# Increasing Trends in the Excess Comovement of Commodity Prices*

Kazuhiko Ohashi† Tatsuyoshi Okimoto‡

Graduate School of International Corporate Strategy

Hitotsubashi University

November 12, 2012

**Abstract**

In this paper, we generalize the model of excess comovement originated by Pindyck and Rotemberg (1990), and extended by Deb, Trivedi, and Varangis (1996), to investigate whether and how excess correlations among seemingly unrelated commodity returns have increased recently. To this end, we develop the STDCC model to capture the long-run trends and the short-run dynamics of excess comovement. Using the commodity return data from 1983 to 2011, in all pairs of agricultural raw materials, beverages, metals , and oil, we find gradually increasing long-run trends since 2000. We also confirm that the increasing trend in excess comovement is robust and not an artifact of the recent financial crisis nor changes in the effects of common macroeconomic factors. Finally, we show that the dynamics of excess comovements in off-index commodities is quite different, which may be taken as additional evidence for the financialization of commodities.

JEL classification: C32, C51, G15

Key Words: Smooth transition model; DCC model; time-varying correlation

---

*We are indebted to seminar participants at Hitotsubashi University and Bank of Japan. We also thank the Grant-in-Aid for Scientific Research for the financial support.

†Graduate School of International Corporate Strategy (ICS), Hitotsubashi University, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8439, JAPAN. Phone: +81-3-4212-3102. Fax: +81-3-4212-3020. E-mail: kohashi@ics.hit-u.ac.jp.

‡Graduate School of International Corporate Strategy (ICS), Hitotsubashi University, 2-1-2 Hitotsubashi, Chiyoda-ku, Tokyo 101-8439, JAPAN. Phone: +81-3-4212-3098. Fax: +81-3-4212-3020. E-mail: tatsuyoshi.okimoto@gmail.com.

# 1 Introduction

Since the early 2000s, commodities have emerged as an additional asset class alongside traditional ones such as stocks and bonds. Much research, using data from prior to the 2000s, has found slightly negative correlations between commodity and stock returns. Moreover, the correlations among commodities in different sectors were found to be small (Greer, 2000; Gorton and Rouwenhorst, 2006; Erb and Harvey, 2006). These characteristics of commodity returns implied an opportunity of diversification and, hence, have attracted investors worldwide.

The environments, however, seem to be changing due to such "financialization" of commodities. Institutional investors and hedge funds have started allocating funds in commodities intensively through trading commodity indices such as the Standard & Poor's Goldman Sachs Commodity Index (GSCI) and Dow-Jones UBS Commodity Index (DJUBS), and commodity derivatives. Thus, commodity markets have become more integrated in traditional markets. Indeed, return correlations between commodities and other assets such as stocks and bonds have been found to be increasing recently, and so have been return correlations between crude oil (Tang and Xiong, 2010; Silvennoinen and Thorp, 2010). As a result, from the viewpoint of investors, time-varying correlations in commodity markets are becoming an important issue.

In this paper, we thus address the questions of whether and how correlations among commodity returns have been increasing recently. For this purpose, we re-examine the excess comovement in commodity returns investigated by Pindyck and Rotemberg (1990) and extended by Deb, Trivedi, and Varangis (1996). To clarify, the excess comovement among commodity returns is the correlation among commodity returns that is not accounted for by the common shocks of exogenous macroeconomic variables. It is hence interpreted as comovement unrelated to market fundamentals.

Pindyck and Rotemberg (1990) are the first to conduct the formal test of excess comovement among commodity returns. For the monthly data from 1960 to 1985, they find that the correlations among commodity returns are significant after accounting for macroeconomic shocks. Deb, Trivedi, and Varangis (1996) extend the model of excess comovement by introducing the conditional heteroskedasticity and time-varying conditional correlation with multi-variate GARCH processes. The time-varying conditional correlation model allows them to decompose the excess comovement into the long-run steady-state (with no trend) and short-run time-varying parts. Using the monthly data from 1960 to 1985 and from 1974 to 1992, they find weaker evidence for excess comovement when the multivariate GARCH is applied to the later sample.

To analyze the effect of rapid growth in commodity investments, in this paper, we further generalize the aforementioned model. Based on the smooth-transition correlation (STC) model by Berben and Jansen (2005) and Kumar and Okimoto (2011), we develop the smooth-transition dynamic conditional correlation (STDCC) model . In the STDCC model with time as a transition variable, the ST part describes the long-run trends, while the DCC part captures the short-run behavior. Thus, combining these two enables us to investigate both long-run trends and short-run dynamics of excess comovement of commodity returns. Indeed, by using the monthly data from 1983 to 2011, the STDCC model finds significant long-run increasing trends in commodity excess comovement and little short-run dynamics. In this sense, unlike the time-varying conditional correlation model by Deb, Trivedi, and Varangis (1996), this paper shows significant increasing trends in excess comovement of commodity returns and its importance relative to short-run conditional correlation dynamics.

The resulting increasing trends in excess comovement in commodity returns may look similar to those in Tang and Xiong (2010) and Silvennoinen and Thorp (2010). However, there are several differences. First, this paper is the direct generalization of the excess comovement model originated by Pindyck and Rotemberg (1990) and captures the correlation in commodity returns that cannot be accounted for by common shocks of exogenous macroeconomic variables, while Tang and Xiong (2010) and Silvennoinen and Thorp (2010) analyze the correlation of commodity returns that do not filter out the common factors. Second, this paper examines the excess comovement among several different commodity sectors, not just their return correlations with crude oil, while Tang and Xiong (2010) and Silvennoinen and Thorp (2010) focus on the commodity return correlations with crude oil and other assets including stocks and bonds. Third, to investigate the long-run trends of excess comovement, this paper develops the STDCC model, which is similar to Silvennoinen and Thorp (2010)'s double smooth transition conditional correlation model, while Tang and Xiong (2010) utilize the linear regression approach.

This paper is organized as follows: Section 2 provides the model and explains the estimation method; Section 3 conducts the empirical analysis; Section 4 gives some discussions; and Section 5 serves as a conclusion.

# 2 Model and Estimation

## 2.1 Model

### 2.1.1 Benchmark Model

Our benchmark model is the one used by Pindyck and Rotemberg (1990) and given by the following equation:

$$\Delta p_{it} = \sum_{k=0}^{K} \alpha_{ik} \Delta x_{t-k} + \rho_i \Delta p_{i,t-1} + u_{it},\ i = 1, \ldots, M,\ t = 1, \ldots, T. \tag{1}$$

Here, $\Delta$ is the difference operator and $p_i$ is the logarithm of the price of the $i$th commodity; hence, the explained variable of regression (1) is a commodity return. In addition, $x$ is a common set of macroeconomic variables to filter out the linear influence of macro shocks. The macroeconomic variables are logarithms of the CPI, industrial production, exchange rate, stock price, money stock, and interest rate (not in logs). $\alpha_{ik}$ is a vector of coefficients of macroeconomic variables with lag $k$ for commodity $i$.

Pindyck and Rotemberg (1990) find a (weak) positive correlation in residuals $u$ of the equation (1) from several commodities and call it excess comovement of commodity prices.

