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18 May 2021

Forecasting Base Metal Prices with an International Stock Index[1]

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May 2021

Abstract

In this paper we show that the MSCI ACWI Metals and Mining Index has the ability to predict base metal prices. We use both in-sample and out-of-sample exercises to conduct such examination. 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. 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, in terms of Mean Squared Prediction Error, forecasts that do not use the information contained in that index.

JEL Codes: 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.

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1. Introduction

In this paper we show that the MSCI ACWI Metals and Mining Index 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 last feature is fairly important since global investments in base metal based instruments 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.

The theoretical underpinning of our paper relies on the present-value model for stock price determination. In short, this model claims that stock prices should be the expected value of the discounted sum of the future revenue of the corresponding firms. In the case of mining and metal companies, the relevant revenue is closely related to the price of the metal or commodity that is produced. As shown by Campbell and Shiller (1987), an important implication of present-value relationships in this set-up is that of Granger causality between these closely related stock indices and commodity prices.

Our paper is connected to a growing literature that in recent years has explored the potential predictability of commodity prices using the exchange rates of commodity exporting countries as predictors. This literature also relies on a present-value model as the theoretical pillar behind their empirical results. Chen, Rossi and Rogoff (2010, 2014) are leading articles exploring these relationships, providing both in-sample and out-of-sample evidence of predictability. They are not alone in the field as some other papers have also reported predictability from exchange rates to commodity prices. See for instance Gargano and Timmermann (2014), Ciner (2017) and Belasen and Demirer (2019) just to name a few. It is also interesting to mention the papers by Pincheira and Hardy (2018, 2019) which have also a focus on base metal returns. They show relatively strong predictability for these metals when building forecasts with either the Chilean exchange rate or survey-based-expectations of the Chilean currency.

While the present-value model has been mostly used to analyze the linkage between exchange rates and commodity prices, Chen, Rogoff and Rossi (2011) and Rossi (2012) show evidence of predictability from equity indices coming from commodity-exporting countries to either some world commodity indices or some particular commodity returns, including Rice, Wheat, Aluminum, Copper and others. One problem with the approach followed by Chen, Rogoff and Rossi (2011) and Rossi (2012) is that aggregated equity indices from commodity-exporting countries may be shaped, or importantly influenced, by the stock performance of companies in non-tradable sectors, or more generally, by companies with little or no relationship at all with commodity prices (retail stores, technological companies and banks, just to give a few examples). In our paper, we address this concern by exploring predictability from a worldwide equity index that focuses exclusively on metals and mining companies: MSCI ACWI Metals and Mining Index (henceforth, MSCI). We tend to believe that this type of equity index should be more closely related to base metals than a general equity index coming from a commodity-exporting country.

Our paper is different to those of Chen, Rogoff and Rossi (2011) and Rossi (2012) in others few key elements as well. First, Chen, Rogoff and Rossi (2011) and Rossi (2012) focus on agricultural commodity prices, global commodity indices and some individual commodities that are indeed produced by the commodity-exporting countries in their database. We instead focus on the whole family of base metal prices and the LMEX. Besides, Chen, Rogoff and Rossi (2011) and Rossi (2012) work with quarterly data previous to the period of the great recession. We instead use monthly data for a sample period including the 2008 financial crisis and the post-crisis period as well.

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 monthly data on MSCI ACWI Metals and Mining Index (henceforth, MSCI) for the following period: 1994m12 to 2019m03. In the appendix we present the composition of this index in terms of countries (Table A.1) and in terms of base metals coverage (Table A.2).

For base metal spot prices we use data in the same frequency and for the same time period. The source of our price data is 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 of our data are displayed in Table A.3 in the appendix.

We use standard specifications to explore predictability relative to common benchmarks in the literature. See for instance Chen, Rossi and Rogoff (2010, 2014) and Pincheira and Hardy (2019)[2]. Both in-sample and out-of-sample analyses are based on the models described in Table 1 next.

[2] Either the Random Walk or simple autoregressions are frequently difficult benchmarks to beat when forecasting assets returns (for details see the following studies as good examples of this literature: Goyal and Welch (2008) and Meese and Rogoff (1983)).

Table 1: Econometric Specifications

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

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 metal price at time t. Similarly, $MSCI_t$ corresponds to the MSCI ACWI Metals and Mining Index at time t. Finally, ε_{ij} for $i = 1,2,3$ represent error terms.

Notice that in our specifications we use two lags of MSCI returns, but imposing the restriction that their coefficients are the same. By reducing the number of parameters in our models we aim at a decrease in estimation error that potentially could improve the accuracy of our forecasts. Our preliminary inspections show that, in general, both coefficients tend to be similar in magnitude and sign. Moreover, Table 2 shows results of Wald tests evaluating the null hypothesis of equality in the coefficients associated to the first two lags of MSCI monthly returns. Table 2 shows that we fail to reject these null hypotheses for all metals and for the LMEX as well.

