Exchange rate Expectations and Base Metal Prices☆

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Abstract

In this paper we show that expectations about the future evolution of the Chilean exchange rate have the ability to predict the returns of the six primary non-ferrous metals: aluminum, copper, lead, nickel, tin and zinc. Predictability is also found for returns of the London Metal Exchange Index. Previous studies have shown that the Chilean exchange rate has the ability to predict copper returns, a world commodity index and base metal prices. Nevertheless, our results indicate that expectations about the Chilean peso have stronger predictive ability relative to the Chilean currency. This is shown both in-sample and out-of-sample. By focusing on expectations of a commodity currency, and not on the currency itself, our paper provides indirect but new evidence of the ability that commodity currencies have to forecast commodity prices.

Keywords:
Forecasting, commodities, prices, univariate time-series models, out-of-sample comparison, exchange rates, copper, primary non-ferrous metals
JEL: C52, C53, G17, E270, E370, F370, L740, O180, R310.

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1. Introduction

In this paper we show that expectations about the future evolution of the Chilean exchange rate have the ability to predict the returns of the six primary non-ferrous metals: aluminum, copper, lead, nickel, tin and zinc. Predictability is also found for returns of the London Metal Exchange Index[2]. Our results are important because they provide indirect but new evidence of the ability that commodity currencies have to forecast commodity prices.

Relatively recent literature has explored the empirical linkages beetween exchange rates and commodity prices in commodity exporters countries. In particular Chen, Rossi and Rogoff (2010, 2014) (hereafter CRR) focus on five commodity exporting countries: Australia, Canada, Chile, New Zealand and South Africa. They show that these commodity currencies have the ability to forecast global commodity prices, and that some country specific exchange rates are able to forecast the price fluctuations of their own country's commodity export bundle. These results have received a lot of attention in the literature, in part because they are important for the forecasting literature per se, but also because they are consistent with the present value model for exchange rate determination. One of the key implications of this model is that exchange rates should have the ability to predict their fundamentals, see Engel and West (2005) and Campbell and Shiller (1987). As in commodity exporter countries one of the important fundamentals of the local currencies is the price of the commodities being exported, the implication of the model is that exchange rates should predict commodity prices.

Besides the influential work by CCR, several other papers have explored the predictive relationship between commodity prices and commodity currencies. See for instance Chen, Rossi and Rogoff (2011), Groen and Pesenti (2011), Gargano and Timmermann (2014), Lof and Nyberg (2017), Ciner (2017) and Pincheira and Hardy (2018). All this papers evaluate directly the predictive ability from commodity currencies to commodity prices. One problem with this strategy is that exchange rates are determined by a variety of different economic forces: some expected, some unexpected. Even in commodity exporting countries, other drivers like interest rate differentials, shocks in import prices or interventions carried out by monetary authorities may play a role in the determination of exchange rates and consequently may erode their ability to predict commodity prices. To partially overcome this shortcoming, in this paper we analyze the predictive relationship between survey-based expectations of commodity currencies and commodity prices. We do so with the hope that survey-based expectations may be free of erratic and unexpected movements in exchange rates generated by sources other than expectations about future developments in the commodity being exported.

We focus on one particular commodity currency: the Chilean peso, which has been traditionally analyzed in the literature. We consider the Survey of Economic Expectations (SEE) carried out on a monthly basis by the Central Bank of Chile to extract expectations about future developments of the Chilean peso. Following Pincheira and Hardy (2018) we explore whether these expectations have the ability to predict all six base metal prices returns plus

[2]The LME index consideres the following weights: aluminum (42.8%), copper (31.2%), zinc (14.8%), lead (8.2%), nickel (2%) and tin (1%).

the returns of the LME Index. Let us recall that copper represents about a half of Chilean exports and nearly 45% of its Foreign Direct Investment (FDI)[3].

Our in sample and out-of sample analyses provide evidence of predictability from survey-based expectations of the Chilean peso to all six base metals returns including those from the LME Index. Our evidence of predictability is even stronger compared to that contained in the Chilean peso itselt. We have two possible explanations for this. First, as mentioned before, survey based expectations are free of unanticipated movements in exchange rates that are related to other reasons not connected with commodity prices. Second, the information set on which market participants based their expectations, contains the lags of the Chilean peso, so these expectations should be at least as accurate as forecasts based on these lags.

