## A Multiclass Queueing Model of Limit Order Book Dynamics

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Joint work with Costis Maglaras.

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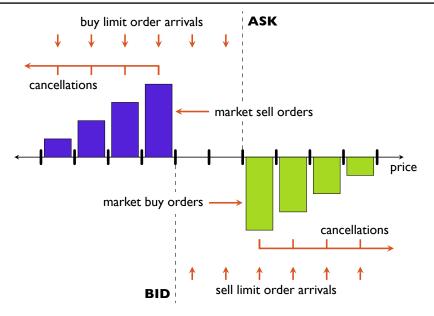
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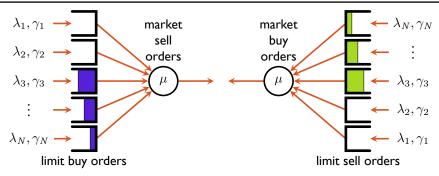
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• Order routing: decides where to send each child order relevant time-scale:  $\sim 1-50$  ms optimizes fee/rebate tradeoff, liquidity/price, latency, etc.

## **The Limit Order Book**



# LOB as Coupled Multi-Class Priority Queues



Arrival rates into two sides of book are coupled

- Arrival rates for buy orders depend on lowest non-empty queue with sell orders (ASK)
- Arrival rates for sell orders depend on highest non-empty queue with buy orders (BID)
- More complicated dependencies could be considered (e.g., distance from best bid/ask, queue length, time-of-day, etc.)

## Questions

• Stochastic analysis of multi-class priority queues steady state characterization of coupled queues characterization of dynamics of price process fluid / diffusion approximations of queueing dynamics

#### • Optimal execution

how to optimize order placement in LOB how to determine rate of trading how to estimate queueing delays design of market-making strategies that exploit LOB dynamics & transient behavior

#### • Market impact modeling

microstructure-based model of market impact

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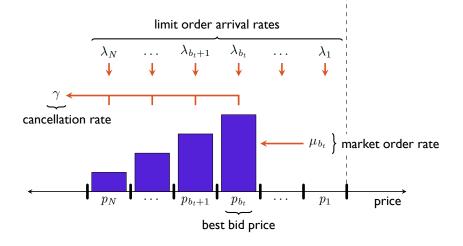
- Market microstructure: Kyle; Glosten-Milgrom; Glosten; ...
- Empirical analysis of limit order books: Bouchaud et al.; Hollifield et al.; Smith et al.; ...
- Econo-physics: Farmer (+ several coauthors); ...
- Transaction cost modeling and estimation: Madhavan; Dufour & Engle; Holthausen et al.; Huberman & Stanzl; Almgren et al.; Gatheral; ...
- Optimal execution / trade scheduling: Bertsimas & Lo; Almgren & Chriss; ...
- Dynamic models and optimal execution in LOB: Obizhaeva & Wang; Cont et al.; Rosu; Alfonsi et al.; Foucault et al.; Parlour; ...
- Stochastic models of multi-class queueing networks

### **One-sided LOB Fluid Model**

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### **One-sided LOB Fluid Model: Summary**

•  $Q_i(t)$  is the quantity of limit orders at price level  $p_i$ 

$$p_N \leq \cdots \leq p_2 \leq p_1$$

- Limit orders arrive into queue i with rate  $\lambda_i > 0$
- Market sell orders arrive to the system with rate μ<sub>bt</sub>, dependent on the best bid queue b<sub>t</sub>

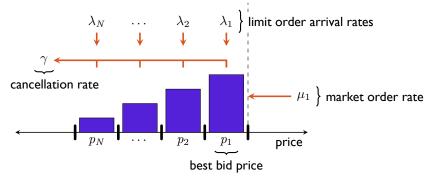
$$\mu_N \leq \cdots \leq \mu_2 \leq \mu_1$$

• Market orders hit resting limit orders according to price/time priority

queue 1 > queue  $2 > \cdots >$  queue N; FIFO within each queue

• Orders individually cancelled at rate  $\gamma$ 

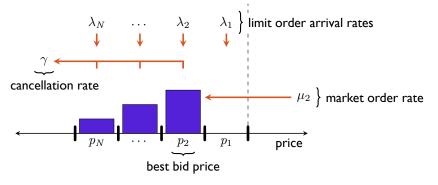
## **LOB Fluid Model Dynamics**



For  $0 \leq t \leq T_1$ :

- $\dot{Q}_1(t) = \lambda_1 \mu_1 \gamma Q_1(t), \quad \dot{Q}_i(t) = \lambda_i \gamma Q_i(t), \ i \ge 2$
- Until time  $T_1 = \frac{1}{\gamma} \log \left( 1 + \frac{\gamma}{\mu_1 \lambda_1} Q_1(0) \right)$ , when  $Q_1(T_1) = 0$

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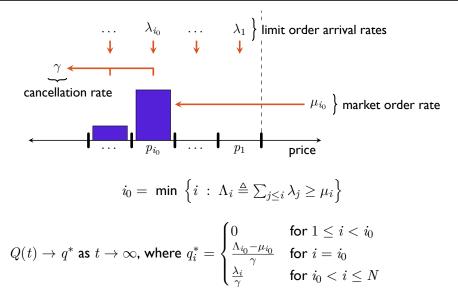


For  $T_1 \leq t \leq T_2$ :

- $Q_1(t) = 0$ ,  $\dot{Q}_2(t) = \lambda_2 (\mu_2 \lambda_1) \gamma Q_2(t)$ ,  $\dot{Q}_i(t) = \lambda_i \gamma Q_i(t)$ ,  $i \ge 3$
- Until time  $T_2$  when  $Q_2(T_2) = 0$

• ...

