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The Interdependence between Commodity-Price and GDP Cycles: A Frequency Domain Approach*

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Abstract

We study the interdependence between real commodity prices and world real GDP using long-term annual data since 1870, by performing two empirical exercises. First, we compute long-term and medium-term cycles and measure their degree of synchronization for different leads and lags. Second, we perform several causality tests in order to better understand the nature of their interdependence. Our results show that GDP and commodity-price cycles are correlated, and there is evidence of short-term causality between them. However, there is no evidence of Granger causality from GDP to medium and long term cycles of commodity prices. This finding is consistent with the technology-based theories of commodity-price cycles. Searching for a supply-side determinant, we study the interdependence between oil-price and the remaining commodity-price cycles. Our results imply that oil prices are key drivers of metal price cycles for all fluctuation frequencies.

JEL Classification: C22, E32, Q02

Key words: medium-term cycles, commodity prices, frequency domain, super cycles

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1 Introduction

In this study, we explore the associations between real commodity prices (CPs) and world output fluctuations. Our estimations are performed using long-term annual data for aggregate CPs and aggregate world real GDP since 1870. Instead of focusing on their long-run trends, we analyze the interdependence among their medium and long-term cycles. This empirical exercise is performed in several steps. First, we compute medium and long-term cycles for all variables using the Band-Pass filter. Then, we estimate the degree of synchronization between CPs and economic activity for different leads and lags, and for both fluctuation frequencies.

Second, alternative causality tests are performed between these variables. Following Erten and Ocampo (2013), we estimate vector error correction (VEC) models and analyze their estimated speeds of adjustment. We also compute instantaneous causality tests between the growth rates of real CPs and global output. In addition, we perform Granger-causality tests on the frequency domain. This methodology is based on Breitung and Candelon (2006) and Wei (2013) who extended the estimation causality tests to allow for the presence of integrated and cointegrated variables.

Our results show that there is a significant correlation between price and GDP cycles mostly on long-term frequencies. For example, periods with booming GDP cycles are associated with future peaks in oil-price super cycles. On the other hand, metal-price booming periods are correlated with future GDP cyclical peaks. Our econometric results show some evidence of short-term causality between GDP and CPs, but find no robust evidence of Granger causality in the case of medium and long-term CP cycles. This latter result is obtained through Granger causality tests on the frequency domain.

Therefore, our results imply that CP medium and long-term cycles cannot be predicted by fluctuations in world GDP. This type of cycles should be instead determined by supply-side or technological determinants. As a first step for exploring supply-side determinants, we study the interdependence between oil-price fluctuations and the remaining CPs. Our results show robust evidence of Granger (predictive) causality from oil prices to metal prices for every fluctuation frequency. This finding leads us to think that CP super cycles must be driven mainly by supply-side determinants.

The rest of this paper is organized as follows. In Section 2, we discuss related literature. Section 3 contains our description of the data. Section 4 presents the econometric methods and their empirical results. Section 5 studies the oil price as a long-run driver of other CP cycles. The last section concludes.

2 Literature Review

Understanding commodities-price (CP) movements is important for policy making for both commodity producer and commodity consumer countries. Therefore, great attention has been devoted to grasp the empirical properties and determinants of the behavior of these prices; see for example, Cashin et al (2000) and Deaton (1999).

The long-run trends of these real prices have been estimated in numerous papers; however, interest on the cyclical components of these series has increased only recently. Following Cashin and McDermott (2002), any effort to stabilize the macroeconomic impact of shocks in CP requires a good understanding of the duration and amplitude of their cycles. Therefore, a rigorous estimation and analysis of these cycles helps policymakers to design the best set of macro policies.

Diverse macroeconomic studies estimate the cyclical components of the business activity using filtering methodologies which are based on the frequency domain. Recent examples of these works are Comin and Gertler (2006) and Boshoff (2010). Both works use the Band-Pass (BP) filter developed by Baxter and King (1999) and Christiano and Fitzgerald (2003). Furthermore, Borio (2012) and Drehmann et al (2012) use similar techniques for a set of financial series, by extracting their short and medium-term cycles. The duration of these cycles ranges between 5 and 32 quarters and between 32 and 120 quarters, respectively.

Cuddington and Jerrett (2008) and Jerrett and Cuddington (2008) apply the BP filter to real metal prices in order to estimate their super cycles (lasting between 20 and 70 years). They identify three super cycles during the period 1850 - 2006. Similarly, Erten and Ocampo (2013) extend these methods to identify cycles within a set of real CP indexes using the database introduced by Grilli and Yang (1988). One of our contributions is updating this database and applying a similar methodology in order to estimate super cycles as well as medium-term cycles for several real CP indices.

Recent papers try to identify the link between CP fluctuations and GDP movements during long and medium term horizons. Collier and Goderis (2012) find that CP booms have an initial positive effect on output growth but this effect is non-significant in the long run. In the case of countries with poor governance, this estimation implies a negative long-run effect. On the other hand, Gubler and Hertweck (2013) find that CP fluctuations are very important to explain the US business cycles within business-cycle frequencies.

