Summary of the Paper Entitled: Forecasting Fuel Prices with the Chilean Exchange Rate

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Summary of the Paper Entitled:

Forecasting Fuel Prices with the Chilean Exchange Rate[1]

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Abstract

This draft is a summary of the paper entitled: Forecasting Fuel Prices with the Chilean Exchange Rate. In that paper we show that the Chilean exchange rate has the ability to predict the returns of oil prices and of three additional oil-related products: gasoline, propane and heating oil. The theoretical underpinnings of our empirical findings rely on the present-value theory for exchange rate determination and on the strong co-movement displayed by some commodity prices. The Chilean economy is heavily influenced by one particular commodity: copper, which represents nearly 50% of total national exports and attracts a similar share in terms of Foreign Direct Investment. As a consequence, the floating Chilean exchange rate is importantly affected by fluctuations in the copper price. As oil-related products display an important co-movement with base metal prices, it is reasonable to expect evidence of Granger causality from the Chilean peso to these oil-related products. We find substantial evidence of predictability both in-sample and out-of-sample. Our paper is part of a growing literature that in the recent years has explored the linkages between commodity prices and commodity currencies.

JEL Codes: C52, C53, C22, C32, E17, E27, E37, E51, E58, F31, F37, F47, G12, Q30, Q41, Q43, Q47

Keywords: Exchange rates, energy, oil, gasoline, commodity prices, predictability, time-series

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1. Introduction

In this draft we present a summary of the findings presented in the paper entitled "Forecasting Fuel prices with the Chilean Exchange Rate". In that paper we find that the Chilean exchange rate has a remarkable ability to forecast fuel returns. These results are interesting for two main reasons. First, we report that the currency of a net oil importer, that is not relevant in the international fuel markets, can predict fuel prices. Secondly, our analysis considers not just the frequently studied crude oil, but also, three oil-derivative products: propane, regular gasoline and heating oil.

Our approach is inspired by the Commodity Currencies Hypothesis (CCH) explained in Chen, Rogoff and Rossi (2010, 2014). This theory implies that floating currencies from commodity exporters may Granger-cause future movements in international prices of primary commodity products. This predictive channel is sustained on the present-value model for nominal exchange rate determination[2]. Campbell and Shiller (1987) demonstrate that in a present-value relationship, Granger causality and economic causality may go in opposite directions: while the commodity price has an impact on the exchange rate of the commodity exporting country, the latter has predictive ability on the former.

The Chilean peso is particularly attractive as a commodity-currency due to the relevance of copper in the country's economy. According to the Central Bank of Chile, copper represented 48.02% of total Chilean exports in 2019. Besides, Chile is a net oil-importer country with about 10% of total imports focused on purchases of crude oil and its derivatives. See Central Bank of Chile (2018).

[2] In this framework, the nominal exchange rate is the discounted sum of its fundamentals:

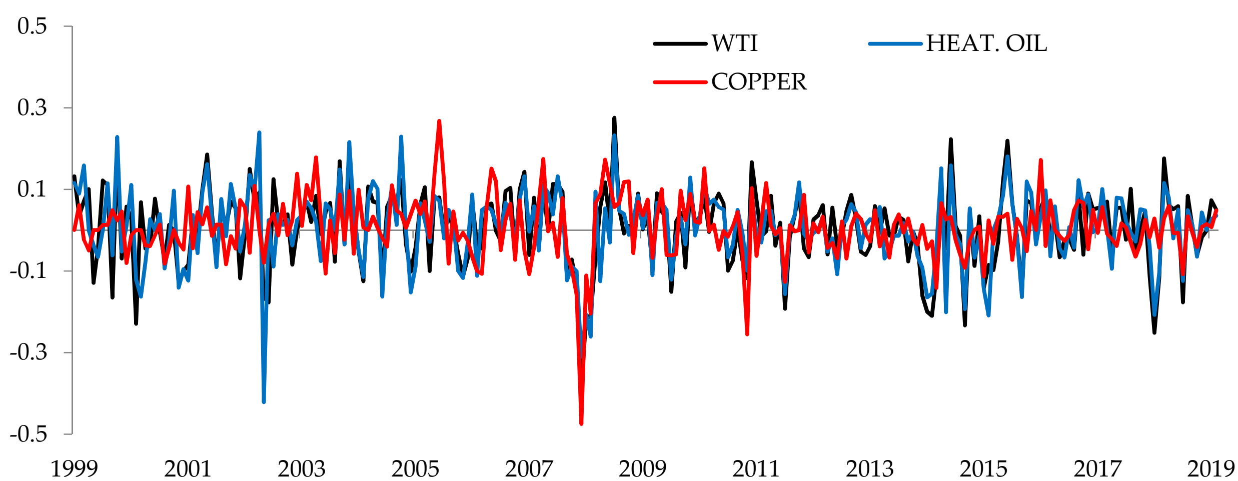
$$s_t = \gamma \sum_{j=0}^{\infty} \psi^j E_t(f_{t+j}|I_t)$$

