



Tractable SPDE Models for Order Books

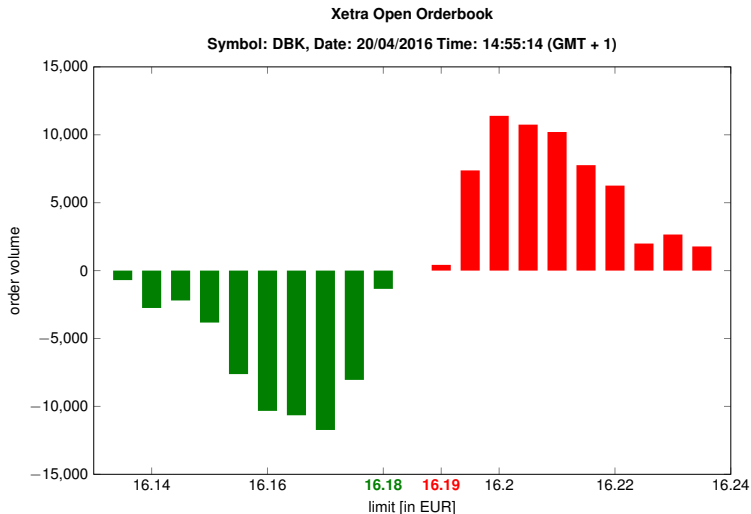
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Joint work in progress with R. Cont (Imperial) and M. Keller-Ressel (TU Dresden)

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Limit Order Books



High-Dimensional Modeling

Mid price: $s := (p_{\text{bid}} + p_{\text{ask}})/2$

LOB Model: $v_t(p)$ density of LOB, centered: $u_t(p) := v_t(p + s_t)$

Observations and Assumptions

- HFT: > 1000 orders per 10sec on average for some US stocks
(Cont et al 2011)
- On average, orders arrive at prices p

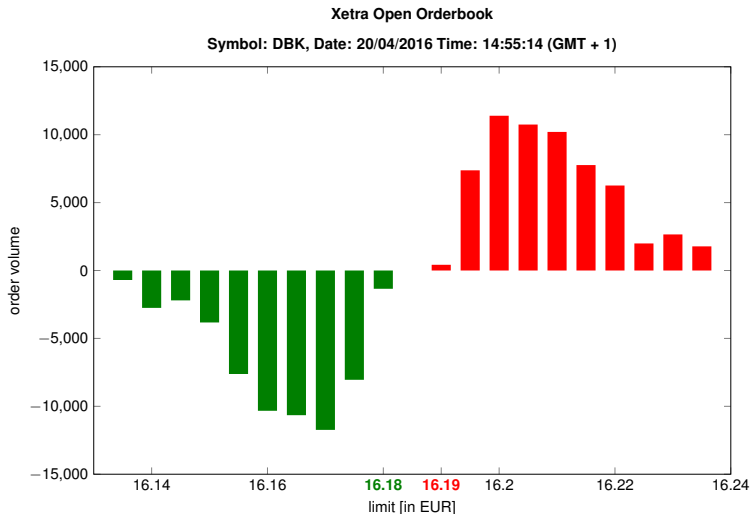
$$\sim a(b + |p - s_t|)^{-1-\mu}, \quad \mu \in [0.6, 1.5]$$

(Bouchaud et al (2002), Zovko, Farmer (2006))

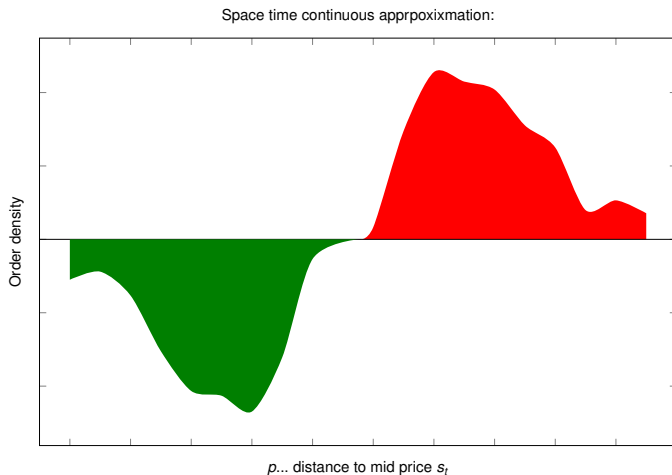
→ price-time-continuous model,

→ no spread, $p_{\text{bid}} = p_{\text{ask}} = s$.

