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# Trading behaviors on knowledge of price discovery in futures markets[1]

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ABSTRACT

The financial market provides a mechanism for aggregating information of heterogeneous traders, who have different beliefs, knowledge and trading strategies. This paper studies the interactions between heterogeneous traders and their impacts on price discovery by developing a pricing model for the futures market. With mathematical analysis, we solve the equilibrium and its stability conditions for the system. As the findings show, behavioral factors such as risk appetites, degree of rationality and market liquidity have a combined effect on stability conditions. When the stability conditions are satisfied, the market can aggregate the information to form "good knowledge" about the price. If investors have high risk appetites or a high degree of rationality, it is difficult for the market to realize the price discovery function.



## 1. Introduction

The futures market is an important part of modern finance. Price discovery is one major contribution of the futures market in the organization of economic activities (Garbade and Silber, 1983). Generally, price discovery refers to the process of uncovering the fundamental value of asset. The futures price is supposed to reflect fundamental information and is equal to the fundamental value. As the maturing date approaches, the futures price and the spot price theoretically converge to each other. However, an increasing amount of empirical evidence has shown that the futures price may deviate greatly from the spot price in the process of price discovery, indicating the existence of mispricing (see Doukas and Pantzalis, 2010; Jacobs, 2016).

It is hard to understand the complicated dynamics of the futures market in standard economic theories. It is usually assumed that the price should be a reflection of fundamentals, which cannot change quickly and greatly in the short term. Instead, recent research has shown that trading activities and investor structure have substantial impacts on the relationship between futures prices and spot prices (Miller et al., 1994; Chen and Chang, 2015; Park and Shi, 2017). Arbitrage in the spot and futures markets plays an especially important role in pushing the basis reversion. The basis refers to the difference between the spot price and the futures price. When the basis widens largely, arbitrageurs buy futures and simultaneously sell the spot, pulling the basis back to a normal level. When the basis narrows, arbitrageurs trade in reverse. The trading behavior of fundamentalists, technical traders and other speculators can also affect price volatility (Miffre and Brooks, 2013; Lin et al., 2018; Bohl et al., 2018). The market price is generated through trading behaviors. Heterogeneous investors have different beliefs and expectations about the price. They usually take different trading strategies. The interactions between heterogeneous traders are potential sources of mispricing. One purpose of this paper is to model market dynamics from trading behaviors.

The market provides a mechanism for aggregating and spreading information. To some extent, it is a self-organized mechanism of knowledge creation. Investors make decisions based on the information they have obtained from fundamentals and charts. Through trading behaviors, the information is aggregated into the price observed by all traders. The price conveys the information of heterogeneous investors. By analyzing the price, investors can speculate what others think and do. Then, they adjust their beliefs and trading strategies in the next period, generating the new price. The price can be regarded as one type of knowledge about the asset. When the price discovery is realized, it is considered as "good knowledge". Otherwise, it is considered "bad knowledge".

In this context, the aim of this study is to analyze the impacts of agents' behaviors on the knowledge about assets in financial markets. We explore the conditions under which good knowledge can be generated.

The rest of this paper is structured as follows. In the next section, we review the literature. Then, we propose the main model. The results are presented and discussed. Finally, we summarize the conclusions.

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## 2. Literature review

### 2.1. Market efficiency and mispricing

As defined by Fama (1970), the efficient market refers to the market in which prices can fully reflect the available information and provide accurate signals for resource allocation. The EMH relies on two assumptions. First, investors are rational and can value the asset rationally. Second, there are arbitrageurs who can correct the price when the mispricing occurs. If irrational investors cannot evaluate the asset correctly and cause the price deviate from the fundamental value, there are profitable opportunities for arbitrageurs to trade, thereby pushing the price back to fundamentals (Friedman, 1953). However, in the past three decades, more and more evidence has shown that investors are irrational and there are limits to arbitrage (Shleifer, 2004). As Shleifer and Vishny (1997) pointed out, few traders have the knowledge and information to engage in arbitrage. Arbitrage is usually conducted by a small number of highly specialized investors. The mispricing caused by irrational investors may persist in the short term and force fund managers to close their trades at a loss. Arbitrage becomes ineffective when the price diverges far from the fundamental value.