### LOB Fluid Model Steady State



#### **Problem:**

• purchase C total shares in time T for lowest possible average price

$$p^*(C, T) \triangleq \text{minimize}$$
 (average price)  
subject to (total time)  $\leq T$   
(total quantity) = C

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- purchase  ${\it C}$  total shares given a target average price  $\bar{p}$  in minimum time

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#### **Efficient frontier:**

$$\mathcal{E} \triangleq \left\{ (C, T, p) : p = p^*(C, T) \right\} \triangleq \left\{ (C, T, p) : T = T^*(C, p) \right\}$$

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#### **Controls:**

 $L_i(t) = \text{cumulative \# of orders placed in queue } i \text{ in } [0, t]$ = RCLL process

**Proposition.** The optimal control places all orders at time t = 0.

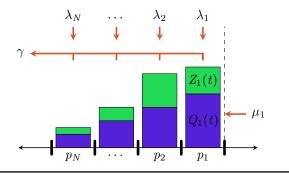
Intuition: place orders at t = 0 to gain priority over future arriving limit orders. Exploit time priority to place limit orders in lower priority queues (better prices).

#### Notation:

 $z_i = initial \ \# \ of \ investor \ orders \ in \ queue \ i$ 

 $Z_i(t) = \text{remaining \# of unexecuted investor orders in queue } i$ 

 $Q_i(t) =$ # of orders from other investors



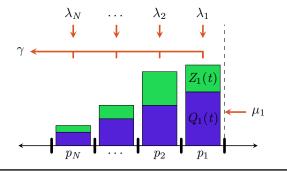
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$$au^{\ell}(z) \triangleq \inf \left\{ t \ge 0 \; : \; Q_{i-1}(t) = 0, \; Z_i(t) = 0, \; i \le \ell \right\}$$



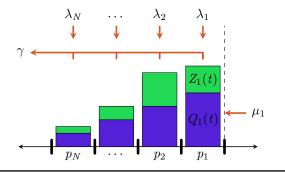
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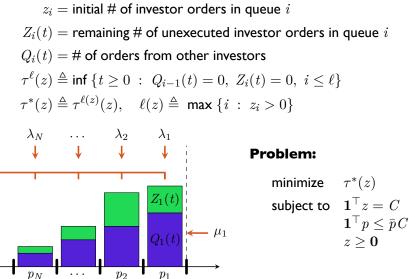
$$Z_i(t)={\sf remaining}\,{\it \#}$$
 of unexecuted investor orders in queue  $i$ 

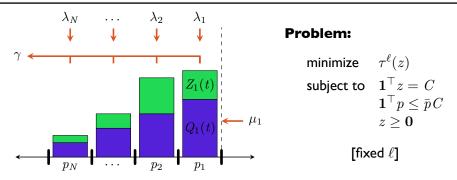
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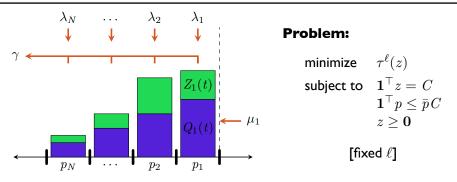
$$\begin{aligned} \tau^{\ell}(z) &\triangleq \inf \left\{ t \ge 0 \ : \ Q_{i-1}(t) = 0, \ Z_i(t) = 0, \ i \le \ell \right\} \\ \tau^*(z) &\triangleq \tau^{\ell(z)}(z), \quad \ell(z) \triangleq \max \left\{ i \ : \ z_i > 0 \right\} \end{aligned}$$



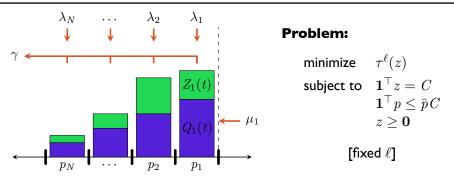
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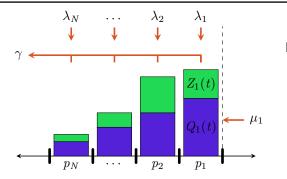


**Lemma.** If  $Q_i(0) \leq \lambda_i / \gamma$ , then  $\tau^{\ell}(z)$  is a concave in z.



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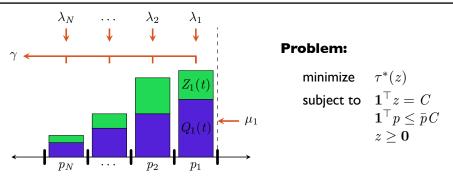
**Theorem.**  $||z^{(\ell)}||_0 \leq 2$ , i.e., optimal to place orders in at most two queues