Recent literature has documented the relation between the recent high-growth periods in developing economies and the dynamics of CP. This relation is discussed, among others, by Garnaut (2012), Byrne, Fazio and Fiess (2013) and Farooki (2009). Furthermore, Erten and Ocampo (2013), using a vector error-correction approach (VEC), find evidence of causality running from global output to CP by performing significance tests on the magnitude of the speed of convergence of these variables to their long-run equilibrium.

This document extends the analysis of Erten and Ocampo (2013) by studying the interdependence between CP and global economic activity using alternative econometric methods. Namely we apply tests for instantaneous causality, standard Granger causality and Granger causality on the frequency domain.

According to Cuddington and Jerrett (2008), the importance of the long-term fluctuations of macroeconomic variables, has been acknowledged recently in the literature. These fluctuations are related to the fact that commodity production implies investments with long gestation periods. For example, the average time between the first exploration and cash-flow generation for metal-base production, is 27.5 years. Therefore, technological innovations give rise to slow under and overinvestment cycles.

These long-run cycles of CPs were also studied by Schumpeter (1939) who explained them through his theory of creative destruction. This hypothesis relies on the prosperity and stagnation phases resulting from evolving technological innovations. Thus, CP increase during prosperity phases due to investments needed for the implementation of the new technology. Then, CPs fall during the stagnation phase once the new technology is standardized.

The interdependence between non-energy CP and economic activity is also studied by Alquist and Coibion (2014). These authors use a factor-based decomposition of CP movements with theory-based restrictions. Their findings imply a significant role for supply-based shocks including those originating from energy CPs. They also identify an economic activity factor which is able to explain a good portion of the CP fluctuations on the business-cycle frequency.

3 Data Description

We use three sources of data. First, we use the non-oil Commodity Price (CP) index (GY-Index) developed by Grilli and Yang (1988) and extended by Ocampo and Parra (2010). This annual index is composed of 24 commodities which spans the period 1865-1961. There are, in addition, 32 CPs which span the period 1962-2010. Next, the oil price series was constructed using data from the World Economic Outlook, Global Financial Data and West Texas International. These sources allow computing an international oil-price series for the period 1875-2010.

Global real GDP is measured in 1990 International Geary-Khamis dollars. This index is obtained from Angus Maddisons data, spans 1820-2003 and is updated until 2008 by the Groningen Growth and Development Centres Total Economy database.

Our dataset, until 2008, is similar to that used by Erten and Ocampo (2013)[1]. We updated this information until 2013 using the World Economic Outlook and the International Financial Statistics.

We use the Manufacturing Unit Value (MUV) as deflator of our CP series. The advantage of working with this deflator is that it includes only prices of tradable goods which are directly comparable with CPs. The MUV index is developed and updated by the United Nations and the World Bank.

[1]We thank Bilge Erten and Jose A. Ocampo for sharing with us their database on commodity prices.

4 Econometric Methods and Results

4.1 Estimating Cyclical Components

We use the asymmetric Band-Pass (BP) filter developed by Christiano and Fitzgerald (2003) in order to estimate the long-term and medium-term cyclical components of Commodity Prices (CP) and global activity. Both series are expressed in natural logarithms. The advantage of this filter is that it allows extracting alternative frequency components. Thus, we decompose each time series into four components: long term trend (LX_T), super cycle (LX_SC), medium term cycle (LX_MTC), and other components (LX_OC).

Long Term Trend and Supercycles: Following Cuddington and Jerrett (2008), and Erten and Ocampo (2013), we define the long term trend as the group of all of the frequency components with periodicities of more than 70 years. Additionally, supercycles correspond to periodicities spanning between 20 and 70 years.

Medium Term Cycles: Following Comin and Gertler (2006) and Drehmann et al (2012), we define medium term cycles to have periodicities between 8 and 20 years.

Other Components: cyclical components with periodicities below 8 years.

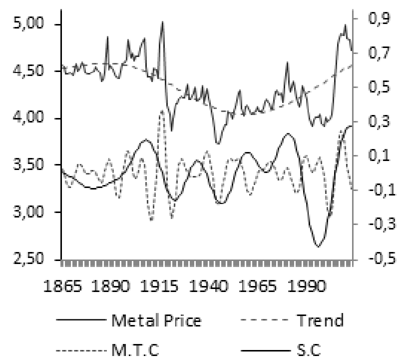
Hence, the level of every series is the sum of their four components, as expressed in Equation (1):

$$LX_t \equiv LX\_T_t + LX\_SC_t + LX\_MTC_t + LX\_OC_t \tag{1}$$

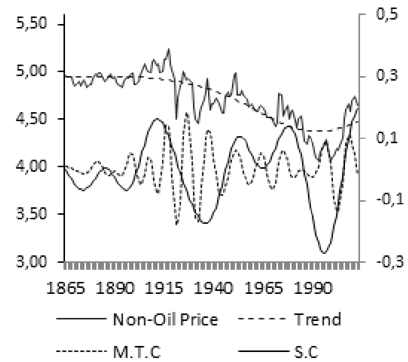
4.2 Results of the Estimation of Cycles

Figure 1 shows the results of our frequency-based decomposition for CPs and global GDP, respectively. Additionally, Tables 1 and 2 present the average amplitude and duration of the estimated super and medium-term cycles, respectively.

