Increasing Trends in the Excess Comovement of Commodity Prices*

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Abstract

We investigate whether and how excess comovement of commodity returns has changed over the period 1983-2011. Using the STDCC model, we find that significant increasing long-run trends in excess comovement have appeared since around 2000. We confirm that these increasing trends are not caused just by the recent financial crisis or the changes in sensitivities to common macroeconomic shocks. Moreover, we find no significant increasing trends among off-index commodity returns and small effects of global demand on increasing trends in excess comovement. These findings provide additional evidence for the timing and scope of the recent increasing commodity-return correlations.

JEL classification: C32, C51, G15

Key Words: excess comovement; commodity returns; time-varying correlation; DCC; smooth transition; regime change; index; financialisation

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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 intensively 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 changed the environments. In particular, commodity markets seem to have become more integrated in traditional markets. For instance, Silvennoinen and Thorp (2013) show that return correlations between commodities and stocks (or bonds) have increased well before the 2008 financial crisis, while Tang and Xiong (2012) find significant increasing trends 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 investigate whether and how correlations among commodity returns have changed recently. We address these questions, however, from a slightly different viewpoint. We focus on excess comovement in commodity returns, initially raised by Pindyck and Rotemberg (1990) and extended by Deb, Trivedi, and Varangis (1996). The excess comovement of commodities is the correlation among commodity returns after filtering out the common macroeconomic shocks. It is hence interpreted as comovement unrelated to market fundamentals. We investigate how such excess comovement has changed over time.[1]

The formal test of excess comovement among commodity returns is originally developed by Pindyck and Rotemberg (1990). For monthly data from 1960 to 1985, they find that the excess comovement among several commodity returns are significant. Deb, Trivedi, and Varangis (1996) extend the model by introducing conditional heteroskedasticity and a time-varying conditional correlation with multivariate GARCH processes. The time-varying conditional correlation model allows them to analyse the short-run time-varying fluctuation in excess comovement, but the long-run mean of the correlation is set to be constant. Using monthly data from 1974 to 1992, they find

[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."

that evidence of excess comovement becomes weaker 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 long-run trends in correlation and the DCC part captures short-run fluctuations. Thus, combining them enables us to investigate changes in long-run trends and short-run dynamics of excess comovement simultaneously. Moreover, the STC part allows us to detect solely from the data when and how a structural change, if any, in correlation occurs. To our best knowledge, this paper is the first to develop the STDCC model and apply it to examine the timing of its structural change in the excess comovement of commodity returns.

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 commodity excess comovement among commodity returns. First, the STDCC model detects significant long-run increasing trends in commodity excess comovement. Indeed, in contrast with the time-varying conditional correlation model by Deb, Trivedi, and Varangis (1996) that cannot detect long-run trends, this paper finds that the effect of long-run trends is much larger than that of short-run fluctuations, suggesting that the STC model is sufficient for characterizing the increasing excess comovement among 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 have appeared since 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) that find increasing trends in correlations between crude oil and non-energy commodities since (exogenously chosen) 2004, and Silvennoinen and Thorp (2013) that detect a structural change in the increasing correlations between commodities and stocks (or bonds) since around 2000, although both sets of researchers analyse return correlations, not excess comovement. This result is also closely related to Le Pen and Sevi (2013) that find by rolling window method small increase of excess comovement among commodities between 2000 and 2004 and large increase after 2008.

Third, we examine the possibility of non-monotonic trends and find that the increasing trends in excess comovement among commodity returns are not entirely explained by the recent financial crisis. To test the possibility that the excess comovement among commodity returns might

decrease after the financial crisis, we extend the two-state STC model to the three-state model and investigate whether and when, if any, there is a decreasing trends in the excess comovement. The results indicate that the increasing trends in excess comovement after 2000 are the dominant feature of the dynamics in commodity excess comovement. This complements the findings of increasing trends in correlations by Tang and Xiong (2012) that examine only monotonic trends and Silvennoinen and Thorp (2013) that use the data up to 2009.

Fourth, we show that the increasing long-run trends of excess comovement are robust to changes in the sensitivities of commodity returns to common macroeconomic factors. Since the STC model assumes that the sensitivities of commodity returns to common macroeconomic factors are constant, there remains a possibility that the increasing trends in excess comovement might be caused by the (ignored) increasing trends in sensitivities to common macroeconomic factors. We examine the model that incorporates such a possibility and obtain qualitatively the same result.

Fifth, we find that, unlike the results above, there are no significant increasing trends in excess comovement among off-index commodity returns.[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.

