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Forecasting aluminum prices with commodity currencies

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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 some commodity prices and the currencies of some commodity exporter countries. We show results using traditional statistical metrics of forecast accuracy: Mean Squared Prediction Error and Mean Directional Accuracy. We also explore different ways in which we can jointly take advantage of the predictive information contained in all of our commodity-currencies. While LASSO and a model equipped with the first principal component of our currencies perform well, the best combination strategies involve the pre-selection of the two best performing individual currencies: The Chilean Peso and the Icelandic Krona.

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 explore different ways in which we can jointly take advantage of the predictive information contained in all of our commodity-currencies. While LASSO and a model equipped with the first principal component perform well, the best combination strategies involve the pre-selection of the two best performing individual currencies: The Chilean Peso and the Icelandic Krona.

Our results are important at least 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 et al. (2010, 2014) (henceforth CRR), but a few other papers have followed with additional supportive evidence. For instance, Chen et al. (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

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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 applied to commodity-currencies are not exempt of controversy. For instance, Chan et al. (2011) find no evidence of predictability from futures of commodity-currencies to future contracts of commodities. Similarly, Groen and Pesenti (2011) find little evidence of predictability when studying ten alternative commodity indices. Moreover, results reported by Bork et al. (2014) and Lof and Nyberg (2017) suggest virtually no predictive relationship between commodities and exchange rates. Furthermore, in his comment to the chapter by Chan et al. (2011), Yang (2011) writes: "… *This present value representation is well-accepted from a theoretical view, but the empirical findings are not supportive*." Yang (2011) page 73. Iwaisako (2011) seems also to endorse the same view when he writes "*Present value formulation of exchange rates is impeccable as a theory. However, its practical importance has always been questioned*, …" Iwaisako (2011) page 71. So, in our view, there is mixed evidence regarding the present-value model for exchange rate determination, and more research is required to broadly understand the scope and limitations of this theory.

In this context, we analyze the potential predictability of aluminum spot and future prices with the Icelandic Krona and with five traditional commodity-currencies: those of Australia, Canada, Chile, New Zealand and South Africa. These last countries are usually considered in studies analyzing predictability from exchange rates to commodity prices. See for instance, Chen et al. (2014) and Lof and Nyberg (2017). To our knowledge, the Icelandic Krona is not a frequently used commodity-currency in the relevant literature, and therefore its addition to the list of commodity-currencies with the ability to predict commodity prices is a by-product of our paper.

Some prior studies supporting the initial findings of CRR 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 indices. 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 comovement with aluminum. For instance CRR show that the South African export share of base metals is zero (see Table A1.1 in Appendix 2).[1] However, Table A2 in the same appendix shows that most of the commodities produced by South Africa (and the other four economies used in CCR) have an important correlation with aluminum. A closely related rationale could be applied for the Chilean currency. While Chile does not export aluminum, it does export copper, which is a close substitute for aluminum in some electrical applications. Consistent with this argument, Table A2 shows a strong correlation of 0.76 between aluminum and copper returns.

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. Our results indicate strong predictability for both spot and futures. This is fairly interesting given that, to our knowledge, the only other article exploring a similar question for future prices is the paper by Chan et al. (2011), which report no predictability whatsoever for futures contracts.

The question about the predictability of spot and futures contracts is quite interesting. Even if we knew that spot prices were predictable, there are arguments in favor and against futures contracts predictability. On the one hand, there is a high correlation between spot and futures contracts. If the former are predictable, then to some extent it is natural to expect predictability for the latter. On the other hand, Chan et al. (2011) argue that future commodity markets are much more efficient than spot prices. This line of argument suggests that predictability should be harder to find in these more efficient derivative markets. Iwaisako (2011) mentions that at first glance the opposite findings of Chan et al. (2011) and Chen et al. (2010) seem stark. Nevertheless, he writes that "… *once we realize the different natures of spot, forward, and futures markets of commodities, the differences between the two empirical results are not so surprising. While spot and forward commodity markets are dominated by transactions directly related to the transaction of real goods, commodity futures markets are essentially financial markets, dominated by investors/speculators. Hence, the arbitrage mechanism is expected to work more effectively in futures markets than in the other two types of commodity markets.*" Iwaisako (2011) page 71.

So, in summary, Chan et al. (2011) and Iwaisako (2011) argue that it is cheaper, easier and more efficient for investors and speculators to operate commodity futures contracts instead of spot contracts. This would explain the poor predictability results in Chan et al. (2011). With opposite arguments in terms of predictability of futures commodity contracts, it seems important to check this potential predictability empirically. Interestingly, our findings challenge the results of Chan et al. (2011) and the logic that supports them. We totally endorse the idea that future contracts at some maturities may represent a much more efficient market, yet our results indicate that this higher level of efficiency does not preclude their predictability.

It is important to emphasize that this paper does not attempt to study the channels or the structural links between aluminum and commodity-currencies. Our results are based on the evaluation of the predictive ability of commodity-currencies by Granger-causality; nevertheless, we do not address empirically "causation" by any means. As mentioned in Rossi (2012), such analysis would require the use of a structural model.[2]

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. We also show some extensions and robustness checks. 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), Iceland (2001Q2 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. For Australia, Canada, New Zealand and South Africa, the starting dates are the same than in CRR. For Chile we use a different starting point. 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

[1] According to http://www.worldstopexports.com/, South Africa did have some aluminum exports in 2019, buy they only represented a 2% of the total bundle of South African exports during that year.

[2] Hamilton (1994) discusses causality in a present-value relationship with a scalar fundamental f_t .In a relationship like this, true economic causality goes from the fundamental variable f_t to the exchange rate S_t, although Granger causality typically goes in the opposite direction. In the present-value model for exchange rate determination we have a vector of fundamentals F_t.

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

strong interventions might interfere in the ability of exchange rates to respond to their market fundamentals. Finally, the starting point for Iceland is given by the date in which a formal inflation target was adopted in that country: March 2001.

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.

For additional exercises we consider two different databases. First, we collect data for a different set of twelve commodities from the IMF commodity database at the monthly frequency.[3] We transform this data to quarterly frequencies by sampling from the last month of the quarter. This database goes from 1980Q1 to 2018Q4. Second, we consider eight different exchange rates from economies that have a significantly lower share of commodities among their main export products. Akin to our six commodity currencies, these exchange rates are obtained from Thomson Reuters Datastream from which we download daily close prices, and transform the data to quarterly frequencies by sampling from de last day of the quarter. We consider the same time period than Chile for these exchange rates (1999Q3 to 2018Q4). Table A3 in the appendix exhibits the ten main exports in 2019 for these economies, as well as the main exports in the same year for our six commodity-currencies. On average for these eight economies, commodity exports in 2019 represented about nine percent of the total exports, while for our six commodity-currencies they represented about sixty percent.

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.[4] Both in-sample and out-of-sample analyses are based on the models described in Table 1 next.

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 Icelandic Krona, the New Zealand Dollar or the South African Rand. ε_{it} 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 (2019) report strong results of predictability for aluminum prices with the Chilean peso.[5] 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.[6]

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

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.[7]

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. 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 Icelandic Krona and the Australian and the New Zealand Dollars. Second, the

[3] Available at https://www.imf.org/en/Research/commodity-prices.

[4] 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.

[5] 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.

[6] 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.

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

Table 2
Forecasting aluminum with commodity currencies.

(1)	(2)	(3)	(4)	(5)
	Aluminum	Aluminum 3 month	Aluminum 15 month	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: Iceland				
ER(-1) + ER (-2)	−0.284**	−0.280**	−0.296***	−0.299***
	(0.127)	(0.126)	(0.111)	(0.106)
Observations	71	71	71	71
R-squared	0.140	0.146	0.164	0.165
Panel E: 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 F: 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. 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.

