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Futures Trading and the Excess Co-movement of Commodity Prices*

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Abstract

We empirically reinvestigate the issue of the excess co-movement of commodity prices initially raised in Pindyck and Rotemberg (1990). Excess co-movement appears when commodity prices remain correlated even after adjusting for the impact of fundamentals. We use recent developments in large approximate factor models to consider a richer information set and adequately model these fundamentals. We consider a set of eight unrelated commodities along with 184 real and nominal macroeconomic variables, from developed and emerging economies, from which nine factors are extracted over the 1993–2013 period. Our estimates provide evidence of time-varying excess co-movement which is particularly high after 2007. We further show that speculative intensity is a driver of the estimated excess co-movement, as speculative trading is both correlated across the commodity futures markets and correlated with the futures prices. Our results can be taken as direct evidence of the significant impact of financialization on commodity-price cross-moments.

JEL classification: C22, C32, G15, E17

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Keywords: Commodity excess co-movement hypothesis, Factor model, Heteroscedasticity-corrected correlation, Commodity index, Futures trading

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1. Introduction

Commodity markets have undergone major changes over the past two decades. The popularity of commodity-related financial instruments, such as commodity indices, has led many observers to conclude that commodity markets are now more intimately connected to financial markets, and so may also co-move more significantly (Tang and Xiong, 2012; Cheng and Xiong, 2014a; Hamilton and Wu, 2015; Basak and Pavlova, 2016). While a greater number of participants in commodity markets may bring about improved risk sharing, the financialization process has been widely criticized as a potential source of excessive price volatility (Stoll and Whaley, 2010). This paper investigates whether the excess co-movement of commodity prices is related to the growing financial influence in commodity markets.

The excess co-movement of commodity prices deserves analysis for at least two reasons. First, residual correlation (or "co-movement") may mean that "[. . .] commodity demands and supplies are affected by unobserved forecasts of the economic variable." [Pindyck and Rotemberg (PR hereafter), 1990, p. 1174], thereby indicating that the standard demand–supply model may not be able to explain commodity returns adequately. This conclusion, which is at odds with standard economic theory, suggests that further research is needed to uncover the new relevant fundamentals, or change the way in which these fundamentals are measured. Second, from a portfolio-management perspective, the presence of co-movement limits the diversification of investors who manage a portfolio containing a number of commodity futures.[1]

PR define excess co-movement as commodity prices remaining correlated even after adjusting for the impact of common macroeconomic variables. They select six variables: the US index of industrial production, the consumer price index, the effective $US exchange rate,[2] the three-month Treasury bill interest rate (cf. Frankel and Rose, 2010), the M1 monetary measure (cf. Frankel, 2006), and the S&P 500 stock index, which are supposed to represent the fundamentals. Nevertheless, the authors recognize that: "[. . .] 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).[3] One major issue in filtering the returns from common factors is indeed the selection of the variables to be considered.

To deal with the issue of omitted variables, we suggest relying on a large approximate factor model, along the lines of Stock and Watson (2002a, 2002b), which allows us to

1 Investment in commodity markets from a portfolio perspective is discussed in Gorton and Rouwenhorst (2006); Erb and Harvey (2006); Rouwenhorst and Tang (2012); and Gorton, Hayashi, and Rouwenhorst (2013), among many others.

2 The early contribution by Gilbert (1989) emphasizes the relevance of the exchange rate as an explanatory variable for commodity prices; see also the recent papers by Chen *et al.* (2010) and Ferraro, Rogoff, and Rossi (2015).

3 The same variables are used in Deb, Trivedi, and Varangis (1996). Leybourne, Lloyd, and Reed (1994) further discuss the issue of omitted variables.

enlarge the information set significantly while preserving a sufficiently low dimension for the econometric estimation.[4] We thus avoid the arbitrariness and computational difficulties of selecting relevant variables, in particular when the number of possible combinations is large. Borensztein and Reinhart (1994) underline the need to consider well-defined supply and demand variables in order to explain commodity prices. In particular, the authors advocate the inclusion of variables for Eastern Europe that are likely to be relevant for their sample period of 1970–92. In the same spirit, we consider a set of economic variables from developed and emerging countries (China, India, and Brazil, among others) that should allow us to filter out commodity returns more accurately, as these countries have played a central role in shaping commodity prices over recent years. While commodity prices are the product of transactions in one particular part of the world, they also reflect a great deal of information which has been generated throughout the world. For instance, the price of crude oil, say US West Texas Intermediate (WTI), is widely accepted as a world price, while being mainly traded in the USA (see Kilian, 2009).

Following the idea of Ludvigson and Ng (2009) of grouping explanatory variables into meaningful categories, we uncover the sets of variables that best explain commodity returns. Our estimates show that monthly commodity returns over the last two decades are mainly correlated with the real aggregate variables in emerging countries, highlighting the important role played by these countries in shaping commodity prices over this period. The paper provides evidence of time-varying excess co-movement, which is particularly high after 2007.[5] As such we extend PR's analysis in two directions. First, we investigate the time-varying behavior of the phenomenon, thereby providing further insights into the analysis of excess co-movement. Second, we look at a recent period that includes both a pronounced increase in commodity prices around 2008 and the recent financial crisis. Last, we take heteroscedasticity into account as this can play a critical role in measures of correlation.[6] Highlighting these stylized facts regarding excess co-movements in commodity prices in recent years is our first contribution.

The main novelty in our paper, which constitutes our second contribution, is that we establish an empirical relationship between the notion of excess co-movement and speculative activity in commodity futures markets. Surprisingly, academic research has not yet investigated the potential determinants of excess co-movement in commodity prices. We suggest

4 Recent economic research on the determination of commodity prices occasionally makes use of factor models. Examples of this growing literature are Byrne, Fazio, and Fiess (2013); Gospodinov and Ng (2013); West and Wong (2014); and Christoffersen, Lunde, and Olesen (2014). While these papers investigate more or less directly the issue of the co-movement of commodity prices, they all extract principal components from a set of commodity prices to explain the evolution of commodity prices, only considering a few additional macroeconomic variables—such as interest rates, exchange rates, and inflation—to analyze the link between these variables and their estimated factors. As such, their approach is very different from ours.

5 As will be made clear in the empirical sections, we adopt a measure of excess co-movement that is similar to that used in Kallberg and Pasquariello (2008), in that we consider the average of the squared residual correlations between all pairs of commodities. We hence allow both positive and negative correlations to contribute to the excess co-movement estimate.

6 As shown by Forbes and Rigobon (2002), the usual sample correlation is a biased measure of the true correlation when volatility is time-varying, which is a well-known stylized fact regarding financial series. As most of our commodity returns are characterized by time-varying volatility, we use the correlation coefficient corrected for heteroscedasticity of Forbes and Rigobon (2002).

an explanation for this phenomenon following the intuition developed in Barberis and Shleifer (2003) that "investors categorize risky assets into different styles and move funds among these styles depending on their relative performance." (p. 161). As such, if most commodities are classified into a "commodity style", seemingly unrelated commodities are likely to co-move more than would be expected based on fundamental analysis.[7] This is precisely what we demonstrate in our present work. Our results are also in line with the recent work by Basak and Pavlova (2016), who go beyond the behavioral approach in Barberis and Shleifer (2003) and develop a multi-asset, multi-good general equilibrium model with heterogeneous investors, some of whom are institutional investors, considering characteristics that are specific to commodities such as the presence of inventories. The model, in the tradition of Lucas-tree models, is solved in closed-form and provides a rich set of implications, among which an increase in the correlation between commodities following institutional positioning, and more so for commodities that are included in an index. Our results provide strong support for the outcome in Basak and Pavlova (2016), and may then be seen as an empirical validation of their model.

Our empirical work makes use of data from the US Commodity Futures Trading Commission (CFTC) to estimate speculative intensity. While the categories in the publicly available data from the CFTC do not distinguish perfectly between the various categories of traders, as discussed previously in Bessembinder (1992) and Stoll and Whaley (2010) among many others, we here show that they are informative for the explanation of excess co-movement. Our measure of speculative activity in futures markets follows the recent work by Han (2008) on sentiments in financial markets but is reminiscent of the so-called Working's T measure. Our empirical strategy provides direct evidence of the explanatory power of speculative intensity for excess co-movement: while the large number of fundamental variables have limited success in explaining the co-movement between commodities, we show that speculative activity is correlated across commodity futures markets and, at the same time, that speculative activity is correlated with futures prices. This last result is obtained from an instrumental-variable analysis to avoid endogeneity issues between returns and positions in futures markets.

The empirical work closest to ours is Tang and Xiong (2012), which also considers the financialization of commodities as a potential source of the recent increase in co-movements between commodity returns. Their "analysis focuses on connecting the large inflow of commodity index investment to the large increase of commodity price co-movements in recent years by examining the difference in these co-movements between indexed and off-index commodities" (p. 55).[8] The authors regress the S&P-GSCI on a measure of the net position change of different categories of traders and, as such, do not pick up the common factors that may affect the behavior of most, if not all, commodity prices. Tang and Xiong (2012) also investigate the relationship between economic activity in emerging countries and the co-movement of commodity prices using a novel time series of

7 Interestingly, Barberis and Shleifer (2003) cite the empirical results in PR as exemplifying their model. Conversely, PR observe that: "[. . .] traders are alternatively bullish or bearish on all commodities for no plausible reason" (p. 1173), which is behind our basic idea to measure the impact of speculation in commodity-futures markets on commodity price co-movements.

8 Their research question builds on Barberis, Shleifer, and Wurgler (2005), who theoretically and empirically analyze the behavior of newly included stocks in a stock index. It is shown that the price co-movement between the stock and the index significantly increases after this inclusion.

Chinese futures prices available since the late 1990s. While commodity prices are usually thought of as being global, the authors show that the picture is actually more complex. Interestingly, while US commodity prices exhibit a pronounced cycle, this is not the case for the Chinese prices of similar commodities, thereby raising "doubt about commodity demands from China as the driver of all commodity prices in the U.S." (p. 63). Our regressions for commodity returns show that the demand from emerging economies does play a role in determining the prices of US non-agricultural commodity futures prices, while leaving a considerable role for other factors. Overall, while dealing with a research question similar to Tang and Xiong (2012), we adopt a very different empirical approach. In particular, we specifically consider fundamentals that are critical in the analysis of co-movements.

The plan for the rest of the paper is as follows. In the next section, we present the data used for the empirical analysis. In Section 3, we very briefly review the factor-model methodology and calculate the factors used to filter the commodity returns. The excess co-movement is then estimated in Section 4, while Section 5 is dedicated to the analysis of the relationship between excess co-movement and speculation. Finally, Section 6 concludes by discussing some limits to and possible future extensions of our work.

2. Data

We consider a set of eight commodity prices: wheat, copper, silver, soybeans, raw sugar, cotton, crude oil, and live cattle. These are representative of the main commodity classes and are assumed to be unrelated as defined in PR, in the sense that their supply or demand cross-elasticities are almost zero. All prices are cash prices except for crude oil, where the front-month contract price is taken as a proxy for the cash price, to avoid the distorting impact of delivery issues for this particular commodity. All prices are in nominal US$. Due to data limitations, in particular for macroeconomic variables from emerging countries, we consider monthly observations from February 1993 to November 2013. Data are from Datastream.

The prices are displayed in Figure 1. They fluctuate around their mean level until 2005, except for oil and silver which have a rising trend. A first large price rise begins in 2005 and ends in 2008. Prices fell in 2009 but rise steeply in 2010; they stabilize or fell in 2012. Returns are log difference of prices.[9] The descriptive statistics in Table I reveals evidence of skewness—negative in six cases out of eight—and excess kurtosis. The Jarque–Bera test consequently rejects the hypothesis of a Gaussian distribution for all returns. The presence of heteroscedasticity, which is a standard feature in financial price series, may lie behind this non-normality.