For specifications 1-3 in Table 1, the null hypothesis H_0 is given by:

$$H_0: \beta = 0$$

This null posits that the MSCI ACWI Metals and Mining Index does not have the ability to predict base metal returns. We evaluate this hypothesis both in-sample and out-of-sample for one-step-ahead forecasts, leaving the multistep ahead analysis as an extension for further research. We consider simple t-statistics when the evaluation is carried out in-sample. For the out-of-sample evaluation we use the ENCNEW test of Clark and McCracken (2001). Even though this test has a non-standard asymptotic distribution, critical values for one-step-ahead forecasts are tabulated in Clark and McCracken (2001). We use a recursive or expanding scheme to update the estimates of the parameters in Table 1. 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 number of available observations. A key parameter to correctly determine the ENCNEW test critical values is the limit of the ratio

P/R, which is consistently estimated by the same ratio (P/R). For robustness, we split our sample in three different ways: considering $P/R = 2$, $P/R = 1$ and $P/R = 0.4$.

Table 2: Wald Test evaluating the linear restriction in MSCI lags

Aluminum	Wald statistic	0.077
	p-value	0.781
Copper	Wald statistic	0.014
	p-value	0.907
Lead	Wald statistic	0.257
	p-value	0.612
Nickel	Wald statistic	0.027
	p-value	0.869
Tin	Wald statistic	1.296
	p-value	0.255
Zinc	Wald statistic	0.101
	p-value	0.751
Lmex	Wald statistic	0.002
	p-value	0.964

Notes: The null hypothesis is that of equality of both coefficients associated to the first two lags of MSCI monthly returns.

3. Empirical Results

3.1 In–Sample Analysis

In Table 3 we report estimates of specification 1 in Table 1 using 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. We observe that the coefficients associated to the MSCI index are always positive and statistically significant at least at the 10% level in all cases with the sole exception of Nickel. So, as expected, higher returns in the MSCI index are associated with higher base metal returns as well. Coefficients of determination tend to be low, however, ranging from 1.4% in the case of Nickel, to 4.8% in the case of LMEX. Despite these low R^2, our in-sample results provide sound statistical evidence of a predictive relationship between the MSCI index and most base metals.

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

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
MSCI(-1) + MSCI(-2)	**0.112****	**0.129***	**0.151***	0.104	**0.109****	**0.088***	**0.114***
	(0.047)	(0.076)	(0.079)	(0.067)	(0.043)	(0.046)	(0.059)
Aluminum(-1)	-0.105						
	(0.072)						
Copper(-1)		0.011					
		(0.081)					
Lead(-1)			-0.094				
			(0.072)				
Nickel(-1)				-0.027			
				(0.07)			
Tin(-1)					0.001		
					(0.074)		
Zinc(-1)						-0.061	
						(0.071)	
Lmex(-1)							-0.017
							(0.076)
Constant	0	0.002	0.004	0.002	0.005	0.004	0.002
	(0.003)	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)
Observations	289	289	289	289	289	289	289
R^2	0.044	0.043	0.04	0.014	0.039	0.015	0.048

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 equation (1) in Table 1. HAC standard errors are reported in parentheses. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

3.2 Out–of-Sample Analysis at the Population Level

In this subsection we explore predictability at the population level using the ENCNEW test of Clark of McCracken (2001) in out-of-sample exercises based on the three specifications of Table 1. In the first column of Tables 4-6 we use the notation used in Table 1 (AR(1), RW and DRW) to identify our benchmarks. Table 4 shows results of the ENCNEW test when the number of forecasts is twice the number of observations in the first estimation window ($P/R = 2$). In Table 5, we show results when the number of forecasts is the same as the number of observations used in the first estimation window ($P/R = 1$). Finally, Table 6 considers the case in which the number of forecasts is 40% of the number of observations used in the first estimation window ($P/R = 0.4$).

Columns 2 to 8 in Tables 4-6 report the ENCNEW test statistic when forecasting base metal spot price returns. In these tables, most of the models including the MSCI index outperform all three benchmarks at least at the 10% significance level. In particular we detect strong and robust predictability of the MSCI for Aluminum, Copper, Lead, Tin and LMEX returns. The evidence for Nickel is slightly weaker, while for Zinc we only find predictability when P/R=0.4, but not when P/R takes other values. Notably, for the case of the LMEX, we reject the null hypothesis at the 1% significance level in all our exercises. For other base metals like the Aluminum, Copper, and Lead, we find evidence of predictability at least at the 5% significance level in all our exercises.