where f_t represents the fundamental variable or the linear combination of variables that determines the nominal exchange rate. The information contained in f_t consists on the relevant economic factors that affect the currency, such as exporting commodity prices, interest rates differentials, money supply, output and inflation rates.

A direct implication of the CCH for Chile would say that the Chilean peso might have the ability to Granger-cause copper returns. In principle it is not clear at all what this theory might imply for the connection between the Chilean exchange rate and fuel returns, provided that the share of oil-related products in the Chilean trade balance is not particularly high. Figure 1 sheds some light on this matter. This figure shows monthly logarithmic differences for three commodities: copper, crude oil (West Texas Intermediate, WTI) and heating oil. The returns of all these products fluctuate closely together. Moreover, in the full version of the paper, that is available upon request, we show correlations between all the commodities in our database. All correlations are positive, and they are in general relatively high, suggesting a tight connection between copper and fuel returns, which we think is behind the predictive relationship between with the Chilean exchange rate and fuel prices.

This summary is structured as follows. In section 2 we present the data and forecasting models. In section 3 we report our empirical results both for our in-sample and out-of-sample exercises. Finally, in section 4 we present a summary of our analysis and the concluding remarks.

Figure 1: Co-movement between copper and fuel returns



Notes: Logarithmic monthly differences for three commodities: WTI, heating oil and copper. Sample period: 1999M11 – 2019M12. WTI and heating oil prices are from the Energy Information Administration database, while copper comes from the Chilean Copper Commission database. Source: Authors' elaboration

2. Data and Methodology

Data

We use two reference measures for the case of crude oil: Brent prices and WTI delivered in Cushing, Oklahoma. We also consider three oil-derivative products: propane, regular gasoline and heating oil. In our empirical analysis we also make use of the London Metal Exchange (LME) index and of the Chilean exchange rate defined as the amount of Chilean pesos required to buy one U.S. dollar. Finally, we also consider WTI futures prices. In particular we pick the series labeled "futures contract 2" from the Energy Information Administration (EIA).

We have three different data sources. For the case of crude oil, refined products and WTI futures prices, the series are obtained from the EIA database. The LME index and the Chilean exchange rate come from Thomson Reuters Datastream. Finally, copper prices come from the Chilean Copper Commission. We downloaded daily prices from our sources for each asset, which we converted to monthly frequencies by sampling from the last observation of the month. The sample period is from October 1999 to December 2019, resulting in 243 monthly observations of prices and 242 observations of one period returns. The starting point of our data coincides with the time when monetary authorities in Chile decided to pursue a pure flotation exchange rate regime.