### 2.1.2 DCC Model

Deb, Trivedi, and Varangis (1996) extend the bench mark model (1) by accommodating the conditional heteroskedasticity and time-varying conditional correlation based on the multi-variate GARCH model developed by Engle and Kroner (1995). Following a similar idea, we use the DCC model proposed by Engle (2002) as a time-varying conditional correlation model. To be more specific, let $\mathbf{u}_t = (u_{1t}, \ldots, u_{Mt})' = \mathbf{H}_t^{1/2}\mathbf{v}_t$, where $\mathbf{H}_t$ is the $M \times M$ conditional covariance matrix at time $t$ of the commodity returns and $\mathbf{v}_t$ is assumed to be independently identically normally distributed with mean $\mathbf{0}$ and covariance matrix $\mathbf{I}_M$, $M \times M$ identity matrix. In the DCC model, $\mathbf{H}_t$ is decomposed as $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$, where $\mathbf{D}_t = \mathrm{diag}(h_{11,t}, \ldots, h_{nn,t})^{1/2}$, $h_{ii,t}$ is the $(i, i)$ element of $H_t$ and the conditional variance at time $t$ of the $i$th commodity return following the GARCH(1,1) model as

$$h_{ii,t} = \omega_i + \beta_i h_{ii,t-1} + \alpha u_{i,t-1}^2, \tag{2}$$

and $\mathbf{R}_t$ is the time-varying conditional correlation model. Following Engle (2002), we model $\mathbf{R}_t$ as

$$\begin{cases} \mathbf{Q}_t = (1 - a - b)\bar{\mathbf{Q}} + b\mathbf{Q}_{t-1} + a\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}' \\ \mathbf{R}_t = \mathrm{diag}(q_{11,t}, \ldots, q_{MM,t})^{-1/2}\mathbf{Q}_t\mathrm{diag}(q_{11,t}, \ldots, q_{MM,t})^{-1/2} \end{cases}, \tag{3}$$

where $\boldsymbol{\varepsilon}_t = \mathbf{D}_t^{-1}\mathbf{u}_t$ is a standardized disturbance vector and $q_{ii,t}$ is the $(i,i)$ element of $\mathbf{Q}_t$. We can test the excess comovement between commodity $i$ and $j$ by testing $\bar{q}_{ij} = 0$, where $\bar{q}_{ij}$ is the $(i,j)$ element of $\bar{\mathbf{Q}}$, since $\bar{\mathbf{Q}}$ is the unconditional correlation matrix of the standardized disturbance $\boldsymbol{\varepsilon}_t$.

### 2.1.3 STC Model

One restriction of the DCC model is that the unconditional correlation, or the stationary level of correlation, is constant, although the conditional correlation is time-varying. The recent development of commodity index investment, however, might affect the stationary level of correlation as the index investment grows. To examine this possibility, we consider the smooth-transition correlation (STC) model as the third model. The smooth transition model is developed by Teräsvirta (1994) in the AR model framework, and later used to model correlation dynamics by, among others, Berben and Jansen (2005) and Kumar and Okimoto (2011). In the STC model, the time-varying correlation $\mathbf{R}_t$ is modeled as

$$\mathbf{R}_t = (1 - G(s_t; \gamma, c))\mathbf{R}^{(1)} + G(s_t; \gamma, c)\mathbf{R}^{(2)}, \tag{4}$$

where $G$ is a logistic transition function given by

$$G(s_t; c, \gamma) = \frac{1}{1 + \exp(-\gamma(s_t - c))}, \quad \gamma > 0. \tag{5}$$

Here, $s_t$ is a transition variable governing the transition, $c$ is a location parameter deciding the center of transition, and $\gamma$ is a smoothness parameter specifying the speed of transition. We use a time trend as a transition variable, namely $s_t = t/T$, to capture a long-run trends in unconditional correlation following Lin and Teräsvirta (1994). In addition, we assume $0.01 \leq c \leq 0.99$ so that we can detect the correlation transition within the sample period. In this framework, the time-varying correlation $\mathbf{R}_t$ changes smoothly from $\mathbf{R}^{(1)}$ to $\mathbf{R}^{(2)}$ with time. Thus, we can interpret $\mathbf{R}^{(1)}$ as a stationary level of correlation around the beginning of the sample and $\mathbf{R}^{(2)}$ as a stationary level of correlation around the end of the sample.

One of the main attractions of the STC model is that it can describe a wide variety of patterns of change in correlation, depending on parameters $c$ and $\gamma$, which can be estimated from the data. Thus, by estimating the STC model, we can estimate the best pattern of long-run trends in correlation. Furthermore, we can test the excess comovement in regime $k$ between commodity $i$ and $j$ by testing $r_{ij}^{(k)} = 0$, where $r_{ij}^{(k)}$ is the $(i,j)$ element of $\mathbf{R}^{(k)}$. In addition, we can test the equality of excess comovement throughout the sample by testing $r_{ij}^{(1)} = r_{ij}^{(2)}$. This hypothesis test is particularly interesting when investigating the increase in excess comovement possibly caused by the development of index investment.

### 2.1.4 STDCC Model

Our final model is the smooth-transition dynamic conditional correlation (STDCC) model, which is a combination of the DCC and STC models and given by

$$\begin{cases} \bar{\mathbf{Q}}_t = (1 - G(s_t;\gamma,c))\bar{\mathbf{Q}}^{(1)} + G(s_t;\gamma,c)\bar{\mathbf{Q}}^{(2)} \\ \mathbf{Q}_t = (1-a-b)\bar{\mathbf{Q}}_t + b\mathbf{Q}_{t-1} + a\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}'_{t-1} \\ \mathbf{R}_t = \mathrm{diag}(q_{11,t},\ldots,q_{MM,t})^{-1/2}\mathbf{Q}_t\mathrm{diag}(q_{11,t},\ldots,q_{MM,t})^{-1/2} \end{cases}, \tag{6}$$

where $G$ is a logistic transition function (5). As we explained above, the DCC model is useful to describe the short-run behavior of conditional correlation, while the STC model can capture the long-run trends on an average level of correlation. Therefore, the STDCC model is expected to shed light on both short- and long-run dynamics of excess comovement of commodity prices. In the STDCC model, we can test the excess comovement in regime $k$ between commodity $i$ and $j$ by testing $\bar{q}_{ij}^{(k)} = 0$, where $\bar{q}_{ij}^{(k)}$ is the $(i,j)$ element of $\bar{\mathbf{Q}}^{(k)}$, like in the STC model, but with taking the time-varying conditional correlation into consideration. Similarly, we can test the equality of excess comovement throughout the sample by testing $\bar{q}_{ij}^{(1)} = \bar{q}_{ij}^{(2)}$ under the dynamic conditional correlation.

## 2.2 Estimation

We estimate all models based on the maximum likelihood estimation (MLE), which is a standard method to estimate the benchmark regression model, the DCC model, and STC model. It is also straight forward to estimate the STDCC model via the MLE. One concern associated with the MLE, however, is that there may be too many parameters to be estimated. To mitigate the problem, we adopt the two-step approach proposed by Engle (2002) to maximize the likelihood function.