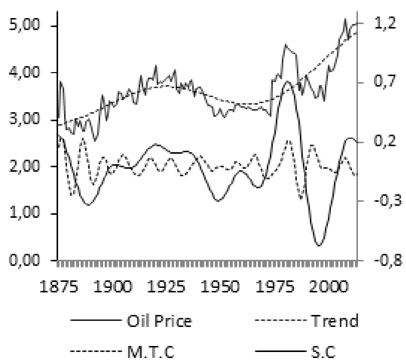
Figure 1: Results of the decomposition into Trend, Medium Trend Cycle (M.T.C) and Super Cycle (S.C) of commodity prices and GDP



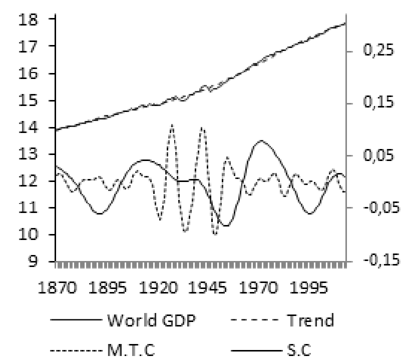
(a) Real Metal Price



(b) Real Non-Oil Price



(c) Real Oil Price



(d) Real World GDP

Source: Author's Calculations

Results in Figure 1 are similar to those described by Erten and Ocampo (2013). An important difference is that we show in addition, the resulting medium-term cycles. We can see that medium-term cycles are not as volatile as super cycles; however, the former have a few periods of high volatility. For example, during the 1910s and 1920s this is the case for metal and non-oil prices. Additionally, it is interesting to note that medium-term cycles are not highly correlated with supercycles which implies that the latter may have alternative sources of innovations.

Table 1: Amplitude and Duration of Super Cycles

	Super Cycles				
	Amplitude*		Duration**		
	Upward Phase	Downward Phase	Upward Phase	Downward Phase	Cycles
Metal Price	34.63%	-34.15%	16.00	12.75	26.00
Non-Oil Price	17.94%	-23.00%	14.00	16.50	31.00
Oil Price	43.56%	-40.94%	11.50	10.40	21.60
World GDP	8.60%	-8.90%	15.25	19.33	32.00

*Avarage percentage variation from trough to peak and from peak to trough. ** Number of years.
Source: Author's Calculations

Table 1 shows some features of the super-cycles of CPs and GDP. While oil prices have the widest super-cycles in Table 1, GDP has the least volatile super cycles. Besides, oil price super cycles are the shortest (21,6 years) while non-oil price and GDP super-cycles are the longest in average (31 and 32 years, respectively).

Table 2: Amplitude and Duration of Medium-Term Cycles

	Medium-Term Cycles				
	Amplitude*		Duration**		
	Upward Phase	Downward Phase	Upward Phase	Downward Phase	Cycles
Metal Price	21.08%	-20.24%	4.80	4.79	9.57
Non-Oil Price	14.24%	-14.39%	5.23	5.42	10.58
Oil Price	18.45%	-19.35%	5.38	4.71	10.15
World GDP	5.74%	-5.68%	4.85	5.62	10.46

*Avarage percentage variation from trough to peak and from peak to trough. ** Number of years.
Source: Author's Calculations

Table 2 is analogous to Table 1 and shows some features of medium-term cycles as defined in Section 4.1. In this case, metal prices have the widest cycles while GDP, again, has the least volatile cycles. Interestingly, the duration of medium-term cycles is similar (around 10 years) across all 4 macroeconomic variables in Table 2. This duration is slightly longest for non-oil CPs (10,58 years). In sum, CP cycles are clearly more volatile than GDP cycles; however their durations are similar. In addition, oil-price cycles tend to be shorter and more volatile than non-oil CP cycles.

4.3 Analyzing the Synchronization of Cycles

We study the degree of synchronization between cycles by estimating their correlation coefficient. This measure defines the interdependence between cycles using a linear relationship which indicates its strength and direction.

The correlation coefficient is performed by using Equation 2 for each series (X_i, X_j).

$$C_c(p) = \frac{Cov(X_{it}, X_{jt-p})}{(\sigma X_{it})(\sigma X_{jt-p})} \tag{2}$$

This coefficient $C_c(p)$ takes values between -1 (negative synchronization) and 1 (positive synchronization). In order to make inferences about synchronization, we perform tests on whether $C_c(p)$ is statistically different from 0. Following Hevia (2008), we perform these significance tests using a GMM approach along with the delta method for the estimation of the variance. We test the null hypothesis: $C_c = 0$, against the alternative: $C_c \neq 0$ for all pairs of cycles under study [2].

In equation (2), p represents the number of lags. By estimating the synchronization between the cycle of one variable and the lagged cycle of another variable, we try to compute their possibly dynamic relationship. Although this measure is not useful to formally establishing causality, it is helpful to understand the interrelation between peaks or troughs of one cycle and future phases of the other. These results are shown in Tables 3 and 4.

Table 3: Correlation Coefficient between Super Cycles.

