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Factors of predictive power for metal commodities

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A B S T R A C T

There are numerous forecasting studies on commodity prices using various micro- and macroeconomic indicator sets. However, commodity markets have undergone a substantial transformation in the last 20 years, with periods of the financialization, and possibly also a de-financialization, which should also be reflected in the commodity price forecasts. To identify the changes in price predictors and determinants, we individually forecast 24 metal prices one-month ahead in the pre- and post financial crisis period, where we identify the autoregressive price components having a large impact across all commodities and periods. However, interest rates are of larger impact in the first sub-sample, whereas commodity- and financial market indices are dominating in the second sub-sample. Further, we perform an out-of-sample forecast over the entire timespan, where we are able to significantly outperform the predefined benchmark forecast models, a random-walk and a random-walk with drift, in 12 of the 24 cases.

1. Introduction

Metals mark a cornerstone for the global economy, for importing and exporting countries alike, see Byrne et al. (2013) for example, while certain industry sectors require large amounts of specific metals, such as lithium and cobalt within the battery industry. While there are numerous forecasting studies on commodity indices and partly also individual prices, using various micro- and macroeconomic indicator sets, commodity markets have undergone a substantial transformation within the last 20 years, with periods of the financialization, and possibly also a de-financialization, which should also be reflected in the commodity price forecasts as well.

Through the increased index investments in commodities since the beginning of the millennium, their prices are hypothesized to be closer related to prices of other commodities, as well as to the conditions of financial markets in general, a phenomenon called financialization, see Cheng and Xiong (2014) for example. Moreover, as the monetary policy changed significantly over the last two decades, from the interest-rates based policy towards unconventional monetary policy in response to the big financial crisis in '07 to '09, so did the policy impact on the determination commodity prices, see Hammoudeh et al. (2015) for example, while these changes may potentially also affect the forecasting of commodity prices.

The commodities considered in our study include the precious metals gold, silver and platinum, the six industrial metals listed on the London Metal Exchange (LME), as well as 15 minor metals. Our literature review of potential metal price predictors and determinants yields in an initial set of 28 variables, which include micro- and macroeconomic conditions, components extracted from the individual metal price time-series and, where available, the corresponding futures price series, as well as monetary policy measures and exchange rates.

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To analyze the changes in metal markets over time, we initially split our data in two sub-samples, spanning from 01/1995 to 12/2008 and 01/2009 to 12/2019, while we additionally compare our forecasts against predefined benchmarks in the total sample. The individual price predictors and determinants are hereby selected through a two-stage model selection. An initial correlation analysis excludes variables with an absolute Pearson-coefficient smaller than 15% and is followed by a BIC based regression selection, whereby models suffering from multicollinearity are excluded. Through a rolling window estimation of one-month ahead predictive regressions in the total sample, we forecast each commodity individually and compare our results against the random-walk and random-walk with drift benchmark, where we significantly outperform the benchmark for 12 of the 24 commodities. Our results are especially noteworthy for the minor metals, where we exceed the benchmark forecasts for 9 of 15 commodities considered.

Therefore, we contribute to the existing literature in multiple ways. First, we combine numerous micro- and macroeconomic variables in metal-specific predictions, while the previous literature mostly either considers only a selection of the displayed attributes or predicts commodity indices, rather than individual metal prices. Second, we identify the autoregressive price components, represented via the value factor and a lagged price series, as the most important predictor variable across all samples, while its impact is decreasing over time. This is in line with the findings of Gargano and Timmermann (2014) and Wang et al. (2020). Third, we reveal various changes in the metal price predictors over time, such as the commodity indices showing stronger predictive abilities in the second sample, whereas their effect in the price determination largely shifted towards the MSCI world index.

The remainder of this study is structured as follows: Section 2 provides a literature overview, while Section 3 displays the data used, followed by the methodology applied in Section 4, whereas Section 5 highlights our empirical findings. Within Section 6 we analyze the robustness of our findings, which we subsequently discuss in Section 7, while Section 8 concludes.

2. Literature overview

The following section provides a short literature overview of the variables considered in metal price forecasts, starting with studies analyzing the predictive and descriptive power of macroeconomic variables, such as exchange rates, inflation measures, monetary policy variables and economic activity indicators. Further, we highlight the relation of commodity prices with financial market variables, as well metal-specific variables, such as the value and momentum factors from the individual price time-series, Futures prices and measures of physical supply and demand.

In their seminal paper, Chen et al. (2010) argue exchange rates of commodity exporting countries are supposed to adjust to a change in the expectations of future commodity spot prices more quickly than commodity markets themselves. Therefore, the current exchange rates possibly already contain information on the expected future development of commodity prices and hence bear predictive abilities for them. The empirical evidence is mixed, as Ciner (2017), Gargano and Timmermann (2014) and Pincheira-Brown and Hardy (2019) do detect significant predictive abilities of exchange rates for commodity prices, while Groen and Pesenti (2011) are unable to support such effects.

Further, a high inflation is supposed to raise the prices for all goods and services, hence metal prices should co-move with inflation, potentially with a lag. Wang et al. (2020) validate this significant positive influence of the inflation in their prediction of precious metal prices, using the U.S. CPI.

Additionally, metal prices should be inversely related to interest rates via various channels. Frankel and Rose (2010) state higher interest rates lead to higher storage costs and therefore a demand decrease. Further, higher rates alter supply as they spark incentives for commodity producers to invest their revenues on capital markets, see Frankel (2014). Ultimately, both channels should lower prices and hence testify the inverse relation of the variables, while it is empirically supported by the findings of Guzmán and Silva (2018), Pierdzioch et al. (2016) and Baffes and Savescu (2014), among others. However, as Frankel and Hardouvelis (1985) and Frankel and Rose (2010) state, markets actually react to changes in monetary policy, where interest rates are only a measure of conventional monetary policy, while the direction and magnitude of the relation depends on the time-period considered, according to Frankel (2008). This may, at least partly, explain why empirically, Hammoudeh et al. (2015), Lombardi et al. (2012) and Nicola et al. (2016) are unable to confirm the inverse relation of interest rates and commodity prices. Therefore, Frankel and Rose (2010) state the long-term inflation expectation may be a broader monetary policy variable to consider.

Further, the industrial production and economic activity are considered as demand variable in various metal market studies, for the price determination and prediction. Traditionally, many studies use U.S. based data, motivated by the historical importance of the U.S. economy for commodity markets and the availability of data, see Gargano and Timmermann (2014) and Issler et al. (2014), for example. However, since the early 2000's, the rising demand for commodities through emerging economies is hypothesized to increasingly influence commodity prices, while data availability for these variables is limited. Therefore, Kilian (2009) constructs an economic activity index, which is based on various shipping rates, to circumvent the data limitation issues.

Bakshi et al. (2011) test the predictive abilities of the Baltic Dry Index (BDI), which is among the most prominent shipping indices, on stock markets and three commodity indices, identifying it as a significant predictor, while Guzmán and Silva (2018) validate the predictive abilities of the index for copper prices.

However, since the financialization of commodity markets connected those more closely with other financial markets, the current situation on stock markets might influence commodity markets. Buncic and Moretto (2015) therefore use the S&P 500 as predictor variable for copper prices in their study, while their additional predictors, as well as their respective sign of the coefficients, varies over time. Similarly, Cifuentes et al. (2020) detect a significant effect of the NASDAQ Emerging Markets Index on the risk premium of copper futures contracts, across all analyzed maturities.

In addition to all previously mentioned attributes, further time-series measures have been created, which are hypothesized to predict future price movements within markets. Asness et al. (2013) transferred the idea of the value factor, initially proposed by Fama and French (1992) for stock markets, as well as the momentum factor, to commodity markets and hereby increase the portfolio performance when the selection is based on the value or momentum factor, respectively. Lutzenberger et al. (2017) include these factors as predictors for the spot prices of 30 metals, where they detect high predictive abilities for both variables.

Since in theory the prices of futures contracts should include information about the future spot prices, numerous studies analyze the impact of the futures prices on commodity spot prices, see Chinn and Coibion (2014) and Hamilton and Wu (2015) for example, whereas the empirical evidence of their predictive content is rather limited. However, Boons and Prado (2019) calculate a momentum factor on futures prices, called basis-momentum, and are able to forecast returns of portfolios from a broader set of commodities, specifically the energy and soft commodities, industrial materials such as cotton, rubber and timber, as well as metals. Further, Fernandez (2020) identifies strong out-of-sample predictive content of the convenience yield for future mineral spot prices. Bernard et al. (2008) conclude the same for aluminum, although their measure of the convenience yield is different.

Another, quite large strand in the commodity forecasting literature, focuses on the individual time-series of commodity prices. Buncic and Moretto (2015), for example, include the time-series data of the copper price in their framework, while Gargano and Timmermann (2014) find the strongest out-of-sample prediction results for a simple AR(1) model. Likewise, Wang et al. (2020) compare forecasts generated with help of technical indicators, such as momentum factors and moving averages for example. Hereby, they highlight the superior forecast abilities of technical indicators, when compared to traditional economic forecasts.

While many of the above mentioned determinants aim to represent the demand for commodities, a good's price is generally assumed as the result of a supply–demand equilibrium. Therefore, also the physical supply and demand of a commodity should, a least partly, determine and potentially predict fluctuations of individual commodity prices, especially at medium- and long-term horizons, according to Guzmán and Silva (2018), while the impact of the variables changes within their study, depending on the time-period analyzed. Ahumada and Cornejo (2014) focus on supply fluctuations, where they detect a significant effect in the price determination. Since the production of metals is very energy intense, see Vansteenkiste (2009) for example, oil can be regarded as an input factor for the production and hence a supply variable, rather than a commodity itself. In general, higher energy prices, approximated by the price of oil, are hypothesized to drive metal prices up, see Akram (2009) for example, while their findings are not statistically significant in this respect. In contrast, Sari et al. (2010) detect a positive, statistically significant response of gold, silver and platinum spot prices to a shock in oil prices. However, the oil price may also be regarded as an indicator for the stance of the global economy and hence may be interpreted as economic activity indicator as well.

Overall, there is a vast amount of potential predictors for commodity prices, originating from macroeconomic, financial and microeconomic backgrounds, while the effects discovered vary largely between different periods analyzed. Buncic and Moretto (2015) detect changes in the predictors for copper prices over time, while Guzmán and Silva (2018) show differences in the price determinants for the metal, where the financial market indices show more significant effects in the most recent sub-sample. The same holds for the impact of interest rate changes on the commodity price determination, where the effects either vanish or change signs, depending on the time-period considered, according to Frankel (2008). Our study contributes to the literature by combining a large set of these variables for metal-specific forecasts, while analyzing the variation of the significant predictors and determinants over time.

3. Data

For the analysis of metal markets, we consider three precious metals, the six LME industrial metals, as well as fifteen further minor metals, as displayed in Table 10. Hereby, the selection of minor metals is primarily based on the availability of historical monthly price series, while we generally use log returns as dependent variable. An overview of the price and potential predictor variables' data sources can be found within Appendix B, while the adjustment of the variables is outlined within Appendix A.

3.1. Metal-specific predictors

In the following, we display all metal-specific price predictors, while we only outline the formulas for the variables that are based on our own calculations. Hereby, we include the metal-specific worldwide primary production, as provided by U.S. Geological Survey (2019), as supply variable and the metal's demand by its global apparent consumption, which we obtain by adjusting the U.S. apparent consumption, drawn from U.S. Geological Survey (2020), by a conversion ratio of the U.S. GDP to the World GDP for the industrial sector.[1]

Additionally, we represent the production concentration of the supply side as a risk measure, via the Herfindahl–Hirschman-Index (HHI):

$$HHI_{i,t} = 10000 \cdot \sum_{r=1}^{R} \left(\frac{prod_{i,t,r}}{\sum_{r=1}^{R} prod_{i,t,r}} \right)^2 , \tag{1}$$

[1] Since the data for the U.S. GDP of the industrial sector is only available from 1997 onward, we extended the series backwards for the years 1995 and 1996 with the conversion ratio of 1997. While this procedure considers forward looking data, it is not as problematic in this analysis, as the respective data points are not within the out-of-sample window of the prediction part of this study.

with $prod_{i,t} = \sum_{r=1}^{R} prod_{i,t,r}$ representing the production for metal i at time $t = 1, \dots, T$, for all production countries $r = 1, \dots, R$, whereby the production data is the per country breakdown of our supply variable, as provided in the annual U.S. Geological Survey Minerals Yearbooks, see U.S. Geological Survey (2019).

As metal-specific financial variables, regarded as technical indicators by Wang et al. (2020), we consider the value and momentum factor, as proposed by Asness et al. (2013). The value factor of commodity i at time t is defined as the log of the average spot price from 4.5 to 5.5 years ago, $\overline{price}_{i,t}$, divided by the most recent spot price:

$$VAL_{i,t} = \ln\left(\frac{\overline{price}_{i,t}}{price_{i,t}}\right). \tag{2}$$

As all predictor variables are lagged one-month in the empirical application of our prediction framework, only the value factor $VAL_{i,t-1}$ is used for the price prediction at time t.

The momentum factor of commodity i at time t is measured as the cumulative raw return,[2] of the past 12 months for each metal, while neglecting the most recent month's return $return_{i,t-1}$:

$$MOM_{i,t} = \prod_{\tilde{t}=2}^{12}(1 + return_{i,t-\tilde{t}}) - 1. \tag{3}$$

It is constructed to represent current market dynamics and measures, as its name indicates, the momentum of the price series. Since we use our data set for a forecast exercise of future spot prices, we include the first-running futures contract as predictor for the future spot prices as well.

Moreover, following the theory of storage, as described in Fama and French (1988) and Fernandez (2020), we approximate the benefit of physically holding a metal via the interest-adjusted basis, which we define as:

$$CY_{i,t} = SIR_t - \frac{1}{T_1 - t}\ln\left(\frac{FUT_{i,t}}{price_{i,t}}\right), \tag{4}$$

with SIR_t denoting the 3-Month U.S. Treasury Rate and $FUT_{i,t}$ the three-month futures contract, which is, according to Table 11, the first-running contract $FUT1_{i,t}$ for the industrial metals, while it represents the second running futures contract $FUT2_{i,t}$ for silver and gold.[3] As for the value factor, only the lagged interest-adjusted basis is used in the price prediction, hence the price prediction is not compromised by information of leading data.

Further, we consider the basis-momentum factor of Boons and Prado (2019), representing a risk component that originates from speculators and financial market participants, defined as the difference between the momentum of the first- and second-running futures contracts, $FUT1_{i,s}$ and $FUT2_{i,s}$:

$$BM_{i,t} = \prod_{\tilde{t}=2}^{12}(1 + return_{FUT1_{i,t-\tilde{t}}}) - \prod_{\tilde{t}=2}^{12}(1 + return_{FUT2_{i,t-\tilde{t}}}) \tag{5}$$

3.2. Macroeconomic and financial market predictors

Additionally, we consider a broad set of macroeconomic and financial market variables, as displayed in Table 12. For interest rates, we include the federal funds rate and the 3-Month U.S. Treasury Rate as U.S. short-term interest rates, as well as the 10-Year U.S. Treasury Rate as U.S. long-term interest rate. Motivated by the rapid growth of the Chinese economy and its importance for the worldwide metal supply and demand, we add the Chinese 3-Month Interbank interest rate and the 10-Year Government bond rate. Further, we include the U.S. term spread as reverse crisis indicator, which, once decreasing, should cause commodity prices to rise, due to the inverse relationship of interest rates and commodity prices, see Idilbi-Bayaa and Qadan (2021) for example. To account for the impact of both conventional and unconventional monetary policy actions, we additionally include the WuXia shadow rate, as well as further variables that we hypothesize to represent the unconventional monetary policy actions. These include and an inflation expectation index, the balance sheet size of the federal reserve, the monetary base and the broad monetary aggregate M4, which specifically represents the assets included in the asset purchases, see Keating et al. (2019). As commodities are quoted in U.S. Dollar on exchanges, we include the U.S. Dollar index as exchange rate measure.

To represent the overall demand for commodities, we include the U.S. industrial production, as well as the equivalent worldwide measure and the corresponding Chinese variable.

Subsequently, to gauge the stance of economy, we include the U.S. Gross Domestic Product and the U.S. Consumer Price Index as an inflation measure, while we represent the worldwide economy via the economic activity indicator of Kilian (2009), which is based on various shipping rates. As metal markets are globalized, with different locations of mining, manufacturing, trading and consumption, we include the Baltic Dry Index, which represents a measure of the current, global freight rates.

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[2] In accordance to the calculations performed in the initial paper of Asness et al. (2013) we use regular first differences of the monthly metal price as return series in this case.

[3] Due to limited data availability and the monthly frequency of our analysis, we neglect the storage costs and rely on the interest-adjusted basis, rather than the convenience yield. Moreover, as the time span of data availability of the second futures contract of platinum is very limited, we base the interest-adjusted basis calculations on the first running, one-month contract in this case, where we consider the 1-month LIBOR as interest rate.

Additionally, we include the WTI crude oil price as production input variable on the one hand side, see Akram (2009) and Baffes (2007) for reference, and as an additional macroeconomic indicator on the other hand side, see Kilian (2009).

