Simulation of Transaction Behavior and Price Volatility in Chinese Soybean Futures Market Using MVAR Model

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Abstract—Traditional vector autoregressive (VAR) modeling theory has the defect that it can not effectively utilize the multiple time scale information contained in the inner of variables. In order to discuss multiscale behavior among economic variables and capture variables' information in different time scale, multiresolution VAR model which can also be called as MVAR model has been established in the paper by combining multiscale analysis and theory of VAR modeling to overcome the defect of traditional model, which can also capture the relationship between variables in different time scale in detail. Taking soybean futures on Dalian Commodity Exchange for example, the paper studies the relationship between transaction behavior of agricultural futures investors and volatility of futures price using MVAR model.

Index Terms—multiscale analysis, transaction behavior, price volatility, soybean futures, MVAR model

I. INTRODUCTION

How does transaction behavior of futures investors result in price volatility of soybean futures? Behavioral finance theory considers price volatility can be explained by transaction behavior of investors. The paper takes China's soybean futures for example to verify the relationship between transaction behavior and futures price. There are two reasons for choosing futures market. First, commodities in this market are standardized and market is in full competition. Second, comparing to other markets, futures market is more important. Futures market provides reference for government to regulate the operation of national economy and enterprise operating in a market economy. It's helpful to establish and perfect market economy system, to perfect resource allocation and adjust market supply and demand, to slow down price volatility and form fair, impartial price signals, to avoid market risk resulting from price volatility, to reduce circulation cost and stabilize the relationship between production and distribution, to lock production cost and stabilize the management profit of enterprises. In China's agricultural futures market, most market subjects are private investors. Statistics show that the sum turnover of customers whose turnover is less than 1 million RMB account for more than 80% of the whole turnover. Because of excessive private investors and shortage of institutional investors who can stabilize market, it's no good for market to act normally. Producers will face huge risk of price volatility because agricultural prices influence by both domestic and overseas

market after the accession to WTO. Price volatility of grain, cotton and some other primary agricultural products affects farmers' income directly. Theoretical circles and governments should grope an effective way for farmers to transfer price risks. Market volatility can be simply summarized as disequilibrium of supply and demand, but this explanation is too general. The aim of transaction in spot market is to meet production and consumption, and that in futures market is to avoid risks and make money with arbitrage. The difference determines the complexity of volatility reasons in futures market. Therefore, it's significant to study the universal volatility law and volatility mechanism of agricultural futures market.

The paper is organized as follows. In the next section, we reviews research references in recent years. Section 3 gives the research methodology and the description of the data used in this study. Section 4 takes soybean dominant future (Non-GMO soybean) on Dalian Commodity Exchange for example, empirically analyzes the relationship between transaction behavior and volatility of price signals using MVAR model. The last section concludes the paper.

II. RESEARCH REVIEW

There are many references related to price volatility in futures market in recent years. But there are few references analyzing price volatility from the perspective of transaction behavior because it's hard to measure transaction behavior. Liao, Peng and Li (2005) analyzed the forming reasons of mineral products price and influence factors of price. They pointed out that futures price of mineral product is the function of its spot price, and they used stochastic process and option method to find out the lognormal distribution model of mineral product's spot price and its explicit solution [1]. Li and Wu (2007) established an EC-TARCH-M model which includes expected risk return and asymmetric information impacts from both spot market and futures market. The empirical results on the volatility characters of the spot-future market of the soybean, corn and soybean meal and wheat are figured out. The results show that the affects of the futures trading activities to the futures markets' price volatility are prominent, but the degrees are different; speculated trading activities increase the futures market volatility; and market depth is helpful to decrease the volatility. Information impacts from spot markets to the future markets' price volatilities are asymmetric, and leverage effects are found in the futures markets' price volatility by the impacts from the futures

