Futures trading and the excess comovement of commodity prices*

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Abstract

We reinvestigate the issue of excess comovement of commodity prices initially raised in Pindyck and Rotemberg (1990) and provide an explanation for this phenomenon. Excess comovement appears when commodity prices remain correlated even after adjusting for the impact of common factors. While Pindyck and Rotemberg and following contributions examine this issue using an arbitrary and limited set of control variables, we use recent developments in large approximate factor models so that a richer information set can be considered and "fundamentals" can be adequately modeled. We consider a set of 8 unrelated commodities along with 187 real and nominal macroeconomic variables from which 9 factors are extracted over the period 1993-2010. Our estimates provide evidence of a time-varying excess comovement, even if heteroscedasticity is controlled for, with a large increase these recent years. Two indices of trading activity used in the literature representing either speculative or hedging pressure in futures markets are able to explain around 30% of the correlation between residuals thus demonstrating the impact of financial markets on commodity price behavior.

JEL Classification: C22, C32, G15, E17

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1 Introduction

Commodity markets have undergone major changes during the last fifteen years. The popularity of commodity-related financial instruments, such as commodity indices, led many observers to consider that commodity markets were more deeply connected to financial markets. While more participants in commodity markets may induce a better risk sharing, the financialization process is also criticized for causing a socially undesirable commodity price volatility. Our purpose in this paper is to examine what has been the impact of the changes in futures trading in commodity markets on the excess comovement of commodities, a concept that will be defined in what follows.

We gather a large dataset of macroeconomic and financial variables from developed and emerging countries and rely on large approximate factor models to extract few principal components from these data. These factors are expected to represent the main forces driving commodities prices. They are used to filter out the returns of a set of 8 seemingly unrelated commodities and residual correlation is examined to investigate the issue of excess comovement. We show that excess comovement between commodity returns does exist in line with Pindyck and Rotemberg (1990). The use of many variables allows us to properly filter the original series thus rendering our results immune to the critic of an insufficient number of (or arbitrary selected) control variables. We show however that excess comovement is time-varying and significant during the last two financial crisis. More interestingly, we show that measures of trading activity are able to explain a significant part of this excess comovement. This provides evidence of the impact of speculative activity and hedging pressure, or more generally was has recently been coined as the "financialization of commodity markets", on commodity prices.

Commodity prices excess comovement is worth studying for several reasons. First, as noted in the seminal contribution of Pindyck and Rotemberg (1990), remaining correlation (or "comovement") may mean that "[...] commodity demands and supplies are affected by unobserved forecasts of the economic variable." (p. 1174). From a theoretical angle, and this is the second point, economists may also argue that the standard model of demand and supply is not sufficient enough to explain commodity returns. Third, if comovement exists and is strong enough, exporters countries may also find an interest in using commodity indexes as an additional hedging instrument beyond their initial interest in using futures and options on the commodity they export.[1]

Studying comovement of commodities is also particularly relevant for developing countries whose revenues sometimes heavily depend on one or two commodities (see Deaton, 1999). Borensztein

[1] See on the issue of exporters countries hedging using futures and options, Rolfo (1980), Larson *et al.* (1998) and the recent contribution by Borensztein *et al.* (2009).

et al. (2009, Table 2) provide recent estimates of the dependence of many developing countries on a very limited number of commodities for the period 2002-2007 using data from the IMF. Collier and Goderis (2007) even present commodities as the main opportunity for developing countries, providing evidence that commodity export foster growth more efficiently than international aid.[2]

The consequences of variations in the price of commodities can be dramatic for households of developing countries. Recent contributions use aggregate historical economic shocks as natural experiments to investigate the impact of commodity prices on human well-being. Edmonds and Pavcnik (2005) analyze the impact of trade liberalization on child labor. Kruger (2007) provide evidence of a significant impact of coffee prices on child labor and schooling in rural Brazil. Miller and Urdinola (2010) demonstrate a significant effect of coffee price variations on child mortality in Colombia. Cogneau and Jedwab (2012) also show that a number of human variables such as school enrollment, labor, height stature and morbidity significantly depend on cocoa price for households of Ivory Coast.

From a macroeconomic perspective, significant changes in commodity prices can be related to currencies and debt among others. Chen *et al.* (2010) provide evidence of the forecastability of commodity prices by commodity currencies (see Chen and Rogoff (2003) for an introduction to "commodity currencies"). The authors explain this phenomenon by the forward-looking feature of currency markets in comparison with commodity markets (even when derivatives are considered). Groen and Pesenti (2011) also show that commodity currencies help in predicting commodity prices beyond macroeconomic and financial variables.[3] Cashin *et al.* (2004) investigate whether "the real exchange rates of commodity-exporting countries and the real prices of their commodity exports move together over time" (p. 239). Arezki and Brückner (2010) show that the level of external debt is significantly reduced in democracies following commodity price shocks while no such effect is observed in autocracies.[4]

A significant amount of research in development economics has been devoted to the issue of the existence of trends in commodity prices and in particular the investigation of the Prebisch-Singer hypothesis of a secular deterioration in relative primary commodity prices (see Cuddington (1992), Kellard and Wohar (2006), Ghoshray (2011)). Our analysis interact with this literature in that the presence of comovement may well distort results from individual series analysis if not considered at the same time.

[2]Interestingly, Collier and Goderis (2012) show that while non-agricultural commodity booms have a positive impact in the short-run for countries with poor governance, the effect is reversed in the long-run.

[3]As in the present paper, the authors build a large dataset of macroeconomic and financial variables to extract common factors for a set of 10 commodity indices. The purpose of their paper is mainly to obtain forecast of commodity prices.

[4]See references therein for other contributions about the relationship between debt and commodity price shocks.

Considering that demand and supply factors are not able to fully explain common variations in commodity prices thus has microeconomic and macroeconomic consequences in developing countries and deserve further investigation. Improving our understanding of the relationship between commodity prices may help developing countries to hedge more accurately their physical position in financial markets thereby limiting the volatility of their revenues.[5]

The main novelty in our paper is that we suggest an *explanation* for the existence of an excess comovement and empirically demonstrate its relevancy. This issue has not been investigated in the literature so far except in Tang and Xiong (2011) but with a different methodology that we briefly describe below. Our explanation relies on the principle developed in Hong and Yogo (2012) that traders have limited absorption capacity towards any order flow thus providing a possible impact of trading activity variables, such as open interest, on returns. Therefore, if institutional traders invest large amounts in commodity indices, they simultaneously invest in many commodity futures and positions in these futures markets may be part of the explanation for a possible excess comovement in these markets.

Our trading activity variables are derived from traders' positions in commodity futures markets. These trading activity variables allow to explain a significant part of the residual correlation (once commodity returns have been filtered by common factors) and thus provide an explanation for the existence of commonalities beyond common factors. In fact, our investigation of the presence of an excess comovement may be partly viewed as a test of the price distortion due to the existence of commodity indices, what Tang and Xiong (2011) coin as "Financialization". We check this assumption by using two different measures of trading activity for the eight commodities of interest and show that the residual correlation is significantly related to these trading activity indices.

From a methodological point of view, examining the excess comovement issue is twofold.[6] Indeed, we are interested in answering the following question: are commodity prices moving together beyond what fundamentals explain? Then our first concern is on how to represent these "fundamentals"? In this paper we gather our own set of 187 real and nominal variables from developed and emerging countries and resort to factor models to sum up the information contained in these

[5]Additional issues related to the question of comovement of commodities are in the field of finance. Consider a hedger or an investor whose aim is to invest in some commodities with a strategy based on the analysis of supply and demand fundamentals. If excess comovement exists then such a strategy may be unrewarding on the ground of irrational behavior such as "herding" for instance. Similarly, from a portfolio management perspective, comovement would reduce diversification and make investment in commodity indexes relatively more interesting than using several futures contracts as investment vehicles. Viewed differently, it would also mean that investing in several commodity futures would not be as much interesting as it would without comovement. It should be noted that commodities have shown to have a very interesting pattern in terms of investment as shown by Gorton and Rouwenhorst (2006). The authors show using 23 years of data that commodities may be an hedge against inflation and are counter-cyclical.

[6]In Deb *et al.* (1996), the first issue which should be considered when dealing with excess co-movement question is the concept of "unrelated commodities". In the present paper, we choose similar commodities as in Pindyck and Rotemberg (1990) and Deb *et al.* (1996).

data by a manageable number of variables. These factors are expected to approximate the "fundamentals" factors driving commodity prices. Note that the issue of incomplete information was first discussed in Pindyck and Rotemberg (1990) in their conclusion.[7] (see also Leybourne *et al.* (1994) on this issue). As noted in Ai *et al.* (2006): "Taken together these studies seem to suggest that excess comovement hypothesis [ECH] is the artifact of econometric modeling, and if the right econometric model could be discovered, the evidence of excess comovements would disappear." (p. 574). Kallberg and Pasquariello (2008) also indicate how some latent factors[8] have been considered in the literature so far and obviate the problem of factor determination : "Indeed, the test for excess comovement is unavoidably also a test of the validity of the specification we use to control for fundamental comovement [...] (p. 488)".

Our second methodological concern is to obtain an unbiased measure of the filtered returns correlation. As shown by Forbes and Rigobon (2002), the usual sample correlation is a biased measure[9] of the true correlation when there is a change in volatility. As a bulk of our commodity returns are characterized by a time-varying volatility, we use a correlation coefficient corrected for heteroscedasticity following Forbes and Rigobon (2002) and Kallberg and Pasquariello (2008). We use a rolling window to estimate the unbiased correlation coefficient and detect change in the strength of excess comovement.

1.1 Related literature

The early contribution by Cooper and Lawrence (1975) is interested in the dramatic increase in commodity prices during the 1973-74 period. While all commodity prices did not increase exactly at the same time, they all reached their twenty-year or historical highs during this two-year period. Interestingly, the authors first raise the issue of comovement of commodity prices as follows: "Interesting tales can be told about many of the individual commodities – the special circumstances that led to the rise in prices and to the subsequent fall. Bad weather reduced harvests of many crops here and there around the world, labor disruptions curtailed mine output, several important materials-producing countries were subject to political unrest, newly rich Arabs were buying disproportionately large amounts, and so on. But the movement in commodity prices was quite general, and while these stories are intriguing and sometimes significant, they do not fill the need for

[7] The authors note: "Indeed, a major limitation of our approach is that we can never be sure we have included all relevant macroeconomic variables and latent variables." (p. 1185)

[8] The critics addressed by Wheatley (1989) to latent variables models (interpretability, etc.) could well be translated to factor models, but we believe that when the point is to aggregate information from a series of economic and financial variables, factors do a reasonable job and the fact that they could not be identified is of minor importance. Latent-factors models have been used in Bekaert and Hodrick (1992) and Pindyck and Rotemberg (1993) among others.

[9] It can be biased upward or downward depending on the whether volatility increases or decreases.

some general explanation – a common cause, or strong linkages among the commodities affected." (p. 672). After exploring the conventional demand-supply factors that could explain such a trend for commodity prices, the authors, as we do, investigate the "speculative" demand for commodities. Nevertheless, a limit to their empirical analysis is the lack of data about the speculative/hedging activity in futures markets.[10]

It appears reasonable to say that, while not the case for many concepts in economics, there is a kind of consensus on the definition of "excess comovement": comovement in excess of common effects of demand and supply determinants such as production indices, inflation, interest rates, etc. (Pindyck and Rotemberg, 1990). Such defined, comovement is a concept which may be confounded with contagion at first sight.[11] However, there is a significant difference between the two concepts. While excess comovement is defined as a remaining significant correlation once common factors are considered, contagion is defined as a significant increase in correlation following a shock in one market. Two remarks come at this point. First, most of the literature on contagion does not consider common factors or these factors are very simply defined.[12] This is a strong difference with the excess comovement literature where "excess" means "beyond common factors". Second, excess comovement does not need an increase in correlation to be observed but only a significant correlation most of the time or on average.

Nevertheless, one tool developed in the contagion literature will reveal useful for our purpose, namely the fact that sample correlation is biased upward or downward in a time-varying volatility environment. The argument is that a simultaneous increase (decrease) in the respective volatility of two variables will spuriously increase (decrease) their correlation if measured using the usual correlation. As such, Forbes and Rigobon (2002) suggested a correction that should be applied to usual sample correlation when heteroscedasticity is present.[13] In such an environment, standard correlation coefficient is misleading. Because our residuals will prove to exhibit heteroscedasticity, this correction will be necessary to evaluate properly comovement.[14] This correction has been applied recently in Kallberg and Pasquariello (2008) to examine excess comovement in sectoral indices in the US.

Another problem beyond heteroscedasticity is the selection of macroeconomic and/or financial vari-

[10] "A further indicator of the "speculative" behavior in 1973 and 1974 was the tremendous expansion of trading in futures in a wide range of commodities. [...] It is possible neither empirically nor conceptually to differentiate between pure speculation and hedging by users [...]" (p. 702). Indeed available data from CFTC about the relative positions of different kind of traders did not exist at this period.

[11] For a survey see Dungey *et al.* (2004).

[12] For instance, Chiang *et al.* (2007) use the US returns to filter their Asian time-series in investigating the recent Asian crisis.

[13] Similar results have been provided in Boyer *et al.* (1999) or Loretan and English (2000). Recently, Campbell (2008) provided similar analysis for the Student-t distribution.

[14] Cashin *et al.* (1999) use an interesting measure of concordance which is nonparametric, but due to the absence of macroeconomic variables in their analysis, defining excess co-movement is difficult.

ables to represent "fundamentals". In the original paper of Pindyck and Rotemberg (1990), 6 variables are selected.[15] These same variables are used in Deb *et al.* (1996). Gilbert (1989) emphasizes the impact of the exchange rates as an explanatory variable for commodity prices. To deal with the issue of omitted variables, we suggest to rely on large approximate factor model which allows to enlarge significantly the set of information while preserving a sufficiently low dimension for the econometric estimation. We thus avoid the arbitrariness of relevant variables and computational difficulties in wanting to select the right variables when the number of possible combinations is large. Borensztein and Reinhart (1994) point out the necessity to consider well-defined supply and demand variables in order to explain the evolution of commodity prices, at least for their time span (1970-1992). In particular, the authors advocate the inclusion of Eastern Europe variables to explain commodity prices. We also consider a larger set of macroeconomic variables, including a number of emerging countries, including Eastern Europe but also China, India or Brazil, and we assume that this will permit to filter out more relevantly our commodity returns. Indeed, despite commodity prices are the product of transactions in one particular place in the world, they are also the outcome of an order flow coming from many regions worldwide and from investors making some arbitrages with other financial places. As such, the price of crude oil, say the U.S. WTI, is a world price.

