.02	0.42	−0.31	0.15	Thomson Reuters	1995M3-2019M12

Note: WB-CPD: World Bank Commodity Price Data, IMF-PGI: IMF Principal global indicators. * Period changes due to data availability.

Furthermore, we have a variable denoted as "SPEC," which stands for a proxy of speculative activity affecting gold, palladium, platinum, and copper prices. To identify speculators' positions, we followed Bosch and Pradkhan (2015) and Su et al. (2020) and formed a variable SPEC by using Equation (1).

$$SPEC_{i,t} = \frac{Noncommercial\ Long\ Position_{i,t} - Noncommercial\ Short\ Position_{i,t}}{Total\ Open\ Interest_{i,t}} \tag{1}$$

The difference between non-commercial long and short positions is scaled with total open interest to calculate the proxy variable to measure the volume of speculative activity in metal trades. Due to the lack of data for some metals, we constructed SPEC variables only for gold, palladium, platinum, and copper. Base_metal_price_index and precious_metal_price_index stand for to demonstrate the contagion effect among each metal groups.

3.3. Methodology

Since this study handles two stages in the empirical procedure, we have two distinct empirical tools. The study uses the GSADF unit root test to detect bubble periods in precious and industrial metal prices in the first step. The study further uses a random forest algorithm to find potential causes of bubbles in metal prices.

3.3.1. GSADF unit root test

Early studies that attempt to detect bubbles employed left-tailed unit root tests, such as ADF, to test the null of a unit root at prices against the alternative of prices are stationary (see Diba and Grossman, 1988). However, one can use the traditional unit root tests to reveal whether a shock is persistent or transitory; as discussed by Evans (1991) and Campbell et al. (1997), that is these tests do not provide any evidence of explosive behavior. To deal with this shortcoming, Phillips et al. (2011) suggest a recursive right-tailed test to test the null hypothesis of a unit root behavior against the alternative of exuberance from fundamentals. Phillips et al. (2011) introduced the Supremum Augmented Dickey-Fuller (SADF) test, while Phillips et al. (2015) proposed the Generalized Supremum Augmented Dickey-Fuller (GSADF) test. The SADF procedure relies on sequentially testing by employing a forward expanding sample, while the GSADF procedure is based on the rolling window approach. In this study, we use the GSADF procedure due to its attractive properties such as; the GSADF test has good size and power properties compared to the other bubble detection tests (see Phillips et al., 2015; Pavlidis et al., 2016), and the GSADF can detect multiple episodes of bubbles in a sample (Li et al., 2020).

To obtain the GSADF test statistic, the following ADF test regression is estimated:

$$\Delta Y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} Y_{t-1} + \sum_{i=1}^{k} \gamma^i_{r_1,r_2} \Delta Y_{t-i} + u_t \tag{2}$$

where Y_t denotes the metal prices of interest at the time t, Δ is the first difference operator. To remedy possible autocorrelation $i = 1, 2, \ldots, k$, lags of the ΔY are included on the right side of the equation. The subscripts, r_1 and r_2 indicate the beginning and ending points of a subsample.

We test the null hypothesis of a unit root, $H_0 : \beta_{r_1,r_2} = 0$, against the alternative of explosive behavior, $H_1 : \beta_{r_1,r_2} > 0$, using the test statistic $ADF^{r_2}_{r_1} = \widehat{\beta}_{r_1,r_2} / s.e.(\widehat{\beta}_{r_1,r_2})$, where s. e. shows the standard error of the slope coefficient.

To obtain the GSADF test statistic, we compute $ADF^{r_2}_{r_1}$ test statistics for all subsamples by changing both r_1 and r_2:

$$GSADF(r_0) = \sup_{r_2 \in [r_0,1],\ r_1 \in [0, r_2 - r_0]} ADF^{r_2}_{r_1}$$

Where r_0 shows the initial subsample size that is obtained as $r_0 = 0.01 + 1.8/\sqrt{T}$, T indicates the number of observations, that is, while the first observation varies from 0 to $r_2 - r_0$, last observation varies from r_0 to 1. To obtain critical values we use bootstrap simulations by following the suggestion of Phillips and Shi (2020). The rejection of the null indicates that there is at least one bubble in the series.

3.3.2. Random forest algorithm

The random forest algorithm is a tree-based machine learning algorithm that can be used for prediction and classification purposes. The random forest algorithm was first proposed by Breiman et al. (2001). The random forest model builds many decision trees using a subset of the learning sample and a sample of predictor variables (James et al., 2013).

The empirical implementation of the random forest algorithm can be summarized in steps as follows (Breiman, 2001; Basuchoudhary et al., 2017).

1st Step: Dataset is divided into two groups as "learning sample" and "test sample."

