A DEEP DIVE INTO COMMODITY MARKETS: EXPLORING THE COMMODITY–INDUSTRIAL PRODUCTION NEXUS

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ABSTRACT

This article explores the commodity–industrial production nexus. More precisely, we assess the cointegration relationships between commodity markets and industrial production during 1993-2011, with an overview for several countries: the USA, the EU, Australia, China, Brazil, Canada, Germany. First, we explore the descriptive statistics and unit root tests of the dataset. Second, we develop two kinds of cointegration analyses (e.g. with/without structural break) between commodities on the one hand, and industrial production indices on the other hand. Third, we conclude on the main results achieved by this econometric procedure. The key contribution of our paper is to revisit the link between industrial production and commodity prices, by using an econometric methodology incorporating structural breaks, and by using a very recently updated dataset. By carrying out a systematic comparison between our results and papers previously published in this literature, we gain a wealth of insights.

Keywords: Cointegration; Commodities; Industrial Production; Structural Break

JEL Classification: C32; C58; E23; E31; Q02

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1. INTRODUCTION

Economic activity can be generally considered as a major factor of commodities demand. For instance, an increase of industrial production will raise directly the demands for metals, minerals, and agricultural raw materials as intermediate inputs, and raise indirectly the demands for final goods through the resulting increases in incomes.

This article proposes a deep dive into the world of commodity markets, by exploring more specifically the commodity–industrial production nexus. To do so, we investigate the cointegration relationships between industrial production and commodity indices in several countries, such as the USA, the EU, Australia, Brazil, China, Canada and Germany during 1993-2011.

Commodity markets do not only display wide price fluctuations reflecting demand and supply disequilibria, they also support trading in futures and options whose prices fluctuate as much as stock prices. In turn, we can subsume pro-cyclical (e.g., industrial metals) or counter-cyclical (e.g., gold) relationships between commodity prices and changes in macroeconomic fundamentals, depending whether the commodity under consideration is a by-product of economic growth or not.[1] This bi-directional relationship is of crucial importance, since it can play a major role in the determination of successful economic policies. When commodity demand rises or declines, for example, changes in business cycles can serve as a causal factor. During an expansion, commodity prices may rise and in response, consumers will require more income to purchase a given commodity. Given the (in)elasticity for a given commodity, consumers will have less income to spend on other commodities. The demand, and consequently the prices, for the other commodities will decline, granted the interactions take place in a market economy in which the money supply is controlled. If a particular market responds slowly to demand and supply changes, a temporary imbalance(s) between supply and demand will occur and consequently be met by variations in production, inventory levels and backlogs of orders. The most direct link concerning business cycle influences on commodity markets is that between GDP and commodity prices. Assuming the income elasticity of commodity demand to be nearly one, increases in GDP – or in industrial production taken as a proxy – would cause the demand for a commodity to increase. Conversely, declines in GDP would cause commodity demand to decline. With respect to other theories on macroeconomic effects, we can also evoke the hypothesis whereby high commodity prices dampen increases in industrial production, because the prices of good increase relative to consumers' income. Low commodity prices can also lower costs of production and stimulate the demand for goods, as well as industrial production.

One of the most popular economic models that analyzes long term relationships among variables is the cointegration model or Error Correction Models (ECM). This model allows the researcher to analyze the balance of long period relationships. Cointegration is interpreted as a long term relationship because cointegrated variables are tied to each other to keep certain linear combinations stationary, and

[1] Note in the case of gold, the counter-cyclical behaviour may be explained by the 'safe-haven' hypothesis.

hence they tend to move together. The idea behind cointegration is that there is a meaningful reason for commodity prices to move together in the long run, despite non-stationary departures from this equilibrium relationship in the short run. A major advantage of cointegration analysis is that it allows for the possibility that commodity prices in two different markets may respond differently to new market information in the short run, but would return to a long-run equilihrium if both are efficient. There are several reasons to explain why one might expect asymmetric responses from different markets in tbe short run. One is that the markets may have different access times to the information being delivered. Another is that the information may be interpreted differently initially. However, because the commodities trade on common trends, arbitrage opportunities between tbe markets would eventually result in a multi-market consensus concerning the value of new information.

Having these economic mechanisms in mind, we aim at developing cointegration analyses between selected variables for commodity and industrial production indices. If the evolutions are similar in the long term, then we may think of similar economic forces at stake to link these variables overtime (such as the state of the macroeconomic environment).

The rest of the article is structured as follows. Section 2 reviews the literature. Section 3 details the cointegration methodology. Section 4 describes the dataset. Section 5 contains the results. Section 6 concludes.

2. LITERATURE REVIEW

- Cody and Mills (1991) evaluate the macroeconomic interactions between industrial production in the US and the Commodity Research Bureau (CRB) basket of commodities by using monthly data over the period 1959-1987. To do so, the authors test for cointegration between the two series, and cannot reject the null hypothesis of no cointegration. In a subsequent VAR analysis, while commodity prices do not respond to changes in the macroeconomic variable of interest here, they are significant in explaining the future path of industrial production. Overall, the authors conclude that commodity prices are an early indicator of the current state of the economy.

- Labys and Maizels (1993) resort to Granger-causality tests to analyze the commodity price fluctuations and macroeconomic adjustments in developed countries (France, Germany, Italy, Japan, UK, USA) during 1953-1987. They use various IMF commodity indices, and to the industrial production index to carry out their econometric work. The main results suggest a causality in the direction of commodity prices to industrial production (except for France).

- Labys et al. (1999) aim at determining the impact of macroeconomic influences on LME metals price fluctuations during 1971-1995 by using factor models. Their study comprises five industrial metals: Aluminum, Copper, Lead, Tin and Zinc. Industrial activity was found to influence metal prices most strongly for France, Italy, Japan, and the OECD. Hence, the direct influence of industrial production on metals price cycles has been paramount during this time period.

- Hua (1998) establishes the cointegration between commodity prices and economic activity in 22 developed countries during 1970-1993. The results are supportive of the hypothesis that the non-oil primary commodity prices are cointegrated with macroeconomic variables, and that there exists long run relationships between them. The author is also able to confirm the existence of an equilibrium adjustment in commodity prices to macroeconomic shocks through a feedback mechanism. The strong significance of the error correction coefficients support the view that non-oil primary commodity prices in particular vary together with the fluctuations of economic activity. The results are more complex to interpret for agricultural commodities.

- Awokuse and Yang (2003) report Granger-causality test results between IMF Commodity Indices and US Industrial Production during 1975-2001. They find unambiguously that commodity prices may provide signals about the future direction of the economy, including inflation and other macroeconomic activities such as industrial production.

- Cunado and de Gracia (2003) examine the oil price-macroeconomy relationship by means of estimating the impact of oil price changes on industrial production indices for 15 European countries during the period 1960-1999. The authors cannot identify a cointegrating long-run relationship between oil prices and economic activity, which suggests that the impact of oil shocks on this variable is limited to the short-run. Besides, they do not find evidence of a long run relationship between these two variables even when allowing for a structural break.[2]

- Bloch et al. (2004) examine the linkages between all commodities (exclusive of fuels) as reported in the World Bank's Development Indicators and Industrial Production data from the OECD countries covering the 102-year period from 1900 to 2001. Their regression results feature that a reduction in the rate of economic growth can lead to reducing the rate of increase in commodity prices. Hence, there is a weak linkage between world economic growth and the rate of change of commodity prices according to the authors over the past century.

- Bloch et al. (2006) use IMF Commodity Indices and Industrial Production indices to show that world commodity prices move pro-cyclically with world industrial production. Their study validates the link between the use of commodities as raw materials and increases in industrial production in the case of Australia and Canada during 1960-2001.

[2] In order to capture the oil market collapse which occurred in 1985.

- Pieroni and Ricciarelli (2005) utilize 1955-2000 US copper data to investigate the properties of a vector error-correction model extended to macroeconomic variables such as industrial production.[3] It can be shown that price adjustments depend on the short run dynamic component of the model, whereas the long run dynamic is statistically rejected. Hence, there is no cointegration between copper and industrial production during this time period.

- Ai et al. (2006) examine the interactions between five agricultural commodity prices (Wheat, Barley, Corn, Oats, Soybean) and US industrial production during 1957-2002. They fail to identify significant cointegration relationships between macro indicators such as industrial production and agricultural commodity prices in this setting.

- Cheung and Morin (2007) evaluate the cointegration between the Bank of Canada Commodity Price Index and Industrial Production in the OECD during 1980-2006, with the possible occurrence of structural breaks. While the authors cannot detect statistically the presence of cointegration, they highlight the role played by emerging Asia's industrial activity in driving the price of Oil and Industrial Metals in particular.[4]

- Hamori (2007) provides Granger causality tests between the Bank of Japan Commodity Price Index and Industrial Production in Japan during 1990-2005. The author finds no causal relationships between the Bank of Japan commodity index and the industrial production index, even when considering a structural break in February 1999.

- Bhar and Hamori (2008) analyze whether commodity prices (Commodity Research Bureau indicator) have causal relationships with industrial production, and *vice versa* by using monthly US data during 1957-2005. Based on Granger causality tests, the authors validate the hypothesis that commodity price indices provide information on future changes in production.

