



**STEVENS**  
INSTITUTE *of* TECHNOLOGY  
THE INNOVATION UNIVERSITY®

# **FE570 Zero Intelligence Model simulation**

## **—— Using Poisson distribution**

Team 8

Rui Zong, Fuyu Sui, Fangfang Xue, Nan Zhao



- Chapter I: Introduction to the Santa Fe model simulation
- Chapter II: Simulation and results
- Chapter III: Shape of LOB: Slope and Depth
- Chapter IV: Price dynamics and Compared with Roll Model

## Part I Santa Fe Model Review

### Assumptions:

Simplest ZI model capturing the main features of the limit order markets.

- 1.The model contains two types of traders:
  - (1) Impatient traders: They place market orders which arrive randomly like a Poisson process with rate  $\mu$  shares/ unit time.
  - (2) Patient traders: They place limit orders which arrive randomly like a Poisson process with rate  $\alpha$  shares/ unit time.
- 2.All limit/market orders are of the same size  $\sigma$ (number of shares)
- 3.Buy and sell orders are equally probable.
- 4.Market and limit orders are independent of each other.

## Part II Santa Fe Model simulation

### Rules:

1. Limit buy orders arrive with equal probability at any price  $p \leq a(t)$
2. Limit sell orders arrive with equal probability at any price  $p \geq b(t)$
3. Market buys arrive as Poisson process with intensity  $\mu$  and are executed

$$a(t) = \text{best-ask}$$

4. Market sells arrive as Poisson process with intensity  $\mu$  and are executed

$$b(t) = \text{best-bid}$$

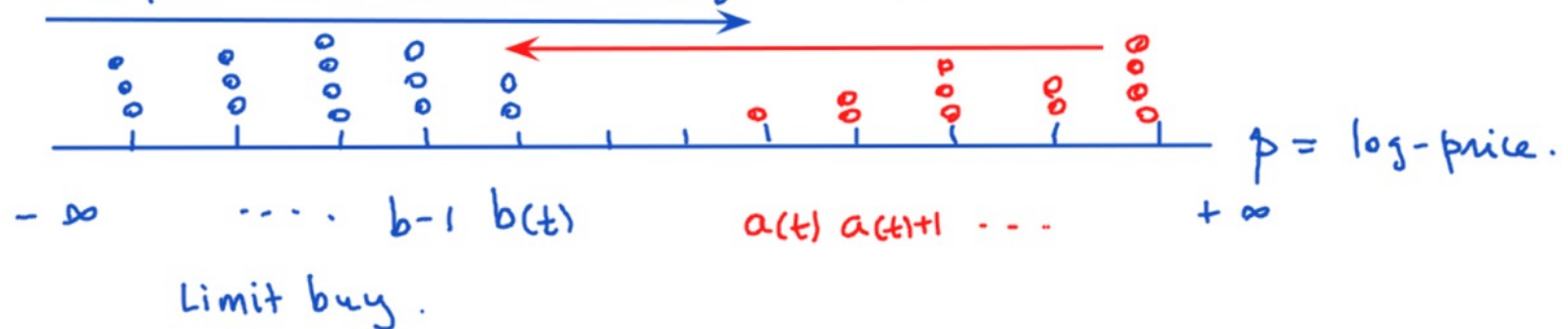
5. Limit orders are cancelled as Poisson process with intensity  $\delta$

# Chapter I



## Part II Santa Fe Model simulation

$p = \log\text{-price}$  can take all integer values.