2nd Step: The algorithm selects a random sample of *n* observations from the learning sample of size N.

3rd Step: Among *P* predictors, the algorithm randomly selects *m* predictors as candidates for the split in each tree. Therefore, the algorithm uses these *m* predictors for each split in trees.

4th Step: In each node of the tree, the algorithm selects the best predictors in each split to minimize the error (minimize the mean square error in each node).

5th Step: The algorithm constructs *M* number of trees until it reaches the stopping criteria based on either minimum improvement in reducing errors in each node or getting the minimum number of observations in the node.

6th Step: The prediction of the random forest algorithm, therefore, is the average bagged prediction of these *M* trees.

The random forest algorithm uses a random sample of the learning sample and a random set of predictor variables to minimize the mean square error in each split. Therefore, this algorithm aims to provide the best out-of-sample fit by minimizing the out-of-sample prediction errors.

Random forest algorithm also provides the variable importance measure and allows us to rank variables according to the reduction in the impurity of the model when a specific variable is selected for splitting in each node. In other words, the fall of error at each split in each tree is the splitting variable's importance measure, and it is evaluated independently for each variable across all trees (Hastie et al., 2017). In classification models, the random forest algorithm offers the average decrease in the Gini index. Gini index is a measure of node purity, and it measures the probability of the randomly chosen variable being classified wrongly. When we categorize the specific observation to a particular class based on the majority rule, then the Gini index is the error rate of this rule in the node (Hastie et al., 2017).

The study also uses partial dependence plots (PDP) to show how the predictor variables affect the likelihood of metal price bubbles. In general terms, PDPs for each variable provide a piece of information about how each input variable affects the respective class probability (Friedman, 2001). In our case, PDPs show the marginal effect of a predictor variable on the likelihood of price bubbles when all other predictor variables are constant (James et al., 2013).

4. Empirical results

4.1. Detecting bubbles

In the first step of our empirical analysis, we aim to detect whether precious and industrial metal prices exhibit bubbles during 1980–2019. To this end, we apply the GSADF test to the price of precious and industrial metals. Table 4 illustrates the GSADF test statistics and bootstrap critical values.

Table 4
The results of the GSADF test.

Metal Group	Test Statistics	Bootstrap Critical Values		
		1%	5%	10%
Precious Metals				
Gold	6.560856*	6.503384	5.031135	4.330417
Palladium	5.754141**	7.439293	5.752426	5.024042
Platinum	5.339576***	7.862491	5.529291	4.556889
Rhodium	7.680288***	12.81482	8.656806	7.526945
Silver	4.283036	8.308497	6.458359	5.267760
Industrial Metals				
Aluminum	3.833697	8.350647	5.478545	4.512383
Copper	6.593204**	8.490144	6.558953	5.612165
Lead	7.005155**	9.836038	6.975169	5.933240
Nickel	6.160432***	8.843335	6.713941	5.798752
Steel	5.579492***	8.343048	6.092274	5.092581
Tin	4.948482	8.072859	6.108221	5.132559

Note: *, **, and *** indicate the significance at the 1%, 5%, and 10% levels, respectively. Critical values are obtained using 2000 bootstrap simulations.

Based on the GSADF test for precious metals, there is evidence of bubbles in the price of gold, palladium, platinum, and rhodium. However, GSADF test results demonstrate no significant evidence of an explosive price bubble for silver. GSADF test results for industrial metals reveal bubbles in copper, lead, nickel, and steel prices. Nevertheless, the prices of aluminum and tin do not exhibit any significant price bubbles over the period 1980 to 2019.

