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ORIGINAL ARTICLE

Commodity Medium-Term Cycles and Transition to Green Energies: A Markov Switching Model

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Abstract

This study uses an AR model with Markov Switching approach to forecast the real growth of copper price using 2 regimes: expansion and contraction. We expect an increase in the demand for metals in the medium term due to the transition to green energies. In the estimated model, we see that the contractive state presents a negative growth, while the expansionary state shows a growth equal to 3.57 percent annually. The filtered and smoothed probabilities show that the real growth of copper is in the expansionary state most of the time (approximately the 82.56 percent of the time of the sample period). Thus, we provide evidence that in the medium-run term (next 20 years), it is expected that the real price of copper grows at the same rate as the expansionary state of its previous medium-run term cycle, which is equal to 3.57 percent annually.

Keywords:

Forecast, Copper price, Medium-term Cycles, Markov Switching, Commodities

JEL Classification:

C24, C53, Q02, Q42

1. Introduction

The study of commodity cycles began in the 1980s. However, the effect of metals on emerging and developed economies was not very relevant due to the context of industrialization and progressive technological advance. However, the effect of commodity prices, mostly metals, has increased in recent decades mainly in emerging economies in economic, political, and social dimensions. Thus, with the emergence of new environmental studies and the awareness of governments for the use of green energies, an expectation is generated about a new cycle of commodities that brings relevant effects for emerging economies.

Figueroa (2017) shows that starting in 2003, a Commodity Supercycle began, driven by the growth of the Chinese economy and its demand for raw materials. For their part, Camacho and González (2020) show that most of the cyclical fluctuations in growth and inflation in Latin America between 2003 and 2011 responded to the Commodity Supercycle.

In Peru, the effects of metal price fluctuations on variables such as economic growth, level of employment, inflation, tax revenues and interest rates have been significant. Regarding mining exports, between 2002 and 2015, they represented about 77% of total Peruvian exports on average. During that period, mining investments increased by 1,131%. Likewise, the mining sector left revenues of S/37,961 million for the mining canon, while tax revenues for income taxes amounted to S/44,250 million. Regarding the level of employment, the mining sector exhausted in 2002, 68 thousand direct jobs and 610 thousand indirect jobs, while in 2015, the mining sector exhausted 195 thousand direct jobs and 1.7 million indirect jobs. In addition, during this period, Peru reached the category of investment grade according to different risk-classified entities, which has allowed financing sources to have competitive interest rates. The GDP growth rate, on average, reached 6% per year (OSINERGMIN, 2017). In that same context, the poverty rate was reduced to 21.8%, while the extreme poverty rate decreased to 4.1%. (INEI, 2017). In this way, the importance of fluctuations in the price of commodities in the Peruvian economy is evident.

On the other hand, since the beginning of the new millennium a discussion has been generated regarding the use of friendly energies for the environment. Thus, with the aim of raising awareness of environmental pollution, in 2015 the Sustainable Development Goals are set (which are intended to be achieved by the year 2030) where it is found as part of the agenda, guaranteeing access to affordable energy and sustainable, thus beginning the transition to renewable energies. This transition brings with it structural economic changes, such as an increase in the demand for the necessary metals (copper, nickel, cobalt and lithium) for the construction of machinery that generates non-polluting technology, thanks to its physical and chemical properties. In this way, it is expected that the increase in prices will behave like a Supercycle, causing significant effects in exporting countries of these metals such as Peru, due to the fact that it is the second country in copper production worldwide and the third in copper holdings. copper reserves (77 million MT).

The objective of this research is to generate a forecast of the real price of copper for the next 20 years, using a Markov regime change model with 2 states: Expansion and contraction. Unlike other nonlinear models, M-S models are suitable for studying cycles of high duration and modeling series with breaks in mean and/or variance (Chang-Jin and Nelson, 2017). Along the same lines, Chevallier and Ielpo (2013a) show that commodities have long cycles and that these models have good predictive properties.

The importance of the copper price forecast for Peru is based on the significant weight on its total exports and, therefore, on the terms of trade, tax revenues, as well as the level of foreign investment. On the other hand, central banks and economic agents use the price of copper as an important source of external shocks in macroeconomic models, so copper price forecasts are relevant for monetary policy and decision-making by economic agents.

2. Brief literature review

Baffes and Nagle (2022) show that, during the 20th century, real copper prices experienced a sustainable price decline. However, this downward trend suffered a reversion when China entered in the World Trade Organization and became the "factory of the world". Because of its fast industrialization process, Chinese consumption of commodities pushed their prices up, including copper. While it is also true that commodity consumption increased also in other emerging economies, their share of global consumption kept relatively constant. This leaves China as the main driver of real copper price since the beginning of the 21st century. In other hand, commodity consumption is pushed up by the growth of global population, which is not a negligible variable if we notice that the global population has more than doubled during the last 50 years. Also, it is easily seen that there is a positive relationship between economic growth and commodity demand, because when people's incomes increase, so do their material demands. Again, income per capita has growth particularly faster in China and low-income countries, leading to an overall proportional rise in commodity demand. Finally, the stage of development has had a mixed effect on the global commodity consumption, because in one side, countries with already high levels of income, a higher level of industrialization make them to increase consumption of services rather than goods, being the former less commodity intensive than the latter; while in the another side, countries with low levels of income and development tend to increase their demand of commodities when they move from mainly agricultural economy to manufacturing, because the latter is more commodity intensive than the former.

Forecasting the future real price of copper in the following years is not an easy task, but we can identify current key drivers which can give us some clues about its long-run trend which is crucial for metal exporter countries like Peru and Australia to project future fiscal and export revenue (Baffes and Nagle, 2022), because their copper reserves account for, according (U.S Geological Survey, 2022), around 10 percent of known global copper reserves each.

