

Optimal portfolio liquidation

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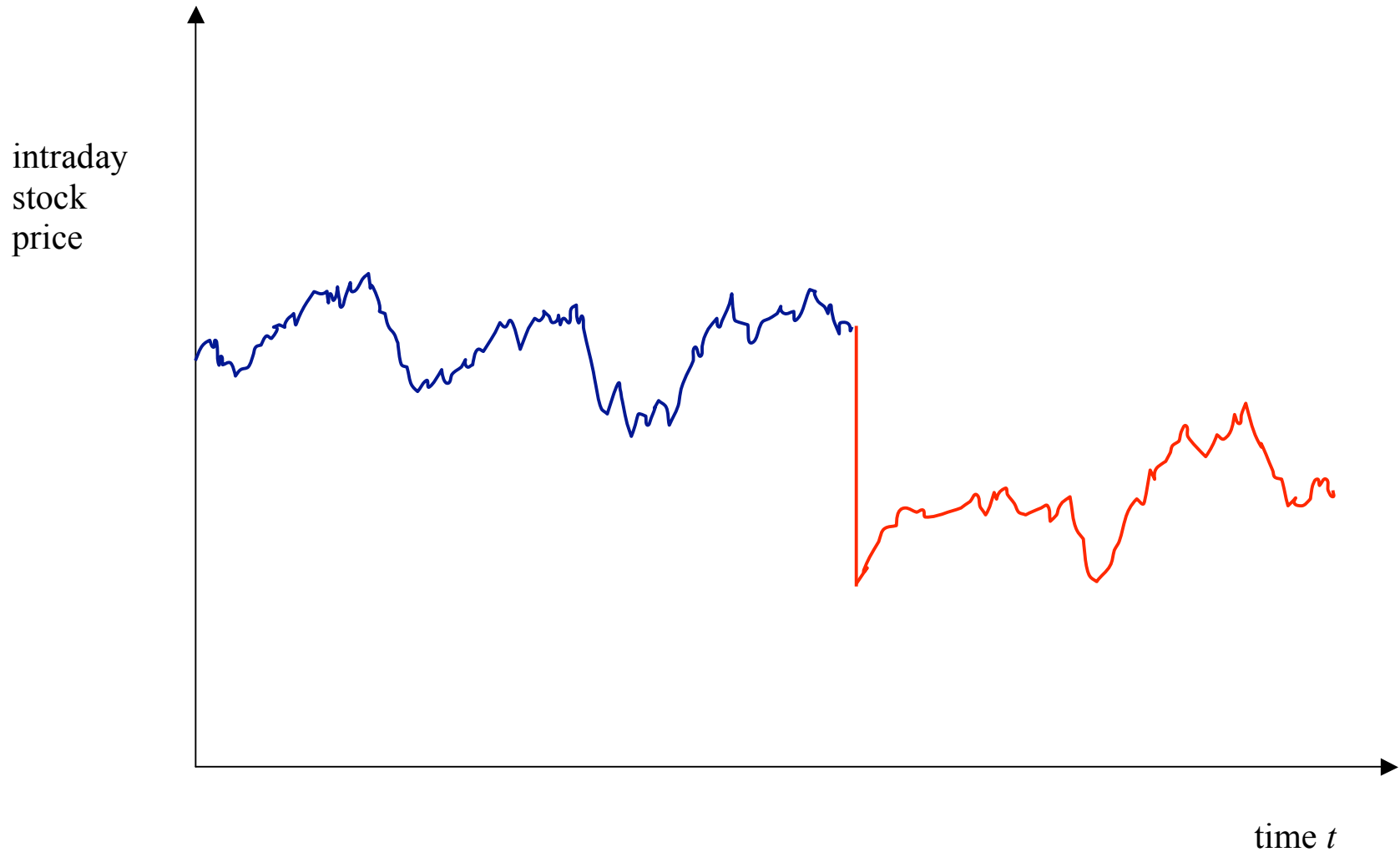
RICAM Linz, September 26, 2008

Joint work with

Aurélien Alfonsi, Antje Fruth, and Torsten Schöneborn

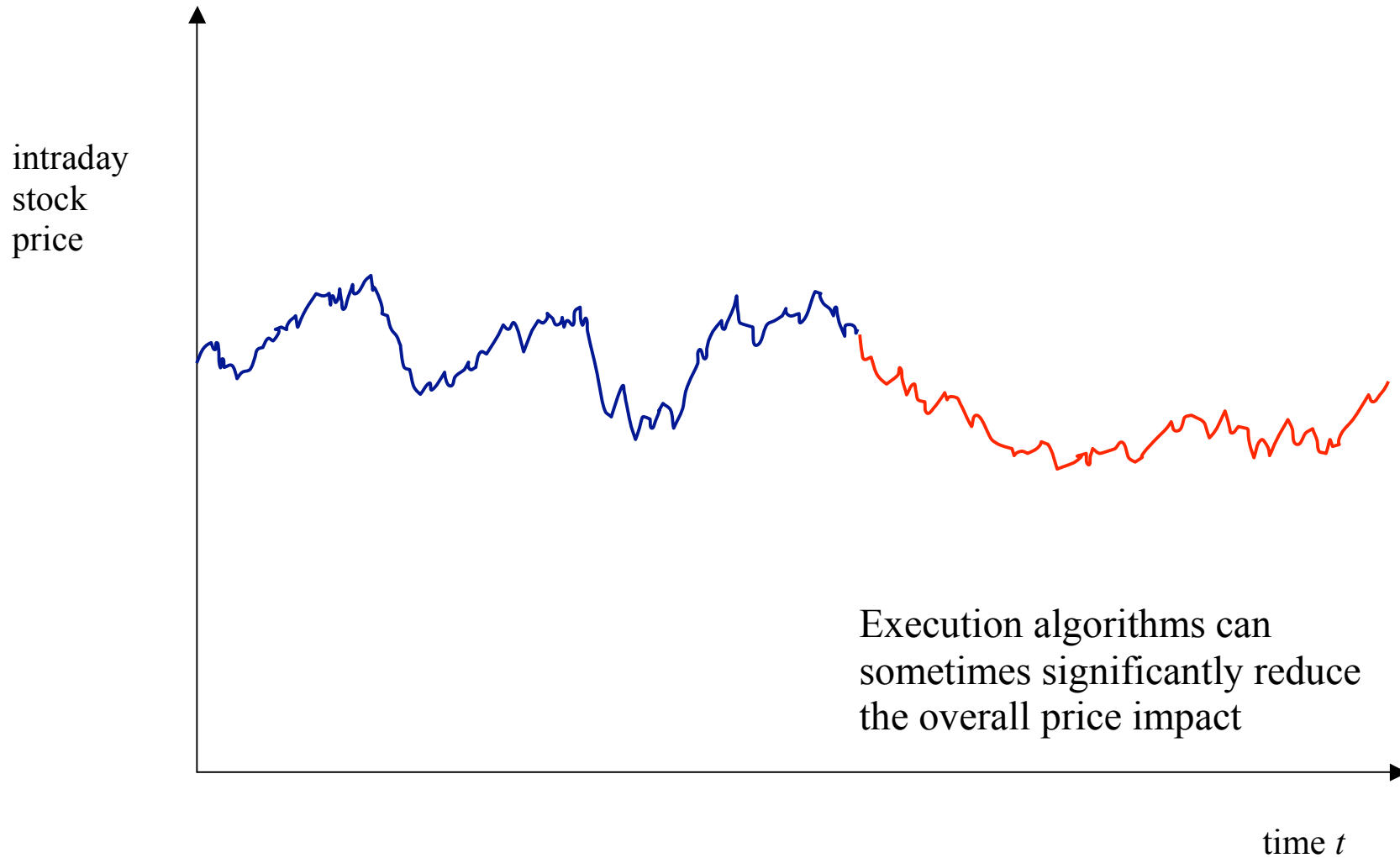
Common problem:

A trader needs to liquidate a large long (short) position by the end of the day



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How to optimally execute a large block order?

Need first:

- How do stock prices react to large orders?
- What is a good model for this?
- How to formulate and solve the optimization problem?

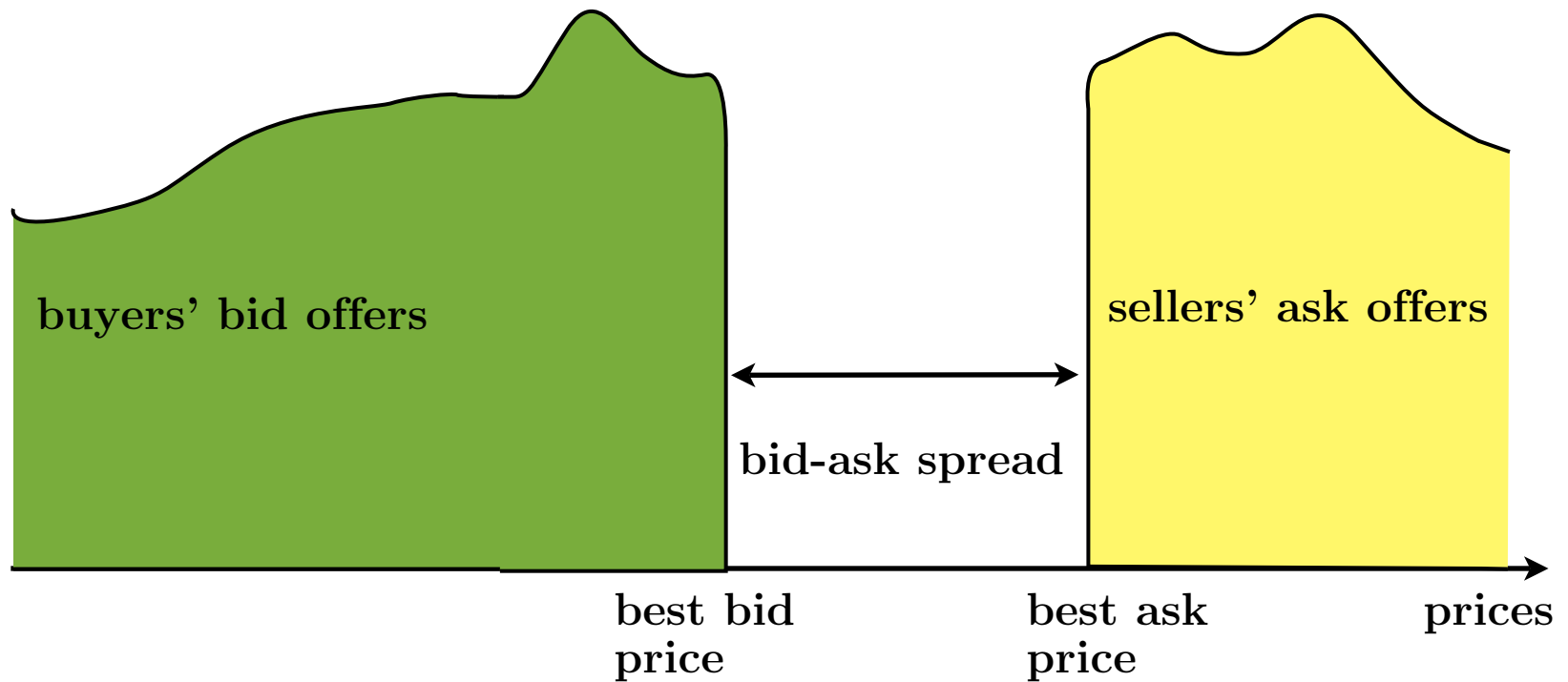
Interesting because:

- Relevant in applications
- Liquidity risk in its purest form
- Interesting mathematics

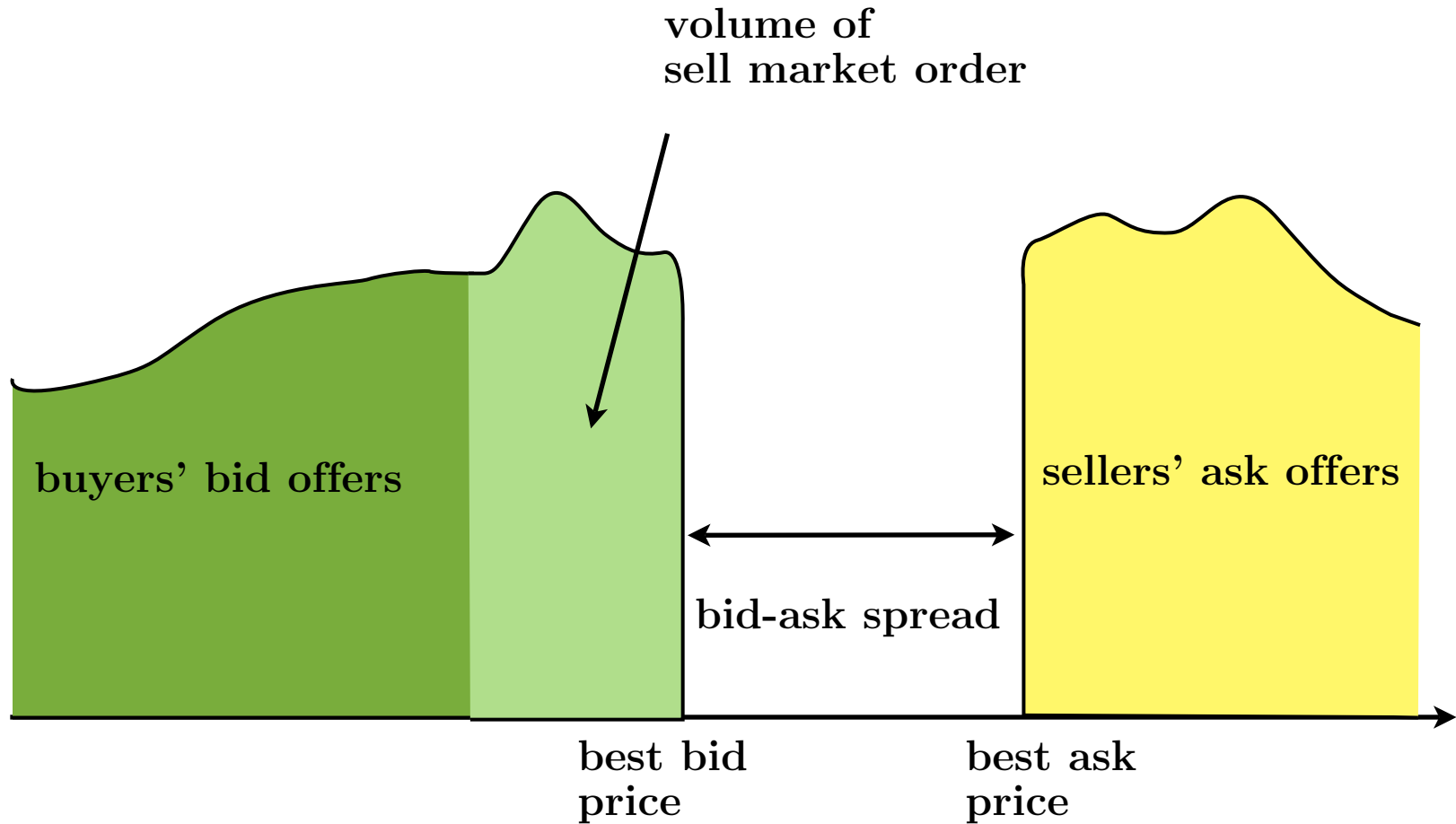
Overview

0. Intuition for market impact
1. Optimal execution in a limit order book
2. Optimal execution and risk aversion
3. Multi-agent equilibrium