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 supposed to generate an inflow of American dollars to these economies, leading to an appreciation of the domestic currency. In the countries with little or no aluminum exports 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.[8] 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, Iceland and New Zealand, the coefficients associated to the exchange rate are significant for all maturities, sometimes at tight significance levels (1%).

The good results with the Chilean Peso are particularly interesting provided that Chile does not produce aluminum. A plausible explanation for this phenomenon relies on the fact that the major Chilean export, copper, is a close substitute for aluminum. Moreover, the correlation between one-period copper and aluminum returns is very high: 0.76 in our sample period. (See Tables A1.1 and A2 in Appendix 2).

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 and 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 $P/R = 2$). 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

Table 3
Forecasting aluminum prices with commodity currencies, $\boldsymbol{P/R} = 2$. 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: Iceland				
AR(1)	0.71	0.70	1.47	1.93*
RW with drift	3.00**	3.09**	4.48**	5.19***
Driftless RW	3.70**	3.80**	5.26***	6.04***
Panel E: 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 F: 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.

[8] Again, in countries with little or no aluminum exports, this can be explained by the positive correlation between aluminum returns and those of their main commodity exports. See Tables A1.1, A1.2 and A3 in Appendix 2.

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: Iceland				
AR(1)	6.68***	6.45***	7.78***	7.84***
RW with drift	8.68***	8.23***	8.54***	7.32***
Driftless RW	8.65***	8.37***	8.90***	7.71***
Panel E: 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 F: 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.

forecasting aluminum spot returns. In both tables, the models including the exchange rates of Australia, Chile, Iceland and New Zealand outperform all three benchmarks at least at the 10% significance level with just two exceptions. 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 and 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, Iceland and New Zealand are surprisingly strong in both tables: our models outperform the benchmarks in 93% 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 four 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. Fig. 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 seem to be reasonably accurate. In particular they show a correlation of 0.26 with actual Aluminum 27-months returns.

3.3. Forecast accuracy

Thus far we have exclusively carried out inference to compare the population Mean Squared Prediction Error (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.[9] 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 positive value indicates just the opposite: our combined forecast outperforms the simple RW at a sample level.

Some interesting features of Table 5 are worth mentioning. First, most 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 in the case of the Canadian Dollar. Additionally, R^2_{OOS} range between −2.5% and 22.3%, with the Icelandic Krona showing a remarkably high average of 12.9%, followed by the Chilean Peso and the New Zealand Dollar with an average of 6.6% and 6.4% respectively. 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 our six commodity-currencies.

3.4. Mean Directional Accuracy

It is also fairly usual in the forecasting literature to study the direction of the forecasts instead of their MSPE, see, for example, Cheung et al. (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:

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

The idea here is to explore the plausible inverse relationship between the currency of commodity exporting countries and the international

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

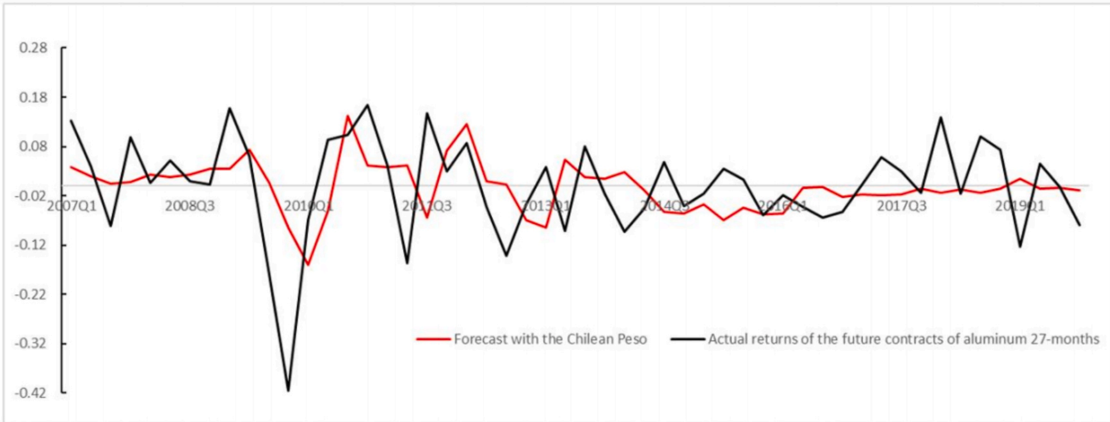

Fig. 1. Forecasting the future price of Aluminum 27-months with the Chilean PesoSource: Authors' elaboration.

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	0.127	0.137	0.156	0.164
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
Iceland				
In-Sample R2	0.140	0.146	0.164	0.165
OOS R2 P/R = 2	0.029	0.030	0.052	0.063
OOS R2 P/R = 0.4	0.223	0.215	0.220	0.197
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.

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 6 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 6. Notice that the DA is above 50% in all exercises. Moreover, we reject the null of "pure luck" in the great majority of the exercises.

The evidence presented in Table 6 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 6. In sharp contrast, results with the Icelandic Krona are the poorest from the table, being no statistically significant whatsoever. This

Table 6
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**
Iceland	0.507	0.522	0.507	0.551
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 forecasts 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).

is again surprising given the good performance shown by the forecasts built with this currency in Table 5. The cases of the South African Rand and the Icelandic Krona illustrate that the performance ranking of a set of forecasts crucially depends on the loss function used in the evaluation process. Third, results with the Australian and New Zealand Dollars are both remarkably good. Their hit rates are well 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 6. Fourth, the case of the Chilean Peso is the best across all our six 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.

3.5. Principal components and other combination strategies

In this subsection we explore different ways in which we can take advantage of the predictive information contained in our six commodity-currencies. First, we forecast aluminum returns using the first principal component of the sum of the first two lags of the returns of our six exchange rates. In Table 7 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 10.1% and 12.8%[10].

We also explore the out-of-sample predictive performance of a model based on the first principal component of the sum of the first two lags of the returns of our six exchange rates. 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 six exchange rate returns.[11] 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 six exchange rate returns in every rolling window. This is to make sure we are implementing a fully out-of-sample exercise.

Table 8 shows out-of-sample coefficients of determination and the hit rates of the exercise with the first principal component. We see that all the R^2_{OOS} displayed in Table 8 are positive but with the same unstable pattern portrayed in Table 5: relatively high coefficients with $P/R = 0.4$ and fairly low ones when $P/R = 2$. Compared with the country specific numbers shown in Table 5, results with the first principal component are in the high side when P/R = 0.4 and on the low side when P/R = 2.

In terms of Mean Directional Accuracy, we see that the hit rate is above 50% in every entry in Table 8, ranging from 55.0% through an outstanding 73.0%. Interestingly, we reject the null of a pure luck benchmark in 6 out of 8 cells in the table.

All in all, the first principal component constructed here seems to be a good tool to summarize the predictive ability of our six currencies. Yet, there could be others strategies with good performance as well. Table 9 next explores the out-of-sample coefficients of determination of six different ways to summarize the predictive content of our set of currencies. Panel A in Table 9 shows results when using the sum of the returns of our six currencies as a predictor. Panel B shows results when forecasting with a model that includes the returns of all our six currencies individually. Panel C focus on a model similar to that used in the exercise in Panel B, but only allowing for the two currencies with the highest share of base metals in their export basket: The Chilean Peso and the Icelandic Krona. Panel D focus on a model similar to that used in the exercise in Panel A, but adding or averaging only the returns of two currencies: The Chilean Peso and the Icelandic Krona. Panel E shows results when selecting the currencies automatically with LASSO, whereas Panel F repeats our results obtained with the first principal component and that are also presented in Table 8. Table A4 in the appendix shows the specifications used in Table 9.

