Financialization and commodity excess spillovers

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Abstract

To identify the relationship between financialization and cross-commodity linkages, this paper proposes the framework of excess spillovers which deals with the connectedness across multiple commodity prices that cannot be explained by macroeconomic fundamentals. We document that excess spillovers rose dramatically during 2004–2008 and peaked during the global financial crisis. The magnitude of excess spillovers is significantly positively related to the extent of participation by financial investors, and the majority of the variations in excess spillovers can be attributed to the activities of managed money traders and index traders. Besides, commodity markets with higher degree of managed money participation are more likely to be net transmitters of excess spillovers. In contrast, commodity markets with higher degree of index fund participation are more likely to be net receivers. Overall, our analysis verifies that the increasing integration of commodity markets is the new normal led by financialization, rather than a temporary change caused by fundamentals.

Key words: Financialization, Commodities, Excess spillovers, Macroeconomic fundamentals

1. Introduction

The last fifteen years witnessed a fundamental change in the composition of commodity market participants. Attracted by the diversification benefits of commodity investments, institutional investors who previously concentrated in traditional financial markets have dramatically increased their participation in commodity markets since the early 2000s. According to conservative estimates, the number of index traders engaged in commodity futures markets more than quadrupled and the number of hedge funds more than tripled between 2000 to 2011 (Cheng, et al., 2015). Consurrent with the growing presence of financial investors in commodity markets, which is referred to as the financialization of commodity markets, prices of seemingly unrelated commodities[1] have become increasingly correlated with each other, suggesting a higher degree of commodity market integration (Tang and Xiong, 2012; Ohashi and Okimoto, 2016; Charlot et al., 2016). This phenomenon raise the question of whether the financialization process has altered the nature of commodity connectedness, which carries important implications for a number of issues including policy decisions of commodity importers and exporters, hedging strategies of commercial traders, and investment strategies of speculators.

Although it is tempting to relate the increasing connectedness of commodity prices to the ongoing process of financialization, cross-commodity linkages can also arise from the common effects of macroeconomic fundamentals, and it is not clear whether the increase in connectedness is a new normal led by financialization or just a result of fundamental shocks. Indeed, the empirical literature has documented several macroeconomic

[1] As defined by Pindyck and Rotemberg (1990), seemingly unrelated commodities are those whose cross-price elasticities of demand and supply are close to zero. In other words, they are largely unrelated through joint production or consumption, and hence are expected to move together only in response to common macroeconomic shocks.

factors which carry important explanatory power for the variation in commodity price comovements, such as industrial production, interest rate, exchange rate and uncertainty (e.g., Lombardi et al., 2012; Byrne et al., 2013; West and Wong, 2014). One influential view considers aggregate demand, especially demand from emerging economies, as the leading force behind the common boom-bust cycle across a wide range of commodities between 2004 and 2008 (e.g., Kilian, 2009; Kilian and Murphy, 2014).

This paper investigates the relationship between financialization and cross-commodity linkages from a new perspective. In particular, we propose the framework of excess spillovers based on the idea of excess comovement (Pindyck and Rotemberg, 1990) and the method of spillover index (Diebold and Yilmaz, 2012, 2014), then we focus on the connectedness of prices across a broad set of commodities beyond the fundamental level to investigate the effect of financialization on excess spillovers. We model excess spillovers as spillovers across residuals from regressions of price changes of seemingly unrelated commodities on a common set of macroeconomic factors, so as to uncover the remaining connectedness among commodity prices once the effects of common fundamentals are filtered out. Therefore, the aim of this paper is twofold: to characterize the nature of excess spillovers across major commodities and to explore the role of financialization in explaining the observed excess spillovers.

Accordingly, our study makes three key contributions.

First, we fully account for the common effects of macro fundamentals by summarizing the information from an extensive set of macroeconomic variables based on large dimensional factor analysis. Specifically, we collect monthly data on 298 economic indicators from major developed and emerging countries over the period 1997–2016, from which 7 factors are extracted and used to filter commodity prices. Generally, there is no consensus on the choice of proxies for common fundamentals that drive the joint behavior of commodity prices. Pindyck and Rotemberg (1990) select 6 US economic variables: the index of industrial production, CPI, the dollar index, the 3-month T-bill rate, M1 and the S&P 500 stock market index. The same set of variables are also employed by Deb et al. (1996) and Ohashi and Okimoto (2016). Pradhananga (2016) uses a relatively broader set including industrial production for OECD and emerging markets, Kilian Index, Federal funds rate, US nominal broad exchange rate, US inflation rate, and WTI price. The aforementioned studies all rely on a small and arbitrary set of economic variables and hence are highly likely to suffer from omitted variable bias. One exception is Le Pen and Sévi (2018) who consider a set of 187 macroeconomic variables (118 variables from developed countries and 66 variables from emerging countries). This paper makes an improvement by significantly enlarging the dataset both in terms of variable category and country range. We select 185 variables from 8 developed countries (US, UK, Japan, Germany, Australia, France, Canada and Italy) and 113 variables from 9 emerging countries (China, Russia, India, Brazil, South Korea, Mexico, Indonesia, South Africa and Singapore). Different from Le Pen and Sévi (2018)'s finding that commodity returns are mainly correlated with real aggregate variables of emerging countries, our analysis shows that real activity of emerging economies does not play a vital role in shaping commodity prices once real variables of developed countries have been adequately controlled. Moreover, after filtering out the effects of macroeconomic fundamentals, residual correlations of commodity prices (namely, excess comovement) estimated in this paper are much lower than those documented in Le Pen and Sévi (2018). Therefore, by exploiting a much richer information set, we eliminate the incompleteness in the selection of control variables and can account for the impact of common fundamentals more adequately.

Second, we develop measures of excess spillovers by combing the basic idea of excess comovement with the spillover index approach of Diebold and Yilmaz (2012, 2014), which are able to capture cross-commodity connectedness unrelated to macroeconomic fundamentals in sufficient detail. Our framework of excess spillovers is motivated by the issue of excess comovement of commodity prices which was initially raised by Pindyck and Rotemberg (1990) and concerns commodity price comovement in excess of what can be explained by macroeconomic fundamentals[2]. Since Pindyck and Rotemberg (1990), several scholars have tested the excess comovement hypothesis and obtained mixed results (e.g., Deb et al., 1996; Ohashi and Okimoto, 2016; Le Pen and Sévi, 2018)[3]. From a methodological perspective, the essential of excess comovement lies in measuring the concurrent pairwise correlation between commodity return residuals (after filtering out the effects of common fundamentals). However, cross-asset connectedness can occur not only in the form of concurrent correlation (i.e., comovement), but also in the form of dynamic linkages like spillovers (Adams and Glück, 2015). Weak comovement does not necessarily mean weak connectedness (Chevallier and Ielpo, 2013). Besides, pairwise association measures are unlikely to fully capture the overall interdependence of a multi-asset system. Consequently, connectedness among commodity return residuals may not be adequately detected within the framework of excess comovement. Our measures of excess spillovers build on the approach of Diebold and Yilmaz (2012, 2014) which can effectively quantify the complex connectedness across filtered commodity returns, capturing the complete information of both concurrent and dynamic linkages and from pairwise to system-wide association. Furthermore, unlike excess comovement which is directionless, excess spillovers can reveal the direction of connectedness and hence enable us to further uncover the structure and transmission mechanism of the spillover network.

Our estimation results show that there exist significant excess spillovers among commodity prices. The size of excess spillovers was high on average over the sample period, and peaked during the 2007–2009 financial crisis. The magnitude of excess spillovers remained high after 2009 and almost touched the crisis level in the more recent period of 2015–2016, suggesting that the observed excess spillovers cannot be interpreted as a phenomenon of financial turmoil. Besides, the increase in excess spillovers emerged as early as 2004, well before the global financial crisis and just in parallel with the time when investment flows into commodity markets surged. Regarding the direction of excess spillovers, our estimates show that different commodities assume different roles in the spillover network and none of the individual commodities was always a net transmitter or a net receiver of excess spillovers throughout the sample period. Generally, the ability of transmitting or receiving excess spillovers is heterogeneous across commodities and over time.

Third, we empirically investigate the impact of activities of specific types of financial traders on the observed excess spillovers from both the aspects of magnitude and direction, providing new evidence for financialization enhancing the integration of commodity markets. Although several recent papers have discussed relevance of financialization for cross-commodity linkages, direct evidence is limited. The studies mostly related to ours are Tang and Xiong (2012) and Le Pen and Sévi (2018). By examining the difference in correlations between indexed and off-index commodities, Tang and Xiong (2012) stress the importance of index trading in the increasing commodity price comovement. Le Pen and Sévi (2018) document time-varying excess comovement over the 1993–2013 period and find that speculative intensity is a driver of the estimated excess comovement. Focusing on concurrent correlations, those two papers only concern the impact of financial activity on the magnitude of cross-commodity linkages, but do not delve into the internal structure of the connectedness network. Within the framework of excess spillovers, we further explore the role of financial trading in determining the direction of cross-commodity linkages, analyzing the impact mechanism in more detail. Furthermore, in addition to overall speculators, our study differentiates between different types of financial

[2] Theoretically, the existence of excess comovement casts doubt on the standard competitive commodity price models and may imply that there are non-fundamental factors driving the joint behavior of commodity prices.

[3] For example, Pindyck and Rotemberg (1990) find strong evidence of excess comovement for the period 1960–1985 and attribute it to the herd behavior of commodity traders. Using univariate and multivariate GARCH models, Deb et al. (1996) only detect weak evidence of excess comovement for the periods 1960–1985 and 1974–1992. Ohashi and Okimoto (2016) document significant increasing long-run trends in commodity excess comovements since around 2000 based on the smooth-transition dynamic conditional correlation model. Le Pen and Sévi (2018) show that excess comovement only appears occasionally over the period 1993–2013 and is particularly high after 2007.

investors, emphasizing the possible roles of index traders as well as managed money traders. Hence, our work complements the two earlier studies by providing more informative and stronger evidence of the impact of financialization on cross-commodity linkages.

We find that the magnitude of excess spillovers is significantly positively related to the extent of participation by financial speculators generally and managed money traders as well as index traders especially. Particularly, for the past decade, the majority of observed excess spillovers can be attributed to the activities of managed money and index traders, whose explanatory power has been increasing in recent years. Moreover, their impacts tend to be amplified by financial stress. Turning to the direction of excess spillovers, our results show that commodity markets with higher degree of participation by managed money traders are more likely to be net transmitters of excess spillovers. In contrast, commodity markets with higher degree of participation by index traders are more likely to be net receivers of excess spillovers. Besides, our estimates provide evidence that in the short run managed money traders may be more important than index traders in driving excess spillovers, while the impact of index tradings seems to be more pronunced in the long run than in the short run. Overall, our analysis verifies that the continuing process of financialization contributes to the stronger cross-commodity connectedness. The increasing integration of commodity markets in recent years is the new normal led by financialization, rather than a temporary change caused by fundamentals. Moreover, our empirical findings highlight the different roles played by managed money traders and index traders in linking commodity markets.

The remainder of this paper is organized as follows. Section 2 introduces the methodology that quantifies cross-commodity excess spillovers. Section 3 presents our estimation results regarding the excess spillovers. In section 4, we examine the impact of financialization on excess spillovers, both in terms of magnitude and direction. Section 5 draws conclusions.

2. Methodology

In this paper, we define excess spillovers to be spillovers that are not driven by macroeconomic fundamentals. The modelling of excess spillovers involves the following three steps. First, a large approximate factor model is employed to extract common factors from a large dataset of economic variables. Second, commodity returns are regressed on the estimated factors to filter out the effects of common macroeconomic shocks. Third, the spillover index approach of Diebold and Yilmaz (2012, 2014) is utilized to quantify the connectedness across the regression residuals, which gives the final measures of excess spillovers.

2.1. *Estimating common factors*

The first issue in modelling excess spillovers is how to fully control for the effects of common macroeconomic shocks. To this end, we estimate factors that represent macroeconomic fundamentals using a large approximate factor model[4]. This method provides a parsimonious way to effectively capture information in a data rich environment, eliminating the arbitrariness and incompleteness in the selection of control variables.

Let *X* denotes a $T \times N$ panel of macroeconomic data, with $x_{i,t}$ being the *i*th cross-section unit at time *t* ($i = 1,...,N,\ t = 1,...,T$). Each $x_{i,t}$ is posited to have an approximate factor structure

$$x_{i,t} = \lambda_i' f_t + e_{i,t} \tag{1}$$

where f_t is an $r \times 1$ ($r \ll N$) vector of common factors, λ_i is an $r \times 1$ vector of factor loadings, and $e_{i,t}$ is the idiosyncratic error. None of the factors, their loadings and the idiosyncratic errors are observable. The large approximate factor model we consider differs from classical factor models in two main aspects[5]: (1) both

[4] See Bai and Ng (2008) for model details about the development of large approximate factor models.