In addition, much empirical research has uncovered market anomalies, indicating that mispricing is persistent and the market is inefficient. Examples include excess volatility, long-term reversal, medium-term momentum and beta anomaly. To explain these anomalies, recent studies have paid attention to other attributes of financial markets. Sadka and Scherbina (2007) found a close link between mispricing and liquidity by investigating stocks with high analyst disagreement. They showed that less liquid stocks tend to be more severely overpriced. Chordia et al. (2008) examined the predictive relationship between returns and order flow across different liquidity regimes. They suggested that the improvement of liquidity can enhance informational efficiency by allowing better incorporation of private information into prices. Griffin et al. (2010) and Jacobs (2016) empirically investigated the relationship between market maturity and efficiency. Although there are higher transaction costs and information costs in emerging markets, their research documented that mispricing associated with anomalies appears to be as prevalent in developed markets as in emerging markets.

In this study, we attempt to develop an asset pricing model. With mathematical analysis, we show the impacts of arbitrage and other behavioral factors, such as risk appetites, rationality of investors and market liquidity.

### 2.2. Bounded rationality and heuristic biases

Theories of behavioral economics have provided accurate assumptions about investors' beliefs, preferences and cognitive limits. It has been proposed that decision makers in economics are boundedly rational, and traditional models under rationality assumptions are psychologically unrealistic (Simon, 1955; Kahneman, 2003). As the studies show, decision makers have various decision-making styles and learn from the knowledge they acquire (Lin and Ho, 2019; Abubakar et al., 2019; Antunes and Pinheiro, 2020; Ghahtarani et al., 2020).

Agents in financial markets are presumed to have heuristic biases such as overconfidence, representative bias, availability bias and anchoring effect (Ackert and Deaves, 2010; Barberis and Thaler, 2003). These biases can affect investors' beliefs, preferences and strategies. Due to the representative bias, investors may believe that similar phenomena recur in the future. If the price increases in the past period, they expect the increase to continue in the next period. This can be considered return extrapolation, much like what technical traders do in financial markets. In contrast, due to the availability bias and anchoring effect, the beliefs of fundamental traders depend mainly on their knowledge about fundamentals. They estimate the fundamental value and expect the price to move toward it. Some research on heuristic biases has achieved success in explaining the anomalies in financial markets (Barberis, 2018; Daniel et al., 1998; Hong and Stein, 1999; Stambaugh et al., 2012; Barberis et al., 2018).

Based on the above-mentioned research, we assume investors are boundedly rational. They can learn and switch their strategies according to the payoffs. The model exhibits the nonlinearities stemmed from the bounded rationality, which are potential sources of mispricing.

### 2.3. The heterogeneous agents model

In order to model the interactions between heterogeneous investors, we resort to the heterogeneous agents model (HAM) with adaptive belief, which was introduced by Brock and Hommes (1997,1998) and further applied to financial markets (see Brock et al., 2009; Chiarella et al., 2006; Chiarella et al., 2011; Grauwe and Grimaldi, 2006; Gong and Yang, 2020). These models study the asset pricing from the perspective of behavioral equilibrium and depict market dynamics with an evolutionary system. Studies have shown that the nonlinearities stem from the interactions of heterogeneous investors and lead to market instability.

In this paper, we propose an asset pricing model with three types of traders. They can learn and switch the trading strategies through the logit response mechanism.