Finally, we show that our results are robust to the global macroeconomic shocks. We examine the STC model taking account of the global macroeconomic variables, instead of the U.S. macroeconomic variables, and still find significant, though a bit weaker, long-run increasing trends in commodity excess comovement. Thus, the increasing trends of excess comovement are not entirely attributed to the recent growth of world economy.

While the main focus of this paper is to examine how excess comovement of commodity returns has changed over time by the STDCC model, it is worth reviewing several related papers that attempt to explain the causes of the increase of return correlations (or excess comovement) among different commodities and/or between commodities and stocks (or bonds). Tang and Xiong (2012) find that the correlations among commodity returns have increasing trends since 2004 and that these increasing trends among the indexed commodities are significantly larger than those among the off-index commodities. They suggest that this result is caused by the increasing capital flows into commodity markets through index trading i.e., financialisation of commodity markets. Silvennoinen and Thorp (2013) show that the return correlations between commodities and stocks (or bonds) have increased since 2000 and also suggest that this is due to integration between markets

[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.

of commodities and traditional assets through capital flows into commodity markets.[3] Using the data of individual trader positions in the U.S. futures markets, Büyükşahin and Robe (2012) investigate the relation between cross-asset correlations and financialisation in more detail. They show that the return correlations between commodities and stocks increase due to greater participation by speculators, especially hedge funds, but not by other types of traders. Le Pen and Sevi (2013) find that the measures of hedging and speculative activities calculated from the CFTC data have significant explanatory power on the excess comovement among commodities. They suggest that this finding show the impact of financialisation on commodity return relations. Basak and Pavlova (2013) develop a theoretical model to analyse the effect of financialisation. They obtain the results that support the empirical findings and show among others that financialisation with the presence of institutional investors leads to an increase in correlations among commodities and/or between commodities and stocks.

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.

2.1.1 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 (**??**) 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

[3] Silvennoinen and Thorp (2013) apply the double smooth transition conditional correlation GARCH (DSTCC-GARCH) model, which is closely related to the STDCC model in this paper.

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 (**??**) from several commodities and call it excess comovement of commodity prices.

2.1.2 DCC model

Deb, Trivedi, and Varangis (1996) extend the benchmark model (**??**) 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. 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 $\boldsymbol{\varepsilon}_t$.

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. However, a large change of market environments such as rapid growth of commodity index investment might affect the stationary level of correlation. 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).[4] 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 determining 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.[5]

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 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

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

[4] See also Silvennoinen and Teräsvirta (2014) for more details of STC model.

[5] This formulation enables us to detect only a monotone change of correlation from $\mathbf{R}^{(1)}$ to $\mathbf{R}^{(2)}$. In subsection 3.4, to investigate the possibility of non-monotonic change, we extend the model to have three 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 results of two-state model and those of three-state model.

where G is a logistic transition function (**??**). 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 straightforward 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 (**??**) 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.[6] 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).[7]

[6]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.

[7]In subsection 3.7, we replace these US variables by the global ones and examine the excess comovement by filtering out the global macroeconomic shocks.

3.1 Weak evidence of the excess comovement of commodity prices

We estimate the benchmark model (**??**) with $K = 1$ as Pindyck and Rotemberg (1990).[8] 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 (**??**). Table 2 reports the estimated correlations and their standard errors. 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 especially when the multivariate GARCH model is applied. To examine the same possibility for the data through 2011, we estimate the DCC model (**??**) using the standardized residual $\hat{\boldsymbol{\varepsilon}}_t = \hat{\mathbf{D}}_t^{-1}\hat{\mathbf{u}}_t$ from the benchmark model (**??**) with a univariate GARCH model (**??**).

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. Three (AGR-OIL, BEV-MET, and MET-OIL) out of six commodity pairs show significant positive correlation, suggesting that evidence of excess comovement becomes weaker once we control the conditional heteroskedasticity and time-varying conditional correlation. The result

[8] We also confirm that residuals from the benchmark model (**??**) with $K = 1$ are serially uncorrelated for all commodities.

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.[9] 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

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 growth 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 (**??**) using the standardized residual $\hat{\boldsymbol{\varepsilon}}_t$ from the benchmark model (**??**) with a univariate GARCH model (**??**).

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 those of Deb, Trivedi, and 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.

[9] 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.

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 between oil and non-energy commodities from (exogenously chosen) 2004 and the structural change in increasing correlations between commodities and stocks (or bonds) from around 2000 detected by Silvennoinen and Thorp (2013), although they analyse return correlations, not excess comovement. Also, this result is consistent with Le Pen and Sevi (2013) that finds by rolling window method small increase of excess comovement among commodities between 2000 and 2004 and large increase after 2008.

