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Forecasting Aluminum Prices with Commodity Currencies[1]

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Abstract

In this paper we show that the exchange rates of some commodity exporter countries have the ability to predict the price of spot and future contracts of aluminum. This is shown with both in-sample and out-of-sample analyses. The theoretical underpinning of these results relies on the present-value model for exchange rate determination and on the tight connection between commodity prices and the currencies of commodity exporter countries. We show results using traditional statistical metrics of forecast accuracy: Mean Squared Prediction Error and Mean Directional Accuracy. We also show that the first principal component of our sample of exchange rates is a useful way to summarize the predictive information contained in our set of commodity currencies.

JEL Codes: C52, C53, G17, E270, E370, F370, L740, O180, R310

Keywords: Forecasting, commodities, aluminum, univariate time-series models, out-of-sample comparison, exchange rates.

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1. Introduction

In this paper we show that the exchange rates of some commodity exporter countries have the ability to predict the price of spot and future contracts of aluminum. We also show that the first principal component of our sample of exchange rates is a useful way to summarize the predictive information contained in our set of commodity currencies. These results are important in two dimensions. First, they are consistent with the present-value model for exchange rate determination and second they provide a useful way to forecast aluminum prices. This last point is fairly relevant since global investments in aluminum based instruments are far from negligible. In fact, in 2018 aluminum was one of the most traded metals in the London Metal Exchange (LME), representing nearly 37% of the total volume in futures contracts and nearly 48% of the total volume in traded options.

As mentioned before, the theoretical underpinning of our paper relies on the present-value model for exchange rate determination. While details of this model can be found in Appendix 1, in short, it claims that an exchange rate should be the expected value of the discounted sum of a linear combination of future fundamentals. As noted in Campbell and Shiller (1987) and Engel and West (2005), one of the key implications of this model is that exchange rates may Granger-cause their own fundamentals. While Engel and West (2005) and Hsiu-Hsin and Ogaki (2015) have reported only modest results when testing this implication for traditional exchange rate fundamentals, stronger results are reported in some papers when exploring the predictive relationship between the exchange rates of commodity exporting countries and the price of the commodities being exported. Probably the most influential articles exploring this relationship are those of Chen, Rossi and Rogoff (2010, 2014) (henceforth CRR), but a few other papers have followed with additional supporting evidence. For instance, Chen, Rossi and Rogoff (2011) find more evidence for the case of agricultural commodities. In the same line, Gargano and Timmermann (2014) show similar results for the Australian dollar and the Indian rupee and Ciner (2017) provides evidence of a predictive relationship between the South African rand and the price of white metals. More recently, Pincheira and Hardy (2018, 2019) show strong results when predicting base metal returns with either the Chilean exchange rate or survey-based-expectations of the Chilean currency. Finally, Belasen and Demirer (2019) report in-sample predictability when forecasting both commodity returns and volatility in an expanded set of commodity-exporters.

Despite this evidence, the empirical implications of the present-value model for exchange rate determination are not exempt of controversy. For instance, Groen and Pasenti (2011) find little evidence of predictability when studying ten alternative commodity indices. Moreover, results reported by Bork, Rovira and Sercu (2014) and Lof and Nyberg (2017) suggest virtually no predictive relationship between commodities and exchange rates. In this context, we analyze the potential predictability of aluminum prices with five traditional commodity-currencies: those of Australia, Canada, Chile, New Zealand and South Africa. These countries are usually considered in studies analyzing predictability from exchange rates to commodity prices. See for instance, CRR, Bork, Rovira and Sercu (2014) and Lof and Nyberg (2017).

Some prior studies supporting the initial findings of CCR have shown predictability from exchange rates to either the returns of the main exporting commodities of the corresponding countries or to the returns of some closely related indexes. Nevertheless, and similar to the results in Pincheira and Hardy (2018, 2019), in this paper we show that the exchange rates of some countries with little or no production of aluminum at all, do have the ability to predict aluminum returns. One rationale for this result relies on the fact that some of the countries in our database export commodities that have an important correlation with aluminum. For instance CRR show that the South African export share of base metals is zero (see Table A1 in Appendix 2). However, in Table A2 in Appendix 2 we show that most of the commodities produced by South Africa (and the other four economies) have an important correlation with aluminum.

Differing from some other papers in the literature, where the focus is mainly placed on spot prices, we also analyze here predictability for futures contracts of aluminum at different maturities. While the results for future prices are not particularly different from those for spot prices, we think that this is a reassuring finding that, to our knowledge, has not been reported previously in the literature, contributing to the debate of the empirical implications of the present-value model for exchange rate determination.

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 quarterly data on each exchange rate relative to the U.S. dollar for the following time periods: Australia (1984Q1 to 2018Q4), Canada (1973Q1 to 2018Q4), Chile (1999Q4 to 2018Q4), New Zealand (1987Q1 to 2018Q4) and South Africa (1993Q2 to 2018Q4). Exchange rates are defined as the amount of local currency that is required to buy one American dollar in the domestic market. The starting dates are the same than in CRR with the only exception of Chile. According to Pincheira (2018), since 1999 the monetary authorities in Chile decided to pursue a pure flotation exchange rate regime, with only a few periods of pre-announced interventions. It seems reasonable to focus only on the period of pure flotation, given that strong interventions might interfere in the ability of exchange rates to respond to their market fundamentals.