A recent interest in commodities has emerged in the economic literature, which draws some conclusions about the usefulness of commodity prices for forecasting financial variables. Part of this literature rely on CFTC data to investigate the role of speculative/hedging activity for various purposes. In the present paper, we also rely on these data to infer different measures of trading activity which are likely to explain the residual correlation between commodity returns.

Hong and Yogo (2012) rely on CFTC data to investigate the informativeness of open interest data for forecasting commodity returns as well as, and it is far more surprising, bond, currency and stock returns. Driesprong *et al.* (2008) show that changes in oil prices are able to predict stock market returns[16] for both developed and emerging countries, a result revivified in Hong and Yogo (2012) using trading data. More recently, Acharya *et al.* (2010) establish a relationship between the default risk of energy producers and energy futures returns. Because the default risk can be viewed as a measure of hedging demand, Acharya *et al.* (2010) show the impact of trading variables on returns. Gospodinov and Ng (2010) provide evidence that the first principal component in a large panel of commodity convenience yields has statistical predictive power for inflation in

[15] These variables are the US index of industrial production, the consumer price index, the effective US $ exchange rate, the three-month Treasury bill interest rate, M1 and the S&P stock index.

[16] See also Pollet (2004) for an earlier unpublished contribution.

developed countries. Interestingly, these principal components, which explain commodity prices, are correlated with economic conditions in the U.S. and the fast growing economies, notably India and China (Gospodinov and Ng, 2010). The convenience yields can thus be seen as informational variables about future demand as conveyed by the futures markets.

The paper closest to ours is Tang and Xiong (2011), which investigate the financialization process of commodity markets as a potential source of the dramatic rise and fall of 2008 commodity (and in particular crude oil) prices. With a very different methodology to ours, Tang and Xiong (2011) provide evidence of an increase in comovement of commodity prices in recent years.[17] Their "analysis focuses on connecting the large inflow of commodity index investment to the large increase of commodity price comovements in recent years by examining the difference in these comovements between indexed and off-index commodities."[18] (p. 3) This increase in correlation may be due to the dramatic increase of commodity index-related investment assets purchased by investors, from a low \$ 15 billion in 2003 to a large \$ 200 billion in mid-2008 (cf. Tang and Xiong (2011), p. 2).[19] However, the research strategy in Tang and Xiong (2011), who regress the S&P-GSCI on a measure of the net position change for different categories of traders, suffers from ignoring common factors that could affect the behavior of most if not all commodity prices. Tang and Xiong (2011) also investigate the impact of emerging economies on the comovement of commodity prices using novel time series of Chinese futures prices which are available since late 1990s. Interestingly, while U.S. commodity prices exhibit pronounced cycle, this is not the case for Chinese prices of similar commodities, thereby raising "doubt about commodity demands from China as the driver of all commodity prices in the US." (p. 15). Our estimates of principal components explaining commodity prices show that the demand from large emerging economies does play a role in shaping the prices of U.S. commodity futures prices while leaving a large place for other factors, the explanatory power of our regressions remaining limited for most of the commodities.

1.2 Main contributions

We think that our paper adds several novelties to the issue of the comovement of commodities.

First, we use the large approximate factor model methodology to uncover the relevant factors that

[17]Note that the authors consider a different set of commodities and a slightly shorter period than ours.

[18]Their research question builds on Barberis, Shleifer and Wurgler (2005) which analyzes theoretically and empirically the behavior of newly-included stocks in a stock index. It is shown that the price comovement between the stock and the index significantly increases after the inclusion.

[19]The large increase in commodity investment is know to have two different while related sources. First, commodities may be used to reduce the risk in a diversified portfolio and, second, commodity may provide interesting returns (see Gorton et al., 2007) in periods of lower returns in more classical financial markets such as bonds and stocks. In addition, investing in commodities is shown to be an efficient hedge against inflation.

allow to explain commodity returns. To our best knowledge, this is the first time that this methodology is used to filter out returns before analyzing comovements.[20] The main advantage of consider factors is that it allows to deal with a large number of variables while maintaining econometric tractability thereby including a richer information set in what we would call "fundamentals". Hence, we avoid to limit artificially the information set, which has been an important limit in previous contributions. As a byproduct of our analysis, we uncover factors that best explain the commodity returns and provide an interpretation of these factors based on the idea of Ludvigson and Ng (2009).

Our second contribution is to offer an explanation to the existence of excess comovement in commodity returns. Previous contributions have used different methodologies to assess the presence or the absence of excess comovement but did not consider the cause of the phenomenon. Our indicators of trading activity computed using traders' positions available from the CFTC work particularly well in explaining the residual correlation (our measure of comovements) and thus help to highlight a possible source of the comovement that we observe between seemingly unrelated commodities. We observe that the variations in trading activity by both speculators and hedgers are highly correlated with our measure of excess comovement thereby indicating the strong role of financialization and demand by investors for commodities as a new asset class.

1.3 Plan of the paper

The plan for the rest of the paper is as follows. In the next section, we present the data used for the empirical implementation. In section 3, we very briefly review the factor model methodology and compute the factors then used to filter commodity returns. Excess co-movement is the evaluated in section 4 while section 5 is dedicated to the analysis of the relation between excess co-movement and excess comovement. Section 6 concludes by providing some limits and possible further extensions of our analysis.

2 Data

Our data are a set of commodity prices and another one of macroecononomic variables used to estimate factors. All data are extracted from DataStream. We consider 8 commodities which are

[20] Interestingly, the methodology may easily be extended to the analysis of contagion episodes, thereby taking into account the information from a possibly very large number of variables before focusing on contagion channels.

unrelated[21] at first sight: wheat, copper, silver, soyabeans, raw sugar, cotton, crude oil, pork bellies. They are representatives of the main classes of commodities. All prices are cash prices except for crude oil for which the current month contract price is taken as a proxy for the cash price. All prices are nominal prices in US \$. Because we do want to include crude oil in our data set and many of our macroeconomic variables are only observed at a monthly frequency, we thus consider monthly observations from 1993:03 to 2010:03.

Returns are computed as the log difference of prices. Prices and returns are respectively displayed in Figures 1 and 2. Except for cotton and pork bellies, the price pattern is rather similar for the other 6 commodities: a first increase in prices during year 1996 is followed by a larger one in year 2008. This last increase has raised much concern on the running of commodities markets. Returns also tend to be more volatile at the end of our sample. Some usual descriptive statistics for returns are reported in Table 1. They show evidence of skewness and excess kurtosis and the Jarque-Bera test rejects accordingly the hypothesis of a Gaussian distribution for most returns. Some heteroscedasticity present in the data may explain non-normality. Table 2 show the sample correlations for returns and their associated p-values. There are respectively 17, 16 and 11 significant correlations at the 10%, 5% and 1 % critical levels. These significant correlations range from 0.4438 (wheat and soya) to 0.1268 (pork bellies and soyabeans).[22] Their average value is 0.239. Interestingly, note that crude oil returns are not correlated with wheat, soya and raw sugar returns. Therefore the interactions between oil and agricultural commodities alleged by the development of ethanol is not apparent in our data. Our aim is to analyze whether these correlations derive from a common set of variables. If some residual correlations remain significant, we will conclude in favor of an excess comovement.

To compute factors, we gather 187 real and nominal macroeconomic variables from developed and emerging countries. The composition of this data set with a short description is given in appendix. Our database differs from Stock and Watson (2002b) and Ludvigson and Ng (2007, 2009) datasets, which are mainly representative of the U.S. economy and therefore not well-suited for our purpose. Our dataset contains variables from developed (128 variables) as well as emerging countries (59 variables from China, Brazil, Korea, India, Indonesia, etc.) which are significant players in the world economy. More specifically, they often are large importers of commodities and their rapid growth may have a significant impact on the world price of these commodities. The whole dataset can be separated into 103 real variables (73 for developed countries and 30 for emerging countries)

[21] These prices are unrelated in the sense that their supply or demand cross-elasticities are almost equal to zero.

[22] Pindyck and Rotemberg (1990) obtain a maximum of 0.322 and a minimum of 0.113 and an average value of 0.161 for significant correlations for the time period 04:1960-11:1985. With great caution, we could infer that correlation between commodities return has increased through time.

and 84 nominal variables (55 for developed countries and 29 for emerging countries). Each variable is stationarized in a proper way as described in the appendix.

3 Filtering commodities returns using large approximate factor model

3.1 Static factors computation

We use the static factor model[23]. We dispose of a sample $\{x_{it}\}$ of $i = 1, ..., N$ cross-section units and $t = 1, ..., T$ times series observations. Each x_{it} is split into a component depending on a set of $r << N$ common factors $F_t = (f_{1t}, f_{2t}, ..., f_{rt})'$ and an idiosyncratic e_{it} part:

$$x_{it} = \lambda_i^{'} F_t + e_{it}$$

where λ_i is the $(r \times 1)$ factor loading.

Let $X_t = (x_{1t}, ..., x_{Nt})'$, $e_t = (e_{1t}, ..., e_{Nt})'$ be the $(N \times 1)$ vectors of observations and idiosyncratic components at date *t* and $\Lambda = (\lambda_1, ..., \lambda_N)'$ the $(N \times r)$ matrix of factor loadings, we have the vector form notation:

$$X_t = \Lambda F_t + e_t$$

If we assume that F_t and e_t are uncorrelated and have zero mean and make the normalisation $E(F_t F_t') = I_d$, we have:

$$\Sigma = \Lambda\Lambda' + \Omega$$

where Σ and Ω respectively denote the population covariance matrices of X_t and e_t. Let $X = (X_1, X_2, ..., X_T)^{'}$ and $e = (e_1, e_2, ..., e_T)^{'}$ be respectively the $(T \times N)$ matrices of observations and idiosyncratic components and $F = (F_1, F_2, ..., F_T)^{'}$ is the $(T \times r)$ matrix of factors, a representation of the model for all dates is:

$$X = F\Lambda^{'} + e$$

As the factors F and the loading matrix Λ are not separately identifiable[24], constraints are imposed to obtain a unique estimate.

In classical factor analysis, F_t and e_t are assumed to be serially and cross-sectionally uncorrelated

[23] We draw on the notation of Bai and Ng (2008) survey on large approximate factors models.
[24] See for instance Bai and Ng (2008) for more details.

and the number of units of observation N is fixed. Stock and Watson's (2002a,b) "large dimensional approximate factor models" differs from the classical model in two ways: the idiosyncratic errors are allowed to be "weakly correlated" across i and t [25] and the sample size tends to infinity in both directions.

We assume k factors and use the principal components method to estimate the $(T \times k)$ factors matrix F^k and the corresponding $(N \times T)$ matrix Λ^k loadings. The estimates solve the following optimization problem:

$$min\, S(k) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \lambda_i^{k'} F_t^k)^2$$

subject to the normalization $\Lambda^{k'} \Lambda^k / N = I_k$.

This classical principal component problem is solved by setting $\hat{\Lambda}^k$ equal to the eigenvectors of the largest k eigenvalues of $X'X$. The principal components estimator of F^k is:

$$\hat{F}^k = X' \hat{\Lambda}^k / N$$

Computation of $\hat{F}^k$ requires the eigenvectors of the $(N \times N)$ matrix $X'X$. When $N > T$, a computationally simpler approach uses the $T \times T$ matrix XX'.

Consistency of the principal component estimator as $N, T \rightarrow \infty$ has been demonstrated by Stock and Watson (2002a) and Bai and Ng (2002). Bai (2003) shows that the factors and loadings estimates have asymptotic normal distributions.

To conclude this section, note that we only apply the static factor model of Stock and Watson (2002a) and do not resort to the dynamic method of Forni *et al.* (2005). A first reason is that the static factor model allows us to estimate the factors needed to filter returns in a much simpler way. Besides, Boivin and Ng (2005) and D'Agostino and Giannone (2012) showed that the dynamic and the static factor model have equivalent performance especially when the dynamics of factors is unknown which is our case.

3.2 Estimating the number of factors

Bai and Ng (2002) proposed two kinds of information criteria to select the number of common factors. If we note $\hat{S}(k) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \hat{\lambda}_i^{k'} \hat{F}_t^k)^2$ the sum of squared residuals (divided

[25] Although Forni *et al.* (1999) and Stock and Watson (2002a) use different sets of assumptions to characterize "weak correlations", the main idea is that cross-correlations and serial correlations have an upper bound.

by NT) when k factors are estimated, these information criteria have the following expressions:

$$\begin{aligned} PCP_i(k) &= S(k) + k\bar{\sigma}^2 g_i(N,T) \\ IC_i(k) &= ln(S(k)) + kg_i(N,T) \end{aligned}$$

where $g(N,T)$ is a penalty function[26] and $\bar{\sigma}^2$ is equal to $S(k_{max})$ for a pre-specified value k_{max}. The estimated number of factors $\hat{k}$ minimises the aforementioned information criteria.

We also apply the sequential test by Kapetanios (2010) to determine the number of factors. This test is based on the property that if the true number of factors is k_0, then, under some regularity conditions, the first k_0 eigenvalues of the population covariance matrix Σ will increase at rate N while the others will remain bounded. If we denote by $\hat{\lambda}_k, k = 1, ..., N$ the N eigenvalues of the sample covariance matrix $X'X$, the difference $\hat{\lambda}_k - \hat{\lambda}_{k^{max}+1}$ will tend to infinity for $k = 1, ..., k_0$ but remain bounded for $k = k_0 + 1, ..., k_{max}$ where k_{max} is some finite number such that $k_0 < k_{max}$. The null hypothesis that the true number of factors k_0 is equal to k ($H_{0,k} : k_0 = k$) against the alternative hypothesis ($H_{1,k} : k_0 > k$) is therefore tested with the test statistics $\hat{\lambda}_k - \hat{\lambda}_{k^{max}+1}$. If there is no factor structure, $\hat{\lambda}_k - \hat{\lambda}_{k^{max}+1}$ properly normalized by a sequence of constant $\tau_{N,T}$ should converge to a law limit. In the presence of factors, it should tend to infinity. The law limit as the rate of convergence $\tau_{N,T} \to \infty$ have to be estimated by resampling technique. The test is sequential. In a first step, we test ($H_{0,k} : k_0 = k = 0$) against ($H_{1,k} : k_0 > 0$). If we reject the null hypothesis, then we consider the null ($H_{0,k} : k_0 = k + 1 = 1$). We stop once we cannot reject the null hypothesis. Kapetanios (2010) called this algorithm the MED (maximal eigenvalue distribution) algorithm.

