Increasing Trends in the Excess Comovement of Commodity Prices*

Kazuhiko Ohashi† Tatsuyoshi Okimoto‡

November 15, 2013

Abstract

In this paper, we develop the STDCC model that can capture long-run trends and short-run dynamics to investigate whether and how excess correlations among commodity returns have increased recently. Using commodity returns data from 1983 to 2011, we find significant increasing long-run trends in excess comovements have appeared since around 2000. We confirm that these increasing trends are not artifacts of the recent financial crisis or changes in the effects of common macroeconomic factors. Moreover, unlike the results above, we find no significant increasing trends in excess comovements among off-index commodity returns. Those findings provide additional evidence for the recent debates about the increasing commodity-return correlations.

JEL classification: C32, C51, G15
Key Words: excess comovement; time-varying correlation; smooth transition model; DCC model; index investment; financialization

---

*This study is conducted as a part of the Project "Exports and the Japanese Economy: Experiences in the 2000s and the lessons for the future" undertaken at Research Institute of Economy, Trade and Industry (RIETI). We are indebted to Jim Hamilton, and seminar participants at RIETI, Hitotsubashi University, University of Tokyo, Australian National University, Bank of Japan, Development Bank of Japan, International Conference on High-Frequency Data Analysis in Financial Markets, and Workshop on Financial Engineering and Financial Econometrics, and International Conference on Frontiers in Macroeconometrics. 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.

‡Corresponding author, 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. Many researchers, using data from before the 2000s, have found slightly negative return correlations between commodity and stock returns (Greer, 2000; Gorton and Rouwenhorst, 2006). Return correlations among commodities in different sectors have also been found to be small (Erb and Harvey, 2006). Moreover, several papers have reported decreasing or non-increasing trends of return correlations between commodities and stocks at least before the recent financial crisis (Chong and Miffre, 2010; Büyükşahin, Haigh, and Robe, 2010).

These characteristics of commodity returns implied an opportunity for diversification and, thus, have attracted investors worldwide. Institutional investors and hedge funds have started allocating funds in commodities intensively through trading commodity indices such as Standard & Poor's Goldman Sachs Commodity Index (GSCI) and the Dow-Jones UBS Commodity Index (DJUBS). Such commodities index investment, however, has been changing the environments. In particular, commodities markets seem to have become more integrated in traditional markets. For instance, Silvennoinen and Thorp (2013) show that return correlations between commodities and other assets such as stocks and bonds have increased well before the 2008 financial crisis, while Tang and Xiong (2012) find a significant increasing trend in the return correlations between crude oil and other commodities since 2004. As a result, time-varying correlations in commodity markets are becoming an important issue.

In this paper, we thus investigate whether and how correlations among commodity returns have been increasing recently. We address these questions, however, from a slightly different viewpoint from the papers above. We focus on excess comovement in commodity returns, developed by Pindyck and Rotemberg (1990) and extended by Deb, Trivedi, and Varangis (1996). The excess comovement of commodities is the correlation among commodity returns not accounted for by the common shocks of exogenous macroeconomic variables. It is thus interpreted as comovement unrelated to market fundamentals, and we investigate how such excess comovement have changed.

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

In this paper, we develop the smooth-transition dynamic conditional correlation (STDCC) model based on the smooth-transition correlation (STC) model by Berben and Jansen (2005) and Kumar and Okimoto (2011) to generalize the aforementioned model of excess comovement further. In the STDCC model with time as a transition variable, the STC part describes the long-run trends, while the DCC part captures the short-run behavior. Thus, combining these two components enables us to investigate long-run trends and short-run dynamics of excess comovement of commodity returns simultaneously. Moreover, the STC part allows us to detect solely from the data when and how structural change, if any, in correlation occurs.

The main contribution of this paper is that using this STDCC model for monthly data from 1983 to 2011, we find several new empirical facts regarding the behavior of excess comovement among commodity returns. First, the STDCC model detects significant long-run increasing trends in commodity excess comovement and small short-run dynamics. Thus, in contrast with the time-varying conditional correlation model by Deb, Trivedi, and Varangis (1996), this paper finds the importance of long-run increasing trends in excess comovement of commodity returns relative to short-run conditional correlation dynamics. This finding also suggests that the STC model is sufficient for characterizing the increasing excess comovement of commodities in the recent period for our monthly data.