	GDP-Metal prices		GDP-Non Oil prices		GDP-Oil prices	
	Lags of GDP	Lags of Price	Lags of GDP	Lags of Price	Lags of GDP	Lags of Price
0	0.486***	0.486***	0.408**	0.408**	0.635***	0.635***
1	0.453**	0.514***	0.408**	0.405**	0.661***	0.597***
2	0.409**	0.532***	0.399*	0.396**	0.674***	0.545***
3	0.357**	0.539***	0.379*	0.383**	0.674***	0.482***
4	0.298	0.534***	0.350*	0.365**	0.664***	0.408***
5	0.234	0.517***	0.309*	0.346**	0.643***	0.324**
6	0.165	0.488***	0.256	0.327**	0.613***	0.233*
7	0.094	0.449***	0.193	0.309**	0.576***	0.136
8	0.022	0.401***	0.120	0.293**	0.531***	0.038
9	-0.050	0.346**	0.039	0.280**	0.481***	-0.059
10	-0.121	0.288*	-0.049	0.270**	0.426**	-0.152

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

Table 3 shows the correlation coefficient between super-cycles with leads and lags going from 0 to 10 years. A first result is that in most columns of Table 3, the highest correlations are observed for the case of 0 lags, that is, for contemporaneous cycles. The highest coefficient in the table is 0.635 which is observed between oil prices and GDP. The highest non-contemporaneous correlation is 0.674 which is observed between GDP and oil-price super-cycles 3 years ahead. This result shows a possible positive causal effect between these variables. Another potential causal effect is observed from metal prices to GDP super cycles 3 years ahead with a correlation of 0.539.

Table 4 shows results of the correlation coefficient between medium-term cycles of GDP and prices for up to ten leads and lags. This table shows low correlation coefficients in all cases. They are not statistically different form zero in the case of contemporaneous correlations. However, there are a few significant coefficients around the table. The highest correlations are found to be negative between lagged (4 and 5 lags) GDP cycles and non-oil prices. Other interesting finding is the positive correlation between lagged (2 and 3 lags) non-oil price cycles and GDP fluctuations. That is, while GDP fluctuations have counter-cyclical effects on CPs, these price movements have later a pro-cyclical feedback on GDP cycles.

[2] We also compute the synchronization measure proposed by Harding and Pagan (2006) with qualitatively similar results.

Table 4: Corrleation Coefficient between Medium-Term Cycles

	GDP-Metal prices		GDP-Non Oil prices		GDP-Oil prices	
	Lags of GDP	Lags of Price	Lags of GDP	Lags of Price	Lags of GDP	Lags of Price
0	0.179	0.179	0.265	0.265	0.083	0.083
1	0.093	0.205***	0.096	0.346**	0.111	0.049
2	-0.022	0.159	-0.114	0.323**	0.124***	0.019
3	-0.131	0.050	-0.299*	0.214	0.110	-0.008
4	-0.204	-0.089	-0.400***	0.061	0.061	-0.034
5	-0.227*	-0.210	-0.384	-0.089	-0.013	-0.061
6	-0.198*	-0.268	-0.255	-0.197	-0.093	-0.088
7	-0.128	-0.230**	-0.055	-0.242	-0.157	-0.106
8	-0.032	-0.100	0.156	-0.227	-0.181***	-0.106
9	0.071	0.081	0.314**	-0.172	-0.149***	-0.079
10	0.164	0.252	0.376**	-0.098	-0.075	-0.025

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

In summary, there is ample evidence of cycle synchronization in the case of very long-run frequencies (super-cycles). This co-movement is very important for contemporaneous GDP and CP fluctuations although there is some evidence of inter-temporal comovement that should be further studied with causality tests. In the case of medium-term cycles, there is no contemporaneous synchronization and only a few inter-temporal correlations are significant[3].

4.4 Standard Causality Tests

In this section, we perform standard causality tests between CPs and GDP for both directions of causality. These results are to be contrasted with those obtained in causality tests on the frequency domain (Section 4.5) and with the correlation analysis of the previous section. .

The first step is performing unit-root and cointegration tests to all three price-GDP pairs. These results show that all CP and GDP series are I(1). Furthermore, all three CP series have cointegration relations with GDP as shown in Tables A1 and A2 in the Appendix.

We perform VEC estimations in these three cases following the procedures suggested by Lütkepohl (2007). The implied cointegration vectors are presented in Table 5. Table A3 in the appendix, shows the results of the residual normality and autocorrelation tests.

Table 5: Long-Run Relation between Commodity Prices and GDP

Cointegrated variables	Long-run Elasticity
Non-Oil prices and GDP	-0.2***
Metal prices and GDP	0.017
Oil prices and GDP	0.631***

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

[3]We also performed this analysis with the correlation Kendalls Tau. The results imply very similar conclusions.

Table 5 shows the estimated cointegration relations between CPs and GDP. Since these numbers are elasticities, a 10% increase of GDP is associated with a 2% decrease in the total (non-oil) CP index, a 0.17% increase in metal prices and a 6.3% increase of oil prices. It is worth noting that these coefficients show a long-run relation between endogenous variables and therefore they are compatible with both directions of causality. Also notice that the elasticity between metal prices and GDP is small and therefore not significantly different from zero. Such a small coefficient is allowed since the cointegration test in this case is conclusive and highly significant, see Table A2.