#### **Problem:**

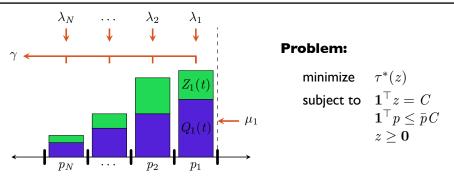
minimize	$ au^*(z)$
subject to	$1^\top z = C$
	$1^\top p \le \bar{p} C$
	$z \ge 0$

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Corollary. Optimal to place orders in two adjacent queues

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**Optimal Policy:** [Q(0) = 0]Recall  $i_0 \triangleq \min \{i : \Lambda_i \triangleq \sum_{j \le i} \lambda_j \ge \mu_i\}$ . Define  $\bar{C}_i \triangleq (\mu_i - \Lambda_{i-1})^+ T$ .

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• 
$$0 \le C \le \overline{C}_{i_0} \implies z_j^* = 0$$
 unless  $j = i_0$ 

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- $\bullet \ \bar{C}_i \leq C \leq \bar{C}_{i-1} \quad \Longrightarrow \quad z_j^* = 0 \text{ unless } j \in \{i-1,i\}$
- $C > \overline{C}_1 \triangleq \mu_1 T \implies$  infeasible! (must use market orders)

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Easy to compute recursively the  $\bar{C}_i$  thresholds starting from arbitrary Q(0)

### **Efficient Frontier**

Price grid is uniformly spaced  $p_i \triangleq p_1 - (i-1)\delta$  ( $\delta = {\rm tick\ size}$ )

$$\begin{split} \bar{C}_1 &= \mu_1 T & \text{shares at } p_1 \\ \bar{C}_2 &= (\mu_2 - \Lambda_1) T & \text{shares at } p_2 \\ \vdots \\ \bar{C}_{i_0} &= (\mu_{i_0} - \Lambda_{i_0-1})^+ T & \text{shares at } p_{i_0} \end{split}$$

$$\lambda_i > 0 \quad \Longrightarrow \quad \bar{C}_1 > \bar{C}_2 > \dots > \bar{C}_{i0}$$

# **Efficient Frontier**

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 $\bar{C}_{1} = \mu_{1}T \qquad \text{shares at } p_{1}$   $\bar{C}_{2} = (\mu_{2} - \Lambda_{1})T \qquad \text{shares at } p_{2}$   $\vdots$   $\bar{C}_{i_{0}} = (\mu_{i_{0}} - \Lambda_{i_{0}-1})^{+}T \qquad \text{shares at } p_{i_{0}}$   $\lambda_{i} > 0 \implies \bar{C}_{1} > \bar{C}_{2} > \cdots > \bar{C}_{i_{0}}$ 

#### **Shape of Efficient Frontier:**

• Determines price impact as a function of trading rate C/T

• 
$$\lambda_1 = \lambda_2 = \cdots = \lambda_{i_0-1} \implies$$
 "linear" cost-per-share

•  $\lambda_1 > \lambda_2 > \cdots > \lambda_{i_0-1} \implies$  "sub-linear" cost-per-share

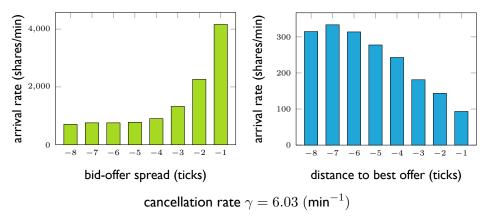
# **Numerical Example**

First Solar, Inc. (ticker: FSLR.Q) 3/22/2010

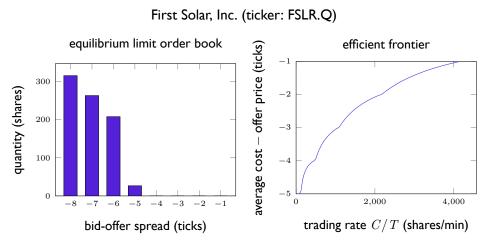
close price = \$109.36 average volume = 2,699,000 shares

market sell orders rates  $\mu_i$ 

limit buy orders rates  $\lambda_i$ 



### **Numerical Example**



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Optimal order placement suggests:

- Break up slice into n child orders to be executed "uniformly" over T (roughly every T/n time units)
- The price of each child order depends on:
  - (a) state of LOB
  - (b) speed of LOB
  - (c) size of the child order = C/n
  - (d) duration = T/n

Precise formulations possible ...

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- Order placement influences arrival rates
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- Not relevant for illiquid names
- Incorporate multiple LOB's / order routing ( $\approx 5$  LOB's matter in practice)

Fluid models are a useful characterization of LOB dynamics

#### **Optimal Execution:**

- Tractable order placement problem
- Allow estimation of queueing delays
- Determine optimal rate of trading

#### Market Impact Modeling:

- A microstructure-based model of market impact
- Exponent directly estimated from rate of events in LOB
- Suggests different exponents for limit orders versus market orders?