THE RESPONSE OF VOLUME AND RETURNS TO THE INFORMATION SHOCKS IN CHINA'S COMMODITY FUTURES MARKETS

GONGMENG CHEN
MICHAEL FIRTH
YU XIN*

This study investigates the response of returns and volume to different information shocks in China's commodity futures markets using bivariate moving average representation (BMAR) and bivariate vector autoregression (BVAR) methodologies. Consistent with the conclusions from stock market studies that have used these methodologies, it is found that the informational/permanent components are the dominant components for returns movements, and the noninformational/transitory components are the dominant components for trading volume. It is also

The authors thank Bob Webb, Editor of the *Journal of Futures Markets,* and an anonymous reviewer for valuable comments on previous versions of the article.
*Correspondence author, School of Business, Zhongshan University, Guangzhou, China, 510275; e-mail: mnsxy@zsu.edu.cn

Received June 2004; Accepted December 2004

- *Gongmeng Chen is an Associate Professor at the School of Accounting and Finance at the Hong Kong Polytechnic University in Hong Kong.*
- *Michael Firth is a Professor at the School of Accounting and Finance at the Hong Kong Polytechnic University in Hong Kong.*
- *Yu Xin is an Assistant Professor at the School of Business at Zhongshan University in Guangzhou, China.*

Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/fut.20165

found that the market response of copper futures improved during the sample period, and the market responses of actively traded futures (copper and soybeans) are better than those of the less actively traded futures (aluminum and wheat). Jrl Fut Mark 25:893–916, 2005

INTRODUCTION

At the end of the 1970s, the Chinese government began a process of economic liberalization that continues to this day. During the past 20-plus years, price controls and production quotas have been lifted, private ownership has been encouraged, and day-to-day government involvement in business affairs has been reduced. To help facilitate the development of the private sector, the government encouraged the formation of financial markets, especially the stock markets of Shanghai and Shenzhen and the regional commodities markets. The stock and commodities markets have faced steep learning curves in the past 14 years and now seems a particularly opportune time, as China has recently joined the World Trade Organization, to review the workings of these financial markets. Restrictions on foreigners operating in China's financial markets are being eased, and so there is a consequent demand for more information and analysis from the international community. The principal objective of this article is to investigate the volume and returns responses to information shocks in the four main commodities futures markets (copper, soybeans, aluminum, and wheat).

Three specific questions are posed in this study:

1. How do futures returns and volume respond to information shocks in China's commodity futures markets?
2. Has there been an improvement in market response over time?
3. Are there any differences in market response between futures that are more actively traded (copper and soybeans) and futures that are less actively traded (aluminum and wheat)?

Bivariate moving average representation (BMAR) and bivariate vector autoregression (BVAR) methodologies are used to investigate the response of returns and volume to different information shocks. In particular, the related components of returns and volume of futures due to different information shocks are identified, and the relative importance of each component and the dynamic effects of each kind of shock are investigated.

Consistent with previous empirical evidence in stock markets,[1] the informational/permanent components are found to be the dominant components for futures returns movements, whereas the noninformational/transitory components are the dominant components for trading volume. Initially, noninformational/transitory shocks have a substantial effect on trading volume, and this effect declines gradually over time. In comparison, informational/permanent shocks initially have a substantial effect on the returns on futures, and this adjustment is very rapid. It is also found that

1. The market response of copper futures improves during the sample period; this is attributed to a regulatory change in 1999.
2. The market response of actively traded futures (copper and soybeans) is greater than those of less actively traded futures (aluminum and wheat) during the period 1999–2002.

The remainder of this study is organized as follows. A brief background on China's commodities markets is given first. The following sections review the related literature, present the research design, analyze the empirical results, and conclude the study.

COMMODITIES MARKETS IN CHINA

On 12 October 1990 the China Zhengzhou Grain Wholesale Market was founded. Authorized by the State Council, this market, which was based on spot transactions, introduced the futures transaction mechanism. On 10 June 1991, the Shenzhen Metal Exchange, the first futures exchange where standardized futures contracts were traded in China, was established. This was followed by the founding of the Shanghai Metal Exchange, the Suzhou Material Exchange, the Nanjing Petroleum Exchange, and so on.

By the end of 1993, more than 50 futures exchanges had been set up in China, providing more than 50 kinds of futures products. In the meantime, more than 1000 futures brokerage corporations had been established. However, the rapid expansion and lack of effective regulations led to overheating and market breakdowns. In 1999, new regulations were introduced to help alleviate the problems. As a consequence of the new regulations, only three futures exchanges, 12 futures products,

[1]The BMAR and BVAR methodologies were previously employed in stock market studies. To the best of the authors' knowledge these techniques have not been used in studies of futures markets.

and less than 200 futures brokerage corporations survived by the end of 2003. The most successful futures products are copper, aluminum, soybeans, and wheat. They are actively traded[2] and have begun to play an important role (for instance, in hedging and price discovery) in China's economy. The futures prices are highly correlated with those on the international exchanges (for example, the London Metal Exchange and the Chicago Board of Trade).

Annual futures transactions have shown a great deal of volatility since the inception of the markets. This volatility is the result of both changes in the economy, where the state has alternatively attempted to spur and then dampen growth, and changes in regulations. By 2002, commodities futures turnover exceeded RMB3, 948.1 billion. Copper, aluminum, soybeans, and wheat are the most actively traded futures in the examination period and so the empirical analyses are restricted to these four products.

LITERATURE REVIEW

Beaver (1968) and Karpoff (1987) stated that there is an important distinction between price change and trading volume. Price changes reflect changes in the expectations of the market as a whole, and can be interpreted as the market's evaluation of new information. In contrast, volume reflects changes in the expectations of individual investors, which can be considered an indication of the extent to which investors disagree about the meaning of the information. These arguments imply that price change and trading volume may be induced or affected by different kinds of information shocks.

Informational Versus Noninformational Shocks

Informational shocks are known and accepted by all investors, and become public information of a sort that causes all investors to change their valuation of the related prices; noninformational shocks include irrational noise trading by market participants.

French and Roll (1986) and Hasbrouck (1991) assumed that public information is produced at a constant rate on days when exchanges and businesses are open and that it affects prices without trading. The arrival

[2]Relatively speaking, copper and soybeans futures are more active than aluminum and wheat futures. Today, China's copper and soybeans futures markets are the second largest in the world; only the LME (the London Metal Exchange) and CBOT (the Chicago Board of Trade) are larger.

of private information, on the other hand, is stochastic, and trading is necessary for such information to affect prices (Jones, Kaul, & Lipson, 1994). Harvey and Huang (1991) argue that although the disclosure of private information through trading can partially explain fluctuations in currency futures markets, the public announcement of macroeconomic news is the prime motivator of price movements in these markets. Jones et al. (1994) derived nontrading and trading classifications[3] to gauge the relative importance of public versus private information. Consistent with Harvey and Huang (1991), they found that private information contributes little to observed volatility, and that public information may be the major determinant of short-run volatility.

Permanent Versus Transitory Shocks

Permanent shocks are the innovation in information concerning changes to the fundamental/intrinsic value of the related prices, whose effects are permanent and exist in the long run; transitory shocks are the innovation in information concerning changes to the nonfundamental/nonintrinsic value of the related prices, whose effects are transitory and exist in the short run.