Moreover, as well as the Bloomberg commodity index and the metals' sub-index of the Rogers International Commodity Index, the total return RICI metals index. To account for the effects of financial markets on commodity prices, we further include the Morgan Stanley Capital International world index, as well as the Standard and Poor's 500, which represents the stock prices of the 500 largest U.S. companies.

All data is averaged to monthly frequency in the period from 01/1995 until 12/2019 and checked for stationarity via an ADF-test, see Appendix A for further details.

4. Methodology

To forecast the returns for commodity $i = 1, \dots, N$ at time $t + 1$, we use a linear regression model, defined as:

$$y_{i,t+1} = \beta_{i,0} + \beta_{i,1} x_{i,1,t} + \dots + \beta_{i,K_i} x_{i,K_i,t} + \varepsilon_{i,t+1} \tag{6}$$

where $\beta_{i,0}$ denotes the intercept, $\beta_{i,1}, \dots, \beta_{i,K_i}$ are the coefficients corresponding to the K_i commodity-specific covariates $X_{i,1}, \dots, X_{i,K_i}$ and $\varepsilon_{i,t+1}$ is the error term.

Due to the wide range of possible input variables in conjunction with limited data availability, we first select the optimal set of covariates for each commodity, prior to forecasting their returns. Therefore, we perform a two-stage model selection. First, we focus on the factors with an absolute correlation higher than a predefined threshold, 0.1 in our case. Second, we choose the optimal covariates among the remaining attributes via the Bayesian Information Criterion (BIC). Hereby, we estimate the linear model in Eq. (6) on the in-sample set for each possible combination of input variables, which does not suffer from the issue of multicollinearity. Then, we choose the model which performs best by the BIC.

As in-sample predictability may occur spuriously and may not be able to hold for out-of-sample forecasts, we base our evaluation only on out-of-sample data. Therefore, we split the data set with observations $t \in \{1, \dots, T+1\}$ in the in-sample set with observations $t \in \{1, \dots, R\}$ and the out-of-sample set with observations $t+1 \in \{R+1, \dots, R+P\}$, with $R+P = T+1$, where in the empirical section we apply $R/(R+P) = 3/4$. Knowing the best input variables for each commodity, we can forecast the returns 1-step ahead by an rolling window procedure. In particular, for each time in the out-of-sample set $\tau \in \{1, \dots, P\}$, which corresponds to $t+1 \in \{R+1, \dots, R+P\}$, we estimate the parameters of the linear regression model in Eq. (6) via OLS, using the covariates specified by the model selection $(X_{i,1}, \dots, X_{i,K_i})$ with observations in the set $\{\tau, \dots, t-1\}$. Knowing the estimators of the parameters $\hat{\beta}_{i,0,t}, \hat{\beta}_{i,1,t}, \dots, \hat{\beta}_{K_i,0,t}$, we predict the return of commodity $i = 1, \dots, N$ in period $t+1$ using the values of the covariates $x_{i,1,t}, \dots, x_{i,K_i,t}$ at time t.

We assess the predictive power of our model in comparison to two benchmark models: First, the random walk (rw) without drift, corresponding to the following model:

$$y_{i,t+1} = \varepsilon_{i,t+1}, \tag{7}$$

with $E[y_{i,t+1}] = E[\varepsilon_{i,t+1}] = 0$. Second, the random walk with drift (rwd):

$$y_{i,t+1} = \beta_{i,0} + \varepsilon_{i,t+1}. \tag{8}$$

Hereby, $E[y_{i,t+1}] = E[\beta_{i,0} + \varepsilon_{i,t+1}] = \beta_{i,0}$ holds. Similar to our model, we estimate the benchmark models given in Eqs. (7) and (8) by OLS using the observations $\{y_\tau, \dots, y_t\}$ for $t \in \{R, \dots, T\}$ to get the predictions $\hat{y}_{t+1}$.

The comparison of our models with the benchmark models is based on the measures Mean Squared Prediction Error (MSPE) and Mean Absolute Prediction Error (MAPE), defined as:

$$MSPE = P^{-1} \sum_{t=R}^{T} (y_{t+1} - \hat{y}_{t+1})^2, \; MAPE = P^{-1} \sum_{t=R}^{T} |y_{t+1} - \hat{y}_{t+1}| \tag{9}$$

where $\hat{y}_{t+1}$ denotes the predicted return. In addition, following Issler et al. (2014) we apply the Clark and West (2007)'s tests for equal predictive accuracy. This test corrects for additional noise caused by estimating parameters whose population values are zero.

The null assumes that our unrestricted model, denoted by model 2, includes excess parameters, whereas in the alternative hypothesis the restricted model 1, the benchmark, underperforms in terms of MSPE. Due to the excess noise in the MSPE of model 2, caused by the additional parameters, whose population values are zero, the MSPE of model 1 is expected to be smaller. Therefore, Clark and West (2007) propose to adjust the MSPE of model 2 as follows:

$$MSPE_{2,adj} = MSPE_2 - adj_2 = P^{-1} \sum_{t=R}^{T} (y_{t+1} - \hat{y}_{2,t+1})^2 - P^{-1} \sum_{t=R}^{T} (\hat{y}_{1,t+1} - \hat{y}_{2,t+1})^2. \tag{10}$$

Then, under the null, $MSPE_1 - MSPE_{2,adj}$ equals zero, which can be tested by a t-test using 1.645 as critical value, proposed by Clark and West (2007) as 95% quantile.

In addition, we also compare our forecasts against a third, AR(1) benchmark, which represents the metals' last month's return as a predictor for the current return. Hereby, the forecast performance in comparison to the AR benchmark is not checked for statistical significance, as the Clark–West test requires the benchmark model to be a nested version of the analyzed model, which is not the case for this benchmark.

5. Empirical results

To analyze how the changes in commodity markets affect the individual price predictors of metals, we perform an analysis for sub-sample one with data from 1995 until 2008, as well as the second sub-sample spanning from 2009 to 2019, where the variable ordering within Section 5.1 is based on the relevance of the predictors. However, as both sub-samples are too short to generate enough out-of sample points for a valid statistical analysis of the forecast performance, we rely on the interpretation of the in-sample estimated β-coefficients in this case.[4] Additionally, within Section 5.2 we perform an out-of sample forecast for the total-sample, covering the period 1995 to 2019 and compare these results to the benchmark forecasts.

5.1. Predictor analysis

First and foremost, we reveal the value factor and lagged price series as the most influential predictors, across all samples and in line with the findings of Asness et al. (2013) and Gargano and Timmermann (2014), see Table 1, Table 3 and Table 6.[5]

When comparing the influence across the samples, we observe the value factor partly looses its predictive abilities in the second sub-sample, with the inclusion in only four models, in comparison to the eight models in the sub-sample one, see Table 1 and Table 3. We attribute this change to the development and data quality of the minor metal markets, which now relates them closer to macroeconomic and financial market conditions, while simultaneously reducing the idiosyncratic component included within each series. However, the value factor still remains an important predictor, while the historic price-series' impact remains unchanged, where it also marks the most important price determinant in both sub-samples.

The four monetary policy variables U.S. monetary base, the federal funds rate, the WuXia shadow rate, and the M4 are included in several prediction models in the first sample, where the federal funds rate, and partly the WuXia rate show a positive sign, while the monetary base and the M4 show a negative one. This is mostly against the hypothesized direction of relation by Frankel and Rose (2010), but in line with the empirical findings of Anzuini et al. (2013) and Hammoudeh et al. (2015). In the second sample, the 3-Month U.S. interest rate is a significant predictor for four of the six industrial metals, with the negative sign that is imposed by the theory. Moreover, the shadow rate of Wu and Xia (2016) is now included in three models, with the hypothesized negative sign, which is in line with theory, as the rate represents conventional and unconventional measures of monetary policy simultaneously.

Moreover, the Bloomberg commodity index, as well as the S&P 500 are included in four and two models respectively within the first sample, always with a positive sign. This is attributable to the co-movement in commodity prices, where a rise in one commodity price leads to an increase in another commodity as well, as well as the integration of metals with financial markets, which is in line with the findings of Basak and Pavlova (2016). For the second sample, the predictive component of the Bloomberg commodity index seems to have shifted to the RICI metals index, which is now included in six models. The MSCI world index shows strong price determining capabilities, especially in the second sub-sample.

The U.S. GDP is a predictor for platinum, as well as the industrial metals aluminum and copper in the first sample, which is in line with the hypothesized direction of relation, while the variable looses the predictive abilities in the second sample. The high, corresponding beta coefficients of this variable relate to variables' very small changes, as can also be seen in Table 13. Additionally, the interest-adjusted basis, as well as the futures prices, are each included within three and two models respectively, with both variables showing less inclusions in the second sample.

The Baltic dry index, which was excluded in the first sub-sample, due to a shortened data availability, is among the most important predictors in the second sub-sample, but included as a determinant only in one model, highlighting the forward looking characteristics of the index, which is in line with the findings of Bakshi et al. (2011) and Guzmán and Silva (2018). Moreover, the metal-specific demand variable is a more important predictor in the second sub-sample, where in all cases the sign is negative, which is in contrast to the theoretical relation, where demand increases should cause rising prices.

While the U.S. Dollar exchange rate has little to no predictive content, it acts as a price determinant for numerous commodities, across all samples and always with a negative sign, see Table 2 , Table 4 and Table 7. This is in contrast to previous findings within the literature, where exchange rates are hypothesized to be strong predictors of commodity prices, see Chen et al. (2010) and partly (Gargano & Timmermann, 2014). However, the differences most likely originate from the scope our exchange rate variable covers, where the U.S. Dollar index is a rather general, broad measure, while studies like Chen et al. (2010), Ciner (2017), Gargano and Timmermann (2014) and Pincheira-Brown and Hardy (2019) focus on the Dollar exchange rates of small, commodity exporting economies, like Chile and South Africa, for example.

While the CPI has comparably poor predictive content, a rising inflation leads to contemporaneously rising commodity prices, which is in line with the theory, see Frankel and Rose (2010) for example.

The interest-adjusted basis also looses some of its descriptive characteristics in the second sample, as does the monetary base, while for the latter the effect probably loads onto the inflation expectation index and the balance sheet size of the FED, which both have been excluded from the sub-sample one, due to shortened data availability. The interest-adjusted basis effect possibly vanishes with modern markets being more often in Contango, caused by the pressure of long-term investors.

[4] Our regressions are generally based on Newey–West estimators to obtain robust standard errors.

[5] Hereby, we exclude the variables of the shaded columns from this analysis, due to the shortened data availability and hence potential biases in the parameter estimation. Due to the short time-series for the second futures contract of platinum, we exclude the corresponding basis-momentum factor from all models and sub-periods.

Table 1

Linear regression results for the metal price predictors — 2008-sample.

	$supply$	hhi	$demand$	VAL	P_{Hist}	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
ag								−0.01 (0.00)																										0.08
au								−0.01 (0.00)																						0.24 (0.04)				0.17
pt							0.28 (0.03)																		47.09 (0.05)					0.57 (0.00)				0.27
al																									32.86 (0.04)					0.46 (0.00)				0.14
cu							0.34 (0.01)												−4.97 (0.01)						48.78 (0.07)									0.23
ni				−0.38 (0.00)																														0.17
pb				−0.30 (0.00)											0.18 (0.00)																			0.15
sn				−0.33 (0.00)						−0.16 (0.05)									−2.80 (0.06)															0.21
zn					0.24 (0.01)			−0.00 (0.00)	0.15 (0.05)						0.15 (0.02)		−0.88 (0.36)																0.30 (0.01)	0.31
bi				−0.60 (0.00)																														0.39
cd					0.39 (0.00)												−1.14 (0.00)									−0.05 (0.00)								0.26
co																																	0.77 (0.01)	0.04
cr				−0.53 (0.00)															−2.13 (0.00)															0.43
ge																0.01 (0.01)																		0.07
in					0.32 (0.00)											−0.02 (0.00)																0.52 (0.00)		0.41
li				−0.51 (0.00)																			−0.41 (0.05)											0.30
mg					0.38 (0.00)												−0.89 (0.00)																	0.26
mn				−0.52 (0.00)													−0.99 (0.00)																	0.42
mo															0.53 (0.00)	−0.02 (0.02)																		0.11
sb					0.45 (0.00)										0.18 (0.00)																			0.25
ti					0.52 (0.00)																													0.27
v				−0.29 (0.03)																										1.53 (0.00)				0.22
w					0.60 (0.00)												−0.74 (0.00)					0.52 (0.02)												0.42

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the 2008-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

The remaining covariates are included in one or no model, which is why we neglect them from further analysis and interpretation. However, when generally analyzing the results within Table 1, we see the sign of the β-coefficients is mostly equal across all metals, indicating the stability of the relations modeled within this prediction analysis.

Although the $Adj.R^2$ is not the appropriate measure to evaluate true forecast performance, we rely on it in the comparison between the sub-samples, as the only ten years of data in the sub-sample two make an evaluation of the out-of-sample predictions infeasible. Hereby, we detect, on average and especially in the minor metals sector, a lower $Adj.R^2$ in sub-sample two, underlining the further state of development within metal markets.

In general, the $Adj.R^2$ values are, obviously, substantially larger in the price determination models for all industrial and precious metals, in comparison to the prediction models. For the minor metal markets, the relation is the other way round, where changes in the covariates are priced with a lag, which we attribute to the market efficiency and speed of markets. For minor metals, the spot markets are most likely less developed, in comparison to the LME and precious metal markets. Hence, changes in economic conditions are priced with a lag, which enables the prediction of these prices based on current economic and financial covariates. Additionally, the minor metals seem to bear a larger idiosyncratic component within each price series, which makes the value factor and the lagged price so influential in the price prediction.

5.2. Forecast comparison

Finally, we model all available data in our total model, where we split the data in an in-sample and out-of-sample part by a 3:1 ratio, to evaluate the oos-forecast improvements our models generate, in comparison to the benchmark models. Hereby, we are able to outperform the random-walk and random-walk with drift benchmark models in all of the six cases for the three precious metals, while only the forecast improvement for platinum is statistically significant, based on the ten percent level and compared against the RWD benchmark, see Table 5. In general, while the RW and the RWD benchmark models perform comparable, the AR benchmark performs substantially worse on average.

Further, we outperform the two above mentioned benchmark models in ten of the twelve cases for the six industrial metals, while the forecast improvements are statistically significant in six cases, for both benchmarks and the metals nickel, tin and zinc, based on the five percent level, while the three metals are among the smaller markets of the industrial metals, see London Metal Exchange (2019).[6] Turning our attention to the fifteen minor metals, we are able to significantly outperform the benchmarks in 18 of the 30 cases, which correspond to the metals bismuth, cadmium, chromium, gallium, indium, lithium, antimony, vanadium, and tungsten. However, for germanium our model is identical to the benchmark model, as none of the potential predictors is selected by our model selection approach.

Overall, the analysis performed within this study reveals the significant forecast improvements through a metal-specific variable selection. Hereby, especially metals of the minor and industrial metal group show predictability. However, over time the predictability of prices seems to be decreasing, as indicated by the lower $Adj.R^2$ values in the second sub-sample, while the autoregressive component within each price series still seems to be the most important predictor. Moreover, we do find numerous changes in the predictors and determinants of prices over time. That is, the commodity indices show stronger predictive abilities in the second sample, whereas their effect in the price determination mostly shifted towards the MSCI world index, indicating the financialization of modern commodity markets. Additionally, the monetary policy variables of predictive power, especially for the industrial metals, also changed, from the federal funds rate in the first sub-sample to the WuXia shadow rate and the U.S. long term interest rate in the second sample.

6. Robustness

To validate the robustness of our results, we start by using a lasso regression model as variable selection, in contrast to our regular, complete enumeration procedure. Moreover, we analyze the importance of each predictor via shuffle analysis, while we additionally evaluate the changes in forecast performance over time via the fluctuation test of Giacomini and Rossi (2010).

6.1. Lasso model selection

As a robustness test, we compare our base variable selection against the selection through a Lasso regression, while this test is performed for the price predictors in the total sample. Hereby, we notice a significantly larger amount of selected variables overall, compared to the sparse selection via the complete enumeration procedure we apply in the main section of our study. However, the relatively large p-values of those additionally selected variables, as displayed in Table 8, indicate the importance of those predictors in the initial in-sample set does not hold for the out-of-sample period. This is further underlined by the prediction error ratios, as displayed in Table 9, where we see only eleven significant forecast improvements, compared to the twelve via the complete enumeration variable selection. Hereby, the models for tin and chrome are no longer able to significantly outperform the benchmark models, while the gold forecast is now additionally beating the benchmark forecast.

Turning our attention to the individual variables, we see, consistent to our main results, the value factor and the historical price remain the most important predictors. However, the U.S. monetary base, the M4 and the GDP variable are also selected numerous

[6] The significance of the forecast improvement is hereby evaluated in comparison to the RW and RWD benchmark models, as the test of Clark and West (2007) requires the benchmark to be a nested version of the tested model, which is not the case for our AR benchmark.

