Forecasting Lithium Prices

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ABSTRACT

The main aim of this paper is to forecast both in-sample and out-of-sample lithium prices. Specifically, we explore the empirical implications of the present value model for exchange rates, market indexes, mining company prices and related company prices in hi-tech, automotive, electric vehicle and micro-mobility industries. Our modelling strategy assumes that a given variable is a linear function of the present discounted value of expected future of its fundamentals, and therefore it should Granger-cause their fundamentals. From our analysis we only find evidence of Granger causality for lithium mining companies. This is to be expected given that lithium accounts for a small percentage of the production of the companies studied. In terms of exchange rates, lithium exports for the economies studied (Australia and Chile) also account for a very low percentage in relation to the export basket. By contrast, for the mining companies, lithium can be considered as their main fundamental.

Keywords: Forecasting; Lithium Prices; Time-Series Models, Out-of-Sample Comparison, Exchange Rates.

JEL Classification: C52; C53; E27; E73; F37; G17; L62

1. Introduction

There is a global trend towards cleaner and more environmentally friendly energies to address different environmental concerns, such as climate change, pollution and decarbonisation goals. Hence, the development and further use of renewable energy technologies is key to promote the reduction of fossil fuels and address the environmental problems caused by them. In recent times a very important resource widely used in the clean energy transition has been lithium, which is consumed as a raw material by battery producers, the hi-tech and automotive industry, the electric vehicle industry, and the micro-mobility industry, as well as for a wider range of products, such as glass, enamel, and ceramic industry, lubricating greases, pharmaceutical products, and aluminum production, however it is among the battery and electric vehicle producers that we find the strongest growth in demand (see for instance Evans, 2014).

Sales of electric vehicles during 2020 accounted for 10.4 million of cars, and it is expected to increase to 114 million cars by 2040 (Liuima & Razvadauskas, 2021). Lithium is a critical component for improving the driving range of electric vehicles. Even though securing a stable supply of lithium remains an issue as the production of electric vehicles accelerates, lithium production is expected to increase by nearly 500 percent by 2050, mainly driven by electric vehicles and battery industry demands (Hund et al., 2014).

In terms of production, lithium is abundant on Earth's continental crust, however unevenly distributed, and only a few large ores and brines are currently under production (Liu, 2019). There are only 8 producing countries of which Australia, Chile, and China account for 85% of global production, while four companies –Talison, SQM, Albemarle, and Livent– control most of lithium production (Azevedo et al., 2018).

Lithium was considered in the past as a "minor metal", unlike other metals such as aluminum, copper, and steel, resulting in lithium prices lacking transparency and liquidity. However, Maxwell (2015) argues that the increased demand for lithium along with large companies seeking to ensure security of supply for batteries and other products will help to make the price of lithium more transparent in the near future. It is in this context that this paper attempts to contribute to the literature by analysing lithium prices. We use a plethora of commodity predictors previously proposed in the literature, including financial and macroeconomic predictors. Particularly, we explore exchange rates, market indexes, mining company prices, and related company prices in the hi-tech, automotive, electric vehicle, and micro-mobility industries. Basically, our modelling strategy assumes that a variable Y_t is a linear function of the present discounted value of expected future of its fundamentals, and therefore it should Granger-cause their fundamentals (for further details see Campbell and Shiller, 1987).

Our work is related to a growing literature which has explored the empirical validity of the present value model. For instance, Engel & West (2005) put forward some evidence that exchange rates help forecast fundamentals, nevertheless, using the same set of data, Ko & Ogaki (2015) show that the existing Granger causality evidence is not strong enough to support the present value model for exchange rates. Another branch of research has focused on the study of commodity exporting countries like Australia, Canada, Chile, New Zealand and South Africa and the predictability of their exchange rates on the relevant commodity price, however the results are mixed. See for instance (Chen, Rogoff & Rossi, 2010), (Groen & Pesenti, 2011), (Gargano and Timmermann, 2014), (Lof & Nyberg, 2017), (Ciner, 2017) and (Pincheira and Hardy, 2019; 2021). Another avenue of this literature studied the relationship between commodity prices and other related assets/markets. In this direction, Chen, Rogoff & Rossi (2010) and Rossi (2012) find out-of-sample predictability of market indices on some commodity prices.

Our work put forward some mixed results. From our analysis on exchange rates, market indexes, mining company prices and related company prices in hi-tech, automotive, electric vehicle and micro-mobility industries, we only find evidence of Granger causality for lithium mining companies. This is to be expected given that lithium accounts for a small percentage of the production of the companies studied. In terms of exchange rates, lithium exports for the economies studied (Australia and Chile) also account for a very low percentage in relation to the export basket. By contrast, for the mining companies, lithium can be considered as their main fundamental. This is a very important result as it provides one of the first empirical paper to test this hypothesis with lithium, key to develop a forecasting model for lithium prices. Moreover, to the best of our knowledge, this is the first paper that performs out-of-sample forecasts for lithium returns and analyses their time series characteristics. With respect to the time series characteristics of lithium, it is worth mentioning that the series of lithium price returns seem to be much more persistent than for other commodities, which allows, in general terms, much better forecasting. We should also note that lithium has a strong autoregressive structure, and therefore, the appropriate benchmark for returns is not a random walk, but an $AR(p)$ model.

The remainder of this paper is organised as follows. In section 2 we present the data and models used in this work. In section 3 we put forward the core in-sample and out-of-sample results, and additional predictive exercises. Finally, section 4 offers some concluding remarks.

2. Data and forecasting models

We consider weekly data on lithium log-returns. Data in the same frequency for exchange rates[1], metal/mining index rates, commodity index rates, energy index rates, mining companies log-returns and log-returns of related companies in the hi-tech, automotive, electric vehicle, and micro-mobility industries are also included. See **Table A.1** in **Appendix A** for a summary of exchange rates, market indexes, mining companies and lithium-related companies. **Table A.2** in **Appendix A** shows a summary of other predictors also used.

All data was obtained from Refinitiv Datastream, from which we downloaded daily close price of each asset and converted to weekly data by sampling the last day of the week. The sample period goes from October 13, 2017, until November 18, 2022, with a total of 266 weekly observations. Some descriptive statistics of our series are found in **Appendix B**.

To motivate the discussion, prior moving on to the econometric models consider the time series of lithium prices and its returns (see **Figures 1 and 2**), which clearly show that lithium does not behave as a typically assets traded in the financial system, since, although lithium log returns are stationary, they do not behave as a random walk (see augmented Dikey-Fuller and Ljung-Box test results for lithium prices and returns, and the correlograms for lithium returns in **Appendix C**).

[1] Exchange rates the amount of foreign currency required to buy an American dollar in the domestic market.

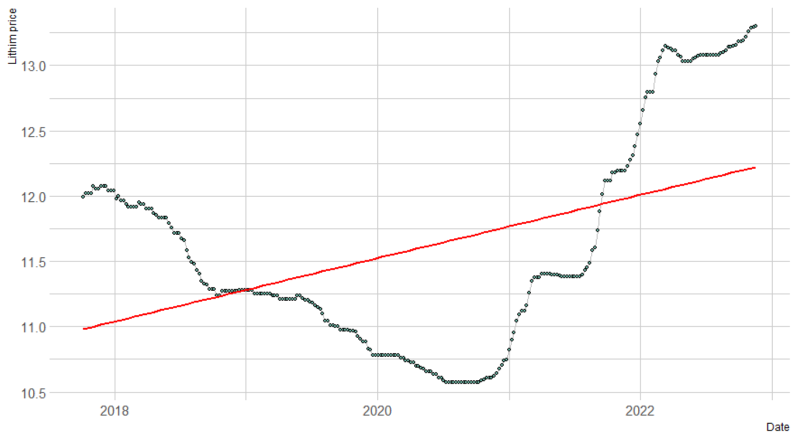

Figure 1: Lithium prices

Source: Authors' elaboration.

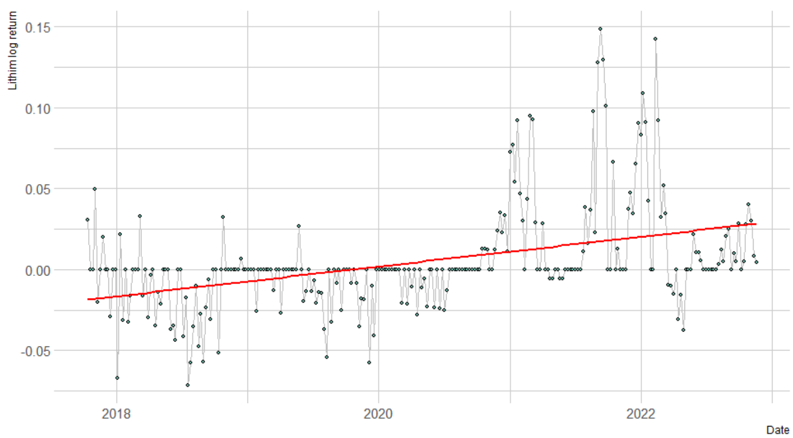

Figure 2: Lithium log returns

Source: Authors' elaboration.

