JEL Classification: C52, C53, G17, E270, E370, F370, L740, O180, R310
Keywords: forecasting, commodities, base metals, univariate time-series models, out-of-sample comparison, base metal equity securities.

Forecasting Base Metal Prices with an International Stock Index

Pablo PINCHEIRA-BROWN - School of Business Universidad Adolfo Ibáñez
(pablo.pincheira@uai.cl) corresponding author

Nicolás HARDY - Facultad de Administración y Economía, Universidad Diego Portales

Cristobal HENRRIQUEZ - School of Economics and Business, Universidad Finis Terrae

Ignacio TAPIA - School of Economics and Business, Universidad Finis Terrae

Andrea BENTANCOR - Facultad de Economía y Negocios, Universidad de Talca

Abstract

In this paper, we show that the MSCI ACWI Metals and Mining Index has the ability to predict base metal returns. We use both in-sample and out-of-sample exercises to conduct such examinations. The theoretical underpinning of these results relies on the present-value model for stock-price determination. This model has the implication of Granger causality from stock prices to their key determinants (fundamentals). In the case of metal and mining producers, one of the key elements determining the value of these firms is the price of the commodity they produce and export. Our results are consistent with this theoretical framework, as forecasts based on a model including the MSCI index outperform forecasts that do not use the information contained in that index. Furthermore, in most of our exercises, models equipped with the MSCI Index fare better than models that use the information of equity indices from major commodity exporting countries. We assess predictive ability considering different criteria, such as Mean Squared Prediction Error, Correlations with the target variable and returns from trading strategies.

1. Introduction

In this paper, we show that the MSCI ACWI Metals and Mining Index (henceforth, MSCI) has the ability to predict the returns of the London Metal Exchange Index (LMEX) and of the six base metals that are part of this index: Aluminum, Copper, Lead, Nickel, Tin and Zinc. This result is consistent with the present-value model for asset price determination and provides a useful approach to forecast base metal prices. This is important since global investments in these metals are sizable. Furthermore, as Chen, Rogoff and Rossi (2011) state, accurate forecasts of commodity prices can be a key budgetary planning tool for government agencies of commodity exporter countries.

https://doi.org/10.32065/CJEF.2023.03.03

We would like to thank three anonymous reviewers for thoughtful comments and suggestions. All remaining errors are, of course, our own.

The theoretical underpinning of our paper relies on the present-value model for stock price determination. This model claims that stock prices should be the expected value of the discounted sum of the future revenue of the corresponding firms. As shown by Campbell and Shiller (1987), an important implication of the present-value relationship is that of Granger causality between the stock price of a firm and its dividends. In other words, lagged stock prices may have the ability to predict dividends. We remark here the importance of this mathematical implication: While the stock price is economically caused by expected future revenues or dividends, predictability goes in the opposite direction, from the stock price to dividends.

In the case of metals and mining companies, it is reasonable to expect a close and positive relationship between their revenues and the price of the metals or commodities they extract or produce. This linkage in connection with the present-value relationship lends support to the main hypothesis of our work: predictability from a Metals and Mining Stock index to base metal prices.

Our paper is connected to a relatively recent literature that has explored the predictability of commodity prices using other related financial assets as predictors, including exchange rates, financial ratios and stock indices. For instance, Gargano and Timmerman (2014) use a number of predictors to evaluate the predictability for several groups of commodities at different forecasting horizons. They consider the S&P Goldman Sachs Commodity Index, the exchange rates of two commodity exporting countries and the dividend price ratio based on the S&P 500 Index. A closely related article is that of Wang, Liu and Wu (2020). While their main interest is to explore if technical indicators can predict commodity prices out-of-sample, they also include the excess returns from S&P 500 and some of the financial variables in Gargano and Timmerman (2014) as additional predictors. Alquist, Kilian and Vigfusson (2013) use the exchange rates of Australia, New Zealand, Canada and South Africa to explore predictability for WTI oil. They also consider as potential and successful predictors both the Commodity Research Bureau Industrial Raw Materials Price Index and the Commodity Research Bureau Metals Price Index.

Gargano and Timmermann (2014) and Alquist, Kilian and Vigfusson (2013) are not the only articles using exchange rates of commodity exporter countries as potential predictors for commodity prices. Since the influential work of Chen, Rossi and Rogoff (2010, 2014) many others have explored this linkage including Ciner (2017), Belasen and Demirer (2019), Chen, Rogoff and Rossi (2011), Pincheira and Hardy (2019), Pincheira, Hardy, Bentancor and Jarsun (2022), Chan, Tse and Williams (2011), Groen and Pesenti (2011), Burgess and Rohde (2011), Lof and Nyberg (2011) and Bork, Rovira and Sercu (2022), just to name a few.

Probably the closest papers to ours are those of Chen, Rogoff and Rossi (2011) and Rossi (2012). In these articles the authors show, amongst other things, evidence of predictability from major equity indices coming from commodity-exporting countries to either some world commodity indices or some particular commodity returns. In particular, Rossi (2012) reports important out-of-sample evidence of predictability two quarters ahead, but less impressive evidence at the shorter horizon of one quarter, given that her models including equity indices are unable to outperform a simple AR(1) at this short horizon. If our line of argument is correct, it would be interesting to compare the predictive ability of the MSCI Index to that of similar equity indices as those used by Chen, Rogoff and Rossi (2011) and Rossi (2012). By doing so we could explore which type of index has the greatest predictive ability for base metals, especially at short horizons, where the results of Rossi (2012) are not very strong. Moreover, we may well think that major aggregated equity indices in commodity exporting countries, like those used in Chen, Rogoff and Rossi (2011) and Rossi (2012), may also be importantly influenced by the stock performance of companies less sensitive to commodity prices relative to mining and metals firms. If this is so, it would be reasonable to expect more predictability from the MSCI: a worldwide equity index that focuses exclusively on metals and mining companies.

To evaluate the predictive ability of the MSCI index we use nested linear specifications following the econometric setup of Clark and West (2006, 2007) and Clark and McCracken (2001). We consider several different benchmarks traditionally used in the literature, like autoregressions and the random walk with and without drift[2]. In addition we consider benchmarks built with the information contained in futures contracts, as in Reeve and Vigfusson (2011); Pincheira, Hardy, Bentancor and Jarsun (2022); Alquist, Kilian and Vigfusson (2013); Alquist and Kilian (2010); Chinn and Coibion (2014); Karolak, Kwas, Rubaszek and Uddin (2020); Fernandez (2017) and Knetsch (2007). Finally, and most important to us, we also use autoregressions augmented with lags of equity indices of major commodity exporter countries as benchmarks. These last models are inspired by the works of Rossi (2012) and Chen, Rossi and Rogoff (2011). In general terms, and for most of our exercises and base metals, our models equipped with the MSCI index, tend to outperform most of the benchmarks, including those of Rossi (2012).

Our paper makes two contributions to the literature: First, it introduces a new variable to the set of predictors for base metals. We do so, by showing in a number of different in-sample and out-of-sample exercises, that the MSCI Index is a useful predictor for several base metals. Second, it complements, improves and extends the work of Rossi (2012) and Chen, Rossi and Rogoff (2011) by providing evidence of predictability from an equity index to base metals. We show that the MSCI Index tends to overshadow the predictive ability of traditional equity indices from major commodity exporter countries. From that point of view, our results are an improvement relative to those of Rossi (2012) and Chen, Rossi and Rogoff (2011). Similarly, by working with a monthly database we successfully showed predictability from the MSCI index to base metals at the short horizon of one month. Let us recall that the equity indices evaluated by Rossi (2012) were unable to outperform a simple AR(1) model at their shortest horizon of one quarter. Furthermore, we provide evidence of predictability from the MSCI to base metals both at the population and at a sample level. While Rossi (2012) and Chen, Rossi and Rogoff (2011) do provide evidence of predictability from their equity indices to some commodities, the core of their analysis is at the population level. Our paper instead contains two exercises devoted to the analysis of forecasts at the sample level, which is very helpful to forecasters and practitioners that make decisions looking at forecasts built with

[2] The list of papers using benchmarks like the random walk or autoregressive models include Chen, Rogoff and Rossi (2011, 2010, 2014); Rossi (2012); Rubaszek, M. (2021); Rubaszek, Karolak and Kwas (2020) and Kwas and Rubaszek (2021) just to name a few.

estimated parameters. In addition, our paper shows that MSCI-based forecasts with estimated parameters are useful to obtain positive gross returns with a simple trading strategy.

The rest of the paper is organized as follows. In section 2, we present our data and forecasting models. In section 3, we present and discuss our in-sample and out-of-sample results. Finally, in section 4 we present our conclusions.

2. Data and Models

We consider a monthly database for the period: 2001m01 to 2022m09. This database contains the MSCI Index, spot and 3-month future values of all six base metals (Aluminum, Copper, Lead, Nickel, Tin and Zinc) and three equity indices from major commodity exporters: IPSA from Chile, ASX from Australia and NZX from New Zealand[3]. Finally, we also consider data from the Invesco DB Base Metals Fund, which is an ETF offering exposure to base metals. In Appendix part 1 we present the composition of the MSCI index in terms of countries (Table A.1) and in terms of base metals coverage (Table A.2). The source of our data is Refinitiv Datastream (ex Thomson Reuters Datastream) from which we obtain daily close prices of each asset. With these daily prices, we transform our data to monthly frequencies by sampling from the last day of the month. Then, we build our monthly returns. Descriptive statistics for our variables are displayed in Table A3 in Appendix part 1.