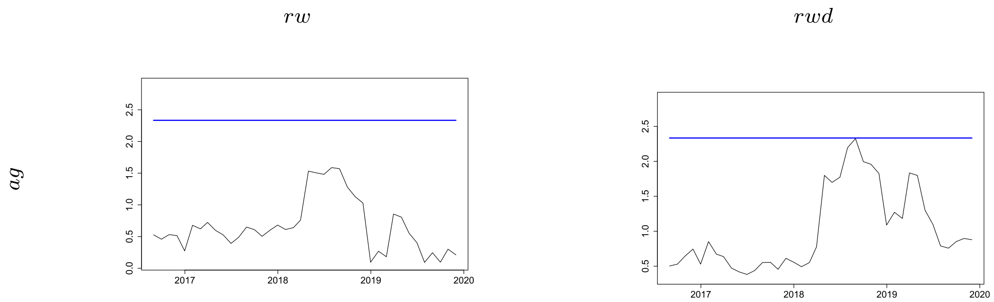


Fig. 1. Results of the Fluctuation Test by Giacomini and Rossi (2010).

times via this procedure, as are the commodity price- and financial market indices, In contrast the futures prices, the interest-adjusted basis, the interest rates as well as the industrial production variables show little to no influence at all. Overall, the results of this robustness analysis testify the importance of the truly important predictors, which are selected via either variable selection, the historical price data and the monetary policy variables.

6.2. Shuffle analysis

In this subsection, we aim to verify the importance of the individual metal price predictors via a shuffle analysis, which we base on our total-sample. Therefore, we lag each predictor variable randomly between three and eight months, and perform the metal price predictions.[7] Subsequently, we measure the average drop in the adjusted R^2 values, compared to the regular price prediction with only one month lag, across all variables and metals, as can be seen in Fig. 2.

We identify the value factor, as well as the historical price series as the most important predictors, which is in line with our previous findings. Hereby, we see a drop of over 20 percent in the adjusted R^2 values for both variables. The two stand out, as the drops in the out-of-sample adjusted R^2 for remaining variables are in the single-digit percentage range.

Within those, we see the U.S. monetary base and the M4 proof some predictability, as well as the U.S. Dollar exchange rate. Moreover, the financial market and commodity price indices are of importance as well, while the industrial production measures and the interest rates show no deviation from the default results. Overall, this is in line with our main results, as well as the results of the lasso model selection.

6.3. Fluctuation test

As price predictability may vary over time, we additionally analyze our forecasts using the Fluctuation test of Giacomini and Rossi (2010). Hereby, we subset our out-of-sample data into a rolling window of length 30-month. Subsequently, we iteratively calculate the test statistic as the standardized difference of our models' MSPE and the MSPE of the benchmark models, which we compare to the critical values proposed by Giacomini and Rossi (2010). Moreover, the test statistic and the critical values are displayed in Fig. 1, which allows for an analysis of the changes in predictability over time.

For gold and silver, we see a stronger predictability in the second half of the out-of-sample period, while the same holds for the industrial metals copper, nickel and lead. The forecasts of the remaining precious- and industrial metals are more or less equally accurate over time. For the minor metals sector the results are mixed, where bismuth, cadmium, magnesium, and antimony show stronger predictability at the beginning of the sample, lithium, manganese, vanadium and tungsten towards the end, whereas the remaining metals show no trend of predictability over time. Overall, when we put those findings in context to the differences in the selected predictor variables of our sub-sample analysis, we see the metals with predictions containing an interest rate variable in the second sub-sample seem to be the ones that perform better towards the end of the overall out-of-sample period.

7. Discussion

Overall, our study differs from previous literature by a metal-specific variable selection, combined with a broad set of potential predictor variables, as well as the identification of changes within the price predictors and determinants over time. Hereby, we observe changes in the development state of markets, as well as changes in the market characteristics over time.

Within previous studies on the predictability of metal prices, they are partly either grouped, see Lutzenberger (2014) for a portfolio on commodities for example, or a commodity-price index is predicted, see Bakshi et al. (2011), Gargano and Timmermann (2014) and Wang et al. (2020), among others. While we observe a clustering in the predictor variables, such as the importance

[7] We thank an anonymous referee for the idea of this robustness check.

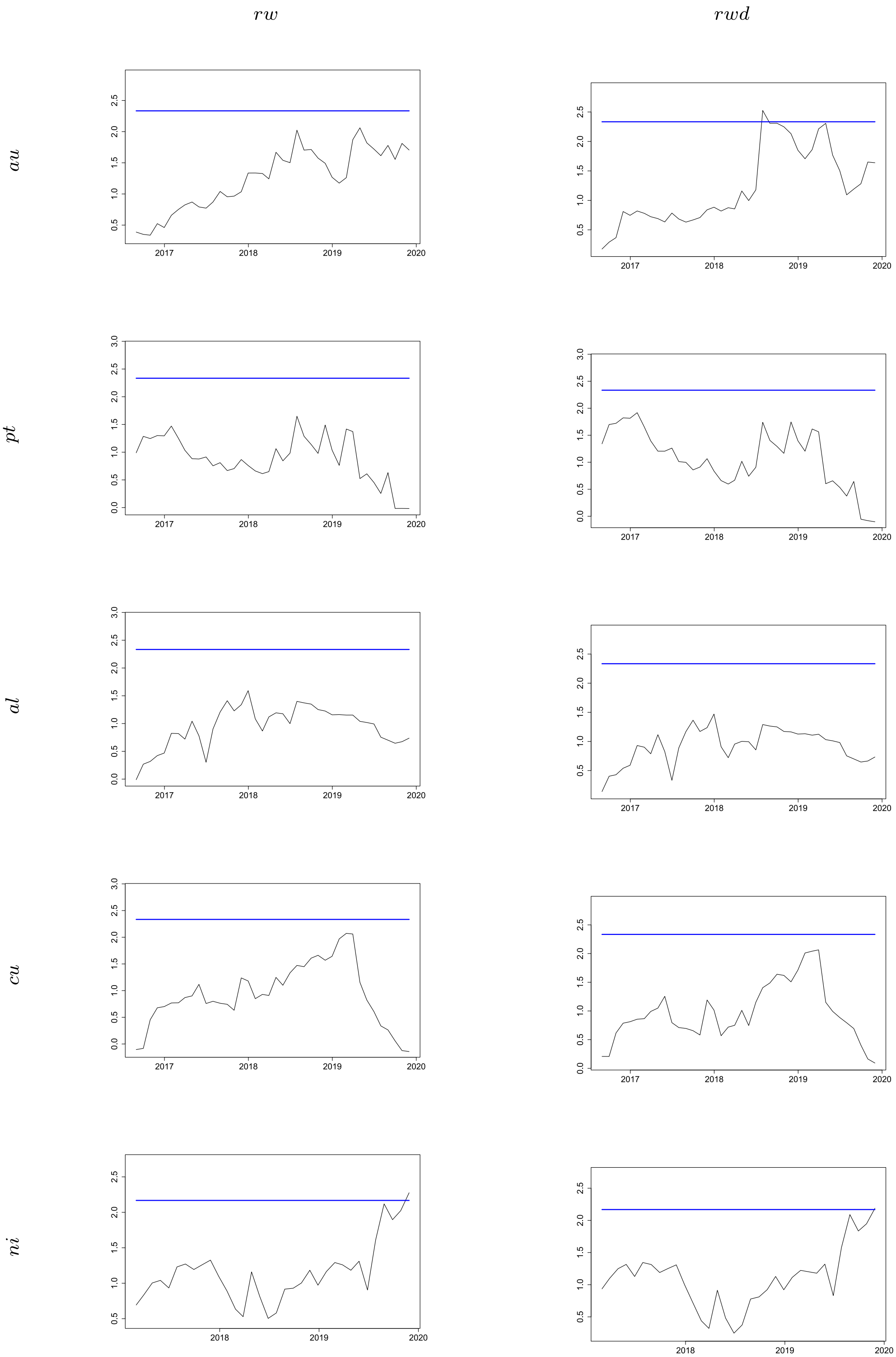


Fig. 1. (*continued*).

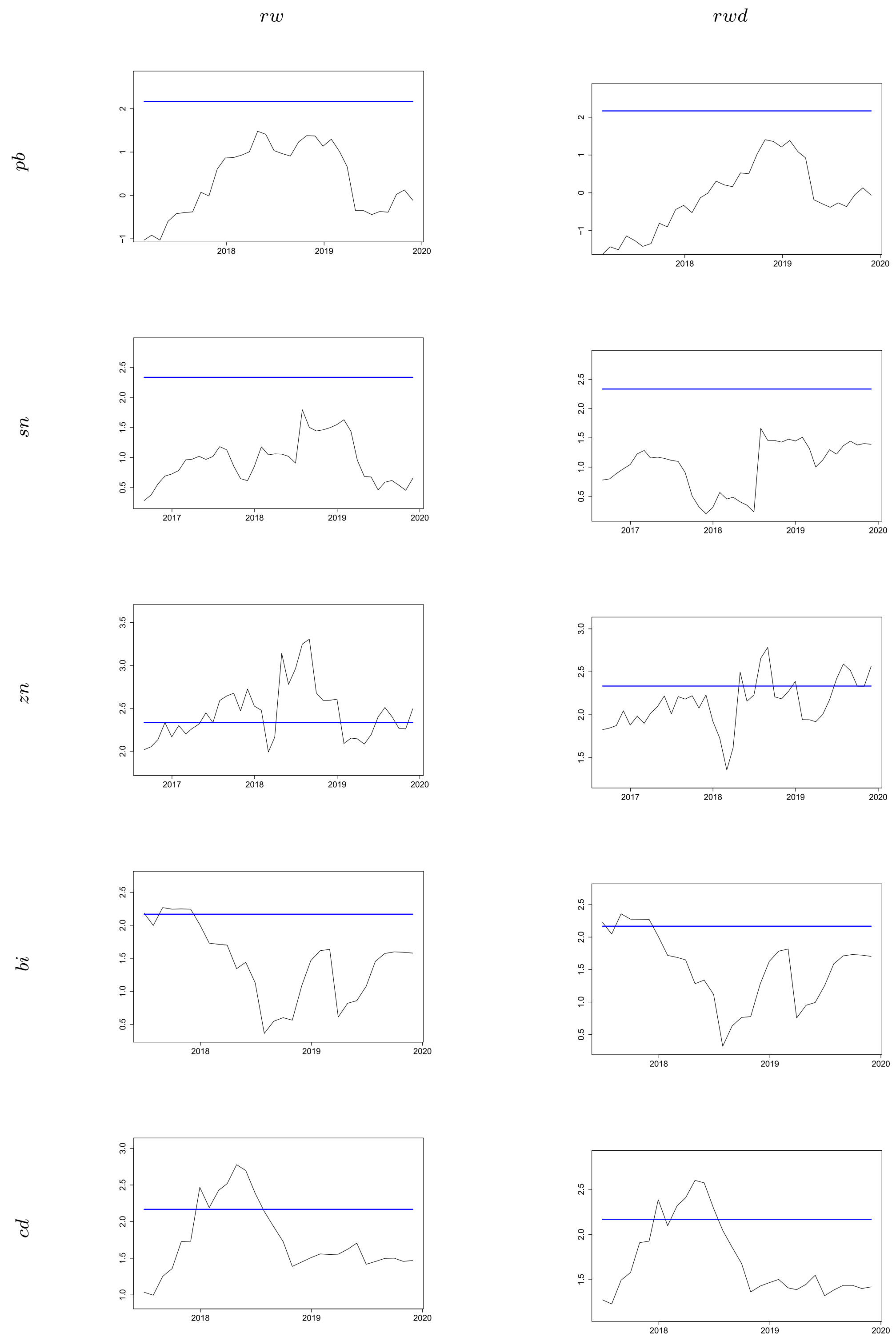


Fig. 1. (*continued*).

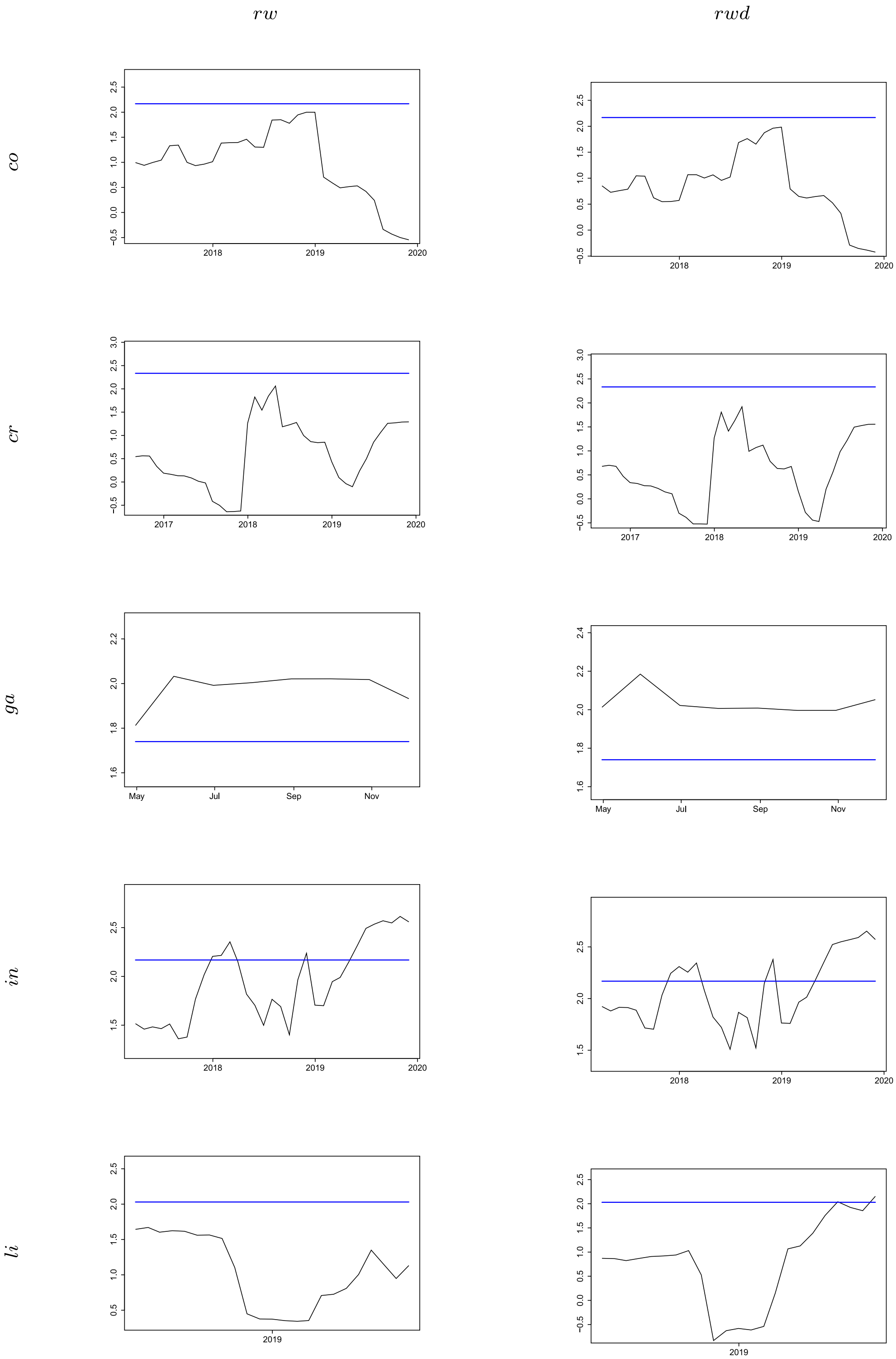


Fig. 1. (*continued*).