Table 9 reveals that the best combination schemes in terms of out-of-sample coefficients of determination are those represented in Panels C and D. In other words, when P/R = 2 the highest R^2_{OOS} are given by a model that includes the returns of the Chilean Peso and the Icelandic

Table 7
In-sample analysis with the first principal component (PC1).

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
PC1	−0.013**	−0.013**	−0.014**	−0.016**
	(0.006)	(0.006)	(0.006)	(0.006)
Aluminum (-1)	0.117	0.125	0.078	0.005
	(0.114)	(0.119)	(0.119)	(0.112)
Constant	0.003	0.002	0.003	0.004
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	70	70	70	70
R-squared	0.101	0.107	0.120	0.128

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 six exchange rates as the relevant predictor. PC1 stands for the first principal component. 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.

Table 8
Out-of-sample analysis with the first principal component (PC1).

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Principal Component R2				
In-Sample R2	0.101	0.107	0.120	0.128
OOS R2 P/R = 2	0.005	0.006	0.019	0.030
OOS R2 P/R = 0.4	0.138	0.141	0.150	0.141
Principal Component Directional Accuracy				
OOS R2 P/R = 2	55%	55%**	60%*	60%
OOS R2 P/R = 0.4	73%***	73%***	73%***	68%**

Notes: For the in-sample analysis, we report R^2 using specification 1 in Table 1. For the out-of-sample analyses, we use specification 2 in Table 1. For both analyses we use the first principal component of the sum of the first two lags of the returns of our six exchange rates as the relevant predictor. The first panel reports the R^2, while the second panel exhibits Mean Directional Accuracy, which 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 six exchange rates) correctly forecasts the sign of aluminum returns. In this case, 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). 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.

[10] 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 six exchange rates.

[11] Here we also use the first principal component of the sum of the first two lags of the returns of the six exchange rates.

Table 9
Out-of-Sample R^2 with different combination strategies.

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Panel A: All currencies (k = 1)				
OOS R2 P/R = 2	0.013	0.017	0.031	0.040
OOS R2 P/R = 0.4	0.189	0.189	0.198	0.187
Panel B: All currencies (k = 6)				
OOS R2 P/R = 2	−0.109	−0.086	−0.041	−0.028
OOS R2 P/R = 0.4	0.101	0.106	0.132	0.143
Panel C: Chile and Icelandic Krona (k = 2)				
OOS R2 P/R = 2	0.074	0.082	0.115	0.126
OOS R2 P/R = 0.4	0.167	0.166	0.182	0.168
Panel D: average (Chile;Iceland) (k = 1)				
OOS R2 P/R = 2	0.054	0.059	0.092	0.105
OOS R2 P/R = 0.4	0.221	0.218	0.221	0.196
Panel E: Lasso				
OOS R2 P/R = 2	0.022	0.027	−0.014	0.012
OOS R2 P/R = 0.4	0.130	0.129	0.147	0.146
Panel F: Principal Component				
OOS R2 P/R = 2	0.005	0.006	0.019	0.030
OOS R2 P/R = 0.4	0.138	0.141	0.150	0.141

Notes: Table A4 in the Appendix summarizes the specification used in each Panel. Panel A uses specification 1, Panel B is based on specification 2, Panel C uses specification 3, and Panel D use specification 4. For Panel E (LASSO), we estimate our model based on specification 2, but the LASSO estimator may set some of the coefficients to zero in each window. Panel F (Principal Component) is based on specification 5; akin to section 3.5, we use the first principal component of the sum of the first two lags of the returns of our six exchange rates as the relevant predictor. See notes in Table A4 for more details on each specification. 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.

Krona as separate regressors. When P/R = 4, the best combination scheme is to add the returns of these two selected currencies. This is interesting because neither the popular LASSO nor our model equipped with the first principal component of our six currencies is able to outperform a strategy the pre-selects a couple of the best performing currencies: The Chilean Peso and the Icelandic Krona.

Table 10 next evaluates the same combination strategies used in Table 9 (and described in Table A4 in the appendix) but now in terms of Mean Directional Accuracy which represents the rate at which each model (using exchange rates) correctly forecasts the sign of aluminum returns.

All figures in Table 10 are greater than 50%, and most of them are statistically significant and greater or equal than 60%. Furthermore, Tables 9–10 carry a similar message as in both tables the forecasting performance of our combination strategies is better when P/R = 0.4 relative to the case in which P/R = 2. Likewise, both tables are similar in indicating that the strategy in Panel B, which includes all six currencies as separate regressors, tends to be outperformed by the others. Similar to Table 9, Table 10 also shows that the best combination schemes in terms of Mean Directional Accuracy tend to be those represented in Panels C and D, that only use information about the Chilean Peso and the Icelandic Krona.

Table 10
Mean Directional Accuracy with different combination strategies.

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Panel A: All currencies (k = 1)				
DA P/R = 2	55%	55%	62%**	60%*
DA P/R = 0.4	75%***	75%***	75%***	70%**
Panel B: All currencies (k = 6)				
DA P/R = 2	51%	51%	53%	62%*
DA P/R = 0.4	60%	60%	60%	60%
Panel C: Chile and Icelandic Krona (k = 2)				
DA P/R = 2	58%	58%	58%	60%
DA P/R = 0.4	73%***	73%***	68%**	64%*
Panel D: average (Chile;Iceland) (k = 1)				
DA P/R = 2	56%	54%	60%*	63%**
DA P/R = 0.4	77%***	77%***	82%***	73%***
Panel E: Lasso				
DA P/R = 2	55%	55%	57%	61%*
DA P/R = 0.4	76%***	76%***	71%**	67%**
Panel F: Principal Component				
DA P/R = 2	55%	55%**	60%*	60%
DA P/R = 0.4	73%***	73%***	73%***	68%**

Notes: Table A4 in the Appendix summarizes the specification used in each Panel. Panel A uses specification 1, Panel B is based on specification 2, Panel C uses specification 3, and Panel D uses specification 4. For Panel E (LASSO), we estimate our model based on specification 2, but the LASSO estimator may set some of the coefficients to zero in each window. Panel F (Principal Component) is based on specification 5; akin to section 3.5, we use the first principal component of the sum of the first two lags of the returns of our six exchange rates as the relevant predictor. See notes in Table A4 for more details on each specification. P represents the number of one-step-ahead forecasts, R the sample size of the first estimation window. DA stands for Mean Directional Accuracy and represents the rate at which each model (using exchange rates) correctly forecasts 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). Source: Authors' elaboration.

3.6. Trading strategy

Here we explore if it is possible to obtain positive returns trading with forecasts based on our six commodity-currencies. To that end, we use the simple trading strategy analyzed by Anatolyev and Gerko (2005) and that we describe next: Let y_t be the one-period aluminum return of a given contract (either spot or future) and let y_t^f be a forecast of y_{t+1} built with one of our commodity-currencies. Our trading strategy is based on the following simple rule:

$$\begin{cases} \textit{buy the commodity if } y_t^f \geq 0 \\ \textit{sell the commodity otherwise} \end{cases}$$

In other words, the investor goes long whenever $y_t^f \geq 0$, otherwise he/she goes short. The investor closes the position at the end of each quarter and opens a new position according to the forecast he gets. The one period return is given by

$$r_{t+1} = sign\left(y_t^f\right) y_{t+1}$$

Where:

$$sign(y_t^f) = \begin{cases} 1 \; if \; y_t^f \geq 0 \\ -1 \; if \; y_t^f < 0 \end{cases}$$

We compare the profits coming from this simple active trading strategy with those coming from the simple "buy and hold" approach. Notice that here we are making an important simplification assumption: we are not considering trading costs, so we present gross returns from both strategies.