markets [2]. Zhang and Wei (1999) considered spot prices of commodities determined by producers, buyers, speculators and managers. Producers will sell short to prevent price decreasing, while buyers will buy long to prevent price increasing. Speculators participate in spot and futures market for profit. Governments play an important role in the market by providing kinds of support policies for producers or intervening marker directly. Authors studied participative behavior of the four subjects and established a general equilibrium model of commodity futures trading, they also groped theories and ways for inhibiting force incidents [3]. Xiao and Wu (2004) used high-frequency data to analyze the intraday interaction between stock index and stock index futures. The results showed there existed instantaneous interaction relationship between the two markets' returns of SP500 index, which was different from foreign studies. The authors adopted three methods which are average yield, the OHLC method proposed by Garman and Klass in 1980 and GARCH（1，1） to test the lead-lag relationship between the two markets' volatilities. Results indicated the stock index futures lead longer than that of the stock index, and the speed was different for the two markets respond to different type information [4]. As current researches on volatility persistence and volatility co-persistence were usually based on low-frequency data, Guo and Zhang (2006) used realized volatility as a new volatility estimator which was based on high-frequency data, and they defined volatility persistence and volatility co-persistence based on realized volatility. In addition, they did empirical research on volatility persistence and volatility co-persistence using the high-frequency data of Chinese stock markets [5]. Irwin, Good and Gomez (2008) investigated the impact of U.S. Department of Agriculture World Agricultural Supply and Demand Estimate (WASDE) reports on   implied volatility in corn and soybean markets over 1985 to 2002. Results revealed that the group of reports   reduces implied volatility by an average of 1.1 percentage points in corn and by almost 1.5 percentage points in soybeans [6]. Ishinishi, etc. (2005) discussed network resource allocation in futures markets through simulation using the proposed model. In their model, all market participants (software agents) observed only market prices and decided to buy or sell bandwidth trying to maximize their utilities over time so that they could secure enough network resources [7]. Garcia and Leuthold (2004) provided a selected review of the research literature on commodity futures and options markets, focusing primarily on empirical studies. The topics featured in their paper include the development of intertemporal price relationships, hedging and basis relationships, price behavior and discussion of the markets' institutional issues [8]. Koekebakker and Lien (2004) extended Bates' Jump-diffusion option pricing model by including both seasonal and maturity effects in the volatility specification. Both in-sample and out-of-sample procedures to fit market option prices on wheat futures showed that the suggested model outperforms previous published models. A numerical example showed the magnitude of pricing errors for option valuation [9]. Jin and Frechette (2004) tested whether the volatility of agricultural futures prices exhibits fractional integration. They also extended a fractional integration model, FIGARCH (1, d, 1), which was performed significantly better than a traditional volatility model, GARCH (1, 1), in modeling agricultural futures price volatility [10]. Ewing, Hammoudeh and Thompson (2006) used the momentum-threshold autoregressive (M-TAR) model to examine the possible asymmetric relationship

between petroleum futures and spot prices for three different markets: crude oil, heating oil, and gasoline in the United States. Their results indicated that the futures and spot prices for each petroleum type are cointegrated when allowing for asymmetric adjustment for each of these energy markets. They further investigated the asymmetric behavior between the futures and spot prices by estimating the M-TAR error-correction model [11]. Using survival probability in the continuous-time random walk theory, Kim and Yoon (2003) studied the tick dynamical behavior of the bond futures in Korean Futures Exchange (KOFEX) market. The results showed that the decay distributions for survival probability were particularly displayed stretched exponential forms with novel scaling exponents beta = 0.82 (KTB203) and 0.90 (KTB112), respectively, for their small time intervals [12].

Most previous researches use parametric models to study price volatility, but estimation of volatility is efficient only if the form of general parametric models is rational and all assumptions are fulfilled. Wavelet analysis has good time-frequency and zoom characteristics, with which we don't need to build volatile model to describe volatility. We get the mathematical model of wavelet analysis in section 3.

III. MATERIALS AND MODELS

A. Wavelet analysis

Assume $\psi(t) \in L^2(R)$, its Fourier transformation is as $\hat{\psi}(\omega)$. When $\hat{\psi}(\omega)$ satisfies admissible condition that as follows,

$$C_{\Psi} = \int_R \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < \infty . \quad (1)$$

In this case, $\psi(t)$ can be defined as basic wavelet. Deducing from admissible condition, basic wavelet $\psi(t)$ must satisfy $\hat{\psi}(0) = 0$ at least, which means that $\int \psi(t)dt = 0$. In other words, $\hat{\psi}(\omega)$ must have the characteristic of bandpass filtering.

We call wavelet sequence as daughter wavelet, which are got from contraction-expansion and translation of basic wavelet,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \psi(\frac{t-b}{a}) \quad (2)$$

Where a, b $\in R$, $a \neq 0$, a is contraction-expansion factor or scale factor; b is displacement factor.