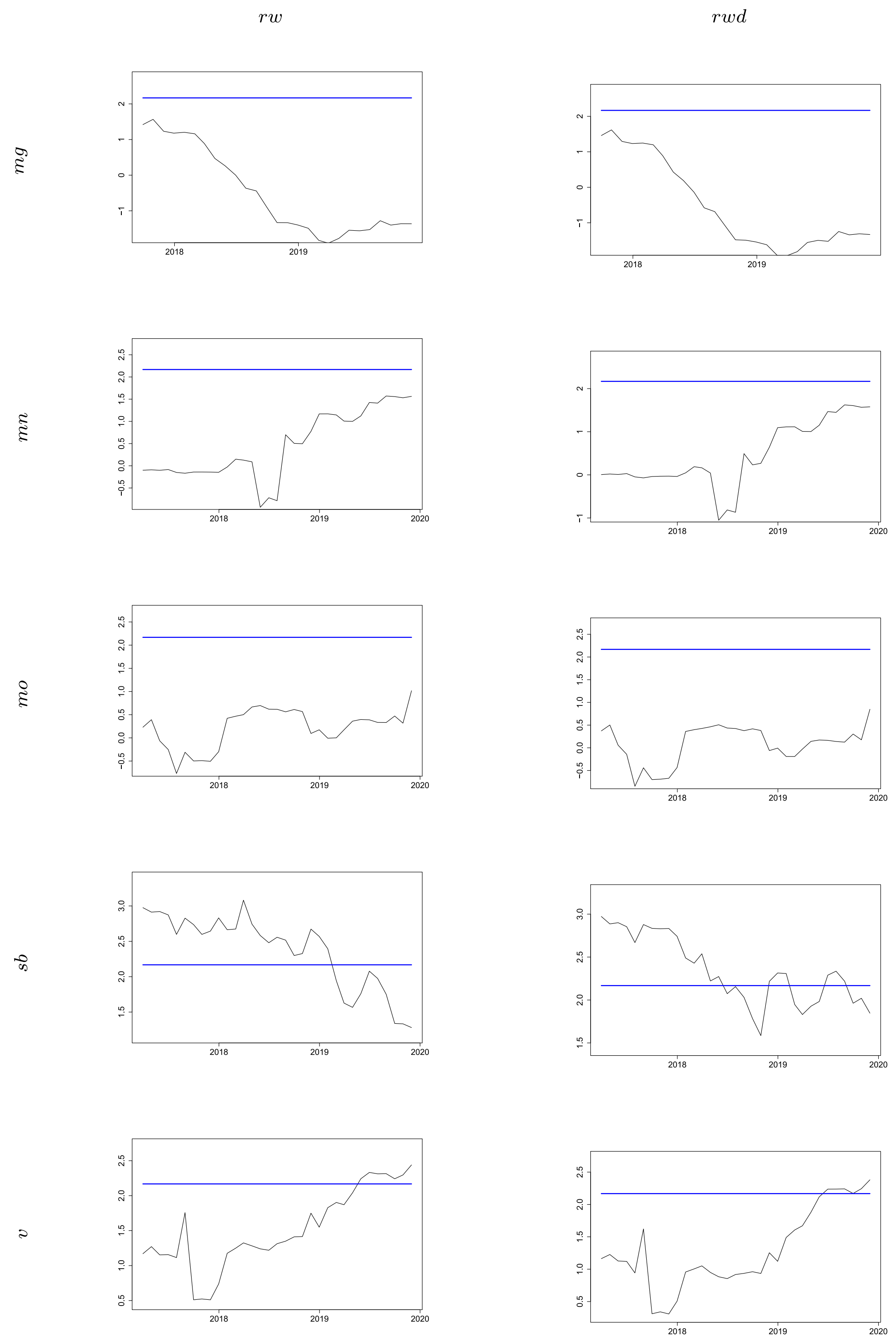
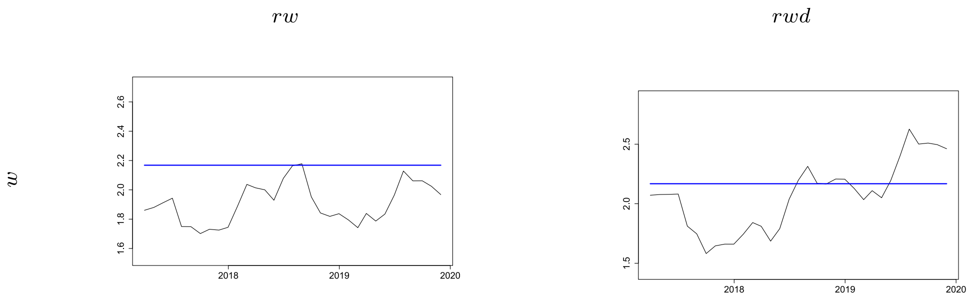
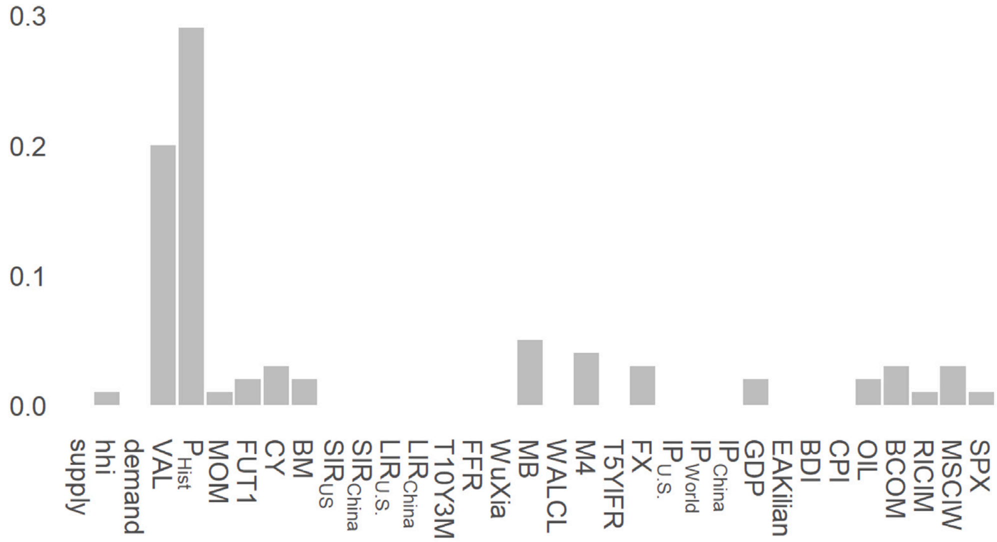


Fig. 1. (*continued*).



These graphics show the results of the fluctuation test, as developed by Giacomini and Rossi (2010), for the individual metal price predictions in comparison to the random-walk and random-walk with drift benchmark. Results are obtained using a rolling window of length $m = 30$, where the blue line represents the one-sided critical value, based on the ten percent significance level.

Fig. 1. (*continued*).



The figure displays the average percentage drop in the out-of-sample adjusted R^2 values, when the predictors are lagged between 3 to 8 months.

Fig. 2. Average Percentage Drop in Out-of-Sample Adjusted R^2 by Variable.

of the M4 for the industrial metals of the historical price for the minor metals sector, our analysis benefits from a commodity-specific variable selection. However, further studies could either combine the two perspectives and predict commodity indices via a combination of individual forecasts or compare panel models to time-series models for metal price predictions.

That is, our prediction results weaken over time, where historically there seem to be larger idiosyncratic price components, paired with a higher degree of autocorrelation in prices, which we capture via the value factor and a lagged price, especially in the minor metals sector, raising the predictive abilities of our models. Through the financialization of commodity markets the index investments into commodities raised significantly, see Tang and Xiong (2012) and Adams and Glück (2015), among others. Hereby, commodity prices are hypothesized to move in a more synchronous way, see Basak and Pavlova (2016), for example. We are able to support this hypothesis, where the commodity indices show a smaller impact in our first sub-sample, compared to the second sub-sample and the total sample, especially in the prediction dimension. In contrast, we see a smaller impact of the commodity indices as price determinants in the second sub-sample, while the price effect of the Bloomberg commodity index seems to have shifted onto the MSCI World, which is in line with the financialization hypothesis, as commodity markets are supposed to be connected closer to financial markets as well, see also Tang and Xiong (2012).

The shift of monetary policy, from a conventional, interest rate based policy prior the financial crisis, to asset purchases and forward guidance afterwards, should be represented in the effects of monetary policy variables on the individual metal prices. Hereby, we detect a larger impact of interest rates in the prediction and determination of prices in the first sub-sample, compared to the overall sample, which is in line with theory, while the interest rates remain a valid predictor in our second sub-sample as well. Further, we see an impact of the unconventional policy measures, the balance sheet size and the inflation expectation index, in the price determination in the second sub-sample, which is in line with the findings of Hammoudeh et al. (2015) and the idea of Frankel and Rose (2010), who regard the long-term expected inflation as monetary policy proxy as well. Additionally, we detect substantial predictive abilities of monetary aggregates, the M4 as well as the monetary base, especially in the first sub-sample, where the sign of relation for the two variables is against the theory, as an increase in either variable represents an easier monetary policy, which should theoretically lead to increasing commodity prices, see Keating et al. (2019).

While the study of Fernandez (2020) identifies the convenience yield as an important predictor for industrial metals, and is able to outperform the benchmark forecast in the one-month ahead dimension for aluminum, copper, lead, nickel, and zinc, independent of the calculation method of the convenience yield and other potential predictor variables that are included, we are only able to outperform the benchmarks for nickel, tin, and zinc, while only the zinc model includes the interest-adjusted basis as predictor variable. Hereby, her study is based on an earlier data, where a large share of the set is in the pre-financialization period, potentially explaining the differences. However, our findings are, except for the zinc model, in line with Chinn and Coibion (2014), who detect no predictive ability of futures prices for the future spot prices.

The value factor shows, when included in the prediction models, a negative sign, which is against the theory of mean reverting prices and the empirical findings of Asness et al. (2013). As the value factor is the ratio of historical, *true* prices, divided by the most recent price, a large value factor represents a currently cheap metal. However, we attribute these differences to the time-series character of our analysis. To obtain stationary time-series, we calculate returns for this variable as well, which basically inverts the factor and leads to the negative sign, see Appendix C for further details.

When comparing our findings to Wang et al. (2020), they detect superior predictive abilities of technical indicator, e.g. components of the individual price series, which is in line with our results for the value factor and the historic price series. However, we do not find significant predictive abilities of the momentum factor, which is in contrast to their findings, as well as the findings of Lutzenberger et al. (2017). We attribute these differences to the different time span of the data sets, as well as the construction of the momentum factor, where Lutzenberger et al. (2017) find predictive abilities for the two to six months momentum, and, in line with our results, no predictive ability for the two to twelve months' factor, which we consider in this study.

However, the application of the linear regression model represents only linear relationships between the variables, where other, more advanced models could be used, based on the consolidated data set generated within this study, to further enhance the predictions of the commodities. Additionally, as the sub-sample analyses revealed the predictors and price determining factors change over time, the model selection procedure could be performed iteratively for each out-of-sample forecast data point and on longer samples.

8. Conclusion

Our individual one-month ahead forecasts of 24 metal commodity prices in the period from 1995 to 2019, as well as in two sub-samples which cover the periods prior and posterior the financial crisis, reveal the idiosyncratic price components, the value factor and the lagged price series, as most important predictors. However, while the historic price-series' impact remains unchanged across both samples, the impact of the value factor is decreasing over time. Further, commodity indices show stronger predictive abilities in the first sample, while in the second sample the financial market indices gained more importance. Further, the exchange rate bears little predictive abilities across both samples, whereas it acts as a important price determinant, especially in the second sub-sample.

Overall, the commodity and financial market variables represent the most important price determinants, especially for the precious and industrial metals. However, our results are especially noteworthy for the minor metals sector, which receive comparably little attention within the commodity market literature, but will gain more and more importance in the future, e.g. through their application within renewable energy technologies. While each metal market was found to be individual to a certain degree, we observed a clustering in the price determinants for the metal groups, such as the MSCI world index and the U.S. Dollar index acting as price determinants for most industrial metals. Moreover, in our forecasts within the total sample, we outperform the predefined benchmark models, a random-walk and random-walk with drift, in 12 cases significantly. Hereby, the results show the highest predictive power for industrial and minor metals, while none of the precious metal forecasts outperforms the benchmarks.

Overall, this study aims to be a foundation for further forecasting models of commodity markets by providing a commodity-specific pre-selection of influential variables.

CRediT authorship contribution statement

Patric Papenfuß: Writing – original draft, Project administration, Formal analysis, Conceptualization. **Amelie Schischke:** Writing – review & editing, Investigation, Data curation. **Andreas Rathgeber:** Writing – review & editing, Supervision, Resources, Funding acquisition.

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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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Appendix A. Data preparation

The data used in this study is consolidated from various data sources and providers, while it differs in its properties and frequencies. To ensure the validity of our empirical analyses, we consider only stationary time-series in our models, and therefore check and adjust our initial data series in the following ways. First, we apply the Augmented Dickey Fuller (ADF) test, based on the ten percent significance level, to each variable. In case non-stationarity is found, we calculate one of following three returns, while we proceed with the original, unadjusted variable names (see Tables 2, 4, 6 and 7).

Log differences:

$$v_t = ln\left(v_t\right) - ln\left(v_{t-1}\right), \tag{11}$$

first differences:

$$v_t = \frac{v_t}{v_{t-1}} - 1, \tag{12}$$

or differences:

$$v_t = v_t - v_{t-1}. \tag{13}$$

The supply, HHI and demand series are only available at annual frequency. To consider those microeconomic determinants within models which require higher frequency data, we apply the following forward-filling procedure: First, the annual return of each variable is taken, according to Eq. (12). We then shift these returns forward by one year and decompose them into monthly values by filling each point in time forward by one-twelfth of the annual change.

For the commodity prices, we obtained the initial series as described in Table 10. Hereby, except for germanium (Ge) and molybdenum (Mo), all series are at daily frequency, which we aggregated to monthly frequency by taking the monthly average price. Subsequently, the individual series are checked for stationarity using the ADF-test and log differences, according to Eq. (11), are calculated in case the initial series were non-stationary, while for the value and momentum factor we calculate differences, according to Eq. (13), in case of non-stationarity. Subsequently, we repeat the procedure until stationarity is ensured across all variables.

All futures prices are available at daily frequency, see Table 11, while we convert them to monthly frequency again by taking the monthly average prices and calculate log-differences according to Eq. (11), in case the monthly series are found to be non-stationary. Since the basis momentum and interest-adjusted basis are rates already, we calculate differences according to Eq. (12) in case of non-stationarity. Again, we recursively apply the procedure until stationarity is ensured for all variables. Descriptive statistics of the adjusted, commodity-specific variables are displayed in .

We proceed in the same way for the macroeconomic attributes. Daily figures are aggregated to monthly data by taking the monthly average, while for the financial- and commodity-indices, shipping indices, industrial production measures, the GDP, as well as the monetary aggregates, we calculate log-returns according to Eq. (11) in case of non-stationarity of the aggregated variables. In contrast, for all interest rate variables, the term spread, as well as the inflation expectation index and the consumer price index, we compute regular returns, according to Eq. (12).

Appendix B. Data sources

See Tables 10–12.

Appendix C. Value factor adjustment

Generally, we check each co-variate for stationarity prior to the model estimation. In case of the value factor, we calculate first differences in case non stationarity is found, as outlined in Appendix A. Within our models, the value factor is included only for metals where the initial variable was found non-stationary and hence adjusted[8]:

[8] With the exception of gallium for the total-sample and the sub-sample two, as well as cadmium and magnesium in sub-sample one.

Table 2
Linear regression results for the metal price determinants — 2008-sample.

	$supply$	hhi	$demand$	VAL	P_{Hist}	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
ag								−0.00 (0.06)									−0.52 (0.01)				−0.94 (0.00)													0.18
au																					−0.90 (0.00)									0.19 (0.06)				0.28
pt								+0.00 (0.00)		−0.14 (0.04)							−0.90 (0.00)													0.49 (0.00)				0.47
al								+0.00 (0.00)													−0.45 (0.00)									0.46 (0.00)		0.21 (0.00)		0.37
cu					0.32 (0.00)																									0.77 (0.00)		0.47 (0.00)		0.39
ni					0.23 (0.00)				0.11 (0.01)																					0.68 (0.00)		0.61 (0.00)		0.36
pb								+0.00 (0.00)	0.18 (0.02)								−0.62 (0.00)				−0.82 (0.00)													0.30
sn					0.25 (0.01)				0.17 (0.03)	−0.13 (0.01)																				0.46 (0.00)		0.24 (0.00)		0.31
zn						−0.08 (0.00)			0.46 (0.00)						0.20 (0.00)																	0.52 (0.00)		0.39
bi					0.54 (0.00)																				44.65 (0.01)									0.36
cd			−0.49 (0.04)		0.39 (0.00)									0.03 (0.03)																				0.25
co																																		
cr					0.54 (0.00)												−0.45 (0.00)								−26.1 (0.09)									0.42
ge																																		
in	−1.06 (0.02)				0.31 (0.00)											−0.01 (0.01)																		0.27
mg					0.39 (0.00)																					0.01 (0.02)		0.03 (0.01)						0.27
mn					0.54 (0.00)																										0.4 (0.00)			0.35
mo															0.43 (0.00)	−0.02 (0.02)																		0.08
sb					0.44 (0.00)																													0.19
ti					0.52 (0.00)														−4.26 (0.01)															0.29
v					0.36 (0.01)																							0.09 (0.02)						0.18
w					0.55 (0.00)																													0.29

This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the 2008-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 3
Linear regression results for the metal price predictors — 20092019-sample.