Our econometric specifications are quite simple. They are inspired in the vast literature that has shown that either a Random Walk (RW) or simple autoregressions are usually difficult benchmarks to beat when forecasting asset returns. Our econometric specification for both the in-sample and out-of-sample models are shown in **Table 1** and **Table 2**. **Table 1** shows the unrestricted specifications for the predictor variable and Table 2 shows the restricted specifications.

Table 1: Core econometric specifications

1.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \sum_{i=1}^{5} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{1t}$
2.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \sum_{i=1}^{4} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{2t}$
3.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \sum_{i=1}^{3} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{3t}$
4.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \varepsilon_{4t}$
5.	$\Delta \ln(y_t) = \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \varepsilon_{5t}$

Source: Authors' elaboration.

where $\Delta \ln(y_t)$ represents the log-return of lithium at time t, $\Delta \ln(x_{it})$ represents log-return of one of the predictors described in **Appendix A**. Finally, ε_{jt} represents the error term of specifications 1 to 5.

To evaluate the predictive ability of the tested predictors, we use nested linear specifications following Clark and West (2006, 2007) and Clark and McCracken (2001). We study several different benchmarks traditionally used in the literature. The list includes a random walk model with and without drift and autoregressive benchmarks. Specifically, in specifications 1, 2 and 3, the one-step-ahead lithium forecasts are constructed using a constant c plus a linear combination of the first two lags of the predictor plus a linear combination of the first five, four and three lags of the lithium return respectively. Specification 4 excludes lags in the lithium price return, and finally, in specification 5 we exclude the constant and the lags in the lithium price return. Specifications 6-10 showed in Table 2 are the restricted form of specifications in Table 1. The choice on the number of lags for lithium and for the predictor comes from our in-sample explorations which reveal that no other lags were consistently statistically significant.

Table 2: Core restricted specifications

6.	$\Delta \ln(y_t) = c + \beta[\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})] + \sum_{i=1}^{5} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{jt}$
7.	$\Delta \ln(y_t) = c + \beta[\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})] + \sum_{i=1}^{4} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{jt}$
8.	$\Delta \ln(y_t) = c + \beta[\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})] + \sum_{i=1}^{3} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{jt}$
9.	$\Delta \ln(y_t) = c + \beta[\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})] + \varepsilon_{jt}$
10.	$\Delta \ln(y_t) = \beta[\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})] + \varepsilon_{jt}$

Source: Authors' elaboration.

We consider the following null hypotheses H_{01} and H_{02} for the specifications in **Table 1** and **Table 2** respectively:

$$\begin{aligned} &H_{01}: \beta_1 = \beta_2 = 0 \\ &H_{02}: \beta = 0. \end{aligned} \tag{1}$$

This means that we are testing the ability of the variables x_i (see **Tables A.1 and A.2** in **Appendix A**) to predict lithium returns. We tested our hypotheses both in-sample and out-of-sample for one-step-ahead forecasts.

In-sample evaluations we use all available data. For H_{01} we use the Wald statistic for all the specifications in **Table 1**. We test H_{02} for all restricted specifications in **Table 2** by simply using the t-statistic associated to the coefficient of x_{it} in the model with a HAC estimator for the long-run variance, following Newey and West (1987, 1994).

It is well documented that, when comparing nested models, the Diebold and Mariano (1995) and West (1996) tests degenerate under the null hypothesis. One of the papers that addresses this problem is Clark McCracken who proposes the ENCNEW, a test designed for the comparison of nested models. This is why in our out-of-sample analysis, we evaluate the null hypotheses with the ENCNEW test proposed by Clark & McCracken (2001)[2]. This test has a non-standard asymptotic distribution under the null, however, the authors show in the appendix of their paper the critical values for one-step-ahead forecasts. The ENCNEW test depends on the number of excess parameters of the nested model and the ratio $\frac{P}{R}$, 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. In our case, specifications 1 to 5 have two excess parameters, while specifications 6 to 10 have only one excess parameter. To show the robustness of our models, we used recursive windows to update the estimates of our parameters and three different ratios $\frac{P}{R} = 0.2$, $\frac{P}{R} = 0.4$, $\frac{P}{R} = 1$ and $\frac{P}{R} = 2$.

3. Results

3.1 In-sample analysis

We perform in-sample analysis for the specifications in **Tables 1** and **2** with all the variables shown in **Tables A.1 and A.2** in **Appendix A**. From those, we only find significance for mining companies. For the exchange rates, market indexes and lithium-related companies, both

[2] We also considered other tests: Enc-t (Clark & McCracken 2001), Clark & West (2006, 2007), and Pincheira, Hardy & Muñoz (2021). Those results are available upon request.

unrestricted and restricted models, we do not reject the null. See these results in **Tables C.1-C.4** in **Appendix C**.

Table 3 shows the estimates for mining companies of the unrestricted specification 3, while **Table 4** shows the restricted estimation of specification 8 for the same group of companies. In both tables, we use HAC standard errors according to Newey & West (1987, 1994). We find in the unrestricted equations that one of the two lags associated with mining companies are significant, where we can highlight Ganfeng in which the null hypothesis for the second lag is rejected at 5% of significance level, as well as the first lag of SQM. For Pilbara's first lag, the null hypothesis is rejected at 1% significance level. The Wald test (see **Table 3**) associated to the null hypothesis that both coefficients of mining company returns are zero is rejected for Ganfeng and Lithium Americas at 10% significance, Tianqui at 5% significance and for Pilbara at 1% significance. Although we cannot reject the null for Albemarle and SQM, both are on the borderline of 10% significance. In the restricted equations in **Table 4**, for all the coefficients associated with mining company returns, the null hypothesis is rejected at least at 10% significance level. In the case of Lithium Americas, the null is rejected at 5% significance level and for SQM, the null is rejected at 1% significance level. Therefore, **Table 3** and **4** show statistically significant evidence of Granger causality from mining companies to lithium return.

In addition, we find that for all models in **Tables 3** and **4**, at least two of the three lags associated with lithium returns are significant, except for the unrestricted model with Pilbara as the predictor variable, where only the first lag of lithium return is significant. Another feature of these models is that for neither of them is the constant significant.

Table 3: In-sample unrestricted regressions with mining companies in specification 3

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Lithium(-1)	0.484***	0.473***	0.475***	0.472***	0.487***	0.471***
	(0.083)	(0.081)	(0.084)	(0.081)	(0.084)	(0.082)
Lithium(-2)	0.179*	0.168*	0.171*	0.160	0.154	0.164
	(0.100)	(0.100)	(0.099)	(0.103)	(0.102)	(0.102)
Lithium(-3)	0.093	0.119**	0.104*	0.105*	0.107	0.109*
	(0.058)	(0.060)	(0.053)	(0.059)	(0.07)	(0.065)
Asset return(-1)	0.008	0.025	0.016	0.058**	0.044***	0.029*
	(0.015)	(0.024)	(0.012)	(0.028)	(0.015)	(0.015)
Asset return(-2)	0.056**	0.038*	0.060***	0.010	-0.013	0.018
	(0.025)	(0.020)	(0.023)	(0.021)	(0.017)	(0.011)
Constant	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	263	263	263	263	263	263
R-squared	0.475	0.466	0.485	0.465	0.473	0.470
Wald test p-value	0.086	0.122	0.017	0.109	0.010	0.056

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 4: In-sample restricted regressions with companies in specification 8

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Lithium(-1)	0.490***	0.474***	0.4792***	0.470***	0.471***	0.468***
	(0.088)	(0.081)	(0.087)	(0.081)	(0.079)	(0.081)
Lithium(-2)	0.155	0.170*	0.152	0.160	0.165	0.166
	(0.103)	(0.100)	(0.103)	(0.103)	(0.102)	(0.102)
Lithium(-3)	0.113**	0.117*	0.122**	0.106*	0.108*	0.109*
	(0.057)	(0.061)	(0.055)	(0.057)	(0.061)	(0.063)
Asset return(-1)+Asset return(-2)	0.032*	0.032*	0.038***	0.035*	0.016*	0.024**
	(0.017)	(0.016)	(0.014)	(0.018)	(0.009)	(0.010)
Constant	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	263	263	263	263	263	263
R-squared	0.469	0.465	0.478	0.462	0.462	0.469

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

In summary, the in-sample results provide evidence of a predictive relationship between mining companies returns and lithium return. However, because in-sample analysis may have overfitting problems and in some cases are not adequate to capture real time predictability, we present the results of out-of-sample in the next section.