Wavelet transformation of signal $f(t)$ can be defined as follows,

$$W_{\psi}f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(t)\hat{\psi}(\frac{t-b}{a})dt . \quad (3)$$

If $\psi(t)$ satisfies admissible condition, signal $f(t)$ can be reconstruction as follows,

$$f(t) = C_{\psi}^{-1} \iint_{R^2} W_{\psi}f(a,b)\psi_{a,b}(t)\frac{dadb}{a^2} \quad (4)$$

We make continuous wavelet discretization in Matlab 7.0. Let $a = a_0^m$, $b = nb_0 a_0^m$, $a_0 > 1$, $b_0 \in R$, and discrete wavelet of signal $f(t)$ is transformed into following form,

$$W_{\psi}f(m,n) = a_0^{-\frac{m}{2}} \int_{-\infty}^{+\infty} f(t)\hat{\psi}(a_0^{-m}t - nb_0)dt \quad (5)$$

While $a_0 = 2$, $b_0 = 1$, the function above becomes dyadic wavelet transformation,

$$W_{\psi}f(m,n) = 2^{-m} \int_{-\infty}^{+\infty} f(t)\hat{\psi}(2^{-m}t - n)dt \quad (6)$$

Sampling step for different frequency components in the time domain is adjustable; sampling stem of high frequency one is small and it corresponds to smaller m; low frequency one is just opposite and corresponds to bigger m. Thereupon, wavelet transformation realized time-frequency localization with fixed window size and variable window shape.

For each $f(t) \in L^2(R)$ corresponding wavelet series can be got from wavelet Ψ, as follows,

$$f(t) = \sum_{j,k} C_{j,k} \psi_{j,k}(t) . \quad (7)$$

If $\{\Psi_{j,k}\}$ comprise orthonormal basis, and let W_j=span<$\Psi_{j,k}$, k∈zz>, which denotes closed space expanding by linear ways of $\Psi_{j,k}$. It's absolutely that the following formula is available.

$$L^2(IR) = \sum_{j \in z} W_j = ... \oplus W_{-1} \oplus W_0 \oplus$$

Accordingly, square integrable signals in every real space have a unique factorization as follows,

$$f(t) = \sum_{j \in z} g_j(t) \quad , \quad g_j(t) \in W_j .$$

Introducing multi-scale analysis in W_j on precondition of its direct sum, where W_j appears in $L^2(IR)$ that we just mentioned above. Letting

$$V_j = W_{j+1} + W_{j+2} + ... \quad , j \in zz$$

If f(t)∈L2(R) and assume f(t)∈V0, then V0=V1+W1 and $f(t)=f_1(t)+g_1(t)$ accordingly; if the decomposition is far from satisfactory, according to $V_1=V_2+W_2$, it must meet the condition $f(t)=f_2(t)+g_2(t)+g_1(t)$. Repeat the process until you feel satisfied with the results. Finally, $f(t)$ will be denoted as follows,

$$f(t)=f_m(t)+g_m(t)+...+g_1(t). \quad (8)$$

Daubechies wavelet is one of the wavelets which are the most widely used at present. It is compactly supported orthonormal wavelet and has nice performance.

Daubechies wavelet doesn't have definite expression, but square norm of its transfer function can be expressed as $P(y) = \sum_{k=0}^{N-1} C_k^{N-1+k} y^k$, where C_k^{N-1+k} is binomial coefficient.

B. MultiscaleVAR model

Vector Autoregressive model, which is put forward by Sims (1980), is established on the basis of data statistics to predict time series system and measure the dynamic effect of random disturbance on the system [13]. It has no advance constraints and views each variable as endogenous variable. But current variables don't use as explanatory variables. General VAR model has three hypotheses as follows: first, time series x_t and y_t are stationary random process; second, random error u_{xt} and u_{yt} are white noise series and $\sigma_x^2 = \sigma_y^2 = 1$; third, random error u_{xt} and u_{yt} are uncorrelated and cov (u_{xt}, u_{yt}) =0.

But time series doesn't meet the above hypotheses at most of the time. When Engle and Kraft (1983) analyzed macro-data, they found that the stability of disturbance variance in time series models is often worse than we supposed [14]. Financial data usually have conditional heteroskedasticity, which makes the prediction of general VAR invalid. Because of the volatility of financial market, heteroskedasticity in financial series may easy to be affected by factors such as rumor, nature disaster, changes of political situation, monetary policy and financial policy. Engle and Grange (1987) combined co-integration with error corrected model to establish vector error corrected

model, but the model still requests the error term to be stable [15]. If you want to know about more discussions of VAR model and VEC model, you can refer to works of Davidson and Mackinnon (1993) [16]. In order to overcome the nonstationarity of financial series bring to the application of VAR, Zhao, etc. (2008) combined wavelet filtering technology and SVAR model to study volatile characteristics of SSE composite index, Heng Seng Index, N225 index, Dow-Jones index and FTSE100 index and their interaction [17]. But traditional VAR modeling theory has the defect that it can't interpret the multiple time scale information contained in the inner of variables. In order to discuss multi-scale behavior among economic variables and capture variables' information in different time scale, multiresolution VAR model has been introduced and combined with wavelet analysis and theory of VAR modeling to overcome the defect of traditional model, which can capture the relationship between variables in different time scale in detail. VAR(2) model of time series x_t and y_t can express as follows,