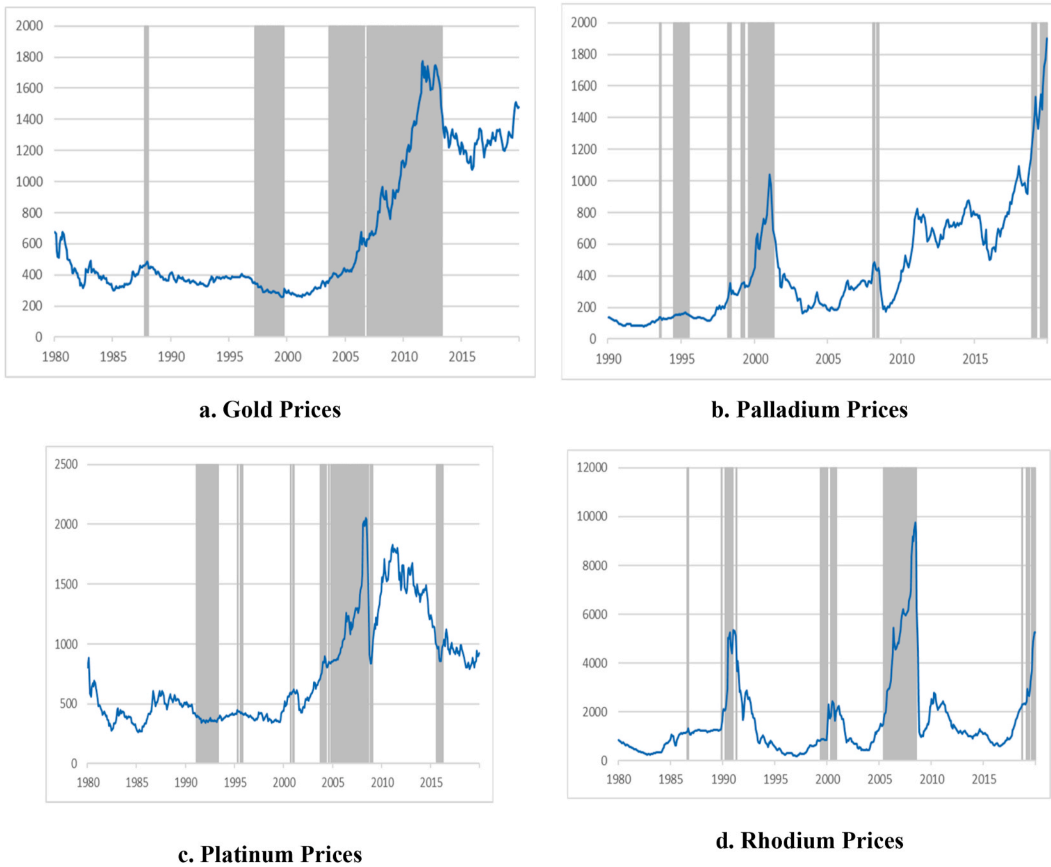
Using the GSADF test, we also provide the start and end dates of price bubbles for precious and industrial metals. Fig. 2 illustrates the bubble periods for each precious metal prices.

Among precious metals, gold prices seem to exhibit long-lived bubble episodes. Gold prices have four significant bubble episodes, while palladium, platinum, and rhodium prices experience several bubble periods. However, in terms of months, gold prices provide lengthier bubble episodes than palladium, platinum, and rhodium prices. Gold prices exhibit four main bubble periods. The first bubble episode in 1987 is relatively short-lived and lasts for four months. However, bubble periods of 1997–1999, 2003–2006, and 2007–2013 are long-lived and takes 30, 35, and 74 months, respectively. On the other hand, price bubbles in palladium, platinum, and rhodium have 9, 10, and 10 distinct bubble episodes, respectively. The average duration of these bubble periods is shorter than nine months.

One of the lengthy and condense bubble episodes in gold prices start in 1997 and prevails up to the end of 1999. This bubble period coincides with the burst of the Asian crisis in July 1997. The impact of this crisis manifests itself partly in the palladium price bubble starting in 1998. On the other hand, at the beginning of the 1990s, platinum and rhodium prices exhibit bubbles which coincides with the Russian crisis.

At the beginning of 2000's palladium, platinum, rhodium prices go into bubble episodes. Furthermore, the impact of the global financial crisis manifests itself in all precious metals, and their prices exhibit long-lived bubble episodes during the crisis period. The duration of bubble episodes in gold prices is quite longer between 2003 and 2013. During this period, the global economy experienced some developments. During the 2006–2007 period, the US dollar depreciated, and inflation fears increased while the oil prices were high. After 2007, the outbreak of the global financial crisis and the ongoing debt crisis in the Euro Area countries over 2009–2013 seem to increase uncertainty in the global economy and increased the demand for gold as a safe haven (Zhao et al., 2015).

As is the case in Fig. 2, price upsurges coincide among precious metals in some periods. However, it is also noteworthy that gold price seems to respond more to global factors so that gold price exhibits bubbles that are more long-lived than other precious metals. In this case, one might argue that gold as a globally accepted means of payment provides an opportunity to get a safe haven during global downturns.



a. Gold Prices

b. Palladium Prices

c. Platinum Prices

d. Rhodium Prices

Fig. 2. GSADF test results of bubble periods for precious metals.
Note: Shaded areas represents bubble periods.

Fig. 3 shows the price bubble episodes for a sample period of each industrial metals by using the GSADF test.

The GSADF test results detect relatively more condensed and long-lived bubble episodes for copper prices among industrial metals. Among industrial metals, copper price bubbles seem to be long-lasting. Once we examine the bubble episodes, we see that copper prices distinct bubble episodes, and they lasted within 12 months on average. However, the average bubble period durations are relatively short in lead, nickel, and steel prices. Fig. 3 illustrates that once the bubble appears in lead, nickel, and steel markets, it bursts within six months on average.

