## Belief Update and Mispricing Theory and Experiment

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Munenori Nakasato
Tomoki Kitamura Hirotaka Fushiya
(Aoyama Gakuin University)
(NLI Research Institute)
(Aoyama Gakuin University)

We theoretically examine the mechanism of asset mispricing using a simple sequential trading model.

We find that investors overly consider the existence of informed traders in stock markets, which causes stock mispricing. However, we also show that the mispricing finally disappears.

This study also contains numerical and experimental examinations.

## 2. Previous Studies

Sequential trading model under asymmetric information

- Glosten and Milgrom (1985)
- Avey and Zemsky (1993)
- Easley and O’ Hara $(1992,1997)$

Asymmetric information and mispricing

- Wang (1992)
- Brunnermeier (2005)
- Barberis, Mukherjee, and Wang (2016)


## 3. Model Setting

We use the sequential trading model
(Glosten and Milgrom, 1985).

- There is one risky asset.
- Value of risky asset $\theta$ is either 0 or 1 .
- The probability is $P(\theta=0)=P(\theta=1)=\frac{1}{2}$ (Price of asset $\in[0,1]$.)
- We assume $\theta=1$ without loss of generality.
- There is one market maker, and informed traders and noise traders.
- Market maker posts bid and ask prices at any time.
- Informed traders have private information which gives true value $\theta=1$.
- Informed traders always buy risky asset.
-Noise traders randomly buy or sell with an equal probability of $\frac{1}{2}$.
- Each trader trades one unit of risky asset with the market maker.
- The market maker does not know who is an informed trader and who is a noise trader.
- $\phi$ represents the probability that an informed trader comes.
- The market maker knows the probability $\phi$.
- $\phi$ There are two types of market; informed market ( $I$ ) and uninformed market $(U)$.
-In an informed market, one or more informed traders exist; $\phi>0$.
-In an uninformed market, no informed trader exists; $\phi=0$.


## Informed Market $(\theta=1)$



The probability of buy is $\frac{1+\phi}{2}$
The probability of sell is $\frac{1-\phi}{2}$

Let $\omega_{k}$ be trade event at time $k$ :
$\omega_{k}=B$, if trader buys at $k$.
$\omega_{k}=S$, if trader sells at $k$.

Let $\xi_{n}\left(h_{n}\right)=P\left(M=I \mid h_{n}\right)$ : market maker's belief that the market is informed under trading history
$h_{n}=\omega_{1} \omega_{2} \cdots \omega_{n}$.

We focus on this conditional probability.

## 4. Trader's belief based on Bayes theory

Using Bayesian theory, we have

$$
\xi_{n}=P\left(M=I \mid h_{n}\right)=\frac{P\left(h_{n}, M=I\right)}{P\left(h_{n}, M=I\right)+P\left(h_{n}, M=U\right)} .
$$

The first term of denominator is
$P\left(h_{n}, M=I\right)$

$$
\begin{aligned}
&=P\left(h_{n}, M=I, \theta=1\right)+P\left(h_{n}, M=I, \theta=0\right) \\
&= P\left(h_{n} \mid M=\right. \\
& \quadI, \theta=1) P(M=I, \theta=1) \\
&+P\left(h_{n} \mid M=I, \theta=0\right) P(M=I, \theta=0) .
\end{aligned}
$$

## Under $M=I$ and $\theta=1$, we have

$$
\begin{aligned}
& P\left(\omega_{k}=B \mid M=I, \theta=1\right)=\frac{1+\phi}{2} \\
& P\left(\omega_{k}=S \mid M=I, \theta=1\right)=\frac{1-\phi}{2}
\end{aligned}
$$

Then, we obtain
$P\left(h_{n} \mid M=I, \theta=1\right)={ }_{n} C_{B_{n}}\left(\frac{1+\phi}{2}\right)^{B_{n}}\left(\frac{1-\phi}{2}\right)^{S_{n}}$,
where $B_{n}$ is the total number of buys and $S_{n}$ is the total number of sells in $h_{n}=\omega_{1} \omega_{2} \cdots \omega_{n}$.