These results are usefully summarized in Table 1. Despite the existence of a strong economic theory background to link commodity prices with industrial production, we observe overall that the conclusions of these various empirical studies seem to vary depending on the commodity, the country and the period considered. We attempt to replicate the best available evidence to date, i.e. the most sucessful cointegration relationships identified in previous academic literature, in our own empirical application.

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[3] When analyzing the US copper consumption, the authors identify two important industrial demands: *(i)* refined copper is largely used in wire rod mills, while brass mills prefer using copper scraps, and *(ii)* wire rod mills and brass mills are both used for the production of cathodes.

[4] As manufacturing activity has been increasingly outsourced for production in that region since 1997.

Table 1: Industrial Production and Commodity Prices: Cointegrating Relationships

Authors	Period	Cointegration Relationship	SS	SB
Cody and Mills (1991)	1959-1987	US Ind. Prod. ∅ CRB	No	No
Labys and Maizels (1993)	1953-1987	IMF Commodity Indices ↔ Ind. Prod. (OECD)	No	No
Labys et al. (1999)	1971-1995	Aluminum, Copper, Lead, Tin, Zinc ↔ Ind. Prod. (OECD)	No	No
Hua (1998)	1970-1993	IMF commodity indices ↔ Ind. Prod. (OECD)	No	No
Awokuse and Yang (2003)	1975-2001	IMF Commodity Indices ↔ Ind. Prod. (US)	No	No
Cunado and de Gracia (2003)	1960-1999	Oil ∅ Ind. Prod. (Europe)	No	Yes
Bloch et al. (2004)	1900-2001	WB Commodity Prices ∅ Ind. Prod. (OECD)	No	No
Bloch et al. (2006)	1960-2001	IMF Commodity Indices ↔ Ind. Prod. (AU, CA)	No	No
Pieroni and Ricciarelli (2005)	1955-2000	Copper ∅ Ind. Prod. (US)	No	No
Ai et al. (2006)	1957-2002	Wheat, Barley, Corn, Oats, Soybean ∅ Ind. Prod. (US)	No	No
Cheung and Morin (2007)	1980-2006	BoC Commodity Price Index ∅ Ind. Prod. (OECD)	Yes	Yes
Hamori (2007)	1990-2005	BoJ Commodity Price Index ∅ Ind. Prod. (JA)	Yes	No
Bhar and Hamori (2008)	1957-2005	CRB ↔ Ind. Prod. (US)	No	No

Note: ↔ indicates the presence of a cointegration relationship. ∅ indicates the absence of a cointegration relationship. SS stands for 'Sub Sample' analysis in the paper considered. SB stands for 'Structural Break' analysis in the paper considered. Ind. Prod. is for Industrial Production. AU stands for Australia, CA for Canada, BoC for Bank of Canada, JA for Japan, BoJ for Bank of Japan, WB for World Bank.

In what follows, we aim at updating these results with a more recent dataset (1993-2011) and the systematic modeling of structural changes.

3. A PRIMER ON COINTEGRATION

3.1 Cointegration without structural breaks

Cointegration can be seen as a useful econometric tool to decompose the long term trend between pairs (or groups) of variables, and the short-term departures from the trend. In the context of commodity markets, a cointegration relationship will tell us whether a pair (or a group) of individual commodities are tied together in the long run (which means that there exists a strong economic rationale to link these variables in the economic analysis), and to which extent exogenous perturbations from this equilibrium can occur.

3.1.1 Preliminary conditions

As a pre-requisite condition for cointegration, the time series need to be integrated of the same order. For instance, the econometrician can check, based on standard stationarity tests, that the prices of the raw time series considered are non stationary and integrated of order one ($I(1)$). This amounts to checking that they are difference stationaryStationarity is a central concern in time series analysis, which implies that the mean of the variable shall be time invariant (in the weak sense of stationarity).[5]

In practice, the Augmented-Dickey-Fuller (1981, ADF) or Phillips-Peron (1988, PP) tests are used. Extensions of these stationarity tests were also developed by Kwiatkowski et al. (1992, KPSS). We apply these three tests in our article.

3.1.2 Johansen cointegration tests

To keep the notations parsimonious, let us consider here the cointegration setting with only two variables.[6] As is standard in a linear cointegration exercise, the econometrican needs to check first if the variables are cointegrated, i.e. if β exists such that $R_t = X_t^e - \beta X_t^{e'}$ is stationary. This can be done by performing an OLS regression of X_t^e on $X_t^{e'}$, or more rigorously by using the Johansen cointegration test (Johansen and Juselius (1990), Johansen (1991)).

Let X_t be a vector of N variables, all $I(1)$:

$$X_t = \Phi_1 X_{t-1} + \ldots + \Phi_p X_{t-p} + \varepsilon_t \quad (1)$$

with $\varepsilon_t : WGN(0,\Omega)$, WGN denotes the White Gaussian Noise, Ω denotes the variance covariance matrix, and Φ_i $(i = 1,\ldots, p)$ are parameter matrices of size $(N \times N)$.

Under the null H_0, there exists r cointegration relationships between N variables, *i.e.* X_t is cointegrated with rank r.

Note that the Johansen cointegration tests can be performed on the logarithmic transformation of the time series under consideration.

For a financial modeling viewpoint, if we find that commodities are cointegrated, i.e. that there exists a stationary combination of these variables in the long term, the direct implication would be that they share at least one common risk factor in the long term. Hence, their joint analysis can bring fruitful results to the econometrician.

3.1.3 Error-correction model

The next step of the cointegration model consists in describing the dynamics of the variables in terms of the residuals of the long-term relation (Johansen (1988)).

[5] See Hamilton (1996) for further reference.

[6] Note however that the Johansen cointegration framework can be generalized to k variables.

We want to introduce an error-correction mechanism on the levels and on the slopes between the variables e and $e^{'}$:

$$\begin{pmatrix} \Delta X_t^e \\ \Delta X_t^{e^{'}} \end{pmatrix} = \begin{pmatrix} \mu_e \\ \mu_{e^{'}} \end{pmatrix} + \sum_{k=1}^{p} \Gamma_k \begin{pmatrix} \Delta X_{t-k}^e \\ \Delta X_{t-k}^{e^{'}} \end{pmatrix} + \begin{pmatrix} \Pi_e \\ \Pi_{e^{'}} \end{pmatrix} R_t + \begin{pmatrix} \varepsilon_t^e \\ \varepsilon_t^{e^{'}} \end{pmatrix} \tag{2}$$

where

- e stands for the first variable, and $e^{'}$ stands for the second variable;
- X_t^e is the log price of variable e at time t;
- the 2×1 vector process $\Delta Z_t = \left(\Delta X_t^e = X_{t+1}^e - X_t^e, \Delta X_t^{e^{'}} = X_{t+1}^{e'} - X_t^{e'}\right)$ is the vector of the variables price returns;
- $\mu = (\mu_{X,e}, \mu_{X,e^{'}})$ is the 1×2 vector composed of the constant part of the drifts;
- Γ_k are 2×2 matrices of real valued parameters expressing dependence on lagged returns;
- $(R_t = X_t^e - \beta X_t^{e^{'}})$ is the process composed of the deviations to the long-term relation between the variables log prices;
- Π is a 2×1 vector matrix expressing the sensitivity to the deviations to the long-term relation between the variables prices;
- the residual shocks $(\varepsilon_t^e, \varepsilon_t^{e^{'}})$ are assumed to be i.i.d with a centered bi-variate normal distribution $N(0,\sum)$.

However, by considering a purely linear model, it is possible that the econometrician will either misspecify the model, or ignore a valid cointegration relationship. That is why we detail below the cointegration methodology with an unknown structural break.

3.2 Cointegration with structural breaks

In this section, we explore the possibility of wrongly accepting a cointegration relationship, when some of the underlying time series are contaminated by a structural break. For instance, sharp deviations from the long-term trend can occur between a group of commodities, which would imply that the cointegration relationship is not valid anymore during specific sub-samples. The structural breakpoint detection allows to take into account these events in the cointegration analysis, instead of simply ignoring them.