During the sample period, the first long-lived bubble episode manifests itself in copper and steel prices and begins in 1987 and ends at the beginning of the 1990s. Watkins and McAleer (2004) argue that this bubble episode corresponds to the volatility spillovers of the melt-down in financial markets (Narayan and Liu, 2011). The second noteworthy bubble period starts in 2003 and continues until the end of 2009 for all industrial metals. It is argued that the more durable bubble episode over 2003–2009 is the result of industrial expansion experienced in industrialized countries, China and India (Su et al., 2020).

The duration and the magnitude of the bubble periods in industrial metal prices seem to convey more common elements than precious metals. Before analyzing the potential causes of price bubbles, one might draw a preliminary conclusion based on the historical events and corresponding bubble periods. Therefore, it seems that financial factors are more practical to explain price bubbles in precious metals. However, real factors and the pace of the business cycle seem to be the factor behind the bubbles in industrial metal prices.

4.2. Random forest results

We further implement an empirical strategy to find the causes of explosive price bubbles in precious and industrial metals. Before exploring global factors in the formation of price bubbles, we first compare the prediction performance of the logit model with the random forest algorithm. The logit model here provides a benchmark model since it is a commonly used econometric model in binomial dependent variable exercises.

We conduct five measures to evaluate the predictive quality of a standard econometric technique with a random forest algorithm. These measures are "sensitivity," "specificity," "positive predicted value (PPV)," "negative predicted value (NPV)," and "overall error rate." As we divide our sample into two categories, as learning sample and test sample for each metal, the random forest algorithm constructs many tree models and provides a prediction for the occurrence of the price bubble, and then compares the predicted outcome with the test sample observation. These measures, therefore, stand for the predictive quality of the random forest model in our analysis.

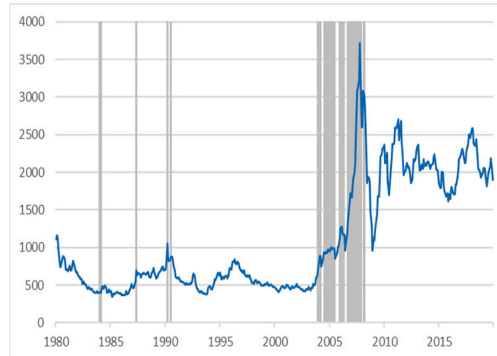
Formulations of these measures are given as follows (Basuchoudhary et al., 2017):

$$Sensitivity = \frac{True\ Positives}{Observed\ Positives}; Specificity = \frac{True\ Negatives}{Observed\ Negatives};$$
$$PPV = \frac{True\ Positives}{Predicted\ Positives}; NPV = \frac{True\ Negatives}{Predicted\ Negatives}; \tag{3}$$
$$Overall\ Error\ Rate = Proportion\ of\ sample\ predicted\ incorrectly$$

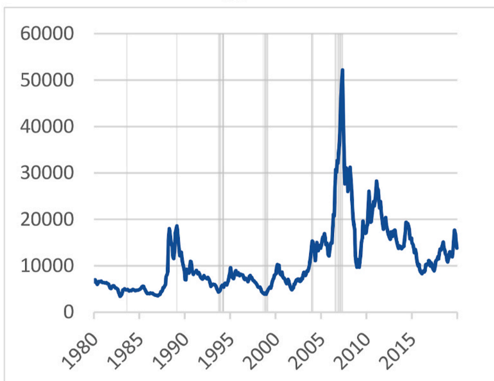
By using these measures, Table 5 shows the predictive accuracy of the logit model versus the random forest model for each metal.

Table 5 demonstrates that the random forest algorithm outperforms the logit model in predicting the potential factors contributing to the metal price bubbles. The random forest algorithm provides higher prediction performance when comparing the predictions on the learning

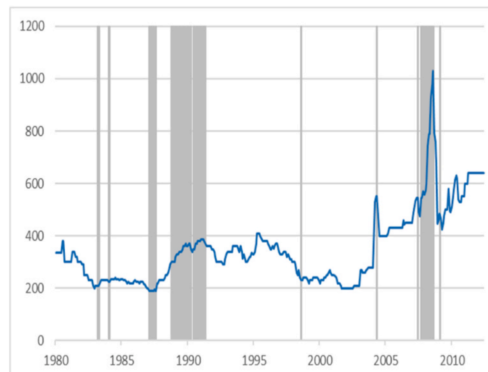
a. Copper Prices



b. Lead Prices



c. Nickel Prices



d. Steel Prices

Fig. 3. GSADF test results of bubble periods for industrial metals.
Note: Shaded areas represents bubble periods.

Table 5
Predictive quality measures.