Muth (1960) first proposed the permanent and transitory components hypothesis in a macroeconomic context. In his model, log prices are composed of two components: a random walk and a stationary process. The random walk process is the fundamental component that reflects the efficient market price, and the stationary process is a zero-mean stationary component that reflects a short-term or transitory deviation from the efficient market price, implying the presence of 'fads' or other market inefficiencies (Campbell, Lo, & MacKinlay, 1997, p. 56). DeLong, Shleifer, and Waldmann (1990) introduced a noise-trading model that claims that a temporary mispricing of financial prices exists in the short run because the activities of noise traders are not based on economic fundamentals. However, in the long run prices move toward their mean values because of the disappearance of the transitory component. Other researchers, including Fama and French (1988) and Poterba and Summers (1988), also model log prices as the sum of a random walk (permanent component) and a first-order autoregressive process (temporary component). The permanent component accounts for long-run trends in stock prices, and the transitory component is left to explain the remaining variation in stock prices.

[3]They defined nontrading periods as periods when exchanges and businesses are open, but traders endogenously choose not to trade.

BMAR and BVAR Methodologies and Stock Market Studies

The responses of returns and volume to informational versus noninformational and permanent versus transitory shocks can be investigated in a bivariate model of returns and volume. The model is characterized by a restriction on the bivariate moving average representation (BMAR) of the returns and volume from the perspectives of informational versus noninformational and permanent versus transitory shocks, respectively. This restriction helps identify the two components of returns and volume due to informational/permanent and noninformational/transitory shocks, and examines the relative importance of each component in determining price movements and trading volumes. The procedure for identification was introduced by Blanchard and Quah (1989) and Quah (1992).

Lee (1995), Chung and Lee (1998), and Lee and Rui (2001) employed bivariate/trivariate moving average representation (BMAR) and bivariate/trivariate vector autoregression (BVAR) methodologies to investigate the response of stock prices to different kinds of information innovations. Lee (1995) investigated the response of stock prices to dividend shocks in a bivariate model of stock prices and price-dividend spreads, where the dividend process is modeled as the sum of a permanent component and a temporary component. Chung and Lee (1998) examined deviations in stock prices in the Pacific Rim—Hong Kong, Singapore, Korea and Japan—from their fundamentals by analyzing how stock prices, dividends and earnings behave in response to three types of shocks: permanent and temporary changes in fundamentals, and nonfundamental factors. Lee and Rui (2001) empirically identified noninformational trades and informational trades using stock returns and trading-volume data from the United States, Japanese, and United Kingdom stock markets and from five individual firms. Their results show that trading volume is mainly driven by noninformational trades, whereas stock price movements are primarily driven by informational trades.

RESEARCH DESIGN

Data and Data Processing

The sample test period extends from January 4, 1999 to December 31, 2002 for aluminum and soybean futures, from January 4, 2000 to December 31, 2002 for wheat futures, and from January 2, 1996 to December 31, 2002 for copper futures. The copper-futures data are further divided into two subperiods, from January 2, 1996 to December 31, 1998, and from January 4, 1999 to December 31, 2002. These products and time periods are chosen because they have active trading. Other commodity futures are characterized by relatively low trading activity and illiquid markets.

The daily closing price series and raw trading-volume data are downloaded from the Web sites of three futures exchanges, the Shanghai Futures Exchange, the Dalian Commodity Exchange, and the Zhengzhou Commodity Exchange. Following previous studies, a nearby price is selected to construct a rollover time series. First, the nearby futures contract, which is a contract with the nearest active trading delivery month to the day of trading, is specified. Prices for the nearby futures contract are selected until the contract reaches the first day of the delivery month. Then, a switch from the nearby contracts to the contracts next nearest to delivery is made during the delivery month of the nearby contracts.[4] The nearby futures contract is selected because it is the most active and has high liquidity. Sample statistics for the four commodity futures returns and raw trading volumes are reported in Table I. Following common practice, the returns (or price changes) are computed as the first difference in the logarithms of the daily closing prices (LOG(NCLOSEP)).

To obtain an aggregate measure of trading activity in each market, volume is summed up across all outstanding contracts for each trading day. Because previous studies have found strong evidence of both linear and nonlinear time trends in raw trading volume series (Gallant, Rossi, & Tauchen, 1992; Lee & Rui, 2001), the raw trading volume series needs to be detrended to achieve stationarity. The following regression is conducted to detrend the raw volume series.

$$\mathrm{LOG(ALLVOLUME)} = c + \alpha_1 \mathrm{TREND} + \alpha_2 \mathrm{TREND} * \mathrm{TREND} + \varepsilon_t \quad (1)$$

where LOG(ALLVOLUME) is the natural log of the daily total trading volume (1000 lots) for all contracts; TREND is a time dummy that takes the values 1, 2, 3, 4, and so on, which is the sequence of the observations for LOG(ALLVOLUME) series; and the residuals are the detrended trading volume series (DEVOLUME), which will be used in the following empirical tests. Here TREND is used to model the linear time trend, and TREND * TREND is used to model the nonlinear time trend. If the coefficients of TREND and/or TREND * TREND are not significant, then the related terms will be excluded to obtain a new OLS

[4]By constructing data in this way, all price data within the delivery month are excluded to avoid the possibility of noise during the delivery month.

TABLE I
Descriptive Statistics

		Close-to-close returns	*LOG(ALLVOLUME)*
Copper (1996–2002)	Mean	−0.000289	9.746786
	Median	0.000000	9.846970
	SD	0.008456	0.870061
	Skewness	−0.091497	−0.744105
	Kurtosis	5.152027	4.055427
	Observations	1705	1706
Aluminum (1999–2002)	Mean	−1.13E-05	8.506592
	Median	0.000000	8.484255
	SD	0.005438	1.249654
	Skewness	−0.447846	−0.424454
	Kurtosis	5.734238	2.442881
	Observations	959	960
Soybeans (1999–2002)	Mean	0.000254	12.14479
	Median	0.000000	12.19407
	SD	0.010942	0.788180
	Skewness	0.326912	−0.206824
	Kurtosis	22.31398	2.639685
	Observations	963	964
Wheat (2000–2002)	Mean	0.000217	10.68839
	Median	0.000000	10.74948
	SD	0.019878	0.619068
	Skewness	10.66680	−0.411815
	Kurtosis	204.2419	3.044584
	Observations	693	694

Note. *Close-to-close returns* are the first difference of the LOG(NCLOSEP); LOG(ALLVOLUME) is the natural log of the daily total trading volume (1000 lots) across all contracts for the futures product.

regression, which will be used to filter the raw volume series.[5] The detailed results of detrended regressions for raw trading volume are listed in Table II.[6] Both linear and nonlinear time trends are found to exist in the copper futures market, and a linear time trend exists in the aluminum and soybeans futures markets. There is no linear and nonlinear time trend in the wheat futures market.

Table III reports the results of ADF tests for the raw volume, detrended volume, and close-to-close returns. For all futures markets

[5]Because soybeans and wheat are seasonal crops, there may be an annual seasonal pattern in volume. Thus, some additional tests were also conducted by further filtering DEVOLUME with month dummy variables to control the seasonal effects in soybeans and wheat futures. The empirical results are quite similar to those reported here; details are available from the authors on request. The authors thank the reviewer for this suggestion.

[6]It should be noted that, based on the DW statistics in Table II, positive serial correlation exists in the residuals series. This is not a very serious problem, because this effect has been considered in the BVAR model, and the main purpose here is to just filter the linear and nonlinear trend factors.