## 3. The dynamical model for futures market

In the model, there are three types of traders: fundamentalists, chartists and arbitrageurs. The utility of traders is assumed to be of the mean-variance type:

$$\Pi_t = E_t(\pi_{t+1}) - \frac{\theta}{2} Var_t(\pi_{t+1}), \tag{1}$$

where $E_t$ is the conditional expectation operator, $Var_t$ represents the conditional variance, $\pi_{t+1}$ is the payoff at time $t+1$, and $\theta > 0$ is the coefficient of risk aversion.

For fundamentalists and chartists, the payoff is represented by:

$$\pi_{i,t+1} = (F_{t+1} - F_t) d_{i,t}, \quad i = f, c, \tag{2}$$

where $F_t$ is the futures price and $d_{i,t}$ is the demand of futures by trader type *i*.

Arbitrageurs trade on both the futures market and the spot market with the same amount and opposite directions. The payoff is expressed by:

$$\pi_{a,t+1} = (F_{t+1} - F_t + S_t - S_{t+1}) d_{a,t}, \tag{3}$$

where $S_t$ is the spot price.

By maximizing the utility with respect to $d_{i,t}$, we derive the optimal demand of futures by trader type *i*:

$$d_{i,t} = \frac{E_{i,t}(F_{t+1} - F_t)}{\theta Var_{i,t}(F_{t+1})}, \quad i = f, c, \tag{4}$$

$$d_{a,t} = \frac{E_{a,t}(F_{t+1} - F_t + S_t - S_{t+1})}{\theta Var_{a,t}(F_{t+1} - S_{t+1})} = \frac{E_{a,t}(B_t - B_{t+1})}{\theta Var_{a,t}(B_{t+1})}, \tag{5}$$

where $B_t$ is the difference between spot price and futures price (i.e., the basis).

Investors are assumed to be boundedly rational. Heterogeneous traders form their expectations differently. Fundamentalists expect that the futures price converges to the fundamental value $F_f$. The forecasting rule is expressed by:

$$E_{f,t}(F_{t+1} - F_t) = \delta(F_f - F_t), \tag{6}$$

where $\delta > 0$ indicates the speed of expected adjustment.

Chartists forecast the futures price by extrapolating the past price movements. The forecasting rule is specified as:

$$E_{c,t}(\Delta F_{t+1}) = \gamma \sum_{j=0}^{T-1} \alpha_j \Delta F_{t-j}, \tag{7}$$

where $\Delta F_t = F_t - F_{t-1}$, $\alpha_j$ is the weight coefficient, and $\gamma > 0$ represents the degree of extrapolation. For simplification, let $T = 1$. Then:

$$E_{c,t}(F_{t+1} - F_t) = \gamma(F_t - F_{t-1}). \tag{8}$$

Arbitrageurs believe that the futures price and the spot price converge to each other as the delivery date approaches. If the difference between the futures price and the spot price is large, it is expected to narrow in the next period. The forecasting rule is set as:

$$E_{a,t}(B_t - B_{t+1}) = \alpha(S_t - F_t), \tag{9}$$

where $\alpha > 0$ represents the speed of adjustment.

We assume that the beliefs about the conditional variance are constant. In other words, $Var_{f,t}(F_{t+1}) \equiv \sigma_f^2, Var_{c,t}(F_{t+1}) \equiv \sigma_c^2, Var_{a,t}(B_{t+1}) \equiv \sigma_a^2$. According to the risk appetites of traders, it is assumed that $\sigma_a^2 > \sigma_f^2 > \sigma_c^2$. With Eqs. (4)-(9), we get:

$$d_{f,t} = \frac{\delta(F_f - F_t)}{\theta\sigma_f^2},\ d_{c,t} = \frac{\gamma(F_t - F_{t-1})}{\theta\sigma_c^2},\ d_{a,t} = \frac{\alpha(S_t - F_t)}{\theta\sigma_a^2}. \tag{10}$$

Heterogeneous traders switch to each other according to their payoffs. The switching mechanism is set as the logit response function (Brock and Hommes, 1997; Golman, 2012). Let $n_{i,t}$ be the probability that one investor is the type $i$. We have

$$n_{i,t} = \frac{e^{\beta U_{i,t}}}{\sum_{j=f,c,a} e^{\beta U_{j,t}}},\ i = f, c, a, \tag{11}$$

where $\beta > 0$ measures the degree of investor rationality (Brock et al., 2009; Golman, 2012). $U_{i,t}$ is the risk adjusted payoff of trader type $i$ (i.e., $U_{i,t} = \pi_{i,t} - \theta\sigma_i^2, i = f, c, a$). When the number of investors is sufficiently large, $n_{i,t}$ represents the fraction of traders of type $i$ in the market.