Measure	Gold		Palladium		Platinum		Rhodium	
	Random Forest	Logit Model	Random Forest	Logit Model	Random Forest	Logit Model	Random Forest	Logit Model
Sensitivity	0.992	0.671	0.717	0.347	0.857	0.714	0.888	0.791
Specificity	0.955	0.689	0.992	0.988	0.969	0.951	0.975	0.958
Positive Predicted Value	0.952	0.657	0.942	0.842	0.895	0.819	0.901	0.826
Negative Predicted Value	0.993	0.703	0.950	0.892	0.956	0.915	0.972	0.948
Overall Error Rate	0.026	0.318	0.050	0.110	0.057	0.104	0.041	0.075
Measure	Copper		Lead		Nickel		Steel	
	Random Forest	Logit Model	Random Forest	Logit Model	Random Forest	Logit Model	Random Forest	Logit Model
Sensitivity	0.870	0.425	0.775	0.550	0.862	0.275	0.875	0.750
Specificity	0.963	0.954	0.978	0.978	0.987	0.987	0.991	0.991
Positive Predicted Value	0.839	0.676	0.815	0.758	0.862	0.666	0.933	0.923
Negative Predicted Value	0.971	0.882	0.972	0.945	0.987	0.939	0.983	0.967
Overall Error Rate	0.053	0.140	0.044	0.069	0.022	0.069	0.022	0.037

sample with the test sample in each of precious and industrial metals. The overall error rate is also lower than 10 percent in a great deal of these models.

In the next step, we explore the relative importance of global factors in predicting the likelihood of metal price bubbles. (a) us_industrial_prod_index stands for the proxy measure of global economic activity, (b) china_production_index is for the industrialization of the emerging economies, (c) precious and industrial metals_price_index used to measure the spillover impact among metal markets, (d) oil_price is used to measure the cost of production and extraction, (e) us_policy_rate stands for the effect of monetary policy, (f) usd_index stands for measuring the US dollar denomination in metal markets, and finally (g) SPEC variable measures the role of speculative activity in the likelihood of metal price bubble. The relative importance of these measures in predicting price bubbles is illustrated in Table 6. It is noteworthy that these measures are used as common predictors in measuring their relative importance to predict price bubbles for each precious and industrial metals.

Table 6 shows the Gini impurity as a measure of variable importance in predicting the likelihood of bubble for each metal. Gini impurity measures the probability of incorrect classification at any node in each tree. Numbers in the table are scaled to 100 percent in total for each metal. To illustrate, the number 14.33 in the gold column for us_industrial_prod_index means that the Gini impurity measure decreases by 14.33% when this predictor is removed from the model.

Our random forest model results argue that relatively more

Table 6
Variable importance.

Variables	Gold	Palladium	Platinum	Rhodium	Copper	Lead	Nickel	Steel
us_industrial_prod_index	14.33	16.03	13.42	**15.00**	13.63	14.35	6.23	**29.02**
oil_price	**14.49**	10.83	**14.09**	10.35	14.58	13.51	**27.34**	10.27
us_policy_rate	5.41	**18.56**	**19.43**	**37.57**	**21.87**	**18.66**	**21.44**	**16.62**
precious_metals_price_index	**15.15**	**16.49**	**30.09**	**15.40**				
base_metals_price_index					**22.55**	**17.21**	**24.27**	7.31
usd_index	**26.63**	**17.19**	5.96	11.21	7.31	15.31	11.21	**31.13**
SPEC	13.20	8.70	4.10		5.29			
china_prod_index	10.78	12.19	12.91	10.48	**14.77**	**20.96**	9.52	5.64

Note: Numbers in the table represent the mean decrease in the Gini impurity measure (%). Bold numbers show the highest tree predictors for each metal.

important predictors to predict price bubbles for precious metals (gold, palladium, platinum, rhodium) are precious_metal_price index, us_policy_rate, usd_index, and oil price. In other words, these measures contribute more to classify the precious metal price bubbles correctly. However, us_policy_rate, base_metals_price_index, and china_prod_index are more critical variables than their counterparts in predicting industrial metal price bubbles. Table 6 also provides noticeable evidence that speculative activity is not essential either in predicting bubbles in precious or industrial metals. The insignificant role of speculative activity on the likelihood of metal price bubbles is consistent with Byrne et al. (2011), Bosch and Pradkhan (2015), and Mayer et al. (2017). These results also demonstrate that financial variables are better at predicting bubbles than real variables.

Before discussing the relative importance of variables at predicting price bubbles, we further provide PDPs of the most important three predictor variables to show the impact of these variables on the likelihood of price bubbles. Fig. 4 provides the PDPs establishing the relationship between predictor variables and the likelihood of a precious metal price bubble.

