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

(Preliminary version)

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Abstract

We study the interdependence between real commodity prices and real GDP in developed economies using long-term annual data since 1870. We perform two empirical exercises. First, we compute long-term and medium-term cycles for these variables and measure their degree of synchronization for different leads and lags. The second exercise consists of performing Granger causality tests, on the frequency domain, between GDP and prices in order to examine the direction of causality. Our main results show that there is a significant feedback between commodity prices (oil and non-oil) and GDP on medium-term fluctuations. However, there is scarce evidence of Granger causality between these variables. In contrast, we find strong causality evidence from oil to metal prices for both short and long-run fluctuations. Therefore, commodity-price cycles seem to be driven by supply-side indicators.

JEL Classification: C22, E3, Q02

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

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♦ This draft: May 2014. The findings, recommendations, interpretations and conclusions expressed in this paper are those of the authors and do not necessarily reflect the view of the Central Bank of Colombia or its Board of Directors.

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1. Introduction

In this study, we explore the cyclical associations between real commodity prices and real GDP in developed economies. Estimations are performed using long-term annual data for aggregate commodity prices and aggregate real GDP for 14 developed economies since 1870[1]. Instead of focusing on the long-run trends of these variables, we analyze the interdependence between their cyclical components at long and medium-term frequencies.

The empirical exercise presented in this document is performed in two steps. A first exercise consists of computing, using the Band-Pass filter, long and medium term cycles for all variables. These cycles are then used to measure the degree of synchronization between pairs of commodity prices and economic activity for different leads and lags, and for both frequency ranges.

The second step of the analysis does not use cycles but the levels of all variables at constant prices. In this case, we perform Granger-causality tests, on the frequency domain, between pairs of real commodity prices and GDP. This methodology is based on Breitung and Candelon (2006) and allows exploring whether there are different degrees of causality on alternative frequency ranges.

Our main results show that there is significant interdependence between non-oil price cycles and GDP cycles on medium-term frequencies. For example, GDP recessions are associated with future peaks in commodity prices. On the other hand, commodity-price booms are associated with future GDP peaks. Nevertheless, our econometric tests show that these relationships are not driven by strong causality links. For example, there is not any evidence of causality between non-oil commodity prices and GDP at any frequency. In the case of real oil prices, causality runs only from prices to GDP, mostly at short-run frequencies. This latter effect implies that oil-price booms have negative effects on short-term GDP fluctuations.

Hence, our results show that although GDP cycles and non-oil commodity-price cycles are correlated, there is not any causality evidence between them. Therefore, commodity-price cycles are not driven by demand-side indicators. In addition, we explore the hypothesis that oil-price fluctuations help to explain the cycles of non-oil commodity prices. Our estimations show that this hypothesis is true in the case of metal prices.

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 interdependence between oil prices and the remaining commodity prices. The last section concludes.

[1] The list of countries is the following: United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom.

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 several papers; however, interest on the cyclical components of these series has increased only recently. Following Cashin and McDermott (2002), efforts to stabilize the macroeconomic impact of shocks in commodity prices requires a good understanding of the duration and amplitude of CP cycles. Therefore, the analysis of these cycles helps policymakers to design the best set of macro policies.

Comin and Gertler (2006), Boshoff (2010) Zhu (2011) among others, estimate cyclical components of the business activity using filtering methodologies which are based on the frequency domain. In particular, they use the Band-Pass (BP) filter developed by Baxter and King (1999) and Christiano and Fitzgerald (2003). Borio (2012) and Drehmann et al (2012) use similar techniques for a set of financial series, and extract short-term as well as medium-term cycles with durations 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 super-cycles (cycles lasting between 20 and 70 years). They find three cycles during the period 1850 - 2006. Erten and Ocampo (2013) use de BP filter to identify cycles in various commodity price indexes using the database introduced by Grilli and Yang (1988). These authors find four super cycles which are similar to those found by Cuddington and Jerrett (2008). In this paper, we use a similar database in order to estimate not only super-cycles but also medium term cycles for real CP indices. We apply the BP technique developed by Christiano and Fitzgerald (2003).

Recent papers try to identify the link between CP fluctuations and GDP movements on both 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. However, countries with poor governance have a negative long-run effect. Gubler and Hertweck (2013) find that commodity price fluctuations are very important to explain the US business cycles on standard frequencies.

