Revisiting the excess co-movements of commodity prices in a data-rich environment*

Yannick Le Pen†
Université de Nantes (LEMNA)

Benoît Sévi‡
Université d'Angers (GRANEM)
London Business School

April 15, 2010

*Acknowledgments to be added.

†Institut d'Économie et de Management de Nantes – IAE, Université de Nantes, Chemin de la Censive du Tertre, BP 52231, 44322 Nantes cedex 3. Email: yannick.le-pen@univ-nantes.fr

‡Department of Economics, Faculty of Law, Economics and Management, University of Angers, 13 allée François Mitterrand, BP 13633, 49036 ANGERS Cedex 01, Email: benoit.sevi@gmail.com

Abstract

We reinvestigate the issue of excess comovements of commodity prices initially raised in Pindyck and Rotemberg (1990). While Pindyck and Rotemberg and following contributions consider this issue using an arbitrary set of control variables, we develop our analysis using recent development in large approximate factor models so that a richer information set can be considered. This ensures that fundamentals, a necessary concept for any excess comovement analysis, are modelled as well as possible. We then consider different measures of correlation to assess comovement and we provide evidence of excess comovement for a set of 8 seemingly unrelated commodities. Our results indicate that excess comovement in returns does exist even when the issue of heteroscedasticity is considered. We extend our analysis to the excess comovement of volatilities and show that, contrary to the case of returns, comovement vanishes once the effect of fundamentals have been taken out.

JEL Classification: C22, C32, G15, E17

Keywords: commodity excess comovement hypothesis, factor models, heteroscedasticity-corrected correlation, spillover index.

1 Introduction

Using large dimensional factor analysis and relevant measures of unconditional and conditional correlation to control for common factords, we show that excess comovement between commodity returns does exist in line with the seminal contribution by Pindyck and Rotemberg (1990). Our statement is true both unconditionally and conditionally to heteroskedasticity and is robust across periods. The use of many macroeconomic and financial variables allows to properly filter the original series thus rendering our results immune to the critic of an insufficient or arbitrary selected set of control variables. We also show that evidence of excess co-movement are weaker in the case of volatility returns.

The issue of commodity excess comovement has an interest for several reasons. First, 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 behaviors such as "herding" for instance. Second, 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.[1] 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. Third, if comovement exists and is strong enough, exporters countries may also find an interest in hedging using commodity indexes beyond their initial interest in using futures and options on the commodity the export.[2]

The issue of examining excess comovement for some financial assets is twofold.[3] Indeed, we are interested in answering the following question: are commodity prices moving together beyond what fundamentals should explain? Then our first concern is on what means "fundamentals"? In this paper we extend the information set to a large number of macroeconomic and financial variables that are more likely to span the information universe and resort to factor models. Note that the issue of incomplete information set first was discussed in Pindyck and Rotemberg (1990) in their conclusion. (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 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, i.e., to compute at each point in time t". We purport that by considering a large set of variables, not the right econometric model but at least the right information set would be under consideration. To approach the right econometric model, we thoroughly consider nonlinear specification in filtering our commodity returns.

Our second concern is on the economic or statistical definition of "comovement". This concept has

[1]Garrett and Taylor (2002) provide some results on this topic.

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

[3]In Deb *et al.* (1996), the first issue which should be considered when dealing with excess comovement 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) and thus do note formally test the unrelatedness of our primary variables.

received several definitions in the literature. In the present paper, we take three different measures of the statistical relation between our filtered residuals to ensure robustness of our results to the methodology employed to measure comovements. We use the correlation coefficient in its original linear version, the correlation coefficient corrected for heteroscedasticity following Forbes and Rigobon (2002) and Kallberg and Pasquariello (2008) and a multivariate GARCH model allowing for dynamic conditional correlation (Engle, 2002).

One originality in our paper is that we also investigate the excess comovement in volatilities. Our analysis is semi-nonparametric in the sense that it relies on some nonparametric estimators of volatilities (realized volatilities) which are then filtered using factors and whose correlation is finally assessed. The advantage of this methodology is that it allows to obtain an estimation of the conditional volatility better than in some parametric models in the lines of multivariate GARCH models.[4] Indeed, these models are based on squared innovations which are known to be a very poor proxy for actual conditional variance.

We think our paper adds several novelties to the issue of the comovement of commodities. First, this is to our best knowledge the first paper exploring the correlation between volatilities for commodities. Second, it is the first time that large dimensional analysis is used to test for comovement or contagion with the exception of the recent contribution of Kallberg and Pasquariello (2008). As such, it opens a door for a large body of research using a very large number of factors to test for contagion. Third we consider the issue of heteroscedasticity which has only been considered in Deb et al. (1996) and which is likely to modify results about comovement by over-estimating correlation (see Forbes and Rigobon, 2002).

Our main contributions are as follows. First, we confirm initial findings by Pindyck and Rotemberg (1990), namely that unconditional excess comovement exist for seemingly unrelated commodities once a reduced number of factors summing a large set of worldwide macroeconomic and financial variables are taken into account. As for the conditional correlation between filtered commodity returns, we uncover a time-varying excess comovement even when heteroscedasticity is properly considered. Our results show that the commonality in commodity prices is mainly driven by excess comovement as initially purported in Pindyck and Rotemberg (1990) and that macroeconomic and financial factors are not sufficient to explain this commonality. Second, we show that this phenomenon does not exist for volatilities. This last result has somme implications on portfolio strategies or on the pricing of basket options including several commodities.

We identify two main inference issues arising for our proposed methodology. First, 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 $\sqrt{T}/N \to 0$.[5]

The second inference problem comes from the heteroscedasticity in many financial time series which is prone to bias classical estimate of correlation. This is an issue in Pindyck and Rotemberg (1990) contribution which has been considered further in Deb *et al.* (1996) by means of a multi-

[4] The literature has mostly explored the issue of volatility transmission through multivariate GARCH models (see Engle *et al.* (1990), Engle and Kroner (1995), Karolyi (1995) or Booth *et al.* (1997) among many others). Recently, Corradi *et al.* (2009) proposed a nonparametric test of volatility transmission based on the comparison of volatility densities.

[5] In a future version, we will 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.

variate GARCH model in its BEKK form (Engle and Kroner, 1995). We also rely on multivariate GARCH models but allow the correlations to vary over time by using a DCC model. The correlation estimated from the DCC model is immune to heteroscedasticity by construction. When testing the unconditional form of excess comovement for our sample, we use the correction developed in Forbes and Rigobon (2002).[6]

The plan for the rest of the paper is as follows. In the next section, we briefly review the relevant literature. Section 3 presents the data used for the empirical implementation. In section 4, we very briefly review the factor model methodology and compute the factors then used to filter the commodity returns series. Unconditional and conditional comovements are considered in section 5 while section 6 is dedicated to the analysis using the spillover index methodology. Section 7 concludes by providing some limits and possible further extensions of our analysis.

2 Brief literature review

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 what is "excess comovement": comovement in excess of anything that can be explained by the common effects of inflation, interest rates, etc. (Pindyck and Rotemberg, 1990). Such defined, comovement is a concept which may be confounded with contagion at first sight.[7] 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.[8] 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 very useful for our purpose, namely the fact that estimate of correlation in time-varying volatility environment may be biased upward or downward. Indeed, Forbes and Rigobon (2002) showed that a correction should be applied to estimate correlation when heteroscedasticity is present.[9] 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.[10] This correction has been applied recently in Kallberg and Pasquariello (2008) to examine excess comovement in sectoral indices in the US.[11]

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

[6]This correction has been used for instance in Kallberg and Pasquariello (2008) or Chng *et al.* (2007).

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

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

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

[10]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.

[11]Kallberg and Pasquariello (2008) provide an alternative method to examine excess comovement for stock indices. The authors apply feasible generalized least squares (FGLS) on a SUR regression to filter their returns both with sector-specific and sector-non-specific factors. Because in the present paper we assume that commodity returns are leaded by some common factors, we choose to filter our returns using the same set of factors and SUR regression simplify to OLS regression equation by equation. In the robustness check section, we provide evidence that filtering our data using different factors, a less intuitive method, has no qualitative impact on our results.

ables to consider to define “fundamentals”. In the original paper of Pindyck and Rotemberg (1990), 6 variables are selected. These same variables are used in Deb *et al.* (1996). Gilbert (1989) emphasizes the impact of the exchange rates as an explanatory factor for commodity prices. To deal with the issue of omitted variables, we suggest to rely on factor methodology which is able 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. As pointed out in Borensztein and Reinhart (1994), it is necessary 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). By including a large set of macroeconomic variables, we assume that these variables are widely considered and this should allow to filter our raw commodity series.

The factor models mainly allow to deal with a large number of series while avoiding the number of degrees-of-freedom problem.[12] Factor models have been developed in the statistical field to deal with this issue of large data sets, particularly when the cross-section is large while the time period remains moderate. We do not present factor further and refer the interested reader to the excellent surveys of Stock and Watson (2006) or Bai and Ng (2008) which emphasize on economic applications.

Another point has to be noted: we consider returns and not prices in the present paper. Some papers have been interested in the excess comovement of prices (Palaskas and Varangis[13] (1991), Leybourne *et al.* (1994)) and thus rely on a co-integration analysis. We assume that return excess comovement is more appealing when dealing with risk management and we thus consider returns. Returns have also been considered recently in Ai *et al.* (2006) for main agricultural commodities and it is shown that storage levels can significantly explain excess comovement.[14]

3 Data

In this section, we discuss the data to be used in empirical work. These data are on one hand the commodity prices, and all macroecononomic variables used to represent the common factors on the other one. All commodity prices are extracted from DataStream. We consider in our data set 8 commodities which may seem unrelated at first sight: wheat, copper, silver, soybean, raw sugar, cotton,crude oil, pork bellies. The exchange places as well as the nature of the price considered are detailed in DataStream. Our choice for such commodities is mainly dictated by data availability. Some alternative commodities are not traded at a public price before 1982. Because we do want to include crude oil in our data set, we thus consider series from 1982:2 to 2007:12.

As many of our macroeconomic variables are only observed at a monthly frequency, we use monthly commodities price series. Returns are computed as the log difference of prices. Prices and returns are respectively displayed on graphs 1 and 2. Standard descriptive statistics for returns are reported in Table 1. Not surprinsingly, these statistics show evidence skewness and excess kurtosis

[12] 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.

[13] Their analysis is criticized and extended in Leybourne *et al.* (1994) who develop a conceptual framework for the analysis of excess comovement.

[14] Malliaris and Urritia (1996) are also interested in the analysis of excess comovement for agricultural only commodities.