The error-correction representation allows estimating the effects, on each endogenous variable, of deviations from the cointegration level. In particular, it is possible to estimate a coefficient for the speed of adjustment. If this coefficient is significant, then it is possible to infer the existence of causality from the errors of the cointegration equation to the variation of the left-hand side variable. This causality approach is employed by Erten and Ocampo (2013). We also estimate these speed of convergence coefficients (using updated information), see Table 6.

Table 6: Speed of Adjustment Coefficients

VEC System	Commodity price variation	GDP variation
Non-Oil prices and GDP	-0.149***	-0.010
Metal prices and GDP	-0.09***	-0.029***
Oil prices and GDP	-0.003	-0.004***

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

The results in Table 6 show that the coefficients have the correct sign and are statistically significant in most cases. This result is in line with the one obtained by Erten and Ocampo (2013) about the adjustment of CPs to the errors with respect to their cointegration vectors. These speed of adjustment coefficients portrait evidence of gradual adjustment of CPs to deviations from the long-run levels of either GDP or the CP itself. We also perform alternative causality tests in order to better understand the interdependence between these variables.

According to Lütkepohl (2007), x_t is Granger-causal for $z_{(t+1)}$ when $z_{(t+1)}$ can be predicted more efficiently if the information of x_t is taken into account in addition to all information available up to and including period t. Therefore, Granger causality tests analyse directly the dynamic effects of variations of one variable (x_t) on future values of another ($z_{(t+1)}$). We apply these kinds of tests within our three price-GDP VEC systems for both directions of causality.

Table 7 shows a matrix of p-values in which the directions of causality go from the row variables to the column variables. These results imply that there is short-run dynamic causality only in the case of the non-oil CP index. This evidence goes in line with the results in Table 6. Notice that there is no evidence of Granger causality form GDP to oil or metal prices in this Table. Further causality tests are therefore useful to understand the underlying nature of these relationships.

Table 7: P-values of Granger Causality Tests within VEC systems

		To	
		GDP	Metals
From	GDP		0.469
	Metals	0.5588	
		GDP	Non-Oil
	GDP		0.0358**
	Non-Oil	0.0051***	
		GDP	Oil
	GDP		0.9304
	Oil	0.0026***	

*,** and *** stand for rejection of H0 (no causality) at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

Instantaneous causality occurs, following Lütkepohl (2007), when in period t, adding $x_{(t+1)}$ to the information set, helps to improve the forecast of $z_{(t+1)}$. This definition of causality is actually symmetric, that is, instantaneous causality between x_t and z_t implies instantaneous causality between z_t and x_t. We apply tests for this very-short concept of causality to our three VEC systems. The results in Table 8 show strong evidence of instantaneous causality between GDP and CPs.

Table 8: Instantaneous Causality Test

VEC System	Symmetric test p-value
Non-Oil prices and GDP	0.0001***
Metal prices and GDP	0.0000***
Oil prices and GDP	0.0158**

*,** and *** stand for rejection of H0 (no causality) at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

In summary, standard causality tests show significant evidence of causality from GDP fluctuations to the aggregate (non-oil) CP index. This result is consistent with the proposition that CPs are demand driven which is also an outcome in Erten and Ocampo (2013). In the case of metal prices, there is no evidence of Granger causality form GDP to prices which implies that this connection has a very short-term nature. A similar result holds for oil prices since there is no evidence of error-correction or Granger causality.

On the other hand, we also find some evidence of causality from CP fluctuations to GDP. This evidence is more significant in the case of oil prices since it is consistent across Tables 6, 7 and 8.

These standard causality tests are able to detect mostly short-term causality. Since one of our goals is studying the interdependence between the medium and long-run cycles of GDP and CPs, we need to use an appropriate methodology which will be explained in the following sub-section.

4.5 Testing for Granger Causality on the Frequency Domain

As mentioned previously, we are interested in testing for causality between CPs and GDP across the frequency domain with a special focus on medium and long-term fluctuations. Following Wei (2013), we use a procedure for the estimation of Vector Auto Regressions (VAR) which is robust to the integration and cointegration properties of the involved series. In this framework, we compute Granger causality tests across the frequency domain by applying the methodology devised by Breitung and Candelon (2006)[4] .

Let us consider a VAR $(p+d)$ on the level of the series, such that p is the optimal lag order and d is the maximum order of integration. Toda and Yamamoto (1995) show that including these additional d lags is helpful to asymptotically correct the estimation distortions which are associated to the presence of integrated and co-integrated variables. The model to estimate is the following:

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{3}$$

In Equation (3),$y_t = [x_t, z_t]'$ is the vector of variables, μ is the constant terms vector, ϕ_j are the coefficient matrices for each lag,and ε_t the error term.