For aluminum spot prices we use data in the same frequency and for the same time periods considered previously. For futures, due to data availability, we consider the following time periods: 1980Q1 to 2018Q4 for 3-months maturity contracts, 1993Q3 to 2018Q4 for 15-months maturity contracts and 1993Q3 to 2018Q4 for 27-months maturity contracts.

The source of our data is Thomson Reuters Datastream from which we obtain daily close prices of each asset. With these daily prices, we transform our data to quarterly frequencies by sampling from the last day of the quarter.

We mainly use the econometric framework in Pincheira and Hardy (2019). These specifications are quite simple and are designed to explore predictability relative to common benchmarks in the literature[2]. Both in-sample and out-of-sample analyses are based on the models described in Table 1 next.

Table 1: Econometric Specifications

1:	$\Delta \ln(Al_t) = c + \beta[\Delta \ln(ER_{t-1}) + \Delta \ln(ER_{t-2})] + \rho\Delta \ln(Al_{t-1}) + \varepsilon_{1t}$
2:	$\Delta \ln(Al_t) = c + \beta[\Delta \ln(ER_{t-1}) + \Delta \ln(ER_{t-2})] + \varepsilon_{2t}$
3:	$\Delta \ln(Al_t) = \beta[\Delta \ln(ER_{t-1}) + \Delta \ln(ER_{t-2})] + \varepsilon_{3t}$

Source: Author's elaboration

Where

$$\Delta ln(Al_t) \equiv ln(Al_t) - ln(Al_{t-1})$$

$$\Delta ln(ER_t) \equiv ln(ER_t) - ln(ER_{t-1})$$

Al_t is the price of aluminum at time t, either spot or future. Similarly, ER_t corresponds to a given exchange rate at time t, which in our case could be the Australian Dollar, the Canadian Dollar, the Chilean Peso, the New Zealand Dollar or the South African Rand. ε_{ij} for $i = 1,2,3$ represent error terms.

Two features of our specifications are worth mentioning. First, we use only two lags of exchange rate returns as exogenous predictors given that with these lags Pincheira and Hardy

[2] A vast literature shows that either the Random Walk or simple autoregressions are usually difficult benchmarks to beat when forecasting assets returns. Goyal and Welch (2008) and Meese and Rogoff (1983) are good examples.

(2019) report strong results of predictability for aluminum prices with the Chilean peso[3]. Second, our specifications impose the restriction that the coefficients associated to both lags of exchange rate returns are the same. We do this because the reduction in the number of parameters may be highly beneficial to mitigate estimation errors[4].

For specifications 1-3 in Table 1, we consider the following null hypothesis H_0:

$$H_0: \beta = 0$$

This null hypothesis posits that exchange rates do not have the ability to predict aluminum returns. We evaluate this hypothesis both in-sample and out-of-sample for one-step-ahead forecasts, leaving the multistep ahead analysis for further research.

In our in-sample analysis the null hypothesis is evaluated using a simple t-statistic, while in the out-of-sample analysis is evaluated with the ENCNEW test proposed by Clark and McCracken (2001). This test has a non-standard asymptotic distribution, but critical values for one-step-ahead forecasts are tabulated in Clark and McCracken (2001). The asymptotic distribution of the ENCNEW test is a functional of Brownian motions depending on the number of excess parameters of the nesting model, which is 1 in our models (since we use restricted specifications), the scheme used to update the estimates of the parameters (rolling, recursive or fixed), and the parameter π defined as the limit of the ratio P/R, where P is the number of one-step-ahead forecasts and R is the size of the first estimation window used in the out-of-sample analysis[5].

For our in-sample analysis we estimate the parameters with all the available observations. In contrast, for the out-of-sample analysis, we split the sample in two windows: an initial estimation window of size R and a prediction window of size P such that $P + R = T$, where T is the total number of observations. To check the robustness of our results, we split our sample in two different ways. First, we use one third of our observations for initial estimation and two thirds for evaluation (this means $P/R = 2$). Second, we use two thirds of our observations for initial estimation and one third for evaluation (this means $P/R = 0.4$). We use a rolling scheme to update the estimates of our parameters in the out-of-sample analysis.

[3] Notice that the present-value model for exchange rate determination says nothing about the number of lags to be considered; this number of lags is an empirical issue.

[4] Furthermore, in the case of aluminum and monthly data, Pincheira and Hardy (2019) show that the coefficients associated to the first two lags of the Chilean peso have the same sign and that they are not statistically different according to results of a Wald test.

[5] See Clark and McCracken (2001) or West (2006) for further details about out-of-sample evaluations in nested environments.

3. Empirical Results

In this section we report in-sample estimates and tests of specification 1 in Table 1. We also report results of the ENCNEW out-of-sample test of Clark and McCracken (2001). We start by reporting our in-sample results.