	Wheat	Copper	Silver	Soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Mean	0.0026	0.0046	0.0017	0.0015	-0.0004	-0.0001	0.0033	0.0001
Maximum	0.2056	0.2624	0.3656	0.2024	0.5337	0.3684	0.4159	0.6222
Minimum	-0.2021	-0.3475	-0.3479	-0.4574	-0.2425	-0.8679	-0.3904	-0.5346
Std. Dev.	0.07	0.07	0.08	0.07	0.11	0.09	0.10	0.16
Skewness	-0.04	-0.14	0.05	-0.90	0.75	-2.92	-0.00	-0.05
Exc. kurtosis	3.21	5.67	6.38	9.27	5.56	33.85	5.04	4.53
Jarque-Bera	133.34	416.88	525.84	1152.17	427.74	15242.35	328.71	264.85
Observations	310	310	310	310	310	310	310	310

Table 1
Descriptive statistics for monthly returns (log differences) for the eight commodities over the period 1982:2-2007:12. Commodity prices are cash prices except in the crude oil cas where the current month contract price is taken as a proxy for the cash price.

for each return and the Jarque-Bera test reject the hypothesis of a gaussian distribution. Some heteroscedasticity present in the data may explain non-normality. We don't explore the issue of heteroscedasticity for our raw series because we are more interested in filtered series, which will be used to compute correlations.

In the empirical analysis presented in the next section, factors are extracted from a large panel of 200 macroeconomic and financial variables from 1982:2 to 2007:12. Our panel extends the data set of 132 variables considered in Ludvigson and Ng (2009) which is itself an extension of the widely used data set of Stock and Watson (2005).[15] We reduce it further in time, while enlarging its cross section, in order to deal with a sufficient number of commodity series. Our aim is to include enough world time-series so as to include world information which is likely to influence commodity returns.

4 Factors computation and filtering of raw data

4.1 Computing static factors

In this section, we proceed to a large dimensional apporximate factor analysis to estimate the latent common factors which may affect the changes in the commodities returns. We proceed in two steps. In the first one, we estimate the factors and the number of factors to retain. In the second step, we filter commodity returns using some possibly nonlinear combinations of the estimated factors so as to enlarge as much as possible the set of possibilities in modelling the relationship between commodities and factors.

4.1.1 Factor models

We consider a static factor model. We dispose of a sample of $i = 1, ..., N$ cross-section units and $t = 1, ..., T$ times series observations.

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

F_t is the vector of the r common factors. e_{it} is referred to as the idiosyncratic error and λ_i as the factor loadings of the (static) common factors. Let $X_t = (x_{1t}, ..., x_{Nt})'$, $e_t = (e_{1t}, ..., e_{Nt})'$ and $\Lambda = (\lambda_1, ..., \lambda_N)'$, we have the vector form notation :

$$X_t = \Lambda F_t + e_t$$

[15]The original data set in Stock and Watson (2005) covers the period 1959:1-2003-12. It is slightly shortened in Ludvigson and Ng (2009) to cover the period 1964:1-2007-12.

Figure 1
Commodity monthly prices over the period 1982:2-2007:12 (311 observations). From top to bottom and from left to right: wheat, copper, silver, soybean, raw sugar, cotton, crude oil, pork bellies.

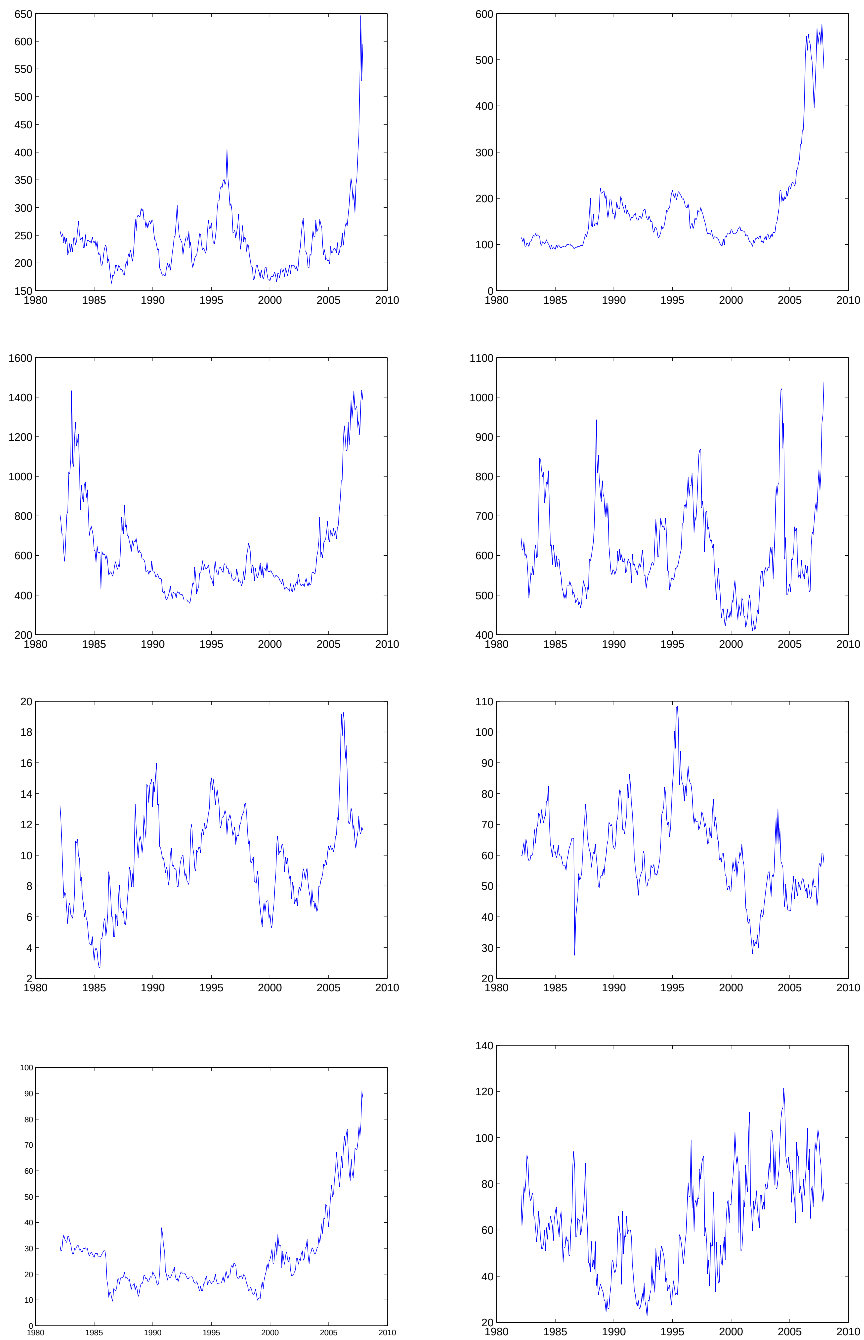
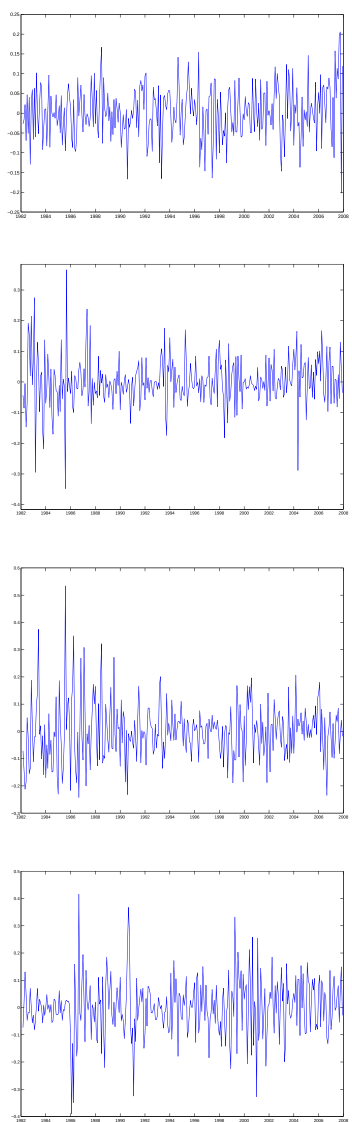


Figure 2
Commodity monthly log returns over the period 1982:3-2007:12 (310 observations). From top to bottom and from left to right: wheat, copper, silver, soybean, raw sugar, cotton, crude oil, pork bellies.



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.

In classical factor analysis, F_t and e_t are assumed to be serially and cross-sectionally uncorrelated. Moreover the number of unit of observations N was supposed to be fixed. A new approach of factor model, known as "large dimensional approximate factor models" was initiated by Stock and Watson (2002a,b)[16]. These new models differ from previous classical factor models in at least two ways: the sample size tends to infinity in both directions in asymptotic theory, the idiosyncratic errors are allowed to be "weakly correlated" across i and t [17].

We make the assumption that there are k factors, we use the method of principal components to estimate the $T \times k$ matrix F^k of estimated factors and the corresponding $N \times T$ matrix Λ^k of estimated loadings.These estimates solve the following optimization problem :

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

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

If we define X as the $T \times N$ matrix with t^{th} row $X_t^{'}$, 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 given by:

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

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) give the asymptotic distribution of the principal component estimator.

4.1.2 Estimating the number of factors

Bai and Ng (2002) proposed several information criterions 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 by *NT*) when k factors are estimated, the information criterions have the following expressions:

$$\begin{aligned} PCP(k) &= S(k) + k\bar{\sigma}^2 g(N,T) \\ IC(k) &= ln(S(k)) + kg(N,T) \end{aligned}$$

[16]See Bai and Ng (2008) for a recent survey on these large factor approximate models.

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

i	1	2	3	R_i^2
1	0.7957	0.7477	0.66391	0.1115
2	-0.1463	-0.2983	0.0641	0.1616
3	0.2245	0.3314	0.4062	0.2019
4	0.5132	0.3269	0.3268	0.2409
5	0.4632	0.3077	0.3733	0.2760
6	0.5083	0.4074	0.4751	0.3089
7	-0.3710	-0.1282	0.2366	0.3391

Table 2
Estimated factors $\widehat{F}_{t,i}$ for $i = 1, ..., 7$ using the principal components method and a panel data with 200 macroeconomic and financial variables for the period 1982:2 to 2007:12 (311 observations). Before computation of the factors, the data are stationarized using the appropriate transformation (see the Appendix). The R_i^2 illustrate the cumulated explanatory power of the factors for the full sample of variables. Autoregressive coefficients up to 3 lags are also computed.

$\bar{\sigma}^2$ is equal to $S(k_{max})$ for a pre-specified value *kmax*. $g(N,T)$ is a penalty function. Penalty functions suggested by Bai and Ng (2002) are:

$$\begin{aligned}
g_1(N,T) &= \frac{N+T}{NT} ln(\frac{NT}{N+T}) \\
g_2(N,T) &= \frac{N+T}{NT} ln(C_{NT}^2) \\
g_3(N,T) &= \frac{ln(C_{NT}^2)}{C_{NT}^2} \\
g_4(N,T) &= (N+T-k)\frac{ln(NT)}{NT}
\end{aligned}$$

The estimator for the number of factors is defined as:

$$\begin{aligned}
\hat{k}_{PCP} &= \underset{0 \le k \le k_{max}}{\text{argmin}}\ PCP(k) \\
\hat{k}_{IC} &= \underset{0 \le k \le k_{max}}{\text{argmin}}\ IC(k)
\end{aligned}$$

Some information on our estimated factors $\widehat{F}_t$ are presented in Table 2. The number of the selected factors, given the information criterion (Bai and Ng, 2002) is 7. These 7 factors are able to explain about 34% of the total variance of the variables and are orthogonal by construction. It is often argued that factors are more persistent. To have an idea of their persistence, we also provide in table 2 the autocorrelations up to 3 lags.