TABLE II

The Results of Detrended Regressions for Volume Series

	Copper (whole sample)	*Copper (subsample 1)*	*Copper (subsample 2)*	*Aluminum (whole sample)*	*Soybeans (whole sample)*	*Wheat (whole sample)*
	Dependent Variable: Raw Volume Series [LOG(ALLVOLUME)]					
Independent Variables	*Coefficient (t Value)*	*Coefficient (t Value)*	*Coefficient (t Value)*	*Coefficient (t Value)*	*Coefficient (t Value)*	*Coefficient (t Value)*
C	1.650699	1.307664	2.670619	−0.134376	4.470977	3.494225
	(36.00872***)	(16.99048***)	(51.67322***)	(−1.890408*)	(73.42605***)	(52.25392***)
TREND	0.001757	0.003622	0.000803	0.003515	0.001349	0.000463
	(14.16433***)	(7.510610***)	(3.267544***)	(10.29034***)	(4.630026***)	(1.041529)
TREND * TREND	−3.20E-07	−1.75E-06	5.36E-07	1.43E-07	3.71E-07	7.81E-07
	(−4.554471***)	(−2.766765***)	(2.184909**)	(0.416114)	(1.267737)	(1.260722)
R square	0.475640	0.342660	0.326759	0.657025	0.364695	0.108044
Adjusted *R* Square	0.475024	0.340866	0.325367	0.656308	0.363373	0.105462
DW statistics	1.093062	0.964035	1.439875	0.656120	0.910753	0.883963
F statistics	772.3843	191.0500	234.6678	916.6454	275.8295	41.85076

Note. LOG (ALLVOLUME) is the natural log of the daily total trading volume (1000 lots) across all contracts for the related futures product; TREND is the time sequence of observations for LOG (ALLVOLUME) series.

*Significant at the 10% level.

**Significant at the 5% level.

***Significant at the 1% level.

TABLE III
ADF Test with a Constant for the Volume, Detrended Volume, and Close-to-Close Returns Series

			LOG(ALLVOLUME) ADF value	*DEVOLUME ADF value*	*Close-to-close returns ADF value*
Copper	Whole sample (1996–2002)	Lag 5	−5.945960***	−10.44399***	−15.76983***
		Lag 10	−3.944368***	−7.335417***	−10.89472***
		Lag 15	−3.204142**	−6.024102***	−9.477387***
		Lag 20	−2.823842*	−5.157085***	−8.853226***
	Subsample 1 (1996–1998)	Lag 5	−4.718275***	−6.978020***	−10.10844***
		Lag 10	−3.215168**	−5.035614***	−6.832493***
		Lag 15	−2.842379*	−4.525588***	−5.467781***
		Lag 20	−2.476234	−3.817800***	−5.654503***
	Subsample 2 (1999–2002)	Lag 5	−5.961207***	−9.458976***	−12.24358***
		Lag 10	−4.056679***	−6.842846***	−8.682189***
		Lag 15	−3.074064**	−5.228225***	−8.200146***
		Lag 20	−2.709030*	−4.584215***	−6.957401***
Aluminum	Whole sample (1999–2002)	Lag 5	−2.950652**	−5.325152***	−12.04447***
		Lag 10	−2.500955	−4.083281***	−7.872839***
		Lag 15	−2.280528	−3.635678***	−6.408500***
		Lag 20	−2.209501	−3.577745***	−5.443323***
Soybeans	Whole sample (1999–2002)	Lag 5	−5.081443***	−7.390976***	−12.16677***
		Lag 10	−3.438250**	−5.340795***	−8.237777***
		Lag 15	−2.709105*	−4.457031***	−7.312682***
		Lag 20	−2.172108	−3.987804***	−6.068303***
Wheat	Whole sample (2000–2002)	Lag 5	−5.551519***	−5.551519***	−11.12655***
		Lag 10	−4.185197***	−4.185197***	−8.578416***
		Lag 15	−3.738460***	−3.738460***	−7.093146***
		Lag 20	−2.825217*	−2.825217*	−5.997040***

Note. LOG(ALLVOLUME) is the natural log of the daily total trading volume (1000 lots) across all contracts for the futures product; DEVOLUME is the detrended trading volume series; Close-to-close returns are the first difference of the LOG(NCLOSEP). For ADF test with a constant, the critical values are –2.57, –2.86, and –3.44 at the 10%, 5%, and 1% significance levels, respectively. The null hypothesis that the series is nonstationary is rejected if the test statistic is greater than the critical value.

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

examined, the null hypotheses of nonstationarity are significantly rejected for detrended volume, whereas the null hypothesis for raw volume cannot be consistently rejected. The detrended volume is therefore used to obtain a stationary series. For all of the futures markets examined, the null hypotheses of nonstationarity are significantly rejected for returns series. The data set comprises daily close-to-close returns,[7] and the detrended trading volume series for four futures products. Based on the

[7]As a robust test, decompositions with settlement-to-settlement returns and the detrended volume series are also conducted. The main conclusions still hold.

ADF analysis, these two variables are stationary, which is considered a necessary condition in the bivariate framework.

Research Methodologies

In order to investigate the response of volume and returns to information innovations, the effects of different shocks need to be empirically identified. Consider a 2×1 vector X_t consisting of detrended trading volume and futures returns: $X_t = [\mathrm{VOL}_t, R_t]'$. By the Wold theorem, this vector has the following bivariate moving average representation (BMAR):[8]

$$X_t = \begin{bmatrix} \mathrm{VOL}_t \\ R_t \end{bmatrix} = B(L)\varepsilon_t = \begin{bmatrix} B_{11}(L) & B_{12}(L) \\ B_{21}(L) & B_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_t^1 \\ \varepsilon_t^2 \end{bmatrix} \tag{2}$$

where $\mathrm{VOL}_t = \mathrm{DEVOLUME}_t$, which is the detrended trading volume; R_t is the close-to-close futures returns; ε_t is a 2×1 vector consisting of ε_t^1 and ε_t^2, and it is an orthonormalized[9] innovation in X_t with $Var(\varepsilon_t) = I$; ε_t^1 is the noninformational/transitory shocks; ε_t^2 is the informational/permanent shocks; L is the lag operator (that is, $L^n X_t = X_{t-n}$); $B_{ij}(L)$ for $i, j = 1, 2$ is a polynomial in the lag operator L; that is, $B_{ij}(L) = \sum_{k=0}^{\infty} b_{ij}(k)L^k$, and $b_{ij}(k)$ is the dynamic effect of the jth disturbance on ith variable in period k, and $B_{ij}(L)$ is the cumulative effect of the jth disturbance on the ith variable from period 0 to ∞. In Equation (2), the current returns/volume is modeled as a linear function of the two kinds of lagged shocks, and the weights are the dynamic effects $b_{ij}(k)$.

The BMAR representation indicates that volume and returns are driven by noninformational/transitory and informational/permanent shocks. The time paths of the dynamic effects of the related disturbances on trading volume and futures returns can be found in the coefficients of the polynomials $B_{ij}(L)$.