We use the standard specifications described in Table 1 to explore predictability relative to common benchmarks in the literature. See for instance Kwas and Rubaszek (2021); Reeve and Vigfusson (2011); Fernandez (2017); Chen, Rossi and Rogoff (2010, 2011, 2014) and Pincheira and Hardy (2019)[4].

[3] Our nominal prices are denominated in US dollars and quoted in the London Metal Exchange.

[4] The Random Walk or simple autoregressions are frequently difficult benchmarks to beat when forecasting some assets returns (see, for instance Goyal and Welch (2008), Goyal, Welch and Zafirov (2022), West and Wong (2014), Kwas and Rubaszek (2021), Rossi (2012) and Meese and Rogoff (1983)).

Table 1 Econometric Specifications

1. MSCI-AR(1):
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \rho\Delta ln(M_{t-1}) + \varepsilon_{1t}$$

2. MSCI-RW:
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \varepsilon_{2t}$$

3. MSCI-DRW:
$$\Delta ln(M_t) = \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \varepsilon_{3t}$$

4. MSCI-Basis:
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \gamma[\ln(Future3_{t-1}) - \ln(M_{t-1})] + \rho\Delta ln(M_{t-1}) + \varepsilon_{4t}$$

5. MSCI-AR(2):
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \rho_1\Delta ln(M_{t-1}) + \rho_2\Delta ln(M_{t-2}) + \varepsilon_{5t}$$

6. MSCI-ASX:
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \rho_1\Delta ln(M_{t-1}) + \delta\Delta ln(ASX_{t-1}) + \varepsilon_{6t}$$

7. MSCI-IPSA:
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \rho_1\Delta ln(M_{t-1}) + \delta\Delta ln(IPSA_{t-1}) + \varepsilon_{7t}$$

8. MSCI-NZX:
$$\Delta ln(M_t) = c + \beta[\Delta ln(MSCI_{t-1}) + \Delta ln(MSCI_{t-2})] + \rho_1\Delta ln(M_{t-1}) + \delta\Delta ln(NZX_{t-1}) + \varepsilon_{8t}$$

Notes: RW stands for Random Walk, whereas DRW stands for Driftless Random Walk. Source: Authors' elaboration.

where

$$\Delta ln(M_t) \equiv ln(M_t) - ln(M_{t-1})$$
$$\Delta \ln(MSCI_t) \equiv ln(MSCI_t) - ln(MSCI_{t-1})$$

M_t stands for a spot metal price at time *t* while $Future3_{t-1}$ stands for the three-month future of the same metal at time t-1. Similarly, $MSCI_t$ corresponds to the MSCI at time *t*. IPSA, AZX and NZX are acronyms that identifies the main equity indices from Chile, Australia and New Zealand respectively. Finally, ε_{it} for $i = 1, 2, \ldots, 8$ represent error terms.

Following Pincheira and Hardy (2019), who use a bimonthly lag of a commodity currency to predict monthly base metal returns, in our specifications we also use a bimonthly return of the MSCI as the predictor under evaluation. This is equivalent to use the first two lags of MSCI returns with equal coefficients. Our preliminary inspections show that, in general, both coefficients tend to be similar in magnitude and sign. Moreover, Table 2 shows results of a Wald test evaluating the null hypotheses of equality in these coefficients. For the construction of this table we considered specification 1 in Table 1. Table 2 shows that we fail to reject these null hypotheses for all metals and for the LMEX as well.

When $\beta = 0$, specifications 1-3 in Table 1 indicate that one period log returns of base metals follow either an AR(1) model or a white noise plus a potentially nonzero constant. These specifications are similar to those used in Chen, Rossi and Rogoff (2010, 2011, 2014); Rossi (2012) and Pincheira and Hardy (2019). Specification 4 in Table 1 follows a long tradition in the literature by adding the information contained in futures as a potential predictor for commodities. See for instance Reeve and Vigfusson (2011) and Fernandez (2017). Specification 5 in Table 1 is simply an AR(2) model for one period log returns of base metals augmented with the first lag of the bimonthly log return of the MSCI. Finally, specifications 6-8 in Table 1 are designed to compare the predictive ability of the MSCI Index relative to the ability of the equity indices of Chile (IPSA), Australia (ASX) and New Zealand (NZX). The idea here is to evaluate the MSCI relative to models similar to those used by Rossi (2012) and Chen, Rossi and Rogoff (2011).

Our null hypothesis that $\beta = 0$ is evaluated both in-sample and out-of-sample for one-step-ahead forecasts, leaving the multistep-ahead analysis as an extension for further research. For the in-sample evaluation we consider a one-sided alternative hypothesis $H_A\colon \beta > 0$ as suggested by Inoue and Kilian (2004) and Neely, Rapach, Tu and Zhou (2014). We follow their advice because we think that a future expected positive shock in metal prices will actually lead to an increment in both the value of firms producing metals and the price of the commodity itself. Consequently, for the in-sample evaluation we consider one-sided t-statistics using standard errors according to Newey and West (1987, 1994).

For out-of-sample evaluation we use three main different strategies. First we use the ENCNEW test of Clark and McCracken (2001) to evaluate the null hypothesis that $\beta = 0$ against the alternative hypothesis $H_A\colon \beta \neq 0$. This test is designed to compare population Mean Squared Prediction Error (MSPE) between nested models. A positive enough ENCNEW statistic indicates that the population MSPE of a model including the MSCI Index is smaller than the MSPE of the same model but under the $\beta = 0$ restriction. As a second strategy we use the Correlation-Based test by Pincheira and Hardy (2022). The null hypothesis here is that the correlation with the target variable of the forecasts coming from the models with and without MSCI is the same. The alternative hypothesis is that forecasts coming from the model including the MSCI Index have higher correlation with the target variable relative to forecasts of the same model but omitting the information contained in this index (case $\beta = 0$). Finally, we use a trading-based test originally proposed by Anatolyev and Gerco (2005). The null hypothesis here is that log commodity prices are just driftless random walks. The alternative hypothesis posits that more adequate models are those in Table 1 with an unrestricted β parameter[5]. Notice that with this last strategy, we can only infer something specific about the predictive ability of the MSCI Index when using model 3 in Table 1. Rejection of the null using model 8 in

[5] Strictly speaking, we use a simple modification of the test by Anatolyev and Gerco (2005). This modification was introduced by Pincheira, Hardy and Bentancor (2022) for the particular case in which the null hypothesis is that of a driftless random walk model. Pincheira, Hardy and Bentancor (2022) show that their modification produces a better sized and more powerful test in this particular drifless random walk case.

Table 1, for instance, should be interpreted as providing evidence against a driftless random walk model, yet we could not tell apart the exact predictability driver: either the MSCI, the NSX, the first lag of the commodity return or some combination of them. We also consider a fourth out-of-sample strategy in Appendix part 2. We use a Mean Directional Accuracy test to evaluate the hypotheses: $\beta = 0$ v/s $\beta \neq 0$. In our application this strategy is not particularly successful, yet, given that it is a common exercise in the literature, we add it for completion.

Table 2 Wald Test Evaluating the Linear Restriction in MSCI Lags

Aluminum	Wald statistic	0.036
	p-value	0.849
Copper	Wald statistic	0.022
	p-value	0.882
Lead	Wald statistic	0.588
	p-value	0.443
Nickel	Wald statistic	0.090
	p-value	0.764
Tin	Wald statistic	0.000
	p-value	0.983
Zinc	Wald statistic	0.091
	p-value	0.763
Lmex	Wald statistic	0.033
	p-value	0.857

Notes: The null hypothesis is that of equality of both coefficients associated to the first two lags of MSCI monthly returns. We use specification 1 in Table 1 for the construction of Table 2.

In the out-of-sample evaluation we consider a recursive or expanding scheme to update the estimates of the parameters in Table 1[6]. As it is standard in the forecasting literature, we denote by P the number of one-step-ahead forecasts and by R the size of the initial estimation window. Then $P + R = T$, where T is the total

[6] The setup for a recursive/expanding scheme is as follows: Let T be the total sample size, P the number of one-step-ahead forecasts and R the number of observations used to obtain the first estimates of our parameters (say, estimates of β) so that R+P=T. In a recursive/expanding scheme, the sample size used to update estimates of β grows as a larger sample size becomes available for estimation. For instance, the first estimate of β is obtained from the first R observations of our sample. This estimate is used to build the forecast for observation R+1. Our second estimate of β is obtained using the first R+1 observations available. Here the estimation window has expanded with one more observation. With this new estimate, we build our forecast for observation R+2. We continue iterating like this until the estimation window has expanded to contain T-1 observations. With this sample we construct the last parameter estimate and forecast for observation T. West (2006), pages 106-107 offers a more detailed explanation of different schemes that are also used to update parameter estimates.

number of available observations. For robustness, we split our sample in three different ways: considering $P/R = 2$, $P/R = 1$ and $P/R = 0.4$.