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 earlier 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 in July 2011.

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 (**??**) 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. 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 relatively small short-run fluctuations in conditional correlation. These results are not surprising, given that the DCC parameters are insignificant.[10]

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 for our monthly data.

3.4 Financial crisis and monotonicity of trends

One limitation of the 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, 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 develop the three-state STC model in which 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 Tang and Xiong (2012) investigate only monotonic trends after 2004 and that Silvennoinen and Thorp (2013), while allowing

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

non-monotonic trends in their DSTCC-GARCH model, use the data up to July 2009.[11]

In Figure 3 the estimated correlation dynamics from the three-state STC model is plotted. 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 commodity excess comovement is not explained entirely by the recent financial crisis.

3.5 Change of sensitivities to common macroeconomic variables

In our STC model, the sensitivities of commodity returns to common macroeconomic variables are assumed to be constant. In reality, there may be changes in the sensitivities over time. One may thus wonder whether our findings are due to ignorance of the changes in sensitivities to 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 (**??**) and the time trend as a transition variable. 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 (**??**) via MLE assuming $\varepsilon_{it} \sim$ iid $N(0, 1)$ to get the standardized residuals $\hat{\varepsilon}_t$.[12] Then, we estimate the STC model (**??**) using the standardized residual from the STR model assuming $\boldsymbol{\varepsilon} = (\varepsilon_{1t}, \ldots, \varepsilon_{Mt})' \sim N(0, \mathbf{R}_t)$.

[11] The DSTCC-GARCH model with time for both transition variables can describe non-monotonic trends. Silvennoinen and Thorp (2013) find this specification fits well for several commodities.

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

The estimation results of correlation of each regime for the standardized disturbance from the STR model are documented in Table 6. 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 sensitivities to common macroeconomic variables are considered.

3.6 Off-index commodities

Tang and Xiong (2012) also show that the increase in average correlation after around 2004 is much larger among indexed commodities that are the components of either the GSCI or DJUBS than among off-index commodities that 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 as components. [13] To examine the dynamics of excess comovement for these off-index commodities, we estimate the two-state STC model using the price data of hides (HID), softwood (SOF), tea (TEA), and tin (TIN).[14]

Table 7 reports the estimated unconditional correlation of standard residuals of each regime for off-index commodities. 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. 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 are in contrast to those for the original price index, similarly to Tang and Xiong (2012). Although other factors such as illiquidity may affect the

[13] 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.

[14] 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.

correlations among off-index commodities, the results are still consistent with the view that the index investment is one of the main sources of increases in the commodity excess comovement.

3.7 Effects of global macroeconomic variables

Another possible explanation of the increasing trends in commodity excess comovement could be a surge of global commodity demand since the early 2000. Since we only control the US macroeconomic variables, increasing trends in the excess comovement might reflect such growth of world economy. To examine this possibility, we obtain the CPB industrial production world production weights index, the IMF world CPI, and MSCI world index from the Bloomberg and estimate the two-state STC model and use these data instead of US industrial production, CPI, and stock index data.[15]

The estimation results of unconditional correlation of standard residuals of each regime are shown in Table 8. The evidence of increase in the excess comovement of commodity prices becomes weaker, but still remains after accounting for global macroeconomic shocks. For instance, although BEV-OIL pair no longer has significant positive correlation in regime 2, the rest of pairs still show a significant excess comovement in more recent years. In addition, the correlations in regime 2 become uniformly smaller compared with those of Table 4 based on the US economic data, suggesting the degree of increase in the excess comovement is smaller. Nonetheless, the results indicate that four pairs out of six have a significant increase in the excess comovement, as can also be seen from the estimated dynamics of correlation shown in Figure 6. Furthermore, the rest of two pairs without significant increase has maintained the relatively high excess comovement throughout the entire sample period.

In sum, the analysis with the global economic variables demonstrates that our finding of increasing trends in excess comovement of commodity returns cannot be attributed entirely to the recent growth of world economy.

4 Conclusion

We investigate whether and how excess comovement of commodity returns have changed over time. For this purpose, we generalize the model of excess comovement, originated by Pindyck and Rotemberg (1990) and extended by Deb, Trivedi, and Varangis (1996), to the STDCC model, which can capture long-run trends of excess comovement in addition to short-run fluctuations. Using monthly data from 1983 to 2011, we find the clear increasing long-run trends and the little

[15] Since the world economic data are available only from 1991:1, the sample period of this exercise is from 1991:2 to 2011:7.

short-run fluctuations in commodity excess comovement. We also find that the long-run trends start increasing since around 2000 and accelerate afterwards.