It is also clear in recent literature that global income growth is an important determinant of commodity prices since it stimulates production which uses commodities as inputs. This finding is discussed, among others, in Garnaut (2012), Byrne, Fazio and Fiess (2013) and Farooki (2009). Additionally, Erten and Ocampo (2013), using VECM, find causality from global output to commodity prices by performing significance tests on the magnitude of the speed of convergence to the long-run equilibrium.

Our document studies the interdependence between commodity prices and global economic activity by using an approach which explores different data frequencies. First, we compute long-run and medium-term cycles and study their degree of synchronization. Second, we perform causality tests, between commodity prices and GDP, across the frequency domain.

3. Data Description:

We use three sources of data. First, we use the non-oil commodity-price 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. Additionally, there are 32 commodity prices which span the period 1962-2010. These commodity prices are aggregated into sub-indices according to the type of good. The oil price series was constructed using data from the World Economic Outlook, Global Financial Data and West Texas International and is available since 1875. All commodity price data are the same used by Erten and Ocampo (2013)[2].

Real GDP data for developed economies is obtained from the on-line annual database of Shularick and Taylor (2012) which includes data for 14 countries during the period 1870-2008. The list of countries is the following: United States, Canada, Australia, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom[3].

In order to work with real price indices, we follow Erten and Ocampo (2013), by using the Manufacturing Unit Value (MUV) as deflator. The advantage of working with this index is that it includes only prices of tradable goods which are more comparable to commodity prices. The MUV index is developed and updated by the United Nations and the World Bank.

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 and GDP. Both series are expressed in natural logarithms. The advantage of this method is that it allows extracting different frequency components from the series. 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).

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

[3] Erten and Ocampo (2013) use a world GDP series which must be interpolated from a few data points before 1950 in order to obtain an annual variable. We chose to work only with the homogeneous series for developed economies with annual data since 1870.

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), the lowest periodicity of a medium term cycle is 8 years. Therefore, we define medium term cycles as all the components with periodicities between 8 and 20 years.

Other Components: cyclical components with periodicities below 8 years.

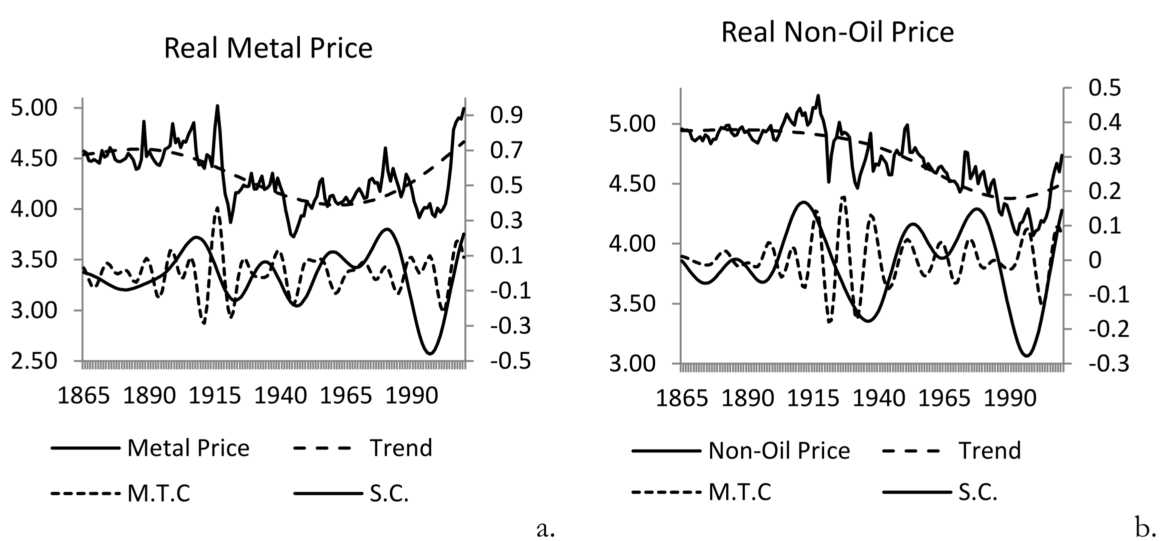
Hence, the level of every series is the sum of their four components, as expressed in Equation (1):