$\alpha$  — limit orders

$\mu/\alpha$  — ticks

$\mu$  — market orders

$\mu/\delta$  — shares

$\delta$  — cancellation of limit orders

$1/\delta$  — time

$\sigma$  — block size

# Chapter II



## Predictions

Prediction #1 Average spread

$$\hat{s} = \frac{\mu}{\alpha} f\left(\sigma \frac{\delta}{\mu}\right)$$

Prediction #2 The standard deviation

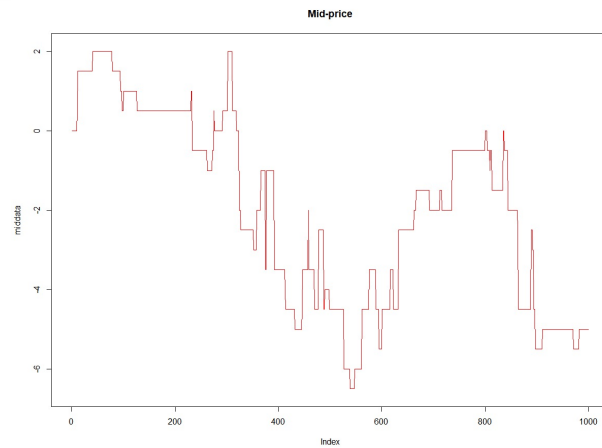
$$D \sim \left( \frac{\mu^{\frac{3}{4}} \delta^{\frac{1}{4}}}{\alpha^{\frac{1}{2}}} \right)$$

- The average spread increases with market orders  $\mu$  or **cancellations**  $\delta$
- The average spread decreases as limit orders  $\alpha$  increases
- The standard deviation of the mid-price and spread is expected to increase with  $\mu$  and  $\delta$  and decrease as  $\alpha$  increases.