3.2 Out-of-sample analysis

Tables 5 and **6** show the results of the ENCNEW test (Clark & McCracken, 2001) in the out-of-sample exercises with mining companies for $\frac{P}{R} = 0.2$, $\frac{P}{R} = 0.4$ and $\frac{P}{R} = 2$. Table 5 focuses on unrestricted core specifications while Table 6 focuses on the restricted core specifications.

The benchmarks of core specifications in **Table 1** and core specifications in **Table 2** are shown in the first column of **Table 5** and **Table 6** respectively. They correspond to autoregressive processes for lithium log returns of order 5, 4 and 3, denoted as AR(5), AR(4) and AR(3) respectively. We also compare with a random walk (RW) and a driftless random walk (DRW) processes.

In **Table 5**, we show strong predictability power for most of the mining companies under study. For instance, for the estimation window $\frac{P}{R} = 0.2$, we reject the null in the five exercises for Ganfeng, Tianqui and Lithium Americas. We also reject the null for all the exercises, except RW for Pilbara. For the estimation window $\frac{P}{R} = 0.4$, we reject the null hypothesis for Pilbara for all the exercises. For Ganfeng and Tianqui, we reject the null in the AR(5), AR(4) and AR(3) exercises. For the estimation window $\frac{P}{R} = 2$, we reject the null in all the exercises for Tianqui, Pilbara and Lithium Americas. For Ganfeng, we reject the null hypothesis for the AR(5), AR(4) and AR(3) exercises. In the case of SQM for all the estimation windows, we only reject the null on the RW and DRW exercises. Finally, for Albemarle we never we reject the null.

In **Table 6** we show stronger results than those shown in **Table 5** in the sense that for all mining companies we reject the null in at least one exercise. For the estimation window $\frac{P}{R} = 0.2$, we reject the null in all the exercises for Ganfeng, Tianqui and Lithium Americas. For Albemarle, we are able to reject the null in AR(5), AR(4) and AR(3) exercises. For SQM, the null is rejected only in for RW and DRW. In the case of Pilbara, we only reject the null hypothesis in the DRW exercise. Also, for the estimation window $\frac{P}{R} = 0.4$, the results are as follows, for Lithium Americas we reject the null in AR(4), AR(3), RW and DRW exercises. For Tianqui, only RW does not reject the null. For Ganfeng, we reject the null hypothesis in AR(5), AR(4) and AR(3) exercises. Albemarle, SQM and Pilbara only reject the null in two of the five exercises, which are AR(4) and AR(3) for Albemarle, and RW and DRW for SQM and Pilbara. In the case of an estimation window $\frac{P}{R} = 2$, for Tianqui and Lithium Americas, we reject the null in all the exercises. For Ganfeng and Albemarle, the null is rejected in the AR(5), AR(4) and AR(3) exercises, while for Pilbara and SQM the null is rejected for RW and DRW.

Table 5: Out-of-sample analysis with unrestricted specifications. Forecasting lithium returns with mining company returns

ENCNEW						
	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Panel A:	$\frac{P}{R} = 0.2$					
AR(5)	1.716**	-0.192	3.204***	-0.276	1.845**	0.787*
AR(4)	1.462**	0.032	2.821***	-0.446	1.654**	1.003*
AR(3)	1.125**	0.042	2.221***	-0.436	1.521**	0.884*
RW	0.985*	-0.334	1.508**	1.546**	0.501	0.911*
DRW	1.014*	-0.217	1.525**	2.234***	0.913*	1.072**
Panel B:	$\frac{P}{R} = 0.4$					
AR(5)	1.464*	0.010	3.447***	0.328	1.883**	0.284
AR(4)	1.310*	0.370	3.449***	0.431	2.116**	0.874
AR(3)	1.205*	0.386	3.071***	0.504	2.049**	0.892
RW	-0.060	-0.233	0.851	3.914***	1.573**	1.473*
DRW	0.114	-0.126	0.956	4.389***	2.013**	1.761**
Panel C:	$\frac{P}{R} = 2$					
AR(5)	4.535**	1.098	9.223***	1.724	3.667**	2.358*
AR(4)	4.125**	1.312	8.499***	1.711	3.872**	2.534*
AR(3)	3.267**	1.326	7.201***	1.771	3.436**	2.241*
RW	0.714	-0.124	3.849**	8.333***	3.955**	3.604**
DRW	0.664	0.140	4.058**	9.765***	4.812**	4.035**

Notes: 10%, 5% and 1% critical values are respectively:

$P/R = 0.2$			$P/R = 0.4$			$P/R = 2$		
0.716	1.028	1.854	1.019	1.481	2.604	1.914	2.889	5.107

*, ** and ***: significance at 10%, 5%, and 1%, respectively.

Source: Authors' elaboration.

Table 6: Out-of-sample analysis with restricted specifications. Forecasting lithium returns with mining company returns

ENCNEW						
	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Panel A:	$\frac{P}{R}=0.2$					
AR(5)	1.286**	0.682*	2.462***	-0.146	0.165	0.769**
AR(4)	1.336**	0.792**	2.388***	-0.269	0.068	0.925**
AR(3)	1.126**	0.790**	1.953***	-0.246	0.031	0.819**
RW	0.549*	0.016	0.793**	1.571***	0.186	0.968**
DRW	0.610*	0.130	0.859**	2.258***	0.627*	1.125**
Panel B:	$\frac{P}{R}=0.4$					
AR(5)	0.816*	0.563	2.337***	0.182	0.099	0.406
AR(4)	1.056*	0.887*	2.526***	0.276	0.270	0.914*
AR(3)	0.951*	0.960*	2.321***	0.301	0.277	0.973*
RW	-0.180	0.026	0.673	3.915***	1.370**	1.592**
DRW	-0.003	0.142	0.781*	4.389***	1.806**	1.880**
Panel C:	$\frac{P}{R}=2$					
AR(5)	2.650**	1.755*	6.793***	1.267	0.871	2.790**
AR(4)	2.521**	2.000*	6.265***	1.194	0.953	3.038**
AR(3)	2.138**	1.923*	5.479***	1.275	0.805	2.724**
RW	0.546	0.345	3.456**	8.425***	3.720**	4.129**
DRW	0.437	0.639	3.632**	9.861***	4.589***	4.510***

Notes: 10%, 5% and 1% critical values are respectively:

$P/R=0.2$			$P/R=0.4$			$P/R=2$		
0.473	0.744	1.397	0.685	1.079	2.098	1.280	2.085	4.134

*, ** and ***: significance at 10%, 5%, and 1%, respectively.

Source: Authors' elaboration.

3.3 Multiple unknown break points

In this section, we explore the possibility of multiple unknown breaks in all the parameters of the models, which means that for each break we estimate the specifications 1-10 using the UDmax test of Bai & Perron (1998) to test the existence of multiple unknown breaks.

For the sake of space, we focus on specifications 3 and 8. **Tables 7** and **8** only report betas associated with those specifications respectively. We reject the null of no breaks for all the exercises, with a minimum of two breaks and a maximum of six breaks.

In **Table 7**, we report betas of our unrestricted specification 3, from which we observe, for almost all the regimes, consistency with the in-sample results obtained in **Table 3**. However, from last week of October 2018 until the beginning of August 2019, Ganfeng, Albemarle and Tianqui report a negative statistical significance relationship with their second lag. In addition, from last week of August 2019 until the beginning of July 2020, none of the mining companies report statistical significance. It is also worth mentioning that all mining companies except SQM and Pilbara report statistical significance in at least 2 of the regimes. SQM only reports statistical significance for the period from late October 2020 to early January 2022. In the case of Pilbara, although it only reports positive statistical significance in one regime, this comprises almost the entire second half of the data (from mid-October 2020 to the end of November 2022).

In **Table 8**, we report betas of our restricted specification 8. These results are less robust than those found with the unrestricted exercises, since there a smaller number of regimes where the results are statistically significant and furthermore, all statistically significant results are within the COVID-19 pandemic period, except for SQM, where in addition to the pandemic period, statistically significant results are found between mid-September 2018 and early June 2019, however this relationship is negative.

Table 7 and **Table 8** show that specifications allowing breaks have a much higher coefficient of determination than those without breaks and therefore indicate that allowing breaks improves the fit of in-sample regressions.