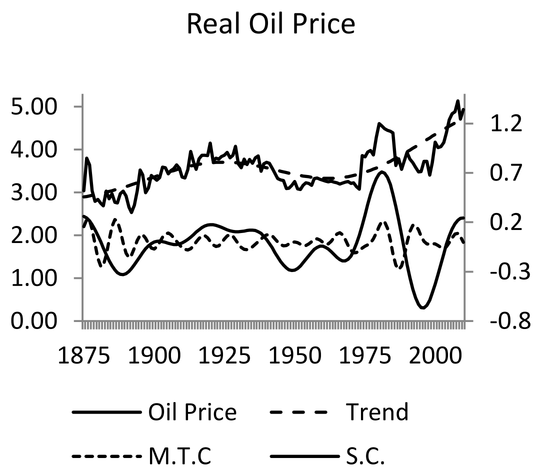
$$LX_t \equiv LX\_T_t + LX\_SC_t + LX\_MTC_t + LX\_OC_t \tag{1}$$

4.2 Results of the estimation of Cycles

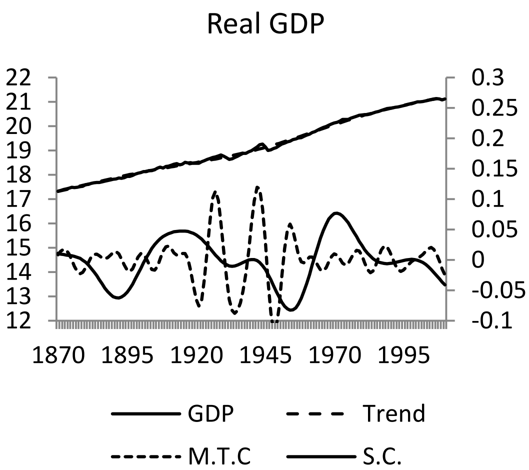
In Figure 1, we show the results of our frequency-based decomposition for commodity prices and GDP, respectively. Additionally, Tables 1 and 2 present the average amplitude and duration of the estimated super and medium-term cycles, respectively.

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





c.



d.

Results in Figure 1 are very similar to those described by Erten and Ocampo (2013). The only difference with these authors is that we show the resulting medium-term cycles. Although medium-term cycles are not as volatile as super cycles, Figure 1 shows that there a few sub-periods when the volatility of medium-term cycles is very important to explain movements in the total series. This is the case, for example, during the 1910s and 1920s for metal prices and non-oil prices. Additionally, it is interesting to note that both types of cycles are not highly correlated and therefore, each one of them may capture different innovations.

Table 1: Amplitude and Duration of Super-Cycles

	Super Cycles				
	Amplitude*		Duration**		
	Upward Phase	Downward Phase	Upward Phase	Downward Phase	Cycles
Metal price	26,1%	-35,3%	16,00	13,00	24,33
Non-Oil price	18,2%	-23,4%	14,00	16,75	30,67
Oil price	34,0%	-40,8%	11,00	10,40	19,75
GDP	7,2%	-7,5%	14,00	16,67	27,67

* Average percentage variation from through to peak and from peak to through. ** Number of years.

Table 1 shows some features of the super-cycles of commodity prices and GDP. While oil price has the widest super-cycles in Table 1, GDP has the least volatile super-cycle. On the other hand, oil price super cycles are the shortest (19,8 years) while non-oil price super-cycles are the longest in average (30,7 years).

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	20,6%	-20,1%	4,86	4,64	9,57
Non-Oil price	14,1%	-14,4%	5,31	5,42	10,58
Oil price	18,7%	-19,8%	5,31	4,85	10,15
GDP	6,4%	-6,4%	5,23	5,00	10,23

* Average percentage variation from through to peak and from peak to through. ** Number of years.

Table 2 is analogous to Table 1 and shows some features of medium-term cycles as defined in Section 4.1. In this case, the metal price has 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 commodity prices (10,6 years). In sum, commodity-price cycles are clearly more volatile than GDP cycles; however their durations are similar.

4.3. Analyzing the Synchronization of Cycles

We are interested in studying the degree of synchronization between the estimated cycles. For this task, we use the concordance index developed by Harding and Pagan (2006). This measure defines the interdependence between cycles as the probability that their phases coincide.