Limit Order Books: Discrete Reality



Limit Order Books: Centered Density $u_t(p)$



Motivation

Since 2000, many authors studied (stochastic) PDEs for demand & supply / order book modeling, often in terms of approximation or MFG results.

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Here:

1. Directly set up *macroscopic* description of order book dynamics in highly liquid markets.
2. Keep assumptions basic, focus on *tractability*.
3. *Calibration!*

Macroscopic Order Book Dynamics

1. Small order readjustments of HF-traders: rate η
2. Tendency to shift orders in direction to bid/ask (HF-traders): rate β
3. Net impact rate for order volume, of LF and HF-traders: α
4. LF-net impact due to exogeneous information: $g(p)$
5. HF-trader impact on volume: dM_t

Order book density

With $dp, dt \rightarrow 0$, we impose for the centered order book density

$$du_t(p) = \underbrace{[\eta_a \Delta u_t(p) + \beta_a \nabla u_t(p) + \alpha_a u_t(p) + g_a(p)]}_{=A_a u_t + g_a} dt + u_t(p) dM_t^a.$$

for $p > 0$ (< 0 resp.) where M^a is a \mathbb{R} -valued cts local martingale.

Linear Models

On an abstract level,

$$\begin{cases} du_t(p) = A_a u_t(p) dt + u_t(p) dM_t^a, & p \in (0, L), \\ du_t(p) = A_b u_t(p) dt + u_t(p) dM_t^b, & p \in (-L, 0). \end{cases} \quad (1)$$

M^a, M^b are cts loc martingales and A_a, A_b are linear (unbounded) maps s. t. $\exists!$ strong solution, for reasonable initial data u_0 .

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Theorem (Cont, Keller-Ressel, M. (2017))

The unique solution of (1) is

$$u_t(p) = g_t(p) \left[\mathcal{E}_t(M^b) \mathbf{1}_{(-L,0)}(p) + \mathcal{E}_t(M^a) \mathbf{1}_{(0,L)}(p) \right].$$

where g solves (1) for $M^{a/b} \equiv 0$.

In particular, u is a local martingale iff $Ah = 0$.

Spectral Analysis

Imposing Dirichlet bdy cond., the real eigenvalues of $A := \eta \Delta + \beta \nabla + \alpha$ on $(0, L)$ are

$$\nu_k := \alpha - k^2 \frac{\eta \pi^2}{L^2} - \frac{\beta^2}{4\eta}, \quad k \in \mathbb{N},$$

for resp. eigenfcts

$$e_k(p) := e^{-\frac{\beta}{2\eta}p} \sin\left(\frac{k\pi}{L}p\right).$$

Observation

The only positive eigenfct is e_1 for the principle eigenvalue $\nu := \nu_1$.

$$\left\{ \begin{array}{l} du_t(p) = [\eta^a \Delta u_t(p) + \beta^a \nabla u_t(p) + \alpha^a u_t(p)] dt \\ \quad \quad \quad + \sigma^a u_t(p) dW_t^a, \quad p \in (0, L), \\ du_t(p) = [\eta^b \Delta u_t(p) - \beta^b \nabla u_t(p) + \alpha^b u_t(p)] dt \\ \quad \quad \quad + \sigma^b u_t(p) dW_t^b, \quad p \in (-L, 0), \\ u_t(0+) = u_t(0-) = u(-L) = u(L) = 0, \\ u_t(p) > 0, \quad p \in (0, L), \quad u_t(p) < 0, \quad p \in (-L, 0), \quad t > 0, \end{array} \right. \quad (1)$$

From parametrization theorem: $u_t(p)$ **explicitly** computable

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From parametrization theorem: $u_t(p)$ **explicitly** computable, and

Corollary

For $u_0(p) = h(p) := \sin(\frac{\pi}{L}p) \exp\left(\pm \frac{\beta^{b/a}}{2\eta_{b/a}}p\right)$ the unique solution is

$$u_t(p) = h(p) (X_t^b \mathbf{1}_{(-L,0)}(p) + X_t^a \mathbf{1}_{(0,L)}(p)),$$

where $dX_t^{a/b} = \nu_{a/b} X_t^{a/b} dt + \sigma_{a/b} X_t^{a/b} dW_t^{a/b}$

Order Book Shape

$$u_0(p) := \begin{cases} e^{\frac{\beta}{2\eta} p} \sin\left(\frac{\pi}{L} p\right), & p < 0 \\ e^{-\frac{\beta}{2\eta} p} \sin\left(\frac{\pi}{L} p\right), & p > 0. \end{cases}$$