Table 4: Forecasting Base Metals Returns with the MSCI ACWI M&M index. ENCNEW statistic for out-of-sample analysis with recursive windows (P/R=2).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Benchmark	**Aluminum**	**Copper**	**Lead**	**Nickel**	**Tin**	**Zinc**	**Lmex**
AR(1)	8.18***	4.82***	5.36***	1.31*	5.97***	0.66	5.80***
RW	5.67***	8.31***	4.66***	1.27	7.87***	0.67	8.34***
DRW	5.70***	8.62***	4.84***	1.34*	7.99***	0.75	8.55***

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. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated to the MSCI is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1 respectively, when the coefficient associated to the MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

Table 5: Forecasting Base Metals Returns with the MSCI ACWI M&M index. ENCNEW statistic for out-of-sample analysis with recursive windows (P/R=1).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Benchmark	**Aluminum**	**Copper**	**Lead**	**Nickel**	**Tin**	**Zinc**	**Lmex**
AR(1)	6.61***	4.55***	5.20***	1.23*	5.80***	-0.48	4.81***
RW	5.17***	8.16***	4.57***	1.38*	7.63***	-0.55	7.76***
DRW	5.33***	8.48***	4.92***	1.64**	8.03***	-0.48	8.11***

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. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated to the MSCI is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1 respectively, when the coefficient associated to the MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

Table 6: Forecasting Base Metals Returns with the MSCI ACWI M&M index. ENCNEW statistic for out-of-sample analysis with recursive windows (P/R=0.4).

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Benchmark	**Aluminum**	**Copper**	**Lead**	**Nickel**	**Tin**	**Zinc**	**Lmex**
AR(1)	4.00***	3.43***	4.14***	1.13**	2.40***	2.51***	4.54***
RW	1.51**	2.20***	1.64**	0.76*	1.09**	1.71**	2.85***
DRW	1.49**	1.89**	1.47**	0.77*	0.90*	1.68**	2.65***

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. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated to the MSCI is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1 respectively, when the coefficient associated to the MSCI is set to zero. *p < 10%, **p < 5%, ***p < 1%. Source: Authors' elaboration.

All in all, results in Tables 4-6 show sound evidence of predictability from the MSCI to most base metal prices.

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 inspired in the work of Goyal and Welch (2008), Pincheira and Hardy (2019), Pincheira and West (2016) and Pincheira (2013). 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 simple average of the forecast coming from the models including the MSCI and the forecast coming from a Random Walk with drift. In other words, we combine the forecasts arising from model 2 in Table 1 with the strategy that simply predicts base metals returns with a constant estimated in recursive windows. We follow this approach because, according to the work in 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[3]. In our notation $MSPE_{benchmark}$ represents the out-of-sample MSPE of the RW with drift. A zero value for R^2_{OOS} means that both predictive strategies (the combination and the RW with drift) produce similarly accurate forecasts. Negative values mean that the benchmark outperforms the strategy that contains information of the MSCI. Finally, a positive R^2_{OOS} shows that the combined strategy that includes the MSCI outperforms the RW with drift.

[3] Pincheira (2013) also shows this interesting property when the benchmark model is the driftless random walk.

Table 7: Out-of-sample R^2 when forecasting base metals with a strategy that includes the MSCI index.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Aluminum	**Copper**	**Lead**	**Nickel**	**Tin**	**Zinc**	**Lmex**
In-sample R2	0.044	0.043	0.040	0.014	0.039	0.015	0.048
OOS-R^2 P/R = 2	0.021	0.029	0.016	0.003	0.028	-0.002	0.030
OOS-R^2 P/R = 1	0.026	0.037	0.022	0.005	0.036	-0.010	0.036
OOS-R^2 P/R = 0.4	0.009	0.006	0.005	0.004	0.000	0.018	0.015

Notes: Results in Table 7 are obtained using specification 2 in Table 1.

Table 7 shows that most out-of-sample R_{OOS}^2 are positive, which indicates that the information contained in the MSCI is valuable to forecast base metals. The only exceptions with either negative or zero R_{OOS}^2 are found for Tin when P/R=0.4 and for Zinc when P/R=2 and P/R=1. Interestingly, this is consistent with the weak results reported in Tables 4-6 for these two metals. Out-of-sample R_{OOS}^2 tend to be small, with a maximum of 3.7% in the case of copper when P/R=1. Furthermore, they are smaller relative to their in-sample counterparts. On the one hand this could be a consequence of the construction of R_{OOS}^2 as a function of a convex combination of forecasts, but on the other hand, 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 R_{OOS}^2 reported in Table 7 shows that the information contained in the MSCI index is useful to predict base metal returns, not only at the population level, but also at the sample level.