Table 11 reports the average quarterly return of both trading strategies expressed as annual rates. We use model 2 from Table 1 to build aluminum forecasts. Given that this is also an out-of-sample evaluation, we are using here the same division of the sample period into estimation and evaluation windows used in the other out-of-sample exercises: P/R = 2 and P/R = 0.4.

Results in Table 11 show that the buy and hold strategy tends to give poor returns. Let us recall that this passive strategy does not use the forecasts coming from our commodity currencies. The cross-country differences that we observe with this strategy are simply due to the different sample periods that we consider for each currency. The average annual returns in Table 11, using this strategy is −0.11%, which is very poor. In sharp contrast, the average annual return using the trading strategy based on our commodity-currencies is 4.63%, much higher. At the country level we see mixed results using the currencies of Australia and Canada: in a few exercises the buy and hold strategy wins, in others, the strategy of Anatolyev and Gerko (2005) takes the lead. We can make a much stronger case when analyzing the currencies of Chile, Iceland, New Zealand and South Africa. For these countries there is only one case in which the buy and hold strategy wins: trading spot contracts of aluminum with forecasts based on the New Zealand Dollar and when P/R = 2. In all the rest of the cases the use of commodity-currencies based forecasts in combination with the strategy of Anatolyev and Gerko (2005) is much more profitable than the simple and passive buy and hold approach. Some striking results are obtained with the Icelandic Krona and the South African Rand, currencies with which annual gross returns of 10% or higher are achieved in some combination of sample periods and contracts.

3.7. Robustness with control groups

Is there important evidence of predictability for aluminum contracts with other currencies from countries that are not major commodity exporters? If this were the case, the evidence presented here could be explained by some general features of flexible exchange rates rather than by our interpretation of the present-value model. To explore this possibility, we take a sample of industrialized countries that are not usually labeled as commodity-currencies. We consider the floating exchange rates of UK, Japan, Hungary, Sweden, Israel, Turkey, Poland and Czech Republic.[12]

Tables 12 and 13 next show in-sample results when using model 2 from Table 1 to build aluminum forecasts using our six commodity-currencies and also our eight exchange rates that are not typically considered by the literature as commodity-currencies. Results are shown for each spot and future aluminum contract.

In Table 12 we see that it is only for a handful of exceptions that the null of no predictability is rejected when using the non-commodity-currencies as predictors for aluminum contracts. Rejection of the null at the 10% significance level is achieved in only 12.5% of the entries in

[12] In 2019, the export share of commodities for these countries ranges from 2.5% for Israel to 17.8% for UK. In contrast, for our commodity exporter countries, the comparable figure goes from 31.4% for Canada, to 78.3% for Chile. A more detailed description of these exports can be found in Table A3 in Appendix 2. Source: http://www.worldstopexports.com/.

Table 11
Average annual returns when trading aluminum contracts based on commodity-currencies.

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
	Australia			
P/R = 0.4				
Forecasts built with Exchange Rate	2.34%	3.15%	2.78%	4.23%
Buy and Hold	0.16%	0.07%	0.44%	0.88%
P/R = 2				
Forecasts built with Exchange Rate	1.50%	−0.58%	0.81%	0.48%
Buy and Hold	2.11%	1.81%	1.41%	1.09%
	Canada			
P/R = 0.4				
Forecasts built with Exchange Rate	−2.72%	3.11%	1.22%	0.36%
Buy and Hold	−1.51%	1.47%	1.88%	1.98%
P/R = 2				
Forecasts built with Exchange Rate	4.85%	5.46%	−0.32%	−0.03%
Buy and Hold	−1.56%	−2.77%	−2.03%	−2.02%
	Chile			
P/R = 0.4				
Forecasts built with Exchange Rate	1.26%	2.03%	3.91%	2.24%
Buy and Hold	−1.56%	−1.61%	−0.73%	−0.06%
P/R = 2				
Forecasts built with Exchange Rate	6.60%	6.22%	5.81%	5.33%
Buy and Hold	1.35%	0.73%	0.45%	0.30%
	Iceland			
P/R = 0.4				
Forecasts built with Exchange Rate	3.81%	4.13%	10.67%	11.68%
Buy and Hold	−3.37%	−3.48%	−2.66%	−1.75%
P/R = 2				
Forecasts built with Exchange Rate	13.30%	13.63%	11.99%	10.73%
Buy and Hold	1.19%	0.50%	0.26%	0.17%
	New Zealand			
P/R = 0.4				
Forecasts built with Exchange Rate	0.08%	4.53%	5.34%	5.30%
Buy and Hold	0.78%	0.67%	0.80%	0.93%
P/R = 2				
Forecasts built with Exchange Rate	6.91%	6.90%	1.86%	1.63%
Buy and Hold	0.04%	−0.25%	−0.30%	−0.21%
	South Africa			
P/R = 0.4				
Forecasts built with Exchange Rate	2.54%	2.54%	3.20%	2.65%
Buy and Hold	1.77%	1.64%	1.74%	1.91%
P/R = 2				
Forecasts built with Exchange Rate	12.02%	11.64%	7.91%	7.02%
Buy and Hold	−1.81%	−2.15%	−2.03%	−2.02%

Notes: This table compares the average one-period return of our strategy using commodity currencies and a simple Buy and Hold approach. All results are annualized. Our forecasts using exchange rates are based on specification 2 in Table 1. P represents the number of one-step-ahead forecasts, R the sample size of the first estimation window. Source: Authors' elaboration.

Table 12
In-sample predictive analysis with a different set of exchange rates (non-commodity-currencies).

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
UK				
ER(-1) + ER (-2)	−0.194	−0.186	−0.169	−0.155
	(0.137)	(0.141)	(0.144)	(0.139)
Observations	78	78	78	78
R-squared	0.018	0.017	0.017	0.017
Japan				
ER(-1) + ER (-2)	−0.225**	−0.208*	−0.165	−0.157
	(0.111)	(0.115)	(0.114)	(0.111)
Observations	78	78	78	78
R-squared	0.029	0.026	0.020	0.021
Hungary				
ER(-1) + ER (-2)	0.027	0.025	−0.003	−0.030
	(0.080)	(0.078)	(0.067)	(0.061)
Observations	78	78	78	78
R-squared	0.001	0.001	0.000	0.001
Israel				
ER(-1) + ER (-2)	0.079	0.068	0.026	−0.015
	(0.157)	(0.161)	(0.140)	(0.120)
Observations	78	78	78	78
R-squared	0.002	0.002	0.000	0.000
Turkey				
ER(-1) + ER (-2)	−0.062	−0.072	−0.078**	−0.075**
	(0.049)	(0.049)	(0.038)	(0.035)
Observations	78	78	78	78
R-squared	0.008	0.011	0.015	0.016
Poland				
ER(-1) + ER (-2)	0.011	0.005	−0.027	−0.054
	(0.074)	(0.074)	(0.068)	(0.065)
Observations	78	78	78	78
R-squared	0.000	0.000	0.001	0.004
Sweden				
ER(-1) + ER (-2)	−0.208	−0.207	−0.197	−0.194
	(0.134)	(0.134)	(0.136)	(0.134)
Observations	78	78	78	78
R-squared	0.029	0.030	0.033	0.037
Czech Rep.				
ER(-1) + ER (-2)	−0.097	−0.098	−0.106	−0.114
	(0.100)	(0.100)	(0.094)	(0.089)
Observations	78	78	78	78
R-squared	0.007	0.008	0.011	0.015

Notes: *ER* stands for Exchange Rates Returns, $ER(-1)$ and $ER(-2)$ represent the first and second lags of Exchange Rates Returns. Table 12 shows estimates of the parameters in specification 2 in Table 1 for spot and futures prices. For the sake of space, we do not report estimates of the constant 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.

the table. In sharp contrast, when using our commodity-currencies the comparable percentage of rejections of the null of no predictability is 100% according to our Table 13.