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

2. Data and forecasting models

We consider monthly data on Chilean exchange rate expectations coming from the Survey of Economic Expectations (SEE) of the Central Bank of Chile. Data in the same frequencies for all six commodity prices included in the LME Index are also considered. We include data for the LME Index and for the Chilean peso against the U.S. dollar as well. Aside from the survey of the Central Bank of Chile, the main source of our data is Thomson Reuters Datastream from which we downloaded the daily close price of each asset. Our data are converted to monthly frequencies by sampling from the last day of the month.

Our sample period goes from September 2001 until April 2018. This gives a total of 200 monthly observations[4]. The starting point of our sample period is determined by data availability on exchange rate expectations. The longest series on expectations covers exactly our sample period. This is also a period of almost pure flotation of the Chilean peso, with only a handful of pre-annouced interventions from the Central Bank of Chile, see Pincheira (2013a). Some descriptive statistics of our series are found in Table A1 in the appendix.

Our econometric specifications are quite simple. They are inspired in the benchmarks used by CRR and by a vast literature that has shown that either the Random Walk (henceforth RW) or simple autoregressions are usually difficult benchmarks to beat when forecasting asset returns[5]. Our in-sample and out-of-sample analyses at the monthly frequency are based on the following simple specifications:

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[3]According to the Central Bank of Chile, copper exports represents 50.4% of total Chilean exports during the period January 2003-October 2017. Similarly, the mining sector has absorved 44.3% of total FDI in Chile during the period 2009-2015.

[4]In terms of one period returns, we have 199 monthly observations.

[5]Examples in the exchange rate literature are given by Meese and Rogoff (1983) and Clark and West (2006) for instance. When forecasting commodity prices, Chenn, Rossi and Rogoff (2010, 2014) consider

Table 1: Basic Specifications

1:	$\Delta \ln (CP_t) = c + \beta\Delta \ln (SEE_{t-1}) + \rho\Delta \ln (CP_{t-1}) + \varepsilon_{1t}$
2:	$\Delta \ln (CP_t) = c + \beta\Delta \ln (SEE_{t-1}) + \varepsilon_{2t}$
3:	$\Delta \ln (CP_t) = \beta\Delta \ln (SEE_{t-1}) + \varepsilon_{3t}$

Source: Authors' elaboration

where

$$\begin{aligned} \Delta \ln(CP_t) &\equiv \ln(CP_t) - \ln(CP_{t-1}) \\ \Delta \ln(SEE_t) &\equiv \ln(SEE_t) - \ln(SEE_{t-1}) \end{aligned}$$

CP_t stands for "Commodity Price" and represents the generic predictand at time t, which in our case represents aluminum, copper, lead, nickel, tin, zinc and the LME Index. Similarly, SEE_t represents the expectations of the Chilean peso available at the Survey of Economic Expectations at time t. Finally, ε_{it} represent error terms.

We also explore some specifications with Chilean exchange rates. This is helpful to evaluate whether there is redundant information in the survey, or it actually adds more information relative to that contained in lags of Chilean peso returns. Consequently, we also consider the following specifications

Table 2: Specifications with Chilean Peso Returns

4:	$\Delta \ln (CP_t) = c + \beta\Delta \ln (SEE_{t-1}) + \rho\Delta \ln (CP_{t-1}) + \gamma\Delta \ln(ER_{t-1}) + \varepsilon_t$
5:	$\Delta \ln (CP_t) = c + \beta\Delta \ln (SEE_{t-1}) + \gamma\Delta \ln(ER_{t-1}) + \varepsilon_t$
6:	$\Delta \ln (CP_t) = \beta\Delta \ln (SEE_{t-1}) + \gamma\Delta \ln(ER_{t-1}) + \varepsilon_t$

Source: Authors' elaboration

For these specifications, we consider the following null hypothesis H_0:

$$H_0 : \beta = 0$$

Our null hypothesis H_0 posits that exchange rate expectations has no role in predicting commodity returns. We test this hypothesis both in-sample and out-of sample focusing on one-step-ahead forecasts only, leaving the analysis of multistep ahead forecasts as an extension for future research.

the RW and an AR(1) as benchmarks, Lof and Nyberg (2017) consider both a causal and noncausal AR(1) whereas Groen and Pesenti (2011) uses autoregressions with more lags, but autoregressions in the end. Also Buncic and Moretto (2015) consider the RW as the benchmark to beat when forecasting copper prices. In stock returns, Goyal and Welch (2008) use the historical average as the benchmark when predicting excess returns.