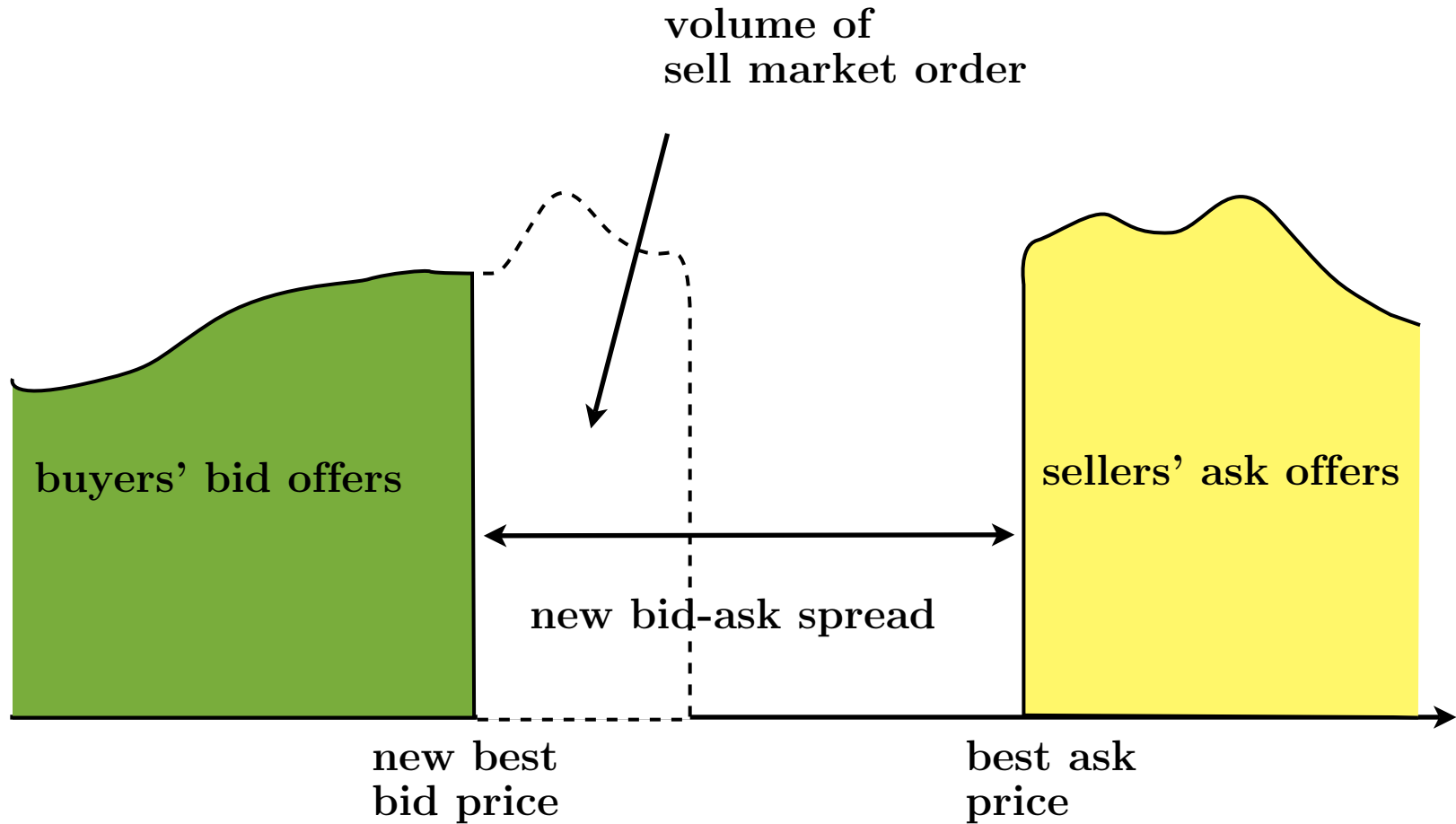
Limit order book before market order



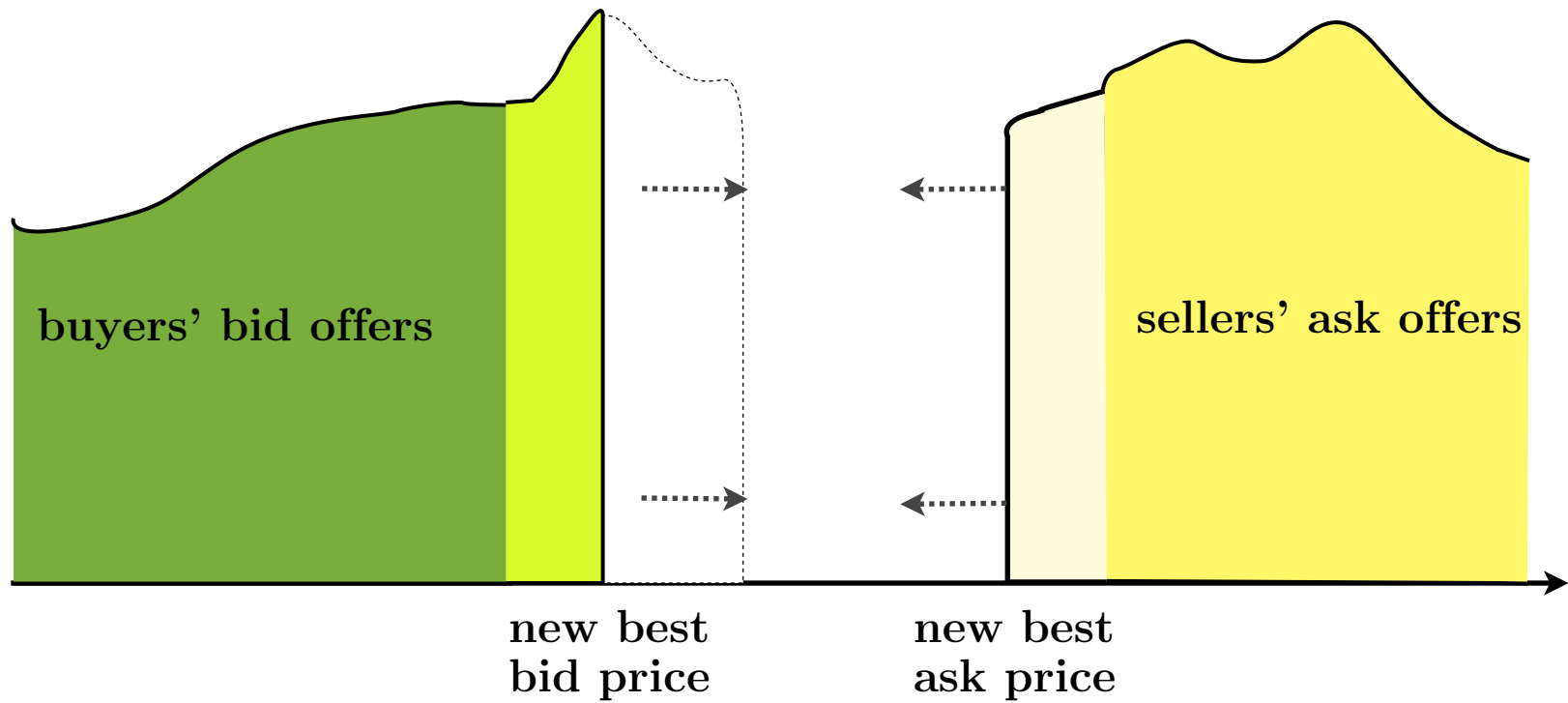
Limit order book before market order



Limit order book after market order



Resilience of the limit order book after market order



1. Optimal execution in a limit order book model

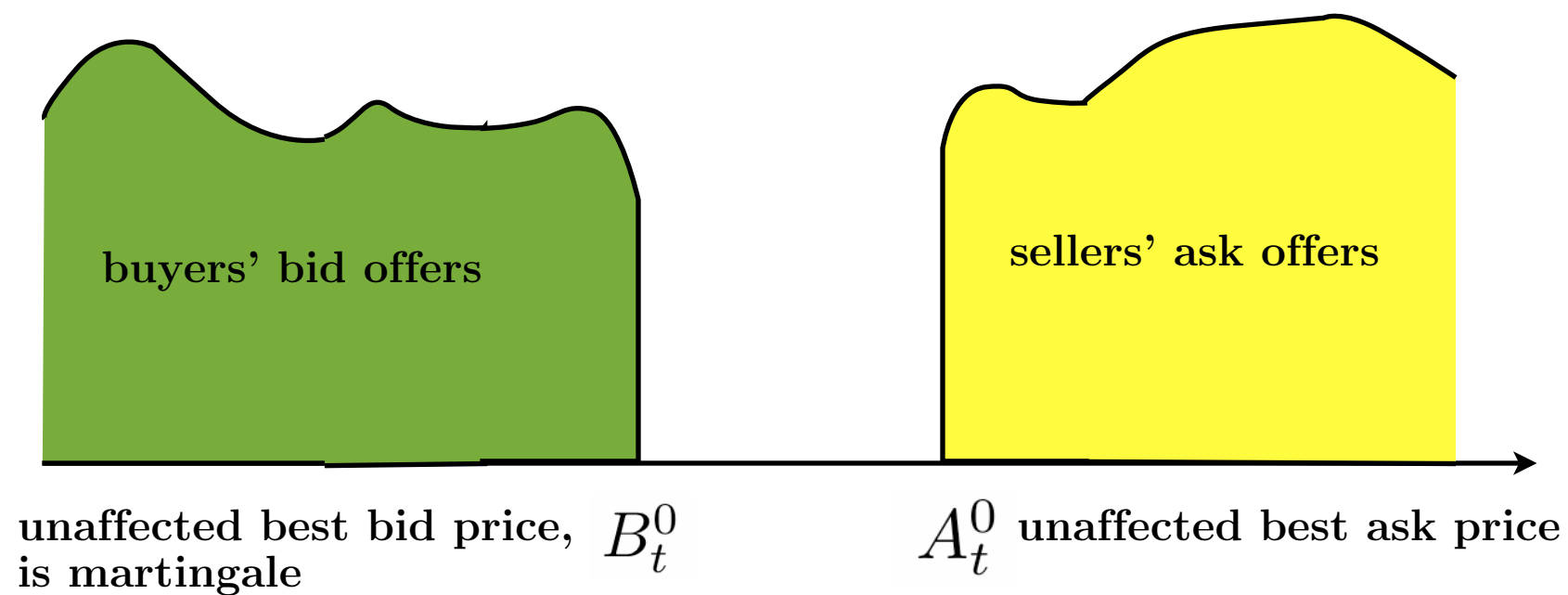
Block-shaped limit order book:

- [1] A. Obizhaeva and J. Wang: *Optimal Trading Strategy and Supply/Demand Dynamics*. To appear in J. Financial Markets

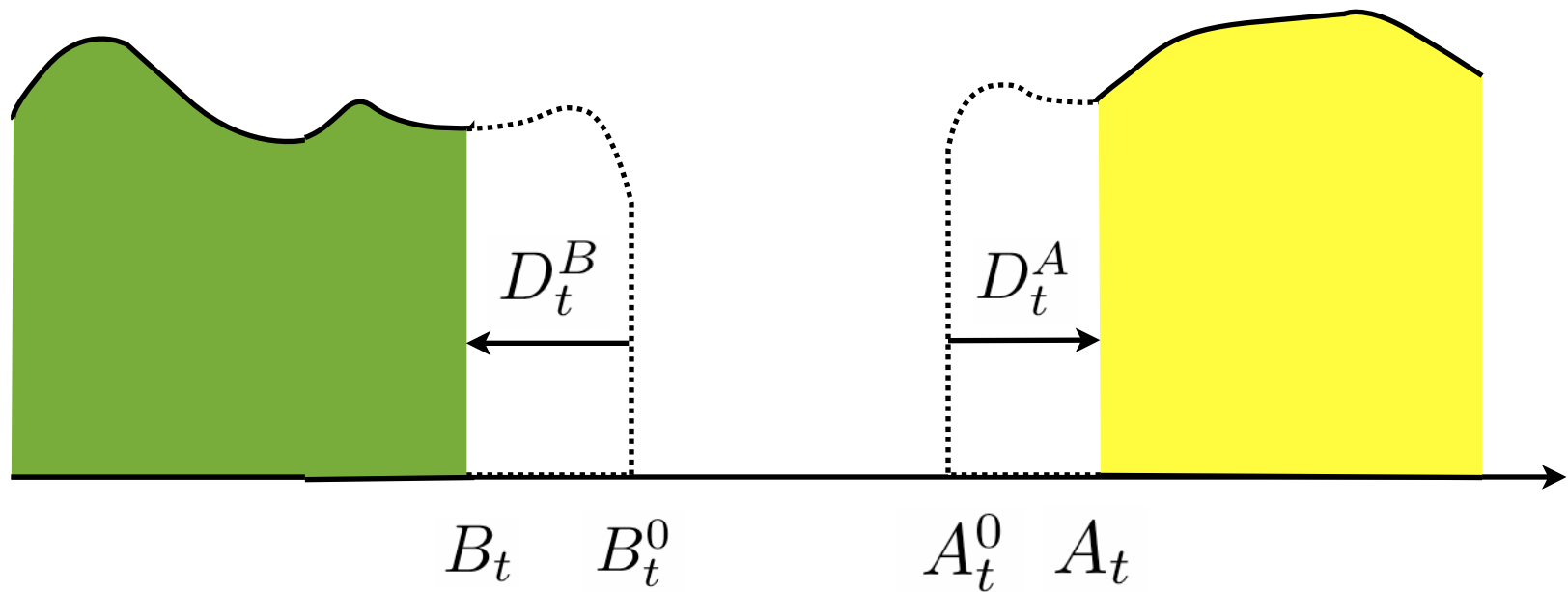
LOB with general shape function and linear constraints:

- [2] (A. Alfonsi, A. Fruth, and A.S.): *Optimal execution strategies in limit order books with general shape functions*. Preprint, 2007
- [3] (A. Alfonsi, A. Fruth, and A.S.): *Constrained portfolio liquidation in a limit order book model*. To appear in Banach Center Publications.