3.1 In–Sample Analysis

In Table 2 next we report estimates of specification 1 in Table 1. We use HAC standard errors according to Newey and West (1987, 1994). Column 2 of Table 2 shows results when forecasting aluminum spot returns. Some findings are worth mentioning. First, the coefficients associated to exchange rates are significant in all cases with the sole exceptions of the South African Rand and the Canadian Dollar; moreover, we do reject the null at the 5% significance level for the Australian and the New Zealand Dollar. Second, the coefficients associated to exchange rates are negative in all cases. This is consistent with an inverse relationship between exchange rates and aluminum returns. This is expected in aluminum exporting countries: higher aluminum prices are expected to generate an inflow of American dollars to these economies, leading to an appreciation of the domestic currency. In the countries that do not export aluminum we can claim a similar statement relying on the positive correlation between aluminum returns and those of the commodities that are exported by these particular countries.

Columns 3-5 show results for futures with maturities of 3, 15 and 27 months. Several findings are worth mentioning. First, all coefficients associated to the exchange rates are negative; this is again consistent with the relationship between aluminum prices and the appreciation of the local currency explained previously[6]. Second, we find evidence of Granger-causality in at least one maturity for all exchange rates, with the sole exception of the South African Rand. Third, for the cases of Australia, Chile and New Zealand, the coefficients associated to the exchange rate are significant for all maturities, sometimes at tight significance levels (1%).

Results for the Chilean Peso and the South African Rand are particularly interesting provided that CCR report that neither of them produces aluminum. On the one hand, Table 2 shows strong predictability for the Chilean Peso. On the other hand, Table 2 shows no predictability at all for the South African Rand. A plausible explanation for this phenomenon relies on the correlations between the main commodity exports of these countries with aluminum. In the ca se of Chile, the correlation between one-period copper and aluminum returns is 0.76, while in

[6] Again, in Chile and South Africa, countries with no aluminum exports, this can be explained by the positive correlation between aluminum returns and those of the main Chilean and South African commodity exports. See Table A2 in Appendix 2.

the case of South Africa the correlation between one-period gold and aluminum returns is only 0.28 (See Tables A1 and A2 in Appendix 2).

Table 2: Forecasting Aluminum with Commodity Currencies

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
		Panel A: Australia		
ER(-1)+ER(-2)	-0.178**	-0.172**	-0.176*	-0.202**
	(0.085)	(0.085)	(0.095)	(0.079)
Observations	140	140	100	100
R-squared	0.043	0.064	0.087	0.080
		Panel B: Canada		
ER(-1)+ER(-2)	-0.160	-0.190	-0.082	-0.147**
	(0.102)	(0.126)	(0.099)	(0.073)
Observations	181	154	100	100
R-squared	0.039	0.066	0.070	0.057
		Panel C: Chile		
ER(-1)+ER(-2)	-0.383*	-0.390*	-0.420**	-0.437**
	(0.214)	(0.211)	(0.205)	(0.192)
Observations	78	78	78	78
R-squared	0.127	0.137	0.156	0.164
		Panel D: New Zealand		
ER(-1)+ER(-2)	-0.327**	-0.306**	-0.248***	-0.263***
	(0.136)	(0.124)	(0.085)	(0.085)
Observations	128	128	100	100
R-squared	0.073	0.093	0.115	0.115
		Panel E: South Africa		
ER(-1)+ER(-2)	-0.077	-0.075	-0.078	-0.076
	(0.056)	(0.056)	(0.054)	(0.053)
Observations	98	98	98	98
R-squared	0.074	0.078	0.070	0.055

Notes: ER stands for Exchange Rates Returns, $ER(-1)$ and $ER(-2)$ represent the first and second lags of Exchange Rates Returns. $Aluminum$ and $Aluminum(-1)$ denote one-quarter returns of aluminum and its first lag respectively. Table 2 shows estimates of the parameters in specification 1 in Table 1 for spot and futures prices. For the sake of space, we do not report estimates either of the constant or the AR(1) term. HAC standard errors are estimated according to Newey and West (1987, 1994). *$p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Source: Author's elaboration.

In summary, our in-sample results provide evidence of a predictive relationship between aluminum prices and most of our sample of "*commodity currencies*". To mitigate the usual overfitting problems associated to in-sample analyses, we move next to an out-of-sample environment.

3.2 Out–of-Sample Analysis

Tables 3-4 show results of the ENCNEW test of Clark and McCracken (2001) in different out-of-sample exercises based on specifications 1, 2 and 3 of Table 1. Table 3 shows results when the number of forecasts is twice the number of observations in the first estimation window (this is $P/R = 2$). In contrast, Table 4 shows results when the number of forecasts is 40% of the number of observations used in the first estimation window (this is $P/R = 0.4$).

In the first column of Tables 3-4 we use the following notation to describe specifications 1, 2 and 3 of Table 1: AR(1) stands for an autoregressive process of order 1 for the one-period return of aluminum (either spot or future), RW with drift stands for Random Walk in the log level of aluminum spot or future price, and Driftless RW denotes the Driftless Random Walk in the log level of aluminum spot or future price.

Column 2 in Tables 3-4 shows out-of-sample results when forecasting aluminum spot returns. In both tables, the models including the exchange rates of Australia, Chile and New Zealand outperform all three benchmarks at least at the 10% significance level with just one exception. The results for the South African Rand and the Canadian Dollar are rather weaker and unstable. In Table 4 we find predictability against the Random Walk and the Driftless Random Walk for both exchange rates, nevertheless, in Table 3 we find no predictability whatsoever.