Baffes and Nagle (2022) point out that the Energy Transition from fossil fuels to green energies may bring an unprecedented demand for copper in the long-run term. This singular situation could make the forecast task be implausible; nonetheless, it is necessary to consider other drivers of the future demand of copper to figure out a more realistic quantifiable forecast. Some drivers which can moderate the enthusiastic Energy Transition scenario are the current Ukraine war and the China's economic slowdown (Brandt et al., 2020) The former is currently complicating the Energy Transition around the world (specially Europe), and it is forcing countries to use back, at least temporarily, coal, oil and natural gas as energy, while the latter may have a long-lasting impact on copper demand because China has leaded the share of global copper consumption during the last 20 years, so its economic rebalancing from investment toward domestic consumption may lead the real price of copper to a downward trend which can offset the Energy Transition boom, although we need to remark that this rebalancing will take time relatively long to reach this goal.

The previous adverse scenarios for future copper demand may be offset by the fact that China is the world's largest producer of wind and solar energy (Chiu, 2017) and this situation does not seem to suffer significant changes in the medium-run term. Also, demand growth in commodities has changed from advanced toward emerging economies which will drive the global economic growth in the following years, copper intensity has recovered its upward trend, its consumption shows no sign of plateauing, and finally, the last 50 years of rapid increase in urbanization rate in emerging markets and developing countries is expected to continue over the next 30 years, mostly in Sub-Saharan Africa and South Asia countries, which will increase the energy consumption (Poumanyvong, Dhakal, and Kaneko, 2012). All these key drivers will likely increase the copper demand in the future (Baffes, Kabundi, and Nagle, 2022).

Based on all these possible future scenarios and weighting them following a conservative approach, we will forecast the real price of copper using the data of the most recent boom in the price of copper, which must be identified. To achieve it, we rely on the research of Baffes and Nagle (2022), which decompose commodity price variations into transitory and permanent components, using a frequency domain approach that has been being applied to business cycles (Corbae and Ouliaris, 2006). It identifies three components of the transitory component: short-term fluctuations (less than 2 years); traditional business cycles which have a duration of 2-8 years, usually associated with economic activity (Burns and Mitchel, 1946); and medium-term cycles with periodicity between 8 and 20 years, often associated with long-term investment trends (Slade, 1982). The permanent component, in other side, catch variations of commodity prices whose periodicity lasts more than 20 years, in line with supercycles (Cuddington and Jerrett, 2008).

Baffes and Nagle (2022) also found that commodity price movements can be decomposed, on average, into the permanent component (responsible for 45 percent of price movements), the medium-term cycles (responsible for 32 percent of price movements), and traditional business cycles (responsible for 17 percent of price movements). Moreover, the prevalence of the medium-term cycle in the transitory component is consistent with recent findings that medium-run cycles have a higher role than short business cycles in output movements or domestic financial cycles (Aldasoro et al., 2020; Cao and L'Huillier, 2018).

Some interesting findings are the particularly higher contribution of the business cycle to metal commodity price variability (around 24 percent of price fluctuations for metals) and the fact that metal prices, especially copper, are usually considered leading indicators of global economic activity (Bernanke, 2016; Hamilton J. , 2015).

Finally, a crucial finding for the purpose of the present paper is the identification of three medium-term cycles: the first, which goes from early 1970s to mid-1980s; the second, which span the 1990s decade; and the third, which goes from the early 2000s to 2022 (Baffes and Nagle, 2022). We include data from the pandemic of Covid-19 period because the abrupt fall that real price of copper experienced during the first half of 2020 was rapidly reversed and continued to follow its previous upward trend. The War in Ukraine (which started at February 24th, 2022) could have marked the end of this cycle? (Clinch, 2022).

Because the last medium-term cycle seemed to have lasted around 20 years, and the key drivers of real price of copper previously mentioned seem to be forecasted for the next 20-30 years, the present research has the intention to forecast the real price of copper for the next 20 years, which can be seen as the next medium-term cycle, based on the assumption that the next medium-term cycle will resemble the previous one. For that purpose, we use the Markov switching model, which will allow to estimate the long-run annual growth rate of real price of copper for different regimes.

3. Model and metodology

The fluctuations of the economic and financial series mainly respond to stochastic economic shocks that can generate structural changes. Thus, to generate an econometric model, the estimated parameters often cannot capture structural breaks or regime changes. In this way, nonlinear models are formulated with the aim of obtaining better statistical and predictive properties.

Models containing parameters that are not constant over time are useful for studying business cycles, dividing the period into different regimes and estimating different values for the parameters. One of the main drawbacks with the estimation of these models is that the exact date in which the parameters change is not known, therefore, it is necessary to make inferences about this inflection point. In a regression context, Quandt (1972) assumes that the probability of change does not depend on the regime in which the series is found, while Goldfeld and Quandt (1973) allow such a dependence by introducing Markov Switching. In this way, using the Markov property, it is possible to filter and estimate the distributions about the regimes considering dependent data. For his part, Hamilton (1989) provides a Markov regime shift methodology in a correlated data context (autoregressive processes) to model

U.S. business cycles, with regime shifts in mean and variance. Following Hamilton (1989), the following AR (1) process is proposed :

$$Y_t - \mu_{S_t} = \theta_1 (Y_{t-1} - \mu_{S_{t-1}}) + \varepsilon_t, \varepsilon_t \sim i.i.d. N(0, \sigma^2_{S_t}) \tag{1}$$

The model presents regime changes in mean and variance, where S_t represents the state of the regime. $S_t = 1$ (expansion regime), $S_t = 0$ (contraction regime). Where S_t is not known a priori, therefore the following probability rules are used. The joint density of Y_t, S_t, S_{t-1}, conditional on all available information φ_{t-1}: |

$$f(Y_t, S_t, S_{t-1} | \varphi_{t-1}) = f\ (Y_t | S_t, S_{t-1}, \varphi_{t-1}) \Pr[S_t, S_{t-1} | \varphi_{t-1}] \tag{2}$$