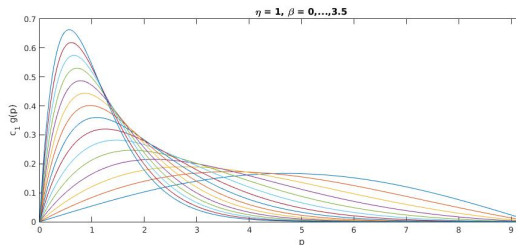
$$\Rightarrow u_t(p) = u_0(p) e^{\sigma_{a/b} W_t^{a/b} + \left(\nu_{a/b} - \frac{1}{2} \sigma_{a/b}^2\right) t},$$

Calibration

- Profile attains its maximum at:

$$\hat{p}_a := \operatorname{argmax}_p g^a(p) = \frac{L}{\pi} \arctan\left(\frac{2\eta_a \pi}{\beta_a L}\right) \approx \frac{2\eta_a}{\beta_a}$$

$\Rightarrow \frac{\beta}{2\eta}$ is determined by initial data!



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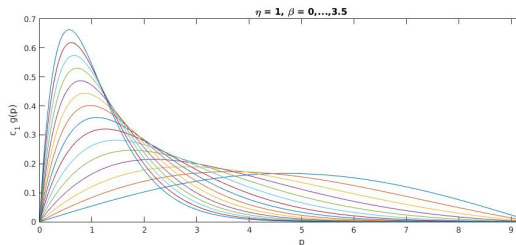
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$$\bullet \int_0^L u_t(p) dp = X_t^a \frac{4\pi L \eta^2}{L^2 \beta^2 + 4\eta^2 \pi^2} \left(e^{-\frac{\beta}{2\eta} L} + 1 \right).$$



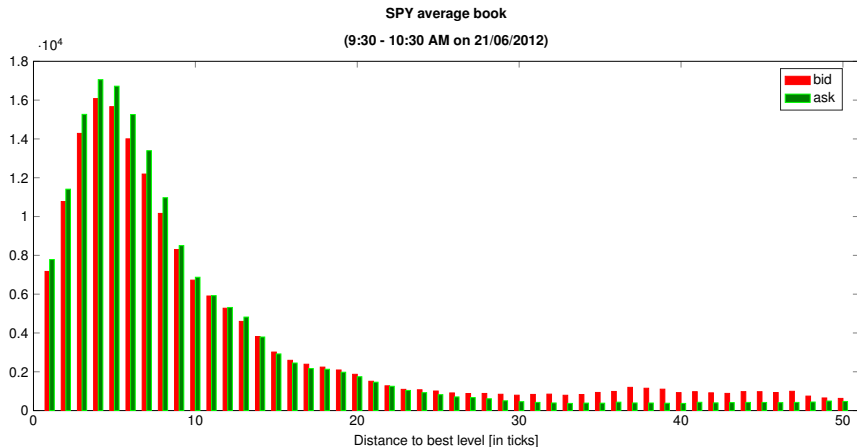


Figure: SPDR S&P 500 ETF NASDAQ data provided by LOBster

Total Order Volume in the Book

Volume in the book at time t is

$$\text{TV}_t := \int_{-L}^L |u_t(p)| \, dp = \text{const}(\eta_a, \beta_a, L) X_t^a + \text{const}(\eta_b, \beta_b, L) X_t^b,$$

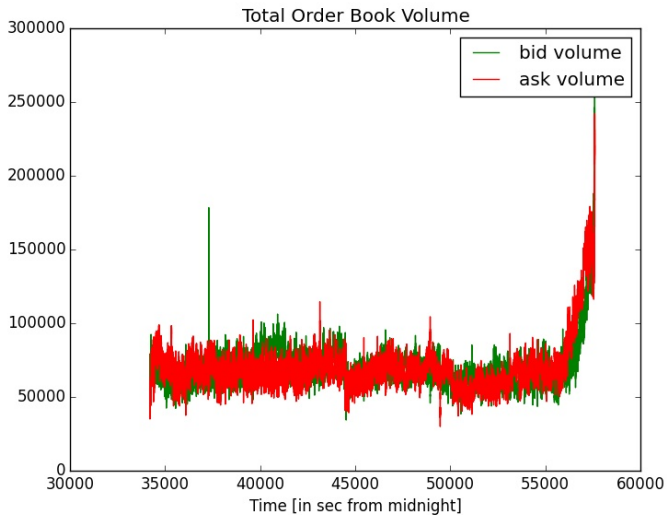
where $X_t = \exp\left(\sigma W_t + \left(\nu - \frac{1}{2}\sigma^2\right) t\right)$.