Table II presents the sample correlations between returns and their associated p-values. There are, respectively, 16, 15, and 11 significant correlations at the 10%, 5%, and 1% critical levels. All of the significant correlations are positive, ranging from 0.4789 (wheat

9 Part of the existing literature (Palaskas and Varangis, 1991; Leybourne, Lloyd, and Reed, 1994) considers excess co-movement of nominal or real price rather than return, and relies on a co-integration analysis. We think that return is more appealing when dealing with risk management issues, and thus consider the excess co-movement of returns as in the seminal work of PR. Returns rather than prices have also been considered more recently in Ai, Chatrath, and Song (2006) and Malliaris and Urritia (1996) for the main agricultural commodities.

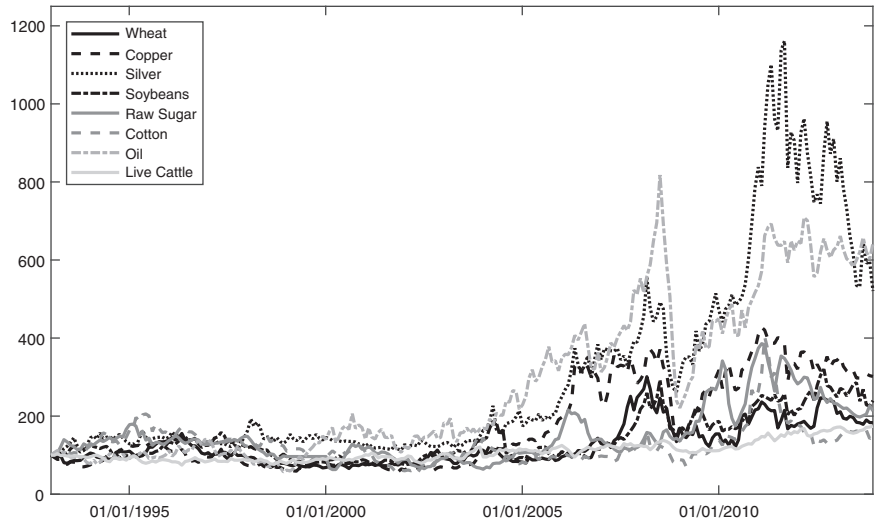

Figure 1. The eight commodity prices—January 1993–November 2013.
Note: Prices are normalized to 100 at January 1993.

Table I. Descriptive statistics for the eight commodities monthly returns—February 1993–November 2013

(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, denote rejection of the null hypothesis of a Gaussian distribution at 1%, 5%, and 10% levels.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Mean	0.0024	0.0047	0.0066	0.0034	0.0030	0.0013	0.0072	0.0022
Max	0.3666	0.3266	0.2309	0.2013	0.2052	0.3855	0.2536	0.1178
Min	−0.2499	−0.3360	−0.3285	−0.4660	−0.3620	−0.2605	−0.3899	−0.2369
Std	0.0845	0.0796	0.0873	0.0835	0.0806	0.0903	0.1016	0.0460
Skewness	0.1660	−0.4043	−0.4079	−1.0658	−0.3611	0.2763	−0.5827	−0.5674
Kurtosis	4.3312	5.9263	4.0502	7.0722	5.1793	4.5636	3.9713	5.2846
Jarque-Bera	19.60***	96.01***	18.42***	220.06***	54.90***	28.64***	23.9759***	67.78***
Number of observations	250	250	250	250	250	250	250	250

and raw sugar) to 0.11 (raw sugar and crude oil), with an average figure of 0.2536. The figures in PR are a maximum of 0.322 and a minimum of 0.113, with an average of 0.161 for the significant correlations between 1960 and 1985. Therefore, it seems that the relationship between commodity prices has tightened over the last two decades.

Our main aim is to analyze whether these correlations result from a common set of variables related to the fundamentals of commodities markets. If significant residual correlations remain, we would conclude in favor of excess co-movement. To model the eight commodity returns, we construct a set of 184 real and nominal macroeconomic variables.

Table II. Correlation between the eight commodities monthly—February 1993–November 2013

The upper triangular matrix reports correlations while the lower reports their *p*-values. ***, **, and *, respectively, denote significance at 1%, 5%, and 10% levels.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Wheat	1	0.2988***	0.2256***	0.4789***	−0.0023	0.2763***	0.1569**	0.0352
Copper	0.0000	1	0.3799***	0.2345***	0.1258**	0.2352***	0.3496***	0.0077
Silver	0.0003	0.0000	1	0.2142***	0.1901**	0.0844	0.2141***	−0.0306
Soybeans	0.0000	0.0002	0.0006	1	−0.0767	0.3877***	0.1095*	−0.0898
Raw sugar	0.9714	0.0468	0.0025	0.2266	1	0.0543	0.1012	0.0530
Cotton	0.0000	0.0002	0.1834	0.0000	0.3930	1	0.1808**	−0.0288
Crude oil	0.0130	0.0000	0.0007	0.0839	0.1103	0.0041	1	0.0455
Live cattle	0.5791	0.9040	0.6302	0.1571	0.4045	0.6506	0.4739	1

These variables, with a short description, are listed in Appendix A.[10] Our data set contains variables from developed (118 variables from Australia, Canada, France, Germany, Japan, the UK, and the USA) and emerging countries (66 variables from China, Brazil, Korea, Taiwan, Mexico, etc.). In recent years, these countries have experienced high growth rates and their commodity demand has had a significant impact on commodity markets. Commonly used US databases such as those in Stock and Watson (2002b) and Ludvigson and Ng (2007, 2009) are thus not well-suited for our current purpose.

We have the same classes of data for both developed and emerging countries. We include measures of the country's aggregate activity level such as the industrial production index and manufacturing orders and capacity utilization. Other real variables are related to household expenditure: household consumption, housing starts, and car sales. We add variables related to the labor market (wages and unemployment) and international trade (exports, imports, and terms of trade). These real variables are assumed to be correlated with the world demand for commodities. The main categories of nominal variables that we include are monetary aggregates, stock indices, interest rates, exchange rates with the dollar, and producer and consumer price indices. These nominal variables help us to model the relationship between commodity returns and interest rate or the inflation rate. Finally, we add the Real Activity Index to the above, as developed in Kilian (2009). This is "based on dry cargo single voyage ocean freight rates and is explicitly designed to capture shifts in the demand for industrial commodities in global business markets" (p. 1055), following a long tradition of economists who have noted the correlation between economic activity and ocean-freight rates.

3. Filtering Commodity Returns Using Large Approximate Factors Models

In this section, we first briefly review the large approximate factors method. Recent techniques to establish the optimal number of factors are presented in Appendix B; additional developments can be found in the survey by Bai and Ng (2008) of large approximate factors models. The remainder of the section is dedicated to the projection of commodity returns on the estimated factors.

10 Each variable is rendered stationary in an appropriate manner: the chosen transformation appears in the penultimate column of the table in Appendix A.

3.1 Static Factors Calculation

We use the static factor model of Stock and Watson (2002a). We do not consider the dynamic version of Forni *et al.* (2005), as recent work (Boivin and Ng, 2005) has shown that the dynamic and static factor models perform equally well, especially when the factors have unknown dynamics, which is often the case in empirical work. In addition, the dynamic factor model is best suited to forecasting, which is not the purpose of our work.

We have a sample $\{x_{it}\}$ of $i = 1, \ldots, N$ cross-section units and $t = 1, \ldots, T$ time-series observations. Each x_{it} is split into a component depending on a set of $r << N$ common factors $F_t = (f_{1t}, f_{2t}, \ldots, f_{rt})'$ and a specific component e_{it}:

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

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

If we define the $(N \times 1)$ vectors of observations and specific components at date t as $X_t = (x_{1t}, \ldots, x_{Nt})'$, $e_t = (e_{1t}, \ldots, e_{Nt})'$, and $\Lambda = (\lambda_1, \ldots, \lambda_N)'$ the $(N \times r)$ matrix of factor loadings, the factor decomposition is written as

$$X_t = \Lambda F_t + e_t.$$

Standard factor analysis makes the assumptions that F_t and e_t are serially and cross-sectionally uncorrelated, and the number of units of observation N is fixed. Stock and Watson's (2002a, 2002b) "large dimensional approximate factor models" allow the specific errors to be "weakly correlated" across i and t[11] and the sample size to tend to infinity in both directions.

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

$$\min S(k) = (NT)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \lambda_i^{k\prime} F_t^k)^2$$

subject to the normalization $\Lambda^{k\prime}\Lambda^k/N = I_k$.[12]

This classical principal component problem is solved by setting $\hat{\Lambda}^k$ equal to the eigenvectors of the largest k eigenvalues of $X'X$ where $X = (X_1, X_2, \ldots, X_T)'$ is the $(T \times N)$ matrices of all observations.[13] The principal components estimator of F^k is:

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

The consistency and asymptotic normal distribution of the principal component estimator as $N, T \to \infty$ have been, respectively, demonstrated by Stock and Watson (2002a), Bai and Ng (2002), and Bai (2003).

The next step is to determine the optimal number of factors. The literature on this issue has not come to a clear consensus on how to select relevant factors and, as shown in Table

11 Although Stock and Watson (2002a) use different sets of assumptions to characterize "weak correlations", the main idea is that the cross-correlations and serial correlations have an upper bound.

12 As the factors F_t and the loading matrix Λ are not separately identifiable [see Bai and Ng (2008) for more details], constraints are imposed to obtain a unique estimate.

13 When $N > T$, a computationally simpler approach is to use the $T \times T$ matrix XX'.

BI in Appendix B, different methods lead to very different outcomes.[14] We follow traditional practice in principal component analysis and choose the first nine factors, as the incremental explanatory power beyond these nine factors is only small. The nine factors explain 37% of the variability of the 184 macroeconomic variables.

3.2 Modeling Commodity Returns

Our measure of excess co-movement makes use of commodity returns which have been filtered for common components. As such, once we have calculated the static factors, the second step of the empirical analysis consists in filtering the returns using these estimated factors. The first step is the linear regression of returns on the first three factors:

$$r_{it} = \alpha_i + \sum_{k=1}^{3} \beta_{ik} \hat{F}_{k,t} + u_{it} \quad i = 1, \ldots, 8 \quad t = 1, \ldots, T$$
$$= \alpha_i + \beta_i' \hat{F}_t + u_{it},$$

where r_{it} represents the ith commodity return at date t, α_i is the constant, β_i the vector of factor coefficients for the ith commodity, and $\hat{F}_t = (\hat{F}_{1,t}, \hat{F}_{2,t}, \hat{F}_{3,t})'$ the vector of the first three factors at date t. The results from seemingly unrelated regressions (SUR) appear in Table III. The R^2 varies from 1.07% for soybeans to 28.58% for crude oil. The factors $\hat{F}_2$ and $\hat{F}_1$ are significant in most regressions. While the explanatory power figures for agricultural commodity returns are not substantially higher than those in PR, we do obtain a much higher R^2 for metals and energy commodities.[15] The ARCH-LM test shows that six out of the eight series of residuals have time-varying variance.

In a second approach, as in Stock and Watson (2002b) and Ludvigson and Ng (2009), we consider all possible combinations of the first nine estimated factors and, for each commodity, select the regression which minimizes the BIC criterion. Once each set of regressors has been selected, we jointly estimate the eight regressions via SUR. Our aim here is to identify the best model from a set of common regressors for each commodity. This approach aims to eliminate as much residual correlation as possible, and so strengthen our evidence for any excess co-movement. The SUR estimates appear in Table IV and show a significant increase in explanatory power for crude oil, while this figure remains low for the other commodities. Again, the $\hat{F}_1$ and $\hat{F}_2$ factors are significant for most of the eight commodities and the ARCH-LM test rejects the null hypothesis of constant variance for three series of residuals.

While the factors cannot be identified econometrically, it is very useful to identify the macroeconomic variables behind the factors affecting commodity returns. To interpret the

14 Methods based on information criteria and Kapetanios (2010) are described in Appendix B.

15 To further improve the explanatory power, we also considered potential nonlinearities with quadratic or cubic factors. We choose the specification with the highest adjusted $\bar{R}^2$. The set of factors is now $\bar{F}_t^{nl} = (\hat{F}_{1,t}, \hat{F}_{2,t}, \hat{F}_{3,t}, \hat{F}_{4,t}, \hat{F}_{2,t}^3, \hat{F}_{4,t}^3)'$ and the regressions become:

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

The best specifications results are not shown here (but are available upon request). We do not find any notable increase in the R^2 for any commodity. We therefore retain linear factors in the returns equation.