4.2 Filtering the data

Our next step consist in estimating each return conditional mean with the help of the estimated factors. It is worthwhile to note that extracted latent factors for the macroeconomic and financial variables may not be the most relevant for the filtering of commodity returns. Consequently, we follow Ludvigson and Ng (2010) and test several specifications using estimated factors and powers of these factors[18]. This ensure that we should be able to detect some nonlinearities. In this frame-

[18] We first evaluate $r = 7$ univariate regressions of returns on each of the $r = 7$ factors. Then only those factors that contribute significantly to the sum of the $\bar{R}^2$ of the $r = 7$ regressions are kept. For these factor, we evaluate whether squared or cubed terms help increase the $\bar{R}^2$ criterion further

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
constante	0.0027	0.0046	0.0017	0.0015	-0.0004	-0.0001	0.0034	(0.0001)
	(0.7146)	(1.1544)	(0.3843)	(0.3871)	(-0.0721)	(-0.0270)	(0.6229)	(0.0135)
$\widehat{F}_1$	0.0006	0.0113	0.0023	0.0044	0.0141	0.0030	0.0115	-0.0037
	(0.1600)	(2.8367)	(0.5183)	(1.1130)	(2.3671)	(0.6098)	(2.1368)	(-0.3968)
$\widehat{F}_2$	-0.0037	-0.0077	0.0008	-0.0023	0.0047	0.0039	-0.0320	0.0007
	(-0.9908)	(-1.9264)	(0.1662)	(-0.5676)	(0.7897)	(0.7900)	(-5.9352)	(0.0778)
$\widehat{F}_3$	0.0041	0.0034	-0.0042	-0.0012	0.0037	0.0026	0.0168	0.0015
	(1.0909)	(0.8496)	(-0.9247)	(-0.3071)	(0.6301)	(0.5229)	(3.1059)	(0.1645)
$\widehat{F}_4$	-0.0009	-0.0035	-0.0018	0.0002	-0.0036	-0.0021	0.0209	-0.0035
	(-0.2513)	(-0.8774)	(-0.4046)	(0.0585)	(-0.6096)	(-0.4173)	(3.8761)	(-0.3774)
$\widehat{F}_5$	-0.0023	-0.0078	-0.0100	-0.0035	-0.0030	-0.0013	0.0026	-0.0081
	(-0.6124)	(-1.9466)	(-2.2210)	(-0.8799)	(-0.5063)	(-0.2535)	(0.4901)	(-0.8677)
$\widehat{F}_7$	-0.0026	-0.0013	-0.0035	-0.0041	-0.0081	0.0000	0.0064	0.0194
	(-0.7041)	(-0.3345)	(-0.7818)	(-1.0221)	(-1.3715)	(0.0011)	(1.1801)	(2.0701)
R^2	0.010229	0.05357	0.022137	0.011346	0.029258	0.0049513	0.17907	0.017419
$\overline{R}^2$	-0.0093709	0.034828	0.0027732	-0.0082308	0.010036	-0.014753	0.16282	-0.0020382
ARCH-LM (2)	36.7827	23.5031	48.4110	26.9469	2.5755	7.9301	13.9943	26.3435

Table 3
The table reports estimates from OLS regressions of monthly commodity returns for the 8 commodities of the contemporaneous variables named in column 1. The dependent variable is the nominal log return for each commodity liste in row 1. $\widehat{F}_i$ denotes the i^{th} estimated factor estimated using principal component method and a panel data with 200 macroeconomic and financial variables for the period 1982:2 to 2007:12 (311 observations). In the present regression, each factor enter linearly and 7 of the eight factors selected initially are considered. t-statistics are reported in parenthesis under the estimates. A constant whose estimate is reported in the second row is always included in the regressions.

work, we will accept the hypothesis of excess comovement if some correlations between pairs of commodity returns remain significant even after controlling for the contribution of selected factors.

Our first specification is linear. Since the 6^{th} factor do not individually significantly to the explanation of returns, we exclude it from our set of regressors and consider the following linear regression:

$$\begin{aligned} r_{it} &= \alpha_i + \sum_{k=1}^{5} \beta_{ik}\widehat{F}_{k,t} + \beta_{i,6}\widehat{F}_{7,t} + u_{it} \qquad i=1,...,8 \quad t=1,...,T && (1)\\ &= \alpha_i + \beta_i^{'}\bar{F}_t^{l} + u_{it} && (2) \end{aligned}$$

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 $\bar{F}_t^l = (\widehat{F}_{1,t}, \widehat{F}_{2,t}, \widehat{F}_{3,t}, \widehat{F}_{4,t}, \widehat{F}_{5,t}, \widehat{F}_{7,t})'$ the vector of selected factors at date t.

Eq. 3 is estimated by a SUR estimator, which is equivalent to OLS equation by equation as the set of regressor is the same for all of them. Results are provided in Table 3. These results show that the explanatory power of these regressions are very low as R^2 vary from 0.49% for cotton to a maximum of 17.9% in the case of crude oil. In spite of using factors computed from a large dataset, our results do not substantially differ from those previously obtained by Pindick and Rotemberg (1990).

We then consider 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 :

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

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
constant	0.0025	0.0044	0.0012	0.0022	0.0000	0.0006	0.0028	0.0003
	(0.6686)	(1.0981)	(0.2601)	(0.5504)	(0.0001)	(0.1204)	(0.5204)	(0.0266)
$\widehat{F}_1$	0.0007	0.0113	0.0027	0.0040	0.0135	0.0025	0.0123	-0.0040
	(0.1739)	(2.8280)	(0.5945)	(0.9973)	(2.2745)	(0.4991)	(2.2944)	(-0.4177)
$\widehat{F}_2$	-0.0066	-0.0113	-0.0061	0.0054	0.0055	0.0120	-0.0336	-0.0000
	(-1.1479)	(-1.8477)	(-0.8769)	(0.8929)	(0.6081)	(1.5810)	(-4.1282)	(-0.0034)
$\widehat{F}_3$	0.0045	0.0039	-0.0035	-0.0019	0.0043	0.0020	0.0161	0.0020
	(1.1866)	(0.9718)	(-0.7624)	(-0.4787)	(0.7223)	(0.3928)	(2.9909)	(0.2051)
$\widehat{F}_4$	0.0013	-0.0000	-0.0026	0.0025	0.0102	0.0022	0.0039	0.0035
	(0.2250)	(-0.0029)	(-0.3845)	(0.4175)	(1.1444)	(0.2941)	(0.4790)	(0.2442)
$\widehat{F}_2^3$	0.0006	0.0007	0.0014	-0.0016	-0.0003	-0.0017	0.0005	0.0001
	(0.6394)	(0.7499)	(1.3234)	(-1.7159)	(-0.2232)	(-1.4548)	(0.4018)	(0.0387)
$\widehat{F}_4^3$	-0.0005	-0.0009	0.0005	-0.0009	-0.0039	-0.0015	0.0049	-0.0020
	(-0.4489)	(-0.6832)	(0.3214)	(-0.7202)	(-2.1150)	(-0.9485)	(2.9008)	(-0.6584)
R^2	0.0093482	0.044576	0.010351	0.016788	0.036843	0.014703	0.19748	0.0025094
$\overline{R}^2$	-0.010269	0.025657	-0.0092462	-0.0026816	0.01777	-0.0048077	0.18159	-0.017243
ARCH-LM (2)	29.7639	19.3448	49.6580	26.2928	2.1961	7.5579	16.2512	21.8082

Table 4
The table reports estimates from OLS regressions of monthly commodity returns for the 8 commodities of the panel on the contemporaneous variable named in column 1. The dependent variable is the nominal log return for each commodity liste in row 1. $\widehat{F}_i$ denotes the estimated factors estimated using principal component method and a panel data with 200 macroeconomic and financial variables for the period 1982:2 to 2007:12 (311 observations). In the present regression, each factor can enter nonlinearly and 4 of the eight factors selected initially are considered. The t-statistics are reported in parenthesis under the estimates. A constant whose estimate is reported in the second row is always included in the regression.

Results of the specification we retained are reported in Table 4. 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).

We finally end up with the residuals which will be our series of interest in the rest of the analysis exploring comovements. These residuals represent the commodity returns once "fundamentals" have been considered, and because we considered fundamentals through factors, we assume that they are taken into account in the most relevant way.

5 Excess comovement in returns

5.1 Unconditional comovement

In this section, we examine the unconditional correlation of our series of residuals using simple sample correlation as in Pindyck and Rotemberg (1990). We report estimated correlations (in the upper triangular matrix) as long with their p-values [19] (in the lower triangular matrix) in Tables 5 and 6 for residuals from linear and nonlinear filtration, respectively. For both linear and nonlinear set of regressions, 9 residuals correlations are significant at a 5% level. We find evidence of correlation between wheat and soybean, copper and silver, copper and raw sugar, copper and cotton, copper and crude oil, silver and crude oil, soybean and cotton, soybean and crude oil, raw sugar and cotton. If we apply a 10% level, we accept three extra significant correlations: wheat and copper, wheat and crude oil, cotton and crude oil for the linear regression. For the nonlinear regression, residuals correlations between wheat and copper, wheat and crude oil are significant at 10% level.

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

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.10326	0.065654	0.37883	0.060549	-0.0048841	-0.095977	0.027041
Copper	0.069436	1	0.21607	0.063101	0.12342	0.11536	0.11697	-0.031479
Silver	0.2491	0.00012588	1	0.048035	0.012917	-0.019496	0.13258	0.093088
soybean	5.13E-12	0.26802	0.39933	1	0.093265	0.1915	-0.13252	0.045368
Raw Sugar	0.2879	0.029816	0.8208	0.10121	1	0.12103	-0.089276	-0.078251
Cotton	0.93175	0.042386	0.73243	0.00070009	0.033151	1	-0.09483	0.016239
Crude Oil	0.091619	0.039564	0.019529	0.019591	0.11673	0.095581	1	-0.014572
Pork Bellies	0.6353	0.58085	0.10186	0.42605	0.16935	0.77581	0.7983	1

Table 5
Correlation between residuals after filtration through a 6 factors linear model. The upper triangular matrix reports correlation while the lower reports the p-values.

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.10486	0.069203	0.38641	0.062392	-0.0027311	-0.097445	0.022761
Copper	0.065197	1	0.22623	0.072333	0.12394	0.11846	0.11871	-0.029398
Silver	0.22437	5.84E-05	1	0.065283	0.023505	-0.010163	0.12157	0.093421
soybean	1.77E-12	0.20406	0.25179	1	0.093523	0.18307	-0.13041	0.039302
Raw Sugar	0.27345	0.02912	0.68017	0.10026	1	0.11465	-0.076271	-0.090432
Cotton	0.9618	0.037107	0.85856	0.001205	0.043676	1	-0.085527	0.015001
Crude Oil	0.086741	0.036706	0.032378	0.021636	0.18043	0.13296	1	-0.0016813
Pork Bellies	0.68975	0.60612	0.10063	0.49054	0.11205	0.79249	0.97648	1

Table 6
Correlation between residuals after filtration through a 6 factors nonlinear model. The upper triangular matrix reports correlation while the lower reports the p-values.