The estimated[27] numbers of factors are displayed in Table 3. There is clearly no agreement on the optimal number of factors. This result is similar to previous empirical studies, which show that there is a great instability in determining the correct number of factors[28]. According to the information criteria by Bai and Ng (2002), the optimal number of factors runs from the 2 to 9. The sequential test by Kapetanios (2010) returns a number of factors equal to 2. Additional information on the autocorrelation and the explanatory power of the estimated factors $\widehat{F}_t$ are displayed in Table 4. The first 3 factors only explain 20% of the variance of the 187 time series, while we reach 36% with 9 factors. Hence, we choose to consider the set of the first 9 factors as potential set of regressors. Factors' autocorrelations (up to 3 lags) provided in Table 4 show that most of them are

[26] Penalty functions suggested by Bai and Ng (2002) are: $g_1(N,T) = \frac{N+T}{NT} ln(\frac{NT}{N+T})$, $g_2(N,T) = \frac{N+T}{NT} ln(C^2_{NT})$, $g_3(N,T) = \frac{ln(C^2_{NT})}{C^2_{NT}}$, $g_4(N,T) = (N+T-k)\frac{ln(NT)}{NT}$

[27] We use the Matlab routine provided by Ng for the estimation and information criteria. The Kapetanios test routine is ours.

[28] See for instance the empirical applications in Kapetanios (2010) which show that there may be some variations in the estimations of the number of factors according to the selection criterion.

persistent.

3.3 Modelling commodity returns

Our next step consist in modelling commodity returns with the estimated factors. We accept excess comovement if commodity returns remain correlated even after controlling for the contribution of selected factors.[29] We consider several specifications. The first one is the linear regression of returns on the first three factors:

$$\begin{aligned} r_{it} &= \alpha_i + \sum_{k=1}^{3} \beta_{ik} \widehat{F}_{k,t} + u_{it} \qquad i = 1, ..., 8 \quad t = 1, ..., T \\ &= \alpha_i + \beta_i^{'} \hat{F}_t + u_{it} \end{aligned}$$

where r_{it} represents the $i^{th}, i = 1, .., 8$ commodity return at date t, α_i is a constant, β_i is the vector of factor coefficients for the i^{th} commodity and $\hat{F}_t = (\widehat{F}_{1,t}, \widehat{F}_{2,t}, \widehat{F}_{3,t})'$ the vector of the three selected factors at date t.

The set of the eight commodity returns equations are a SUR estimator.[30] Results are reported in Table 5. The explanatory power measured by R^2 varies from 1.24% for pork bellies to 23.47% for copper. Factors $\widehat{F}_1$ and $\widehat{F}_2$ are significant in most regressions except raw sugar and pork bellies. We obtain a higher R^2, except for raw sugar and pork bellies, than Pindyck and Rotemberg (1990). This could be attributed to using factors computed from a large dataset. Our results for agricultural commodities returns do not substantially differ from those obtained by Pindyck and Rotemberg (1990).[31] The ARCH-LM test provides evidence of a time-varying volatility for 5 residuals which will have some consequences on the estimation of residual correlation as exposed beneath.

[29] Since factors will be used as regressors to compute the spillover index, the sampling uncertainty associated with the estimation of principal components has to be considered. Following Ludvigson and Ng (2007, p. 178), we first proceed as if factors were observed in view of asymptotic theory in the case of a large panel with $N, T \to \infty$ and $\sqrt{T}/N \to 0$.As indicated in the concluding section, we also can relax this assumption and use bootstrap inference as in Gospodinov and Ng (2010, section 4) and Ludvigson and Ng (2010) to deal with the issue of estimation uncertainty.

[30] As regressors are identical, it amounts to OLS equation by equation.

[31] We then consider possible nonlinearities by assuming that factors can enter the regression in their quadratic or cubic form. We choose the specification which gives us the higher sum of $\bar{R}^2$. The set of factors is now $\bar{F}_t^{nl} = ((\widehat{F}_{1,t}, \widehat{F}_{2,t}, \widehat{F}_{3,t}, \widehat{F}_{4,t}, \widehat{F}_{2,t}^3, \widehat{F}_{4,t}^3)')$ and our set of regressions becomes :

$$\begin{aligned} r_{it} &= \omega_i + \sum_{k=1}^{4} \gamma_{ik} \widehat{F}_{k,t} + \omega_{i,5} \widehat{F}_{2,t}^3 + \omega_{i,6} \widehat{F}_{4,t}^3 + u_{it} \qquad i = 1, ..., 8 \quad t = 1, ..., T \\ &= \omega_i + \gamma_i^{'} \bar{F}_t^{nl} + v_{it} \end{aligned}$$

Results of the specification we retained are not reported here but available upon request. We observe that the explanatory power of our factors remains rather low except for crude oil and to a lesser extent copper. Introducing factors in a nonlinear way improves slightly the explanatory power of the regressions. Therefore the coefficients of determination in our regressions are of the same order than in Pindyck and Rotemberg (1990).

In our second strategy, we consider all possible combinations of the 9 estimated factors and select the regression which minimizes the BIC criterion[32] for each commodity. Once regressors are selected, we jointly estimate the full set of regressions with a SUR estimator. By doing so, we aim to find the best model from a set of common regressors for each commodity returns. This approach is intended to eliminate as much as possible residual correlation, hence strengthening our evidence of excess comovement if any. Estimates are displayed on Table 6. Results are similar as those obtained with the first three factors, even if we can observe some improvement for crude oil, sugar and pork bellies. As previously, the ARCH-LM test rejects the null hypothesis of a constant variance for 5 residuals.

As already noticed, $\widehat{F}_1$ and $\widehat{F}_2$ are significant and with the same sign for almost all commodities, except cotton and pork bellies. Even if factors are not identifiable as mentioned in section 3.1, Ludvigson and Ng (2009) suggest a simple method to give them an economic interpretation. In practice, each original variable is regressed on a single factor to measure the correlation between the former and the latter. After sorting the variables along the horizontal axis (say, beginning with real variables and then with nominal variables), it is graphically possible to show the variables for which the highest R^2 are obtained. The factor can then be considered as representative of this set of variables. We separate our 187 series into developed countries/emerging countries and within each of the previous categories between real and nominal variables. A finer classification would be difficult to illustrate and is relevant, in our opinion, only when a single country is at play.[33]

Figures 4 display the R^2 for factors $\widehat{F}_1$ and $\widehat{F}_2$. $\widehat{F}_1$ can be interpreted as a real factor as it records its highest explanatory power for real variables. More precisely $\widehat{F}_1$ is mostly correlated with real variables from emerging countries. The correlation of $\widehat{F}_1$ with crude oil and copper returns can be interpreted as a new evidence of the growing role played by emerging countries in shaping these commodities prices. China is for instance known as an important importer of copper and heating oil. This finding corroborates the rather weak support of previous studies (e.g. Hamilton (2009), Kilian and Murphy (2012) and the survey in Fattouh *et al.* (2012)) to the hypothesis that oil prices are mainly driven by speculative activity rather than by real supply and demand variables.[34] Our results are also in line with Vansteenkiste (2009) which emphasizes the role of demand, including the demand from emerging countries, for commodities in explaining the common factor estimated by the author to explain non-fuel commodity prices. To confirm our conclusions, $\widehat{F}_1$ is neither

[32] Stock and Watson (2002) and Ludvigson and Ng (2009) proceed the same way.

[33] Ludvigson and Ng (2009) rely indeed on a finer classification, but they only use US variables. We do not think that this methodology is applicable when several economies are considered if we want to preserve some interpretability.

[34] Kilian and Lewis (2011) further highlight the endogeneity of the real price of oil which has strong implications for the design of relevant monetary policy.

significant for sugar, silver or pork bellies, that is commodities for which the demand from emerging countries creates less tensions.

The interpretation of $\widehat{F}_2$ is less obvious. $\widehat{F}_2$ is highly correlated with a small number of real variables but its explanatory power for interest rates, producer and consumer price indices and monetary aggregates of developed as well as emerging countries is higher than for $\widehat{F}_1$. This leads us to interpret $\widehat{F}_2$ as representative of these latter variables. The correlation of $\widehat{F}_2$ with commodity returns is known to follow several classical channels. Interest rate affects demand for commodities through its impact on aggregate demand and macroeconomic equilibrium. In addition, as argued in Frankel (2006): "[...] a negative effect of interest rates on the desire to carry commodity inventories." seems to exist. The price indices and the monetary aggregates account for the effect of inflation on commodity prices.

Taken together, our results support the findings that demand from emerging economies is partly responsible for the price increase of some commodities in the recent period. Our estimations show, however, that this effect only applies to commodities that are input into the industrial process of production and to transport. Furthermore, we also find an effect of interest rate and variables related to inflation rates on some commodity returns.

4 Testing for commodity returns excess comovement

4.1 Conditional comovement

Residuals from previous regressions represent commodity returns once "fundamentals" have been adjusted for, and because we considered fundamentals through factors, we assume that they are taken into account in the most relevant way. We first evaluate residuals correlation as in Pindyck and Rotemberg (1990). Sample correlations (in the upper triangular matrix) with their p-values [35] (in the lower triangular matrix) are respectively reported in Tables 7 and 8 for residuals from the 3 factors and BIC linear filtration.

Results are quite similar for both regressions and confirm the excess comovement hypothesis. We find 7, 9 and 14 significant correlations at 1%, 5% and 10% for the three factor regressions. For the BIC selected regressions, 6, 13 and 14 correlations are respectively significant at 1 %, 5 %, and 10 %. The Breusch-Pagan LM test rejects the null hypothesis of no residual correlation in both cases.

[35] The p-value is computed by transforming the correlation $\hat{\rho}$ to create a t statistic having $T-2$ degrees of freedom, where T is the number of observations.

These correlations range from 0.4293 (wheat and soyabeans) to 0.1189 (silver and raw sugar) in Table 7 and are quite the same in Table 8. The level of residual correlation remains therefore quite substantial. Compared to raw returns correlations displayed in table 2, only two correlations (silver and crude oil, cotton and crude oil) become insignificant after adjusting returns for common factors.

4.2 Correction for heteroscedasticity

In a second step, we proceed as in Kallberg and Pasquariello (2008) to deal with residual time-varying volatility.[36] The main idea is to correct sample correlation for the bias induced by change in volatility using Forbes and Rigobon (2002) estimator.[37] Applied on a rolling window, this estimate is able to track the true conditional correlation and its variation through time.[38] The estimate is non-parametric and obviates the mean-reversion problem inherent in the DCC parametric approach. As noted in Kallberg and Pasquariello (2008), financial literature offered a number of examples where rolling filters do perform well in comparison with more elaborate parametric specifications (see Bauwens *et al.* (2006) for a recent survey of multivariate GARCH models and Asai *et al.* (2006) for a survey of stochastic volatility models).

4.2.1 A nonparametric estimation of correlation

We use the residuals $\{\hat{u}_{i,t}\}$ from each commodity returns' conditional mean equation to compute for each pairs of non redundant returns $i \neq j$ the excess comovement measured by the residuals correlation:

$$\hat{\rho}_{ij,t} = \frac{cov(\hat{u}_{i,t}, \hat{u}_{j,t})}{[var(\hat{u}_{i,t})var(\hat{u}_{j,t})]^{1/2}}$$

Boyer *et al.* (1999), Loretan and English (2000) and Forbes and Rigobon (2002) show that sample correlation $\hat{\rho}_{ij,t}$ is biased in case of change in volatility. $\hat{\rho}_{ij,t}$ is therefore named *conditional* correlation. Hence, in the presence of heteroscedasticity, it is not an adequate measure of excess comovement. The aforementioned authors propose a correction for this bias and define an *unconditional* correlation measure for each pair of returns under the assumption of no omitted variables or endogeneity. We employ their unconditional correlation as a measure of excess comovement. The

[36] This is an issue in Pindyck and Rotemberg (1990) contribution which has been considered further in Deb *et al.* (1996) by means of a multivariate GARCH model in its BEKK form (Engle and Kroner, 1995).

[37] Dufour and Khalaf (2002) propose a test for contemporaneous correlation in SUR regression. However their test doesn't accommodate time-varying volatility.

[38] Tang and Xiong (2011) also correct correlation for time-varying volatility using Forbes and Rigobon's (2002) method but only with a limited (insignificant) impact on their estimate.

unconditional correlation is defined as:

$$\hat{\rho}^*_{ij,t} = \frac{\hat{\rho}_{ij,t}}{[1 + \hat{\delta}_{i,t}(1 - (\hat{\rho}^2_{ij,t})]^{1/2}}$$

where the ratio $\hat{\delta}_{i,t} = \frac{var(\hat{u}_{i,t})}{var(\hat{u}_{i,t})_{LT}} - 1$ corrects the conditional correlation $\hat{\rho}_{ij,t}$ for the relative difference between the i^{th} return short-term $var(\hat{u}_{i,t})$ and the long-term volatility $var(\hat{u}_{i,t})_{LT}$. As we don't make any *ex ante* assumption on the direction of propagation of shocks from one commodity to another, we alternatively assume that the source of these shocks is asset i (in $\hat{\rho}^*_{ij,t}$) or asset j (in $\hat{\rho}^*_{ji,t}$). Therefore, the two unconditional correlations $\hat{\rho}^*_{ij,t}$ and $\hat{\rho}^*_{ji,t}$ can be different.