Second, both STC and STDCC models find that such long-run increasing trends in excess comovement among commodities started around 2000. Until 2000, the excess comovement of commodity returns was almost constant and remained at low levels, which is fairly consistent with Deb, Trivedi, and Varangis (1996). However, it has increased gradually since 2000 and reached much higher levels toward 2011. This result complements Tang and Xiong (2012), who find increasing trends in correlations between crude oil and non-energy commodities since (exogenously chosen) 2004, and Silvennoinen and Thorp (2013), who detect a structural change in the increasing cross-asset correlations between commodities and stocks (or bonds) since around 2000, although both sets of researchers analyze return correlations, not excess comovement. Note also that both Tang and Xiong (2012) and Silvennoinen and Thorp (2013) suggest index investment of commodities as a cause of the increasing trends. Since excess comovement is interpreted as correlation unrelated to market fundamentals, our result is generally consistent with their index-investment story of the increasing trends of correlations.[1]

Third, we examine the possibility of non-monotonic trends, and find that the increasing trends

[1]A possible explanation of the excess comovement of commodity prices suggested by Pindyck and Rotemberg (1990) is that "commodity price comovements are to some extent the result of 'herd' behavior in financial markets."

in excess comovement among commodity returns are not an artifact produced by the recent financial crisis, but the intrinsic nature of the excess comovement during the period including the post-crisis era. To test the possibility that the correlations among commodity returns might decrease after they hit their peak in the financial crisis, we extend the two-state STC model used above to the three-state model and investigate whether and when, if any, there is a decrease in the excess comovement trends. The results indicate that the increasing trends in excess comovement after 2000 are the dominant feature of the dynamics of the excess comovement of commodity prices. This finding complements the finding of an increasing trend in the correlation of commodities with crude oil and other traditional assets by Tang and Xiong (2012) and Silvennoinen and Thorp (2013), since they examine only monotonic trends.

Fourth, we show that the increasing long-run trends of excess comovement are robust to the change in the sensitivities of commodity returns to common macroeconomic factors. Since the STC model assumes that the effects of common macroeconomic factors to commodity returns are constant, there is a possibility that the increasing excess comovement trends might be an artifact by ignoring the change in the effects of common factors. We extend the model to incorporate such a possibility of the change in effects and obtain qualitatively the same increasing trends in excess comovement.

Fifth and finally, we find that, unlike the results above, there are no significant increasing trends in excess comovements among off-index commodity returns in our data.[2] This is generally consistent with Tang and Xiong (2012), who show a larger increase in correlations for indexed commodities than for off-index commodities.

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

2 Model and Estimation

2.1 Model

We investigate the following four models: the benchmark model with constant correlation, the DCC model with time-varying conditional correlation, the STC model with smoothly changing stationary level of correlation, and the STDCC model with time-varying conditional correlation around smoothly changing stationary level of correlation.

[2] Following Tang and Xiong (2012), we call those commodities listed in either the GSCI or DJUBS indexed commodities and those commodities listed in neither off-index commodities.

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, Δ is the difference operator and p_i is the logarithm of the price of the ith 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 macroeconomic shocks. The macroeconomic variables are logarithms of the CPI, industrial production, exchange rate, stock price index, money stock, and interest rate (not in logs). α_{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 BEKK 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.[3] 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 $\mathbf{H}_t$ and the conditional variance at time t of the ith commodity return following the GARCH(1,1) model as

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

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

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

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 $\boldsymbol{\varepsilon}_t$.

[3] We use the DCC model instead of the BEKK model because it is more widely used to model time-varying conditional correlation nowadays.

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 assumed to be time-varying. The recent development of commodity index investment, however, might affect the stationary level of correlation as the index investment grows, and hence the assumption of the constant stationary level of correlation might not be appropriate.

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

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

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 γ 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 and monotonically 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.[4]

One of the main attractions of the STC model is that it can detect from the data when and how structural change, if any, in correlation occurs. The STC model can describe a wide variety of patterns of change in correlation, depending on parameters c and γ, 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 across regimes by testing $r_{ij}^{(1)} = r_{ij}^{(2)}$. This hypothesis test

[4]This formulation enables us to detect only a monotone change of correlation from $\mathbf{R}^{(1)}$ to $\mathbf{R}^{(2)}$. In section 4, to investigate the possibility of non-monotonic change, we extend the model to have 3 states of correlation $\mathbf{R}^{(1)}$, $\mathbf{R}^{(2)}$, and $\mathbf{R}^{(3)}$. We then estimate the model and find that there is no significant difference between the 2-state model and the 3-state model.

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

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

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 stationary 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 across regimes 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 standard error 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 the standard error, which should not be a serious problem if the sample size is large.

3 Empirical Results

Our empirical analysis is based on 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.[5] We exclude food and energy indices from our analysis, since they are available only 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 US 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 shocks. These data include the seasonally adjusted consumer price index (CPI, Π), the seasonally adjusted industrial production (Y), the 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 Weak evidence of the excess comovement of commodity prices

We first estimate the benchmark model (1) with $K = 1$, as Pindyck and Rotemberg (1990). Our 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 the exchange rate have some explanatory power on BEV. More macroeconomic variables are important for the 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 the macroeconomic variables and the lagged dependent variable is 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 benchmark model (1). Table 2 reports the estimated correlations and their standard errors. As can be seen, four (AGR-MET, AGR-OIL, BEV-MET, and MET-OIL) out of six commodity pairs have a 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.