Forecasting Models

Following Pincheira and Hardy (2019), in our econometric specifications we use the six previous monthly returns of the Chilean exchange rate to predict fuel prices. These six lags of monthly returns are aggregated into two quarters, where each one is constructed by adding three subsequent individual monthly returns. Following this procedure, we have two parameters associated with the Chilean exchange rate in each model, one for each quarter[3]. We estimate five different models that are constructed by adding the information about the Chilean peso to an oil-forecasting benchmark method. These standard models include the AR(1) for commodities returns, the random walk (RW), the no-change model (DRW), a spread model based on crude oil futures prices and a last model considering the returns of non-oil commodities. The first three specifications come from the fact that auto-regressions and the random walk (with and without drift) are standard benchmarks to beat when predicting assets' returns. The fourth model follows the tradition of the oil price forecasting literature by considering a specification based on crude oil future prices. Our fifth specification is based on the linkages between non-oil commodities and fuel prices that stems from the global demand for primary products. Consequently, we employ a benchmark model based on the LME index, which is an index of industrial metals. In Table 1 we present our econometric specifications.

Table 1: Econometric Specifications

1: AR(1)	$\Delta\ln(FP_t) = c + \beta_1[\Delta\ln(ER_{t-1}) + \cdots + \Delta\ln(ER_{t-3})] + \beta_2[\Delta\ln(ER_{t-4}) + \cdots + \Delta\ln(ER_{t-6})]$ $+ \rho\Delta\ln(FP_{t-1}) + \varepsilon_{1t}$
2: RW	$\Delta\ln(FP_t) = c + \beta_1[\Delta\ln(ER_{t-1}) + \cdots + \Delta\ln(ER_{t-3})] + \beta_2[\Delta\ln(ER_{t-4}) + \cdots + \Delta\ln(ER_{t-6})] + \varepsilon_{2t}$
3: DRW	$\Delta\ln(FP_t) = \beta_1[\Delta\ln(ER_{t-1}) + \cdots + \Delta\ln(ER_{t-3})] + \beta_2[\Delta\ln(ER_{t-4}) + \cdots + \Delta\ln(ER_{t-6})] + \varepsilon_{3t}$
4: Futures	$\Delta\ln(FP_t) = c + \beta_1[\Delta\ln(ER_{t-1}) + \cdots + \Delta\ln(ER_{t-3})] + \beta_2[\Delta\ln(ER_{t-4}) + \cdots + \Delta\ln(ER_{t-6})]$ $+ \theta(Spread_{t-1}) + \varepsilon_{4t}$
5: Non-Oil	$\Delta\ln(FP_t) = c + \beta_1[\Delta\ln(ER_{t-1}) + \cdots + \Delta\ln(ER_{t-3})] + \beta_2[\Delta\ln(ER_{t-4}) + \cdots + \Delta\ln(ER_{t-6})]$ $+ \psi_1[\Delta\ln(LMEX_{t-1}) + \cdots + \Delta\ln(LMEX_{t-3})]$ $+ \psi_2[\Delta\ln(LMEX_{t-4}) + \cdots + \Delta\ln(LMEX_{t-6})] + \varepsilon_{5t}$

Notes: FP_t stands for "fuel price at time t" while ER_t represents the Chilean Exchange Rate at time t as well. For a generic variable x_t we define $\Delta\ln(x_t) \equiv \ln(x_t) - \ln(x_{t-1})$. $LMEX_t$ refers to the London Metal Exchange index at time t, while ε_{it} with $i = 1, \ldots, 5$ represent error terms. The variable $Spread_t$ is defined in equation (1) right next to Table 1. Source: Authors' elaboration.

[3] Basically, we use quarterly returns of the Chilean peso as predictors. This is useful because we can benefit from reducing the number of parameters in our models.

For the fourth model we define:

$$Spread_{t-1} = \ln\left(\frac{WTI_{t-1}^{F(t)}}{WTI_{t-1}}\right) \quad (1)$$

Where $WTI_{t-1}^{F(t)}$ is the WTI futures price in time "t-1" for a contract with maturity in time t. We focus on one-step-ahead forecasts, that is, we use the available information at the end of month t to make a forecast for the value that fuel returns will take at the end of month $t+1$.