Then, the marginal density of Y_t integrating the joint density:

$$f(Y_t | \varphi_{t-1}) = \sum_{S_t}^{M} \sum_{S_{t-1}}^{M} f(Y_t, S_t, S_{t-1} | \varphi_{t-1})$$

$$= \textstyle\sum_{S_t}^{M} \sum_{S_{t-1}}^{M} f(Y_t |\ S_t, S_{t-1}, \varphi_{t-1}) \Pr[S_t, S_{t-1} | \varphi_{t-1}] \tag{3}$$

where the marginal density $f(Y_t | \varphi_{t-1})$ is weighted by $\Pr[S_t = j, S_{t-1} = i \mid \varphi_{t-1}]$, $i = 1,2$; $j = 1,2$.

where the marginal density $f(Y_t | \varphi_{t-1})$ is weighted by $\Pr[S_t = j, S_{t-1} = i \mid \varphi_{t-1}]$, $i = 1,2$; $j = 1,2$.

Then the likelihood function would be:

$$lnL = \textstyle\sum_{t=1}^{T} ln\{\sum_{S_t=1}^{M} \sum_{S_{t-1}=1}^{M} f(Y_t |\ S_t, S_{t-1}, \varphi_{t-1}) \Pr[S_t, S_{t-1} | \varphi_{t-1}]\} \tag{4}$$

Where:

$$f(Y_t |\ S_t, S_{t-1}, \varphi_{t-1}) = \frac{1}{\sqrt{2\pi\sigma^2_{S_t}}} exp(-\frac{\{(Y_t - \mu_{S_t}) - \vartheta_1 (Y_{t-1} - \mu_{S_{t-1}})\}^2}{2\sigma^2_{S_t}}) \tag{6}$$

In this way, the distribution $\Pr[S_t, S_{t-1}|\varphi_{t-1}]$ using the Hamilton filter (1989):

$$\Pr[S_t, S_{t-1}|\varphi_{t-1}] = \Pr[S_t = j|S_{t-1} = i]\Pr[S_{t-1} = \mathrm{i}|\varphi_{t-1}] \tag{7}$$

Where $\Pr[S_t = j|S_{t-1} = i], i = 1, \ldots, M$, are the transition probabilities [3] . Observing Y_t until the end of the period, it is updated in terms of probability as follows:

$$\Pr[S_t = j\,, S_{t-1} = \mathrm{i}|\varphi_t]$$

$$= \Pr[S_t = j\,, S_{t-1} = \mathrm{i}|\varphi_{t-1}, Y_t]$$

$$= \frac{f(S_t = j\,, S_{t-1} = i\,, Y_t \mid \varphi_{t-1})}{f(Y_t|\varphi_{t-1})}$$

$$= \frac{f(Y_t|S_t = j\,, S_{t-1} = i\,, \varphi_{t-1}) \Pr[S_t = j\,, S_{t-1} = \mathrm{i}|\varphi_{t-1}]}{\sum_{S_t=1}^{M} \sum_{S_{t-1}=1}^{M} f(Y_t|S_t = j\,, S_{t-1} = i\,, \varphi_{t-1}) \Pr[S_t = j\,, S_{t-1} = \mathrm{i}|\varphi_{t-1}]}$$

Finally, we can get:

$$\Pr[S_t = \mathrm{j}|\varphi_t] = \sum_{S_{t-1}=1}^{M} \Pr[S_t = j\,, S_{t-1} = \mathrm{i}|\varphi_t] \tag{8}$$

Subsequently, and in order to obtain inferences from the estimated parameters, smoothing is performed using the Kim algorithm (1994).

Empirical results

4.1 Data

The variables used are the monthly nominal price of copper and the US Producer Price Index for 1991M01-2022M07. The series were obtained from the Federal Reserve Bank of St. Louis (FRED). To obtain the real price of copper, we discount the US Producer Price index from the nominal price of copper y_t=y_st/〖IPP〗_t . Thus, we use the monthly variation in the model (ΔY_t=(log (y_t)- log (y_(t-1))*100).

Figure 1 shows the real price of copper. It shows a downward trend from January 1991 until October 2001, which coincides with the terrorist attacks of September 11, 2001. From there, real price of copper follows an upward trend which is abruptly stopped in September 2008, when the 2008 financial crisis started. Although it quickly recovered its upward trend, it finally finished in March 2011, where it began to follow a downward trend which, excepting some periods of short increases in prices, has lasted until now. According to this exploratory analysis, and in line with previous discussions, this paper will use the 2001M10-2022M02 sample which is the last medium-term cycle of real prices of copper, where it is assumed that October 2001 and February 2022 mark the beginning and the end of this cycle, respectively. Figure 2 shows the real prices of copper for this sample period.

Because the real price of copper is wandering up and down through the time, clearly it has a stochastic trend, the monthly growth rate of copper variable is created by taking the first difference of the logarithm of real price of copper. Figure 3 shows the monthly real growth rate of copper. It is seen that the real growth rate of copper is highly volatile, showing periods of high and low returns, although the figure seems to suggest that volatility is higher when returns are negative.