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. Indeed, for the monthly data from 1960 to 1985 and from 1974 to 1992, they find weaker evidence of excess comovement espe-

[5] 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.

cially when the multivariate GARCH model is applied. To examine the same possibility for the data through 2011, 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 (AGR-OIL, BEV-MET, and MET-OIL) 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).

Although we do not report them here, the time-series of conditional correlations between all commodity-pairs are mostly stable at the low level with no increasing trends. No increasing trend is similar to the results by Chong and Miffre (2010), who find decreasing trends and Büyükşahin, Haigh, and Robe (2010), who find no increasing trends of conditional correlations between stocks and commodities.[6] Note, however, that it may be difficult to detect the trends in the time-series of conditional correlations estimated by the DCC model, since it assumes no trend in correlation. The following subsection shows this point.

3.2 Increasing trends in excess comovement

As mentioned, one restriction of the benchmark and DCC models 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 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 (AGR-OIL and BEV-MET) out of six pairs. In addition, even for these two pairs, the magnitude of excess comovement is small with a correlation of 0.126 (AGR-OIL) and 0.098 (BEV-MET). These results are consistent with that of Deb, Trivedi, and

[6]The time-series of conditional correlations exhibit much larger variation in Chong and Miffre (2010) and Büyükşahin, Haigh, and Robe (2010) probably because they use weekly futures data.

Varangis (1996), who find the excess comovement among commodities is weak for the data from 1974 to 1992 when the time-varying conditional correlation is considered.

In contrast, 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 regimes. The Wald statistic and its p-value are reported in the last two rows in Table 4. The results 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 neither the benchmark nor the DCC model can capture.

Since our analysis demonstrates a significant increase in excess comovement, it is instructive to see when and how the increase occurred based on the STC model. 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 was almost constant and remained at low levels with an average correlation of 0.084 at the end of 1999. Note that these results are consistent with that of Deb, Trivedi, and Varangis (1996), who find excess comovement among commodities is weak for data from 1974 to 1992 when the time-varying conditional correlation is considered. However, excess comovement 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. These results are generally consistent with Tang and Xiong's (2012) finding of increasing trends in correlations from (exogenously chosen) 2004 and the structural change in increasing correlations from around 2000 detected by Silvennoinen and Thorp (2013), although they analyze return correlations, not excess comovement, of commodities with crude oil, stocks, and bonds. Recall that the excess comovement of commodities is the correlation among commodity returns that is not accounted for by the common shocks of exogenous macroeconomic variables and thus is interpreted as comovement unrelated to market fundamentals. Thus, our results are additional evidence that supports the claims by Tang and Xiong (2012) and Silvennoinen and Thorp (2013) that the financialization of commodities is the cause of increasing correlations among commodity returns.

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 of a significant increase in excess comovement in the more recent regime. In particular, excess comovement has increased gradually since 2000 and become important in recent years with an average correlation of about 0.4.

3.3 Long-run trends vs short-run dynamics

Although the STC model with time as a transition variable is suitable for capturing 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, accommodating the short-run behavior of the conditional correlation in the STC model is instructive. 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 the DCC model where $\hat{b} = 0.844$ is significant, suggesting that it is relatively more important to capture the long-run trends in correlation than the short-run dynamics in conditional correlation at least in the recent period. The estimation results for the 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, all excess comovements are significant with significant increases. The dynamics of correlation in Figure 2 are also similar to those in Figure 1, with a relatively small short-run fluctuation in conditional correlation. These results are not surprising, given that the DCC parameters are insignificant.[7]

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 at least to capture the recent increasing trends in the excess comovement of commodity prices. Thus, the STC model seems to be sufficient for characterizing the increasing excess comovement in commodity prices from 1983 to 2011.

3.4 Financial crisis and monotonicity of trends

One limitation of our favored STC model with a time trend as a transition variable is that our model allows only the monotonic transition from the initial stationary correlation level $\mathbf{R}^{(1)}$ to the terminal stationary correlation level $\mathbf{R}^{(2)}$. However, the correlations among commodity returns may change non-monotonically over time. For example, Büyükşahin, Haigh, and Robe (2010) find that the correlation between stock and commodity returns is positive and become much larger during the financial crisis, especially in the autumn of 2008, than in the preceding period. Thus,

[7] One possible reason for the small short-run fluctuation may be that we use monthly spot data.

the return correlation may peak in the middle of the financial crisis and become lower afterwards. If this is the case, the STC model could exaggerate the increase in excess comovement.