Columns 3-5 of Tables 3-4 report results when forecasting aluminum future prices. Some features are worth mentioning. First, we still have modest results with the currencies of Canada and South Africa. Table 4 indicates that we find predictability with the South African Rand in six out of nine exercises (never beating the AR(1)), while in Table 3 we do not reject the null in any case. Similarly, with the Canadian Dollar and considering both Tables 3 and 4, we find predictability in only 7 out of 18 exercises with futures. Second, results with the currencies of Australia, Chile and New Zealand are surprisingly strong in both tables: our models outperform the benchmarks in 94% of the exercises (with those including the Chilean Peso and the New Zealand Dollar rejecting the null in all exercises). Our results show that these commodity currencies can predict different returns of aluminum: spot and futures. Moreover, this evidence of predictability is robust to the choice of the point in time in which we split our sample. Figure 1 shows a comparison between our forecasts for 27-months futures using specification 2 of Table 1 with the Chilean Peso. Consistent with the results of the ENCNEW test, our forecasts seems to be reasonably accurate. In particular they show a correlation of 0.26 with actual Aluminum 27-months returns.

Table 3: Forecasting Aluminum Prices with Commodity Currencies, $P/R = 2$.

Out-of-Sample Analysis with the ENCNEW Test

ENCNEW				
(1)	(2)	(3)	(4)	(5)
Panel A: Australia				
Benchmark Model	*Aluminum*	*Aluminum 3 month*	*Aluminum 15 month*	*Aluminum 27 month*
AR(1)	0.13	0.36	0.60	1.84*
RW with drift	3.64**	4.55**	5.52***	5.74***
Driftless RW	4.00**	4.89**	4.81**	5.31***
Panel B: Canada				
AR(1)	-2.64	-0.89	-1.03	-0.58
RW with drift	-1.90	2.02*	1.35	2.34*
Driftless RW	-0.58	1.80	1.44	2.43*
Panel C: Chile				
AR(1)	2.77*	3.36**	5.87***	8.68***
RW with drift	5.56***	6.17***	7.53***	7.81***
Driftless RW	7.01***	7.65***	9.13***	9.49***
Panel D: New Zealand				
AR(1)	3.06**	2.68*	3.76**	4.73**
RW with drift	5.34***	5.46***	7.72***	8.00***
Driftless RW	5.94***	6.07***	7.61***	8.14***
Panel E: South Africa				
AR(1)	0.19	0.15	0.21	0.29
RW with drift	1.13	1.18	1.32	1.23
Driftless RW	1.16	1.21	1.32	1.17

Notes: 10%, 5% and 1% critical values are 1.808, 2.836 and 5.065 respectively for ENCNEW when excess parameters are 1. P is the number of one-step-ahead forecasts, R the sample size of the first estimation window. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated with the exchange rates is set to zero. Similarly, the RW with drift and the Driftless RW benchmarks correspond to models 2 and 3 in Table 1 respectively, when coefficients associated with the exchange rates are set to zero. Source: Author's elaboration.

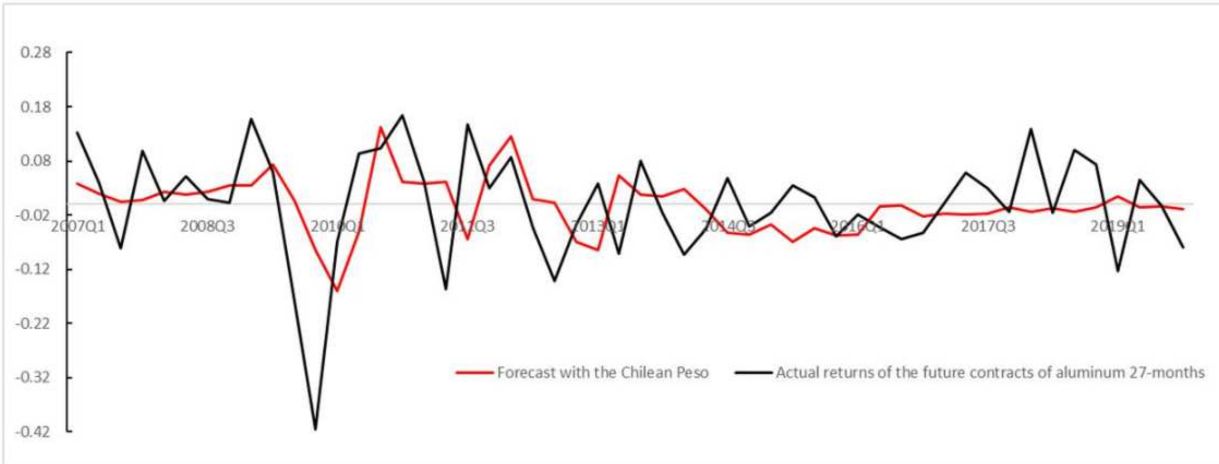
Table 4: **Forecasting Aluminum Prices with Commodity Currencies, $P/R = 0.4$.**