	supply	hhi	demand	VAL	P_{Hist}	MOM	FUT1	CY	BM	SIR_{US}	SIR_{CN}	LIR_{US}	LIR_{CN}	T10Y3M	FFR	WuXia	MB	WALCL	M4	TSY1FR	FX	IP_{US}	IP_{WLD}	IP_{CN}	GDP	EAK	BDI	CPI	OIL	BCOM	RICIM	MSCIW	SPX	Adj.R^2
ag																														0.53 (0.00)			0.09
au		−0.25 (0.00)						−0.01 (0.00)																			−0.03 (0.01)							0.19
pt																											−0.04 (0.02)				0.34 (0.00)			0.11
al			−1.25 (0.00)													−0.02 (0.00)	0.41 (0.00)																	0.20
cu			−1.04 (0.03)					−0.01 (0.00)		−0.13 (0.00)						−0.02 (0.00)											−0.05 (0.00)							0.32
ni										−0.11 (0.01)						−0.03 (0.00)														0.56 (0.01)				0.14
pb						−0.04 (0.05)				−0.09 (0.00)																								0.11
sn				−0.21 (0.02)																							−0.06 (0.00)							0.11
zn			−2.76 (0.00)			−0.07 (0.00)				−0.10 (0.00)									−2.29 (0.01)								−0.05 (0.00)							0.27
bi				−0.28 (0.00)																											0.42 (0.01)			0.17
cd					0.26 (0.00)																	−1.67 (0.00)												0.12
co																															0.66 (0.00)			0.06
cr			−0.21 (0.02)									0.16 (0.01)																						0.09
ga				−0.31 (0.00)																											0.40 (0.02)			0.22
ge	−1.45 (0.00)																0.71 (0.01)																	0.11
in		−0.26 (0.01)		−0.23 (0.00)																												0.57 (0.03)		0.19
li					0.51 (0.00)																													0.25
mg																				0.17 (0.01)														0.06
mn													0.36 (0.01)		0.09 (0.01)																			0.10
mo																							−0.58 (0.00)					0.08 (0.00)						0.08
sb			−0.57 (0.07)		0.26 (0.01)																										0.43 (0.00)	0.37 (0.04)		0.31
ti																									15.45 (0.03)									0.05
v					0.39 (0.00)										0.12 (0.00)					0.46 (0.00)														0.23
w					0.24 (0.00)																									0.73 (0.03)				0.15

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the 20092019-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 4

Linear regression results for the metal price determinants — 20092019-sample.

	supply	hhi	demand	VAL	P_{Hist}	MOM	FUT1	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	T10Y3M	FFR	W_uXia	MB	WALCL	M4	T5Y1FR	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	EAKilian	BDI	CPI	OIL	BCOM	RICIM	MSCIW	SPX	Adj.R^2
ag					0.19 (0.04)			−0.01 (0.00)													−1.02 (0.00)													0.28
au					0.23 (0.00)			−0.01 (0.00)				−0.16 (0.00)						−0.36 (0.02)			−0.45 (0.02)							0.02 (0.01)						0.42
pt																					−0.75 (0.00)							0.03 (0.01)					0.35 (0.01)	0.23
al																				0.20 (0.01)	−0.68 (0.00)											0.34 (0.01)		0.32
cu		−0.39 (0.03)																		0.30 (0.00)										0.51 (0.00)		0.31 (0.09)		0.42
ni					0.20 (0.02)																									0.53 (0.01)		0.87 (0.00)		0.30
pb																					−1.26 (0.00)											0.50 (0.00)		0.27
sn																					−1.21 (0.00)											0.72 (0.00)		0.36
zn						−0.07 (0.00)			1.13 (0.00)											0.22 (0.02)	−1.10 (0.00)											0.34 (0.04)		0.43
bi					0.31 (0.00)													1.01 (0.02)																0.15
cd					0.20 (0.00)																													0.04
co	−2.19 (0.03)													−0.03 (0.05)																				0.09
cr					0.21 (0.02)																		0.24 (0.02)											0.06
ga					0.33 (0.00)										−0.13 (0.04)	0.02 (0.00)					−0.93 (0.00)													0.27
ge					0.19 (0.02)																									0.52 (0.11)				0.07
in		−0.20 (0.05)																1.67 (0.00)							29.19 (0.01)			0.06 (0.00)						0.23
li					0.43 (0.00)																					−0.00 (0.01)				0.33 (0.06)				0.29
mg																																		
mn																																		
mo																						1.37 (0.05)						0.09 (0.00)						0.09
sb		0.14 (0.01)			0.20 (0.04)																					+0.00 (0.02)	0.04 (0.04)	0.05 (0.00)						0.24
ti																						0.64 (0.05)												0.04
v					0.42 (0.00)																													0.17
w					0.25 (0.00)																							0.05 (0.01)						0.11

This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the 20092019-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 5
Prediction error ratios for the out-of-sample forecasts.

	MSPE			*MAPE*		
	rw	*rwd*	*AR*(1)	*rw*	*rwd*	*AR*(1)
ag	0.95	0.91	0.63	0.99	0.97	0.79
au	0.89	0.89	0.69	0.99	0.96	0.79
pt	0.89	0.85.	0.64	0.98	0.96	0.76
al	0.92	0.92	0.59	1.05	1.05	0.78
cu	0.88	0.88	0.72	1.09	1.06	0.85
ni	0.80**	0.80**	0.73	0.94	0.94	0.83
pb	1.11	1.10	0.80	1.07	1.05	0.86
sn	0.81*	0.76**	0.75	1.01	0.97	0.89
zn	0.69***	0.69***	0.69	0.85	0.85	0.77
bi	0.55**	0.55**	0.63	1.09	1.07	0.81
cd	0.83*	0.84*	0.71	1.04	1.03	0.85
co	0.99	0.99	0.61	1.08	1.09	0.77
cr	0.81*	0.81*	0.59	1.07	1.05	0.77
ga	0.66*	0.58*	0.76	1.00	0.93	0.92
ge						
in	0.74**	0.72***	0.65	0.96	0.93	0.74
li	0.55*	0.59*	0.73	1.06	0.92	0.87
mg	0.89	0.89	0.60	1.09	1.07	0.81
mn	0.89	0.88	0.63	1.07	1.03	0.82
mo	0.95	0.95	0.63	1.21	1.18	0.83
sb	0.60***	0.56***	0.69	1.03	0.97	0.86
ti	0.89	0.89	0.62	1.09	1.04	0.74
v	0.75**	0.76**	0.79	1.01	1.01	0.92
w	0.69**	0.65**	0.65	1.07	1.00	0.82

This table displays the metal-specific out-of-sample forecast error ratios, which are the models' forecast error divided by the benchmark forecast error, for the mean squared prediction error (MSPE) and the mean absolute prediction error (MAPE) measures and the three benchmark models: random walk (*rw*), random walk with drift (*rwd*), and $AR(1)$. For the *rw* and the *rwd* benchmark, the significance of the forecast improvements is tested via the test of Clark and West (2007), which is not applicable for the $AR(1)$ benchmark model.

$$\begin{aligned}\Delta VAL_{i,t} &= \ln\left(\frac{\frac{1}{12}\sum_{\tau=55}^{66} Price_{i,t-\tau}}{Price_{i,t}}\right) - \ln\left(\frac{\frac{1}{12}\sum_{\tau=56}^{67} Price_{i,t-\tau}}{Price_{i,t-1}}\right)\\ &= \ln\left(\frac{\sum_{\tau=55}^{66} Price_{i,t-\tau}}{\sum_{\tau=56}^{67} Price_{i,t-\tau}}\cdot\frac{Price_{i,t-1}}{Price_{i,t}}\right).\end{aligned} \tag{14}$$

As can be seen in Eq. (14), the stationary value factor consists of two components, where the first one represents the coefficient between two annual averages, where the respective time periods overall for eleven of the twelve months.[9] Hence, this coefficient should be comparably small, while the second coefficient represents the AR component of the series. The inverse characteristic of this return, in conjunction with the negative sign for the β-coefficients within the regression results, showcase the trend following pattern of metal prices, at least at the one month horizon we analyze within this study.

Appendix D. Data description

See Tables 13 and 14.

Data availability

Data will be made available on request.

[9] Please note we refer to all variables with their initial variable names in our analysis, disregarding whether they were adjusted or not.

Table 6
Linear regression results for the metal price predictors — total-sample.

	$supply$	hhi	$demand$	VAL	P_{Bias}	MOM	$FUT1$	CY	BM	$SIR_{U.S.}$	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$TSYIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
ag								−0.01 (0.02)																								0.31 (0.01)		0.08
au								−0.01 (0.00)																						0.17 (0.11)				0.12
pt						−0.04 (0.04)	0.26 (0.02)																							0.41 (0.01)				0.19
al		−0.11 (0.01)																							13.27 (0.00)					0.28 (0.00)				0.20
cu							0.30 (0.00)				−0.80 (0.01)						−0.36 (0.03)		−2.44 (0.01)															0.25
ni				−0.29 (0.00)															−3.04 (0.02)															0.14
pb									0.19 (0.03)								−0.42 (0.11)				−0.71 (0.04)													0.12
sn				−0.29 (0.00)															−1.9 (0.05)															0.13
zn					0.26 (0.00)			−0.00 (0.09)	0.14 (0.09)										−2.59 (0.01)															0.21
bi					0.50 (0.00)																										0.34 (0.00)			0.34
cd					0.27 (0.00)												−0.93 (0.14)																	0.16
co																					−1.48 (0.01)												0.62 (0.08)	0.08
cr				−0.38 (0.00)															−1.25 (0.01)										0.10 (0.01)					0.39
ga				−0.34 (0.00)																														0.14
ge																																		
in	−1.36 (0.00)			−0.31 (0.00)																												0.51 (0.00)		0.32
li					0.51 (0.00)																													0.26
mg					0.34 (0.00)																											0.38 (0.01)		0.22
mn				−0.36 (0.00)																											0.24 (0.1)			0.28
mo																	−1.29 (0.00)				−1.66 (0.00)													0.17
sb					0.34 (0.00)																								0.16 (0.00)					0.23
ti					0.44 (0.01)																													0.19
v					0.28 (0.02)												−0.68 (0.01)													0.86 (0.01)				0.24
w					0.44 (0.00)																−0.76 (0.01)													0.30

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 7

Linear regression results for the metal price determinants — total-sample.

	$supply$	hhi	$demand$	VAL	P_{Hist}	MOM	$FUT1$	CY	BM	$SIR_{U.S}$	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	$WuXia$	MB	$WALCL$	$M4$	$T5Y1FR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
ag								−0.01 (0.00)													−1.16 (0.00)							0.03 (0.01)						0.19
au								−0.00 (0.08)													−0.78 (0.00)							0.01 (0.04)						0.22
pt								+0.00 (0.00)									−0.2 (0.18)											0.03 (0.01)		0.28 (0.16)		0.35 (0.00)		0.36
al								+0.00 (0.00)													−0.43 (0.03)								0.10 (0.09)	0.29 (0.01)		0.33 (0.00)		0.42
cu					0.19 (0.02)						−0.61 (0.02)						−0.33 (0.00)												0.16 (0.02)	0.28 (0.15)		0.48 (0.00)		0.47
ni					0.15 (0.03)				0.16 (0.00)																				0.17 (0.00)			0.85 (0.00)		0.34
pb								+0.00 (0.02)	0.18 (0.03)								−0.39 (0.08)				−0.91 (0.00)											0.41 (0.00)		0.28
sn																					−0.60 (0.03)							0.02 (0.1)		0.32 (0.05)		0.50 (0.00)		0.31
zn					0.13 (0.04)				0.20 (0.00)												−0.77 (0.00)											0.59 (0.00)		0.33
bi					0.53 (0.00)																													0.28
cd			−0.44 (0.09)		0.30 (0.00)									0.03 (0.06)			−1.14 (0.02)																	0.24
co																															0.58 (0.12)			0.02
cr					0.34 (0.00)														−1.03 (0.07)							+0.00 (0.00)		0.02 (0.00)						0.42
ga					0.37 (0.00)							0.01 (0.01)									−0.45 (0.09)													0.29
ge																																		
in					0.43 (0.00)					−0.00 (0.1)																								0.18
li					0.46 (0.00)												−0.30 (0.00)																	0.29
mg					0.30 (0.00)																					+0.00 (0.1)		0.03 (0.01)						0.24
mn					0.40 (0.00)																							0.05 (0.01)	−0.19 (0.01)		0.44 (0.00)			0.35
mo																	−1.02 (0.03)																	0.07
sb					0.40 (0.00)																							0.04 (0.00)						0.21
ti																																		
v					0.34 (0.00)																							0.09 (0.00)						0.22
w		0.15 (0.02)			0.35 (0.00)																					+0.00 (0.01)		0.03 (0.01)						0.31

This table displays the averaged β-coefficients and corresponding p-values of the metal price determinants in the total-sample, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 8

Linear regression results for the metal price predictors – total-sample – model selection via Lasso.

	$supply$	hhi	$demand$	VAL	P_{Hist}	MOM	$FUT1$	CY	BM	SIR_{US}	SIR_{China}	$LIR_{U.S.}$	LIR_{China}	$T10Y3M$	FFR	W_uXia	MB
ag					−2.58		2.67	−0.00									
					(0.00)		(0.00)	(0.61)									
au	−1.65							−0.01			−0.44						
	(0.09)							(0.00)			(0.06)						
pt							0.27										
							(0.03)										
al		−0.10															
		(0.02)															
cu				−0.10			0.31				−0.80						−0.30
				(0.51)			(0.19)				(0.02)						(0.06)
ni				−0.24													
				(0.00)													
pb				0.02	0.07				0.14		−1.04						−0.29
				(0.88)	(0.66)				(0.11)		(0.02)						(0.25)
sn				−0.20							−0.67						
				(0.02)							(0.05)						
zn					0.74		−0.49	−0.00	0.13								
					(0.30)		(0.44)	(0.08)	(0.12)								
bi				−0.19	0.26										+0.00		
				(0.09)	(0.10)										(0.39)		
cd					0.28										−0.01	0.01	−0.57
					(0.00)										(0.58)	(0.34)	(0.25)
co																	−0.35
																	(0.59)
cr				−0.31													−0.07
				(0.00)													(0.50)
ga				−0.34													
				(0.00)													
ge				0.15	0.29					−0.02					0.02		
				(0.49)	(0.17)					(0.02)					(0.01)		
in	−0.77		0.84	−0.15	0.14	0.01				−0.01							
	(0.21)		(0.24)	(0.33)	(0.43)	(0.53)				(0.07)							
li	−0.07	0.06	0.25	−0.17	0.28	−0.01											−0.14
	(0.28)	(0.20)	(0.48)	(0.34)	(0.15)	(0.47)											(0.30)
mg					0.23										0.01		−0.01
					(0.07)										(0.03)		(0.75)
mn				−0.27	0.10												−0.08
				(0.03)	(0.62)												(0.74)
mo	−2.17																−0.76
	(0.12)																(0.03)
sb				−0.06	0.24						−0.54						−0.24
				(0.68)	(0.20)						(0.15)						(0.12)
ti					0.44												
					(0.01)												
v				0.09	0.34												−0.64
				(0.50)	(0.07)												(0.01)
w		0.11		−0.13	0.24												−0.10
		(0.13)		(0.52)	(0.32)												(0.57)

	$WALCL$	$M4$	$T5YIFR$	FX	$IP_{U.S.}$	IP_{World}	IP_{China}	GDP	$EAKilian$	BDI	CPI	OIL	$BCOM$	$RICIM$	$MSCIW$	SPX	$Adj.R^2$
ag								1.25					−0.01	0.14	0.60	−0.47	0.11
								(0.81)					(0.86)	(0.55)	(0.19)	(0.29)	
au		−0.03											0.14				0.13
		(0.89)											(0.15)				
pt								4.11					0.33		−0.01		0.16
								(0.47)					(0.06)		(0.83)		
al		−0.32						11.54				−0.01	0.24	0.06	0.07		0.19
		(0.61)						(0.00)				(0.82)	(0.06)	(0.56)	(0.48)		
cu		−2.24		−0.06				6.79			+0.00		0.05	−0.37	1.22	−1.24	0.28
		(0.03)		(0.81)				(0.17)			(0.80)		(0.72)	(0.11)	(0.02)	(0.02)	
ni		−2.91		−0.43				6.48									0.15
		(0.03)		(0.24)				(0.36)									
pb				−0.41				2.07							0.20		0.14
				(0.3)				(0.75)							(0.27)		
sn		−1.34						7.32						0.06	0.01		0.14
		(0.18)						(0.17)						(0.72)	(0.79)		
zn		−2.38						5.63						−0.19	1.17	−1.11	0.23
		(0.01)						(0.24)						(0.30)	(0.02)	(0.02)	
bi								2.64						0.31			0.34
								(0.47)						(0.01)			
cd											0.08	−0.28		0.11		0.55	0.18
											(0.01)	(0.01)		(0.69)		(0.04)	
co				−1.24				6.80						0.19		0.36	0.09
				(0.06)				(0.61)						(0.43)		(0.21)	
cr		−1.39		−0.16					+0.00		0.01	0.03	0.05				0.39
		(0.01)		(0.38)					(0.10)		(0.16)	(0.52)	(0.62)				
ga																	0.14
ge									+0.00								0.04
									(0.13)								
in				−0.11					+0.00					0.12	0.41		0.33
				(0.65)					(0.12)					(0.47)	(0.05)		
li																	0.27
mg				−0.29			0.25	4.03			0.02		0.05			0.31	0.29
				(0.32)			(0.35)	(0.51)			(0.18)		(0.79)			(0.04)	
mn		−1.83		−0.33										0.15			0.29
		(0.08)		(0.28)										(0.27)			
mo				−1.16				12.56			0.07	−0.02		−0.01	0.07		0.18
				(0.13)				(0.16)			(0.03)	(0.75)		(0.79)	(0.78)		
sb								0.04				0.09		0.10	0.09		0.23
								(0.86)				(0.10)		(0.51)	(0.59)		
ti																	0.19
v				−0.63				0.72			0.04	−0.24	0.78	0.07	1.08	−0.96	0.25
				(0.35)				(0.87)			(0.19)	(0.12)	(0.08)	(0.79)	(0.36)	(0.36)	
w				−0.64					+0.00						0.15		0.31
				(0.03)					(0.12)						(0.27)		

This table displays the averaged β-coefficients and corresponding p-values of the metal price predictors in the total-sample, where the variables are selected via a lasso regression, as well as the respective adjusted R^2. The corresponding significance levels are 0.1% (***), 1% (**), 5% (*) and 10% (.). Blank fields indicate the co-variate has been excluded by the model selection process, while shaded cells have been excluded prior to the models' calculation due to limited data availability.