Let $\boldsymbol{\theta}$ be a vector of parameters to be estimated. Assuming $\mathbf{v}_t$ follows multivariate standard normal distribution independently, we can write the log likelihood function, $\mathcal{L}(\boldsymbol{\theta})$, of our model as

$$\mathcal{L}(\boldsymbol{\theta}) = -\frac{1}{2}\sum_{t=1}^{T}\left(M\log(2\pi) + \log|\mathbf{H}_t| + \mathbf{u}'_t\mathbf{H}_t^{-1}\mathbf{u}_t\right) \tag{7}$$

Noting that $\mathbf{H}_t = \mathbf{D}_t\mathbf{R}_t\mathbf{D}_t$ and $\boldsymbol{\varepsilon}_t = \mathbf{D}_t^{-1}\mathbf{u}_t$, we can rewrite (7) as

$$\begin{aligned} \mathcal{L}(\boldsymbol{\theta}) &= -\frac{1}{2}\sum_{t=1}^{T}\left(M\log(2\pi) + \log|\mathbf{D}_t\mathbf{R}_t\mathbf{D}_t| + \mathbf{u}'_t\mathbf{D}_t^{-1}\mathbf{R}_t^{-1}\mathbf{D}_t^{-1}\mathbf{u}_t\right) \\ &= -\frac{1}{2}\sum_{t=1}^{T}\Big(M\log(2\pi) + 2\log|\mathbf{D}_t| + \mathbf{D}_t^{-1}\mathbf{u}'_t\mathbf{u}_t\mathbf{D}_t^{-1} + \log|\mathbf{R}_t| + \boldsymbol{\varepsilon}'_t\mathbf{R}_t^{-1}\boldsymbol{\varepsilon}_t - \boldsymbol{\varepsilon}'_t\boldsymbol{\varepsilon}_t\Big) \\ &= \mathcal{L}_m(\boldsymbol{\theta}_m) + \mathcal{L}_c(\boldsymbol{\theta}_m,\boldsymbol{\theta}_c), \end{aligned}$$

where $\boldsymbol{\theta}_m$ and $\boldsymbol{\theta}_c$ are the parameters of marginal distribution and correlation, respectively, and

$$\begin{aligned}\mathcal{L}_m(\boldsymbol{\theta}_m) &= -\frac{1}{2}\sum_{t=1}^{T}\left(M\log(2\pi)+2\log|\mathbf{D}_t|+\mathbf{D}_t^{-1}\mathbf{u}_t'\mathbf{u}_t\mathbf{D}_t^{-1}\right)\\ \mathcal{L}_c(\boldsymbol{\theta}_m,\boldsymbol{\theta}_c) &= -\frac{1}{2}\sum_{t=1}^{T}\left(\log|\mathbf{R}_t|+\boldsymbol{\varepsilon}_t'\mathbf{R}_t^{-1}\boldsymbol{\varepsilon}_t-\boldsymbol{\varepsilon}_t'\boldsymbol{\varepsilon}_t\right)\end{aligned}$$

Thus, the log likelihood function can be decomposed into two parts. The first part is related only with the parameters of marginal distribution and can be maximized by separately maximizing marginal likelihood for each commodity return. The second part of the likelihood is associated with the correlation dynamics, which can be used to estimate correlation parameters.

The two-step approach to estimate all parameters is to find

$$\hat{\boldsymbol{\theta}}_m = \arg\max \mathcal{L}_m(\boldsymbol{\theta}_m)$$

and then take this value as given in the second stage to get

$$\hat{\boldsymbol{\theta}}_c = \arg\max \mathcal{L}_c(\hat{\boldsymbol{\theta}}_m, \boldsymbol{\theta}_c).$$

This two step estimation is consistent and asymptotically normal under reasonable regularity conditions. Although the formula to calculate the covariance matrix of the correlation parameters is given in Engle (2002), it might be too complicated to calculate it accurately, when the number of parameters is large, which is so in this paper. For this reason, we ignore the effect of the first-step estimation and use the usual MLE formula to evaluate it, which should not be a serious problem if the sample size is large.

# 3 Empirical Analysis

Our empirical analysis is based on the monthly data with the sample period lasting from 1983:1 to 2011:7. For commodity prices, we obtain the indices of primary commodity prices published by the International Monetary Fund (IMF). Specifically, we use agricultural raw material (AGR), beverage (BEV), and metal (MET) indices.[1] We exclude food and energy indices from our analysis, since they are only available from 1991 and 1992, respectively. Instead, we adopt the average oil prices (OIL), which is the average of U.K. Brent, Dubai, and West Texas Intermediate. In addition, we obtain the same macroeconomic variables as those used by Pindyck and Rotemberg (1990) from the Federal Reserve Economic Data (FRED) to filter out the linear influence of macroeconomic

[1] The agricultural raw material index consists of timber, cotton, wool, rubber, and hides. The beverage index includes coffee, cocoa beans, and tea, while the metal index consists of copper, aluminum, iron ore, tin, nickel, zinc, lead, and uranium.

shocks. These data include the seasonally adjusted consumer price index (CPI, $\Pi$), the seasonally adjusted industrial production ($Y$), 3-month treasury bill rate ($R$), the trade weighted exchange rate index ($E$), the seasonally adjusted money supply (M1, $M$), and the S&P 500 stock price index ($S$).

## 3.1 Empirical results

### 3.1.1 Results for the benchmark model

We first estimate the benchmark model (1) with $K = 1$, as Pindyck and Rotemberg (1990). The estimation results are given in Table 1. As can be seen, CPI, industrial production, and exchange rate are significant at least at the 10% level for AGR, while the interest rate and exchange rate have some explanatory power on BEV. More macroeconomic variables are important for two other commodities. Specifically, all variables but money supply are significant for MET, whereas all variables but stock price are significant for OIL. In addition, the lagged dependent variable ($AR1$) is significant for all commodities. Overall, the explanatory power of macroeconomic variables and lagged dependent variable are relatively high with $R^2$ ranging from 0.142 (BEV) to 0.331 (OIL). Thus, some of comovement of commodity prices can be explained by common macroeconomic shock.

To examine the excess comovement, we estimate the correlations among residuals from the bench mark model (1). Table 2 reports the estimated correlations and their standard errors. As can be seen, four out of six commodity pairs have significant positive correlation at the 5% significance level, suggesting the existence of excess comovement of commodity prices. Although our significant correlations ranging from 0.116 to 0.199 are slightly lower than those of Pindyck and Rotemberg (1990), which range from 0.118 to 0.281, our result of excess comovement is fairly consistent with theirs.

### 3.1.2 Results for the DCC model

Deb, Trivedi, and Varangis (1996) point out that the finding of excess comovement of commodity prices by Pindyck and Rotemberg (1990) is sensitive to neglected conditional heteroskedasticity and time-varying conditional correlation in the commodity returns. To examine the possibility, we estimate the DCC model (3) using the standardized residual $\hat{\boldsymbol{\varepsilon}}_t = \hat{\mathbf{D}}_t^{-1}\hat{\mathbf{u}}_t$ from the benchmark model (1) with a univariate GARCH model (2).

The estimated DCC parameters are $\hat{a} = 0.004$ with a standard error of 0.013 and $\hat{b} = 0.844$ with a standard error of 0.319. Thus, although $a$ is not significant, $b$ is statistically significant, implying the importance of capturing the short-run fluctuation and serial correlation in conditional correlation. The estimated unconditional correlation of standardized disturbances is shown in Table 3. The result indicates that three out of six commodity pairs show significant positive correlation, suggesting that evidence of excess comovement still exists but becomes weaker once we control the conditional heteroskedasticity and time-varying conditional correlation. The result is also arguably consistent with that of Deb, Trivedi, and Varangis (1996).

### 3.1.3 Results for the STC model

One restriction of the DCC model is that the unconditional correlation, or the stationary level of correlation, is constant, although the conditional correlation is time-varying. However, the recent development of commodity index investment might affect the stationary level of correlation gradually as the index investment grows. To investigate this possibility, we estimate the STC model (4) using the standardized residual $\hat{\boldsymbol{\varepsilon}}_t$ from the benchmark model (1) with a univariate GARCH model (2).