Let $\phi_{12,j}$ be the (1,2) element of the coefficient matrix ϕ_j and $\beta = [\phi_{12,1}, \phi_{12,2}, \ldots, \phi_{12,p}]'$. In order to test for Granger causality, we should contrast the following null hypothesis:

$$H_0 : R\beta = 0 \tag{4}$$

Notice that if R is an identity matrix of order p, the null hypothesis in Equation (4) would correspond to the conventional Granger causality test. The approach by Breitung and Candelon (2006) changes this null hypothesis by modifying the linear restrictions on their parameters:

$$R = \begin{bmatrix} \cos(w)\cos(2w)\ldots\cos(pw) \\ \sin(w)\sin(2w)\ldots\sin(pw) \end{bmatrix} \qquad \omega \;\epsilon\; (0,\pi) \tag{5}$$

The Wald test statistic computed from Equations 4 and 5, is asymptotically distributed $\chi^2(2)$ for each $w\epsilon(0,\pi)$ We compare this tests statistic with their respective critical values for alternative confidence levels.

[4]This procedure is also based on the developments by Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996).

4.6 Results of Causality Tests on the Frequency Domain

Figure 2 is composed of three graphs which show results of the Granger causality tests across frequencies. Each graph shows results only for frequencies greater than four years, which implies a range from 0 to $\frac{\pi}{2} \approx 1.57$ in radians. In order to better distinguish these frequency regions, Table 9 shows the ranges in radians. The reason for studying only fluctuations lasting more than 4 years is that in Section 4.4 we already performed standard causality tests with the first difference of the annual data which is sufficient for understanding causality on short-run fluctuations. Since the tests applied on this section use the level of the data, they allow studying causality within medium and long-term cycles.

Table 9: Ranges for Frequencies

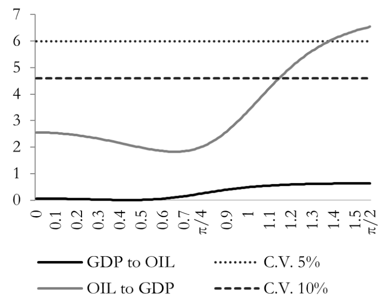
	Radians	
	From	To
Trend	0.0	0.09
Long-Term Cycles	0.091	0.31
Medium-Term Cycles	0.311	0.79
Short-run Cycles	0.791	$\pi/2$

Source: Author's Calculations

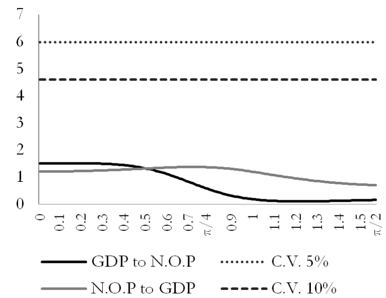
Figure 2 shows two main results. First, the only evidence of Granger causality, at the 5% significance level, goes from oil prices to GDP on of 4 to 8-year fluctuations. Second, there is no evidence of Granger causality going neither from GDP to CPs nor from CPs to GDP at any other frequency. Since our results in Section 4.4 only apply for short-run fluctuations, the outcomes about lack of causality in Figure 2 imply that medium-term and super-cycles are not caused by demand fluctuations.

In a nutshell, our causality tests on the frequency domain imply that medium and long-term CP cycles are not demand driven. This implication stands in contrast with the results for short-run fluctuations described in Section 4.4. We also find that, similarly to the evidence in Section 4.4, GDP fluctuations shorter than 8 years are caused by oil-price movements. The latter result is a motivation for Section 5, since we now want to explore whether oil prices are a key determinant for the dynamics of the remaining CPs.

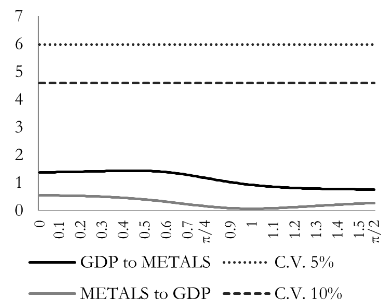
Figure 2: Granger Causality Tests on the Frequency Domain between GDP and Prices



(a) Real Oil Price and REal GDP



(b) Real Non-Oil Commodity Price and Real GDP



(c) Real Metal Price and Real GDP

Source: Author's Calculations

5 Are Commodity-Price Cycles Driven by Oil-Price Fluctuations?

In this section, we explore the interdependence between oil prices and the remaining commodity prices (CP). We follow the same methodology described in Section 4. The motivation for this section is finding out whether the oil price, as a supply-side indicator, is a determinant of the remaining CP super cycles.

5.1 Synchronization of Cycles

First, we use the super cycles and medium-term cycles already described in Section 4.1. We compute the correlation coefficients between oil-price cycles and the remaining CP cycles.

Table 10 shows synchronization results in the case of super-cycles. Contemporaneous correlations are positive and significant. It is bigger in the case of metal prices than for non-oil prices. All these correlations have similar features for the first 5 lags except in the case of lagged oil prices and non-oil prices. The two highest correlations in the Table are from 1 lag of metal

Table 10: Correlation Coefficient between Super Cycles

	Oil Prices -Metal prices		Oil Prices -Non Oil prices	
	Lags of Oil	Lags of Metals	Lags of Oil	Lags of Non-Oil
0	0.711***	0.711***	0.496***	0.496***
1	0.679***	0.720***	0.448**	0.532***
2	0.620***	0.703***	0.384**	0.552***
3	0.534***	0.659***	0.305	0.557***
4	0.424***	0.591***	0.213	0.545***
5	0.293*	0.502***	0.111	0.517***
6	0.148	0.399***	0.001	0.476***
7	-0.006	0.290**	-0.113	0.425***
8	-0.162	0.180	-0.227	0.365***
9	-0.313	0.077	-0.337**	0.301
10	-0.452***	-0.014	-0.438***	0.236

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

prices to oil prices, and their contemporaneous correlation.