## Then, we obtain

$$
\begin{aligned}
& \xi_{n}=P\left(M=I \mid h_{n}\right) \\
& =\frac{(1+\phi)^{B_{n}}(1-\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+(1-\phi)^{B_{n}}(1+\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}}{(1+\phi)^{B_{n}}(1-\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+(1-\phi)^{B_{n}}(1+\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+\left(1-\xi_{0}\right)}
\end{aligned}
$$

So, $\xi_{n}$ depends only on the number of buys and sells and does not depend on the order of them.

## 5. Bayesian update of trader's belief

We have

$$
\begin{gathered}
\xi_{n+1}=P\left(M=I \mid h_{n+1}\right) \\
=\frac{P\left(\omega_{n+1}, M=I \mid h_{n}\right)}{P\left(\omega_{n+1}, M=I \mid h_{n}\right)+P\left(\omega_{n+1}, M=U \mid h_{n}\right)} .
\end{gathered}
$$

In the case of $\omega_{n+1}=B$, the first term of denominator is

$$
\begin{aligned}
& P\left(\omega_{n+1}, M=I \mid h_{n}\right)= P\left(\omega_{n+1}=B \mid M=I, \theta=1, h_{n}\right) \\
& \times P\left(\theta=1 \mid M=I, h_{n}\right) P\left(M=I \mid h_{n}\right) \\
&+ P\left(\omega_{n+1}=B \mid M=I, \theta=0, h_{n}\right) \\
& \times P\left(\theta=0 \mid M=I, h_{n}\right) P\left(M=I \mid h_{n}\right) .
\end{aligned}
$$

Under $M=I$ and $\theta=1$, the probability of $\omega_{n+1}=B$
is $P\left(\omega_{n+1}=B \mid M=I, \theta=1, h_{n}\right)=\frac{1+\phi}{2}$.
In order to update $\left\{P\left(M=I \mid h_{n}\right)\right\}$, we need $P\left(\theta=1 \mid M=I, h_{n}\right)=: \mu_{n}\left(h_{n}\right)=\mu_{n}\left(\omega_{1} \omega_{2} \cdots \omega_{n}\right)$.

Using $\mu_{n}$, the first term of the denominator of $\xi_{n+1}=P\left(M=I \mid h_{n+1}\right)$ is

$$
P\left(\omega_{n+1}, M=I \mid h_{n}\right)=\frac{1+\phi}{2} \mu_{n} \xi_{n}+\frac{1-\phi}{2}\left(1-\mu_{n}\right) \xi_{n} .
$$

Under $M=I$, we have the Bayesian update for $\left\{\mu_{n}\right\}$ when $\omega_{n+1}=B$ as follows:

$$
\begin{aligned}
& \mu_{n+1}\left(\omega_{1} \omega_{2} \cdots \omega_{n} B\right)=P\left(\theta=1 \mid \omega_{n+1}=B, h_{n}\right) \\
& =\frac{P\left(\omega_{n+1}=B \mid \theta=1\right) P\left(\theta=1 \mid h_{n}\right)}{P\left(\omega_{n+1}=B \mid \theta=1\right) P\left(\theta=1 \mid h_{n}\right)+P\left(\omega_{n+1}=B \mid \theta=0\right) P\left(\theta=0 \mid h_{n}\right)} \\
& =\frac{\frac{1+\phi}{2} \mu_{n}\left(h_{n}\right)}{\frac{1+\phi}{2} \mu_{n}\left(h_{n}\right)+\frac{1-\phi}{2}\left(1-\mu_{n}\left(h_{n}\right)\right)}=\frac{(1+\phi) \mu_{n}\left(h_{n}\right)}{1-\phi+2 \phi \cdot \mu_{n}\left(h_{n}\right)} .
\end{aligned}
$$

Similarly, we can have a Bayesian update for $\mu_{n}$ when $\omega_{n+1}=S$. Then, we obtain

$$
\mu_{n+1}\left(h_{n+1}\right)= \begin{cases}\frac{(1+\phi) \mu_{n}}{1-\phi+2 \phi \mu_{n}} & \omega_{n+1}=B \\ \frac{(1-\phi) \mu_{n}}{1+\phi-2 \phi \mu_{n}} & \omega_{n+1}=S\end{cases}
$$

where $\mu_{0}(\omega)=\frac{1}{2}$.