The concordance index is computed in the following way. First, we create one dummy variable S_{it} for each series i. This variable takes the value 1 when the cycle is going through an upward phase and 0 otherwise. The concordance index is defined, for a given pair of cycles, as the probability that both cycles are simultaneously going through the same phase (upward or downward): (Pr[$S_{it} = S_{jt}$]). Therefore, the estimation of this index is performed by using Equation 2.

$$I_C(p) = \frac{1}{T}\{\sum_{t=1}^{T} S_{it}S_{jt-p} + \sum_{t=1}^{T}(1 - S_{it})(1 - S_{jt-p})\} \qquad (2)$$

This index takes values between 0 (always in the opposite phase) and 1 (phases always coincide). When the index takes the value 0.5, there is not any synchronization between these cycles during the sample period. Therefore, in order to make conclusions about synchronization, we perform tests on whether the index I_C is statistically different from 0.5. Following Harding and Pagan (2006), we perform these tests by computing the correlation coefficient ρ_{ij} between both dummy variables in Equation 2. Significance tests use a GMM approach along with the delta method for the estimation of the variance. We test the null hypothesis: $\rho_{ij} = 0$, against the alternative: $\rho_{ij} \neq 0$ for all pairs of cycles under study[4].

In equation (2), p represents the lagged values of the cyclical phases represented by the variable S_{jt}. Therefore, by estimating the concordance index between the cycle of one variable and the lagged cycle of another variable, we try to capture the possible dynamic relationship between both cycles. It is useful to note that this index does not give any rigorous statistical evidence of causality. However, this index is helpful to understand the interrelation between peaks or troughs on one cycle and future phases of the other cycle.

4.4 Results on the Synchronization of Cycles

We employ the previous methodology for estimating the synchronization between GDP and commodity-price cycles. The results are shown in Tables 3 and 4. We also calculate the concordance index between contemporaneous and lagged cycles in order to analyze the dynamic relations among them. Significance tests are computed under the null hypothesis of no synchronization.

Table 3: Concordance Index 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	0,426	0,426	0,496	0,496	0,522	0,522
1	0,404	0,440	0,532	0,454	0,515	0,522
2	0,397	0,468	0,567	0,440	0,507	0,522
3	0,390	0,511	0,603	0,426	0,515	0,537
4	0,383	0,553	0,617*	0,411	0,522	0,551
5	0,376	0,596*	0,631**	0,397	0,529	0,551

*, ** and *** are significant at 10%, 5% and 1% respectively.

Table 3 shows the concordance index between super-cycles with lags and leads going from 0 to 5 years. This table shows scarce evidence of synchronization among these super cycles. The only exception is the positive relation found between GDP and non-oil commodity prices five years ahead. There is some evidence of a negative relation between GDP and future metal prices but it is statistically non-significant.

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[4] Hevia (2008) explains in detail the use of GMM along with the delta method for the estimation of correlation coefficients.

Table 4: Concordance Index 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	0,596**	0,596**	0,504	0,504	0,404	0,404
1	0,560	0,589*	0,390**	0,582*	0,493	0,390*
2	0,539	0,560	0,291***	0,638***	0,566	0,404*
3	0,447	0,518	0,291***	0,667***	0,640***	0,471
4	0,433**	0,447	0,383***	0,624**	0,654***	0,551
5	0,433*	0,418*	0,475	0,553	0,581	0,574

*, ** and *** are significant at 10%, 5% and 1% respectively.

Table 4 shows results of the concordance index between medium-term cycles for up to five leads and lags of GDP and price cycles. From GDP to future price cycles, we find a negative relation for metal and non-oil prices; however, in the case of the oil price this link is positive. The latter effect can be explained by the increasing demand of oil-related products during periods of economic boom.

From commodity prices to future GDP cycles, we find negative connections in the case of metal and oil prices; but this association is positive in the case of the non-oil aggregate price index. The negative links can be described by the effect of higher production costs due to the increase of input prices.

4.5 Testing for Granger Causality

We are interested in examining both directions of causality between commodity prices and GDP. Erten and Ocampo (2013) make a similar exercise by estimating a VECM and performing causality tests. We extend this exercise in two new directions. First, following Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996), we use a procedure for the estimation of Vector Auto Regressions (VAR) which is robust to the integrating and cointegrating properties of the involved series. Second, we compute Granger causality tests across the frequency domain by applying the methodology devised by Breitung and Candelon (2006).