3. Empirical Results

3.1 In–Sample Analysis

Table 3 reports estimates of the β coefficient associated to the first lag of bimonthly returns of the MSCI Index for all eight specifications in Table 1. We use HAC standard errors according to Newey and West (1987, 1994). Columns 2-8 in Table 3 show results for Aluminum, Copper, Lead, Nickel, Tin, Zinc and the LMEX. In column 9 we report the average coefficient of determination obtained across all commodities. We observe that the estimated β coefficients associated to the MSCI are always positive. So, as expected, higher MSCI returns are associated to higher base metal returns in the near future as well. With only two exceptions, these estimated β coefficients are all statistically significant at usual significance levels. Average coefficients of determination tend to be low, however, in a range of 3.7% to 4.7%. Despite these low R^2, our in-sample results provide sound statistical evidence of a predictive relationship between the MSCI and all base metals.

Specifications 6, 7 and 8 from Table 1 are particularly important to us, because we see in action two relevant competing forecasts for base metals: the MSCI and an equity index from a relevant commodity exporter country. These specifications resemble those of Chen, Rossi and Rogoff (2011) and Rossi (2012).

Table 4 shows a full description of our estimates of specification 7 in Table 1. Similar results for specifications 6 and 8 are not presented to save space, but they are available upon request. Specification 7 considers three main predictors for base metal returns: bimonthly MSCI returns, monthly IPSA returns, and the first lag of each base metal return. Table 4 shows that MSCI returns are the only statistically significant variables in each regression. Table 5 shows estimates of the same regression but restricting to zero the coefficient associated to MSCI. It can be seen that IPSA returns have no ability to predict base metal returns as their associated estimated coefficients are close to zero, with no statistical significance at usual confidence levels and R^2 are, in general, quite low.

Results for specifications 6 and 8 are similar to those presented in Table 4. They show that the equity indices from either Australia or New Zealand do not overshadow the predictability of MSCI returns as their coefficients are always positive and statistically significant in most of the entries of the respective tables. It is relevant to mention, however, that differing from the equity indices from Chile or Australia, the New Zealand index does have an important predictive ability for base metals. Nevertheless, the message is sound and clear, MSCI returns are not overshadowed by these equity indices.

Table 3 Forecasting Base Metal Returns with the MSCI ACWI Metals and Mining Index

(1)	*(2)* *Aluminum*	*(3)* *Copper*	*(4)* *Lead*	*(5)* *Nickel*	*(6)* *Tin*	*(7)* *Zinc*	*(8)* *Lmex*	*(9)* *Average R^2*
MSCI-AR1	**0.114***** **(0.044)**	**0.141**** **(0.074)**	**0.149**** **(0.070)**	**0.109*** **(0.070)**	**0.100**** **(0.050)**	**0.078*** **(0.049)**	**0.124**** **(0.059)**	0.043
MSCI-RW	**0.107**** **(0.047)**	**0.147**** **(0.071)**	**0.126**** **(0.073)**	**0.108**** **(0.060)**	**0.134***** **(0.049)**	**0.063*** **(0.043)**	**0.123**** **(0.057)**	0.040
MSCI-DRW	**0.108**** **(0.047)**	**0.149**** **(0.071)**	**0.128**** **(0.071)**	**0.110**** **(0.055)**	**0.136***** **(0.048)**	**0.065*** **(0.045)**	**0.125**** **(0.056)**	0.037
MSCI-Basis	**0.115***** **(0.045)**	**0.141**** **(0.076)**	**0.149**** **(0.069)**	**0.109*** **(0.069)**	**0.103**** **(0.050)**	**0.072*** **(0.049)**	**0.124**** **(0.059)**	0.047
MSCI-AR2	**0.129***** **(0.045)**	**0.112*** **(0.084)**	**0.153**** **(0.085)**	**0.113*** **(0.076)**	**0.068*** **(0.050)**	0.061 (0.060)	**0.106*** **(0.066)**	0.046
MSCI-ASX	**0.109***** **(0.044)**	**0.143**** **(0.071)**	**0.146**** **(0.073)**	**0.124*** **(0.078)**	**0.107**** **(0.054)**	**0.071*** **(0.050)**	**0.124**** **(0.058)**	0.043
MSCI-IPSA	**0.125***** **(0.045)**	**0.150**** **(0.075)**	**0.163**** **(0.075)**	**0.124**** **(0.072)**	**0.109**** **(0.054)**	**0.085*** **(0.056)**	**0.134**** **(0.060)**	0.045
MSCI-NZX	**0.105***** **(0.044)**	**0.129**** **(0.068)**	**0.151**** **(0.072)**	0.083 (0.068)	**0.090**** **(0.051)**	**0.062*** **(0.048)**	**0.113**** **(0.056)**	0.047

Notes: MSCI stands for MSCI ACWI Metal & Mining Index returns. MSCI(-1) and MSCI(-2) are the first and second lags of MSCI returns respectively. Aluminum, Copper, Lead, Nickel, Tin, Zinc and Lmex denote one-month returns of the respective assets. Table 3 reports estimations of the β coefficient associated to the first lag of bimonthly returns of the MSCI Index for all eight specifications in Table 1. We use HAC standard errors according to Newey and West (1987, 1994). *p < 10%, **p < 5%, ***p < 1%.

Source: Authors' elaboration.

Table 4 Forecasting Base Metal Returns with the MSCI ACWI Metals and Mining Index and the Main Equity Index from Chile (IPSA)

	Aluminum	*Copper*	*Lead*	*Nickel*	*Tin*	*Zinc*	*Lmex*
MSCI(-1)+MSCI(-2)	**0.125*****	**0.150****	**0.163****	**0.124****	**0.109****	**0.085***	**0.134****
	(0.045)	**(0.075)**	**(0.075)**	**(0.072)**	**(0.054)**	**(0.056)**	**(0.060)**
IPSA(-1)	-0.072	-0.070	-0.096	-0.108	-0.065	-0.045	-0.077
	(0.086)	(0.090)	(0.112)	(0.136)	(0.108)	(0.111)	(0.079)
M(-1)	-0.028	0.022	-0.083	0.003	0.124	-0.051	0.007
	(0.083)	(0.086)	(0.075)	(0.074)	(0.090)	(0.071)	(0.076)
c	0.001	0.005	0.005	0.005	0.004	0.004	0.004
	(0.004)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.004)
Wald statistic	0.776	1.776	1.721	1.145	1.891	0.605	1.887
R^2	0.054	0.061	0.043	0.019	0.064	0.012	0.064
Obs	258	258	258	258	258	258	258

Notes: MSCI stands for MSCI ACWI Metal & Mining Index returns. IPSA corresponds to the main equity index in Chile. MSCI(-1) and MSCI(-2) are the first and second lags of MSCI returns respectively. Aluminum, Copper, Lead, Nickel, Tin, Zinc and Lmex denote one-month returns of the respective assets. Table 4 reports estimates of specification 7 in Table 1. We use HAC standard errors according to Newey and West (1987, 1994). *p < 10%, **p < 5%, ***p < 1%.

Source: Authors' elaboration.

Table 5 Forecasting Base Metal Returns with the Main Equity Index from Chile (IPSA)

	Aluminum	*Copper*	*Lead*	*Nickel*	*Tin*	*Zinc*	*Lmex*
IPSA(-1)	0.028	0.033	0.044	-0.008	0.019	0.026	0.004
	(0.088)	(0.094)	(0.126)	(0.136)	(0.107)	(0.094)	(0.077)
M(-1)	0.080	0.145	-0.015	0.058	0.197**	-0.001	0.150
	(0.111)	(0.106)	(0.074)	(0.068)	(0.096)	(0.067)	(0.113)
c	0.001	0.005	0.005	0.004	0.004	0.004	0.003
	(0.004)	(0.005)	(0.006)	(0.007)	(0.005)	(0.006)	(0.005)
Wald statistic	0.191	1.224	0.977	0.440	0.669	0.669	0.594
R^2	0.008	0.023	0.001	0.003	0.040	0.000	0.023
Obs	259	259	259	259	259	259	259

Notes: IPSA(-1) corresponds to the first lag of the monthly returns of the main equity index in Chile. Aluminum, Copper, Lead, Nickel, Tin, Zinc and Lmex denote one-month returns of the respective assets. M(-1) represents the first lag of the respective commodity return. Table 5 reports estimates of specification 7 in Table 1 when β=0. We use HAC standard errors according to Newey and West (1987, 1994). *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

To mitigate the potential overfitting problems associated to in-sample analyses, in the next subsections we engage in an out-of-sample evaluation.

3.2 Out–of-Sample Analysis at the Population Level

Now we explore predictability out-of-sample, at the population level, using the ENCNEW test of Clark of McCracken (2001). Table 6 shows results of this test when the number of forecasts is twice the number of observations in the first estimation window ($P/R = 2$). Table 7 shows results when $P/R = 1$ while Table 8 considers the case in which $P/R = 0.4$.

Tables 6-8 indicate that most of the models including MSCI returns outperform all the eight benchmarks in Table 1. In particular, 79.2% of the entries in

Tables 6-8 are statistically significant at least at the 10% significance level. We detect strong and relatively robust predictability of the MSCI for Aluminum, Copper, Lead, and LMEX returns. In particular, we reject the null hypothesis in 100% of the entries for Aluminum, in 96% of the entries for LMEX and Lead, and in 92% of the entries for Copper. The evidence for Tin and Nickel is slightly weaker, while for Zinc we only find predictability in 21% of the corresponding entries. Notably, for the case of Aluminum, we reject the null hypothesis at the 1% significance level in 91.7% of the entries.