To examine this possibility, we use the three-state STC model. In this model, the time-varying correlation $\mathbf{R}_t$ is modeled as

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

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 through three stationary levels from $\mathbf{R}^{(1)}$ via $\mathbf{R}^{(2)}$ to $\mathbf{R}^{(3)}$ over time, as first the function G_1 changes from 0 to 1, followed by a similar change in G_2. As a consequence, depending on the estimated values of $\mathbf{R}^{(1)}$, $\mathbf{R}^{(2)}$, and $\mathbf{R}^{(3)}$, we can detect non-monotonic as well as monotonic trends of excess comovement of commodity prices solely from the data. Note that this type of non-monotonicity of trends in correlation has not been investigated by either Tang and Xiong (2012) or Silvennoinen and Thorp (2013).

In Figure 3 the estimated correlation dynamics from the three-state STC model is plotted. As can be seen from the figure, the correlation dynamics is quite similar to that of the two-state STC model. Four pairs (AGR-MET, AGR-OIL, BEV-OIL, and MET-OIL) out of six show a monotonic increase in correlation with almost the same dynamics as that of the two-state model. Although the other two pairs (AGR-BEV and BEC-MET) have some decrease in correlation in some regimes, the magnitude of the decrease is smaller compared with the increase in the 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 the Akaike information criterion (AIC) support the two-state model over the three-state one. That is, the two-state model that captures only monotonic trends in correlation is enough to describe the dynamics of the excess comovement of commodity prices over almost the last three decades.

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

3.5 Effects 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 assumed to be constant throughout the sample. In reality, however, there may be changes in the sensitivities of commodity returns to macroeconomic variables over time. Therefore, one may wonder whether our findings of increasing excess comovement of commodity prices are due to ignorance of the changes in the effects of common macroeconomic factors. To explore this possibility, we develop the following smooth transition regression (STR) model:

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

where ε_{it} is a standardized disturbance of commodity i. Thus, in the STR model, the coefficients of the macroeconomic variables can change, following a smooth transition model. We use logistic transition function (5) and the 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 $\hat{\varepsilon}_t$.[8] Then, we estimate the STC model (4) using the standardized residual from the STR model assuming $\boldsymbol{\varepsilon} = (\varepsilon_{1t}, \ldots, \varepsilon_{Mt})' \sim N(0, \mathbf{R}_t)$.

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 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, all excess comovements are significant with significant increases. Although the correlation dynamics plotted in Figure 4 become more linear than those in Figure 1, the increasing trends are still quite similar. Those results clearly indicate that our finding of increasing trends in excess comovement in commodity prices still holds after changes in the effects of common macroeconomic variables are considered.

3.6 Off-index commodities

Although our finding of increasing trends in the excess comovement of commodity prices is generally consistent with the increase in correlation between non-energy commodities and oil demonstrated by Tang and Xiong (2012), they also show that the increase in average correlation after around 2004 is much larger among indexed commodities, which are the components of either the GSCI or DJUBS, than among off-index commodities, which are not components of the GSCI or DJUBS. We thus investigate whether we find a similar difference for the excess comovement among off-index commodities.

The IMF commodity price indexes used for our analysis contain several off-index commodities

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

as components. [9] Therefore, it is 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).[10]

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 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 an increase in excess comovement for five pairs out of six. Furthermore, although the HID-TIN pair has a 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, similarly to Tang and Xiong (2012). Although other factors such as illiquidity may affect the correlations among off-index commodities, the results are still consistent with the view that the indexed commodities are one of the main sources of increases in the excess comovement of commodity prices. Thus, our finding of increasing excess comovement can be considered as additional supporting evidence of the effect of the financialization of commodities.

4 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 with a time trend as a transition variable, unlike those used in the previous studies, can capture the long-run trends of excess comovements, in addition to its short-run fluctuations. 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 fluctuations.

[9] 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.

[10] 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 in our analysis, since they are the only components from the beverage and metal categories that can be used. We also choose hides and softwood, since they have greater weight than wool and rubber. However, our result here is qualitatively similar even if we use wool and rubber instead of hides or softwood.

The long-run increasing trends in excess comovement are generally consistent with those shown by Tang and Xiong (2012) and Silvennoinen and Thorp (2013), although they analyze commodity-return correlations, not excess comovement. Moreover, Tang and Xiong (2012) and Silvennoinen and Thorp (2013) focus their formal 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 (2012) and Silvennoinen and Thorp (2013), who attribute this phenomenon 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 supporting evidence of such an interpretation.