5.2 Conditional comovement using DCC

To investigate the behavior of the conditional correlation, it seems appealing to use a dynamic correlation model[20]. Our choice goes to the widely used DCC model of Engle (2002) in its scalar form in order to maintain tractability with 8 time series. The DCC approach has several advantages over a standard unconditional approach. First, because residuals are devolatilized using an appropriate measure of volatility computed from a univariate GARCH model, the issue of heteroscedasticity is implicitly considered and no posterior correction has to be applied. Second, the DCC model allows to investigate the evolution of the excess comovement through time. These changes could be related to changes of the macroeconomic framework (expansion, recession) and thus permits an interpretation of our results.

Estimated conditional correlations are depicted on graphs 3. These graphs show that conditional correlations present some peaks or troughs. Therefore, the strengh of excess comovement appears to be time-varying.

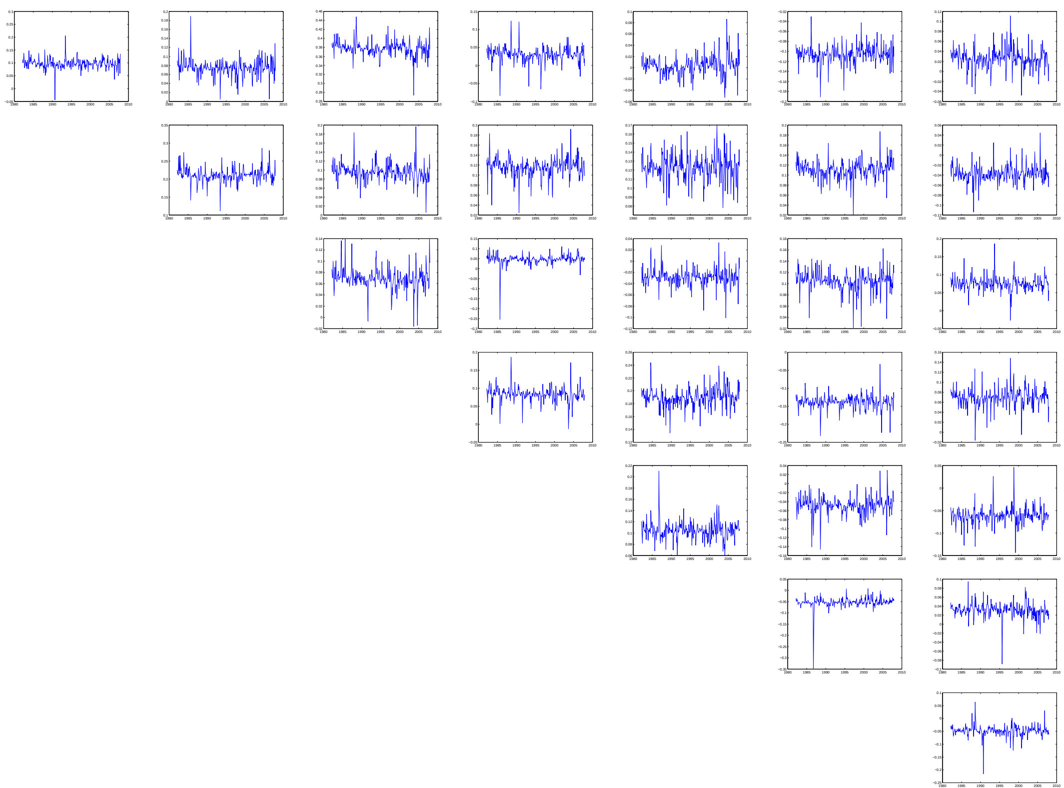
However, the original DCC model of Engle (2002) postulates a constant unconditional correlation and is not suitable to illustrate level change in unconditional correlation. In other words, the model is mean-reverting by construction and does not allow any structural change in the conditional correlation. Evidence of mean-reversion appears in Figure 3. It can be observed that the DCC model does not allow conditional correlation to deviate much from the unconditional (sample) correlation.

5.3 Conditional comovement using Forbes and Rigobon (2002)

In this section, we proceed as in Kallberg and Pasquariello (2008) to deal with the issue of mean-reversion in the DCC model. The main idea is to compute sample correlation coefficients and then correct them using Forbes and Rigobon (2002) methodology. Applied on a rolling basis, this esti-

[20] For almost all residuals, the arch-Lm test shows evidence of conditional heteroskedasticity. Furthermore we reject the null hypothesis of constant condtional correlation with the Tse (2000) test.

Figure 3
The figure plots the conditional correlation over the period 1982:2-2007:12 computed from a scalar DCC model (Engle, 2002) for series of residuals and QMLE for estimation. Plots are presented as in a correlation matrix. The first row considers correlation between wheat and copper, silver, soybean, raw sugar, cotton, crude oil, pork bellies, respectively. The second row considers correlations between copper and silver, soybean, raw sugar, cotton, crude oil, pork bellies, respectively. Etc.



mate is able to track the true conditional correlation. The estimate is nonparametric 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).[21]

5.3.1 A non parametric estimation of correlation

Once we have fit the commodities returns' conditional mean equation, we use the residuals $\hat{u}_{i,t}$ to compute for each pairs of non redundant returns $i \neq j$ the excess comovement measured by the residuals correlation coefficient:

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

Boyer *et al.* (1999), Loretan and English (2000) and Forbes and Rigobon (2002) show that the correlation coefficient is conditional on returns volatility. Hence, in the presence of heteroskedasticity, tests for contagion based on such coefficient may be biased toward rejection of the null hypothesis of no excess comovement among commodity returns. These 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 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 short-term volatility $var(\hat{u}_{i,t})$ and the long-term volatility $var(\hat{u}_{i,t})_{LT}$ of the i^{ith} return. 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, $\hat{\rho}^*_{ij,t}$ and $\hat{\rho}^*_{ji,t}$ may be different.

As suggested by King *et al.* (1994) and Kallberg and Pasquariello (2008), we compute the arithmetic means of pairwise 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 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:

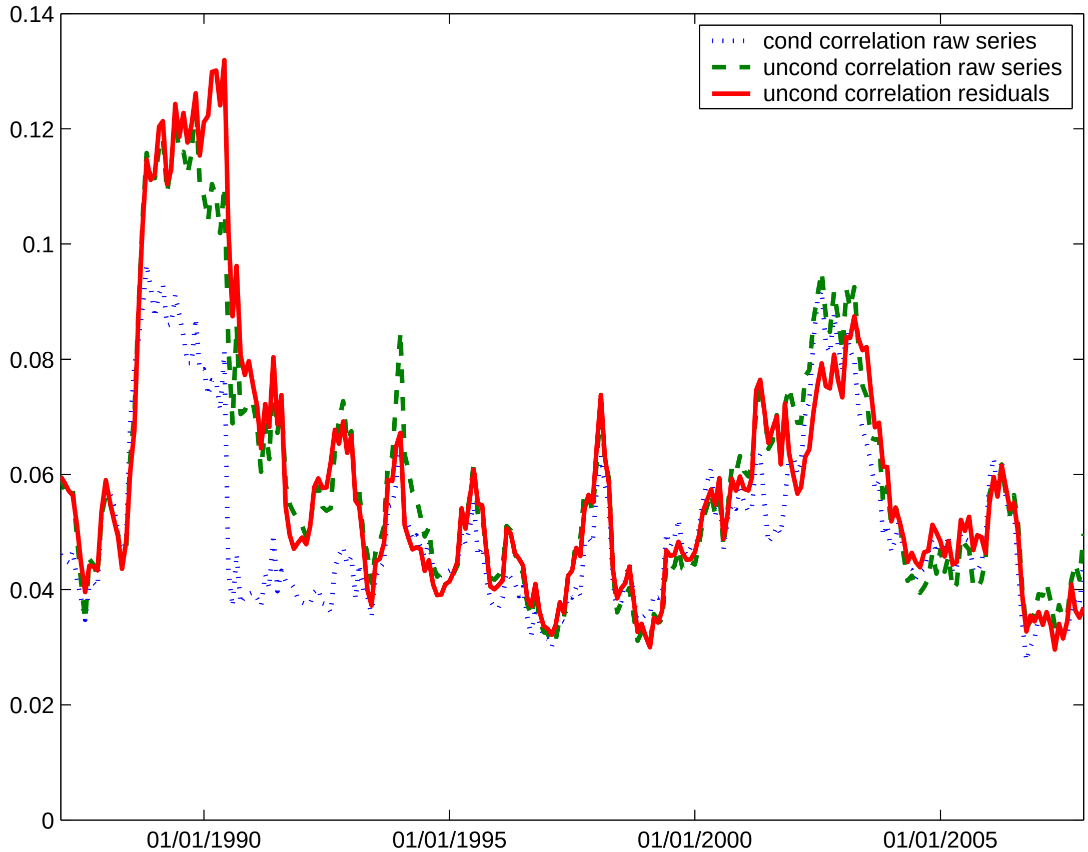
$$\hat{\rho}^*_{i,t} = \frac{1}{K-1} \sum_{j=1, j\neq i}^{K} (\hat{\rho}^*_{ij,t})^2$$

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

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

[21]The recent multivariate stochastic volatility model in conjunction with a dynamic correlation structure developed in Asai and McAleer (2009) is less prone to change in correlation level

Figure 4
Mean excess squared correlation for all commodities from 1985:2 to 2007:12.



In this paper, we treat the covariance matrix of returns residuals as observable and construct 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 $g>1$) $[t-gN+1,t]$.

5.3.2 Empirical results

We estimate sample correlations and correlations corrected for changes in conditional volatilities with a rolling windows of N=24 observations for short-term volatilities and gN = 60 observations for long-term volatilities. With the corrected correlations, we compute the average excess squared correlations for all commodidities and the average excess squared correlation of each commodity with the other ones. The all commodities average excesse correlation is represented on graph 4. We can clearly see that there is noticeable excess correlations between commodities returns and that the pattern of this excess correlation has changed through time. There is one peak around 1990 and another one 2004. Average excess square correlation for each individual commmodities are representeed on graphs 4 and 6. These graphs show a noticeable level of excess correlations for

Figure 5
Excess squared correlation for each individual commodity from 1985:2 to 2007:12. Commodities are ordered as follows from upper left to bottom right: wheat, copper, silver and soybean.