Table 7: In-sample unrestricted regressions allowing for breaks in specification 3

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Regime 1	11/10/2017 -	11/10/2017 -	11/10/2017 -	11/10/2017 -	11/10/2017 -	11/10/2017 -
	10/19/2018	10/19/2018	10/19/2018	10/19/2018	10/09/2020	9/07/2018
Obs.	50	50	50	50	153	44
Asset(-1)	-0.007	-0.059	-0.02	-0.042	0.004	0.026
	(0.042)	(0.053)	(0.059)	(0.109)	(0.013)	(0.026)
Asset(-2)	0.061*	0.064	0.107**	0.064	-0.020	-0.017
	(0.032)	(0.039)	(0.043)	(0.099)	(0.013)	(0.033)
Regime 2	10/26/2018 -	10/26/2018 -	10/26/2018 -	10/26/2018 -	10/16/2020 -	9/14/2018 -
	8/09/2019	8/16/2019	8/09/2019	8/09/2019	11/18/2022	8/16/2019
Obs.	42	43	42	42	110	49
Asset(-1)	0.029	0.032	0.036	0.043	0.079***	0.035*
	(0.022)	(0.040)	(0.025)	(0.066)	(0.025)	(0.021)
Asset(-2)	-0.045**	-0.053*	-0.037*	-0.076	-0.029	-0.026
	(0.019)	(0.028)	(0.021)	(0.057)	(0.042)	(0.024)
Regime 3	8/16/2019 -	8/23/2019 -	8/16/2019 -	8/16/2019 -		8/23/2019 -
	7/03/2020	11/20/2020	7/24/2020	11/13/2020		11/13/2020
Obs.	47	66	50	66		65
Asset(-1)	0.005	-0.008	0.007	0.020		0.0002
	(0.027)	(0.016)	(0.017)	(0.029)		(0.007)
Asset(-2)	-0.006	0.012	-0.004	-0.012		0.006
	(0.024)	(0.015)	(0.009)	(0.028)		(0.006)
Regime 4	7/10/2020 -	11/27/2020 -	7/31/2020 -	11/20/2020 -		11/20/2020 -
	5/21/2021	9/24/2021	5/21/2021	1/14/2022		10/08/2021
Obs.	46	44	43	61		47
Asset(-1)	0.044***	0.149*	0.025	0.162**		0.094
	(0.015)	(0.078)	(0.015)	(0.070)		(0.058)
Asset(-2)	0.117***	0.137***	0.088***	-0.013		0.064**
	(0.037)	(0.047)	(0.030)	(0.077)		(0.027)
Regime 5	5/28/2021 -	10/01/2021 -	5/28/2021 -	1/21/2022 -		10/15/2021 -
	2/18/2022	11/18/2022	2/18/2022	11/18/2022		11/18/2022
Obs.	39	60	39	44		58
Asset(-1)	-0.027	-0.012	0.025	-0.024		0.003
	(0.038)	(0.031)	(0.051)	(0.039)		(0.039)
Asset(-2)	0.106	-0.035	0.128*	0.021		0.0012
	(0.077)	(0.024)	(0.071)	(0.030)		(0.020)
Regime 6	2/25/2022 -		2/25/2022 -			
	11/18/2022		11/18/2022			
Obs.	39		39			
Asset(-1)	0.084*		0.052			
	(0.044)		(0.033)			
Asset(-2)	0.011		0.008			
	(0.038)		(0.044)			
R-squared	0,578	0,562	0,585	0,551	0,549	0,589

Notes: (-1) and (-2) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.
*, ** and ***: significance at 10%, 5%, and 1%, respectively. Authors' elaboration

Table 8: In-sample restricted regressions allowing for breaks in specification 8

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Regime 1	11/10/2017 - 9/07/2018	11/10/2017 - 9/07/2018	11/10/2017 - 9/07/2018	11/10/2017 - 9/07/2018	11/10/2017 - 9/07/2018	11/10/2017 - 9/07/2018
Obs.	44	44	44	44	44	44
Asset(-1) +	0.027	-0.012	0.048	-0.015	-0.037	0.006
Asset(-2)	(0.036)	(0.039)	(0.050)	(0.094)	(0.042)	(0.019)
Regime 2	9/14/2018 - 6/07/2019	9/14/2018 - 6/07/2019	9/14/2018 - 6/07/2019	9/14/2018 - 6/07/2019	9/14/2018 - 6/07/2019	9/14/2018 - 6/07/2019
Obs.	39	39	39	39	39	39
Asset(-1) +	-0.017	-0.023	-0.009	-0.048*	-0.003	0.003
Asset(-2)	(0.016)	(0.019)	(0.010)	(0.025)	(0.013)	(0.013)
Regime 3	6/14/2019 - 7/03/2020	6/14/2019 - 11/20/2020	6/14/2019 - 7/10/2020	6/14/2019 - 7/03/2020	6/14/2019 - 7/03/2020	6/14/2019 - 3/06/2020
Obs.	56	76	57	56	56	39
Asset(-1) +	0.005	0.006	0.002	0.023	-0.006	0.005
Asset(-2)	(0.022)	(0.012)	(0.010)	(0.020)	(0.009)	(0.028)
Regime 4	7/10/2020 - 1/14/2022	11/27/2020 - 9/24/2021	7/17/2020 - 11/18/2022	7/10/2020 - 5/21/2021	7/10/2020 - 4/16/2021	3/13/2020 - 12/18/2020
Obs.	80	44	123	46	41	41
Asset(-1) +	0.061**	0.143***	0.056***	0.077***	0.051**	0.001
Asset(-2)	(0.027)	(0.035)	(0.018)	(0.021)	(0.021)	(0.005)
Regime 5	1/21/2022 - 11/18/2022	10/01/2021 - 11/18/2022		5/28/2021 - 2/18/2022	4/23/2021 - 1/14/2022	12/25/2020 - 10/08/2021
Obs.	44	60		39	39	42
Asset(-1) +	0.082*	-0.023		0.077	0.039	0.087***
Asset(-2)	(0.043)	(0.021)		(0.085)	(0.071)	(0.026)
Regime 6				2/25/2022 - 11/18/2022	1/21/2022 - 11/18/2022	10/15/2021 - 11/18/2022
Obs.				39	44	58
Asset(-1) +				0.004	-0.018	0.002
Asset(-2)				(0.014)	(0.028)	(0.017)
R-squared	0,563	0,555	0,575	0,556	0,557	0,581

Notes: (-1) and (-2) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.
*, ** and ***: significance at 10%, 5%, and 1%, respectively. Authors' elaboration

3.4 Mean directional accuracy

Typically, traditional measures of prediction accuracy are based on the idea of a quadratic loss function, where larger errors have a proportionally larger weight than smaller errors. The most common of those loss functions is the mean squared error. However, in the forecasting literature, the direction of forecasts in addition to the mean square error is also common. See for example Cheung et al. (2019). Hence, in this section we study the success rate of our specifications using mining companies to predict whether lithium returns will go up or down.

Let z_t be defined as:

$$z_t = \begin{cases} 1 & if \quad \Delta\ln\left(y_t^f\right) \cdot \Delta\ln(y_t) \geq 0 \\ 0 & if \quad \Delta\ln\left(y_t^f\right) \cdot \Delta\ln(y_t) < 0, \end{cases} \tag{2}$$

where y_t is the actual value of the log return of lithium in period t and $\Delta\ln\left(y_t^f\right)$ is the value of the forecast in period t. The idea is to explore if our forecast and the actual value of lithium return have the same sign. We consider the following hypotheses:

$$\begin{aligned} &H_0: E(z) \leq 0.5 \\ &H_1: E(z) > 0.5, \end{aligned} \tag{3}$$

where $E(z)$ is the sample average of our z_t variable, compute as $E(z) = \frac{1}{P}\sum_{i=R+1}^{P} z_i$. When we reject the null, it implies that on average our forecast beats a pure chance forecast. We compute a Diebold & Mariano (2002) test to analyse the differences against the pure chance benchmark.

Table 9 shows the results of the mean directional accuracy test for all restricted specifications using mining companies. The results of the unrestricted specifications are shown in **Table D.1** in **Appendix D**.

The results presented in **Table 9** are interesting in manifold. First, it is worthwhile to mention that the hit rate is larger than 0.5 in specifications 6, 7 and 8. Notice that specifications 9 and 10 correspond to a RW and DRW plus the sum of lag returns of an asset (in this case, mining companies), and we have already mentioned that lithium returns does not behave as a random walk process, and therefore it is not surprising that the hit rate is low. Second, although in our previous results SQM was one of the companies with the weakest predictability power, it is the best performer in terms of directional accuracy, with a hit rate close to 60% in almost all exercises. Third, despite the predictive power of Ganfeng, Tianqui, Pilbara and Lithium Americas shown in the above results, in terms of directional accuracy, these companies performance is weak.