Table 6 Forecasting Base Metals Returns with the MSCI Index. ENCNEW Statistic for Out-Of-Sample Analysis with Recursive Windows (P/R=2).

	Aluminum	*Copper*	*Lead*	*Nickel*	*Tin*	*Zinc*	*Lmex*
MSCI-AR(1)	**7.46*** **	**5.83*** **	**6.70*** **	-0.46	**5.24*** **	-0.81	**6.56*** **
MSCI-RW	**8.45*** **	**14.79*** **	**6.07*** **	0.73	**11.45*** **	-0.10	**12.98*** **
MSCI-DRW	**9.22*** **	**17.00*** **	**7.87*** **	**2.17** **	**12.61*** **	0.32	**15.02*** **
MSCI-Basis	**7.79*** **	**6.70*** **	**4.60*** **	-0.56	**5.75*** **	-1.69	**7.75*** **
MSCI-AR(2)	**8.67*** **	**1.81* **	**6.06*** **	-0.09	**2.41** **	-2.84	**2.75** **
MSCI-ASX	**5.16*** **	**4.65*** **	**6.36*** **	-0.25	**4.14*** **	-1.40	**5.33*** **
MSCI-IPSA	**8.82*** **	**7.00*** **	**9.15*** **	0.21	**4.93*** **	-0.53	**8.03*** **
MSCI-NZX	**5.3*** **	**3.67** **	**6.38*** **	-1.85	**3.67** **	-1.72	**4.45*** **

Notes: 10%, 5% and 1% critical values are 1.280, 2.085 and 4.134 respectively when P/R=2 and there is only one excess parameter. P stands for the number of one-step-ahead forecasts and R for the sample size of the first estimation window. We consider for benchmarks all the models from Table 1, when the coefficient associated to MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

Table 7 Forecasting Base Metals Returns with the MSCI Index. ENCNEW Statistic for Out-Of-Sample Analysis with Recursive Windows (P/R=1).

	Aluminum	*Copper*	*Lead*	*Nickel*	*Tin*	*Zinc*	*Lmex*
MSCI-AR(1)	**5.28*** **	**5.66*** **	**5.47*** **	**2.26** **	**1.65** **	**1.73** **	**5.94*** **
MSCI-RW	**3.46*** **	**5.01*** **	**2.38** **	**2.13** **	**3.23*** **	0.91	**5.62*** **
MSCI-DRW	**3.34*** **	**3.98*** **	**1.74** **	**2.00** **	**2.73** **	0.84	**4.92*** **
MSCI-Basis	**5.40*** **	**2.85** **	**2.24** **	**1.82** **	**1.36* **	0.10	**4.84*** **
MSCI-AR(2)	**5.18*** **	**1.20* **	**4.41*** **	**1.82** **	-0.64	0.71	**1.41* **
MSCI-ASX	**4.16*** **	**6.05*** **	**3.66*** **	**2.95** **	**2.35** **	**1.54* **	**6.12*** **
MSCI-IPSA	**6.63*** **	**6.31*** **	**5.22*** **	**2.96** **	**2.24** **	**2.02** **	**7.14*** **
MSCI-NZX	**4.41*** **	**5.02*** **	**4.75*** **	**1.31* **	**1.10* **	**1.17* **	**5.08*** **

Notes: 10%, 5% and 1% critical values are 0.984, 1.584 and 3.209 respectively when P/R=1 and there is only one excess parameter. P stands for the number of one-step-ahead forecasts and R for the sample size of the first estimation window. We consider for benchmarks all the models from Table 1, when the coefficient associated to MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

Table 8 Forecasting Base Metals Returns with the MSCI Index. ENCNEW Statistic for Out-Of-Sample Analysis with Recursive Windows (P/R=0.4).

	Aluminum	*Copper*	*Lead*	*Nickel*	*Tin*	*Zinc*	*Lmex*
MSCI-AR(1)	**1.65****	**2.95*****	**3.39*****	**1.30****	-0.02	0.50	**2.73*****
MSCI-RW	**2.81*****	**2.10*****	**1.45****	**1.30****	**3.97*****	0.47	**3.33*****
MSCI-DRW	**2.89*****	**2.36*****	**1.60****	**1.38****	**4.19*****	0.54	**3.56*****
MSCI-Basis	**1.67****	0.25	0.63	**0.94***	**1.42****	-0.55	**0.70***
MSCI-AR(2)	**2.29*****	0.28	**2.52*****	**1.08****	-1.05	0.28	0.30
MSCI-ASX	**2.51*****	**3.13*****	**2.86*****	**1.79****	0.57	**0.80***	**3.25*****
MSCI-IPSA	**2.77*****	**3.42*****	**2.39*****	**1.78****	**0.71***	0.43	**3.49*****
MSCI-NZX	**1.98****	**2.6*****	**3.02*****	**0.78***	-0.42	0.36	**2.49*****

Notes: 10%, 5% and 1% critical values are 0.685, 1.079 and 2.098 respectively when P/R=0.4 and there is only one excess parameter. P stands for the number of one-step-ahead forecasts and R for the sample size of the first estimation window. As benchmarks we consider all the models from Table 1, when the coefficient associated to MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

All in all, results in Tables 6-8 show sound out-of-sample evidence of predictability from the MSCI to most base metal prices at the population level.

3.3 Out-of-Sample Analysis at the Sample Level: Forecast Accuracy

The out-of-sample analyses presented in subsection 3.2 evaluate differences in MSPE at the population level. Due to sampling error, however, the most accurate model at the population level may not necessarily be the most accurate at the sample level. This distinction is particularly relevant when comparing nested models, because the nested and nesting models contain a different number of parameters which might penalize the forecasting performance of the bigger nesting model. For this reason, we compute out-of-sample R^2_{OOS} coefficients following Goyal and Welch (2008) and Pincheira and West (2016). These out-of-sample R^2_{OOS} are useful to compare the predictive performance of the models in a given sample. They are computed as follows:

$$R^2_{OOS} = 1 - \frac{MSPE_{average}}{MSPE_{benchmark}}$$

where $MSPE_{average}$ denotes the out-of-sample MSPE when predicting base metals returns with the average of the forecasts coming from the models including the MSCI and their respective benchmarks excluding this index. We follow this approach because, according to Pincheira and West (2016), with some convex combinations between the nesting and nested models we should be able to outperform the nested benchmark at the sample level whenever the core statistic of the ENCNEW test is positive. In our notation $MSPE_{benchmark}$ represents the out-of-sample MSPE of each benchmark in Table 1. A zero value for R^2_{OOS} means that both predictive strategies (the combination and the benchmark itself) produce similarly accurate forecasts. Negative values mean that the benchmark outperforms the strategy that contains the

MSCI. Finally, a positive R^2_{OOS} shows that the combined strategy that includes the MSCI outperforms its benchmark.

Table 9 Average Out-Of-Sample R2 when Forecasting Base Metals with a strategy that Includes the MSCI Index

(1)	*(2)* Aluminum	*(3)* Copper	*(4)* Lead	*(5)* Nickel	*(6)* Tin	*(7)* Zinc	*(8)* Lmex
Average In-Sample R^2 across all models	0.053	0.060	0.038	0.019	0.061	0.013	0.062
Average OOS-R^2 across all models P/R=2	0.030	0.025	0.026	-0.004	0.023	-0.014	0.028
Average OOS-R^2 across all models P/R=1	0.023	0.020	0.014	0.013	0.005	0.007	0.024
Average OOS-R^2 across all models P/R=0.4	0.020	0.021	0.021	0.015	0.006	0.004	0.025

Notes: Average across all models in Table 1.

Table 9 shows that most averages of out-of-sample R^2_{OOS} are positive, which indicates that the information contained in the MSCI is valuable to forecast base metals not only at the population level but also at the sample level, at least in some specifications. The only exceptions with negative R^2_{OOS} are found for Nickel and Zinc when P/R=2. At least for Zinc, this is consistent with the weak results reported in Tables 6-8. Average out-of-sample R^2_{OOS} are relatively small. In particular, they are smaller than their in-sample counterparts. This could be a consequence of the construction of R^2_{OOS} as a function of a convex combination of forecasts, yet this is also consistent with a literature reporting discrepancies between in-sample and out-of-sample evaluations probably due to overfitting related issues. All in all, the high percentage of positive average R^2_{OOS} reported in Table 9 shows that the information contained in the MSCI is useful to predict base metal returns at the sample level at least with some of our specifications.

In this subsection we have studied the accuracy of the models equipped with the MSCI Index at the sample level. Yet, we have refrained from carrying out statistical significance analyses. We do that in the following subsection with a recent approach based on correlations.

3.4 Out-of-Sample Analysis: Correlations with the Target Variable

In a recent paper, Pincheira and Hardy (2022) pointed out that MSPE comparisons between two forecasts may be controversial. In particular, when some conditions of efficiency are not met, the forecast displaying the highest MSPE may also exhibit the highest correlation with the target variable. The authors label this result as “the MSPE paradox,” and propose the use of correlations between the forecasts and the target variable as an additional measure of predictive ability. Using the Delta method, they provide a simple test to evaluate the null hypothesis of equal correlations with the target variable.

Using almost all the models in Table 1, Table 10 next reports differences in correlations with the target variable between the models with and without MSCI. The only model we leave out from Table 1 is the driftless random walk which predicts exactly zero future returns. Given that a zero forecast has also zero variance, a correlation coefficient cannot be defined for this benchmark.