We present the procedure for estimating a vector error-correction model (VECM) with a structural shift in the level of the process, as developed by Lütkepohl et al. (2004). By doing so, we draw on the notations by Pfaff (2008).[7]

3.2.1 Framework

Let $\vec{y}_t$ be a $K \times 1$ vector process generated by a constant, a linear trend, and level shift termsNote that Lütkepohl et al. (2004) develop their analysis in the context where $\vec{x}_t$ can be represented as a VAR(p), whose components are at most $I(1)$ and cointegrated with rank r .:

$$\vec{y}_t = \vec{\mu}_0 + \vec{\mu}_1 t + \vec{\delta} d_{t\tau} + \vec{x}_t \tag{3}$$

with $d_{t\tau}$ a dummy variable which takes the value of one when $t \geq \tau$, and zero otherwise. The shift point τ is unknown, and is expressed as a fixed fraction of the sample size:

$$\tau = [T\lambda], \quad 0 < \underline{\lambda} \leq \lambda \leq \overline{\lambda} < 1 \tag{4}$$

where $\underline{\lambda}$ and $\overline{\lambda}$ define real numbers, and $[\cdot]$ the integer part. Therefore, the shift cannot occur at the very beginning or the very end of the sample. The estimation of the structural shift is based on the regressions:

$$\vec{y}_t = \vec{v}_0 + \vec{v}_1 t + \vec{\delta} d_{t\tau} + \vec{A}_1 \vec{y}_{t-1} + \ldots + \vec{A}_1 \vec{y}_{t-p} + \varepsilon_{t\tau}, \quad t = p+1, \ldots, T \tag{5}$$

with $\vec{A}_i, \quad i = 1, \ldots, p$ the $K \times K$ coefficient matrices, and ε_t the white noise K -dimensional error process. The estimator for the breakpoint is defined as:

$$\hat{\tau} = \arg\min_{\tau \in \mathrm{T}} \det\left(\sum_{t=p+1}^{T} \hat{\vec{\varepsilon}}_{t\tau} \hat{\vec{\varepsilon}}_{t\tau}^{'} \right) \tag{6}$$

with $\mathrm{T} = [T\underline{\lambda}, T\overline{\lambda}]$, and $\hat{\vec{\varepsilon}}_{t\tau}$ the least squares residuals of Eq. (5). Once the breakpoint $\hat{\tau}$ has been estimated, the data are adjusted as follows:

$$\hat{\vec{x}}_t = \vec{y}_t - \hat{\vec{\mu}}_0 - \hat{\vec{\mu}}_1 t + \hat{\vec{\delta}} d_{t\hat{\tau}} \tag{7}$$

[7] Note that the single-equation Fully Modified OLS estimator can also be adopted as an alternative to the VECM approach. Alternative approaches to cointegration with structural breaks include Andrade and Bruneau (2000) and Arranz and Escribano (2000). We do not further explore these alternative approaches, since we are fully satisfied with the approach by Lutkepohl et al. (2004), which is very close in spirit to the well-known structural break tests by Bai-Perron. Similarly,we are not interested here in testing for exogeneity, which is left for further advanced econometric research. We wish to thank anonymous referees for these remarks.

The test statistic writes:

$$LR(r) = T \sum_{j=r+1}^{N} \ln(1+\hat{\lambda}_j) \tag{8}$$

with corresponding critical values found in Trenkler (2003).

3.2.2 Estimation of the VECM

The error-correction model (ECM) writes:

$$\Delta X_t = \Pi_1 \Delta X_{t-1} + \ldots + \Pi_{p-1} \Delta X_{t-p+1} + \Pi_p X_{t-p} + \varepsilon_t \tag{9}$$

where the matrices Π_i $(i = 1,\ldots, p)$ are of size $(N \times N)$. All variables are $I(0)$, except X_{t-p} which is $I(1)$. For all variables to be $I(0)$, $\Pi_p X_{t-p}$ needs to be $I(0)$ as well.

Let $\Pi_p = -\beta\alpha'$, where α' is an (r, N) matrix which contains r cointegration vectors, and β is an (N, r) matrix which contains the weights associated with each vector. If there exists r cointegration relationships, then $Rk(\Pi_p) = r$. Johansen's cointegration tests are based on this condition. We can thus rewrite Eq.(9):

$$\Delta X_t = \Pi_1 \Delta X_{t-1} + \ldots + \Pi_{p-1} \Delta X_{t-p+1} - \beta\alpha' X_{t-p} + \varepsilon_t \tag{10}$$

The estimation of the corresponding vector error-correction model (VECM) is performed through maximum likelihood methods (Johansen and Juselius (1990), Johansen (1991)).

Before proceeding to the formal cointegration analysis of cross-market linkages, we report in the next section the results of the standard unit root tests.

4. DATASET AND UNIT ROOT TESTS RESULTS

Table 2 provides the descriptive statistics of the time series used in the article. To facilitate the exposition, we rely on the Goldman Sachs Commodity Index (GSCI) sub-indices to carry out our analysis, instead of the individual commodity price series. Besides, we use industrial production indices from the USA, China (CH), Brazil (BR), Australia (AU), Canada (CA), the EU and Germany (GE). All the data used in this article comes from Bloomberg in monthly frequency (due to the availability of macroeconomic time series in monthly frequency at best) from 1993 to 2011, totalling 187 observations.

Table 2: Descriptive statistics

	Min	Max	Mean	Std. Dev.	Skew.	Kurt.	JB
GSCI Agri.	6.1964	7.2869	6.6240	0.2862	0.8215	0.6213	3.3815
GSCI Energy	5.5698	7.9818	6.8226	0.5273	-0.1528	0.9402	11.7205
GSCI Ind. Metals	6.1480	7.7478	6.7902	0.5358	0.5176	3.2463	94.8298
GSCI Prec. Metals	5.8347	7.7111	6.4565	0.5347	0.7049	1.6517	23.4517
Industrial Production US	4.2816	4.6126	4.4968	0.0736	-0.8004	7.2675	510.8818
Industrial Production CH	6.1620	8.0959	7.0780	0.5845	0.1568	4.2581	150.3156
Industrial Production BR	4.4403	4.8752	4.6579	0.1311	0.1944	10.8290	1039.6271
Industrial Production AU	4.3412	4.6220	4.4925	0.0813	-0.1928	6.2129	343.1431
Industrial Production CA	4.5726	4.7562	4.6432	0.0449	0.6319	14.7366	1902.8239
Industrial Production EU	4.4116	4.7113	4.5651	0.0721	-0.1375	2.4034	77.0835
Industrial Production GE	4.3981	4.7493	4.5654	0.0943	0.2663	2.8235	85.0722

Note: The number of observations is equal to 187. Std. Dev. stands for Standard Deviation, Kurt. for Kurtosis, Skew. for Skewness, and JB for the Jarque Bera test statistic.

The raw data can be seen in Figure 1 for the GSCI sub-indices, in Figures 2 and 3 for industrial production variables. We can remark that the evolution pattern is quite similar for all these time series, i.e. with an upward trend (except perhaps the GSCI energy sub-index which has been characterized by a high degree of volatility during the summer 2008). Besides, most industrial production variables record a decrease on the onset of the 2008 financial crisis and the recessionary period. Hence, the time series can be considered as good candidates to be regrouped in a cointegration analysis.

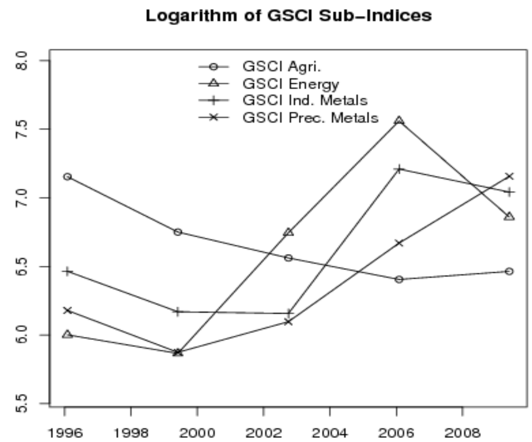

Figure 1: Logarithm of time series for GSCI monthly sub-indices

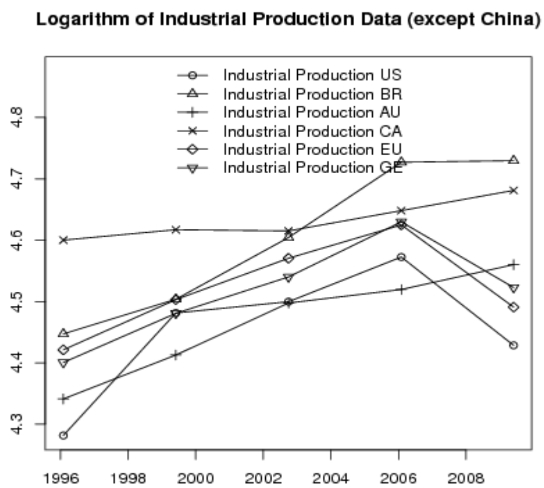

Figure 2: Logarithm of industrial production variables (except China)

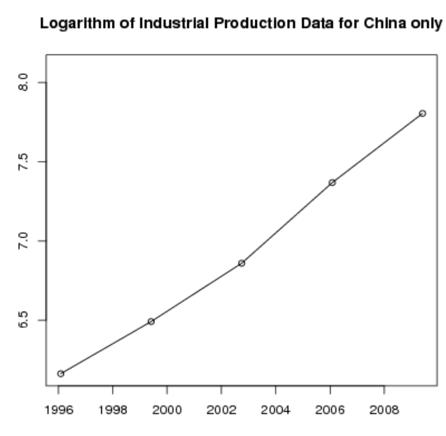

Figure 3: Logarithm of time series for industrial production variables: China

Unit root tests are presented in Table 3. This Table allows us to verify that the time series are integrated of the same order (*I(1)*), as a pre-requisite for cointegration.

