How Public and Private Transaction Information Affect Transaction Pattern

Qiong Wu

October 30, 2016

1 Introduction

The transaction information in capital markets can be classified as public transaction information and private transaction information. Both public and private transaction information affect the transaction pattern in the market, such as transaction volume, transaction price and the distribution of intraday price. The target of this project is to study for the completed transaction, what is the probability of driven by the public information and the probability of driven by the private information.

2 Modeling and Parameter Estimation

Suppose the types of motivation of transactions are as follows:
1. Liquidity transaction. The investors balance the asset allocation through security purchasing or they obtain cash revenue through selling the securities;
2. Public information transaction. The central bank pronounces to raise or lower the basic interest rate, then the investors sell or purchase the securities accordingly;
3. Private information transaction. The unconfirmed information spreads among the investors and drives them to make the transaction decision.
In addition, the bidding volume and asking volume of one security are supposed to follow log normal distribution simply.
Let's denote the transaction volume at certain price as V=Min{B,S}, here B represents the volume of bidding, S represents the volume of asking. Then the possible transactions distributions are as follows:
If both bidding and asking sides transact based on pure liquidity motivation, then we set B$\sim$N(μ_1,σ_1^2), S$\sim$N(μ_2,σ_2^2);
If both bidding and asking sides transact based on positive public information, then we set B$\sim$N(μ_1+δ_{pub},σ_1^2), S$\sim$N(μ_2-δ_{pub},σ_2^2);
If both bidding and asking sides transact based on negative public information, then we set

B~N(μ_1-δ_{pub},σ_1^2), S~N(μ_2+δ_{pub},σ_2^2);
If both bidding and asking sides transact based on positive private information, then we set B~N(μ_1+δ_{pri},σ_1^2),S~N(μ_2-δ_{pri},σ_2^2);
If both bidding ans asking sides transact based on negative private information, then we set B~N(μ_1-δ_{pri},σ_1^2), S~N(μ_2+δ_{pri},σ_2^2).
A simple assumption is set here that both positive and negative information take the **same** level of influence on the transaction volume but only opposite in the direction. For convenience, we define the probability of private information as α; the probability of positive information as α_1; the probability of negative information as 1-α_1; the probability of public information as β; the probability of positive information as β_1; the probability of negative information as 1-β_1. The actual transaction is the synthesizing of all possibilities.
The following figure1 describes the transaction scenario.

Figure1

In figure1, there are nine situations at final points. Here, the probability density functions of bidding and asking are set as f_1(x) and f_2(x) then the corresponding cumulative distribution functions are set as F_1(x) and F_2(x). Let's define the cumulative distribution functions of transaction volume as F_V(x,μ_1,μ_2,σ_1,σ_2). And its probability density function of transaction volume satisfies that f_V(x,μ_1,μ_2,σ_1,σ_2)=(1-F_1(x))f_2(x)+(1-F_2(x))f_1(x). Based on the information in each scenario, the likelihood function of transaction volume V is:
L(V)=$\sum_{i=1}^{9} m_i$;
m_1=$\alpha\alpha_1\beta\beta_1 f_v$(V,$\mu_1$+$\delta_{pri}$+$\delta_{pub}$,$\mu_2$-$\delta_{pub}$,$\sigma_1$,$\sigma_2$);