Table 9: Mean directional accuracy for specifications 6-10

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
Panel A:	$\frac{P}{R} = 0.2$					
Spec 6	0.578	0.578	0.578	0.600	0.578	0.578
Spec 7	0.600	0.600	0.600	0.644**	0.600	0.600
Spec 8	0.622*	0.600	0.600	0.644**	0.622*	0.622*
Spec 9	0.578	0.511	0.622*	0.511	0.489	0.511
Spec 10	0.356	0.444	0.422	0.422	0.467	0.422
Panel B:	$\frac{P}{R} = 0.4$					
Spec 6	0.592	0.592	0.592	0.605*	0.592	0.579
Spec 7	0.592	0.605*	0.605*	0.605*	0.605*	0.592
Spec 8	0.605*	0.605*	0.605*	0.605*	0.605*	0.605*
Spec 9	0.461	0.408	0.513	0.500	0.461	0.434
Spec 10	0.329	0.408	0.382	0.487	0.461	0.395
Panel C:	$\frac{P}{R} = 2$					
Spec 6	0.511	0.517	0.511	0.517	0.511	0.517
Spec 7	0.517	0.517	0.517	0.523	0.517	0.523
Spec 8	0.523	0.523	0.511	0.517	0.523	0.523
Spec 9	0.393	0.360	0.416	0.410	0.382	0.388
Spec 10	0.315	0.343	0.343	0.382	0.433	0.337

Notes: Each cell reports the proportion of forecasts that correctly predict the direction of the lithium log return. Statistical significance is carried out with Diebold & Mariano (1995) t-test against a 0.5 pure chance benchmark. We use HAC standard errors according to Newey & West (1987, 1994).
*, ** and ***: significance at 10%, 5%, and 1%, respectively. Authors' elaboration.

3.5 Trading strategy

We do a trading exercise to explore whether it is possible to make a positive profit (excluding any associated transaction costs or short selling constraints). To that end, we consider a trading strategy analysed by Anatolyev & Gerko (2005), which can be defined as follows:

Let y_t^f be the forecast of lithium return, y_t, in period t, which depends only of previous information, $I_{t-1} = \{y_{t-1}, y_{t-2}, \ldots, x_{t-1}, x_{t-2}, \ldots\}$. The trading strategy is based on the following rule:

$$\begin{cases} \textit{buy the commodity if } y_t^f \geq 0 \\ \textit{sell the commodity otherwise.} \end{cases} \tag{4}$$

In other words, the investor goes long if the prediction of the next period return is positive and goes short otherwise. The investor modifies her position each trading period (weekly), closing it at the end of the period. Then the one-period return of the trading strategy is:

$$r_t = sign(y_t^f) y_t, \tag{5}$$

where:

$$sign(y_t^f) = \begin{cases} 1 \; if \; y_t^f \geq 0 \\ -1 \; if \; y_t^f < 0. \end{cases} \tag{6}$$

This trading rule describes the behaviour of a risk neutral investor, and we compare the profits of the rule described above with a "buy and hold" strategy. We compute a Straightforward Excess Profitability (SEP) test, proposed by Pincheira, Hardy & Betancor (2022) to analyse whether the gains obtained with the trading strategy are statistically significant.

Tables 10 and **11** show the result of the trading strategy, where some interesting results are found. First, for almost all the exercises, the gains are positive. Second, specifications 1-3 and 6-8 are always positive and statistically significant at 1% level. This result is actually not surprising, because the lithium returns are highly autoregressive. In these specifications, for the estimation window $\frac{P}{R} = 0.2$ gains are around 2.9%. In the case of $\frac{P}{R} = 0.4$ gains are close to 3.5% and when the estimation window is $\frac{P}{R} = 2$ gains can be as high as 6.9%. Third, specifications 4-5 and 9-10 correspond to a RW and DRW plus an asset, consequently it is in these cases where we are effectively seeing how much the asset helps in positive gains and, therefore, when there is a statistically significant relationship, it is due entirely to the effect of the asset.

Table 10: Annualised profits of unrestricted specifications using the trading strategy of Anatolyev & Gerko (2005)

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
$\frac{P}{R} = 0.2$						
Spec 1	2.93%***	2.93%***	2.93%***	2.97%***	2.96%***	2.93%***
Spec 2	2.91%***	2.90%***	2.91%***	2.94%***	2.95%***	2.90%***
Spec 3	2.89%***	2.89%***	2.88%***	2.93%***	2.92%***	2.88%***
Spec 4	0.08%	0.08%	0.17%*	0.35%***	0.20%**	0.19%*
Spec 5	0.00%	0.00%	0.10%	0.30%***	0.15%**	0.13%
$\frac{P}{R} = 0.4$						
Spec 1	3.55%***	3.53%***	3.56%***	3.59%***	3.58%***	3.53%***
Spec 2	3.53%***	3.5%***	3.54%***	3.56%***	3.56%***	3.5%***
Spec 3	3.50%***	3.49%***	3.5%***	3.54%***	3.53%***	3.48%***
Spec 4	0.10%	0.09%	0.22%**	0.42%***	0.24%**	0.22%*
Spec 5	0.03%	0.01%	0.16%	0.36%***	0.18%**	0.16%
$\frac{P}{R} = 2$						
Spec 1	6.12%***	6.03%***	6.09%***	6.12%***	6.16%***	6.06%***
Spec 2	6.18%***	6.10%***	6.17%***	6.18%***	6.25%***	6.14%***
Spec 3	6.23%***	6.16%***	6.21%***	6.25%***	6.30%***	6.19%***
Spec 4	0.11%	0.09%	0.24%*	0.72%***	0.36%**	0.34%**
Spec 5	0.02%	-0.02%	0.15%	0.64%***	0.3%*	0.26%

Source: Authors' elaboration.

Table 11: Annualised profits of restricted specifications using the trading strategy of Anatolyev & Gerko (2005)

	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
$\frac{P}{R} = 0.2$						
Spec 6	2.91%***	2.94%***	2.91%***	2.96%***	2.92%***	2.94%***
Spec 7	2.89%***	2.91%***	2.89%***	2.93%***	2.9%***	2.91%***
Spec 8	2.88%***	2.90%***	2.87%***	2.92%***	2.88%***	2.89%***
Spec 9	0.08%	0.10%	0.17%*	0.36%***	0.20%**	0.20%**
Spec 10	0.00%	0.02%	0.10%	0.30%***	0.15%**	0.14%*
$\frac{P}{R} = 0.4$						
Spec 6	3.52%***	3.54%***	3.52%***	3.57%***	3.53%***	3.54%***
Spec 7	3.5%***	3.51%***	3.49%***	3.54%***	3.5%***	3.51%***
Spec 8	3.48%***	3.5%***	3.47%***	3.53%***	3.48%***	3.49%***
Spec 9	0.10%	0.11%	0.2%**	0.42%***	0.23%**	0.24%**
Spec 10	0.02%	0.03%	0.14%	0.37%***	0.18%**	0.17%*
$\frac{P}{R} = 2$						
Spec 6	6.08%***	6.06%***	6.03%***	6.08%***	6.03%***	6.07%***
Spec 7	6.14%***	6.13%***	6.11%***	6.15%***	6.11%***	6.14%***
Spec 8	6.21%***	6.19%***	6.17%***	6.22%***	6.18%***	6.2%***
Spec 9	0.09%	0.13%	0.21%*	0.72%***	0.33%*	0.35%**
Spec 10	0.00%	0.02%	0.12%	0.64%***	0.27%*	0.28%

Source: Authors' elaboration.

3.6 Some placebo exercises

To emphasize the strong evidence for the existence of the empirical validity of the present value model, we regress other commodities as dependent variables with the stock price of lithium companies. We should expect that stock price of lithium companies are not good predictors of commodities other than lithium. To show this, we develop the following econometric specifications:

Table 12: Econometric specifications for placebo exercises

11.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \rho \Delta \ln y_{t-1} + \varepsilon_{1t}$
12.	$\Delta \ln(y_t) = c + \beta_1 \Delta \ln(x_{it-1}) + \beta_2 \Delta \ln(x_{it-2}) + \sum_{i=1}^{3} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{2t}$
13.	$\Delta \ln(y_t) = c + \beta(\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})) + \rho \Delta \ln y_{t-1} + \varepsilon_{3t}$
14.	$\Delta \ln(y_t) = c + \beta(\Delta \ln(x_{it-1}) + \Delta \ln(x_{it-2})) + \sum_{i=1}^{3} \rho_i \Delta \ln(y_{t-i}) + \varepsilon_{4t}$

Source: Authors' elaboration.

where $\Delta \ln(y_t)$ represents the log-return of a commodity at time t. In particular we test spot copper price, West Texas Intermediate (WTI), and London Metal Exchange Index (LMEX), $\Delta \ln(x_{it})$ represents log-return of lithium mining companies (Ganfeng, Albemarle, Tianqui, SQM and Pilbara). Finally, ε_{jt} represents the error term.

Tables 13-18 show those results for specifications 11-14. All in-sample regressions performed corroborate the non-existence of predictability of lithium producing companies for commodities such as copper, WTI or commodity baskets such as LMEX.