Figure 1

Time Series in Levels of the real price of copper: Sample 1992M01-2022M07 (Index 1982=100)

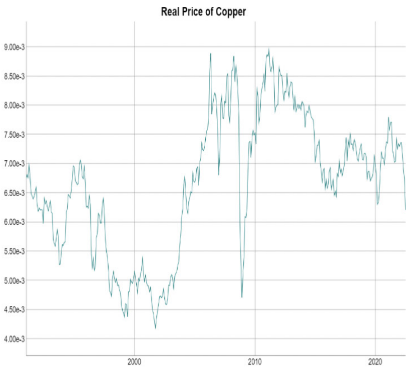

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Figure 2

Time Series in Levels of the real price of copper: Sample 2001M10-2022M02 (Index 1982=100)

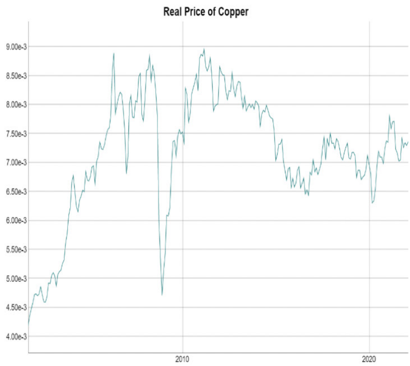

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Figure 3

Time Series in Levels of the real price of copper: Sample 2001M10-2022M02 (Index 1982=100)

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4.2 Results

The Augmented Dickey-Fuller test reveals that the real price of copper and the real growth rate of copper are I(1) and I(0) processes, respectively. Thus, we focus on the real growth rate of copper, because it is a stationary process, and it is possible to forecast using the traditional Box-Jenkins methodology.

In a first place, we can observe that the monthly real growth rate of copper shows a volatility that varies through time, with periods of low and high volatilities, being the latter more notorious when the returns are negative, as it was pointed out before. Thus, this series is likely to follow a nonlinear process. Several statistics have been developed in the literature for testing the nonlinearity of a stationary process. We use the F-test proposed by Tsay (1986), which improve the power of Keenan's and RESET tests (Tsay and Cheng, 2018). The null hypothesis is that the process is linear. The p-value of this test is 0.0528. Therefore, at the 5% significance level, we reject the null hypothesis of linearity, and conclude that the real growth rate of copper is a nonlinear time series process.

Next, it is assumed that real growth rate of copper follows an autoregressive process AR(p). To choose p, we can use the Akaike information criterion, which select the value of 8 as the optimal level of lags, having this model the lowest Akaike value. However, with the purpose to use a more parsimonious model, we identify that the value of 3 has the second smallest value of the Akaike information criterion. Table 1 shows The estimated parameters of the linear AR(3) process:

Table 1					
Estimation of the linear AR (3) process					
Parameters	Intercept	AR (1)	AR (2)	AR (3)	$\hat{\sigma}^2$
Estimates	0.2291	0.1816**	-0.0014	-0.1278**	15.44
S. E	0.2658	0.0634	0.0644	0.0633	-
Note. The log likelihood is -680.21, the AIC criteria 1368.42.*significance at 90% confidence ** at 95% confidence.					

We can see that the estimated values autoregressive coefficients are statistically significant at the 10% of significance level, but the estimated intercept is not statistically significant at the same significance level. It means that the annualized long-run real growth rate of copper is zero percent, and the annualized standard deviation of the real growth rate of copper is equal to 13.61%. Using the Ljung-Box test in its estimated residuals, we see that the null hypothesis of no autocorrelation cannot be rejected even at the 10% significance level. Thus, we conclude that the residuals follow a white-noise process, and the AR(3) process is a suitable model for the studied variable. However, because this linear AR(3) process does not seem to capture some important characteristics of the data, such as the periods where real growth rate of copper shows high and low values, and the time-varying levels of volatility previously detected, we proceed to estimate the nonlinear AR(3) process using the Markov Switching model.

There is extensive literature regarding the use of Markov switching model to modeling economic and financial time series, such as Chauvet and Potter (2000), Ang and Bekaert (2002), Maheu et al. (2012) among others. However, while most of the previous articles study equity markets, more recent studies, as Chevallier and Ielpo (2013b) use this methodology to model a variety of commodity returns.

One of the crucial issues with respect the Markov Switching model is to select the proper number of regimes. Gatumel and Ielpo (2011) have developed a test to make possible to estimate the number of regimes in a financial time series. Chevallier and Ielpo (2013) use this test, and based on it, estimate the Markov Switching model for daily closing returns over January 1995 to April 2012 on several commodities. Specifically, they found that copper returns have five different regimes. However, we should take account that this study was carried on with daily returns, which can show larger fluctuations than monthly returns.

Also, Henry (2009), Al-Anaswah and Wilfling (2011) or Dione et al. (2011) assume that two regimes are enough to correctly capture the movement of the main equity indices. This is consistent with a large part of the literature which assumes that markets are driven by two types of trends: an upward trend, with a low volatility; and a downward trend, with a high volatility (Chevallier and Ielpo, 2013). Furthermore, Chevallier and Ielpo (2013) point out that when commodities present marked trends (up and down), the test diagnoses that a two-regimes model is enough, which is in line with the pattern of the real price of copper that we can see in Figure 1.

Finally, some articles as Barnhart (1989) or Frankel and Hardouvelis (1985) found that the USA is the leading business cycle for commodity markets, which is in line with the finding that the US GDP is closely related to the global business cycle. This is consistent with the previous point remarked before that the copper is a leading indicator of global economic activity. Because global business cycles experience expansion and contraction phases, it is expected that real price of copper, which resemble the global economic activity, also presents the same phases or regimes: expansionary and contractionary. Therefore, we select two regimes for the monthly real growth rate of copper.