[5] In classical factor models, *N* is fixed as *T* tends to infinity, and the factors and errors are assumed to be serially and cross-sectionally uncorrelated (Bai and Ng, 2008).

the cross-section dimension N and the time dimension T are large and converge to infinity in the asymptotic theory; (2) the idiosyncratic errors are allowed to be weakly correlated across i and t.

As shown in Bai and Ng (2002), the true factor space in a large N and large T environment can be consistently estimated by the method of asymptotic principal components. Formally, it estimates the factors and the corresponding loadings simultaneously by solving the optimization problem

$$\min_{\Lambda, f}(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t}-\lambda_i' f_t)^2 \tag{2}$$

where $\Lambda=(\lambda_1',...,\lambda_N')'$ is the $N\times r$ matrix of factor loadings and $f=(f_1,...,f_T)'$ is the $T\times r$ matrix of factors. Since f and Λ are not separately identifiable, the normalization $f'f/T=I_r$ is imposed to obtain a unique solution. As a result, the estimated factor matrix $\hat{f}$ equals $\sqrt{T}$ times the eigenvectors corresponding to the r largest eigenvalues of the $T\times T$ matrix XX', and the estimated factor loading matrix $\hat{\Lambda}$ equals $X\hat{f}/T$.

Following McCracken and Ng (2016), we use an adapted version of PCA which allows for missing values. This is essentially a combination of PCA with EM algorithm. First, the raw data are rebalanced by setting missing observations to the unconditional mean based on the non-missing values, and then are standardized to have zero means and unit variances. Second, the factors and loadings are estimated from this rebalanced and standardized panel using the principal components method described above. Third, the data are updated by replacing the original missing observations with the fitted values of the factor model (after undoing the standardization). After that, the updated data are standardized again from which the factors and loadings are re-estimated. The iteration continues until the factor estimates do not change.

Before estimating the factor model, the number of common factors is determined based on the IC_p criteria developed in Bai and Ng (2002). Let $S(k)=(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{i,t}-\hat{\lambda}_i^{k\prime}\hat{f}_t^{k})^2$ be the sum of squared residuals (divided by NT) when k factors are estimated, where k is not necessarily equal to the true number of factors r. The general form of Bai and Ng (2002)'s IC_p criteria is

$$IC_p(k)=\ln(S(k))+kg(N,T) \tag{3}$$

where $g(N,T)$ is a penalty function[6]. A consistent estimate of the true number of factors is obtained by minimizing the above criterion. Specifically, we choose $\frac{N+T}{NT}\ln C_{NT}^2$ where $C_{NT}=\min(\sqrt{N},\sqrt{T})$ to be the penalty term and the corresponding criterion is referred to as IC_{p2} in Bai and Ng (2002). As suggested by Bai and Ng (2008) and McCracken and Ng (2016), this penalty function has better finite sample properties and hence is more frequently used in empirical work.

2.2. *Filtering commodity returns*

The next step is to filter commodity returns based on the estimated factors. To account for the potential heteroskedasticity and non-normality in commodity price distributions, we model each return series of the M commodities using a factor-augmented regression (FAR) where the residual follows a GJR-GARCH (1,1) process with Student-t distribution. Specifically, the model used for filtering commodity returns takes the following form[7]

$$R_{i,t}=\delta_i+\rho_i R_{i,t-1}+\varphi_i'\hat{F}_t+u_{i,t} \qquad i=1,...,M,\ \ t=1,...,T \tag{4}$$

$$u_{i,t}=h_{i,t}^{1/2}z_{i,t} \tag{5}$$

$$h_{i,t}=\omega+\left(\alpha_i+\gamma_i I_{t-1}\right)u_{i,t-1}^2+\beta_i h_{i,t-1} \tag{6}$$

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[6] Three penalty functions are suggested by Bai and Ng (2002): $g_1(N,T)=\frac{N+T}{NT}\ln(\frac{NT}{N+T})$, $g_2(N,T)=\frac{N+T}{NT}\ln C_{NT}^2$, $g_3(N,T)=\ln C_{NT}^2/C_{NT}^2$ where $C_{NT}=\min(\sqrt{N},\sqrt{T})$.

[7] The one-period lagged return appears on the right side of equation (4) to account for the potential serial correlation in residuals (Pindyck and Rotemberg, 1990).

where $R_{i,t}$ denotes the log-return for commodity *i* at time *t*; $\hat{F}_t$ is a vector of generated regressors[8] consisting of subsets and/or functions of $\hat{f}_t$; δ_i is the constant term; φ_i is a vector of factor coefficients; $h_{i,t}$ denotes the conditional variance; $z_{i,t}$ is an i.i.d. random variable which is assumed to follow a standardized Student-*t* distribution with zero mean and unit variance; I_{t-1} is an indicator function that equals 1 when $u_{i,t-1} < 0$, and 0 otherwise; α_i, β_i and γ_i are the ARCH, GARCH and leverage effect parameters, respectively. Naturally, the regression residual $\hat{u}_{it}$ would then represent the filtered commodity returns that are not driven by macroeconomic fundamentals.

The use of $\hat{F}_t$ instead of $\hat{f}_t$ comes from the fact that factors that are pervasive for the large dataset are not necessarily important for explaining commodity returns. To determine the composition of $\hat{F}_t$ for each commodity, we search over a range of possible specifications using the BIC criterion as described in Ludvigson and Ng (2009). To be specific, in a first step, *r* univariate regressions of commodity returns on each of the *r* factors (together with the conditional variance equation) are estimated and only the significant ones are kept. Then different candidate sets of regressors are formed based on the selected factors as well as the squared and cubed terms of these factors, among which the one resulting in the lowest BIC is chosen to be the optimal $\hat{F}_t$ [9]. Note that if $\hat{F}_t$ is replaced with a common set of macroeconomic variables including CPI, industrial production, exchange rate, interest rate, money stock and stock index, then equation (4) becomes the conventional model used by Pindyck and Rotemberg (1990) and many other scholars (e.g., Deb et al., 1996; Ohashi and Okimoto, 2016) to filter commodity returns.

2.3. *Quantifying excess spillovers*

Once the effects of macroeconomic fundamentals are filtered out, we apply the spillover index approach of Diebold and Yilmaz (2012, 2014) to measure linkages in the filtered commodity returns (i.e., the residuals from the factor-augmented regression), which we call excess spillovers. Diebold and Yilmaz (2012, 2014) propose a simple and intuitive framework for measuring cross-market connectedness, based on variance decompositions in generalized vector autoregressions (VARs). This approach have several appealing virtues. First, it allows to quantify the intensity of cross-market linkages by distilling a wealth of information into a single measure. Second, it can reveal the direction of connectedness so as to further uncover the transmission mechanism. Finally, dynamics of connectedness can be traced continuously using rolling-window estimation. To be specific, we calculate the total spillover index as well as directional and net spillover indexes of Diebold and Yilmaz (2012, 2014), which are renamed as total excess spillover index, directional excess spillover index and net excess spillover index in this study to emphasize our idea of excess spillovers. Thus, applying the spillover index framework to the filtered commodity returns $\hat{u}_{it}$ allows us to extend the directionless excess comovement to excess spillovers, by which we can assess the magnitude, time-varying character and direction of the cross-commodity connectedness that cannot be attributed to macroeconomic fundamentals.

2.3.1. *Generalized variance decomposition*

The starting point is a p-order, M-variable VAR

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t \tag{7}$$

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[8] Conventionally, the use of generated regressors may introduce errors-in-variables bias, and standard errors of the second-step parameter estimates must be adjusted for the sampling error from first-step estimation. Under the assumption that $\sqrt{T}/N \to 0$ as $N,T \to \infty$, Bai and Ng (2008) demonstrate that no such adjustment is necessary for a FAR where the generated regressors are factors estimated by PCA.

[9] This allows commodity returns to be possibly nonlinear in the common factors.

where $y_t = \left(\hat{u}_{1,t},....,\hat{u}_{M,t}\right)'$ is a $M \times 1$ vector of residual returns, $\Phi_i (i=1,...,p)$ are $M \times M$ parameter matrices and ε_t is a $M \times 1$ vector of independently and identically distributed disturbances. By covariance stationary, model (7) has a moving average representation as $y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $M \times M$ coefficient matrices A_i are recursively defined as $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with $A_0 = I_M$ and $A_i = 0$ for $i < 0$.

In a generalized VAR framework where forecast error variance decompositions are invariant to the variable ordering, the *H*-step-ahead forecast error variance decomposition is computed as

$$\theta_{i,j}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{8}$$

where Σ denotes the variance matrix of ε_t, σ_{jj} is the standard deviation of the *j*th element in ε_t and e_i is a $M \times 1$ vector with the *i*th element being one and other elements being zeroes. Then $\theta_{i,j}(H)$ gives the fraction of the *H*-step-ahead forecast error variance of $\hat{u}_i$ due to shocks to $\hat{u}_j$. Since the sum of the own- and cross-variable variance contribution shares is not equal to one under the generalized variance decomposition, i.e., $\sum_{j=1}^{M} \theta_{i,j}(H) \neq 1$, each $\theta_{i,j}(H)$ is normalized as

$$\tilde{\theta}_{i,j}(H) = \frac{\theta_{i,j}(H)}{\sum_{j=1}^{M} \theta_{i,j}(H)} \tag{9}$$

with $\sum_{j=1}^{M} \tilde{\theta}_{i,j}(H) = 1$ and $\sum_{i,j=1}^{M} \tilde{\theta}_{i,j}(H) = M$ by construction.

2.3.2. *Total excess spillover*

Based on equation (9), a total excess spillover index measuring the degree of excess spillovers among commodities can be constructed

$$ES(H) = \frac{\sum_{i,j=1, i\neq j}^{M} \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^{M} \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{M} \tilde{\theta}_{i,j}(H)}{M} \times 100 \tag{10}$$

2.3.3. *Directional and net excess spillovers*

One salient feature of the Diebold-Yilmaz spillover index approach is that it allows a decomposition of spillover effects by source and recipient, revealing the direction of connectedness. Particularly, the directional excess spillovers received by commodity *i* from all other commodities *j* are calculated as

$$ES_{i\leftarrow}(H) = \frac{\sum_{j=1, j\neq i}^{M} \tilde{\theta}_{i,j}(H)}{\sum_{i,j=1}^{M} \tilde{\theta}_{i,j}(H)} \times 100 = \frac{\sum_{j=1, j\neq i}^{M} \tilde{\theta}_{i,j}(H)}{M} \times 100 \tag{11}$$

Similarly, the directional excess spillovers transmitted by commodity *i* to all other commodities *j* are defined as

$$ES_{i\to}(H)=\frac{\sum_{j=1,j\neq i}^{M}\tilde{\theta}_{j,i}(H)}{\sum_{i,j=1}^{M}\tilde{\theta}_{j,i}(H)}\times 100=\frac{\sum_{j=1,j\neq i}^{M}\tilde{\theta}_{j,i}(H)}{M}\times 100 \tag{12}$$

Then a net excess spillover index for commodity i can be obtained as

$$NES_i(H)=ES_{i\to}(H)-ES_{i\leftarrow}(H) \tag{13}$$

with a positive value indicating that commodity *i* is a net transmitter of excess spillovers and a negative value indicating that commodity *i* is a net receiver of excess spillovers.

3. Empirical analysis

3.1. *Data*

Our empirical work is based on two broad sets of data: one relates to commodity markets, and the other relates to macroeconomic fundaments. Since most economic indicators are available at a monthly frequency and due to the limited history of macro data on emerging countries, we use monthly observations from January 1997 to December 2016.

For commodity data, price series of 8 commodities are obtained from the IMF Primary Commodity Prices database. Our sample of commodities includes wheat, cotton, copper, crude oil, cocoa, sugar, lean hogs and gold. They are representatives of main commodity sectors, namely agriculture, energy, livestock, industrial metals and precious metals. The selection of commodities is guided by two criteria: (1) They should be largely *unrelated* in the sense that their cross-elasticities of demand and supply are close to zero, and henceforth are expected to move together only in response to common macroeconomic shocks (Pindyck and Rotemberg, 1990); (2) They should have data on trader positions in the corresponding futures markets. The first criterion is important for modelling excess spillovers; while the second criterion allows us to construct measures of financial investor activity and examine whether they can explain the variation in excess spillovers. Pindyck and Rotemberg (1990) and Deb et al. (1996) provide references for the first criterion, based on which we make further choice using the second criterion[10]. Commodity returns (in percent) are computed as the change in log prices $R_t = 100*\ln(P_t/P_{t-1})$.