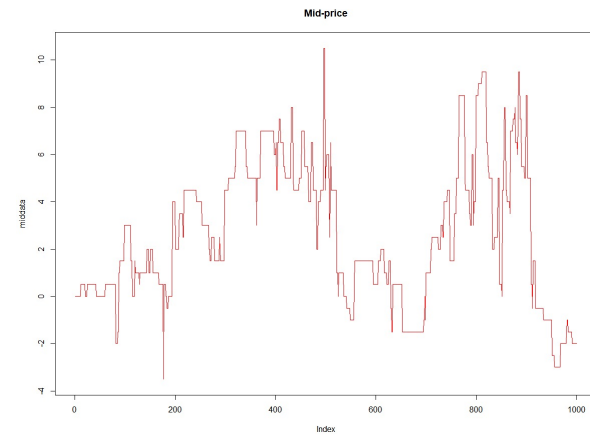
# Chapter II



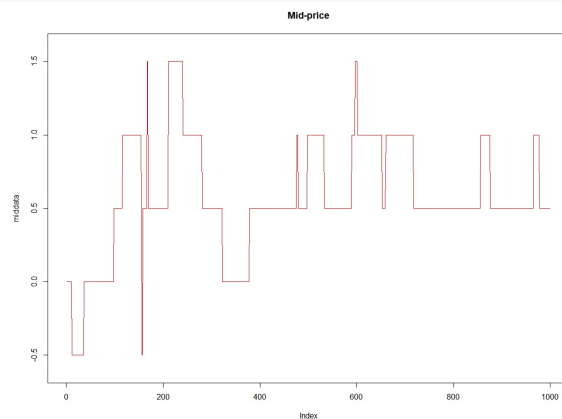
## Mid-price



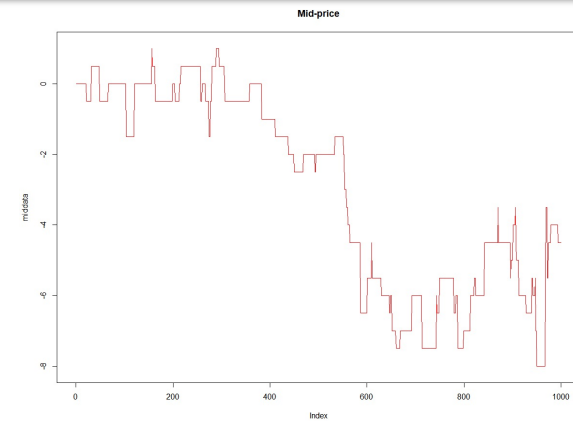
$$\alpha=1, \mu=10, \delta=1/5$$



$$\alpha=1, \mu=20, \delta=1/5$$



$$\alpha=5, \mu=10, \delta=1/5$$

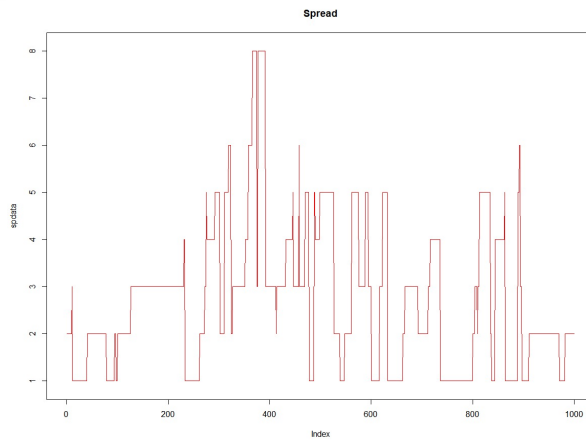


$$\alpha=1, \mu=10, \delta=2/5$$

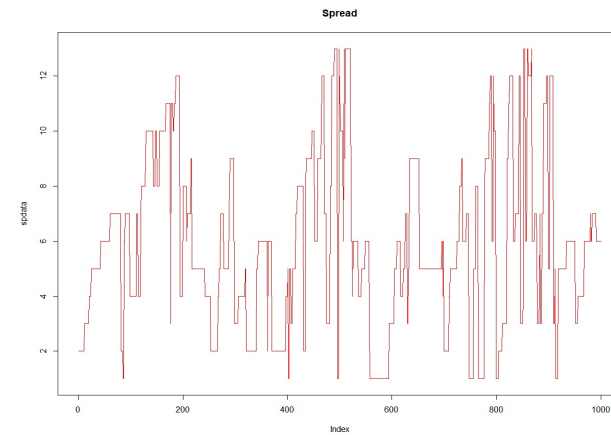
# Chapter II



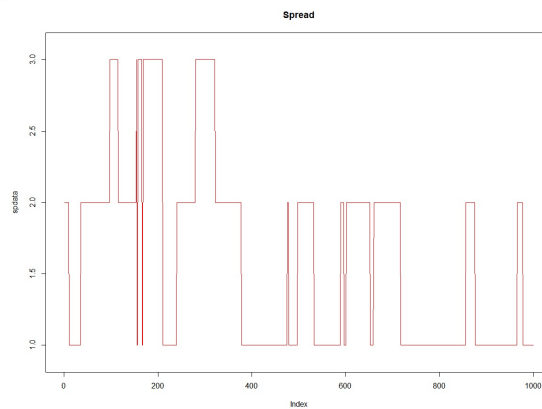
## Spread



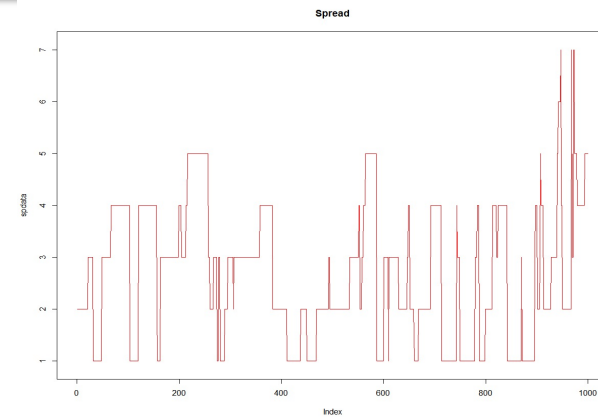
$$\alpha=1, \mu=10, \delta=1/5$$



$$\alpha=1, \mu=20, \delta=1/5$$



$$\alpha=5, \mu=10, \delta=1/5$$



$$\alpha=1, \mu=10, \delta=2/5$$



# Chapter II



## Results

Scenario	$\mu$	$\alpha$	$\delta$	Comments	Spread	Mid-price
1	10	1	1/5	Base scenario	$2.72 \pm 1.58$	$-1.96 \pm 2.38$
2	20	1	1/5	High rate of market orders arrival	$5.84 \pm 3.13$	$2.64 \pm 2.97$
3	10	5	1/5	High rate of limit orders arrival	$1.61 \pm 0.68$	$0.58 \pm 0.39$
4	10	1	2/5	High rate of limit orders cancellations	$2.64 \pm 1.31$	$-2.95 \pm 2.78$

- The average spread increases with market orders  $\mu$
- The average spread decreases as limit orders  $\alpha$  increases
- The standard deviation of the mid-price and spread is expected to increase with  $\mu$  and decrease as  $\alpha$  increases.