Once the number of regimes is selected to be N=2, it is necessary to choose the estimated parameter that are allowed to vary in each regime:

We allow all parameters $\{\emptyset_{0s}\ \emptyset_{1s},\ \emptyset_{2s},\ \emptyset_{3s},\ \sigma^2_{\varepsilon ts}\}$ to change for each regime. Where S indicates the regime state[5]. The model to be estimated would be:

$$Y_t \begin{cases} \emptyset_{01} + \emptyset_{11}Y_{t-1} + \emptyset_{21}Y_{t-2} + \emptyset_{31}Y_{t-3} + \varepsilon_{t1}\,;var(\varepsilon_{t1}) = \sigma^2_{\varepsilon_{t1}} \\ \\ \emptyset_{02} + \emptyset_{12}Y_{t-1} + \emptyset_{22}Y_{t-2} + \emptyset_{32}Y_{t-3} + \varepsilon_{t2}\,;var(\varepsilon_{t2}) = \sigma^2_{\varepsilon_{t2}} \end{cases}$$

Estimating the nonlinear AR (3) model using the MSwM package of the R software, we get the estimated parameters for each regime in Table 2:

Table 2

Estimation of the no linear AR (3) process

	Regime 1			Regime 2		
	Estimation	S. E	P valor	Estimation	S. E	P valor
Intercept	-0.2920	0.9035	0.746544	0.4101	0.0731	0.000000
AR (1)	0.5217	0.1603	0.001136	-0.1128	0.0657	0.08600
AR (2)	0.0430	0.2035	0.832653	-0.1236	0.0645	0.05533
AR (3)	-0.2261	0.3198	0.479566	-0.1428	0.0391	0.00026
$\hat{\sigma}^2_{\varepsilon_t}$	6.847693	-	-	2.571973	-	-

Note. The multiple R – Squared for the regime 1 is 0.206 while for regime 2 is 0.09691.

And the fitted transition probability matrix is:

Table 3

Transition Matrix

	Regime 1	Regime 2
Regime 1	0.60	0.40
Regime 2	0.08	0.92

Note. This table shows the transition probability according the Markov Property.

The pooled residuals of the fitted model and the autocorrelation and partial autocorrelation functions of the residuals and squared residuals do not show strong serial correlation (see the appendix), which suggest that the model fits the data reasonably well.

With respect to the fitted two-state AR(3) model, we notice that the regime 1 model's all estimated coefficients (except the coefficient of the first lag) are not statistically significant, because their p-values are more than 0.1. This implies that the long-run expected real growth rate of copper of state 1, either monthly or annualized, is essentially zero percent, and that the actual model of the real growth of copper in the regime 1 is an AR(1) process. Also, the monthly volatility of the regime 1 model is 6.85 percent, and its annualized volatility is 23.72 percent.

On the other hand, for state 2, all three AR coefficients are statistically significant at the 10% significance level, and the estimated coefficient of the intercept is positive. This means that the annualized long-run expected real growth of copper is equal to 3.57 percent. Based on these long-run expected values, we can classify the regime 1 as the "contractionary" state, and the regime 2 as the "expansionary" state. Also, the monthly volatility of the regime 2 model is 2.57 percent, and its annualized volatility 8.9 percent. This is consistent with the previous analysis where we noticed that volatility seemed to be higher in periods of low levels of growth than periods of high levels of growth. In addition, its estimated characteristic equation is approximately:

$$\Phi(L) = 1-\emptyset_{1s} L-\emptyset_{2s} L^{2}-\emptyset_{3s} L^{3}$$

Which has one real and two complex roots. Using these complex roots, we get an average length of 5.1 months for copper's business cycles. Therefore, in addition of regime switching, the fitted Markov Switching model also show the business cycles of the copper, which may be identified as the short-term fluctuations (less than two years) of the transitory component of copper.

Moving to the transition probability matrix, it reveals some remarkable features of the model. Firstly, if the process is currently at the contractionary state, the probability of staying in this regime in the next period is 60 percent, while the probability to jump into the expansionary state is 40 percent. These results show that the contractionary state is relatively unstable, jumping to the next regime relatively often. This finding agrees with the high volatility found in this regime. Secondly, if the process is currently at the expansionary state, the probability of staying in this regime in the next period is 91.6 percent, while the probability to jump into the contractionary state is 8.4 percent. These results show that the expansionary state is very stable, jumping to the other state very rarely, which is in line with the low volatility found in this regime.

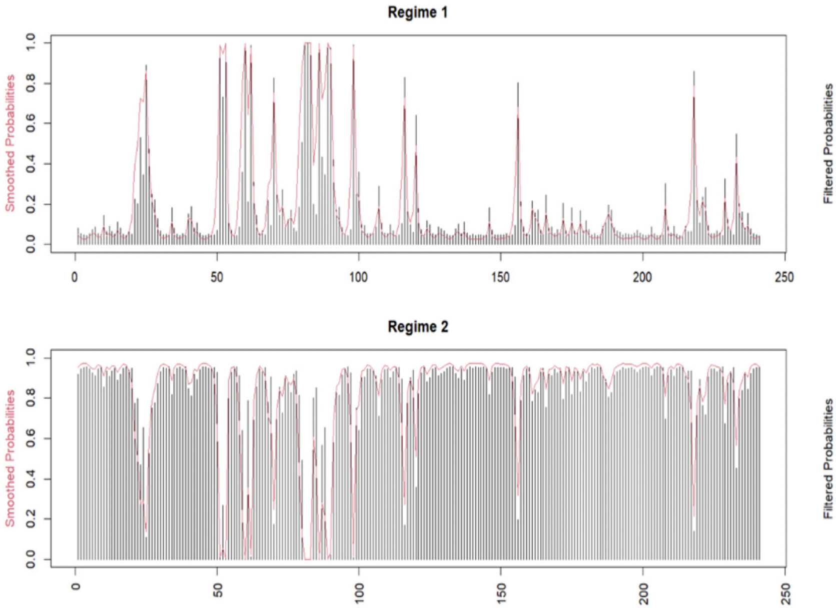
Thirdly, the unconditional probability that the process will be in the regime 1 (contractionary state) at any given date is 17.44 percent, and the unconditional probability that the process will be in the regime 2 (expansionary state) at any given date is 82.56 percent.