Table III. Modeling the eight commodities returns: the three factors regressions—February 1993–November 2013

(i) This table reports the SUR estimates of the regression of the eight commodities monthly returns. The explanatory variables are reported in far-left column. A constant is always included in the regression and $\hat{F}_i$ denotes the ith 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, denote rejection of the null hypothesis of no ARCH effect at the 1%, 5%, and 10% levels.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Intercept	0.0024	0.0047	0.0066	0.0034	0.0030	0.0013	0.0072	0.0022
	(0.45)	(1.05)	(1.22)	(0.66)	(0.59)	(0.24)	(1.32)	(0.78)
$\hat{F}_1$	−0.0254	−0.0951***	−0.0271	−0.0242	−0.0114	−0.0517**	−0.1200***	−0.0164**
	(−1.19)	(−6.55)	(−1.40)	(−1.10)	(−0.87)	(−2.44)	(−7.10)	(−2.00)
$\hat{F}_2$	0.0377**	0.0867***	0.0526***	0.0400**	0.0288*	0.0566***	0.1445***	0.0108
	(2.28)	(6.32)	(2.77)	(2.15)	(1.73)	(2.93)	(8.34)	(1.04)
$\hat{F}_3$	0.0020	0.0212	0.0060	0.0288	−0.0012	−0.0024	−0.0609**	−0.0062
	(0.09)	(0.95)	(0.23)	(1.21)	(−0.05)	(−0.08)	(−2.34)	(−0.52)
R^2	0.0222	0.2184	0.0343	0.0290	0.0107	0.0577	0.2858	0.0165
$\bar{R}^2$	0.0103	0.2089	0.0226	0.0172	−0.0014	0.0462	0.2771	0.0045
ARCH_LM(2)	13.10***	52.18***	7.31**	29.66***	3.54	5.84*	5.18*	1.63

Table IV. Modeling the eight commodities returns: the BIC minimizing regressions—February 1993–November 2013

This table reports the SUR estimates of the regression of the eight commodities monthly returns. The explanatory variables are reported in left column. A constant is always included in the regression and $\hat{F}_i$ denotes the ith 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, denote rejection of the null hypothesis of no ARCH effect at the 1%, 5%, and 10% levels.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Intercept	0.0024	0.0047	0.0066	0.0034	0.0030	0.0013	0.0072	0.0022
	(0.44)	(1.05)	(1.24)	(0.66)	(0.59)	(0.24)	(1.45)	(0.78)
$\hat{F}_1$		−0.0844***				−0.0422**	−0.1194***	
		(−6.29)				(−2.51)	(−7.39)	
$\hat{F}_2$	0.0371*	0.0875***	0.0533***	0.0419**	0.0279	0.0577***	0.1449***	
	(1.84)	(5.17)	(2.64)	(2.12)	(1.45)	(2.74)	(7.72)	
$\hat{F}_3$							−0.0617***	
							(−2.65)	
$\hat{F}_6$							0.1142***	
							(4.00)	
$\hat{F}_8$			0.0967***				0.1858***	
			(3.01)				(5.74)	
$\hat{F}_9$								−0.0393**
								(−2.05)
R^2	0.0138	0.2136	0.0728	0.0159	0.0088	0.0566	0.4079	0.0171
$\bar{R}^2$	0.0098	0.2072	0.0653	0.0119	0.0048	0.0489	0.3958	0.0131
ARCH_LM(2)	7.65**	1.49	3.31	18.54***	2.83	5.50*	4.12	0.96

factors, we follow Ludvigson and Ng (2009) and divide our 184 series into developed and emerging countries, and then real and nominal variables.[16] Each of the 184 original variables is then regressed on one factor with the resulting R^2 appearing on the horizontal axis. We can thus see which macroeconomic variables obtain the highest R^2. The factor in question can then be thought to represent this set of variables.

Figure 2 plots R^2 for both $\hat{F}_1$ (top panel) and $\hat{F}_2$ (bottom panel) factors. $\hat{F}_1$, which explains a significant part of crude oil and copper returns, is mostly correlated with real variables in emerging economies. This illustrates the importance of emerging countries in shaping commodity prices.[17] This result corroborates recent work that also demonstrates that oil (e.g., Hamilton, 2009 or Kilian and Hicks, 2013) and agricultural prices (e.g., Hamilton and Wu, 2015) are partly driven by demand from emerging countries and that speculative activity only plays a minor role.

The interpretation of factor $\hat{F}_2$ is less obvious. It is highly correlated with a small number of real variables but its explanatory power with respect to interest rates, producer and consumer price indices, and monetary aggregates in both developed and emerging countries is greater than that of $\hat{F}_1$. $\hat{F}_2$ is likely to represent these nominal variables. Earlier contributions (Barsky and Kilian, 2002; Frankel and Rose, 2010) only provide mixed evidence on the relationship between interest rates and commodity prices. Our estimates give additional support to such a link. In this regard, price indices and monetary aggregates may pick up the impact of inflation on commodity prices.

The activity index from Kilian (2009) brings no additional information as it attracts only an insignificant estimated coefficient—except for copper, at the 10% threshold only—indicating that $\hat{F}_1$ does a better job of modeling commodity returns. This conclusion is of interest as this real-activity index is considered to be as a proxy for economic activity. We believe that this result confirms the ability of statistical factors to aggregate information from a large number of variables and capture high-frequency growth rates. To better understand the insignificance of Kilian's index, Table V shows the estimates from univariate regressions of the nine empirical factors on Kilian's index. The estimates are very significant but with little explanatory power. This is likely due to the low-frequency nature of the Kilian Index, and further demonstrates the benefit from using statistical factors in modeling monthly commodity returns.

Finally, the omission of inventory data in our analysis is worthy of mention. It is commonly thought that stock levels may help us to better model commodity returns, following Working's Theory of Storage. For instance, Pindyck (2001) uses weekly inventory data from the US Department of Energy to model the convenience yield in the WTI crude oil market. Geman and Nguyen (2005) rely on a number of worldwide sources to construct their own inventory series for soybeans which they use to model this commodity's forward curve. Baumeister and Kilian (2012) consider a number of oil-specific inventory series to forecast real-time monthly oil prices. We do not include inventory information in our empirical analysis as we wish to filter returns using fundamentals that are, at least partly, common to all commodities. By doing so, data related to commodity demands that we proxy via our factors are relevant as they represent common fundamentals. Conversely, data such

16 The classification in Ludvigson and Ng (2009) is finer but is applied to US variables only. Their classification is likely not applicable when a number of economies are considered for reasons of interpretability.

17 China imports 30% of all the copper traded in the world.

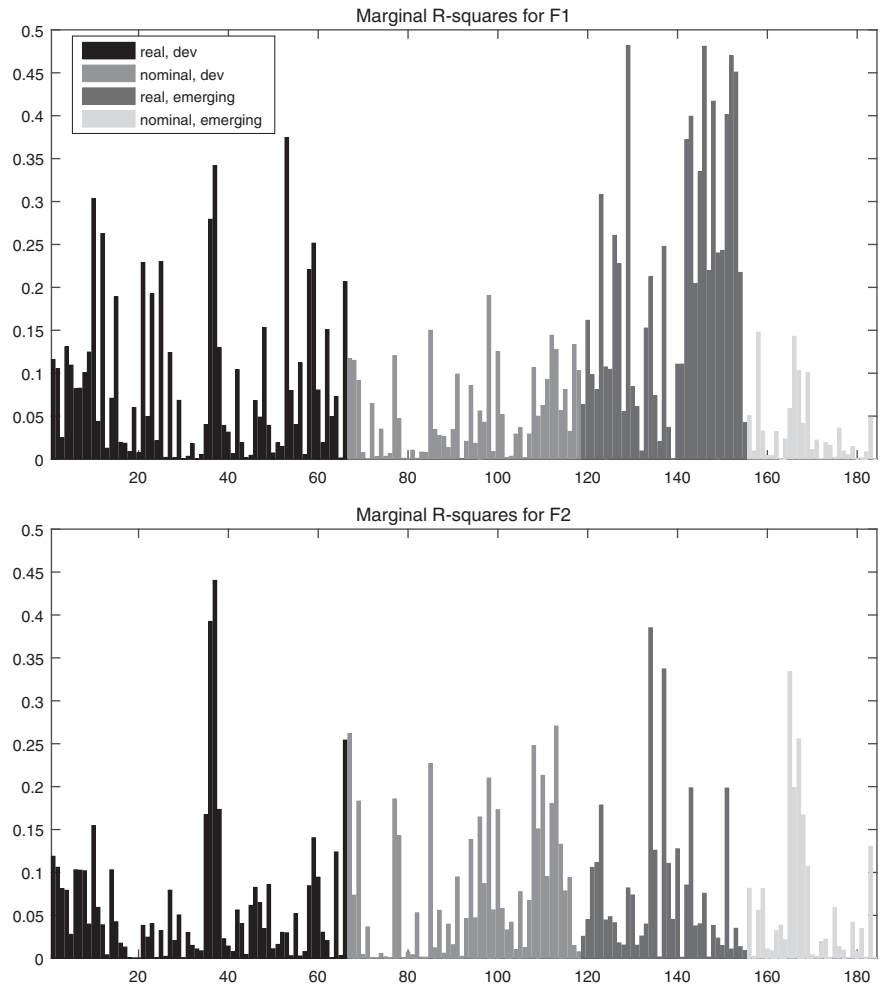

Figure 2. Marginal R^2 of macroeconomic and financial variables regressed on the first two estimated factors.

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

Table V. Regression of the Kilian real activity index on each of the nine factors

Coefficient reports the estimated coefficient of each factor and *t*-stat its Student's statistic. ***, **, and *, respectively, denote rejection of the null hypothesis of no significance at the 1%, 5%, and 10% levels. The real activity index is taken from Lutz Kilian's homepage. See Kilian (2009) for a definition of this index.

	$\hat{F}_1$	$\hat{F}_2$	$\hat{F}_3$	$\hat{F}_4$	$\hat{F}_5$	$\hat{F}_6$	$\hat{F}_7$	$\hat{F}_8$	$\hat{F}_9$
Coefficient	−17.8231***	19.3546***	−5.6256	28.5721***	1.6348	−2.0679	4.7489	−9.6327	4.0327
t-stat	−3.78	3.504	−0.77	4.77	0.19	−0.21	0.48	−0.85	0.34
R^2	0.0438	0.0387	0.0021	0.0434	0.0001	0.0002	0.0008	0.0032	0.0005
$\bar{R}^2$	0.0400	0.0349	−0.0019	0.0396	−0.0039	−0.0038	−0.0031	−0.0008	−0.0035

Table VI. Correlation between residuals from the three factors linear model

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

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Wheat	1	0.3452***	0.2564***	0.4939***	0.0204	0.3133***	0.2330***	0.0660
Copper	0.0000	1	0.4317***	0.2817***	0.1698***	0.3386***	0.5312***	0.0913
Silver	0.0000	0.0000	1	0.2398***	0.2110***	0.1439**	0.3017***	0.0101
Soybeans	0.0000	0.0000	0.0001	1	−0.0568	0.4140***	0.1842***	−0.0574
Raw sugar	0.7478	0.0071	0.0008	0.3709	1	0.0884	0.1567**	0.0740
Cotton	0.0000	0.0000	0.0228	0.0000	0.1636	1	0.3102***	0.0225
Crude oil	0.0002	0.0000	0.0000	0.0035	0.0131	0.0000	1	0.1337
Live cattle	0.2986	0.1499	0.8739	0.3663	0.2438	0.7228	0.0346	1
Breusch–Pagan LM test					186.20			
p-value					0			

as inventories are very particular to each commodity and so less likely to explain any correlation in commodity returns. As such, even if we recognize that inventories matter in particular cases such as, for instance, forecasting commodity prices [see Baumeister and Kilian (2012, 2014) for the case of oil], they do not do so here, where it is rather common factors that are our primary concern.