Table 11 shows the corresponding measures for medium-term cycles. In contrast to the previous table, correlation coefficients are low. The only significant contemporaneous correlation is that between oil and metal prices (17%). The highest correlation (in absolute value) corresponds to the negative relation between oil prices and future metal prices six years ahead (-29%).

In sum, there is a strong positive correlation between oil-price and the remaining CP super cycles contemporaneously and up to 3 lags. In the case of medium-term cycles, the correlation is low and non-significant except for a few cases between oil and metal prices.

5.2 Results of Standard Causality Tests

Similarly to Section 4.4, we perform standard causality tests between all pairs of CPs. We described the results of unit-root tests in section 4. The results in Table A4 of the Appendix show that there is no evidence of cointegration between either pair of CPs. Therefore, we perform causality tests using estimated VARs with the log-variations of prices.

Table 12 shows the results of Granger causality tests for each pair of prices. The results imply some evidence of short-run causality from variations of oil prices to those of metal prices. In addition, there is clear evidence of causality from non-oil prices to the annual growth rate of oil prices.

On the other hand, Table 13 shows the results of instantaneous causality tests. There is strong evidence of instantaneous causality for both VAR systems implying that he annual variation of both pairs of prices and very useful for short-run forecasting. In addition of this mixed evidence of short-run causality, we use a frequency based method which allows computing causality tests between CPs in levels and for long-run fluctuations.

Table 11: Correlation Coefficient between Medium-Term Cycles

	Oil Prices -Metal prices		Oil Prices -Non Oil prices	
	Lags of Oil	Lags of Metals	Lags of Oil	Lags of Non-Oil
0	0.1703***	0.170***	0.147	0.147
1	0.095	0.193**	0.101	0.154
2	-0.003	0.161	0.024	0.124
3	-0.107	0.078	-0.063	0.067
4	-0.199	-0.031	-0.138	0.001
5	-0.265***	-0.123	-0.184*	-0.051
6	-0.292***	-0.163*	-0.190**	-0.078
7	-0.266***	-0.131	-0.158**	-0.079
8	-0.179	-0.030	-0.094	-0.060
9	-0.038	0.0991	-0.012	-0.036
10	0.130	0.199**	0.070	-0.019

*, ** and *** are significant at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

Table 12: P-values of Granger Causality Tests within VAR systems

		To	
		ΔOil Prices	ΔMetal Price
From	ΔOil Prices		0.0829*
	ΔMetal Prices	0.1085	
		ΔOil Prices	Δ Non-Oil Prices
	ΔOil Prices		0.2016
	ΔNon-Oil Prices	0.0045***	

*,** and *** stand for rejection of H0 (no causality) at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

5.3 Causality Results on the Frequency Domain

Similarly to Section 4, we perform Granger causality tests on the frequency domain following Breitung and Candelon (2006) and Wei (2013). The purpose of this analysis is to discover the causality relations among the levels of CPs in the case of medium and long-term fluctuations. In particular, we want to find out whether oil prices determine long-term fluctuations of the remaining CPs. An advantage of this methodology is that it allows for testing causality between a pair of I(1) variables even though there is no evidence of cointegration between them.

The results in Figure 3a suggest strong evidence of Granger causality from oil prices to metal prices at all frequencies. This result is consistent with those in both Tables 10 and 12 about high correlation and short-run causality, respectively. The transmission channel for this new

Table 13: Instantaneous Causality Test

VAR System	Symmetric test p-value
Non-Oil prices and Oil Prices	0.0045***
Metal prices and Oil Prces	0.0011***

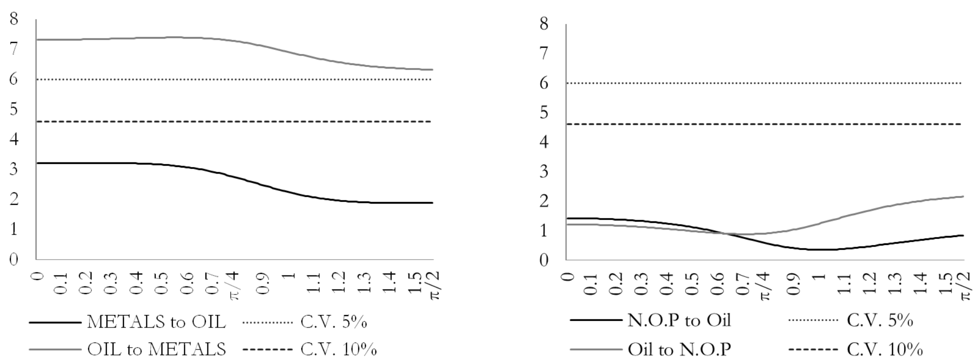
*,** and *** stand for rejection of H0 (no causality) at 90%, 95% and 99% confidence levels, respectively.
Source: Author's Calculations

finding is, very likely, the effect of oil-price fluctuations on fuel and transportation costs during metal production.