Table 4 documents the estimated unconditional correlation of the standardized disturbance of each regime. As can be seen, there is only weak evidence of excess comovement in regime 1 with a significant positive correlation for two out of six pairs. In addition, even for these two pairs, the magnitude of excess comovement is small with a correlation of 0.126 and 0.098. On the contrary, all pairs show significant excess comovement in regime 2 with a much larger correlation. Indeed, all correlations are estimated at more than 0.4, suggesting that the excess comovement becomes much larger in more recent periods. To examine an increase in excess comovement more formally, we test the null hypothesis of the equivalence of correlation across regime. The Wald statistic and its $p$-value are reported in the last two rows in Table 4. Thu result indicate that the null hypothesis is rejected for all pairs at least at the 10% significance level, meaning there has been an increase in excess comovement in recent years. Note also that the results suggest the importance of considering a possible regime change in unconditional correlation, which the DCC model cannot capture.

Since our analysis demonstrates the significant increase in excess comovement, it is instructive to see when and how the increase has occurred. To this end, we plot the estimated time series of correlation from the STC model in Figure 1. As can be seen, until 2000 the correlation of each pair has been almost constant and remained at low levels with an average correlation of 0.084 at the end of 1999. However, it has increased gradually since 2000 and reached more than 0.25 for all pairs with an average correlation of about 0.4 in July 2011.

In summary, our results indicate the importance of accommodating a regime change in unconditional correlation or stationary level of correlation. More importantly, we find only weak evidence of excess comovement of commodity prices in the early regime, but clear evidence in the more recent regime with a significant increase in the excess comovement. In particular, the excess comovement has increased gradually since 2000 and become important in the recent years with an average correlation about 0.4.

### 3.1.4 Results for the STDCC model

Since the STC model with time as a transition variables is suitable to capture the long-run trends in unconditional correlation, one might wonder whether our finding of increasing excess comovement is an artifact by neglecting the short-run fluctuation of conditional correlation. Therefore, it is instructive to accommodate the short-run behavior of conditional correlation into the STC model. To this end, we estimate the STDCC model (6) to take both long- and short-run dynamics of correlation into consideration.

The estimation results indicate that the DCC parameters turn out to be insignificant with the estimates of $\hat{a} = 0.017$ and $\hat{b} = 0.000$. This is in great contrast to the results of DCC, suggesting the relative importance to capture the possible regime change in unconditional correlation. The estimation results for unconditional correlation of each regime are reported in Table 5. As can be seen, the results are very similar to those of the STC model. In particular, the results show no significant excess comovement for all commodity pairs in regime 1, but in regime 2, there is significant excess comovement with significant increases. The dynamics of correlation in Figure 2 are also similar to those in Figure 1, with relatively small short-run fluctuation in conditional correlation. These results are not surprising, given that the DCC parameters are insignificant.

In sum, our results are clear. It is more important to capture the possible regime change in unconditional correlation than to accommodate the short-run fluctuations in conditional correlation. Thus, the STC model seems to be enough to characterize the increasing excess comovement in commodity prices.

# 4 Discussion

## 4.1 Effect of the Financial Crisis

Our favored STC model with a time trend as a transition variable allows only the monotonic transition from the initial correlation level $\mathbf{R}^{(1)}$ to the terminal correlation level $\mathbf{R}^{(2)}$. Meanwhile, the correlations among commodity returns might become lower from their peak in the middle of the financial crisis. If this is the case, the STC model could exaggerate the increase in excess comovement. To examine this possibility, we consider the three-state STC model. In this model, the time-varying correlation $\mathbf{R}_t$ is modeled as

$$\mathbf{R}_t = \mathbf{R}^{(1)} + G_1(s_t;\gamma_1,c_1)(\mathbf{R}^{(2)} - \mathbf{R}^{(1)}) + G_2(s_t;\gamma_2,c_2)(\mathbf{R}^{(3)} - \mathbf{R}^{(2)}),$$

where $G_1$ and $G_2$ are a logistic transition function with different location and smoothness parameters. We assume $0.01 \leq c_1 < c_2 \leq 0.99$ so that we can detect the correlation transition within the sample period. Under this assumption, time-varying correlation $\mathbf{R}_t$ changes smoothly from $\mathbf{R}^{(1)}$ via $\mathbf{R}^{(2)}$ to $\mathbf{R}^{(3)}$ with time, as first function $G_1$ changes from 0 to 1, followed by a similar change in $G_2$. As a consequence, we can capture non-monotonic trends of excess comovement of commodity prices.

Figure 3 plots the estimated correlation dynamics from the three-state STC model. As can be seen from the figure, the correlation dynamics is quite similar to that of the two-state STC model. Four pairs out of six show the monotonic increase in correlation with almost the same dynamics as that of the two-state model. Although the other two pairs have some decrease in correlation in some regimes, the magnitude of decrease is smaller compared with the increase in other regime. In addition, the log-likelihood of the three-state model ($-1906.21$) indicates a marginal increase from that of the two-state model ($-1909.49$). Indeed, usual information criteria such as Akaike information criteria (AIC) support the two-state model over the three-state model, meaning that the two-state one is enough to describe the dynamics of excess comovement of commodity prices over the last two decades.

In sum, the results of the three-state model demonstrate that our finding of increasing trends in excess comovement of commodity prices is not an artifact produced by the recent financial crisis, but intrinsic nature of the excess comovement.

## 4.2 Effect of Common Macroeconomic Variables

In our STC model, we assume that there are some trends in excess comovement, but the effects of common macroeconomic variables are constant throughout the sample. However, in reality, there may be changes in sensitivities of commodity returns to macroeconomic variables in the long run. Therefore, one might consider that our findings of increasing excess comovement of commodity prices are due to ignorance of the changes in the effects of common macroeconomic factors. Thus, to explore this possibility, we consider the following smooth transition regression (STR) model:

$$\begin{aligned}\Delta p_{it} &= (1 - G(s_t;\gamma,c))(\alpha_i^{(1)}\Delta x_t + \rho_{i1}^{(1)}\Delta p_{i,t-1} + \sigma^{(1)}\varepsilon_{it}) \\ &\quad + G(s_t;\gamma,c)(\alpha_i^{(2)}\Delta x_t + \rho_i^{(2)}\Delta p_{i,t-1} + \sigma^{(2)}\varepsilon_{it}), \qquad i = 1,\ldots,M,\ t = 1,\ldots,T.\end{aligned} \tag{8}$$

where $\varepsilon_{it}$ is a standardized disturbance of commodity $i$. Thus, in the STR model, the coefficients of macroeconomic variables can change, following a smooth transition model. We use logistic transition function (5) and time trend as a transition variable, as before. In addition, we allow the volatility to change, following the same smooth transitions to capture possible regime changes in volatility. We estimate the STR model (8) via MLE assuming $\varepsilon_{it} \sim$ iid $N(0,1)$ to get the standardized residuals $\hat{\varepsilon}_t$.[2] Then, we estimate the STC model (4) using the standardized residual from the STR model.