4. Testing for the Excess Co-movement of Commodity Returns

4.1 Testing for Residual Correlation

The residuals from the regressions above reflect commodity returns after controlling for fundamentals. We first evaluate the correlation in residuals, as in PR. Tables VI and VII show the sample correlations (in the upper triangular part) and their *p*-values[18] (in the lower triangular part) for the residuals from the three-factor and BIC linear filters.

The results from both sets of regressions confirm the hypothesis of excess co-movement. We find 16 and 18 significant sample correlations at the 1% and 5% significance levels, respectively, for the three-factor regressions; the analogous numbers for the BIC-minimizing regressions are 9 and 10. Unsurprisingly, the Breusch–Pagan LM test rejects the null hypothesis of no residual correlation in both cases. In the BIC-minimizing regressions, five sample correlations are no longer significant, mostly related to crude oil.[19] Filtering commodity returns therefore somewhat reduces the number of significant correlations. However, as the significant correlations range from 0.4711 (wheat and soybeans) to 0.1066 (copper and crude oil) the level of residual correlation remains quite substantial.

18 The *p*-value is calculated by transforming the correlation $\hat{\rho}$ to create a *t*-statistic with $T-2$ degrees of freedom, where T is the number of observations.

19 One possible explanation is that the oil-return filtering is more successful than that for other commodities.

Table VII. Correlation between residuals from the BIC minimizing regressions

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

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Wheat	1	0.2674***	0.1990***	0.4711***	−0.0135	0.2528***	0.0609	0.0287
Copper	0.0000	1	0.3328***	0.1930***	0.0962	0.1458**	0.1068*	−0.0431
Silver	0.0016	0.0000	1	0.1869***	0.1733***	0.0375	0.0411	−0.0390
Soybeans	0.0000	0.0022	0.0030	1	−0.0897	0.3677***	−0.0087	−0.0990
Raw sugar	0.8324	0.1294	0.0060	0.1572	1	0.0337	0.0251	0.0450
Cotton	0.0001	0.0211	0.5552	0.0000	0.5957	1	0.0261	−0.0496
Crude oil	0.3375	0.0920	0.5179	0.8912	0.6929	0.6812	1	−0.0249
Live cattle	0.6512	0.4978	0.5389	0.1184	0.4783	0.4345	0.6956	1
Breusch–Pagan LM test					99.39			
p-value					0			

4.2 A Global, Unbiased, and Time-Varying Measure of Excess Co-movement

One major limit of the use of sample correlation to gauge excess co-movement is the bias in the former when volatility is time-varying.[20] This argument has been put forward in the contagion literature[21] by Forbes and Rigobon (2002), among others.[22] When there is a simultaneous rise in the respective volatility of two variables, the typical sample correlation measure overestimates the true correlation. Forbes and Rigobon (2002) propose an unbiased correlation estimator: as our residuals very often have time-varying volatility, this is the estimator we use to evaluate excess co-movement.

We follow Kallberg and Pasquariello (2008), who apply the Forbes and Rigobon estimator on a moving-window basis to yield a more precise estimator of the true correlation. We end up with a global measure, as we treat all residual correlations equally, without focusing on the correlation of one particular commodity with another. We calculate a time-varying

20 This is an issue in the contribution of PR which was further considered in Deb, Trivedi, and Varangis (1996) by means of the multivariate GARCH model in its BEKK form (Engle and Kroner, 1995). Multivariate GARCH models deal with standardized returns and no further correction for heteroscedasticity is needed [see Brenner, Pasquariello, and Subrahmanyam (2009) for a recent application using standardized returns for the analysis of co-movements in US financial markets around scheduled macroeconomic announcements].

21 Co-movement is a concept which may at first sight be confused with contagion. However, there is a significant difference between the two concepts. While excess co-movement is defined as significant residual correlation once common factors are considered, contagion is defined as a significant increase in correlation following a shock in one market. At this point, two remarks are in order. First, most of the literature on contagion either uses very simple common factors or ignores them entirely. This is quite different from the excess co-movement literature where "excess" means "beyond common factors", and the determination of common factors strongly affects the estimated co-movement. Second, we do not need to observe an increase in correlation to confirm excess co-movement, but rather a significant correlation most of the time or on average over a given period.

22 Similar results appear in Boyer, Gibson, and Loretan (1999) and Loretan and English (2000). Tang and Xiong (2012) also correct the correlation for time-varying volatility using the method in Forbes and Rigobon (2002), which has only a small insignificant effect on their estimates.

measure of excess co-movement which will show us whether excess co-movement is a permanent feature of commodity markets or if it is only occasional. Our global measure of excess co-movement is the average of all the squared unbiased correlations. We use squared correlation measures as some of the estimated correlations are negative. Our estimate is non-parametric and avoids the mean-reversion problem inherent in the parametric approach, such as in the dynamic conditional correlation (DCC) model (Engle, 2002). Indeed, in many instances (cf. Kallberg and Pasquariello, 2008, among others), methods based on rolling windows filters are very competitive with parametric methods when the object of interest is the estimation of correlations. In the following, we present the bias-corrected correlation estimator and the aggregation process to obtain our overall excess co-movement measure.

For all pairs of non-redundant returns $i \neq j$, we calculate the residual correlation:

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

where $\hat{u}_{i,t}$ is the residual from the ith commodity-return equation. As the sample correlation $\hat{\rho}_{ij,t}$ is biased in the case of heteroscedasticity, this is called the "conditional correlation".

The Forbes and Rigobon (2002) bias-corrected correlation estimator is

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

where the ratio $\hat{\delta}_{i,t} = \frac{\mathrm{var}(\hat{u}_{i,t})}{\mathrm{var}(\hat{u}_{i,t})_{\mathrm{LT}}} - 1$ corrects the conditional correlation $\hat{\rho}_{ij,t}$ for the change between the ith return's short-term $\mathrm{var}(\hat{u}_{i,t})$ and long-term $\mathrm{var}(\hat{u}_{i,t})_{\mathrm{LT}}$ volatilities.[23] $\hat{\rho}^*_{ij,t}$ is called the unconditional correlation. As we do not make any *ex ante* assumption regarding the direction of the propagation of shocks from one commodity to another, we alternately assume that the source of these shocks is asset i (in $\hat{\rho}^*_{ij,t}$) or asset j (in $\hat{\rho}^*_{ji,t}$). We therefore have two unconditional and possibly different correlations, $\hat{\rho}^*_{ij,t}$ and $\hat{\rho}^*_{ji,t}$. Our global excess co-movement measure is based on these unconditional correlations.

As suggested in King, Sentana, and Wadhwani (1994) and Kallberg and Pasquariello (2008), we compute the arithmetic mean of the pairwise squared unbiased correlations for each commodity i. A non-null unconditional correlation $\hat{\rho}^*_{ij,t} \neq 0$ and $\hat{\rho}^*_{ji,t} \neq 0$, whatever its sign, is taken as evidence of excess co-movement between commodities i and j. A measure of excess co-movement between commodity i and the others is defined as:

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

for all commodity returns $i = 1, \ldots, K$, where $K = 8$ is the number of commodities.

Our global and time-varying measure of excess co-movement is then the mean of the excess squared unconditional correlations over all commodities:

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

We treat the covariance matrix of return residuals as observable, and construct a time series of rolling realized excess squared correlations for each commodity i. $\hat{\delta}_{i,t}$ and $\hat{\rho}^*_{i,t}$ are

23 This correction is valid if we assume no omitted variables or endogeneity.

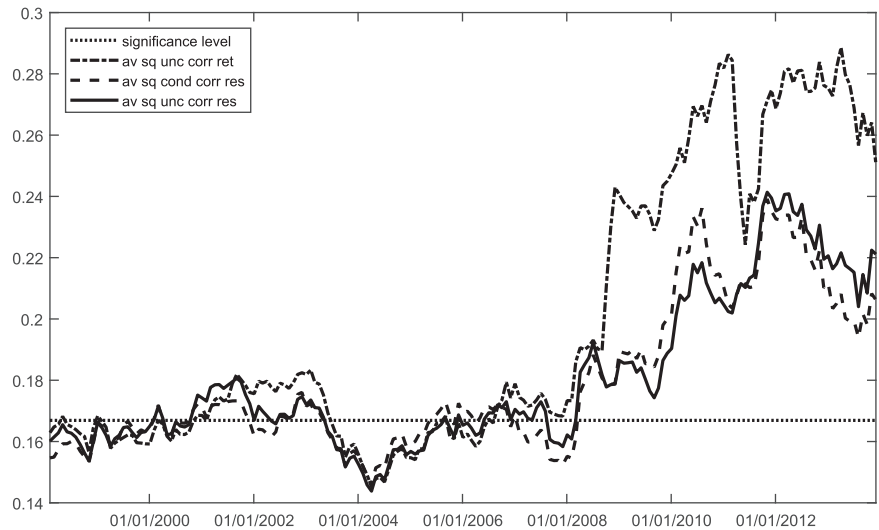

Figure 3. Mean excess squared correlation for commodity returns and residuals.
Notes: (i) "av sq unc corr ret" is the average squared unconditional correlation of returns: $\rho^*_{\text{ret},t}$. (ii) "av sq cond corr res fund" is the average squared conditional correlation of factors regression residual: ρ^*_t. (iii) "av sq unc corr res all" is the average squared unconditional of factors regression residual. (iv) The confidence band is the minimal value above which squared correlation is significant at 5% level. It is computed from the *t*-squared ratio test $\hat{t}^2_{ijt} = (\hat{\rho}^*_{ijt})^2[1-\hat{\rho}^*_{ijt}]^{-1}(N-2) \sim F(1.N-2)$ and is equal to 1.6990.

estimated over short- and long-term intervals of fixed length N $[t-N+1,t]$ and gN (with $g>1$) $[t-gN+1,t]$, respectively. We use a rolling window of $N=30$ monthly observations for short-term volatility and $gN=60$ monthly observations for long-term volatility.

4.3 Estimation Results

We compute three averages of squared correlations, all of which appear in Figure 3, to evaluate the importance of filtering returns and illustrate the time-variation in volatility. The first (dashed–dotted line) is the average of the squared unconditional correlations in returns: $\hat{\rho}^*_{\text{ret},t} = \frac{1}{K}\sum_{i=1}^{K}\hat{\rho}^*_{\text{reti},t}$, where the unbiased correlations are calculated for non-filtered returns. The second (dashed line) is the average of the squared conditional correlations between residuals: $\hat{\rho}_t = \frac{1}{K}\sum_{i=1}^{K}\hat{\rho}_{i,t}$, where $\hat{\rho}_{i,t} = \frac{1}{K-1}\sum_{j=1,j\neq i}^{K}(\hat{\rho}_{ij,t})^2$. We here use residual correlations that are not corrected for changes in volatility. The solid line is the average of the unconditional squared correlations $\hat{\rho}^*_t$ as defined in the previous section, which is our estimate of excess co-movement.

Table VIII shows the descriptive statistics for the returns and residual average squared correlations estimated over the full sample. We draw three main conclusions from this table. First, while the means of $\hat{\rho}^*_{\text{ret},t}$ and $\hat{\rho}^*_t$ are very similar over the whole sample, there is a notable difference—almost equal to 10% in some months—between the two measures over the 2008–13 period. This emphasizes the importance of filtering returns using some measures of fundamentals and shows that the rise in commodity-returns correlation is partly due to common factors. Juvenal and Petrella (2015) find that the co-movements between the prices of oil and other commodities reflect global demand shocks. We are partially in line with them in that, once factors related to demand are taken into account, the

Table VIII. Descriptive statistics on returns and residuals average squared unconditional correlations

(i) This table reports summary statistics on average squared unconditional return correlation $\hat{\rho}^{*}_{\text{ret}.t}$ and average squared unconditional residual correlation $\hat{\rho}^{*}_{t}$. (ii) $F\rho^{*2}$ is the mean percentage of average squared unconditional correlation significant at the 5% level using the t-squared 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, denote significance at 1%, 5%, and 10%, levels. (iv) C_{ρ} is the correlation between $\hat{\rho}^{*}_{\text{ret}.t}$ and $\hat{\rho}^{*}_{t}$.