Table 9
Prediction error ratios for the out-of-sample forecasts — model selection via Lasso.

	MSPE			*MAPE*		
	rw	*rwd*	$AR(1)$	*rw*	*rwd*	$AR(1)$
ag	0.81*	0.77**	0.57	0.94	0.92	0.75
au	0.89.	0.89*	0.69	0.97	0.94	0.78
pt	0.89.	0.85*	0.61	0.98	0.96	0.76
al	1.00	1.00	0.59	1.05	1.04	0.77
cu	0.82.	0.82.	0.68	1.05	1.02	0.82
ni	0.76**	0.76**	0.70	0.92	0.92	0.81
pb	1.05	1.00	0.77	1.04	1.02	0.84
sn	0.88	0.82*	0.80	1.05	1.00	0.93
zn	0.76**	0.72**	0.72	0.90	0.90	0.82
bi	0.55**	0.55**	0.62	1.05	1.03	0.79
cd	0.81*	0.81*	0.71	1.03	1.02	0.85
co	0.98	0.98	0.59	1.03	1.04	0.73
cr	0.84.	0.84*	0.57	1.02	0.99	0.73
ga	0.66*	0.58*	0.76	1.00	0.93	0.92
ge	0.91.	0.91*	0.64	1.13	1.05	0.70
in	0.67***	0.64***	0.63	0.94	0.91	0.72
li	0.50*	0.45**	0.73	0.99	0.86	0.82
mg	0.95	0.95	0.60	1.13	1.11	0.84
mn	0.87	0.85	0.63	1.07	1.03	0.82
mo	0.87.	0.87.	0.59	1.16	1.13	0.79
sb	0.68**	0.63**	0.72	1.04	0.98	0.87
ti	0.89	0.89	0.62	1.09	1.04	0.74
v	0.81*	0.81*	0.82	1.03	1.04	0.95
w	0.71**	0.65**	0.64	1.07	1.00	0.82

This table displays the metal-specific out-of-sample forecast error ratios, generated via the model using Lasso regressions as variable selection. These are the models' forecast error divided by the benchmark forecast error, for the mean squared prediction error (MSPE) and the mean absolute prediction error (MAPE) measures and the three benchmark models: random walk (*rw*), random walk with drift (*rwd*), and $AR(1)$. For the *rw* and the *rwd* benchmark, the significance of the forecast improvements is tested via the test of Clark and West (2007), which is not applicable for the $AR(1)$ benchmark model.

Table 10
Data sources — metal spot prices.

	Name	Unit	Database ticker	Source	Start	Freq
Ag	LBMA Silver Price	$/t oz		ICE Benchmark Administration (2022b)	02/1968	d
Au	LBMA Gold Price	$/t oz		ICE Benchmark Administration (2022a)	02/1968	d
Pt	LBMA Platinum Price	$/.9995 fine oz		London Metal Exchange (2022)	04/1990	d
Al	LME-Aluminum 99.7% Cash	$/t	[MAL0]	Thomson Reuters Eikon (2022j)	01/1957	d
Cu	LME-Copper Grade A Cash	$/t	[MCU0]	Thomson Reuters Eikon (2022k)	01/1957	d
Ni	LME-Nickel Cash	$/t	[MNI0]	Thomson Reuters Eikon (2022m)	07/1993	d
Pb	LME-Lead Cash	$/t	[MPB0]	Thomson Reuters Eikon (2022l)	07/1993	d
Sn	LME-Tin 99.85% Cash	$/t	[MSN0]	Thomson Reuters Eikon (2022o)	01/1957	d
Zn	LME-SHG Zinc 99.995% Cash	$/t	[MZN0]	Thomson Reuters Eikon (2022n)	01/1957	d
Bi	Bismuth CIF NWE	$/lb	[BIS-LON]	Thomson Reuters Eikon (2022b)	11/1994	d
Cd	Cadmium 99.99% CIF NWE	$/lb	[CAD-99.99-LON]	Thomson Reuters Eikon (2022c)	10/1994	d
Co	Cobalt Cathode 99.8% CIF NWE	$/lb	[COB-CATT-LON]	Thomson Reuters Eikon (2022e)	10/1993	d
Cr*	Chromium =99.2%, Coarse Particle	$/t	[SOTHCRM]	Thomson Reuters Eikon (2022d)	01/1990	d
Ga	Gallium Ingots CIF NWE	$/kg	[GAL-ING-LON]	Thomson Reuters Eikon (2022f)	03/2002	d
Ge	Germanium 50ohm CIF NWE	$/kg	[GERM-DIOX-LON]	Thomson Reuters Eikon (2022g)	06/1995	m
In	Indium CIF NWE	$/t	[IND-ING-LON]	Thomson Reuters Eikon (2022h)	10/1993	d
Li*	Lithium Metal =99%, Battery Grade	$/t	[SMINLTM]	Thomson Reuters Eikon (2022i)	01/1997	d
Mg	Magnesium 99.9% China CIF NWE	$/t	[MGN-CHINA]	Thomson Reuters Eikon (2022p)	10/1995	d
Mn	Manganese Electro CIF NWE	$/t	[MGN-LON]	Thomson Reuters Eikon (2022q)	10/1993	d
Mo	Molybdenum Mo3 CIF NWE	$/lb	[MLY-OXIDE-LON]	Thomson Reuters Eikon (2022r)	10/1993	m
Sb	Antimony 99.65% CIF NWE	$/t	[ANT-LON]	Thomson Reuters Eikon (2022a)	10/1993	d
Ti	Titanium Sponge CIF NWE	$/kg	[TIT-SPONGE-LON]	Thomson Reuters Eikon (2022s)	10/1993	d
V	Vanadium Fe 80 CIF NWE	$/kg	[VAN-FERRO-LON]	Thomson Reuters Eikon (2022u)	10/1993	d
W	Tungsten Ferro CIF NWE	$/kg	[TUN-FERRO-LON]	Thomson Reuters Eikon (2022t)	10/1993	d

This table displays per metal the name of the price series (Name), as well as the corresponding unit of notation (Unit), the database ticker (Ticker), the source of the data (Source), as well as the start date (Start) and the frequency (Freq) of the series. For chromium (Cr) and lithium (Li), indicated by a *, the Thomson Reuters spot price data is historically extended by metalbulletin data.

Table 11
Data sources — Metal futures prices.

		Name	Unit	Contract Spec.	Ticker	Source	Start	Freq
Ag	$FUT1$	CMX-SILVER - SETT. PRICE - 1 Months	$/t oz	5000t oz	[SIc1]	Thomson Reuters Eikon (2021c)	01/1973	d
	$FUT2$	CMX-SILVER - SETT. PRICE - 3 Months	$/t oz	5000t oz	[SIc3]	Thomson Reuters Eikon (2021d)	01/1973	d
Au	$FUT1$	CMX-GOLD - SETT. PRICE - 1 Months	$/t oz	100t oz	[GCc1]	Thomson Reuters Eikon (2021a)	11/1979	d
	$FUT2$	CMX-GOLD - SETT. PRICE - 3 Months	$/t oz	100t oz	[GCc3]	Thomson Reuters Eikon (2021b)	11/1979	d
Pt	$FUT1$	NYM-PLATINUM - SETT. PRICE - 1 Months	$/t oz	50t oz	[PLc1]	Thomson Reuters Eikon (2021q)	01/1973	d
	$FUT2$	NYM-PLATINUM - SETT. PRICE - 5 Months	$/t oz	50t oz	[PLc3]	Thomson Reuters Eikon (2021r)	12/2004	d
Al	$FUT1$	LME-Aluminum 99.7% 3 Months	$/t	25t	[MAL3]	Thomson Reuters Eikon (2021f)	01/1980	d
	$FUT2$	LME-Aluminum 99.7% 15 Months	$/t	25t	[MAL15]	Thomson Reuters Eikon (2021e)	07/1993	d
Cu	$FUT1$	LME-Copper, Grade A 3 Months	$/t	25t	[MCU3]	Thomson Reuters Eikon (2021h)	07/1993	d
	$FUT2$	LME-Copper, Grade A 15 Months	$/t	25t	[MCU15]	Thomson Reuters Eikon (2021g)	04/1991	d
Ni	$FUT1$	LME-Nickel 3 Months	$/t	6t	[MNI3]	Thomson Reuters Eikon (2021l)	04/1979	d
	$FUT2$	LME-Nickel 15 Months	$/t	6t	[MNI15]	Thomson Reuters Eikon (2021k)	07/1993	d
Pb	$FUT1$	LME-Lead 3 Months	$/t	25t	[MPB3]	Thomson Reuters Eikon (2021j)	07/1993	d
	$FUT2$	LME-Lead 15 Months	$/t	25t	[MPB15]	Thomson Reuters Eikon (2021i)	07/1993	d
Sn	$FUT1$	LME-Tin 99.85% 3 Months	$/t	5t	[MSN3]	Thomson Reuters Eikon (2021p)	06/1989	d
	$FUT2$	LME-Tin 99.85% 15 Months	$/t	5t	[MSN15]	Thomson Reuters Eikon (2021o)	07/1993	d
Zn	$FUT1$	LME-SHG Zinc 99.995% 3 Months	$/t	25t	[MZN3]	Thomson Reuters Eikon (2021n)	11/1988	d
	$FUT2$	LME-SHG Zinc 99.995% 15 Months	$/t	25t	[MZN15]	Thomson Reuters Eikon (2021m)	07/1993	d

This table displays per metal and futures contract the corresponding name (Name), the unit of price notation (Unit), the quantity specification per contract (Contract Spec.), the database ticker (Ticker), the source of the data (Source), as well as the start date (Start) and the frequency (Freq) of the series.

Table 12
Data sources — General metal price determinants.

Covariate	Description	Source	Start	Freq.
$SIR_{U.S.}$	U.S. 3-Month Short-term interest rates	Organization for Economic Co-operation and Development (OECD) (2022)	06/1964	m
SIR_{China}	China (Mainland) Interbank lending weighted average interest rate, 3-Month	State Administration of Foreign Exchange, China (2022b)	01/1996	m
$LIR_{U.S.}$	U.S. 10-Year Constant Maturity Market Yield, Quoted on an Investment Basis	Board of Governors of the Federal Reserve System (US) (2022d)	04/1953	m
LIR_{China}	China (Mainland) 10-Year Government Benchmarks, Bid, CNY	State Administration of Foreign Exchange, China (2022a)	06/2002	m
$T10Y3M$	U.S. 10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity	Federal Reserve Bank of St. Louis (2022a)	01/1982	m
FFR	Effective Federal Funds Rate	Board of Governors of the Federal Reserve System (US) (2022b)	01/1955	m
$WuXia$	Wu-Xia Shadow Federal Funds Rate	Federal Reserve Bank of Atlanta (2022)	01/1990	m
MB	Monetary Base; Total, Millions of Dollars, Monthly, Not Seasonally Adjusted	Board of Governors of the Federal Reserve System (US) (2022e)	01/1959	m
$WALCL$	Assets: Total Assets: Total Assets (Less Eliminations from Consolidation): Wednesday Level	Board of Governors of the Federal Reserve System (US) (2022a)	12/2002	w
$M4$	Divisia M4 - Including Treasuries - U.S.	Center for Financial Stability (CFS) (2022)	01/1990	m
$T5YIFR$	5-Year Forward Inflation Expectation Rate, Percent, Daily, Not Seasonally Adjusted	Federal Reserve Bank of St. Louis (2022b)	01/2003	d
FX	U.S. Dollar Index	ICE Futures U.S. (2022)	12/1970	d
$IP_{U.S.}$	U.S. Industrial Production	Board of Governors of the Federal Reserve System (US) (2022c)	01/1919	m
IP_{World}	World Industrial Production	The World Bank (2022)	01/1991	m
IP_{China}	China (Mainland) Production, Overall, Industrial production	National Bureau of Statistics of China (2022)	01/1990	m
GDP	Gross Domestic Product, normalized for the United States	Organization for Economic Co-operation and Development (2022b)	01/1959	m
$EAKilian$	Index of Global Real Economic Activity	Federal Reserve Bank of Dallas (2022)	01/1968	m
BDI	Baltic Dry Index London	The Baltic Exchange (2022)	07/1999	m
CPI	Consumer Price Index: Total, All Items for the United States	Organization for Economic Co-operation and Development (2022a)	01/1960	m
OIL	Global price of WTI Crude	Fund (2022)	01/1990	d
$BCOM$	The Bloomberg Commodity Index	Bloomberg Index Services Limited (2022)	01/1991	d
$RICIM$	RICI Metals Total Return Index	Rogers (2022)	12/1987	d
$MSCIW$	MSCI World Index	MSCI (2022)	01/1980	d
SPX	Standard & Poor's 500 Index	Standard & Poor's (2022)	02/1970	d

This table displays the name of the co-variate (Covariate), the description of the series (Description), as well as the corresponding data source (Source), the start date of the series (Start) and the frequency (Freq) for the general metal price determinants.

Table 13
Descriptive statistics of the adjusted, general metal price determinants.

	Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
$SIR_{U.S.}$	0.11	0.13	0.44	2.04	2.69	5.31	6.05	6.73	2.24	0.33	−1.51	300	−1.92 *	33.95 ***
SIR_{China}	0.01	0.02	0.03	0.04	0.05	0.05	0.12	0.13	0.03	1.70	2.48	288	−2.39 *	212.52 ***
$LIR_{U.S.}$	1.50	1.76	2.54	3.97	3.96	5.11	6.53	7.78	1.56	0.24	−1.04	300	−2.25 *	16.40 ***
LIR_{China}	−0.17	−0.06	−0.03	−0.00	0.00	0.03	0.08	0.18	0.05	0.29	1.92	211	−13.45 **	35.37 ***
$T10Y3M$	−4.29	−0.66	−0.13	−0.02	0.03	0.11	0.70	8.00	0.98	3.72	33.93	300	−18.80 **	15 082.48 ***
FFR	0.07	0.09	0.18	1.75	2.50	5.20	5.85	6.54	2.25	0.37	−1.50	300	−1.94 *	34.97 ***
$WuXia$	−2.99	−1.97	−0.19	1.65	2.05	5.02	5.85	6.65	2.69	0.00	−1.27	300	−2.08 *	20.16 ***
MB	−0.09	−0.02	−0.00	0.00	0.01	0.01	0.04	0.24	0.03	4.09	31.12	300	−8.74 **	12 942.09 ***
$WALCL$	−0.09	−0.01	−0.00	0.00	0.01	0.01	0.03	0.54	0.04	9.28	106.55	205	−8.05 **	99 915.09 ***
$M4$	−0.01	−0.00	0.00	0.00	0.00	0.01	0.01	0.03	0.00	−0.15	3.65	300	−9.39 **	167.66 ***
$T5YIFR$	−0.73	−0.07	−0.03	0.00	0.00	0.03	0.09	0.64	0.09	−0.47	34.44	204	−17.70 **	10 089.48 ***
FX	−0.05	−0.03	−0.01	0.00	0.00	0.01	0.03	0.06	0.02	−0.12	0.25	300	−12.61 **	1.50
$IP_{U.S.}$	−0.05	−0.03	−0.01	−0.00	0.00	0.01	0.03	0.05	0.02	0.12	0.51	300	−28.18 **	3.97
IP_{World}	−0.10	−0.07	−0.03	−0.00	0.00	0.03	0.09	0.12	0.05	0.23	−0.22	300	−25.52 **	3.25
IP_{China}	−0.14	−0.03	−0.01	−0.00	−0.00	0.01	0.03	0.15	0.03	−0.19	12.96	272	−27.76 **	1905.20 ***
GDP	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.00	0.00	0.00	−1.81	5.74	300	−2.16 *	575.65 ***
$EAKilian$	−162.97	−84.08	−43.54	−8.34	4.07	40.38	127.66	188.20	66.62	0.66	0.09	300	−2.42 *	21.88 ***
BDI	−1.33	−0.34	−0.11	0.01	0.00	0.12	0.33	0.67	0.23	−1.13	5.46	246	−13.39 **	357.92 ***
CPI	−1.92	−0.34	0.00	0.19	0.18	0.40	0.68	1.22	0.34	−0.90	4.81	300	−8.79 **	329.70 ***
OIL	−0.34	−0.14	−0.05	0.02	0.00	0.06	0.12	0.22	0.08	−0.75	1.51	300	−13.16 **	56.63 ***
$BCOM$	−0.22	−0.06	−0.01	0.01	0.01	0.03	0.05	0.11	0.04	−1.38	5.85	300	−13.31 **	523.00 ***
$RICIM$	−0.22	−0.06	−0.02	0.01	0.00	0.03	0.06	0.13	0.04	−0.69	3.63	300	−12.26 **	188.52 ***
$MSCIW$	−0.25	−0.06	−0.01	0.01	0.00	0.03	0.05	0.12	0.04	−1.49	7.54	300	−12.95 **	821.65 ***
SPX	−0.19	−0.07	−0.02	0.01	0.01	0.03	0.07	0.10	0.04	−0.89	1.74	300	−16.02 **	77.45 ***

This table displays the descriptive statistics minimum (Min), the five-percent quantile (Q5), the twenty-five percent quantile (Q25), the median (Med), the mean (Mean), the seventy-five quantile (Q75), the ninety-five percent quantile (Q95), the maximum (Max), as well as the standard deviation (SD), the skewness (Skew) and the excess kurtosis (Kurt), as well as the number of observations available for each adjusted series and the results of the test statistics of the Augmented Dickey–Fuller test (ADF) and the Jarque–Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)).