Fig. 4 provides important implications for the early warning indicators of price bubbles in precious metals. First, we see that the rise in the usd_index up to the level of 120 increases the likelihood of a gold price bubble. However, one can conclude that the increase in usd_index does not provide any additional evidence for bubbles in gold prices after this threshold level. The appreciation of the US dollar makes the gold cheaper for other countries, so they increase their demand for gold which accelerates the gold prices Lucey and O'Connor (2013). For palladium price, the usd_index exhibits a U-shaped relationship that also provides evidence that the appreciation of the US drives the gold price and might create an explosive bubble. Also, Hammoudeh et al. (2013) argue that the appreciation of the US dollar directs investors to the outflow of funds from the commodity markets (Su et al., 2020).

The relation between the probability of a precious metal price bubble and the precious metal price index supports the idea that rising metal prices pull up the price of their counterparts (Batten et al., 2010; Zhu et al., 2015). However, we can also argue that after a certain threshold level of 120, the ongoing rise in the precious metal price index cannot provide any additional evidence for the likelihood of price bubbles in all of these precious metals.

Although the contribution of the oil prices to the likelihood of metal price might be attributed to the idea that the production of metals is energy-intensive (Dutta, 2018), our findings do not provide clear evidence between oil prices and the likelihood of bubbles in precious metal prices. Finally, our results suggest a negative relationship between the us_policy_rate and the likelihood of precious metals price bubbles. Therefore, during the FED's monetary contraction periods, precious metal prices are likely to fall. One reason for this negative association may be that as interest rates rise, the cost of holding precious metals rises, causing the price of these metals to fall (Lucey and O'connor, 2013). Furthermore, Chen et al. (2019) argue that an increase in interest rates raises borrowing costs, damage economic activity and production, reduces demand, and leads to the fall of metal prices.

Overall, financial factors seem to play a critical role in predicting precious metal price bubbles. However, the power of speculative activity is relatively weaker than its counterparts. This means that the deviation of the precious metal prices from the fundamentals is not caused by the exercise of non-commercial traders.

Furthermore, Fig. 5 illustrates the PDPs showing the relationship between predictor variables and the likelihood of bubbles in industrial metal prices.

As is the case in precious metals, speculative activity does not play a critical role in affecting the likelihood of industrial metal price bubbles. However, other financial factors perform well to predict the price bubbles as well as real factors. At this point, Fig. 5 demonstrates that industrial production variables are more significant in predicting industrial metal price bubbles than those of precious metals.

Fig. 5 shows that the relationship between the likelihood of a price bubble and the base metal price index is U-shaped. The U-shaped relationship in copper, lead, and nickel indicates that a certain threshold level base_metal_price_index drives up these industrial metals' prices. When the index value is between 40 and 60, the index value signals a reduction in the risk of bubbles. However, when the base metal price index rises, the probability of a price bubble rises to its maximum when the index reaches 90. In the nickel market, when the base metal price index is between 60 and 90, the likelihood of a nickel price bubble is not increased.

Another important variable to predict the industrial metal price bubble is the us_policy_rate. The FED's policy rate seems to decrease the probability of bubbles in copper and nickel prices once the policy rate exceeds 4 percent. It appears that monetary tightening and rising interest rates reduce investment spending, which in turn reduces demand for industrial metals (Hammoudeh and Yuan, 2008).

Finally, the industrial production of advanced and emerging economies, which are proxied by us_industrial_prod_index and china_prod_index, respectively, play a significant role in predicting the industrial metal price bubble. Although the rise in industrial metal prices is mainly attributed to the increase in industrial production in advanced and especially emerging countries like China (Arango et al., 2011; Su et al., 2020), our findings exhibit a U-shaped relationship between the likelihood of an industrial metal price bubble and the industrial production indexes. As a result, one might argue that an ongoing increase in global industrial demand does not catalyze a sharp rise in the price of industrial metals, nor does it increase the risk of a bubble.

5. Conclusion

Since the real allocation of an economy is influenced by asset prices (Brunnermeier, 2016; Stiglitz, 1990), it is critical to comprehend when and why these prices depart from their fundamental values. This understanding can also help relevant stakeholders develop early warning systems (EWS) that guide them in making informed decisions. For instance, EWSs for real estate bubbles can help policymakers take precautions to prevent bubble migration or crisis contagion across markets. As far as precious commodities are concerned, the EWS can help investors reallocate their portfolios to be more efficient. For industrial commodities, the knowledge of bubbles improves procurement