	$\hat{\rho}^{*}_{\text{ret}.t}$	$\hat{\rho}^{*}_{t}$
μ	0.1982**	0.1803**
σ	0.0455	0.0246
$F\rho^{*2}$	0.6230	0.6440
C_{ρ}	0.9319	

residual correlation is lower, with this effect being stronger in recent years when demand shocks were larger.

Second, looking at both $\hat{\rho}^{*}_{t}$ and $\hat{\rho}_{t}$, taking time-variation in volatility into consideration only moderately affects the estimated correlation: the two lines are almost identical except in periods of high volatility, where there is a difference (although only small) between the two measures.

Third, and most importantly, our measure of excess co-movement is significant at the 5% level only half of the time in the period under consideration.[24] We thus conclude that the excess co-movement in commodity prices cannot be viewed as a general feature of commodity markets but is rather sample-dependent. As PR do not investigate time-variation in their excess co-movement measure, our results cannot be compared to theirs. There is a possibility, however, that the estimated excess co-movement over the 1960–85 period that PR find is insignificant over some sub-samples, thereby questioning the determinants of this phenomenon. In the same vein as the correlation plot in Tang and Xiong (2012), the chart of average squared correlations in Figure 1 provides a finer description of the estimated excess co-movement. This latter is mostly significant during periods of financial crisis: from mid-2000 to early 2003, and from 2008 onward. In their "convective risk flows" model, Cheng, Kirilenko, and Xiong (2015) show that financial traders cut their net long positions in response to market distress. A coordinated drop in the long positions of financial traders may help explain excess co-movement. Alternatively, excess co-movement may also reflect a "flight-to-quality" phenomenon, where investors decide to partly leave the stock market and invest heavily in commodities to diversify their positions. Moreover, the period starting in 2000 also corresponds to the growing financialization of commodity futures markets, as excellently surveyed in Cheng and Xiong (2014a). As such, excess co-movement might be related to speculative activity in commodity futures markets. Whether excess co-movement comes the changing nature of trading in commodity markets is a central question that we answer in the next section.

5. Explaining Excess Co-movement

The literature on institutional investors and their possible impact on commodity prices has grown dramatically in recent years [see the nice surveys in Irwin and Sanders (2011), Cheng

24 The significance threshold is 0.1669 and is plotted as a horizontal dotted line in Figure 3.

and Xiong (2014a), and Haase, Zimmermann, and Zimmermann (2016)]. Prior research has, however, produced mixed results. While some authors have produced evidence of a significant effect of index funds on commodity prices (Tang and Xiong, 2012; Singleton, 2013, among others), others have found evidence to the contrary (Rouwenhorst and Tang, 2012; Hamilton and Wu, 2015; Lehecka, 2015). Surprisingly, there is no work dealing with the impact of financialization on cross-market return linkages except for that in Tang and Xiong (2012).[25] The latter attempt to explain the recent rise in the co-movement of a number of commodity prices via five hypotheses: (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. Our research question is linked to the arguments in Tang and Xiong (2012), in that we arguably jointly test their first and third hypotheses, and consider the second and fourth in Section 3 when we filter returns using common factors. In particular, we have shown that growth in emerging economies leads commodity prices (hypothesis (ii)), and that commodity returns are correlated with a "nominal variables" factor (hypothesis (iv)). Both of these effects likely contribute to excess co-movement and are expressly taken into account in our work.

This section aims to show that speculation in commodity futures markets is a significant determinant of our estimated excess co-movement. The issue is new and challenging, as no significant evidence has been put forward in the literature to date. Our empirical approach is as follows. In a first step, we show that speculative activity and filtered futures returns are correlated for most of the commodities in our sample. Then, in a second step, we show that measures of speculative activity are correlated across commodities. Taken together, these results provide direct evidence of speculation as a driver of excess co-movement.[26]

5.1 Measure of Speculative Intensity

Our measure of speculative intensity builds on the work in Han (2008), where a new speculative index is developed following the literature on investor sentiment (see Baker and Wurgler, 2007).[27] The basic idea is to pick up the net view of speculators in a given futures market by comparing their long and short positions. Han's index is given by the number of long non-commercial contracts minus the number of short non-commercial contracts, scaled by the total open interest in futures markets for the commodity of interest; as such this is a directional index of speculative activity in the futures market. We calculate Han's index for our eight commodities using CFTC data.

All traders who are considered as large enough—positions are above a specified level that is commodity-dependent—are required to provide the CFTC with their daily positions. The Commitments of Traders (COT) Report corresponds to the weekly aggregation of the daily positions and is released each Tuesday. CFTC differentiates between "commercial" and "non-commercial" traders and provides long and short positions for both categories.[28]

25 See also Bruno, Büyüksahin, and Robe (2016), who consider co-movement across food commodities along with financialization, but whose main focus is rather on the commodity–equity relationship.

26 We wish to thank a referee for suggesting this methodological approach.

27 The analysis in Han (2008) deals with S&P 500 futures contracts. The author also relies on a proxy base on the Investors Intelligence's weekly that is not relevant for commodity markets.

28 Since 2006, the CFTC has also released a weekly Disaggregated Commitments of Traders (DCOT) report each Friday. This complements the COT report by providing more detailed categories of

"Commercial" traders should be able to prove an involvement in the physical market and are thus considered as hedgers while "non-commercial" traders have no relation with the cash business: this latter group then consists of speculators. The usefulness of these CFTC data has previously been discussed in Bessembinder (1992) and Cheng and Xiong (2014b), as many traders carry out activities which cover both hedging and speculation. In particular, Cheng and Xiong (2014b) show that hedgers may react to changes in commodity futures prices in a number of US Agricultural markets, which is undoubtedly a form of speculation. In what follows, we show that CFTC data are informative for our purpose despite the potential bias in the definition of categories of traders.

We also experiment with alternative measures of trading activity. The first of these is the Working's T speculative index, as recently used in Byksahin and Robe (2014). A second measure of trading activity is hedging pressure, as defined in de Roon, Nijman, and Veld (2000), who showed that futures risk premia depend on both own-market and cross-market hedging pressure. Their measure of hedging pressure is calculated as the difference between the number of short and long hedge positions, divided by the total number of hedge positions. This measure focuses on the positions of traders who are hedgers, that is, who have a cash business for the commodity. It is different from the Han index, where the denominator is the total open interest and not the total number of speculative positions, but the idea is roughly similar as hedging pressure also picks up the difference between long and short positions.[29] Results from using either Working's T or hedging pressure are very similar to those presented here, and are not reported to save space (but available upon request).

5.2 Empirical Results

To deal with the potential correlation of Han's indices and the business cycle, we regress our speculative indices on the same set of factors ($\hat{F}_{1t}, \hat{F}_{2t}, \hat{F}_{3t}, \hat{F}_{6t}, \hat{F}_{8t}$) as was used to filter commodity returns. Then, to gauge the explanatory power of Han's indices, we include them in univariate regressions of the form:

$$\text{Res}_{i,t} = a_i + \sum_{j=1}^{8} b_{i,j} H_{j,t} + e_{i,t},$$

where $\text{Res}_{i,t}$ is the ith commodity return residual at time t and $H_{j,t}$ is Han's index for the jth commodity at time t adjusted for the factors. Our choice to use contemporaneous variables in the regressions is motivated by the monthly frequency and the efficient-market hypothesis stating that any impact of index funds should be instantaneously reflected in prices [see Gilbert and Pfuderer (2014) for further developments on this issue]. We also choose to consider all the Han indices in each univariate regression following existing research on cross-commodity trading and its potential impact on prices (e.g., de Roon, Nijman, and Veld, 2000).[30]

traders such as Index Traders who have played a significant role in recent years. We do not use the DCOT data here, as it would considerably restrict the analysis sample period.

29 The sample correlation between Han's index and hedging pressure ranges from −0.78 for live cattle to − 0.98 for cotton.

30 Singleton (2014) implicitly considers the role of cross-positions, as his measure of index funds in oil markets is derived from index funds positions in grain markets.

Table IX. OLS regressions of residual returns on speculative Han indices

(i) This table reports OLS estimates of the regression of the eight commodities monthly residual returns on Han speculative indices. (ii) The Han indices are corrected for the factors $\{\hat{F}_{1t}, \hat{F}_{2t}, \hat{F}_{3t}, \hat{F}_{6t}, \hat{F}_{8t}\}$ to control for the effect of the business cycle. (iii) *t*-statistics are reported in parenthesis under the estimates. ***, **, and *, respectively, denote rejection of the null hypothesis of no significance at the 1%, 5%, and 10% levels.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Intercept	0.0009			−0.0002	−0.0013	−0.0001	0.0004	0.0000
	(0.20)			(−0.04)	(−0.23)	(−0.03)	(0.10)	(0.02)
Han_Wheat	0.0778***							0.0429*
	(2.67)							(1.88)
Han_Copper	−0.0597*							
	(−1.92)							
Han_Silver								
Han_Soybeans				0.0639*				
				(1.79)				
Han_Raw Sugar	−0.0514*				0.2063***			
	(−1.90)				(5.52)			
Han_Cotton						0.0636***	−0.0396*	
						(2.98)	(−1.79)	
Han_Crude Oil								
Han_Live Cattle								0.0816***
								(4.05)
R^2	0.0286			0.0110	0.1229	0.0206	0.0101	0.0397
$\bar{R}$	0.0166			0.0070	0.1194	0.0166	0.0061	0.0318

The estimated coefficients appear in Table IX. We observe that, with the exception of oil, copper, and silver, commodity returns are correlated with their own Han's index. The R^2 mostly ranges between 1% and 3%, but reaches 12.29% for raw sugar. We find a positive and significant impact of the Han index on its corresponding commodity for wheat, raw sugar, soybeans, and live cattle. For these commodities, speculative trading and returns move in the same direction. We also observe some cross-effects: the raw sugar and copper Han indices have an impact on wheat returns, and the cotton Han index has an effect on crude oil returns. In these cases, the estimated coefficient is negative but only weakly significant. The Han index for wheat has a positive effect on live cattle residual. The interpretation of these cross-effects is quite challenging as there is no link, such as substitutability or complementarity, between the commodities concerned.

One may rightly suspect that these OLS estimates are plagued by endogeneity. To assess the presence of endogeneity, we estimate all previous regressions via GMM and use one-period and two-period lagged Han indices as instruments.[31] The results in Table X show

31 Our methodology resembles the approach in Raman, Robe, and Yadav (2016), who gauge the effect of the participation of financial traders in oil futures post-electronification using two-stage least squares, or the method in Gilbert and Pfuderer (2014), who investigate the causal role of index trading on grain markets using instrumental variables. As changes in futures positions and futures returns are simultaneously determined, these methods are naturally relevant when analyzing financialization.

Table X. GMM regressions of residual returns on speculative Han indices; Instruments $\{\text{Han}_{t-1}, \text{Han}_{t-2}\}$ (i) This table reports GMM estimates of the regression of the eight commodities monthly residuals returns. The explanatory variables are reported in far-left column. (ii) The Han indices are corrected for the factors $\{\hat{F}_{1t}, \hat{F}_{2t}, \hat{F}_{3t}, \hat{F}_{6t}, \hat{F}_{8t}\}$ to control for the effect of the business cycle. (iii) *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. (iv) *J*-test is the Hansen (1982) test of overidentifying restrictions and the Diff *in J*-test is the test for endogeneity of regressors. *P*-values are reported under the test-statistics.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Intercept	0.0010			0.0008	0.0009	−0.0008	0.0003	0.0005
	(0.21)			(0.17)	(0.18)	(−0.16)	(0.09)	(0.20)
Han_Wheat	−0.0351							0.0555*
	(−0.61)							(1.85)
Han_Copper	0.0010							
	(0.02)							
Han_Silver								
Han_Soybeans				−0.0252				
				(−0.65)				
Han_Raw Sugar	−0.1018**				0.0987**			
	(−2.57)				(2.33)			
Han_Cotton						0.0439	−0.0362	
						(1.59)	(−1.47)	
Han_Crude Oil								
Han_Live Cattle								0.0122
								(0.36)
Exogeneity test								
Diff in *J*-test	9.64**			7.75***	17.28***	1.83	0.0678	10.75***
*p*val	0.0219			0.0054	0.0000	0.1750	0.79	0.00
Overidentifying test								
J-test	1.1770			1.3462	2.5290	0.4705	0.0077	1.028
*p*val	0.75			0.9966	0.11	0.2459	0.49	0.31

that the test for exogeneity based on the difference in the *J*-test does not reject the exogeneity of the Han index for cotton, crude oil. We therefore consider the previous OLS estimates as valid: the Han index has a positive effect on its own commodity for cotton while that for cotton has a negative impact on oil. We reject the exogeneity of the Han index in the wheat, raw sugar, soybeans, and live cattle regressions. Hansen's (1982) *J*-test for overidentifying restrictions validates our set of instruments. We also check that the instruments are not weak. With the exception of soybeans, the GMM estimates are in line with the previous OLS regressions for these four commodities. Wheat return is still negatively and significantly impacted by the Han index for raw sugar, although the indices for wheat and copper are no longer significant. The raw sugar Han index still has a positive impact on its return. The wheat Han indices have a positive and significant impact on live cattle residual return.