There remain several issues worth investigating. First, although we find that the short-run fluctuations in excess comovement are much smaller than the long-run trends and thus conclude that the STC model seems sufficient for characterizing the increasing excess comovement in commodity prices from 1983 to 2011, this may be due to our use of monthly spot data of commodity returns. It is instructive to see whether we obtain similar results for weekly/daily futures returns. Second, although Silvennoinen and Thorp (2013) use the DSTCC (Double Smooth Transitions Conditional Correlation)-GARCH model, which is similar to our STDCC model, we may still apply the STDCC model to investigate the dynamics of return correlations among commodities, stocks, and bonds. Especially, we can investigate the possible non-monotonicity of trends in correlation using the three-state STDCC model. Third, recent empirical studies on the limit of arbitrage find that changes in the risk-bearing capacity of financial institutions and/or movements of commodity open interests predict commodity returns (Etula, 2013; Hong and Yogo, 2012). It is thus interesting to see how the results of this paper on commodity excess comovement may change if we include those variables in addition to macroeconomic ones. These are issues left for future research.

References

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

[2] Büyükşahin, B, Haigh, M. S., and Robe, M. A., 2010. Commodities and equities: Ever a "market of one"? Journal of Alternative Investments, 76-95.

[3] Chong, J. and Miffre, J., 2010. Conditional correlation and Volatility in Commodity Futures and Traditional Asset Markets. Journal of Alternative Investments, 61-75.

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

[5] 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.

[6] Engle, R.F., Kroner, K.F., 1995. Multivariate simultaneous generalized ARCH. Econometric Theory 11, 122-150.

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

[8] Etula, E., 2013. Broker-dealer risk appetite and commodity returns, forthcoming in Journal of Financial Econometrics.

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

[10] Greer, R., 2000. The nature of commodity index returns. Journal of Alternative Investments, 45-53.

[11] Hong, H., and Yogo, M., 2012. What does futures market interest tell us about the macroeconomy and asset prices?. Journal of Financial Economics 105, 473-490.

[12] Kumar, M.S., Okimoto, T., 2011. Dynamics of international integration of government securities' markets. Journal of Banking and Finance 35, 142-154.

[13] Lin, C.-F.J., Teräsvirta, T., 1994. Testing the constancy of regression parameters against continuous structural change. Journal of Econometrics 62, 211-228.

[14] Pindyck, R.S., Rotemberg, J.J., 1990. The excess co-movement of commodity prices. Economic Journal 100, 1173-1187.

[15] Silvennoinen, A., Thorp, S. 2013. Financialization, crisis and commodity correlation dynamics. Journal of International Financial Markets, Institutions and Money 24, 42-65.

[16] Tang, K., Xiong, W., 2012. Index investment and the financialization of commodities, Financial Analysts Journal 68, 54-74.

[17] 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

	Agriculture		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	

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

Note: */**/*** indicates that the variable is significant at the 10%/5%/1% level of significance, respectively.