Finally, using the previously estimated probabilities of jumping to other states, the expected durations for the contractionary and expansionary states are 2.5 and 11.83 months, respectively. They imply that the high growth period of copper is expected to last one year on average, almost five times the expected duration of the low growth period.

Figure 4 shows the filtered and smoothed state probabilities of the fitted regime 1 and regime 2 models. From the plot, it is seen that real growth of copper has been most of time in the expansionary state than the contractionary state.

Figure 4

Filtered and smoothed probabilities for regime 1 and regime 2



Note: Own Elaboration

The forecast of the future real growth rate of copper will be the annualized long-run expected real growth of copper under the expansionary state, which is equal to 3.57 percent. Therefore, based on this result and the previous discussion about the possible future path of cooper, we expect that in the next medium-term cycle of copper (20 years onward), the real growth rate of copper is expected to be 3.57 percent annually on average.

5.Conclusions

Real price of copper has been driven by the extraordinary growth of China's economy, the growth of global population, and the increase of income in emerging and low-income countries during the last 20 years.

Copper is expected to experience an unprecedented demand in the long-run term, because of the Energy Transition from fossil fuels to green energies. However, there are some variables which may moderate this scenario in the future, such as the China's economic slowdown and the current war in Ukraine. Nevertheless, even with these adverse scenarios, it is expected that copper enter in a new expansionary regime during the next 20 years, resembling the previous expansionary cycle.

Real copper price shows clear expansionary and contractionary phases during the last 21 years. These features allow to model it using the Markov Switching model, where it is assumed that real growth of copper has two regimes.

In the estimated model, we see that the contractionary state presents a negative growth, although it is not statistically significant, while the expansionary state shows a growth equal to 3.57 percent annually. The filtered and smoothed probabilities show that the real growth of copper is in the expansionary state most of the time (approximately the 82.56 percent of the time of the sample period). This implies that the real price of copper is growing at the 3.57 percent annually most of the time.

In the medium-run term (next 20 years), it is expected that the real price of copper grows at the same rate as the expansionary state of its previous medium-run term cycle, which is equal to 3.57 percent annually.

We need to be careful about this forecast, because its long horizon allows that some unexpected changes that are not currently observed, as the future development of the current war in Ukraine, can make that the future real growth of copper deviate from the estimated forecast in great extent. However, the forecast presented here can still be used as a baseline scenario for copper exporter countries as Australia, Chile, and Peru, to project their future fiscal and export revenue.

Finally, this research has not estimated the impact of the real growth of copper on fiscal and export revenues of copper exporter countries, and their respective forecast conditioned on the estimated future growth of copper. The latter can be estimated using the Bayesian conditional forecast method used recent studies as (Álvarez and Velita, 2022) or using more complex methods such as the Markov Switching VAR model. Further research can study these interesting topics.