Our approach through instrumental variables unambiguously shows that there is a significant impact of changes in the speculative index on contemporaneous returns, even after controlling for endogeneity for most commodities. This impact is positive when the Han index and the return pertain to the same commodity.

Table XI. Correlation between the eight Han indices

(i) The upper triangular matrix reports correlations while the lower reports their *p*-values. ***, **, and *, respectively, denote significance at 1%, 5%, and 10% levels. (ii) The Han indices are corrected for the factors $\{\hat{F}_{1t}, \hat{F}_{2t}, \hat{F}_{3t}, \hat{F}_{6t}, \hat{F}_{8t}\}$ to control for the effect of the business cycle.

	Wheat	Copper	Silver	Soybeans	Raw sugar	Cotton	Crude oil	Live cattle
Wheat	1	0.1744***	0.0107	0.2133***	−0.0334	0.1394**	−0.0226	−0.1194*
Copper	0.00	1	0.2146***	0.0029	0.1271**	0.1888***	0.1071*	0.2227***
Silver	0.86	0.00	1	−0.1408**	−0.1128*	−0.0935	−0.1024	−0.0925
Soybeans	0.00	0.96	0.02	1	0.1853***	0.4619***	0.2787***	0.0830
Raw sugar	0.59	0.04	0.07	0.00	1	0.0222	0.1060*	0.2280***
Cotton	0.02	0.00	0.14	0.00	0.72	1	0.3005***	0.1324**
Crude oil	0.72	0.09	0.10	0.00	0.09	0.00	1	0.1102*
Live cattle	0.06	0.00	0.14	0.19	0.00	0.03	0.08	1

We now focus on sample cross-correlations between speculative intensities in commodity futures markets. As expected from the "style investing" hypothesis developed in Barberis and Shleifer (2003) or the more general increase in non-commercial positions in commodity-futures markets in the last decades (see Cheng and Xiong, 2014a), the cross-correlations between speculative indices are mostly positive and significant as shown in Table XI. There are, respectively, 10, 15, and 19 significant cross-correlations at the 1%, 5%, and 10% significance levels. The cross-correlations are significantly negative in only three cases (silver and raw sugar, silver and soybeans, wheat and live cattle). We therefore have evidence that speculative indices move together, even for commodities of different classes such as, for instance, wheat and copper, cotton and crude oil, or raw sugar and live cattle.

Overall, our empirical results demonstrate that speculative activity is a significant driver of excess co-movement. We thus confirm the implications in Basak and Pavlova (2016) that institutional investors do play a role in linking commodity futures prices. Our results are also in line with those in Tang and Xiong (2012), but provide stronger evidence of the impact of speculation on co-movements as we on purpose control for the impact of real variables on commodity prices. More generally, our results demonstrate the critical role of trading for price determination, and the overall importance of the "financialization of the commodity markets", a concept that has attracted growing interest in academic and political spheres over recent years.

6. Concluding Remarks

The aim of this paper was to reconsider the question of the excess co-movement of commodity prices and to provide an explanation of this phenomenon, if it was found to be present in the data.

We believe that our paper offers new perspectives for the analysis of co-movement in commodity returns. First, as discussed above, we use the large approximate factor model method to uncover the relevant factors that allow us to explain commodity returns. To the best of our knowledge, this is the first time that this method has been used to filter out returns before looking for excess co-movement. The main advantage of factors is that they allow us to deal with a large number of variables, while retaining econometric tractability,

thereby including a richer set of fundamentals. We thus avoid any artificial limit on the information set, which has been a major constraint in previous work.

Our second contribution is to provide an explanation of the excess co-movement in commodity returns. Previous work has emphasized the methodological aspects of the assessment of the hypothesis of excess co-movements. Surprisingly, however, the issue of which variables are related to this phenomenon has not been analyzed to date. Our indicator of speculative activity, calculated using traders' positions available from CFTC, is both correlated across commodities and with futures prices, thereby providing evidence of speculation as a driver of excess co-movement.

The limits of our analysis are good topics for future research. First, we consider, as in most factor-models in the literature, the factors as if they were data rather than being estimated. Even if this may have only a small effect on our results, it would be useful to investigate the small-sample case using simulation techniques as in Ludvigson and Ng (2007, 2009).

Second, mixed-data sampling (MIDAS) regressions may be used to include more information at different frequencies. Tang and Xiong (2012) consider daily and monthly regressions, and MIDAS may help to combine the two data sources, with daily market indices and monthly or quarterly macroeconomic variables. This is the setting in Karali and Power (2013), who mix high- and low-frequency variables to explain the volatility of commodity returns. Such a setting may allow us to consider volatility spillovers, as in the penultimate section in Tang and Xiong (2012). The analysis of commodity volatility co-movement may have interesting implications for financial risk management.

Third, alternative measures of trading activity, such as liquidity measures, may help better explain excess co-movement. In this respect, the recent contributions of Marshall, Nguyen, and Visaltanachoti (2012, 2013) may aid in the selection of appropriate liquidity measures for commodities and the evaluation of the explanatory power of their common liquidity factor. These measures may additionally be calculated on a daily basis, thereby permitting the high-frequency analysis of the common evolution of commodity prices.

Appendix A

Table AI. List of the 184 variables considered in the computation of the common factors

In the Trans column, we report the transformation used to ensure the stationarity of each variable. ln denotes the logarithm, Δln and Δ^2ln 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: USA	USIPMAN.G	Δln	US INDUSTRIAL PRODUCTION—MANUFACTURING (NAICS) VOLA
2	IP: France	FRIPMAN.G	Δln	FR INDUSTRIAL PRODUCTION—MANUFACTURING VOLA
3	IP: France	FRINDSYNQ	lv	FR SURVEY: MANUFACTURING—SYNTHETIC BUSINESS INDICATOR SADJ
4	IP: Germany	BDIPMAN.G	Δln	BD INDUSTRIAL PRODUCTION: MANUFACTURING VOLA
5	IP: UK	UKIPMAN.G	Δln	UK INDUSTRIAL PRODUCTION INDEX—MANUFACTURING VOLA
6	IP: Japan	JPIPMAN.G	Δln	JP INDUSTRIAL PRODUCTION—MANUFACTURING VOLAJ
7	IP: Japan	JPIPTOT.G	Δln	JP INDUSTRIAL PRODUCTION—MINING & MANUFACTURING VOLA (2005 = 100)
Orders and capacity utilization				
8	Capacity utilization: USA	USCUMANUG	Δlv	US CAPACITY UTILIZATION—MANUFACTURING VOLA
9	Manufct. new ord.: USA	USNOCOGMC	Δln	US MANUFACTURERS NEW ORDERS—CONSUMER GOODS & MATERIALS CONN (BASE 1982)
10	Manufct. new ord.: USA	USNOMXTRB	Δln	US NEW ORDERS—MANUFACTURING. EXCLUDING TRANSPORTATION CURA
11	New orders: Canada	CNNEWORDB	Δln	CN NEW ORDERS: ALL MANUFACTURING INDUSTRIES (SA) CURA
12	Manufct. ord.: Germany	BDNEWORDE	Δln	BD MANUFACTURING ORDERS SADJ (2000 = 100)
13	Manufct. ord.: Japan	JPNEWORDB	Δln	JP MACHINERY ORDERS: DOM.DEMAND–PRIVATE DEMAND (EXCL. SHIP) CURA
14	Operating ratio: Japan	JPCAPUTLQ	Δlv	JP OPERATING RATIO—MANUFACTURING SADJ (2005 = 100)
15	Business failures: Japan	JPBNKRPTP	Δln	JP BUSINESS FAILURES VOLN

(continued)

Table AI. Continued

Developed countries				
Series number	Short name	Mnemonic	Trans	Description
Housing start				
16	Housing permits: USA	USHOUSE.O	Δln	US NEW PRIVATE HOUSING UNITS STARTED (AR) VOLA
17	Housing permits: Canada	CNHOUSE.O	Δln	CN HOUSING STARTS: ALL AREAS (SA. AR) VOLA
18	Housing permits: Germany	BDHOUSE.G	Δln	BD CONSTRUCTION ORDERS RECEIVED—RESIDENTIAL CONSTRUCTION VOLA
19	Housing permits: Australia	AUHOUSE_A	Δln	AU BUILDING APPROVALS: NEW HOUSES CURN
20	Housing permits: Japan	JPHOUSSTF	ln	JP NEW HOUSING CONSTRUCTION STARTED VOLN
Car sales				
21	Car registration: USA	USCAR...P	Δln	US NEW PASSENGER CARS—TOTAL REGISTRATIONS VOLN
22	Car registration: France	FRCARREGP	Δln	FR NEW CAR REGISTRATIONS VOLN
23	Car registration: Germany	BDRVNCARP	ln	BD NEW REGISTRATIONS—CARS VOLN
24	Car registration: UK	UKCAR...P	Δln	UK CAR REGISTRATIONS VOLN
25	Car registration: Japan	JPCARREGF	ln	JP MOTOR VEHICLE NEW REGISTRATIONS: PASSENGER CARS EXCL. BELOW 66
Consumption				
26	Consumer sentiment: USA	USUMCONEH	Δln	US UNIV OF MICHIGAN CONSUMER SENTIMENT—EXPECTATIONS VOLN (BASE 1966 = 100)
27	Pers. cons. exp.: USA	USPERCONB	Δln	US PERSONAL CONSUMPTION EXPENDITURES (AR) CURA
28	Pers. saving: USA	USPERSAVE	Δlv	US PERSONAL SAVING AS % OF DISPOSABLE PERSONAL INCOME SADJ
29	Retail sale: Canada	CNRETTOTB	Δln	CN RETAIL SALES: TOTAL (ADJUSTED) CURA
30	Household confidence: France	FRCNFCONQ	Δlv	FR SURVEY—HOUSEHOLD CONFIDENCE INDICATOR SADJ
31	Household confidence: Germany	BDCNFCONQ	lv	BD CONSUMER CONFIDENCE INDICATOR—GERMANY SADJ
32	Retail sales: UK	UKRETTOTB	Δln	UK RETAIL SALES (MONTHLY ESTIMATE. DS CALCULATED) CURA
33	Household confidence: UK	UKCNFCONQ	Δlv	UK CONSUMER CONFIDENCE INDICATOR—UK SADJ
34	Retail sales: Australia	AURETTOTT	Δln	AU RETAIL SALES (TREND) VOLA

(continued)