This result complements Tang and Xiong (2012) that find increasing trends in correlations between crude oil and non-energy commodities since 2004, and Silvennoinen and Thorp (2013) that find a structural change in increasing correlations between commodities and stocks (or bonds) since around 2000, although both analyse return correlations. This result is also consistent with Le Pen and Sevi (2013) that find small increase of excess comovement among commodities between 2000 and 2004 and large increase after 2008.

We conduct several robustness checks and confirm that these increasing trends are not just due to the recent financial crisis, the changes in sensitivities to common macroeconomic shocks, or the recent growth of world economy. Moreover, we find no significant increasing trends among off-index commodity returns. These findings provide additional evidence for the timing and scope of the increasing commodity-return correlations in the recent period.

There remain several issues worth investigating. First, while we find that the short-run fluctuations in excess comovement are much smaller than the long-run trends for monthly data, it is instructive to see whether we obtain similar results for weekly/daily futures returns. Second, to avoid somewhat arbitrary choice of macroeconomic variables that set "fundamentals", it is worth applying the large approximation factor model used by Le Pen and Sevi (2013) to extract the fundamental factors from a larger set of variables and analysing the trends in excess comovement. Finally, recent empirical studies find that changes of commodity open interests predict asset returns (Etula, 2013; Hong and Yogo, 2012). It is interesting to see how the results change if we include those variables in addition to macroeconomic ones. These are issues left for future research.

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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.

Table 8: Estimation results of excess comovement based on global economic variables

		AGR-BEV	AGR-MET	AGR-OIL	BEV-MET	BEV-OIL	MET-OIL
Regime 1	Estimate	-0.0850	-0.2388*	0.3925***	0.1570	-0.2177*	-0.1031
	Std. Error	0.1380	0.1402	0.1225	0.1122	0.1341	0.1558
Regime 2	Estimate	0.2315***	0.2416***	0.2515***	0.1487**	0.0759	0.2373***
	Std. Error	0.0822	0.0685	0.0662	0.0822	0.0776	0.0752
Test of equality	Wald stat	3.3206	9.3030	0.9154	0.0030	3.1749	3.4070
	P-value	0.0684	0.0023	0.3387	0.9563	0.0748	0.0649

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 1 plots the dynamics of excess comovement of commodity prices for each commodity pair based on the STC model.