We define $a_{n}=\frac{1}{\mu_{n}}-1$, then we have
$\mu_{n} \rightarrow 0 \Leftrightarrow a_{n} \rightarrow \infty, \mu_{n} \rightarrow \frac{1}{2} \Leftrightarrow a_{n} \rightarrow 1, \mu_{n} \rightarrow 1 \Leftrightarrow a_{n} \rightarrow 0$.
So, we have the following proposition 1 and corollary 2.

## Proposition 1:

$$
a_{n}=\left(\frac{1+\phi}{1-\phi}\right)^{S_{n}-B_{n}}
$$

## Corollary 2:

$\mu_{n}$ depends on the number of buys and sells and not on the order in which they are executed.

In the case of informed markets, $\mu_{n}$ converges to 1 a.s. when $\theta=1$, and 0 a.s. when $\theta=0$.

In the case of uninformed markets, $\mu_{n}$ converges to either 0 or 1 a.s. The probability that $\mu_{n}$ converges to 0 is $\frac{1}{2}$ and vice versa.

Remember

$$
\begin{gathered}
\xi_{n+1}=P\left(M=I \mid h_{n+1}\right) \\
=\frac{P\left(\omega_{n+1}, M=I \mid h_{n}\right)}{P\left(\omega_{n+1}, M=I \mid h_{n}\right)+P\left(\omega_{n+1}, M=U \mid h_{n}\right)} .
\end{gathered}
$$

In the case of $\omega_{n+1}=B$, the first term of the denominator is

$$
P\left(\omega_{n+1}=B, M=I \mid h_{n}\right)=\frac{1+\phi}{2} \mu_{n} \xi_{n}+\frac{1-\phi}{2}\left(1-\mu_{n}\right) \xi_{n} .
$$

When $\omega_{n+1}=B$, the second term of the denominator is

$$
P\left(\omega_{n+1}=B, M=U \mid h_{n}\right)=\frac{1}{2}\left(1-\xi_{n}\right) .
$$

Therefore, we have the following Bayesian update for $\xi_{n}=\xi_{n}\left(h_{n}\right)=P\left(M=I \mid h_{n}\right)$.

$$
\xi_{n+1}= \begin{cases}\frac{\frac{1}{2}+\phi\left(\mu_{n}-\frac{1}{2}\right)}{\frac{1}{2}+\phi\left(\mu_{n}-\frac{1}{2}\right) \xi_{n}} \cdot \xi_{n} & \omega_{n+1}=B \\ \frac{\frac{1}{2}-\phi\left(\mu_{n}-\frac{1}{2}\right)}{\frac{1}{2}-\phi\left(\mu_{n}-\frac{1}{2}\right) \xi_{n}} \cdot \xi_{n} & \omega_{n+1}=S\end{cases}
$$

Note: $\mu_{n}=P\left(\theta=1 \mid M=I, h_{n}\right)$ is easier to consider than $\xi_{n}=P\left(M=I \mid h_{n}\right)$.

## Example:

Let us consider the case of $h_{5}=B S B B B$,
$\xi_{5}=P\left(M=I \mid h_{5}\right)$ is not close to one because
$\mu_{5}=P\left(S_{5}=1\right.$ or $\left.4 \mid M=U\right) \fallingdotseq \frac{1}{3}$,
but $P\left(\theta=1 \mid M=I, h_{5}\right)$ is close to one.

We have an explicit form of $\xi_{n}$ as follows.