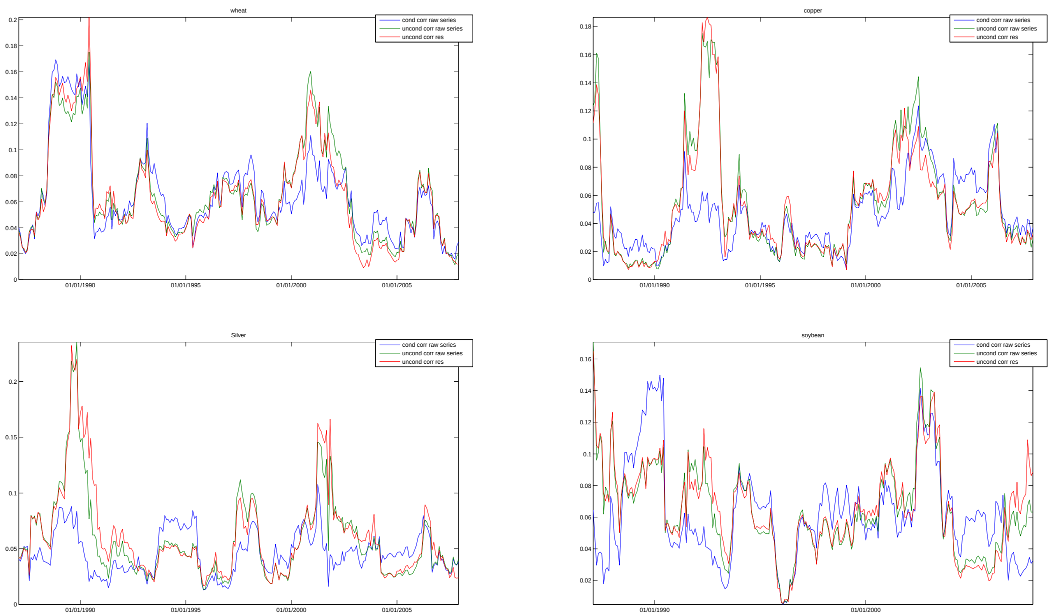
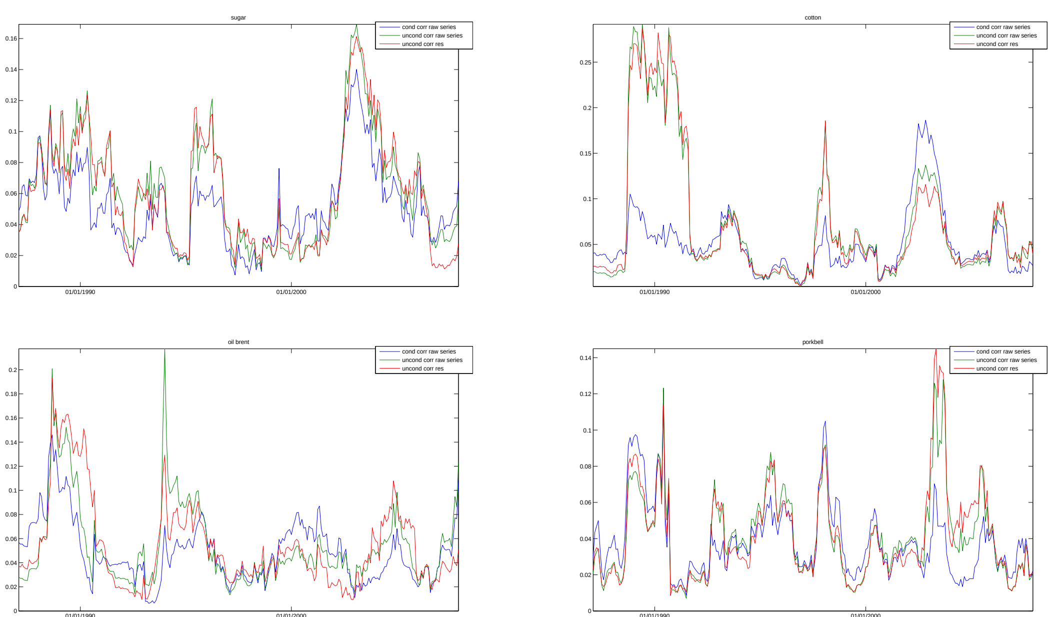


Figure 6
Excess squared correlation for each individual commodity 1985:2 to 2007:12. Commodities are ordered as follows from upper left to bottom right: raw sugar, cotton, crude oil and pork bellies.



	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
constant	0.086511	0.047928	0.12765	0.07859	0.13968	0.11406	0.075701	0.26388
	(6.3202)	(3.9189)	(6.0568)	(5.5997)	(5.9419)	(5.867)	(4.2013)	(6.1355)
r_{t-1}	0.45748	0.49616	0.59277	0.56543	0.28314	0.76963	0.32888	0.4998
	(8.7356)	(8.9616)	(11.025)	(10.548)	(5.4819)	(14.292)	(5.9951)	(8.9046)
r_{t-2}	0.062451	0.070303	-0.2178	0.046896	0.16756	-0.025033	0.22042	0.042992
	(1.0836)	(1.142)	(-3.4703)	(0.76969)	(3.0974)	(-0.38004)	(3.8225)	(0.68554)
r_{t-3}	0.12884	0.1833	0.14546	-0.089808	0.027618	-0.38708	0.17345	-0.023746
	(2.2013)	(2.9587)	(2.307)	(-1.4678)	(0.50486)	(-5.8593)	(3.0515)	(-0.37803)
r_{t-4}	-0.05187	0.016316	0.0075121	0.10092	0.10655	0.22061	-0.038534	0.022487
	(-0.97836)	(0.29385)	(0.13988)	(1.8768)	(2.0616)	(4.1141)	(-0.70911)	(0.39973)
$\widehat{F}_1$	8.14E-05	0.0051571	0.0029825	0.0091537	-0.0068615	-0.0076326	-0.0076997	-0.011328
	(0.022036)	(1.2267)	(0.33539)	(1.9723)	(-0.97145)	(-0.74063)	(-0.9383)	(-0.76901)
$\widehat{F}_3$	0.010419	0.0071509	0.0083125	0.0096252	-0.00092941	0.018187	0.023779	0.020788
	(2.9556)	(1.7995)	(0.99036)	(2.2413)	(-0.13876)	(1.865)	(3.0326)	(1.5034)
$\widehat{F}_4^2$	0.002318	0.0015546	-0.0047285	-0.00064249	0.0072827	-0.002931	0.022465	0.010777
	(0.99103)	(0.58411)	(-0.85033)	(-0.22411)	(1.6301)	(-0.45053)	(4.3257)	(1.1615)
$\widehat{F}_5$	-0.005683	0.006971	0.0016687	0.00064896	0.0086938	-0.0049211	0.0068209	0.018484
	(-1.6359)	(1.6964)	(0.2018)	(0.15272)	(1.3051)	(-0.50675)	(0.8898)	(1.2918)
$\widehat{F}_5^2$	-0.0011449	0.0021124	0.0019934	0.00043143	-0.0050244	-0.003472	0.00089563	-0.0061279
	(-0.55038)	(0.88375)	(0.40172)	(0.1702)	(-1.2563)	(-0.59821)	(0.19388)	(-0.73706)
$\widehat{F}_6$	-0.0011378	-0.0038894	-0.014838	-0.0057094	-0.015227	-0.028078	-0.0027737	0.02062
	(-0.31888)	(-0.93229)	(-1.7502)	(-1.3164)	(-2.1972)	(-2.7932)	(-0.34568)	(1.4177)
$\widehat{F}_7$	0.0099269	0.0054998	0.0063759	0.0087592	0.031411	-0.0052861	0.014537	0.035614
	(2.8279)	(1.3693)	(0.76292)	(2.0536)	(4.7098)	(-0.54226)	(1.8869)	(2.56)
R^2	0.35954	0.52282	0.33045	0.39563	0.31227	0.53106	0.49842	0.32439
$\overline{R}^2$	0.33557	0.50497	0.30539	0.37301	0.28654	0.51351	0.47966	0.29911

Table 7
The table reports estimates from OLS regressions of monthly commodity realized annualized volatilities for the 8 commodities of the panel on their lagged values up to order 4 and estimated common factors. The dependent variable is the monthly realized volatility in its annual form using daily returns for each commodity listed in row 1. $\widehat{F}_i$ denotes the estimated factors estimated using principal component method and a panel data with 200 macroeconomic and financial variables for the period 1982:2 to 2007:12 (311 observations). In the present regression, each factor can enter nonlinearly and 6 of the eight factors selected initially are considered. The t-statistics are reported in parenthesis under the estimates. A constant whose estimate is reported in the second row is always included in the regression.

each commodity. The peak time periods are more or less the same as for the global indicator.

6 Excess comovement in volatilities

In this section we investigate the issue of excess comovement in volatilities. Our methodology follows the one used for returns except that we only consider the raw correlation coefficient to detect excess comovement.

6.1 Filtering raw series

Our measure of volatility is a realized measure which is more efficient than the range-based used in Diebold and Yilmaz (2009) among others. It is used in Schwert (1990) and more recently in Ghysels *et al.* (2005) or Ludvigson and Ng (2007).[22] We simply sum squared return in order to estimate monthly variance. Our volatility estimates are then filtered using the SUR methodology. We only report in Table 7 results for the nonlinear specification with lags up to order 4.[23] It can be observed that the explanatory power of our factors is much larger for the volatility series than for return series. Indeed, all the series have an R^2 higher to 30% and three of them (copper, cotton, crude oil) have a R^2 around 50%.

[22] French *et al.* (1987) suggest to correct for autocorrelation using an additional term in the regression. It has a main advantage, namely that estimate of the volatility may be negative in some cases. So we opt for the Schwert (1990) estimator.
[23] Order 4 is sufficient to remove most of the autocorrelation which is a main feature of the variance series.

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.06199	0.0330	0.3838	0.0647	0.0424	0.1665	0.1044
Copper	0.2765	1	0.2408	0.1984	-0.0197	-0.0942	-0.0356	0.0705
Silver	0.5615	1.81E-05	1	0.0959	0.2975	-0.0650	-0.1899	0.1223
soybean	2.54E-12	0.0004	0.0917	1	0.0328	0.0307	-0.0316	0.0517
Raw Sugar	0.2553	0.7296	9.29E-08	0.5650	1	0.1416	0.0072	0.1654
Cotton	0.4566	0.0975	0.2533	0.5899	0.0125	1	0.2557	-0.0154
Crude Oil	0.0032	0.5315	0.0007	0.5793	0.8993	5.08E-06	1	0.0826
Pork Bellies	0.0662	0.2155	0.0312	0.3642	0.0034	0.7858	0.1465	1

Table 8
Correlation between raw data series. The upper triangular matrix reports correlation while the lower reports the p-values.

	Wheat	Copper	Silver	soybean	Raw Sugar	Cotton	Crude Oil	Pork Bellies
Wheat	1	0.0117	0.0365	0.3297	0.1256	-0.1192	0.0655	0.0512
Copper	0.8378	1	0.1997	0.0110	-0.0574	-0.0482	-0.0049	-0.0108
Silver	0.5237	0.0004	1	0.0515	0.2406	-0.0725	-0.0376	0.0999
soybean	3.42E-09	0.8474	0.3684	1	0.0981	-0.0471	0.0326	0.0306
Raw Sugar	0.0279	0.3166	2.09E-05	0.0866	1	0.0490	-0.0211	0.1193
Cotton	0.0371	0.4002	0.2054	0.4107	0.3923	1	0.0800	-0.0387
Crude Oil	0.2527	0.9315	0.5113	0.5699	0.7128	0.1622	1	0.03450
Pork Bellies	0.3713	0.8505	0.0808	0.5932	0.0368	0.4993	0.5476	1

Table 9
Correlation between residuals after filtration through a 7 factors nonlinear model. The upper triangular matrix reports correlation while the lower reports the p-values.