In sample evaluations are simply carried out using a t-statistic. For out-of-sample evaluations we use the ENCNEW test proposed by Clark and McCracken (2001) and also used by CRR. This test has a non-standard asymptotic distribution, but critical values for one-step-ahead forecasts are available in the appendix of that paper. In general, Clark and McCracken (2001) show that the resulting 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 regressions, 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-sampe analyses. The asymptotic distribution of the test varies also with the scheme used to update the estimates of the parameters: either rolling, expanding or fixed. See Clark and McCracken (2001) or West (2006) for further details about the implementation of out-of-sample tests of predictive ability in nested environments.

For our in-sample analysis we estimate our models with all the available observations. 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. We consider three different ways of splitting our samples. First we use one quarter of our observations for initial estimation and three quarters for evaluation. This means that we pick $R = 50$ and $P = 150$. Second, we split our sample in two halfs, which means $R = 100$ and $P = 100$. Finally, we also consider a different situation in which we pick aproximately 70% of our sample for initial estimation and 30% for evaluation. This means $R = 143$ and $P = 57$[6].

3. Empirical Resuls

In this section we report in sample estimates and tests of equations 1 and 4 in Tables 1 and 2. We also show 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

Tables 3 and 4 next show estimates of equations 1 and 4 in Tables 1 and 2. In Table 3 we show results when estimating equation 1, whereas in Table 4 we show results when estimating equation 4. In both tables we use HAC standard errors according to Newey and West (1987, 1994).

[6]The shortest initial estimation window spans the period September 2001-October 2005. The second shortest initial estimation window spans the period September 2001-December 2009. The longest initial estimation window spans the period September 2001-July 2013. These choices are partly driven by the table of asymptotic critical values in Clark and McCracken (2001). This table provides critical values for specific values of the ratio P/R. We consider three values: 3, 1 and 0.4.

Table 3: Forecasting Base Metals Returns with Expectations of the Chilean Peso
In-sample analysis with monthly data

	(1) *Copper*	(2) *Aluminum*	(3) *Zinc*	(4) *Nickel*	(5) *Lead*	(6) *Tin*	(7) *Lmex*
SEE(-1)	-1.167***	-0.824***	-1.169***	-1.112***	-1.228***	-0.827***	-1.046***
	(0.356)	(0.200)	(0.290)	(0.424)	(0.365)	(0.270)	(0.255)
Copper(-1)	-0.008						
	(0.086)						
Aluminum(-1)		-0.125					
		(0.121)					
Zinc(-1)			-0.152*				
			(0.091)				
Nickel(-1)				-0.078			
				(0.086)			
Lead(-1)					-0.116		
					(0.075)		
Tin(-1)						0.036	
						(0.088)	
Lmex(-1)							-0.064
							(0.095)
Constant	0.007	0.003	0.007	0.005	0.008	0.008	0.006
	(0.006)	(0.005)	(0.006)	(0.008)	(0.006)	(0.006)	(0.005)
Observations	198	198	198	198	198	198	198
R-squared	0.122	0.088	0.097	0.055	0.089	0.078	0.128

SEE stands for the log difference in exchange rate expectations

Table 3 presents estimations of equation 1 in Table 1. * p<10%, ** p<5%, *** p<1%

Source: Authors' elaboration.

In the first row of Table 3 we see that our null hypothesis is rejected at the 1% significance level in all seven cases. Moreover, all the coefficients asssociated to exchange rate expectations are negative, which is consistent with the intuition of a negative relationship between the Chilean peso and the copper price.