Our results are striking. First, 90.5% of the entries in Table 10 are positive: this means that the correlation of the MSCI-based forecasts with the target variable is higher than the correlation between the benchmark and the target variable. Moreover, in 69% of our exercises we reject the null hypothesis of equal correlations at least at the 10% significance level.

The second panel in Table 10, labeled MSCI-RW, compares the correlations with the target variable of the historical mean model (a constant estimated in recursive windows) and a model with a constant and MSCI lags. Results are striking in favor of models containing the MSCI, as we reject the null hypothesis in all the entries of that panel. In terms of individual commodities, the most robust results are obtained for Copper, Lead, LMEX and Aluminum. For these assets rejections of the null hypothesis in favor of the models containing the MSCI are achieved in 90% of the entries for Copper and Lead, in 86% of the entries for LMEX and in 81% of the entries for Aluminum. The worst performing commodities are Tin and Zinc.

The last three panels in Table 10 compare the performance of models including MSCI returns relative to models predicting base metals with equity indices from major commodity exporters, as in Rossi (2012). For LMEX, Copper and Aluminum, results in favor of the forecasts built with MSCI returns are striking. The null hypothesis is rejected in 26 out of 27 cases. Relatively good results are also obtained for Lead and Nickel. For Zinc the null hypothesis is rejected in 4 out of 9 cases, whereas for Tin we find no rejections whatsoever.

Our main conclusions of the results in Table 10 are the following: First, from the second panel of the table, we see that MSCI returns have important information to predict base metals, information that can be also used at the sample level. Second, from the last three panels in Table 10, we see that MSCI returns can be useful to predict some base metal returns beyond the information contained in other equity indices. This is especially relevant for Copper, Lead, LMEX and Aluminum. These last results are important in two dimensions. First, they refine the results in Chen, Rossi and Rogoff (2011) and Rossi (2012) by showing another equity index with the ability to predict base metals, and second, our results extend those presented in the aforementioned papers by providing evidence of predictability from equity indices to base metals not only at the population level, but also at the sample level.

Table 10 Differences in Correlations with the Target Variable. The Forecasts under Comparison are those from Table 1 Including and Excluding the Information Contained in the MSCI Index.

(1)	*(2)* *Aluminum*	*(3)* *Copper*	*(4)* *Lead*	*(5)* *Nickel*	*(6)* *Tin*	*(7)* *Zinc*	*(8)* *Lmex*
				MSCI-AR(1)			
P/R=2	**0.15***	**0.08**	**0.23***	0.02	0.05	**0.09***	**0.09**
P/R=1	**0.25**	**0.20***	**0.37***	**0.19***	-0.01	**0.39***	**0.18***
P/R=0.4	0.01	**0.20**	**0.50**	**0.19**	-0.13	**0.24**	**0.14***
				MSCI-RW			
P/R=2	**0.39***	**0.35**	**0.29**	**0.18***	**0.33**	**0.22***	**0.38**
P/R=1	**0.30***	**0.22**	**0.15**	**0.25***	**0.19***	**0.26***	**0.27***
P/R=0.4	**0.35**	**0.30**	**0.21**	**0.31**	**0.34***	**0.22***	**0.35**
				MSCI-Basis			
P/R=2	**0.15***	**0.08**	**0.23***	0.02	0.06	-0.01	**0.09***
P/R=1	**0.26**	**0.20***	**0.36***	**0.18***	0.00	0.02	**0.19***
P/R=0.4	0.03	**0.20**	**0.49**	**0.18**	-0.06	-0.03	**0.14***
				MSCI-AR(2)			
P/R=2	**0.17***	0.02	**0.25***	0.05	0.01	-0.02	0.03
P/R=1	**0.23**	**0.06***	**0.21***	**0.15**	-0.07	0.04	0.03
P/R=0.4	0.12	0.02	**0.16***	**0.15**	-0.08	0.03	-0.01
				MSCI-ASX			
P/R=2	**0.07**	**0.06**	0.13	0.01	0.04	0.01	**0.07***
P/R=1	**0.10**	**0.15***	0.05	**0.19***	0.03	**0.06**	**0.14***
P/R=0.4	**0.11**	**0.15**	**0.13***	**0.22***	-0.03	0.07	**0.14**
				MSCI-IPSA			
P/R=2	**0.18***	**0.10**	**0.29***	0.05	0.06	**0.10**	**0.12**
P/R=1	**0.27***	**0.20***	**0.26**	**0.23***	0.03	**0.20***	**0.21***
P/R=0.4	0.14	**0.20***	**0.21***	**0.24**	-0.05	0.08	**0.16**
				MSCI-NZX			
P/R=2	**0.09**	**0.06**	**0.25***	-0.06	0.03	0.01	**0.06***
P/R=1	**0.14**	**0.16***	**0.20**	**0.06**	-0.02	**0.05***	**0.14***
P/R=0.4	**0.11***	**0.14**	**0.22***	**0.06***	-0.10	0.03	**0.11***

Notes: We use models Table 1 to build the forecasts used in Table 10. Stars indicate statistical significance when testing the null hypothesis of equal correlations with the target variable. We use the correlation-based test by Pincheira and Hardy (2022), which is asymptotically normal.

3.5 Out-of-Sample Analysis: A Trading-Based Test

Based on the trading strategy proposed by Anatolyev and Gerko (2005), Pincheira, Hardy and Bentancor (2022) provide a Straightforward Excess Profitability test (SEP) to evaluate the driftless random walk hypothesis. When this test detects predictability, it means that the rate of returns of a trading strategy based on our forecasts is "positive enough". In this sense it provides a more practical notion of predictability that measures based only on statistical loss functions. The trading strategy is as follows: buy the commodity if its predicted return is positive, and sell the commodity otherwise. Intuitively, the investor modifies its decision each month based on the latest forecast. The one-period return is simply $r_{t+1} = sign(Forecast_t) * Y_{t+1}$ where Y_{t+1} is the realized return of the target variable, and $sign(Forecast_t) = 1$ if $Forecast_t \geq 0$, and $sign(Forecast_t) = -1$ otherwise. Given that trading on spot commodity prices is unlikely due to delivery, transaction and storage costs, we mainly evaluate this test using three months futures for our six base metals[7]. We stick to LMEX given that this is an index. We also add an ETF Base Metal Fund to evaluate this trading strategy. We adopt here the vision of Anatolyev and Gerko (2005), in the sense of using their approach as a thought experiment aimed at evaluating predictive ability from a financial perspective without fully taking into account market frictions. Consequently, it is important to add a word of caution to practitioners: a real-life implementation of our strategy would require a thorough evaluation of all the costs associated to the trading process: transaction costs, margin requirements, short-selling constraints and profit taxes. As we are about to show, our paper provides promising results, but a practical implementation would require a serious evaluation of the costs involved in the process, costs that we are not considering here.

We emphasize that the null hypothesis posits that Y_{t+1} is a martingale difference. Pincheira, Hardy and Bentancor (2022) show that

$$SEP = \frac{\frac{\sqrt{P}}{P}\sum_{t=R+1}^{T+1} r_t}{\sqrt{\hat{V}}} \xrightarrow{P\to\infty} N(0,1)$$

where $\hat{V}$ is a consistent estimator of the variance of r_t.

Table 11 next shows the annualized returns when following this trading strategy using all the eight benchmarks in Table 1. Some features of Table 11 are worth mentioning. First, the great majority of the entries are nonnegative, with only one exception. This means that our forecast-based trading strategy yields positive gross returns in most exercises. Second, the average annualized return, considering all the entries in the table, is 9.6%. Third, according to the SEP statistic, we reject the null hypothesis of the random walk in 61% of the entries. Furthermore, we reject the null in all the exercises involving the LMEX, in 83% of the exercises involving Copper futures and in 79% of the exercises for the ETF Base Metal Fund.

Panel 3 in Table 11, labeled MSCI-DRW, allows us to infer something specific about the predictive ability of the MSCI Index when using model 3 in Table 1. Robust rejection of the null hypothesis is obtained for futures of Aluminum, Copper and Nickel. Likewise, robust rejection of the null is obtained for the LMEX Index and the ETF Base Metal Funds. These results show that the information contained in the MSCI is not only useful to increase the statistical accuracy of the forecast, but also to obtain positive and statistically significant gross returns with several of our assets using the trading strategy of Anatolyev and Gerco (2005).

Table 12 next is similar to Table 11, but it reports the excess return of our approach compared to the Buy and Hold strategy (henceforth B&H). In this regard, positive entries mean that our strategy leads to higher returns relative to those coming

[7] We also carried out the same exercise with spot prices with similar results. Details are available upon request.

from the B&H benchmark. There are two features of this table worth mentioning. First, our results are generally very good: 183 out of 192 of the entries are positive (95%), indicating superior gross returns from our strategy compared to the B&H[8]. Notably, the average excess return across all exercises is 8%. Second, the superiority of our approach seems to be robust to the time period and the asset being considered: all entries are positive, for all assets and time periods, with the sole exception of Zinc. Consistent with these results, Table A4 in Appendix part 1 shows annualized gross returns for the B&H benchmark for the same assets included in Table 12. The B&H strategy shows rather poor results. In particular, 8 out of the 24 exercises display negative gross returns, and the average profit across all commodities and time periods is just 1%. It is also fair to mention some exceptions of good behavior. The maximum figure in Table A4 is 11% (Nickel, P/R=0.4). Other remarkable exceptions are achieved for Copper when P/R=0.4 (7%) and for the LMEX index, also for P/R=0.4. (6%). Other than these few exceptions, the B&H strategy does not seem to work very well.