Similarly, Table 14 shows outstanding differences in the coefficients of determination between in-sample regressions with and without commodity-currencies. When predicting with our sample of non-commodity-currencies, R^2 coefficients are on average only slightly above 1%. With our six commodity-currencies things are different, with the comparable figures of R^2 coefficients ranging from 6.7% on average for spot contracts to 9.1% on average for futures of long maturity.

We also implemented out-of-sample evaluations comparing our commodity-currencies versus non-commodity-currencies. We do not present these results for the sake of brevity, but they are available upon request and basically carry the same message embedded in our in-sample Tables 12 and 13: our commodity-currencies do have an overwhelming superiority relative to the set of non-commodity-currencies to predict spot and future aluminum contracts.

We can consider a different robustness check as well. For instance, should the predictive relationship between commodity-currencies and

Table 13
In-sample predictive analysis for our six commodity-currencies.

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Australia				
ER(-1) + ER (-2)	−0.254**	−0.258**	−0.251**	−0.249**
	(0.098)	(0.098)	(0.100)	(0.096)
Observations	78	78	78	78
R-squared	0.049	0.052	0.06	0.068
Canada				
ER(-1) + ER (-2)	−0.254***	−0.254***	−0.243***	−0.258***
	(0.074)	(0.075)	(0.071)	(0.075)
Observations	78	78	78	78
R-squared	0.024	0.025	0.028	0.037
Chile				
ER(-1) + ER (-2)	−0.441**	−0.449**	−0.443**	−0.421**
	(0.207)	(0.202)	(0.191)	(0.179)
Observations	78	78	78	78
R-squared	0.124	0.133	0.155	0.163
Iceland				
ER(-1) + ER (-2)	−0.329***	−0.327***	−0.328***	−0.314***
	(0.118)	(0.119)	(0.108)	(0.103)
Observations	78	78	78	78
R-squared	0.116	0.119	0.144	0.153
New Zealand				
ER(-1) + ER (-2)	−0.274**	−0.282**	−0.292**	−0.297**
	(0.126)	(0.128)	(0.127)	(0.123)
Observations	78	78	78	78
R-squared	0.057	0.063	0.081	0.097
South Africa				
ER(-1) + ER (-2)	−0.149**	−0.148*	−0.136*	−0.120*
	(0.072)	(0.074)	(0.074)	(0.070)
Observations	78	78	78	78
R-squared	0.029	0.03	0.03	0.027

Notes: *ER* stands for Exchange Rates Returns, $ER(-1)$ and $ER(-2)$ represent the first and second lags of Exchange Rates Returns. Table 13 shows estimates of the parameters in specification 2 in Table 1 for spot and futures prices. For the sake of space, we do not report estimates of the constant 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.

Table 14
In-sample average R^2 comparison: commodity v/s non-commodity-currencies.

(1)	(2) Aluminum	(3) Aluminum 3 month	(4) Aluminum 15 month	(5) Aluminum 27 month
Average IS R2 Commodity currencies	0.067	0.070	0.083	0.091
Average IS R2 Non-commodity currencies	0.012	0.012	0.012	0.014
Difference %	466%	492%	585%	555%

Notes: This table compares the average In-sample R^2s of our six commodity-currencies and the eight non-commodity-currencies. Difference % is simply the differences in R^2 between commodity and non-commodity-currencies relative to the minimum. Source: Author's elaboration.

commodity prices be taken for granted for any pairs of currencies/commodities? The following Tables 15–17 show in-sample and out-of-sample results of a predictive exercise in which we try to predict quarterly returns of a variety of commodity prices with our six commodity-currencies. We use specification 2 in Table 1 to evaluate predictability in-sample but for the out-of-sample analysis we use all three specifications detailed in Table 1. With a few exceptions, results in Tables 15–17 are really poor as only sporadic results of predictability are reported. As a matter of fact, out of the 432 out-of-sample exercises, the null of no predictability is rejected in only 8% of the cases at the 10% significance level. In sharp contrast, when forecasting aluminum contracts with our six commodity-currencies, the null is rejected in 74% of the comparable exercises.

Notice than in Tables 15–17 we are considering a wide variety of commodities from bananas to wheat. Some of these commodities are not exported by our set of countries, but one could expect some connection between them given that they are all denominated in dollars and are potentially affected by a "dollar effect" as shown by Akram (2009). In addition, one could expect some connection between them given the long tradition reporting a strong comovement between commodity prices, see for instance West and Wong (2014). Despite these arguments, predictability is only found for a few cases.

Some other commodities in Tables 15–17 are indeed exported by some of the countries we are considering: Chile is a major copper exporter, Australia is a gold exporter, South Africa is a major gold and platinum exporter and finally New Zealand is a lamb exporter (see Chen et al., 2010). If we analyze these pairs of currencies and commodities, Tables 15–17 only shows consistent predictive results in the case of Chile and copper. For the other pairs the evidence is either weak or simply non-existent. In a similar line of argument, we see from Table 15 that aside from a few exceptions, coefficients of determination are very low. In fact most of them are below 2%.

Beyond the specific reasons behind the poor predictive results shown in Tables 15–17, these tables perfectly illustrate our main message: the potential predictive relationship between commodity-currencies and commodity prices is not something that should be taken for granted. Consequently, empirical papers showing compelling evidence are useful to point out the currencies that do have a strong ability to predict specific commodity prices.

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 explore different ways in which we can jointly take advantage of the predictive information contained in all of our commodity-currencies. While LASSO and a model equipped with the first principal component perform well, the best combination strategies involve the pre-selection of the two best performing individual currencies: The Chilean Peso and the Icelandic Krona. Our results are consistent with the

Table 15
In-sample analysis for a different set of commodities.