To find common fundamentals explaining commodity returns, we collect 298 macroeconomic series from major developed and emerging countries. All the series are taken from Bloomberg and can be classified into 10 categories: labor market, domestic trade and consumption, industrial activity, housing market, international trade, prices, money and credit, interest rates, exchange rates, and stock market indices. A striking feature of our macroeconomic dataset is the inclusion of a wide range of countries which are important players in the world economy. Specifically, we select 185 variables from 8 developed countries including US, UK, Japan, Germany, Australia, France, Canada and Italy, and 113 variables from 9 emerging countries including China, Russia, India, Brazil, South Korea, Mexico, Indonesia, South Africa and Singapore. These countries are all large importers or exporters of commodities, and hence are expected to play an important role in shaping commodity prices. The raw macro data are transformed to ensure stationarity and standardized prior to the estimation of common factors. Moreover, outliers are removed from the transformed data and treated as missing values. Following McCracken and Ng (2016), we define an outlier as an observation that deviates from the sample median by more than ten interquartile ranges. A detailed description of our macroeconomic dataset is given in Table A1 in the Appendix.

[10] Pindyck and Rotemberg (1990) select 7 seemingly unrelated commodities: wheat, cotton, copper, gold, crude oil, lumber and cocoa. Deb et al. (1996) consider 9 commodities to be largely unrelated: cocoa, cotton, coffee, copper, gold, lead, maize, sugar, and wheat.

After losing two observations due to data transformation, the panel of data we use for factor analysis spans the period 1997:3–2016:12 with 238 time-series observations.

3.2. *Properties of the estimated factors*

According to Bai and Ng (2002)'s IC_{p2} criterion, the optimal number of common factors is 7. Table 1 shows summary statistics for the estimated factors $\hat{f}_t$ which are mutually orthogonal by construction. The autocorrelation coefficients indicate that the factors exhibit various degrees of persistence, with the second estimated factor (denoted $\hat{f}_2$) and the seventh estimated factor (denoted $\hat{f}_7$) being the most and the least persistent, respectively. The first 3 factors only explain about 21% of the total variation in the panel of macroeconomic data. The cumulative explanatory power increases to nearly 30% for 5 factors and reaches 36% for 7 factors.

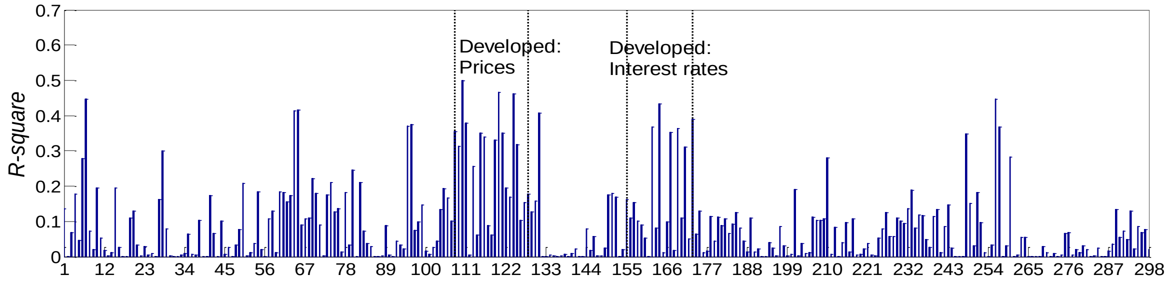
Table 1 Summary statistics for estimated factors

Factor *i*	ρ_1	ρ_2	ρ_3	R_i^2
1	0.800	0.651	0.516	0.094
2	0.958	0.927	0.893	0.160
3	-0.262	-0.167	0.401	0.212
4	0.559	0.422	0.479	0.259
5	0.675	0.561	0.580	0.296
6	0.357	0.180	0.180	0.327
7	-0.024	-0.008	0.040	0.355

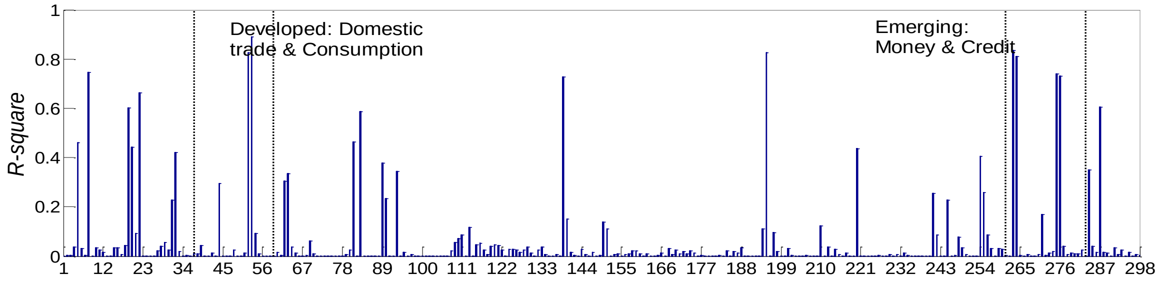
This table shows summary statistics for the estimated factors which are extracted by PCA from a panel of 298 monthly macroeconomic series over the period 1997:3–2016:12. The raw data are transformed (i.e., taken logs and differenced where appropriate) and standardized prior to estimation. ρ_1, ρ_2 and ρ_3 are the first-, second-, and third-order autocorrelation coefficients, respectively. R_i^2 denotes the cumulative explanatory power of the first *i* factors, which is calculated as the fraction of total variation in the data explained by factors 1 to *i*.

To give an economic interpretation to each estimated factor, we resort to the method suggested by Ludvigson and Ng (2009) which is based on the marginal R^2s. The statistics are obtained by regressing each of the 298 series in the macro dataset on the seven estimated factors, one at a time. The individual series are grouped into multiple categories by country type (i.e., developed and emerging countries) and economic sector and labeled with numbers as given in the Appendix. For a particular factor, the series with the highest R^2 are considered to represent the most relevant information captured by that factor.

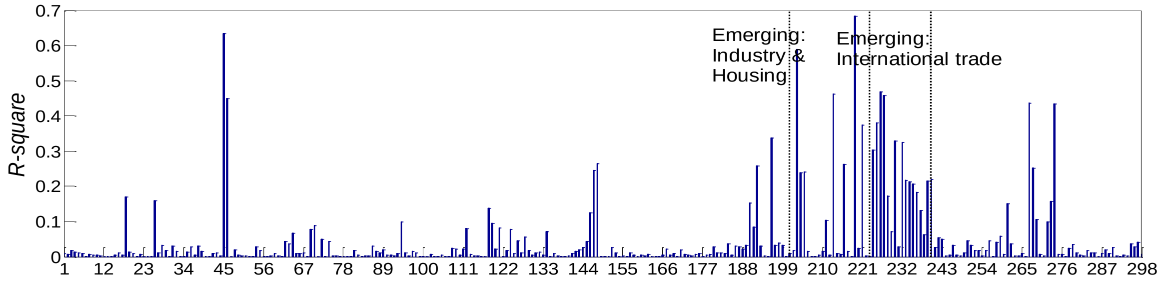
Figure 1 displays the marginal R^2s for the estimated factors $\hat{f}_i\,(i=1,...,7)$. The vertical axis is the R^2 statistic and the horizontal axis is the series number of each economic indicator. Evidently, $\hat{f}_1$ loads heavily on price indices of developed countries, explaining 50% of the variation in the US import price index and 47% of the variation in the German import price index, and also displays strong correlation with developed countries' interest rates such as the 3-month gilt repo rate of UK. Therefore, $\hat{f}_1$ can be interpreted as an *inflation factor*. The economic content of $\hat{f}_2$ is less clear. It has good explanatory power for domestic trade and consumption variables of developed countries (explaining 89% of the variation in French consumer spending), and is also highly correlated with money and credit variables of emerging countries (explaining 83% of the variation in Russian M_0). $\hat{f}_3$ loads predominantly on variables relating to industrial activity, housing market and international trade of emerging countries. Overall, $\hat{f}_3$ can be interpreted as a *real activity factor* mainly reflecting the strength of emerging economies. $\hat{f}_4$ loads most heavily on stock market indices of developed countries and hence can be viewed as a *stock market factor*. $\hat{f}_5$ is highly correlated with developed countries' labor market variables and hence is a *real activity factor* mainly reflecting the strength of developed economies. $\hat{f}_6$ is a global *real activity factor* that loads heavily on measures of industrial activity from both developed and emerging countries. $\hat{f}_7$ is strongly related to interest rates and exchange rates of developed countries. Table A2 in the Appendix lists the top 4 series with the highest R^2 for each factor.



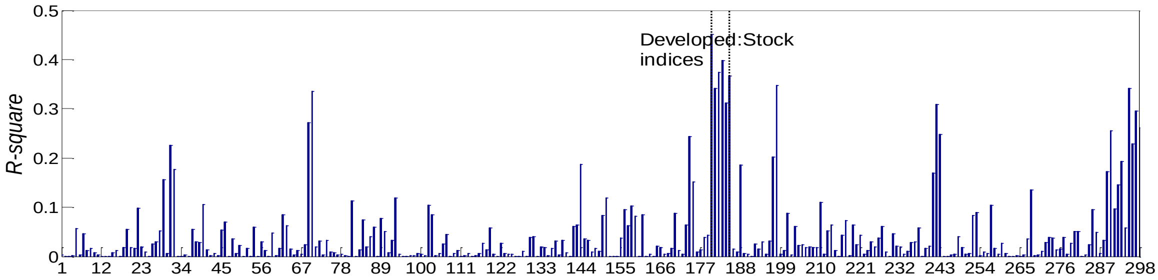
(a) Marginal R-squares for $\hat{f}_1$



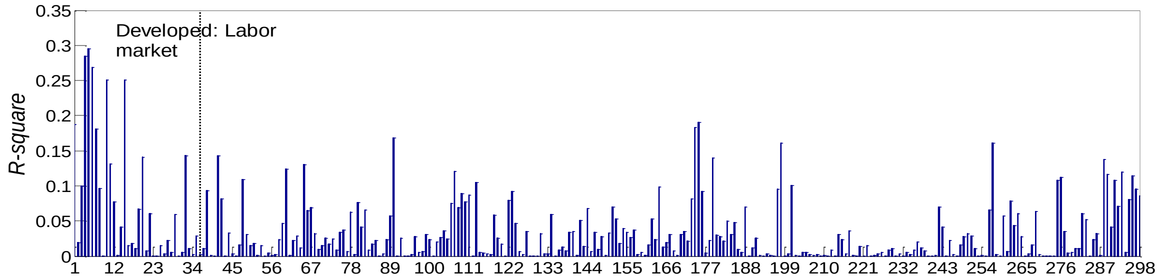
(b) Marginal R-squares for $\hat{f}_2$



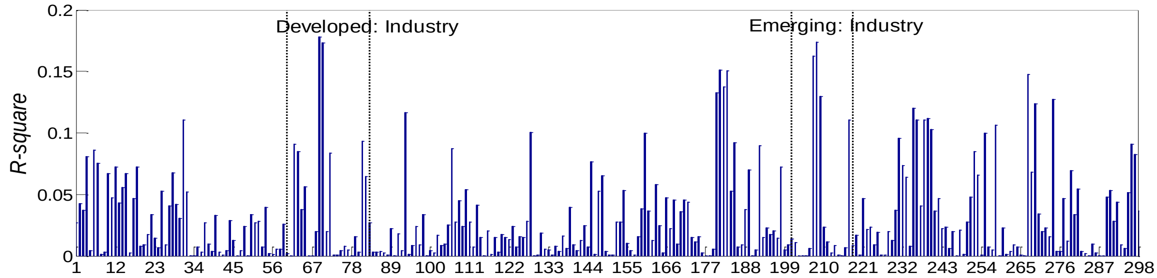
(c) Marginal R-squares for $\hat{f}_3$



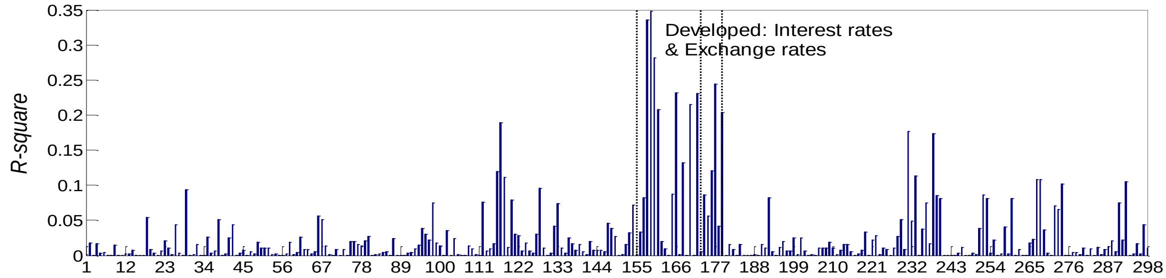
(d) Marginal R-squares for $\hat{f}_4$



(e) Marginal R-squares for $\hat{f}_5$



(f) Marginal *R*-squares for $\hat{f}_6$



(g) Marginal *R*-squares for $\hat{f}_7$

Figure 1 Marginal *R*-squares for estimated factors

This figure displays the R^2 statistics from regressing the series number given on the horizontal axis onto each estimated factors $\hat{f}_i (i = 1,...,7)$. Detailed information on the numbered series is given in Table A1 in the Appendix.