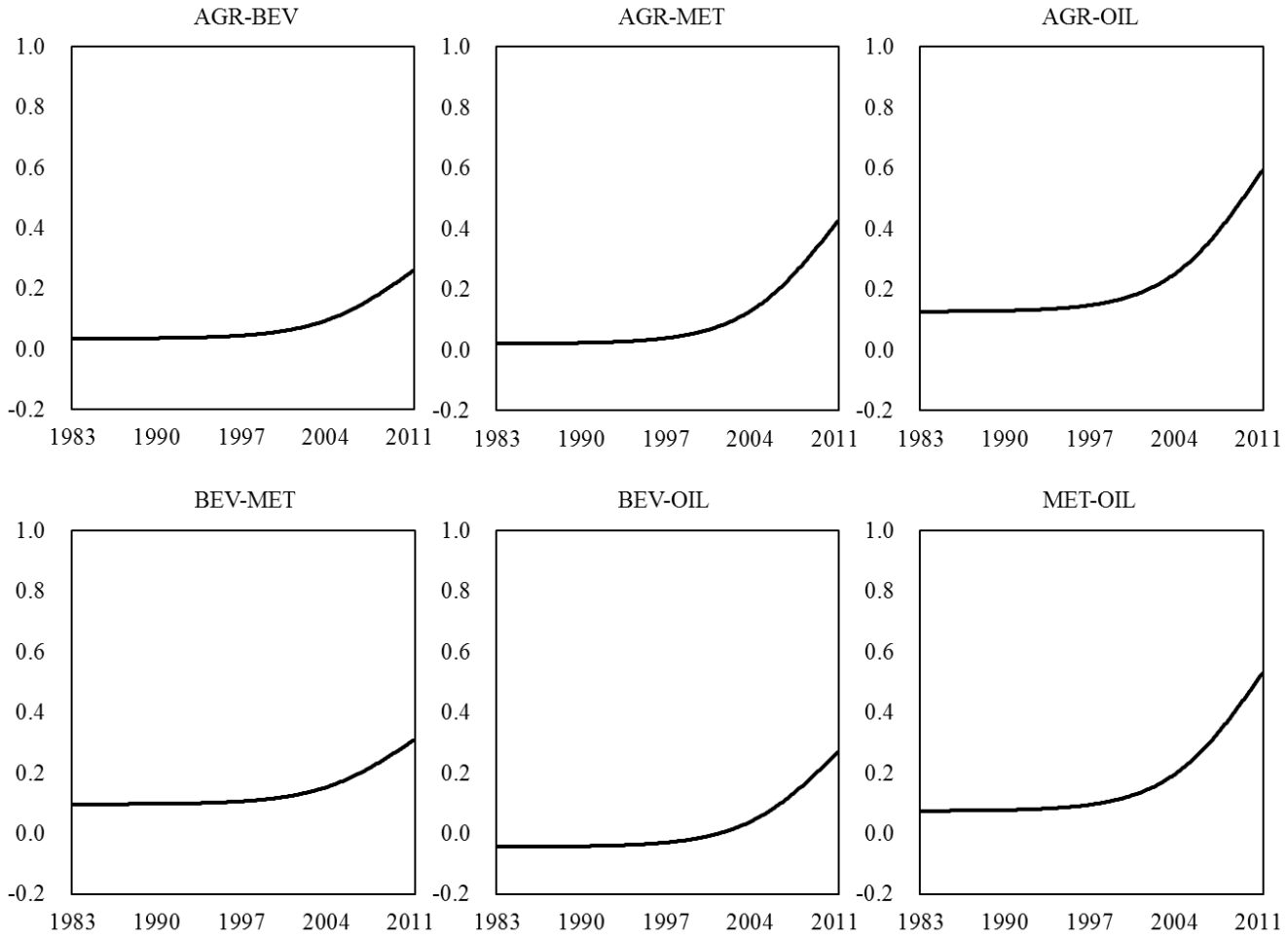

Figure 2: Dynamics of excess comovement of commodity prices (STDCC model)

Figure 2 plots the dynamics of excess comovement of commodity prices for each commodity pair based on the STDCC model.