(1)	(2) Bananas	(3) Cocoa Beans	(4) Copper	(5) Gold	(6) Lamb	(7) Oats	(8) Palm Oil	(9) Platinum	(10) Poultry (chicken)	(11) Tea	(12) Uranium	(13) Wheat
Panel A: Australia												
ER(-1) + ER (-2)	−0.004	−0.056	−0.215	−0.082	−0.108	−0.126	−0.166	−0.016	−0.061	−0.063	−0.257**	−0.059
	(0.153)	(0.091)	(0.143)	(0.053)	(0.078)	(0.137)	(0.184)	(0.136)	(0.047)	(0.133)	(0.118)	(0.125)
Observations	140	140	112	140	140	140	140	140	140	140	140	140
R-squared	0.000	0.002	0.015	0.010	0.012	0.005	0.008	0.000	0.006	0.002	0.025	0.001
Panel B: Canada												
ER(-1) + ER (-2)	−0.165	−0.052	−0.032	−0.122	−0.096	−0.430**	−0.290	−0.134	−0.037	0.079	−0.108	−0.321
	(0.204)	(0.136)	(0.228)	(0.112)	(0.121)	(0.218)	(0.286)	(0.148)	(0.083)	(0.175)	(0.237)	(0.203)
Observations	155	155	112	181	155	155	155	171	155	155	155	155
R-squared	0.001	0.001	0.000	0.004	0.003	0.024	0.009	0.003	0.001	0.001	0.002	0.018
Panel C: Chile												
ER(-1) + ER (-2)	−0.230	−0.149	−0.569**	−0.089	−0.049	−0.204	−0.160	−0.191	−0.110	−0.215	−0.164	−0.123
	(0.267)	(0.159)	(0.230)	(0.069)	(0.132)	(0.320)	(0.195)	(0.120)	(0.078)	(0.157)	(0.168)	(0.193)
Observations	78	78	78	78	78	78	78	78	78	78	78	78
R-squared	0.014	0.012	0.089	0.011	0.003	0.013	0.008	0.015	0.019	0.020	0.008	0.005
Panel D: New Zealand												
ER(-1) + ER (-2)	0.063	−0.064	−0.267*	−0.077*	−0.078	−0.196	−0.188	−0.092	−0.022	−0.015	−0.194	−0.105
	(0.174)	(0.102)	(0.143)	(0.044)	(0.098)	(0.164)	(0.135)	(0.096)	(0.048)	(0.089)	(0.118)	(0.118)
Observations	128	128	112	128	128	128	128	128	128	128	128	128
R-squared	0.000	0.002	0.023	0.009	0.007	0.012	0.013	0.005	0.001	0.000	0.014	0.004
Panel E: South Africa												
ER(-1) + ER (-2)	0.120	0.054	−0.165*	−0.040	−0.001	−0.033	0.081	−0.149	−0.038	−0.108	−0.162	−0.073
	(0.170)	(0.120)	(0.097)	(0.061)	(0.052)	(0.135)	(0.113)	(0.101)	(0.052)	(0.078)	(0.104)	(0.119)
Observations	98	98	98	98	98	98	98	98	98	98	98	98
R-squared	0.004	0.003	0.015	0.004	0.000	0.001	0.004	0.019	0.004	0.010	0.016	0.003
Panel F: Iceland												
ER(-1) + ER (-2)	−0.095**	0.019	−0.266*	−0.035	−0.151*	−0.086	−0.198	−0.259***	0.009	0.009	−0.220	−0.351**
	(0.043)	(0.089)	(0.156)	(0.051)	(0.089)	(0.270)	(0.189)	(0.093)	(0.017)	(0.117)	(0.138)	(0.152)
Observations	71	71	71	71	71	71	71	71	71	71	71	71
R-squared	0.004	0.000	0.032	0.003	0.046	0.004	0.022	0.047	0.000	0.000	0.026	0.066

Notes: *ER* stands for Exchange Rates Returns, $ER(-1)$ and $ER(-2)$ represent the first and second lags of Exchange Rates Returns. Table 15 shows estimates of the parameters in specification 2 in Table for spot and futures prices. For the sake of space, we do not report estimates of the constant 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.

Table 16
Out-of-sample analysis for a different set of commodities P/R = 0.4.

ENCNEW												
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Bananas	Cocoa Beans	Copper	Gold	Lamb	Oats	Palm Oil	Platinum	Poultry (chicken)	Tea	Uranium	Wheat
Panel A: Australia												
AR(1)	−0.51	−0.06	−1.53	0.45	−0.24	−0.19	−1.86	−0.54	−0.15	−1.14	0.53	−0.72
RW	0.03	−0.02	−3.02	0.21	0.27	−0.02	−2.09	−0.54	−0.16	−1.14	0.58	−0.82
DRW	0.08	−0.08	−3.05	0.10	0.25	−0.02	−2.22	−0.66	−0.14	−1.14	0.53	−0.81
Panel B: Canada												
AR(1)	−0.41	−0.31	−0.60	1.05	−0.36	0.90*	−0.66	−0.12	−0.26	−0.46	−0.50	0.02
RW	0.32	−0.21	−1.03	0.85*	−0.13	1.21**	−0.26	−0.03	−0.35	−0.46	−0.49	0.42
DRW	0.21	−0.27	−1.05	0.79*	−0.12	1.26**	−0.26	−0.03	−0.34	−0.46	−0.43	0.37
Panel C: Chile												
AR(1)	0.42	0.52	4.33***	0.41	0.25	0.50	−0.46	0.84*	−0.02	−0.50	0.18	−0.23
RW	−0.53	0.70	4.91***	0.07	0.81*	0.35	0.26	0.87*	−0.02	−0.07	0.15	0.03
DRW	−1.17	0.49	3.19***	−0.37	0.72	0.30	0.10	0.54	−0.05	−0.07	0.03	−0.03
Panel D: New Zealand												
AR(1)	−0.38	0.03	0.69	0.38	−0.20	0.00	−0.18	0.42	−0.15	−0.40	−0.20	−0.06
RW	−0.18	0.04	1.46**	0.23	0.09	0.09	0.37	0.43	−0.15	−0.48	−0.46	−0.15
DRW	−0.15	0.01	1.55**	0.25	0.11	0.12	0.46	0.45	−0.13	−0.51	−0.55	−0.14
Panel E: South Africa												
AR(1)	−0.38	−0.15	0.14	−0.04	−0.17	−0.35	0.19	−0.37	0.24	0.66	0.51	0.11
RW	0.96*	−0.16	0.34	−0.18	−0.10	−0.40	−0.07	−0.46	0.10	0.60	0.51	0.18
DRW	0.77*	−0.23	0.17	−0.20	−0.03	−0.49	−0.21	−0.45	0.04	0.45	0.46	0.13
Panel F: Iceland												
AR(1)	−0.62	−0.22	1.16*	−0.27	0.31	1.05*	0.19	0.15	−0.10	−0.04	−0.19	0.45
RW	−0.54	−0.25	1.58**	−0.26	1.25**	0.27	0.55	0.51	−0.05	−0.01	−0.52	0.30
DRW	−0.06	−0.10	2.61***	−0.01	1.23**	0.29	0.87*	0.84*	−0.04	−0.01	−0.35	0.36

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.

Table 17
Out-of-sample analysis for a different set of commodities P/R = 2.

ENCNEW												
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Bananas	Cocoa Beans	Copper	Gold	Lamb	Oats	Palm Oil	Platinum	Poultry (chicken)	Tea	Uranium	Wheat
Panel A: Australia												
AR(1)	−0.73	−0.99	−1.07	−0.33	0.70	−0.62	−1.61	−1.85	−0.33	0.09	2.08*	−1.55
RW	−0.96	−0.93	−0.26	−0.29	0.86	−0.78	−1.60	−1.84	−0.42	−1.17	2.31*	−1.28
DRW	−1.02	−0.90	0.14	−0.19	0.76	−0.79	−1.54	−1.77	−0.50	−1.07	2.31*	−1.10
Panel B: Canada												
AR(1)	−1.39	−1.61	−2.06	5.23***	−0.63	−0.08	−3.18	−0.61	−0.77	−1.72	−1.77	0.34
RW	−1.79	−1.55	−2.25	4.84**	−0.13	0.00	−2.24	−0.45	−1.20	−2.06	−1.65	0.98
DRW	−1.93	−1.46	−1.90	4.35**	−0.21	0.51	−2.16	−0.42	−1.50	−2.03	−1.67	1.11
Panel C: Chile												
AR(1)	2.88**	−0.18	4.88**	0.14	−2.28	2.64*	−0.92	−0.17	1.08	−1.05	−1.33	−1.38
RW	0.22	−0.40	1.97*	0.41	−0.96	1.33	−1.39	0.06	0.33	−1.83	−1.00	−1.60
DRW	0.50	0.17	3.33**	0.61	−0.54	1.58	−0.61	0.71	0.07	−1.29	−1.00	−1.36
Panel D: New Zealand												
AR(1)	−1.14	−0.97	−1.20	0.42	−1.57	0.33	−2.13	−0.56	−0.82	0.21	1.50	−0.28
RW	−1.36	−0.60	0.15	0.21	−0.88	−0.14	−1.90	−0.53	−0.89	−0.14	2.05*	0.12
DRW	−1.43	−0.53	0.52	0.08	−0.85	−0.09	−2.04	−0.60	−0.98	−0.10	2.18*	0.07
Panel E: South Africa												
AR(1)	−1.29	−2.69	−0.77	−0.76	−1.02	−0.51	−0.09	0.11	1.00	−0.12	0.25	−1.06
RW	−0.98	−1.90	0.02	−0.85	−0.72	−0.47	−0.65	0.36	−0.01	−0.78	0.31	−1.02
DRW	−1.06	−0.89	−0.19	−1.21	−0.59	−0.16	−0.73	−0.09	−0.50	−0.79	−0.01	−0.54
Panel F: Iceland												
AR(1)	−0.69	−1.19	−3.57	−0.52	0.31	0.37	−0.39	−1.90	−1.04	−0.02	−0.61	1.83*
RW	−0.55	−1.40	−2.62	−0.77	2.94**	−1.27	0.03	−1.09	−0.82	−0.89	−0.17	2.44*
DRW	−0.46	−1.31	−2.04	−0.06	1.94*	−0.89	0.85	−0.41	−0.75	−0.49	−0.15	2.84*