The estimation results of correlation of each regime for the standardized disturbance from the STR model are documented in Table 6. As can be seen, the results are qualitatively similar with those of the STC model. In particular, the results show no significant excess comovement for all commodity pairs in regime 1, but in regime 2, there is significant excess comovement in with significant increases. Although the correlation dynamics plotted in Figure 4 become more linear compared with those in Figure 1, increasing trends are still quiet similar. Thus, the results clearly indicate that our finding of increasing trends in excess comovement in commodity prices are not due to ignorance of changes in the effects of common macroeconomic variables.

## 4.3 Off-index commodities

Our finding of increasing trends in excess comovement of commodity prices is generally consistent with the increase in correlation between non-energy commodities and oil demonstrated by Tang and Xiong (2010). They also show that the increase in correlation is much larger for indexed commodities, which are the component of either the GSCI and DJUBS, compared with off-index commodities, which are not components of GSCI or DJUBS. Thus, their results strongly suggest that the financialization of commodities through index investment contributes to the increase in correlation.

The IMF commodity price indexes used for our analysis contain several off-index commodities as a component.[3] It is, therefore, very instructive to examine the dynamics of excess comovement for these off-index commodities. To this end, we estimate the two-state STC model using the price data of hides (HID), softwood (SOF), tea (TEA), and tin (TIN).[4]

Table 7 reports the estimated unconditional correlation of standard residuals of each regime for off-index commodities. As can be seen, there is only weak evidence of excess comovement in

[2]To save space, the estimation results of the STR model are not reported, but are available from the authors upon request.

[3]These include hides, timber (hardwood and softwood), wool (fine and coarse), rubber for the agricultural raw material index; tea for the beverage index; and iron ore, tin, and uranium for the metal index.

[4]Among off-index commodities, monthly data for iron ore are available only as of recently. In addition, uranium prices did not change often for the first several years of the sample. Therefore, we exclude iron ore and uranium from our analysis. We include tea and tin into our analysis, since they are the only components that can be used from the beverage and metal categories. We also choose hides and softwood, since they have greater weight than wool and rubber. Our result here is qualitatively similar even if we use wool and rubber instead of hides or softwood.

regime 1 with a significant positive correlation only for the SOF-TIN pair. More importantly, the excess comovement of off-index commodity prices remains low in regime 2 with a significant positive correlation only for the HID-TIN pair. In addition, the test of equality of correlation across regimes indicates that there is no evidence of increase in excess comovement for five pairs out of six. Furthermore, although the HID-TIN pair has significant increase in excess comovement, its correlation is still below 0.15. Additionally, we can see the mostly stable low excess comovement of off-index commodities from the estimated time series of correlation plotted in Figure 5.

These results for off-index commodities provide a striking contrast to those for the original price index, suggesting that the indexed commodities are the main source of increases in the excess comovement of commodity prices. Thus, our finding of increasing excess comovement can be considered as additional evidence for the financialization of commodities.

# 5 Conclusion

We investigate whether and how correlations among commodity returns have increased recently. For this purpose, we generalized the model of excess comovement originated by Pindyck and Rotemberg (1990) and extended by Deb, Trivedi, and Varangis (1996) to the STDCC model. The STDCC model, unlike that used in the previous studies, can capture the long-run trends of excess comovements, in addition to its short-run dynamics. Using the commodity-return data from 1983 to 2011, we found that in all pairs of agricultural raw materials, beverage, metal, and oil, there are clear increasing long-run trends in excess comovement, while there is little short-run fluctuation in excess comovement.

The long-run increasing trends in excess comovement are generally consistent with those of Tang and Xiong (2010) and Silvennoinen and Thorp (2010), although they analyze commodity-return correlations, not excess comovement, which do not account for the effects of common macroeconomic factors. Moreover, Tang and Xiong (2010) and Silvennoinen and Thorp (2010) focus their analyses on the commodity return correlations with crude oil and other assets including stocks and bonds. Our findings show that the increasing trends of excess comovement are common and found in all pairs of commodities, not only those with crude oil, while the excess comovement with crude oil tends to be greater in recent periods.

It is also worth noting that in our analysis, the increasing long-run trends appear around 2000 and accelerate afterwards. This result is again consistent with those in Tang and Xiong (2010) and Silvennoinen and Thorp (2010) that attribute this phenomena to the financialization of commodities. Since the excess comovement is the return correlation that is not accounted for by common macroeconomic shocks and, hence, is interpreted as comovement unrelated to market fundamentals, the results in this paper may be taken as additional evidence for such interpretation.

## References


[1] Berben, R.-P., and Jansen, W.J. (2005). “Comovement in international equity markets: A sectoral view,” *Journal of International Money and Finance* 24, 832-857.

[2] Deb, P., Trivedi, P.K. and Varangis, P. (1996). “The excess comovement of commodity prices reconsidered.” *Journal of Applied Econometrics* 11(3), 275-291.

[3] Engle, R. F. (2002). “Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models,” *Journal of Business and Economic Statistics* 20(3), 339-350.

[4] Engle, R. F., and Kroner, K.F. (1995). “Multivariate simultaneous generalized ARCH,” *Econometric Theory* 11, 122-150.

[5] Erb, C.B., and Harvey, C.R. (2006). ”The strategic and tactical value of commodity futures.” Financial Analysts Journal 62, 69-97.

[6] Gorton, G.B., and Rouwenhorst, G.K. (2006). ”Facts and fantasies about commodity futures.” Financial Analysts Journal 62, 47-68.

[7] Greer, R. (2000). ”The nature of commodity index returns.” Journal of Alternative Investments, 45-53.

[8] Kumar, M.S., and Okimoto, T. (2011). “Dynamics of international integration of government securities’ markets.” *Journal of Banking and Finance* 35, 142-154.

[9] Lin, C.-F.J., and Teräsvirta, T. (1994). “Testing the constancy of regression parameters against continuous structural change.” *Journal of Econometrics* 62, 211-228.

[10] Pindyck, R.S. and Rotemberg, J.J. (1990). “The excess co-movement of commodity prices.” *Economic Journal* 100, 1173-1187.

[11] Silvennoinen, A. and Thorp, S. (2010). ”Financialization, Crisis and Commodity Correlation Dynamics.” Research Paper 267, Quantitative Finance Research Center, University of Technology Sydney.

[12] Tang, K. and Xiong, W. (2010). "Index investing and the financialization of commodities." NBER Working Paper, No. 16385.

[13] Teräsvirta, T. (1994). "Specification, estimation, and evaluation of smooth transition autoregressive models," *Journal of the American Statistical Association* 89(425), 208-218.