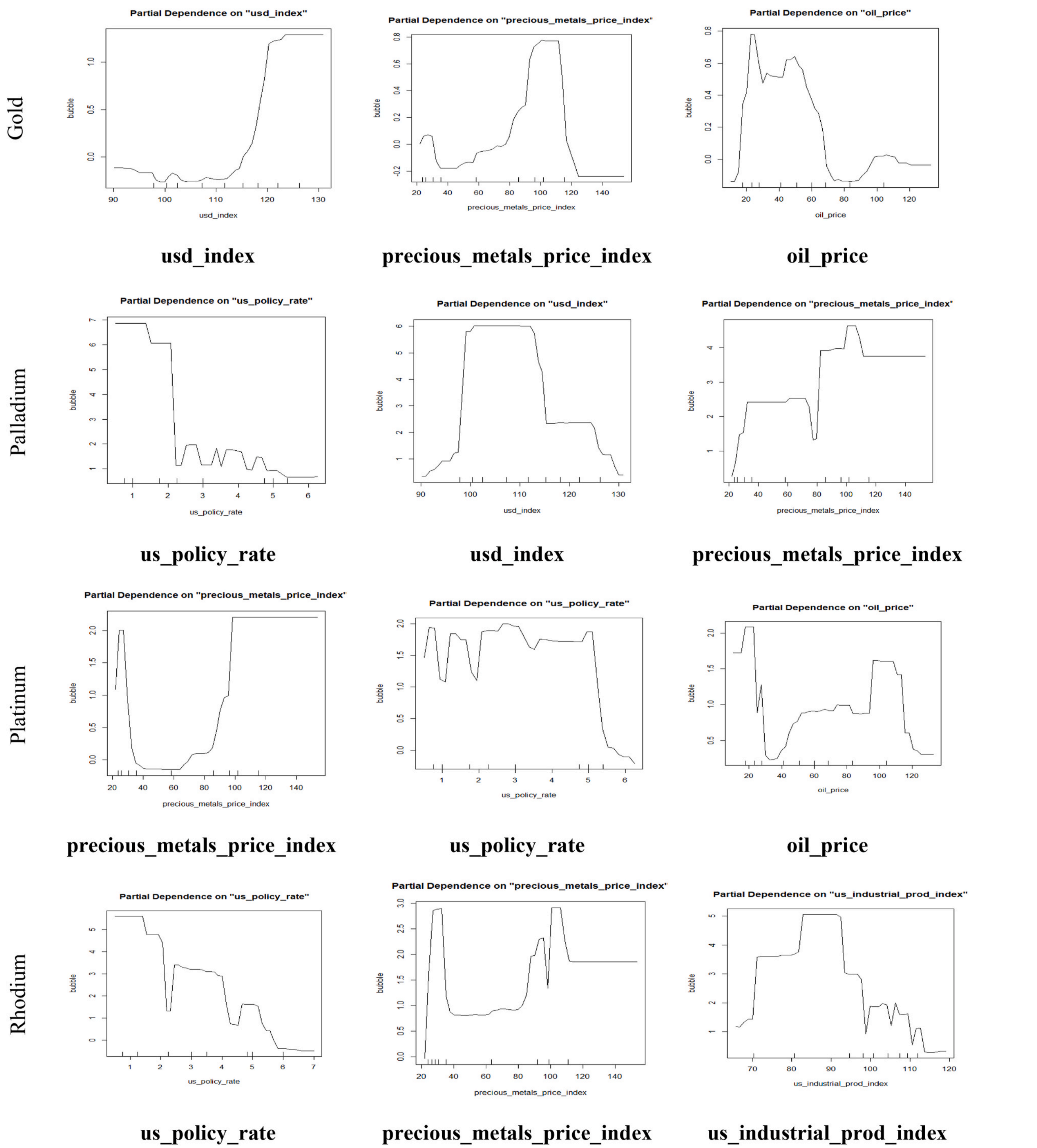


Fig. 4. Partial Dependence Plots for Precious Metals (gold, palladium, platinum, rhodium).
Note: The vertical axis shows the log of the odds ratio. The odds ratio is measured as "$\frac{p}{1} - p$" where p represents the probability of bubble. The horizontal axis is the values of predictor values in their levels.

activities and resource planning of industrial consumers who use these commodities in their production activities.

The current study analyzes the global prices of 11 precious and industrial metals (gold, platinum, palladium, rhodium, silver, aluminum, copper, lead, nickel, steel, tin). It attempts to detect bubbles in the prices of these commodities. In the first stage, a time-series analysis of monthly prices from 1980M1–2019M12 is performed using the GSADF test. The advantage of this test is that it offers an efficient estimation and provides a better way of detecting potential bubbles in any frequency without subjective judgments. The results of the first stage analysis indicate that each commodity had experienced bubbles with varying durations. In the second stage of the study, the relationship between various financial, real, and speculative factors and bubbles are investigated in a machine learning setup, which is first in the related literature. The superiority of employing machine learning is that machine learning algorithms do not require any prior functional form between variables and allows not having precise distributional properties for variables. These algorithms additionally provide out-of-sample performance of predicted models.