Notice that when trading with futures we need to impose a particular assumption. Given that the trading strategy of Anatolyev and Gerko (2005) requires closing the position at every month, we have the following asymmetry: We open a position with a 3-month future, but after a month, we close this position with a time to maturity of only 2 months. Since we do not have the price of a three-month future with a time to maturity of only two months, we are approximating that price with that of a three-month future with a time to maturity of three months. The implicit assumption here is that the average return of the strategy using our approximation is very close to the average return of the same strategy computed with the correct prices.

To circumvent this assumption, we also computed results of our trading strategy for spot prices. While trading on spot commodity prices is unlikely, as mentioned earlier, in the spirit of the thought experiment of Anatolyev and Gerko (2005) it is equally important to evaluate predictability in spot markets from a financial perspective. For those two reasons (to circumvent assumptions and for the importance of a financial evaluation of predictability) we also computed the annualized excess returns of our strategy relative to the B&H benchmark for spot prices. In general, these results are quantitatively very similar to those reported in Table 12. In particular i) the average return of the B&H strategy across all exercises is 2%, ii) the average excess return of our strategy compared to the B&H benchmark is 7%, and iii) 93% of the equivalent entries in Table 12 are positive, showing that our strategy fares better also for spot prices.

Finally, it is important to remark here that when trading our ETF, transactions are feasible and no particular assumptions are required.

[8] In unreported results, we notice that this superiority is not overshadowed when including transaction costs. According to Wang et al. (2020), transaction costs in futures markets range from 0.0004% (low cost) to 0.033% (high cost) (Locke and Venkatesh, 1997). Notably, our results remain qualitatively unaltered even considering the conservative "high cost" of 0.033%.

Table 11 Annualized Returns from the Forecast-Based Trading Strategy of Anatolyev and Gerco (2005)

(1)	*(2)* *Aluminum*	*(3)* *Copper*	*(4)* *Lead*	*(5)* *Nickel*	*(6)* *Tin*	*(7)* *Zinc*	*(8)* *Lmex*	*(9)* *ETF Base Metals Fund*
				MSCI-AR(1)				
P/R=2	**0.08****	**0.14*****	0.03	0.09	**0.13****	0.06	**0.10****	**0.09****
P/R=1	0.06	**0.09****	0.04	**0.16****	0.09	0.06	**0.08****	**0.13****
P/R=0.4	0.11	**0.10***	0.02	**0.22****	**0.18***	0.02	**0.11***	0.09
				MSCI-RW				
P/R=2	**0.11****	**0.13****	0.05	**0.13***	0.08	0.04	**0.11****	0.05
P/R=1	**0.09****	**0.08****	0.04	**0.19*****	0.04	0.03	**0.10****	**0.07***
P/R=0.4	**0.16****	0.09	0.01	**0.23****	0.09	0.01	**0.11***	0.08
				MSCI-DRW				
P/R=2	**0.12****	**0.18*****	0.06	**0.16****	**0.17****	0.07	**0.15*****	**0.10****
P/R=1	**0.09***	**0.10****	0.01	**0.14****	0.06	0.05	**0.09****	**0.14*****
P/R=0.4	**0.14****	**0.14****	0.06	**0.23****	**0.16***	**0.13***	**0.15****	**0.11***
				MSCI-Basis				
P/R=2	**0.09***	**0.14*****	0.03	0.08	**0.14****	0.05	**0.11****	**0.09****
P/R=1	0.04	**0.09****	0.03	**0.14***	**0.1***	0.07	**0.08****	**0.14****
P/R=0.4	0.08	0.09	-0.01	**0.22****	**0.18****	**0.15****	**0.10***	**0.11***
				MSCI-AR(2)				
P/R=2	0.04	**0.15*****	0.05	0.09	**0.14****	0.05	**0.10****	**0.06***
P/R=1	**0.07***	**0.10****	0.06	**0.15****	0.08	0.07	**0.09****	**0.09****
P/R=0.4	0.09	**0.11***	0.02	**0.20****	**0.16***	0.03	**0.12****	0.09
				MSCI-ASX				
P/R=2	**0.11****	**0.11****	0.07	0.08	**0.13***	0.04	**0.09****	**0.10****
P/R=1	0.05	**0.08****	0.04	**0.11***	0.09	0.01	**0.07***	**0.14*****
P/R=0.4	0.09	**0.10***	0.02	**0.21****	**0.19****	0.01	**0.11***	**0.11***
				MSCI-IPSA				
P/R=2	**0.11****	**0.14*****	**0.10***	0.09	**0.13***	0.05	**0.13*****	**0.07***
P/R=1	**0.09****	**0.10****	**0.08***	**0.16****	0.09	0.05	**0.13*****	**0.09****
P/R=0.4	**0.11***	**0.11***	0.02	**0.22****	**0.18***	0.00	**0.12****	0.07
				MSCI-NZX				
P/R=2	**0.11****	**0.11****	0.06	0.02	**0.15****	0.01	**0.12*****	**0.09****
P/R=1	**0.07***	0.06	**0.08***	0.07	**0.11***	0.00	**0.09****	**0.12****
P/R=0.4	0.08	0.09	0.04	**0.19***	**0.19****	0.02	**0.11***	**0.11***

Notes: We consider models in Table 1 to build the forecasts used in Table 11. Stars indicate statistical significance when testing the null hypothesis of commodity returns being martingale differences. Each entry reports the annualized return from a trading strategy based on our forecasts. We use the SEP test by Pincheira, Hardy and Bentancor (2022), which is asymptotically normal.

Table 12 Annualized Excess Returns from Our Models Compared to the Buy&Hold Strategy for 3-Month Futures Returns

(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
	Aluminum	***Copper***	***Lead***	***Nickel***	***Tin***	***Zinc***	***Lmex***	***ETF Base Metals Fund***
				MSCI-AR(1)				
P/R=2	**0.10**	**0.15**	**0.06**	**0.12**	**0.14**	**0.04**	**0.11**	**0.10**
P/R=1	**0.06**	**0.10**	**0.05**	**0.14**	**0.09**	**0.03**	**0.08**	**0.12**
P/R=0.4	**0.06**	**0.03**	**0.01**	**0.11**	**0.15**	-0.02	**0.05**	**0.09**
				MSCI-RW				
P/R=2	**0.13**	**0.14**	**0.08**	**0.15**	**0.09**	**0.02**	**0.12**	**0.06**
P/R=1	**0.09**	**0.09**	**0.05**	**0.17**	**0.04**	**0.00**	**0.09**	**0.06**
P/R=0.4	**0.11**	**0.02**	**0.00**	**0.12**	**0.07**	-0.03	**0.05**	**0.08**
				MSCI-DRW				
P/R=2	**0.14**	**0.19**	**0.09**	**0.18**	**0.17**	**0.05**	**0.16**	**0.11**
P/R=1	**0.08**	**0.10**	**0.02**	**0.13**	**0.06**	**0.02**	**0.09**	**0.13**
P/R=0.4	**0.09**	**0.07**	**0.06**	**0.12**	**0.13**	**0.09**	**0.09**	**0.11**
				MSCI-Basis				
P/R=2	**0.10**	**0.15**	**0.05**	**0.10**	**0.15**	**0.03**	**0.12**	**0.10**
P/R=1	**0.04**	**0.09**	**0.04**	**0.12**	**0.10**	**0.04**	**0.08**	**0.13**
P/R=0.4	**0.03**	**0.02**	**-0.02**	**0.11**	**0.16**	**0.10**	**0.04**	**0.11**
				MSCI-AR(2)				
P/R=2	**0.06**	**0.16**	**0.08**	**0.11**	**0.15**	**0.03**	**0.11**	**0.07**
P/R=1	**0.06**	**0.10**	**0.07**	**0.14**	**0.08**	**0.04**	**0.09**	**0.08**
P/R=0.4	**0.03**	**0.04**	**0.01**	**0.09**	**0.13**	-0.02	**0.06**	**0.09**
				MSCI-ASX				
P/R=2	**0.13**	**0.12**	**0.09**	**0.10**	**0.14**	**0.02**	**0.10**	**0.11**
P/R=1	**0.05**	**0.09**	**0.05**	**0.09**	**0.09**	-0.02	**0.06**	**0.13**
P/R=0.4	**0.03**	**0.03**	**0.01**	**0.10**	**0.16**	-0.03	**0.05**	**0.11**
				MSCI-IPSA				
P/R=2	**0.12**	**0.15**	**0.13**	**0.11**	**0.14**	**0.03**	**0.14**	**0.08**
P/R=1	**0.09**	**0.11**	**0.09**	**0.14**	**0.09**	**0.02**	**0.12**	**0.08**
P/R=0.4	**0.06**	**0.04**	**0.01**	**0.11**	**0.15**	-0.04	**0.06**	**0.07**
				MSCI-NZX				
P/R=2	**0.13**	**0.12**	**0.09**	**0.04**	**0.16**	-0.01	**0.13**	**0.10**
P/R=1	**0.06**	**0.06**	**0.09**	**0.05**	**0.11**	-0.04	**0.09**	**0.11**
P/R=0.4	**0.03**	**0.02**	**0.03**	**0.08**	**0.17**	-0.03	**0.05**	**0.11**

Notes: Figures in bold indicate higher returns with the trading strategy of Anatolyev and Gerko (2005) relative to the buy and hold approach. Source: Authors' elaboration.