## Proposition 3:

$$
\begin{gathered}
\xi_{n}=P\left(M=I \mid h_{n}\right) \\
\frac{(1+\phi)^{B_{n}}(1-\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+(1-\phi)^{B_{n}}(1+\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}}{(1+\phi)^{B_{n}}(1-\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+(1-\phi)^{B_{n}}(1+\phi)^{S_{n}} \cdot \frac{1}{2} \xi_{0}+\left(1-\xi_{0}\right)}
\end{gathered}
$$

The above equation is the same as the solution based on the Bayesian theory in section 4.

From the proposition 3, we have the following corollaries 4 and 5.

Corollary 4: $\xi_{n}$ does not depend on the order of buys and sells and only depends on their number.

In the case of informed markets, $\xi_{n}$ converges to 1 a.s.
In the case of uninformed markets, $\xi_{n}$ convergesto 0 a.s.

Corollary 5: In the case of uninformed markets, $E\left[\xi_{n}\right]$ monotonically decreases and converges to 0 .

On the contrary, in the case of informed markets, $E\left[\xi_{n}\right]$

## Let us define asset price $p_{n}$ :

$$
p_{n}=\xi_{n} \mu_{n}+\frac{1}{2}\left(1-\xi_{n}\right) .
$$

We also define market efficiency in Definition 6.

## Definition 6:

In the case of informed markets, the market is efficient with respect to price $p$ if $p=\theta$.
Similarly, in the case of uninformed markets, the market is efficient if $p=\frac{1}{2}$.

From corollary 2 and corollary 4, we have the theorem7.

## Theorem 7:

The probability that the market is efficient under $p_{n}$ converges to 1 a.s.


Figure 1 The transition of price by Bayesian updates when the market is uninformed.


Figure 2 The transition of $\xi_{n}$ by Bayesian updates when the market is uninformed.

## 6.Quasi-Bayesian update of market maker's belief

Remember, the update of $\left\{\xi_{n}\right\}$.

$$
\xi_{n+1}= \begin{cases}\frac{\frac{1}{2}+\phi\left(\mu_{n}-\frac{1}{2}\right)}{\frac{1}{2}+\phi\left(\mu_{n}-\frac{1}{2}\right) \xi_{n}} \cdot \xi_{n} & \omega_{n+1}=B \\ \frac{\frac{1}{2}-\phi\left(\mu_{n}-\frac{1}{2}\right)}{\frac{1}{2}-\phi\left(\mu_{n}-\frac{1}{2}\right) \xi_{n}} \cdot \xi_{n} & \omega_{n+1}=S\end{cases}
$$

Bayesian update
Quasi-Bayesian

$$
\begin{array}{ccc}
P\left(\theta=1 \mid M=I, h_{n}\right) & : \mu_{n} \rightarrow \mu_{n+1} \\
\searrow \\
P\left(M=I \mid h_{n}\right) \quad & : \xi_{n} \rightarrow \xi_{n+1}
\end{array} \quad \Longrightarrow \begin{gathered}
\mu_{n} \rightarrow \mu_{n+1} \\
\downarrow
\end{gathered} \quad \begin{gathered}
\widetilde{\xi}_{n} \rightarrow \widetilde{\xi}_{n+1}
\end{gathered}
$$

We define Quasi-Bayesian update as follows by replacing $\mu_{n}$ to $\mu_{n+1}$ :

$$
\widetilde{\xi}_{n+1}= \begin{cases}\frac{\frac{1}{2}+\phi\left(\mu_{n+1}-\frac{1}{2}\right)}{\frac{1}{2}+\phi\left(\mu_{n+1}-\frac{1}{2}\right)} \widetilde{\xi}_{n} & \widetilde{\xi}_{n} \\ \frac{\frac{1}{2}-\phi\left(\mu_{n+1}-\frac{1}{2}\right)}{\frac{1}{2}-\phi\left(\mu_{n+1}-\frac{1}{2}\right) \widetilde{\xi}_{n}} \cdot \widetilde{\xi}_{n} & \omega_{n+1}=S\end{cases}
$$

where $\widetilde{\xi}_{0}=\xi_{0}$.

We have the following propositions and theorems.

