Resources Policy 45 (2015) 151–164

Contents lists available at ScienceDirect

Resources Policy

journal homepage: www.elsevier.com/locate/resourpol

Influence in commodity markets: Measuring co-movement globally ☆

Viviana Fernandez [1]

Business School, Universidad Adolfo Ibañez, Avenida Diagonal Las Torres 2700, Office 512-C, Santiago, Chile

ARTICLE INFO

Article history:
Received 12 November 2014
Received in revised form
22 April 2015
Accepted 23 April 2015
Available online 15 May 2015

JEL classification:
C22
E31
O13

Keywords:
Commodity markets
Conditional correlation
Portfolio investment

ABSTRACT

This article focuses on a new measure of global co-movement defined as influence: the average partial correlation of one asset with respect to others. The influence of nominal returns and real price cycles of various commodities is computed for the period of January 1968–December 2013. The estimation results show that there is strong co-movement among the average influences of nominal returns of industrial and precious metals since 2003. From an investor's perspective, this suggests a reduction in the benefits of portfolio diversification and a convergence towards a single metal class. On the other hand, and as expected, average influence among unrelated commodity returns is generally negligible, except for the period of financial turmoil of 2007–2010. By contrast the influence of real price cycles tends to be highly significant over the whole sample period, even among unrelated commodities. These findings indicate that economic agents' perceiving all commodities as a sole asset class is essentially a short-term phenomenon linked to business cycles. Two extensions of this framework are discussed: macroeconomic determinants of commodity influence and portfolio investment decisions.

Introduction

Co-movement in commodity prices has been extensively analyzed since Pindyck and Rotemberg (1990)'s pioneering study about the persistence of the prices of largely unrelated commodities to move together. For instance, Cashin et al. (1999) utilized a measure of concordance (i.e., the proportion of time that the prices of two commodities are simultaneously in the same slump or boom period) to gauge co-movement in the seven unrelated commodities analyzed by Pindyck and Rotemberg.[2] The authors found no evidence of co-movement, and, hence, they ruled out the existence of irrational trading or liquidity constraints in commodity markets suggested by Pindyck and Rotemberg.[3]

More recent work by Lescaroux (2009) showed evidence of co-movement at the cyclical or short-term price components of 51 commodities during the period of 1980–2008. However, when focusing on oil and the London Metal Exchange metals, and after controlling for inventory level, Lescaroux concluded that the evidence in favor of excess co-movement was weak. In the same vein, Ai et al. (2006) found that there was no co-movement in agricultural commodity prices beyond what a partial equilibrium model, based on harvest and inventory information, could explain.

A very recent article, by De Nicola et al. (2014), analyzed the degree of co-movement among the nominal price returns of 11 major energy, agricultural and food commodities between 1970 and 2013. The authors concluded that the price returns of energy and agricultural commodities are highly correlated; that the overall level of co-movement among commodities increased in recent years, especially between energy and agricultural commodities, and that, after 2007, stock market volatility is positively associated with the co-movement of price returns across markets. Along this line of research, Natanelov et al. (2011) explored the co-movement of agricultural commodities futures and crude oil during July 1989 and February 2010, on the basis of an error correction model and threshold cointegration. The authors concluded that co-movement is a dynamic concept, and that crude oil exhibits strong linkages with wheat and cocoa. [4]

☆Funds from Fondecyt Grant No 1130003 are greatly acknowledged. The helpful comments of two anonymous referees contributed to improve upon an early version of this paper. The usual disclaimer applies.

E-mail address: viviana.fernandez@uai.cl

[1] http://www.uai.cl/docentes/viviana-fernandez-maturana

[2] These are cocoa, copper, cotton, gold, lumber, oil, and wheat. Pindyck and Rotemberg's approach consisted of correlating unrelated commodity returns after removing the variation explained by macroeconomic factors (i.e., fundamentals). Significant correlation was referred to by Pindyck and Rotemberg as excess co-movement.

[3] An article, by Deb et al. (1996), found much weaker evidence in favor of Pindyck and Rotemberg's study, after controlling for univariate- and multivariate-GARCH effects in commodity returns.

[4] Related research includes the article by Sieczka and Holyst (2009), who gauged correlations among commodity futures contracts by means of a minimal spanning tree, and the book chapter by Chevallier and Ielpo (2013), chapter 5, who analyzed the existence of long-term commodity cross-linkages on the basis of cointegration analysis.

http://dx.doi.org/10.1016/j.resourpol.2015.04.008
0301-4207/

Another strand of the literature on co-movement has focused on commodity cycles and super-cycles. For instance, Jerrett and Cuddington (2008) studied decades-long above-trend movements in the steel group (i.e., steel, pig iron, and molybdenum) and the six metals traded on the London Metal Exchange (LME6). The authors documented the existence of long cycles, with periodicity of 35–70 years, for the steel group, and the existence of co-movement among the first principal component of the steel and LME6 groups' super cycles.

More recently, Jacks (2013) analyzed real prices of 30 commodities over 160 years, and characterized long-term trends, medium-term cycles, and short-term boom and bust episodes. Specifically, and regarding super-cycles, Jacks concluded that these are punctuated by booms and busts which are historically pervasive and becoming more exacerbated over time. In Jacks' view, commodity booms and busts are key determinants of commodity price volatility, which in turn may influence growth in commodity exporting economies. This issue was also explored by Jacks et al. (2011).