In line with the previous work (Chiarella et al., 2006; Chiarella et al., 2011), we assume that the futures price is arrived at via a market maker scenario. The futures price $F_{t+1}$ is obtained through the adjustment of $F_t$ according to the aggregate excess demand $D_t$. The adjustment mechanism is set as:

$$F_{t+1} = F_t + \mu D_t, \tag{12}$$

where $\mu > 0$ indicates the level of market liquidity. The aggregate excess demand $D_t$ is obtained by:

$$D_t = \sum_{i=f,c,a} n_{i,t} d_{i,t}. \tag{13}$$

The adjustment of spot price is determined by the fundamental value and futures price. It is specified as:

$$S_{t+1} - S_t = \nu(F_f - S_t) + (1 - \nu)(F_t - S_t) + \varepsilon_t, \tag{14}$$

where $\nu \in [0, 1]$ reflects the dependence on fundamental value. $\varepsilon_t$ represents the random shock. Since we focus on the deterministic dynamics, the random shock is not considered. For simplification, the adjustment mechanism is rewritten as:

$$S_{t+1} = \nu F_f + (1 - \nu)F_t. \tag{15}$$

From the above equations, we obtain the market dynamical system of nonlinear time-delay difference equations. To reduce the order of difference equations, we set $\tilde{F}_{t+1} = F_t$. The dynamical system is expressed as:

$$\begin{cases} \tilde{F}_{t+1} = F_t \\ n_{f,t} = \dfrac{e^{\beta U_{f,t}}}{\sum_{j=f,c,a} e^{\beta U_{j,t}}} \\ n_{c,t} = \dfrac{e^{\beta U_{c,t}}}{\sum_{j=f,c,a} e^{\beta U_{j,t}}} \\ F_{t+1} = F_t + \mu\left[n_{f,t} d_{f,t} + n_{c,t} d_{c,t} + (1 - n_{f,t} - n_{c,t}) d_{a,t}\right] \\ S_{t+1} = \nu F_f + (1 - \nu)F_t \end{cases} \tag{16}$$

## 4. Analysis of steady state

When the system reaches a steady state, we have $\tilde{F}_t = \tilde{F}_{t+\tau} = \tilde{F}^*$, $n_{f,t} = n_{f,t+\tau} = n_f^*$, $n_{c,t} = n_{c,t+\tau} = n_c^*$, $F_t = F_{t+\tau} = F^*$, $S_t = S_{t+\tau} = S^*$, for $\forall \tau = 1, 2, \cdots, \infty$. In the equilibrium, the aggregate excess demand is equal to zero. After some algebra, we obtain the equilibrium $E^*(\tilde{F}^*, n_f^*, n_c^*, F^*, S^*)$, where

$$\tilde{F}^* = S^* = F^* = F_f, \tag{17}$$

$$n_f^* = \frac{e^{-\beta\theta\sigma_f^2}}{\sum_{j=f,c,a} e^{-\beta\theta\sigma_j^2}},\ n_c^* = \frac{e^{-\beta\theta\sigma_c^2}}{\sum_{j=f,c,a} e^{-\beta\theta\sigma_j^2}}. \tag{18}$$

Furthermore, $n_a^* = 1 - n_f^* - n_c^*$. The fractions of heterogeneous traders in the equilibrium are determined by the degree of rationality and the risk appetites. The traders with high risk appetites are the majority. In the equilibrium, the futures price and the spot price converge to the fundamental value, realizing the price discovery function. We express the results as the following proposition.