Out-of-Sample Analysis with the ENCNEW Test

	ENCNEW			
(1)	(2)	(3)	(4)	(5)
Panel A: Australia				
Benchmark Model	*Aluminum*	*Aluminum 3 month*	*Aluminum 15 month*	*Aluminum 27 month*
AR(1)	1.22**	1.00*	0.44	0.99*
RW with drift	3.30***	3.72***	3.99***	3.92***
Driftless RW	3.18***	3.60***	3.92***	3.84***
Panel B: Canada				
AR(1)	-0.09	-0.21	0.11	0.35
RW with drift	0.88*	1.38**	0.90*	0.86*
Driftless RW	0.84*	1.34**	0.63	0.54
Panel C: Chile				
AR(1)	3.78***	3.72***	4.47***	4.80***
RW with drift	2.57***	2.71***	2.94***	2.78***
Driftless RW	2.51***	2.65***	2.81***	2.58***
Panel D: New Zealand				
AR(1)	2.36***	2.32***	2.44***	3.19***
RW with drift	4.03***	4.01***	4.02***	4.16***
Driftless RW	4.07***	4.11***	4.15***	4.27***
Panel E: South Africa				
AR(1)	0.51	0.44	0.48	0.52
RW with drift	1.58**	1.49**	1.36**	1.13*
Driftless RW	1.49**	1.43**	1.30**	1.07*

Notes: 10%, 5% and 1% critical values are 0.764, 1.161 and 2.278 respectively for ENCNEW when excess parameters are 1. P is the number of one-step-ahead forecasts, R the sample size of the first estimation window. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated with the exchange rates is set to zero. Similarly, the RW with drift and the Driftless RW benchmarks correspond to models 2 and 3 in Table 1 respectively, when coefficients associated with the exchange rates are set to zero. Source: Author's elaboration.

Figure 1: Forecasting the future price of Aluminum 27-months with the Chilean Peso



Source: Authors' elaboration.

3.3 Forecast Accuracy

Thus far we have exclusively carried out inference to compare the population MSPE of the models in Table 1 with the population MSPE of our benchmarks. Nevertheless, due to sampling error, the model displaying the lowest MSPE at the population level, may not necessarily be displaying the lowest MSPE at the sample level. For this reason, Table 5 shows out-of-sample coefficients of determination (R^2_{OOS}) inspired in Goyal and Welch (2008) and Pincheira (2013). This statistic is defined as

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

Where $MSPE_{\overline{X}}$ denotes the out-of-sample MSPE when predicting aluminum returns with a combined prediction built as the simple average of the forecast coming from the models including commodity currencies and the forecast coming from a Random Walk with drift. We use a combined forecast instead of the pure forecast built with commodity currencies, because by allowing for some shrinkage, we should be able to outperform the benchmarks at the sample level whenever the core statistic of the ENCNEW test is positive. See Pincheira (2013) for further details about this interesting property. In our notation $MSPE_{benchmark}$ represents the out-of-sample MSPE of the RW with drift[7]. Notice that a zero value for R^2_{OOS} implies that both predictive strategies, our combination and the RW with drift, produce similarly accurate forecasts at the sample level. In contrast, negative values indicate that the simple RW outperforms our combination that contains the information of commodity currencies. Finally, a

[7] In other words, a model that predicts commodity returns with a constant only.

positive value indicates just the opposite: our combined forecast outperforms the simple RW at a sample level.

Table 5: In-Sample and Out-of-Sample R^2 when Forecasting Aluminum Prices with Commodity Currencies

(1)	*(2)* Aluminum	*(3)* Aluminum 3 month	*(4)* Aluminum 15 month	*(5)* Aluminum 27 month
		Australia		
In-Sample R2	*0.033*	*0.045*	*0.068*	*0.073*
OOS R2 P/R=2	*0.020*	*0.027*	*0.037*	*0.040*
OOS R2 P/R=0.4	*0.058*	*0.063*	*0.066*	*0.064*
		Canada		
In-Sample R2	*0.015*	*0.029*	*0.026*	*0.036*
OOS R2 P/R=2	*-0.025*	*0.006*	*0.007*	*0.018*
OOS R2 P/R=0.4	*0.008*	*0.014*	*0.018*	*0.014*
		Chile		
In-Sample R2	*0.132*	*0.142*	*0.164*	*0.169*
OOS R2 P/R=2	*0.058*	*0.066*	*0.083*	*0.086*
OOS R2 P/R=0.4	*0.054*	*0.058*	*0.062*	*0.059*
		New Zealand		
In-Sample R2	*0.070*	*0.083*	*0.096*	*0.106*
OOS R2 P/R=2	*0.038*	*0.041*	*0.059*	*0.063*
OOS R2 P/R=0.4	*0.077*	*0.077*	*0.076*	*0.079*
		South Africa		
In-Sample R2	*0.026*	*0.027*	*0.029*	*0.027*
OOS R2 P/R=2	*0.011*	*0.012*	*0.013*	*0.012*
OOS R2 P/R=0.4	*0.043*	*0.040*	*0.036*	*0.031*

Notes: P represents the number of one-step-ahead forecasts, R the sample size of the first estimation window. OOS R2 stands for Out-of-Sample R^2. OOS R2 are constructed inspired in Goyal and Welch (2008) and Pincheira (2013). Source: Authors' elaboration.