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

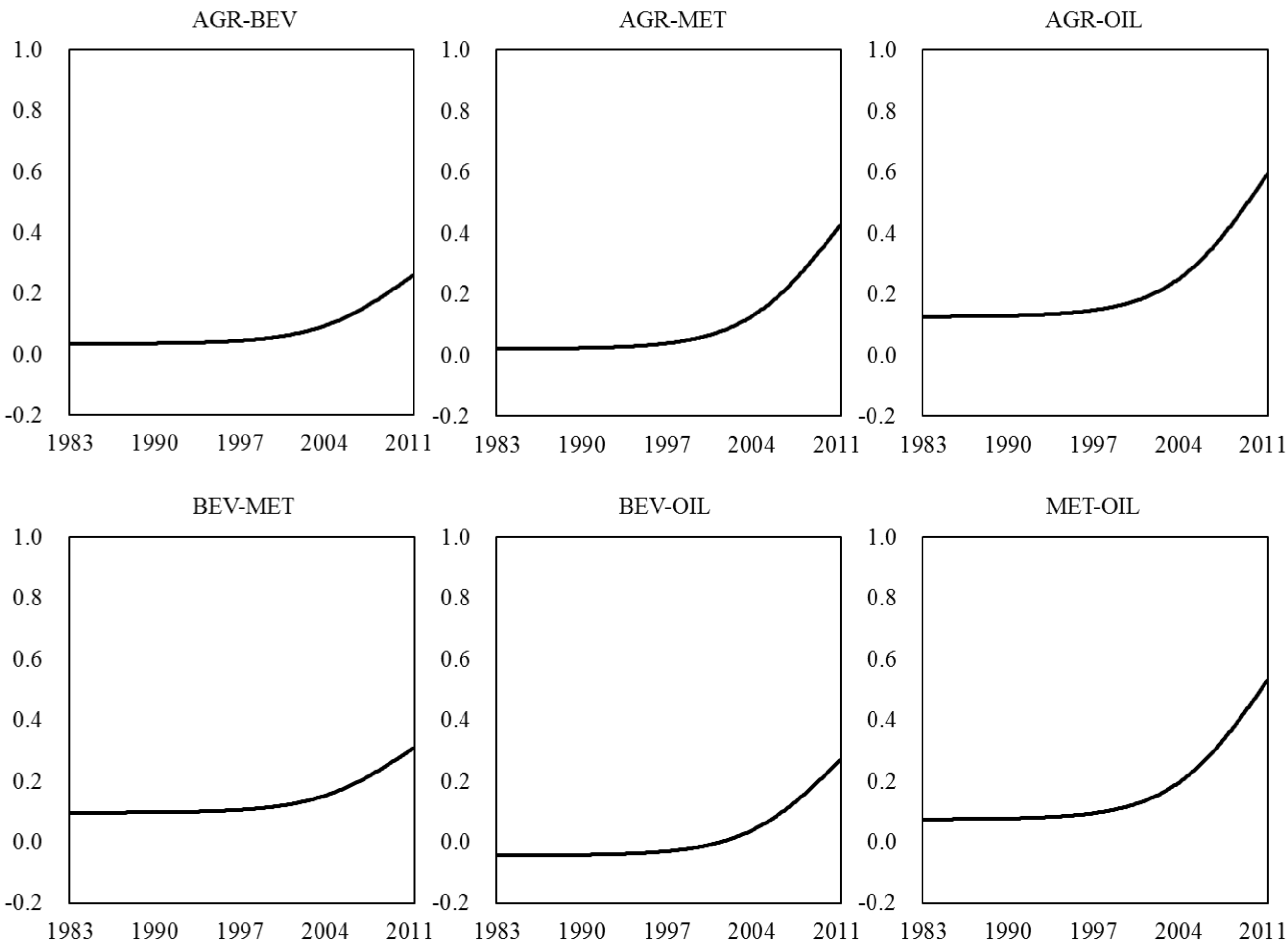

Figure 2: Dynamics of excess comovement of commodity prices (STDCC model)