3.3. ***Fundamental drivers of commodity returns***

Table 2 reports estimation results for models used for filtering commodity returns with a general form given by equations (4)–(6). As mentioned earlier, we select the best model for each commodity from a range of specifications with different subsets of the estimated factors using the BIC criterion[11].

As can be seen from Table 2, $\hat{f}_5$ enters significantly in all regressions except the one for lean hogs, suggesting that real activity of developed countries tends to be the dominate fundamtal prices of different commodities. $\hat{f}_1$ appears in 5 regressions and is significant for wheat (agricultural), copper (base metals), crude oil (energy) and lean hogs (livestock), confirming the pervasive association between inflation and commodity prices. $\hat{f}_2$ is significant for cotton, copper, crude oil and gold. This agrees with the fact that cotton (as a raw material), copper (as an industrial input) and crude oil (as an energy source) are extensively involved in domestic trade and consumption activities of developed countries. While monetary and credit variables of emerging countries should be relevant for gold price. The correlation of $\hat{f}_4$ with copper and crude oil can be interpreted as evidence that these two commodity prices assume the same role of economic barometers as stock market indexes, corroborates the conclusions of Hu and Xiong (2013). Factors $\hat{f}_3$, $\hat{f}_6$ and $\hat{f}_7$ are less important in driving commodity prices, for they are only significant for one commodity, respectively. The connection between $\hat{f}_6$ and crude oil returns reinforces the importance of crude oil in global industrial activities. As shown by $\hat{f}_7$, developed countries' interest rates and exchanges rates have significant explanatory power for gold returns.

$\hat{f}_3$, which is highly correlated with industrial and international trade variables from emerging countries, is significant for cocoa. Interesting, prices of crude oil and copper, which are heavily imported by large emerging economies such as China, do not exhibit close relation with $\hat{f}_3$. This contrasts the findings of Le Pen and Sévi

[11] We also consider specifications including one-period lagged values of the factors and observe that the lagged factors only improve the explanatory power of the regressions slightly. In addition, a dummy variable which equals 0 before September 2008 and 1 afterwards is added to control for the potential structural changes led by the recent financial crisis. The dummy is found to be insignificant for most commodities except for lean hogs. Thus, we proceed with the specifications in Table 2.

(2018) who show that commodity returns are mainly correlated with real variables of emerging countries. Although emerging countries' soaring demand for industrial raw materials has been blamed for the surge in industrial commodity and oil prices since the early 2000s (Kilian, 2009; Kilian and Murphy, 2014), we find that real activity of emerging economies does not play a vital role in shaping international commodity prices once real factors of developed countries have been fully controlled. This corroborate the finding of Tang and Xiong (2012) who refutes growing demands from emerging economies as the prominent cause for the recent increase in cross-commodity correlations. Overall, our estimates suggest that aggregate demand from developed countries seem to be more important than that from emerging economies in driving commodity prices over the past fifteen years.

The GARCH parameter is significant and positive in all cases and the sum of GARCH and ARCH parameters is always smaller than unit, confirming that the conditional volatility processes are time-varying and stationary. With regards to the leverage effect, we only find significant GJR parameters for crude oil (negative) and lean hogs (positive). According to Silvennoinena and Thorp (2013), commodity price volatility may increase when prices are abnormally high due to stress on inventories and this is the case for crude oil which results in a negative GJR parameter. While the positive GJR parameter for lean hogs is consistent with the traditional view that higher volatility is linked to bear markets. To avoid overparameterization, we drop the GJR term and re-estimate a standard GARCH model for the rest 6 commodities.

Table 2 Estimation results for models used for filtering commodity returns

	Wheat	Cotton	Copper	Crude Oil	Cocoa	Sugar	Lean Hogs	Gold
AR(1)	0.061	0.349***	0.120**	-0.174***	0.207***	0.249***	0.124**	0.065
	(0.061)	(0.055)	(0.056)	(0.048)	(0.056)	(0.057)	(0.054)	(0.053)
$\hat{f}_1$	-1.430**	-0.596	-2.261***	-5.478***			-1.447***	
	(0.581)	(0.388)	(0.597)	(0.310)			(0.451)	
$\hat{f}_2$		0.579***	0.990***	1.563***				0.472***
		(0.189)	(0.302)	(0.338)				(0.148)
$\hat{f}_3$					0.695**			
					(0.342)			
$\hat{f}_4$			-1.906***	-2.004***				
			(0.441)	(0.365)				
$\hat{f}_5$	-1.130***	-0.508*	-1.623***	-2.748***	-1.171***	-0.951**		-1.009***
	(0.311)	(0.272)	(0.334)	(0.399)	(0.319)	(0.463)		(0.225)
$\hat{f}_5^2$	0.876**							
	(0.348)							
$\hat{f}_6$				-2.017***			-0.877	
				(0.268)			(0.561)	
$\hat{f}_7$								-1.043***
								(0.256)
ARCH	0.236**	0.265***	0.081**	0.238***	0.135***	0.088	-0.061***	0.094**
	(0.115)	(0.083)	(0.035)	(0.060)	(0.048)	(0.058)	(0.002)	(0.047)
GARCH	0.585***	0.590***	0.878***	0.186***	0.733***	0.810***	0.788***	0.721***
	(0.162)	(0.130)	(0.046)	(0.042)	(0.057)	(0.130)	(0.003)	(0.084)
GJR				-0.068**			0.320***	

				(0.028)			(0.012)	
Log-L	-768.492	-697.749	-695.658	-761.176	-736.895	-812.330	-865.125	-627.860
Q(5)	4.622	7.819	14.747	9.395	4.537	0.737	7.277	5.895
	[0.464]	[0.167]	[0.012]	[0.094]	[0.475]	[0.981]	[0.201]	[0.317]
$Q^2(5)$	2.813	4.818	3.424	0.626	10.947	5.874	6.902	1.947
	[0.729]	[0.439]	[0.635]	[0.987]	[0.052]	[0.319]	[0.228]	[0.856]

This table reports estimation results for the models used to filter commodity returns with a general form given by equations (4)–(6). The sample period is 1997:3–2016:12. Commodities are listed in the top row. Constants are always included in the mean and variance equations even though their estimates are not reported. Log-L is the value of log-likelihood function. Q(5) and $Q^2(5)$ are the Ljung–Box tests at lag 5 for standardized residuals and squared standardized residuals with p-values in square brackets. The values in parentheses are Newey-West standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 presents the simple correlations of commodity returns. Coefficients above the diagonal relate to the unfiltered returns while coefficients below the diagonal relate to the filtered returns (i.e., the residuals from the regressions in Table 2). For the raw return series, 22 (18) out of the 28 pairwise coefficients are significant at the 10% (5%) level, ranging from 0.487 (copper–oil) to 0.109 (copper–lean hogs). Both the number and magnitudes of significant correlations are larger than those observed by Pindyck and Rotemberg (1990) for the period 1960–1985. It can be inferred that correlations between commodities have increased through time. As expected, the correlations reduce substantially after accounting for the impacts of macroeconomic fundaments. Nonetheless, for the filtered returns, there are still 7 (5) correlations significant at the 10% (5%) level, with a maximum of 0.242 (gold-copper) and a minimum of 0.123 (cocoa-wheat). Moreover, the magnitudes and significance levels of filtered return correlations are much lower than those documented in Le Pen and Sévi (2018) for the period 1993–2013. Given that our set of economic variables is significantly larger than theirs, this highlights the importance of thoroughly controlling for fundamental information in modelling excess comovement.

Table 3 Simple correlations of unfiltered and filtered commodity returns

	Wheat	Cotton	Copper	Oil	Cocoa	Sugar	LH	Gold
Wheat	1	0.180***	0.237***	0.171***	0.184***	0.242***	0.086	0.155**
Cotton	0.096	1	0.248***	0.242***	0.113*	0.154**	0.040	0.041
Copper	0.142**	0.040	1	0.487***	0.150**	0.210***	0.109*	0.295***
Oil	0.100	0.000	0.076	1	0.118*	0.132**	0.127*	0.137**
Cocoa	0.123*	0.039	0.058	0.052	1	0.229***	-0.010	0.217***
Sugar	0.231***	0.086	0.125*	0.064	0.191***	1	-0.053	0.173***
LH	0.079	-0.021	0.008	0.028	-0.009	-0.027	1	-0.011
Gold	0.065	-0.027	0.242***	0.013	0.161**	0.085	-0.038	1
		Filtered $\chi^2(28)$ = 61.240* **				**Unfiltered $\chi^2(28)$ = 185.052*** **		

This table shows the simple correlations in commodity returns for the period April 1997–December 2016. Coefficients above the diagonal relate to the unfiltered returns while coefficients below the diagonal relate to the filtered returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Since our main interest is the significance of correlations as a group, like in Pindyck and Rotemberg (1990), we perform a likelihood ratio test against the hypothesis that the correlation matrix is equal to the identity matrix. The test statistics is $-2\log(|R|^{N/2})$, which is distributed as χ^2 with $(1/2)M(M-1)$ degrees of freedom, where $|R|$ is the determinant of the correlation matrix, N is the sample size and M is the number of commodities. The

χ^2 statistic related to the raw returns is 185.052 and significant at the 1% level, rejecting the null that the 8 commodities in our sample are uncorrelated. For the filtered returns, the χ^2 statistic is 61.240, smaller than that for the raw returns, but is still highly significant at the 1% level, confirming the existence of excess comovement.

The standard framework of excess comovement focuses on the strength of contemporaneous correlation among filtered commodity returns (Pindyck and Rotemberg, 1990; Deb et al., 1996; Ohashi and Okimoto, 2016; Le Pen and Sévi, 2018). However, connectedness can occur not only in the form of concurrent association, but also in the form of dynamic interdependence[12]. For illustration, Table 4 briefly shows the cross-correlation matrices of filtered commodity returns at lags 1, 2 and 4. The (*i*, *j*)th element of the lag-*l* cross-correlation matrix is the correlation coefficient between $\hat{u}_{it}$ and $\hat{u}_{j,t-l}$. The figures in bold are the coefficients whose absolute values are greater than those of the corresponding concurrent correlation coefficients between the same pairs of commodities (as presented in Table 3). For example, the cross-correlation between one-period lagged filtered returns of wheat and current filtered returns of cotton is 0.173, significantly larger than the contemporaneous wheat-cotton correlation (0.096). It can be seen from Table 4 that for a number of commodity pairs, the dynamic linear dependence is of greater size than the concurrent correlation, indicating that there is valuable connectedness information that will not be detected in the framework of excess comovement.

Table 4 Cross-correlations of filtered commodity returns at lags 1, 2 and 4

	Wheat	Cotton	Copper	Oil	Cocoa	Sugar	LH	Gold
				Lag 1				
Wheat	0.167	0.012	-0.010	0.057	0.084	0.002	-0.040	0.055
Cotton	**0.173**	0.070	0.006	**-0.043**	**0.071**	0.060	**0.035**	-0.022
Copper	0.047	-0.023	0.117	-0.020	**0.086**	0.052	**-0.013**	-0.023
Oil	**-0.104**	**0.001**	0.011	0.139	**-0.060**	-0.002	**0.082**	**0.052**
Cocoa	0.079	**0.042**	-0.046	0.047	0.034	0.087	**0.073**	-0.030
Sugar	0.025	**0.092**	0.031	0.051	0.007	-0.001	0.001	0.047
LH	**-0.130**	**0.028**	**0.090**	0.015	**-0.030**	**-0.123**	0.003	0.023
Gold	**0.108**	**0.058**	-0.029	0.002	0.131	**0.117**	-0.029	-0.020
				Lag 2				
Wheat	-0.034	0.064	0.032	0.027	-0.003	-0.002	**-0.098**	-0.015
Cotton	**0.115**	-0.094	**0.078**	**0.004**	-0.014	0.027	**-0.024**	**0.071**
Copper	0.031	-0.011	-0.098	**-0.090**	0.000	0.066	**-0.025**	0.027
Oil	0.025	**0.038**	**0.096**	-0.021	0.023	0.042	**0.082**	**-0.055**
Cocoa	-0.042	**0.072**	**0.077**	-0.047	-0.119	-0.016	**0.036**	0.033
Sugar	0.034	**-0.147**	0.040	**0.084**	-0.039	0.073	0.019	-0.006
LH	-0.032	-0.021	**-0.090**	**-0.181**	**-0.030**	**-0.058**	-0.168	**-0.040**
Gold	-0.008	**0.074**	-0.071	**-0.087**	-0.156	-0.013	**0.040**	-0.142
				Lag 4				
Wheat	-0.028	-0.046	0.012	-0.094	-0.029	-0.124	0.030	-0.009

[12] This notion has been stressed by several scholars. For instance, Chevallier and Ielpo (2013) point out that "observing a low correlation between commodity markets does not imply necessarily that there are no dynamic cross-asset linkages". Adams and Glück (2015) emphasize that "the interconnectedness between stocks and commodities can occur in the form of comovement and/or spillovers".