Some interesting features of Table 5 are worth mentioning. First, with some exceptions, R^2_{OOS} tend to be smaller than their in-sample counterparts; this is consistent with a vast literature reporting discrepancies between in-sample and out-of-sample forecast evaluations. Second, R^2_{OOS} are always positive across all exercises and exchange rates with only one exception. Additionally, they range between -2.5% and 8.6%, with the Chilean Peso showing a remarkably high average of 6.6%, followed by the New Zealand Dollar with an average of 6.4%. Third, results with the South African Rand are decently good as all entries are positive. This is in sharp contrast with the poor outcomes shown previously with the ENCNEW test. Finally, we find some instability in R^2_{OOS} across different exercises. For instance, the average R^2_{OOS} using the Australian Dollar with $P/R = 0.4$ is 6.3%, while the comparable figure with $P/R = 2$ is only

3.1%. All in all, even considering these instabilities, at the sample level we find encouraging results with the five currencies.

3.4 Mean Directional Accuracy and Principal Components (PC)

In this section we report some additional evidence of predictability. First, we forecast aluminum returns using the first principal component of the sum of the first two lags of the returns of our five exchange rates. In Table A3 in Appendix 2 we report our in-sample results. In this case, using quite similar specifications as those in Table 1, this first principal component is statistically significant at the 5% level for spot and future returns, with a coefficient of determination varying between 8.7% and 10.3%[8].

Additionally, Table 6 next shows results of the ENCNEW out-of-sample test when predicting with this principal component. The evidence here is remarkably strong. In 22 out of 24 cases, our models outperform the benchmarks at the 10% significance level. Furthermore, in 20 out of 24 cases our models outperform the benchmarks at the 1% significance level.

All in all, the first principal component constructed here seems to be a good tool to summarize the predictive ability of the five currencies, with remarkably strong out-of-sample results.

Table 6: Out-of-sample analysis with the first principal component

(1)	*(2)* *Aluminum*	*(3)* *Aluminum 3 month*	*(4)* *Aluminum 15 month*	*(5)* *Aluminum 27 month*
		PCA		
ENCNEW P/R=2				
AR(1)	*9.223****	*8.496****	*6.43****	*4.939***
RW	*1.38*	*1.60*	*2.090**	*2.304**
DRW	*2.843***	*3.088***	*3.674***	*3.974***
ENCNEW P/R=0.4				
AR(1)	*3.761****	*3.567****	*4.551****	*4.641****
RW	*4.187****	*4.295****	*4.728****	*4.575****
DRW	*4.078****	*4.183****	*4.527****	*4.297****

Notes: P is the number of one-step-ahead forecasts, R the sample size of the first estimation window. The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated with the exchange rates is set to zero. Similarly, the RW with drift and the Driftless RW benchmarks correspond to models 2 and 3 in Table 1 respectively, when coefficients associated with the exchange rates are set to zero. The main difference with specifications in Table 2 is that here we now replace the sum of the first two lags of currency returns with the first principal component of the sum of the first two lags of the returns of our five exchange rates. Critical values of the ENCNEW test are reported in Clark and McCracken (2001). Source: Author's elaboration.

[8] The only difference with specifications in Table 1 is that we now replace the sum of the first two lags of currency returns with the first principal component of the sum of the first two lags of the returns of our five exchange rates.

It is also fairly usual in the forecasting literature to study the direction of the forecasts instead of their MSPE, see, for example, Yin-Wong, Chinn, García-Pascual and Zhang (2019). With this in mind, we place our attention next on the success rate of our currencies when predicting whether aluminum contracts are going up or down. Our test is based on the simple average of the following variable z_t:

$$z_t = \begin{cases} 1 & if \quad -(\Delta ln(Al_t))(\Delta ln(ER_{t-1})) > 0 \\ 0 & \quad\quad -(\Delta ln(Al_t))(\Delta ln(ER_{t-1})) \leq 0 \end{cases}$$

The idea here is to explore the plausible inverse relationship between the currency of commodity exporting countries and the international price of key commodities like aluminum. Therefore, an increase in the price of the American dollar in a given country in period *t* should forecast a decrease in aluminum prices in the next period. The variable z_t computes a "hit" every time an exchange rate movement is followed by an opposite movement in aluminum prices. In Table 7 we report the Mean Directional Accuracy (DA) for each currency and each type of aluminum contract during our sample period. DA is simply computed as the sample average of our z_t variable.

For inference we consider the following hypotheses:

$$H_0: E(z_t) \leq 0.5$$

$$H_A: E(z_t) > 0.5$$

When the null hypothesis is rejected, it means that the "hit rate" that can be achieved by looking at exchange rates is greater than the 50% rate of a pure luck forecast. We compute a Diebold and Mariano (1995) and West (1996) test (DMW t-stat) to analyze differences against this pure luck benchmark. Results are displayed in Table 7. Notice that the DA is above 50% in all exercises. Moreover, we reject the null of "pure luck" in all exercises with just two exceptions.