In our in-sample and out-of-sample evaluations we test the following null hypothesis:

$$H_0: \quad \beta_1 = \beta_2 = 0$$

By doing so, we are testing if the information added by the Chilean exchange rate is useful to improve the forecasts of the benchmark models. In our in-sample exercises we test the null hypothesis H_0 using a traditional Wald statistic. In our out-of-sample evaluation we test H_0 with the ENCNEW test proposed by Clark and McCracken (2001). This test is an adequate tool to evaluate the null of equality in population MSPE in two nested models[4].

In our in-sample analysis the parameters of the models are estimated using all the available observations. In our out-of-sample analysis we divide the total available sample in two windows: an initial estimation window of R observations and a prediction window of size P. This results in $R + P = T$, where T is the total number of observations in our sample. In the full version of the paper, that is available upon request, we work with two different values for the ratio P/R for robustness. First, we employ one third of the observations for the initial estimation window, leaving two thirds for forecast evaluation. Second, we use approximately 60% of the observations for the initial estimation window, leaving 40% for evaluation. In this summary we only present results for the first division of our sample. We update the estimates of our parameters in each expanding estimation window. Please see West (2006) for additional details about out-of-sample evaluations in nested environments.

[4] The asymptotic distribution of this test depends on the number of excess parameters in the nesting model (two in our econometric specifications), the parameter $\pi \approx P/R$ (where P is the number of forecasts and R is the size of the initial estimation window), and on the scheme employed to update the estimates of the parameters (expanding in our case).

3. Empirical Results

In-sample Analysis

In the full version of the paper, that is available upon request, we show tables with in-sample estimates of all the models from Table 1 using HAC standard errors according to Newey and West (1987, 1994). In this summary we only present results for the last specification in Table 1, which is model 5.

Table 2: Forecasting Fuel Returns with the Chilean Exchange Rate
In-sample analysis with specification (5) from Table 1: The Non-Oil benchmark

	WTI	*Brent*	*Propane*	*Gasoline*	*Heating Oil*
ER(-1)+ER(-2)+ER(-3)	-0.303***	-0.304**	-0.314**	-0.336***	-0.235**
	(0.112)	(0.119)	(0.132)	(0.126)	(0.114)
ER(-4)+ER(-5)+ER(-6)	-0.516***	-0.614***	-0.422*	-0.584**	-0.474***
	(0.150)	(0.211)	(0.236)	(0.272)	(0.163)
LMEX(-1)+LMEX(-2)+LMEX(-3)	0.057	0.043	0.026	0.014	0.075
	(0.045)	(0.050)	(0.065)	(0.052)	(0.047)
LMEX(-4)+LMEX(-5)+LMEX(-6)	-0.193***	-0.230***	-0.089	-0.233**	-0.149***
	(0.063)	(0.080)	(0.073)	(0.106)	(0.056)
Constant	0.008**	0.010**	0.003	0.009***	0.008*
	(0.004)	(0.004)	(0.006)	(0.003)	(0.004)
Observations	236	236	236	236	236
R-squared	0.141	0.128	0.044	0.078	0.119
Wald test p-value	0.001	0.007	0.010	0.013	0.007

Notes: ER stands for Chilean Exchange Rate Returns. WTI, Brent, propane, gasoline and heating oil represent one-month returns of each fuel. LMEX denotes London Metal Exchange index returns. Table 6 presents estimates of equation 5 in Table 1. *p<10%, **p<5%, ***p<1%. Source: Authors' elaboration

In-sample estimates of our econometric specification from model 5 in Table 1 show an outstanding forecasting ability of the Chilean peso. In particular Table 2 shows that the coefficients associated with both distributed lags of the Chilean exchange rate are statistically significant at the 10% level for all fuels. In the last row of Table 2 we also present the Wald statistic p-value when the null hypothesis is that both coefficients associated to the Chilean exchange rate are zero. This null is rejected at the 5% significance level for all fuels. There is also a fair amount of cases where the null is rejected at the 1% level. As to the coefficients of determination, there is an interesting "U-shape" pattern in Table 2. By this we mean that the highest coefficient of determination is achieved for WTI while the lowest is achieved for Propane. For Gasoline, the coefficients of determination are just slightly higher than those of Propane. Brent gets the second highest coefficient of determination.