m_2=$\alpha\alpha_1\beta$(1-β_1)f_v(V,μ_1+δ_{pri}-δ_{pub},μ_2+δ_{pub},σ_1,σ_2);
m_3=$\alpha\alpha_1$(1-β)f_v(V,μ_1+δ_{pri},μ_2,σ_1,σ_2);
m_4=α(1-α_1)$\beta\beta_1 f_v$(V,μ_1+δ_{pub},μ_2-δ_{pub},σ_1,σ_2);
m_5=α(1-α_1)β(1-β_1)f_v(V,μ_1-δ_{pub},μ_2+δ_{pub}+δ_{pri},σ_1,σ_2);
m_6=α(1-α_1)(1-β)f_v(V,μ_1,μ_2+δ_{pri},σ_1,σ_2);
m_7=(1-α)$\alpha_1\beta\beta_1 f_v$(V,μ_1+δ_{pub},μ_2-δ_{pub},σ_1,σ_2);
m_8=(1-α)α_1(1-β_1)f_v(V,μ_1-δ_{pub},μ_2+δ_{pub},σ_1,σ_2);
m_9=(1-α)(1-β)f_v(V,μ_1,μ_2,σ_1,σ_2);
For the discrete time t=1,2,...,T, the series of observed transaction volume is:V_0,V_1,...,V_T. The sum of log-likelihood functions is: $\sum_{i=1}^{T} \ln\left[L\left(V_i\right)\right]$. Parameter estimation results can be obtained through maximizing the log-likelihood functions. Here, the parameters in above model are under certain constraints:0≤ α ≤1;0≤ β ≤1;0≤α_1≤1;0≤β_1≤1.

3 Empirical Analysis

In this project, the data applied is 5 minutes CSI 300 (HS) index from Nov.16th, 2015 to Feb.24th, 2016.
Figure2 shows the transaction volume of this period.

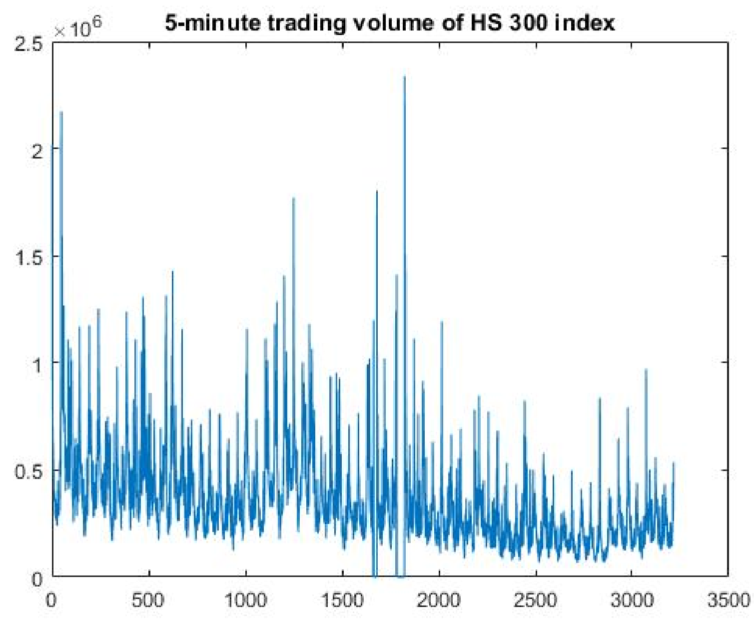

Figure2

Since the relative transaction which means number of transaction per unit time is more attractive, then the statistical relative transaction frequency is showed in figure3.

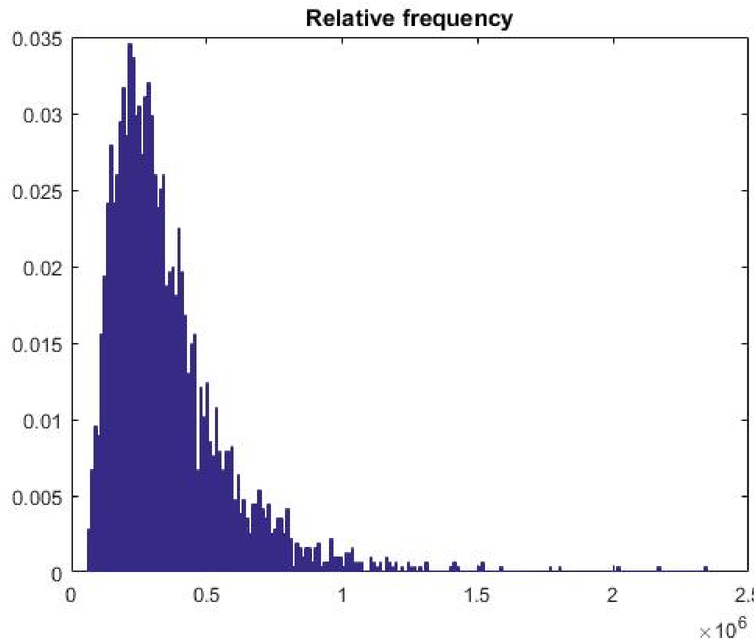

Figure3

Figure4 shows the empirical result of probability density of transaction volume.