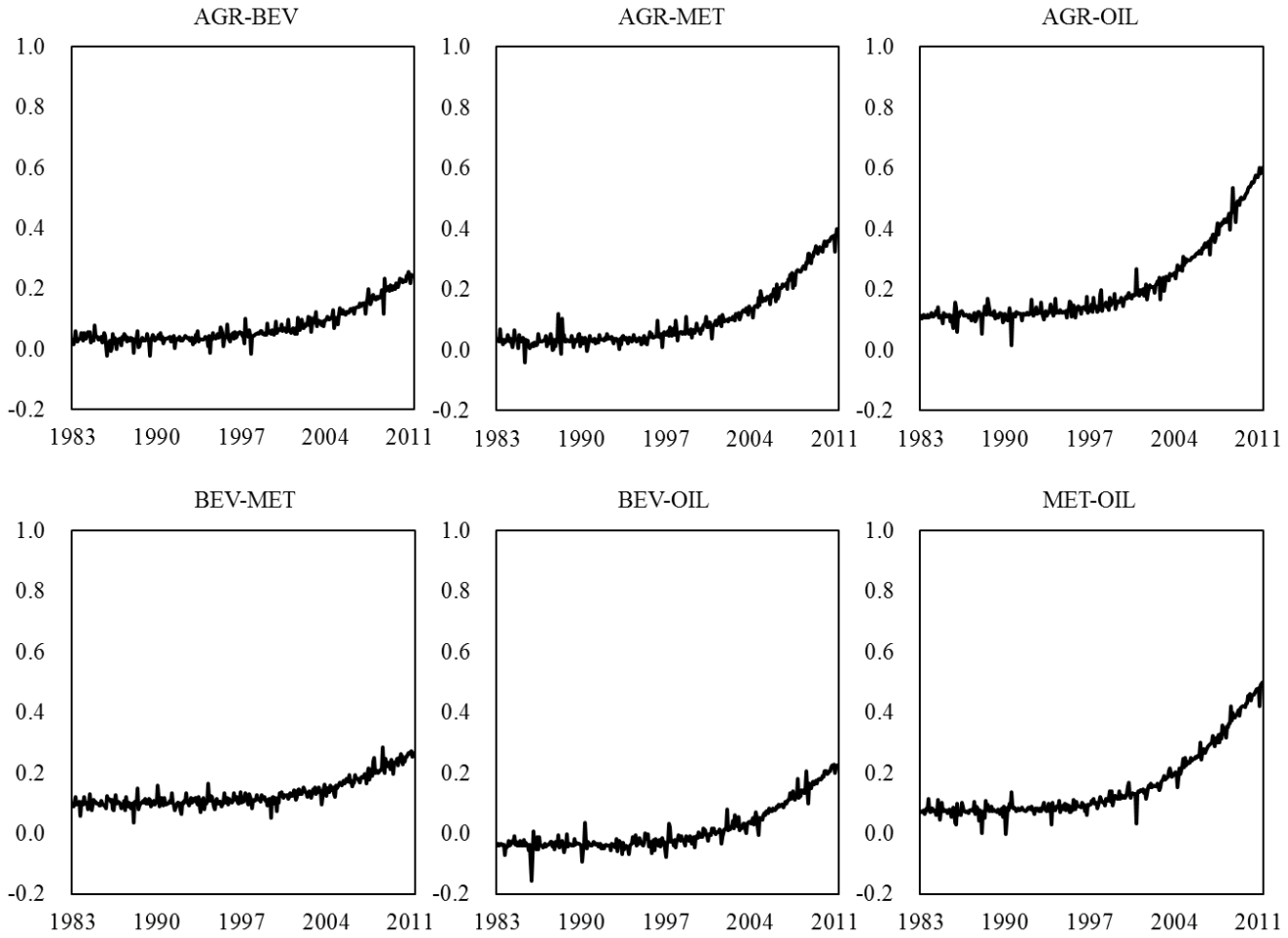

Figure 3: Dynamics of excess comovement of commodity prices (three-state STC model)

Figure 3 plots the dynamics of excess comovement of commodity prices for each commodity pair based on the three-state STC model.