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 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.

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.

Two interesting contributions of our paper are the use of the Icelandic Krona and our results and discussion about the predictability of future prices. To our knowledge, the Icelandic Krona is not a frequently used commodity-currency in the relevant literature, and therefore its addition to the list of commodity-currencies with the ability to predict commodity prices is a by-product of our paper. Regarding futures contracts, we discuss arguments in favor and against their predictability. In summary, some authors argue that it is cheaper, easier and more efficient for investors and speculators to operate commodity futures contracts instead of spot contracts. This will lead to low or no predictability. Nevertheless, it is also true that spot and future prices are highly correlated. If the former are predictable, it would be natural to expect predictability for the latter. Our findings challenge the no predictability results of Chan et al. (2011) and the logic that supports them. We totally endorse the idea that future contracts at some maturities may represent a much more efficient market, yet our results indicate that this higher level of efficiency does not preclude their predictability.

It is important to emphasize that this paper does not attempt to study the channels or the structural links between aluminum and commodity-currencies. Our results are based on the evaluation of the predictive ability of commodity-currencies by Granger-causality; nevertheless, we do not address empirically "causation" by any means. As mentioned in Rossi (2012), such analysis would require the use of a structural model.

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 moderate or little production of base metals, like Australia, Canada, New Zealand and South Africa, have also 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, but maybe there are some other explanations that could be addressed in further research.

Provided that the debate on the ability that commodity-currencies have to predict commodity prices is far from settled and that there is mixed empirical evidence regarding the present-value model for exchange rate determination, we think that the crystal clear results that we report here are useful to shed some light to a discussion that requires more research to broadly understand the scope and limitations of the theory. 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 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:

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

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 A1.1
Main commodity exports of our countries according to Chen et al. (2010).

Composition of the commodity price indices including Iceland									
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						
Total Base Metals	Wt.	Total Base Metals	Wt.	Total Base Metals	Wt.	Total Base Metals	Wt.	Total Base Metals	Wt.
	13.10		11.70		100.00		8.30		-

Source: Chen et al. (2010).

Table A1.2
Main commodity exports of our countries including Iceland.

Composition of the commodity price indices including Iceland											
Australia		Canada		Chile		New Zealand		South Africa		Iceland	
Main Products	Wt.	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	Fish	48.99
Steaming Coal	9.70	Lumber	13.60			Wholemeal	10.60	Platinum	30.00	Iron	3.41
Gold	9.40	Pulp	12.80			Beef	9.40	Coal	22.00	Oils	2.15
Iron ore	9.30	Nat. Gas	10.70							Mineral Fuels	2.02
Base metals	Wt.	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	-	-	Aluminum	43.43
Copper	2.80	Copper	2.00								
Lead	0.70	Nickel	2.40								
Zinc	1.50	Zinc	2.30								
Total Base Metals	Wt. 13.10	Total Base Metals	Wt. 11.70	Total Base Metals	Wt. 100.00	Total Base Metals	Wt. 8.30	Total Base Metals	Wt. -	Total Base Metals	Wt. 43.43

Source: Chen et al. (2010) for Australia, Canada, Chile, New Zealand and South Africa. For the case of Iceland, we compute these weights based on information available at http://www.worldstopexports.com/

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

Correlations									
Australia									
	Coal	Gold	Iron ore	Copper	Lead	Zinc	Bloomberg index	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	0.38	
Canada									
	Oil	Lumber	Pulp	Nat. Gas	Copper	Nickel	Zinc	Bloomberg Index	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
Chile									
	Copper	Average Correlation							
1999Q3-2018Q4	0.76	0.76							
2007Q3-2018Q4	0.84	0.84							
20013Q1-2018Q4	0.69	0.69							
Iceland									
	Fish	Aluminum	Average Correlation						
1999Q3-2018Q4	0.25	1.00	0.63						
2007Q3-2018Q4	0.24	1.00	0.62						
20013Q1-2018Q4	0.00	1.00	0.50						
New Zealand									
	Lamb	Beef	Agricultural Index	Non Fuel Index	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				
South Africa									
	Gold	Platinum	Coal	Bloomberg Index	Average Correlation				
	0.28	0.53	-	0.68	0.49				

(continued on next page)

Table A2 (*continued*)

Correlations					
1999Q3-2018Q4					
2007Q3-2018Q4	0.27	0.56	-	0.78	0.54
20013Q1-2018Q4	0.30	0.33	0.24	0.44	0.33
Futures					
	3-month	15-month	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. Source: Author's elaboration.

Table A3
Main commodity exports in 2019 for commodity and non-commodity-currencies.

Main exports							
Panel A							
UK		Japan		Hungary		Sweden	
Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports
Machinery	15.60	Vehicles	21.10	Electrical Machinery	22.90	Machinery	16.00
Vehicles	10.80	Machinery	19.40	Machinery	16.60	Vehicles	14.90
Gems, precious metals	9.00	Electrical Machinery	14.60	Vehicles	16.30	Electrical Machinery	8.90
Mineral fuels (including oil)	8.80	Optical, medical apparatus	5.50	Pharmaceutical	5.20	Mineral fuels (including oil)	6.80
Electrical machinery	6.10	Iron, steel	3.70	Plastics	3.60	Pharmaceutical	6.40
Pharmaceutical	5.80	Plastics	3.60	Mineral fuels (including oil)	3.40	Paper	5.40
Optical, medical apparatus	4.30	Organic chemichals	2.50	Optical, medical apparatus	3.20	Iron, steel	4.20
Aircraft, spacecraft	3.90	Mineral fuels (including oil)	2.00	Rubber	2.10	Plastics	3.40
Organic chemichals	2.70	Ships, boats	2.00	Furniture	1.50	Fish	2.70
Collector items	2.60	Other chemical	1.70	Articles of Iron	1.40	Optical, medical apparatus	2.60
Total Commodity Exports	17.80	Total Commodity Exports	5.70	Total Commodity Exports	5.50	Total Commodity Exports	13.70
Panel B							
Israel		Turkey		Poland		Czech Rep.	
Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports
Electrical Machinery	13.70	Vehicles	15.30	Machinery	13.90	Vehicles	20.40
Optical, medical apparatus	9.40	Machinery	9.60	Vehicles	11.40	Machinery	19.80
Machinery	8.60	Iron, steel	5.80	Electrical Machinery	11.10	Electrical Machinery	18.30
Organic chemichals	7.40	Crochet clothing	5.30	Furniture	5.70	Articles of Iron	3.50
Pharmaceutical	5.70	Electrical Machinery	5.10	Plastics	4.90	Plastics	3.40
Other chemical	5.10	Gems, precious metals	4.30	Articles of Iron	3.30	Furniture	2.70
Plastics	4.70	Mineral fuels (including oil)	4.30	Mineral fuels (including oil)	2.20	Optical, medical apparatus	2.10
Aircraft, spacecraft	4.20	Articles of Iron	3.80	Meat	2.20	Iron, steel	2.00
Mineral fuels (including oil)	2.50	Clothing	3.80	Rubber	2.10	Rubber	2.00
		Plastics	3.70	Wood	2.00	Mineral fuels (including oil)	1.80
Total Commodity Exports	2.50	Total Commodity Exports	14.40	Total Commodity Exports	8.50	Total Commodity Exports	5.80
Panel C							
Australia		Canada		Chile		Iceland	
Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports
Mineral fuels (including oil)	32.60	Mineral fuels (including oil)	22.00	Ores	29.00	Fish	38.80
Ores	28.90	Vehicles	13.80	Copper	21.60	Aluminum	34.40
Gems, precious metals	6.60	Machinery	7.80	Fish	8.40	Aircraft, spacecraft	3.00