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:

$$y_t = \mu + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \cdots + \Phi_{p+d} y_{t-(p+d)} + \varepsilon_t \qquad (3)$$

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.

Ler $\theta_{12,j}$ be the (1,2) element of the coefficient matrix Φ_j and $\beta = [\theta_{12,1}, \theta_{12,2}, \ldots, \theta_{12,p}]'$. 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:

$$R = \begin{bmatrix} \cos(w) & \cos(2w) \ldots \cos(pw) \\ \sin(w) & \sin(2w) \ldots \sin(pw) \end{bmatrix} \tag{5}$$

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

4.6. Results of the Granger Causality Tests

Figure 2 is composed of three graphs which show results of the Granger causality tests across frequencies. There are three vertical lines on each graph which split the range of frequencies in four intervals. From left to right, these frequency intervals are: trend, long-term cycles, medium-term cycles and short-run fluctuations, respectively. Additionally, there are two horizontal dotted lines showing critical values of the test at 5% and 10% significance levels.

Figure 2 shows that the only evidence of Granger causality, at the 5% significance level, goes from oil prices to GDP on short-term frequencies. Therefore, oil-price fluctuations are found to have a significant effect on future GDP (short-run) fluctuations. Table 4 tells that the sign of this effect is negative since the concordance index shows that these variables tend to move counter-cyclically. We believe that the most likely channel for this effect is the oil-price influence on production and transportation costs.

There is and additional piece of causality evidence which is almost significant with a 10% significance level and goes from GDP to metal prices on long-term fluctuations. However, the corresponding concordance index in Table 3 is not found to be significant.