Table 13: In-sample unrestricted regressions with copper as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
Copper(-1)	-0.035	-0.034	-0.072	-0.072	-0.024	-0.022	-0.029	-0.028	-0.042	-0.041
	(0.077)	(0.074)	(0.075)	(0.076)	(0.081)	(0.077)	(0.071)	(0.072)	-0.070	(0.071)
Copper(-2)		0.040		0.001		0.049		0.006		0.034
		(0.068)		(0.073)		(0.066)		(0.064)		(0.067)
Copper(-3)		-0.002		0.007		0.001		-0.007		0.005
		(0.06)		(0.064)		(0.058)		(0.064)		(0.063)
Asset return(-1)	0.005	0.005	0.041	0.041	-0.016	-0.017	-0.006	-0.007	0.013	0.013
	(0.027)	(0.027)	(0.035)	(0.035)	(0.026)	(0.026)	(0.034)	(0.036)	(0.025)	(0.026)
Asset return(-2)	-0.019	-0.023	0.028	0.028	-0.023	-0.028	0.053	0.052	-0.010	-0.012
	(0.025)	(0.026)	(0.029)	(0.034)	(0.021)	(0.022)	(0.036)	(0.039)	-0.020	(0.022)
Constant	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	264	263	264	263	264	263	264	263	264	263
R-squared	0.004	0.005	0.011	0.011	0.008	0.010	0.008	0.008	0.003	0.004

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 14: In-sample restricted regressions with copper as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
Copper(-1)	-0.027	-0.025	-0.067	-0.068	-0.020	-0.017	-0.041	-0.040	-0.034	-0.031
	(0.077)	(0.076)	(0.074)	(0.073)	(0.08)	(0.078)	(0.07)	(0.07)	(0.071)	(0.072)
Copper(-2)		0.030		-0.005		0.045		0.014		0.024
		(0.064)		(0.069)		(0.064)		(0.065)		(0.064)
Copper(-3)		-0.001		0.007		0.000		0.003		0.000
		(0.06)		(0.064)		(0.058)		(0.062)		(0.061)
Asset return(-1)+	-0.008	-0.009	0.034	0.035	-0.020	-0.022	0.024	0.023	0.001	0.000
Asset return(-2)	(0.018)	(0.018)	(0.025)	(0.027)	(0.017)	(0.017)	(0.025)	(0.025)	(0.017)	(0.018)
Constant	0.001	0.001	0.000	0.000	0.001	0.001	0.001	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	264	263	264	263	264	264	264	263	264	263
R-squared	0.002	0.003	0.010	0.010	0.007	0.009	0.004	0.004	0.001	0.002

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 15: In-sample unrestricted regressions with London Metal Exchange Index (LMEX) as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
LMEX(-1)	0.030	0.031	0.018	0.020	0.048	0.050	0.052	0.055	0.029	0.030
	(0.073)	(0.074)	(0.07)	(0.073)	(0.075)	(0.076)	(0.065)	(0.067)	(0.069)	(0.07)
LMEX(-2)		-0.018		-0.050		-0.020		-0.061		-0.015
		(0.063)		(0.063)		(0.062)		(0.056)		(0.058)
LMEX(-3)		0.005		0.012		0.002		-0.010		0.006
		(0.056)		(0.059)		(0.056)		(0.058)		(0.058)
Asset return(-1)	0.001	0.001	0.011	0.011	-0.023	-0.024	-0.032	-0.031	0.003	0.002
	(0.026)	(0.026)	(0.028)	(0.029)	(0.024)	(0.024)	(0.031)	(0.031)	(0.024)	(0.025)
Asset return(-2)	-0.009	-0.008	0.026	0.033	-0.006	-0.005	0.072	0.081	-0.010	-0.008
	(0.023)	(0.024)	(0.03)	(0.033)	(0.018)	(0.02)	(0.034)	(0.035)	(0.018)	(0.018)
Constant	0.001	0.001	0.001	0.000	0.001	0.001	0.000	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	264	263	264	263	264	263	264	263	264	263
R-squared	0.002	0.002	0.005	0.008	0.007	0.007	0.020	0.024	0.002	0.002

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 16: In-sample restricted regressions with London Metal Exchange Index (LMEX) as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
LMEX(-1)	0.033	0.034	0.012	0.011	0.039	0.040	0.021	0.021	0.035	0.035
	(0.073)	(0.074)	(0.068)	(0.07)	(0.073)	(0.074)	(0.067)	(0.069)	(0.066)	(0.067)
LMEX(-2)		-0.022		-0.039		-0.012		-0.039		-0.021
		(0.058)		(0.058)		(0.061)		(0.059)		(0.057)
LMEX(-3)		0.005		0.011		0.003		0.011		0.005
		(0.056)		(0.059)		(0.056)		(0.06)		(0.059)
Asset return(-1)+	-0.004	-0.004	0.019	0.022	-0.015	-0.014	0.022	0.026	-0.004	-0.003
Asset return(-2)	(0.017)	(0.018)	(0.022)	(0.023)	(0.016)	(0.017)	(0.023)	(0.023)	(0.017)	(0.017)
Constant	0.001	0.001	0.001	0.000	0.001	0.001	0.000	0.000	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	264	263	264	263	264	263	264	263	264	263
R-squared	0.001	0.002	0.005	0.006	0.005	0.005	0.004	0.005	0.001	0.002

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 17: In-sample unrestricted regressions with West Texas Intermediate (WTI) as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
WTI(-1)	0,047	0,054	0,052	0,055	0,055	0,062	0,078	0,065	0,063	0,072
	(0.116)	(0.12)	(0.131)	(0.14)	(0,102)	(0,112)	(0,117)	(0,116)	(0.164)	(0.184)
WTI(-2)		-0,122		-0,117		-0,113	-0,155			-0,154
		(0.122)		(0.136)		(0,117)	(0,112)			(0.137)
WTI(-3)		0,019		0,028		0,029	0,030			0,020
		(0.087)		(0.08)		(0,08)	(0,08)			(0.104)
Asset return(-1)	0,058	0,055	0,037	0,054	-0,007	-0,001	-0,081	-0,073	-0,024	-0,023
	(0.07)	(0.07)	(0.14)	(0.149)	(0,042)	(0,044)	(0,093)	(0,088)	(0.076)	(0.072)
Asset return(-2)	-0,051	-0,031	-0,111	-0,079	-0,093	-0,076	0,182	0,125	0,025	0,070
	(0.06)	(0.053)	(0.1)	(0.076)	(0,061)	(0,05)	(0,094)	(0,089)	(0.087)	(0.079)
Constant	0,001	0,001	0,002	0,002	0,002	0,002	0,001	0,001	0,001	0,001
	(0.005)	(0.005)	(0.005)	(0.005)	(0,005)	(0,005)	(0,005)	(0,005)	(0.005)	(0.005)
Observations	264	263	264	263	264	263	264	263	264	263
R-squared	0,008	0,023	0,013	0,027	0,014	0,026	0,033	0,011	0,004	0,026

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

Table 18: In-sample restricted regressions with West Texas Intermediate (WTI) as dependable variable

	Ganfeng		Albemarle		Tianqui		SQM		Pilbara	
WTI(-1)	0,053	0,059	0,064	0,065	0,064	0,071	0,050	0,056	0,053	0,054
	(0.116)	(0.119)	(0.13)	(0.139)	(0,101)	(0,112)	(0,109)	(0,111)	(0.164)	(0.183)
WTI(-2)		-0,130		-0,126		-0,118		-0,135		-0,139
		(0.121)		(0.13)		(0,115)		(0,113)		(0.142)
WTI(-3)		0,022		0,024		0,029		0,020		0,021
		(0.086)		(0.085)		(0,08)		(0,082)		(0.104)
Asset return(-1)+	0,003	0,012	-0,039	-0,011	-0,051	-0,039	0,028	0,051	0,002	0,023
Asset return(-2)	(0.03)	(0.033)	(0.089)	(0.086)	(0,034)	(0,029)	(0,066)	(0,065)	(0.071)	(0.067)
Constant	0,001	0,001	0,002	0,002	0,002	0,002	0,001	0,001	0,001	0,001
	(0.005)	(0.005)	(0.005)	(0.005)	(0,005)	(0,005)	(0,005)	(0,005)	(0.005)	(0.005)
Observations	264	263	264	263	264	263	264	263	264	263
R-squared	0,003	0,020	0,005	0,020	0,009	0,023	0,003	0,021	0,003	0,021

Notes: (-1), (-2) and (-3) represent the first, second and third lags on the returns of the variable of interest, respectively. In parentheses the standard error.

*, ** and ***: significance at 10%, 5%, and 1%, respectively. Source: Authors' elaboration.

4. Concluding remarks

In this paper we build a model to forecast both in-sample and out-of-sample lithium prices. Specifically, we use the present value model for exchange rates, market indexes, mining company prices and related company prices in hi-tech, automotive, electric vehicle and micro-mobility industries. The relevance of this work is that this specific raw material has received little attention from the forecasting literature, despite the fact it is becoming increasingly important as a so-called environmentally friendly material. While lithium prices will most likely be more transparent in the near future than they are today (Maxwell, 2015), lithium has already become an important commodity in the world metal markets and it is therefore key to advance in the understanding of its economic drivers.