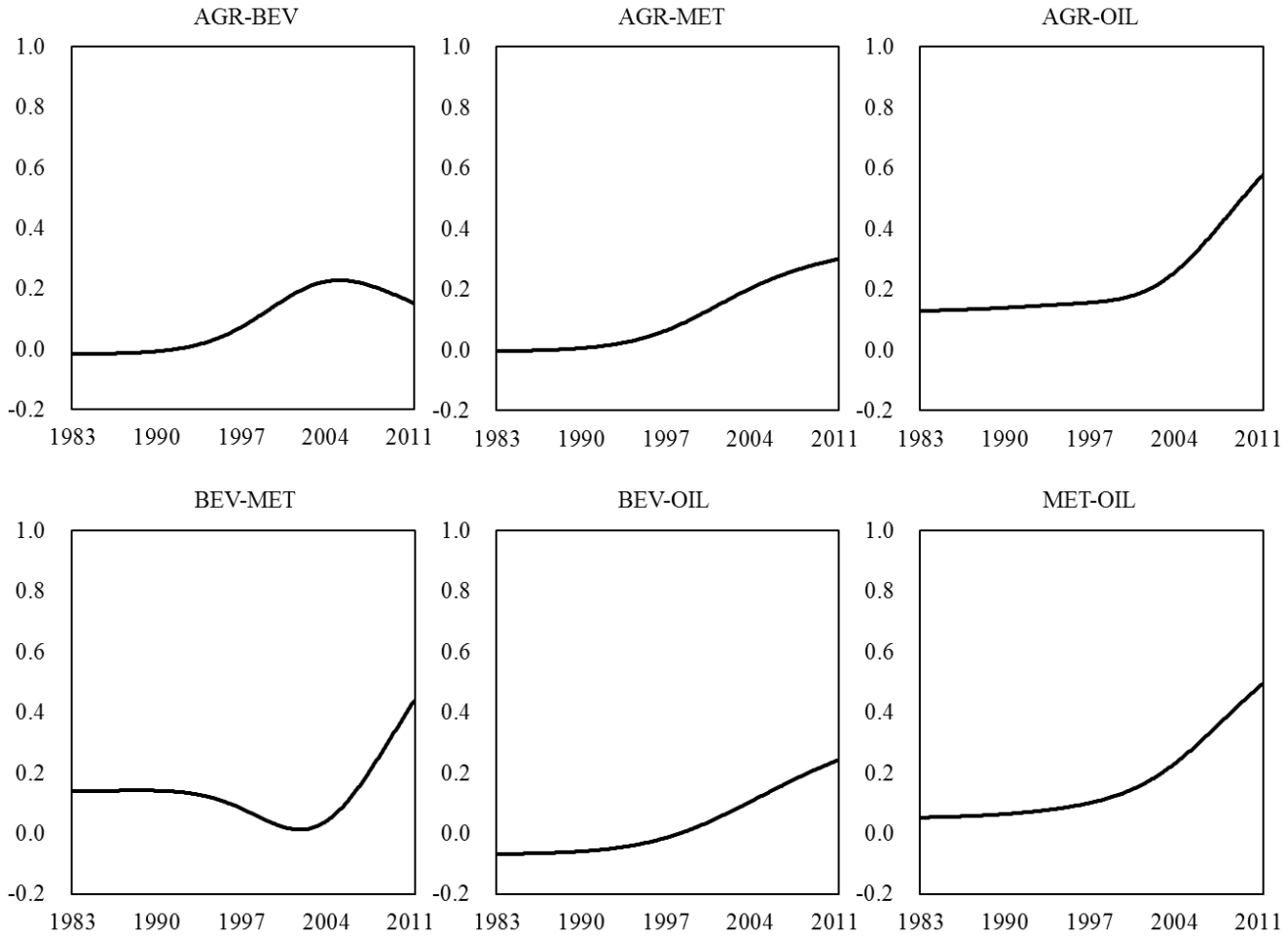

Figure 4: Dynamics of excess comovement of commodity prices (STR residuals)

Figure 4 plots the dynamics of excess comovement of commodity prices for each commodity pair based on the residuals from STR model.

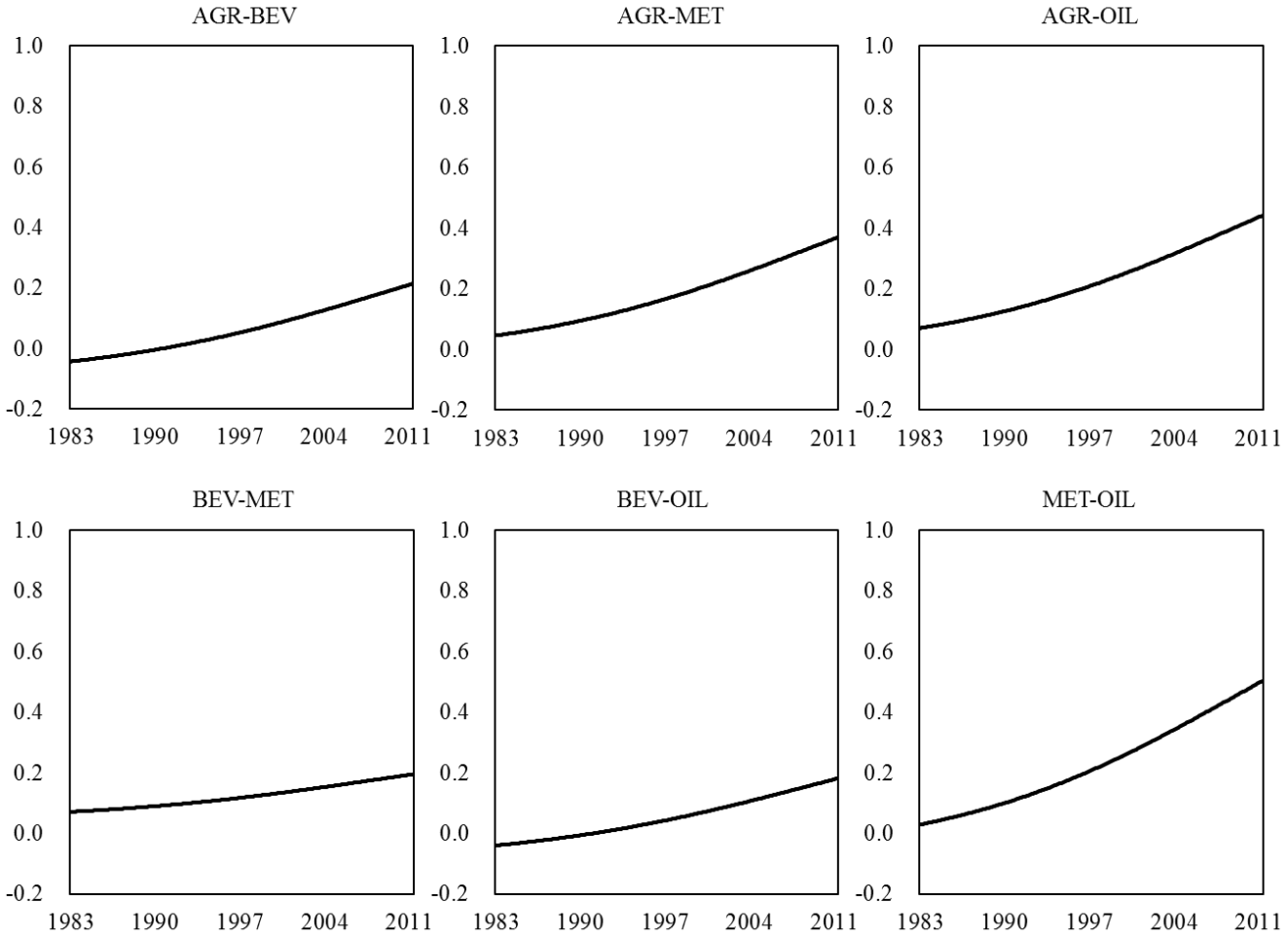

Figure 5: Dynamics of excess comovement of off-index commodity prices (STC model)

Figure 5 plots the dynamics of excess comovement of commodity prices based on the STC model using the price data of hides (HID), softwood (SOF), tea (TEA), and tin (TIN).