In contrast, Figure 3b shows that there is not any causality evidence between oil prices and the index of non-oil CPs. This result confirms the short-run finding on Table 12 and is informative about the fact that a significant correlation does not necessarily lead to causality due to the presence of common drivers.

Summarizing, our Granger causality test detects the presence of a consistent causality relation from oil-price fluctuations to metal-price at every frequency of fluctuation, short and long term. A similar result is likely to hold for other specific groups of commodities if they depend on oil as an important production input. On the other hand, oil prices (or GDP) are not useful to explain fluctuations of the aggregate (non-oil) CP index at any frequency. This latter result is likely driven by the heterogeneity of commodities involved in this aggregated index.

Figure 3: Granger Causality Tests on the Frequency Domain between Oil-Price and Other Prices



(a) Real Metal Price and Real Oil Price

(b) Real Non-Oil Commodity Price and Real Oil Price

Source: Author's Calculations

6 Conclusions

In this paper we study the relation between commodity prices (CP) and world GDP with a special interest on medium and long-term fluctuations. First, we find that there is a significant synchronization between the long-term cycles of these variables. Standard causality tests are able to confirm this relation from GDP to CPs in the case of the aggregated non-oil CP index. In the case of oil prices, the causality goes from prices to GDP. Since these tests are done within multivariate systems of differentiated variables, they cannot capture well the slow dynamics of super cycles.

Therefore, we estimate Granger causality tests on the frequency-domain following Breitung and Candelon (2006) and Wei (2013). These tests are performed on the level of all the variables and can be interpreted for specific ranges of frequencies. The results show that GDP does not cause CP cycles for any frequency of fluctuation. On the other hand, we find that oil prices are able to cause short-term GDP fluctuations.

Next, we explore the interdependence between oil and the remaining CP prices in order to explore such supply-side determinant of medium and long-term CP fluctuations. Standard causality tests find some evidence of interdependence between these prices. However, the frequency-domain approach allows detecting a strong causality relation from oil prices to metal prices for all frequency ranges. This result suggests that supply-side determinants might be important alternative drivers of the long and medium-term CP cycles.

Finally, it is important to point out a few policy implications of our findings. If medium and long-term CP cycles are mainly driven by supply-side variables, policy makers in commodity-rich countries should not worry about the effect of large recessions on future CPs. However, these policy makers should monitor the specific supply and demand determinants of their own commodity exports. Furthermore, policy makers in manufacturing economies should be aware of the positive effect of volatile oil prices on the cost of their future metallic inputs.

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Appendix

Table A1. ADF Unit Root Test

Variable	ADF	
	Level	First Difference
Real World GDP (LY)	1.33645	-7.45464***
Real Metal Price (LM)	-2.49719	-10.87977***
Real Oil Price (LO)	-1.64504	-10.61684***
Real Non-Oil Price (LT)	-2.15142	-10.19042***

*, ** and *** stands for rejection H0: unit root with confidence of 90%, 95% and 99% respectively.
Source: Author's Calculations

Table A2. Johansen Cointegration Test for price-GDP

	Johansen Cointegration Trace Test			
	Null Hypothesis	Alternative	λtrace stat.	Prob.
LT and LY	$r \leq 0$	$r = 1$	17.71	0.0228**
	$r \leq 1$	$r = 2$	2.58	0.1081
LM and LY	$r \leq 0$	$r = 1$	31.94	0.0001 ***
	$r \leq 1$	$r = 2$	0.00	0.951
LO and LY	$r \leq 0$	$r = 1$	33.15	0.0005***
	$r \leq 1$	$r = 2$	4.92	0.2922

*, ** and *** stands for rejection of the null hypothesis with confidence of 90%, 95% and 99% respectively.
Source: Author's Calculations

Table A3. Normality and autocorrelation test

Cointegrated variables[1]	Normality test[2]	LM type test for auto-correlation
LT and LY	3.8454	17.59***
LM and LY	8.53*	4.8
LO and LY	8.53*	4.07

*, ** and *** are significant at 10%, 5%, 1% respectively.
1/ A few time-dummy variables were added to each cointegration system in order to correct for outliers and meet the requirement on residual normality.
2/ Doornik and Hansen, 1994.
Source: Author's Calculations

Table A4. Johansen Cointegration Test for Pairs of Commodity Prices

	Johansen Cointegration Trace Test			
	Null Hypothesis	Alternative	λtrace stat.	Prob.
Oil and Non-Oil Prices	r $\leq$ 0	r = 1	2.744	0.9772
	r $\leq$ 1	r = 2	0.028	0.8674
Oil and Metal Prices	r $\leq$ 0	r = 1	7.545	0.5151
	r $\leq$ 1	r = 2	0.226	0.6341

*, ** and *** stands for rejection of the null hypothesis with confidence of 90%, 95% and 99% respectively.
Source: Author's Calculations