Table 1: Estimation results of the benchmark model

| | Agriculature | | Beverage | | Metal | | Oil | |
|---|---|---|---|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error | Estimate | Std. Error | Estimate | Std. Error |
| π | 1.7580** | 0.7394 | 1.1726 | 1.1430 | 1.6743 | 1.0163 | 15.0280*** | 1.8339 |
| π (-1) | 0.6650 | 0.7564 | -0.6274 | 1.1761 | -1.8244* | 1.0393 | -8.0614*** | 1.7882 |
| Y | 0.5186* | 0.2790 | 0.5465 | 0.4313 | 0.9371** | 0.3820 | 0.8236 | 0.6564 |
| Y(-1) | 0.3431 | 0.2809 | 0.2598 | 0.4338 | 0.4803 | 0.3852 | 1.1411* | 0.6629 |
| R | 0.0118 | 0.0086 | 0.0251* | 0.0133 | 0.0249** | 0.0118 | 0.0448** | 0.0204 |
| R(-1) | 0.0025 | 0.0087 | -0.0003 | 0.0133 | 0.0062 | 0.0119 | -0.0087 | 0.0205 |
| E | -0.2144** | 0.1065 | -0.4199** | 0.1641 | -0.8472*** | 0.1466 | -0.6384** | 0.2515 |
| E(-1) | 0.0857 | 0.1064 | -0.0505 | 0.1644 | -0.0913 | 0.1460 | -0.3575 | 0.2514 |
| M | -0.2405 | 0.2264 | 0.2985 | 0.3525 | -0.1414 | 0.3104 | -1.1522** | 0.5343 |
| M(-1) | 0.1147 | 0.2225 | -0.3312 | 0.3460 | -0.2577 | 0.3055 | -0.3350 | 0.5258 |
| S | 0.0050 | 0.0380 | -0.0791 | 0.0585 | 0.0040 | 0.0523 | -0.1069 | 0.0899 |
| S(-1) | 0.0539 | 0.0383 | 0.0348 | 0.0590 | 0.1814*** | 0.0526 | -0.1449 | 0.0907 |
| AR1 | 0.1685*** | 0.0550 | 0.2898*** | 0.0533 | 0.1859*** | 0.0548 | 0.1836** | 0.0576 |
| $R^2$ | 0.1446 | | 0.1423 | | 0.2442 | | 0.3309 | |

Table 2: Estimation results of excess comovement for the benchmark model

| | AGR-BEV | AGR-MET | AGR-OIL | BEV-MET | BEV-OIL | MET-OIL |
|---|---|---|---|---|---|---|
| Estimate | 0.0493 | 0.1159** | 0.1933*** | 0.1316** | 0.0110 | 0.1992*** |
| Std. Error | 0.0542 | 0.0539 | 0.0533 | 0.0538 | 0.0543 | 0.0532 |

Table 3: Estimation results of excess comovement for the DCC model

| | AGR-BEV | AGR-MET | AGR-OIL | BEV-MET | BEV-OIL | MET-OIL |
|---|---|---|---|---|---|---|
| Estimate | 0.0663 | 0.0941 | 0.2134*** | 0.1343** | 0.0049 | 0.1600*** |
| Std. Error | 0.0631 | 0.0599 | 0.0544 | 0.0587 | 0.0608 | 0.0560 |

Table 4: Estimation results of excess comovement for the STC model

| | | AGR-BEV | AGR-MET | AGR-OIL | BEV-MET | BEV-OIL | MET-OIL |
|---|---|---|---|---|---|---|---|
| Regime 1 | Estimate | 0.0334 | 0.0204 | 0.1261*** | 0.0978** | -0.0427 | 0.0756 |
| | Std. Error | 0.0484 | 0.0511 | 0.0340 | 0.0494 | 0.0458 | 0.0546 |
| Regime 2 | Estimate | 0.4372*** | 0.7462*** | 0.9647*** | 0.4800** | 0.5176*** | 0.8931*** |
| | Std. Error | 0.1925 | 0.0789 | 0.1512 | 0.0833 | 0.0901 | 0.1242 |
| Test of equality | Wald stat | 3.4396 | 51.8552 | 27.3220 | 12.9783 | 19.4645 | 27.5511 |
| | P-value | 0.0637 | 0.0000 | 0.0000 | 0.0003 | 0.0000 | 0.0000 |

Table 5: Estimation results of excess comovement for the STDCC model

| | | AGR-BEV | AGR-MET | AGR-OIL | BEV-MET | BEV-OIL | MET-OIL |
|---|---|---|---|---|---|---|---|
| Regime 1 | Estimate | 0.0309 | 0.0286 | 0.1116 | 0.1004 | -0.0388 | 0.0741 |
| | Std. Error | 0.1217 | 0.0968 | 0.0813 | 0.0655 | 0.0967 | 0.1085 |
| Regime 2 | Estimate | 0.4157*** | 0.6722*** | 0.9732*** | 0.3992*** | 0.4415*** | 0.8245*** |
| | Std. Error | 0.1362 | 0.1864 | 0.3901 | 0.1502 | 0.1017 | 0.3488 |
| Test of equality | Wald stat | 2.9897 | 6.2469 | 4.2997 | 2.7483 | 7.9954 | 2.8039 |
| | P-value | 0.0838 | 0.0124 | 0.0381 | 0.0974 | 0.0047 | 0.0940 |

Table 6: Estimation results of excess comovement for the residuals from the STR model

| | | AGR-BEV | AGR-MET | AGR-OIL | BEV-MET | BEV-OIL | MET-OIL |
|---|---|---|---|---|---|---|---|
| Regime 1 | Estimate | -0.1023 | -0.0279 | -0.0144 | 0.0443 | -0.0882 | -0.0771 |
| | Std. Error | 0.0691 | 0.0723 | 0.0906 | 0.0751 | 0.0816 | 0.1103 |
| Regime 2 | Estimate | 0.4706*** | 0.6930*** | 0.8156*** | 0.3212*** | 0.4041*** | 0.9819*** |
| | Std. Error | 0.1190 | 0.1387 | 0.1966 | 0.1025 | 0.1162 | 0.2328 |
| Test of equality | Wald stat | 12.8188 | 16.2639 | 9.6229 | 3.1250 | 7.9782 | 11.3053 |
| | P-value | 0.0003 | 0.0001 | 0.0019 | 0.0771 | 0.0047 | 0.0008 |

Table 7: Estimation results of excess comovement for off-index commodities

| | | HID-SOF | HID-TEA | HID-TIN | SOF-TEA | SOF-TIN | TEA-TIN |
|---|---|---|---|---|---|---|---|
| Regime 1 | Estimate | 0.1112 | 0.1021 | -0.1401* | -0.0234 | 0.1509 | -0.0679 |
| | Std. Error | 0.0815 | 0.0771 | 0.0784 | 0.0852 | 0.0828 | 0.0806 |
| Regime 2 | Estimate | 0.0027 | 0.0380 | 0.1398* | -0.1052 | 0.0022 | -0.0331 |
| | Std. Error | 0.0727 | 0.0758 | 0.0722 | 0.0710 | 0.0704 | 0.0733 |
| Test of equality | Wald stat | 0.9842 | 0.3550 | 6.9105 | 0.5261 | 1.8681 | 0.1015 |
| | P-value | 0.3212 | 0.5513 | 0.0086 | 0.4682 | 0.1717 | 0.7500 |

Figure 1: Dynamics of excess comovement of commodity prices (STC model)