As suggested by King *et al.* (1994) and Kallberg and Pasquariello (2008), we compute the arithmetic means[39] of pairwise squared adjusted correlations coefficients for each commodity i. As we are interested in excess comovement of commodity returns, we consider that a non-null unconditional correlation $\hat{\rho}^*_{ij,t} \neq 0$ and $\hat{\rho}^*_{ji,t} \neq 0$ whatever its sign is an evidence of excess comovement between commodities i and j beyond what is implied by their fundamentals. To prevent the correlation coefficients to cancel each other, we use the mean of excess square correlations as a measure of excess comovement:

$$\hat{\rho}^*_{i,t} = \frac{1}{K-1} \sum_{j=1, j\neq i}^{K} (\hat{\rho}^*_{ij,t})^2$$

for all commodity returns $i = 1, ..., K$ where $K = 8$ is the number of commodities. We finally compute a global measure of excess comovement as the mean of excess square correlation coefficients for all commodities:

$$\hat{\rho}^*_t = \frac{1}{K} \sum_{i=1}^{K} \hat{\rho}^*_{i,t}$$

In this paper, we treat the covariance matrix of returns residuals as observable and construct a time series of rolling realized excess square correlations for each commodity i. We estimate $\hat{\delta}_{i,t}$ and $\hat{\rho}^*_{i,t}$ over short-term and long-term intervals of the data of fixed length *N* $[t - N + 1, t]$ and *gN* (with $g > 1$) $[t - gN + 1, t]$.

4.2.2 Empirical results

We use a rolling windows of *N*= 30 observations for short-term volatilities and *gN* = 60 observations for long-term volatilities. We compute three average of squared correlations . The first one is a the average value of squared unconditional returns correlation: $\hat{\rho}^*_{ret,t} = \frac{1}{K}\sum_{i=1}^{K} \hat{\rho}^*_{ret\,i,t}$ where

[39] Peña and Rodríguez (2003) propose to use $1- \mid \Gamma \mid^{1/N}$ where Γ is the correlation matrix of N variables as a measure of multivariate linear dependence. However, as we have two heteroscedasticity corrected correlation, we did not apply their criterion.

correlations are computed for returns. The second one is the average value of squared conditional residual correlation: $\hat{\rho}_t = \frac{1}{K}\sum_{i=1}^{K}\hat{\rho}_{i,t}^2$. In that case, we use estimated residuals (after filtration by factors) but do not correct sample correlation for change in volatility. The last indicator is the average squared unconditional correlation $\hat{\rho}_t^*$ as previously defined. These average correlations are displayed in Figure 3 which is in the same vein as the correlation plot in Tang and Xiong (2011). Table 9 gives some summary statistics on average returns and residual squared correlations. Their mean value are above the 5 % percent significance level. These measures of correlation are significant in almost 60 % of the time periods considered and both measures are highly correlated.

The first conclusion is that filtering raw returns reduces somewhat returns correlation in spite of the rather low explanatory power of the regressions. This property is observed during the two periods where our index of correlation is significant. This is a strong indication that increases in correlation may be due to common factors. This is also an important result since Pindyck and Rotemberg (1990) as it shows that time-varying excess comovement and not only unconditional comovement has to be considered in light of the time-varying nature of macroeconomic and financial variables.

Secondly, the unconditional average squared residuals correlation is lower that the conditional one, which stresses the need for correcting the effect of change in volatility. It demonstrates that we should be cautious about looking for excess comovement in financial time series because the sample correlation coefficient may overestimate excess comovement and lead to a spurious excess comovement.

More importantly, our central conclusion is about the timing of excess comovement. Returns, as well as residuals, correlation indices are significant during two periods of financial crisis: from 2000 to 2004 and after the beginning of 2008. In these periods, commodity markets are no more isolated from financial markets. This feature contrasts sharply with Gorton and Rouwenhorst (2006) who show that the correlation between commodities returns and the S&P 500 was negligible before the beginning of the 2000s. We note that the more severe the financial crisis, the higher residuals correlation. This relation can be explained by the fact that commodities can be used as a mean of diversifying portfolios. As reminded by Tang and Xiong (2011), the finding of a negative correlation between commodities returns and stock returns (see Gorton and Rouwenhorst (2006) among others) has given an incentive to include commodities into portfolio assets classes. Hence, a negative shock on stocks market could trigger a rebalancing strategy from stocks to commodities inducing a commodity returns excess comovement. This may also be a simple flight-to-quality phenomenon where low returns in classical financial markets lead to increase the share of alternative assets in portfolios.

We now turn to our proposed explanation for the residual correlation between commodity returns.

5 Explaining the excess comovement

In this section, we offer an explanation for the residual correlation between commodities after filtration by our factors. We use regression analysis where the endogenous variable is the previously estimated residual correlation and the explanatory variable is a measure of trading activity derived from traders' positions publicly available from the CFTC. We use two different measures of trading activity suggested in the finance literature (see below).

This research is related to Tang and Xiong (2011) which is also an attempt to explain the recent increase in comovement found in a number of commodity prices. Among the possible reasons for a comovement, these authors suggest five hypothesis: (i) the financialization of commodities, (ii) the rapid growth of emerging economies, (iii) the recent world financial crisis, (iv) inflation and (v) the adoption of biofuels. In the present section, we test for the first hypothesis while having considered the second one in the previous sections. Indeed, we showed that the growth in emerging economies could be considered as a common factor leading commodity prices and as such as a factor explaining comovement. We are now interested in *excess* comovement, i.e. what remains when commodity returns have been optimally filtrated using principal components.

As previously exposed commodities markets have become more connected with financial markets since the beginning of the 2000s. These tighter links could be beneficial to commodity hedgers as more investors would facilitate and reduce the cost of commodity price risk sharing. However, this positive effect is balanced by the greater sensitivity of commodities markets to shocks originated on financial markets.

The idea behind the potential impact of trading activity on commodity prices is that large institutional investors may go beyond the normal absorption capacity of other market participants (speculators, hedgers) thereby influencing commodity prices when their investment capacity increases. This is the main idea behind Hong and Yogo's (2012) contribution.[40] We investigate the link between the estimated excess comovement and trading activity measures because we believe that

[40]"If there is excess hedging demand from producers that want to be short futures, the futures price will fall due to limited arbitrage by speculators.Conversely, if there is excess hedging demand from consumers that want to be long futures, the futures price will rise due to limited arbitrage by speculators. Because the futures price can either fall or rise in response to anticipation of higher economic activity, the futures price is a less reliable signal of future economic activity and asset prices than open interest." (Hong and Yogo (2012), p. 474) The authors provide a simple while convincing model of this assertion which is then empirically validated using similar data to ours. Note that they are mainly interested in the raw open interest while we use measures of trading activity measures that make sense either for speculative or hedging pressure.

hedging or speculative pressure may be a significant source of simultaneous trading in comovements futures markets for reasons beyond simple demand and supply arguments.

Klitgaard and Weir (2004) also use CFTC positions' traders data to investigate the relation between trading activity and changes in FX markets. An interesting question in their paper is the predictability that can be obtained using these data. We do not investigate predictability in the present paper but Hong and Yogo (2012) show how trading variables help in predicting commodity returns, stock returns, bond returns and currency returns. This demonstrates how positions in commodity markets are very anticipating by nature.

5.1 Two different measures of trading activity

We consider two different measures of trading activity that represent either the speculative or the hedging intensity. Our first variable follows Han's (2008) investor sentiment index computed using CFTC data.[41] Following requirements of the U.S. Commodity Futures Trading Commission (CFTC), large traders holding positions above a specified level to report their positions on a daily basis. Then, the CFTC aggregates the reported data, and releases the breakdown of each Tuesday's open interest in its Commitments of Traders Report (COT). The COT report includes total long and short positions for both 'commercial' traders and 'noncommercial' traders as well as more detailed variables that we do not use here.[42] In words, 'commercial' traders have to prove an interest for the physical market and are thus considered as hedger while 'noncommercial' traders have no relation with the cash business and are simply large speculators. The sentiment proxy in Han (2008) is then the number of long noncommercial contracts minus the number of short noncommercial contracts, scaled by the total open interest in the futures market, or:

$$\text{Han Index} = \frac{\text{number of long speculative positions} - \text{number of short speculative positions}}{\text{total open interest}}$$

The *Han Index* is inspired by the literature on Investor Sentiment[43] and allows to estimate the sentiment of speculators in the futures market of interest in considering their relative long and

[41] Han (2008) computes the net position of large speculators in S&P 500 futures contract. The author also considers another investment sentiment proxy based in Investors Intelligence's weekly survey that we do not use in the present study.

[42] Since 2006, the CFTC also releases weekly Commodity Index Traders (CIT) report on each Friday. This complements the COT report by providing more detailed categories of traders such as Index Traders who played a significant role these last years. We also do not consider the CIT as it would considerably restrain the sample period for the analysis. The CIT is used in Tang and Xiong (2011) to build their variable of trading activity which is the variation in the value of the net long position by index traders.

[43] see Baker and Wurgler (2007) for a presentation of recent contributions in this field.

short positions. This is such a directional index of speculative activity in the futures market. We use this index for 7 out of our 8 commodities because for pork bellies data are not available for the period of interest. In an investigation of changes in exchange rates markets, Klitgaard and Weir (2004) also rely on a speculative index computed from CFTC data. Note that their measure is not scaled.

Our second measure of trading activity follows de Roon *et al.* (2000) who study the hedging pressure in futures markets. In particular, the authors show that futures risk premia depend on both own-market and cross-market hedging pressures. The variable corresponds to the difference between the number of short hedge positions and the number of long hedge positions, divided by the total number of hedge positions or:

$$\text{RNV Index} = \frac{\text{number of short hedge positions} - \text{number of long hedge positions}}{\text{total number of hedge positions}}$$

The idea behind this measure is to focus on positions of traders who are hedgers, i.e. who have a cash business for the commodity. This estimate of hedging pressure is quite different of the Han Index for which the denominator is the total open interest and not the total number of speculative positions. As a consequence, we believe that these measures may be complement in our regression analysis while being well related to the existing literature on futures market trading activity.

5.2 Empirical findings

We estimate the following regression:

$$\hat{\rho}_t^{*2} = \alpha + \beta \times \text{Trading Activity Index}_t + \varepsilon_t$$

Our empirical estimates are reported in Table 10. Estimation is performed using OLS with a White correction for possible heteroscedasticity. We do not rely on regression analysis with both measures to avoid multicolinearity.[44]

Our Han index explains 24 % of the variation of the average square correlation while the explanatory power of the RNV index is even better with a R^2 of 30%. The global explanatory power is good for monthly regressions and we thus validate the assumption that trading behaviors (and traders'

[44] The average correlation between the two measures for the different commodities is around 0.9. Nevertheless, as will be mentioned below, the explanatory power for each measure is significantly different. In addition, each measure has been suggested in the literature in a different context and we emphasize the need for testing both of them in our regressions.

choices) in commodity financial markets do constitute an significant part of the explanation for the existence of an excess comovement in commodity prices. As noted in the seminal Pindyck and Rotemberg's (1990) paper, "[...] traders are alternatively bullish or bearish on *all* commodities for no plausible reason"[45] (p. 1173). Our empirical evidence validates the herding hypothesis suggested in Pindyck and Rotemberg (1990) as a possible channel for the existence of an excess comovement.

A number of measures of hedging or speculative pressure are highly significant, in particular for wheat, copper and cotton. Our measures using data from silver, soyabeans and sugar futures markets are also significant at the 1 or 5 % threshold and their significance is improved with the RNV index. It thus seem that 'hedging pressure' has more explanatory power than speculative pressure for the estimated excess comovement. Interestingly, the trading activity measures are not significant for crude oil, which is questioning in light of recent findings in Driesprong *et al.* (2008) which show the forecastability of stock returns using oil returns as a predictor. Gorton and Rouwenhorst (2006) may provide an answer to this issue in that the correlation between oil and stock returns does not seem to be contemporaneous. One may then understand the poor explanatory power of crude oil trading data for the excess comovement.

Our regressions using both measures of trading activity are able to explain a much larger part of the total variability than in Tang and Xiong (2011) best regression where only 8% of the total variance is explained using control variables. Our hypothesis concerning this difference in the explanatory power, beyond the fact that empirical methodologies are different in nature, is that using large approximate factor models, we gather much more information than using market indices. For instance, in the case of emerging markets, our database includes more than fifty variables, while Tang and Xiong (2011) use the MSCI Emerging Market Index as the control variable for this effect, which is a poor proxy for an economy as a whole.

6 Concluding remarks

The aim of this paper is to reconsider the question of excess comovement of commodities and to provide an explanation for this comovement, if present in the data.

Our contribution to the literature on excess comovement on commodity markets is twofold. First, we enlarge the data set of macroeconomic and financial variables compared with previous contributions thus allowing to conclude that "fundamentals" should be well taken into account. We therefore believe that the empirical evidence of excess comovement is robust, at least with respect

[45] Italic original from the authors.

to the set of information to be considered. Second, we provide an explanation for this excess comovement based on respective positions of hedgers or speculators in commodity futures markets. We obtain highly significant estimates for the two measures of trading activity that we consider thereby validating the hypothesis of the impact of market variables on the comovement of returns.

The limits of our analysis are also good topics for future research. First, we consider, as in most of the factor-models literature, factors as if they were observed while they are estimated in practice. Despite this should only have a limited impact on our results, it could be relevant to investigate the small sample case using some simulation techniques as in Ludvigson and Ng (2007, 2009 and 2010) and Gospodinov and Ng (2010). Second, our analysis may be conducted using dynamic factor models (DFM) following Forni *et al.* (2005) as, for instance, in Vansteenkiste (2009). Nevertheless, the bulk of the literature has concluded to a weak improvement in using DFM and we have some doubts that for our purpose it would add much to the present analysis. In particular, d'Agostino and Giannone (2012) emphasize the limited impact of DFM for forecasting purpose with macroeconomic data.[46] Third, MIDAS regressions may be used to include more information with different frequencies. Tang and Xiong (2011) use daily and monthly regressions and MIDAS may help to reconcile both approaches, with market indices at the daily frequency and macroeconomic variables at the monthly or quarterly frequency. Fourth, the issue of volatility spillover, as investigated in the penultimate section in Tang and Xiong (2011) may also be considered as a complement to our analysis on returns. Note that the analysis of commodity volatility comovement may have interesting implications for the purpose of financial risk management.