Limit order book model without large trader

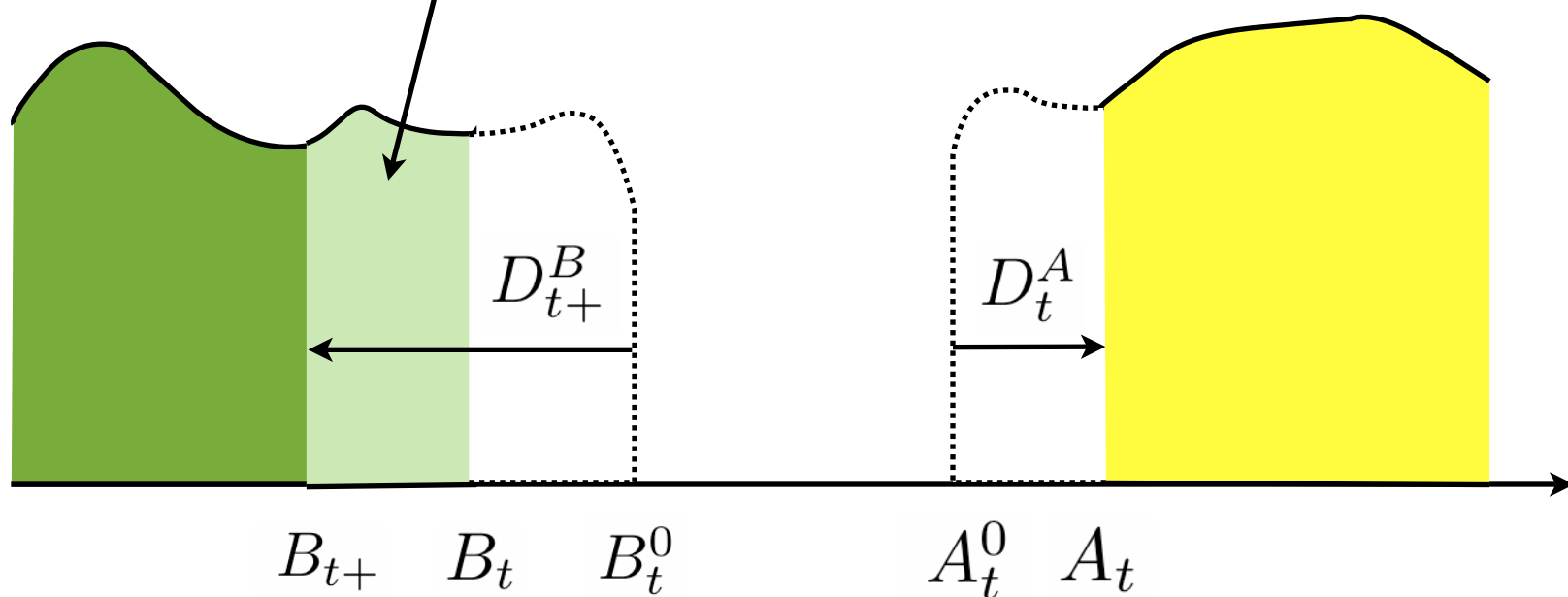


Limit order book model after large trades

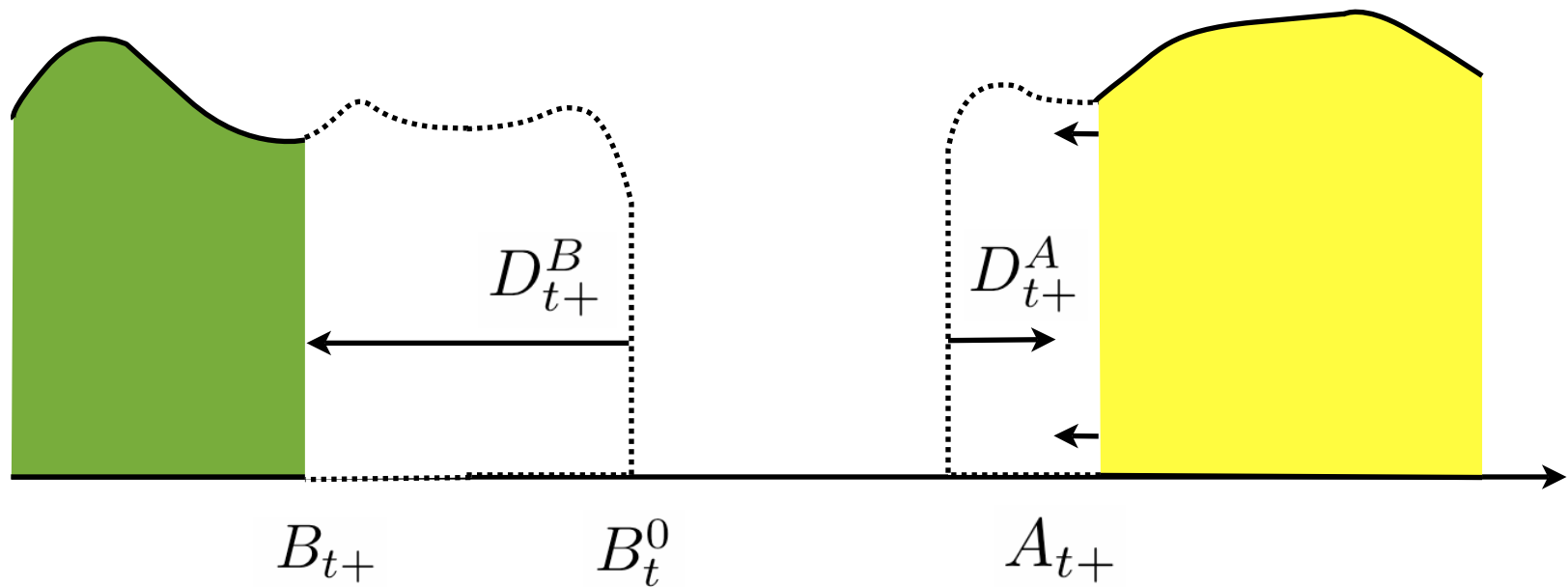


Limit order book model at large trade

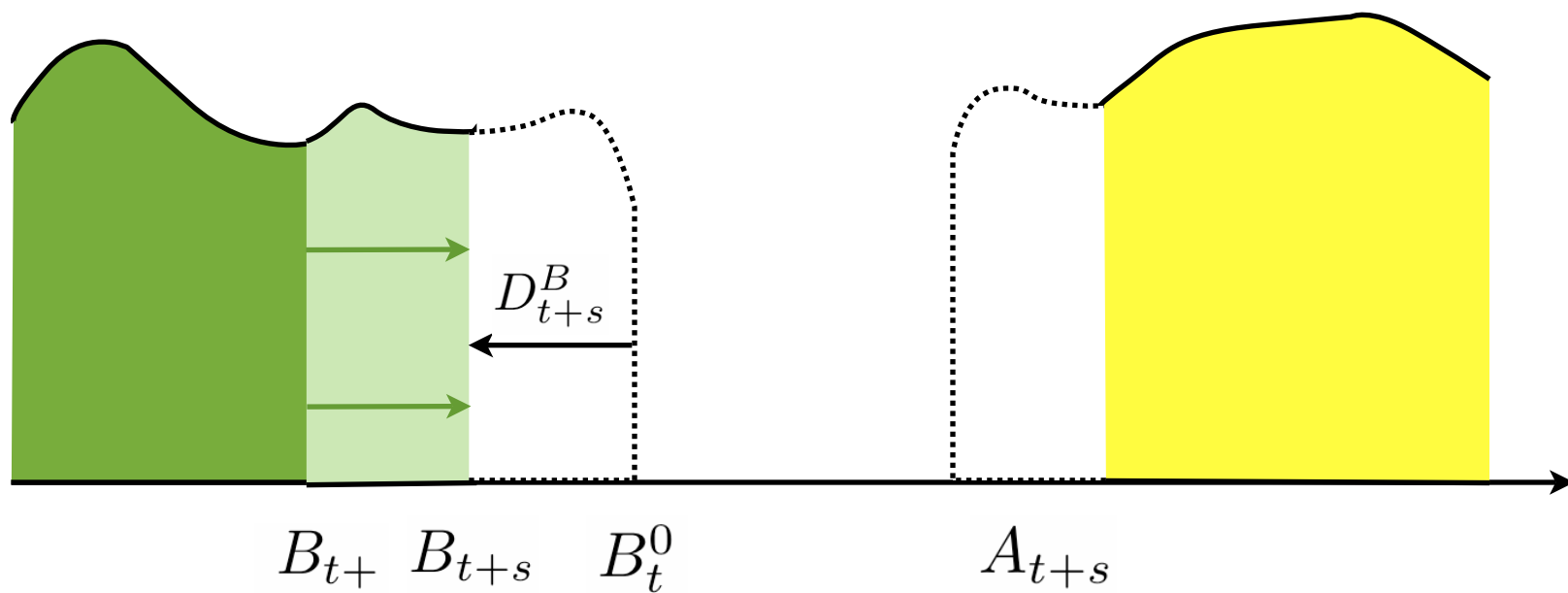
$$x_t = \int_{D_{t+}^B}^{D_t^B} f(x) dx$$



Limit order book model immediately after large trade



Limit order book model with resilience



The LOB model:

$f(x)$ = shape function = densities of bids for $x < 0$, asks for $x > 0$

B_t^0 = ‘unaffected’ bid price at time t , is **martingale**

B_t = bid price after market orders before time t

$$D_t^B = B_t - B_t^0$$

If **sell order** of $\xi_t \geq 0$ shares is placed at time t :

D_t^B changes to D_{t+}^B , where

$$\int_{D_{t+}^B}^{D_t^B} f(x) dx = \xi_t$$

and

$$B_{t+} := B_t + D_{t+}^B - D_t^B = B_t^0 + D_{t+}^B,$$

\implies **nonlinear price impact**

The LOB model:

A_t^0 = ‘unaffected’ ask price at time t , satisfies $B_t^0 \leq A_t^0$

A_t = bid price after market orders before time t

$$D_t^A = A_t - A_t^0$$

If buy order of $\xi_t \leq 0$ shares is placed at time t :

D_t^A changes to D_{t+}^A , where

$$\int_{D_t^A}^{D_{t+}^A} f(x) dx = -\xi_t$$

and

$$A_{t+} := A_t + D_{t+}^A - D_t^A = A_t^0 + D_{t+}^A,$$

If the large investor is **inactive** during the time interval $[t, t + s[$, there are *two* possibilities:

- **Exponential recovery of the extra spread**

$$D_{t+s}^B = e^{-\rho s} D_t^B$$

- **Exponential recovery of the order book volume**

$$E_{t+s}^B = e^{-\rho s} E_t^B$$

where

$$E_t^B = \int_{D_t^B}^0 f(x) dx =: F(D_t^B).$$

In both cases: analogous dynamics for D^A or E^A

The optimization problem:

- $N + 1$ market orders: ξ_n shares placed at time $t_n = n\tau$ s.th.

1) ξ_n is adapted and bounded from below (can be negative),

2) we have $\sum_{n=0}^N \xi_n = X_0$

- When **selling** $\xi_n \geq 0$ shares, we sell $f(x) dx$ shares at price $B_t^0 + x$ with x ranging from D_{t+}^B to D_t^B , i.e., the **revenues** are **positive**:

$$\rho_{t_n}(\xi_n) := \int_{D_{t_n+}^B}^{D_{t_n}^B} (B_{t_n}^0 + x) f(x) dx = \xi_n B_{t_n}^0 + \int_{D_{t_n+}^B}^{D_{t_n}^B} x f(x) dx$$

- When **buying** shares ($\xi_n \leq 0$), the **revenues** are **negative**:

$$\rho_{t_n}(\xi_n) := \xi_n A_{t_n}^0 - \int_{D_{t_n}^A}^{D_{t_n+}^A} x f(x) dx$$

- The **expected revenues** from the strategy $\xi = (\xi_n)$ are

$$\mathcal{R}(\xi) = \mathbb{E} \left[\sum_{n=0}^N \rho_{t_n}(\xi_n) \right]$$

The goal is to maximize the expected revenues over all admissible strategies.

Theorem 1 (Optimal strategy for exponential recovery of volume).