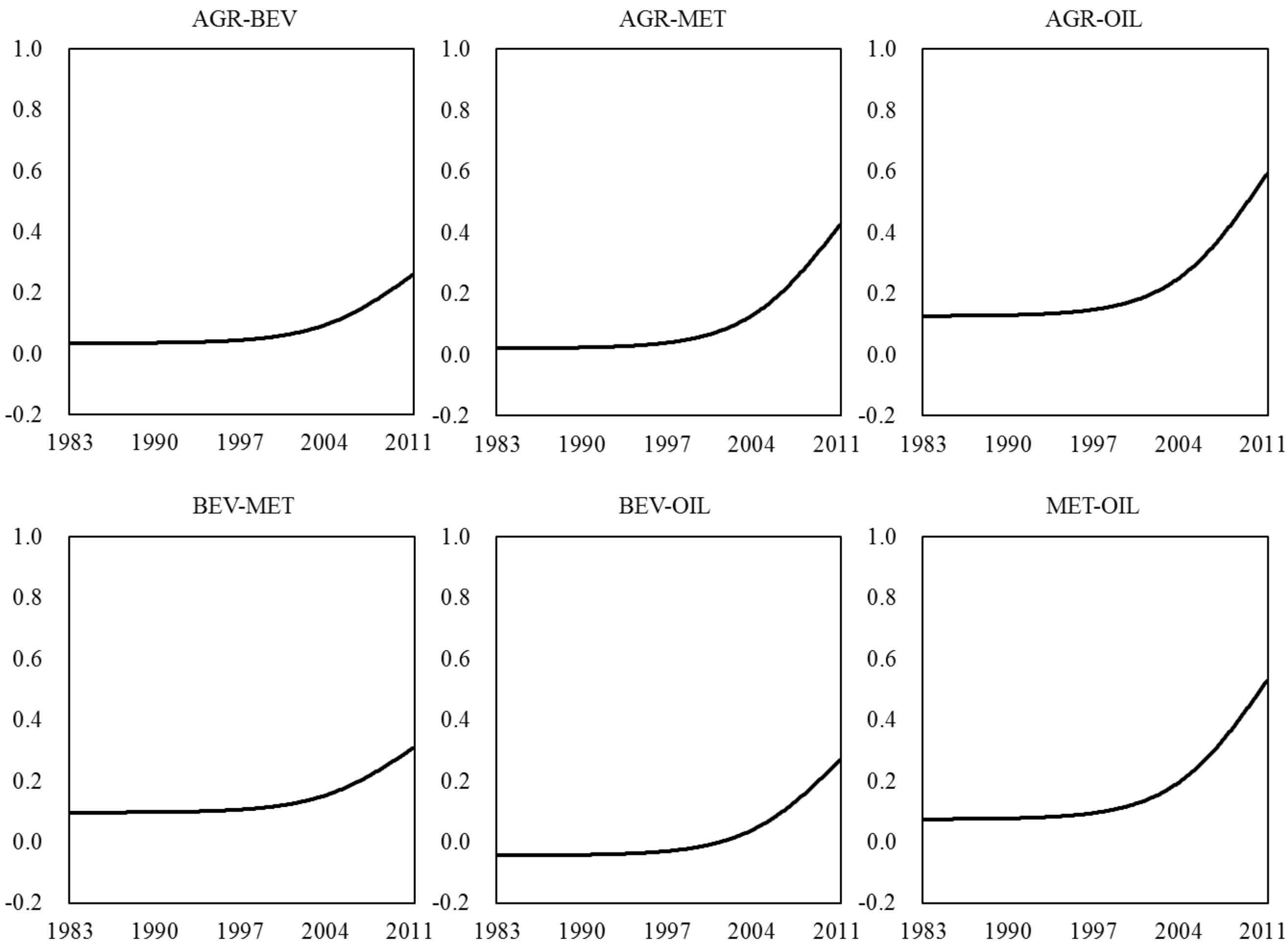

Figure 2: Dynamics of excess comovement of commodity prices (STDCC model)

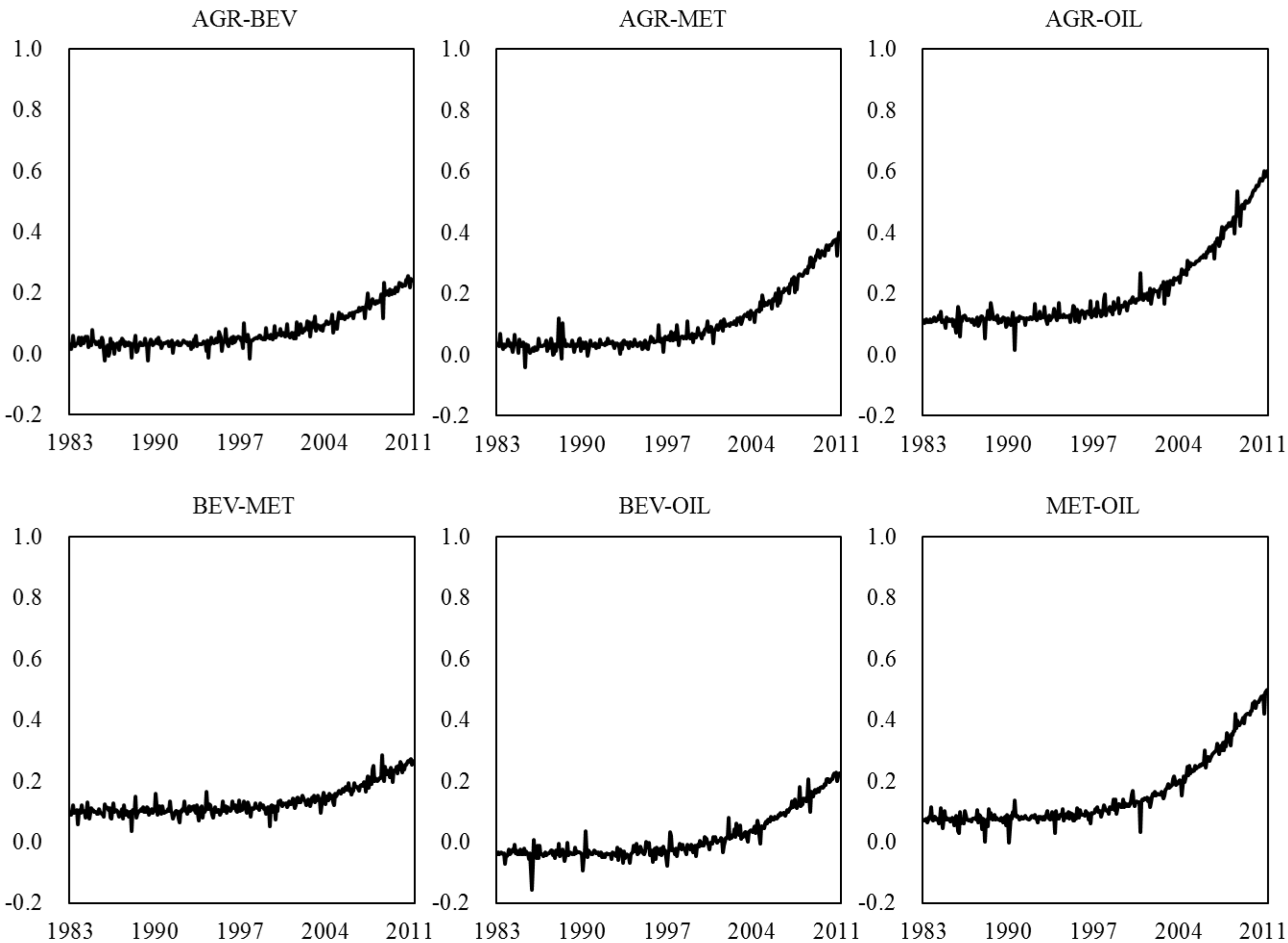

Figure 3: Dynamics of excess comovement of commodity prices (3state STC model)