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Anexos

Figure 5

Pooled residuals of the Markov switching estimation of the AR(3) model

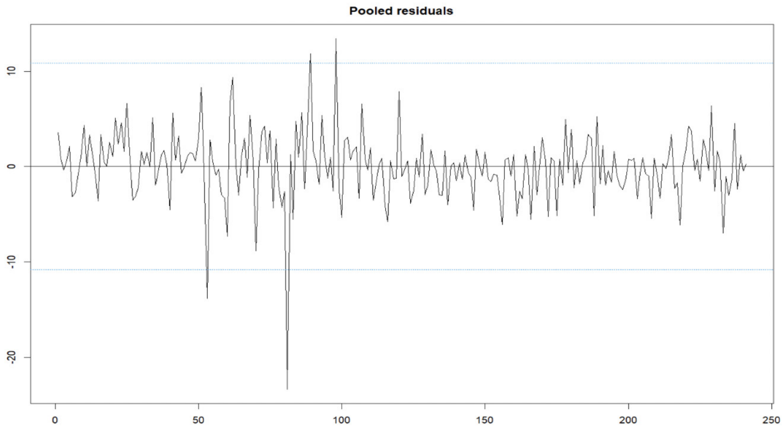


Figure 6

Normal Q-Q plot of the pooled residuals

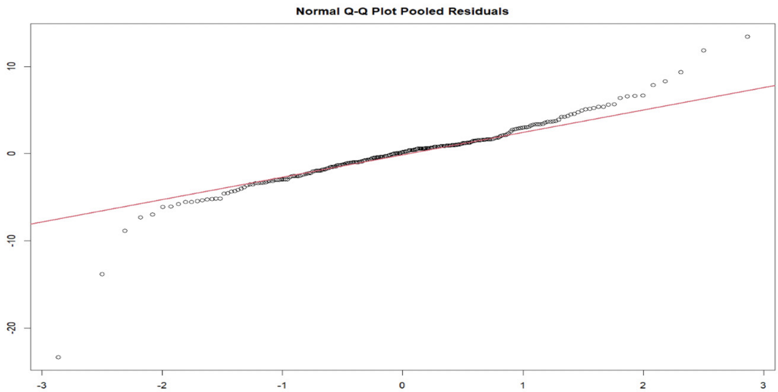


Figure 7

Normal Q-Q plot of the pooled residuals

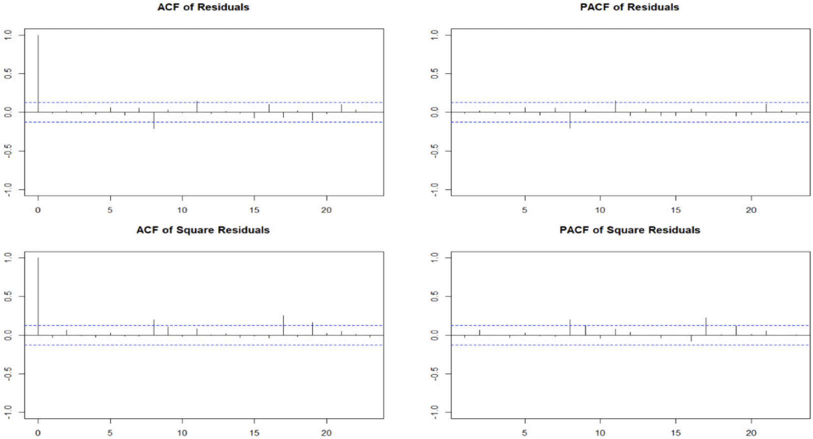


Figure 8

State-1 probability

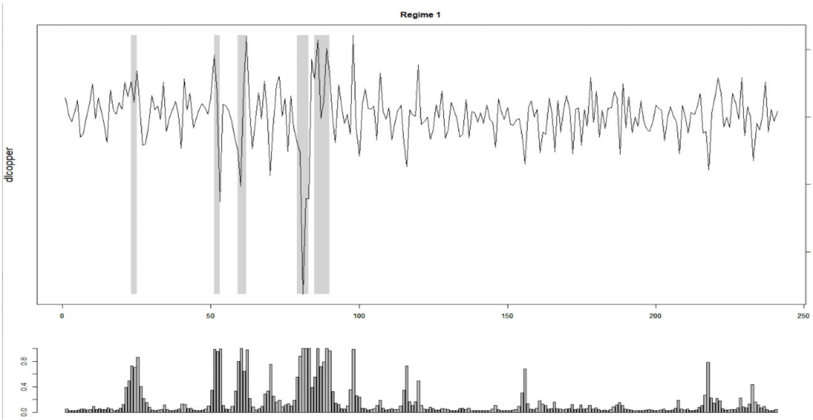


Figure 9

State-2 probability

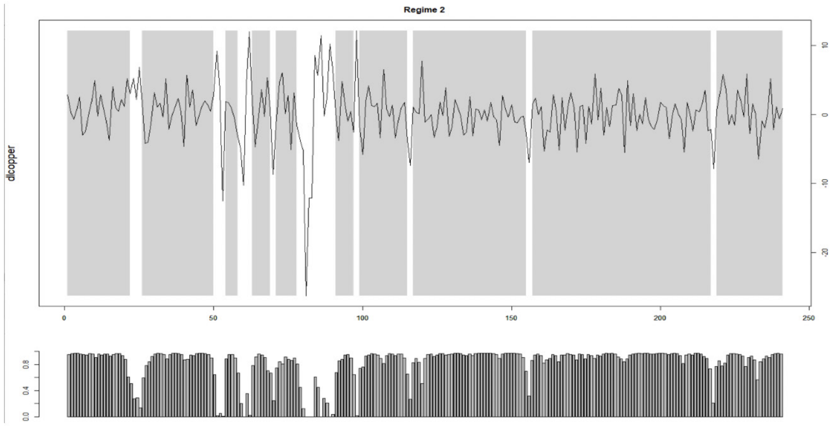
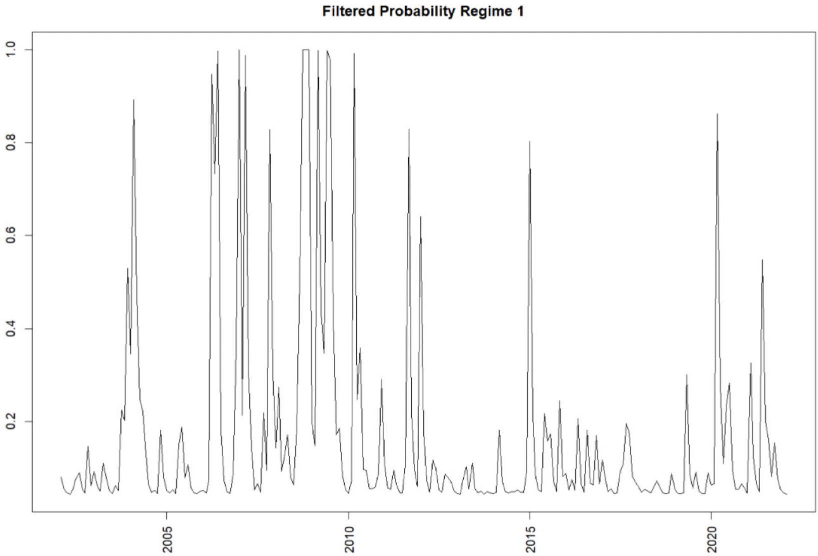