Figure 2. Granger Causality Tests on the Frequency Domain between GDP and prices

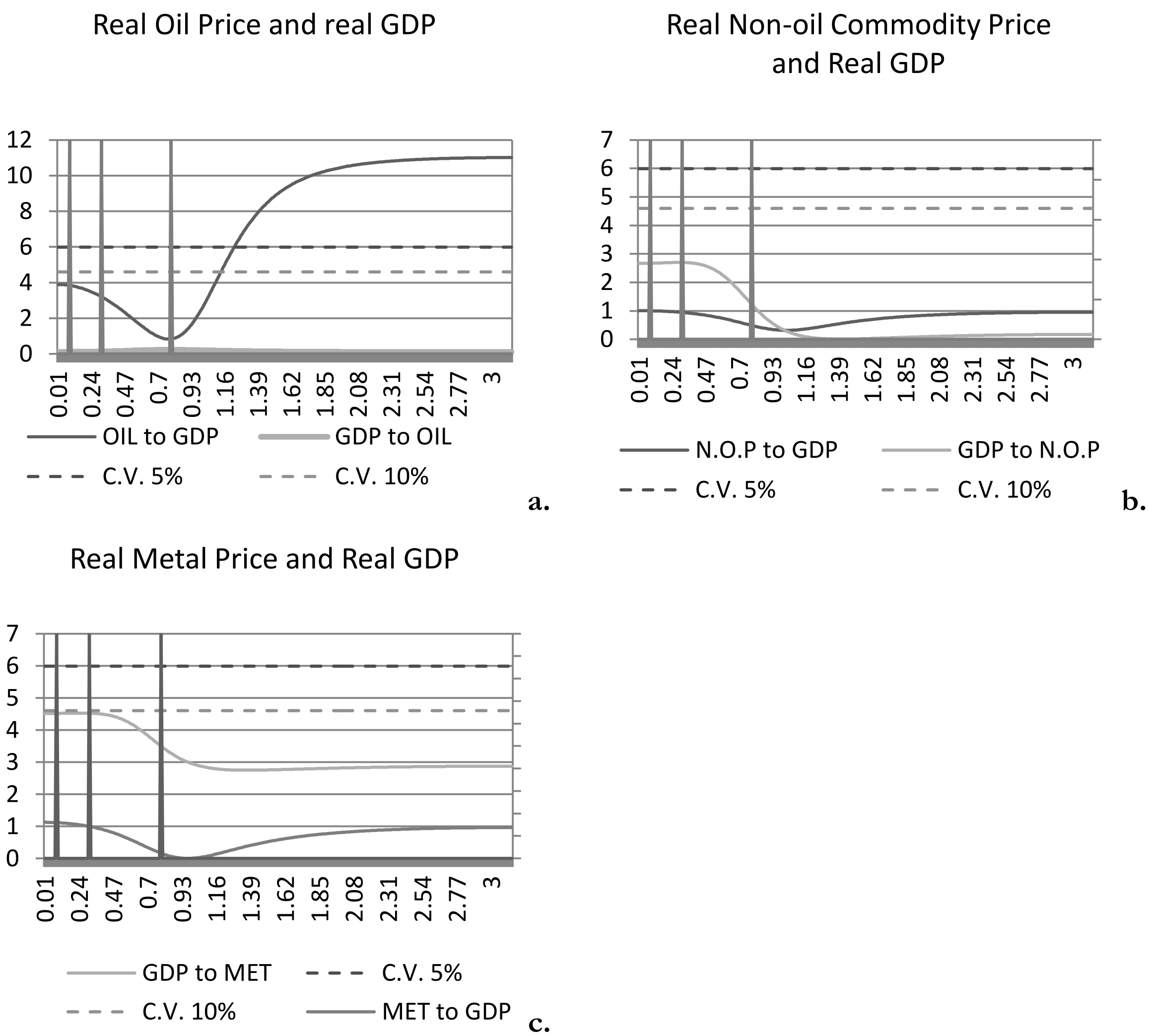


Figure 2 shows that there is no evidence of Granger causality going from GDP to commodity prices at any frequency. This result contrasts with some of the findings in Erten and Ocampo (2013) who identify that non-oil commodity prices are demand (GDP) determined. These authors also find that GDP is driven by oil-price fluctuations. We obtain a similar result in Figure 2 but this causality is found to be significant only in the case of short-run fluctuations[5].

In a nutshell, our results imply that commodity-price cycles are not demand driven, which stands in contrast to previous results in the literature. We also find that GDP cycles are partially determined by oil-price fluctuations. Next section addresses whether oil prices are influential for the dynamics of the remaining commodity prices.

[5] Erten and Ocampo (2013) perform causality tests by estimating the significance of the speed of adjustment in the context of a Vector Error Correction (VEC) model. We use a different approach to causality.

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. We follow the same steps described in Sections 4.3 to 4.6.

5.1 Synchronization of Cycles

First, we use the super cycles and medium-term cycles already described in Section 4, in order to compute concordance indices between oil-price cycles and the aggregated (non-oil) commodity price cycles. Additionally, this index is also computed between oil prices and metal prices.

Table 5: Concordance Index between Super Cycles

	Oil prices vs Metal prices		Non-Oil prices vs Oil prices	
	lags of oil	lags of metal	lags of oil	lags of Non-Oil
0	0,669***	0,669**	0,596	0,596
1	0,691***	0,647**	0,588	0,603
2	0,713***	0,610	0,566	0,625*
3	0,721***	0,574	0,544	0,632*
4	0,728***	0,537	0,515	0,640*
5	0,721***	0,500	0,500	0,632*

*, ** and *** are significant at 10%, 5% and 1% respectively.

Table 5 shows synchronization results in the case of super-cycles. It is clear in this table that oil-price booms are positively related with contemporaneous and future metal-price booms. In contrast, the relation between oil prices and non-oil commodity prices is found to be weak in Table 5. However, there is some evidence of positive synchronization between non-oil price booms and oil-price booms four years ahead.

Table 6 shows the corresponding measures for medium-term cycles. In contrast to the previous table, the contemporaneous correlation between oil-price and metal-price cycles is negative, which implies a concordance index significantly below 0,5. There is also evidence that metal-price booms are associated with oil price troughs 2 and 3 years ahead. Table 6 also shows that there is not any significant correlation between oil-price and non-oil commodity-price cycles on medium-term frequencies.

In sum, these concordance indices show a strong positive relation between lagged oil-price and metal-price super cycles. Additionally, they show a significant negative relation between lagged metal-price and oil-price medium-tern cycles.