Table 2 shows that the sign of the coefficients associated with the distributed lags of the Chilean peso are negative. A similar finding is reported in Pincheira and Hardy (2019) when predicting copper prices with the Chilean exchange rate. The key difference between these two exercises is that Chile is a major copper exporter while a net oil importer. Negative coefficients associated to the Chilean peso are easy to explain in the copper forecasting exercise using a trade channel: if copper is expected to increase, then the Chilean exchange rate goes down in anticipation to future inflows of American dollars into the Chilean economy. The same line of argument would suggest positive coefficients associated to the Chilean peso in the fuel forecasting exercise, yet Table 2 shows negative coefficients as well, just like in the copper forecasting exercise in Pincheira and Hardy (2019). A plausible explanation for our findings relies on two well-known effects in the market of commodities: a dollar effect (See Akram, 2009) and a co-movement effect. The first effect is related to the fact that fuel prices are denominated in American dollars. This implies that a higher value of the US dollar induces a decrease in fuels' demand and a fall in their prices. The second effect simply indicates that commodity returns are positively correlated. If the Chilean peso is a good predictor of copper returns, it might as well be a good predictor of commodities that are highly correlated with copper, like our sample of fuels. In the next subsection we will see if these in-sample results hold true in the context of an out-of-sample analysis.

Out-of-sample Analysis

Table 3 shows ENCNEW statistics for econometric specifications from Table 1 when we use one third of the full sample as the first expanding window. In the full version of the paper, that is available upon request, we also show results when we employ approximately 60% of the sample for the first estimation of the parameters.

In the first column of Table 3 we list the name of the benchmark model being considered (specifications 1 through 5 from Table 1). In the rest of the entries we show the ENCNEW statistic. As usual, we use stars to indicate statistically significant results.

Table 3 shows an outstanding forecasting ability of the Chilean peso relative to all our benchmarks and for all of our commodities. For WTI, Brent, Gasoline and Heating oil, the null of no predictability of the Chilean exchange rate is rejected at the 1% significance level. For Propane our results are slightly less compelling, but again, rejection of the null is achieved in every entry of the table at least at the 10% significance level.

Table 3: Forecasting Fuel Returns with the Chilean Exchange Rate
Out-of-sample analysis with specifications from Table 1 and P/R= 2

ENCNEW Statistic					
Benchmark Model	WTI	Brent	Propane	Gasoline	Heating Oil
AR (1)	14.80***	17.42***	9.02***	11.78***	19.75***
RW	19.60***	18.52***	8.25***	10.81***	21.37***
DWR	19.20***	18.18***	8.41***	10.56***	20.73***
FUTURES	21.45***	20.56***	8.50***	11.84***	21.47***
NON-OIL	10.71***	14.38***	2.18*	7.80***	11.10***

Notes: 10%, 5% and 1% critical values are 1.914, 2.889 and 5.107 respectively, when there are two excess parameters and P/R=2. P represents the number of one-step-ahead forecasts and R the sample size of the first estimation window. AR(1), RW, DWR, FUTURES and NON-OIL benchmarks correspond to models 1,2,3,4 and 5 from Table 1 when the coefficients associated to the Chilean peso are zero. *p<10%, **p<5%, ***p<1%.
Source: Authors' elaboration.

Our out-of-sample results have relied on the ENCNEW test of Clark and McCracken (2001) which is designed to compare the population MSPE of two nested models. In this framework, we show that the Chilean peso does a remarkable job at reducing the population MSPE of our benchmark models. A specification that yields lower population MSPE relative to a benchmark means that it has superior predictive ability. Nevertheless, population MSPE based on true parameters may be quite different from their finite sample counterparts. This means that the remarkable predictive ability already reported for the Chilean peso, may not translate into accurate forecasts when the model is put into practice with estimates of the actual unknown population parameters. In the next subsection with explore in some detail this finite sample behavior of our forecasts.