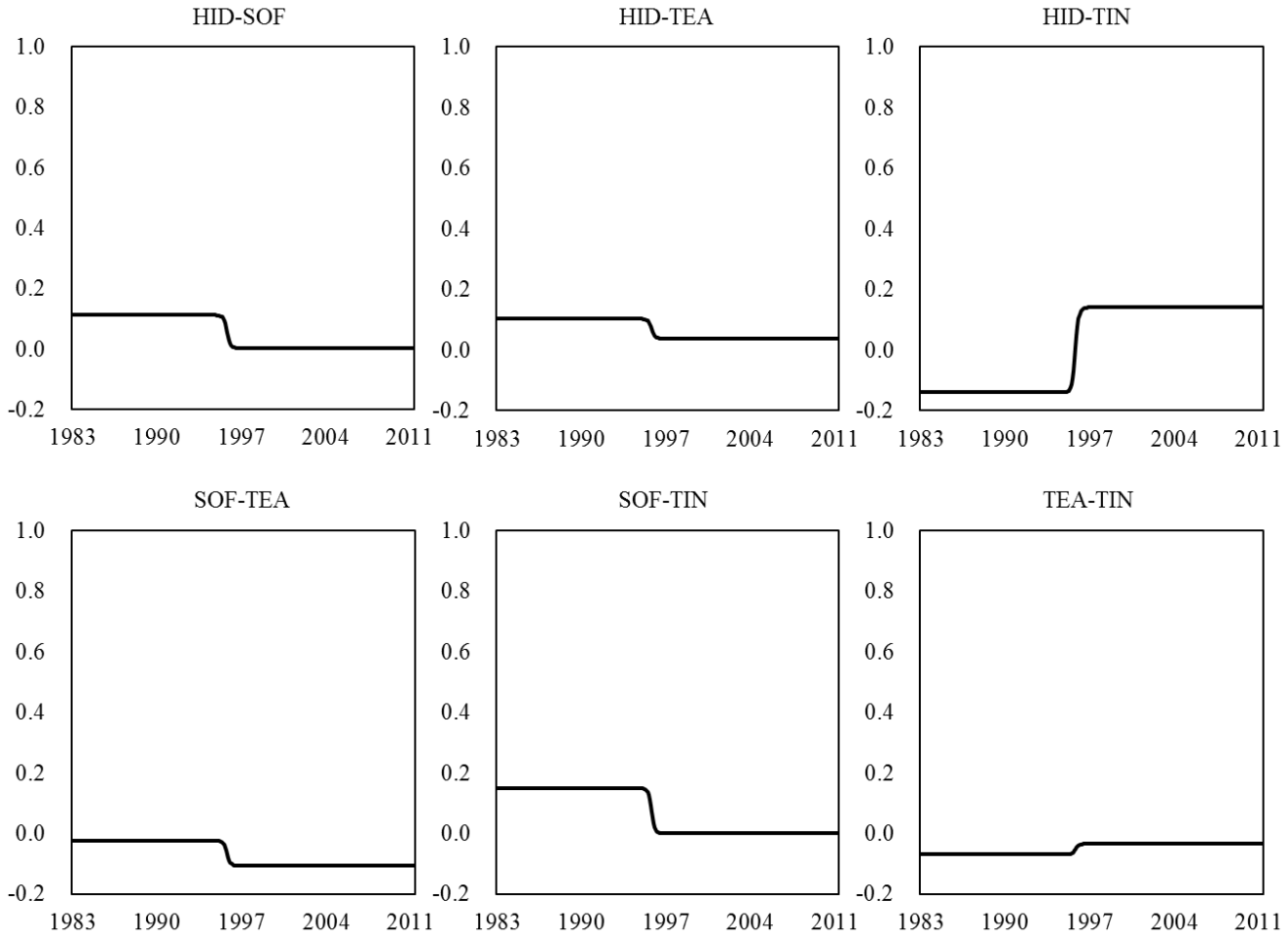

Figure 6: Dynamics of excess comovement of commodity prices (global economic variables)