Table 6: Concordance Index between Medium-Term Cycles

	Oil prices vs Metal prices		Non-Oil prices vs Oil prices	
	lags of oil	lags of metal	lags of oil	lags of Non-Oil
0	0,397**	0,397**	0,478	0,478
1	0,471	0,338***	0,500	0,478
2	0,544	0,353**	0,493	0,522
3	0,603*	0,441	0,500	0,507
4	0,610	0,529	0,515	0,478
5	0,588*	0,588*	0,529	0,478

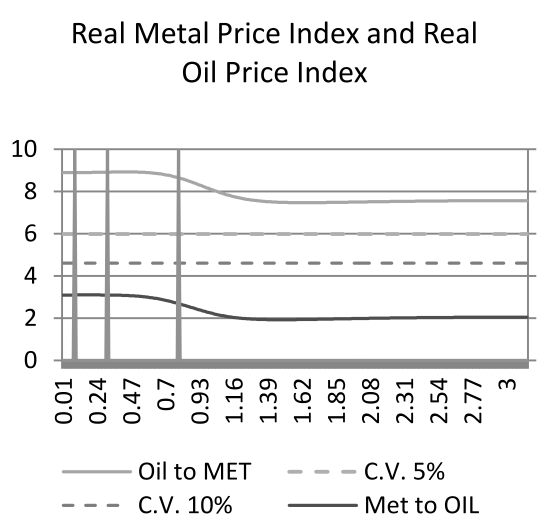
*, ** and *** are significant at 10%, 5% and 1% respectively.

5.2 Granger Causality tests

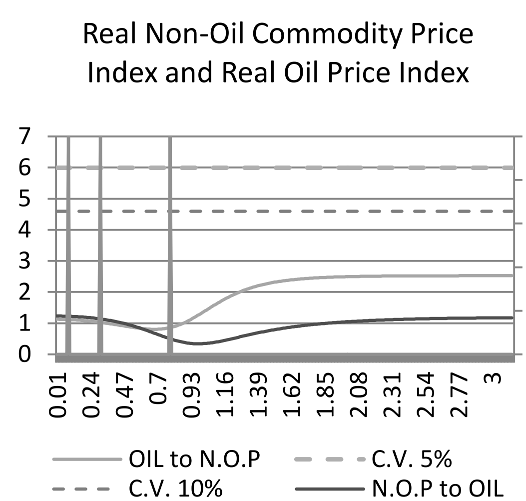
Figure 3 shows the results of Granger causality tests on the frequency domain, following the methodology of Section 4.5, between oil-prices and the other two commodity-price indices.

The results in Figure 3a suggest strong Granger causality from oil prices to metal prices on all frequencies. Therefore, Figure 3 confirms and strengthens the findings in Tables 5 and 6 about the positive correlation between lagged oil-price cycles and metal-price fluctuations. The transmission channel for this causality is, very likely, the effect of oil-price fluctuations on fuel and transportation costs during metal production.

Figure 3. Granger Causality Tests on the Frequency Domain between oil-price and other prices



a.



b.

In contrast, Figure 3b shows that there is not any causality evidence between oil prices and the index of non-oil commodity prices. This result confirms the findings about a poor cycle synchronization between these variables in Tables 5 and 6. Therefore, oil-price fluctuations seem to be useful to predict cycles of metal prices, and a similar result is likely to hold for other specific groups of commodities which depend on oil as an important production input. However, oil prices are not useful to explain fluctuations of the aggregate commodity-price index.

6. Conclusions

In this paper we study the relation between commodity prices and GDP for developed economies with a special interest on medium-run and long-run fluctuations. First, we find that there is a significant correlation between the cycles of these variables. However, there is not any evidence of Granger causality between them, with the exception of the short-run effects of oil-price shocks on GDP. Therefore, according to these results, long and medium-term commodity-price cycles do not seem to be demand driven in the case of developed economies.

In addition, we find evidence of Granger causality from oil-price fluctuations to metal prices for all frequencies. Therefore, supply-side determinants might be important alternative determinants of long and medium-term commodity-price cycles. The identification of the appropriate supply-side indicator for each type of commodity is, in this sense, a future avenue of research.

Erten and Ocampo (2013) obtain similar results about the effect of oil-price fluctuations on GDP cycles. However, they find that commodity-price cycles are driven by GDP fluctuations. These contrasting results can be explained by the use of alternative definitions of causality and by the use of a different series of GDP. Namely, while we focus on long-term series of GDP in 14 developed countries, Erten and Ocampo (2013) use an estimation of world GDP for the whole period. Additionally, we use Granger causality and a frequency-domain approach in our testing procedures.