Table 14
Descriptive statistics of the adjusted, metal-specific variables.

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Silver (Ag)	*supply*	−0.01	−0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	−1.16	1.76	300	−5.53 **	106.00 ***
	HHI	−0.06	−0.04	−0.01	0.01	0.02	0.03	0.09	0.18	0.05	1.64	4.17	300	−6.31 **	351.84 ***
	demand	−0.03	−0.02	−0.00	0.00	0.00	0.01	0.02	0.02	0.01	−0.46	0.57	300	−4.53 **	14.64 ***
	price	−0.22	−0.09	−0.03	−0.00	0.00	0.04	0.11	0.19	0.06	−0.09	1.19	300	−19.68 **	18.11 ***
	VAL	−1.44	−1.15	−0.74	−0.18	−0.26	0.12	0.60	0.74	0.54	−0.21	−0.87	300	−1.81.	11.67 ***
	MOM	−0.37	−0.26	−0.10	0.00	0.07	0.18	0.61	1.28	0.27	1.44	2.73	300	−5.20 **	196.84 ***
	FUT1	−0.22	−0.09	−0.03	0.00	0.00	0.04	0.11	0.19	0.06	−0.11	1.25	300	−18.28 **	20.14 ***
	FUT2	−0.22	−0.09	−0.03	0.00	0.00	0.04	0.11	0.19	0.06	−0.11	1.25	300	−18.44 **	20.14 ***
	CY	−7.50	−2.41	−0.38	0.98	1.27	2.76	5.97	12.69	2.54	0.53	1.19	300	−8.98 **	31.75 ***
	BM	−0.01	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.01	0.00	0.39	2.47	300	−20.74 **	83.87 ***
Gold (Au)	*supply*	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.01	0.01	0.00	−0.17	−0.45	300	−3.83 **	3.98
	HHI	−0.15	−0.11	−0.05	−0.04	−0.04	−0.02	0.00	0.01	0.04	−1.16	1.23	300	−2.80 **	86.19 ***
	demand	−0.02	−0.02	−0.00	0.00	−0.00	0.00	0.01	0.02	0.01	−0.71	0.77	300	−5.55 **	32.62 ***
	price	−0.12	−0.05	−0.02	0.00	0.00	0.03	0.07	0.16	0.04	0.34	1.56	300	−18.16 **	36.20 ***
	VAL	−1.06	−0.98	−0.76	−0.11	−0.25	0.16	0.35	0.40	0.46	−0.34	−1.33	300	−2.59 **	27.89 ***
	MOM	−0.27	−0.15	−0.04	0.04	0.06	0.15	0.33	0.57	0.15	0.54	0.06	300	−3.58 **	14.63 ***
	FUT1	−0.12	−0.05	−0.02	0.00	0.00	0.03	0.06	0.16	0.04	0.32	1.41	300	−17.98 **	29.97 ***
	FUT2	−0.12	−0.05	−0.02	0.00	0.00	0.03	0.06	0.16	0.04	0.33	1.41	300	−18.11 **	30.30 ***
	CY	−2.56	−1.38	−0.03	0.87	1.05	2.37	3.45	5.33	1.55	0.05	−0.70	300	−6.36 **	6.25 *
	BM	−0.01	−0.00	−0.00	−0.00	0.00	0.00	0.00	0.01	0.00	0.50	1.34	300	−8.95 **	34.95 ***
Platinum (Pt)	*supply*	−0.02	−0.01	−0.00	0.00	0.00	0.01	0.01	0.02	0.01	−0.74	2.47	300	−8.60 **	103.64 ***
	HHI	−0.22	−0.10	−0.05	−0.00	−0.01	0.02	0.11	0.19	0.07	−0.07	1.75	300	−8.75 **	38.53 ***
	demand	−0.12	−0.04	−0.02	0.00	−0.00	0.01	0.03	0.03	0.03	−2.26	6.82	300	−6.05 **	836.79 ***
	price	−0.29	−0.08	−0.03	0.01	0.00	0.03	0.08	0.23	0.05	−0.77	5.37	300	−14.50 **	390.11 ***
	VAL	−0.21	−0.08	−0.03	−0.00	0.00	0.03	0.08	0.32	0.06	0.89	5.09	290	−11.79 **	351.34 ***
	MOM	−0.52	−0.27	−0.08	0.03	0.05	0.18	0.44	0.66	0.22	0.36	0.34	300	−3.36 **	7.92 *
	FUT1	−0.34	−0.08	−0.02	0.00	0.00	0.03	0.08	0.18	0.05	−1.19	7.90	300	−18.38 **	850.93 ***
	FUT2	−0.50	−0.07	−0.03	0.00	0.00	0.03	0.08	0.32	0.07	−1.97	19.56	180	−12.02 **	2985.88 ***
	CY	−166.25	−10.91	−1.13	0.02	−0.26	1.60	15.68	41.86	15.89	−6.45	65.23	181	−10.12 **	33 344.45 ***
	BM	−0.44	−0.14	−0.00	−0.00	−0.00	0.00	0.10	0.55	0.08	1.01	20.29	169	−11.74 **	2927.68 ***
Aluminum (Al)	*supply*	−0.01	−0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.00	−2.02	6.17	300	−5.55 **	679.88 ***
	$supply_M$	−0.11	−0.06	−0.02	0.00	0.00	0.02	0.07	0.16	0.04	0.32	1.46	300	−27.76 **	31.70 ***
	HHI	−0.12	−0.05	−0.01	0.05	0.05	0.11	0.20	0.21	0.08	0.15	−0.55	300	−5.60 **	4.91.
	demand	−0.02	−0.02	−0.00	0.00	0.00	0.01	0.01	0.01	0.01	−0.82	−0.00	300	−2.23 *	33.62 ***
	$demand_M$	−0.11	−0.07	−0.03	−0.00	0.00	0.03	0.08	0.19	0.05	0.45	0.68	300	−24.54 **	15.89 ***
	price	−0.21	−0.07	−0.03	0.00	−0.00	0.03	0.07	0.14	0.05	−0.43	1.73	300	−23.37 **	46.66 ***
	VAL	−0.77	−0.66	−0.19	−0.05	−0.06	0.12	0.37	0.48	0.27	−0.65	0.40	300	−1.90.	23.12 ***
	MOM	−0.55	−0.22	−0.11	0.02	0.03	0.16	0.40	0.72	0.20	0.39	1.15	300	−4.54 **	24.14 ***
	FUT1	−0.21	−0.07	−0.03	0.00	−0.00	0.03	0.07	0.14	0.04	−0.49	2.15	300	−16.64 **	69.79 ***
	FUT2	−0.21	−0.05	−0.02	0.00	0.00	0.02	0.05	0.13	0.04	−0.69	4.06	300	−12.54 **	229.85 ***
	CY	−10.64	−9.47	−4.43	−2.49	−2.10	0.08	5.36	16.50	4.42	0.87	2.19	300	−15.06 **	97.80 ***
	BM	−0.13	−0.07	−0.02	0.00	0.00	0.03	0.08	0.23	0.05	0.31	2.20	300	−4.11 **	65.31 ***
Copper (Cu)	*supply*	−0.00	−0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.45	−0.40	300	−5.69 **	12.13 ***
	$supply_M$	−0.18	−0.08	−0.02	0.00	0.00	0.03	0.08	0.12	0.05	−0.32	0.56	300	−23.84 **	9.05 **
	HHI	−0.06	−0.06	−0.03	0.00	0.00	0.04	0.10	0.12	0.05	0.69	−0.09	300	−7.81 **	23.91 ***
	demand	−0.19	−0.09	−0.04	0.00	0.00	0.04	0.10	0.23	0.06	0.22	0.41	300	−24.60 **	4.51
	$demand_M$	−0.02	−0.02	−0.00	0.00	−0.00	0.00	0.01	0.01	0.01	−1.25	2.36	300	−5.83 **	147.74 ***
	price	−0.35	−0.09	−0.03	0.00	0.00	0.04	0.08	0.23	0.06	−0.65	5.33	300	−16.32 **	376.24 ***
	VAL	−0.25	−0.09	−0.04	−0.00	0.00	0.03	0.10	0.41	0.07	0.96	6.66	300	−14.19 **	600.52 ***
	MOM	−0.60	−0.31	−0.11	0.01	0.08	0.22	0.68	1.28	0.31	1.14	2.00	300	−3.99 **	114.98 ***
	FUT1	−0.36	−0.08	−0.03	0.00	0.00	0.03	0.08	0.23	0.06	−0.73	6.04	300	−11.78 **	482.66 ***
	FUT2	−0.33	−0.07	−0.02	0.00	0.00	0.03	0.08	0.23	0.05	−0.76	6.49	300	−12.21 **	555.38 ***
	CY	−4.52	−3.42	−1.11	0.54	3.73	6.32	21.45	38.85	8.09	1.85	3.17	300	−3.45 **	296.74 ***
	BM	−0.25	−0.10	−0.02	−0.00	0.00	0.02	0.15	0.30	0.07	0.79	4.18	300	−3.61 **	249.61 ***
Nickel (Ni)	*supply*	−0.02	−0.02	−0.00	0.00	0.00	0.01	0.02	0.02	0.01	−0.36	0.40	300	−5.79 **	8.48 **
	$supply_M$	−0.26	−0.12	−0.02	0.00	0.00	0.04	0.13	0.25	0.07	−0.33	2.01	300	−17.73 **	55.70 ***
	HHI	−0.27	−0.18	−0.05	−0.01	−0.01	0.05	0.22	0.26	0.11	0.14	0.80	300	−5.80 **	8.98 **
	demand	−0.02	−0.02	−0.00	0.00	0.00	0.01	0.01	0.02	0.01	−0.55	−0.35	300	−6.03 **	16.66 ***
	$demand_M$	−0.31	−0.14	−0.06	0.01	0.00	0.06	0.15	0.26	0.09	−0.22	0.50	300	−22.91 **	5.59.
	price	−0.38	−0.12	−0.05	−0.01	0.00	0.06	0.14	0.24	0.08	−0.22	1.17	300	−12.62 **	19.53 ***
	VAL	−0.27	−0.14	−0.06	−0.01	−0.00	0.06	0.16	0.42	0.09	0.49	1.03	251	−9.61 **	21.14 ***
	MOM	−0.66	−0.39	−0.17	0.00	0.10	0.31	0.94	1.75	0.43	1.21	1.81	300	−2.69 **	114.16 ***
	FUT1	−0.37	−0.12	−0.05	−0.00	0.00	0.06	0.13	0.20	0.08	−0.25	1.01	300	−15.29 **	15.88 ***
	FUT2	−0.34	−0.11	−0.05	−0.00	0.00	0.05	0.12	0.17	0.07	−0.23	1.07	300	−13.03 **	16.96 ***
	CY	−6.07	−1.97	−1.31	−0.47	2.33	1.95	18.16	48.41	7.37	2.92	9.67	300	−4.01 **	1595.18 ***
	BM	−0.34	−0.11	−0.01	−0.00	0.02	0.03	0.24	0.54	0.11	1.72	5.70	300	−3.80 **	554.04 ***

(*continued on next page*)

Table 14 (*continued*).