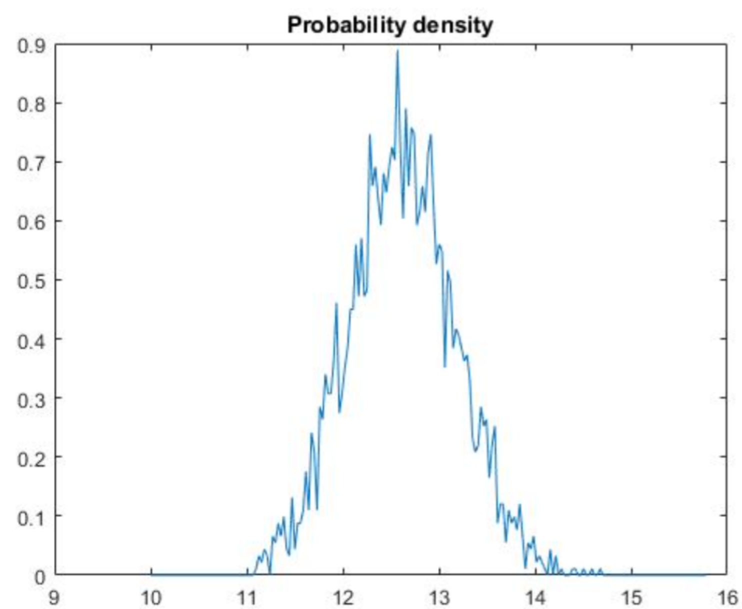

Figure4

Since the total daily transaction time is four hours, then there are forty-eight five minutes transaction volume information. All of thes data in this period is used to estimate the probability of private information; the probability of positive private information; the probability of public information and the probability of positive public information. Figure 5,6,7,8 show the evolution of the probabilities during this period.