# Chapter III



## Part I : Depth and Slope

Prediction #1 Depth: the density of shares far away from the mid-price.

$$Depth \sim \frac{\alpha}{\delta}$$

Prediction #2 Slope: a measure of market order liquidity, the ratio of depth to spread.

$$Slope \sim \frac{\alpha^2}{\mu\delta}$$

## Simulation vs Theoretical

Scenario	$\mu$	$\alpha$	$\delta$	Comments	Slope	Slope ( $\alpha^2/\mu\delta$ )	Depth (Prediction)	Depth ( $\alpha/\delta$ )
1	10	1	1/5	Base scenario	0.495565	0.5	5.015938	5
2	20	1	1/5	High rate of market order arrival	0.3360431	0.25	4.392948	5
3	10	5	1/5	High rate of limit orders arrival	1.4501796	12.5	24.419772	25
4	10	1	2/5	High rate of limit orders cancellations	0.2078544	0.25	2.441263	2.5

- For depth:

The simulation result of depth agree with the Santa Fe model prediction.

- For slope:

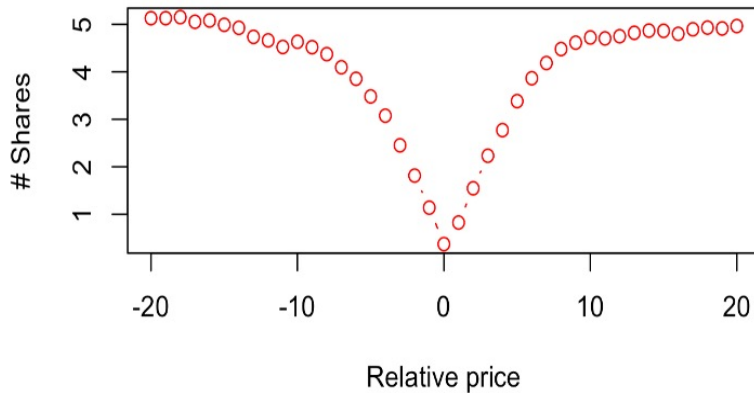
The simulation result for scenario 3 doesn't match with the theoretical outcome. Because we use the relative price for regression.