We then compute correlations between residuals. The latter are reported in Table 9. It can be noted that filtration allow a large reduction of the number of significant correlation (see Table 8 which reports sample correlation for raw data) compared to raw volatilities and to returns residuals. As displayed in table 9., there are only 6 significant correlations between volatility residuals when the level of the test is equal to 5% and 8 when it is equal to 10%. Our conclusion is that evidence of excess comovement in commodity volatilities is rather weak once fundamentals are considered.

7 Conclusion

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" are well taken into account. Second, we provide different definitions for what could be called "comovement" thus rendering our analysis more robust.

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, as in Ludvigson and Ng (2009), grouping variables to make factors more interpretable may be interesting in order to improve our understanding of which variables are the most fundamental variables. Third, our analysis may be conducted using dynamic factor models following Forni *et al.* (2005). 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.

References

AI, C., CHATRATH, A., SONG, F., 2006. On the comovement of commodity prices. *American Journal of Agricultural Economics* 88, 574-588.

ASAI, M., MCALEER, M., YU, J., 2006. Multivariate stochastic volatility: a review. *Econometric Reviews* 25, 145-175.

ASAI, M., MCALEER, M., 2009. The structure of dynamic correlations in multivariate stochastic volatility models. *Journal of Econometrics* 150, 182-192.

BAE, K.-H., KAROLYI, G.A., STULZ, R.M., 2003. A new approach to measuring financial contagion. *Review of Financial Studies* 16, 717-763.

BAE, S.C., KWON, T.H., PARK, J.W., 2009. Derivatives trading, volatility spillovers, and regulation:evidence from the Korean securities markets. *Journal of Futures Markets* 29, 563-597.

BAI, J., NG, S., 2002. Determining the number of factors in approximate factor models. *Econometrica* 70, 191-221.

BAI, J., NG, S., 2006. Confidence intervals for diffusion index forecasts and inference with Factor-Augmented Regressions. *Econometrica* 74, 1133-1150.

BAI, J., NG, S., 2008. Large dimensional factor analysis. *Foundations and Trends in Econometrics* 3, 89-163.

BARTLETT, M. S., 1951. The effect of standardization on a chi square approximation in factor analysis. *Biometrika* 38, 337-344.

BEKAERT, G., HODRICK, R.J, 1992. Characterizing predictable component in excess returns on equity and foreign exchange markets. *Journal of Finance* 47, 467-509.

BEKAERT, G., HODRICK, R.J, ZHANG, X., 2009. International stock return comovements. *Journal of Finance* 64, 2591-2626.

BERNANKE, B., BOIVIN, J., ELIASZ, P., 2002. Factor Augmented Vector Autoregressions (FAVAR) and the Analysis of Monetary Policy. *Quarterly Journal of Economics* 120, 387-422.

BOIVIN, J., NG, S., 2005. Understanding and comparing factor based forecasts. *International Journal of Central Banking* 1, 117-152.

BOIVIN, J., NG, S., 2006. Are more data always better for factor analysis. *Journal of Econometrics* 132, 169-194.

BOOTH, G.G., CHOWDHURY, M., MARTIKAINEN, T., TSE, Y., 1997. Intraday volatility in international stock index futures markets: Meteor showers or heat waves? *Management Science* 43, 1564-1576.

BORENSZTEIN, E., JEANNE, O., SANDRI, D., 2009. Macro-hedging for commodity exporters. CEPR Discussion Paper, International Macroeconomics Series, no. 7513.

BORENSZTEIN, E., REINHART, C.M., 1994. The macroeconomic determinants of commodity prices. *IMF Staff Papers* 41, 236-261.

BOYER, B., GIBSON, M., LORETAN, M., 1999. Pitfalls in tests for changes in correlations. Working Paper, vol. 597R. Federal Reserve Board.

MCALEER, M., CAPORIN, M., 2009. Do we really need both BEKK and DCC? A tale of two covariance models. Unpublished manuscript.

CASHIN, P., MCDERMOTT, C.J., SCOTT, A., 1999. The myth of comoving commodity prices. *IMF Working Paper* 169.

CORRADI, V., DISTASO, W., FERNANDES, M., 2009. International market links and volatility transmission. Working Paper, Imperial College London.

CROUX, C., FORNI, M., REICHLIN, L., 2001. A measure of comovement for economic variables: theory and empirics. *Review of Economics and Statistics* 83, 232-241.

DEB, P., TRIVEDI, P.K., VARANGIS, P., 1996. The excess comovement of commodity prices reconsidered. *Journal of Applied Econometrics* 11, 275-91.

DIEBOLD, F.X., YILMAZ, K., 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 119, 158-171.

DIEBOLD, F.X., YILMAZ, K., 2008. Equity market spillovers in the Americas. Unpublished manuscript.

DIEBOLD, F.X., YILMAZ, K., 2009. Better to give than to receive: predictive directional measurement of volatility spillovers. Unpublished manuscript.

DUNGEY, M., FRY, R., GONZÁLEZ-HERMOSILLO, B., MARTIN, V.L., 2005. Empirical modelling of contagion: a review of methodologies. *Quantitative Finance* 5, 9-24.

EICHENBAUM, M., 1983. A rational expectations equilibrium model of inventories of finished goods and employment. Journal of Monetary Economics 12, 259-77.

EICHENBAUM, M., 1984. Rational expectations and the smoothing properties of inventories of finished goods. Journal of Monetary Economics 14, 71-96.

ENGLE, R.F., ITO, T., LIN, W.-L., 1990. Meteor showers or heat waves? Heteroskedastic intra-day volatility in the foreign exchange market. *Econometrica* 58, 525-542.

ENGLE, R.F., KRONER, F.K., 1995. Multivariate simultaneous generalized ARCH. *Econometric Theory* 11, 122-150.

FORBES, K., RIGOBON, R., 2002. No contagion, only interdependence: measuring stock market co-movements. *Journal of Finance* 57, 2223-2261.

FORNI, M., HALLIN, M., LIPPI, M., REICHLIN, L., 2005. The generalized dynamic factor model, one sided estimation and forecasting. *Journal of the American Statistical Association* 100, 830-840.

GILBERT, C.L., 1989. The impact of exchange rates and developing country debt on commodity prices. *Economic Journal* 99, 773-84.

GORTON, G., ROUWENHORST, K.G., 2006. Facts and fantasies about commodity returns. *Financial Analysts Journal* 62, 47-68.

GOSPODINOV, N., NG, S., 2010. Commodity prices, convenience yields, and inflation. Working Paper.

KALLBERG, J., LIU, C.H., PASQUARIELLO, P., 2009. On the price comovement of U.S. residential real estate markets. Unpublished working paper.

KALLBERG, J., PASQUARIELLO, P., 2008. Time-series and cross-sectional excess comovement in stock indexes. *Journal of Empirical Finance* 15, 481-502.

KAROLYI, G.A., 1995. A multivariate GARCH model of international transmissions of stock returns and volatility: the case of the United States and Canada. *Journal of Business and Economic Statistics* 13, 11-25.

KING, M., SENTANA, E., WADHWANI, S, 1994, Volatility links between national stock markets. Econometrica, 62, 901-934.

LARSON, D.F., VARANGIS, P., YABUKI, N., 1998. Commodity risk management and development. World Bank Working Paper Series No. 1963, International Economics Department, Washington DC.

LEYBOURNE, S.J., LLOYD, T.A., REED, G.V., 1994. The excess comovement of commodity prices revisited. *World Economy* 22, 1747-1758.

LORETAN, M., ENGLISH, W., 2000. Evaluation "correlation breakdowns" during periods of market volatility. In: Bank of International Settlements (BIS), International Financial Markets and the Implications for Monetary and Financial Stability. BIS, Switzerland.

LUDVIGSON, S.C., NG, S., 2007. The empirical risk return relation: A factor analysis approach. *Journal of Financial Economics* 83, 171-222.

LUDVIGSON, S.C., NG, S., 2009. A factor analysis of bond risk premia. Manuscript in Progress for the *Handbook of Applied Econometrics*.

LUDVIGSON, S.C., NG, S., 2010. Macro factors in bond risk premia. *Review of Financial Studies*, forthcoming.

LÜTKEPOHL, H., 2005. *New introduction to multiple time series analysis*. Springer, Berlin.

MALLIARIS, A.G., URRITIA, J.L., 1996. Linkages between agricultural commodity futures contracts. *Journal of Futures Markets* 16, 595-610.

PALASKAS, T.B., VARANGIS, P.N., 1991. Is there excess co-movement of primary commodity prices? A co-integration test. World Bank Working Paper Series No. 758, International Economics Department, Washington DC.

PESARAN, M.H., PICK, A., 2007. Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control* 31, 1245-1277.

PINDYCK, R.S., ROTEMBERG, J.J., 1990. The excess co-movement of commodity prices. *Economic Journal* 100, 1173-89.

PINDYCK, R., ROTEMBERG, J., 1993. The comovement of stock prices. *Quarterly Journal of Economics* 108, 1073-1104.

ROACHE, S.K., 2008. Commodities and the market price of risk. IMF Working Paper WP/08/221.

STOCK, J.H., WATSON, M.W., 1999. Forecasting inflation. *Journal of Monetary Economics* 44, 293-335.

STOCK, J.H., WATSON, M.W., 2002a. Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association* 97, 1167-1179.

STOCK, J.H., WATSON, M.W., 2002b. Macroeconomic forecasting using diffusion indexes. *Journal of Business and Economic Statistics* 20, 147-62.

STOCK, J.H., WATSON, M.W., 2006. Forecasting with many predictors. In: G. Elliott, C.W.J. Granger, A. Timmermann (Eds.), *Handbook of Economic Forecasting*, vol. 1, Elsevier.

TSE, Y.K., 2000. A test for constant correlations in a multivariate GARCH model. *Journal of Econometrics* 98, 107-127.

WHEATLEY, S., 1989. A critique of latent variable tests of asset pricing models. *Journal of Financial Economics* 23, 325-338.

Appendix: Detail of the macroeconomic and financial variables considered

This appendix provides the list of the variables considered in the computation of the common factors.