The "comovement in commodity prices" issue is now more than twenty years old and the debate on how commodity prices evolve according to fundamentals has never been more intense. Numerous contributions investigated the impact of the 2008 financial crisis, recent increase index trading, diversification incentives, etc., on commodity prices but without considering the fact that an increasing correlation between commodities, and beyond fundamentals, may simply invalidate the demand/supply model. Showing that the recent financialization of commodity markets plays a important role in shaping simultaneously the price of commodities, we emphasize the need for policy makers to implement stabilizing mechanisms that could limit the impact of trading on food and energy commodity prices.

[46] See also Boivin and Ng (2005) and the discussion in section 3.

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Tables

Table 1
Descriptive statistics for the 8 commodities monthly returns over the period 1993:03-2010:03.

	Wheat	Copper	Silver	Soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Mean	0.0014	0.0059	0.0073	0.0025	0.0052	0.0020	0.0069	0.0049
Maximum	0.2056	0.2243	0.2665	0.2069	0.2231	0.2281	0.3320	0.5225
Minimum	-0.2308	-0.4099	-0.2885	-0.4574	-0.2382	-0.2540	-0.4367	-0.5346
Std. Dev.	0.0796	0.0783	0.0776	0.0860	0.0865	0.0850	0.1092	0.1732
Skewness	-0.2086	-0.6844	-0.3053	-1.0893	-0.0825	-0.1109	-0.4060	-0.0690
Kurtosis	3.0794	6.8325	4.5219	7.1735	3.3749	3.4968	4.1207	4.3201
Jarque-Bera	1.5400	141.46***	22.96***	189.31***	1.43	2.52	16.36***	15.04***
Nb of Obs	205	205	205	205	205	205	205	205

Notes: (i) Monthly returns are computed as price log differences. (ii) Commodity prices are cash prices except crude oil where the current month contract price is taken as a proxy for the cash price. (iii) ***, ** and * respectively denotes rejection of the null hypothesis of a Gaussian distribution at 1%, 5 % and 10 % levels.

Table 2
Correlation between the 8 commodities monthly returns over the period 1993:03-2010:03.

	Wheat	Copper	Silver	Soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.2832 ***	0.1777 **	0.4438 ***	0.0149	0.2510 ***	0.1031	0.1039
Copper	0.0000	1	0.3211 ***	0.2030 ***	0.2042 ***	0.2644 ***	0.3706 ***	0.0487
Silver	0.0108	0.0000	1	0.1116	0.1382 **	0.1019	0.1644 **	0.1463 **
Soyabeans	0.0000	0.0035	0.1110	1	0.0863	0.3978 ***	0.0354	0.1268 *
Raw Sugar	0.8315	0.0033	0.0482	0.2183	1	0.1465 **	0.0653	0.0184
Cotton	0.0003	0.0001	0.1461	0.0000	0.0360	1	0.1857 ***	0.0137
Crude Oil	0.1412	0.0000	0.0185	0.6142	0.3526	0.0077	1	-0.0014
Pork Bellies	0.1380	0.4879	0.0363	0.0701	0.7938	0.8450	0.9836	1

Note: The upper triangular matrix reports correlation while the lower reports the p-values. ***, ** and * respectively denotes significance at 1%, 5 % and 10 % levels.

Table 3
Static factors selection results

Method	No of static factors
MED	2
IC_1	3
IC_2	2
IC_3	20
IC_4	20
PCP_1	9
PCP_2	7
PCP_3	20
PCP_4	20

Note: MED denotes the number of factors given by the Maximum Eigenvalue Distribution algorithm. IC_i and PCP_i denote, respectively, the number of factors given by the information criteria IC and PCP estimated with the penalty function $g_i(N,T)$.

Table 4
Summary statistics for estimated static factors $\widehat{F}_{t,i}$ for $i = 1, ..., 9$.

factor i	ρ_1	ρ_2	ρ_3	R_i^2
1	0.1614	0.1256	0.3176	0.0951
2	0.1357	0.0805	0.3110	0.1581
3	-0.0748	0.0145	-0.0294	0.1988
4	-0.0285	-0.0694	0.1866	0.2310
5	-0.1439	-0.0966	0.0950	0.2600
6	0.2546	0.0328	-0.0091	0.2874
7	0.1012	0.3234	0.3844	0.3124
8	0.3405	0.4066	0.1768	0.3357
9	-0.0065	-0.0413	-0.1447	0.3576

Note: For i = 1,..,9, $\hat{F}_{it}$ is estimated by the method of principal components using a panel of data with 187 indicators of economic activity from 1993:03 to 2010:03 (205 time series observations). The data are transformed (taking logs and differenced where appropriate) and standardized prior to estimation. ρ_i denotes the i^{th} autocorrelation. The 95% confidence bounds are ± 0.1397. The relative importance of the common component,R_i^2, is calculated as the fraction of total variance in the data explained by factors 1 to i.

Table 5
Modelling the 8 commodities returns: the three factors regressions - time period 1993:03-2010:03.

	Wheat	Copper	Silver	Soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Intercept	0.0011	0.0055	0.0073	0.0025	0.0052	0.0020	0.0069	0.0049
	(0.19)	(1.14)	(1.36)	(0.42)	(0.86)	(0.34)	(1.03)	(0.40)
$\widehat{F}_1$	-0.0396	-0.0928	-0.0279	-0.0407	-0.0286	-0.0566	-0.1241	0.0193
	(-2.21)	(-5.93)	(-1.59)	(-2.12)	(-1.45)	(-3.00)	(-5.67)	(0.49)
$\widehat{F}_2$	-0.0194	-0.0782	-0.0427	-0.0136	-0.0250	-0.0420	-0.1447	-0.0724
	(-0.88)	(-4.06)	(-1.98)	(-0.57)	(-1.03)	(-1.81)	(-5.38)	(-1.49)
$\widehat{F}_3$	0.0106	0.0749	0.0115	0.0665	0.0121	0.0280	-0.0011	0.0115
	(0.38)	(3.13)	(0.43)	(2.26)	(0.40)	(0.97)	(-0.03)	(0.19)
R^2	0.0282	0.2347	0.0322	0.0472	0.0165	0.0619	0.2335	0.0124
$\overline{R}^2$	0.0136	0.2233	0.0178	0.0330	0.0018	0.0479	0.2220	-0.0024
ARCH-LM (2)	14.62*	0.3362	4.8693***	13.85*	3.5515	14.11*	4.7081***	12.20*

Notes: (i) This table reports OLS estimates of the regression of the 8 commodities monthly returns with the variables reported in left column. Commodities are reported in upper row. A constant is always included in the regression and $\widehat{F}_i$ denotes the i^{th} factor. (ii) t-statistics are reported in parenthesis under the estimates. ***, **, and * respectively denotes rejection of the null hypothesis of no significance at the 1%, 5% and 10% levels. (iii) For the ARCH_LM, ***, **, and * respectively denotes rejection of the null hypothesis of no ARCH effect at the 1%, 5% and 10% levels.

Table 6
Modelling the 8 commodities returns: the BIC minimizing regressions - time period 1993:03-2010:03.

	Wheat	*Copper*	Silver	Soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Intercept	0.0014	0.0059	0.0073	0.0025	0.0052	0.0020	0.0069	0.0049
	(0.25)	(1.24)	(1.37)	(0.42)	(0.89)	(0.34)	(1.15)	(0.41)
$\widehat{F}_1$	-0.0252	-0.0843				-0.0383	-0.1245	
	(-1.58)	(-5.76)				(-2.20)	(-6.42)	
$\widehat{F}_2$		-0.0682	-0.0330	-0.0683			-0.1420	
		(-3.76)	(-1.58)	(-2.32)			(-5.97)	
$\widehat{F}_3$		0.0669						
		(3.11)						
$\widehat{F}_4$							0.1081	
							(3.32)	
$\widehat{F}_5$					0.1019			
					(3.18)			
$\widehat{F}_6$								
$\widehat{F}_7$							0.1521	
							(4.12)	
$\widehat{F}_8$							0.1672	
							(4.36)	
$\widehat{F}_9$								0.1809
								(2.28)
R^2	0.0224	0.2396	0.0180	0.040	0.0499	0.0377	0.3759	0.0211
$\overline{R}^2$	0.0176	0.2282	0.0132	0.0353	0.0452	0.0330	0.3602	0.0163
ARCH-LM (2)	16.03*	0.23	4.49**	0.04	1.2092e-004	12.88*	14.73*	12.15*

Notes: This table reports OLS estimates of the regression of the 8 commodities monthly returns with the variables reported in left column. Commodities are reported in upper row. A constant is always included in the regression and $\widehat{F}_i$ denotes the i^{th} factor. (ii) t-statistics are reported in parenthesis under the estimates. ***, **, and * respectively denotes rejection of the null hypothesis of no significance at the 1%, 5% and 10% levels. (iii) For the ARCH_LM, ***, **, and * respectively denotes rejection of the null hypothesis of no ARCH effect at the 1%, 5% and 10% levels.

Table 7
Correlation between residuals from the 3 factors linear model.

	Wheat	Copper	Silver	Soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1.0000	0.2361 ***	0.1558 **	0.4293 ***	0.0047	0.2109 ***	0.0309	0.1048
Copper	0.0007	1	0.2791 ***	0.1251 *	0.1831 ***	0.1568 **	0.2045 ***	0.0376
Silver	0.0257	0.0001	1	0.0889	0.1189 *	0.0630	0.0926	0.1383 **
Soyabeans	0.0000	0.0739	0.2051	1	0.0663	0.3729 ***	-0.0335	0.1294 *
Raw Sugar	0.9462	0.0086	0.0895	0.3448	1	0.1195 *	0.0063	0.0141
Cotton	0.0024	0.0247	0.3695	0.0000	0.0880	1	0.0857	0.0072
Crude Oil	0.6606	0.0033	0.1868	0.6337	0.9291	0.2216	1	-0.0278
Pork Bellies	0.1347	0.5926	0.0479	0.0644	0.8412	0.9187	0.6921	1
Breusch Pagan LM test	688.98							
p-value	1							

Note: The upper triangular matrix reports correlation while the lower reports the p-values. ***, ** and * respectively denotes significance at 1%, 5 % and 10 %.

Table 8
Correlation between residuals from the BIC minimizing regressions.

	Wheat	Copper	Silver	soyabeans	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.2395 ***	0.1636 **	0.4248 ***	0.0022	0.2287 ***	0.0209	0.1101
Copper	0.0005	1	0.2841 ***	0.1352 **	0.1492 **	0.1766 **	0.2027 ***	0.0442
Silver	0.0191	0.0000	1.0000	0.0946	0.1252 *	0.0754	0.0839	0.1411 **
soyabeans	0.0000	0.0532	0.1774	1.0000	0.0537	0.3716 ***	-0.0606	0.1375 **
Raw Sugar	0.9753	0.0328	0.0736	0.4446	1.0000	0.1458 **	-0.0167	0.0228
Cotton	0.0010	0.0113	0.2829	0.0000	0.0370	1	0.0828	0.0336
Crude Oil	0.7661	0.0036	0.2319	0.3880	0.8116	0.2378	1	-0.0362
Pork Bellies	0.1159	0.5289	0.0436	0.0493	0.7456	0.6321	0.6065	1
Breusch Pagan LM test	713.78							
p-value	1							

Note: The upper triangular matrix reports correlation while the lower reports the p-values. ***, ** and * respectively denotes significance at 1%, 5 % and 10 %.

Table 9
Descriptive statistics on returns and residual squared correlations - time period 1998:02 to 2010:03 (146 observations)

	$\hat{\rho}^{*2}_{ret,t}$	$\hat{\rho}^{*2}_{t}$
μ	0.1844**	0.1792**
σ	0.0342	0.0271
$F\rho^{*2}$	59.59%	58.22%
C_ρ	0.9743	

Notes: (i) This table reports summary statistics for the excess square unconditional correlation of SUR residuals $\hat{\rho}^{*2}_{SUR,t}$ and the benchmark square unconditional correlation of gross returns $\hat{\rho}^{*2}_{ret,t}$. (ii) $F\rho^{*2}$ is the mean percentage of square unconditional correlation significant at the 5 % level using the *t*-square ratio test $\hat{t}^2_{ijt} = (\hat{\rho}^*_{ijt})^2[1 - \hat{\rho}^*_{ijt}]^{-1}(N-2) \sim F(1, N-2)$. (iii) ***, ** and * respectively denotes significance at 1%, 5 % and 10 %. (iv) C_ρ is the correlation between each pair $\hat{\rho}^{*2}_{ret,t}$ and $\hat{\rho}^{*2}_{SUR,t}$.

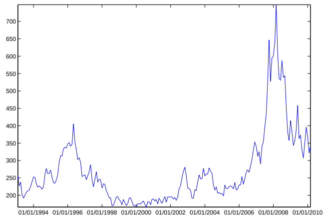
Table 10
Regression of average excess residual correlation on Han and RNV indices - time period 1998:02 to 2010:03 (146 observations).

	$\hat{\rho}_t^{*2}$	
	Han Index	*RNV Index*
Intercept	0.1696***	0.1611***
	(47.36)	(44.52)
Wheat	-0.0415**	-0.0207***
	(-2.24)	(-3.42)
Copper	-0.0539***	-0.0255***
	(-3.27)	(-4.05)
Silver	0.0125	0.0198***
	(0.79)	(3.25)
Soyabeans	0.0396*	0.0124**
	(1.66)	(2.24)
Sugar	0.0358**	0.0107***
	(2.53)	(3.70)
Cotton	0.0634***	0.0129***
	(4.07)	(3.81)
Crude oil	0.0644	0.0039
	(1.26)	(0.67)
R^2	0.2420	0.3003
$\overline{R}^2$	0.2035	0.2648

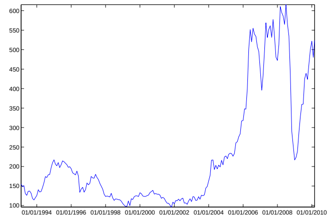
Notes: (i) t-statistics are reported in parenthesis. Standard errors are computed with the White (1980) covariance matrix. (ii) ***, ** and * respectively denotes significance at the 1 %, the 5 % and the 10 % significance levels.