**Proposition 1.** *In the market depicted by Eq. (16), there exists one equilibrium $E^*(\tilde{F}^*, n_f^*, n_c^*, F^*, S^*)$, where the futures price and the spot price converge to the fundamental value simultaneously.*

*To examine the local stability of the equilibrium, we derive the Jacobian matrix $J$ at $E^*$:*

$$J(E^*) = \begin{pmatrix} 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ -\dfrac{\mu\gamma n_c^*}{\theta\sigma_c^2} & 0 & 0 & 1 + \dfrac{\mu\gamma n_c^*}{\theta\sigma_c^2} - \dfrac{\mu\delta n_f^*}{\theta\sigma_f^2} - \dfrac{\mu\alpha n_a^*}{\theta\sigma_a^2} & \dfrac{\mu\alpha n_a^*}{\theta\sigma_a^2} \\ 0 & 0 & 0 & 1 - \nu & 0 \end{pmatrix}. \tag{19}$$

*Let $P(\lambda)$ denote the characteristic polynomial of $J(E^*)$,*

$$P(\lambda) = \lambda^5 + p_1\lambda^4 + p_2\lambda^3 + p_3\lambda^2 + p_4\lambda + p_5. \tag{20}$$

*By calculation, $p_1 = \frac{\mu\delta n_f^*}{\theta\sigma_f^2} + \frac{\mu\alpha n_a^*}{\theta\sigma_a^2} - \frac{\mu\gamma n_c^*}{\theta\sigma_c^2} - 1$, $p_2 = \frac{\mu\gamma n_c^*}{\theta\sigma_c^2} - \frac{\mu\alpha n_a^*}{\theta\sigma_a^2} + \frac{\nu\mu\alpha n_a^*}{\theta\sigma_a^2}$, $p_3 = p_4 = p_5 = 0$.*

According to the Schur-Cohn criterion (Elaydi, 2005), $E^*$ is locally stable if all the eigenvalues of $J(E^*)$ lie inside the unit disk. The necessary and sufficient conditions are given by:

(i) $P(1) > 0$;

(ii) $(-1)^5 P(-1) > 0$;

(iii) The determinants of the $2 \times 2$ matrices $M_2^{\pm}$ and the $4 \times 4$ matrices $M_4^{\pm}$ are all positive, where

$$M_2^{\pm} = \begin{pmatrix} 1 & 0 \\ p_1 & 1 \end{pmatrix} \pm \begin{pmatrix} 0 & p_5 \\ p_5 & p_4 \end{pmatrix}, M_4^{\pm} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ p_1 & 1 & 0 & 0 \\ p_2 & p_1 & 1 & 0 \\ p_3 & p_2 & p_1 & 1 \end{pmatrix} \pm \begin{pmatrix} 0 & 0 & 0 & p_5 \\ 0 & 0 & p_5 & p_4 \\ 0 & p_5 & p_4 & p_3 \\ p_5 & p_4 & p_3 & p_2 \end{pmatrix}.$$

After some algebra, we get the local stability conditions:

$$\frac{\theta}{\mu} + (1-\nu)\frac{\alpha n_a^*}{\sigma_a^2} > \frac{\gamma n_c^*}{\sigma_c^2} > \left(1 - \frac{\nu}{2}\right)\frac{\alpha n_a^*}{\sigma_a^2} + \frac{\delta n_f^*}{2\sigma_f^2} - \frac{\theta}{\mu}. \tag{21}$$

The result is expressed as the following proposition.