Suppose that the LOB has infinite depth, i.e., $|F(x)| \rightarrow \infty$ as $|x| \rightarrow \infty$, and that the function

$$h(u) := e^{-\rho\tau} F^{-1}(e^{-\rho\tau} u) - F^{-1}(u)$$

is one-to-one. Let ξ_0^* be the unique solution of the equation

$$F^{-1}(N\xi_0^*(1 - e^{-\rho\tau}) - X_0) = \frac{h(-\xi_0^*)}{1 - e^{-\rho\tau}},$$

and

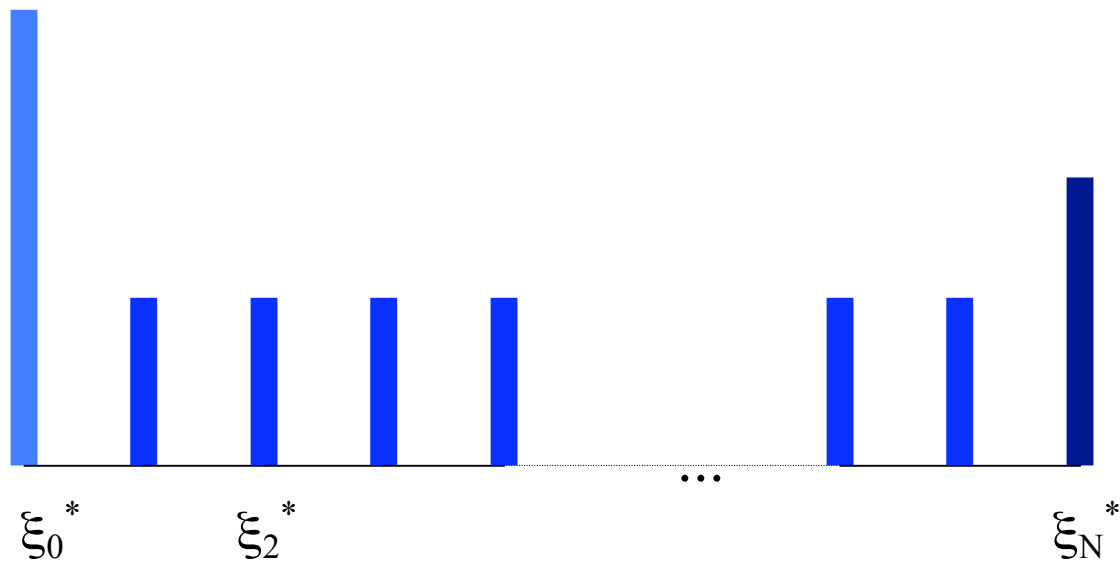
$$\xi_1^* = \dots = \xi_{N-1}^* = \xi_0^*(1 - e^{-\rho\tau}),$$

as well as

$$\xi_N^* = X_0 - \xi_0^* - (N - 1)\xi_0^*(1 - e^{-\rho\tau}).$$

Then $\xi_n^* > 0$ for all n , and ξ^* is the unique optimal strategy.

The optimal strategy for the minimization of the expected liquidation costs is deterministic:



Optimal sell market orders for $N+1$ equidistant time steps

Remark: The impact of ξ^* is such that

$$D_{t_{k+1}}^B = e^{-\rho\tau} D_{t_k}^B$$

for all k .

Corollary 2 (Closed-form solution for block-shaped LOB).

In a block-shaped LOB, the unique optimal strategy ξ^ is*

$$\xi_0^* = \xi_N^* = \frac{X_0}{(N-1)(1-e^{-\rho\tau})+2} \quad \text{and} \quad \xi_1^* = \dots = \xi_{N-1}^* = \frac{X_0 - 2\xi_0^*}{N-1}.$$

Improves the entangled forward-backward recursive scheme by Obizhaeva and Wang (X_t = number of shares at time t):

$$(1) \quad \begin{aligned} \xi_n^* &= \frac{1}{2} \delta_{n+1} [\epsilon_{n+1} X_{t_n} - \phi_{n+1} D_{t_n}], \quad n = 0, \dots, N-1, \\ \xi_N^* &= X_T, \end{aligned}$$

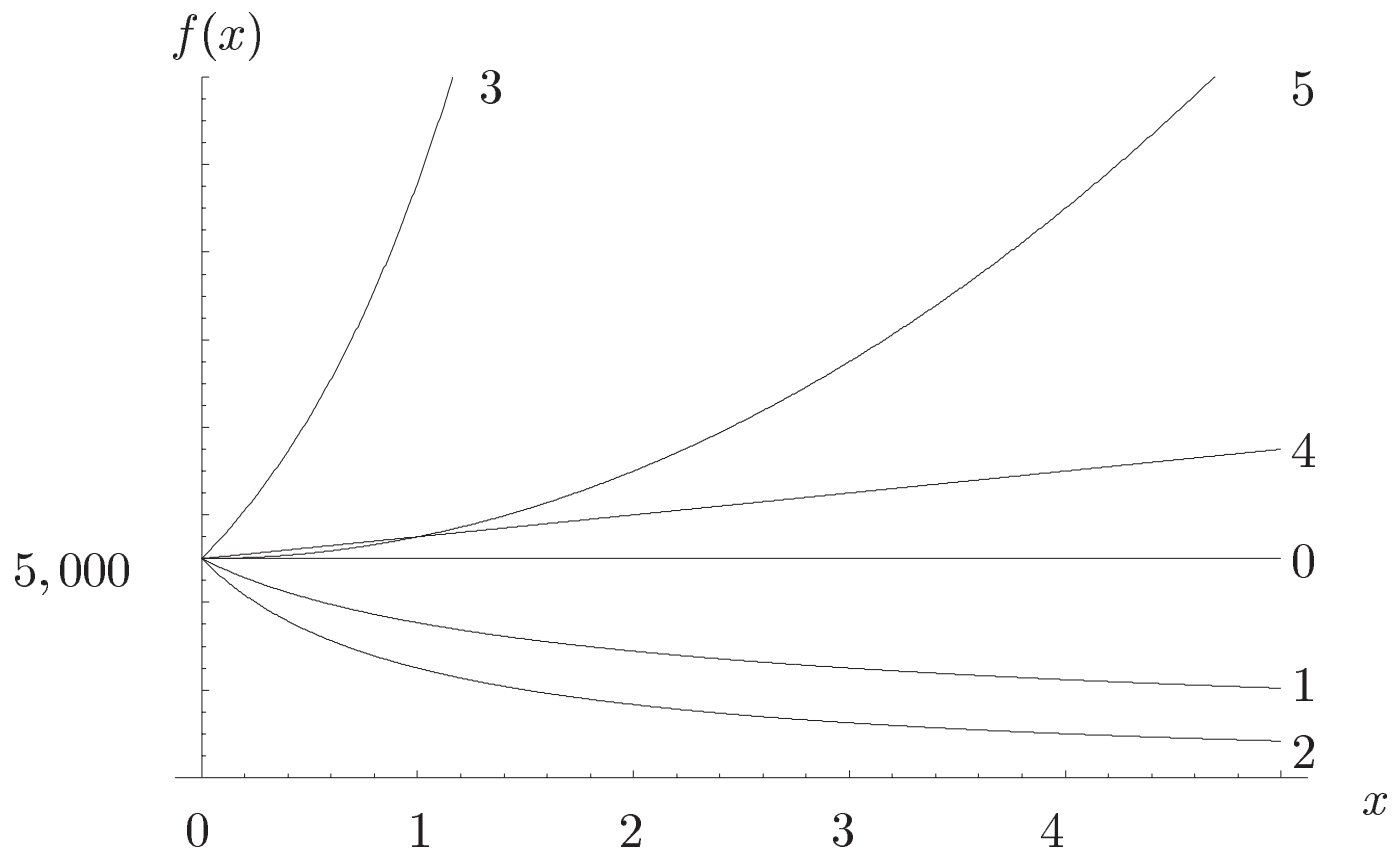
$$(2) \quad \begin{aligned} \delta_n &:= \left(\frac{1}{2q} + \alpha_n - \beta_n \kappa e^{-\rho\tau} + \gamma_n \kappa^2 e^{-2\rho\tau} \right)^{-1} \\ \epsilon_n &:= \lambda + 2\alpha_n - \beta_n \kappa e^{-\rho\tau} \\ \phi_n &:= 1 - \beta_n e^{-\rho\tau} + 2\gamma_n \kappa e^{-2\rho\tau}. \end{aligned}$$

$$(3) \quad \begin{aligned} \alpha_N &= \frac{1}{2q} - \lambda \quad \text{and} \quad \alpha_n = \alpha_{n+1} - \frac{1}{4} \delta_{n+1} \epsilon_{n+1}^2, \\ \beta_N &= 1 \quad \text{and} \quad \beta_n = \beta_{n+1} e^{-\rho\tau} + \frac{1}{2} \delta_{n+1} \epsilon_{n+1} \phi_{n+1}, \\ \gamma_N &= 0 \quad \text{and} \quad \gamma_n = \gamma_{n+1} e^{-2\rho\tau} - \frac{1}{4} \delta_{n+1} \phi_{n+1}^2. \end{aligned}$$

Further **Theorems:**

- Analogous (but different) result for exponential recovery of E^B .
- Explicit solution for inhomogeneous recovery (block-shaped LOB)
- Explicit solutions under linear constraints (block-shaped LOB).

Example shape functions:



Example number	$f(x)$	Recovery of E			Recovery of D		
		ξ_0^*	ξ_1^*	ξ_N^*	ξ_0^*	ξ_1^*	ξ_N^*
0	q	10,223	8,839	10,223	10,223	8,839	10,223
1	$\frac{q}{\sqrt{ x +1}}$	10,257	8,869	9,925	10,756	8,724	10,726
2	$\frac{q}{ x +1}$	10,303	8,909	9,520	13,305	8,154	13,305
3	$qe^{ x }$	10,139	8,767	10,962	9,735	8,947	9,741
4	$\frac{q}{10} x + q$	10,211	8,829	10,326	10,130	8,860	10,131
5	$\frac{q}{10}x^2 + q$	10,192	8,812	10,498	10,101	8,868	10,091

Table 1: The table shows optimal strategies for various choices of the shape function f . We set $X_0 = 100,000$ and $q = 5,000$ shares, $\rho = 20$, $T = 1$ and $N = 10$.