Cotton	-0.029	0.078	0.038	**0.022**	**0.067**	-0.023	**-0.072**	**0.071**
Copper	-0.065	0.038	-0.030	**0.113**	0.020	0.050	**-0.014**	0.092
Oil	0.048	**-0.009**	-0.035	-0.065	**0.054**	**0.066**	**-0.042**	**0.067**
Cocoa	0.101	0.012	-0.023	0.039	0.021	0.022	**-0.082**	-0.091
Sugar	-0.032	**0.118**	-0.002	**0.095**	0.002	0.016	**0.142**	-0.059
LH	0.051	**0.057**	**0.056**	**0.048**	**-0.054**	**-0.092**	0.006	**0.082**
Gold	**0.086**	**-0.102**	-0.129	**0.020**	0.147	**0.089**	**-0.087**	0.083

This table shows the cross-correlations of filtered commodity returns for the period April 1997–December 2016. The (i, j)th element of the lag-l cross-correlation matrix is the correlation coefficient between $\hat{u}_{it}$ and $\hat{u}_{j,t-1}$. The figures in bold are the coefficients whose absolute values are greater than those of the corresponding concurrent correlation coefficients between the same pairs of commodities.

Overall, the correlation estimates provide preliminary evidence that cross-commodity linkages exist even after accounting for common economic effects. However, the cross-correlation matrices have several limitations. First, it is difficult to read information effectively from so many coefficients, especially when our commodity dimension is as large as 8. Second, they measure only pairwise relationships, giving incomplete information regarding the systemwide connectedness. In what follows, we turn to excess spillovers which model the dynamic cross-commodity linkages as a system and hence are more informative and straightforward than the correlation-based measures.

3.4. Estimation results for *excess spillovers*

This subsection presents the estimation results for excess spillovers. Given that dependence structures both across commodities and between commodities and other asset classes have undergone structural changes during the process of financialization and/or in the severe financial crisis of 2007–2009 (Tang and Xiong, 2012; Adams and Glück, 2015), it is inappropriate to conduct analysis in a static full-sample framework. Besides, identifying the dynamic nature of excess spillovers is essential for our study, since we try to explain it by exploring the role of financialization. For these reasons, we estimate model (7) using rolling samples. In particular, we use a second-order VAR with 10-step-ahead forecasts and 60-month rolling windows[13].

3.4.1. *Total excess spillover index*

Figure 2 presents the total excess spillover index. On average, 35.24% of the forecast error variance in all 8 filtered returns comes from spillovers, indicating that there is significant connectedness among commodities that cannot be attributed to macroeconomic fundamentals. Clearly, this form of linkages is unlikely to be fully detected through correlations which only deal with pairwise contemporaneous relations. Furthermore, the intensity of excess spillovers varied substantially over the period May 2002 to December 2016[14], ranging from 26.79% to 40.98%. After hitting the bottom in February 2004, the index started a deep upward movement, just in parallel with the onset of financialization (Tang and Xiong, 2012). It then peaked in October 2008, coincided with the most severe phase of the global financial crisis, and fluctuated above 38% in the following two years until 2010. After that, it generally experienced large swings, with two significant jumps in in July 2012 (39.69%) and March 2015 (40.90%).

[13] To check for the robustness of our spillover estimates, we also considered different forecast horizons (from 4 to 10 months), different rolling window widths (48 and 72), and different VAR orders (from 2 to 4). Results are qualitatively similar and shown in Figure A1 in the Appendix.

[14] The original sample of residual returns is from April 1997 to December 2016. Then, the rolling window and lag lengths in VARs lead to discarding the first 62 months. Consequently, the estimated excess spillovers span the period of May 2002 to December 2016.

When we examine the evolution of the total excess spillover index in economic perspective, three key observations emerge.

First, there was a sizeable degree of cross-commodity connectedness that is irrelevant to macroeconomic fundamentals during 2004–2008. The synchronized rise and fall in prices of seemingly unrelated commodities in that period has attracted increasing attention from academics and policymakers. One popular view is that it was driven by economic fundamentals, especially aggregate demand from emerging countries, while had little to do with financial speculation (e.g., Kilian and Murphy, 2014). Our findings do not support this argument. As shown in Figure 2, the intensity of excess spillovers was high on average and increased generally over the 2004–2008 period. Yet there is little reason to believe that the boom-bust commodity price cycle was solely driven by macroeconomic shocks.

Second, the total excess spillover index reached its peak during the 2007–2009 financial crisis. Thus it is tempting to view the excess spillover effects as a phenomenon of financial turmoil. One convincing explanation is the "liquidity spiral" theory of Brunnermeier and Pedersen (2009), which states that deteriorating funding conditions during crisis periods will reduce financial investors' liquidity provision in all markets and hence cause substantial rises in comovement across multiple assets, irrespective of whether or not they are related by economic fundamentals. Another similar argument is the wealth effect of Kyle and Xiong (2001), which emphasizes that reduced risk appetite due to large losses incurred in one market may cause liquidation across several markets. As a result, cross-market linkages will intensify in turbulence times. Nevertheless, financial stress alone seems to be insufficient for the whole story. A common implication of the liquidity spiral and the wealth effect theories is that market interdependence is expected to revert to its pre-crisis level after 2009. However, our results show strong excess spillovers among commodities even during tranquil times. Although the total excess spillover index exhibits a moderate decline with the end of the global financial crisis, it is still above its pre-crisis average and remains high in the following years, almost reaching the crisis level in the more recent period of 2015—2016. Besides, the increase in excess spillovers emerged as early as 2004 which is well before the recent financial crisis, corroborating with the findings of Tang and Xiong (2012), Charlot et al. (2016) and Pradhananga (2016).

Third, as mentioned above, the beginning of the index's upward trend in 2004 is just the time when investment flows into commodity markets surged, initiating the process of financialization. Characterized by the inceasing involvement of financial institutions, the process of financialization has led to a fundamental change in the compositon of commodity market participants over the past decade. Institutional investors who previously concentrated in traditional financial markets have dramatically increased their engagement in commodity markets, particularly through direct or indirect investment in commodity futures. It is plausible that their trading strategies in different commodity markets are interdependent and hence influnence the way commodities are linked to each other. Taken together, it is reasonable to hypothesize that financialization is the key source behind the cross-commodity excess spillovers whose effect is amplified by financial turbulence[15]

[15] In a sense, the effects of financial crisis on the excess spillovers are also a reflection of financialization. If commodities were not held as a typical financial asset in investors' portfolios, the "loss spiral" theory would not apply and we would not expect a crisis outside to have any significant effect on commodity markets.

Figure 2 Total excess spillover index

3.4.2. *Directional and Net excess spillovers*

Having assessed the degree and the time evolution of excess spillovers via the total excess spillover index, we now explore the direction of spillover transmission using the directional and net excess spillover indexes.

Table 4 reports summary statistics for directional excess spillover indexes. The columns labelled "From" and "To" give the directional excess spillovers From ($ES_{i\rightarrow}$) and To ($ES_{i\leftarrow}$) a specific commodity, respectively. As with the total index, these directional indexes vary greatly over time (as shown by their standard deviations, maximum and minimum values). Besides, they behave rather heterogeneously across commodities. As for the "From" directional spillovers, the average degree of excess spillovers from wheat to all others is the largest (44.74%), followed by copper (43.39%), while the average value of excess spillovers from cocoa is the smallest (28.97%). At the other end of the spectrum, the average degree of excess spillovers from all others to gold is the largest (37.10%), followed by copper (36.76%), while the average value of excess spillovers received by cotton is the smallest (32.89%).

Table 5 Summary statistics for directional excess spillovers

	Wheat		Cotton		Copper		Crude Oil	
	From	To	From	To	From	To	From	To
Mean	44.74	34.41	31.90	32.89	43.39	36.76	30.43	34.32
Median	43.80	34.40	32.12	32.71	44.07	37.98	28.94	34.03
Max	68.80	47.41	50.42	47.60	67.22	48.11	59.98	47.25
Min	18.47	26.12	19.09	21.55	19.79	17.54	15.32	15.42
Std. dev.	12.94	4.20	6.62	5.27	10.34	6.26	9.72	6.90
	Cocoa		Sugar		Lean Hogs		Gold	
	From	To	From	To	From	To	From	To
Mean	28.97	36.00	37.22	34.61	31.16	35.82	34.10	37.10
Median	28.49	36.00	37.61	34.52	30.41	34.04	31.02	37.95
Max	48.77	46.99	69.19	51.93	55.24	58.75	66.75	53.49
Min	13.34	24.66	14.29	18.53	14.54	21.45	12.90	20.53
Std. dev.	8.21	4.72	13.98	8.10	9.02	7.53	12.68	8.41

This table reports the summary statistics for the directional excess spillovers over the period May 2002–December 2016. The columns labelled "From" and "To" give the directional excess spillovers From ($ES_{i\rightarrow}$) and To ($ES_{i\leftarrow}$) a specific commodity, respectively.

Figure 3 displays the net excess spillover indexes which more clearly uncover the transmission mechanism. Values in the positive domain indicate that the commodity is a net transmitter of excess spillovers and values in the negative domain are associated with a net receiver role.

Until mid-2005, wheat was a moderate net transmitter, and then switched to a net receiver until mid-2008. Over the same period, the case was reversed for gold, with its role shifting from a net receiver to a net transmitter. However, things changed substantially after mid-2008. The net excess spillovers from wheat stayed positive until the end of 2016, reaching as high as 37.70% in October 2011. Therefore, the net transmitting power of wheat is more persistent that what can be explained by the effect of the 2007–2009 financial crisis alone, implying again that there must be other dominant forces driving the excess spillovers which we hypothesis to be financialization. While for gold, it acted as an efficient net receiver from August 2010 to May 2013, but the net excess spillovers were weak for other parts of the post-crisis period.

Copper behaved as a strong net transmitter for most of the time (with the exceptions of July 2004–May 2005, November 2005–March 2006 and June 2011–December 2012), while cocoa was predominantly a receiver over the whole time span (with the exceptions of July 2008–March 2009 and September 2012–January 2013). For crude oil, there are two major episodes of net excess spillovers taking place: the first was from mid-2002 to the first half of 2004 when it was a net transmitter and the second was from mid-2009 to the end of 2016 when it was a net receiver.

Net excess spillovers from lean hogs tend to be more volatile than those from other commodities, fluctuating around -30% during the period 2002–2003, changing to positive and staying around 20% until 2006. During the market distress period of 2008 and the more recent period of 2014–2016, lean hogs generally received substantial net excess spillovers from all others. Cotton and sugar were relatively moderate in transmitting and receiving net excess spillovers and frequently switched roles before 2012. But after 2012, they exhibited significant and persistent abilities in giving (sugar) or receiving (cotton) spillovers.

Generally, three conclusions can be reached. First, none of the commodities investigated was always a net transmitter or a net receiver of excess spillovers throughout the sample period. In fact, the transmitting or receiving ability is heterogeneous across commodities and over time. Second, the 2008 financial crisis triggers spikes in net excess spillovers from two markets (wheat and copper), changes the role of cocoa temporarily and brings considerable shocks to lean hogs, while causing nothing special for others. Apparently, financial turmoil may have played a role but cannot be the sole engine in the transmission of excess spillovers. Third, net excess spillovers are of large magnitude throughout the post-crisis period. Particularly, commodities such as copper and sugar even exhibit stronger transmitting power in the more recent period of 2012–2016. This is just in line with the increasing back-flow of institutional investors in those markets, further advocating for the dominant role of financialization in creating the transmission channel for excess spillovers.