Table 3: Unit root test results for the GSCI sub-indices, industrial production, monetary and inflation variables

	ADF None	ADF Drift	ADF Trend	PP Constant	PP Trend	KPSS
GSCI Agri.	-8.5965	-8.6006	-8.6885	-13.1401	-13.1983	0.0308
GSCI Energy	-8.7648	-8.7632	-8.7578	-11.3029	-11.2997	0.0473
GSCI Ind. Metals	-7.4832	-7.5426	-7.5796	-11.0095	-11.0279	0.0757
GSCI Prec. Metals	-10.4528	-11.0234	-11.8022	-15.7345	-16.7938	0.0407
Industrial Production US	-5.8379	-6.0067	-6.2046	-11.0378	-11.3245	0.1112
Industrial Production CH	-4.4308	-10.1549	-10.3068	-13.6028	-13.7126	0.1076
Industrial Production BR	-9.4054	-9.5636	-9.5373	-12.9916	-12.9550	0.0233
Industrial Production AU	-9.6923	-10.1436	-10.1178	-14.0240	-14.0226	0.0236
Industrial Production CA	-8.5891	-8.6350	-8.6271	-10.9285	-10.9168	0.0255
Industrial Production EU	-6.8494	-6.9180	-6.9579	-13.1694	-13.1965	0.0538
Industrial Production GE	-8.4634	-8.6225	-8.5971	-14.0966	-14.0637	0.0552

Note: Test statistics are given. ADF stands for the Augmented Dickey-Fuller unit root test, PP for the Phillips-Perron unit roor test, and KPSS for the Kwiatkowski Phillips Schmidt Shin unit root test. Corresponding critical values (at 5% level) can be found in Greene (2011): -1.9409 for ADF None, -2.8623 for ADF Drift, -3.4114 for ADF Trend, -2.8623 for PP Constant, -3.4114 for PP Trend, and 0.4630 for KPSS.

5. ESTIMATION RESULTS

Cointegration tests have been performed during the full period [1993-2011], as well as during the corresponding sub-periods [1993-2000] and [2000-2011]. To study the relationship between industrial production and commodity prices in the cointegration framework, we have attempted to reproduce most of the results from previous literature based on our updated dataset.

By following the methodology outlined in Section 3, we consider systematically cointegration with and without structural breaks. To conserve space, we reproduce in what follows the results of the best model only, i.e. the econometric model which is the most satisfactory statistically speakingAdditional results can be obtained upon request.

The main findings are summarized in Table 4.

Table 4: Cointegration Analyses of Industrial Production and Commodity Prices: Summary of the Main Results

Period	Cointegration Relationship	SB
-2011	GSCI Sub-Indices ∅ Industrial Production US	No
-2000	GSCI Sub-Indices ↔ Industrial Production US	No
-2011	GSCI Sub-Indices ∅ Industrial Production US	No
-2011	GSCI Sub-Indices ↔ Industrial Production US	Yes
-2011	GSCI Sub-Indices ∅ Industrial Production CH	No
-2000	GSCI Sub-Indices ∅ Industrial Production CH	No
-2011	GSCI Sub-Indices ∅ Industrial Production CH	No
-2011	GSCI Sub-Indices ↔ Industrial Production CH	Yes
-2011	GSCI Sub-Indices ↔ Industrial Production BR	No
-2000	GSCI Sub-Indices ∅ Industrial Production BR	No
-2011	GSCI Sub-Indices ∅ Industrial Production BR	No
-2011	GSCI Sub-Indices ↔ Industrial Production BR	Yes
-2011	GSCI Sub-Indices ∅ Industrial Production AU	No
-2000	GSCI Sub-Indices ∅ Industrial Production AU	No
-2011	GSCI Sub-Indices ∅ Industrial Production AU	No
-2011	GSCI Sub-Indices ↔ Industrial Production AU	Yes
-2011	GSCI Sub-Indices ↔ Industrial Production CA	No
-2000	GSCI Sub-Indices ∅ Industrial Production CA	No
-2011	GSCI Sub-Indices ↔ Industrial Production CA	No
-2011	GSCI Sub-Indices ↔ Industrial Production CA	Yes
-2011	GSCI Sub-Indices ∅ Industrial Production EU	No
-2000	GSCI Sub-Indices ∅ Industrial Production EU	No
-2011	GSCI Sub-Indices ∅ Industrial Production EU	No
-2011	GSCI Sub-Indices ↔ Industrial Production EU	Yes
-2011	GSCI Sub-Indices ∅ Industrial Production GE	No
-2000	GSCI Sub-Indices ∅ Industrial Production GE	No
-2011	GSCI Sub-Indices ∅ Industrial Production GE	No
-2011	GSCI Sub-Indices ↔ Industrial Production GE	Yes

Note: ↔ indicates the presence of a cointegration relationship. ∅ indicates the absence of a cointegration relationship. SB stands for 'Structural Break' analysis. US stands for USA, CH for China, BR for Brazil, AU for Australia, CA for Canada, EU for European Union, and GE for Germany.

5.1 GSCI Sub-Indices and Industrial Production in Australia

Starting with the adjustment between industrial production in Australia and the GSCI Sub-indices, we get from Table 3 that a cointegration relationship could only be detected during the 1993-2011 full period with the modeling of a structural break.

Table 5: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in Australia

1993-2011	Max. Eigen.	10%	5%	1%
$r \leq 4$	5.20	5.42	6.79	10.04
$r \leq 3$	14.30	13.78	15.83	19.85
$r \leq 2$	27.81	25.93	28.45	33.76
$r \leq 1$	49.08	42.08	45.2	51.6
$r = 0$	82.66	61.92	65.66	73.12

Table 5 reveals that the rank of the cointegration r between these variables is at least equal to 1 (i.e. $r = 1$) at the 1% level.

Table 6: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in Australia

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	0.646				
GSCI Prec. Met.	-1.745				
GSCI Energy	0.162				
Prod. Ind. AU	8.625				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. AU
ECT	-0.052	-0.123	0.004	-0.067	-0.006
(t.stat)	(-2.05)	(-5.65)	(0.20)	(-1.45)	(-2.07)
Δ GSCI Agri.(-1)	0.005	0.013	0.095	0.266	0.017
(t.stat)	(0.06)	(1.85)	(1.35)	(1.77)	(1.70)
Δ GSCI Ind. Met.(-1)	-0.026	-0.016	-0.076	0.032	-0.001
(t.stat)	(-0.30)	(-0.21)	(-0.98)	(0.20)	(-0.11)
Δ GSCI Prec. Met.(-1)	0.194	0.020	0.066	-0.286	-0.024
	(1.93)	(0.23)	(0.77)	(-1.55)	(-2.01)
Δ GSCI Energy(-1)	-0.059	-0.037	-0.052	-0.057	0.007
(t.stat)	(-1.33)	(-0.98)	(-1.37)	(-0.70)	(1.28)
Δ Prod. Ind. AU(-1)	0.369	-0.121	-0.633	-0.366	-0.018
(t.stat)	(0.59)	(-0.22)	(-1.17)	(-0.32)	(-0.24)

The VECM reproduced in Table 6 brings fruitful results. Indeed, four error-correction terms (except for precious metals) are negative. GSCI Industrial Metals stand out as the most significant variable (at the 1% level), followed by the GSCI Agricultural Products and the Australian Industrial Production Index (at the 5% level). The GSCI Energy Prices are close to the 10% significance level. The economic logic unfolds as follows. In a context of high economic growth (and associated tensions on industrial production capacities), the demand for commodities is inherently higher which triggers price adjustments, especially in the agricultural and industrial metals sectors. The magnitude of the ECTs is the strongest for Industrial Metals (-0.123), which implies that the feedback mechanism occurs especially through this channel. However, we verify as well that changes in macroeconomic conditions (i.e. industrial production) in Australia are able to produce adjustment mechanisms in the long term. Also, we may suggest another interpretation in that Australia has become over the period one the main exporters of industrial metals. Therefore, when the worldwide demand for industrial metals is falling, the Australian economy may be adversely impacted.

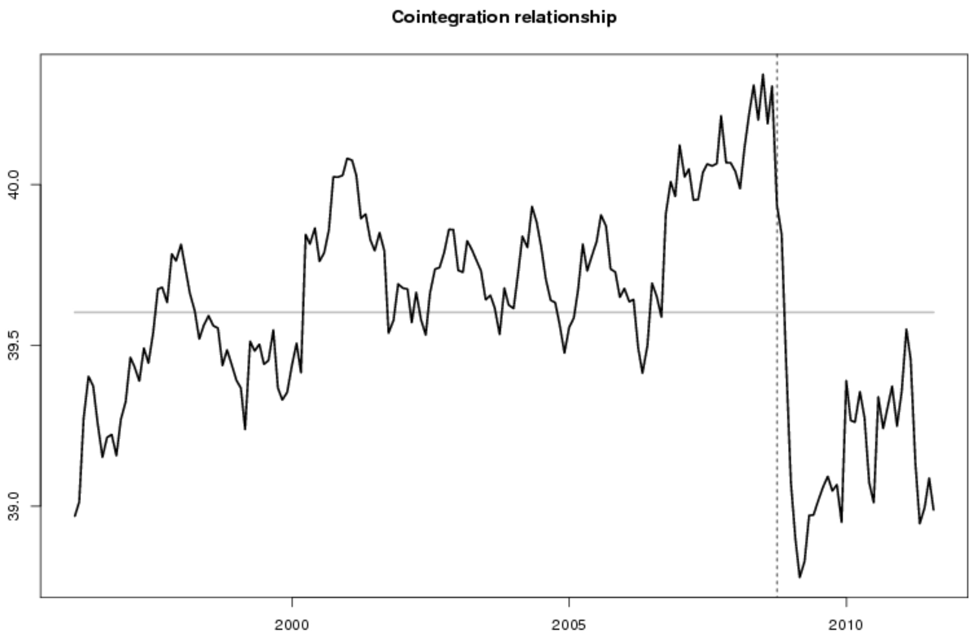

Figure 4: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in Australia

This hypothesis of a macroeconomic link in Australia with commodity markets is further validated by the stationarity of the cointegration relationship, which is visible in Figure 4. Indeed, it appears stable during each of the two regimes separated by the structural break date on September 30, 2008. Hence, we can make a strong case of linkages between macroeconomic variables and commodity markets (in various segments such as agricultural products, industrial metals and perhaps even energy markets) in the Australian region.