Based on the previous theoretical considerations, there is a distinction between noninformational and informational shocks (and transitory and permanent shocks). From the perspective of informational versus noninformational shocks, noninformational shocks should affect trading volume because selling pressure by noninformational traders must have a substantial effect on trading volume, whereas informational shocks

[8]It should be noted that the volume and returns equations in Equation (2) can be analyzed independently. However, the matrix representation is more concise, clear, and understandable.
[9]Orthonormalization of ε_t is one of the most important assumptions in the BMAR framework. Because of the orthonormalization of ε_t, the dynamic responses due to different information shocks can be examined, and the related empirical results can be compared to each other.

may have no contemporaneous effect on trading volume, because public information has been accepted by all investors. As the BMAR coefficients $b_{12}(k)$ measure the effect of the second type of shocks (that is, informational shocks) on the first variable (that is, trading volume) after k periods, the restriction[10] that the informational shocks have no contemporaneous effect on trading volume is given by

$$b_{12}(0) = 0 \tag{3}$$

From the perspective of permanent versus transitory shocks, the cumulative effect (that is, the long-run effect) of transitory shocks on returns over time adds up to zero, whereas the cumulative effect of permanent shocks on returns over time is nonzero. Because the BMAR coefficients $b_{21}(k)$ measure the effect of the first type of shocks (that is, the transitory shocks) on the second variable (that is, the futures returns) after k periods, the restriction that the cumulative effect of transitory shocks on futures returns over time adds up to zero is represented by $\sum_{k=0}^{\infty} b_{21}(k) = 0$. Because $B_{ij}(L) = \sum_{k=0}^{\infty} b_{ij}(k)L^k$, we have $B_{21}(1) = \sum_{k=0}^{\infty} b_{21}(k)$. The restriction is

$$B_{21}(1) = 0 \tag{4}$$

Following the procedure for identification introduced by Blanchard and Quah (1989) and Quah (1992), the BMAR model is derived by inverting a bivariate vector autoregression (BVAR) model of X_t. The following BVAR of X_t with m lags[11] is estimated:

$$X_t \equiv \begin{bmatrix} \mathrm{VOL}_t \\ R_t \end{bmatrix} = A(L)X_{t-1} + \mu_t \equiv \begin{bmatrix} A_{11}(L) & A_{12}(L) \\ A_{21}(L) & A_{22}(L) \end{bmatrix} \begin{bmatrix} VOL_{t-1} \\ R_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_t^1 \\ \mu_t^2 \end{bmatrix} \tag{5}$$

where $A(L) = [A_{ij}(L)] = [\sum_{k=1}^{m} a_{ij}(k)L^{k-1}]$, for $i, j = 1, 2$; $\mu_t = \begin{bmatrix} \mu_t^1 \\ \mu_t^2 \end{bmatrix} = X_t - E(X_t \mid X_{t-s}, s \geq 1)$. μ_t is a nonorthonormalized innovation in the BVAR process of X_t with $Var(\mu_t) = \Omega$ [that is, $Var(\mu_t) \neq I$], and ε_t is an

[10]It should be noted that this restriction accords with the theory. Because public information has been accepted by all investors, this kind of shock cannot induce any transactions, as there are no differences in information sets among investors. However, it should be also noted that this restriction is unlikely to be completely true in practice. The authors thank the reviewer for pointing this out.

[11]Here, the lags are determined by AIC (Akaike Information Criterion) and FPE (Final Prediction Error) techniques, where the two techniques obtain the same lags for each futures market that is examined. For copper (whole sample) futures, $m = 9$; for copper (subsample 1) futures, $m = 3$; for copper (subsample 2) futures, $m = 5$; for aluminum futures, $m = 9$; for soybeans futures, $m = 4$; and for wheat futures, $m = 4$.

orthonormalized innovation in the BMAR process of X_t with $Var(\varepsilon_t) = I$.[12] The estimates of $A(L)$, μ_t, and Ω are then obtained.

Inverting the BVAR of X_t leads to

$$X_t = [I - A(L)L]^{-1}\mu_t \tag{6}$$

Comparing the X_t in Equation (6) with that in Equation (2) leads to

$$X_t = B(L)\varepsilon_t = [I - A(L)L]^{-1}\mu_t$$

Then, $B(L)$ can be estimated by noting that

$$B_0\varepsilon_t = \mu_t \tag{7}$$

$$\varepsilon_t = B_0^{-1}\mu_t \tag{8}$$

and

$$X_t = B(L)\varepsilon_t = [I - A(L)L]^{-1}B_0\varepsilon_t \tag{9}$$

Thus,

$$B(L) = [I - A(L)L]^{-1}B_0 \tag{10}$$

Equations (8) and (10) imply that to determine ε_t and $B(L)$, only the estimate of B_0 is needed, because the estimates of $A(L)$ and μ_t have been obtained from the BVAR process in Equation (5). The estimate of B_0 can be obtained by taking the variance of each side of Equation (7):

$$B_0B_0' = \Omega \tag{11}$$

Equation (11) is computed as:

$$\begin{bmatrix} b_{11}(0) & b_{12}(0) \\ b_{21}(0) & b_{22}(0) \end{bmatrix}\begin{bmatrix} b_{11}(0) & b_{21}(0) \\ b_{12}(0) & b_{22}(0) \end{bmatrix} = \begin{bmatrix} \sigma_{11} & \cdot \\ \sigma_{21} & \sigma_{22} \end{bmatrix} \tag{12}$$

Here, three restrictions are obtained for the four elements of B_0: $b_{11}(0)$, $b_{12}(0)$, $b_{21}(0)$, and $b_{22}(0)$, which means that Equation (12) is underidentified. By introducing Equation (3) for noninformational and informational contexts and Equation (4)[13] for transitory and permanent contexts as additional restrictions, Equation (12) can be just-identified, and B_0

[12]Here μ_t is the observed residuals, whereas ε_t is the unobserved structural innovations.

[13]Equation (4) needs to be further rearranged to serve as an additional restriction; please see the Appendix.

can be solved. Then, by employing Equations (8) and (10), the estimates of ε_t and $B(L)$ can be obtained.

Thus, the volume and returns series can be decomposed as follows: the noninformational/transitory volume is $B_{11}(L)\varepsilon_t^1$, the informational/permanent volume is $B_{12}(L)\varepsilon_t^2$, the noninformational/transitory returns are $B_{21}(L)\varepsilon_t^1$, and the informational/permanent returns are $B_{22}(L)\varepsilon_t^2$.

Because the BMAR model provides nonrecursive orthogonalization of the error terms for the impulse response analysis, the orthonomalized moving average coefficients $[b_{ij}(k)]$ can be plotted to describe the dynamic response of trading volume and futures returns to noninformational/transitory and informational/permanent shocks of 1 *SD* magnitude.

EMPIRICAL RESULTS

Decomposition of Futures Returns and Detrended Volume Series

Table IV reports the standard deviation of returns, volume, and their components. Based on this table, it is found that informational/permanent returns account for the majority of the standard deviation of returns (that

TABLE IV

The Standard Deviation of Close-to-Close Returns, Detrended Volume, and Their Components

	Close-to-close returns and its components				
	Returns	*Info.*	*Noninfo.*	*Perm.*	*Tran.*
Copper (1996–2002)	0.008456	0.008417	0.000774	0.008432	0.000572
Copper 1 (1996–1998)	0.008963	0.009148	0.000815	0.009172	0.000434
Copper 2 (1999–2002)	0.008038	0.008028	0.000822	0.008028	0.000789
Aluminum (1999–2002)	0.005438	0.005473	0.000671	0.005463	0.000735
Soybeans (1999–2002)	0.010942	0.010908	0.000888	0.010884	0.001021
Wheat (2000–2002)	0.019878	0.019666	0.002862	0.019670	0.002816
	Detrended volume and its components				
	Volume	*Info.*	*Noninfo.*	*Perm.*	*Tran.*
Copper (1996–2002)	0.630034	0.035621	0.637635	0.045858	0.636330
Copper 1 (1996–1998)	0.693163	0.040704	0.729891	0.069849	0.728442
Copper 2 (1999–2002)	0.534892	0.072469	0.538075	0.070221	0.538329
Aluminum (1999–2002)	0.731914	0.078276	0.883460	0.065594	0.885270
Soybeans (1999–2002)	0.628752	0.013411	0.635787	0.049124	0.634580
Wheat (2000–2002)	0.619068	0.031936	0.623557	0.032299	0.622343

Note. Info. means informational component; Noninfo. means non-informational component; Perm. means permanent component; Tran. means transitory component.

is, a proxy for price volatility), whereas noninformational/transitory volume accounts for the majority of the standard deviation of trading volumes. It is also found that the effects of noninformational/transitory shocks on the standard deviation of returns and informational/permanent shocks on the standard deviation of volume are negligible.