A few additional features are worth noticing. First, aside from the case of zinc, neither the constant term nor the first lag of the asset returns being predicted are statistically significant. This is consistent with very little autocorrelation in asset returns. Notably, the coefficients associated to the expectations of the Chilean peso are, in general, close to one in absolute value. Finally, the coefficient of determinations are in the range of 5%-13%, being the highest for the LME Index and the lowest for Nickel. All in all, our results suggest an interesting ability of the the expectations of the Chilean peso to predict base metals returns.

Table 4: Forecasting Base Metals Returns with Expectations of the Chilean Peso
Regressions including one lag of Chilean Peso Returns

	(1) Copper	(2) Aluminum	(3) Zinc	(4) Nickel	(5) Lead	(6) Tin	(7) Lmex
SEE(-1)	*-1.796****	*-1.033****	*-1.560****	*-1.575***	*-1.092***	*-1.395****	*-1.492****
	(0.542)	*(0.330)*	*(0.524)*	*(0.514)*	*(0.484)*	*(0.429)*	*(0.405)*
CLP(-1)	*0.634***	*0.196*	*0.384*	*0.442*	*-0.129*	*0.521**	*0.452**
	(0.293)	*(0.225)*	*(0.328)*	*(0.438)*	*(0.342)*	*(0.268)*	*(0.250)*
Copper(-1)	*0.036*						
	(0.091)						
Aluminum(-1)		*-0.117*					
		(0.120)					
Zinc(-1)			*-0.129*				
			(0.092)				
Nickel(-1)				*-0.064*			
				(0.090)			
Lead(-1)					*-0.120*		
					(0.077)		
Tin(-1)						*0.046*	
						(0.085)	
Lmex(-1)							*-0.027*
							(0.101)
Constant	*0.007*	*0.003*	*0.007*	*0.005*	*0.008*	*0.008*	*0.006*
	(0.005)	*(0.005)*	*(0.006)*	*(0.008)*	*(0.006)*	*(0.006)*	*(0.005)*
Observations	*198*	*198*	*198*	*198*	*198*	*198*	*198*
R-squared	*0.147*	*0.092*	*0.106*	*0.062*	*0.090*	*0.098*	*0.147*

SEE stands for the log difference in exchange rate expectations. CLP stands for Chilean Peso Returns
Table 4 presents estimations of equation 4 in Table 2. * p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

Results from Table 4 are more or less equally striking as those from Table 3. In particular, we find no signs of autocorrelation, and all the coefficients associated to expectations of Chilean peso returns are statistically significant at tight significance levels. They are also all negative and important in magnitude. Notable, in only three cases the returns of the Chilean peso are statistically significant (copper, LMEX and tin) and their coefficients are postive, indicating that most of the action between exchange rates and base metal prices is indeed captured by expectations to the detriment of actual lags of the Chilean peso returns. Now the coefficients of determinaton are higher, in the range of 6%-15%. Remarkably, the lowest coefficient is again achieved for Nickel, and the highest for the LME Index and copper. Of course this last point must not be considered too seriously as it is a textbook fact that the addition of irrelevant variables may induce an increment in the R^2 diagnostic statistic.

All in all, our in-sample estimates provide evidence of a strong relationship between the time series on base metal returns and exchange rate expectations. In-sample estimates, however, are usually criticized because they are relatively different from a real time forecasting exercise and also because they are prone to overfitting. To mitigate these shortcomings, we move next to an out-of-sample analysis.

3.2. Out-of-sample Analysis

Tables 5-7 show results of the ENCNEW test of Clark and McCracken (2001) in different out-of-sample exercises. Table 5 show results when the number of forecasts is three times the number of observations of the first estimation window ($\pi \equiv P/R = 3$). Tables 6 is similar to Tables 5 but reports results when the number of forecasts is the same as the number of observations used in the first estimation window ($\pi \equiv P/R = 1$). Finally, in Table 7 we consider a situation in which the number of forecasts is 40% of the number of observations used in the first estimation window ($\pi \equiv P/R = 0.4$). We consider rolling instead of expanding windows, because they probably take better into account potential instabilities that are likely to exist in the data.