Our results are conform to the previous findings by Bloch et al. (2006), who found evidence in favor of a cointegration relationship between IMF Commodity Indices and Industrial Production in Australia during 1960-2001.

5.2 GSCI Sub-Indices and Industrial Production in the US

Next, we move to the relationship between GSCI sub-indices (Agricultural Products, Industrial Metals, Precious Metals, Energy Markets) and the US industrial production index. The US economy could be considered in this setting as a proxy for world GDP (or economic activity) growth. Table 3 tells us that there exists one cointegration relationship during the first sub-period (1993-2000), as well as during the full period 1993-2011 with the occurrence of one structural break.

In our current setting, the best results were obtained with the full sample estimates in presence of one structural break. Hence, we shall comment these results below.

Table 7: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in the US

1993-2011	Max. Eigen.	10%	5%	1%
$r \leq 4$	1.62	5.42	6.79	10.04
$r \leq 3$	7.96	13.78	15.83	19.85
$r \leq 2$	18.40	25.93	28.45	33.76
$r \leq 1$	42.37	42.08	45.2	51.6
$r = 0$	72.10	61.92	65.66	73.12

First, we verify in Table 7 that there exists at least one cointegration relationship between the GSCI Sub-Indices and the US Industrial Production Index, i.e. the rank of the cointegration r is at least equal to 1 (at the 5% level).

Second, we obtain the VECM estimates as reproduced in Table 8. They show, by and large, that the VECM has been correctly specified, since three Error-Correction Terms are negative (GSCI Agri., GSCI Energy, Prod. Ind. US). However, only the ECT for the US Industrial Production Index is statistically significant (at the 1% level), which implies that the deviations from the long term equilibrium are solely corrected by the macroeconomic variable in this system. This result means that variations in the industrial production index in the US are able to correct for the short term deviations in the various commodity markets, provided that a long term and meaningful relationship between these variables indeed exists.

Third, we examine the validity of the cointegration relation in Figure 5. This graph clearly shows that the relationship is not stationary over the 1993-2011 full period. On the contrary, it is downward sloping with the presence of one structural break on September 30, 2005. Therefore, we cannot consider that the cointegration exercise between the GSCI Sub-Indices and the US Industrial Production Index has been successful from an econometric viewpoint. Indeed, some key characteristics of cointegration are missing, such as the presence of several negative and significant ECTs, as well as the stationarity of the long term relationship observed.

Table 8: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in the US

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	-0.642				
GSCI Prec. Met.	-1.008				
GSCI Energy	0.178				
Prod. Ind. US	-0.323				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. US
ECT	-0.045	0.079	0.100	-0.043	-0.015
(t.stat)	(-1.29)	(1.68)	(3.30)	(-0.85)	(-4.18)
Δ GSCI Agri.(-1)	0.065	0.116	0.142	0.058	-0.014
(t.stat)	(0.75)	(0.99)	(1.86)	(0.46)	(-1.60)
Δ GSCI Ind. Met.(-1)	-0.048	0.043	0.006	0.211	0.001
(t.stat)	(-0.66)	(0.43)	(0.09)	(1.98)	(0.02)
Δ GSCI Prec. Met.(-1)	0.142	0.053	-0.056	-0.134	0.003
	(1.36)	(0.38)	(-0.62)	(-0.88)	(0.29)
Δ GSCI Energy(-1)	-0.087	-0.016	-0.066	0.124	0.015
(t.stat)	(-1.76)	(-0.23)	(-1.53)	(1.71)	(2.95)
Δ Prod. Ind. US(-1)	1.529	2.513	1.934	2.337	0.189
(t.stat)	(2.11)	(2.58)	(3.06)	(2.22)	(2.60)

Figure 5: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in the US

With respect to previous literature on this subject, we agree with the early findings by Cody and Mills (1991) pointing out the absence of a cointegration relationship between the US Industrial Index and commodity indices during 1959-1987. However, our results contradict the findings by Awokuse and Yang (2003) – who used IMF Indices instead of GSCI Indices – during 1975-2001, and those of Bhar and Hamori (2008) – who used CRB Indices – during 1957-2005. We believe that the systematic inclusion of sub-periods and structural breaks enriches the results on this literature. Besides, we use an updated database compared to these latter authors to account for the effect of the 2008 financial crisis in the adjustment mechanism under consideration.

5.3 GSCI Sub-Indices and Industrial Production in China

Next, we consider the relationship between the GSCI Sub-Indices and the Chinese industrial production index. This region is of particular interest, since China has recorded the world's fastest growing GDP rate over the last two decades. Hence, it attracts much of the demand in terms of raw materials and primary commodities for production and construction. We learn from Table 3 that only one cointegration relationship could be detected during the full period with the modeling of one structural break.

Table 9: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in China

1993-2011	Max. Eigen.	10%	5%	1%
$r \leq 4$	4.68	5.42	6.79	10.04
$r \leq 3$	12.58	13.78	15.83	19.85
$r \leq 2$	24.19	25.93	28.45	33.76
$r \leq 1$	39.90	42.08	45.2	51.6
$r = 0$	67.47	61.92	65.66	73.12

Table 9 confirms this view, i.e. the rank of the cointegration r is equal to at least 1 (at the 5% confidence level).

In Table 10, the VECM estimates provide very interesting results. Indeed, four (out of five) error correction term are negative. Two of them are highly significant (at the 1% level) for GSCI Agricultural Products and GSCI Industrial Metals. One of them is barely significant (at the 10% level). However, in this practical example, the ECT for the Chinese industrial production index is negative but not significant. We could infer that the economic logic whereby higher demand from the industry translates into higher consumption of raw materials does not hold in the context of China. On the contrary, the variation of the commodity sub-indices in agricultural and industrial metals markets (and to a lesser extent in energy markets) is found to correct the deviations from the long term equilibrium in this system of equations. Therefore, this result is both original and surprising, since we could have intuitively expected opposite effects.

Table 10: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in China

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	0.470				
GSCI Prec. Met.	-2.154				
GSCI Energy	0.189				
Prod. Ind. CH	1.280				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. CH
ECT	-0.076	-0.081	0.059	-0.087	-0.004
(t.stat)	(-2.51)	(-2.94)	(2.25)	(-1.54)	(-0.97)
Δ GSCI Agri.(-1)	-0.018	0.073	0.076	0.227	0.013
(t.stat)	(-0.23)	(1.00)	(1.10)	(1.53)	(1.10)
Δ GSCI Ind. Met.(-1)	-0.007	0.057	-0.073	0.051	0.025
(t.stat)	(-0.09)	(0.74)	(-1.00)	(0.32)	(2.01)
Δ GSCI Prec. Met.(-1)	0.137	0.027	0.108	-0.360	0.036
	(1.35)	(0.30)	(1.24)	(-1.93)	(2.41)
Δ GSCI Energy(-1)	-0.057	-0.056	-0.059	-0.058	0.001
(t.stat)	(-1.33)	(-1.44)	(-1.60)	(-0.73)	(0.20)
Δ Prod. Ind. CH(-1)	0.737	1.533	0.891	1.768	-0.051
(t.stat)	(1.47)	(3.39)	(2.07)	(1.91)	(-0.69)