$$x_t = \beta_{10} + \beta_{11} y_{t-1} + \beta_{12} y_{t-2} + \alpha_{11} x_{t-1} + \alpha_{12} x_{t-2} + u_{xt}$$
$$y_t = \beta_{20} + \beta_{21} y_{t-1} + \beta_{22} y_{t-2} + \alpha_{21} x_{t-1} + \alpha_{22} x_{t-2} + u_{yt} \quad (9)$$

We get MVAR(2) model as formula (10) by applying wavelet transform as formula (11) to random processes x_t and y_t.

$$W_{jt} = \beta_{10} + \beta_{11} V_{jt-1} + \beta_{12} V_{jt-2} + \alpha_{11} W_{jt-1} + \alpha_{12} W_{jt-2} + \varepsilon_{x,jt}$$
$$V_{jt} = \beta_{20} + \beta_{21} V_{jt-1} + \beta_{22} V_{jt-1} + \alpha_{21} W_{jt-1} + \alpha_{22} W_{jt-1} + \varepsilon_{y,jt} \quad (10)$$

$$W_{jt} = \sum_{l=0}^{L_j-1} h_{jt}*x_{t-l} \quad , \quad V_{jt} = \sum_{l=0}^{L_j-1} h_{jt}*y_{t-l} \quad (11)$$

Where $t \in Z$ and L_j=(2^j-1)(L-1)+1. L is the length of filter $\{h_{jt}\}$. j is the layers of wavelet transform. $\{W_{jt}\}$ and $\{V_{jt}\}$ are series after wavelet transform. Define variance of time varying wavelet under scaling τ_j as,

$$v_{xt}^2(\tau_j) = \text{var}(W_{jt}), v_{yt}^2(\tau_j) = \text{var}(V_{jt}) \quad (12)$$

Wavelet variance can decompose random process x_t and y_t according to scaling τ_j (Zhang, etc., 2008) [18], that is,

$$\sum_{j=1}^{\infty} v_{xt}^2(\tau_j) = \text{var}(x), \sum_{j=1}^{\infty} v_{yt}^2(\tau_j) = \text{var}(y)$$

According to wavelet variance, define multiscale relative variance contribution as,

$$MRVC_x(\infty) = \frac{\text{var}(W_{jt})}{\sum_{j=1}^{\infty} v_{xt}^2(\tau_j)}, MRVC_y(\infty) = \frac{\text{var}(V_{jt})}{\sum_{j=1}^{\infty} v_{yt}^2(\tau_j)}$$

Decompose random processes x_t and y_t into the k-th layer and we can get the approximate multiscale relative variance contribution as follows,

$$MRVC_x(k) = \frac{\text{var}(W_{jt})}{\sum_{j=1}^{k} v_{xt}^2(\tau_j)}, MRVC_y(k) = \frac{\text{var}(V_{jt})}{\sum_{j=1}^{k} v_{yt}^2(\tau_j)}$$

Where $MRVC(k)$ have characteristics as follows,

$$0 \leq MRVC(k) \leq 1, \quad \sum_{j=1}^{k} MRVC(k) = 1 .$$

C. Transaction Behavior & Volatility of Price

The paper uses dominant future of soybean in Chinese soybean futures market during January 4, 2005 and April 30,

2009 as research object, and there are 1051 samples. Absolute values of "change rate of position" are used to measure transaction behavior.

$$Behavior_t = \frac{|\Delta Position_t|}{Position_t} \quad (12)$$

Here $Behavior_t$ denotes transaction behavior. $Position_t$ denotes position and $\Delta Position_t = Position_t - Position_{t-1}$.
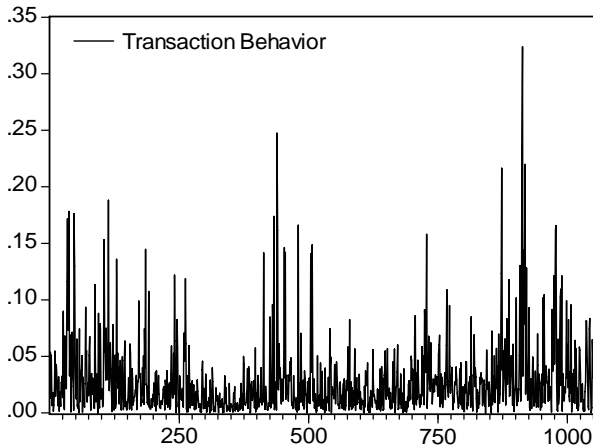