We investigate the existence of Granger causality based on present value theory, finding mixed results, consistent with the forecasting literature. Particularly, we explore the empirical implications of the present value model for exchange rates, market indexes, mining company prices and related company prices in hi-tech, automotive, electric vehicle and micro-mobility industries. We examine the predictive power of the Australian and Chilean exchange rates on lithium, both being the main lithium producing and exporting countries, however, neither of them has predictive power on lithium. This is to be expected, given that in both economies lithium exports represent a very low percentage of the export basket.

Following present value theory, we also examine asset prices of companies related to the growth of lithium consumption. These are: battery producers, hi-tech and automotive, electric vehicle, and micro-mobility. Again, the results were non-significant in all cases. Similar to the case of the lithium exporting economies, lithium is a small percentage of all components required for the manufacture of these products and, therefore, it is to be expected that the price of these companies has no predictive power on the lithium price. In addition, we tested indices, which also show no Ganger causality for lithium.

For the case of lithium mining companies, we find Granger causality and consequently predictability. The interesting point to note is that while economic causality says that the price of lithium affects the share price of lithium mining companies, predictability goes in the opposite direction. The intuition behind this result is the following: investors in the lithium mining companies' stock market form their expectations with information on future developments and uses of lithium. If investors are efficient in including this information, the share price of mining companies should reflect any relevant changes in expectations of the future price of lithium.

To show that lithium mining companies have the ability to predict lithium prices, we perform several exercises, both in-sample and out-of-sample with interesting results. Although lithium returns have a very high autoregressive component and therefore beating a random walk is relatively easy, our models also beat models such as AR(5), AR(4) and AR(3). When doing some robustness tests, our models also perform well, in terms of directional accuracy and also from a trading point of view, where the returns, while not very high (best model with 6.9% annual returns), are reasonable.

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Appendix A: List of predictors

Table A.1: Exchange rates, market indexes, mining companies and lithium-related companies under study

Exchange rates	Market indexes	Mining Companies	Lithium-related companies			
			Battery producers	Hi-tech and automotive	Electric vehicle	Micro-mobility
Australia	Lme-Lmex	Ganfeng Lithium	LG	Toyota Motor	Tesla	Niu
Chile	Msci Acwi Met & Min	Albemarle	LG Chemicals	Volkswagen	Byd	
	Msci World Met & Min	Tianqi	LG Electronics	Hon Hai	Nio	
	S&P Gsci Commodity	Sqm	Panasonic	Daimler Truck		
	S&P Gsci Energy	Pilbara Minerals	Panasonic E. India	Ford Motor		
	S&P 500 Composite	Lithium Americas	Samsung Electronics	Honda Motor		
	S&P500 Metals & Mining		Samsung Sdi	GM		
			Sk Innovation			
			Eve Energy			
			Eve Holding			

Source: Authors' elaboration.

Table A.2: Other predictors

Exchange rates	Fossil fuels	Commodities
Canada	WTI	Gold
Colombia	Brent	Copper
Iceland	Propane	
New Zeeland		
Peru		
South Africa		

Source: Authors' elaboration.

Appendix B: Descriptive statistics

Table B.1: Descriptive statistics of weekly returns of lithium and exchange rates

	Lithium	**Chilean peso**	**Australian dollar**
n° obs.	267	267	267
min	-0,0718	-0,0633	-0,0506
max	0,1484	0,0722	0,0745
range	0,2202	0,1355	0,1251
sum	1,3082	0,3906	0,1484
median	0,0000	0,0005	0,0005
mean	0,0049	0,0015	0,0006
std.dev	0,0326	0,0193	0,0149

Source: Authors' elaboration.

Table B.2: Descriptive statistics of weekly returns of market indexes

	Lme	Msci acwi met&min	Msci world met&min	SP gsci commodity	SP gsci energy	SP500 composite	SP500 metals&mining
n° obs.	267	267	267	267	267	267	267
min	-0,1009	-0,2291	-0,2420	-0,1546	-0,2658	-0,1623	-0,2362
max	0,1012	0,1192	0,1258	0,1826	0,2341	0,1142	0,1888
range	0,2020	0,3483	0,3679	0,3372	0,4999	0,2765	0,4251
sum	0,1825	0,2187	0,2717	0,4352	0,4819	0,4418	0,6723
median	0,0017	0,0023	0,0011	0,0033	0,0069	0,0047	0,0029
mean	0,0007	0,0008	0,0010	0,0016	0,0018	0,0017	0,0025
std.dev	0,0265	0,0396	0,0405	0,0338	0,0548	0,0284	0,0459

Source: Authors' elaboration.

Table B.3: Descriptive statistics of weekly returns of mining companies

	Ganfeng	Albemarle	Tianqi	Sqm	Pilbara	Lithium Americas
n° obs.	267	267	267	267	267	267
min	-0,2695	-0,2409	-0,2473	-0,1878	-0,3161	-0,4076
max	0,2269	0,2404	0,3248	0,1742	0,3114	0,5428
range	0,4965	0,4813	0,5721	0,3621	0,6276	0,9504
sum	0,6583	0,7026	0,5559	0,8520	1,8732	1,3677
median	-0,0012	0,0025	-0,0009	0,0000	0,0000	-0,0073
mean	0,0025	0,0026	0,0021	0,0032	0,0070	0,0051
std.dev	0,0755	0,0673	0,0861	0,0472	0,0896	0,1097

Source: Authors' elaboration.

Table B.4: Descriptive statistics of weekly returns of battery producers

	LG	LG Chem	LG Electronics	Panasonic	Panasonic Energy India
n° obs.	267	267	267	267	267
min	-0,2260	-0,2228	-0,1519	-0,2288	-0,1723
max	0,1929	0,2726	0,2373	0,2047	0,2785
range	0,4189	0,4954	0,3893	0,4335	0,4508
sum	0,0899	0,5855	0,1102	-0,2581	0,0822
median	0,0000	-0,0013	0,0000	-0,0031	-0,0034
mean	0,0003	0,0022	0,0004	-0,0010	0,0003
std.dev	0,0444	0,0601	0,0516	0,0455	0,0581

	Samsung Electronics	Samsung SDI	SKI	Eve Electronics	Eve
n° obs.	267	267	267	267	97
min	-0,1232	-0,2482	-0,2888	-0,1922	-0,4700
max	0,0919	0,2051	0,3984	0,1898	0,3644
range	0,2152	0,4534	0,6873	0,3821	0,8344
sum	0,1866	1,2617	-0,1429	1,8407	-0,0954
median	0,0000	0,0065	-0,0010	0,0050	0,0000
mean	0,0007	0,0047	-0,0005	0,0069	-0,0010
std.dev	0,0356	0,0561	0,0666	0,0758	0,0999

Source: Authors' elaboration.

Table B.5: Descriptive statistics of weekly returns of high-tech and automotive industries

	Toyota	Volkswagen	Hon Hai	Daimler Truck	Ford	Honda	GM
n° obs.	267	267	267	49	267	267	267
min	-0,1263	-0,2470	-0,1173	-0,2491	-0,2625	-0,1833	-0,3091
max	0,1010	0,2013	0,1603	0,0828	0,2511	0,1226	0,2880
range	0,2273	0,4483	0,2776	0,3319	0,5137	0,3059	0,5970
sum	0,3692	0,2415	-0,2513	-0,0177	0,1279	-0,0184	-0,1220
median	0,0016	0,0010	0,0000	0,0035	0,0010	-0,0003	0,0010
mean	0,0014	0,0009	-0,0009	-0,0004	0,0005	-0,0001	-0,0005
std.dev	0,0343	0,0511	0,0350	0,0552	0,0608	0,0406	0,0592

Source: Authors' elaboration.

Table B.6: Descriptive statistics of weekly returns of electric vehicle and micro-mobility

	Tesla	BYD	NIO	NIU
n° obs.	267	267	218	213
min	-0,2992	-0,2332	-0,5522	-0,2347
max	0,2744	0,2374	0,4681	0,3190
range	0,5736	0,4706	1,0204	0,5537
sum	2,0247	0,8306	0,0560	-0,8963
median	0,0072	0,0000	-0,0051	-0,0120
Mean	0,0076	0,0031	0,0003	-0,0042
std.dev	0,0879	0,0691	0,1317	0,0973

Source: Authors' elaboration.

Appendix C: Some tests for lithium prices and returns

Table C.1: Augmented Dickey Fuller and Ljung-Box test

	ADF test p-value	Ljung-Box test p-value
Lithium price	0.8981	<0.01***
Lithium log return	<0.01***	<0.01***

Notes: ADF stands for Augmented Dickey Fuller.

ADF test H_0: not stationary, H_1: stationary

Ljung Box test H_0: white noise, H_1: not white noise

*, ** and ***: significance at 10%, 5%, and 1%, respectively.

Source: Authors' elaboration.