Sketch of proof:

1. Step: reduction to deterministic optimization problem

Introduce simplified dynamics with [collapsed bid-ask spread](#)

- $E_0 = D_0 = 0$ and

$$E_t = F(D_t) \quad \text{and} \quad D_t = F^{-1}(E_t).$$

- Regardless of the sign of ξ_n ,

$$E_{t_n+} = E_{t_n} + \xi_n \quad \text{and} \quad D_{t_n+} = F^{-1}(\xi_n + F(D_{t_n})).$$

- For $k = 0, \dots, N - 1$,

$$D_{t_{k+1}} = e^{-\rho\tau} D_{t_k+}$$

Then

$$E_t^B \leq E_t \leq E_t^A \quad \text{and} \quad D_t^B \leq D_t \leq D_t^A.$$

Introduce simplified revenues

$$\bar{\rho}_{t_n}(\xi_n) := B_{t_n}^0 \xi_n + \int_{D_{t_n+}}^{D_{t_n}} x f(x) dx,$$

They satisfy

$$\bar{\rho}_{t_n}(\xi_n) \geq \rho_{t_n}(\xi_n) \quad \text{with equality if } \xi_k \geq 0 \text{ for all } k.$$

The simplified revenues functional is

$$\bar{\mathcal{R}}(\xi) = \mathbb{E} \left[\sum_{n=0}^N \bar{\rho}_{t_n}(\xi_n) \right].$$

With $X_t = X_0 - \sum_{t_k < t} \xi_k$ for $t \leq T$ and $X_{t_{N+1}} := 0$,

$$\sum_{n=0}^N B_{t_n}^0 \xi_n = - \sum_{n=0}^N B_{t_n}^0 (X_{t_{n+1}} - X_{t_n}) = X_0 B_0 + \sum_{n=1}^N X_{t_n} (B_{t_n}^0 - B_{t_{n-1}}^0).$$

Hence,

$$\bar{\mathcal{R}}(\xi) = B_0 X_0 + \mathbb{E} \left[R(\xi_0, \dots, \xi_N) \right],$$

where for any deterministic strategy (x_0, \dots, x_N)

$$R(x_0, \dots, x_N) := \sum_{n=0}^N \int_{D_{t_n}^+}^{D_{t_n}} x f(x) dx.$$

2. Step: deterministic optimization problem

Let

$$\Xi := \left\{ (x_0, \dots, x_N) \in \mathbb{R}^{N+1} \mid \sum_{n=0}^N x_n = X_0 \right\}.$$

We will show that R has a unique minimum on Ξ that coincides with the optimal strategy.

With

$$\tilde{F}(x) = \int_0^x y f(y) dy, \quad G(x) = \tilde{F}(F^{-1}(x)), \quad \text{and } a := e^{-\rho\tau}$$

we have

$$\begin{aligned} R(x_0, \dots, x_N) &= \sum_{n=0}^N \left(\tilde{F}(F^{-1}(E_{t_n})) - \tilde{F}(F^{-1}(E_{t_{n+}})) \right) \\ &= \sum_{n=0}^N \left(G(E_{t_n}) - G(E_{t_n} + x_n) \right) \\ &= G(0) - G(x_0) \\ &\quad + G(ax_0) - G(ax_0 + x_1) \\ &\quad + G(a^2x_0 + ax_1) - G(a^2x_0 + ax_1 + x_2) \\ &\quad + \dots \\ &\quad + G(a^N x_0 + \dots + ax_{N-1}) - G(a^N x_0 + \dots + x_N). \end{aligned}$$

Lemma 3 *We have $R(x_0, \dots, x_N) \rightarrow -\infty$ for $|\xi| \rightarrow \infty$, and therefore there exists a local maximum of R in Ξ .*

Thanks to Lemma 3, there is at least one optimal strategy $\xi^* = (x_0^*, \dots, x_N^*) \in \Xi$, and so there exists a Lagrange multiplier $\nu \in \mathbb{R}$ such that

$$\frac{\partial}{\partial x_j} R(x_0^*, \dots, x_N^*) = \nu \quad \text{for } j = 0, \dots, N.$$

Note

$$G'(x) = F^{-1}(x).$$

$$\frac{\partial}{\partial x_j} R(x_0, \dots, x_N) = a \left[\frac{\partial}{\partial x_{j+1}} R(x_0, \dots, x_N) + G' (a(a^j x_0 + \dots + x_j)) \right] - G' (a^j x_0 + \dots + x_j)$$

Hence

$$\nu = a\nu + h(a^j x_0^* + \dots + x_j^*).$$

and

$$x_0^* = h^{-1} (\nu (1 - a))$$

$$x_j^* = x_0^* (1 - a) \quad \text{for } j = 1, \dots, N - 1$$

$$x_N^* = X_0 - x_0^* - (N - 1)x_0^* (1 - a).$$

More computations now yield equation for x_0^*

2. Optimal execution and risk aversion

Risk-neutral evaluation does not capture **volatility risk**. Must introduce **risk aversion**.

The limit order book model is **too complicated**.

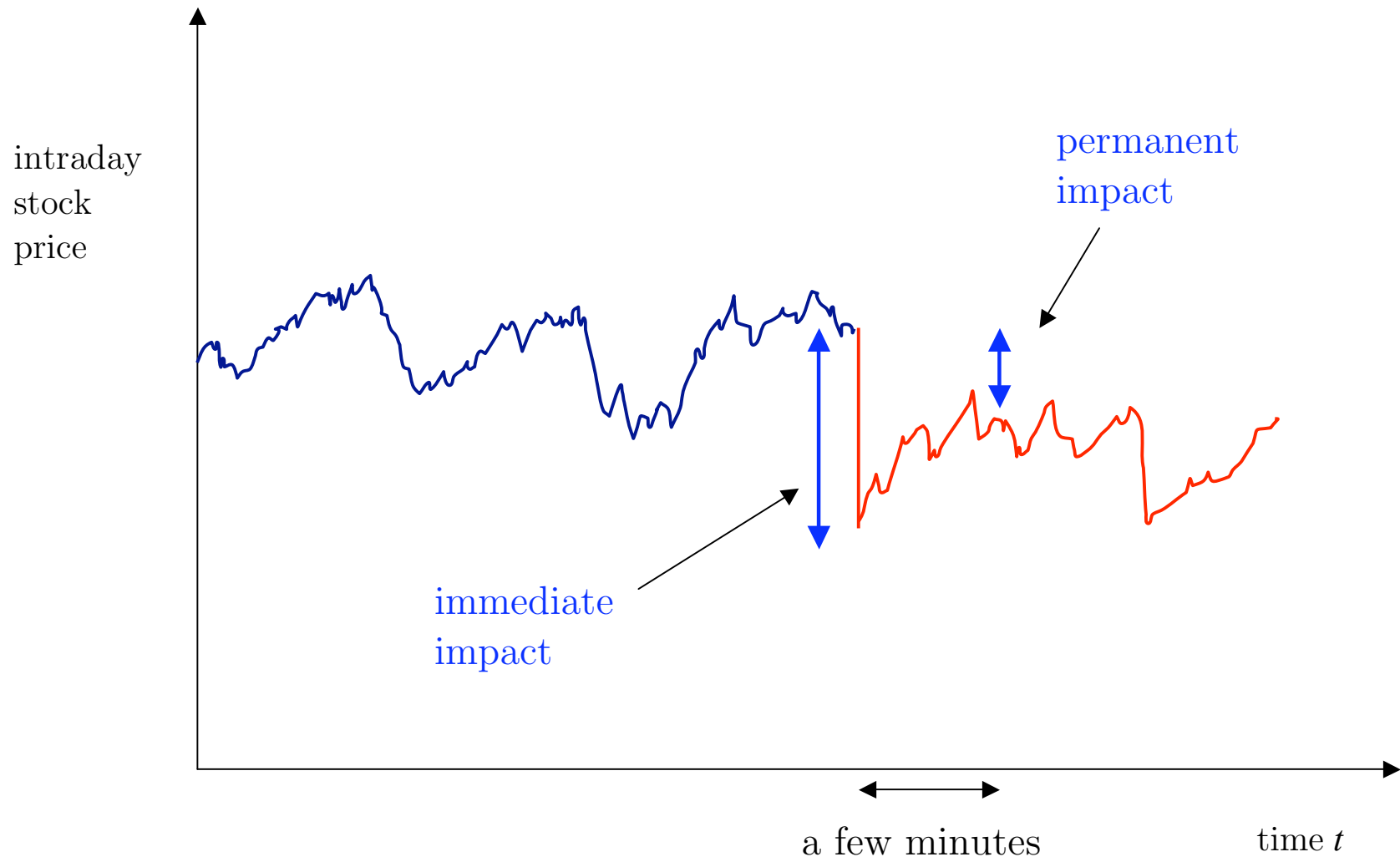
Results are based on simpler model.

- Almgren & Chriss, Almgren & Lorenz: **mean-variance optimization**.
- with Torsten Schöneborn: **expected utility maximization**
 - absolute risk aversion determines qualitative behavior of optimal strategies.
 - CARA case is special.

- [1] Almgren, R., Chriss, N. *Value under liquidation*. Risk, Dec. 1999.
- [2] Almgren, R., Chriss, N. *Optimal execution of portfolio transactions*. J. Risk 3, 5-39 (2000).
- [3] Almgren, R. *Optimal execution with nonlinear impact functions and trading-enhanced risk*. Applied Mathematical Finance 10, 1-18 (2003).
- [4] Almgren, R., Lorenz, J. *Adaptive arrival price*. In: Algorithmic Trading III: Precision, Control, Execution, Brian R. Bruce, editor, Institutional Investor Journals (2007).

- [5] (A.S. and T. Schöneborn) *Optimal basket liquidation with finite time horizon for CARA investors*. Preprint (2007).
- [6] (A.S. and T. Schöneborn) *Risk aversion and the dynamics of optimal liquidation strategies in illiquid markets*. Preprint (2008).

Temporary and permanent price impacts



Liquidation time: $T \in [0, \infty]$.

Strategy: X adapted with $X_0 > 0$ fixed and $X_T = 0$.

Admissible: X_t bounded, absolutely continuous in t .

Market impact model: Following Almgren (2003),

$$S_t^X = S_0 + \sigma B_t + \gamma (X_t - X_0) + h(-\dot{X}_t)$$

	↑		↑		↑		↑
	initial		Brownian		permanent		temporary
	price		motion		impact		impact
					(linear)		(nonlinear)

Most common model in practice, *drift, multiple assets* possible.

Assumption:

$$f(x) := xh(x)$$

is convex, C^1 , and satisfies $f(x)/x \rightarrow \infty$ for $|x| \rightarrow \infty$.

E.g., $h(x) = \alpha \operatorname{sign}(x) \sqrt{|x|} + \beta x$.

Sales revenues:

$$\begin{aligned} \mathcal{R}_T(X) &= \int_0^T (-\dot{X}_t) S_t^X dt = \dots \\ &= S_0 X_0 - \frac{\gamma}{2} X_0^2 + \sigma \int_0^T X_t dB_t - \int_0^T f(-\dot{X}_t) dt. \end{aligned}$$

Goal: maximize expected utility

$$\mathbb{E}[u(\mathcal{R}_T(X))]$$

over admissible strategies for u increasing, concave.

Setup as control problem

- Control process ξ_t , corresponding to $-\dot{X}_t$.