Table 7: Mean directional accuracy using the sign of the lagged exchange rates

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Australia	*0.575**	*0.560**	*0.634***	*0.584*
Canada	*0.525*	*0.555**	*0.604***	*0.574**
Chile	*0.636****	*0.623****	*0.662****	*0.597***
New Zealand	*0.589***	*0.589***	*0.654****	*0.584**
South Africa	*0.615****	*0.606****	*0.604****	*0.594****

Notes: DA stands for Mean Directional Accuracy and represents the rate at which each currency return correctly forecast the sign of aluminum returns. Statistical significance is carried out with a Diebold and Mariano (1995) and West (1996) t-test against a 0.5 pure luck benchmark. We use HAC standard errors according to Newey-West (1987, 1994).

The evidence presented in Table 7 is quite interesting in several ways. First, despite our previous results of weak predictability with the South African Rand, the evidence using the DA metric is striking: the hit rate is close to 60% in every exercise, rejecting the null at the 1% significance level for both spot and futures aluminum contracts. Surprisingly, the South African Rand provides one of the highest hit rates in Table 7. Second, results with the Australian and New Zealand Dollars are also remarkably good. Their hit rates are above 50% across all aluminum contracts. Furthermore, the null of a pure luck benchmark is rejected in 7 out of the 8 corresponding entries in Table 7. Third, the case of the Chilean Peso is the best across all our five currencies, with a hit rate ranging from 59.7% to 66.2%. The null of pure luck is rejected for all aluminum contracts with the Chilean currency.

We also explore DA using principal component analysis. To that end we engage again in the traditional environment used for out-of-sample evaluation. This means that we divide our sample period in two windows: an initial estimation window of size R, and an evaluation window of size P, just like we explain by the end of section 2. We focus on the following simple specification:

$$\Delta ln(Al_{t+1}) = c + \beta f_t + \varepsilon_{t+1}$$

where f_t represents the first principal component of the set of five exchange rate returns[9]. Differing from the out-of-sample exercise carried out in sections 3.2 and 3.3, where we only update the estimates of the parameters c and β in each rolling window, here we also update the computation of the first principal component of the five exchange rate returns in every rolling window. This is to make sure we are implementing a fully out-of-sample exercise.

[9] As explained in footnote 8, here we also use the first principal component of the sum of the first two lags of the returns of the five exchange rates.

Table 8 shows the hit rates of these exercises. We see that DA in every entry in Table 8 is above 50%, ranging from 52.9% through an outstanding 81.0%. Interestingly, we reject the null of a pure luck benchmark in 6 out of 8 cells in the table.

In summary, taken individually or jointly in a principal component, the evidence presented here suggests that our commodity currencies perform remarkably well when forecasting the direction-of-change of aluminum contracts.

Table 8: Mean directional accuracy using principal components

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
P/R=2	*DA*	*DA*	*DA*	*DA*
PC1	*0.529*	*0.529*	*0.588****	*0.608***
P/R=0.4	*DA*	*DA*	*DA*	*DA*
PC1	*0.810****	*0.810****	*0.810****	*0.762****

Notes: DA stands for mean Directional Accuracy and represents the rate at which our simple model (loaded with the first principal component of the sum of the first two lags of the returns of the five exchange rates) correctly forecast the sign of aluminum returns. Statistical significance is evaluated with a Diebold and Mariano (1995) and West (1996) t-test against a 0.5 pure luck benchmark. We use HAC standard errors according to Newey-West (1987, 1994).

4. Concluding Remarks

In this paper we show that the exchange rates of some commodity exporter countries have the ability to predict the price of spot and future contracts of aluminum. We show this using a number of different exercises including in-sample regressions and out-of-sample analyses. We also show that the first principal component of our sample of exchange rates is a useful way to summarize the predictive information contained in our set of commodity currencies. Our results are consistent with the present-value model for exchange rate determination and provide new evidence about the ability that commodity currencies may have to forecast both futures and spot commodity prices.

While we detect some heterogeneity in the predictive ability of different individual currencies, the evidence presented here suggests that our commodity currencies, either individually or jointly, perform remarkably well when forecasting spot and futures contracts of aluminum.

Our results indicate that some of the exchange rates of countries that heavily rely on base metal exports have the ability to predict aluminum contracts. Nevertheless, our analyses also indicate that the currencies of economies with little or no production of base metals, like New Zealand

and South Africa, have some ability to forecast aluminum prices. One possible explanation for this result relies on the important and positive correlation between the commodity exports of these countries and aluminum prices.

Provided that the debate on the ability that commodity currencies have to predict commodity prices is far from settled, we think that the crystal clear results that we report here are useful to shed some light to the discussion. An interesting avenue for further research would consider the extension of our analysis to explore the ability that commodity currencies may have to predict aluminum prices at long horizons.

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Appendix

Appendix 1. **Present-value model for exchange rate determination.**

The present-value model posits that an exchange rate S_t is closely related to a vector of fundamentals F_t containing observable and unobservable components. Using this model, Engel and West (2005) express the exchange rate as follows:

$$S_t = \gamma \sum_{j=0}^{\infty} \vartheta^j \, E_t[\omega' F_{t+j}]$$

where E_t represents the conditional expectation based on information available at time t, and ω is a vector of unobservable weights.

One of the key implications of this result is that exchange rates may Granger-cause their individual fundamentals. We remark here that this result poses a major empirical challenge since weights and some fundamentals are unobservable.