# Chapter III

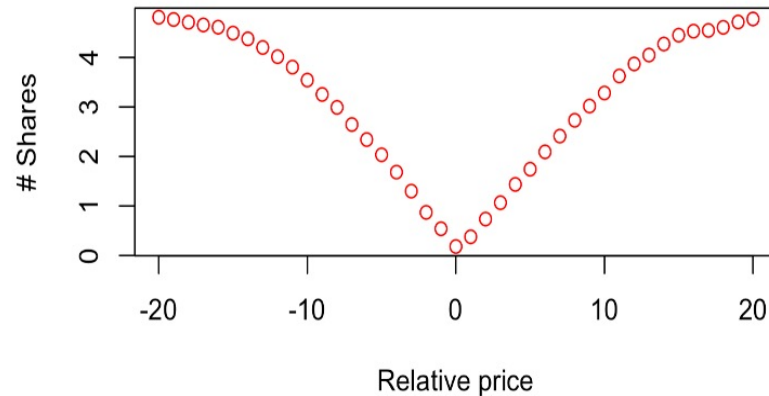


## Part II: Shape of LOB

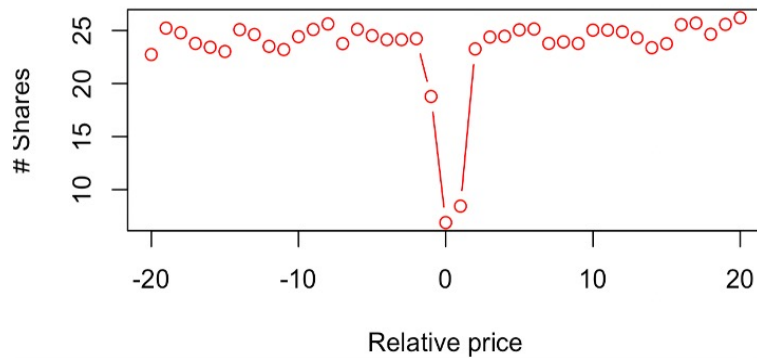
I



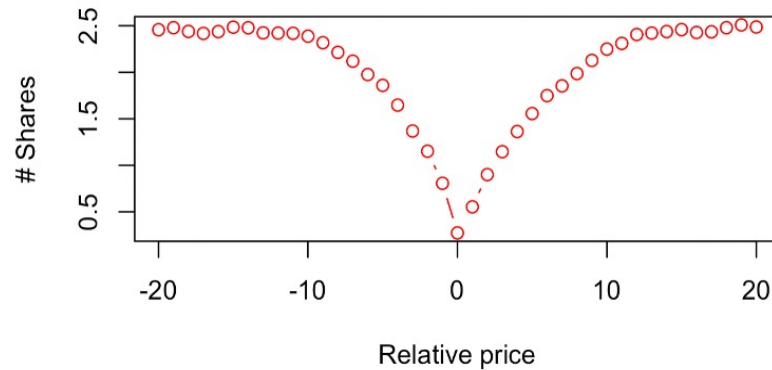
II



III



IV



# Chapter III



## Part III : Price impact

For  $\epsilon \sim 0.01$ , the Price impact:

$$\Delta p(w) \sim \sqrt{\frac{2w}{\text{slope}}}$$

In our simulation, the  $\epsilon = \frac{\sigma\delta}{\mu}$  is small.

There is small accumulation of orders at best bid and ask, and near the midpoint price the depth profile increases nearly linear with price. As a result, as a crude approximation, the price impact increases roughly the square root of order size.

# Chapter IV

## Part I : Price dynamics

- ❖ Data: fake TAQ data (1000 events)
- ❖ Collect all market orders (number: 74)
  - 37 market sells and 37 market buys

> tqdata\_ms

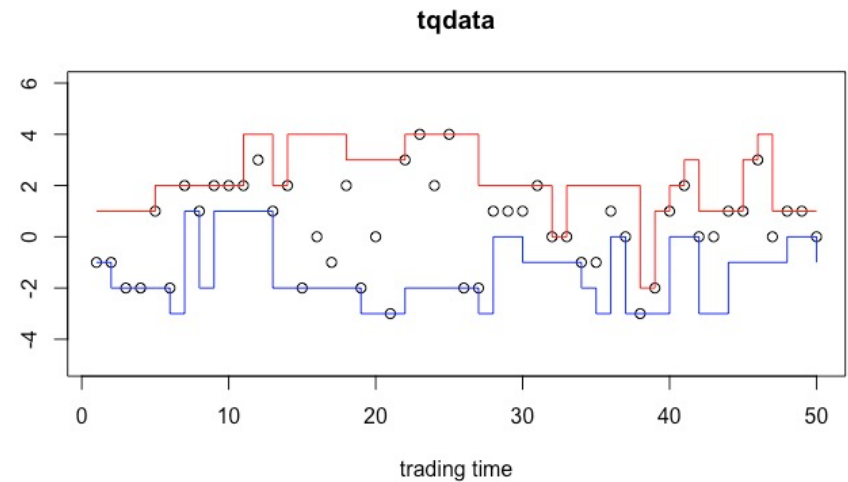
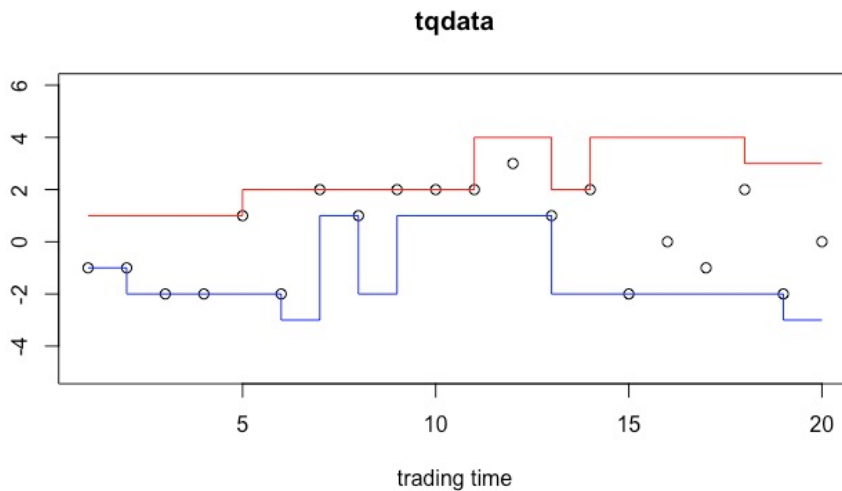
	SYMBOL	EX	BID	BIDSIZ	OFR	OFRSIZ	MODE	PRICE	DIR
4	YYY	None	-1	5	1	5	20	-1	MS
46	YYY	None	-1	5	2	5	20	-1	MS
68	YYY	None	-1	5	0	5	20	-1	MS
82	YYY	None	-2	5	0	5	20	-1	MS
92	YYY	None	-2	5	0	5	20	-2	MS