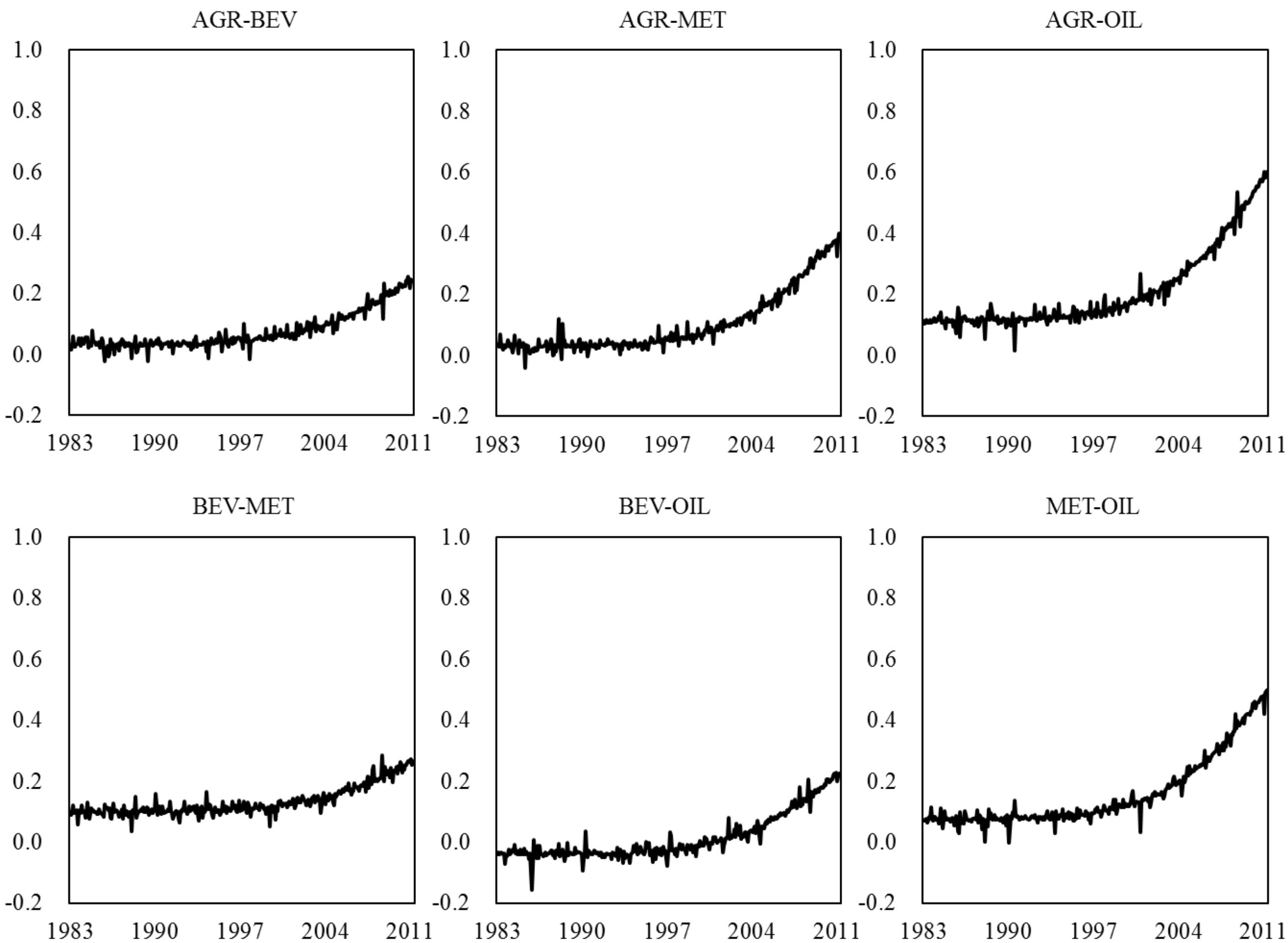

Figure 3: Dynamics of excess comovement of commodity prices (three-state STC model)

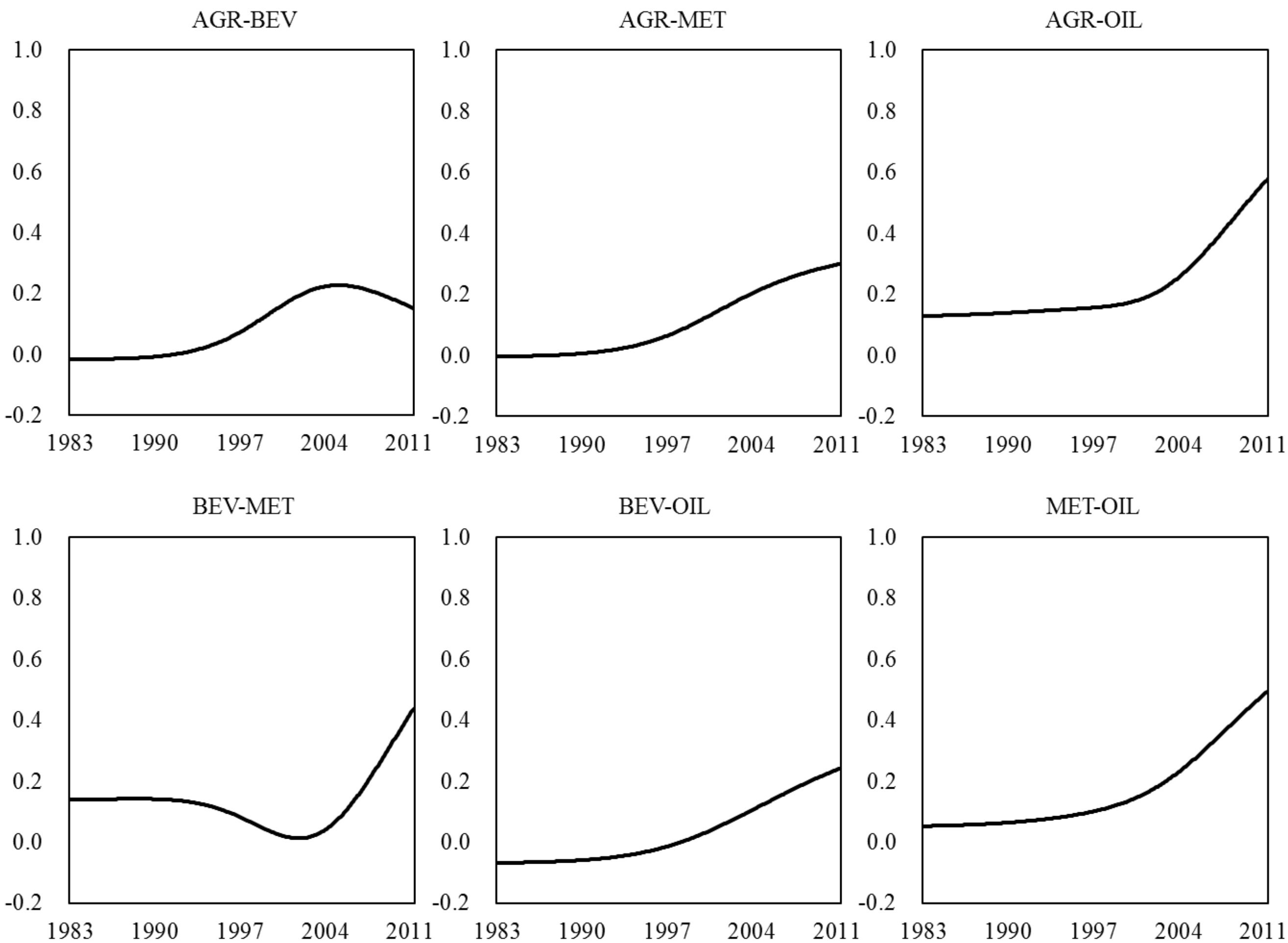

Figure 4: Dynamics of excess comovement of commodity prices (STR residuals)