Table AI. Continued

Developed countries				
Series number	Short name	Mnemonic	Trans	Description
35	Household confidence: Australia	AUCNFCONR	lv	AU MELBOURNE/WESTPAC CONSUMER SENTIMENT INDEX NADJ
36	Household expenditure: Japan	JPHLEXPWA	Δln	JP WORKERS HOUSEHOLD LIVING EXPENDITURE (INCL. AFF) CURN
37	Retail sales: Japan	JPRETTOTA	Δln	JP RETAIL SALES CURN
Wages and labor				
38	Av. Hourly Real Earnings: USA	USWRIM.D	Δln	US AVG HOURLY REAL EARNINGS—MANUFACTURING CONA (BASE 82–84)
39	Av. overtime hours: USA	USOOL024Q	Δlv	US OVERTIME HOURS—MANUFACTURING. WEEKLY VOLA
40	Av. wkly hours: USA	USHKIM_O	Δlv	US AVG WKLY HOURS—MANUFACTURING VOLA
41	Av. hourly real earnings: Canada	CNWAGES.A	Δln	CN AVG. HOURLY EARN—INDUSTRIAL AGGREGATE EXCL. UNCLASSIFIED CURN
42	Labor productivity: Germany	BDPRODVTQ	Δln	BD PRODUCTIVITY: OUTPUT PER MAN-HOUR WORKED IN INDUSTRY SADJ (2005 = 100)
43	wages: Germany	BDWAGES.F	Δln	BD WAGE & SALARY.OVERALL ECONOMY—ON A MTHLY BASIS (PAN BD M0191)
44	wages index: Japan	JPWAGES_E	Δln	JP WAGE INDEX: CASH EARNINGS—ALL INDUSTRIES SADJ
Unemployment				
45	U rate: USA	USUNEM15Q	Δlv	US UNEMPLOYMENT RATE—15 WEEKS & OVER SADJ
46	U rate: USA	USUNTOTQ_pc	Δlv	US UNEMPLOYMENT RATE SADJ
47	Employment: Canada	CNEMPTOTO	Δln	CN EMPLOYMENT—CANADA (15 YRS & OVER SA) VOLA
48	U all: Germany	BDUNPTOTP	Δln	BD UNEMPLOYMENT LEVEL (PAN BD FROM SEPT. 1990) VOLN
49	U rate: UK	UKUNTOTQ_pc	Δlv	UK UNEMPLOYMENT RATE SADJ
50	Emp: Australia	AUEMPTOTO	Δln	AU EMPLOYED: PERSONS VOLA
51	U all: Australia	AUUNPTOTO	Δln	AU UNEMPLOYMENT LEVEL VOLA
52	U rate: Japan	JPUNTOTQ_pc	Δlv	JP UNEMPLOYMENT RATE SADJ

(continued)

Table AI. Continued

Developed countries				
Series number	Short name	Mnemonic	Trans	Description
International trade				
53	Exports: USA	USI70_A	Δln	US EXPORTS CURN
54	Exports: France	FREXPGDSB	Δln	FR EXPORTS FOB CURA
55	Exports: Germany	BDEXPBOPB	Δln	BD EXPORTS FOB CURA
56	Exports: UK	UKI70_A	Δln	UK EXPORTS CURN
57	Exports: Australia	AUEXPG&SB	Δln	AU EXPORTS OF GOODS & SERVICES (BOP BASIS) CURA
58	Exports: Japan	JPEXPGDSB	Δln	JP EXPORTS OF GOODS—CUSTOMSBASIS CURA
59	Imports: USA	USIMPGDSB	Δln	US IMPORTS F.A.S. CURA
60	Imports: France	FRIMPGDSB	Δln	FR IMPORTS FOB CURA
61	Imports: Germany	BDIMPGDSB	Δln	BD IMPORTS CIF (PAN BD M0790) CURA
62	Imports: UK	UKIMPBOPB	Δln	UK IMPORTS—BALANCE OF PAYMENTS BASIS CURA
63	Imports: Australia	AUIMPG&SB	Δln	AU IMPORTS OF GOODS & SERVICES (BOP BASIS) CURA
64	Imports: Japan	JPOXT009B	Δln	JP IMPORTS CURA
65	Terms of trade: UK	UKTOTPRCF	Δln	UK TERMS OF TRADE—EXPORT/IMPORT PRICES (BOP BASIS) NADJ
66	Terms of trade: Japan	JPTOTPRCF	Δln	JP TERMS OF TRADE INDEX NADJ
Money and credit				
67	Money supply: USA	USM0_A	Δln	US MONETARY BASE CURA
68	Money supply: USA	USM2_B	Δln	US MONEY SUPPLY M2 CURA
69	Money supply: France	FRM2_A	Δln	FR MONEY SUPPLY—M2 (NATIONAL CONTRIBUTION TO M2) CURN
70	Money supply: France	FRM3_A	Δln	FR MONEY SUPPLY—M3 (NATIONAL CONTRIBUTION TO M3) CURN
71	Money supply: Germany	BDM1_A	Δln	BD MONEY SUPPLY—GERMAN CONTRIBUTION TO EURO M1 (PAN BD M0790)
72	Money supply: Germany	BDM3_B	Δln	BD MONEY SUPPLY—M3 (CONTRIBUTION TO EURO BASIS FROM M0195) CURA
73	Money supply: UK	UKM1_B	Δln	UK MONEY SUPPLY M1 (ESTIMATE OF EMU AGGREGATE FOR THE UK) CURA

(continued)

Table AI. Continued

Developed countries				
Series number	Short name	Mnemonic	Trans	Description
74	Money supply: UK	UKM3_B	Δln	UK UK MONEY SUPPLY M3 (ESTIMATE OF EMU AGGREGATE FORTHE UK) CURA
75	Money supply: Australia	AUM1_B	Δln	AU MONEY SUPPLY—M1 CURA
76	Money supply: Australia	AUM3_B	Δln	AU MONEY SUPPLY - M3 (SEE AUM3…OB) CURA
77	Money supply: Japan	JPM1_A	Δln	JP MONEY SUPPLY: M1 (METHO-BREAK. APR. 2003) CURN
78	Money supply: Japan	JPM2_A	Δln	JP MONEY SUPPLY: M2 (METHO-BREAK. APR. 2003) CURN
79	Credit: USA	USCOMILND	Δln	US COMMERCIAL & INDUSTRIAL LOANS OUTSTANDING (BCI 101) CONA (BASE 2005)
80	Credit: USA	USCILNNCB	lv	US COMMERCIAL & INDL LOANS. NET CHANGE (AR) (BCI 112) CURA
81	Credit: USA	USCRDNRVB	Δln	US NONREVOLVING CONSUMER CREDIT OUTSTANDING CURA
82	Credit: France	FRBANKLPA	Δln	FR MFI LOANS TO RESIDENT PRIVATE SECTOR CURN
83	Credit: Germany	BDBANKLPA	Δ^2ln	BD LENDING TO ENTERPRISES & INDIVIDUALS CURN
84	Credit: Australia	AUCRDCONB	Δ^2ln	AU FINANCIAL INTERMEDIARIES: NARROW CREDIT—PRIVATE SECTOR CURA
85	Credit: Japan	JPBANKLPA	Δ^2ln	JP AGGREGATE BANK LENDING (EXCL. SHINKIN BANKS) CURN
Stock index				
86	Stock index: USA	USSHRPRCF	Δln	US DOW JONES INDUSTRIALS SHARE PRICE INDEX (EP) NADJ
87	Stock index: France	FRSHRPRCF	Δln	FR SHARE PRICE INDEX—SBF 250 NADJ
88	Stock index: Germany	BDSHRPRCF	Δln	BD DAX SHARE PRICE INDEX. EP NADJ
89	Stock index: UK	UKOSP001F	Δln	UK FTSE 100 SHARE PRICE INDEXNADJ (2005 = 100)
90	Stock index: Japan	JPSHRPRCF	Δln	JP TOKYO STOCK EXCHANGE—TOPIX (EP) NADJ (1968 = 100)
Interest rate				
91	Interest rate: USA	USFEDFUN	Δlv	US FEDERAL FUNDS RATE (AVG.)
92	Interest rate: USA	USCRBBAA	Δlv	US CORPORATE BOND YIELD—MOODY'S BAA. SEASONED ISSUES
93	Interest rate: USA	USGBOND	Δlv	US TREASURY YIELD ADJUSTED TO CONSTANT MATURITY—20 YEAR

(continued)

Table AI. Continued

Developed countries				
Series number	Short name	Mnemonic	Trans	Description
94	Interest rate: France	FRPRATE	Δlv	FR AVERAGE COST OF FUNDS FOR BANKS/EURO REPO RATE
95	Interest rate: France	FRGBOND	Δlv	FR GOVERNMENT GUARANTEED BOND YIELD (EP) NADJ
96	Interest rate: Germany	BDPRATE	Δlv	BD DISCOUNT RATE/SHORT TERM EURO REPO RATE
97	Interest rate: Germany	BDGBOND	Δlv	BD LONG TERM GOVERNMENT BOND YIELD—9–10 YEARS
98	Interest rate: UK	UKPRATE	Δlv	UK BANK OF ENGLAND BASE RATE (EP)
99	Interest rate: UK	UKGBOND	Δlv	UK GROSS REDEMPTION YIELD ON 20 YEAR GILTS (PERIOD AVERAGE) NADJ
100	Interest rate: Australia	AUPRATE	Δlv	AU RBA CASH RATE TARGET
101	Interest rate: Australia	AUBOND	Δlv	AU COMMONWEALTH GOVERNMENT BOND YIELD 10 YEAR (EP)
102	Interest rate: Japan	JPGBOND	Δlv	JP INTEREST-BEARING GOVERNMENT BONDS—10-YEAR (EP)
Exchange rate				
103	Exchange rate: DM to US$	BBDEMSP	Δln	GERMAN MARK TO US$ (BBI)—EXCHANGE RATE
104	Exchange rate: SK to US$	SDXRUSD	Δln	SD SWEDISH KRONOR TO US$ (BBI. EP)
105	Exchange rate: to $	UKDOLLR	Δln	UK TO US$ (WMR)—EXCHANGE RATE
106	Exchange rate: Yen to $	JPXRUSD	Δln	JP JAPANESE YEN TO US$
107	Exchange rate: Aus.$ to US$	AUXRUSD	Δln	AU AUSTRALIAN $ TO US$ (MTH. AVG.)
Producer price index				
108	PPI: USA	USPROPRCE	Δln	US PPI—FINISHED GOODS SADJ
109	PPI: Canada	CNPROPRCF	Δln	CN INDUSTRIAL PRICE INDEX: ALL COMMODITIES NADJ
110	PPI: Germany	BDPROPRCF	Δln	BD PPI: INDL. PRODUCTS. TOTAL. SOLD ON THE DOMESTIC MARKET NADJ (2005 = 100)
111	PPI: UK	UKPROPRCF	Δln	UK PPI—OUTPUT OF MANUFACTURED PRODUCTS (HOME SALES) NADJ
112	PPI: Japan	JPPROPRCF	Δln	JP CORPORATE GOODS PRICE INDEX: DOMESTIC—ALL COMMODITIES NADJ

(continued)

Table AI. Continued

Developed countries

Series number	Short name	Mnemonic	Trans	Description
Consumer price index				
113	CPI: USA	USCONPRCE	Δln	US CPI—ALL URBAN: ALL ITEMS SADJ
114	CPI: Canada	CNCONPRCF	Δln	CN CPI NADJ
115	CPI: France	FRCONPRCE	Δln	FR CPI SADJ
116	CPI: Germany	BDCONPRCE	Δln	BD CPI SADJ
117	CPI: UK	UKCONPRCF	Δln	UK CPI INDEX 00: ALL ITEMS- ESTIMATED PRE-97 2005 = 100 NADJ
118	CPI: Japan	JPCONPRCF	Δln	JP CPI: NATIONAL MEASURE NADJ

Emerging countries

Series number	Short name	Mnemonic	Trans	Description
Industrial production				
119	IP: Argentina	AGIPTOT.G	Δln	AG INDUSTRIAL PRODUCTION VOLA
120	IP: Chile	CLIPMAN.H	Δln	CL INDUSTRIAL PRODUCTION INDEX BY INE—MANUFACTURING TOTAL VOLN
121	IP: Brazil	BRIPTOT_G	Δln	BR INDUSTRIAL PRODUCTION VOLA index 2002 = BASE
122	IP: Brazil	BRIPMAN.G	Δln	BR INDUSTRIAL PRODUCTION—MANUFACTURING VOLA
123	IP: China	CHPBRENTP (electricity)	Δln	CH INDUSTRIAL PRODUCTION: ELECTRICITY VOLN
124	IP: Korea	KOIPTOT.G	Δln	KO INDUSTRIAL PRODUCTION VOLA (2005 = 100)
125	IP: Korea	KOIPMAN.G	Δln	KO MANUFACTURING PRODUCTION INDEX VOLA
126	IP: Mexico	MXIPTOT_H	Δln	MX INDUSTRIAL PRODUCTION INDEX VOLN
127	IP: Philippines	PHIPMAN_F	Δln	PH MANUFACTURING PRODUCTION NADJ
128	IP: South Africa	SAIPMAN.G	Δln	SA INDUSTRIAL PRODUCTION (MANUFACTURING SECTOR) VOLA
129	IP: Taiwan	TWIPMAN.H	Δln	TW INDUSTRIAL PRODUCTION INDEX—MANUFACTURING VOLN