Series Number	Short name	Mnemonic	Tran	Description
1	PI	a0m052	$\Delta \ln$	Personal Income (AR, Bil. Chain 2000 $) (TCB)
2	PI less transfers	a0m051	$\Delta \ln$	Personal Income Less Transfer Payments (AR, Bil. Chain 2000 $) (TCB)
3	Consumption	a0m224$_r$	$\Delta \ln$	Real Consumption (AC) a0m224/gmdc (a0m224 is from TCB)
4	M&T sales	a0m057	$\Delta \ln$	Manufacturing and Trade Sales (Mil. Chain 1996 $) (TCB)
5	Retail sales	a0m059	$\Delta \ln$	Sales of Retail Stores (Mil. Chain 2000 $) (TCB)
6	IP: total	ips10	$\Delta \ln$	Industrial Production Index - Total Index
7	IP: products	ips11	$\Delta \ln$	Industrial Production Index - Products, Total
8	IP: final prod	ips299	$\Delta \ln$	Industrial Production Index - Final Products
9	IP: cons gds	ips12	$\Delta \ln$	Industrial Production Index - Consumer Goods
10	IP: cons dble	ips13	$\Delta \ln$	Industrial Production Index - Durable Consumer Goods
11	IP: cons nondble	ips18	$\Delta \ln$	Industrial Production Index - Nondurable Consumer Goods
12	IP: bus eqpt	ips25	$\Delta \ln$	Industrial Production Index - Business Equipment
13	IP: matls	ips32	$\Delta \ln$	Industrial Production Index - Materials
14	IP: dble matls	ips34	$\Delta \ln$	Industrial Production Index - Durable Goods Materials
15	IP: nondble matls	ips38	$\Delta \ln$	Industrial Production Index - Nondurable Goods Materials
16	IP: mfg	ips43	$\Delta \ln$	Industrial Production Index - Manufacturing (Sic)
17	IP: res util	ips307	$\Delta \ln$	Industrial Production Index - Residential Utilities
18	IP: fuels	ips306	$\Delta \ln$	Industrial Production Index - Fuels
19	NAPM prodn	pmp	lv	Napm Production Index (Percent)
20	Cap util	a0m082	Δlv	Capacity Utilization (Mfg.) (TCB)
21	Help wanted indx	lhel	Δlv	Index of Help-Wanted Advertising in Newspapers (1967=100;Sa)
22	Help wanted/emp	lhelx	Δlv	Employment: Ratio; Help-Wanted Ads:No. Unemployed Clf
23	Emp CPS total	lhem	$\Delta \ln$	Civilian Labor Force: Employed, Total (Thous.,Sa)
24	Emp CPS nonag	lhnag	$\Delta \ln$	Civilian Labor Force: Employed, Nonagric. Industries (Thous.,Sa)
25	U: all	lhur	Δlv	Unemployment Rate: All Workers, 16 Years & Over (%,Sa)
26	U: mean duration	lhu680	Δlv	Unemploy. By Duration: Average (Mean) Duration in Weeks (Sa)
27	U ¡ 5 wks	lhu5	$\Delta \ln$	Unemploy. By Duration: Persons Unempl.Less than 5 Wks (Thous.,Sa)
28	U 5-14 wks	lhu14	$\Delta \ln$	Unemploy. By Duration: Persons Unempl. 5 to 14 Wks (Thous.,Sa)
29	U 15+ wks	lhu15	$\Delta \ln$	Unemploy. By Duration: Persons Unempl. 15 Wks + (Thous.,Sa)
30	U 15-26 wks	lhu26	$\Delta \ln$	Unemploy. By Duration: Persons Unempl. 15 to 26 Wks (Thous.,Sa)
31	U 27+ wks	lhu27	$\Delta \ln$	Unemploy. By Duration: Persons Unempl. 27 Wks + (Thous,Sa)
32	UI claims	a0m005	$\Delta \ln$	Average Weekly Initial Claims, Unemploy. Insurance (Thous.) (TCB)
33	Emp: total	ces002	$\Delta \ln$	Employees on Nonfarm Payrolls: Total Private
34	Emp: gds prod	ces003	$\Delta \ln$	Employees on Nonfarm Payrolls - Goods-Producing
35	Emp: mining	ces006	$\Delta \ln$	Employees on Nonfarm Payrolls - Mining
36	Emp: const	ces011	$\Delta \ln$	Employees on Nonfarm Payrolls - Construction
37	Emp: mfg	ces015	$\Delta \ln$	Employees on Nonfarm Payrolls - Manufacturing
38	Emp: dble gds	ces017	$\Delta \ln$	Employees on Nonfarm Payrolls - Durable Goods
39	Emp: nondbles	ces033	$\Delta \ln$	Employees on Nonfarm Payrolls - Nondurable Goods
40	Emp: services	ces046	$\Delta \ln$	Employees on Nonfarm Payrolls - Service-Providing
41	Emp: TTU	ces048	$\Delta \ln$	Employees on Nonfarm Payrolls - Trade, Transportation, and Utilities
42	Emp: wholesale	ces049	$\Delta \ln$	Employees on Nonfarm Payrolls - Wholesale Trade
43	Emp: retail	ces053	$\Delta \ln$	Employees on Nonfarm Payrolls - Retail Trade
44	Emp: FIRE	ces088	$\Delta \ln$	Employees on Nonfarm Payrolls - Financial Activities
45	Emp: Govt	ces140	$\Delta \ln$	Employees on Nonfarm Payrolls - Government
46	Avg hrs	ces151	lv	Avg Weekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls - Goods-Producing
47	Overtime: mfg	ces155	Δlv	AvgWeekly Hrs of Prod or Nonsup Workers on Private Nonfarm Payrolls - Mfg Overtime Hours
48	Avg hrs: mfg	aom001	lv	Average Weekly Hours, Mfg. (Hours) (TCB)
49	NAPM empl	pmemp	lv	Napm Employment Index (Percent)

Series Number	Short name	Mnemonic	Tran	Description
50	Starts: nonfarm	hsfr	ln	Housing Starts: Nonfarm (1947-58); Total Farm & Nonfarm (1959-) (Thous.,Saar)
51	Starts: NE	hsne	ln	Housing Starts: Northeast (Thous.U.)S.A.
52	Starts: MW	hsmw	ln	Housing Starts: Midwest (Thous.U.)S.A.
53	Starts: South	hssou	ln	Housing Starts: South (Thous.U.)S.A.
54	Starts: West	hswst	ln	Housing Starts: West (Thous.U.)S.A.
55	BP: total	hsbr	ln	Housing Authorized: Total New Priv Housing Units (Thous.,Saar)
56	BP: NE	hsbne*	ln	Houses Authorized by Build. Permits: Northeast (Thou.U.)S.A
57	BP: MW	hsbmw*	ln	Houses Authorized by Build. Permits: Midwest (Thou.U.)S.A.
58	BP: South	hsbsou*	ln	Houses Authorized by Build. Permits: South (Thou.U.)S.A.
59	BP: West	hsbwst*	ln	Houses Authorized by Build. Permits: West (Thou.U.)S.A.
60	PMI	pmi	lv	Purchasing Managers' Index (Sa)
61	NAPM new ordrs	pmno	lv	Napm New Orders Index (Percent)
62	NAPM vendor del	pmdel	lv	Napm Vendor Deliveries Index (Percent)
63	NAPM Invent	pmnv	lv	Napm Inventories Index (Percent)
64	Orders: cons gds	a0m008	Δ ln	Mfrs' New Orders, Consumer Goods and Materials (Bil. Chain 1982 $) (TCB)
65	Orders: dble gds	a0m007	Δ ln	Mfrs' New Orders, Durable Goods Industries (Bil. Chain 2000 $) (TCB)
66	Orders: cap gds	a0m027	Δ ln	Mfrs' New Orders, Nondefense Capital Goods (Mil. Chain 1982 $) (TCB)
67	Unf orders: dble	a1m092	Δ ln	Mfrs' Unfilled Orders, Durable Goods Indus. (Bil. Chain 2000 $) (TCB)
68	M&T invent	a0m070	Δ ln	Manufacturing and Trade Inventories (Bil. Chain 2000 $) (TCB)
69	M&T invent/sales	a0m077	lv	Ratio, Mfg. and Trade Inventories to Sales (Based on Chain 2000 $) (TCB)
70	M1 US	fm1	Δ^2 ln	Money Stock: M1(Curr, Trav.Cks, Dem Dep, Other Ck'able Dep) (Bil$,Sa)
71	M2 US	fm2	Δ^2 ln	Money Stock: M2(M1+O'nite Rps,Euro$,G/P&B/D Mmmfs&Sav&Sm Time Dep(Bil$,Sa)
72	M3 US	fm3	Δ^2 ln	Money Stock: M3(M2+Lg Time Dep,Term Rp's&Inst Only Mmmfs) (Bil$,Sa)
73	M2 (real) US	fm2dq	Δ ln	Money Supply - M2 in 1996 $ (Bci)
74	MB US	fmfba	Δ^2 ln	Monetary Base, Adj. tor Reserve Requirement Changes (Mil$,Sa)
75	Reserves tot	fmrra	Δ^2 ln	Depository Inst Reserves: Total, Adj. tor Reserve Req Chgs (Mil$,Sa)
76	Reserves nonbor	fmrnba	Δ^2 ln	Depository Inst Reserves: Nonborrowed, Adj. Res Req Chgs (Mil$,Sa)
77	C&I loans	fclnq	Δ^2 ln	Commercial & Industrial Loans Oustanding in 1996 $ (Bci)
78	ΔC&I loans	fclbmc	lv	Wkly Rp Lg Com'l Banks: Net Change Com'l & Indus Loans (Bil$,Saar)
79	Cons credit	ccinrv	Δ^2 ln	Consumer Credit Outstanding - Nonrevolving (G19)
80	Inst cred/PI	a0m095	Δlv	Ratio, Consumer Installment Credit to Personal Income (Pct.) (TCB)
81	S&P 500	fspcom	Δ ln	S&P's Common Stock Price Index: Composite (1941-43=10)
82	S&P: indust	fspin	Δ ln	S&P's Common Stock Price Index: Industrials (1941-43=10)
83	S&P div yield	fsdxp	Δlv	S&P's Composite Common Stock: Dividend Yield (% per Annum)
84	S&P PE ratio	fspxe	Δ ln	S&P's & Composite Common Stock: Price-Earnings Ratio (%,Nsa)
85	Fed Funds	fyff	Δlv	Interest Rate: Federal Funds (Effective) (% per Annum,Nsa)
86	Comm paper	cp90	Δlv	Commercial Paper Rate (AC)
87	3 mo T-bill	fygm3	Δlv	Interest Rate: U.S.Treasury Bills, Sec Mkt, 3-Mo. (% per Ann,Nsa)
88	6 mo T-bill	fygm6	Δlv	Interest Rate: U.S.Treasury Bills, Sec Mkt, 6-Mo. (% per Ann,Nsa)
89	1 yr T-bond	fygt1	Δlv	Interest Rate: U.S.Treasury Const Maturities, 1-Yr. (% per Ann,Nsa)
90	5 yr T-bond	fygt5	Δlv	Interest Rate: U.S.Treasury Const Maturities, 5-Yr. (% per Ann,Nsa)
91	10 yr T-bond	fygt10	Δlv	Interest Rate: U.S.Treasury Const Maturities, 10-Yr. (% per Ann,Nsa)
92	Aaa bond	fyaaac	Δlv	Bond Yield: Moody's Aaa Corporate (% per Annum)
93	Baa bond	fybaac	Δlv	Bond Yield: Moody's Baa Corporate (% per Annum)
94	CP-FF spread	scp90	lv	cp90-fyff (AC)
95	3 mo-FF spread	sfygm3	lv	fygm3-fyff (AC)
96	6 mo-FF spread	sfygm6	lv	fygm6-fyff (AC)
97	1 yr-FF spread	sfygt1	lv	fygt1-fyff (AC)
98	5 yr-FF spread	sfygt5	lv	fygt5-fyff (AC)
99	10 yr-FF spread	sfygt10	lv	fygt10-fyff (AC)