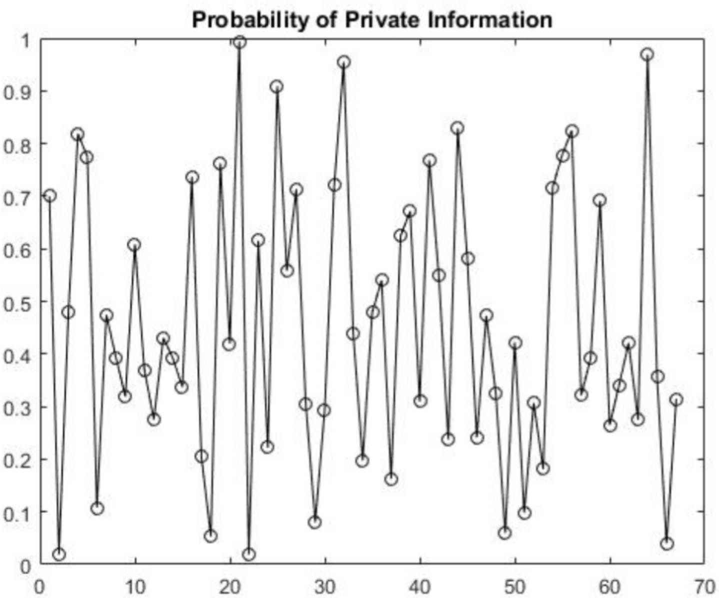

Figure5

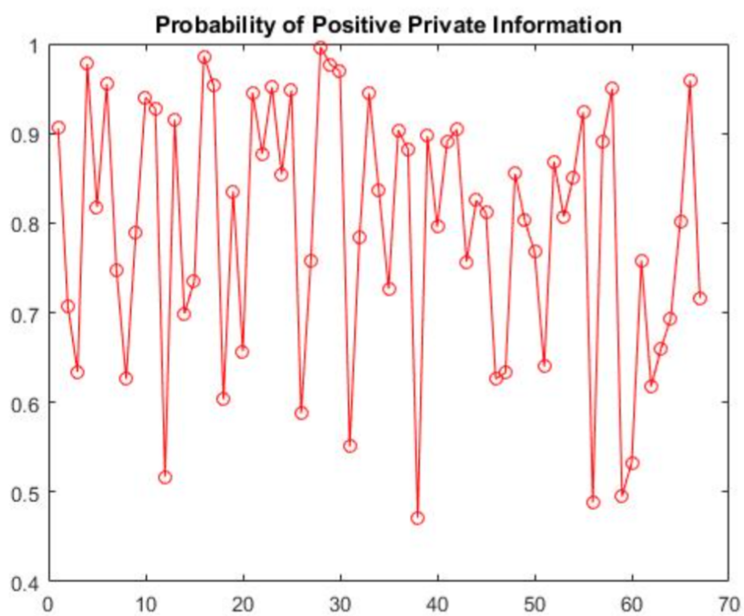

Figure6

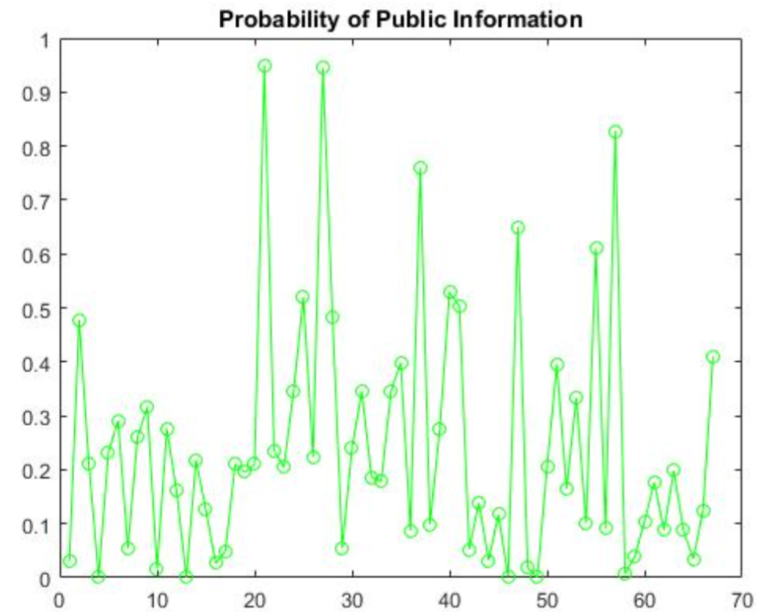

Figure7

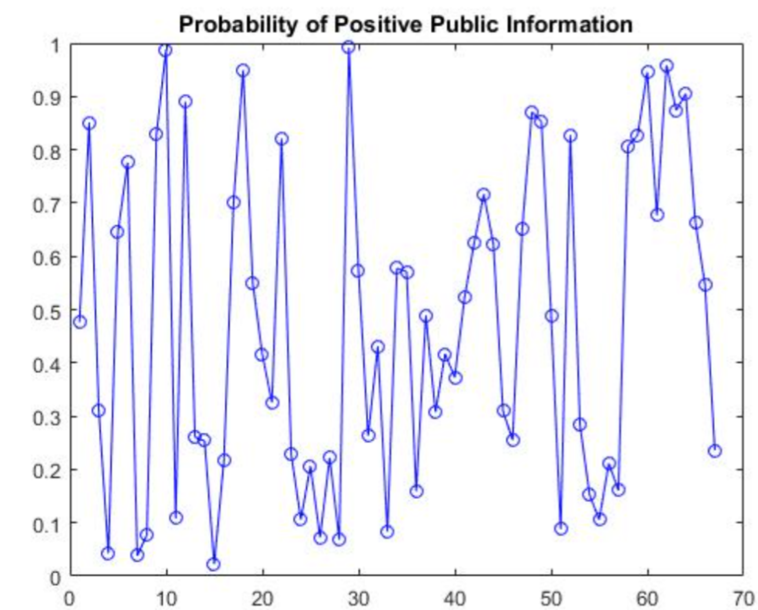

Figure8

Furthermore, let's focus on the transaction based on private information. As we know, there are nine transaction scenarios. We define E_1,... E_9 as the average transaction level of each scenarios.