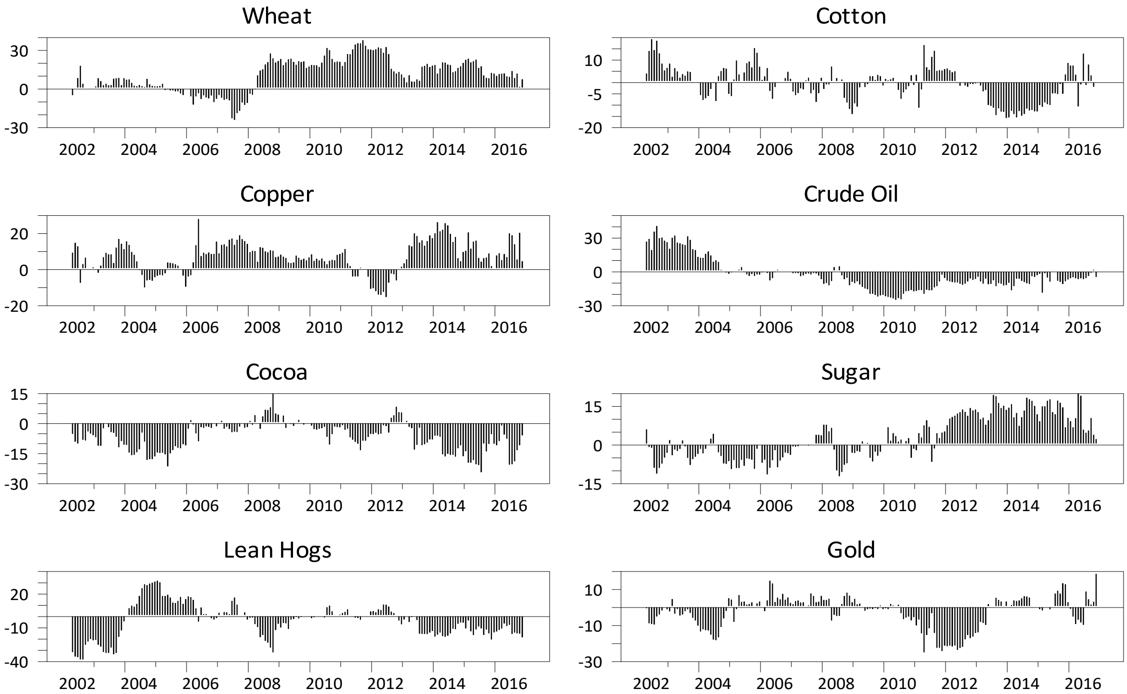


Figure 3 Net excess spillovers

4. Financialization and excess spillovers

Having documented that there are considerable spillovers among unrelated commodites that cannot be explained by macroeconomic fundamentals, and having established prima facie evidence on the potential role of financialization, we now directly examine the relevance of financialization for excess spillovers. Section 4.1 introduces our measures of financial trading activity in commodity markets. Then we use regression analysis to explore the impact of financialization on excess spillovers. Specifically, the analysis proceeds in two steps. Section 4.2 focuses on the magnitude of excess spillovers using the total excess spillover index. Section 4.3 deals with the direction of spillover transmission using the net excess spillover indexes.

4.1. *Measuring financial trading activity*

4.1.1. *Overall speculative activity*

We employ Working (1960)'s T index to gauge the extent of overall speculative activity in commodity markets. This index is widely used to measure the degree of "excess speculation" in commodity markets and has been adopted by many studies on financialization. Specifically, it quantifies the extent to which speculative positions exceed the level that is minimally necessary to satisfy net hedging needs at the market-clearing price. Büyükşahin and Robe (2014) present emprical evidence that Woking's T effectively captures the role of financial speculators in linking commmodity and equity markets. Bruno et al. (2016) further illustrate the usefulness of Working's T for reflecting the relative importance of financial institutions in commodity markets and apply it to examine the effect of financialization on commodity-equity linkages[16]. Formally, using data from the Commodity Futures Trading Commission (CFTC)'s Commitments of Traders (COT) report[17], Working's T index for the *i*th

[16] See Bruno et al. (2016) for a detailed discussion of the rationale for using Working's T as a proxy for financialization of commodity markets.

[17] The legacy COT report classifies reportable traders into two groups: commercials who are commonly considered as hedgers, and non-commercials who are referred to as speculators. Particularly, non-commercial traders include various types of mostly financial traders, such as managed money traders, floor brokers and traders and other on-commercial traders not registered as managed money traders.

commodity market at time t is calculated as

$$T_{i,t} = \begin{cases} 1 + \dfrac{NCS_{i,t}}{CL_{i,t} + CS_{i,t}} & if\, CS_{i,t} \geq CL_{i,t} \\ 1 + \dfrac{NCL_{i,t}}{CL_{i,t} + CS_{i,t}} & if\, CL_{i,t} > CS_{i,t} \end{cases} \tag{14}$$

where $NCS_{i,t}$ and $NCL_{i,t}$ are short and long positions held by non-commercial traders (speculators) in the *i*th commodity market at time *t*, respectively; $CS_{i,t}$ and $CL_{i,t}$ are short and long positions held by commercial traders (hedgers), respectively.

Particularly, Working's T index is calculated for each of the 8 commodities in our sample. Then, to provide a holistic picture of speculative activity across all commodity markets, we compute the aggregate T index (*Tindex*) as an equally weighted average of the individual T values.

4.1.2. *Activities of managed money traders and commodity index traders*

While Working's T is useful in capturing the intensity of overall speculative activity, it aggregates all non-commercials as a whole. Generally, two types of investors have increased their participation in commodity markets most dramatically during the financialization process: managed money traders (MMTs) and commodity index traders (CITs) (Büyükşahin and Robe, 2014; Girardi, 2015; Bruno et al., 2016).

MMTs, who are mostly hedge funds, typically follow active strategies and make extensive use of leverage; while CITs, who gain exposure to a particular commodity index mainly through contracts with swap dealers, tend to use passive strategies and invest in a larger scale (Cheng et al., 2015; Girardi, 2015). It is plausible that they play different roles in the transmission mechanism of excess spillovers. When investigating the impact of financial activity on cross-market linkages, only limited studies differentiate between these two specific types of investors[18]. Büyükşahin and Robe (2014) document that hedge funds (i.e., managed money traders)' activity significantly impacts long-term fluctuations in commodity-equity correlations, while index traders' activity seems exert no such effect. Girardi (2015) report that money managers are more important than index traders in transmitting financial shocks into agricultural markets in the short run, but the effect of commodity index traders appears to be greater in the long run than in the short run.

Motivated by these studies, we proceed to further distinguish between these two types of investors. The legacy COT report combines MMTs with other groups of financial traders in the broad category of non-commercials. Moreover, it classifies swap dealers whose positions represent CIT activity to a large extent and are often used as a proxy for index investment (Sanders and Irwin, 2011; Büyükşahin and Harris, 2011; Büyükşahin and Robe, 2014; Cheng et al., 2015) as commercials. Given this, the COT report and hence Working's T index is insufficient for our purpose of disentangling the effects of MMTs and CITS. Since September 2009, the CFTC began publishing the Disaggregated Commitments of Traders (DCOT) report as a supplement to the COT data. In the DCOT data, which are now available after June 2006, the reportable positions are broken down into four groups: managed money, swap dealers, processors and merchants, as well as other reportables. Therefore, we rely on the DCOT data to explicitly obtain MMT positions, and to proxy CIT positions by swap dealer positions as numerous studies do[19].

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[18] Others either view financial speculators as a whole using the legacy COT data (e.g.,Solvennoinen and Thorp, 2013; Bruno et al, 2016), or focus on the role of commodity index traders (e.g., Tang and Xiong, 2012; Adams and Glück, 2015).

[19] There are alternative sources provided by the CFTC in which CITs positions are explicitly reported: the Supplemental Commitments of Traders (SCOT) report and the Index Investment Data (IID) report. The SCOT report only covers agricultural commodities and lacks disaggregated categories for managed money and commercial hedgers. The IID data are only available on a quarterly (monthly) basis since 2008(2010) and thus severely restrain the sample size. There is also a handful of studies, including Büyükşahin and Harris (2011), Büyükşahin and Robe (2014) and Cheng et al. (2015), utilize the CFTC's non-public trader-level

Following Büyükşahin and Robe (2014) and Girardi (2015), we gauge the extent of participation for a given trader type by its market share: $\left(L_{i,type}+S_{i,type}+2SP_{i,type})\right)/2TOI_i$, where $L_{i,type}, S_{i,type}, SP_{i,type}$ stand for long, short and spreading positions held by that specific trader type in the *i*th commodity market[20], respectively and TOI_i is the total open interest. Again, we obtain the aggregate activity measure related to each trader type by averaging its commodity-specific market shares with equal weights. To be specific, we compute the aggregate market shares of managed money traders (*MMT*) and commodity index traders (*CIT*) (as well as processors and merchants (*PM*)), respectively.

4.2. *Impact of financializaiton on excess spillovers: magnitude*

In what follows, we draw on a time-series framework to test empirically the impact of financialization on the magnitude of excess spillovers. In this context, we focus on the total excess spillover index. First, we examine whether and how financial activity affects the excess spillover intensity from a long-term and overall perspective using an autoregressive distributed lag (ARDL) model. Next, we supplement the ARDL results with a short-run multivariate regression analysis showing further evidence supporting the role of financialization in explaining the observed excess spillovers.

4.2.1. *Long-run analysis*

An ARDL model provides consistent estimators of long-run coefficients by including lags of both the dependent and explanatory variables in the least squares regression. With the aim of explaining excess spillovers in terms of magnitude, we use the total excess spillover index as the dependent variable

$$ES_t=\alpha+\sum_{i=1}^{p}\gamma_i ES_{t\text{-}i}+\sum_{j=1}^{k}\sum_{i=1}^{q_j}\beta_{j,i}x_{j,t\text{-}i}+\varepsilon_t \tag{15}$$

where ES_t is the total excess spillover index at time *t*, $x_{j,t\text{-}i}$ is the *j*th explanatory variable at time *t-i*, *p* and q_j are the number of lags of the dependent variable and the *j*th explanatory variable, respectively. Then the estimate of the long-run coefficient for x_j is $\hat{\theta}_i=\sum_{i=1}^{q_j}\hat{\beta}_{j,i}\Big/(1-\sum_{i=1}^{p}\hat{\gamma}_i)$.

The main regressors are the aggregate financial activity variables. To identify the effect of financial turmoil, we also include an indicator of financial stress and its interactions with the financial activity variables. Specifically, we use the Kansas City Financial Stress Index, denoted *FS*, as a proxy for financial turmoil. It is constructed from 11 financial variables such as TED spread and VIX, and is released on a monthly basis by the Federal Reserve Bank of Kansas City. Since the US financial market conditions reflect, to a significant degree, the overall conditions in global financial market, *FS* provides a good measure of systemic risk in global financial markets (Chen et al., 2014). The total excess spillover index is stationary according to the ADF tests, validating the use of the ARDL model. Following Pesaran et al. (2001), we use the AIC criterion to select the optimal lag orders.

Table 6 summarizes the estimation results in which all coefficients are standardized. In Panel A of Table 6, we use the aggregate T index (*Tindex*) derived from the legacy COT data as the financial activity variable. By doing so, we preliminarily test for the impact of overall speculative activity over the longer period of May 2002–December 2016.

Column (1) applies to the baseline specification that includes *FS*, *Tindex*, and the interaction term *Tindex*FS*

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data that provide a more-detailed classification of trader types as well as contract-specific information. Absent access to that confidential information, this paper relies on the public CFTC data. Empirical evidence shows that data from the public COT and DCOT reports can provide effective information with respect to the very types of traders in which we are interested, namely, managed money traders and index traders (Sanders and Irwin, 2011; Büyükşahin and Robe, 2014; Cheng et al., 2015). Besides, using data from the COT and DCOT reports makes our results comparable to numerous studies that rely on the public CFTC data.

[20] For processors and merchants, the numerator is the sum of long and short positions since they do not hold spreading positions.

as the explanatory variables. The total excess spillover is positively related to *FS*, consistent with the prediction of the liquidity spiral as well as the wealth effect arguments that cross-asset connectedness strengthens in turmoil times. Crucially, the coefficient for *Tindex* is positive and significant. Therefore, greater intensity of financial speculation is associated with higher excess spillovers and this relationship is not swamped by the effect of financial stress in the long run. The sign of the interaction term *Tindex*FS* is also positive, indicating that the impact of speculative activity gets stronger during periods of financial turmoil, but this amplifying effect is statistically insignificant. In column (2), we add a time dummy (*DUM*) that equals 1 for the period July 2007–December 2009 and 0 otherwise[21], to account for the possibility that the recent global financial crisis is different from earlier episodes of financial stress (Büyükşahin and Robe, 2014). The time dummy is found to be redundant once we have controlled for financial market conditions using *FS*.

In Panel B of Table 6, we replace the aggregate T index with the aggregate market shares of managed money traders (*MMT*) and commodity index traders (*CIT*) derived from the DCOT data. As previously pointed out, the use of the DCOT data allows us to disentangle the effects of different financial investors at the expense of restricting our analysis to the relatively shorter period of June 2006–December 2016.