Figures

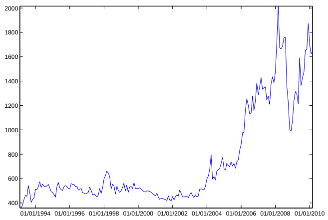
Figure 1
Commodity monthly prices over the period 1993:02-2010:03 (206 observations).



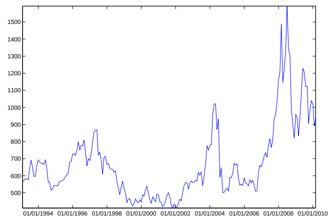
(a) *Wheat*



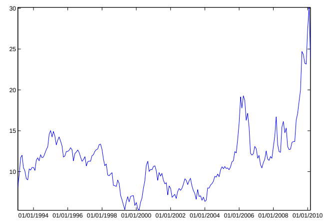
(b) *Copper*



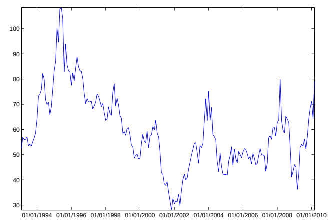
(c) *Silver*



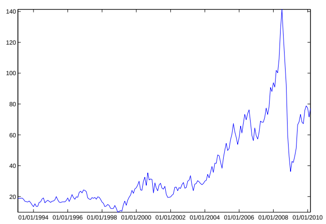
(d) *Soyabeans*



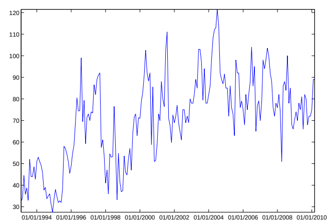
(e) *Sugar*



(f) *Cotton*

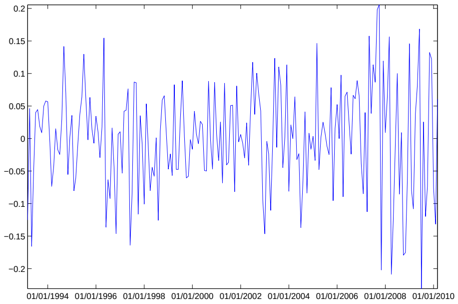


(g) *Oil*

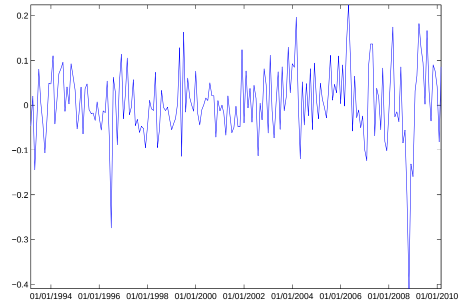


(h) *Pork Bellies*

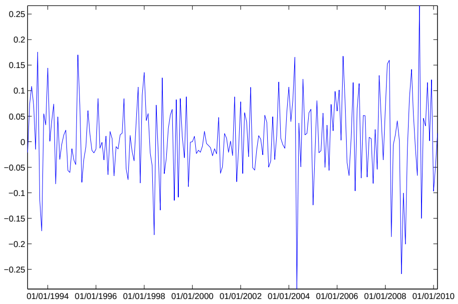
Figure 2
Commodity monthly log returns over the period 1993:03-2010:03 (205 observations).



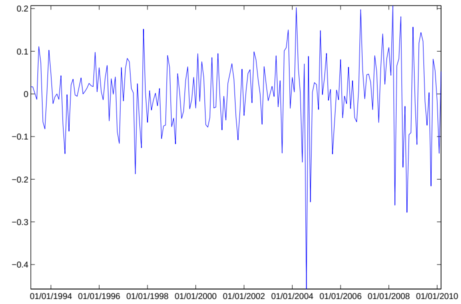
(a) *Wheat*



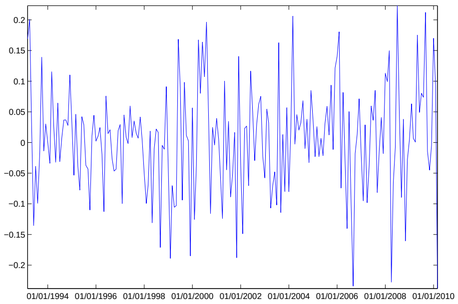
(b) *Copper*



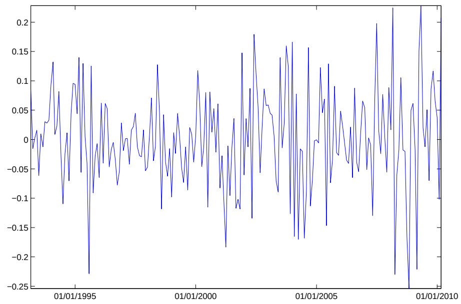
(c) *Silver*



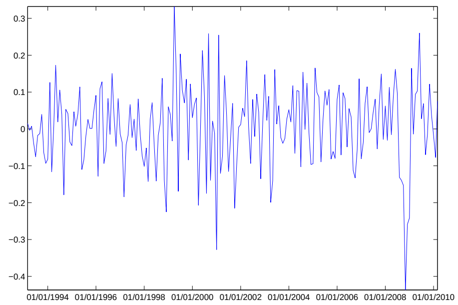
(d) *Soyabeans*



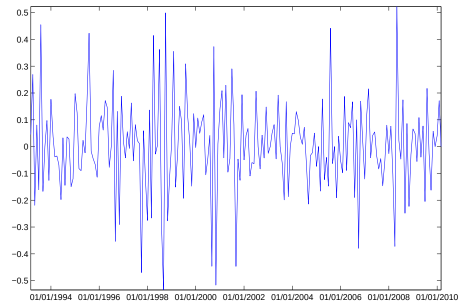
(e) *Sugar*



(f) *Cotton*

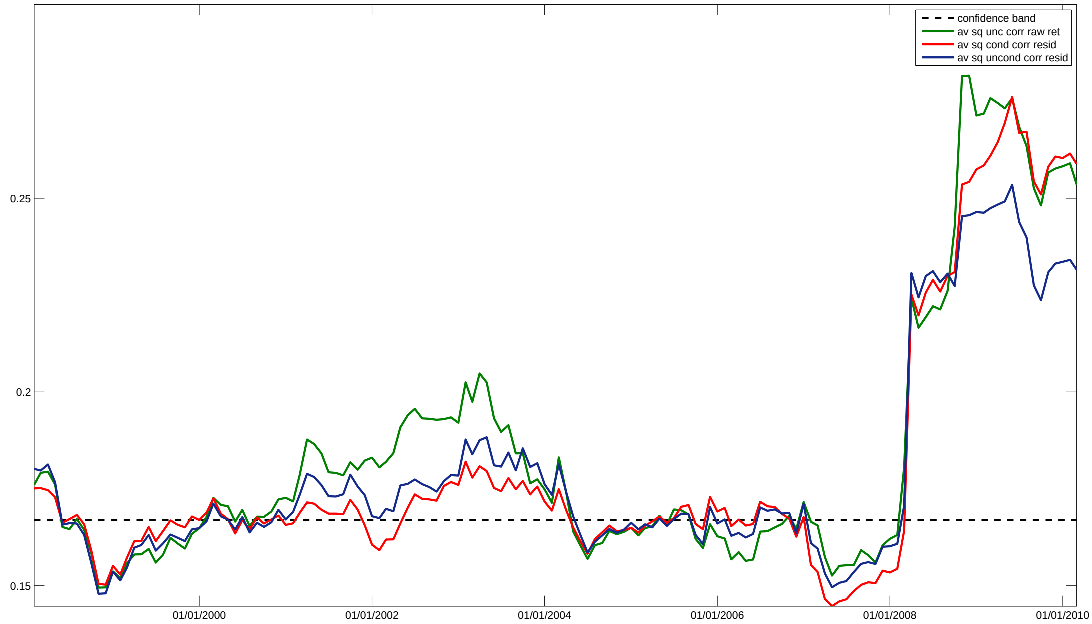


(g) *Oil*



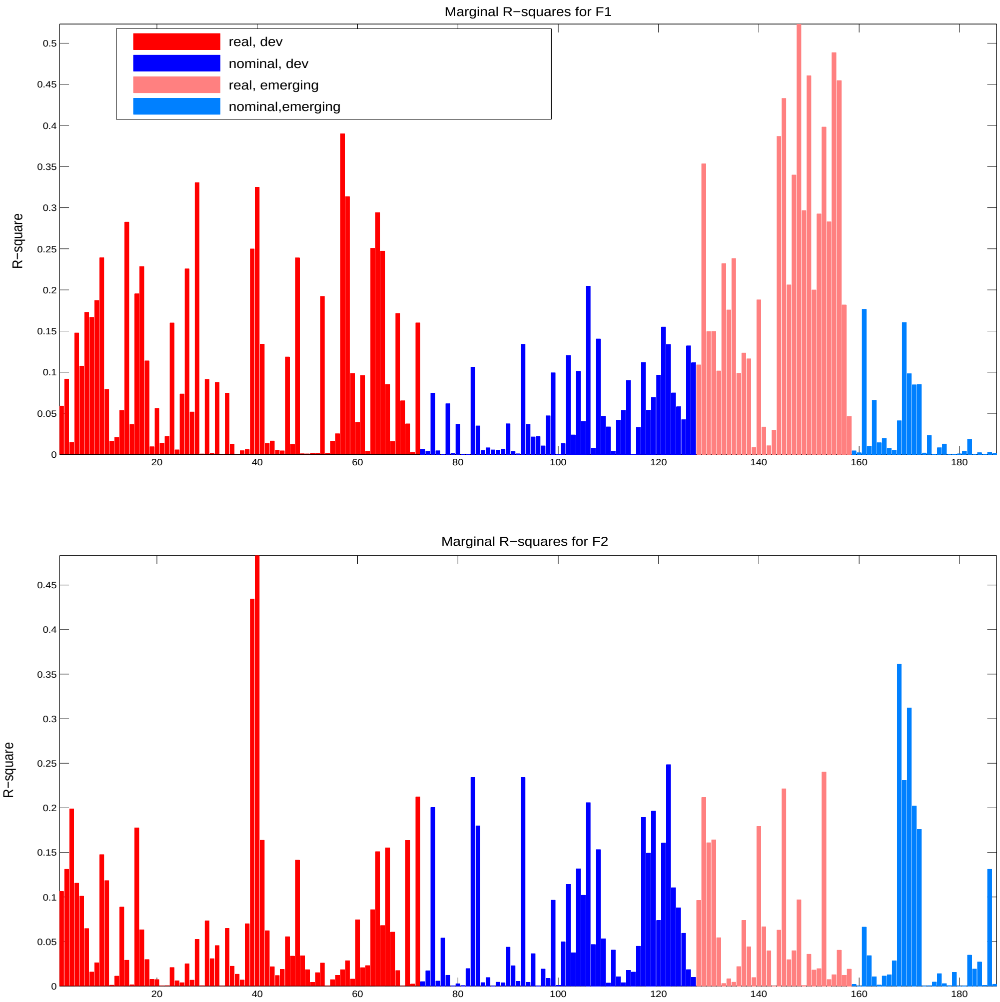
(h) *Pork bellies*

Figure 3
Mean excess squared correlation for raw returns and SUR residuals - time period 1998:02 to 2010:03 (146 observations)



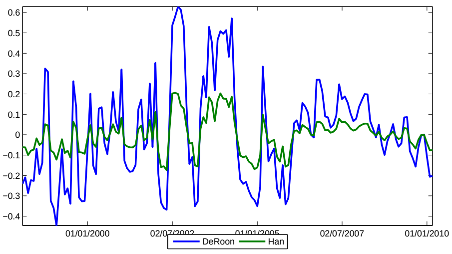
Notes: (i) "av sq unc corr raw ret" is the average squared unconditional correlation of raw returns: $\rho^*_{ret,t}$. (ii) "av sq cond corr resid " is the average square conditional residual. (iii) "av sq uncond corr resid " is ρ^*_t. (iv) The confidence band the minimal value above which square correlation is significant at 5 % level. It is computed from the t-square ratio test $\hat{t}^2_{ijt} = (\hat{\rho}^*_{ijt})^2[1-\hat{\rho}^*_{ijt}]^{-1}(N-2) \sim F(1, N-2)$.

Figure 4
Marginal R^2 of macroeconomic and financial variables regressed on the first two estimated factors.

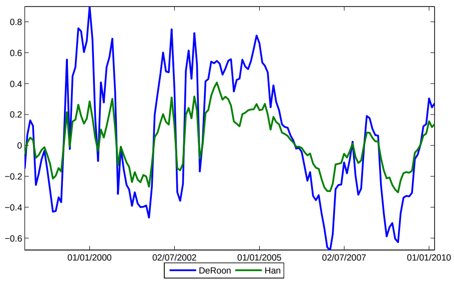


Note: Each panel shows the R^2 from regressing the series number given on the x-axis onto each individual factor $\hat{F}_i$. The series are detailed in the Appendix, and sorted as they appear in the Figure (real variables for developed countries, nominal variables for developed countries, real variables for emerging countries, nominal variables for emerging countries).

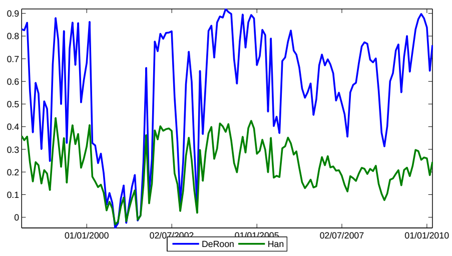
Figure 5
1998:02-2010:03 (146 observations). From top to bottom and from left to right: wheat, copper, silver, soyabeans, raw sugar, cotton, crude oil, pork bellies.