Series Number	Short name	Mnemonic	Tran	Description
100	Aaa-FF spread	sfyaaac	lv	fyaaac-fyff (AC)
101	Baa-FF spread	sfybaac	lv	fybaac-fyff (AC)
102	Ex rate: avg	exrus	$\Delta \ln$	United States; Effective Exchange Rate (Merm) (Index No.)
103	Ex rate: Switz	exrsw	$\Delta \ln$	Foreign Exchange Rate: Switzerland (Swiss Franc per U.S.$)
104	Ex rate: Japan	exrjan	$\Delta \ln$	Foreign Exchange Rate: Japan (Yen per U.S.$)
105	Ex rate: UK	exruk	$\Delta \ln$	Foreign Exchange Rate: United Kingdom (Cents per Pound)
106	Ex rate: Canada	exrcan	$\Delta \ln$	Foreign Exchange Rate: Canada (Canadian $ per U.S.$)
107	PPI: fin gds	pwfsa	$\Delta^2 \ln$	Producer Price Index: Finished Goods (82=100,Sa)
108	PPI: cons gds	pwfcsa	$\Delta^2 \ln$	Producer Price Index: Finished Consumer Goods (82=100,Sa)
109	PPI: int mat'ls	pwimsa	$\Delta^2 \ln$	Producer Price Index: Intermed Mat.Supplies & Components (82=100,Sa)
110	PPI: crude mat'ls	pwcmsa	$\Delta^2 \ln$	Producer Price Index: Crude Materials (82=100,Sa)
111	Spot market price	psccom	$\Delta^2 \ln$	Spot market price index: bls & crb: all commodities (1967=100)
112	Sens mat'ls price	psm99q	$\Delta^2 \ln$	Index Of Sensitive Materials Prices (1990=100) (Bci-99a)
113	NAPM com price	pmcp	lv	Napm Commodity Prices Index (Percent)
114	CPI-U: all	punew	$\Delta^2 \ln$	Cpi-U: All Items (82-84=100,Sa)
115	CPI-U: apparel	pu83	$\Delta^2 \ln$	Cpi-U: Apparel & Upkeep (82-84=100,Sa)
116	CPI-U: transp	pu84	$\Delta^2 \ln$	Cpi-U: Transportation (82-84=100,Sa)
117	CPI-U: medical	pu85	$\Delta^2 \ln$	Cpi-U: Medical Care (82-84=100,Sa)
118	CPI-U: comm.	puc	$\Delta^2 \ln$	Cpi-U: Commodities (82-84=100,Sa)
119	CPI-U: dbles	pucd	$\Delta^2 \ln$	Cpi-U: Durables (82-84=100,Sa)
120	CPI-U: services	pus	$\Delta^2 \ln$	Cpi-U: Services (82-84=100,Sa)
121	CPI-U: ex food	puxf	$\Delta^2 \ln$	Cpi-U: All Items Less Food (82-84=100,Sa)
122	CPI-U: ex shelter	puxhs	$\Delta^2 \ln$	Cpi-U: All Items Less Shelter (82-84=100,Sa)
123	CPI-U: ex med	puxm	$\Delta^2 \ln$	Cpi-U: All Items Less Medical Care (82-84=100,Sa)
124	PCE defl	gmdc	$\Delta^2 \ln$	Pce, Impl Pr Defl: Pce (1987=100)
125	PCE defl: dlbes	gmdcd	$\Delta^2 \ln$	Pce, Impl Pr Defl: Pce; Durables (1987=100)
126	PCE defl: nondble	gmdcn	$\Delta^2 \ln$	Pce, Impl Pr Defl: Pce; Nondurables (1996=100)
127	PCE defl: service	gmdcs	$\Delta^2 \ln$	Pce, Impl Pr Defl: Pce; Services (1987=100)
128	AHE: goods	ces275	$\Delta^2 \ln$	Avg Hourly Earnings of Prod or NonsupWorkers on Private Nonfarm Payrolls - Goods-Producing
129	AHE: const	ces277	$\Delta^2 \ln$	Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls - Construction
130	AHE: mfg	ces278	$\Delta^2 \ln$	Avg Hourly Earnings of Prod or Nonsup Workers on Private Nonfarm Payrolls - Manufacturing
131	Consumer expect	hhsntn	Δlv	U. of Mich. Index of Consumer Expectations (Bcd-83)
132	TOPIX	tokyose	$\Delta \ln$	TOPIX – Price Index
133	FOOTSIE	ftallsh	$\Delta \ln$	Ftse all share - Price Index
134	HANG SENG	hngkngi	$\Delta \ln$	HANG SENG - Price Index
135	MSCI World	mswrld	$\Delta \ln$	MSCI World Price Index US$
136	MSCI Europe	mserop	$\Delta \ln$	MSCI Europe Price Index US$
137	KOSPI	korcomp	$\Delta \ln$	Korea SE Composite (KOSPI) - Price Index
138	Dvp. Markets DS Indus.	indusdv	$\Delta \ln$	Developed markets – DS Industrials Price Index
139	Australasia DS Indus.	indusaz	$\Delta \ln$	Australasia – DS Industrials Price Index
140	Eur. excl. Emg DS Indus.	indusee	$\Delta \ln$	Europe excluding Emerging markets – DS Indus. Price Ind.
141	UK Overni. Interb.	ldnibon	Δlv	UK interbank overnight – middle rate
142	Swiss 3mo	swibk3m	Δlv	Swiss interbank 3 months (ZRC:SNB) – bid rate
143	UK 3mo	ldnib3m	Δlv	UK interbank 3 months – middle rate
144	Taiwan 90days	tamm90d	Δlv	Taiwan money market 90 days – middle rate
145	HK prime	hkprime	Δlv	Hong Kong Prime – middle rate
146	Swiss 10y	swgbond	Δlv	Swiss Confederation 10 years bond yield
147	China 10y+	cngbond	Δlv	China Government over 10 years (EP)
148	Germany 9-10y	bdgbond	Δlv	German 9-10 years government bond yield
149	Japan 10y	jpgbond	Δlv	Japanese 10 years government bon yield (EP)

Series Number	Short name	Mnemonic	Tran	Description
150	M1 Japan	jpm1	$\Delta^2 \ln$	Japan money supply: M1 (metho-break, Apr. 03)
151	M1 Australia	aum1	$\Delta^2 \ln$	Australia money supply: M1
152	M1 Swiss	chm1	$\Delta^2 \ln$	Swiss money supply: M1
153	M1 EM??	emecbm1	$\Delta^2 \ln$	?? money supply: M1 (EP)
154	M2 Japan	jpm2	$\Delta^2 \ln$	Japan money supply: M2 (metho-break, Apr. 03)
155	M2 Korea	kom2	$\Delta^2 \ln$	Korea money supply: M2 (EP)
156	M2 France	frm2	$\Delta^2 \ln$	France money supply: M2 (national contribution to M2)
157	M3 Sweden	sdm3	$\Delta^2 \ln$	Sweden money supply: M3 (EP)
158	M3 India	inm3	$\Delta^2 \ln$	India money supply: M3 (EP)
159	M3 France	frm3	$\Delta^2 \ln$	France money supply: M3 (national contribution to M3)
160	Japan wages	jpwages	$\Delta \ln$	Japan wage index: cash earnings – all industries
161	UK retail sales	ukrettotb	$\Delta \ln$	Uk retail sales (monthly estimate, DS calculated)
162	Korea retail sales	korettotf	$\Delta \ln$	Korea retail sales
163	Mexico CPI	mxconprcf	$\Delta^2 \ln$	Mexico Consumer Price Index NADJ
164	Sweden CPI	sdconprcf	$\Delta^2 \ln$	Sweden Consumer Price Index NADJ
165	India CPI	inconprcf	$\Delta^2 \ln$	India Consumer Price Index NADJ ind. labourers (DS calc.)
166	Korea CPI	koconprcf	$\Delta^2 \ln$	Korea Consumer Price Index NADJ
167	Japan unempl.	jpunptoto	$\Delta \ln$	Japan unemployment level vol. adj.
168	France unempl.	frunptoto	$\Delta \ln$	France unemployment level vol. adj.
169	Germany unempl.	bdvactoto	$\Delta \ln$	Germany unemployment level (pan from Jan 94) vol. adj.
170	US Pers. Saving	uspersave	Δlv	US personal saving as % of disposable personal income
171	Hous. Conf. Ind.	frcnfconq	Δlv	France survey – Household confidence indicator
172	China Cons. Cred.	cncrdcona	$\Delta \ln$	China consumer credit: total
173	China Bus. Loans	cnbanklpb	$\Delta \ln$	China chartered banks: CN$ business loans
174	Germany lend. bus.+ind.	bdbanklpa	$\Delta \ln$	Germany lending to firms and individuals
175	France lend. resid. priv.	frbanklpa	$\Delta \ln$	france MFI loans to resident private sector
176	Hong Kong loans	hkbanklpa	$\Delta^2 \ln$	Hon Kong loans and advances
177	Japan exports	jpexpgdsb	$\Delta \ln$	Japan exports of goods – custom basis
178	NW total exports	nwexpgdsa	$\Delta \ln$	NW total exports
179	Venezuela imports	veimpgdsa	$\Delta \ln$	Venezuela imports (US$)
180	France imports	frimpgdsb	$\Delta \ln$	France imports FOB
181	Japan Terms of Trade	jptotprcf	Δlv	Japan terms of trade index NADJ
182	Brazil Terms of Trade	brtotprcf	Δlv	Brazil terms of trade NADJ
183	France IP	friptotg	$\Delta \ln$	France Industrial Production excluding construction vol. adj.
184	Japan IP	jpiptotg	$\Delta \ln$	Japan industrial production – Mining & manufacturing vol. adj.
185	Germ. IP incl. constr.	bdiptotg	$\Delta \ln$	Germany IP including construction vol. adj.
186	Korea IP	koiptotg	$\Delta \ln$	Korean IP vol. adj.
187	India IP (excl. constr./util.)	iniptoth	$\Delta \ln$	India IP (excluding construction and gas utility) vol. non. adj.
188	Germany manufct. ord.	bdneworde	$\Delta \ln$	Germany manufacturing orders SADJ
189	Korea Mach. Orders	koneworda	$\Delta \ln$	Korea machinery orders received
190	China New Orders	cnnewordb	$\Delta \ln$	China new orders: all manufacturing industries (SA)
191	Starts Jap.	jphousste	$\Delta \ln$	japan new housing construction started vol. adj.
192	Starts Australia	auhousea	$\Delta \ln$	Australia building approvals: new houses
193	Germany Productivity	bdprodvtq	$\Delta \ln$	German productivity: output per man-hour worked in indus. SADJ
194	Japan productivity	jpprodvte	$\Delta \ln$	Japan labor productivity index all industries SADJ
195	Japan Operat. Ratio	jpcaputlq	Δlv	Japan operating ratio manufacturing sadj
196	Korea Manuf. Prod. Cap.	kocaputlf	Δlv	Korean manufacturing production capacity NADJ
197	Germany PPI	bdproprcf	$\Delta^2 \ln$	Germany PPI: indl. products, total, sold domestic market NADJ
198	Japan PPI	jpproprcf	$\Delta^2 \ln$	Japan corporate goods price index: domestic all commodities NADJ
199	Japan Bus. Failures	jpbnkrptp	$\Delta \ln$	Japan Business failures vol. non adj.
200	German Insolvencies	bdbnkrptp	$\Delta \ln$	Germany insolvencies Business enterprises vol. non adj.