Through applying probability theory, the unconditional mean of transaction volume is:

E(V)=$\alpha\beta\alpha_1\beta_1 E_1$+$\alpha\beta(1-\alpha_1)\beta_1 E_2$+$\alpha\beta$(1-$\beta_1$)$E_3$+$\alpha$(1-$\beta$)$\alpha_1\beta_1 E_4$+$\alpha$(1-$\beta$)$\alpha_1(1-\beta_1)E_5$+$\alpha$(1-$\beta$)$(1-\beta_1)E_6$+(1-$\alpha$)$\alpha_1\beta_1 E_7$+(1-$\alpha$)(1-$\alpha_1$)$\beta_1 E_8$+(1-$\alpha_1$)$(1-\beta_1)E_9$
Then, the probability that transaction derived from private information can be deduced as:
I_0=1-[(1-α)$\alpha_1\beta_1 E_7$+(1-α)β_1(1-α_1)E_8+(1-α)(1-β_1)E_9]/E(V)
Similarly, we can define the probability that transaction derived from private information when the information is positive:
I_1=[$\alpha\beta\alpha_1\beta_1 E_1$+$\alpha\beta\alpha_1(1-\beta_1)E_2$+$\alpha\beta$(1-$\alpha_1$)$E_3$]/E(V)
and the probability that transaction derived from private information when the information is negative:
I_2=[α(1-β)$\alpha_1\beta_1 E_4$+α(1-β)$\alpha_1(1-\beta_1)E_5$+α(1-β)(1-α_1)E_6]/E(V)
Figure9,10,11 show I_0,I_1,I_2.