Several ratios are used to examine the importance of informational and noninformational shocks and the importance of permanent and transitory shocks. In particular, the following are calculated: the ratios of informational standard deviations to noninformational standard deviations for futures returns (RATIO1), the ratios of permanent standard deviations to transitory standard deviations for futures returns (RATIO2), the ratios of noninformational standard deviations to informational standard deviations for trading volume (RATIO3), and the ratios of transitory standard deviations to permanent standard deviations for trading volume (RATIO4). The ratios are shown in Table V.

Based on the ratio results reported in Table V, it is clear that the informational/permanent components are the dominant components for futures returns movements (RATIO1 and RATIO2), whereas the noninformational/transitory components are the dominant components for trading volume (RATIO3 and RATIO4). The empirical results imply that trading volume is primarily driven by noninformational/transitory shocks, whereas futures returns are mainly driven by informational/permanent shocks. These results are consistent with those of Lee and Rui (2001). The empirical results are also consistent with the arguments of French and Roll (1986), Hasbrouck (1991), Harvey and Huang (1991), and Jones et al. (1994), who claim that public information is the major determinant of short-run price volatility.

TABLE V

Ratio1–Ratio4

	RATIO1	*RATIO2*	*RATIO3*	*RATIO4*
Copper (1996–2002)	10.87	14.74	17.90	13.88
Copper 1 (1996–1998)	11.22	21.13	17.93	10.43
Copper 2 (1999–2002)	9.77	10.17	7.42	7.67
Aluminum (1999–2002)	8.16	7.43	11.29	13.50
Soybeans (1999–2002)	12.28	10.66	47.41	12.92
Wheat (2000–2002)	6.87	6.99	19.53	19.27

Note. RATIO1 are the ratios of informational standard deviations to noninformational standard deviations for futures returns; RATIO2 are the ratios of permanent standard deviations to transitory standard deviations for futures returns; RATIO3 are the ratios of noninformational standard deviations to informational standard deviations for trading volume; RATIO4 are the ratios of transitory standard deviations to permanent standard deviations for trading volume.

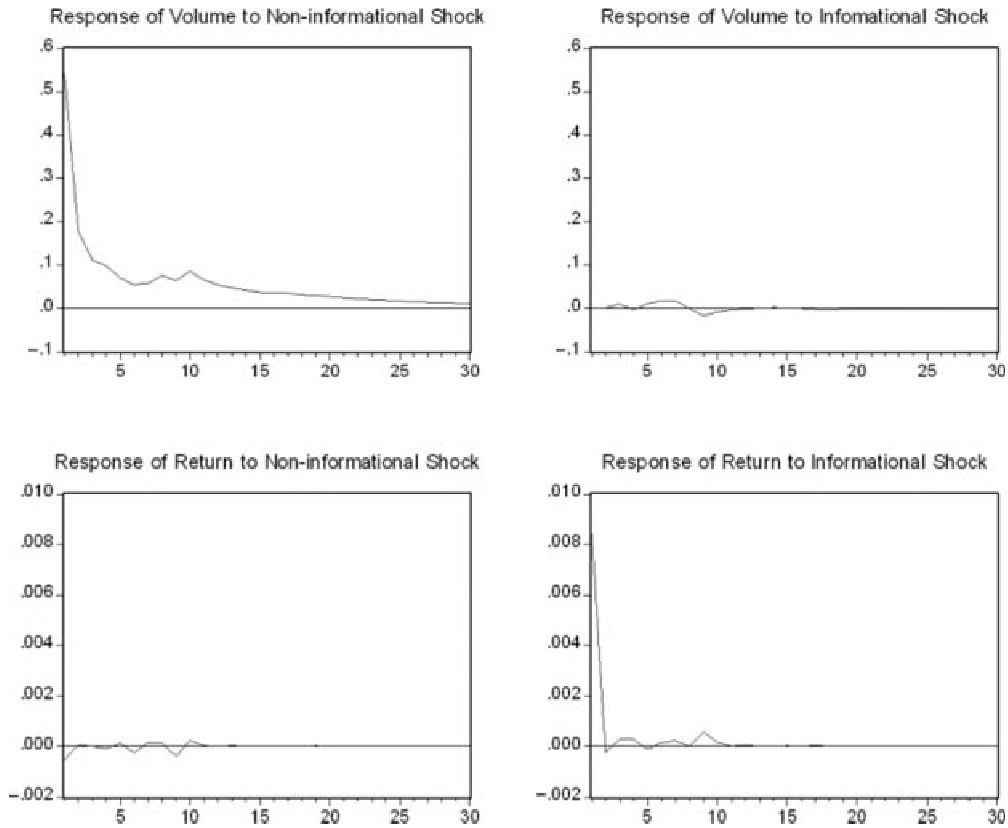

FIGURE 1
Detrended volume and close-to-close return responses to informational and noninformational shocks for copper futures (1996–2002).

Dynamic Effects of Information Innovations

With the use of the impulse response method, the orthonormalized moving average coefficients $[b_{ij}(k)]$ are plotted in Figures 1–6. These figures show the response of trading volume and futures returns to informational and noninformational disturbances of 1-*SD* magnitude.[14] Some interesting empirical results are found.

1. Noninformational/transitory shocks initially have a substantial effect on trading volume, and this effect declines gradually over time in all of the futures markets examined. However, the noninformational/transitory shocks have no major effect on futures returns.

[14]Permanent (transitory) components have a similar pattern as informational (noninformational) components, and so they are not separately reported. The results are available from the authors. It should be noted that volume has been detrended with the use of Equation (1), and then the related graphs represent the change in volume from some norms based on Equation (1). Thus, volume may sometimes go negative.