Figure1. Transaction behavior in soybean futures market

Alizadeh, Brandt and Diebold (1999) found fluctuation range of daily price can simulate real volatility of price well, as well as Gallant，Hsu and Tauchen (1999) [19][20]. Record fluctuation range of daily price as V_t, so we can use the highest price H_t and lowest price L_t to define fluctuation range:
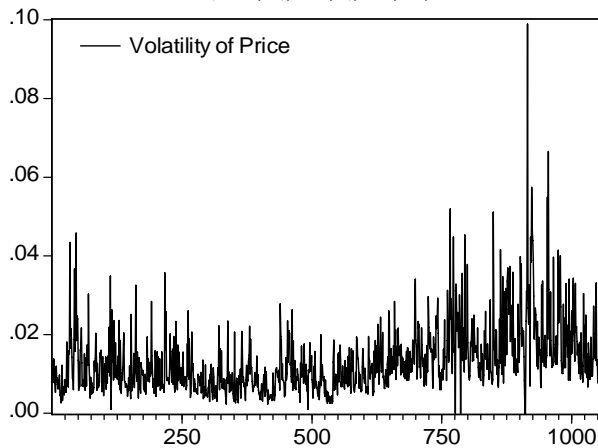
$$V_t = \ln(H_t) - \ln(L_t) \quad (13)$$

Figure 2. Price volatility of soybean futures

IV. RESULTS

Use *VAR(3)* model to estimate causality between transaction behavior and price volatility. Estimation results are listed in Table 1. All calculations and figures are achieved in Matlab7.0 and Eveiws5.0.

Parameters in Table 1 shows there are Granger causality between transaction behavior and price volatility. Transaction behavior, whose lagged order is 2, increases price volatility. Price volatility whose lagged order is 2 also results in the change of transaction behavior. But R^2 indicates degree of fitting of the whole equation is not good.

Because VAR model can't capture the relationship between behavioral variables and volatile variables in different scale, the paper adopts MVAR model to reestimate parameters of the model.

TABLE 1. PARAMETRIC ESTIMATION OF VAR MODEL

	V_t	$Behavior_t$
V_{t-1}	0.2729***	-0.0194
	[8.4308]	[-0.1429]
V_{t-2}	0.2164***	0.2835**
	[6.6244]	[2.0691]
V_{t-3}	0.1047***	0.1990
	[3.2656]	[1.4806]
$Behavior_{t-1}$	0.0060	0.2496***
	[0.7744]	[7.7154]
$Behavior_{t-2}$	0.0176**	0.0162
	[2.2205]	[0.4856]
$Behavior_{t-3}$	0.0071	0.0958***
	[0.9109]	[2.9473]
C	0.0045***	0.0119***
	[8.8176]	[5.5319]
R^2	0.2699	0.1101
$Adj.\ R^2$	0.2657	0.1049
F-statistic	64.0757	21.4348
Log likelihood	3632.605	2131.711
Akaike AIC	-6.9257	-4.0587
Schwarz SC	-6.8926	-4.0255

Note: Numbers in [ ] are t statistics. *** denotes significant at confidence level of 1%. ** denotes significant at confidence level of 5%.

Density of singular point is very large while dealing with high-frequency data, so vanishing moment can't be very high. Therefore the paper chooses db5 function to apply wavelet transform. According to multiresolution analysis theory, the higher the decomposed layer is, the more the low-frequency ingredients are culled out. So, it's easy to result in distortion of low-frequency parts. Through repeatedly testing high-frequency data of share price and its return, Ma, etc. (2008) believed the decomposed layers of series with higher volatility were unfavorable to be more than 3, because the series have many high-frequency ingredients [21]. Decompose price behavior into $Behavior_{1t}$, $Behavior_{2t}$, $Behavior_{3t}$ and $Behavior_{4t}$ respectively; decompose price volatility into V_{1t}, V_{2t}, V_{3t} and V_{4t}, and we get the following equations:

$Behavior_t = Behavior_{1t} + Behavior_{2t} + Behavior_{3t} + Behavior_{4t}$,
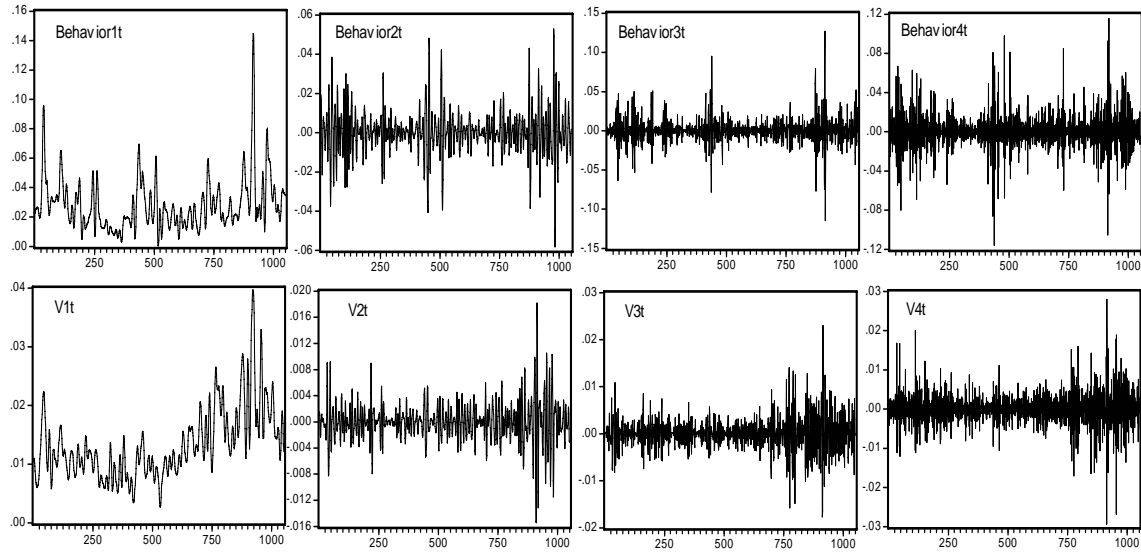$V_t = V_{1t} + V_{2t} + V_{3t} + V_{4t}$.

Figure 3. Series after wavelet transform

By using MVAR model to estimate causality between transaction behavior and price volatility, all of R^2, *Adj. R^2, F-statistic, Akaike AIC and Schwarz SC* have significant improvement (Table 2, appendix). Precision of MVAR model is higher than that of VAR model with the same order, so the effect will be much better if we use MVAR model to predict transaction behavior and price volatility.

Time scale of equations 1 in Table 2 is 8. Here relationship between transaction behavior and price volatility is Granger causality, and the degree of fitting is very high. Time scale of equations 2, 3 and 4 are 8, 4, and 2 respectively. It indicates that there is no Granger causality between transaction behavior and price volatility in the latter three equations. Both the high-frequency parts of transaction behavior and price volatility are autoregression processes and interaction of the high-frequency parts of the two variables is weak.

According to the definition of multiscale variance contribution, simulate contribution and cumulative contribution of all variances in different layers which have dealt with wavelet transform (Figure 4 and Figure 5). From

Figure 4 and Figure 5, we can see that main factors that affect prediction effect are the high-frequency parts of transaction behavior and price volatility. Variance prediction results of MVAR model indicate that the smaller the time scale is, the more energy the series contain and the fiercer the series volatility is. Variance of low-frequency parts basically stays the same. But variance of high-frequency parts changes with time and characteristic of conditional variance is obvious. When time scale is 2, variance contribution and variance cumulative contribution of $Behavior_{4t}$ are stable above 60%. But sum of variance contribution in other scales is less than 40%. When time scale is 8, the sum of variance contribution of $Behavior_{1t}$ and $Behavior_{2t}$ is less than 10%. When time scales are 2 and 4, variance changes of price volatility V_{4t} and V_{3t} are bigger, but they tend to be stable in the end. Variance contribution and variance cumulative contribution of V_{4t} are stable at 60%, which means information content in soybean futures market is higher. But information will be gradually digested by market with time flies.
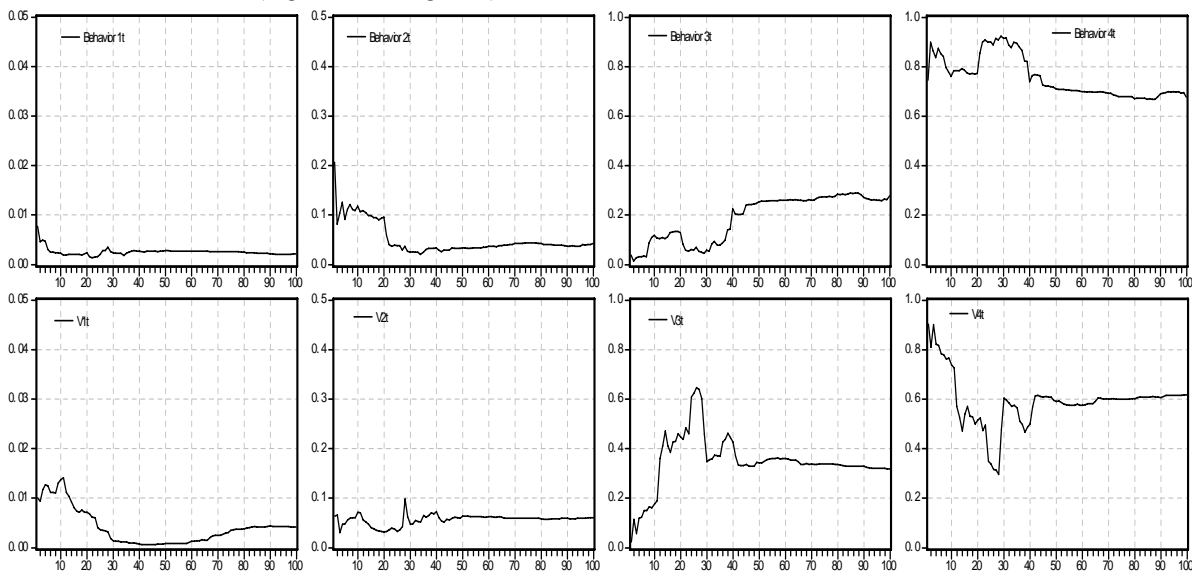