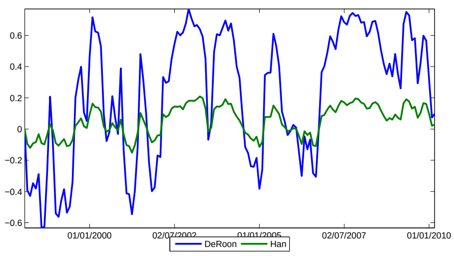
(a) *Wheat*



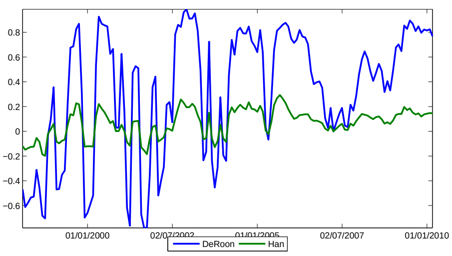
(b) *Copper*



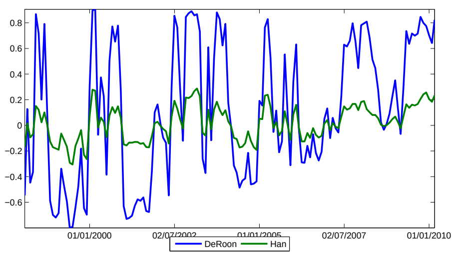
(c) *Silver*



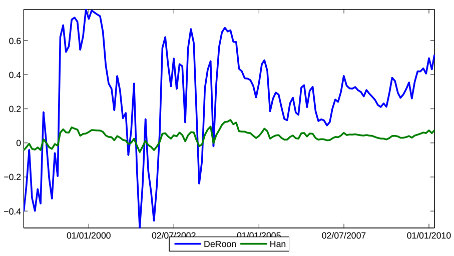
(d) *Soyabeans*



(e) *Sugar*



(f) *Cotton*



(g) *Oil*

Appendix: list of the 187 variables considered in the computation of the common factors

Note: In the Trans column, we report the transformation used to ensure the stationarity of each variable. ln denotes the logarithm, $\Delta \ln$ and $\Delta^2 ln$ denote the first and second difference of the logarithm, lv denotes the level of the series, and Δlv denotes the first difference of the series.

Developed countries				
Series Number	Short name	Mnemonic	Trans	Description
Industrial production				
1	IP: US	USIPTOT_G	Δ ln	US INDUSTRIAL PRODUCTION - TOTAL INDEX VOLA (2002=100)
2	IP: US	USIPMFGSG	Δ ln	US INDUSTRIAL PRODUCTION - MANUFACTURING (SIC) VOLA (1997=100)
3	IP: Canada	CNIPTOT.C	Δ ln	CN GDP - INDUSTRIAL PRODUCTION CONN
4	IP: France	FRIPMAN.G	Δ ln	FR INDUSTRIAL PRODUCTION - MANUFACTURING VOLA
5	IP: France	FRIPTOT_G	Δ ln	FR INDUSTRIAL PRODUCTION EXCLUDING CONSTRUCTION VOLA INDEX (2005=100)
6	IP: Germany	BDIPTOT_G	Δ ln	BD INDUSTRIAL PRODUCTION INCLUDING CONSTRUCTION VOLA (2005=100)
7	IP: UK	UKIPTOT.G	Δ ln	UK INDEX OF PRODUCTION - ALL PRODUCTION INDUSTRIES VOLA (2003=100)
8	IP: UK	UKIPMAN.G	Δ ln	UK INDUSTRIAL PRODUCTION INDEX - MANUFACTURING VOLA (2003=100)
9	IP: Japan	JPIPTOT_G	Δ ln	JP INDUSTRIAL PRODUCTION - MINING & MANUFACTURING VOLA (2005=100)
Orders and capacity utilization				
10	Capacity utilization: US	USCUMANUG	Δlv	US CAPACITY UTILIZATION - MANUFACTURING VOLA
11	Manufct. new ord.: US	USNOCOGMC	Δ^2 ln	US MANUFACTURERS NEW ORDERS - CONSUMER GOODS AND MATERIALS CONN (base 1982)
12	Manufct. new ord.: US	USBNKRTEQ	Δ ln	US MANUFACTURERS NEW ORDERS,NONDEFENSE CAPITAL GOODS SADJ (base 1982)
13	New orders: Canada	CNNEWORDB	Δ ln	CN NEW ORDERS: ALL MANUFACTURING INDUSTRIES (SA) CURA
14	Manufct. ord.: Germany	BDNEWORDE	Δ ln	BD MANUFACTURING ORDERS SADJ (2000=100)
15	Manufct. ord.: Japan	JPNEWORDB	Δ ln	JP MACHINERY ORDERS: DOM.DEMAND-PRIVATE DEMAND (EXCL. SHIP) CURA
16	Operating ratio: Japan	JPCAPUTLQ	Δlv	JP OPERATING RATIO - MANUFACTURING SADJ (2005=100)
17	Business failures: Japan	JPBNKRPTP	Δ ln	JP BUSINESS FAILURES VOLN
Housing start				
18	Housing permits: US	USHOUSETOT	ln	US HOUSING AUTHORIZED VOLN
19	Housing permits: Canada	CNHOUSE.O	ln	CN HOUSING STARTS: ALL AREAS (SA, AR) VOLA
20	Housing permits: Germany	BDHOUSINP	ln	BD HOUSING PERMITS ISSUED FOR BLDG.CNSTR.: BLDG.S-RESL, NEW VOLN
21	Housing permits: Australia	AUHOUSE_A	ln	AU BUILDING APPROVALS: NEW HOUSES CURN
22	Housing permits: Japan	JPHOUSSTF	ln	JP NEW HOUSING CONSTRUCTION STARTED VOLN
Car sales				
23	Car registration: US	USCAR_P	ln	US NEW PASSENGER CARS - TOTAL REGISTRATIONS VOLN
24	Car registration: Canada	CNCARSLSE	ln	CN PASSENGER CAR SALES:TOTAL SADJ
25	Car registration: France	FRCARREGP	ln	FR NEW CAR REGISTRATIONS VOLN
26	Car registration: Germany	BDRVNCARP	ln	BD NEW REGISTRATIONS - CARS VOLN
27	Car registration: UK	UKCARTOTF	ln	UK CAR REGISTRATIONS VOLN
28	Car registration : Japan	JPCARREGF	ln	JP MOTOR VEHICLE NEW REGISTRATIONS: PASSENGER CARS EXCL.BELOW 66
Consumption				
29	Consumer sentiment: US	USUMCONEH	Δ ln	US UNIV OF MICHIGAN CONSUMER SENTIMENT - EXPECTATIONS VOLN (base 1966=100)
30	Pers. cons. exp.: US	USPERCONB	Δ ln	US PERSONAL CONSUMPTION EXPENDITURES (AR) CURA
31	Pers. saving: US	USPERSAVE	Δlv	US PERSONAL SAVING AS % OF DISPOSABLE PERSONAL INCOME SADJ
32	Retail sale: Canada	CNRETTOTB	Δ ln	CN RETAIL SALES: TOTAL (ADJUSTED) CURA
33	Household confidence: France	FRCNFCONQ	Δlv	FR SURVEY - HOUSEHOLD CONFIDENCE INDICATOR SADJ
34	Household confidence: Germany	BDCNFCONQ	Δlv	BD CONSUMER CONFIDENCE INDICATOR - GERMANY SADJ
35	Retail sales: UK	UKRETTOTB	Δ ln	UK RETAIL SALES (MONTHLY ESTIMATE, DS CALCULATED) CURA
36	Household confidence: UK	UKCNFCONQ	Δlv	UK CONSUMER CONFIDENCE INDICATOR - UK SADJ
37	Retail sales: Australia	AURETTOTT	Δ ln	AU RETAIL SALES (TREND) VOLA
38	Household confidence: Australia	AUCNFCONR	Δlv	AU MELBOURNE/WESTPAC CONSUMER SENTIMENT INDEX NADJ
39	Household expenditure: Japan	JPHLEXPWA	Δ ln	JP WORKERS HOUSEHOLD LIVING EXPENDITURE (INCL. AFF) CURN
40	Retail sales: Japan	JPRETTOTA	Δ ln	JP RETAIL SALES CURN

Series Number	Short name	Mnemonic	Trans	Description
Wages and labor				
41	Av. hourly real earnings: US	USWRIM_D	$\Delta \ln$	US AVG HOURLY REAL EARNINGS - MANUFACTURING CONA (base 82-84)
42	Av. overtime hours: US	USOOL024Q	$\Delta \ln$	US OVERTIME HOURS - MANUFACTURING, WEEKLY VOLA
43	Av. wkly hours : US	USHKIM_O	$\Delta \ln$	US AVG WKLY HOURS - MANUFACTURING VOLA
44	Purchasing manager index: US	USPMCUE	$\Delta \ln$	US CHICAGO PURCHASING MANAGER DIFFUSION INDEX - EMPLOYMENT NADJ
45	Av. hourly real earnings: Canada	CNWAGES.A	$\Delta \ln$	CN AVG.HOURLY EARN- INDUSTRIAL AGGREGATE EXCL. UNCLASSIFIED CURN
46	Labor productivity: Germany	BDPRODVTQ	$\Delta \ln$	BD PRODUCTIVITY: OUTPUT PER MAN-HOUR WORKED IN INDUSTRY SADJ (2005=100)
47	wages: Germany	BDWAGES.F	$\Delta \ln$	BD WAGE & SALARY,OVERALL ECONOMY-ON A MTHLY BASIS(PAN BD M0191)
48	Labor productivity: Japan	JPPRODVTE	$\Delta \ln$	JP LABOR PRODUCTIVITY INDEX -ALL INDUSTRIES SADJ
49	wages index: Japan	JPWAGES_E	$\Delta \ln$	JP WAGE INDEX: CASH EARNINGS - ALL INDUSTRIES SADJ
Unemployment				
50	U rate: US	USUNEM15Q	$\Delta^2 \ln$	US UNEMPLOYMENT RATE - 15 WEEKS & OVER SADJ
51	U rate: US	USUNTOTQ_pc	$\Delta^2 \ln$	US UNEMPLOYMENT RATE SADJ
52	Employment: Canada	CNEMPTOTO	$\Delta^2 \ln$	CN EMPLOYMENT - CANADA (15 YRS & OVER, SA) VOLA
53	U all: Germany	BDUNPTOTP	$\Delta \ln$	BD UNEMPLOYMENT LEVEL (PAN BDFROM SEPT 1990) VOLN
54	U rate: UK	UKUNTOTQ_pc	$\Delta^2 \ln$	UK UNEMPLOYMENT RATE SADJ
55	Emp: Australia	AUEMPTOTO	$\Delta \ln$	AU EMPLOYED: PERSONS VOLA
56	U all: Australia	AUUNPTOTO	$\Delta \ln$	AU UNEMPLOYMENT LEVEL VOLA
57	U rate: Japan	JPUNTOTQ_pc	Δlv	JP UNEMPLOYMENT RATE SADJ
International trade				
58	Exports: US	USI70_A	$\Delta \ln$	US EXPORTS CURN
59	Exports: EU	EKEXPGDSA	$\Delta \ln$	EK EXPORTS TO EXTRA-EA17 CURN
60	Exports: France	FREXPGDSB	$\Delta \ln$	FR EXPORTS FOB CURA
61	Exports: Germany	BDEXPBOPB	$\Delta \ln$	BD EXPORTS FOB CURA
62	Exports: UK	UKI70_A	$\Delta \ln$	UK EXPORTS CURN
63	Exports: Australia	AUEXPG&SB	$\Delta \ln$	AU EXPORTS OF GOODS & SERVICES (BOP BASIS) CURA
64	Exports: Japan	JPEXPGDSB	$\Delta \ln$	JP EXPORTS OF GOODS - CUSTOMSBASIS CURA
65	Imports: US	USIMPGDSB	$\Delta \ln$	US IMPORTS F.A.S. CURA
66	Imports: EU	EUOXT_09B	$\Delta \ln$	EU IMPORTS CURA
67	Imports: France	FRIMPGDSB	$\Delta \ln$	FR IMPORTS FOB CURA
68	Imports: Germany	BDIMPGDSB	$\Delta \ln$	BD IMPORTS CIF (PAN BD M0790) CURA
69	Imports: UK	UKIMPBOPB	$\Delta \ln$	UK IMPORTS - BALANCE OF PAYMENTS BASIS CURA
70	Imports: Australia	AUIMPG&SB	$\Delta \ln$	AU IMPORTS OF GOODS & SERVICES (BOP BASIS) CURA
71	Imports: Japan	JPOXT009B	$\Delta \ln$	JP IMPORTS CURA
72	Terms of trade: UK	UKTOTPRCF	$\Delta \ln$	UK TERMS OF TRADE - EXPORT/IMPORT PRICES (BOP BASIS) NADJ
73	Terms of trade: Japan	JPTOTPRCF	$\Delta \ln$	JP TERMS OF TRADE INDEX NADJ
Money and credit				
74	Money supply: US	USM0_B	$\Delta^2 \ln$	US MONETARY BASE CURA
75	Money supply: US	USM2_B	$\Delta^2 \ln$	US MONEY SUPPLY M2 CURA
76	Money supply: France	FRM2_A	$\Delta \ln$	FR MONEY SUPPLY - M2 (NATIONAL CONTRIBUTION TO M2) CURN
77	Money supply: France	FRM3_A	$\Delta \ln$	FR MONEY SUPPLY - M3 (NATIONAL CONTRIBUTION TO M3) CURN
78	Money supply: Germany	BDM1_A	$\Delta \ln$	BD MONEY SUPPLY-GERMAN CONTRIBUTION TO EURO M1(PAN BD M0790)
79	Money supply: Germany	BDM3_B	$\Delta \ln$	BD MONEY SUPPLY-M3 (CONTRIBUTION TO EURO BASIS FROM M0195) CURA
80	Money supply: UK	UKM1_B	$\Delta \ln$	UK MONEY SUPPLY M1 (ESTIMATE OF EMU AGGREGATE FOR THE UK) CURA
81	Money supply: UK	UKM3_B	$\Delta \ln$	UK UK MONEY SUPPLY M3(ESTIMATE OF EMU AGGREGATE FORTHE UK) CURA
82	Money supply: Australia	AUM1_B	$\Delta \ln$	AU MONEY SUPPLY - M1 CURA
83	Money supply: Australia	AUM3_B	$\Delta^2 \ln$	AU MONEY SUPPLY - M3 (SEE AUM3...OB) CURA
84	Money supply: Japan	JPM1_A	$\Delta \ln$	JP MONEY SUPPLY: M1 (METHO-BREAK, APR. 2003) CURN
85	Money supply: Japan	JPM2_A	$\Delta \ln$	JP MONEY SUPPLY: M2 (METHO-BREAK, APR. 2003) CURN