## Proposition 9:

$\xi_{n}<\widetilde{\xi}_{n}$. for any $\omega, n \geq 1$.

This proposition states that the probability of $M=I$ is always higher for Quasi-Bayesian updates than for Bayesian updates.

## Proposition 10:

$\widetilde{\xi}_{n}$ depends on the order of buys and sells.
We have the following inequalities of paths where the number of buys are the same as that of $h_{n}$.

$$
\begin{cases}\widetilde{\xi}_{n}(B B \cdots B S S \cdots S) \leq \widetilde{\xi}_{n}\left(h_{n}\right) \leq \widetilde{\xi}_{n}(B S B S \cdots B S B \cdots B) & B_{n} \geq S_{n} \\ \widetilde{\xi}_{n}(S S \cdots S B B \cdots B) \leq \widetilde{\xi}_{n}\left(h_{n}\right) \leq \widetilde{\xi}_{n}(S B S B \cdots S B S \cdots S) & B_{n} \leq S_{n}\end{cases}
$$

For example: $\widetilde{\xi}_{5}(B S B S B)>\widetilde{\xi}_{5}(B B S S B)>\widetilde{\xi}_{5}(B B S B S)>\widetilde{\xi}_{5}(B B B S S)$

Theorem 11: When the market is uninformed, there exists a function $m(n), n \in N$ that has the following three properties:

1. $\mathbf{E}\left[\widetilde{\xi}_{n}\right]>m(n) \quad$ for all $n \in \mathbf{N}$,
2. $m(0)=\xi_{0}, \lim _{n \rightarrow \infty} m(n)=0$,
3. $m(n)$ has a local maximum in $0<n<\infty$.

This theorem states that we have a local maximum for
$E\left[\widetilde{\xi}_{n}\right]$, indicating that the probability of $M=I$ increases erroneously initially even though $M=U$.
On the contrary, $E\left[\xi_{n}\right]$ monotonically converges to 0 .

## Theorem 12:

If the market is informed, $\widetilde{\xi}_{n}$ diverges to 1 a.s., and if the market is uninformed, $\widetilde{\xi}_{n}$ converges to 0 a.s.

This theorem means that $\widetilde{\xi}_{n}$ finally converges to the true value.

## Let us define asset price $\widetilde{p}_{n}$ :

$$
\widetilde{p}_{n}=\widetilde{\xi}_{n} \mu_{n}+\frac{1}{2}\left(1-\widetilde{\xi}_{n}\right) .
$$

Then, we have the following theorem 13.

## Theorem 13:

The probability that the market is efficient with respect to price $\widetilde{p}$ converges to 1 a.s.


Figure 3 The transition of Price by the QuasiBayesian updates when the market is uninformed.


Figure 4 The transition of $\widetilde{\xi}_{n}$ by the QuasiBayesian updates when the market is uninformed.

## 7. Experiments



Figure 5 Answer sheet used in experiments






1357911131517192123252729

- red $\qquad$ $\longrightarrow$ xid
0.1
1357911131517192123252729
- red $\qquad$ $\longrightarrow$ xid

Figure 6 Results of the experiment

## 8. Conclusion

In this study, we investigate the belief update process of market makers regarding risky asset.

We assume two uncertainties in stock markets: uncertainty of asset value and that of existence of informed traders.

By using the sequential trading model, we first show that the updating process for the asset value $\mu_{n}$ and the existence of informed traders $\xi_{n}$ are consistent with the Bayesian theory.

Next, we introduce the quasi-Bayesian update model which investors tend to apply to their belief updating.

We find that
(1) the probability of the existence of informed traders by the quasi-Bayesian update model $\widetilde{\xi}_{n}$ is always higher than that of Bayesian model,
(2) $E\left[\widetilde{\xi}_{n}\right]$ rises erroneously initially even though there is no informed trader in the market,
(3) $\widetilde{\xi}_{n}$ converges to the true value regarding the existence of informed traders and the market becomes efficient.

We experimentally investigate the belief update process of traders and find that traders' behavior is consistent with the quasi-Bayesian update model.