- $X_t^\xi := X_0 - \int_0^t \xi_s ds$

- controlled diffusion:

$$R_t^\xi = R_0 + \sigma \int_0^t X_s^\xi dB_s - \int_0^t f(\xi_s) ds$$

- value function

$$v(T, X_0, R_0) = \sup_{\xi \in \mathcal{X}_T(X_0)} \mathbb{E} [u(R_T^\xi)],$$

where

$$\mathcal{X}_T(X_0) = \left\{ \xi \mid X^\xi \text{ is bounded and } \int_0^T \xi_t dt = X_0 \right\}$$

Heuristic derivation of HJB equation

$$dv(T - t, X_t^\xi, R_t^\xi) = \sigma v_R X_t^\xi dB_t + \left(-v_t - \xi_t v_X + v_R f(\xi_t) + \frac{\sigma^2}{2} (X_t^\xi)^2 v_{RR} \right) dt$$

Hence

$$v_t = \frac{\sigma^2}{2} X^2 v_{RR} - \inf_{\xi} (\xi v_X + v_R f(\xi))$$

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What about the constraint $\int_0^T \xi_t dt = X_0$? It is in the initial condition:

$$\lim_{T \downarrow 0} v(T, X, R) = \begin{cases} u(R) & \text{if } X = 0, \\ -\infty & \text{otherwise.} \end{cases}$$

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Theorem: If $u(x) = -e^{-\alpha x}$ for some $\alpha > 0$, then the unique optimal strategy ξ^* is a deterministic function of t . Moreover, v is a classical solution of the singular HJB equation.

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The fact that optimal strategies for CARA investors are deterministic is very **robust**. Is also true

- if Brownian motion is replaced by a Lévy process;
- for the limit order book model in part 1.

(A.S., T. Schöneborn, and M. Tehranci, in preparation).

Example: For linear temporary impact, $f(x) = \lambda x^2$, the optimal strategy is

$$\xi_t^* = X_0 \sqrt{\frac{\alpha \sigma^2}{2\lambda}} \cdot \frac{\cosh\left((T-t)\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right)}{\sinh\left(T\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right)}$$

$$X_t^{\xi^*} = X_0 \cdot \frac{\cosh\left(t\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right) \sinh\left(T\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right) - \cosh\left(T\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right) \sinh\left(t\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right)}{\sinh\left(T\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right)}$$

The value function is

$$v(T, R_0, X_0) = -\exp\left[-\alpha(R_0 + \tilde{S}_0 X_0 - \frac{\gamma}{2} X_0^2) + X_0^2 \sqrt{\frac{\lambda \alpha^3 \sigma^2}{2}} \coth\left(T\sqrt{\frac{\alpha \sigma^2}{2\lambda}}\right)\right]$$

Results for other utility functions not available at this time, because of difficult PDE.

⇒ Consider infinite-time horizon instead

- Assume also linear temporary impact:

$$f(x) = \lambda x^2$$

- Utility function $u \in C^6(\mathbb{R})$ such that the absolute risk aversion,

$$A(R) := -\frac{u''(R)}{u'(R)} \quad (= \text{constant for exponential utility}),$$

satisfies

$$0 < A_{min} \leq A(R) \leq A_{max} < \infty.$$

Recall

$$R_t^\xi = R_0 + \sigma \int_0^t X_s^\xi dB_s - \lambda \int_0^t \xi_s^2 ds.$$

- Optimal liquidation:

$$\text{maximize } \mathbb{E}[u(R_\infty^\xi)]$$

- Maximization of asymptotic portfolio value:

$$\text{maximize } \lim_{t \uparrow \infty} \mathbb{E}[u(R_t^\xi)]$$

Note: Liquidation enforced by the fact that a risk-averse investor does not want to hold a stock whose price process is a martingale.

Recall

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Note: Liquidation enforced by the fact that a risk-averse investor does not want to hold a stock whose price process is a martingale.

Theorem: Both problems are equivalent.

HJB equation for finite time horizon:

$$v_t = \frac{\sigma^2}{2} X^2 v_{RR} - \inf_{\xi} (\xi v_X + v_R \xi^2)$$

Guess for infinite time horizon:

$$0 = \frac{\sigma^2}{2} X^2 v_{RR} - \inf_{\xi} (\xi v_X + v_R \xi^2)$$

Initial condition:

$$v(0, R) = u(R).$$

HJB equation for finite time horizon:

$$v_t = \frac{\sigma^2}{2} X^2 v_{RR} - \inf_{\xi} (\xi v_X + v_R \xi^2)$$

Guess for infinite time horizon:

$$0 = \frac{\sigma^2}{2} X^2 v_{RR} - \inf_{\xi} (\xi v_X + v_R \xi^2)$$

Initial condition:

$$v(0, R) = u(R).$$

Corresponding reduced-form equation:

$$v_X^2 = -2\lambda\sigma^2 X^2 v_R \cdot v_{RR}$$

Not very nice either.....

Way out: consider optimal Markov control in HJB equation

$$\widehat{\xi}(X, R) = -\frac{v_X(X, R)}{2\lambda v_R(X, R)}$$

and let

$$\widetilde{c}(Y, R) = \frac{\widehat{\xi}(\sqrt{Y}, R)}{\sqrt{Y}}.$$

If v solves the HJB equation, then \widetilde{c} solves

$$(*) \quad \begin{cases} \widetilde{c}_Y = \frac{\sigma^2}{4\widetilde{c}}\widetilde{c}_{RR} - \frac{3}{2}\lambda\widetilde{c}\widetilde{c}_R \\ \widetilde{c}(0, R) = \sqrt{\frac{\sigma^2 A(R)}{2\lambda}} \end{cases}$$

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Theorem: (*) admits a unique classical solution $\widetilde{c} \in C^{2,4}$ satisfying

$$\sqrt{\frac{\sigma^2 A_{min}}{2\lambda}} \leq \widetilde{c}(Y, R) \leq \sqrt{\frac{\sigma^2 A_{max}}{2\lambda}}$$

Next, there exists a $C^{2,4}$ -solution \tilde{w} of the transport equation

$$\begin{cases} \tilde{w}_Y = -\lambda \tilde{c} \tilde{w}_R \\ \tilde{w}(0, R) = u(R). \end{cases}$$

Next, there exists a $C^{2,4}$ -solution \tilde{w} of the transport equation

$$\begin{cases} \tilde{w}_Y = -\lambda \tilde{c} \tilde{w}_R \\ \tilde{w}(0, R) = u(R). \end{cases}$$

Theorem: $w(X, R) := \tilde{w}(X^2, R)$ is a smooth solution of the HJB equation

$$0 = \frac{\sigma^2}{2} X^2 w_{RR} - \inf_{\xi} (\xi w_X + w_R \xi^2), \quad w(0, R) = u(R).$$

The unique minimizer is

$$\hat{\xi}(X, R) = -\frac{w_X(X, R)}{2\lambda w_R(X, R)} = \tilde{c}(X^2, R)X$$

Estimates on w and a verification argument yield

Theorem: w is the value function:

$$w(X_0, R_0) = v(X_0, R_0) = \max_{\xi} \mathbb{E}[u(R_{\infty}^{\xi})].$$

The unique optimal strategy is given by

$$\xi_t^* = -\dot{X}_t^* = \widehat{\xi}(X_t^*, R_t^{X^*}).$$

Moreover, $R \mapsto v(X, R)$ is a utility function for each X and

$$\tilde{c}(X, R) = \sqrt{\frac{\sigma^2 A(X, R)}{2\lambda}},$$

where $A(X, R)$ is the absolute risk aversion of $v(X, \cdot)$ at R .

Corollary: If $u(R) = -e^{-AR}$, then

$$X_t^{\xi^*} = X_0 \exp\left(-t\sqrt{\frac{\sigma^2 A}{2\lambda}}\right).$$

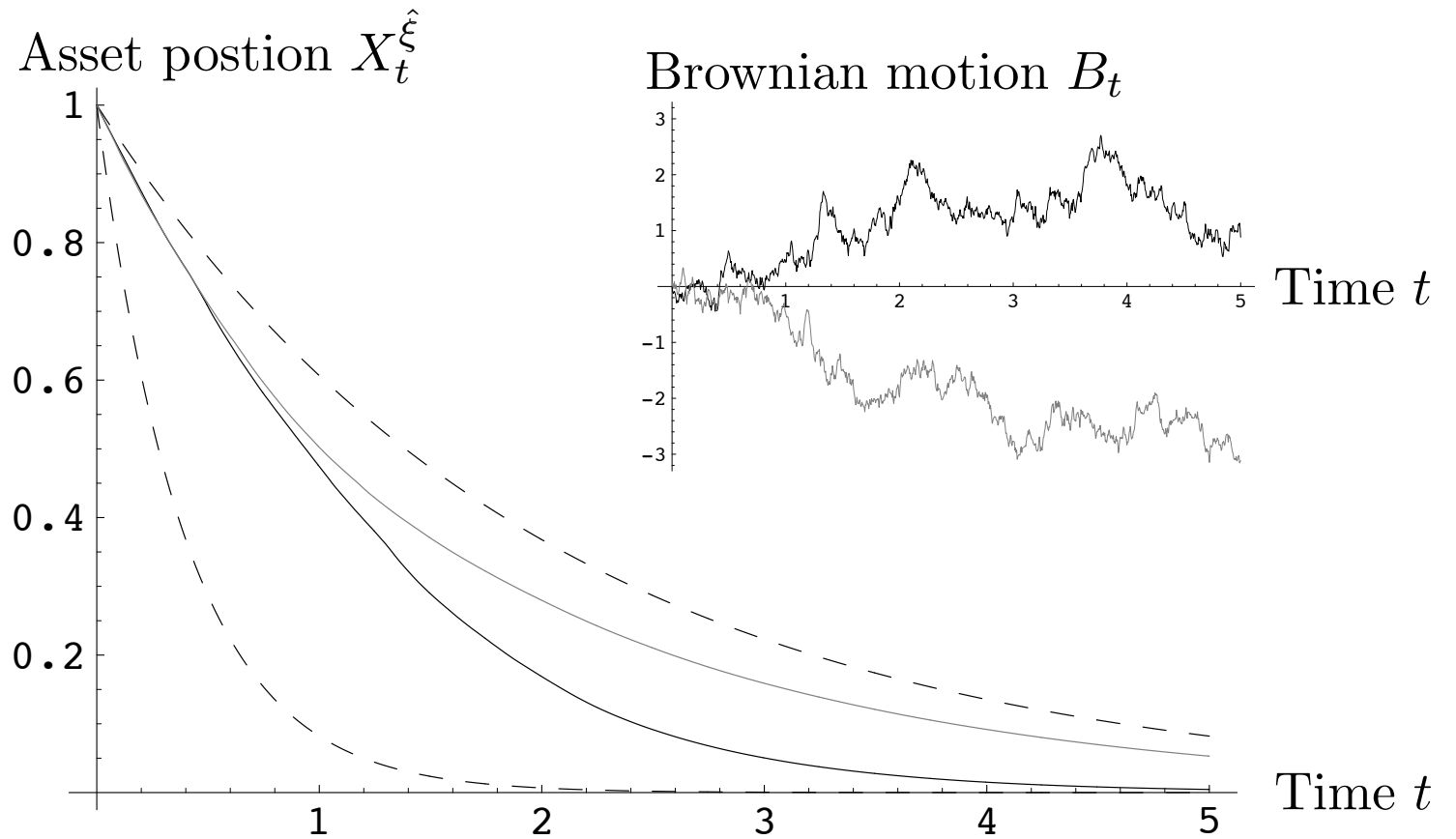
Corollary: If $u(R) = -e^{-AR}$, then

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General result:

Theorem: The optimal strategy $\hat{\xi}(X, R)$ is **increasing** (**decreasing**) in R iff $A(R)$ is **increasing** (**decreasing**). I.e.,

Utility function		Optimal trading strategy
DARA	\iff	Passive in the money
CARA	\iff	Neutral in the money
IARA	\iff	Aggressive in the money



Two optimal strategies for the IARA utility function with

$$A(R) = 2(1.5 + \tanh(R - 100))^2.$$

Theorem: If u^1 and u^0 are such that $A^1 \geq A^0$ then $\hat{\xi}^1 \geq \hat{\xi}^0$.