Observation:

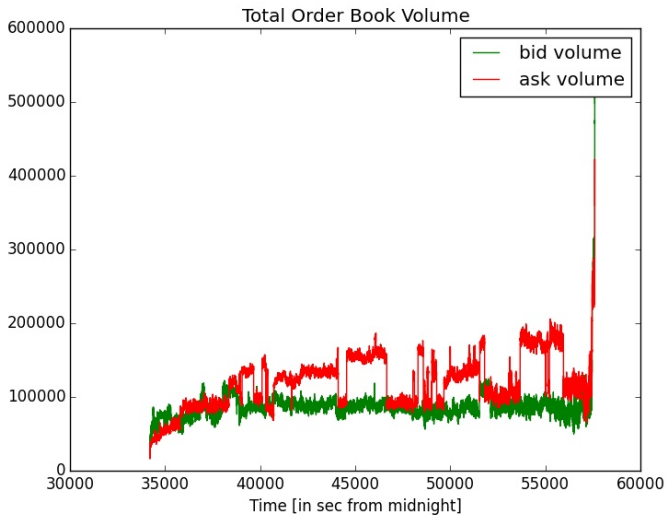
u_t and TV_t are martingales, iff

$$\alpha_{a/b} = \frac{\beta^2}{4\eta} + \frac{\pi^2\eta}{L^2}$$

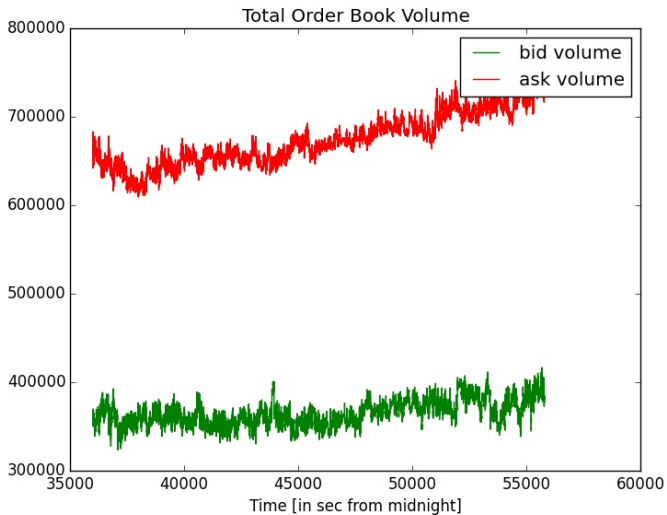
SPY 2016-06-13, first 50 levels:



MSFT 2016-09-13, first 50 levels:



INTC 2015-10-06, first 200 levels:



Linear Inhomogeneous Models

Now, keep $f(p) := \exp\left(-\frac{\beta}{2\eta}p\right) \sin\left(\frac{\pi}{L}p\right)$ and consider the inhom. model

$$\begin{aligned} du_t(p) = & \left[\eta_{a/b} \Delta u_t(p) + \beta_{a/b} \nabla u_t(p) + \alpha_{a/b} u_t(p) + \lambda_{a/b} f_{a/b}(p) \right] dt \\ & + \sigma_{a/b} u_t(p) dW_t^{a/b} \end{aligned}$$

Compared with the hom. model we hope to get

- Mean reversion for “right” choice of parameters?
- Invariant distribution, ergodicity?
- Similiar parametrization?

Linear Inhomogeneous Models II

Consider now the one-sided problems,

$$du_t(p) = [Au_t(p) + \lambda f(p)] dt + \sigma u_t(p) dW_t, \quad u_0(p) = z_0 f(p), \quad (2)$$

$p \in (0, L)$, with initial data $z_0 \in \mathbb{R}$.

Theorem (Cont, Keller-Ressel, M. (2017))

- *If f is an eigenfct for A with eigenvalue $-\nu$, then*

$$u_t(p) = f(p)Z_t,$$

where $Z_0 = z_0$ and

$$dZ_t = [\lambda - \nu Z_t] dt + \sigma Z_t dW_t.$$

- *If f is not an eigenfct, then no “reasonable” parametrization!*

The polynomial processes of type

$$dZ_t = \nu [\mu - Z_t] dt + \sigma Z_t dW_t.$$

are known in the frameworks of Pearson diffusions, GARCH-diffusion models (stoch vol), and if $\nu > 0$ in the notation:

$$dZ_t = \nu \left[\frac{\alpha}{\beta - 1} - Z_t \right] dt + \sqrt{\frac{2\nu}{\beta - 1}} Z_t^2 dW_t,$$

as reciprocal gamma diffusion.