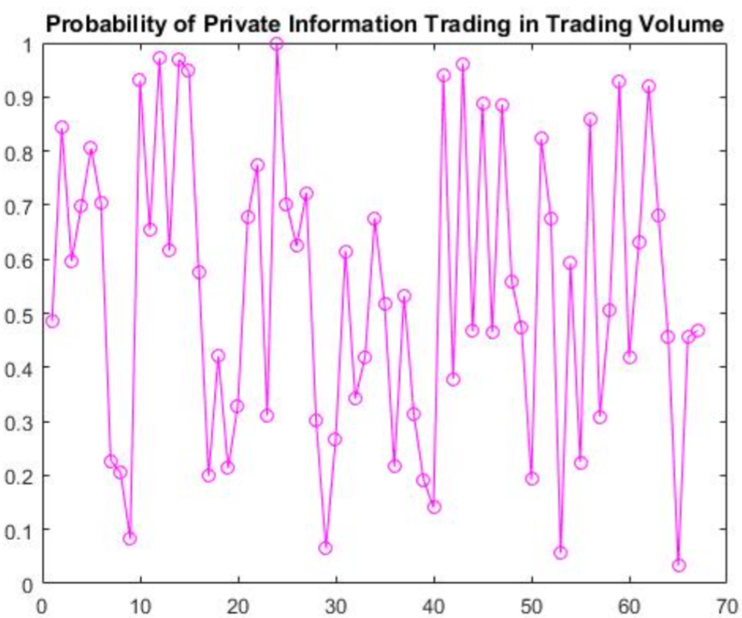

Figure9

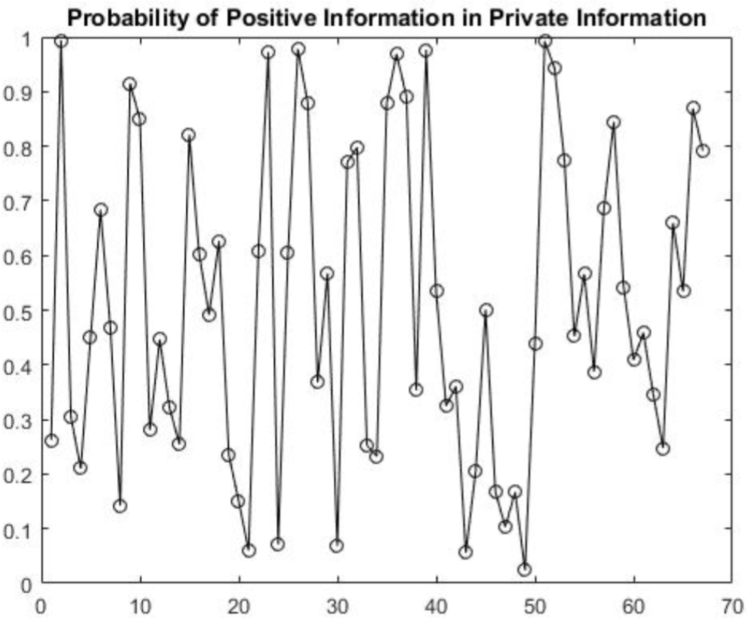

Figure10

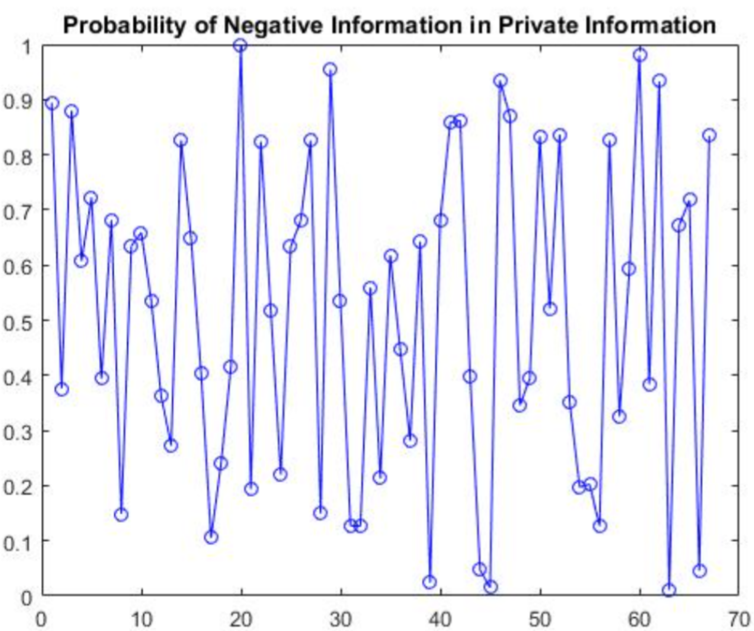

Figure11

4 Explore Economic Meaning

During this period, the average probability of private information is 51.5%; the average probability of public information is 29.3% and the average probability of negative public information is 55.8%. The difference implies that **the strong asymmetric information phenomenon exists in the market.**

The SSE Composite Index is 3603 on Nov.16th, 2015 and 2928.9 on Feb.24th, 2016. The minimum index of this period is 2655.66 which appeared on Jan.28th, 2016. Hence the maximum plugging range is 26.35%. Since the elements of CSI 300 Index includes SSE Index, then the parameters estimated imply a situation that **the investors tend to make the decision based on their own information in the turn down economic channel, even they can not confirm the accuracy of the information.** When most of the agents behave in this way, it raises the volatility potentially. The efficiency of macro-economy policy will be weaken, even the government has already sent out strong policy signal to the market.

There are two main ways of future research. First, this project only checks data of several months, longer period data should be applied to verify the conclusion; second, the structure of the probability distribution can be extended to a deeper level, more complex and mixed distributions can match the transaction pattern in real market better.