Table 5: Forecasting Base Metals Returns with Expectations of Chilean Exchange Rates
Out-of-sample analysis in rolling windows of size R=50, ($\pi \equiv P/R = 3$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ENC-NEW						
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	12.93***	10.76***	8.28***	5.43**	9.91***	10.94***	14.92***
RW	15.95***	20.78***	8.46***	5.89**	11.34***	10.98***	22.76***
DRW	15.62***	22.12***	9.67***	5.72**	11.78***	10.37***	23.51***

10%, 5% and 1% critical values are 2.322, 3.444 and 5.976 respectively for ENCNEW when excess parameters are 1.
P representes 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 to the SEE is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1, respectively, when the coefficient associated to the SEE is set to zero
* p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

Table 6.: Forecasting Base Metals Returns with Expectations of Chilean Exchange Rates
Out-of-sample analysis in rolling windows of size R=100, ($\pi \equiv P/R = 1$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ENC-NEW			
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	6.89***	4.25***	8.49***	1.85*	4.61***	7.59***	6.21***
RW	2.20**	1.44*	3.51***	0.34	4.46***	3.02**	2.57**
DRW	2.01**	0.55	2.57**	0.27	3.60**	2.53**	1.84*

10%, 5% and 1% critical values are 1.210, 1.946 and 3.676 respectively for ENCNEW when excess parameters are 1.
P representes the number of one-step-ahead forecasts, R the sample size of the estimation windows.
The AR(1) benchmark corresponds to model 1 in Table 1 when the coefficient associated to the SEE
is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1,
respectively, when the coefficient associated to the SEE is set to zero
* p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

The null hypothesis of no predictability is rejected in the vast majority of the cases at least at the 10% significant level. This means that we detect predictability against all our three benchmark models, for most of the base metals and also for the LME Index. Actually, rejections of the null are found in 57 of the total of 63 entries in tables 5-7. Robust evidence of predictability across all three tables and all three benchmarks are found for lead, tin, zinc and the LME Index. Moreover, in many entries of the tables, we reject the null hypothesis at tight significance levels of 1%.

Table 7: Forecasting Base Metals Returns with expectations of Chilean exchange rates
Out-of-sample analysis with rolling windows of size R=143 ($\pi \equiv P/R = 0.4$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ENC-NEW			
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	1.84**	2.29***	8.18***	3.21***	5.73***	5.66***	3.76***
RW	-0.70	1.85**	4.46***	2.20**	5.27***	4.28***	3.00***
DRW	-0.99	0.50	3.58****	1.85**	4.31***	3.48***	1.74**

10%, 5% and 1% critical values are 0.764, 1.161 and 2.278 respectively for ENCNEW when excess parameters are 1.
P representes 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 to the SEE
is set to zero. Similarly, the RW and DRW benchmarks correspond to models 2 and 3 in Table 1,
respectively, when the coefficient associated to the SEE is set to zero
* p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

To explore whether the predictive relationship between base metals and exchange rate expectations is overshadowed by the presence of the lag of the Chilean exchange rate, tables 8-10 next show the ENCNEW statistic when the relevant models are those in Table 2, in other words, when we augment our benchmarks with one lag of monthly returns of the Chilean peso.

Table 8: Forecasting with Expectations of Chilean Exchange Rates and Exchange Rates
Out-of-sample analysis in rolling windows of size R=50, ($\pi \equiv P/R = 3$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ENC-NEW						
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	8.02***	18.41***	1.47	5.57**	12.80***	13.44***	18.83***
RW	11.93***	19.23***	3.69**	6.84***	11.40***	11.49***	18.65***
DRW	11.15***	18.28***	3.91**	7.06***	14.39***	11.25***	18.17***

10%, 5% and 1% critical values are 2.322, 3.444 and 5.976 respectively for ENCNEW when excess parameters are 1.
P representes the number of one-step-ahead forecasts, R the sample size of the first estimation window.
The AR(1) benchmark corresponds to model 4 in Table 2 when the coefficient associated to the SEE
is set to zero. Similarly, the RW and DRW benchmarks correspond to models 5 and 6 in Table 2,
respectively, when the coefficient associated to the SEE is set to zero
* p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