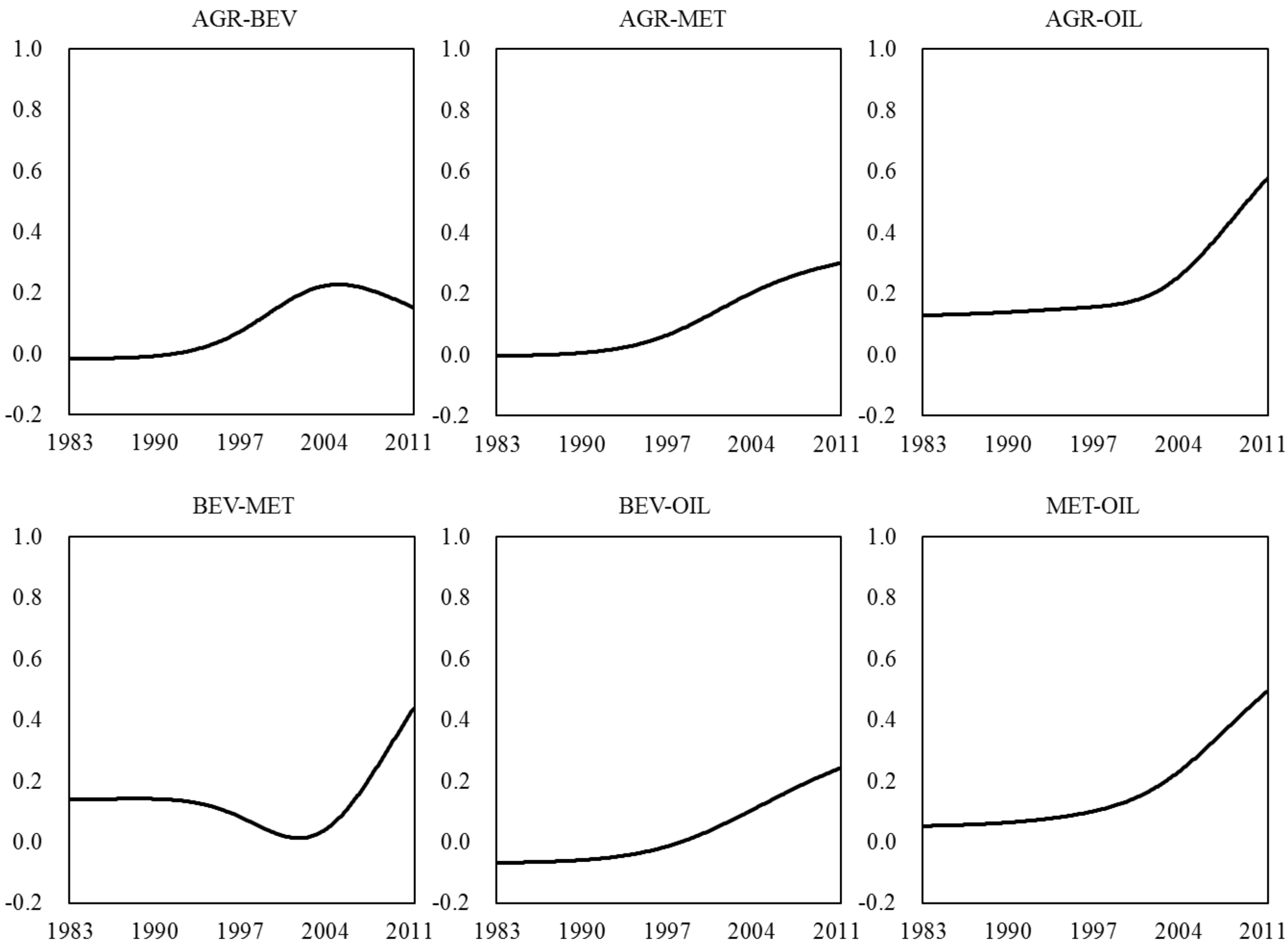

Figure 4: Dynamics of excess comovement of commodity prices (STR residuals)

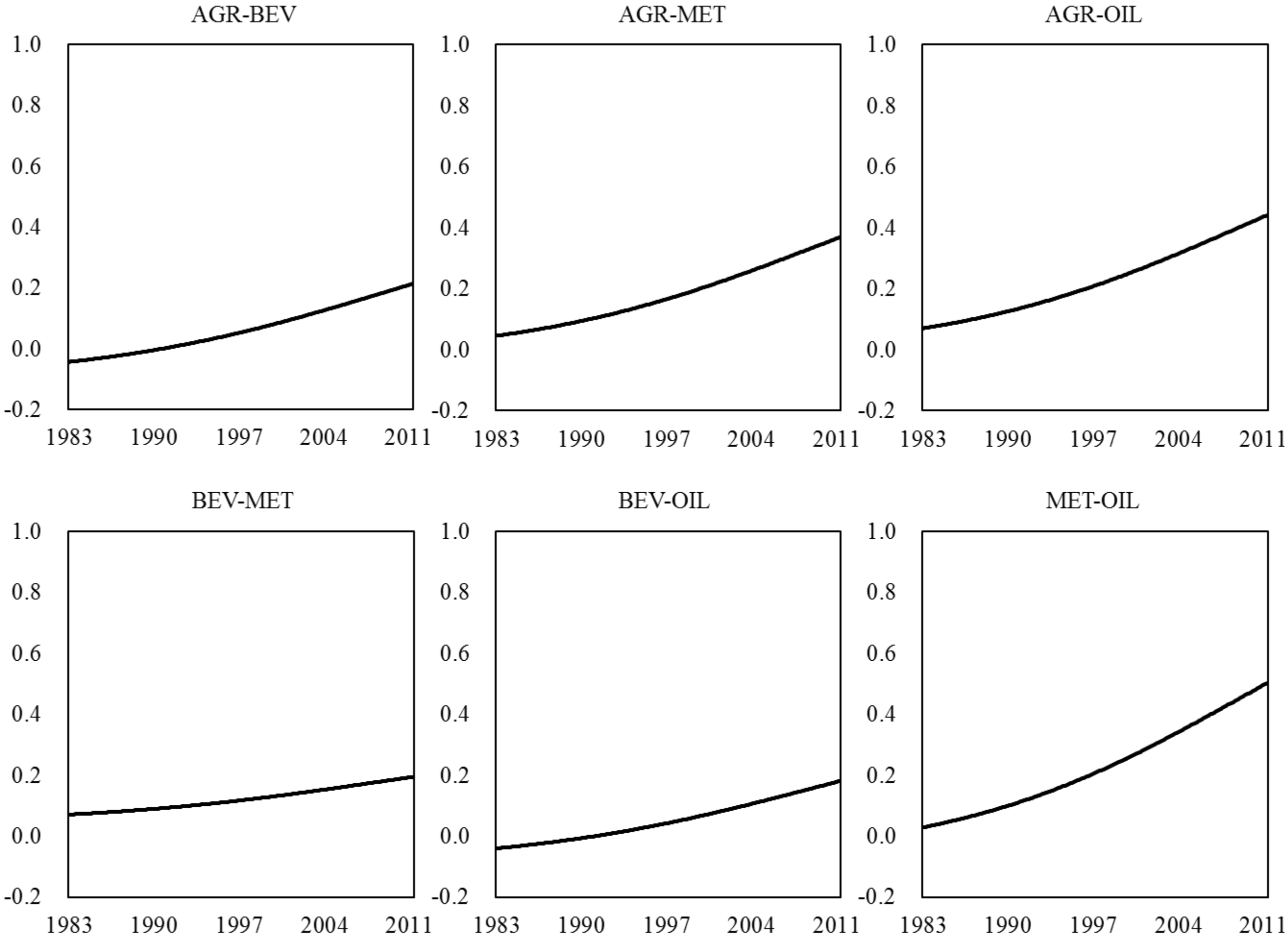

Figure 5: Dynamics of excess comovement of off-index commodity prices (STC model)