> tqdata\_mb

	SYMBOL	EX	BID	BIDSIZ	OFR	OFRSIZ	MODE	PRICE	DIR
18	YYY	None	-1	5	2	5	20	1	MB
21	YYY	None	-1	5	2	5	20	2	MB
45	YYY	None	-1	5	2	5	20	2	MB
103	YYY	None	-2	5	2	5	20	0	MB
111	YYY	None	-2	5	3	5	20	2	MB

## Part I : Price dynamics

- ❖ Plot the first 20 and 50 events which described the changes in Best Bid and Best Ask price after each execution
- ❖ Red line: Best Ask  
Blue line: Best Bid

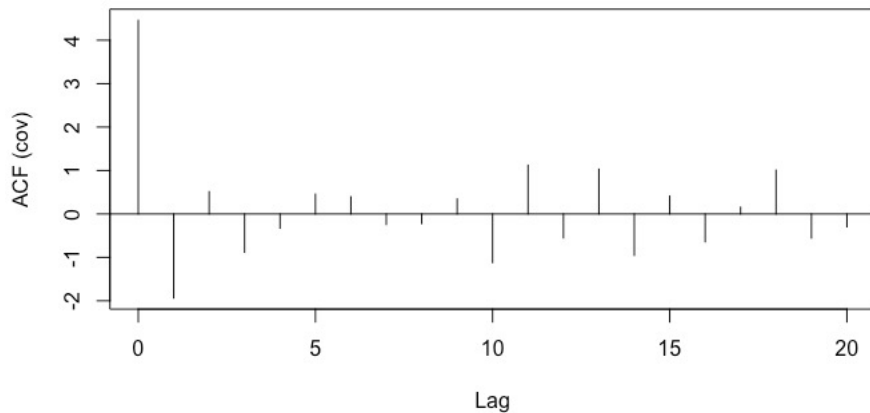


## Part I : Price dynamics

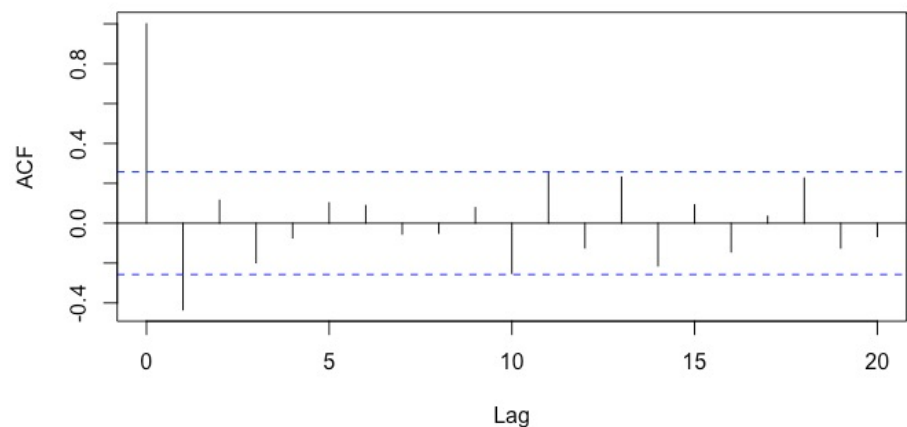
❖ Then, let us see the covariance and autocorrelation

```
price <- as.numeric(tqdata$PRICE)
price.diff <- diff(price)
price.diff.acf <- acf(price.diff, lag.max=20, type="covariance")
price.diff.acfc <- acf(price.diff, lag.max=20, type="correlation",
                        main="ACF(correl)")
```