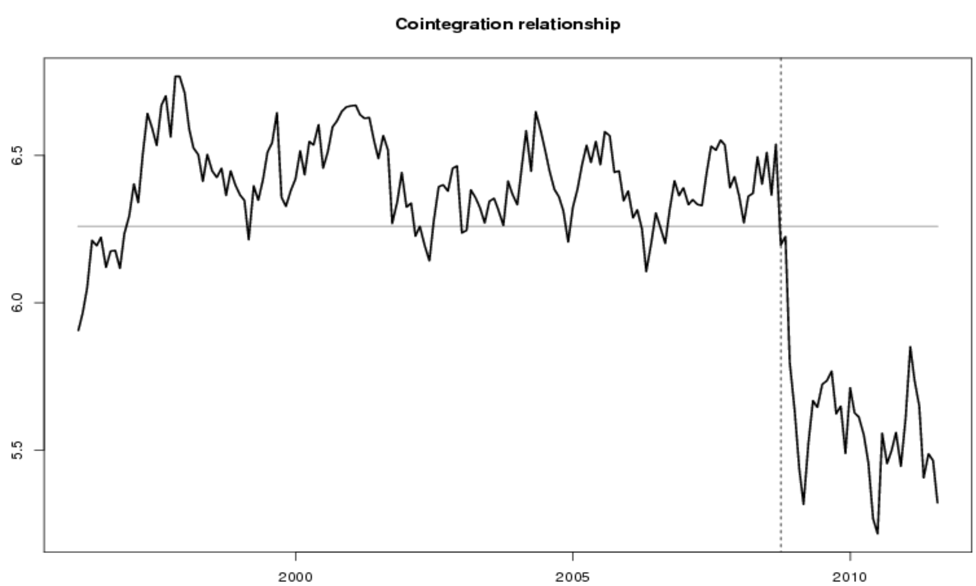

Figure 6: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in China

When examining the cointegration relationship in Figure 6, we notice that it is stationary before and after the structural break detected on September 30, 2008. This break could be characteristic of the commodity price 'boom and bust' during the summer 2008. Consequently, we conclude our analysis of the relationship between the GSCI Sub-Indices and the Chinese industrial production index by uncovering new (original) but also puzzling results. On the one hand, we have been to estimate satisfactorily a VECM between these variables. On the other hand, the results contradict the macroeconomy-commodity markets view, whereby changes in industrial production induce a higher demand, and thus higher consumption of commodities. Why agricultural and industrial metals prices are able to act as a feedback mechanism when faced with deviations from the long term equilibrium in this system needs to be strenghtened by further research on this topic.

To our best knowledge, most of the results (as well as subsequent results on OECD countries) are new with respect to the econometric methodology used and the sample data contained in this study.

5.4 GSCI Sub-Indices and Industrial Production in Brazil

Brazil constitutes another area of potential strong economic growth, in terms of associated commodity demand as well. We examine here the link between the various GSCI Sub-Indices and the Brazilian industrial production index. In Table 3, we detect two cointegration relationships during the full period without and with structural break. We reproduce below the results obtained during 1993-2011 with break.

Table 11: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in Brazil

1993-2011	Max. Eigen.	10%	5%	1%
$r \leq 4$	6.48	5.42	6.79	10.04
$r \leq 3$	14.73	13.78	15.83	19.85
$r \leq 2$	27.64	25.93	28.45	33.76
$r \leq 1$	52.10	42.08	45.2	51.6
$r = 0$	85.65	61.92	65.66	73.12

In Table 11, we verify that the null hypothesis of no cointegration between the variables of interest can be safely rejected (at the 1% level).

Table 12 contains the VECM estimates. Again, we obtain mostly satisfactory results, since four error-correction terms (out of five) record a negative sign. Among them, the ECTs for the GSCI Industrial Metals and the Brazilian Industrial Production Index are statistically significant at the 1% level. Unlike in the Chinese case, we highlight here that there exists a clear mechanism linking the variation of commodity prices and economic activity in the long term.

Table 12: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in Brazil

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	0.133				
GSCI Prec. Met.	-2.815				
GSCI Energy	-0.349				
Prod. Ind. BR	11.854				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. BR
ECT	-0.014	-0.043	0.011	-0.010	-0.020
(t.stat)	(-1.07)	(-3.68)	(1.01)	(-0.43)	(-5.23)
Δ GSCI Agri.(-1)	-0.017	0.096	0.104	0.248	0.055
(t.stat)	(-0.21)	(1.31)	(1.49)	(1.65)	(2.28)
Δ GSCI Ind. Met.(-1)	-0.003	0.007	-0.061	0.072	0.014
(t.stat)	(-0.03)	(0.09)	(-0.78)	(0.43)	(0.53)
Δ GSCI Prec. Met.(-1)	0.230	0.110	0.090	-0.212	-0.036
	(2.30)	(1.24)	(1.06)	(-1.16)	(-1.24)
Δ GSCI Energy(-1)	-0.072	-0.078	-0.054	-0.079	0.027
(t.stat)	(-1.63)	(-1.96)	(-1.44)	(-0.98)	(2.08)
Δ Prod. Ind. BR(-1)	0.116	0.474	-0.095	0.101	0.058
(t.stat)	(0.45)	(2.07)	(-0.44)	(0.21)	(0.78)

The feedback mechanism governing the adjustment of short term deviations to the long term equilibrium is driven in this setting by the demand for industrial metals and the level of industrial production. These results correspond to the following intuitive reasoning: in a context of high demand for goods, industrial production capacities are tense, and hence the demand for raw materials is high (and vice-versa). If some categories of commodity markets do not fit temporarily in this price profile, then the long term relationship between the macroeconomic and commodity variables will be restored by the variation of the industrial production index and the variation of industrial metals prices. By looking at the magnitude of the coefficients for the ECTs, we could even state that the feedback mechanism coming from industrial metals (-0.043) is slightly stronger than that coming from the industrial production index (-0.020).

The last step to confirm the validity of this model is to examine the cointegration relationship, which is pictured in Figure 7. Despite the occurrence of one structural break on September 30, 2008 (which could be due as well to the episode of strong price adjustment of all commodities to the economic context of financial crisis), we clearly observe visually that the relationship is stable and stationary in each of the two regimes highlighted by the structural break test. Hence, we can confirm that the VECM is valid concerning the relationship between the GSCI Sub-Indices and the

Brazilian industrial production index. This cointegration exercise has brought us a wealth of insights, since we have been able to validate empirically the macroeconomy-commodity markets link in Brazil.

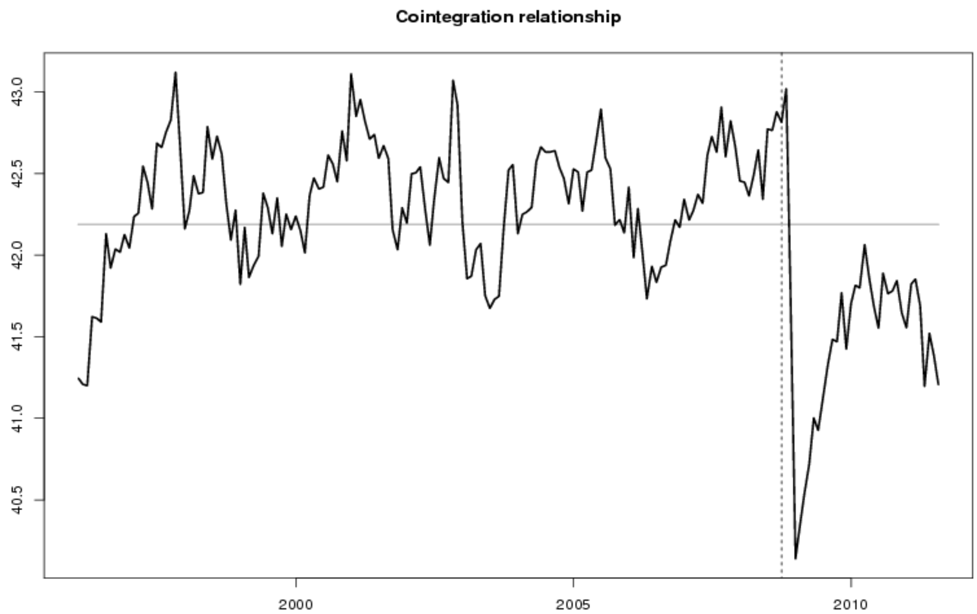

Figure 7: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in Brazil

5.5 GSCI Sub-Indices and Industrial Production in Canada

In the case of the Canadian economy, we uncover in Table 3 the existence of cointegration relationships between its industrial production index and the GSCI Sub-Indices in all specifications (except the first 1993-2000 sub-period). In what follows, we choose to reproduce the results relative to the 1993-2011 full period with one break.

Table 13: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in Canada

1993-2011	Max. Eigen.	10%	5%	1%
r ≤ 4	5.54	5.42	6.79	10.04
r ≤ 3	12.89	13.78	15.83	19.85
r ≤ 2	31.09	25.93	28.45	33.76
r ≤ 1	57.88	42.08	45.2	51.6
r = 0	88.94	61.92	65.66	73.12

Table 13 states that there exists at least one cointegration relationship between the GSCI Sub-Indices and the Canadian Industrial Production Index (at the 1% level).