Figure 4. Simulation of multiscale variance contribution

V. CONCLUSION AND DISCUSSION

When time scale is 2, interaction between transaction behavior and price volatility is not significant. Equations 4 have proved this conclusion. When time scale is 4, traders are more cautious for the shock of price volatility. Change of traders' position is not big at the moment and transaction behavior doesn't have influence on soybean futures price yet. And equations 3 have proved it. There are two situations when time scale is 8. Equations 1 estimated by low-frequency data indicates transaction behavior and price volatility of soybean futures influence each other. But equations 2 estimated by high-frequency data don't have the same conclusion. It shows that transaction behavior and price volatility of soybean futures are independent to each other.

This discovery indicates price of soybean futures has influence on traders' invest decisions. But traders need 4 days or more to response to the information sent back by price signals. Thus, the assumption investors are rational people in classical financial theory need to be questioned. Behavior finance extends the assumption that traders are rational and divides traders into information trader and noise trader (Shefrin and Statman, 1994) [22]. Use MVAR model to decompose transaction behavior into low-frequency part and high-frequency part, which are corresponding to information trader and noise trade respectively. This makes MVAR model have economic meaning.

Position, as one of transaction behavior of investors, its change has some effect on the price of soybean futures contract, while price volatility's impact on change of investors' position is very clear. In equations 1, information traders have captured information provided by price volatility and adjusted position. Then this adjustment influences market price. Equations 2 show that noise traders can't use existing information of price volatility to adjust their invest decisions.

Equations 1 indicate transaction behavior increases price volatility of soybean futures. It also indicates Chinese soybean futures market is inefficient at present. This phenomenon may relate to price manipulation causing by oligopoly in soybean futures market. Chinese soybean futures market is only 16 years old. Though it grows rapidly and has become world's biggest futures market of non-GMO soybean, its risk management system is imperfect, so price manipulation is easy to take place. Coincidentally, information traders just have ability to utilize their information advantages to influence price.