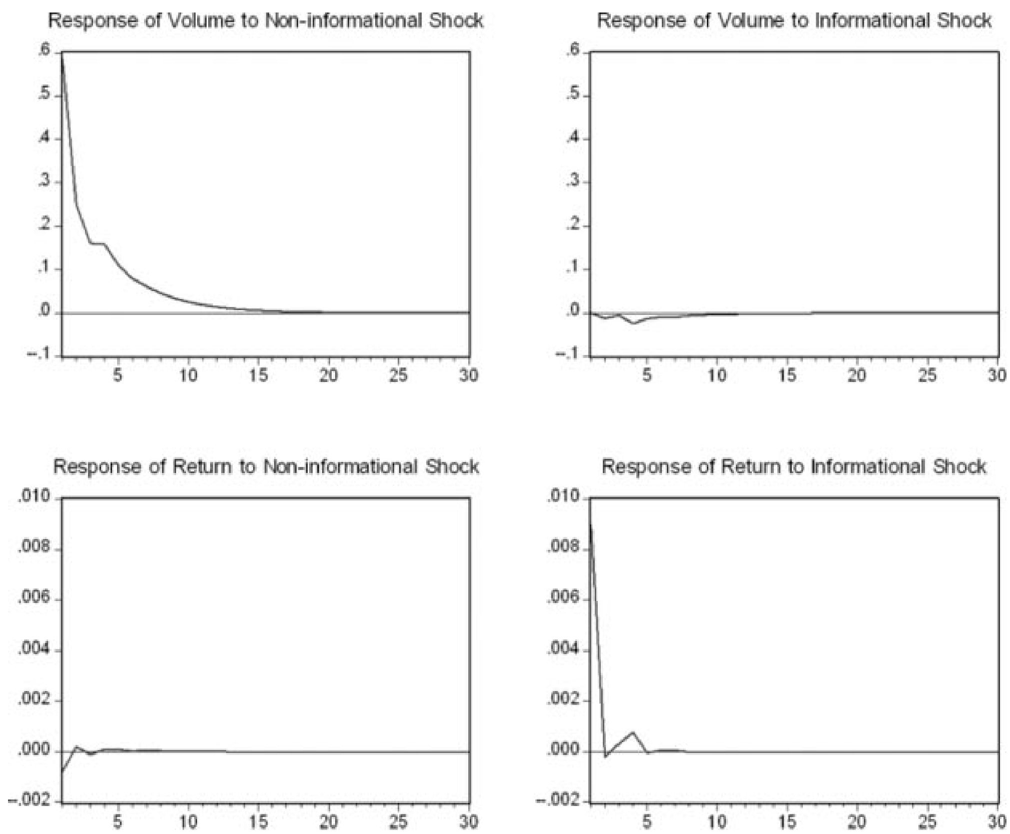

FIGURE 2
Detrended volume and close-to-close return responses to informational and noninformational shocks for copper futures (1996–1998).

2. Informational/permanent shocks initially have a substantial effect on futures returns, but this effect declines dramatically within 2 days. However, the informational/permanent shocks have no major effect on trading volume.
3. The above two findings indicate that trading volume is mainly caused by noninformational/transitory shocks, whereas futures returns are primarily driven by informational/permanent shocks. Futures prices absorb the informational/permanent shocks quickly (within 2 days), whereas trading volume absorbs the noninformational/transitory shocks gradually over 10–60 days.
4. Comparing the slopes of the response lines for copper (subsample 1) and copper (subsample 2) futures markets (see Figures 2 and 3) reveals that the response line is steeper during the second subsample period (1999–2002). This implies that the market response of copper futures improved during the sample period. The improvement in

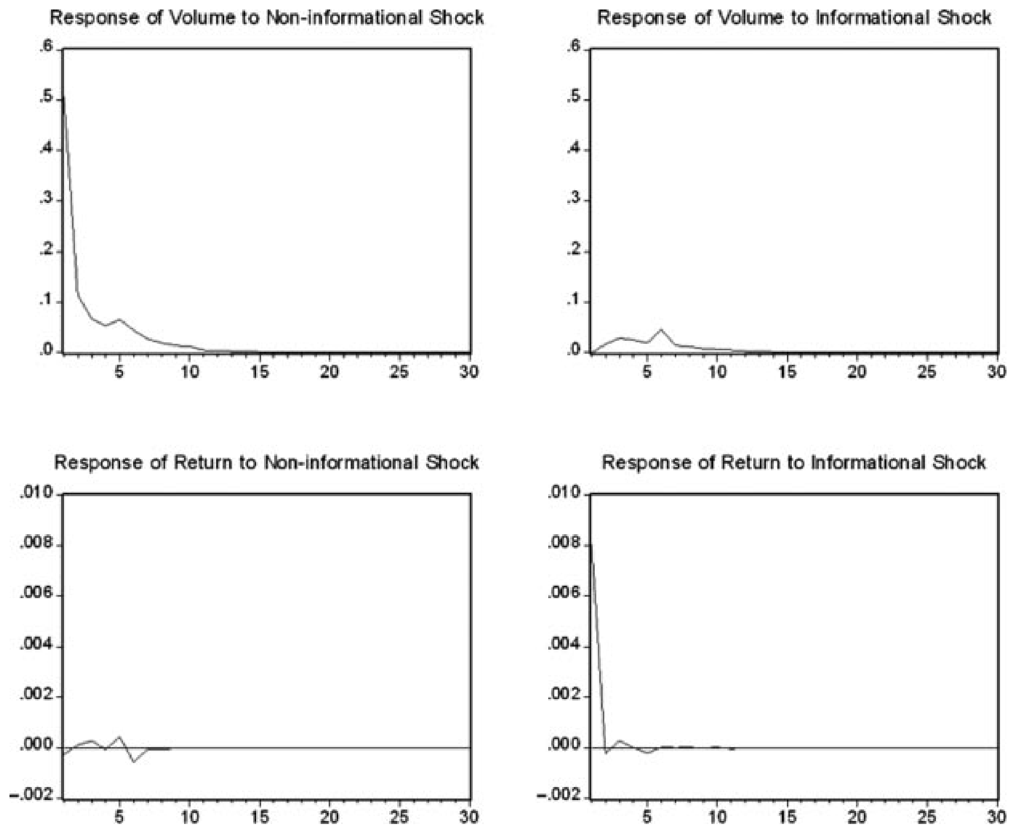

FIGURE 3

Detrended volume and close-to-close return responses to informational and noninformational shocks for copper futures (1999–2002).

market response is attributed to regulatory changes in 1999 that resulted in more participants becoming involved and a greater inflow of funds.

5. A modest overresponse effect on returns due to informational/permanent shocks can be observed in the wheat futures market (see Figure 6). On the second day, the effect of informational/permanent shocks on the returns on wheat futures changes to negative, whereas the effect is positive on the first day. On the third day the effect reverses to zero. This implies that the returns for wheat futures overrespond to informational/permanent shocks on the first day, followed by a modest adjustment occurring on the second day.
6. The volume response period for the noninformational/transitory shocks can be listed as follows: copper (subsample 1), approximately 15 days; copper (subsample 2), approximately 10 days; aluminum, approximately 60 days; soybeans, approximately 20 days; and wheat,