**Proposition 2.** *The equilibrium $E^*$ is locally stable if Eq. (21) is satisfied. Equation (21) provides the necessary conditions for price discovery in the futures market. It shows the combined effect of behavioral factors on price discovery. When investors have high risk appetites, Eq. (21) may be violated. The increase of market liquidity can offset the destabilizing effect of high risk appetites. Moreover, if investors adjust their expectations frequently, Eq. (21) is likely to be unsatisfied. Besides, as $\beta \to +\infty$, $n_c^* \to 1$, $n_f^*$ and $n_a^* \to 0$, then Eq. (21) reduces to:*

$$\frac{\theta}{\mu} > \frac{\gamma}{\sigma_c^2} > -\frac{\theta}{\mu}. \tag{22}$$

*Obviously, Eq. (22) cannot always hold true. It indicates that the high degree of investor rationality is not necessarily beneficial to price discovery. Additionally, when the dependence of the futures price on the spot price becomes weak, the right inequality of Eq. (21) may be violated. The proper correlation between spot prices and futures prices is needed to make the market efficient.*

## 5. Conclusions

This paper proposes a dynamical model characterizing the futures market with heterogeneous traders. Investors are assumed to be boundedly rational. They form their beliefs about the price, learn and choose trading strategies according to their recent payoffs. The model characterizes the interactions between heterogeneous traders. The derived system depicts the evolution of market price and the fractions of heterogeneous traders. Moreover, it shows how the information of different traders is aggregated into the price.

As the findings show, the price discovery function can be realized through a self-organized process. Investors trade in the market with the purpose of maximizing their utilities. The price is generated through trading behaviors. As the system evolves, the futures price and the spot price converge to the fundamental value simultaneously, reaching the steady state. In the equilibrium, the price fully reflects the information about fundamentals. It is considered that the equilibrium price is reasonable and “good knowledge” about the asset. In such a situation, the market is efficient.

However, the equilibrium may be destabilized in some cases. In this paper, we derived the stability conditions, which are also the necessary conditions for price discovery. Only when the parameters coordinate with each other, the stability conditions can be satisfied. It implies a combined effect of behavioral factors on market stability. When investors have high risk appetites, they trade with a large amount and cause a great impact on the price. In such cases, the price mainly reflects the information of investors with high risk appetites. It may deviate greatly from the fundamental value and is not “good knowledge” about the asset. To create “good knowledge”, the participants should adopt the correct way of trading.

Moreover, when the parameter $\beta$ takes large values, the stability conditions may be violated. It implies that the high degree of investor rationality is not a good thing for market efficiency. Highly rational investors are sensitive to the payoffs and switch their trading strategies frequently to maximize their utilities. The intense switch between trading strategies can increase price volatility. In this case, it becomes hard for the market to reach a steady state. The market cannot aggregate the information to form “good knowledge”.

As the results show, market liquidity is an important factor for market stability. If the liquidity is adequate, it can smooth the impulse of high demand and offset the destabilizing effect of high risk appetites. Hence, the methods for increasing market liquidity should be taken into account to create “good knowledge” about the asset.

To some extent, the participation of heterogeneous investors can reduce the aggregate excess demand in the market and decrease price volatility. However, the actual effect is complicated. As Eq. (21) shows, if $\alpha = 0$, the left inequality is violated. In this case, the impact of arbitrage is absent, as if there were no arbitrageurs in the market. It implies that arbitrage can offset the impacts of technical traders. However, if $\alpha > 0$, the arbitrageurs participate in the market, and the right inequality may be violated. It implies that arbitrage has a conflicting effect with fundamental trading. Arbitrageurs can amplify the destabilizing impact of fundamentalists. Hence, the role of arbitrageurs should be carefully analyzed.

Notably, the technical traders have a larger fraction than fundamentalists and arbitrageurs in the equilibrium. Although the equilibrium price fully reflects fundamentals, the technical traders whose decision-making does not depend on fundamental information can survive in the market. This finding sends a message regarding the role of agents who do not care about knowledge in the knowledge creation process.

Finally, the findings provide implications for policy interventions. Market regulators can facilitate price discovery and promote market stability by increasing market liquidity, curbing speculation and smoothing market sentiment.

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