This article analyzes the time dynamics of a global measure of co-movement of one commodity versus others called influence. This is a new statistical technique developed by Kenett et al. (2014)[5], who extracted the underlying relationships between stocks belonging to the United States, the United Kingdom, Japan, and India. The focus is the average influence of several commodities over the period of January 1968–December 2013, computed on the basis of nominal price returns and cyclical components of real prices.

The commodity categories under analysis are industrial and precious metals (i.e., aluminum, copper, lead, nickel, tin, zinc, gold, platinum, and silver); unrelated commodities as defined by Pindyck and Rotemberg (1990) (i.e., cocoa, copper, cotton, gold, oil, wheat, and logs); and, aggregate indices (i.e., metals & minerals, precious metals, energy, non-energy, agriculture, beverages, fats & oils, grains, other food, agricultural raw materials, and fertilizers).

The empirical results show that the average influence of nominal returns of industrial and precious metals and aggregate indices are statistically different from zero for most of the period of 1972–2013. In particular, since 2003 there is strong co-movement among the average influences of nominal returns of industrial and precious metals. This finding indicates a reduction in the benefits of portfolio diversification and convergence to a single asset class.[6]

On the other hand, and as expected, average influence among unrelated commodity returns tends to be insignificant, except for the period of financial turmoil of 2007–2010. During this time period, there was also a significant co-movement among aggregate indices, such as energy, fats & oils and metals & minerals.

When focusing on real price cycles, average influence tends to be highly significant over the whole sample period, even among unrelated commodities. These results suggest that economic agents' perceiving all commodities as a sole asset class is essentially a short-term phenomenon linked to business cycles. As an extension, this article concentrates on aggregate indices' average influence and their determinants. The empirical findings show that the term spread of interest rates, the volatilities of an aggregate commodity index and of the OECD industrial production, and the S&P 500 dividend yield capture some of commodity influence variation.

This article also discusses investment implications of the empirical findings by focusing on a well-diversified portfolio of commodities, corporate bonds, and stock shares. It is concluded that optimal commodity portfolio weights, derived by maximizing Conditional Value at Risk (CVaR), depend on the evolution of real price cycles and average commodity influence.

To the author's knowledge, this is the first study that quantifies co-movement of one single commodity with respect to the remaining commodities of a given class. Techniques usually utilized to measure co-movement involve some sort of bivariate correlation only: cross-section unconditional correlation, dynamic conditional correlation, and rolling unconditional correlation (see, for instance, De Nicola, De Pace, and Hernandez op cit.) In addition, this study contributes to the extant literature by exploring the potential financial/economic drivers of such global co-movement measure, and by deriving financial investment implications.

This article is organized as follows. Sections "Methodology" and "The data" respectively present relevant statistical and mathematical tools and the commodity price indices under analysis. Section "Empirical results" in turn discusses the statistical results of this study, while Section "Extensions" analyzes the macroeconomic determinants of commodity influence and discusses the usefulness of influence for guiding portfolio investment decisions. Finally, Section "Conclusions" closes by summarizing the main findings.

Methodology

Sections "Influence a global measure of co-movement" and "Cycles concordance" are aimed at measuring co-movement in the raw data and its short-term component. In particular, the concept of influence represents a global measure of co-movement of one asset return with respect to all others', after filtering out the effect of a market index (portfolio) return. Hence, influence gauges (net) co-movement in raw returns (Section "Influence: a global measure of co-movement").

One may also be interested in quantifying short-term asset price co-movement. To that end, a decomposition of each (real) price time series into a cycle and a trend (i.e., short- and long-term component, respectively) is called for. A widely used procedure to that end is Hodrick and Prescott (1997) filter (e.g., Lescaroux, 2009), which is nowadays canned in most econometric packages. In essence, the Hodrick–Prescott (HP) filter is used to obtain a smooth estimate of the long-term trend component of a series. Its cycle is subsequently obtained as the difference between the original series and its long-term trend.[7] Once price cycles have been obtained, it is possible to test for their concordance (Section "Cycles concordance").

Once co-movement has been gauged, it is natural to ask oneself about the economic/financial implications of its existence. By no means exhaustive, this article focuses on portfolio allocation on the basis of optimizing Conditional Value at Risk (Section "Conditional Value at Risk (CVaR)").

[5] A previous article along this line of research is Kenett et al. (2012).

[6] Two recent articles discussed these issues in the context of precious metals: Sensoy (2013) and Batten et al. (2010).

[7] Specifically, the HP filter computes a smoothed series, s, by minimizing the variance of the original series, y, around s, subject to a penalty that constraints the second difference of s: $\underset{s}{Min} \sum_{t=1}^{T} (y_t - s_t)^2 + \lambda \sum_{t=2}^{T-1} \{(s_{t+1} - s_t) - (s_t - s_{t-1})\}^2$The penalty parameter controls the smoothness of s. In their article, Hodrick and Prescott advise using a smoothing parameter based on the data frequency: $\geq$ 14,400, 1,600, and 100 for monthly, quarterly, and annual data, respectively. It is worth pointing out that the HP filter does not distinguish between super-cycles and other shorter cyclical components as Christiano–Fitzgerald band pass method discussed, for instance, by Jerrett and Cuddington (2008). Our aim is only to extract the cycle from the original series.