Finally, it is important to point out a few policy implications of our findings. Since medium and long-term commodity-price cycles are not driven by the aggregate demand of developed economies, policy makers in commodity-rich countries should not worry about the effect of large recessions in these countries on future commodity prices. Since these cycles seem to be driven by supply-side indicators and other determinants, these policy makers should monitor the specific supply and demand determinants of their own commodity exports. On the other hand, policy makers in manufacturing economies should be concerned about the positive effect of booming oil prices on the cost of their future metallic inputs.

7. References

Baxter, M., & King, R. (1999). Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series. *The Review of Economics and Statistics , 81* (4), 575-593.

Borio, C. (2012). The financial cycle and macroeconomics: what have we leanrt? *BIS Working Papers* (395).

Boshoff, W. (2010). Band-pass filters and business cycle analysis: High frequency and medium-term deviation cycles in South Africa and what they measure. *Working Paper 200, Stellenbosch University.*

Breitung, J., & B. Candelon. (2006). Testing for short- and long-run causality: A frequency-domain approach. *Journal of Econometrics , 132*, 363-378.

Byrne, J., Fazio, G., & Fiess, N. (2013). Primary commodity prices: Co-movements, common factors and fundamentals. *Journal of Development Economics , 101*, 16-26.

Cashin, P., & McDermott, J. (2002). The Long-Run Behavior of Commodity Prices: Small Trends and Big Variability. *IMF Staff Papers , 49* (2), 175-199.

Cashin, P., Hong, L., & McDermott, J. (2000). How Persistent Are Shocks to World Commodity Prices? *IMF Staff Papers, 47* (2), 177-217.

Christiano, L., & Fitzgerald, T. (2003). The Band Pass Filter. *International Economic Review , 44* (2).

Collier, P., & Goderis, B. (2012). Commodity prices and growth: An empirical investigation. *European Economic Review , 56* (6), 1241-1260.

Comin, D., & Gertler, M. (2006). Medium-Term Business Cycles. *American Economic Review , 96* (3), 523-551.

Cuddington, J., & Jerrett, D. (2008). Super Cycles in Real Metals Prices? *IMF Staff Papers , 55* (4), 541-565.

Deaton, A. (1999). Commodity Prices and Growth in Africa. *Journal of Economic Perspeectives , 13*, 23-40.

Dolado, J., & Lütkepohl, H. (1996). Making wald tests work for cointegrated VAR systems. *Econometric Reviews , 15*, 369-386.

Drehmann, M., Borio, C., & Tsatsaronis, K. (2012). Characterising the financial cycle: don't lose sight of the medium term! *BIS Working Papers* (380).

Erten, B., & Ocampo, J. A. (2013). Super Cycles of Commodity Prices Since the Mid-Nineteenth Century. *World Development , 44*, 14-30.

Farooki, M. (2009). China's structural demand and the commodity supercycle: implications for Africa. *Paper prepared for research workshop China–Africa development relations. Leeds University (UK)* .

Garnaut, R. (2012). The Contemporary China Resources Boom. *Australian Journal of Agricultural and Resource Economics , 56* (2), 222-43.

Grilli, E., & Yang, M. C. (1988). Primary commodity prices, manufactured goods prices, and the terms of trade of developing countries: What long run shows. *The World Bank Economic Review , 2* (1), 1-47.

Gubler, M., & Hertweck, M. (2013). Commodity price shocks and the business cycle: Structural evidence for the U.S. *Journal of International Money and Finance , 37*, 324-352.

Harding, D., & Adrian, P. (2002). Dissecting the cycle: a methodological investigation. *Jorunal of Monetary Economics , 49* (2), 365-381.

Harding, P., & Pagan, A. (2006). Synchronization of cycles. *Journal of Econometrics , 132*, 59-79.

Hevia, C. (2008). Standard Errors Using the Delta Method and GMM. *Unpublished Manuscript* .

Jerrett, D., & Cuddington, J. (2008). Broadening the statistical search for metal price super cycles to steel and related metals. *Resources Policy , 33*, 188-195.

Ocampo, J. A., & Parra, M. (2010). The terms of trade for commodities since the mid-nineteenth century. *Journal of Iberian and Latin American Economic History , 28* (1), 11-43.

Toda, H., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics , 98*, 225-255.

Zhu, F. (2011). Credit and business cycles: some stylised facts. *Unpublished Manuscript* .