Column (3) shows the basic specification that include *FS*, *MMT*, *MMT*FS*, *CIT* and *CIT*FS* as the explanatory variables, where *MMT*FS* and *CIT*FS* are interactions between market share variables and the financial stress index. Both the coefficients for *MMT* and *CIT* are positive and significant. To wit, excess spillovers tend to raise amid greater participation of either or both MMTs and CITs. Besides, their trading activities also enhance the transmission channel of financial shocks into commodity markets, as evidenced by the positive and significant interaction terms *MMT*FS* and *CIT*FS*. The coefficient for *FS*, though consistently positive, becomes insignificant when we explicitly consider the activities of MMTs and CITs. This suggests that activities of these two types of financial investors are more important to excess spillovers than financial turmoil.

Like in the case of overall speculative activity, column (4) includes *DUM* to account for specificities of the 2007–2009 financial crisis that might not be captured by *FS*. Interestingly, whereas Büyükşahin and Robe (2014) find that the recent financial crisis has an exceptional impact on commodity-equity linkages, our results suggest that the exceptionality of the recent crisis has not been reflected in cross-commodity connectedness. Although our analysis focuses on the effect of financial investors, we add the aggregate share of processors and merchants (*PM*) and its interaction with *FS* (*PM*FS*) in column (5) to see if traditional commercial users also contribute to the observed excess spillovers. Trading activities of traditional hedgers in different commodity markets are either correlated on the basis of macroeconomic fundamentals, or independent given the unique demand-supply condition of each individual market. Intuitively, they should not be relevant for excess spillovers. As expected, column (5) shows that neither the coeffecient for *PM* nor the coeffecitent for *PM*FS* is significant. The interaction terms *MMT*FS* and *CIT*FS* are positive and significant, close to the corresponding estimates in columns (3) and (4). The coefficients for *MMT* and *CIT* are consistently positive but become insignificant. Since financial positions partly change to absorb the demands of hedgers, the lack of significance is most likely an artifact of multicollinearity. Indeed, a comparison of log-likelihood values supports that the activities of MMTs and CITs (rather than that of PMs) are a significant source of excess spillovers.

In addition to the specifications in Table 6, we also control for possible seasonality effects by introducing seasonal dummies and obtain quantitatively similar results. Besides, our results remain robust when we use the St. Louis Fed Financial Stress Index as an alternative proxy for financial turmoil.

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[21] We take July 2007 when two Bear Sterns hedge funds collapsed as the beginning of the recent subprime mortgage and global financial crisis. Our results are robust if we take the collapse of Lehman Brothers in September 2008 as the starting point and include an alternative dummy for the post-Lehman period.

Table 6 The long-run relationship between excess spillovers and financial trading activity

Panel A: Overall speculative activity, 2002:5–2016:12			Panel B: Activities of different trader types, 2006:6–2016:12			
	(1)	(2)		(3)	(4)	(5)
FS	0.756***	0.663**	FS	0.388	0.295	0.303
	(0.257)	(0.323)		(0.331)	(0.480)	(0.362)
Tindex	0.835***	0.830***	MMT	0.717***	0.714***	0.144
	(0.304)	(0.296)		(0.257)	(0.262)	(0.542)
Tindex*FS	0.647	0.629	MMT*FS	1.501***	1.483***	1.128***
	(0.531)	(0.517)		(0.483)	(0.519)	(0.378)
			CIT	0.360**	0.365**	0.240
				(0.159)	(0.152)	(0.233)
			CIT*FS	1.633***	1.656***	1.284**
				(0.393)	(0.360)	(0.524)
			PM			-0.560
						(0.418)
			PM*FS			-0.009
						(0.673)
DUM		0.310	DUM		0.200	
		(0.721)			(0.598)	
Log-L	-60.147	-60.066	Log-L	-87.527	-87.463	-95.508
F statistic	315.881***	251.483***	F statistic	35.444***	31.983***	20.062***

This table shows the estimation results for the long-run relationship between excess spillovers and financial trading activity. The dependent variable is the total excess spillover index. Long-run estimates are from the ARDL regressions. Lag lengths are determined based on the AIC criterion. Panel A explores the impact of overall speculative activity and the sample period is May 2002–December 2016. *FS* is the financial stress indicator. *Tindex* is the aggregate T index. *DUM* is a time dummy that equals 1 during July 2007–December 2009 and 0 otherwise. Panel B examines the impacts of different trader types and the sample period is June 2006–December 2016. *MMT*, *CIT* and *PM* stand for the aggregate market shares of managed money traders, commodity index traders, and processors and merchants, respectively. A constant is always included whose estimate is not reported for the sake of brevity. All variables are standardized except for *DUM*. The values in parentheses are Newey-West standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

In sum, the results in Table 6 confirm our conjecture that financialization is a main driver behind cross-commodity excess spillovers with financial turmoil temporarily amplifying this effect. This general conclusion corroborates the findings of Tang and Xiong (2012) on cross-commodity correlations, and those of Adams and Glück (2015) regarding commodity-equity spillovers. However, our results differ from theirs in that we show that both the activity of MMTs and that of CITs are important in driving excess spillovers, whereas those two studies only consider the impact of CIT activity. Our results also provide an interesting counterpoint to the findings of Büyükşahin and Robe (2014) and Girardi (2015), who disentagle the effects of MMTs and CITs as well but focus on commodity-equity linkages instead. Generally, the impact of financial trading by type of investor on connectedness among commodities (as shown in Table 6) appears to be different from that on connectedness between commodity and stock markets (as documented by the above two studies). Büyükşahin and Robe (2014) report that CIT activity holds little explanatory power for commodity-equity correlations and the effect of MMT activity is weaker during periods of financial stress. However our findings with respect to cross-commodity excess spillovers suggest a significant CIT impact and an apmlifying effect of financial turmoil. Girardi (2015) argue that financial activity will increase commodity-equity correlations during financial turmoil, but its effect is ambigous during normal times. In contrast, we find that in addition to the amplifying effect of financial stress, the activity of either MMTs or CITs alone can drive up cross-commodity excess spillovers.

4.2.2. ***Short-run analysis***

The ARDL results above confirm that financialization play a significant role in driving up excess spillovers. In addition to the existence of long-turn impact, we also want to know how much of the variation in excess spillovers can be explained by financial activity. To this end, we perform a short-run analysis by regressing the total excess spillover index on the individual (instead of aggregate) financial trading variables. In this context, we exploit the commodity-specific market shares of CITs and MMTs to incorporate more-detailed information on financial trading activity. Furthermore, to isolate the effect of the recent financial crisis, we split the sample into two time periods: the crisis period (July 2007–December 2009) and the post-crisis period (January 2010–December 2016).

Generally, there are 16 commodity-specific financial trading variables (each of the 8 commodities has two market share indicators related to MMTs and CITs, respectively). Evidently, including the whole set of individual financial activity variables will introduce multicollinearity in the regression. Besides, it will use up many degrees of freedom. Given this, we simplify the model through the stepwise method. To control for the direct impact of financial shocks in different periods, we always include the financial stress indicator (*FS*) as a regressor. The procedure begins with no additional regressors in the model and adds the financial trading variable which most increases R^2 . In the next step, the remaining variables are re-considered for inclusion in the current model with the one that produces the largest incremental increase in R^2 added. The procedure stops when there remains no financial trading variables that meet the statistic criterion for entry. Besides, at each successive step, before the next variable is added, all the previously added variables are checked for removal and anyone that meets the statistic criterion for deletion is removed. Following the literature, we use a significance level of 0.2 for the entry and deletion criteria[22].

Table 7 presents the estimation results in which all coefficients are standardized. First, the positive and significant coefficient for *FS* holds all the time, with the magnitude larger in the crisis period (column (2)) than in the post-crisis period (column (3)). This is consistent with the theoretical implication that negative financial shocks trigger increases in cross-market linkages with the effect particularly strong during a crisis (Kyle and Xiong, 2001; Cheng et al., 2015). Second, as indicated by the Wald test statistics for the joint significance of the commodity-specific market share variables, the activities of MMTs and CITs as a whole have significant explanatory power for the excess spillover variation, either during the full sample period (column (1)) or during the sub-periods (columns (2) and (3)), reinforcing the ARDL results in Table 6. Note that a financial activity variable not being selected by the stepwise regression does not mean that it has no relation with the dependent variable. This is simply because that its impact has been represented by that of others, which it is highly correlated with. Therefore, we are less concerned with the individual coefficients. Instead, we focus on the joint explanatory power of the financial trading variables.

As shown by the adjusted R^2 values in Table 7, the overall explanatory power of financial stress and financial trading activity is largest during the recent crisis period of 2007–2009, and is higher in the post-crisis period than in the pre-crisis period, supporting the graphical evidence in Figure 2. To measure the joint contribution of financial trading activities, we compute the incremental adjusted R^2 values ($\Delta Adj.R^2$), as the difference between the adjusted R^2 s from the regressions specified in Table 7 and the adjusted R^2 s from the corresponding regressions only including *FS* (and a constant). It can been seen that when the financial trading

[22] Bendel and Afifi (1977) suggest that a significance level of between 0.15 and 0.25 for the entry criterion is large enough to keep noise variables from being included in the model yet small enough to allow authentic variables to enter the model. Draper and Smith (1981) suggest that the significance levels should be equal for the entry and deletion criteria. Following their recommendation, Flack and Chang (1987) use a value of 0.15. In this paper, we are more conservative and choose a value of 0.2. Note that using alternative significance levels would not change the relative performance of the subsample regressions.

variables are added, the adjusted R^2 values increase substantially (0.458 for the full sample period; 0.615 for the crisis period; 0.640 for the post-crisis period), and the incremental adjusted R^2 s exceed the adjusted R^2 s when only a constant and *FS* are included. Overall, the activities of MMTs and CITs can explain a substantial fraction of the variation in excess spillovers. Furthermore, their explanatory power is even higher in the post-crisis period than in the recent financial crisis or pre-crisis periods. In other words, the contribution of financial trading activity to excess spillovers has increased over time.

Table 7 The explanatory power of financial trading activity in different periods

	2006:6–2016:12	2007:7–2009:12	2010:1–2016:12
	(1)	(2)	(3)
FS	0.772 [10.256]***	0.552 [5.239]***	0.479 [4.013]***
Cotton_MMT	0.551 [7.159]***		0.268 [3.081]***
Copper_MMT	0.139 [1.355]		0.153 [1.181]
Crude oil_MMT	-0.378 [-3.998]***	-0.774 [-9.348]***	
Cocoa_MMT	-0.332 [-2.922]***		-0.761 [-7.264]***
Lean hogs_MMT	0.329 [5.043]***		0.183 [2.124]**
Gold_MMT	0.419 [4.752]***		0.470 [4.504]***
Wheat_CIT	0.184 [2.120]**		0.549 [4.979]***
Cotton_CIT		0.564 [2.257]**	
Crude oil_CIT		-0.450 [-1.578]	0.636 [5.489]***
Lean hogs_CIT	0.488 [2.585]**	0.295 [3.266]***	
Gold_CIT	0.697 [4.333]***		0.768 [5.012]***
R^2	0.673	0.846	0.724
Adj.R^2	0.645	0.814	0.690
ΔAdj.R^2	**0.458**	**0.615**	**0.640**
Wald test	20.151***	81.025***	32.862***

This table reports the stepwise regression results for explaining the variation in the magnitude of excess spillovers over different time periods. The dependent variable is the total excess spillover index. *FS* is the financial stress indicator. The variables denoted in the general form of *Commodity_trader type* are the commodity-specific market shares by trader type. For instance, *Wheat_MMT* and *Wheat_CIT* stand for the shares of MMTs and CITs in wheat market, respectively. *Wald test* reports the F-statistics for the joint significance of the commodity-specific market share variables. A constant is always included whose estimates is not reported for the sake of brevity. All coefficients are standardized. The values in square brackets are t-statistics based on Newey-West standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Overall, our empirical results reject the notion that the excess spillovers existing in commodity markets are essentially a phenomenon of financial turmoil alone. Indeed, the majority of the observed excess spillovers can be attributed to financial investors' activities, especially the activities of MMTs and CITs, both playing an increasingly important role in recent years. We interpret the impact mechanism as a style effect.

According to the literature on style investing (Barberis et al., 2005; Wahal and Yavuz, 2013), the formation of investment styles could generate comovement among assets within a style which are unrelated on a fundamental level. While the idea of the style effect stemmed from stock and mutual fund markets, the same logic would also apply to commodity markets given the ongoing process of financialization. During the last decade, institutional investors have been increasingly engaging in commodity investments. They include multiple commodities as a distinct asset class in portfolios, aiming to obtain diversification benefits and/or to improve investment returns. As a result, commodities have become an investment style. Similar views have been proposed by several studies: Tang and Xiong (2012) emphasize that the belief that commodities could be used to reduce portfolio risk has promoted them as a new asset class. Bessler and Wolff (2015) point out that commodities have emerged as an attractive asset class for institutional asset managers during the past ten years. Adams and Glück (2015) and Charlot et al. (2016) apply the concept of style investing to explain commodity-equity linkages. Consequently, portfolio rebalancing and strategic allocation based on styles create a channel for shocks in one commodity market to spill over to other commodity markets, generating cross-commodity connectedness irrelevant to macroeconomic fundamentals.