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Lead (Pb)	$supply$	−0.01	−0.00	−0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.22	−0.74	300	−5.78 **	9.26 ***
	$supply_M$	−0.27	−0.09	−0.02	0.00	0.00	0.03	0.10	0.35	0.06	0.42	7.03	300	−23.41 **	626.72 ***
	HHI	−0.10	−0.06	0.00	0.05	0.05	0.07	0.17	0.23	0.07	0.39	0.89	300	−8.62 **	17.51 ***
	$demand$	−0.01	−0.01	−0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.05	−1.02	300	−4.80 **	13.13 ***
	$demand_M$	−0.20	−0.08	−0.03	0.00	0.00	0.03	0.09	0.19	0.05	0.15	1.49	300	−24.75 **	28.93 ***
	$price$	−0.29	−0.10	−0.03	0.01	0.00	0.04	0.11	0.23	0.07	−0.60	2.66	300	−13.88 **	106.45 ***
	VAL	−0.24	−0.11	−0.05	−0.00	0.00	0.04	0.13	0.34	0.08	0.83	2.48	251	−10.69 **	93.14 ***
	MOM	−0.63	−0.24	−0.10	0.01	0.10	0.23	0.72	1.60	0.34	1.49	3.49	300	−3.04 **	263.26 ***
	$FUT1$	−0.30	−0.10	−0.03	0.01	0.00	0.04	0.11	0.23	0.06	−0.67	3.30	300	−13.56 **	158.57 ***
	$FUT2$	−0.30	−0.08	−0.02	0.01	0.00	0.03	0.09	0.25	0.06	−0.61	4.76	300	−13.41 **	301.82 ***
	CY	−10.67	−7.04	−3.71	−1.29	0.75	2.86	17.47	29.42	7.11	1.51	2.22	300	−5.00 **	175.61 ***
	BM	−0.30	−0.08	−0.02	0.00	0.01	0.02	0.15	0.36	0.08	1.02	5.57	300	−4.08 **	439.83 ***
Tin (Sn)	$supply$	−0.03	−0.02	−0.00	0.00	0.00	0.01	0.01	0.01	0.01	−1.40	2.01	300	−7.43 **	148.50 ***
	$supply_M$	−0.32	−0.12	−0.03	0.00	0.00	0.04	0.11	0.22	0.08	−0.61	2.49	300	−21.92 **	96.14 ***
	HHI	−0.20	−0.13	−0.02	0.03	0.01	0.06	0.10	0.14	0.08	−0.89	0.13	300	−5.89 **	39.82 ***
	$demand$	−0.02	−0.02	−0.00	0.00	0.00	0.00	0.01	0.02	0.01	−0.40	0.82	300	−6.69 **	16.41 ***
	$demand_M$	−0.31	−0.14	−0.04	0.00	0.00	0.04	0.14	0.36	0.09	0.15	2.36	300	−26.39 **	70.79 ***
	$price$	−0.24	−0.09	−0.03	0.00	0.00	0.03	0.10	0.16	0.06	−0.14	1.40	300	−18.31 **	25.48 ***
	VAL	−0.16	−0.11	−0.04	0.00	−0.00	0.03	0.10	0.29	0.06	0.50	1.66	300	−15.10 **	46.94 ***
	MOM	−0.51	−0.29	−0.09	0.03	0.08	0.19	0.67	1.01	0.28	0.93	0.57	300	−3.68 **	47.31 ***
	$FUT1$	−0.24	−0.09	−0.03	0.00	0.00	0.03	0.10	0.16	0.06	−0.20	1.57	300	−14.24 **	32.81 ***
	$FUT2$	−0.23	−0.08	−0.02	0.00	0.00	0.03	0.10	0.15	0.05	−0.36	2.03	300	−13.20 **	57.99 ***
	CY	−1.97	−1.45	−0.11	1.98	2.63	4.08	9.71	22.42	3.64	1.51	3.42	300	−4.47 **	260.21 ***
	BM	−0.13	−0.06	−0.01	−0.00	0.00	0.01	0.07	0.28	0.05	1.65	8.75	300	−3.79 **	1093.16 ***
Zinc (Zn)	$supply$	−0.01	−0.01	−0.00	0.00	0.00	0.00	0.01	0.01	0.00	−0.24	0.79	300	−6.28 **	10.68 ***
	$supply_M$	−0.20	−0.07	−0.02	0.00	0.00	0.03	0.07	0.19	0.05	0.27	2.89	300	−21.70 **	107.80 ***
	HHI	−0.11	−0.07	0.00	0.04	0.03	0.06	0.13	0.18	0.06	0.09	0.36	300	−7.58 **	2.02
	$demand$	−0.02	−0.01	−0.00	0.00	−0.00	0.00	0.01	0.01	0.01	−0.55	−0.60	300	−5.05 **	19.63 ***
	$demand_M$	−0.33	−0.08	−0.03	0.00	0.00	0.04	0.09	0.24	0.06	−0.61	4.29	300	−23.67 **	248.27 ***
	$price$	−0.29	−0.10	−0.03	0.00	0.00	0.04	0.09	0.23	0.06	−0.50	2.23	300	−19.74 **	74.66 ***
	VAL	−1.69	−1.32	−0.33	−0.07	−0.14	0.14	0.52	0.65	0.49	−1.12	1.29	300	−2.17 *	83.52 ***
	MOM	−0.55	−0.37	−0.12	0.02	0.09	0.21	0.74	1.78	0.36	1.86	5.19	300	−4.09 **	509.68 ***
	$FUT1$	−0.28	−0.10	−0.03	0.00	0.00	0.04	0.09	0.22	0.06	−0.38	1.89	300	−13.79 **	51.87 ***
	$FUT2$	−0.26	−0.08	−0.02	0.00	0.00	0.03	0.08	0.16	0.05	−0.49	2.32	300	−13.37 **	79.28 ***
	CY	−8.83	−7.86	−4.84	−2.10	−1.02	0.49	8.84	55.34	6.64	3.61	22.63	300	−7.48 **	7053.07 ***
	BM	−0.14	−0.08	−0.02	0.01	0.02	0.03	0.12	0.45	0.07	2.68	11.17	300	−3.55 **	1918.73 ***
Bismuth (Bi)	$supply$	−0.02	−0.01	−0.00	0.00	0.00	0.01	0.02	0.04	0.01	0.85	1.28	300	−4.81 **	56.60 ***
	HHI	−0.09	−0.07	−0.01	0.01	0.05	0.09	0.28	0.39	0.11	1.54	2.16	300	−3.61 **	176.90 ***
	$demand$	−0.05	−0.05	−0.02	0.00	−0.00	0.01	0.03	0.04	0.02	−0.45	−0.40	300	−4.76 **	12.13 ***
	$price$	−0.31	−0.10	−0.03	0.00	−0.00	0.02	0.11	0.26	0.07	0.16	3.69	300	−10.57 **	171.48 ***
	VAL	−0.27	−0.11	−0.02	0.00	0.01	0.04	0.13	0.33	0.08	0.12	2.98	235	−7.65 **	87.52 ***
	MOM	−0.62	−0.44	−0.16	0.01	0.06	0.17	0.46	3.15	0.46	3.84	20.34	289	−2.37 *	5692.07 ***
Cadmium (Cd)	$supply$	−0.01	−0.01	−0.00	0.00	0.00	0.00	0.01	0.01	0.01	−0.16	−0.55	300	−9.51 **	5.06.
	HHI	−0.05	−0.03	−0.01	0.03	0.04	0.06	0.12	0.28	0.07	1.75	4.23	300	−5.52 **	376.79 ***
	$demand$	−0.13	−0.09	−0.01	−0.00	−0.01	0.01	0.03	0.04	0.04	−2.26	5.60	300	−5.56 **	647.38 ***
	$price$	−0.77	−0.21	−0.05	0.00	−0.00	0.02	0.23	0.55	0.13	0.14	6.62	300	−12.12 **	548.79 ***
	VAL	−2.57	−2.04	−1.04	−0.18	−0.12	0.86	1.68	2.49	1.22	0.04	−0.83	237	−1.82.	6.87 *
	MOM	−0.78	−0.55	−0.31	−0.03	0.14	0.45	1.36	2.99	0.65	1.66	3.54	290	−3.05 **	284.61 ***
Cobalt (Co)	$supply$	−0.02	−0.01	0.00	0.01	0.01	0.01	0.02	0.02	0.01	−0.38	0.30	300	−6.22 **	8.34 **
	HHI	−0.33	−0.17	−0.02	0.02	0.04	0.11	0.24	0.25	0.13	−0.47	0.42	300	−8.24 **	13.25 ***
	$demand$	−0.03	−0.02	−0.00	0.00	−0.00	0.01	0.01	0.03	0.01	−0.24	0.51	300	−8.01 **	6.13 *
	$price$	−0.77	−0.16	−0.06	0.00	−0.00	0.06	0.17	0.72	0.13	0.08	8.57	300	−17.61 **	918.38 ***
	VAL	−0.63	−0.20	−0.07	−0.00	−0.00	0.07	0.18	0.85	0.14	0.85	7.35	248	−13.50 **	588.10 ***
	MOM	−0.75	−0.48	−0.23	−0.03	0.10	0.23	1.26	2.21	0.52	1.39	2.00	300	−3.60 **	146.60 ***
Chromium (Cr)	$supply$	−0.02	−0.02	0.00	0.00	0.00	0.01	0.02	0.02	0.01	−0.56	−0.07	300	−6.01 **	15.74 ***
	HHI	−0.17	−0.13	−0.04	0.03	0.00	0.05	0.13	0.14	0.08	−0.27	−0.81	300	−6.27 **	11.85 ***
	$demand$	−0.14	−0.08	−0.00	0.00	−0.01	0.01	0.04	0.05	0.04	−2.14	5.65	300	−6.61 **	628.01 ***
	$price$	−0.17	−0.06	−0.02	0.00	0.00	0.01	0.08	0.26	0.05	0.83	5.28	300	−12.41 **	382.93 ***
	VAL	−0.23	−0.09	−0.02	0.00	0.00	0.03	0.08	0.18	0.05	−0.36	2.50	293	−9.42 **	82.63 ***
	MOM	−0.42	−0.29	−0.10	0.04	0.05	0.21	0.38	0.67	0.21	0.08	−0.46	300	−2.89 **	2.97
Gallium (Ga)	$supply$	−0.07	−0.01	−0.00	0.00	0.00	0.01	0.02	0.03	0.02	−2.12	7.31	300	−4.13 **	892.67 ***
	HHI	−0.21	−0.14	0.00	0.00	0.05	0.09	0.33	0.44	0.14	0.95	1.20	300	−2.76 **	63.12 ***
	$demand$	−0.05	−0.04	−0.01	0.01	−0.00	0.01	0.02	0.03	0.02	−1.00	0.36	300	−3.90 **	51.62 ***
	$price$	−0.30	−0.11	−0.03	0.00	−0.00	0.01	0.11	0.23	0.06	0.20	3.52	213	−9.19 **	111.38 ***
	VAL	−0.22	−0.14	−0.03	0.00	0.01	0.06	0.14	0.38	0.08	0.43	2.69	147	−6.14 **	48.85 ***
	MOM	−0.59	−0.42	−0.20	−0.03	0.04	0.18	0.88	1.40	0.39	1.31	1.89	201	−2.15 *	87.41 ***

(*continued on next page*)

Table 14 (*continued*).

		Min	Q5	Q25	Med	Mean	Q75	Q95	Max	SD	Skew	Kurt	Obs	ADF	JB
Germanium (Ge)	*supply*	−0.03	−0.02	−0.01	0.00	0.00	0.01	0.02	0.04	0.02	0.30	0.46	300	−4.68 **	7.14 *
	HHI	−0.19	−0.15	−0.02	0.00	−0.01	0.03	0.06	0.20	0.07	−0.09	1.78	300	−5.61 **	40.01 ***
	demand	−0.03	−0.02	−0.00	−0.00	0.00	0.00	0.02	0.04	0.01	1.02	3.06	300	−4.36 **	169.06 ***
	price	−0.27	−0.08	0.00	0.00	0.00	0.00	0.09	0.32	0.06	0.25	6.88	294	−13.73 **	582.91 ***
	VAL	−0.29	−0.10	−0.03	−0.00	−0.00	0.02	0.10	0.25	0.07	−0.11	3.39	228	−11.12 **	109.63 ***
	MOM	−0.49	−0.40	−0.21	−0.02	0.06	0.27	0.71	1.35	0.35	1.04	1.08	282	−2.62 **	64.54 ***
Indium (In)	*supply*	−0.06	−0.02	−0.00	0.00	0.00	0.01	0.03	0.04	0.02	−1.24	4.86	300	−8.30 **	372.13 ***
	HHI	−1.11	−0.19	−0.06	−0.00	−0.03	0.04	0.27	0.44	0.26	−2.67	10.26	300	−8.16 **	1672.29 ***
	demand	−0.02	−0.01	−0.00	0.00	0.00	0.01	0.02	0.03	0.01	0.14	0.26	300	−4.71 **	1.83
	price	−0.35	−0.13	−0.04	−0.00	0.00	0.03	0.16	0.50	0.09	1.18	4.64	300	−10.61 **	338.74 ***
	VAL	−0.33	−0.15	−0.05	0.00	0.01	0.06	0.20	0.36	0.11	0.08	1.22	248	−7.39 **	15.64 ***
	MOM	−0.68	−0.53	−0.28	−0.07	0.22	0.32	2.46	4.37	0.91	2.43	5.94	300	−1.96 *	736.29 ***
Lithium(Li)	*supply*	−0.02	−0.02	−0.00	0.01	0.01	0.01	0.02	0.05	0.01	0.77	1.71	300	−6.17 **	66.20 ***
	HHI	−0.35	−0.33	−0.07	0.06	0.03	0.15	0.31	0.32	0.17	−0.47	−0.37	300	−7.12 **	12.76 ***
	demand	−0.09	−0.07	−0.01	0.00	−0.00	0.01	0.03	0.04	0.03	−1.73	3.79	300	−4.32 **	329.20 ***
	price	−0.16	−0.04	0.00	0.00	0.01	0.00	0.07	0.32	0.05	3.24	18.41	275	−9.54 **	4364.69 ***
	VAL	−0.33	−0.09	−0.01	0.00	−0.00	0.02	0.07	0.16	0.06	−2.44	11.51	209	−7.99 **	1361.06 ***
	MOM	−0.36	−0.22	−0.04	0.00	0.11	0.16	0.79	1.60	0.32	2.10	4.98	263	−2.21 *	465.08 ***
Magnesium(Mg)	*supply*	−0.01	−0.01	0.00	0.00	0.00	0.01	0.02	0.02	0.01	0.17	−0.17	300	−7.00 **	1.81
	HHI	−0.17	−0.16	−0.01	0.03	0.04	0.06	0.25	0.27	0.11	0.36	−0.13	300	−4.87 **	6.69 *
	demand	−0.05	−0.03	−0.00	−0.00	−0.00	0.01	0.02	0.02	0.01	−1.75	4.25	300	−5.51 **	378.91 ***
	price	−0.24	−0.08	−0.02	0.00	−0.00	0.01	0.07	0.19	0.05	−0.21	6.54	290	−11.26 **	518.96 ***
	VAL	−1.22	−0.78	−0.36	0.03	−0.04	0.30	0.58	0.82	0.44	−0.47	−0.45	225	−1.83.	10.18 ***
	MOM	−0.55	−0.29	−0.11	−0.02	0.02	0.11	0.45	1.29	0.27	2.16	7.30	278	−2.66 **	833.45 ***
Manganese (Mn)	*supply*	−0.16	−0.01	−0.00	0.00	−0.00	0.01	0.02	0.02	0.03	−4.19	17.06	300	−6.85 **	4515.85 ***
	HHI	−0.19	−0.17	−0.06	0.04	0.02	0.09	0.16	0.21	0.11	−0.25	−0.84	300	−6.24 **	11.94 ***
	demand	−0.07	−0.03	−0.01	0.00	−0.00	0.01	0.03	0.04	0.02	−1.21	3.01	300	−6.40 **	186.46 ***
	price	−0.34	−0.09	−0.02	0.00	0.00	0.02	0.11	0.43	0.07	1.00	9.61	300	−11.15 **	1204.40 ***
	VAL	−0.44	−0.12	−0.02	−0.00	0.00	0.04	0.11	0.39	0.08	−0.55	6.45	248	−8.54 **	442.40 ***
	MOM	−0.46	−0.31	−0.13	−0.04	0.07	0.18	0.75	2.70	0.39	3.16	14.41	300	−2.87 **	3094.88 ***
Molybdenum (Mo)	*supply*	−0.01	−0.01	−0.00	0.00	0.00	0.01	0.02	0.02	0.01	0.35	−0.52	300	−7.04 **	9.50 ***
	HHI	−0.14	−0.13	−0.03	0.00	0.01	0.06	0.11	0.12	0.07	−0.31	−0.32	300	−5.85 **	6.08 *
	demand	−0.11	−0.06	−0.01	0.00	−0.00	0.02	0.04	0.04	0.03	−1.51	3.19	300	−5.52 **	241.21 ***
	price	−0.65	−0.18	−0.04	0.00	0.00	0.03	0.18	0.83	0.14	1.07	10.39	300	−15.34 **	1406.65 ***
	VAL	−0.85	−0.17	−0.05	0.00	0.00	0.05	0.18	0.75	0.14	−0.42	10.98	248	−12.32 **	1253.08 ***
	MOM	−0.75	−0.53	−0.16	0.00	0.20	0.31	1.62	4.82	0.74	2.85	11.02	300	−3.83 **	1924.13 ***
Anitmony (Sb)	*supply*	−0.03	−0.03	−0.00	0.00	0.00	0.01	0.02	0.02	0.01	−0.67	0.03	300	−6.81 **	22.46 ***
	HHI	−0.26	−0.15	−0.02	−0.01	−0.01	0.02	0.12	0.17	0.08	−0.70	1.97	300	−5.07 **	73.01 ***
	demand	−0.04	−0.02	−0.01	0.00	−0.00	0.00	0.02	0.03	0.01	−0.27	0.23	300	−6.85 **	4.31
	price	−0.29	−0.11	−0.04	0.00	0.00	0.03	0.11	0.35	0.07	0.39	4.09	300	−10.62 **	216.71 ***
	VAL	−0.33	−0.12	−0.03	−0.00	−0.00	0.04	0.12	0.20	0.07	−0.56	2.58	248	−8.29 **	81.74 ***
	MOM	−0.43	−0.34	−0.18	−0.03	0.10	0.26	0.94	2.61	0.44	2.15	6.67	300	−5.29 **	787.24 ***
Titanium (Ti)	*supply*	−0.01	−0.01	−0.00	0.00	0.00	0.00	0.02	0.02	0.01	0.77	1.06	300	−6.90 **	43.69 ***
	HHI	−0.14	−0.12	−0.07	0.00	−0.01	0.03	0.09	0.27	0.09	1.04	2.23	300	−6.19 **	116.24 ***
	demand	−0.05	−0.04	−0.00	0.01	0.00	0.01	0.02	0.03	0.02	−1.05	0.38	300	−4.39 **	56.93 ***
	price	−0.41	−0.07	0.00	0.00	0.00	0.00	0.07	0.82	0.08	5.12	56.81	300	−11.16 **	41 652.92 ***
	VAL	−0.81	−0.08	−0.01	0.00	0.00	0.03	0.11	0.41	0.09	−3.78	37.79	248	−9.03 **	15 347.46 ***
	MOM	−0.67	−0.24	−0.09	−0.02	0.12	0.07	0.52	4.48	0.71	4.64	22.58	300	−2.83 **	7449.68 ***
Vanadium (V)	*supply*	−0.01	−0.01	−0.00	0.00	0.00	0.01	0.01	0.01	0.01	−0.15	0.19	300	−6.41 **	1.58
	HHI	−0.21	−0.12	−0.03	0.01	0.00	0.05	0.10	0.18	0.08	−0.55	0.93	300	−7.04 **	25.94 ***
	demand	−0.48	−0.16	−0.01	0.01	−0.02	0.02	0.04	0.07	0.10	−3.63	13.22	300	−5.84 **	2843.45 ***
	price	−0.57	−0.17	−0.05	−0.00	0.00	0.04	0.21	0.74	0.13	0.49	6.36	300	−11.19 **	517.62 ***
	VAL	−0.73	−0.20	−0.06	0.01	0.00	0.06	0.21	0.58	0.14	−0.34	4.77	248	−9.45 **	239.89 ***
	MOM	−0.77	−0.60	−0.19	0.04	0.22	0.56	1.48	3.99	0.69	2.03	6.68	300	−3.13 **	763.82 ***
Tungsten (W)	*supply*	−0.05	−0.01	−0.00	0.00	0.00	0.01	0.03	0.03	0.01	−1.40	4.83	300	−5.90 **	389.61 ***
	HHI	−0.24	−0.22	−0.04	0.01	0.01	0.06	0.19	0.34	0.12	0.37	1.45	300	−6.65 **	33.13 ***
	demand	−0.02	−0.02	−0.00	0.00	0.00	0.01	0.02	0.03	0.01	0.23	−0.19	300	−5.55 **	3.10
	price	−0.34	−0.07	−0.02	0.00	0.01	0.03	0.11	0.34	0.07	0.55	7.83	300	−11.25 **	781.49 ***
	VAL	−0.33	−0.10	−0.02	0.00	0.00	0.04	0.10	0.39	0.08	−0.06	7.17	248	−8.81 **	531.37 ***
	MOM	−0.55	−0.29	−0.09	0.04	0.13	0.21	0.74	2.54	0.41	2.67	10.50	300	−2.57 **	1734.57 ***

This table displays the descriptive statistics minimum (Min), five-percent quantile (Q5), twenty-five percent quantile (Q25), median (Med), mean (Mean), seventy-five quantile (Q75), ninety-five percent quantile (Q95), maximum (Max), the standard deviation (SD), skewness (Skew), and excess kurtosis (Kurt), as well as the number of observations available for each adjusted series and the results of the test statistics of the Augmented Dickey–Fuller test (ADF) and the Jarque–Bera test (JB), with the corresponding significance levels (0.1% (***), 1% (**), 5% (*) and 10% (.)).

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