4. Concluding Remarks

In this paper we show that the MSCI index has the ability to predict base metal returns one month ahead. We do this with a number of in-sample regressions and out-of-sample analyses. For some of our assets, like the LMEX, Aluminum and Copper, the evidence of predictability is strong and consistent across the great majority of our exercises; yet for some others like Lead, Nickel and Tin the evidence is clear but less robust. Zinc is the worst performing asset, probably because its predictability with MSCI returns is rather subtle as suggested by our in-sample regressions. Our results are in line with a present-value model for stock price determination and provide new evidence about the ability that stock market indices may have to forecast commodity prices.

One of the most interesting findings of our paper is that the MSCI Index tends to overshadow the predictive ability of three equity indices from major commodity exporter countries. From that point of view, our results are an improvement relative to those of Rossi (2012) and Chen, Rossi and Rogoff (2011). Furthermore, we provide evidence of predictability from the MSCI to base metals both at the population and at a sample level. While Rossi (2012) and Chen, Rossi and Rogoff (2011) do provide evidence of predictability from their equity indices to some commodities, the core of their analysis is at the population level. Our paper instead contains two exercises devoted to the analysis of the forecasts at the sample level, which is very helpful to forecasters and practitioners that make decisions looking at forecasts built with estimated parameters. In addition, our paper shows that MSCI-based forecasts with estimated parameters are useful to obtain positive gross returns with a simple trading strategy.

We leave as an extension for further research a formal evaluation of the predictive content of the MSCI relative to other successful predictors for commodity prices, like commodity-currencies. Similarly, it would be interesting to explore in further research the ability of the MSCI index to predict some other relevant industrial commodities and its derivatives both at short and long horizons.

APPENDIX

1. Some Additional and Useful Information

Table A1 Developed Markets Countries and Emerging Markets Countries of MSCI ACWI

MSCI ACWI *Index*					
Developed Markets Countries			Emergin Market Countries		
America	Europe	Pacific	America	Europe	Pacific
Canada	Austria	Australia	Brazil	Czech R.	China
USA	Belgium	Hong Kong	Chile	Egypt	India
	Denmark	Japan	Colombia	Greece	Indonesia
	Finland	N. Zealand	Mexico	Hungary	S. Korea
	France	Singapore	Peru	Poland	Malaysia
	Germany			Qatar	Pakistan
	Ireland			Russia	Philippines
	Israel			South Africa	Taiwan
	Italy			Turkey	Thailand
	Holland			UAE	
	Norway				
	Portugal				
	Spain				
	Sweden				
	Switzerland				
	U.K				

Source: msci.com - Market Cap Index

Table A2 MSCI ACWI Composition

	MSCI *Index*		
Subindustry	WCP	ACWI SM & MP	*Metal & Mining*
Agricultural Products	1.75%	-	-
Aluminium	0.38%	4.01%	2.44%
Copper	1.32%	6.81%	5.56%
Diversified Metals & Mining	13.51%	53.91%	49.09%
Fertilizers & Agricultural Chem	2.88%	-	-
Gold	3.75%	-	14.99%
Integrated Oil & Gas	53.46%	-	-
Oil & Gas Exploration & Produ	17.07%	-	-
Paper Products	1.41%	-	-
Precious Metals & Minerals	-	1.67%	1.39%
Silver	0.42%	-	1.38%
Steel	3.60%	33.61%	25.15%
Other	0.47%	-	-
Total Energy Industry	70.53%	0%	0%
Total Metals Industry	22.98%	100%	100%
Total Agricultural Industry	6.04%	0%	0%

Source: msci.com - March 2019

Table A3 Descriptive Statistics of Returns of Our Data. Sample Period (2001m01 to 2022m09)

(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*
	Aluminum	***Copper***	***Lead***	***Nickel***	***Tin***	***Zinc***	***Lmex***	***MSCI***	***ETF Base Metals***
Mean	0.001	0.006	0.005	0.004	0.005	0.004	0.004	0.003	-0.001
Median	-0.001	0.007	0.009	0.005	0.005	0.006	0.006	0.009	0.003
Std	0.059	0.075	0.086	0.102	0.073	0.080	0.062	0.083	0.063
Max	0.156	0.271	0.240	0.300	0.238	0.245	0.203	0.197	0.132
Min	-0.178	-0.443	-0.320	-0.297	-0.269	-0.412	-0.330	-0.395	-0.305
Obs	260	260	260	260	260	260	260	260	188
(11)	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**	**(19)**	**(20)**
	Aluminum-3	**Copper-3**	**Lead-3**	**Nickel-3**	**Tin-3**	**Zinc-3**	**ASX**	**IPSA**	**NZX**
Mean	0.001	0.005	0.005	0.004	0.005	0.004	0.003	0.006*	0.003
Median	0.000	0.007	0.010	0.005	0.004	0.007	0.010	0.004	0.008
Std	0.056	0.073	0.082	0.100	0.073	0.078	0.040	0.049	0.035
Max	0.148	0.260	0.229	0.298	0.237	0.237	0.095	0.149	0.075
Min	-0.173	-0.439	-0.318	-0.270	-0.271	-0.401	-0.238	-0.167	-0.147
Obs	260	260	260	260	260	260	260	260	260

Notes: Aside from monthly spot returns of the six base metals, Table A.3 contains information from monthly returns of the following indices: *London Metal Exchange* Index, MSCI ACWI *Metal* & *Mining Index*, IPSA, ASX, NZX and for the ETF Invesco DB Base Metals Fund. Table A.3 also includes descriptive statistics of 3 months future returns of all six base metals.

Table A4 Annualized Gross Returns from the Buy&Hold Strategy for the Lmex Index, 3-month Futures Returns of Base Metals and the Invesco DB Base Metals Fund

(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
	Aluminum	***Copper***	***Lead***	***Nickel***	***Tin***	***Zinc***	***Lmex***	***ETF Base Metals Fund***
Buy&Hold Strategy								
P/R=2	-0.02	-0.01	-0.02	-0.02	-0.01	0.02	-0.01	-0.01
P/R=1	0.01	0.00	-0.01	0.02	0.00	0.03	0.00	0.01
P/R=0.4	0.05	0.07	0.01	0.11	0.02	0.04	0.06	0.00

Source: Authors' elaboration.

2. Out-of-Sample Analysis at the Sample Level: Mean Directional Accuracy

Here we place our attention on the direction of the forecasts rather than in their MSPE. This type of analysis is also common in the forecasting literature. See for instance Pesaran and Timmermann (1992) and Cheung, Chinn, García-Pascual and Zhang (2019). Accordingly, we explore the success rate of our forecasts when predicting whether base metal returns are moving up or down[9]. We use a test based on the average of the following variable w_t:

$$w_t = \begin{cases} 1 & if \quad (\Delta ln(M_t))(f_{t-1}) > 0 \\ 0 & \quad\quad (\Delta ln(M_t))(f_{t-1}) \leq 0 \end{cases}$$

where f_{t-1} represents a generic forecast for the one-period return of one of the base metals $\Delta ln(M_t)$. Our w_t variable computes a "hit" whenever f_{t-1} signals an equivalent movement in $\Delta ln(M_t)$. Table A.4 reports the hit rate or Mean Directional Accuracy (DA) for our seven target variables when forecasting with models in Table 1[10]. Figures in Table A.4 report hit rates of the models containing MSCI returns, whereas inference is carried out with a one-sided Diebold and Mariano (1995), West (1996) test over the difference in hit rates between models equipped with MSCI returns and the corresponding benchmark excluding these latter returns[11]. Hit rates are computed as the simple average of w_t. We acknowledge that we do not try to address issues about parameter uncertainty here, so we simply applied the Diebold and Mariano (1995), West (1996) test in the spirit of Giacomini and White (2006).

While most of the entries in Table A.4 report figures greater than 50%, it is only for Copper that in the great majority of the relevant cells (86%) we reject the null hypothesis in favor of the models with MSCI returns. For Aluminum, Lead, Nickel and the LMEX, it is only in a few exercises that we reject the null in this direction. For Lead, Tin and Zinc, the situation is worst, as in only 1 exercise out of 63 we find statistically significant evidence of a superior hit rate from models containing MSCI returns. Aside from Copper, the Mean Directional Accuracy analysis we have carried out, does not provide important evidence for MSCI returns as a relevant ingredient to successfully forecast the change of direction in the rest of our commodities.

---

[9] The success rate is also known as "hit rate".

[10] We again omit the dritfless random walk benchmark from Table A.4 because its forecasts are exactly zero. According to our definition of w_t this would also imply a zero hit rate.

[11] Positive values in the Diebold and Mariano (1995), West (1996) statistic indicate a higher hit rate for the model containing MSCI returns.

Table A4 Mean Directional Accuracy when Forecasting Base Metals with the MSCI.