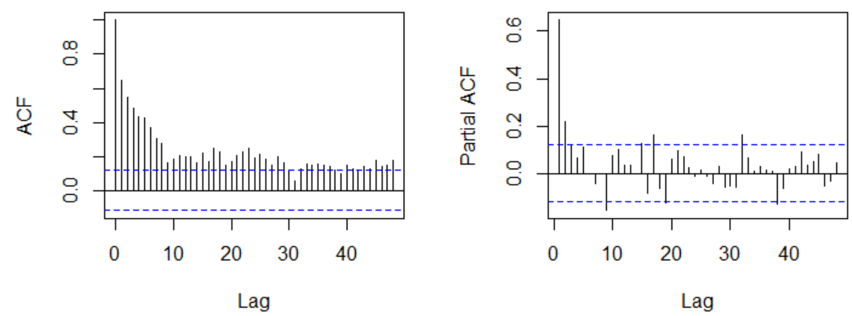

Figure C.1: Lithium Return Correlograms

Left panel corresponds to the autocorrelation function. Right panel corresponds to the partial autocorrelations

Source: Authors' elaboration.

Appendix D: Some other results

Table D.1: In-sample results for producer countries exchange rates for specs 3 and 8

Unrestricted specification			Restricted specification		
	Coefficient	R^2		Coefficient	R^2
Chilean Peso(-1)	0.022	0.459	Chilean Peso(-1) +	0.042	0.459
	(0.066)		Chilean Peso(-2)	(0.061)	
Chilean Peso(-2)	0.063				
	(0.094)				
Australian Dollar(-1)	-0.103	0.461	Australian Peso(-1) +	-0.028	0.458
	(0.107)		Australian Peso(-2)	(0.073)	
Australian Dollar(-2)	0.048				
	(0.109)				

*, ** and ***: significance at 10%, 5%, and 1%, respectively. All t-statistics for predictors shown are less than 1.645.

Standard deviation in parenthesis. Source: Authors' elaboration.

Table D.2: In-sample results of market indexes for specs 3 and 8

Unrestricted specification			Restricted specification		
	Coefficient	R^2		Coefficient	R^2
LMEX(-1)	0.048	0.460	LMEX(-1) +	0.041	0.460
	(0.051)		LMEX(-2)	(0.041)	
LMEX(-2)	0.034				
	(0.070)				
ACWI M&M(-1)	0.053	0.462	ACWI M&M(-1) +	0.028	0.460
	(0.034)		ACWI M&M(-2)	(0.021)	
ACWI M&M(-2)	0.002				
	(0.046)				
WORLD M&M(-1)	0.048	0.461	WORLD M&M(-1) +	0.023	0.459
	(0.032)		WORLD M&M(-2)	(0.020)	
WORLD M&M(-2)	-0.002				
	(0.045)				
S&P Commodity(-1)	0.044	0.460	S&P Commodity(-1) +	0.011	0.458
	(0.037)		'S&P Commodity(-2)	(0.018)	
S&P Commodity(-2)	-0.022				
	(0.036)				
S&P Energy(-1)	0.026	0.460	S&P Energy(-1) +	0.004	0.458
	(0.023)		'S&P Energy(-2)	(0.010)	
S&P Energy(-2)	-0.018				
	(0.022)				
S&P500 COMPOSITE(-1)	0.016	0.459	S&P500 COMPOSITE(-1) +	0.029	0.459
	(0.041)		'S&P500 COMPOSITE(-2)	(0.031)	
'S&P500 COMPOSITE(-1)	0.043				
	(0.037)				
S&P500 M&M(-1)	0.040	0.461	S&P500 M&M(-1) +	0.014	0.458
	(0.032)		S&P500 M&M(-2)	(0.017)	
S&P500 M&M(-2)	-0.012				
	(0.036)				

*, ** and ***: significance at 10%, 5%, and 1%, respectively. All t-statistics for predictors shown are less than 1.645. Standard deviation in parenthesis. Source: Authors' elaboration.

Table D.3: In-sample results of selected lithium-related companies for specs 3 and 8

Unrestricted specification			Restricted specification		
	Coefficient	R^2		Coefficient	R^2
LG(-1)	-0.020	0.460	LG(-1) + LG(-2)	0.004	0.458
	(0.028)			(0.022)	
LG(-2)	0.028				
	(0.037)				
Samsung Electronics (-1)	0.016	0.461	Samsung Electronics (-1) +	0.035	0.461
	(0.037)		Samsung Electronics (-2)	(0.027)	
Samsung Electronics (-2)	0.053				
	(0.042)				
EVE ENERGY(-1)	-0.005	0.461	EVE ENERGY(-1) +	0.009	0.459
	(0.017)		EVE ENERGY(-2)	(0.012)	
EVE ENERGY(-2)	0.023				
	(0.019)				
Toyota(-1)	0.050	0.461	Toyota(-1) +	0.021	0.459
	(0.049)		Toyota(-2)	(0.021)	
Toyota(-2)	-0.007				
	(0.049)				
Ford(-1)	0.001	0.458	Ford(-1) +	-0.006	0.458
	(0.018)		Ford(-2)	(0.011)	
Ford(-2)	-0.012				
	(0.022)				
Tesla(-1)	0.002	0.460	Tesla(-1) +	0.009	0.459
	(0.014)		Tesla(-2)	(0.008)	
Tesla(-2)	0.016				
	(0.015)				
Niu(-1)	0.004	0.488	Niu(-1) +	0.005	0.488
	(0.018)		Niu(-2)	(0.011)	
Niu(-2)	0.006				
	(0.017)				

*, ** and ***: significance at 10%, 5%, and 1%, respectively. All t-statistics for predictors shown are less than 1.645. Standard deviation in parenthesis. Source: Authors' elaboration.

Table D.4: In-sample results of other predictors for specs 3 and 8

Unrestricted specification			Restricted specification		
	Coefficient (Standard Deviation)	R^2		Coefficient (Standard Deviation)	R^2
Canadian dollar(-1)	-0.035	0.459	Canadian dollar(-1) +	0.044	0.458
	(0.170)		Canadian dollar(-2)	(0.093)	
Canadian dollar(-2)	0.122				
	(0.177)				
South African Rand(-1)	-0.009	0.458	South African Rand(-1) +	-0.017	0.458
	(0.075)		South African Rand(-2)	(0.057)	
South African Rand(-2)	-0.026				
	(0.082)				
Gold(-1)	-0.061		Gold(-1) +	-0.029	0.458
	(0.052)		Gold(-2)	(0.050)	
Gold(-2)	0.004				
	(0.081)				
WTI(-1)	0.016		WTI(-1) +	-0.002	0.458
	(0.011)		WTI(-2)	(0.007)	
WTI(-2)	-0.020				
	(0.013)				
Copper(-1)	0.055		Copper(-1) +	0.053	0.462
	(0.050)		Copper(-2)	(0.037)	
Copper(-2)	0.051				
	(0.059)				

*, ** and ***: significance at 10%, 5%, and 1%, respectively. All t-statistics for predictors shown are less than 1.645. Standard deviation in parenthesis. Source: Authors' elaboration.

Table D.5: Mean directional accuracy using specifications 1-5

Panel A:	$\frac{P}{R} = 0.2$					
	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
AR5	0.5333	0.5778	0.5556	0.5778	0.5778	0.5778
AR4	0.5778	0.6	0.5556	0.6	0.5778	0.6
AR3	0.6	0.6	0.6	0.6	0.6	0.6222*
RW	0.5333	0.5333	0.5333	0.4889	0.4889	0.5333
DRW	0.4	0.3556	0.4222	0.4222	0.4444	0.4222
Panel B:	$\frac{P}{R} = 0.4$					
	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
AR5	0.5658	0.5921	0.5789	0.5789	0.5921	0.5658
AR4	0.5789	0.6053*	0.5789	0.5789	0.5789	0.5921
AR3	0.5789	0.6053*	0.5921	0.5789	0.5921	0.6053*
RW	0.4342	0.4474	0.4605	0.4868	0.4605	0.4474
DRW	0.3553	0.3684	0.4079	0.4868	0.4474	0.3947
Panel C:	$\frac{P}{R} = 2$					
	Ganfeng	Albemarle	Tianqui	SQM	Pilbara	Lithium Americas
AR5	0.5112	0.5169	0.5112	0.5169	0.5112	0.5169
AR4	0.5169	0.5169	0.5169	0.5225	0.5169	0.5225
AR3	0.5225	0.5225	0.5112	0.5169	0.5225	0.5225
RW	0.3933	0.3596	0.4157	0.4101	0.382	0.3876
DRW	0.3146	0.3427	0.3427	0.382	0.4326	0.3371

Notes: Each cell reports the proportion of forecasts that correctly predict the direction of the lithium log return. Statistical significance is carried out with Diebold & Mariano (2002) t-test against a 0.5 pure chance benchmark. We use HAC standard errors according to Newey & West (1987, 1994).

*, ** and ***: significance at 10%, 5%, and 1%, respectively.

Source: Authors' elaboration