4.3. *Impact of financializaiton: direction*

As previously mentioned, an apealing virtue of the Diebold-Yilmaz spillover index approach is that it provides directional information with respect to spillover transmission. As can be seen in Figure 3, the transmitting or receiving ability is largely heterogeneous across commodities and over time. In this subsection, we combine the panel of net excess spillover indexes with the panel of commodity-specific financial trading variables to examine the roles played by certain types of financial traders (speculators in general and MMTs or CITs in particular) in determining the direction of excess spillovers.

We relate the probability of a commodity being a net transmitter/receiver of excess spillovers to the intensity of financial activity in the corresponding market using a panel logit model. The dependent variable is 1 if a commodity has a positive net excess spillover value (net transmitter), and 0 otherwise (net receiver).

The main explanatory variables are the financial activity variable by type of investor and its interaction with the financial stress indicator. We estimate the model separately for general speculators, managed money traders (MMTs) and index traders (CITs) (as well as commercial hedgers, i.e., PMs)[23]. Besides, one may argue that the effect of financial trading might be more pronounced for commodities with higher liquidity (Tang and Xiong, 2012; Adams and Glück, 2015). To address this concern, we also add the growth rate of open interest to account for the liquidity effect. This is in line with Adams and Glück (2015) who stress that open interest is a preferred measure of liquidity for commodity markets. In addition, Hong and Yogo (2012) show that the growth rate of open interest is a powerful predictor for commodity returns even after controlling for a number of systematic and idiosyncratic factors. Our panel model captures unobserved commodity specific characteristics using individual fixed effects, and controls for common shocks such as changes in financial conditions, occurrences of natural events as well as policy shifts using year fixed effects[24]. Following Petersen (2009), we cluster standard errors by two dimensions—both by time and by commodity.

Panels A, B, and C of Table 8 present the estimation results for the models regarding overall speculative activity, MMT activity and CIT activity, respectively.[25] First, as shown in Panel A, the coefficient for Working's T index (*Tindex*) is positive and significant. That is, commodities with higher intensity of financial speculation appear more likely to be net transmitters of excess spillovers. Equivalently, those with lower intensity of financial speculation are more likely to be net receivers. The interaction term *Tindex*FS* implies that financial turmoil tends to amplify the effect of speculative activity, consistent with the earlier results based on the total excess spillover index. Nonetheless, this impact is weak in statistical significance.

Second, Panel B of Table 8 shows that the probability of being a net transmitter is positively related to the market share of MMTs. Likewise, this relation is slightly stronger during periods of financial turmoil. Clearly, the results in Panel B much resemble those in Panel A, with the significance level of *MMT* higher than that of *Tindex*. This reinforces the argument of Büyükşahin and Robe (2014) that Working's T can provide a useful

[23] As pointed out in Wang (2002), the futures market clearing condition leads to high corrections between positions of different trader types in an individual market. Therefore, it is appropriate to estimate the panel model separately for each trader type.
[24] We do not include time dummies in the strict sense, that is, one for each time point in our monthly sample data, since this will use up too many degrees of freedoms.
[25] Our results remain robust to using an alternative indicator of financial stress, to controlling for possible seasonality effects, to fitting a probit model for the directional dummy variable where standard errors are clustered both by time and by commodity, and to using the conditional fixed-effects estimator with bootstrapped standard errors.

proxy for the activity of MMTs (or equivalently, hedge funds).

Third, Panel C of Table 8 shows that the probability of being a net transmitter is inversely related to the market share of CITs. This means that commodity markets with higher participation degrees of CITs are more likely to be net receivers of excess spillovers. Although not significant in tranquil times, this relation is particularly evident during financial stress. Interestingly, MMTs and CITs seem to assume opposite roles in determining the direction of excess spillovers. To further verify this observation, we estimate the impact of the relative share of MMTs to CITs (*MMT-to-CIT*). As shown in Panel D, an increase in the market share of MMTs relative to CITs is associated with an increase in the probability of being a net transmitter. Conversely, an increase in the market share of CITs relative to MMTs is associated with an increase in the probability of being a net receiver. The relation in either direction is significantly stronger during periods of financial stress.

Finally, the inclusion of open interest does not quantitatively change the results. Generally, there is a tendency for a commodity market with higher degree of liquidity to be a net transmitter. However, the coefficient for open interest is insignificant in all regressions. Besides, we find little evidence for the activity of PMs to affect the direction of excess spillovers, which is consistent with the intuition as well as the earlier findings in Table 6 (the results are not reported for the sake of brevity).

Table 8 The impact of financial trading activity on the direction of excess spillovers

	Panel A: Overall speculative activity, 2002:5–2016:12				
	Tindex	Tindex*FS	Open interest	Pseudo R^2	Chi-square
(1)	**5.963** (2.517)**	0.002 (0.105)		0.165	291.05***
(2)	**6.056** (2.561)**	0.011 (0.094)	0.656 (0.856)	0.167	293.61***
	Panel B: Activity of MMTs, 2006:6–2016:12				
	MMT	MMT*FS	Open interest	Pseudo R^2	Chi-square
(3)	**0.138** (0.040)***	0.002 (0.036)		0.280	294.70***
(4)	**0.135** (0.040)***	0.002 (0.036)	0.530 (1.331)	0.281	296.28***
	Panel C: Activity of CITs, 2006:6–2016:12				
	CIT	CIT*FS	Open interest	Pseudo R^2	Chi-square
(5)	-0.015 (0.028)	**-0.079** (0.033)**		0.262	270.16***
(6)	-0.012 (0.031)	**-0.080** (0.033)**	0.755 (1.171)	0.264	269.69***
	Panel D: Relative share of MMTs to CITs, 2006:6—2016:12				
	MMT-to-CIT	MMT-to-CIT*FS	Open interest	Pseudo R^2	Chi-square
(7)	**0.642** (0.289)**	**0.560** (0.216)***		0.261	260.68***
(8)	**0.631** (0.284)**	**0.559** (0.214)***	0.519 (1.181)	0.263	261.42***

This table shows the estimation results for the panel logit model exploring the impact of financial trading activity by type of investor on the direction of excess spillovers. The dependent variable is 1 if a commodity has a positive net excess spillover value (net transmitter), and 0 otherwise (net receiver). The cross-sectional dimension is 8 commodities. Panel A examines the impact of overall speculative activity and the time-series dimension is May 2002–December 2016. *FS* is the financial stress indicator. *Tindex* is commodity-specific Working's T index. *Open interest* represents the growth rate of total open interest. Panel B and Panel C examine the impacts of MMTs and CITs, respectively, with the sample period spanning from June 2006 to December 2016. *MMT* and *CIT* stand for the commodity-specific market shares of MMTs and CITs, respectively. Panel D explores the impact of the relative share of MMTs to CITs. The relative share, denoted as *MMT-to-CIT*, is calculated as the ratio of MMTs' market share to CITs' market share. All regressions include commodity fixed effects and year fixed effects. The values in parentheses are standard errors clustered both by time and by commodity. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

At this point, our emprical evidence confirms that MMTs and CITs indeed play different roles in the transmission mechanism of excess spillovers. These different impacts might be explained by the differentiated characteristics inherent in their trading strategies.

First, commodity markets with higher degrees of participation by MMTs are more likely to be net transmitters of excess spillovers. In contrast, commodity markets with higher degrees of participation by CITs are more likely to be net receivers of excess spillovers. Typically, MMTs follow active investment strategies. Besides, the extensive use of leverage makes them more exposed to funding/liquidity risks than other investor groups (Cheng et al., 2015). Insofar as these active investors engage in value arbitraging across several commodity markets, commodities traded by more MMTs tend to be more “active”, in the sense that they are more capable of sending shocks to others. Furthermore, according to Büyükşahin and Robe (2014), MMTs make up the majority of cross-market traders who are active in both equity and commodity markets. Indeed, there is evidence that MMTs are more important in linking equity and commodity markets (Büyükşahin and Robe, 2014; Girardi, 2015). For this reason, commodities dominated by MMTs are more vulnerable to outside shocks from financial markets than others, and consequently they are likely to be transmitting these shocks to other commodities with lower degrees MMT particiaption. Unlike MMTs, CITs typically follow passive strategies with a larger investment scale. They do not actively buy and sell commodity contracts, but instead track a specific commodity index. When a shock transmitted by MMTs (in particular from the stock market) severely impacts the diversification level, CITs tend to respond by rebalancing their portofolios between commodities and other asset classes based on index weights, further enhancing cross-commodity connectedness. Their passiveness in trading could make commodities with higher concentration of CITs more likely to be at the receiving ends of excess spillovers.

Second, the activity of MMTs exerts a significant impact on average, whether in normal times or in stress times; whease the impact of CIT activity is only manifest in periods of financial stress. It can be inferred that in the short run MMTs play a more important role than CITs in driving excess spillovers. Similar evidence can be found in Table 7 where the number of selected/signicant commodity-specific financial activity variables related to MMTs is larger than the number of selected/signicant financial activity variables related to CITs, either over the full sample period or over the post-crisis period. Combing the results in Table 6, it appears that CITs’ impact tends to be more appereant in the long run than in the short run. These observations resonate well with the findings of Girardi (2015) and are plausible given the difference in investment horizons of the two trader types. Particarlly, the active investing by MMTs is usually associated with a relatively short investment horizon. Whease the passive investing by CITs depends on a relatively long invesntment horizon. Normally, CITs do not alter their positions frequently in the short term, but their investment flows into and out of commodity markets could be large over a long period. So we would expect the CIT impact to become more pronunced in the long run than in the short run.

5. Conclusion

This paper contributes to a fast-growing literature that analyzes the relationship between the changes in commodity behaviors and the financialization process over the past fifteen years. In this context, different aspects of financializaiton are under study, including the impact of financial speculation on commodity returns and volatilities, the closer integration between commodities and stock markets, and the appearance of linkages across many economically unrelated commodities. In this paper, we focus on the cross-commodity linkages. Different from the previous studies, we sidestep the debate over whether macroeconomic fundamentals or financial speculation dominates in strengthening cross-commodity connectedness, but directly address the questions of how much connectedness remains after fully accounting for fundamental effects and whether financialization matters for such connectedness.

In particular, we extend the concept of excess comovement, which only deals with concurrent association and is directionless, to excess spillovers, which can capture dynamic linkages and reveal connectedness direction. Our excess spillover estimates provide preliminary evidence that financialization contributes to the stronger cross-commodity connectedness whose impact is further amplified by financial stress. We then confirm this conjecture by empirically examining the relationship between excess spillovers and financial activity variables. Distinguishing between different types of financial investors, we find that both the activities of managed money traders and commodity index traders have explanatory power for excess spillovers. However, in the short run managed money traders may be more important than index traders in driving excess spillovers, while the impact of index tradings seems to be more pronunced in the long run than in the short run. Moreover, commodity markets with higher degrees of participation by managed money traders are more likely to be net transmitters of excess spillovers. In contrast, commodity markets with higher degrees of participation by index traders are more likely to be net receivers of excess spillovers.

We interpret the impact mechanism of financialization on excess spillovers as a style effect. That is, during the continuing process of financialization, the broad category of commodities has become an investment style. Then style investing, which refers to portfolio investment strategies based on styles, tends to connect individual assets within a style even when there are no supports from market fundamentals. While the different roles played by managed money traders and index traders in the transmission of excess spillovers seems to be related to their differences in investment strategies. However, such style effects are difficult to measure directly. There may be other possible explanations. For instance, herding behavior of financial investors (in particular during turbulent times) can be also relevant. Generally, a much wider dataset (account and trade data at ownership level) is required to prove these intuitions. These are issues left for future research.

Overall, our study highlights the need for empirical research to address various aspects of the connectedness among commodity returns and supports the notion that the composition of trading activity (i.e., who trades) matters for cross-market linkages (Büyükşahin and Robe, 2014). We expect our findings to have important welfare implications. As long as commodity investments remain popular among institutional investors, price fluctuations in one commodity market may spill over to a broad set of economically important commodities, triggering inflation risk for commodity import countries. Besides, countries exporting a portfolio of seemingly unrelated commodities would enjoy only limited diversification of revenues. Therefore, both commodity importers and exporters need to account for the financialization-related connectedness among commodities when implement policies to diversify shocks to the current account, to manage domestic imbalances and to resist inflation pressures.

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