Table 14: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in Canada

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	-0.267				
GSCI Prec. Met.	-2.043				
GSCI Energy	0.661				
Prod. Ind. CA	14.129				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. CA
ECT	-0.051	-0.030	-0.013	-0.016	-0.008
(t.stat)	(-4.23)	(-2.59)	(-1.25)	(-0.68)	(-4.37)
Δ GSCI Agri.(-1)	-0.065	0.049	0.089	0.215	0.009
(t.stat)	(-0.82)	(0.65)	(1.26)	(1.43)	(0.75)
Δ GSCI Ind. Met.(-1)	-0.050	0.043	-0.103	0.057	-0.005
(t.stat)	(-0.59)	(0.54)	(-1.36)	(0.35)	(-0.38)
Δ GSCI Prec. Met.(-1)	0.170	0.126	0.049	-0.224	-0.012
	(1.81)	(1.41)	(0.58)	(-1.25)	(-0.83)
Δ GSCI Energy(-1)	-0.040	-0.060	-0.047	-0.075	0.019
(t.stat)	(-0.95)	(-1.50)	(-1.25)	(-0.92)	(3.05)
Δ Prod. Ind. CA(-1)	-0.157	0.957	0.277	1.388	0.211
(t.stat)	(-0.34)	(2.18)	(0.67)	(1.58)	(3.07)

The VECM estimates shown in Table 14 are extremely satisfactory. In this specification, all error-correction terms are negative. Three of them are statistically significant: the Canadian Industrial Production Index and the GSCI Agricultural Products Sub-Index (at the 1% level), as well as the GSCI Industrial Metals Sub-Index (at the 5% level). By examining the magnitude of the ECTs, we can establish in this setting that agricultural products produce the strongest feedback mechanism (-0.051). It is therefore very interesting to confirm for a fourth world region that the link between the macroeconomy and the commodity markets hold. In light of the Canadian economy, it can indeed be said that the Industrial Production Index, Agricultural Products and Industrial Metals prices will correct any deviations from the long term equilibrium in this system. Thus, the existence of a meaningful economic mechanism can be inferred from this cointegration exercise: in the long run, the variation in industrial production is able to trigger price adjustement in commodity prices (as an input to production). The size of the Canadian economy in terms of production of agricultural products and its role in the industrial metals industry also allows us to establish a reverse relationship.

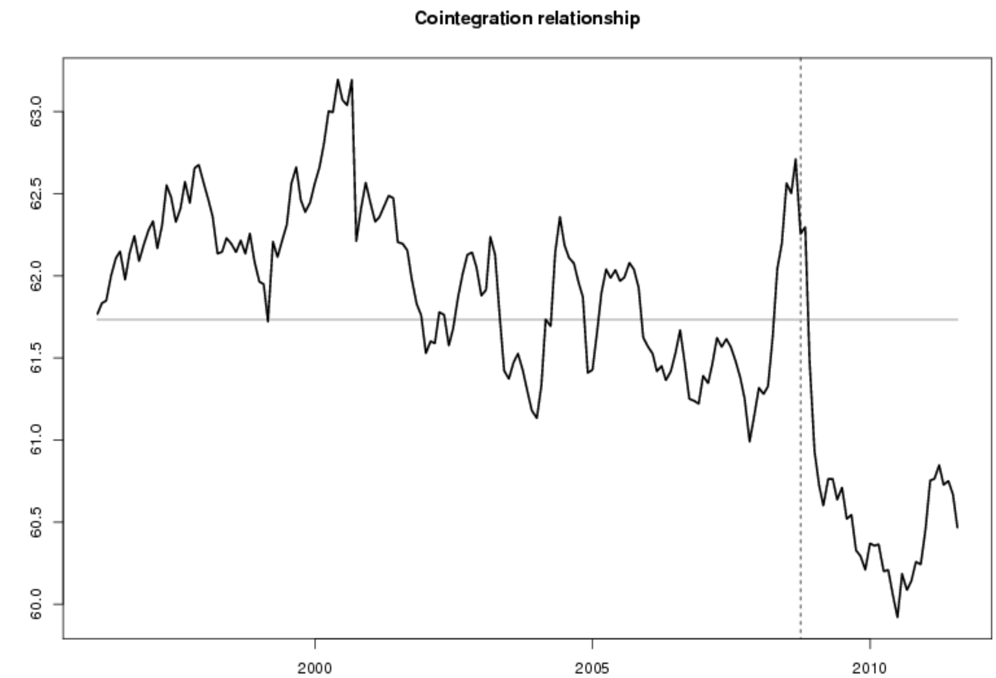

Figure 8: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in Canada

In Figure 8, we can observe the occurrence of the structural break on September 30, 2008. Before and after that date, the two regimes can be considered as being broadly stationary. The stability of the cointegration relationship is not as neat in this graph as it was in the case of the Chinese, Brazilian and Australian economies. Nevertheless, it could be considered as being broadly stationary. Consequently, we can validate the results highlighted in this section.

Note also that, similarly to the previous case for Australia, our results confirm the previous findings by Bloch et al. (2006), who found evidence in favor of a cointegration relationship between IMF Commodity Indices and Industrial Production in Canada during 1960-2001.

5.6 GSCI Sub-Indices and Industrial Production in the EU

We now turn to the study of the relationship between industrial production in the EU and commodity markets. According to Table 3, only one cointegration relationship could be found during the 1993-2011 full period and with the modeling of one break.

From Table 15, we get the insight that the rank of the cointegration matrix r is indeed at least equal to 1 (at the 1% level).

Table 15: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in the EU

1993-2011	Max. Eigen.	10%	5%	1%
r ≤ 4	6.96	5.42	6.79	10.04
r ≤ 3	16.39	13.78	15.83	19.85
r ≤ 2	29.69	25.93	28.45	33.76
r ≤ 1	54.40	42.08	45.2	51.6
r = 0	84.52	61.92	65.66	73.12

Table 16: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in the EU

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	0.684				
GSCI Prec. Met.	-2.219				
GSCI Energy	0.364				
Prod. Ind. EU	4.186				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. EU
ECT	-0.034	-0.079	0.030	-0.100	-0.008
(t.stat)	(-1.73)	(-4.63)	(1.78)	(-2.82)	(-1.77)
Δ GSCI Agri.(-1)	-0.027	0.060	0.078	0.212	0.019
(t.stat)	(-0.33)	(0.85)	(1.13)	(1.44)	(0.94)
Δ GSCI Ind. Met.(-1)	0.003	0.062	-0.018	0.049	0.038
(t.stat)	(0.03)	(0.78)	(-0.24)	(0.30)	(1.72)
Δ GSCI Prec. Met.(-1)	0.184	-0.001	0.045	-0.416	-0.052
	(1.79)	(-0.01)	(0.51)	(-2.25)	(-2.08)
Δ GSCI Energy(-1)	-0.045	0.001	-0.016	0.013	0.008
(t.stat)	(-0.92)	(0.01)	(-0.39)	(0.15)	(0.67)
Δ Prod. Ind. EU(-1)	-0.217	-0.722	-0.846	-0.877	-0.160
(t.stat)	(-0.55)	(-2.09)	(-2.52)	(-1.23)	(-1.66)

Table 16 contains the VECM estimates, which are also quite satisfactory. We record four negative error-correction terms (except for precious metals). The GSCI Industrial Metals record an ECT equal to -0.079 significant at the 1% level, followed by the GSCI Energy Markets equal to -0.100 significant at the 5% level. Both the error-correction terms of the GSCI Agricultural Products (-0.034) and the EU Industrial Production (-0.008) are significant at the 10% level. Hence, we find results similar to previous regions where the macroeconomy-commodity markets link has been established previously, with the exception that the magnitude of the ECT is the strongest in this setting for energy markets. Therefore, it could be said that all commodity markets (except precious metals) play a role here in correcting the errors towards the long term fundamental value between these time series, in addition to the role played by the macroeconomic variable (that is, the industrial production index).

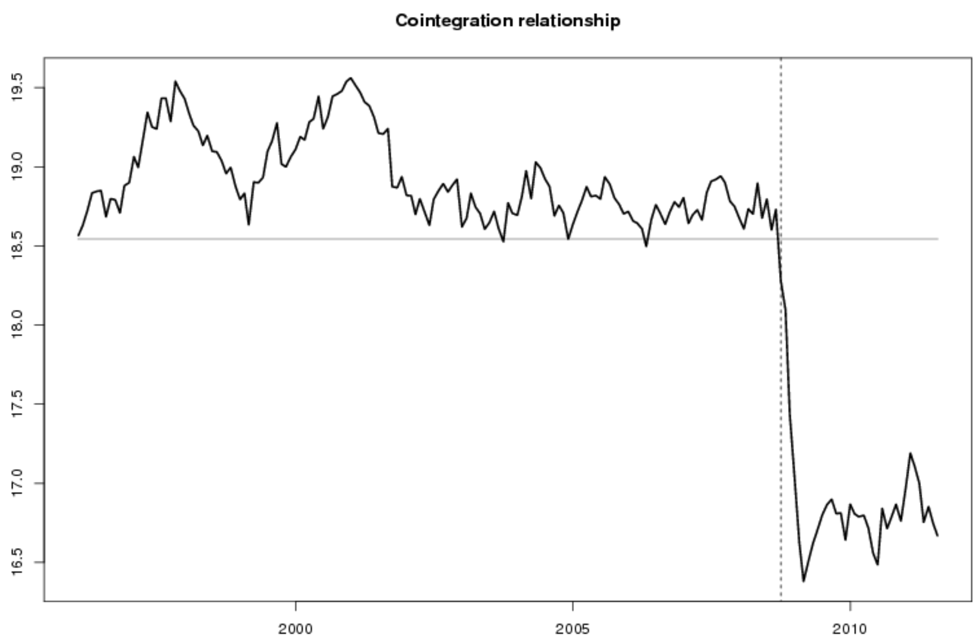

Figure 9: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in the EU

The examination of Figure 9 allows us to conclude that the cointegration relationship identified between the GSCI Sub-Indices and the European Industrial Production Index is valid. Indeed, the graph appears roughly stationary before and after the structural break date on September 30, 2008. This stands in sharp contrast with the results obtained for the USA, where the results could not be validated at this stage. There seems to exist significant differences in the linkages between economic activity and commodity markets between both sides of the Atlantic.