(continued)

Table AI. Continued

Emerging countries Series number	Short name	Mnemonic	Trans	Description
Orders and capacity utilization				
130	Operating ratio: Brazil	BRCAPUTLR	Δlv	BR CAPACITY UTILIZATION—MANUFACTURING NADJ
131	Mach. ord.: Korea	KONEWORDA	Δln	KO MACHINERY ORDERS RECEIVEDCURN
132	Manufct. prod capa.: Korea	KOCAPUTLF	Δlv	KO MANUFACTURING PRODUCTION CAPACITY NADJ (2005 = 100)
Consumption				
133	Car sales: Argentina	AGCARSLSP	Δln	AG SALES—NATIONAL CARS TO DEALERS VOLN
134	Retail sales: Chile	CLRETTOTH	Δln	CL RETAIL SALES AT SUPERMARKETS (REAL INDEX) VOLN
135	Gasoline consumption: Korea	KOOPCGSLP	Δln	KO OIL PRODUCTS CONSUMPTION—GASOLINE VOLN
136	Retail sales: Singapore	SPRETTOTG	Δlv	SP RETAIL SALES INDEX (CONSTANT) VOLA
137	Retail sales: Russia	RSRETTOTA	Δln	RS RETAIL TRADE TURNOVER—TOTAL CURN
Wages and labor				
138	Labor cost: Brazil	BRLCOST.F	Δln	BR UNIT LABOR COST NADJ
Unemployment				
139	Unemployment: Hong Kong	HKUNPTOTP	Δln	HK UNEMPLOYMENT (3 MONTHS ENDING) VOLN
140	U rate: Taiwan	TWUN%TOTQ	Δlv	TW UNEMPLOYMENT RATE SADJ
141	Unemployment: Russia	RSUNPTOTP	Δln	RS ECONOMICALLY ACTIVE POPULATION—UNEMPLOYED VOLN
International trade				
142	Exports: Brazil	BREXPBOPA	Δln	BR BOP: CURRENT ACCOUNT—GOODS (CREDIT) CURN
143	Exports: China	CHEXPGDSA	Δln	CH EXPORTS CURN
144	Exports: India	INEXPGDSA	Δln	IN EXPORTS FOB CURN
145	Exports: Indonesia	IDEXPGDSA	Δln	ID EXPORTS FOB CURN
146	Exports: Korea	KOEXPGDSA	Δln	KO EXPORTS FOB (CUSTOMS CLEARANCE BASIS) CURN
147	Exports: Philippines	PHEXPGDSA	Δln	PH EXPORTS CURN
148	Exports: Singapore	SPEXPGDSA	Δln	SP EXPORTS CURN
149	Exports: Taiwan	TWEXPGDSA	Δln	TW EXPORTS CURN

(continued)

Table AI. Continued

Emerging countries Series number	Short name	Mnemonic	Trans	Description
150	Imports: Brazil	BRIMPBOPA	Δln	BR BOP: CURRENT ACCOUNT—GOODS (DEBIT) CURN
151	Imports: China	CHIMPGDSA	Δln	CH IMPORTS CURN
152	Imports: Korea	KOIMPGDSA	Δln	KO IMPORTS CIF (CUSTOMS CLEARANCE BASIS) CURN
153	Imports: Singapore	SPIMPGDSA	Δln	SP IMPORTS CURN
154	Imports: Taiwan	TWIMPGDSA	Δln	TW IMPORTS CURN
155	Terms of trade: Brazil	BRTOTPRCF	Δln	BR TERMS OF TRADE NADJ (2006 = 100)
Money and credit				
156	Money supply: Brazil	BRM1_A	Δln	BR MONEY SUPPLY—M1 (EP) CURN
157	Money supply: Brazil	BRM3_A	Δln	BR MONEY SUPPLY—M3 (EP) CURN
158	Money supply: China	CHM0_A	Δln	CH MONEY SUPPLY—CURRENCY IN CIRCULATION CURN
159	Money supply: China	CHM1_A	Δln	CH MONEY SUPPLY—M1 CURN
160	Money supply: India	INM1_A	Δ^2ln	IN MONEY SUPPLY: M1 (EP) CURN
161	Money supply: India	INM3_A	Δ^2ln	IN MONEY SUPPLY: M3 (EP) CURN
162	Money supply: Indonesia	IDM1_A	Δln	ID MONEY SUPPLY: M1 CURN
163	Money supply: Indonesia	IDM2_A	Δln	ID MONEY SUPPLY—M2 CURN
164	Money supply: Korea	KOM2_B	Δln	KO MONEY SUPPLY—M2 (EP) CURA
165	Money supply: Mexico	MXM1_A	Δln	MX MONEY SUPPLY: M1 (EP) CURN BASE = END OF PERIOD
166	Money supply: Mexico	MXM3_A	Δ^2ln	MX MONEY SUPPLY: M3 (EP) CURN
167	Money supply: Philippines	PHM1_A	Δln	PH MONEY SUPPLY—M1 (METHO BREAK AT 12/03) CURN
168	Money supply: Philippines	PHM3_A	Δln	PH MONEY SUPPLY—M3 (METHO BREAK AT 12/03) CURN
169	Money supply: Russia	RSM 0_A	Δln	RS MONEY SUPPLY—M0 CURN
Stock index				
170	Stock index: Brazil	BRSHRPRCF	Δln	BR BOVESPA SHARE PRICE INDEX (EP) NADJ
171	Stock index: Hong Kong	HKSHRPRCF	Δln	HK HANG SENG SHARE PRICE INDEX (EP) NADJ (31 JULY 1964 =100)

(continued)

Table AI. Continued

Emerging countries Series number	Short name	Mnemonic	Trans	Description
Exchange rate				
172	Exchange rate: Br.R. to US$	BRXRUSD	Δln	BR BRAZILIAN REAIS TO US$ (AVG)
173	Exchange rate: Ch.Y. to US$	CHXRUSD	Δln	CH CHINESE YUAN TO US$ (AVERAGE AMOUNT)
174	Exchange rate: In.R. to US$	INXRUSD	Δln	IN INDIAN RUPEES PER US$ (RBI)
175	Exchange rate: Id.R. to US$	IDXRUSD	Δln	ID INDONESIAN RUPIAHS TO US$
176	Exchange rate: Mx.P. to US$	MXXRUSD	Δln	MX MEXICAN PESOS TO US$—CENTRAL BANK SETTLEMENT RATE (AVG)
177	Exchange rate: Rs.R. to US$	RSXRUSD	Δln	RS RUSSIAN ROUBLES TO US$ NADJ
Consumer price index				
178	CPI: Brazil	BRCPIGENF	Δln	BR CPI—GENERAL NADJ
179	CPI: China	CHCONPRCF	Δln	CH CPI NADJ
180	CPI: India	INCONPRCF	Δln	IN CPI: INDUSTRIAL LABOURERS(DS CALCULATED) NADJ (2001 = 100)
181	CPI: Korea	KOCONPRCF	Δln	KO CPI NADJ (2005 = 100)
182	CPI: Mexico	MXCONPRCF	Δln	MX CPI NADJ (JUN 2002 = 100)
183	CPI: Philippines	PHCONPRCF	Δln	PH CPI NADJ
184	CPI: Russia	RSCONPRCF	Δln	RS CPI NADJ

Table BI. Static factor selection results

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 $g_i(N.T)$.

Method	Number of static factors
MED	2
IC_1	4
IC_2	3
IC_3	12
IC_4	20
PCP_1	9
PCP_2	8
PCP_3	18
PCP_4	20

Appendix B: Estimating the Number of Factors

Bai and Ng (2002) propose to select the number of common factors which minimize the following information criteria:

$$\mathrm{PCP}_i(k) = S(k) + k\bar{\sigma}^2 g_i(N.T),$$

$$\mathrm{IC}_i(k) = \ln(S(k)) + k g_i(N.T),$$

where k is the number of factors, $S(k) = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it} - \hat{\lambda}_i^{k\prime}\hat{F}_t^k)^2$ is the sum of squared residuals (divided by NT), $g(N.T)$ is a penalty function,[32] and $\bar{\sigma}^2$ equals $S(k_{\max})$ for a pre-specified value of $k_{\max}$. The optimal number of factors $\hat{k}$ minimizes these information criteria.

Kapetanios (2010) proposes a sequential test to determine the number of factors. When the true number of factors is k_0, under some regularity condition, the first k_0 eigenvalues of the population covariance matrix Σ increase at rate N while the others are bounded. Let's note $\hat{\lambda}_k$, $k = 1, \ldots, N$, the N eigenvalues (in decreasing order) of the sample covariance matrix $X'X$ and $k_{\max}$ a finite number such that $k_0 < k_{\max}$. The difference $\hat{\lambda}_k - \hat{\lambda}_{k^{\max}+1}$ will go to infinity for $k = 1, \ldots, k_0$, but is bounded for $k = k_0 + 1, \cdots, k_{\max}$. $\hat{\lambda}_k - \hat{\lambda}_{k^{\max}+1}$ is then used as a the test statistics to discriminate the null hypothesis that the true number of factors k_0 equals k $(H_{0.k} : k_0 = k)$ against the alternative hypothesis $(H_{1.k} : k_0 > k)$. When there is no factor structure, $\hat{\lambda}_k - \hat{\lambda}_{k^{\max}+1}$, appropriately normalized, converge to a law limit, but tend to infinity in the presence of factors. We begin by testing $(H_{0.k} : k_0 = k = 0)$ 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 maximal eigenvalue distribution (MED) algorithm.

32 The penalty functions suggested by Bai and Ng (2002) are: $g_1(N.T) = \frac{N+T}{NT}\ln\left(\frac{NT}{N+T}\right)$, $g_2(N.T) = \frac{N+T}{NT}\ln(C_{NT}^2)$, $g_3(N.T) = \frac{\ln(C_{NT}^2)}{C_{NT}^2}$, and $g_4(N.T) = (N + T - k)\frac{\ln(NT)}{NT}$.

Table BII. Summary statistics for estimated static factors $\hat{F}_{t,i}$ for $i = 1, \ldots, 9$ For $i = 1, \ldots, 9$. $\hat{F}_{it}$ is estimated by the method of principal components using a panel of data with 184 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 ith 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.

Factor i	ρ_1	ρ_2	ρ_3	R_i^2
1	0.1614	0.1256	0.3176	0.0930
2	0.1357	0.0805	0.3110	0.1623
3	−0.0748	0.0145	−0.0294	0.2066
4	−0.0285	−0.0694	0.1866	0.2424
5	−0.1439	−0.0966	0.0950	0.2740
6	0.2546	0.0328	−0.0091	0.3035
7	0.1012	0.3234	0.3844	0.3288
8	0.3405	0.4066	0.1768	0.3518
9	−0.0065	−0.0413	−0.1447	0.3739

As shown in Table BI, there is no agreement on the optimal number of factors.[33] Bai and Ng (2002) information criteria select between two and nine factors while Kapetanios (2010) sequential test suggests two. Previous empirical work also reveals considerable variance in estimates of the correct number of factors.[34] The factors autocorrelation of factors $\hat{F}_t$ are displayed in Table BII. They show that most factors are persistent. Statistics on their explanatory power reveals that only 20% of the variance in the 184 time series is explained by the first three factors. This figure is equal to 36% for the first nine factors, which leads us to keep the first nine factors as potential regressors for modeling commodity returns.

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

34 See for example the empirical applications in Kapetanios (2010) which show that there may be some variation in the estimation of the number of factors under different selection criteria.

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