Figure 10

Filtered and Smoothed Probability Regime 1



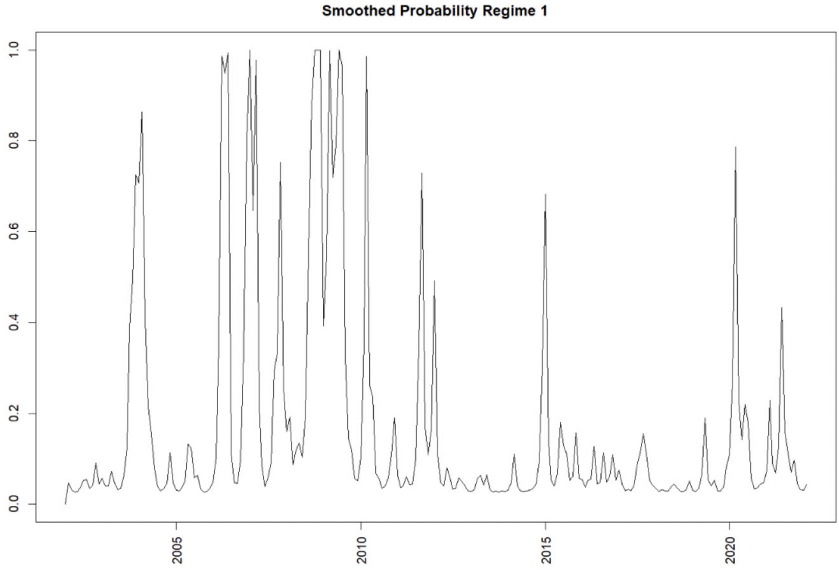
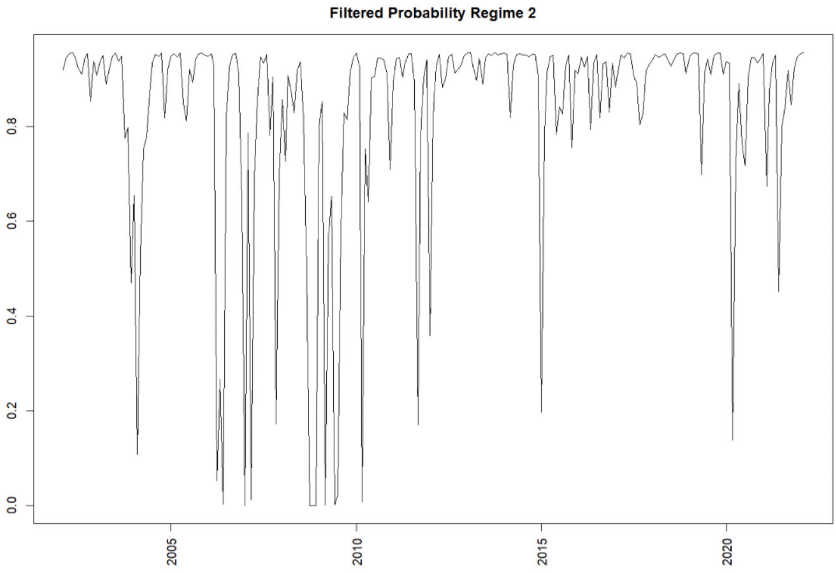


Figure 11

Filtered and Smoothed Probability Regime 2



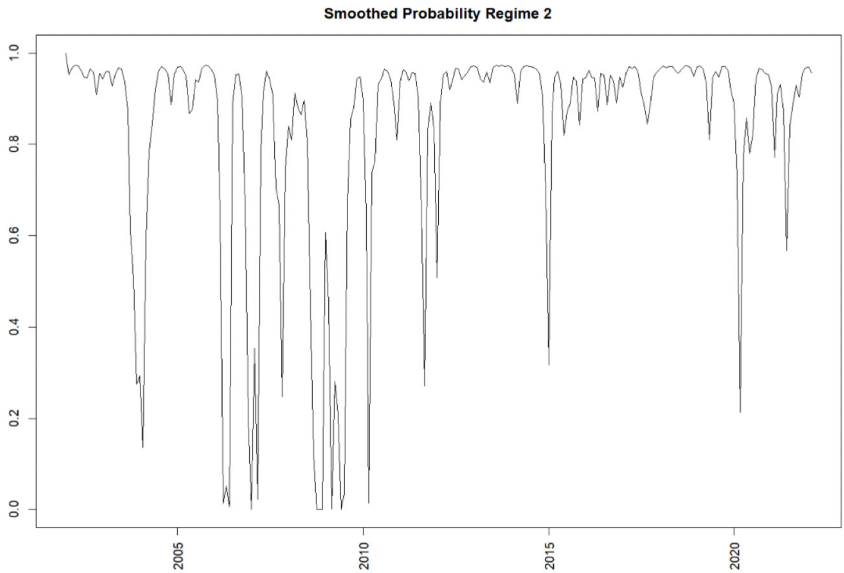
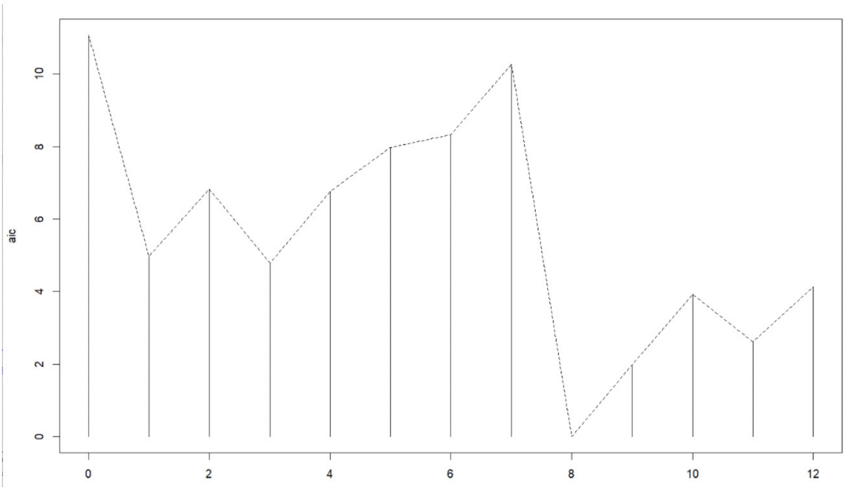


Figure 12

Akaike information criterion for the linear AR(p) model of the real growth rate of copper



TABLES

Table 3			
Test ADF without drift			
	H_0: *The series has unit root*		
Series	P- value	Test - Statistic	
Real price of cooper	0.09721*	0.1185	
Real Growth rate of cooper	0.00000**	-10.1683	

Note. *The residual standard error is 0.0002 **The residual standard error is 3.991.

Table 4			
F nonlinearity test			
Test	t-stat	P-valor	Interval. Confianza
Tsay	1.897	0.00208	95%
Nota. Global parametic test			