3.4 Out-of-Sample Analysis at the sample level: Mean Directional Accuracy

Here we place our attention in the direction of the forecasts rather than in their MSPE. This type of analysis is also common in the forecasting literature. See for instance, Pincheira and Neumann (2020) 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 in the next period[4]. 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 $\Delta ln(M_t)$. In Table 8 we report the hit rate or Mean Directional Accuracy (DA) for our seven

[4] The success rate is also known as "hit rate". See for instance, Pincheira and Medel (2015).

target variables when forecasting with model 1 in Table 1. The top panel in Table 8 reports hit rates of the model containing the MSCI, whereas the bottom panel report hit rates of the nested AR(1) benchmark. The hit rate (or DA) is computed as the simple average of w_t.

To evaluate statistical significance we consider the following null $H_0: E(w_t) \leq 0.5$, against the alternative $H_A: E(w_t) > 0.5$. We test these hypothesis with a Diebold and Mariano (1995) and West (1996) test statistic (DMW t-stat) to analyze differences against a "pure luck" benchmark[5]. Rejection of the null hypothesis means that the "hit rate" of our models is greater than the 50% rate of a "pure luck" forecast.

Quantitatively speaking results in Table 8 are striking, as all the hit rates of the model that includes the MSCI are well above 50%. This is in sharp contrast with the hit rate of the AR(1) that rarely surpasses the 50% threshold. It is a bit disappointing, however, that in only 9 cases in the top panel of Table 8 we reject our null hypothesis. Nevertheless, the number of rejections with our AR(1) benchmark is much lower as there is only one rejection of the null in the bottom panel of Table 8. This suggests that the MSCI contains relevant information regarding future movements of some base metal returns.

Table 8: Mean Directional Accuracy when forecasting base metals with the MSCI index.

(1)	(2) Aluminum	(3) Copper	(4) Lead	(5) Nickel	(6) Tin	(7) Zinc	(8) Lmex
			Our Model				
P/R = 2	0.53	0.54	0.59***	0.53	0.57**	0.57**	0.54
P/R = 1	0.53	0.53	0.60***	0.54*	0.57**	0.53	0.53
P/R = 0.4	0.53	0.54	0.59***	0.53	0.57**	0.57**	0.54
			Benchmark				
P/R = 2	0.48	0.47	0.55	0.47	0.53	0.48	0.45
P/R = 1	0.48	0.48	0.55	0.44	0.53	0.49	0.45
P/R = 0.4	0.47	0.40	0.55*	0.41	0.51	0.52	0.41

Notes: We use model 1 in Table 1 to build the forecasts used in Table 8. Stars indicate statistical significance when testing the null hypothesis that the models outperform a "pure luck" benchmark.

4. Concluding Remarks

In this paper we show that the MSCI has the ability to predict base metal returns. We evaluate this predictability with a number of different exercises: in-sample regressions and out-of-sample analyses (ENCNEW, R^2_{OOS} and Mean Directional Accuracy). For some base metals, the evidence

[5] A "pure luck" benchmark predicts an upward movement with a probability of 50%. Likewise for a downward movement.

of predictability is strong and consistent across all exercises; yet for some others it is less robust. Our results are in line with the present-value model for stock price determination and provide new evidence about the ability that stock market indices may have to forecast spot commodity prices.

Our paper shows that the MSCI should be added to the list of variables with the ability to predict base metal returns. According to the papers by Pincheira and Hardy (2019, 2021) and Rossi (2012) and Chen, Rossi and Rogoff (2011), commodity-currencies and stock indices from countries that heavily rely on commodity exports are other variables in the same list. We leave as an extension for further research a formal evaluation of the predictive content of the MSCI relative to these other predictors.

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Appendix

Table A.1 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 A.2 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 Chemi	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 A.3: Descriptive Statistics of Monthly Returns of the Six Base Metals, the *London Metal Exchange* Index and the MSCI ACWI *Metal & Mining Index* for our Series. Sample Period (1995m01 to 2019m03)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Aluminum	**Copper**	**Lead**	**Nickel**	**Tin**	**Zinc**	**Lmex**	**MSCI**
Mean	0.000	0.003	0.004	0.001	0.004	0.003	0.002	0.002
Median	-0.002	-0.001	0.002	-0.006	0.006	0.006	0.003	0.008
Std	0.057	0.074	0.066	0.099	0.082	0.076	0.059	0.079
Max	0.156	0.271	0.238	0.301	0.240	0.245	0.203	0.205
Min	-0.179	-0.443	-0.236	-0.320	-0.320	-0.412	-0.330	-0.395
N	291	291	291	291	291	291	291	291

Source: Authors' elaboration