(*continued on next page*)

Table A3 (*continued*)

Main exports							
Panel A							
UK		Japan		Hungary		Sweden	
Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports	Main Exports	% of total exports
Meat	4.20	Gems, precious metals	4.80	Fruits, nuts	8.40	Iron, steel	2.70
Inorganic chemicals	2.30	Electrical Machinery	3.00	Woodpulp	3.90	Machinery	2.60
Machinery	1.80	Plastics	2.80	Wood	3.40	Food industry waste	2.50
Pharmaceutical	1.40	Wood	2.60	Inorganic chemicals	3.10	Optical, medical apparatus	2.30
Electrical Machinery	1.30	Aircraft, spacecraft	2.50	Beverages	2.80	Meat/seafood prepar.	2.30
Cereals	1.30	Ores	2.00	Gems, precious metals	2.00	Oils	1.70
Optical, medical apparatus	1.20	Pharmaceutical	1.90	Meat	1.60	Mineral fuels (including oil)	1.60
Total Commodity Exports	73.60	Total Commodity Exports	31.40	Total Commodity Exports	78.30	Total Commodity Exports	77.50
Panel D							
New Zealand		South Africa					
Main Exports	% of total exports	Main Exports	% of total exports				
Dairy, eggs, honey	27.90	Gems, precious metals	17.00				
Meat	13.90	Ores	14.50				
Wood	8.70	Vehicles	12.70				
Fruits, nuts	5.90	Mineral fuels (including oil)	10.10				
Cereal/milk preparations	3.90	Machinery	6.10				
Beverages	3.70	Iron, steel	6.00				
Fish	3.20	Fruits, nuts	3.80				
Machinery	2.60	Aluminum	2.00				
Miscellaneous food prepar.	2.30	Electrical Machinery	1.90				
Modified starches	2.10	Plastics	1.60				
Total Commodity Exports	59.60	Total Commodity Exports	53.40				

Source: Author's elaboration based on data available at http://www.worldstopexports.com/

Table A4
Econometric specifications for Tables 9 and 10.

$$1: \ \Delta\ln(Al_t) = c + \beta[\Delta\ln(Australia_{t-1}) + \Delta\ln(Australia_{t-2}) + \Delta\ln(Canada_{t-1}) + \Delta\ln(Canada_{t-2}) + \Delta\ln(Chile_{t-1}) + \Delta\ln(Chile_{t-2}) + \Delta\ln(Iceland_{t-1}) + \Delta\ln(Iceland_{t-2}) + \Delta\ln(NewZealand_{t-1}) + \Delta\ln(NewZealand_{t-2}) + \Delta\ln(SouthAfrica_{t-1}) + \Delta\ln(SouthAfrica_{t-2})] + \varepsilon_{1t}$$

$$2: \ \Delta\ln(Al_t) = c + \beta_1[\Delta\ln(Australia_{t-1}) + \Delta\ln(Australia_{t-2})] + \beta_2[\Delta\ln(Canada_{t-1}) + \Delta\ln(Canada_{t-2})] + \beta_3[\Delta\ln(Chile_{t-1}) + \Delta\ln(Chile_{t-2})] + \beta_4[\Delta\ln(Iceland_{t-1}) + \Delta\ln(Iceland_{t-2})] + \beta_5[\Delta\ln(NewZealand_{t-1}) + \Delta\ln(NewZealand_{t-2})] + \beta_6[\Delta\ln(SouthAfrica_{t-1}) + \Delta\ln(SouthAfrica_{t-2})] + \varepsilon_{2t}$$

$$3: \ \Delta\ln(Al_t) = c + \beta_1[\Delta\ln(Chile_{t-1}) + \Delta\ln(Chile_{t-2})] + \beta_2[\Delta\ln(Iceland_{t-1}) + \Delta\ln(Iceland_{t-2})] + \varepsilon_{3t}$$

$$4: \ \Delta\ln(Al_t) = c + \beta[\Delta\ln(Chile_{t-1}) + \Delta\ln(Chile_{t-2}) + \Delta\ln(Iceland_{t-1}) + \Delta\ln(Iceland_{t-2})] + \varepsilon_{4t}$$

$$5: \ \Delta\ln(Al_t) = c + \beta f_{t-1} + \varepsilon_{5t}$$

Notes: This table summarizes the specifications used in Tables 9 and 10. Similar to specification 2 in Table 1 in the paper, we use a constant and two lags of the exchange rates; however, here we combine different exchange rates in the same model. Specification 1 uses the sum of the first two lags of each of our six exchange rates as the only predictor. Specification 2 considers the sum of the first two lags of each exchange rate as different predictors. Specification 3 is akin to specification 2, but just using the Chilean Peso and the Icelandic Krona as predictors. Specification 4 is akin to specification 1, but just adding up the first two lags of the Chilean Peso with those of the Icelandic Krona. Finally, specification 5 uses just the first principal component of the sum of the first two lags of the returns of our six exchange rates as the relevant predictor. Notice that Tables 9 and 10 also consider forecasts based on LASSO; in this case, we estimate our parameters based on specification 2, but obviously some parameters in each out-of-sample window may be set automatically to zero by LASSO.

So economic causality runs from the whole linear combination $\omega' F_t$ to the exchange rate S_t. Therefore, using the ceteris paribus argument, each fundamental in the vector F_t has a causal impact on the exchange rate. An empirical identification of the true causal effect of each fundamental may be troublesome due to endogeneity issues and also because some fundamentals may be unobservable. Irrespective of how difficult the identification is, the implication of the model is that of a causal linkage between fundamentals and the exchange rate. According to either Chen et al. (2010) or http://www.worldstopexports.com/five out of our six commodity exporter countries produce and export aluminum either with a small or a large share in their export basket. The only country with no production of aluminum whatsoever is Chile. Following the present-value model for exchange rate determination, this means that aluminum has an economic causal impact on the respective currencies. This impact should be proportional to the weights in the linear combination of fundamentals, so the causal effect is likely to be higher in Iceland than in South Africa for instance. Chile does not export aluminum, but about a half of its exports are copper, which is a substitute of aluminum in some electrical industrial applications. A causal effect from aluminum prices to the Chilean exchange rate is also likely: a rise in aluminum prices would boost the demand for its substitutes, including copper, and consequently the copper price will rise. The rise in copper price triggered by the rise in the price of its substitute will have a causal impact on the exchange rate via the present-value model. Therefore, at least in theory, aluminum would have a causal economic impact on the exchange rates of our six commodity exporters.

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