Forecasting Accuracy

To see if the fuel forecasts produced with the aid of the Chilean peso are useful in finite samples, we follow Goyal and Welch (2008) to build out-of-sample coefficients of determination defined as:

$$OOS\ R^2 = 1 - \frac{SMSPE}{SMSPE_c}$$

where $SMSPE$ stands for the Sample Mean Squared Prediction Error of the model with the Chilean peso, and $SMSPE_c$ stands for the Sample Mean Squared Prediction Error of the model that predicts fuel returns just with a constant term. In Table 4 next we show these out-of-sample coefficients of determination. We also include traditional in-sample R^2 for comparison.

Table 4: Out-of-sample R^2 when Forecasting Fuel Returns with the Chilean Exchange Rate

	WTI	Brent	Propane	Gasoline	Heating Oil
In-sample R^2	0.104	0.088	0.041	0.050	0.095
OOS-R^2 with P/R=2	0.109	0.106	0.036	0.054	0.129

Notes: P represents the number of one-step-ahead forecasts and R the sample size of the first estimation window. OOS-R^2 denotes out-of-sample R^2. The benchmark model in this table corresponds to Model 2 in Table 1. Source: Authors' elaboration

From Table 4 we see that the models with the Chilean peso have better finite sample performance than the updating-constant benchmark. This indicates that the information contained in the Chilean exchange rate is useful to forecast fuel returns in finite samples.

4. Concluding Remarks

In the last decade a vast literature has evaluated the ability of commodity-currencies to predict commodity returns. In this paper we make a contribution to this literature by showing that the Chilean exchange rate has the ability to predict the returns of oil prices and of three additional oil-related products: gasoline, propane and heating oil. The rationale behind our empirical findings relies on the present-value theory for exchange rate determination and on the strong co-movement displayed by some commodity prices. The

Chilean economy is heavily influenced by one particular commodity: copper, which represents nearly 50% of total national exports and attracts a similar share in terms of Foreign Direct Investment. As a consequence, the floating Chilean exchange rate is importantly affected by fluctuations in the copper price. As oil-related products display an important co-movement with base metal prices, it is reasonable to expect evidence of Granger causality from the Chilean peso to these oil-related products. We do report substantial evidence of this predictability using both in-sample and out-of-sample analyses.

Our results are consistent with the studies of Alquist, Kilian and Vigfusson (2013), Gillman and Nakov (2009), Funk (2018), Baumeister and Kilian (2015) and Garratt, Vahey and Zhang (2019) that have also shown that crude oil returns are indeed predictable. They are also consistent with the results in Alquist, Kilian and Vigfusson (2013) that show predictive ability from other commodity-currencies to crude oil returns. Our results also resemble those in Pincheira and Hardy (2019) in two dimensions: first by showing predictability from a commodity-currency to returns of commodities that are not key elements in the export basket of the relevant country, and second, by reporting strong evidence of predictability at the population level, yet moderate evidence at the sample level.

Despite these similarities with other studies, we contribute to the literature by presenting evidence of predictability for a relatively diverse set of fuel prices. This differs from many papers that have mostly centered their attention on crude oil only. In addition, we think we are unique in showing that the currency of a net oil importer like Chile can predict fuel returns. We attribute our findings to the combination of the commodity-currencies-hypothesis with the co-movement in commodity prices that is driven by the global demand for these products. Our empirical findings are consistent with this argument because in our in-sample regressions the coefficients associated with the Chilean peso turned out to be negative. This is expected for a commodity exporter because a higher value of the primary product is associated with an increase in the inflow of US dollars to the domestic economy. Put it differently, our evidence suggests that a key feature in the commodity-currencies hypothesis is the sensitivity of a given currency to one relevant commodity presenting a lot of co-movement with others. In these conditions evidence of predictability can be found between currencies and commodities not directly related by the export bundle of the corresponding country.

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