There are two types of people in futures market: information trader and noise trader. How to distinguish the two based on known information is a complex issue. Maybe MVAR model can help to solve this problem. Multi-resolution VAR model has been introduced into the paper on the basis of VAR model. Multi-resolution VAR model make it possible to discuss shocks between variables in different time scale. It can capture multiple time scale information contained in the inner of variables and describe economic relationship in detail. Our next work is to predict volatility of financial signals on the basis of MVAR model.
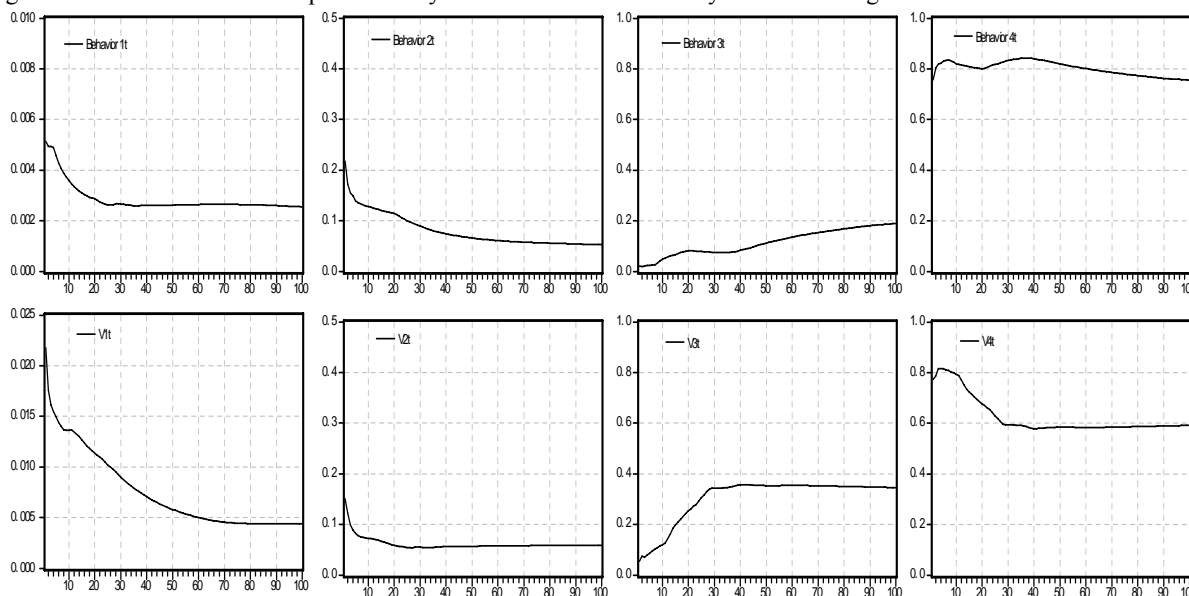

Figure 5. Simulation of cumulative contribution of multiscale variance

APPENDIX

TABLE 2. PARAMETRIC ESTIMATION OF MVAR MODEL

	Equations 1, scaling=8		Equations 2, scaling=8		Equations 3, scaling=4		Equations 4, scaling=2	
	V_{1t}	$Behavior_{1t}$	V_{2t}	$Behavior_{2t}$	V_{3t}	$Behavior_{3t}$	V_{4t}	$Behavior_{4t}$
lag t-1	2.5521***	0.1950**	1.7275***	-0.0553	0.7635***	0.0611	-1.3150***	-0.1118
	[111.868]	[2.3968]	[52.6920]	[-0.45178]	[24.8749]	[0.4234]	[-46.7712]	[-0.8516]
lag t-2	-2.2599***	-0.3669**	-1.2241***	0.1491	-0.8989***	0.0443	-1.0949***	-0.0196
	[-51.3566]	[-2.3380]	[-23.4148]	[0.76380]	[-33.5891]	[0.3525]	[-29.8664]	[-0.1143]
lag t-3	0.7017***	0.1915**	0.2021***	-0.1203	0.1672***	-0.2462*	-0.5010***	0.207
	[31.3108]	[2.3967]	[6.1606]	[-0.9819]	[5.4550]	[-1.7087]	[-17.8120]	[1.5754]
$Behavior_{\cdot t-1}$	0.0114*	2.5274***	0.008	1.7729***	0.0055	0.7586***	0.001	-1.1600***
	[1.6460]	[102.477]	[0.9125]	[54.3816]	[0.8425]	[24.8821]	[0.16675]	[-42.8095]
$Behavior_{\cdot t-2}$	-0.0153	-2.1866***	-0.0075	-1.2851***	0.0057	-0.9137***	0.0005	-1.0486***
	[-1.1362]	[-45.5401]	[-0.5370]	[-24.5985]	[1.0324]	[-35.1570]	[0.0711]	[-33.1043]
$Behavior_{\cdot t-3}$	0.0064	0.6487***	0.0056	0.2460***	-0.0082	0.2013***	-0.0009	-0.5637***
	[0.9157]	[25.9624]	[0.6403]	[7.5475]	[-1.2651]	[6.5815]	[-0.1520]	[-20.8126]
R^2	0.9985	0.998	0.9435	0.9441	0.6893	0.6867	0.7116	0.6742
$Adj.R^2$	0.9985	0.9979	0.9432	0.9438	0.6878	0.6852	0.7102	0.6726
F-statistic	138922	101719	3475	3517	462	456	514	431
Akaike AIC	-13.8895	-11.3467	-11.5481	-8.9133	-9.6688	-6.5734	-9.2079	-6.1253
Schwarz SC	-13.8611	-11.3183	-11.5198	-8.8849	-9.6404	-6.545	-9.1795	-6.0969

Notes: parameters are marked with asterisk. Numbers in bracket are t test value. *** indicates significance at 1 % level, ** indicates significance at 5 % level, * indicates significance at 10 % level.

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