(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
	Aluminum	***Copper***	***Lead***	***Nickel***	***Tin***	***Zinc***	***Lmex***
				MSCI-AR(1)			
P/R=2	0.517	**0.523****	0.546	**0.563*****	0.540	0.523	0.523
P/R=1	0.519	**0.504*****	0.527	**0.565****	0.519	0.534	**0.519***
P/R=0.4	0.520	**0.493****	0.547	0.560	0.520	0.493	0.507
				MSCI-RW			
P/R=2	0.546	0.529	0.546	**0.569***	0.506	0.506	0.534
P/R=1	0.557	0.511	0.534	**0.580***	0.489	0.511	0.527
P/R=0.4	0.573	0.507	0.560	0.573	0.493	0.493	0.507
				MSCI-Basis			
P/R=2	**0.523***	**0.529****	0.546	0.534	0.534	0.534	0.517
P/R=1	**0.534***	**0.511*****	0.527	0.527	0.519	0.557	**0.511***
P/R=0.4	0.547	**0.507*****	0.547	0.520	0.520	0.573	0.493
				MSCI-AR(2)			
P/R=2	0.489	**0.540***	0.540	0.529	0.534	0.500	0.523
P/R=1	0.511	**0.527****	0.534	0.519	0.527	0.496	0.534
P/R=0.4	0.533	0.533	0.547	0.547	0.520	0.453	0.533
				MSCI-ASX			
P/R=2	0.500	**0.506****	0.552	0.529	0.529	0.471	0.506
P/R=1	0.489	**0.511*****	0.527	0.527	0.511	0.450	**0.504****
P/R=0.4	0.480	**0.493*****	0.547	**0.547***	0.520	0.440	**0.507****
				MSCI-IPSA			
P/R=2	0.534	**0.529****	0.586	**0.552****	0.529	0.523	**0.552****
P/R=1	0.550	**0.511*****	0.588	**0.557*****	0.511	0.550*	**0.565****
P/R=0.4	0.533	**0.493****	0.573	0.560	0.520	0.520	0.533
				MSCI-NZX			
P/R=2	0.534	**0.506***	**0.552***	0.477	0.540	0.471	**0.552****
P/R=1	0.534	**0.489****	0.550	0.473	0.534	0.458	**0.542****
P/R=0.4	0.507	**0.493****	0.560	0.493	0.547	0.450	0.507

Notes: We use models in Table 1 to build the forecasts used in Table A.4. Stars indicate statistical significance when testing the null hypothesis that the models outperform the relative benchmark in terms of mean directional accuracy.

REFERENCES

Alquist R, Kilian L, Vigfusson RJ (2013): Forecasting the Price of Oil. In Handbook of Economic Forecasting, vol. 2:427-507.

Anatolyev S, Gerco A (2005): A Trading Approach to Testing for Predictability. Journal of Business & Economic Statistics 2005(4):455–461.

Belasen AR, Demirer R (2019): Commodity-Currencies or Currency-Commodities: Evidence from Causality Tests. Resources Policy, 60:162-168.

Bork L, Rovira Kaltwasser P, Sercu P (2022): Aggregation Bias in Tests of the Commodity Currency Hypothesis. Journal of Banking & Finance, 135:106392.

Burgess K, Rohde N (2013): Can Exchange Rates Forecast Commodity Prices? Recent Evidence using Australian Data. Economics Bulletin, 33(1):511-518.2.

Campbell JY, RJ Shiller (1987): Cointegration and Tests of Present Value Models, Journal of Political Economy, 1987, 95 (5):1062--88.

Chan K, Tse Y, Williams M (2011): The Relationship between Commodity Prices and Currency Exchange Rates. Commodity Prices and Markets, *20:*47.

Chen Y, Rogoff K, Rossi B (2010) Can Exchange Rates Forecast Commodity Prices? The Quarterly Journal of Economics, August 2010, 125 (3):1145--1194.

Chen Y, Rogoff K, Rossi B (2014) Can Exchange Rates Forecast Commodity Prices? An Update, manuscript, February 2014.

Chen Y, Rogoff K, Rossi B (2011) Predicting Agri-Commodity Prices: An Asset Pricing Approach, World Uncertainty and the Volatility of Commodity Markets, ed. B. Munier, IOS, 2011.

Cheung Y, Chinn MD, Garcia Pascual A, Zhang Y (2019): Exchange Rate Prediction Redux: New Models, New Data, New Currencies. Journal of International Money and Finance. 95:332–362.

Chinn MD, Coibion O (2014): The Predictive Content of Commodity Futures. Journal of Futures Markets, 34(7):607-636.

Ciner C (2017): Predicting White Metal Prices by a Commodity Sensitive Exchange Rate. International Review of Financial Analysis 52:309-315.

Clark TE, McCracken MW (2001): Tests of equal forecast accuracy and encompassing for nested models. Journal of Econometrics, 105(1):85--110.

Clark TE, West KD (2006): Using Out-Of-Sample Mean Squared Prediction Errors to Test the Martingale Difference Hypothesis. Journal of Econometrics, 135(1-2):155-186.

Clark TE, West KD (2007): Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. Journal of Econometrics, 138(1):291-311.

Diebold FX, Mariano R (1995): Comparing Predictive Accuracy. Journal of Business and Economic Statics, 13(3):253–263. 10.

Fernandez V (2017): A Historical Perspective of the Informational Content of Commodity Futures. Resources Policy, 51:135-150.

Gargano A, Timmermann A (2014): Forecasting Commodity Price Indexes Using Macroeconomic and Financial Predictors. International Journal of Forecasting 30:825-843.

Giacomini R, White H (2006): Tests of Conditional Predictive Ability. Econometrica, Volume 4, issue 6. Pages 1545-1578.

Goyal A, Welch I (2008): A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. Review of Financial Studies, 21(4):1455-1508.

Goyal A, Welch I, Zafirov A (2022): A Comprehensive Look at the Empirical Performance of Equity Premium Prediction II. Swiss Finance Institute Research Paper, (21-85)

Groen JJ, Pesenti PA (2011): Commodity Prices, Commodity Currencies, and Global Economic Developments. In *Commodity prices and markets, east Asia seminar on economics* 20:15-42. Chicago, IL: University of Chicago Press.

Inoue A, Kilian L (2004) In-Sample or Out-Of-Sample Tests of Predictability: Which One Should We Use? Econometric Reviews 23:371–402.

Karolak Z, Kwas M, Rubaszek M, Uddin G (2020): The Role of the Threshold Effect for the Dynamics of Futures and Spot Prices of Energy Commodities. Studies in Nonlinear Dynamics & Econometrics 24(5), Article 2019-0068.

Kwas M, Rubaszek M (2021): Forecasting Commodity Prices: Looking for a Benchmark. Forecasting, 3(2):447-459.

Lof M, Nyberg H (2017): Noncausality and the Commodity Currency Hypothesis. Energy Economics, *65:*424-433.

Meese R, K Rogoff (1983): Empirical Exchange Rate Models of the Seventies. Do They Fit Out-of-Sample? Journal of International Economics 14:3-24.

Neely CJ, Rapach DE, Tu J, Zhou G (2014): Forecasting the Equity Risk Premium: the Role of Technical Indicators. Management science, 60(7):1772-1791.

Newey W, West KD (1987): A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica, 55(3):703-708.

Newey W, West KD (1994) Automatic Lag Selection in Covariance Matrix Estimation. The Review of Economic Studies. 61(4):631-53.

Pesaran H, Timmermann A (1992): A Simple Nonparametric Test of Predictive Performance. Journal of Business &Economic Statistics, October 1992, 10(4).

Pincheira P, Hardy N, Bentancor A (2022): A Simple Out-of-Sample Test of Predictability against the Random Walk Benchmark. Mathematics, 10(2), 228.

Pincheira-Brown P, Bentancor A, Hardy N, Jarsun N (2022): Forecasting Fuel Prices with the Chilean Exchange Rate: Going Beyond the Commodity Currency Hypothesis. Energy Economics, 106:105802.

Pincheira PM, Hardy N (2019): Forecasting Base Metal Prices with the Chilean Exchange Rate. Resources Policy, 62:256-281.

Pincheira P, Hardy N (2022): Correlation Based Tests of Predictability. University Library of Munich, Germany.

Pincheira PM, West KD (2016): A Comparison of Some Out-Of-Sample Tests of Predictability in Iterated Multi-Step-Ahead Forecasts, Research in Economics, Elsevier, vol. 70(2):304-319.

Reeve T, Vigfusson R (2011): Evaluating the Forecasting Performance of Commodity Future Prices. International Finance Discussion Papers N° 1025. Board of Governors of the Federal Reserve System.

Rossi B (2012): The Changing Relationship between Commodity Prices and Equity Prices in Commodity Exporting Countries. IMF Economic Review 60, December 2012:533-569.

Rubaszek M, Karolak Z, Kwas M (2020): Mean-Reversion, Non-Linearities and the Dynamics of Industrial Metal Prices. A Forecasting Perspective. Resources Policy, 65:101538.

Rubaszek M (2021): Forecasting Crude Oil Prices with DSGE Models. International Journal of Forecasting, 37:531-546.

Wang Y, Liu L, Wu C (2020): Forecasting Commodity Prices Out Of-Sample: Can Technical Indicators Help? International Journal of Forecasting 36 (2020):666-683.

West KD (1996): Asymptotic Inference about Predictive Ability. Econometrica, 64(5):1067.

West KD, Wong KF (2014): A Factor Model for Co-Movements of Commodity Prices. Journal of International Money and Finance, 42, 289-309.