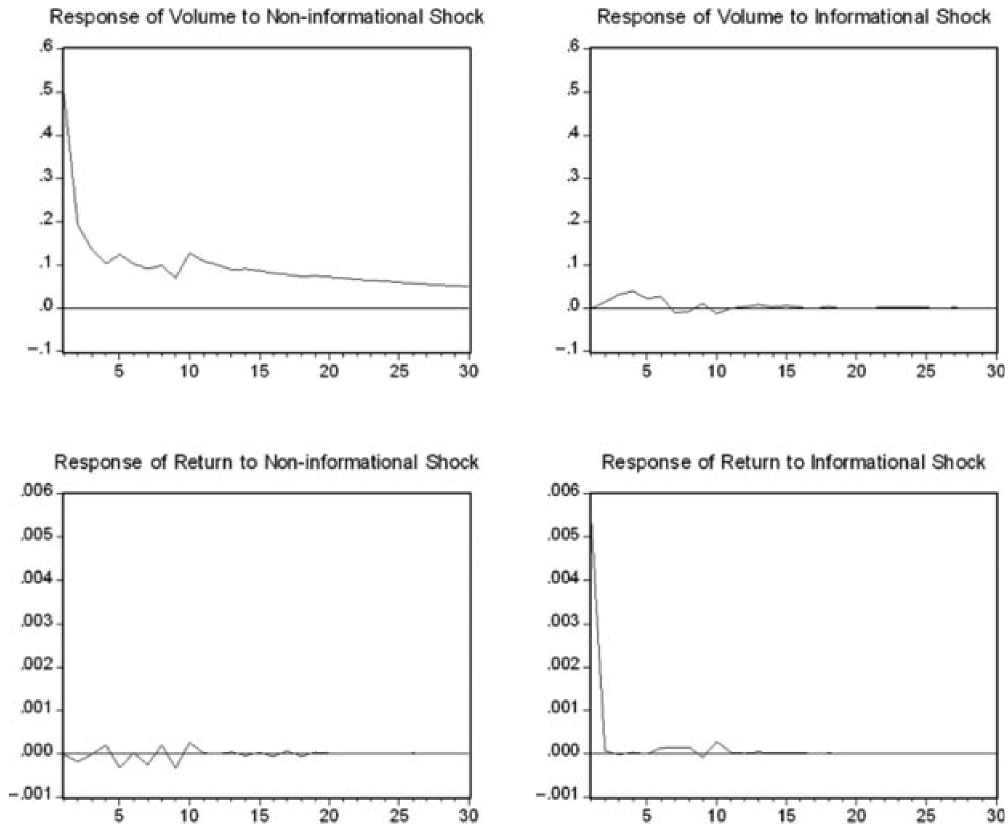

FIGURE 4
Detrended volume and close-to-close return responses to informational and noninformational shocks for aluminum futures (1999–2002).

approximately 25 days. The relatively long response period for aluminum futures can be attributed to relatively inactive trading during the first 2 years (1999 and 2000).

7. The market responses of actively traded futures (copper and soybeans) were greater than those of the less actively traded futures (aluminum and wheat) during the period 1999–2002. This follows as there is a modest overreaction to informational/permanent shocks for wheat futures returns, and the volume of aluminum futures responds to noninformational/transitory shocks more slowly than other futures.

Further Tests

In additional tests, the Pearson and Spearman correlations between informational and permanent components and between noninformational

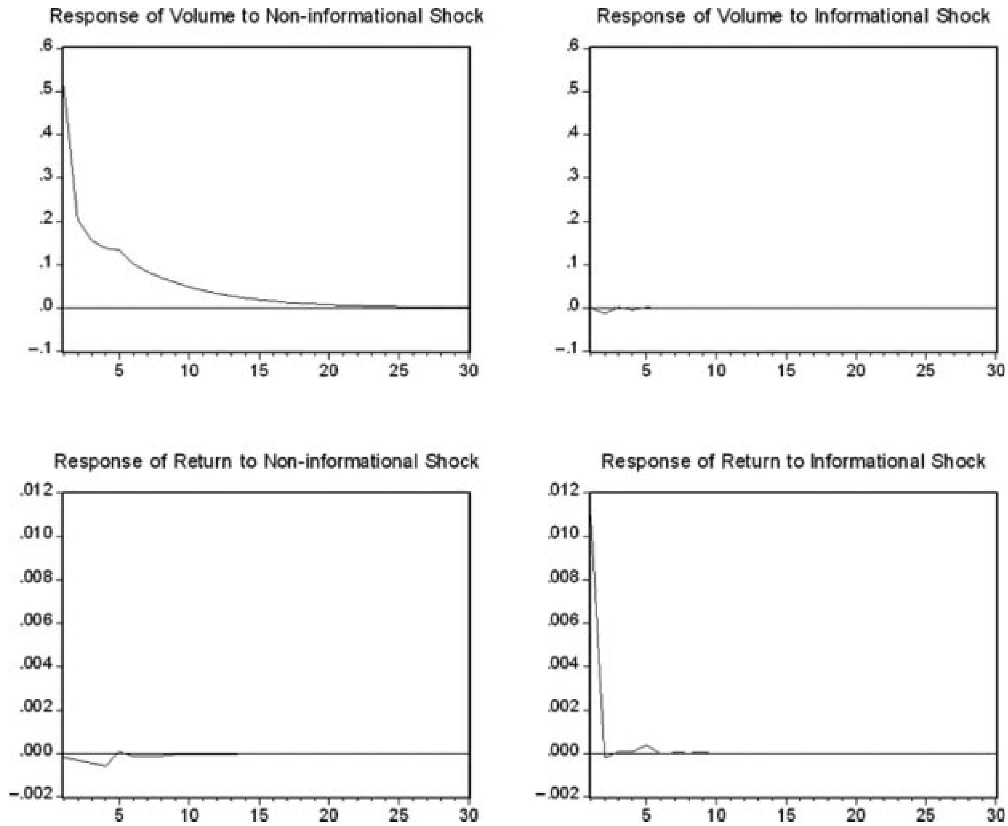

FIGURE 5

Detrended volume and close-to-close return responses to informational and noninformational shocks for soybean futures (1999–2002)

and transitory components are calculated, and the related significant tests are also conducted.[15] It was found that informational and permanent shocks (and the noninformational and transitory shocks) are highly correlated and have similar characteristics, even though they are investigated from two different perspectives.[16] Specifically, informational shocks are more likely to have a long-term effect on returns, whereas permanent shocks are more likely to be understood and absorbed by all investors and thus become public information. Noninformational shocks are more likely to have only a short-term effect on returns, whereas transitory shocks are more likely to be the result of noise trading.

[15]The empirical results are available from the authors.

[16]Because of just-identification, futures returns and trading volume were decomposed from two different perspectives based on theoretical motivations, although these two kinds of shocks (informational vs. noninformational and permanent vs. transitory shocks) may be highly correlated and have similar characteristics.