Table 9: Forecasting with Expectations of Chilean Exchange Rates and Exchange Rates
Out-of-sample analysis in rolling windows of size R=100, ($\pi \equiv P/R = 1$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ENC-NEW						
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	6.83***	10.84***	3.43**	4.93***	7.18***	6.42***	11.13***
RW	3.79***	6.70***	5.67***	4.85***	5.83***	6.74***	7.18***
DRW	3.52**	6.43***	5.16***	5.24***	5.57***	6.65***	7.03***

10%, 5% and 1% critical values are 1.210, 1.946 and 3.676 respectively for ENCNEW when excess parameters are 1.
P representes the number of one-step-ahead forecasts, R the sample size of the estimation windows.
The AR(1) benchmark corresponds to model 4 in Table 2 when the coefficient associated to the SEE
is set to zero. Similarly, the RW and DRW benchmarks correspond to models 5 and 6 in Table 2,
respectively, when the coefficient associated to the SEE is set to zero
* p<10%, ** p<5%, *** p<1%
Source: Authors' elaboration.

Table 10: Forecasting with Expectations of Chilean Exchange Rates and Exchange Rates
Out-of-sample analysis with rolling windows of size R=143 ($\pi \equiv P/R = 0.4$)

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				ENC-NEW			
Benchmark Model	*aluminum*	*copper*	*lead*	*nickel*	*tin*	*zinc*	*lmex*
AR(1)	0.90*	3.97***	2.63***	1.80**	5.36***	4.88***	4.46***
RW	0.42	2.73***	3.32***	0.73	3.68***	5.15***	3.13***
DRW	0.20	1.93**	3.34***	0.35	2.92***	5.77***	2.67***

10%, 5% and 1% critical values are 0.764, 1.161 and 2.278 respectively for ENCNEW when excess parameters are 1.

P representes the number of one-step-ahead forecasts, R the sample size of the estimation windows.

The AR(1) benchmark corresponds to model 4 in Table 2 when the coefficient associated to the SEE is set to zero. Similarly, the RW and DRW benchmarks correspond to models 5 and 6 in Table 2, respectively, when the coefficient associated to the SEE is set to zero

* p<10%, ** p<5%, *** p<1%

Source: Authors' elaboration.

Results in Tables 8-10 clearly show that the predictive ability of exchange rate expectations is not overshadowed by the presence of one lag of Chilean peso returns.

4. Concluding remarks

In recent years, and starting with the paper by Chen, Rossi and Rogoff (2010), a growing literature has evaluated the ability of commodity currencies to forecast commodity prices. In this paper, we contribute to this literature by showing that survey-based expectations of the Chilean exchange rate have the ability to predict the returns of the London Metal Exchange Index and of the six primary non-ferrous metals that are part of the index: aluminum, copper, lead, nickel, tin and zinc. Using both in-sample and out-of-sample analysis we find strong evidence of this predictability at the population level.

Our results show that exchange rate expectations have stronger ability to predict commodity returns relative to the Chilean exchange rate. We have two possible explanations for this. First, survey based expectations are free of unanticipated movements in exchange rates that are related to other reasons not connected with commodity prices. Second, the information set on which market participants base their expectations contains the lags of the Chilean peso, so these expectations should be at least as accurate as forecasts based on these lags.

An interesting avenue for future research could extend the analysis to consider other commodity currencies, aside from the Chilean peso. It would be also interesting to explore if this predictive relationship survives at longer horizons.

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Appendix A. Descriptive Statistics

Table A1: Descriptive Statistics of our Series

Sample Period

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Aluminum	*Copper*	*Nickel*	*Zinc*	*Lead*	*Tin*	*Lmex*	*Clp*	*SEE*
Mean	0.0027	0.0079	0.0052	0.0070	0.0082	0.0088	0.0059	-0.0006	-0.0003
Median	0.0003	0.0133	0.0073	0.0080	0.0119	0.0081	0.0101	-0.0011	0.0000
Standard Deviation	0.0606	0.0795	0.1051	0.0817	0.0921	0.0739	0.0648	0.0334	0.0244
Max	0.1563	0.2709	0.3009	0.2450	0.2399	0.2382	0.2030	0.1988	0.0929
Min	-0.1686	-0.4208	-0.2965	-0.3802	-0.3231	-0.2093	-0.3109	-0.0699	-0.0535

Source: Authors' elaboration.