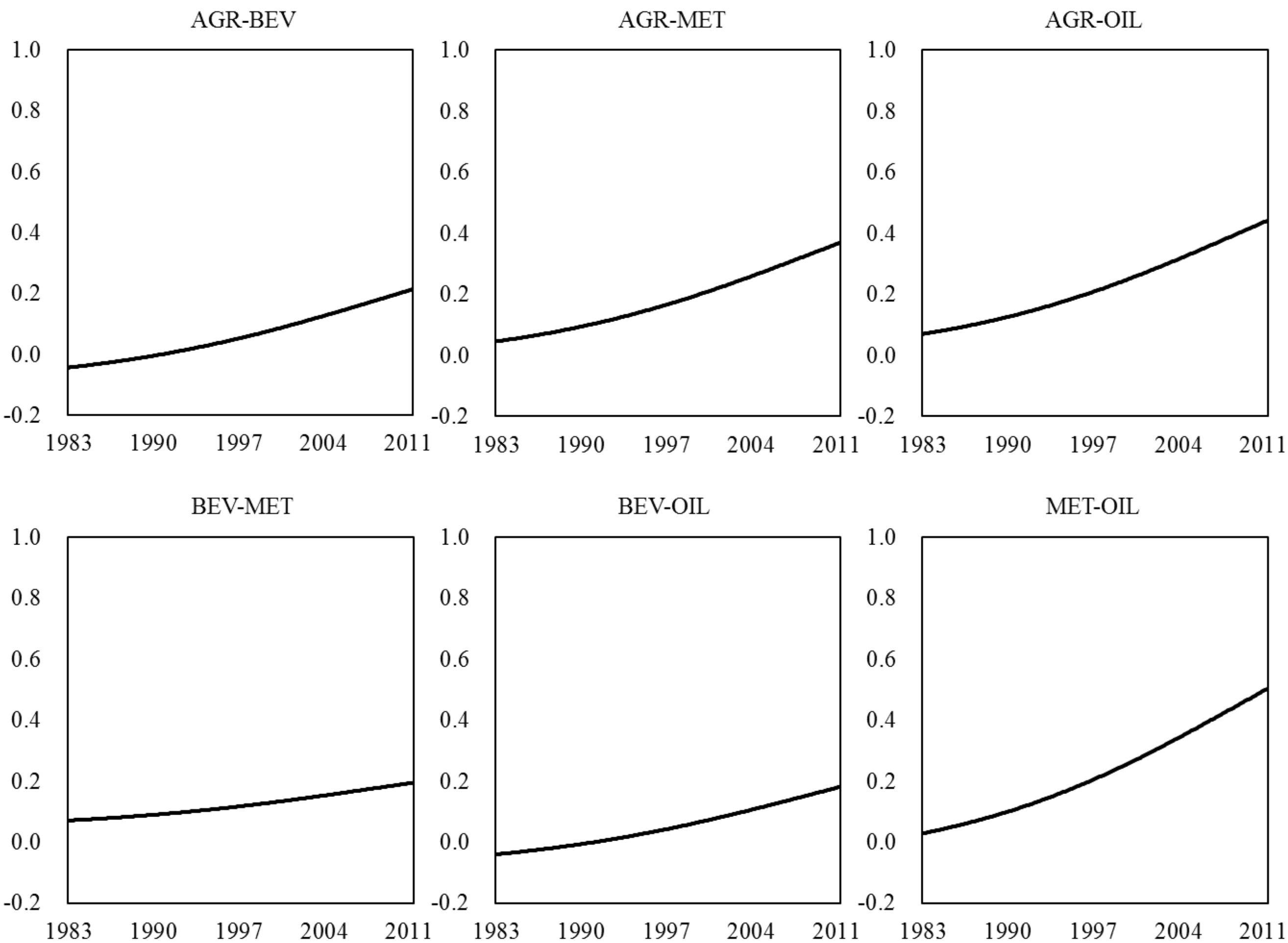

Figure 5: Dynamics of excess comovement of off-index commodity prices (STC model)