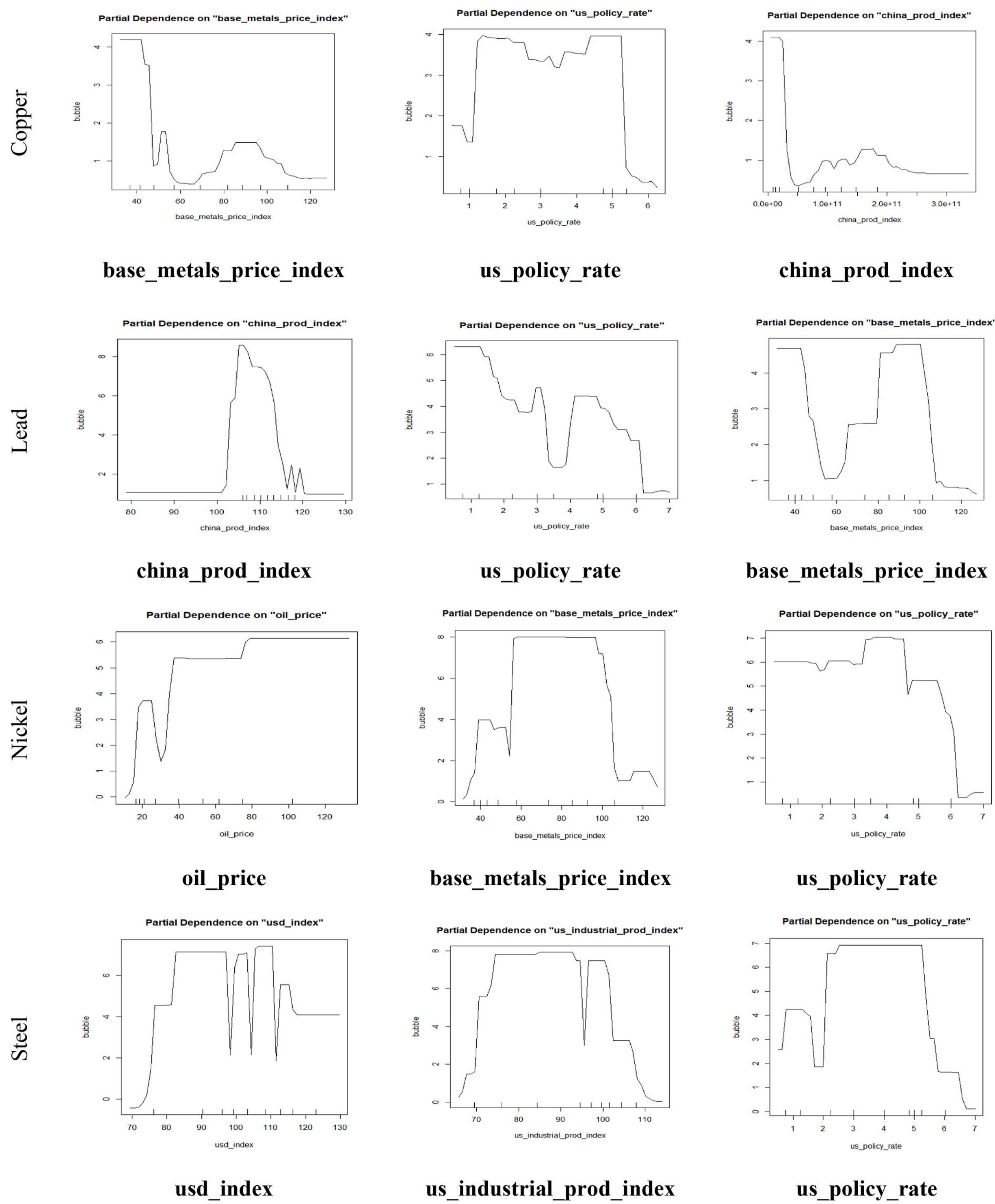


Fig. 5. Partial Dependence Plots for Industrial Metals (copper, lead, nickel, steel).
Note: The vertical axis shows the log of the odds ratio. The odds ratio is measured as "$\frac{p}{1}-p$" where p represents the probability of bubble. The horizontal axis is the values of predictor values in absolute terms.

The findings of machine learning analyzes indicate that the emergence of price bubbles may display commodity market-specific characteristics. Furthermore, the threshold values for the variables that influence bubble formation for each commodity price can be used to develop early warning indicators to detect bubbles.

CRediT authorship contribution statement

Onder Ozgur: Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Veli Yilanci:** Conceptualization, Investigation, Methodology, Data curation, Writing – original draft, Software. **Fatih Cemil Ozbugday:** Investigation, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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