Series price.diff



ACF(correl)





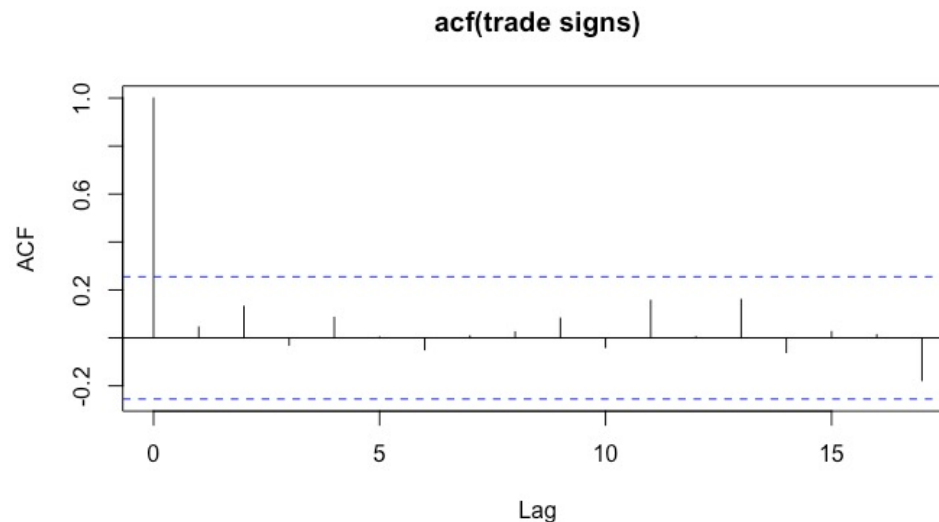
## Part II : Autocorrelation of trade signs and compared with Roll Model

❖ trade signs are  $d_t$ , where  $d_t = \begin{cases} 1, \text{buy} \\ -1, \text{sell} \end{cases}$

```
trade.dir <- coredata(tqdata$DIR[,1])[,1]
trade.sign.recorded <- ifelse(trade.dir=="MB",1,-1)

plot(trade.sign.recorded, type="l")

acf(trade.sign.recorded, main="acf(trade signs)")
```



## Part II : Autocorrelation of trade signs and compared with Roll Model

### ❖ Roll Model Result

Scenario	$\mu$	$\alpha$	$\delta$	Comments	$c$	$\sigma_u$	spread
1	10	1	1/5	Base scenario	1.39	0.77	2.78
2	20	1	1/5	High rate of market order arrival	2.07	3.06	4.14
3	10	5	1/5	High rate of limit orders arrival	0.67	0.17	1.35
4	10	1	2/5	High rate of limit orders cancellations	1.61	1.16	3.22

### ❖ Compared with ZI model

Scenario	$\mu$	$\alpha$	$\delta$	Comments	Spread	Mid-price
1	10	1	1/5	Base scenario	$2.72 \pm 1.58$	$-1.96 \pm 2.38$
2	20	1	1/5	High rate of market orders arrival	$5.84 \pm 3.13$	$2.64 \pm 2.97$
3	10	5	1/5	High rate of limit orders arrival	$1.61 \pm 0.68$	$0.58 \pm 0.39$
4	10	1	2/5	High rate of limit orders cancellations	$2.64 \pm 1.31$	$-2.95 \pm 2.78$



# Chapter V

## Improvements with relevant topic

**If there is extra time one could explore further along different situations.**

1. Change the assumptions with uniformed distributed arrival rate or Erlang distribution.
2. Add more simulation times.
3. Discuss the slope of LOB using absolute price.
4. Maybe use the real-world data to estimate the validity of Zero Intelligence Model.
5. Discuss the price impact of different size of arrival order



**STEVENS**  
INSTITUTE *of* TECHNOLOGY  

---

THE INNOVATION UNIVERSITY®

**stevens.edu**