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Idea of Proof: $g := \tilde{c}^1 - \tilde{c}^0$ solves

$$g_Y = \frac{1}{2}ag_{RR} + bg_R + Vg,$$

where

$$a = \frac{\sigma^2}{2\tilde{c}^0}, \quad b = -\frac{3}{2}\lambda\tilde{c}^1, \quad \text{and} \quad V = -\frac{\sigma^2\tilde{c}^1_{RR}}{4\tilde{c}^0\tilde{c}^1} - \frac{3}{2}\lambda\tilde{c}^0_R.$$

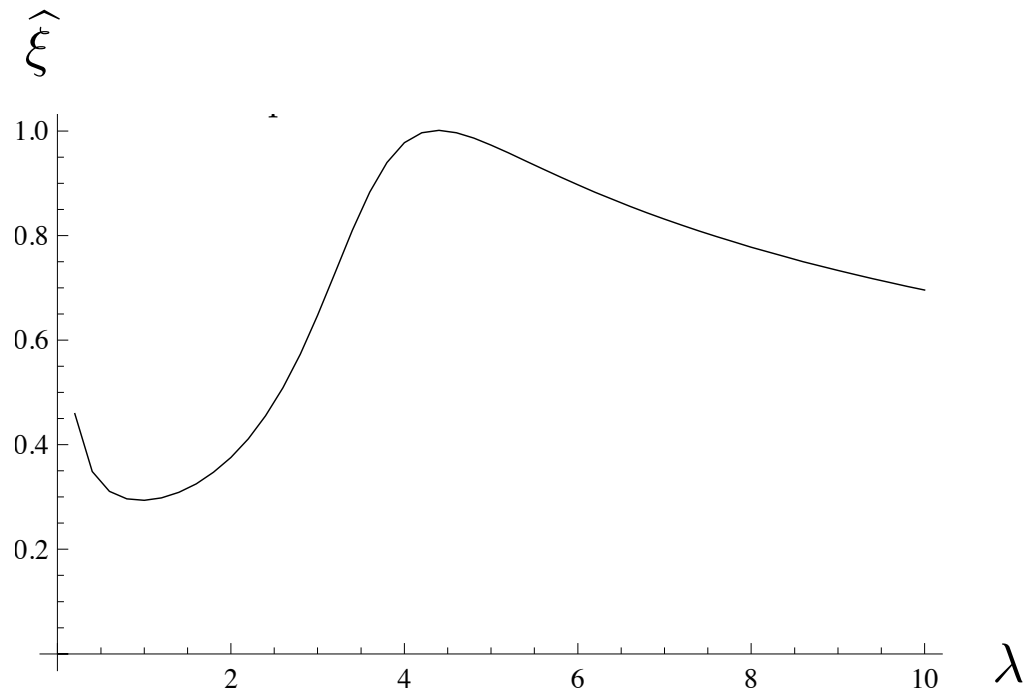
The boundary condition of g is

$$g(0, R) = \sqrt{\frac{\sigma^2 A^1(R)}{2\lambda}} - \sqrt{\frac{\sigma^2 A^0(R)}{2\lambda}} \geq 0$$

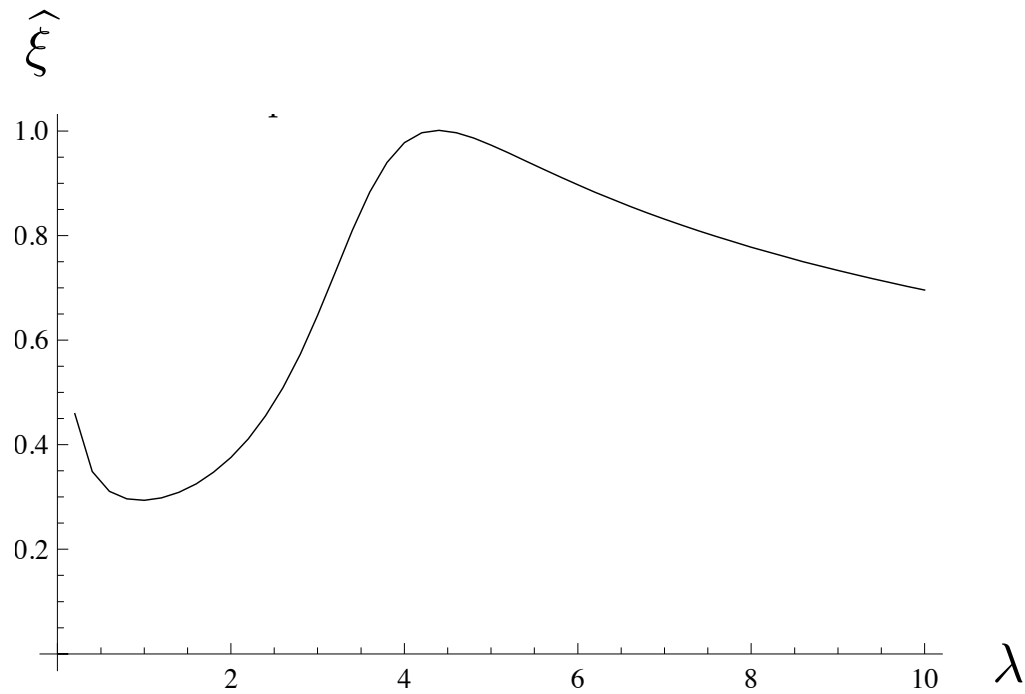
Now maximum principle or Feynman-Kac argument....
(plus localization)

What about other monotonicity relations?

- Monotonicity in λ : intuitively, an increase in liquidation costs should lead to a decrease of liquidation speed.



Dependence of the optimal strategy $\hat{\xi}$ on λ for the DARA utility function with $A(R) = 2(1.2 - \tanh(15R))^2$.

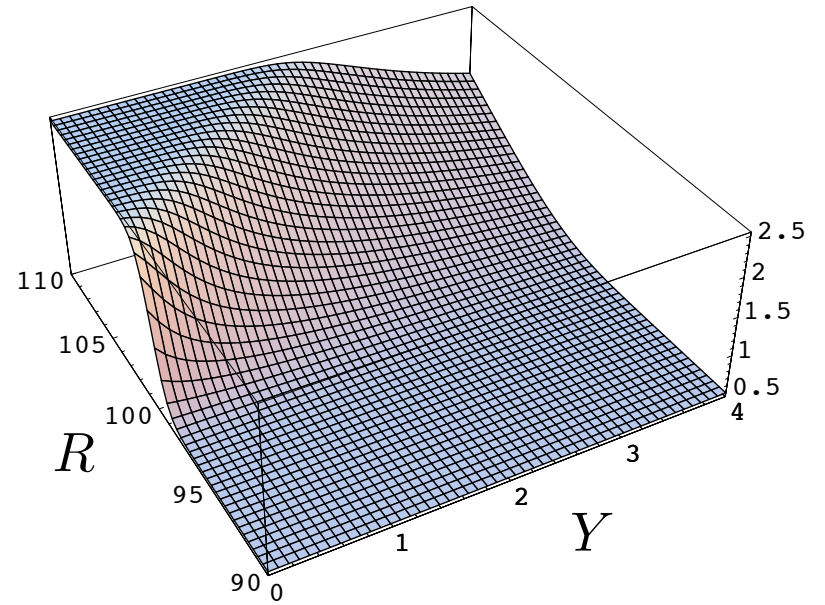
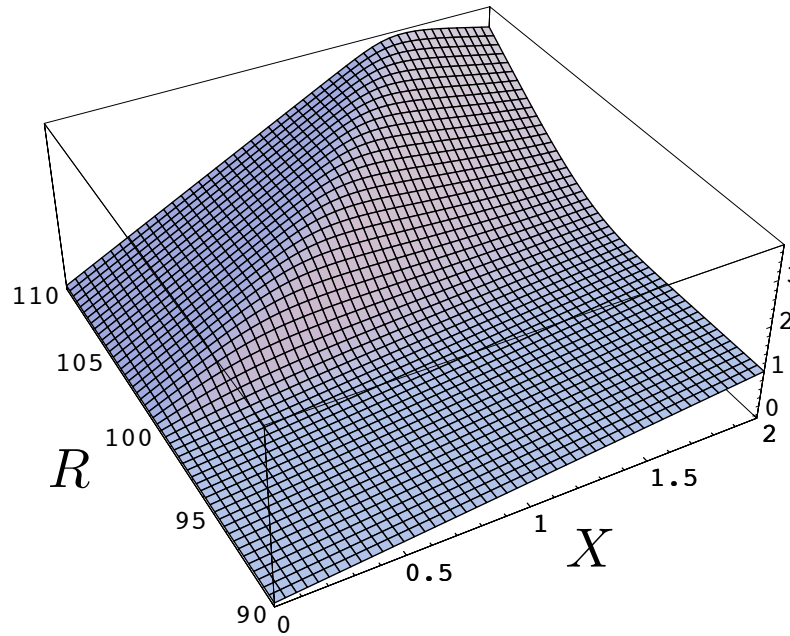


Dependence of the optimal strategy $\hat{\xi}$ on λ for the DARA utility function with $A(R) = 2(1.2 - \tanh(15R))^2$.

Theorem: IARA $\implies \hat{\xi}$ is decreasing in λ .

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- Monotonicity in λ : intuitively, an increase in liquidation costs should lead to a decrease of liquidation speed.
- Monotonicity in X : intuitively, larger asset position should lead to an *increased* liquidation speed.



$$\hat{\xi}(X, R)$$

and

$$\tilde{c}(Y, R)$$

IARA utility function with $A(R) = 2(1.5 + \tanh(R - 100))^2$ and parameter $\lambda = \sigma = 1$.

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Thank you for your attention