Appendix 2. Tables

Table A1: Main commodity exports of our countries according to CRR (2010).

Composition of the commodity price indices in CRR									
Australia		*Canada*		*Chile*		*New Zealand*		*South Africa*	
Main Products	*Wt.*	*Main Products*	*Wt.*	*Main Products*	*Wt.*	*Main Products*	*Wt.*	*Main Products*	*Wt.*
Coking Coal	*14.70*	*Crude Oil*	*21.40*	*Copper*	*100.00*	*Lamb*	*12.50*	*Gold*	*48.00*
Steaming Coal	*9.70*	*Lumber*	*13.60*			*Wholemeal*	*10.60*	*Platinum*	*30.00*
Gold	*9.40*	*Pulp*	*12.80*			*Beef*	*9.40*	*Coal*	*22.00*
Iron ore	*9.30*	*Nat. Gas*	*10.70*						
Base metals	*Wt.*	*Base metals*	*Wt.*	*Base metals*	*Wt.*	*Base metals*	*Wt.*	*Base metals*	*Wt.*
Aluminum	*8.10*	*Aluminum*	*5.00*	*Copper*	*100.00*	*Aluminum*	*8.30*	-	-
Copper	*2.80*	*Copper*	*2.00*						
Lead	*0.70*	*Nickel*	*2.40*						
Zinc	*1.50*	*Zinc*	*2.30*						
	Wt.		*Wt.*		*Wt.*		*Wt.*		*Wt.*
Total Base Metals	*13.10*	*Total Base Metals*	*11.70*	*Total Base Metals*	*100.00*	*Total Base Metals*	*8.30*	*Total Base Metals*	-

Source: Chen, Rossi and Rogoff (2010).

Table A2: Correlations with aluminum of the main exports of our countries in different sample periods.

Correlations

Panel A: Australia									
	Coal	*Gold*	*Iron ore*	*Copper*	*Lead*	*Zinc*	*Bloomberg*		*Average Correlation*
1999Q3-2018Q4	-	*0.28*	-	*0.76*	*0.55*	*0.71*	*0.68*		*0.57*
2007Q3-2018Q4	-	*0.27*	*0.51*	*0.84*	*0.60*	*0.70*	*0.78*		*0.60*
20013Q1-2018Q4	*0.24*	*0.30*	*0.24*	*0.69*	*0.55*	*0.57*	*0.44*		*0.42*

Panel B: Canada									
	Oil	*Lumber*	*Pulp*	*Nat. Gas*	*Copper*	*Nickel*	*Zinc*	*Bloomberg*	*Average Correlation*
1999Q3-2018Q4	*0.55*	*0.41*	*0.48*	*0.28*	*0.76*	*0.56*	*0.71*	*0.68*	*0.53*
2007Q3-2018Q4	*0.65*	*0.42*	*0.59*	*0.40*	*0.84*	*0.70*	*0.70*	*0.78*	*0.61*
20013Q1-2018Q4	*0.43*	*0.39*	*0.39*	*0.27*	*0.69*	*0.56*	*0.57*	*0.44*	*0.44*

Panel C: Chile		
	Copper	*Average Correlation*
1999Q3-2018Q4	*0.76*	*0.76*
2007Q3-2018Q4	*0.84*	*0.84*
20013Q1-2018Q4	*0.69*	*0.69*

Panel D: New Zealand					
	Lamb	*Beef*	*Agricultur*	*Non Fuel*	*Average Correlation*
1999Q3-2018Q4	*0.38*	*0.21*	*0.61*	*0.76*	*0.49*
2007Q3-2018Q4	*0.50*	*0.32*	*0.68*	*0.81*	*0.58*
20013Q1-2018Q4	*0.21*	*0.38*	*0.10*	*0.41*	*0.28*

Panel E: South Africa					
	Gold	*Platinum*	*Coal*	*Bloomberg*	*Average Correlation*
1999Q3-2018Q4	*0.28*	*0.53*	-	*0.68*	*0.49*
2007Q3-2018Q4	*0.27*	*0.56*	-	*0.78*	*0.54*
20013Q1-2018Q4	*0.30*	*0.33*	*0.24*	*0.44*	*0.33*

Panel F: Futures				
	3-month	*15-mont*	*27-month*	*Average Correlation*
1999Q3-2018Q4	*0.996*	*0.976*	*0.945*	*0.97*
2007Q3-2018Q4	*0.998*	*0.991*	*0.972*	*0.99*
20013Q1-2018Q4	*0.9895*	*0.973*	*0.949*	*0.97*

Note: These correlations are calculated over the log-differences of each series.

Table A3. In-sample analysis with the first principal component

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
PC1	-0.010**	-0.010**	-0.012**	-0.014***
	(0.004)	(0.004)	(0.005)	(0.005)
Aluminum(-1)	0.142	0.150	0.110	0.037
	(0.109)	(0.110)	(0.108)	(0.100)
Constant	0.002	0.002	0.002	0.003
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	77	77	77	77
R-squared	0.087	0.093	0.099	0.103

Note: We use specification 1 in Table 2 but using the first principal component of the sum of the first two lags of the returns of our five exchange rates as the relevant predictor.