Money and credit - continuation				
Series Number	Short name	Mnemonic	Tran	Description
86	Credit: US	USCOMILND	$\Delta^2 \ln$	US COMMERCIAL & INDUSTRIAL LOANS OUTSTANDING (BCI 101) CONA (base 2005)
87	Credit: US	USCILNNCB	Δlv	US COMMERCIAL & INDL LOANS, NET CHANGE (AR) (BCI 112) CURA
88	Credit: US	USCRDNRVB	$\Delta^2 \ln$	US NONREVOLVING CONSUMER CREDIT OUTSTANDING CURA
89	Credit: US	USCSCRE_Q	$\Delta^2 \ln$	US CONSUMER INSTALLMENT CREDIT TO PERSONAL INCOME (RATIO) SADJ
90	Credit: France	FRBANKLPA	$\Delta^2 \ln$	FR MFI LOANS TO RESIDENT PRIVATE SECTOR CURN
91	Credit: Germany	BDBANKLPA	$\Delta^2 \ln$	BD LENDING TO ENTERPRISES & INDIVIDUALS CURN
92	Credit: UK	UKCRDCONB	$\Delta^2 \ln$	UK TOTAL CONSUMER CREDIT: AMOUNT OUTSTANDING CURA
93	Credit: Australia	AUCRDCONB	$\Delta^2 \ln$	AU FINANCIAL INTERMEDIARIES: NARROW CREDIT - PRIVATE SECTOR CURA
94	Credit: Japan	JPBANKLPA	$\Delta^2 \ln$	JP AGGREGATE BANK LENDING (EXCL. SHINKIN BANKS) CURN
Stock index				
95	Stock index: US	USSHRPRCF	$\Delta \ln$	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ
96	Stock index: France	FRSHRPRCF	$\Delta \ln$	FR SHARE PRICE INDEX - SBF 250 NADJ
97	Stock index: Germany	BDSHRPRCF	$\Delta \ln$	BD DAX SHARE PRICE INDEX, EP NADJ
98	Stock index: UK	UKOSP001F	$\Delta \ln$	UK FTSE 100 SHARE PRICE INDEXNADJ (2005=100)
99	Stock index: Japan	JPSHRPRCF	$\Delta \ln$	JP TOKYO STOCK EXCHANGE - TOPIX (EP) NADJ (1968=100)
Interest rate				
100	Interest rate: US	USFEDFUN	Δlv	US FEDERAL FUNDS RATE (AVG.)
101	Interest rate: US	USCRBBAA	Δlv	US CORPORATE BOND YIELD - MOODY'S BAA, SEASONED ISSUES
102	Interest rate: US	USGBOND	Δlv	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY - 20 YEAR
103	Interest rate: France	FRPRATE	Δlv	FR AVERAGE COST OF FUNDS FOR BANKS / EURO REPO RATE
104	Interest rate: France	FRGBOND	Δlv	FR GOVERNMENT GUARANTEED BOND YIELD (EP) NADJ
105	Interest rate: Germany	BDPRATE	Δlv	BD DISCOUNT RATE / SHORT TERM EURO REPO RATE
106	Interest rate: Germany	BDGBOND	Δlv	BD LONG TERM GOVERNMENT BOND YIELD - 9-10 YEARS
107	Interest rate: UK	UKPRATE	Δlv	UK BANK OF ENGLAND BASE RATE (EP)
108	Interest rate: UK	UKGBOND	Δlv	UK GROSS REDEMPTION YIELD ON 20 YEAR GILTS (PERIOD AVERAGE) NADJ
109	Interest rate: Australia	AUPRATE	Δlv	AU RBA CASH RATE TARGET
110	Interest rate: Australia	AUBOND	Δlv	AU COMMONWEALTH GOVERNMENT BOND YIELD 10 YEAR (EP)
111	Interest rate: Japan	JPPRATE	Δlv	JP OVERNIGHT CALL MONEY RATE, UNCOLLATERALISED (EP)
112	Interest rate: Japan	JPGBOND	Δlv	JP INTEREST-BEARING GOVERNMENT BONDS - 10-YEAR (EP)
Exchange rate				
113	Exchange rate: DM to US $	BBDEMSP	$\Delta \ln$	GERMAN MARK TO US $ (BBI) - EXCHANGE RATE
114	Exchange rate: SK to US $	SDXRUSD	$\Delta \ln$	SD SWEDISH KRONOR TO US $ (BBI, EP)
115	Exchange rate: £ to $	UKDOLLR	$\Delta \ln$	UK £ TO US $ (WMR) - EXCHANGE RATE
116	Exchange rate: Yen to $	JPXRUSD	$\Delta \ln$	JP JAPANESE YEN TO US $
117	Exchange rate: Aus.$ to US $	AUXRUSD	$\Delta \ln$	AU AUSTRALIAN $ TO US $ (MTH.AVG.)
Producer price index				
118	PPI: US	USPROPRCE	$\Delta \ln$	US PPI - FINISHED GOODS SADJ
119	PPI: Canada	CNPROPRCF	$\Delta \ln$	CN INDUSTRIAL PRICE INDEX: ALL COMMODITIES NADJ
120	PPI: Germany	BDPROPRCF	$\Delta \ln$	BD PPI: INDL. PRODUCTS, TOTAL, SOLD ON THE DOMESTIC MARKET NADJ (2005=100)
121	PPI: UK	UKPROPRCF	$\Delta \ln$	UK PPI - OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ
122	PPI: Japan	JPPROPRCF	$\Delta \ln$	JP CORPORATE GOODS PRICE INDEX: DOMESTIC - ALL COMMODITIES NADJ
Consumer price index				
123	CPI: US	USCONPRCE	$\Delta \ln$	US CPI - ALL URBAN: ALL ITEMS SADJ
124	CPI: Canada	CNCONPRCF	$\Delta \ln$	CN CPI NADJ
125	CPI: France	FRCONPRCE	$\Delta \ln$	FR CPI SADJ
126	CPI: Germany	BDCONPRCE	$\Delta \ln$	BD CPI SADJ
127	CPI: UK	UKD7BT_F	$\Delta \ln$	UK CPI INDEX 00 : ALL ITEMS- ESTIMATED PRE-97 2005=100 NADJ
128	CPI: Japan	JPCONPRCF	$\Delta \ln$	JP CPI: NATIONAL MEASURE NADJ

Emerging countries				
Series Number	Short name	Mnemonic	Trans	Description
Industrial production				
129	IP: Brasil	BRIPTOT_G	$\Delta \ln$	BR INDUSTRIAL PRODUCTION VOLA index 2002=base
130	IP: China (cement)	CHVALCEMH	$\Delta \ln$	CH OUTPUT OF INDUSTRIAL PRODUCTS - CEMENT VOLN
131	IP: India	INIPTOT_H	$\Delta \ln$	IN INDUSTRIAL PRODN. (EXCLUDING CONSTRUCTION & GAS UTILITY) VOLN index
132	IP: India	INIPMAN_H	$\Delta \ln$	IN INDUSTRIAL PRODUCTION: MANUFACTURING VOLN index
133	IP: Korea	KOIPTOT.G	$\Delta \ln$	KO INDUSTRIAL PRODUCTION VOLA (2005=100)
134	IP: Mexico	MXIPTOT_H	$\Delta \ln$	MX INDUSTRIAL PRODUCTION INDEX VOLN
135	IP: Mexico	MXIPMAN_H	$\Delta \ln$	MX INDUSTRIAL PRODUCTION INDEX: MANUFACTURING VOLN
136	IP: Philippines	PHIPMAN_F	$\Delta \ln$	PH MANUFACTURING PRODUCTION NADJ 2000 prices
137	IP: South Africa	SAIPMAN.G	$\Delta \ln$	SA INDUSTRIAL PRODUCTION (MANUFACTURING SECTOR) VOLA
Orders and capacity utilization				
138	Operating ratio: Brazil	BRCAPUTLR	Δlv	BR CAPACITY UTILIZATION - MANUFACTURING NADJ
139	Mach. ord.: Korea	KONEWORDA	$\Delta \ln$	KO MACHINERY ORDERS RECEIVEDCURN
140	Manufct. prod capa.: Korea	KOCAPUTLF	Δlv	KO MANUFACTURING PRODUCTION CAPACITY NADJ (2005=100)
Consumption				
141	Retail sales: Korea	KORETTOTF	$\Delta \ln$	KO RETAIL SALES NADJ (2005=100)
Wages and labor				
142	Labor cost: Brazil	BRLCOST.F	$\Delta \ln$	BR UNIT LABOR COST NADJ
Unemployment				
143	U rate: Korea	KOUNTOTQ_pc	Δlv	KO UNEMPLOYMENT RATE SADJ
International trade				
144	Exports: Brazil	BREXPBOPA	$\Delta \ln$	BR EXPORTS (BOP BASIS) CURN
145	Exports: China	CHEXPGDSA	$\Delta \ln$	CH EXPORTS CURN
146	Exports: India	INI70_A	$\Delta \ln$	IN EXPORTS CURN
147	Exports: Indonesia	IDEXPGDSA	$\Delta \ln$	ID EXPORTS FOB CURN
148	Exports: Korea	KOEXPGDSA	$\Delta \ln$	KO EXPORTS FOB (CUSTOMS CLEARANCE BASIS) CURN
149	Exports: Philippines	PHEXPGDSA	$\Delta \ln$	PH EXPORTS CURN
150	Exports: Singapore	SPEXPGDSA	$\Delta \ln$	SP EXPORTS CURN
151	Exports: Taïwan	TWEXPGDSA	$\Delta \ln$	TW EXPORTS CURN
152	Imports: Brazil	BRIMPBOPA	$\Delta \ln$	BR IMPORTS (BOP BASIS) CURN
153	Imports: China	CHIMPGDSA	$\Delta \ln$	CH IMPORTS CURN
154	Imports: Indonesia	IDIMPGDSA	$\Delta \ln$	ID IMPORTS CIF CURN
155	Imports: Korea	KOIMPGDSA	$\Delta \ln$	KO IMPORTS CIF (CUSTOMS CLEARANCE BASIS) CURN
156	Imports: Singapore	SPIMPGDSA	$\Delta \ln$	SP IMPORTS CURN
157	Imports: Taïwan	TWIMPGDSA	$\Delta \ln$	TW IMPORTS CURN
158	Terms of trade: Brazil	BRTOTPRCF	$\Delta \ln$	BR TERMS OF TRADE NADJ (2006=100)

Series Number	Short name	Mnemonic	Tran	Description
Money and credit				
159	Money supply: Brazil	BRM1_A	Δ ln	BR MONEY SUPPLY - M1 (EP) CURN
160	Money supply: Brazil	BRM3_A	Δ ln	BR MONEY SUPPLY - M3 (EP) CURN
161	Money supply: China	CHM0_A	Δ ln	CH MONEY SUPPLY - CURRENCY IN CIRCULATION CURN
162	Money supply: China	CHM1_A	Δ ln	CH MONEY SUPPLY - M1 CURN
163	Money supply: India	INM1_A	Δ ln	IN MONEY SUPPLY: M1 (EP) CURN
164	Money supply: India	INM3_A	Δ ln	IN MONEY SUPPLY: M3 (EP) CURN
165	Money supply: Indonesia	IDM1_A	Δ ln	ID MONEY SUPPLY: M1 CURN
166	Money supply: Indonesia	IDM2_A	Δ^2 ln	ID MONEY SUPPLY- M2 CURN
167	Money supply: Korea	KOM2_B	Δ^2 ln	KO MONEY SUPPLY - M2 (EP) CURA
168	Money supply: Mexico	MXM1_A	Δ ln	MX MONEY SUPPLY: M1 (EP) CURN base=end of period
169	Money supply: Mexico	MXM3_A	Δ^2 ln	MX MONEY SUPPLY: M3 (EP) CURN
170	Money supply: Philippines	PHM1_A	Δ ln	PH MONEY SUPPLY - M1 (METHO BREAK AT 12/03) CURN
171	Money supply: Philippines	PHM3_A	Δ^2 ln	PH MONEY SUPPLY - M3 (METHO BREAK AT 12/03) CURN
172	Money supply: Russia	RSM2_A	Δ^2 ln	RS MONEY SUPPLY- M2 CURN
Stock index				
173	Stock index: Brazil	BRSHRPRCF	Δ^2 ln	BR BOVESPA SHARE PRICE INDEX (EP) NADJ
174	Stock index: Hong-Kong	HKSHRPRCF	Δ ln	HK HANG SENG SHARE PRICE INDEX (EP) NADJ (31 july 1964 =100)
Exchange rate				
175	Exchange rate: Br.R. to US $	BRXRUSD	Δ^2 ln	BR BRAZILIAN REAIS TO US DOLLAR (AVG)
176	Exchange rate: Ch.Y. to US $	CHXRUSD	Δ^2 ln	CH CHINESE YUAN TO US DOLLAR (AVERAGE AMOUNT)
177	Exchange rate: In.R. to US $	INXRUSD	Δ^2 ln	IN INDIAN RUPEES PER US DOLLAR (RBI)
178	Exchange rate: Id.R. to US $	IDXRUSD	Δ^2 ln	ID INDONESIAN RUPIAHS TO US DOLLAR
179	Exchange rate: Mx.P. to US $	MXXRUSD	Δ^2 ln	MX MEXICAN PESOS TO US $-CENTRAL BANK SETTLEMENT RATE (AVG)
180	Exchange rate: RS.R. to US $	RSXRUSD	Δ^2 ln	RS RUSSIAN ROUBLES TO US $ NADJ
Consumer price index				
181	CPI: Brazil	BRCPIGENF	Δ^2 ln	BR CPI - GENERAL NADJ
182	CPI: China	CHCONPRCF	Δ ln	CH CPI NADJ
183	CPI: India	INCONPRCF	Δ ln	IN CPI: INDUSTRIAL LABOURERS(DS CALCULATED) NADJ (2001=100)
184	CPI: Korea	KOCONPRCF	Δ ln	KO CPI NADJ (2005=100)
185	CPI: Mexico	MXCONPRCF	Δ^2 ln	MX CPI NADJ (JUN 2002=100)
186	CPI: Philippines	PHCONPRCF	Δ ln	PH CPI NADJ
187	CPI: Russia	RSCONPRCF	Δ^2 ln	RS CPI NADJ