5.7 GSCI Sub-Indices and Industrial Production in Germany

With respect to Germany, which constitutes the economic stronghold of the EU in terms of growth, our specifications in Table 3 reveal that only one cointegration relationship is valid during the full period and with the occurrence of one structural break.

Table 17 is able to confirm this statement: we can detect at least one cointegration relationship between the GSCI Sub-Indices and the German Industrial Production Index (at the 1% level).

Table 17: Lütkepohl et al. (2004) Cointegration Test Results with Structural Break for GSCI Sub-Indices and Industrial Production in Germany

1993-2011	Max. Eigen.	10%	5%	1%
$r \leq 4$	7.20	5.42	6.79	10.04
$r \leq 3$	16.88	13.78	15.83	19.85
$r \leq 2$	29.57	25.93	28.45	33.76
$r \leq 1$	51.62	42.08	45.2	51.6
$r = 0$	82.10	61.92	65.66	73.12

Table 18: VECM Results with Structural Break (1993-2011) for GSCI Sub-Indices and Industrial Production in Germany

Err. Correction Term					
GSCI Agri.	1				
GSCI Ind. Met.	0.609				
GSCI Prec. Met.	-2.593				
GSCI Energy	0.427				
Prod. Ind. GE	4.618				
VECM	Δ GSCI Agri.	Δ GSCI Ind. Met.	Δ Prec. Met.	Δ GSCI Energy	Δ Prod. Ind. GE
ECT	-0.028	-0.070	0.024	-0.089	-0.010
(t.stat)	(-1.69)	(-4.73)	(1.70)	(-2.92)	(-2.26)
Δ GSCI Agri.(-1)	-0.022	0.081	0.104	0.239	0.006
(t.stat)	(-0.28)	(1.14)	(1.53)	(1.64)	(0.30)
Δ GSCI Ind. Met.(-1)	0.004	0.024	-0.025	-0.015	0.048
(t.stat)	(0.04)	(0.30)	(-0.32)	(0.09)	(1.99)
Δ GSCI Prec. Met.(-1)	0.175	0.036	0.059	-0.340	-0.037
	(1.74)	(0.41)	(0.70)	(-1.87)	(-1.37)
Δ GSCI Energy(-1)	-0.037	-0.026	-0.027	-0.041	0.009
(t.stat)	(-0.79)	(-0.63)	(-0.69)	(-0.48)	(0.71)
Δ Prod. Ind. GE(-1)	-0.434	-0.342	-0.736	0.034	-0.094
(t.stat)	(-1.39)	(-1.24)	(-2.78)	(0.06)	(-1.13)

We record four negative error-correction terms (except precious metals) in the VECM, as shown in Table 18. By order of significance, we can state that the GSCI Industrial Metals (1% level) precede the GSCI Energy and the EU Industrial Production Index (5% level), followed by the GSCI Agricultural Products (10% level). Similarly to the EU case, the strongest ECT is registered for the GSCI Energy. As a matter of fact, deviations from the long run equilibrium relationship between these variables will be primarily corrected by the energy variable, followed by industrial metals, agricultural products and the German industrial production index.

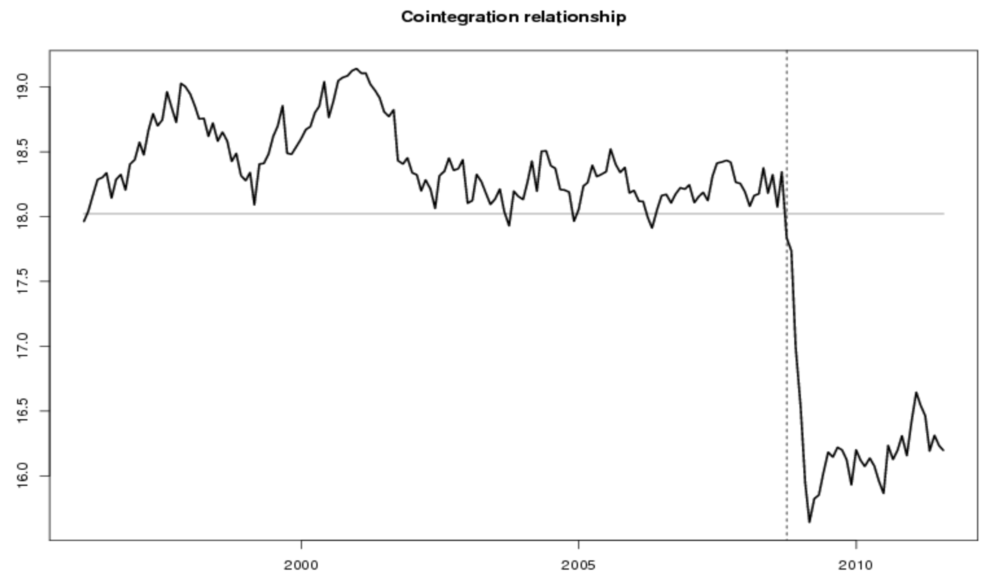

Figure 10: Cointegration relationship with structural break for GSCI Sub-Indices and Industrial Production in Germany

According to Figure 10, this overall cointegration exercise is valid, since we can notice that the cointegration relationship is stationary in each of the two regimes delimited by a structural break date on September 30, 2008. Therefore, we obtain very successful results in the EU and German cases (as a proxy of the EU 27 economic region), where we document that the macroeconomy-commodity markets link is active.

6. CONCLUDING REMARKS

When investigating the link between commodity markets and a central macroeconomic variable such as industrial production, several economic forces are of interest. First, in a context of sustained economic growth, the demand for commodity markets is strong. Hence, consumers' demand triggers extra production effort from companies, which resort to various commodities as an input to their productionAssuming the income elasticity of commodity demand to be near one..

Conversely, in a context of decreasing economic activity, some segments of the economy will be characterized by declining demand, and thus the associated demand in terms of commodities will be lower. We can thus expect both cyclical movements in commodity prices, if they are synchronized with economic activityObviously, we can also expect counter-cyclical effects. For instance, when industrial production decreases, the price of gold increases as a refuge for value..

The purpose of our article is to review empirically these relationships between commodities and industrial production in a cointegration framework during 1993-2011 for a sub-set of countries: Australia, Brazil, Canada, China, the EU, Germany and the USA.

With respect to the adjustment between industrial production (as a proxy of economic activity) and commodity markets, we have considered various cointegration exercises depending on the geographic zone and the sectors covered by commodities: agricultural products, industrial and precious metals, energy markets. The main results feature a satisfactory long term relationship between industrial production and various segments of commodity markets. Most of the time, precious metals are unable to trigger this adjustment, whereas industrial metals and agricultural products play a prime role. In terms of geographic coverage, we could verify that the adjustment of macroeconomic conditions to (and from) commodity markets is especially valid in China, Brazil, Australia, Canada, the EU and Germany – but not in the US. In China and in some other regions, we also find that commodity markets act as the central feedback mechanisms, which implies that they will be leader in the recovery towards the long run state, should any short term deviations occur. Overall, we can certainly verify that changes in macroeconomic conditions induce higher demand for construction, production and therefore higher demand for raw materials and commodities as an input. But we have also documented firmly that the cross-market linkages are especially strong when developing that kind of cointegration exercises.

Compared to previous academic literature, we can consider the similarities between our results and various studies which included industrial production in the OECD. Indeed, our results for the economic regions aforementioned broadly confirm the findings by Labys and Maizels (1993) and Hua (1998) – who used IMF Commodity indices instead of GSCI indices – during 1953-1987 and 1970-1993, respectively. We are therefore successful in updating their results on this matter, which were favorable to the existence of a cointegration relationship between commodity markets and industrial production. Note however that we disagree with Bloch et al. (2004), who could not find evidence of such a phenomenon during 1900-2001. Perhaps the difference between these latter authors and the present study comes from their choice of World Bank Indicators of Commodity Markets, or the period under consideration.

Therefore, it seems that feedback mechanisms that we are looking for between commodities and the macroeconomy are only valid for baskets of commodities (as represented by the GSCI Sub-Indices), while there lacks a credible body of evidence in favor of that hypothesis for individual commodity price series. Our results are globally in line with previous literature on this topic. The originality of the present work lies in the systematic inclusion of sub-periods and structural breaks, as well as in the use of an updated dataset compared to most of the previous studies. Finally, note that we have not further considered cointegration exercises with the gold price, since it seemed that there were little (or no) feedback mechanisms at stake in that category of commodities when using the GSCI Sub-Index for Precious Metals (which nearly all lacked conclusive evidence of acting as effective error-correction effects).

Overall, we have enriched our standing of the commodity–industrial production nexus not only within the class of commodities, but with other categories of variables within the global economy. These effects are especially interesting to highlight in the wider context of the 2008-2009 financial crisis, where commodities seemed to adjust quite well to the changes in the macroeconomic conditions.

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