Prop

- Z_t is ergodic, stationary distribution is invers gamma with scale and shape parameters $\alpha > 0$ and $\beta > 1$, resp.
- $\mathbb{E} |Z_t|^k < \infty$ for all $k \leq k^{\max}$, iff $k^{\max} < \beta = 1 + \frac{2\nu}{\sigma^2}$.
- explicit solution for $Z_0 > 0$
- autocorellation $\mathbb{E} Z_{t+s} Z_t = e^{-\nu t}$.

Calibration

Estimators for the parameters have been studied by many authors, e. g. Leonenko and Suvak (2010):

Method of moments

Given observations $(\bar{Z}_t)_{t=1}^N$, set $\bar{m}_1 := \frac{1}{N} \sum_{t=1}^N \bar{Z}_t$, $\bar{m}_2 := \frac{1}{N} \sum_{k=1}^N \bar{Z}_t^2$.

Then,

$$\hat{\alpha} := \frac{\bar{m}_1 \bar{m}_2}{\bar{m}_2 - \bar{m}_1}, \quad \hat{\beta} := 1 + \frac{\bar{m}_2}{\bar{m}_2 - (\bar{m}_1)^2}.$$

are P -consistent estimators, if $\beta > 4$.

Martingale estimating function for discr. observed diffusion processes (Bibby, Sørensen (1995), Leonenko and Suvak (2010)) yields P -cons. estimator for autocorrelation parameter ν (given α, β).

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$$\Rightarrow \hat{\mu} := \frac{\hat{\alpha}}{\hat{\beta}-1}, \quad \hat{\sigma} := \sqrt{\frac{\hat{\nu}}{\hat{\beta}-1}}.$$

Price Prediction

- Empirical observation (Cont et al. '13):

$$ds_t^{b/a} \approx \pm \frac{OF_{b/a}(t)}{D_{b/a}(t)}, \quad D \dots \text{depths}, \quad OF \dots \text{order flow.}$$

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- First order approx for tick size δ ,

$$D_{a/b}(t) = \pm \int_0^\delta u_t(\pm p) dp \approx \frac{\delta}{2} \nabla u_t(0\pm) = \frac{\delta \pi}{2L} Z_t^{a/b}, \quad (3)$$

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Induced Price Model I

$$ds_t = \frac{1}{2} (ds_t^b + ds_t^a) = \frac{1}{2} \left(\frac{dZ_t^b}{Z_t^b} - \frac{dZ_t^a}{Z_t^a} \right),$$

where Z^a and Z^b are the factor processes from before.

Price Dynamics

Induced Price Model II

Summarizing the price dynamics are

$$ds_t = \frac{1}{2} \left(\frac{\mu_b}{D_b(t)} - \frac{\mu_a}{D_a(t)} + (\nu_b - \nu_a) \right) dt + \sigma_b dW_t^b - \sigma_a dW_t^a,$$
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- Time inhom. extension of classical Bachelier model, based on empirical observations!
- $D_{b/a}^{-1} =: Y$ is unique solution of *logistic* SDE

$$dY_t = Y_t(\nu - \mu Y_t) dt + \sigma Y_t dW_t, \quad Y_0 = \frac{1}{D(0)}$$

Calibration: Setup

Model for depths:

$$dD_{a/b}(t) = \nu_{a/b}(\mu_{a/b} - D_{a/b}(t)) dt + \sigma_{a/b} dW_t^{a/b}, \quad (5)$$

with $[W^a, W^b]_t = \rho t$. First try:

1. Split trading day in 50ms time intervals
 \rightarrow observations $D_a(t_i)$, $D_b(t_i)$ of depths in first two levels, $i = 1, \dots, N$.
2. For t_i estimate parameters based on $D_a(t_j)$ and $D_b(t_j)$,
 $t_j \in [t_i - 30\text{min}, t_i]$.
3. Recalibrate at $t_{i+2} = t_i + 100\text{ms}$.

Run on NASDAQ data for some of most liquid large-tick stocks and SPY.

Summary

- General class of linear models
- Specific, simple subclass admits explicit solutions and fits average profiles very well (at least close to bid/ask)
⇒ Empirical justification on assumptions on the dynamics
- Linear inhomogeneous models reproduce mean-reversion of volume / depths, which is observed in the data
- Induced price models for prediction of price moves
- Fast calibration!