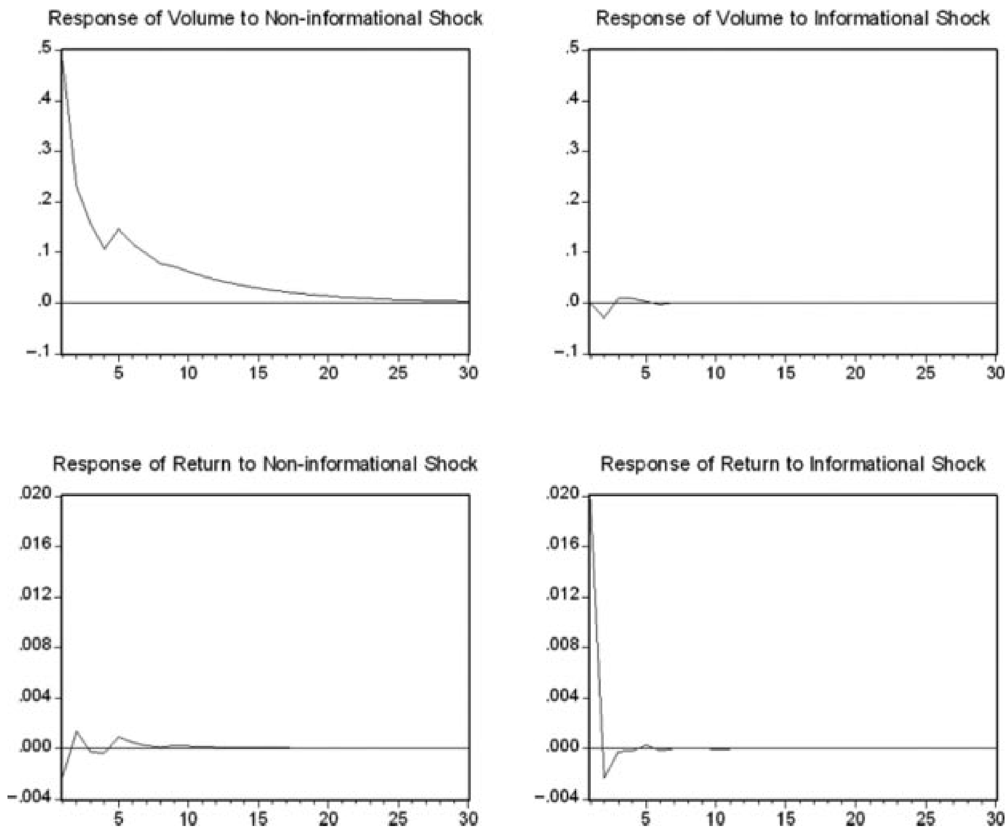

FIGURE 6
Detrended volume and close-to-close return responses to informational and noninformational shocks for wheat futures (2000–2002).

CONCLUSIONS

This study investigates how futures returns and trading volume of China's commodity futures behave in response to informational/permanent and noninformational/transitory innovations. The identification of related innovations is achieved by imposing restrictions reflecting the special characteristics of innovations. Using the BMAR and BVAR methodologies, the returns and volume series are decomposed into informational/permanent and noninformational/transitory components. The empirical results imply that the informational/permanent components are the dominant components for futures returns movements, whereas the noninformational/transitory components are the dominant components for trading volume. Noninformational/transitory shocks initially have a substantial effect on trading volume, and its effect declines gradually over time. Informational/permanent shocks initially have a substantial effect on futures returns, and this adjustment is very rapid. There is found to be a modest overresponse to the effects of informational/permanent shocks on the returns of wheat futures, and the volume of aluminum futures responds to noninformational/transitory information for a much longer period than that of other futures. The market responses of futures with active trading (copper and soybeans) are better than those of futures with relatively less active trading (aluminum and wheat). Based on the results for copper futures, it is found that the regulatory changes made in 1999 have led to improved market responses. In particular, higher trading volume has resulted. Future policy changes should be directed toward further increasing trading volume and market liquidity.

As discussed by Lee and Rui (2001), there are a number of ways to identify the components of volume and returns, and these represent future lines of research inquiry. For example, Bessembinder and Seguin (1992, 1993) detrend futures volume, and then decompose the variance of volume into informed and noninformed shocks with the use of an ARIMA process; another approach would be to use ARCH processes for futures returns.[17] Further, the empirical model used in this study could be expanded to include more than two types of shocks; this would make it more complete but also more complex.[18]

Finally, other futures markets, especially the mature Western futures markets, could be examined using the methodology outlined in this article. By comparing the results between China and Western countries, a more detailed understanding of commodity futures can be obtained.

APPENDIX

Based on Equation (10), Equation (4) can be rearranged as follows:

$$\begin{aligned} B(1) = \begin{bmatrix} B_{11}(1) & B_{12}(1) \\ B_{21}(1) & B_{22}(1) \end{bmatrix} = [I - A(1)]^{-1}B_0 &= \begin{bmatrix} 1 - A_{11}(1) & -A_{12}(1) \\ -A_{21}(1) & 1 - A_{22}(1) \end{bmatrix}^{-1} \\ &\quad \times \begin{bmatrix} b_{11}(0) & b_{12}(0) \\ b_{21}(0) & b_{22}(0) \end{bmatrix} \\ &= \frac{1}{\Delta}\begin{bmatrix} 1 - A_{22}(1) & A_{12}(1) \\ A_{21}(1) & 1 - A_{11}(1) \end{bmatrix}\begin{bmatrix} b_{11}(0) & b_{12}(0) \\ b_{21}(0) & b_{22}(0) \end{bmatrix} \end{aligned} \tag{A1}$$

where Δ is the determinant of $[I - A(1)]$.

[17]It is widely accepted that futures returns follow an ARCH process. To some extent the ARCH effect in return series has been considered in the BVAR model employed in this study. However, a more detailed investigation of the ARCH effects in return series is a possible extension to this study. The authors thank the reviewer for this comment.

[18]In this context, more restrictions on identification would be needed.

Because $B_{21}(1) = 0$, the additional restriction can be determined as follows:

$$B_{21}(1) = A_{21}(1) * b_{11}(0) + (1 - A_{11}(1)) * b_{21}(0) = 0$$

BIBLIOGRAPHY

Beaver, W. H. (1968). The information content of annual earnings announcements. Empirical research in accounting: Selected studies. Journal of Accounting Research (Supplement), 6, 67–92.

Bessembinder, H., & Seguin, P. J. (1992). Futures-trading activity and stock price volatility. Journal of Finance, 47, 2015–2034.

Bessembinder, H., & Seguin, P. J. (1993). Price volatility, trading volume and market depth: Evidence from futures markets. Journal of Financial and Quantitative Analysis, 28, 21–39.

Blanchard, O. J., & Quah, D. (1989). The dynamic effects of aggregate demand and supply disturbances. American Economic Review, 79, 655–673.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). The econometrics of financial markets. Princeton, NJ: Princeton University Press.

Chung, H., & Lee, B. S. (1998). Fundamental and nonfundamental components in stock prices of Pacific-Rim countries. Pacific-Basin Finance Journal, 6, 321–346.

DeLong, J. A., Shleifer, L. S., & Waldmann, B. (1990). Positive feedback, investment strategies and destabilizing rational speculation. Journal of Finance, 45, 379–395.

Fama, E. F., & French, K. (1988). Permanent and temporary components of stock prices. Journal of Political Economy, 96, 246–273.

French, K., & Roll, R. (1986). Stock return variances: The arrival of information and the reaction of traders. Journal of Financial Economics, 17, 5–26.

Gallant, A. R., Rossi, P. E., & Tauchen, G. (1992). Stock prices and volume. Review of Financial Studies, 5, 199–242.

Harvey, C. R., & Huang, R. D. (1991). Volatility in foreign currency futures markets. Review of Financial Studies, 4, 543–569.

Hasbrouck, J. (1991). Measuring the information content of stock trades. Journal of Finance, 46, 179–208.

Jones, C. M., Kaul, G., & Lipson, M. L. (1994). Information, trading, and volatility. Journal of Financial Economics, 36, 127–154.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. Journal of Financial and Quantitative Analysis, 22, 109–126.

Lee, B. S. (1995). The response of stock prices to permanent and temporary shocks to dividends. Journal of Financial and Quantitative Analysis, 30, 1–22.

Lee, B. S., & Rui, O. M. (2001). Empirical identification of non-informational trades using trading volume data. Review of Quantitative Finance and Accounting, 17, 327–350.

Muth, J. (1960). Optimal properties of exponentially weighted forecasts. Journal of The American Statistical Association, 55, 299–306.
Poterba, J., & Summers, L. (1988). Mean reversion in stock returns: Evidence and implications. Journal of Financial Economics, 22, 27–60.
Quah, D. (1992). The relative importance of permanent and transitory components: Identification and some theoretical bounds. Econometrica, 60, 107–118.